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CONTENTS

1 Introduction and overview

In modern economic systems the supplier (marketer) of a product or service generally encounters two major parties in the marketplace:

(i) the buyers (consumers) with their needs and preferences, who can decide whether or not to buy the offered product, and

(ii) the competitors who offer more or less similar alternative products or services, which these buyers may choose instead of the offered product to satisfy their needs.

In marketing, over a period of more than three decades, the dominant research tradition has been the study of the links between suppliers and the first party - the buyers - with an emphasis on consumer behaviour. This emphasis is understandable given that the basic characteristic of marketing is customer orientation. The work on consumer behaviour has produced important knowledge about consumer decision making and has yielded a large variety of models that can be used to predict the market share of a product, given the characteristics of the consumer population and the marketing mix of the supplier. Generally, in these models, competition is included implicitly.

Up to now, the link between suppliers and the second party - the competitors - has received a limited, but growing attention in marketing science. In the economic literature, the study of competition has a long standing tradition with 'classic' authors such as Cournot, Schumpeter, Chamberlin and Bain. In marketing, however, the early publications explicitly devoted to the issue of competition only stem from the late seventies and early eighties. In those years, competition became fiercer in many consumer markets, due to market saturation and decline, rapid development of superior technologies, and growing internationalisation of competition. As a result, firms were forced to view competitors as a more substantial market party than before. Parallel to this development, marketing scholars researched the competition issue with increasing frequency. Looking at the general textbooks on marketing one can observe this development. The early ones almost totally neglected the competition issue, treating it as a rather vague environmental factor relevant for marketing planning. For instance, in the first edition of Kotler's 'Marketing Management' (1967), competition is mentioned only casually on five pages. In Howard's early textbook 'Marketing: executive and buyer behavior' (1963), the term competition is even not included in the index at all. In contrast, in Kotler's 8th edition of 'Marketing Management' (1994), six substantial sections on competition are included (covering in total more than 50 pages), focusing on competitive intelligence systems, competitive analysis, competitive attack and defence strategies, etc. Another illustration of the growing and serious attention marketing scholars are paying to the competition issue is the fact that a special issue of the Journal of Marketing Research (August 1985) was entirely devoted to the theme 'competition in marketing'. Since then, more than 120 papers, dealing with several aspects of competition in marketing, have been published in the top scientific marketing journals.

In modern economies, the most dominant market form is the oligopolistic market where the number of suppliers is rather small and their products are typically different to some degree, but remain potential substitutes in the perception of the consumers. This implies that changes in the marketing policies of a supplier will not only affect his own marketing performance (i.e. sales, market shares, profits), but also the marketing performances of his competitors. We say that the competing firms are '***competitively linked***' to each other, which means that they are mutually dependent on each other's marketing activities with respect to their marketing performance. In this thesis we will use the term *'competitive link'* to address the mutual dependency relationship between competing firms[1]. Being competitively linked to each other implies that marketing instruments of one firm influence to some extent the marketing performance of the other. It also implies that in deciding on optimal marketing policies, each competitor has to consider the (contingent) decisions of the other competitors (Zajac and Bazerman, 1991). As a result of being involved with both parties - buyers and competitors - competing firms are continuously in a process of acting and reacting to both consumers as well as to each other. In Figure 1.1, the situation is visualised with a number of competing *firms* (Firm 1 to Firm N), each directing its own marketing proposition (i.e. product, price, communication and distribution) towards the consumers in the market and each aiming to sell its products and services to those consumers. The fully drawn arrows in Figure 1.1 represent these attempts of the firms in the direction of the *consumers*.

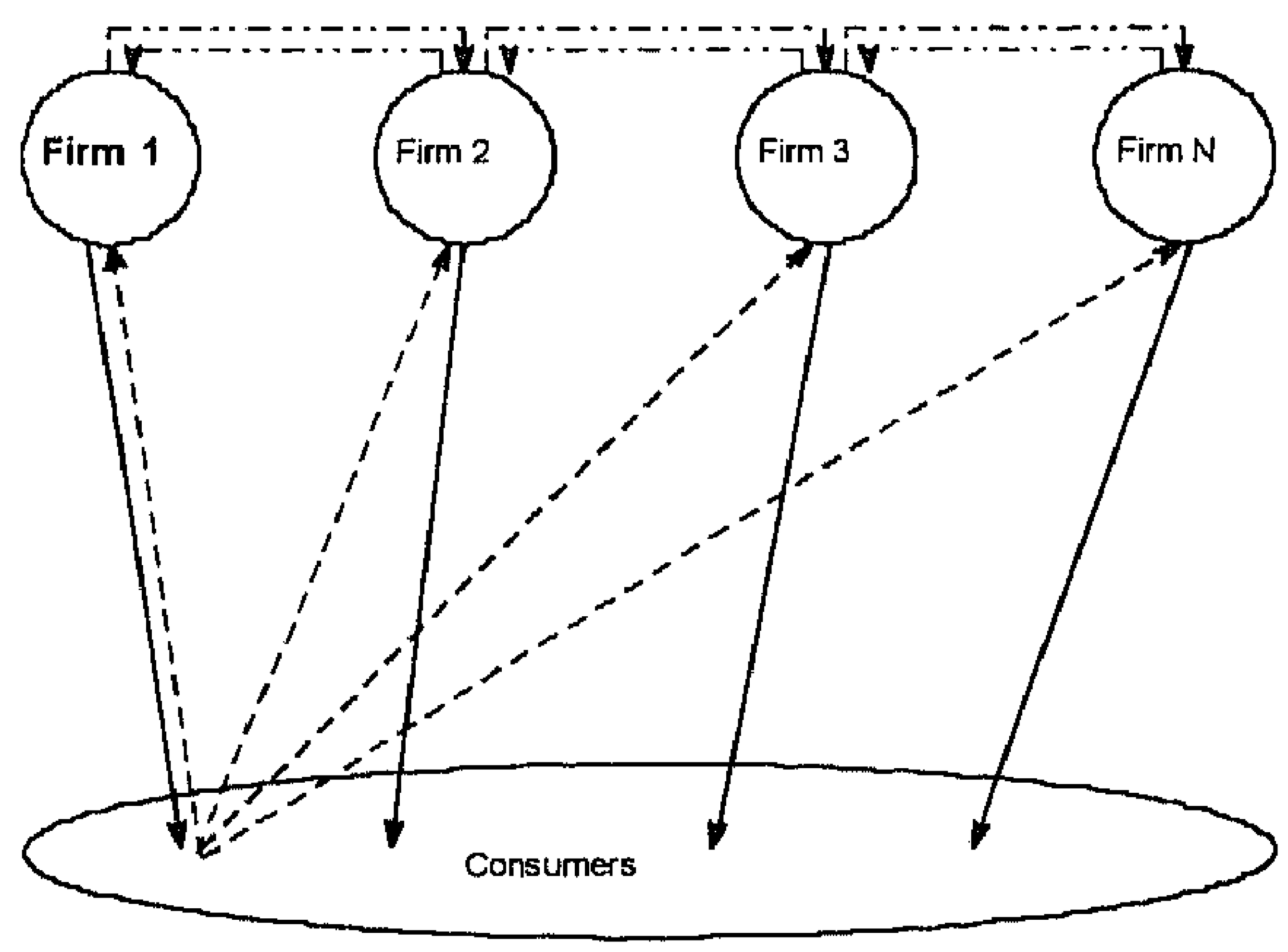

Figure 1.1 Competitive Links in Marketing

[1] Friedman (1983, p.1) calls those links 'strategic links'. In order to avoid any confusion about what is meant with the term 'strategic' we will call these links 'competitive'.

There is also a flow back from the consumers to the firms: the response of the consumers in terms of product purchases (i.e. money for the goods sold) and market information. Such a flow is represented in Figure 1.1 by a dotted arrow, back from the consumers to the acting firm (for clarity, an arrow has been drawn only for Firm 1). Because a deliberate marketing action by a firm is typically meant to influence consumers' buying behaviour (e.g., to attract more consumers and increase sales), consumers' responses to the action will not only affect the performance of the acting firm itself, but will also affect to some extent the performance of the competing firms (which might lose sales and market share). In other words, there are *cross-effects* of the marketing activities of one firm on the performance of the competitors. In Figure 1.1, these cross-effects are indicated by the dotted crosswise arrows from the consumers back to the *competing* firms (for clarity, also these arrows are drawn only from the perspective of Firm 1). These arrows can be viewed as a summary indicator of the actual competitive links between firms. They summarise the actual dependency relationships between firms, which may vary in strength toward different competitors and may also vary for the distinctive marketing instruments a firm may use.

Finally, due to their mutual dependencies via the buying behaviour of consumers, firms are continuously in a process of acting and reacting to *each other*. For example, a price reduction by one firm may be matched by the other competitors or warded off by them using promotion activities. A new product introduced by one firm may be followed by the others, etc. These marketing actions and reactions are represented by the dotted arrows between the competing firms at the top of Figure 1.1.

The framework presented in Figure 1.1 leads to three fundamental questions regarding competitive links addressed in this dissertation:

(i) With which other firms does a firm have a competitive link? We will call this the issue of the *identification* of competitive links. In terms of Figure 1.1, this issue poses the question of who are the Firms 1 to N?

(ii) How do competitive links become apparent in terms of the cross-effects of marketing instruments? We will call this the issue of the *content* of competitive links[2]. In relation to Figure 1.1, this points to the nature of the backward drawn arrows from the consumers towards the competitors.

(iii) How does a firm behave towards firms it is competitively linked with? We will call this the issue of the *conduct* regarding competitive links. It refers to the top arrows between the firms in Figure 1.1.

For diagnosing competition, a distinction has been made by Day & Wensley (1988) between 'customer-focused' and 'competitor-centered' approaches. Customer-focused approaches take the vantage point of diagnosing competition by analysing the competitors' propositions from the perspective of the customers. By contrast, competitor-centered approaches study competition by analysing the activities and performances of competitors directly. Following on this distinction, in this thesis we distinguish *three* perspectives from which competitive links will be studied: two customer-focused perspectives and a competitor-centered perspective.

The *first* perspective is customer-focused. It addresses competitive links from the vantage point of *individual consumers*. From this perspective one may try to detect the 'closeness' of products in terms of product similarities and product substitutabilities as perceived by customers. This perceived 'closeness' of products essentially forms the foundation for the competitive dependency relationships, i.e. for the competitive links between the supplying firms.

The *second* perspective is also customer-focused, but has its focal point at the *aggregate market* level. Here, competitive links may be investigated, for example, by studying the cross-elasticities regarding a firm's marketing activities with respect to the competitors' sales and shares.

The *third* perspective is competitor-centered and departs from customer-focus by analysing competition from the vantage point of the *competitors* themselves. This can be done, for example, by analysing the competing firms' action-reaction behaviour.

[2] The term 'content' is also used in connection with strategic management (cf. Pettigrew, 1988; Mintzberg, 1990). There, the content of a strategy refers to the 'what' of the strategies. Likewise, in this thesis, the content of a competitive link refers to the 'what' of a dependency relationship between competing firms.

Since these three perspectives are focused at different levels of the market constellation exhibited in Figure 1.1, we will refer to them as *levels of perspective*: (1) the *individual consumers* level, (2) the *aggregate market* level and (3) the *competitors* level. If these three levels of perspective are applied to the *identification, content, and conduct* issues of analysing competitive links, we arrive at the structure of this dissertation. It contains three main parts addressing the three research issues formulated above, while each of the issues is studied from a different perspective: Part 1 focuses on 'The identification of competitive links' and is studied in this thesis from the perspective of the individual consumers. Part 2 deals with 'The content of competitive links' which will be studied from the perspective of the aggregate market. Part 3 examines 'The conduct regarding competitive links' and will be studied from the perspective of the competitors. We will now briefly elaborate on the content of each part of the research.

Part 1 The identification of competitive links

The question to which other firms a firm is competitively linked, i.e. with whom is there a dependency relationship, can be studied on each of the three levels of perspective described above. On the competitors level one may, for instance, focus on objective technical similarities between products. Standard industry classifications (e.g., SBI- and SIC-classifications) are typical examples of such an approach. From a marketing point of view, however, the technical similarity of products is neither a necessary nor a sufficient condition for being competitively linked. In marketing science, most methods for identifying competitive links take the perspective of the consumers and can therefore be classified as customer-focused. The analysis can be done either from the aggregate market level perspective or from the individual consumer perspective. In the former case, one typically measures and analyses actual cross-effects of marketing instruments on possibly competing products (e.g., by analysing cross-elasticities). This is a *direct* way of investigating actual dependency relationships between competitors. A limitation of this approach is the fact that it depends on actual marketing activities firms have performed in the past, and one can only observe competitive links occurring as a result of those activities.

Alternatively, one can also try to identify (potential) competitive links from the individual consumers perspective. After all, in essence, competitive links arise as a result of the consumers' choice processes regarding the product offerings available to them. By studying the choice processes of consumers, for instance by analysing brand perceptions or by analysing brand switching behaviour, much can be learned about which products are 'close' to each other, at least in the mind of the consumer[3,4]. Note that this is an *indirect* way of identifying potential competitive links between firms. One assumes that if products are close to each other in the eyes of the consumer, the supplying firms will probably be mutually competitively linked. In the marketing literature, many *market structure analyses* techniques have been published, which specifically aim at identifying levels of competition among brands within a product category, based on the closeness of brands while using information from and about individual consumers. Researchers either use *judgment* information (e.g., perception data as input for MDS-analyses) or *behaviour* information (e.g., consumer purchase data for analysing brand switching behaviour) to analyse to what extent products are in competition (cf. Day, Shocker and Srivastava, 1979). Currently, new technologies are rapidly emerging, which enables the market researcher to monitor the purchase behaviour of consumers far more closely than ever before. The availability of behavioural data will probably increase further, for instance due to the development of electronic shopping. Parallel to the growing availability of data, the need for methods to analyse these data will also grow. Since, in marketing science, many methods have already been developed to this end, we devote the first research part of this thesis to investigating these methods. Chapter 2, '*Identifying competitive links based on consumer choice behaviour*', provides a review of the numerous methods developed during the past twenty-five years, which may be used by a market researcher to identify competitive links, using information about the consumers' purchase behaviour. Thus, in terms of the subtitle of this dissertation ('*a three-level perspective*'), in this part of the research, we analyse competitive links from the first-level perspective, i.e. the individual consumers.

[3] Here we refer to choice processes at the product/brand level, i.e. the process of choosing brands within a particular product category (e.g., the choice between different brands of soft drinks). Of course, choice processes and competition also exist on the level of product categories (e.g., the choice between soft drinks and coffee) or even on the generic level (e.g., the choice between food products and leisure products, cf. Abell, 1980; Kotler, 1994).

[4] In this thesis we alternately use the terms products and brands, both indicating the supplying firms' offerings to the market, unless a distinction between the two terms is necessary in the context of the discussion.

Part 2 The content of competitive links

The second research part in this dissertation (Chapters 3 and 4) focuses on the issue of the *content* of competitive links. After having identified with whom a firm is (potentially) competitively linked, the next key question is how each of these links becomes apparent in terms of the cross-effects of the marketing instruments. The cross-effects demonstrate how each pair of competing firms is actually mutually interdependent, especially with respect to their marketing activities. We will use the term 'content' of a competitive link here to address the notion that each link is 'filled' with a specific configuration of cross-effects that the different marketing instruments have on the mutual performances. Figure 1.2 illustrates this conception. The various dashed and dotted arrows can be seen as a magnification of the crosswise dotted arrows towards the competing firms exhibited in Figure 1.1. The approach for analysing the content of competitive links is essentially customer-focused. The perspective is on the aggregate market level, i.e. the *second-level* perspective.

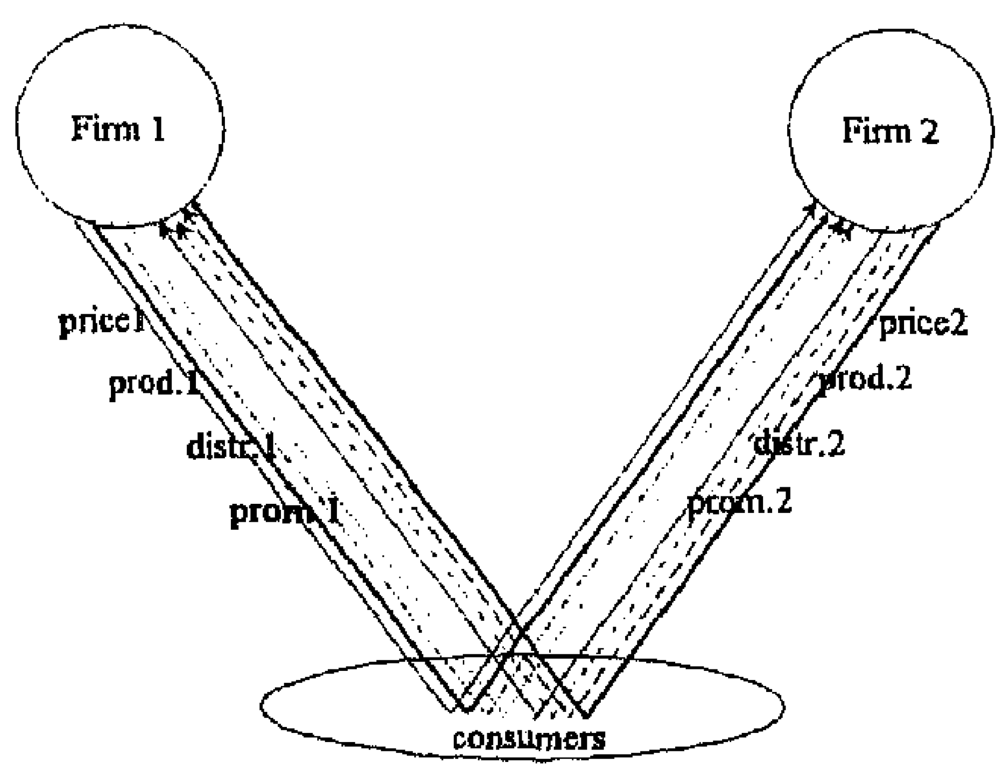

Figure 1.2 Illustration of the 'content' of a competitive link between firm 1 and a competing firm 2

This thesis contains two chapters devoted to the content issue. Chapter 3, *'Methods for analysing the content of competitive links'*, describes how in the marketing literature the content of competitive links has been studied up to now. In particular, we will discuss two prominent, but very different approaches for analysing the content of competitive links. On the one hand, an econometric approach developed by Cooper & Nakanishi (1988), called 'Competitive Maps', which analyses cross-effects in an attraction-model framework. On the other hand an abstract-deductive approach, called the 'Defender model', developed by Hauser & Shugan (1983) and Hauser & Gaskin (1984), which builds upon a consumer choice model to infer competitive links on the aggregate market level. As will be demonstrated in Chapter 3, the two approaches are similar in the sense that they both aim at inferring and analysing competitive effects of marketing instruments. They are quite divergent, however, with respect to the modelling, the methodology, the applicability, and the information provided about the content of competitive links.

One of the few methods that combine the virtues of both approaches was developed by Shugan (1987). He developed a method for inferring the brand locations in the Defender model from supermarket scanning data. While Shugan's idea is appealing, the proposed method for inferring the brand positions is subject to a number of restrictions. In Chapter 4, *'Full-information maximum likelihood estimation of brand positioning maps using supermarket scanning data'*, we will build forth on Shugan's approach, and develop an alternative method with a number of advantages. One of the main advantages of our method is, that it makes it possible to simultaneously infer both the brand locations and the consumer preference distribution from scanning data.

Part 3 The conduct regarding competitive links

The third and final part of research in this thesis concentrates on the *conduct* issue regarding competitive links. The key question is how firms go about inter(re)acting to each other, given the fact that they are mutually dependent on each others' marketing activities. This is an issue that has been studied for a long time by oligopoly theorists. Since the 1838 Cournot-model, many studies have been performed, predominantly using an abstract-deductive way of reasoning. Also in marketing science, a vast abstract-deductive research tradition exists, where 'optimal' marketing policies are deduced, given a specific set of assumptions about the market, about the behaviour of consumers, and about the firms and their offerings (cf. Eliashberg & Chatterjee, 1985). Often, game theoretical concepts are used for these purposes (cf. Moorthy, 1985, 1993). Moorthy (1993) points out, though, that the usefulness of such deductive approaches for practical competitive marketing decisions is limited: "problems arise, therefore, in using these models to recommend competitive strategies for firms...", due to the fact that "..optimal competitive strategies must necessarily be situation-specific. And the dimensionality of the 'situation-space' is large" (Moorthy, 1993, p.186).

In this thesis, however, we are not so much interested in the normative side of the conduct question ('how <u>should</u> firms behave') but rather we focus on the descriptive, empirical side of marketing conduct in competitive situations ('how <u>do</u> firms behave'). The approach for studying this issue is essentially competitor-centered, because the subject of observation is competitor response and <u>not</u> market (consumer) response. We look at competitive links as it were 'through the eyes of competitors'. Accordingly, this part of research looks at competitive links from the *third-level* perspective.

In Chapter 5, *'Analysing the conduct regarding competitive links'*, the various ways in which competitive marketing conduct has been studied so far will be discussed. In particular, we will focus on the 'reaction-matrices approach', a general research methodology for diagnosing competitive behaviour, which was initiated by Lambin, Naert & Bultez (1975) and further developed by Hanssens, Leeflang, and others (cf. Hanssens, 1980; Plat & Leeflang, 1988; Leeflang & Wittink, 1992). In addition to this general methodology, we will also address the current descriptive body of knowledge concerning actual competitive reaction behaviour. One of the conclusions will be that empirical research on competitive reaction behaviour is quite scarce. There is a lack of knowledge, especially concerning the factors explaining competitive reaction behaviour.

In Chapter 6, *'Competitive marketing reactions to new product introductions'*, we contribute to the descriptive body of knowledge on competitive reaction behaviour, by conducting an empirical study focusing on the explanation of marketing reactions by firms, as a response to new product introductions by competitors. The empirical findings from this study are based on

98 interviews held with marketing managers responsible for a particular product(group) in a fast moving consumer good product category.

We conclude this dissertation with a brief '*epilogue*', that addresses some general research developments in the field of marketing and competition. It also gives a reflection on the specific research performed in this thesis.

Let us now summarise the structure of this thesis. We view competition in marketing as a process by which mutually dependent firms act and react to the consumers and to each other with the aim of fulfilling their respective marketing objectives. The mutual dependencies between the firms considered here are customer-driven and arise because of the autonomy of consumers deciding to buy products from one firm or from another. We call the mutual dependency relationships between firms *'competitive links'*. We are concerned with three issues related to competitive links, the *identification* of competitive links ('with whom does a firm have a competitive link'), the *content* of competitive links ('how does a competitive link become apparent in terms of the mutual cross-effects of marketing instruments'), and the *conduct* regarding competitive links ('how do firms behave towards firms they are competitively linked with'). These three issues will be addressed in this dissertation. We further distinguish three levels of perspective from which competitive links are studied: the *individual consumers* level, the *aggregate market* level, and the *competitors* level. Figure 1.3 summarises the structure of this thesis, combining the three research issues with the three distinctive levels of perspectives we use for analysing them. While in the first two parts of research in this thesis the emphasis will be on investigating and developing methodologies for analysing competition, in the third part we will focus on and extend the substantive body of knowledge on competitive behaviour.

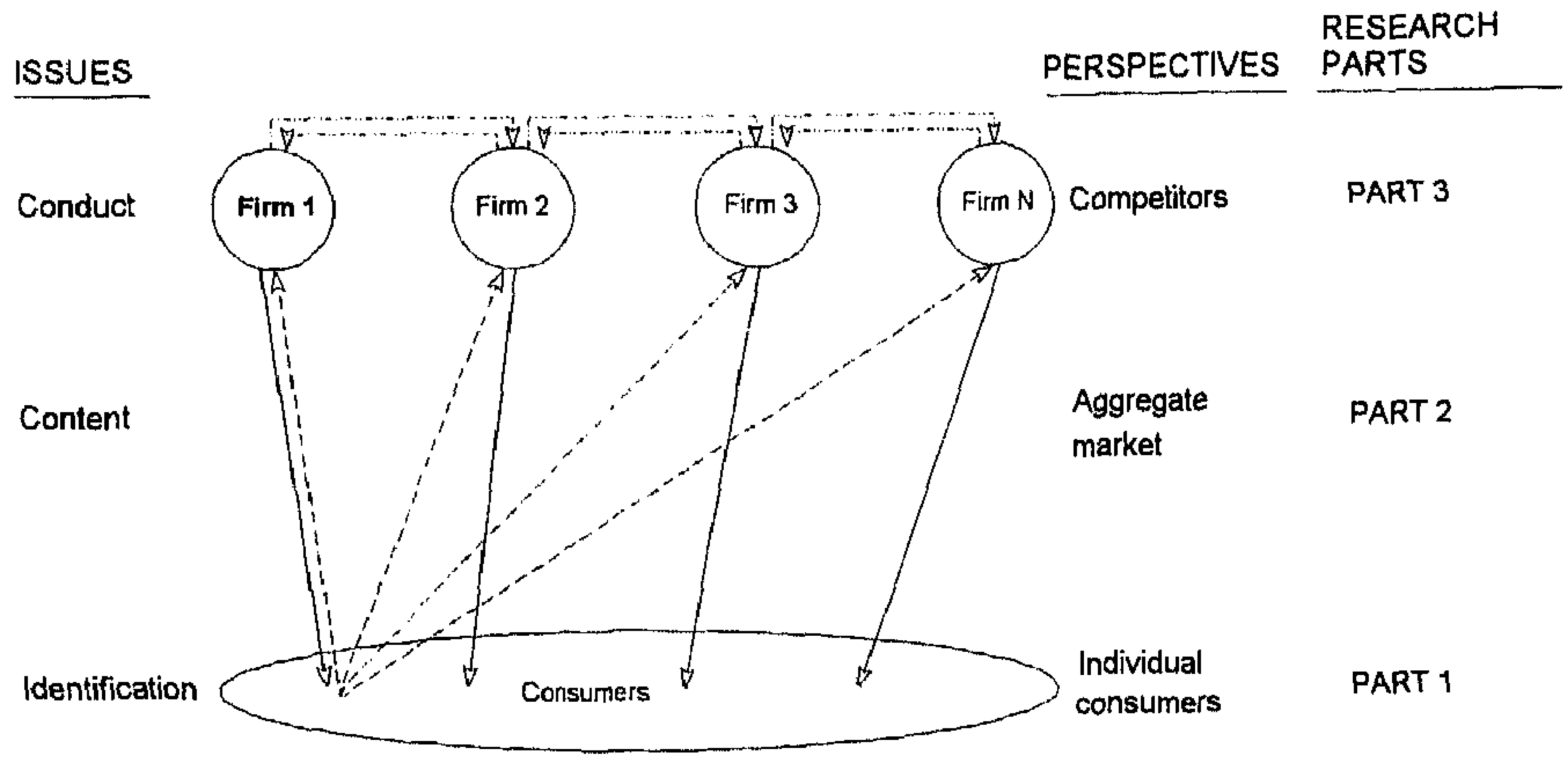

Figure 1.3 Issues and perspectives for analysing competitive links in marketing

We conclude this introduction with some remarks about the boundaries of this thesis. First of all, it is clear that we confine ourselves to the 'tactical' competitive setting of marketing managers operating with their products in a certain, existing consumer market. Main focus is on 'internal competition', that is on rivalry between incumbent firms. We do not explicitly address the more strategic competitive settings where the environment is defined broader and decisions typically are taken at the level of strategic business units, and focus on such issues as new business development, internationalisation, merging and partnering, etc. Many studies on this issue have been performed at interface of marketing and strategy (cf. Porter, 1980, 1985; Hamel & Prahalad, 1994; Prahalad, 1995). For our purposes, the broad, 'Porterian' competitive environment is only relevant for as much as it influences competition at the product/brand level.

Another observation is that, in our conception of competition, marketing channels (e.g., retailer organisations) are not explicitly defined as a third market party as proposed by Wensley (1994). Certainly, retailers form an important factor, especially in consumer markets. In this thesis, we focus on 'horizontal' competition between suppliers of products. Retailers are treated as being a part of this competition if and only if they act as autonomous suppliers in the market by offering their own products (i.e. 'distributor owned brands') to the consumer market. In that sense, marketing channels indeed form a factor in this study.

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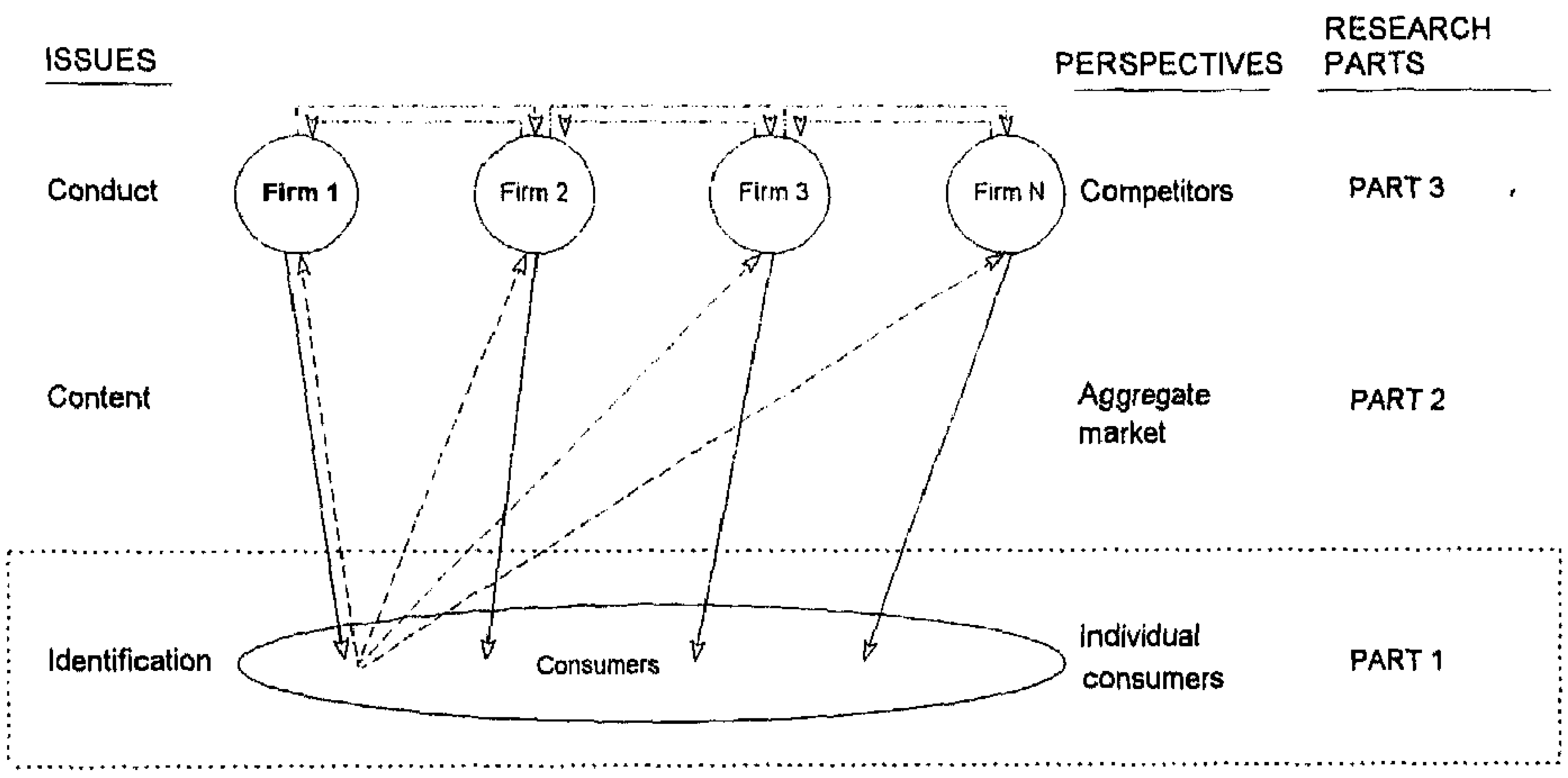
Part 1

The identification of competitive links



2 Identifying competitive links based on consumer choice behaviour*

2.1 Introduction

For practically every product there exist competing products. For a marketing decision maker it is of paramount importance to know with which products he is competing, i.e. with whom he is competitively linked. The aim of this chapter is to review the methods and techniques available for identifying competitive links. We discuss the way the so-called 'market structure analysis' techniques can be helpful for this purpose. In particular, we focus on methods based on data about the actual product choice behaviour of consumers. Before going into the specific methods and techniques, however, we will first elaborate on the specific objectives and demarcations of this chapter.

For many marketing decisions that need to be made in an organisation, the analysis and understanding of the competitive environment is of great importance. After all, even elementary matters such as market share analysis and product positioning are strongly dependent on how one defines and experiences the market and the competitive arena (Weitz, 1985; Prahalad, 1995). It depends on the type of decision under consideration, how narrow or broad the competitive arena should be defined. For instance, when dealing with strategic issues, such as new business development, internationalisation, mergers and acquisitions, the strategic window must be opened

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* This research part builds on an earlier publication: Waarts, E., 1992. Concurrentiestructuren ontrafeld: analysemethoden gebaseerd op geobserveerd gedrag. *Jaarboek voor de Nederlandse Vereniging van Marktonderzoekers*, 95-118.

wider and the competitive arena defined broader than when dealing with a tactical marketing decision. In this thesis, as has already been pointed out in the first chapter, we will *not* focus on the broad, strategically relevant competitive environment, but rather we will zoom in on the tactical level of the product-market combination[1]. The starting point is the situation (as in Figure 1.1) of the marketing decision maker who, for a specific product or brand, wants to use marketing instruments with the goal of influencing the market position and/or the profit performance of the product. These decisions take place in a market context in which a number of competing, though not identical, products exists and where each of the firms strives for the favours of consumers. The implication of this setting is that the firms marketing these products are mutually dependent or *competitively linked* to each other with respect to the effectiveness of their marketing policies and, thus, with respect to their marketing performances.

The central question in this chapter is: how can a firm identify to which other firms it is competitively linked? There is a large number of formal methods and techniques developed over the past twenty-five years that can be helpful for this purpose. Generally, these methods can be classified as customer-focused because they rely on information from or about consumers. A distinction can be made, though, between approaches focusing on the aggregate market level and approaches departing from the (individual) consumer level. From the aggregate market perspective one can identify competitive links *directly* through the analysis of the actual cross-effects of marketing instruments. Typically, when taking this approach, one would first select a set of potentially competing products. Thereafter, one would measure, instrument by instrument, the actual cross-effects between each of pair of products, based on information about the marketing instruments employed (e.g., shelf-prices, advertising expenditures, etc.) and about the sales performances of the products. The output of such analyses can produce detailed information, in fact addressing not only the identification of competitive links, but also addressing their content. We will focus on that issue in the second part of this thesis.

[1] For the 'strategic' decisions category, a large number of methods and techniques has been developed (e.g., portfolio analysis, strategic group analysis) that aid managers in the structuring and understanding of their environment. A useful overview of methods and techniques for this type of decisions can be found in e.g., Prescott and Grant (1988).

Identifying competitive links based on consumer choice behaviour

As an alternative approach, one can investigate the possible existence of competitive links from the individual consumers' perspective. In that case, briefly speaking, one tries to identify competitive links in an *indirect* way, by assessing the 'closeness' of products in the perception of consumers. In the literature, methods for identifying levels of competition (i.e. closeness) among products are called '*market structure analysis*' methods (cf. Srivastava, Leone and Shocker, 1981; Urban, Johnson and Hauser, 1984, Kumar and Sashi, 1989). These methods predominantly utilise data about customers, their perceptions, their preferences, and their purchase behaviour. Hence, they address the fundaments of competitive links, namely the 'closeness' of products in the eyes of consumers.

Within the large collection of market structure analysis techniques, Day, Shocker and Srivastava (1979) and Lilien & Kotler (1983) make a distinction between methods based on *judgment* information (e.g., consumers' perceptions of products) and methods based on information about the actual purchase *behaviour* of consumers (i.e. the outcomes of this behaviour in terms of actual products purchases). Day et al. (1979) state that purchase behaviour provides the best indication of what people do, or have done, but not necessarily what they might do under changed circumstances. Judgment information gives better understanding into future patterns of competition and the reasons for present patterns. Within both categories - judgment-based and behaviour-based - a large number of research methodologies has been developed. While both approaches are interesting in their own right, in this thesis we have chosen to investigate further one of the two, namely the behaviour-oriented methods[2]. This specific class of methodologies is especially interesting, given the fact that behavioural data are becoming increasingly inexpensive and available to the manager and the market researcher, for instance due to the emergence of scanner panels. The challenge for the market researcher and the marketing manager will be to transform the often large quantities of data into relevant information (Wierenga, 1995).

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[2] For the other category, methods based on judgment data, we refer the reader to the existing overviews by Day et al. (1979), Rao and Sabavala (1980), Srivastava, Leone and Shocker (1981), Srivastava, Alpert and Shocker (1984), Hruschka (1986) and Bucklin and Srinivasan (1991).

Objectives

To summarise the scope of this chapter: we will address the issue of the identification of competitive links between products. We have already discussed briefly the main research avenues in this respect. The objective of the remainder of this chapter is to review and investigate the possibilities of identifying competitive links using market structuring analysis methods. Especially, we will confine ourselves to a certain 'class' of methods, namely those which are based on information regarding actual consumer choice behaviour, as opposed to methods which are based on judgment data. Within the chosen class of methods, many techniques have been proposed in the literature. In this chapter, we will review the key developments in this field in the context of their value for identifying competitive links. In that respect, we will not discuss all the published methodologies in depth, but concentrate on those methods which we consider 'landmarks' in the development of inferring levels of competition from consumer choice data. For each selected methodology we will discuss the underlying model principles. While the original publications sometimes use different notation systems, we will use a uniform notation system, for as much as possible. Therefore the formulation of a model in this chapter might differ slightly from the original formulation. Also, for each methodology we will present an example illustrating the methodology and assess its value for identifying competitive links. In addition, we present a taxonomy of methods, classifying the various methods according to a number of attributes concerning the data requirements, the methodology, the output and the information that can be inferred from the methods about the possible existence of competitive links between brands.

2.2 Market structure analysis

A market structure can be defined as a configuration of products which are perceived as substitutes by consumers (cf. DeSarbo, Manrai & Manrai, 1993). The structuring problem is usually conceptualised as one of identifying levels of competition among brands in a well defined product-market (cf. Fraser & Bradford, 1983; Urban, Johnson and Hauser, 1984; Kumar and Sashi, 1989). As has been mentioned already, many techniques have been developed in order to derive market structures, including those using information about the brand choice behaviour of consumers. Typically, what happens for developing such a method is that the researcher has a data set containing information about the actual purchases made within a particular product category by a group of consumers on a number of consecutive purchase occasions. This may, for instance, be in the form of strings of brand purchases by consumers over a number of consecutive purchase occasions, or in the form of a single aggregate brand switching matrix. Furthermore, the researcher also specifies a theoretical model for structuring markets, including assumptions about the choice behaviour of consumers. In the analysis phase, the data are used to parameterise and to validate the model. The type of model used in the method is essential, because it forms the fundament of the structuring principles.

Generally, the theoretical models for translating the data into meaningful market structures borrow from consumer behaviour research. For example, a substantial collection of the earlier methods is based on the paradigm that consumers simplify the process of product choice according to a hierarchical scheme (cf. Tversky and Sattath, 1979; DeSarbo, Manrai & Manrai, 1993; Engel, Blackwell and Miniard, 1995). The assumption is that a total set of products can continually be divided into subsets (or 'partitions'), within which increasingly strong similarities exist between products, with respect to the attributes. In this context, consumers are assumed to make use of a set of decision rules, including noncompensatory and compensatory rules, to decide on which product they will prefer (cf. van Raaij, 1988). Some structuring methods assume a process of sequential elimination by aspect (e.g., Butler and Butler, 1970). In that case, a consumer decides on his product choice in a sequential fashion, each time making further choices among subsets in a category. The process starts with a subset decision at the highest level in the hierarchy, that is the attribute the consumer first decides on. All products belonging to the non-selected subgroups are eliminated for further consideration. Next, the consumer chooses a sub-subset for the second most important attribute, the other products are eliminated again, and so on. Finally, at the bottom of the hierarchy a number of products remain in the choice set of the consumer, from which he makes a final choice.

Such a process can yield various market structures. Consider, for example, Figure 2.1, exhibiting two hypothetical hierarchical structures for a (lower) part of the soft drink market, in particular focusing on the product subset cola's. In this example, consumers may first decide on the *type* of cola they wish (light or regular), before deciding on the *brand*. In that case the structure would be type primary (Figure 2.1, Structure A; cf. Kalwani & Morrison, 1979). Alternatively, the process may be the other way around, if consumers first choose the brand and thereafter decides on the type (Figure 2.1, Structure B; Brand primary structure).

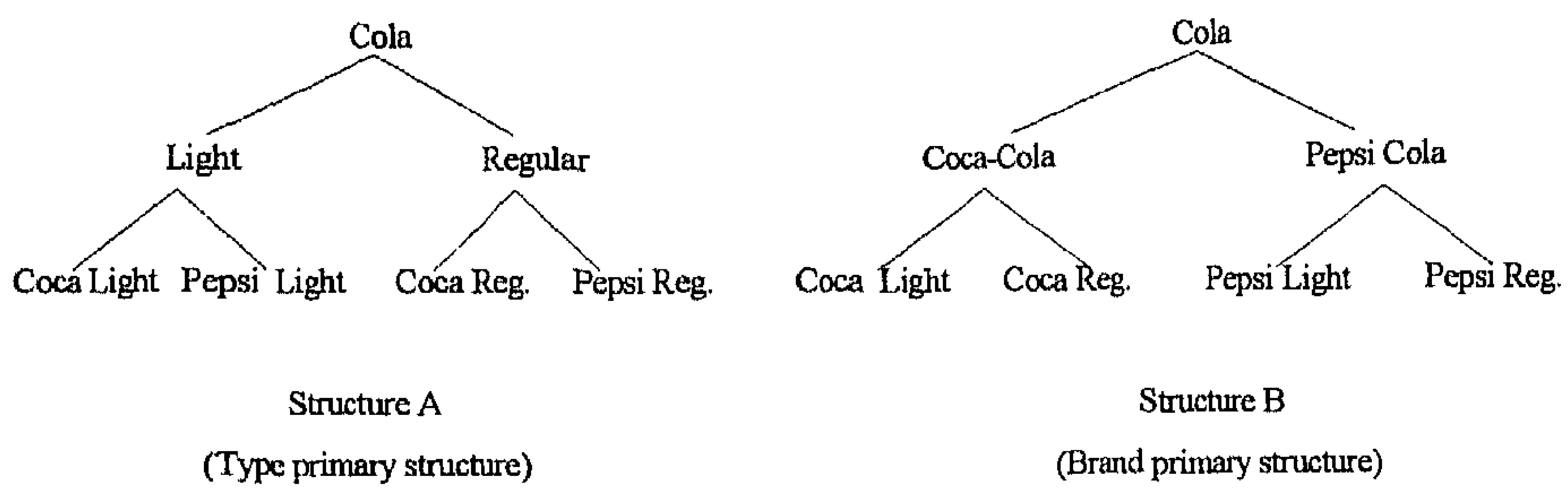

Figure 2.1 Hypothetical hierarchical market structure diagrams for colas

According to this approach, each product competes more directly with products located in the same subset than with products belonging to another subset. In terms of competitive links, links can be assumed to be stronger between products within the same subset than between products belonging to different subsets. For example, probably the link between Coca Light and Pepsi Light is stronger in the Type primary structure than in the Brand primary structure. This can be presumed because consumers perceive products in the same subset to be relatively close substitutes as compared to product from different subsets. Therefore, consumers are expected to be more easily influenced by marketing instruments in making a different product choice within subsets than between subsets. For example, in a Type primary structure, a 10-cents price-off for Coca Light would probably cause a number of consumers to buy Coca Light instead of Pepsi Light, because they compete closely on the same level in the market structure. One would thus expect a relatively strong competitive link between the two. In the Brand primary structure, though, the same 10-cents off action for Coca Light would probably draw customers from Coca Regular, and cause less effect on Pepsi Light because in that structure it is relatively difficult to let consumers switch from buying

Pepsi to buying the Coca brand, regardless the type of cola. The competitive link between the two is therefore expected to be relatively weak[3].

While the methods for analysing market structures use models describing hypothesised consumer choice behaviour, the consumer choice decision process itself is not directly observable. Instead, based on observed actual purchases resulting from the decision processes, one may test a model against the data and try to infer a market structure that could be responsible for the observed purchase behaviour. This is essentially what the market structure techniques described here attempt to do. Many of the methods yield a hierarchical diagram of the inferred market structure (e.g., Butler and Butler, 1970/71; Urban, Johnson and Hauser, 1984; Grover and Srinivasan, 1987; Kumar and Sashi, 1989). In addition, a number methods have been developed that capture the structure responsible for the choice behaviour in a multi-dimensional space (e.g., Elrod, 1988, Elrod & Keane, 1995).

General limitations

Before we enter into the developments of the market structure analysis methods for identifying competitive links, we will first review a number of general limitations that stem from the exclusive use of actual product choice data. In this context, Day et al. (1979) mention:

- Methods using data on various consecutive purchase choices of the consumer as input for the analysis, are only suitable for the analysis of frequently purchased products (thus not for durable goods), unless the purchase data is experimentally acquired in a lab situation. Furthermore, the market has to be stable, especially during the time period in which the purchase data is gathered. This is so, because the researcher has to assume that the observed product choice behaviour during the research period was stochastic in nature, and was not influenced by the marketing activities during that period.

[3] Note that this does not imply that the intensity of *rivalry* between Coca and Pepsi would be greater in the Type primary structure as compared to the Brand primary structure. It could well be that in the Brand primary structure Coca cola would even do more to draw customers away from the Pepsi brand (e.g., offer 25-cent price-off) than in the Type primary structure.

- Generally, the methods are not capable of generating the relevant product set. They depart from an *ex ante* defined collection, and may be sensitive to changes thereof. One should already take this into consideration when collecting the data. In fact, one of the basic demands that Shocker, Zahorik and Stewart (1984) place on a good market structure analysis method, namely that the derived structure should not be sensitive to changes in the product set, is generally not fulfilled.
- switching probabilities are usually based on panel data, which may obscure individual switching behaviour if the data are reported by only one member of the household. Observed switching can then result from different members of the household making consistent but different purchase decisions. Also, the analysis of purchase data can be distorted if consumers buy multiple products at the same time. In that case it is not possible to determine the sequence of switching.
- The methods generally do not differentiate according to usage occasions. For example, if a consumer usually buys a brand, say 'Amstel regular beer', for normal use, and sometimes buys 'Kylian special beer' for special occasions, one would register a switch from Amstel to Kylian, although the products are not direct substitutable. Already during the specification of the product set to be researched, one should take this problem into account. This, however, requires *a priori* knowledge about the structure. But then again, it is the structure that one is looking for in the first place.

Notwithstanding these general restrictions, methods based on actual choice data do have relevance for identifying possible competitive links, because they basically aim to infer levels of competition between groups of products. The restrictions point to the fact that one should be careful in applying the methods in the right situation and that one should be careful when drawing conclusions about market structures and possible competitive links.

Since the beginning of the seventies, a series of methods has been developed, which differ with respect to the underlying model, type of analysis, type of representation, and/or applicability. As was pointed out before, the objective of this part of the research is to discuss those methods which can be considered 'landmarks' in the development of this research field. We start with the first landmark in the history of market structuring, the Hendry-model.

The Hendry model

One of the first market structuring methods was the 'Hendry model', developed for the Hendry corporation by Butler and Butler (1970/71)[4]. The Hendry model still is commonly referred to as a benchmark in the history of market structure analysis. Although the model was never published in detail, a description is given by Kalwani & Morrison (1977) and Rubinson, Vanhonacker & Bass (1980). Below, we provide a brief description of the structuring part of the Hendry system, followed by an overview of the developments in market structuring techniques that have taken place since then. We primarily discuss the key principles of the models and the estimation procedures. For more technical details we refer the reader to the specific publication concerned. With respect to the Hendry model, see discussions in Kalwani & Morrison (1977), Rubinson et al. (1980) and Rao & Sabavala (1980).

Starting point of the Hendry model is the 'zero-order effect' assumption, stating that for every consumer *h* within a (heterogeneous) group of consumers it holds that he or she chooses a product *i* from a (sub)set of products and that every product has a constant probability p_{ih} of being bought by that consumer, regardless of the choices that consumer has made in the past. The p_{ih}'s can vary over consumers. The market share s_i of brand *i* will then be equal to the expected value of the purchase probability distribution of that brand over the (heterogeneous) consumer population. It can be shown that if the zero-order assumption holds, and the market is in equilibrium, the brand switching frequencies between products will be *proportional* to their market shares (Kalwani & Morrison, 1977). The intensity of switching, however, can vary over product categories and subgroups of products (called 'partitions') and is described by the switching constant K_w (the *w* comes from s<u>w</u>itching). This switching constant allows for product (sub)categories having different brand-loyalty factors (Rubinson et al., 1980). Kalwani and Morrison (1977) show that, in the Hendry model, the expected unconditional probability $p_{(i,j)}$ of switching from brand *i* to brand *j* is:

(1) $p_{(i,j)} = K_w s_i s_j$

[4] Actually, the Hendry market structuring model is only one of various models incorporated in the total Hendry system, called HendroDynamics, a system meant for analysing consumer behaviour in order to suggest marketing strategies.

where s_i is the market share of brand i in the (sub)group and K_w is the (sub)group switching constant and K_w is *independent of i and j*. Thus, if brands are competing within the same partition they must all obey the same K_w. In fact, the Hendry model *defines* a partition as a group of products sharing the same K_w. To illustrate the effect of K_w, Kalwani & Morrison consider a three-brand market with market shares 0.5, 0.3, and 0.2, respectively. From (1) it follows that the transition probability of a random consumer switching from brand i to brand j is:

(2) $p_{(i,j)}/s_i = K_w s_j$ for $i \neq j$, and

(3) $p_{(i,i)}/s_i = (1-K_w) + K_w s_i$

where $p_{(i,i)}/s_i$ stands for the repeat purchase probability of brand i. If, for example, K_w takes the value 0.4, then the transition and repeat probabilities can be calculated using (2) and (3). The resulting probabilities are shown in Table 2.1. These probabilities describe the overall switching behaviour of consumers switching out of a brand, given the market shares of the brands and given K_w.[5]

Table 2.1 Conditional repeat and switching probabilities for a three brand market with $K_w = 0.4$ (taken from Kalwani & Morrison, 1979)

buyers of brand	proportion who buy brand on next occasion		
	1	2	3
1	0.8	0.12	0.08
2	0.2	0.72	0.08
3	0.2	0.12	0.68
all buyers	0.5	0.3	0.2

Observe that the switching probabilities into a brand (say brand 1) are identical for the brands switching from (2 and 3 in this case). It can also been seen that the repeat purchase probability of a brand increases as its market share increases. If the switching constant K_w increases, the repeat

[5] These probabilities relate to an aggregate of consumers, they do not relate to the choice behaviour of each individual consumer.

purchase probabilities will decrease and the switching probabilities will increase. Thus, K_w describes the expected switching behaviour for a (sub)group of brands, and indicates both the total switching within the subgroup as well as the mutual switching between pairs of brands within the subgroup. The Hendry model anticipates that the lower a partition is located in the hierarchy, the greater the substitutability between the products within that partition, and the larger the K_w (Rao and Sabavala, 1980). Applied to the partitioning of markets, the Hendry theory expects that, when there is *no* (sub)structure present in the market - in other words, all products compete on the same level with each other - the brand switching frequencies between pairs of products will be proportional to market shares relative to the total market T. There would be one single K_w, describing the total switching in the market and describing the switching levels for all pairs of products. If a single K_w is not confirmed by the empirical data, the Hendry model expects that the market is partitioned. The brand switching levels within a partition are expected to share the same K_w, and the K_w's are expected to increase if a partition is lower in the hierarchy.

The Hendry methodology makes use of an iterative procedure for finding a market structure. The researcher draws up a number of alternative hypothetical structures, possibly in consultation with managers involved, that could describe the hierarchical choice process of the consumer. Subsequently, for each hypothesised structure, it is checked whether the observed switching behaviour *within* the partitions can be approximated by a single switching constant and whether the K_w's increase as partitions are lower in the hierarchy. If such is not the case, the same procedure will be followed for another hypothetical structure. The structure that best fits with the data may then be accepted. Various statistical measures (for example, chi^2) are proposed to test the fit of the structures[6].

The Hendry approach can be characterised as a combination of a theoretical model of consumer behaviour and a confirmative procedure based on data on actual brand switching behaviour of consumers. Rubinson et al. (1980) mention that the Hendry system has been used by a number of

[6] Rubinson et al. (1980) point out that the Hendry model also provides *theoretical* values of K_w, based on only the shares of the brands, given a hypothesized structure. The Hendry model derives the theoretical values using a maximum entropy criterion. The theoretical switching constant is given by $K_w = TS/\sum s_i(1-s_i)$, where TS is the theoretical total switching and $TS=\sum[-s_i^2 \ln s_i/(1-s_i \ln s_i)]$. The theoretical K_w's serve as a benchmark for testing the structures.

large, well-known companies which sell frequently purchased consumer goods. The output of the Hendry model provides the manager with a more clear understanding of the market and its partitions, and shows switching levels within and between partitions, thereby serving as a basis for assessing potential competitive links between brands.

The most important restrictions of this early method, besides the already mentioned general restrictions that accompany the use of brand choice data, are:

- the assumption of zero-order processes, which implies that consumers have constant purchase probabilities. Basically, this means that brand preferences do not change in time. As Kalwani & Morrison (1977) and Bass, Givon, Kalwani, Reibstein & Wright (1984) point out, this can only assumed to be true in very stable markets or during a very short period of time, where nothing happens marketing-wise to influence the brand attitudes and purchase processes substantially.
- the results of the different applications of the Hendry model show that sometimes very different structures can produce the same fit quality on the same data (cf. Grover & Dillon, 1985). Furthermore, it seems that the Hendry model is not always capable of discovering a structure, while this does seem possible by applying other methods (cf. Rao & Sabavala, 1980; Urban, Johnson & Hauser, 1984).
- the method does not take into account the possibility that segments exist in the market, which are different where the structure of their purchase decision making process is concerned. The method produces one aggregated structure, while one can imagine that in many markets the behaviour of different groups of consumers needs to be explained and described by different hierarchical structures.

2.3 Developments

Inspired by the Hendry model and its restrictions, various attempts have been made to develop an improved method for analysing market structures using consumer choice data. During the nineteen seventies and eighties, the emphasis has predominantly been placed on improving consumer choice data methods on two key aspects[7]: i) the explicit incorporation of consumer heterogeneity through identification of market segments and ii) the development of 'explorative' methods instead of the confirmative, iterative method as in the Hendry system. Table 2.2 exhibits those methodologies which we consider to be 'landmarks' in the development of the market structuring research avenue. The selected methods are classified according to two dimensions: 1) 'confirmative', where structures hypothesised in advance are tested against the data (as in the Hendry approach), versus 'explorative', where structures are suggested based on the data, which subsequently need to be interpreted and 2) 'homogeneous', where the method generates only one aggregated structure, versus 'heterogeneous', where it is possible for the particular method to detect or test different structures for different consumer groups.

Table 2.2 Selection and classification of 'landmark' structuring methods using brand choice data only[8]

	confirmative	explorative
homogeneous	Butler & Butler ('Hendry') (1970) Urban, Johnson & Hauser (1984) Kumar & Sashi (1989) Novak (1993)[9]	Rao & Sabavala (1981) Novak (1993)
heterogeneous	Grover & Dillon (1985).	Grover & Srinivasan (1987) Elrod (1988) Ramaswamy & DeSarbo (1990) Givon (1985); Lattin & McAlister (1985)

[7] As has been pointed out before, recently researchers try to make further progress in structuring markets by combining consumer choice data with aggregate marketing instrument and sales data. We will only briefly address such developments in this chapter, because our main interest in this research part is in identifying competitive links from consumer choice data only.

[8] Brand choice data refers here to any form of registered product purchases by consumers collected at either the individual consumer or household level. The data may, for instance, be transformed into switching matrices or into strings of consecutive purchase choices.

[9] This method can be used for both suggesting and testing structures. Therefore, the Novak method has been classified as both homogeneous/confirmative and as homogeneous/explorative in Table 2.2.

Below we will continue with a discussion of the selected methods in each of the quadrants, starting with the methods in the same category as the Hendry model: 'homogeneous and confirmative'.

♦ Homogeneous, confirmative methods

Prodegy (Urban, Johnson & Hauser, 1984)

As explained before, the Hendry system is one of the first methods that falls in the category 'homogeneous and confirmative'. More than a decade later, Urban, Hauser and Johnson (1984) suggested a method called 'Prodegy' (*prod*uct strat*egy*), which is also comparable to the Hendry approach where the type of output is concerned: both yield single hierarchical market structures. However, the conceptualisation of the model, the type of data and the testing procedure are different. Like in the Hendry model, Urban et al. (1984) argue that in an ideal *un*structured market a manager expects his brand to draw customers in proportion to the other products market shares. Thus, his brand would draw more customers from high share alternatives than from low share ones. If the manager observes that his brand hurts specific products more than market shares would predict, then his brand may belong to a certain grouping of products. Urban et al. (1984) define a market structure from the perspective of a product *deletion* as "a market is defined by a series of *sub*markets, if, when a product is deleted from a submarket, its former consumers are more likely to buy again in that submarket than would be predicted by market shares" (Urban et al., 1984, p.88).

To operationalise the 'would be predicted by market share' notion, Prodegy uses the 'aggregate constant ratio model' (ACRM). It implies that an aggregate of consumers behave such that if a brand j is deleted from the market they would switch to the other brands in proportion to their market shares. Under the null-hypothesis of an *un*structured market, consumers will switch to other brands, proportional to the market shares of those other brands in the total market T. The null-hypothesis yields *theoretical* switching values for switching to any subset s of products, under the ACRM assumption, as will be shown in the example below. The Prodegy procedure is a confirmative one. A number of possible structures is drawn up by the researcher and each one is tested against the null-hypothesis of 'no structure'. For testing structures, Prodegy needs empirical switching data describing how consumers behave if a product is deleted from the market. One way of collecting these data is by first observing a consumer's first product choice and then putting him in the situation where that particular product is deleted from choice set. This yields a so-called 'forced switching matrix'.

Consider, for example, Table 2.3, which is a hypothetical forced switching data matrix for a soft drink market (obtained from 100 consumers). In this market, seven products make up the total choice set for the consumers: three regular soft drinks and four light ones, under various brand names. The numbers in the first column of the matrix represent the number of consumers who choose the particular product as their first choice (n_j), and can be viewed in this example as the market share of product *j*. The cell counts in the matrix represent the number of consumers whose first choice was the product designated in the first column, and whose second choice is the product designated by the column label. For instance, the matrix shows that of the 15 consumers preferring Coca Light, 6 people switch to Pepsi Light if Coca Light is no longer available.

Table 2.3 Hypothetical forced switching matrix for the soft drink market (N=100)

		Light				Regular		
	n_j	Coca	Pepsi	7-Up	Spa	Coca	Pepsi	7-Up
Light								
Coca	15	-	6	2	3	3	1	0
Pepsi	10	4	-	2	2	1	1	0
7-Up	10	2	3	-	1	0	1	3
Spa	20	8	2	3	-	2	2	3
Regular								
Coca	20	4	1	0	0	-	5	10
Pepsi	15	0	1	1	0	4	-	9
7-Up	10	0	0	3	1	2	4	-

This particular matrix enables us to test two different possible market structures, a type-structure 'Light vs. Regular' and a brand-structure 'Coca vs. Pepsi, vs. 7-Up, vs. Spa'. A cursory glance at the matrix suggests that 'light' buyers tend to stay with light products and 'regular' buyers tend to stay with regular products if they were forced to switch from their favourite product. In Prodegy, this observation is statistically tested. First, per product, the expected proportion of switching to products in the same category is calculated under the null-hypothesis of no structure. For example, the 15 consumers switching out of Coca Light would be expected to spread over all other products in proportion to the market shares. Thus, we expect a fraction of 0.47 ((10+10+20)/85) of the 15 consumers ($\approx$7 consumers) to buy a product in the Light category again. We observe in the data matrix that actually 11 consumers bought again in the light category, corresponding with a fraction of 0.73. The difference between the expected and observed fractions is statistically tested by Urban et al. (1984) by using a one-tailed Z-test[10]. This particular example shows that over all products, people stay statistically more often within the 'Light' or 'Regular' subgroup than would be predicted under the no-structure hypothesis. The conclusion is that in this case the Type primary structure fits quite well with the data. One can do the same calculations for the Brand primary structure. In this particular example, the Brand primary structure does not fit very well with the data. In practice, though, it is possible that more than one structure fit the data. Urban et al. (1984) suggest that, in that case, the manager selects the 'best' structure based on judgment aided by the statistical measures[11].

The simplicity of the model and the type of data required makes 'Prodegy' a convenient method for the analysis of various sorts of markets. The necessary data can be gathered in various ways, varying from experimental 'forced switching' settings to preference ranking surveys. This makes Prodegy not only suitable for analysing frequently bought products, but also for durable goods such as cars and television sets. Urban et al. (1984) indicate that Prodegy was applied in practice several times in different markets, including consumer products (beers, coffees, deli-products) as well as industrial products (financial decision support systems and heart pacemakers). While Prodegy can provide useful information for assessing possible competitive links, it has of course some limitations. One is that, contrary to the Hendry model, Prodegy does not provide information about switching intensities within the subgroups of products. Because the method uses forced switching data, it is unknown to what extent consumers would be loyal to their first choice. This makes it more difficult to assess the real strength of competitive interdependencies in the market. Also,

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[10] For this product the Z-value equals 2.01, calculated by $(0.73-0.47)/[(0.47(1-0.47)/15]^{-0.5}$, which is significant at the .05 level.

[11] Novak and Stangor (1987) proposed an alternative for the estimation procedure of 'Prodegy'. They apply a W(eighted) L(east) S(quares) estimation procedure, with the advantage that the hypothesised structures can be better tested. For technical details, see Novak and Strangor (1987).

Prodegy is not able to handle situations where only one single product defines a subgroup. In that case, forced switching would be ambiguous, because actually there would be no alternative for consumers to switch to.

We will now turn to a next key development in this category of methods, namely the 'Directed Graphs' approach, introduced by Kumar and Sashi (1989).

Directed Graphs (Kumar & Sashi, 1989)

A further extension in the developments of market structure analysis was made by Kumar & Sashi (1989). Actually, the basis for partitioning the market is identical to the Hendry model and to Urban et al. in 'Prodegy', in the sense that they too use the proportionality to market share criterion for identifying subgroups in the market. However, Kumar & Sashi (1989) use a different estimation procedure, and the managerial information acquired with this method is more complete. The method tests various hypothesised structures in the form of a 'directed graph'. A directed graph is defined as a set of nodes together with a set of arcs, where each arc connects a pair of nodes (see Figure 2.2 for an illustration). Products are situated at the lowest level of the graph. Each arc is assigned a weight (e.g., denoted by a θ). Weights can be seen here as conditional probabilities: the probability that, starting from a given intersection, a certain direction is taken in the hierarchy. For assessing the transition probability from any brand i to any brand j, the θ's are multiplied, taking the shortest path in the graph from i to j.

For illustration, see a hypothetical example regarding sodas (soft drinks) and beers in Figure 2.2. Suppose, in this market there are eight products, four beers and four sodas. Also, some are regular drinks and some are low-calorie ('light') drinks. The output of Kumar and Sashi's analysis would yield a tree-structured 'graph' together with the weights (thetas) like the one shown in Figure 2.2. For instance, θ_1 in Figure 2.2 can be viewed as the transition probability from Amstel light to itself, which indicates a loyalty factor to the Amstel light product. θ_{34} stands for the probability of a transition from a light drink to a regular drink. From Figure 2.2 one can, for example, also derive that the transition probability from Amstel light to Amstel beer is equal to $\theta_9 \times \theta_{25} \times \theta_{34} \times \theta_{30} \times \theta_{18}$, taking the shortest path in the graph. Note that there are two-way arcs between the nodes, each having its own weight, which allows the transition probabilities to be asymmetric.

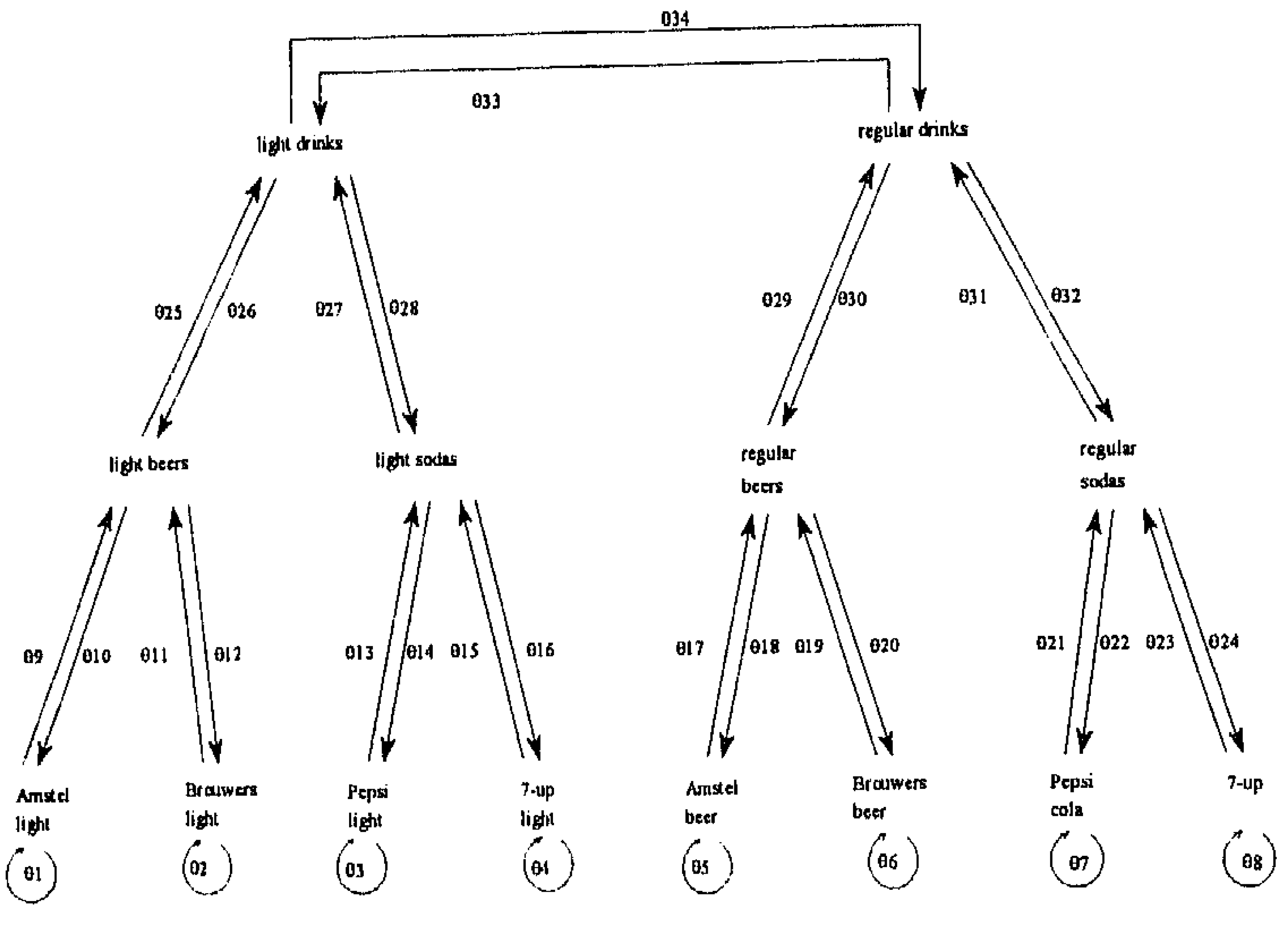

Figure 2.2 Structure with 'Directed Graphs' (adapted from Kumar and Sashi, 1989)

To derive a directed graph, the Kumar and Sashi method requires an aggregate brand switching matrix. It must be a full data matrix, including the diagonals (contrary to Prodegy, which only uses off-diagonal cells). Criteria for a 'good' graph are twofold. First, it should obey the market share proportionality criterion for partitioning. At the same time, the graph should comply to certain restrictions with respect to the transition probabilities. In the context of Figure 2.2, for instance, the partitioning assumption implies that the transition probability from light beers to regular beers must be smaller than the transition probability from light beers to light soda's. So, $\theta_{25}\times\theta_{34}\times\theta_{30}$ must be smaller than $\theta_{25}\times\theta_{28}$. A good graph solution should satisfy this and similar inequalities. To calibrate the parameters in a graph, the authors propose using a maximum log-likelihood procedure. In practice, the researcher specifies a number of possible structures *a priori*, calibrates the graphs, and then selects the one which fits the data best. It is possible, though, that more graphs fit the same data reasonably well. Kumar and Sashi suggest using the Akaike information criterion (Akaike, 1973) to select the best model.

Although the estimation procedures used by Kumar and Sashi is less straightforward as compared to 'Prodegy', the method does provide interesting extra information, particularly about the transition probabilities between the different partitions and brands. One can use this information for identifying possible competitive links between products. In general, the larger the transition probability between brand i and brand j (established via the multiplication of the arc weights connected to the shortest route in the graph), the stronger the competitive link is expected to be. The information from the graph can easily be used for marketing purposes: if, for example, it turns out that θ_1 is small, this indicates a problem in the repeat purchases of Amstel light. The manager might react to this with marketing actions to increase consumer brand loyalty for Amstel Light, for instance by introducing consumer loyalty-programs. One might also find that θ_{10} is small. This would mean that, given a choice for light beer, the probability of choosing Amstel light is small relative to the probability of choosing the competing product, Brouwers light. This indicates a competitive brand problem for Amstel light, which may be solved by perceptually differentiating the brand, increasing advertising expenditures, etc. On balance, the method of Kumar and Sashi seems to provide a useful diagnosis of competitive structures. Unfortunately, no information is provided, though, about the number of times the method is applied in practice. Again, no market segmentation is included, although it is possible to apply the model to several segments.

The methods discussed up till now were confirmative in nature. They test structures rather than suggest structures. We will now turn to two 'landmark' developments in explorative, 'suggesting' methods for deriving market structures from purchase data: a hierarchical clustering-based method proposed by Rao & Sabavala (1981) and a similar, but more advanced method suggested by Novak (1993), using log-linear trees[12]. These methods still are 'homogeneous' in nature, inferring only one aggregate structure of the market.

[12] The Novak method can also be used for testing structures and is therefore also classified as homogeneous/confirmative in Table 2.2. Because the method is suggested primarily for explorative purposes we will discuss the Novak method in the section referring to homogeneous/explorative methods.

- Homogeneous, explorative methods

Rao & Sabavala (1981)

As was already pointed out, some of the structuring methods are not 'confirmative' in the sense that they test various alternative structures against the data, but are 'explorative' in the sense that they try to estimate 'best' structure parameters directly. Rao & Sabavala (1981) were among the first to suggest an explorative method, using a hierarchical cluster procedure. Actually, their basic consumer purchase model is essentially the same as in the methods discussed previously in the Hendry model, the Prodegy model, and Kumar & Sashi's directed graphs model. Rao & Sabavala (1981) too use the proportionality-to-share criterion for partitioning the market into subgroups of products. However, their operationalisation and estimation procedure are quite different from the former methods. Rao & Sabavala use the observed brand switching frequencies between pairs of products directly, by transforming them into a measure of similarity between these products.

There are three key phases in this transformation process. In the first phase, an aggregate two-period switching (transition) matrix N is derived from the product-purchase histories of a segment of consumers, which are expected to be homogeneous with respect to their hierarchical decision tree. Segments are selected *a priori*, based on the researchers judgment. For instance, the researcher may distinguish between light and heavy users, or between brand loyal and non-brand-loyal consumers. In the second phase of the transformation process, an inter-item proximity measure f_{ij} is derived from the transition matrix for each pair of products. This is done in the following way. Let $n.$ denote the total number of consumers in the segment. Let n_{ij} denote the transition frequency from brand i to brand j, let $n_{i.}$ denote the number of consumers buying brand i on the first purchase occasion, and let $n_{.j}$ denote the number of consumers buying brand j on the second purchase occasion. Then, Rao & Sabavala define the inter-item proximity measure f_{ij} as:

This f_{ij} measure is interpreted as the proportionality factor in a switching relationship. It corresponds with the ratio between the actual numbers switching from brand i to brand j to the expected number of switching under the proportionality to market shares criterion. The proximity measure f_{ij} ranges from zero, if no switching is observed from brand i to brand j, to a large number (infinity) if the actual switching between the brands largely exceeds the expected switching based on the markets shares of the brands. So, the higher the relative switching level between a pair of brands, the larger the f_{ij}, and the 'closer' the brands compete. As an illustration, Table 2.4a shows a hypothetical transition matrix for four brands. Transformations into f_{ij}'s yields the proximity matrix F shown in Table 2.4b.

Table 2.4a

Hypothetical transition matrix N

for four brands

from \ to	A	B	C	D	
A	20	7	1	2	30
B	8	15	3	4	30
C	3	3	8	6	20
D	4	2	6	8	20
	35	27	18	20	100

Table 2.4b

Proximity matrix F resulting from Rao & Sabavala (1981) transformations

	A	B	C	D
A	-	.87	.19	.33
B	.76	-	.55	.67
C	.43	.56	-	1.50
D	.57	.37	1.67	-

The third phase of the transformation process involves the application of a hierarchical clustering method on matrix F (=f_{ij}). Note that F contains measures of *dis*similarity between brands, and that F is not symmetric (see Table 2.4b). Rao & Sabavala (1981) suggest using either the upper or lower triangle of F. Of course, one may also use both triangles separately and check afterward whether the derived hierarchical structures are different. The clustering procedure yields hierarchical tree structures, depending on the choices one makes regarding the cluster analysis, for instance with respect to type of algorithm, the levels, and the number and sizes of the clusters. Rao & Sabavala suggest using standard procedures (e.g., the simulation approach 'clustsiz' developed by McClain & Rao, 1975) to test for the stability and goodness-of-fit of the derived structures. Rao & Sabavala present an application of the procedure to the soft drink market. Figure 2.3 shows the hierarchical structure Rao & Sabavala inferred in this application. The market contains 17 items (brands). For each of the brands in the hierarchical structure, specifications are shown on the dimensions r(egular) or l(ight); n(ational) of r(egional), and c(ola), l(emon) or g(inger). Rao & Sabavala interpret this structure as a tree with 'national' versus 'regional' distribution as most important attribute, with a subtree for the 'national' brands according to the attribute 'regular' versus 'diet'.

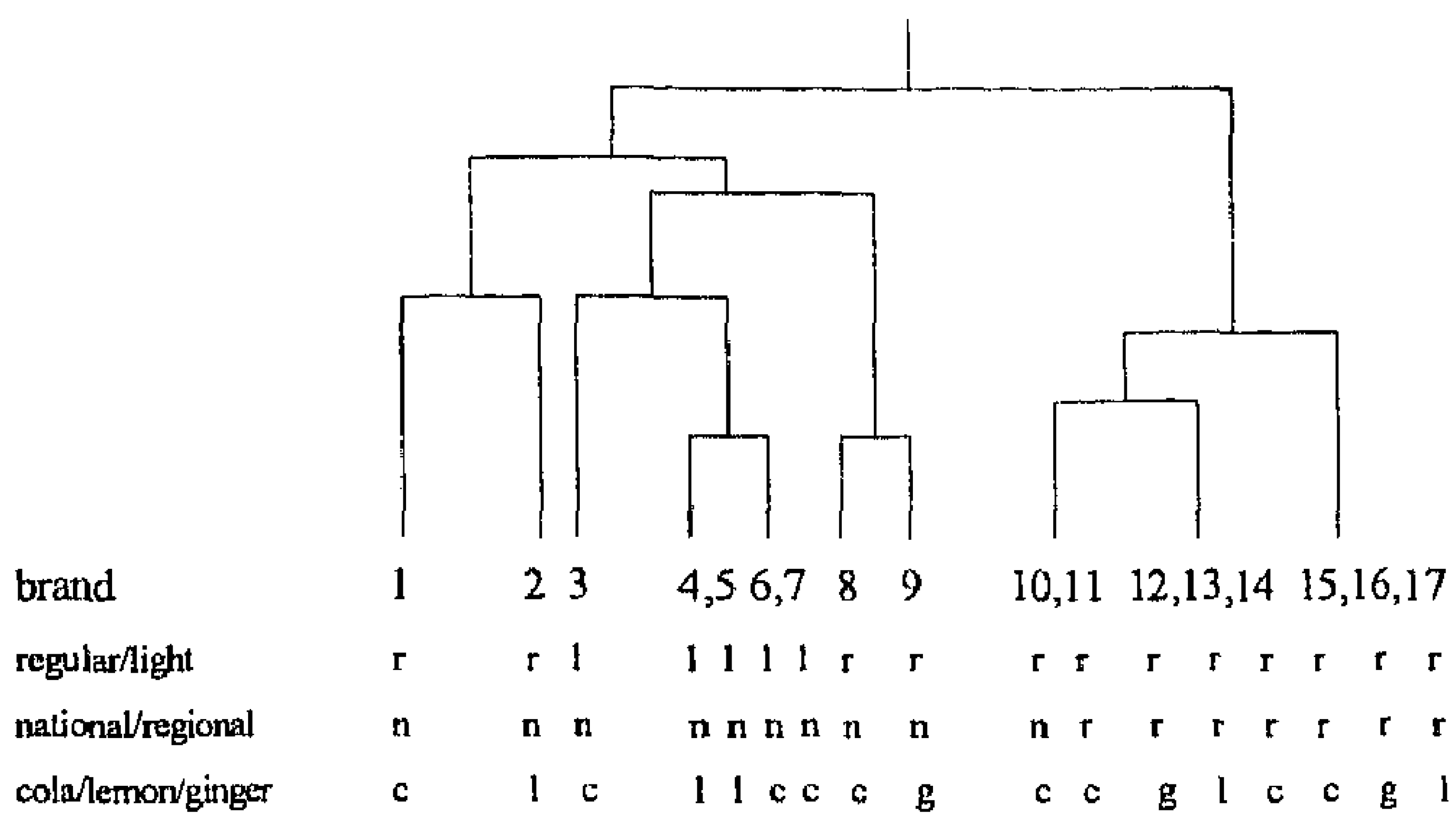

Figure 2.3 Illustration of a hypothetical hierarchical structure produced by the Rao & Sabavala method (adapted from Rao & Sabavala, 1981)

Compared to the methods discussed previously, the main advantage of the Rao & Sabavala (1981) approach is that structures are estimated directly. This means that one does not have to employ the trial-and-error procedure, which makes the Rao & Sabavala approach convenient when the researcher tries to identify competitive links in markets with many different possible structures. Confirmative approaches may become cumbersome for that purpose. The Rao & Sabavala approach may function as a starting point for suggesting structures. Thereafter, the structures inferred by the Rao & Sabavala method may be tested and calibrated using a confirmative methodology, such as Kumar & Sashi's directed graphs method. One should be careful, though, because the results of the cluster analysis may be sensitive to the specific proximity measure, to the choice of the upper or lower triangle of $\boldsymbol{F}$, and to the applied clustering specifications[13].

[13] DeSarbo, Manrai and Manrai (1993) discuss several technical restrictions of the Rao & Sabavala (1981) methodology, and review the developments in the psychometric literature addressing some of these limitations.

The other claim of Rao and Sabavala (1981) was the incorporation of market segments in their model. However, actually they do not provide a method for simultaneously estimating segments and structures. In fact, their proposition is that the researcher divides the data set according to certain groups of subjects, before the structure analysis starts. Afterward the analysis, it can be determined whether the division was correct, based on a comparison between the estimated trees. Naturally, this way of 'segmenting' is not exclusive to the Rao & Sabavala model. One can apply this approach for segmenting the market for all other methods. Hence, we have classified the Rao & Sabavala methodology as being 'homogeneous' in Table 2.2.

Next, we will proceed with a method proposed by Novak (1993), which uses a log-linear model approach for inferring market structures.

Log-Linear Trees (Novak, 1993)

Basically, the approach of Rao & Sabavala (1981) was firstly to transform a switching matrix into a proximity matrix, and secondly to apply a cluster algorithm to the proximity matrix to obtain hierarchical representations of the data. While the idea is appealing, the clustering methodology used by Rao & Sabavala has some drawbacks. For instance, one of the properties of the hierarchical clustering techniques is that all intra-cluster distances between brands should be smaller than all inter-cluster distances, and that all the intra-cluster distances between brands are equal (Corter and Tversky, 1986). This property is particularly restrictive for representing real life proximity data in a hierarchical cluster structure. To overcome such restrictions accompanying strictly hierarchical structures, Novak (1993) proposed using a log-linear tree (LLT) modelling approach. An (additive) tree is defined by Novak (1993) as a connected graph in which every pair of nodes (e.g., brands) is connected by a unique path in the graph. The distance between two nodes is the sum of the arc lengths connecting them. It should hold that the smaller the distance between two brands in the tree, the more switching is observed between the two brands.

Similar to Rao & Sabavala (1981), Novak (1993) starts with transforming a transition matrix N into a matrix containing proximity measures between the brands. Novak, however, uses a different proximity measure, λ_{ij}, which represents the log-odds ratio of switching between brands i and j. It is defined as:

$$\lambda_{ij} = \ln (n_{ii}n_{jj}/n_{ij}n_{ji}),$$

where n_{ij} represents the number of consumers switching from brand i to brand j. If this transformation is applied to the four brand switching data of Table 2.4a, we obtain Table 2.5, which forms the proximity input data for further analysis. Observe that, in contrast to the Rao & Sabavala (1981) transformations, the log-odds ratio transformations yield a single value describing the proximity between two brands. Another difference is that the λ-values measure similarities, whereas the Rao & Sabavala f-values measure *dis*similarities.

Table 2.4a (repeated)

Hypothetical transition matrix N

for four brands

from \ to	A	B	C	D	
A	20	7	1	2	30
B	8	15	3	4	30
C	3	3	8	6	20
D	4	2	6	8	20
	35	27	18	20	100

Table 2.5

Proximity matrix Λ, resulting from

Novak (1993) transformations

	A	B	C	D
A	-	1.7	3.9	3.0
B			2.6	2.0
C				0.6
D				

Next, Novak uses the λ-proximities as input for further transformation into a graphical representation. The λ's form the basis for the arc lengths in the tree. Because they are based on log-odds ratio's, Novak refers to the parameterisation of the graphs as a *log-linear tree (LLT) model*. Novak proposes using a maximum likelihood procedures to estimate the model.

A graph can take different levels of complexity. The nodes in a graph can be *external* (representing the brands) or *internal* (representing common brand features). The most simple tree (called a 'singular tree') has one internal node, and an external node for each brand. Such a graph is shown Figure 2.4. There are three brands (B1, B2, and B3) each represented by an external node. The graph has only one internal node (I) connecting the brands. Observe that, although the three brands belong to the same 'partition', the distances between the brands are not equal.

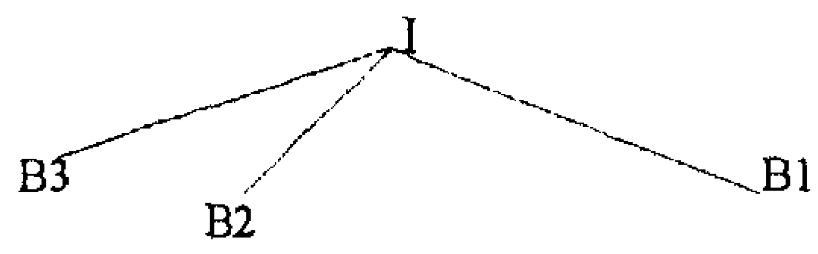

Figure 2.4 Singular tree for three brands

The LLT model can also handle more complex graphs. For example, Novak shows a factorial tree describing the structure of the U.S. coffee market (see figure 2.5). In the centre of the graph is a box. The corners of the box represent the common feature nodes (caffeinated or decaffeinated coffee; regular or freeze dried coffee). The brands are connected with the common feature nodes by an arc. Some of the brands offer different types of coffee (e.g., brand N). In the tree, the level of competition between two brands is represented by the sum of the arc lengths between the brands, taking the shortest path in the graph. This particular example shows, for instance, a relatively short arc length (indicating a high level of switching) connecting brand H (decaffeinated regular coffee) with brand S (decaffeinated regular coffee). The distances between brand N and brands H and S (within the same type of coffee) are larger, indicating relatively low switching levels[14].

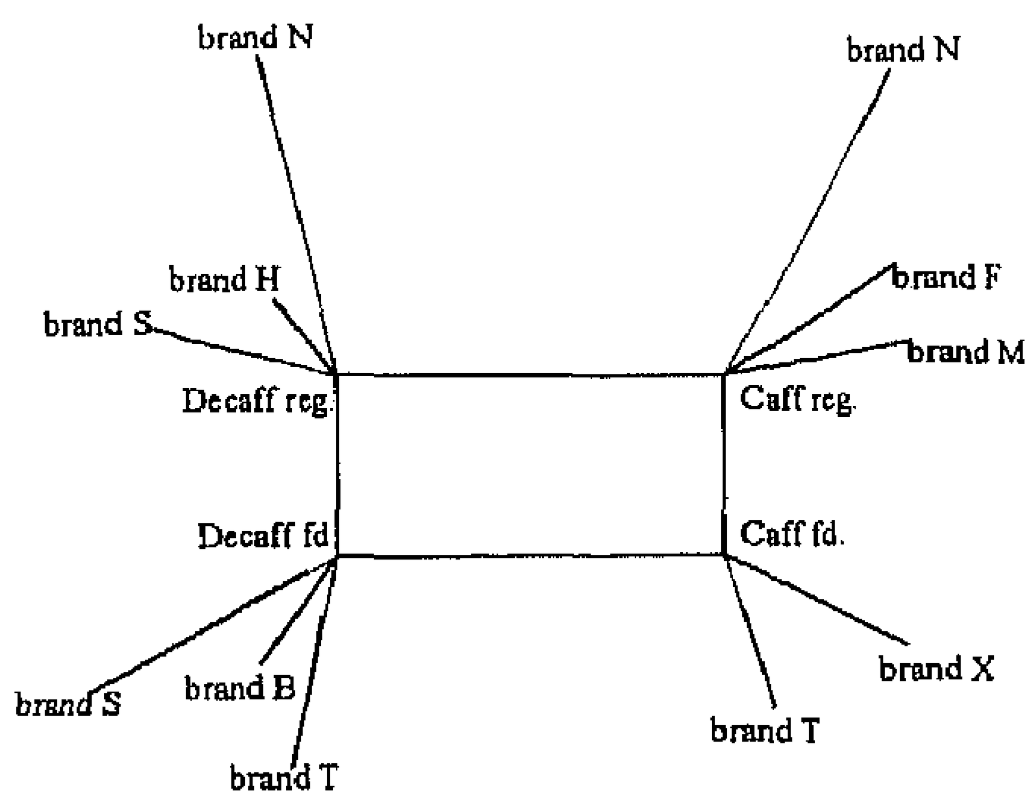

Figure 2.5 Illustration of a factorial Log-Linear Tree Model (taken from Novak, 1993)

[14] For assessing the switching level between different product forms of the same brand, the thin arcs should be ignored.

One of the advantages compared to the confirmative methods described in the preceding section, is that the LLT methodology is able to suggest structures instead of only to test them. Furthermore, it is very flexible in the way it represents actual switching behaviour in a meaningful graph. From the viewpoint of identifying possible competitive links, the method seems comparable with the Directed Graphs approach by Kumar & Sashi (1989), in the sense that levels of competition can easily be assessed from the output. While the Kumar & Sashi (1989) approach gives extra information about the asymmetric transition probabilities per brand and per attribute-node, the methodology developed by Novak (1993) is useful for exploring structures and is more flexible in representing structures in a (non-hierarchical) graph.

All the methods described thus far, derive a single aggregate market structure from an aggregate transition matrix from a sample of consumers. Although each of the methodologies acknowledge the possibility that there may exist different structures for different groups of consumers, these methods are restricted in coping with that phenomenon. They either come up with various 'fitting' structures which may be associated with different consumer segments (cf. Urban, Johnson & Hauser, 1984), or they require the researcher to specify possible segments *a priori*, assuming that the consumers within a segment are homogeneous with respect to their choice structure (cf. Rao & Sabavala, 1981). However, these methods are not suitable for simultaneously inferring different structures and different consumer groups. From the viewpoint of identifying possible competitive links, it is important to analyse heterogeneity among consumers, because the competitive links may work out differently for different consumers groups. For instance, a competitive link between Pepsi Light and Coca Light might be strong in a calorie conscious 30+ age-segment, but it might be weak in a brand-conscious teenager-segment. The methods to be discussed in the next section explicitly address the heterogeneity aspect. We start with the confirmative method proposed by Grover & Dillon (1985).

♦ Heterogeneous, confirmative methods

Grover & Dillon (1985)

Grover and Dillon (1985) specifically address the issue of structure heterogeneity. Actually, they require different data compared to the methods discussed thus far. Instead of analysing an aggregate transition matrix, they follow the brand choice behaviour of consumers over a number of consecutive decisions (e.g., five brand switches), and determine whether the observed brand switching corresponds with the expected ones. Expected switching is based on a hypothesised market structure and a number of assumptions. The most fundamental assumption of the model is: the probability that a consumer switches out of a certain subset of brands *decreases*, the more often that consumer has bought within that subset in the past. The Grover & Dillon (1985) procedure tests whether a hypothesised decision-tree structure is in line with the decreasing brand switching probability assumption. To illustrate this, consider a hypothesised tree structure in Figure 2.6, describing the choice behaviour in a soft drink market with eight brands (for simplicity called B1 to B8), differing on aspect A1 (nationally versus regionally distributed) and on aspect A2 (colas versus noncolas). According to this structure, consumers are assumed to first decide on aspect A1, and then on aspect A2, yielding the corresponding choice (sub)sets. On the lowest level of the tree there are four choice subsets {B1,B2},{B3,B4},{B5,B6}, and {B7,B8}.

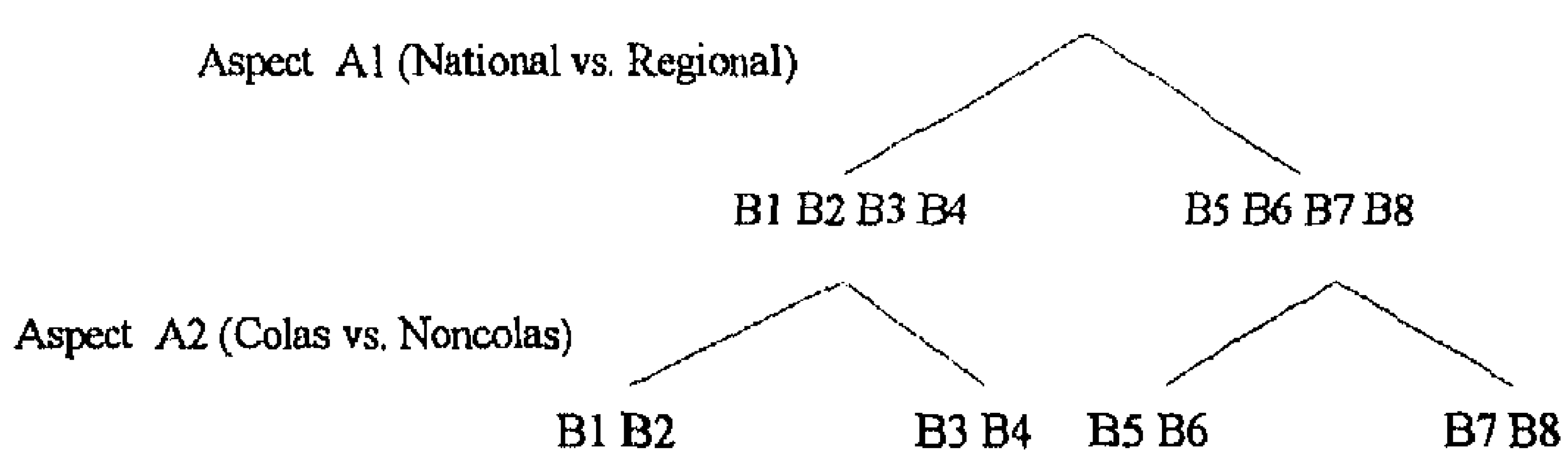

Figure 2.6 Hypothetical tree structure for the soft drink market (eight-brands/two aspects) (adapted from Grover and Dillon, 1985)

Grover & Dillon reason that if the structure is correct (at least for a number of consumers), it should hold that if the number of consecutive purchases increases, the ratio between the number of consumers switching at low levels in the hierarchy to the number of consumers switching at higher levels in the hierarchy must also increase. Thus, the more we observe consumers to switch within a subset (e.g., subset {B1, B2}), the less we expect the consumers to switch to a brand belonging to another subset (e.g., subset {B3, B4}) on the next occasion. Grover & Dillon (1985) specify the model in a latent class form, and use a maximum likelihood procedure to test whether the actual purchase behaviour of a group of consumers fits with the hypothesised tree structure. They use the theoretically expected choice behaviour (i.e. decreasing switching-out probabilities) as a criterion. Several goodness-of-fit indicators are suggested.

Grover & Dillon's procedure can provide different hierarchical structures describing the purchase behaviour of different customer groups. The different tree structures divide the sample of households into mutually exclusive groups of consumers. If so desired, the groups may be further analysed with respect to the consumers' background characteristics. For instance, Grover and Dillon provide an application to the U.S. instant coffee market, based on the purchase histories of 1595 households, each having five or more switches. They found two alternative structures fitting the data. Discriminant analysis on the sample split revealed that older and more educated consumers tend to first decide on the caffeinated versus decaffeinated aspect, and then decide on freeze-dried or the regular type of coffee. The younger and less educated consumers tend to decide the other way around.

Compared to the methods described before, the Grover & Dillon approach has the advantage of being able to identify segments. After all, it can hardly be denied that in practice the existence of segments is common rather than uncommon. The price of this advantage is, that the Grover & Dillon approach requires more data, i.e. strings of purchase choices at the individual consumer level, instead of an aggregate switching matrix. A practical disadvantage of this type of data is that they must be collected during a relatively long time period. This causes the observed switching to be ambiguous if there are substantial changes in the marketing instruments of the brands, which will be generally the case in practice. Another disadvantage of the Grover & Dillon method, like all other confirmative methods, is that it can get laborious when the structures become complex in terms of number of levels and subsets, and when there are many market segments. In such cases, any confirmative 'trial-and-error' approach becomes inconvenient.

Alternatively, a number of *explorative* methodologies has been developed that simultaneously suggest both market segments and market structures. In the next section we will discuss three key methods of such kind, developed by Grover & Srinivasan (1987), Elrod (1988), and Ramaswamy & DeSarbo (1990) respectively. Thereafter, we will conclude this section by elaborating on the complicating issue of variety-seeking behaviour in a market structuring context, which was first brought to attention by Givon (1985) and Lattin & McAlister (1985).

♦ Heterogeneous, explorative methods

Grover & Srinivasan (1987)

Grover & Srinivasan (1987, 1992) developed a latent-class model which directly and simultaneously estimates structures and segments, while using just one aggregate switching matrix, based on two consecutive purchase choices by a sample of consumers. Basically, their reasoning is that the cell frequencies in the aggregate switching matrix are the aggregation of the outcomes of the choice processes of groups of consumers, called segments. The idea is to decompose the total switching of the sample into the switching of a number of segments, or classes, consisting of consumers sharing the same choice behaviour. The segments are not observed directly, but are latent, and must be inferred from the data. The behaviour of consumers is assumed to follow the zero-order choice behaviour, i.e. each consumer has stable brand choice probabilities over the period observed. Grover & Srinivasan distinguish between two types of segments. First, each brand is assumed to be bought by a number of brand loyal consumers, which constitute a so-called 'brand loyal' segment. Consumers belonging to a brand loyal segment are assumed to purchase the particular brand with probability 1 on all occasions (i.e. the first and second purchase occasion). The other consumers switch on various occasions and belong to one of a number of 'switching-segments'[15]. The assumption is that each segment consists of a number of consumers which are homogeneous with respect to their brand choice probabilities. There are as many brand loyal

[15] Following on the Grover/Srinivasan (1987) model, a number of authors have elaborated on the concept of 'loyal' versus 'switching' segments (cf. Colombo & Morrison, 1989; Bordley, 1989; Greene, 1989; Jain, Bass & Chen, 1990; and McCarthy, Kannan, Chandrasekharan & Wright, 1992). Colombo & Morrison divide the market into 'hard-core loyals' and 'potential switchers' and use asymmetric switching matrices. Jain et al. propose a model that is similar to the one of Grover & Srinivasan, but estimate the number of segments in a more convenient way (Jain & Rao, 1994). McCarthy et al. distinguish between 'loyals' and 'shoppers' and allow choice processes to be first-order instead of zero-order.

segments as there are brands. The number of switching segments, however, must be determined by the analysis. Grover & Srinivasan specify the model as follows:

$$S_{ij} = \sum_{k=1}^{m} W_k p_{ik} p_{jk} \qquad \text{for } i \neq j \quad i=1,2,\ldots N, \text{ and}$$

$$S_{ii} = V_i + \sum_{k=1}^{m} W_k p_{ik}^2 \qquad \text{for } i = 1,2,\ldots N$$

where

S_{ij} = proportion of consumers switching from brand i to brand j,

S_{ii} = proportion of consumers buying brand i on two consecutive occasions,

W_k = proportion of consumers belonging to switching segment k,

V_i = proportion of consumers loyal to brand i,

p_{ik} = probability of choosing brand i, for consumers belonging to switching segment k (= share of brand i within segment k),

m = number of switching segments, and

N = number of brands.

Thus, the total observed switching from brand i to brand j in the aggregate matrix is the sum of the switching from brand i to brand j over all switching segments. The switching within a segment is assumed to be proportional to the shares of brand i and brand j in the segment (this follows from the zero-order assumption). The total observed 'stayers' with a brand (the diagonal cell frequencies in the aggregate matrix) is composed of the number of loyal consumers to that brand, plus the number of consumers in the switching segments that 'by chance' purchased that brand on two consecutive occasions.

Unknown are the number and sizes of the switching segments k, and the choice probabilities of the brands within the segments. Grover & Srinivasan specify their model in a latent class form as:

where

β_s = the weight of segment s (both switching and loyal segments), and

q_{is} = the probability of buying brand i by consumers belonging to the s-th segment.

This equation yields a latent class model of market structure, which can be estimated directly by a maximum likelihood procedure. In the estimation procedure, the number of switching segments must be prespecified. The optimal number of segments can be assessed from the goodness-of-fit statistics for different numbers of segments. Various test statistics are provided in Grover & Srinivasan (1987).

Grover & Srinivasan provide an application of their method to the U.S. instant coffee market, containing 11 brands. The aggregate transition matrix was analysed in accordance with the model and procedures described above. Table 2.6 shows the output of the Grover & Srinivasan application. The 11 coffee brands have different combinations of features (caffeinated (C) or decaffeinated (D); regular (R) or freeze dried (FD) as shown in the second column. The aggregate market shares of the brands are shown in the third column. For instance brand 1 (decaffeinated, regular coffee) has an overall market share of .13. The market consists of 11 brand loyal segments corresponding to 35% of the market (e.g., brand 1's loyal consumers make up 5% of the total market). In addition, four switching segments are identified corresponding to 65% of the market. For each segment, the market shares of the brands in the segment are given (e.g., brand 1 has a share of .09 within switching segment 1).

Segments are interpreted by looking at the strong brands within the segments. For example, segment 1 consists of two important brands (4 and 5), which are caffeinated, regular coffees. Segment 2, though, consists of two other key brands (1 and 6) which are *de*caffeinated, regular coffees. The table shows that a brand can belong to different switching segments at the same time. For example, brand 5 has its largest share in segment 1 (42%), but is also substantially present in segment 2 (15%).

Table 2.6 Four switching segment solution for the U.S. instant coffee market (taken from Grover & Srinivasan, 1987).

Brand, type		aggregate market share	weight loyal segment	switching segment 1 weight .19	switching segment 2 weight .22	switching segment 3 weight .18	switching segment 4 weight .06
				Within-segment market shares			
1	D,R	.13	.05	.09	<u>.20</u>	.13	.08
2	C,FD	.10	.04	.07	.03	<u>.18</u>	.03
3	D,FD	.07	.01	-	-	<u>.32</u>	.12
4	C,R	.12	.04	<u>.20</u>	.16	.04	-
5	C,R	.21	.08	<u>.42</u>	.15	.07	.06
6	D,R	.16	.07	.04	<u>.22</u>	.11	.15
7	D,FD	.03	.01	-	.05	.03	-
8	C,FD	.04	.01	.04	.03	.04	-
9	C,R	.06	.01	.14	-	-	<u>.27</u>
10	D,R	.03	.01	-	.07	-	<u>.27</u>
11	D,FD	.05	.02	.-	.09	.08	.02
total		1.00	.35	1.00	1.00	1.00	1.00

From the table, one can derive the expected total switching between two brands, by adding the expected switching between the brands within the segments. For example, the expected proportion of consumers switching from brand 1 to 2 is 0.69% ($.19 \times .09 \times .07 + .22 \times .20 \times .03 + .18 \times .13 \times .18 + .06 \times .08 \times .03$). These calculated, theoretical switching values should match the observed switching values as closely as possible. In fact, the Grover & Srinivasan procedure essentially searches for a configuration of segments and shares that minimises the differences between theoretical and observed switches.

A strong feature of the Grover & Srinivasan model, compared to the methods discussed previously, is the explicit inclusion of segments of consumers with different preferences regarding brands and types of brands. For a particular brand, the output shows its percentage loyal consumers, the switching segments it operates in, and its competing products in these switching segments. From the perspective of identifying competitive links this is particularly insightful, because it appreciates the idea that dependency relationships between brands may vary across consumer segments. Jain and Rao (1994) conclude, based on results of a simulation study, that the Grover & Srinivasan (1987) method can recover the aggregate market shares very well. However, the method proves sensitive to noise in the data with respect to the within segment shares. Therefore, one should be careful when interpreting the segments, and when assessing possible competitive links within the segments.

Choice Map Elrod (1988)

An alternative methodology for inferring 'heterogeneous' market structures from consumer choice data is developed by Elrod (1988). Contrary to the methods discussed previously, this method, called 'Choice Map', does not provide a hierarchical structure, but is meant to derive a multi-attribute product representation from panel purchase data. Due to computational restrictions, though, the model is limited to keep the dimensionality of the space to one or two. Also, the required type of data is different from the methods discussed so far. Elrod does not use transition data, but purchase frequencies, i.e. the number of times each consumer purchased each brand during a certain observational period of time (Elrod shows an application, using purchase data over 60 weeks, on average reflecting 12 consecutive purchases).

The Choice Map model uses the structure of a multinomial logit model. The assumption is that a consumer always buys the brand which, at that moment, has the highest perceived utility. The utility u_{ih} of brand i as perceived by consumer h is assumed to consist of two components: i) a preference component v_{ih}, constant in time, explained by the (constant) product attributes and ii) a stochastic component ε which causes the total 'utility' of the product to vary, under the influence of the specific situation of the consumer and the marketing activities of the suppliers. The constant preference component v is further investigated by Choice Map. The model assumes that differences in preferences between consumers arise because consumers attach different weights to the product attributes perceived by them. The product attributes themselves are assumed to be identically perceived by all consumers. In other words, in the model, all consumers perceive the same product picture and consumers differ from each other in terms of the importance they attach to the product attributes. Elrod specifies the probability p_{ih} that brand i is chosen by consumer h on any purchase occasion as a logit model:

$$p_{ih} = \exp[v_{ih}] / \sum_{i=1}^{N} \exp[v_{ih}]$$

Further, the vector v of a consumer's brand preferences is assumed to be a linear function of the brands attributes[16]:

$$v = Aw,$$

where A is the matrix of brand positions in the multi-dimensional map and w is the vector of importance weights for the dimensions. Consumers differ in their preferences because they differ in the important weights they attach to the brand attributes. The model specification allows Choice Map to simultaneously estimate the (homogeneous) perceptual positions and the distribution of consumer preferences, such that the estimated individual purchase frequencies coincide with the observed purchase frequencies, as best as possible. A maximum likelihood algorithm is used to search for the optimal solution.

Figure 2.7 exhibits a two-dimensional solution reported by Elrod of an application to the detergents market. In this market, eight brands exist, four liquid ones (L1, L3, L4 and L6) and four powder ones (P2, P8, P7 and P8). Figure 2.7 shows a clustering of Powder brands (P5, P7 and P8) and Liquid ones (L1, L4, L3 and L6). P2, although a powder brand, is positioned quite differently from all other powder brands. Also, there are position differences within the clustered powder brands and liquid brands. A difficulty with Choice Map is that the dimensions of the maps are not labelled. These dimensions must be interpreted by the researcher and the manager after the analysis has taken place.

[16] Elrod has also developed an ideal point version of Choice Map (Elrod, 1988b; Elrod and Keane, 1995).

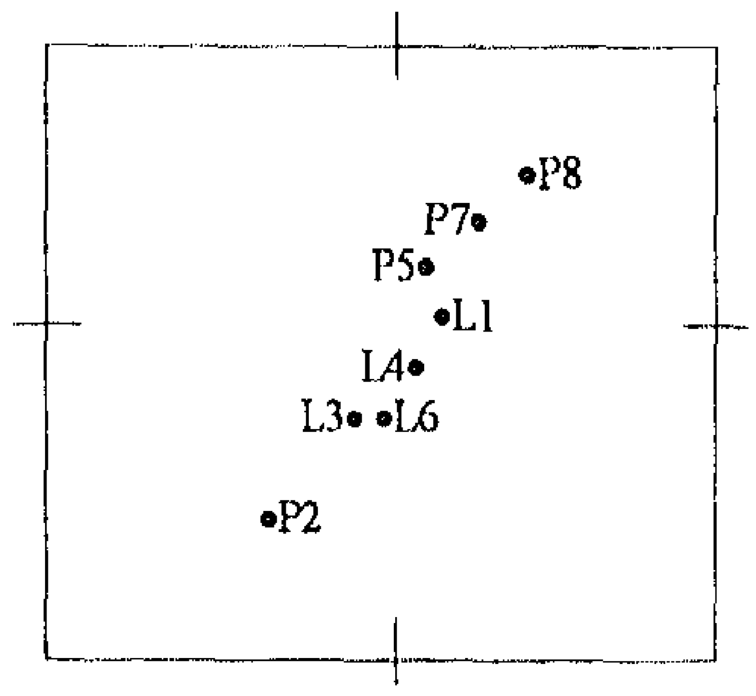

Figure 2.7 Display of a two-dimensional product map resulting from Choice Map (ideal point version, taken from Elrod, 1988b)

From the viewpoint of identifying competitive links between brands, Choice Map has the advantage of providing additional information about the closeness of brand in a product-attribute space. The (inferred) attributes do not necessarily coincide with the traditional physical features type of partitioning (e.g., powder versus liquid; caffeinated versus decaffeinated; light versus regular, etc.) which are generally used methods described thus far. Thus, in a market where brands do not so much compete on tangible features but rather on intangible aspects, Choice Map has a advantage above the other methods discussed[17]. However, the chosen structure for Choice Map, and the estimation method limit the applicability of the model. As with all logit models, it also holds here that the maps resulting from Choice Map can be sensitive to changes in the initial product set. This makes the pre-selection of the product set a critical step in the research. A further restriction is that, due to the technical specification of the model, the number of dimensions is limited to one or two. Finally, it must be noted that, although Choice Map captures consumer heterogeneity via the consumer preference distribution, it only yields one single product map for all consumers. In other words, all consumers are assumed to perceive the brands the same way. Strictly speaking, this makes Choice Map not a really 'heterogeneous' market structure approach with different 'maps' for different segments.

[17] More recently, Chintagunta (1994) and Elrod and Keane (1995) exploited methods for estimating ***logit*** and ***probit*** models from panel data to infer market structures. Their models produced a better fit to the data as compared to Choice Map. Shugan (1987) and Waarts, Carree and Wierenga (1991) estimate maps similar to Choice Map, but their maps are not based on individual consumer choice data, but on aggregate price and market share data.

We proceed by discussing the following key method developed in this category, 'Sculptre' (Ramaswamy & DeSarbo, 1990) which explicitly shows both products and segments in the market structure representation.

Sculptre

The final contribution discussed here in the category 'heterogeneous and explorative' is 'Sculptre' (*S*tochasti*C* *U*ltrametric *P*urchase *TR*Ee), developed by Ramaswamy and DeSarbo (1990). It has the same starting point as Choice Map (Elrod, 1988) in the sense that Sculptre too tries to infer both consumer preferences and product positions simultaneously from purchase frequency data. The main difference is that the output of Sculptre is a hierarchical tree with products and segments, in contrast with the single product attribute map produced by Choice Map. The vantage point of the Sculptre model is that a product-market combination can best be represented by a hierarchical tree, in which both products and segments are included. The idea is that the consumer's choice is determined by the (dis)similarity between products and the preferences of the segment to which the consumer belongs. The model is specified as follows:

Let:

n_{ih} = the observed number of choices of brand i by consumer h in a given time period,

d_{si} = the *distance* between segment s and brand i defined on a hierarchical product-market tree whose terminal nodes consists of both brands and segments,

d_{ij} = the *distance* between brand i and brand j defined on the same hierarchical tree, and

d_{rs} = the *distance* between segment r and segment s defined on the same hierarchical tree.

Then, Ramaswamy & DeSarbo express the conditional probability $p_{hi|s}$ of consumer h belonging to segment s choosing brand i as the multinomial logit expression:

$$p_{hi|s} = \exp(-d_{si}) \Big/ \left[\sum_j \exp(-d_{sj})\right],$$

which indicates that the shorter the distance between brand i and segment s in the tree to be derived, the higher the conditional probability that a consumer belonging to segment s chooses brand i. The actual observed purchase frequencies of consumers can be viewed as the *un*conditional purchase probabilities. The idea of the Sculptre model is to decompose these unconditional probabilities into a weighted average of conditional, segment-level probabilities. Ramaswamy & DeSarbo (1990) specify a maximum likelihood algorithm to derive the product-segment tree optimally satisfying the product-segment (dis)similarity criterion. The Akaike's information criterion (Akaike, 1973) is used to decide on the optimal number of segments in the tree.

Ramaswamy & DeSarbo (1990) provide a comparison of the Sculptre output with the output of Choice Map (Elrod, 1988). Both models were applied to the same data on the Liquid and Powder detergent market. Figure 2.8 shows the Sculptre tree output, which can be compared with the Choice Map shown in Figure 2.7. The products in the Sculptre tree are denoted by capital letters P and L and the segments are denoted by the capital letters A-F. From the tree one can read the competitive links of brands to each other and to the market segments. For instance, the upper branch splits into powders (brands P5, P7, P8) and one liquid brand (L1), which are relatively close to each other and to segments B, C, A and D respectively. The lower branch consists of brand L6, which is close to segment E, and of brands L3, L4, and P2 all relatively close to segment F. The 'clustering' of the brands in the Sculptre tree is quite similar to what is shown in the output of Choice Map.

Compared to Choice Map, the Sculptre tree provides additional information with respect to the indication of different preference segments. For the purpose of identifying competitive links this is useful information. Sculptre, at the other hand, does not show product positions in terms of (in)tangible attributes. Because Choice Map and Sculptre make use of the same type of data, they can readily be viewed as complementary to each other.

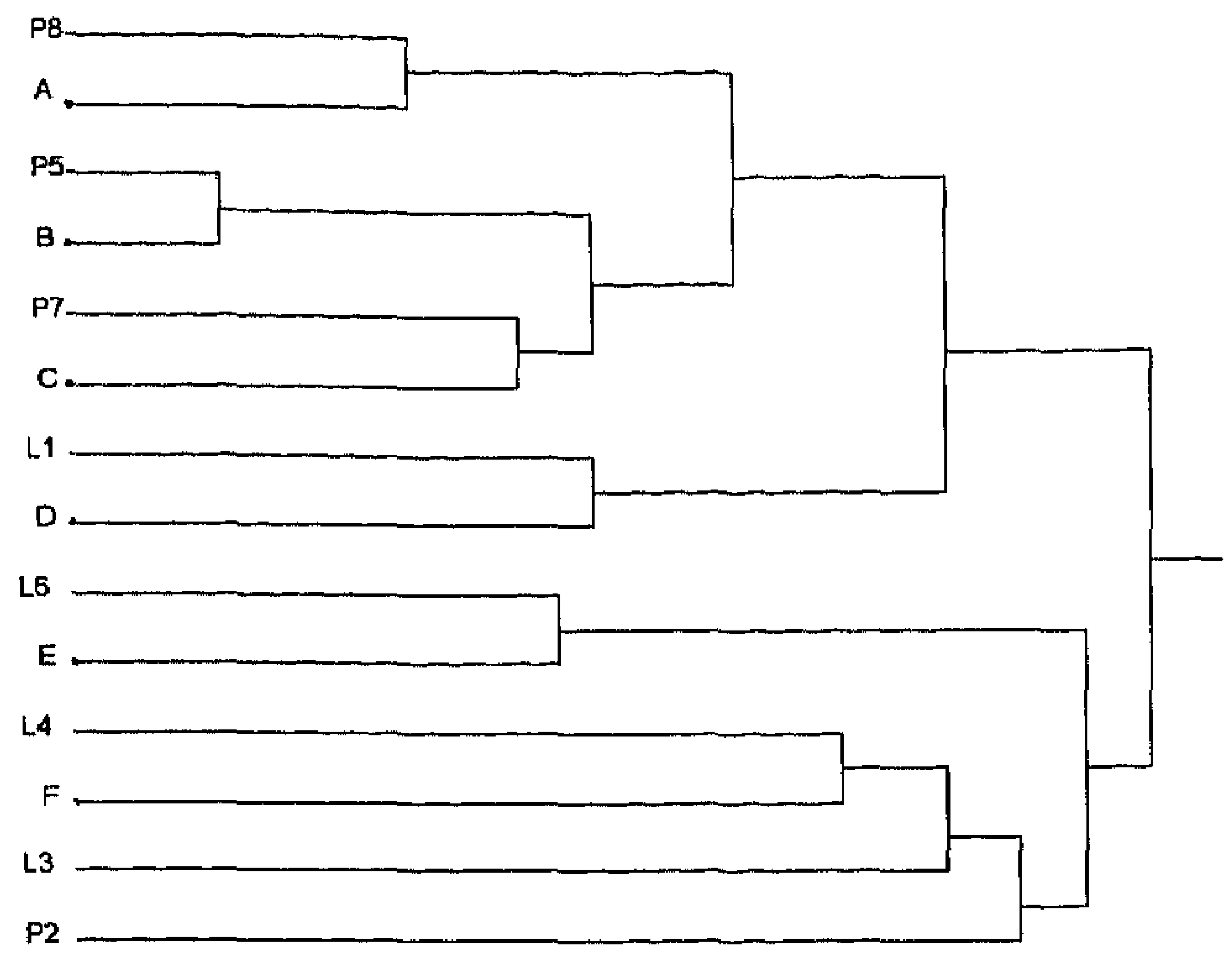

Figure 2.8 Example of a product-segment tree generated by the Sculptre methodology (taken from Ramaswamy and DeSarbo, 1990)

In terms of input-output, the Sculptre model also comes close to the latent class model of Grover & Srinivasan (1987). Although both methods use purchase data as input, the difference is that Sculptre requires brand purchase counts and the Grover & Srinivasan method needs an aggregate brand switching matrix. In terms of output, Sculptre gives a product-segment tree, from which the closeness of products to segments can easily be assessed. It is more difficult to read the closeness of two products to each other from the tree, which makes it rather inconvenient to assess possible competitive links between products. On the other hand, the Sculptre method can provide estimates of the purchase probabilities of brands per segment, which is similar to the information provided by the Grover & Srinivasan method.

Up till now, we have described the key developments and presented various methodologies for deriving competitive market structures from consumer choice data. In the next section, we will present a taxonomic overview of the methods. However, before doing so and before drawing general conclusions about the value of the methods for identifying possible competitive links between brands, we will first address the issue of variety-seeking behaviour, which is a complicating factor in the context of research on market structures.

Variety-seeking behaviour

The issue of variety-seeking behaviour was first brought to attention - at least in the context of market structuring - by Givon (1984, 1985) and Lattin & McAlister (1985). Basically, the argument is that aggregate hierarchical structures derived from choice data are usually based on certain assumptions about switching behaviour, that may not always be valid in practice. One of the usual assumptions is that high switching levels between brands indicate close competition. Givon and Lattin & McAlister argue that this need not always be the case, for instance due to consumers' need for variety of consumption. A consumer may prefer to buy various types of soft drinks alternately. For example, he first buys a bottle of Coca cola or Pepsi cola, and thereafter, for reasons of variety, he buys a bottle of 7-Up, then a bottle of cola again, etc. (cf. McAlister & Pessemier, 1982). Although the consumer may perceive the colas as similar, he does switch frequently between different subcategories of products. The implication of this behaviour is that, when variety-seeking is present, the level of brand switching becomes an ambiguous indicator for competition. It can mean brands being close substitutes as well as to brands being complementary to each other.

Theoretically, one of the implications of variety-seeking behaviour is that the probability of buying a similar brand on the next occasion diminishes. In that case, one can not assume that the zero-order effect holds, i.e. brand purchase probabilities can not be considered independent of previous purchases. Still, most of the methods discussed in this chapter explicitly assume a zero-order process during the observation time period (cf. the Hendry model; Grover & Dillon, 1985; Grover & Srinivasan, 1987). If the zero-order assumption holds, there is no problem and the method will derive a structure where higher switching levels point to closer competition. But, if switching actually occurs due to a 'variety drive' then the zero-order assumption does not hold and the derived market structures strictly become invalid. In that sense, variety-seeking can cause a problem for all methods discussed so far, except for the Prodegy method of Urban, Johnson & Hauser, because their forced switching data unambiguously indicate levels of substitutability between brands.

Whether there is a serious problem when the other methods are used, depends on the level of variety-seeking behaviour in the market to be researched. Both Givon (1985) and Lattin & McAlister (1985) propose a method to measure the degree of variety-seeking in a market and to solve the research problem. Both Givon and Lattin & McAlister present a method by which, for every respondent, the degree of variety-seeking is estimated, based on the actual purchase history of each individual consumer. Givon views the actual purchases of a consumer as the result of a combination of a variety-seeking force and a preference alone force. Givon searches for a structure *per respondent*, explaining both types of switching, using a maximum likelihood procedure. Lattin and McAlister specify a model that assumes that if a variety drive is present, the preference for a product at time $t+1$ is influenced by the brand bought at time t. When the need for variety is high, the probability of buying the same or a highly similar product the next time is smaller than the unconditional probability of buying that product. Lattin and McAlister use the difference between the unconditional and conditional probabilities as an indicator for the level of variety-seeking. Because both methods take place on an individual level, a sufficient series of consecutive purchases needs to be registered. For example, Givon already uses 30 sequential purchases for each consumer in a simple 6 product/2 attribute market. Lattin and McAlister use purchase histories of consumers consisting of more than 30 consecutive purchases. Therefore, although these methods solve a potential disturbing element in standard structure analysis methods due to variety-seeking behaviour, they have the disadvantage of requiring very long data strings at the individual consumer level. Thus, they are only suitable for analysing very stable market situations, where little happens with marketing instruments to influence the choice processes of consumers.

The discussion about variety-seeking leads us to conclude that for identifying levels of competition, the existence of a substantial variety drive on a market may disturb the applicability of the methods that explicitly assume choice processes to be zero-order. Most of the methods discussed so far do assume zero-order processes, except for the method developed by Urban, Johnson & Hauser (1984). Because there is evidence that in many consumer markets variety-seeking behaviour does occur (cf. McAlister and Pessemier, 1982; Givon, 1984; Wierenga, 1984; Van Trijp, 1995), the seriousness of the problem should be investigated before the structure analysis takes place. If variety-seeking behaviour is indeed strongly present, then methods assuming zero-order processes should not be applied[18]. Methods proposed by, amongst others, Givon (1985) and Lattin & McAlister (1985) can be used to assess the level of variety-seeking in a market, and can be used to investigate market structures if long strings of purchase data are available, and if the market conditions do not alter substantially during the observation period. After the methods developed by Givon and Lattin & McAlister, also other methods for market structuring have been suggested which account for possible variety-seeking behaviour in markets[19].

2.4 A taxonomy of methods

Previously, an overview was given of the main different approaches for identifying possible competitive links using data about consumers choice behaviour, that have been developed over the past twenty-five years. We may conclude that the subject is apparently of such complexity, that in the marketing literature, continuous reference is made to new methods for analysing competitive structures. Talking only about the 'behavioural data' based methods described here, more than 30 different models and methods have been developed, each having its own data requirements, theoretical model, estimation procedure, etc. To facilitate comparisons between the different methods, in this paragraph we will classify the methods according to a number of characteristics. Table 2.7 provides a taxonomy of the methods described in this chapter. Each of the methods is

[18] In a discussion about the validity of the zero-order assumption, Bass et al. (1984) conclude that, for frequently purchased goods, the majority of consumers do follow a zero-order process or something close to it, although they do not conclude that 'the world is zero-order'. In addition, Kahn, Morrison & Wright (1986) show that switching behaviour at the household level is always more zero-order than switching behaviour at the individual consumer level. These findings can be viewed as a support for 'zero-order' market structuring techniques taking place at the household level. Nevertheless, if variety-seeking is strongly present on a market - as is for instance the case with vegetables (Wierenga, 1984) - zero-order models may not yield valid structures.

[19] Cf. McCarthy, Kannan, Chandrasekharan & Wright (1992), Kannan & Sanchez (1993) and Zahorik (1994). McCarthy et al. (1992) use both switching data as well as forced switching data to estimate market structures, explicitly not assuming that choice processes are zero-order. Kannan & Sanchez (1993) use the first-order Markov model of Givon (1984) to account for potential variety-seeking. Zahorik (1994) distinguishes between 'consistency switches' and 'variety switches' and use a latent class model to infer market structures.

classified according to nine characteristics, grouped in terms of data requirements, methodology, and output. Below, we will briefly outline the characteristics used in the taxonomy.

Data Requirements

The first group of attributes concerns the input that is required to implement a particular method. This is specified according to the *type of data* and the relative amount (*# of data*). We base ourselves here on indications from the author(s), and the empirical applications described by them. The *type of data* varies from a full aggregate switching matrix (cf. the Hendry model, 1970; Novak, 1993) to individual brand purchase histories (cf. Grover & Dillon, 1985). Also the amount of data varies over the specific methodologies. It ranges from a relatively small forced switching matrix that is sufficient to estimate the parameters of the Prodegy model (Urban, Johnson & Hauser, 1984), to more sizeable samples for estimating the latent class models of Grover & Srinivasan (1987), and Ramaswamy & DeSarbo (1990).

Methodology

Next, five 'methodology' characteristics are included in the taxonomy. The first aspect concerns whether or not a method uses the *zero-order* assumption, i.e. the assumption that brand purchase probabilities are not influenced by past purchases, and are stable during the observation period. The only method that strictly does not assume this is Prodegy (Urban, Johnson and Hauser, 1984). All other methods assume that brand the choice process is zero-order. This poses restrictions on the applicability of these methods, especially if variety-seeking behaviour is present and, thus, the brand choice probabilities are not independent of the brand choices made previously.

The second methodological aspect describes whether or not a method is suitable for analysing heterogeneity in the market via the inclusion of different market *segments*. Some of the methods are capable of testing or suggesting different market structures (e.g., Kumar & Sashi, 1987). Although these methods appreciate the fact that there may exist segments in the markets, they do not explicitly derive different structures for different segments. Other methods (e.g., Grover & Srinivasan) explicitly incorporate the possible existence of different segments in their methodology and simultaneously estimate structures and segments.

Table 2.7 Taxonomy of key market structure analysis techniques for identifying competitive links based on consumer product purchase data

	data requirements		methodology					output	
Approach	type of data	# of data	zero-order	segments	test/suggest	estimation	statistics	form	information about competitive links (c.l.) of a brand
Kalwani & Morrison (1977) 'Hendry model'	full aggregate switching matrix	medium	yes	no	testing	fit theoretical vs. observed	various	hierarch. structure	c.l. stronger if another brand belongs to the same partition, if switching constant k_w is higher, and if the partition is lower in the hierarchy
Urban, Johnson & Hauser (1984) 'Prodegy'	aggregate forced switching matrix	low/medium	no	no	testing	fit theoretical vs. observed	limited	hierarch. structure	c.l. stronger if another brand belongs to the same partition, and if the partition is lower in the hierarchy
Kumar & Sashi (1989)	full aggregate switching matrix	medium/high	yes	no	testing	max. likelihood	limited	hierarch. structure+ trans. prob.	c.l. stronger if another brand belongs to the same partition, and if the partition is lower in the hierarchy. Intensities can be inferred from repeat and switching probabilities
Rao & Sabavala (1981)	full aggregate switching matrix	medium	yes	no	suggesting	cluster analysis	limited	hierarch. structure	c.l. stronger if the distance to another brand (to common node) is smaller. No differentiation regarding brands within a partition
Novak (1993)	full aggregate switching matrix	medium/high	yes	no	testing and suggesting	max. likelihood	various	log linear add. tree	c.l. stronger if the distance to another brand in the tree is smaller. Differentiation possible for brands within the same partition
Grover & Dillon (1985)	brand purchase histories	high	yes	yes	testing	max. likelihood	various	hierarch. structure	c.l. stronger if another brand belongs to the same partition and if the partition is lower in the hierarchy. Different c.l.'s across segments
Grover & Srinivasan (1987)	full aggregate switching matrix	medium/high	yes	yes	suggesting	max. likelihood	various	table	c.l. stronger if the switching intensity with another brand is higher. Different c.l.'s across segments
Elrod (1988) 'Choice Map'	brand purchase frequencies	high	yes	no	suggesting	max. likelihood	various	multi-dim. attrib. map	c.l. stronger if the distance to another brand in the multi-dimensional map is smaller
Ramaswamy & DeSarbo (1990) 'Sculptre'	brand purchase frequencies	high	yes	yes	suggesting	max. likelihood	various	hierarch. structure + table	c.l. stronger if the switching intensity with another brand is higher. Different c.l.'s across segments

The third methodological aspect (*test/suggest*) describes whether a method is confirmative or explorative in nature. A method is confirmative if a method requires prespecified structures and is testing different structures on the data (e.g., the Hendry model; Urban, Johnson & Hauser, 1984; Kumar & Sashi 1987). Alternatively, a method is explorative, when it can be applied to suggest structures based on the data (e.g., Grover & Srinivasan, 1987; Ramaswamy & DeSarbo, 1990).
The fourth methodological aspect (*estimation*) describes the basic way a method infers market structures from the data. This varies from relatively 'simple' calculations regarding the fit between theoretical switching values versus observed ones (as in the Hendry model and in the Prodegy model), to sophisticated maximum likelihood algorithms that search for optimal satisfaction of certain model criteria (e.g., Grover & Dillon, 1985; Elrod, 1988; Novak, 1993).
The final methodological aspect (*statistics*), specifies to what extent a proposed methodology is accompanied by model statistics that provide information about the quality of the structures. Most authors do suggest using certain statistical quality tests, but the tests vary in extensiveness. For example, in the case of the hierarchical cluster approach developed by Rao & Sabavala (1981) few statistics are proposed, while Elrod (1988) provides various statistics to evaluate the inferred structures.

Output

The third and final group of attributes concerns the output of the methods. Firstly, the *form* of output is indicated. Some methods yield hierarchical structure diagrams (e.g., the Prodegy model), sometimes accompanied with additional information (e.g., the Hendry model with switching constant K_w; Kumar & Sashi (1989) with transition probabilities). Others present the output in the form of a multi-dimensional representation (e.g., Elrod, 1988) or in the form of tables (e.g., Grover & Srinivasan, 1987).

Finally, we comment on each method according to the '*inferences about competitive links (c.l.) of a brand*'. This points to the information a method delivers for a manager of a particular brand, with respect to the competitive links this brand potentially has with other brands in the market. After all, the main objective of this chapter is to investigate the value of market structuring methods for identifying possible competitive links between brands. Indeed, the common characteristic of the methods described in this chapter is that they all attempt to infer levels of competition, i.e. closeness between brands, from consumer choice data. The methods and means differ, and so does the output for assessing levels of competition. When an aggregate hierarchical structure is inferred, the key criterion for assessing the closeness between brands is their membership of subgroups of brands. Brands that belong to the same subgroup are assumed to be relatively close substitutes, and are thus expected to have a strong competitive link with each other. Some methods provide additional information in the form of switching intensities (e.g., the Hendry model), or transition probabilities (e.g., Kumar & Sashi, 1989). In that case, higher brand switching/transition probability levels are assumed to indicate stronger competitive links. Methods that yield non-hierarchical tree structures or maps, use the distance between the brands in the trees or maps for assessing the level of competition between the brands (e.g., Rao & Sabavala, 1981; Elrod, 1988; Ramaswami & DeSarbo, 1990; Novak, 1993). Finally, Grover & Srinivasan provide the competition information in the form of a table, from which the level of competition between brands is inferred from the shares of brands in each segment.

2.5 Conclusions

The main objective of this chapter was to investigate if and how competitive links between brands can be identified using the perspective of the individual consumers. While there are different main avenues for approaching the problem (e.g., perceptual mapping, cross-elasticity analysis), we have chosen to further investigate one of them, namely the approach of inferring levels of competition from consumer brand choice data. Although such analyses will not directly identify actual competitive links, they may provide information about the closeness of brands in the perception of the consumers. Therefore, they may give indications about possible competitive links between brands. After having described and classified a number of 'landmark' methods for inferring levels of competition from brand choice data, we will now summarise the developments which have taken place in this field and assess the value of the methods for identifying possible competitive links.

Since the early seventies, much progress has been made in analysing brand choice data. This is undoubtedly partly due to the ready availability of such data. Probably, the availability of this type of data will continue to increase, due to the emergence of new technologies. The efforts made in the past, to infer levels of competition from consumer choice data, have resulted in the current presence of a rich collection of methods. Each method has its own features and virtues, which are pointed out in this chapter. Two development areas are clear.

- Firstly, much effort has been devoted to the analysis of heterogeneity in consumer markets. The general idea is that brands can have different levels of competition within different segments of the consumer population. The result of the various efforts is, that many of the contemporary methods account for consumer heterogeneity and try to infer structures that combine both products as well as market segments (cf. Grover & Srinivasan, 1987; Ramaswamy & DeSarbo, 1990; Zahorik, 1994).

- A second dimension on which much progress has been made has, to do with the methodologies by which the data are analysed. A variety of model specifications is available, as well as a rich collection of estimation procedures (e.g., regression analysis, cluster analysis, various maximum likelihood procedures). The advantages of the more sophisticated methods can primarily be found in the quality of the fit between the models and the data. Sometimes, researchers compare the output of their method with the output from one or two other method (cf. Ramaswamy & DeSarbo, 1990; Jain & Rao, 1994). However, to our knowledge, no study yet exists that formally tests a number of methods against each other. In addition, usually only one illustrative application of a proposed method is described in the publication concerned, and very little is mentioned about the success of applying the proposed method in practice. Unfortunately, the lack of formal comparisons between the various methods, and the lack of evidence of practical use, will probably hamper the 'penetration' of the more sophisticated methodologies in marketing research practice.

While much progress has been made, at the same time, there are certain restrictions that most of the methods described here share, which also limit their applicability in practice.

- The first restriction relates to the presence of variety-seeking behaviour in markets, which may make a zero-order assumption questionable. In case, in a market, variety-seeking is strongly driving consumers purchase behaviour, methods assuming zero-order processes may mistakenly interpret high switching levels as an indication for close substitutability between brands (cf. Givon, 1985, Lattin & McAlister, 1985). Many of the methods discussed in this chapter are indeed restricted in this respect. However, currently a number of methodologies has been suggested coping with variety-seeking behaviour (cf. McCarthy, Kannan, Chandrasekharan & Wright, 1992; Kannan & Sanchez, 1993; Zahorik, 1994).

- The second main restriction is inherent to the type of data utilised. One of the main fundamental problems with analysing brand purchase data exclusively, as was already mentioned by Day et al. (1979), is the fact that one assumes that the product offerings by firms are constant over time, at least during the observation period. In practice, though, marketers are continuously changing their marketing instruments - and are thus changing their product offerings - in an attempt to improve on their performance. The effect is that brand choice is not just a stochastic process, whether or not driven by a variety-seeking motive. Brand choice is also actively influenced by marketers. For instance, a 25-cent promotional discount on a bottle of Amstel beer could easily cause some consumers to buy that brand instead of their usual brand. Also, new product introductions and product relaunces cause shifts in brand attitudes and purchase probabilities. Depending on the magnitude of the changes, this can not be dealt with as just being 'noise' in the data. The methods described in this chapter do not explicitly account for changes in the marketing propositions. Therefore, the inferred structures will only be valid if it can be assumed that the changes that have taken place during the observation period did not substantially affect the consumers' choices.

  Besides the 'purchase-data-alone' methods described in this chapter, there are also methods available that infer levels of competition from both (scanner) household data and retail panel data, containing both brand purchase data as well as marketing instrument data. Typically, the output of this type of methods provide interesting information about competition, showing product/segment parameters combined with marketing-mix activity response parameters. Such methods go further than just *identifying* possible competitive links: they also partly analyse the *content* of the links, in terms of the effects of marketing activities on sales and market shares (cf. Carpenter & Lehmann, 1985; Moore & Winer, 1987; Grover & Srinivasan, 1989; Kamakura & Russell, 1989; Gupta, 1991; Kannan & Wright, 1991; Zenor & Srivastava, 1993; Russell & Kamakura, 1994; and Wedel, Kamakura, DeSarbo & Ter Hofstede (1995).

We will not describe each of these methods in detail here, but refer the reader to the publications concerned.

We started this part of the research with the observation that, due to new technologies the marketing manager is confronted with the possibility of having access to large quantities of marketing data. The availability of these data should make marketing management life more easy, because more can be learned about marketing processes. However, these large quantities of data will not mean anything to the manager, unless proper analytical methods transform these data into meaningful management information. This area of tension between data and information holds for numerous marketing management problems, including the identification of competitive links. The overview presented here reveals that many attempts have been made and are still being made to transform data into useful information. For the purpose of identifying competitive links from consumer purchase data, these attempts may yield valuable information. However, the actual value of the output provided by the methods described in this chapter is dependent on the market circumstances at hand. Important key value determining aspects are threefold: the level of consumer heterogeneity (i.e. the existence of market segments), the level of variety-seeking behaviour of the consumers, and the marketing activity level of the suppliers.

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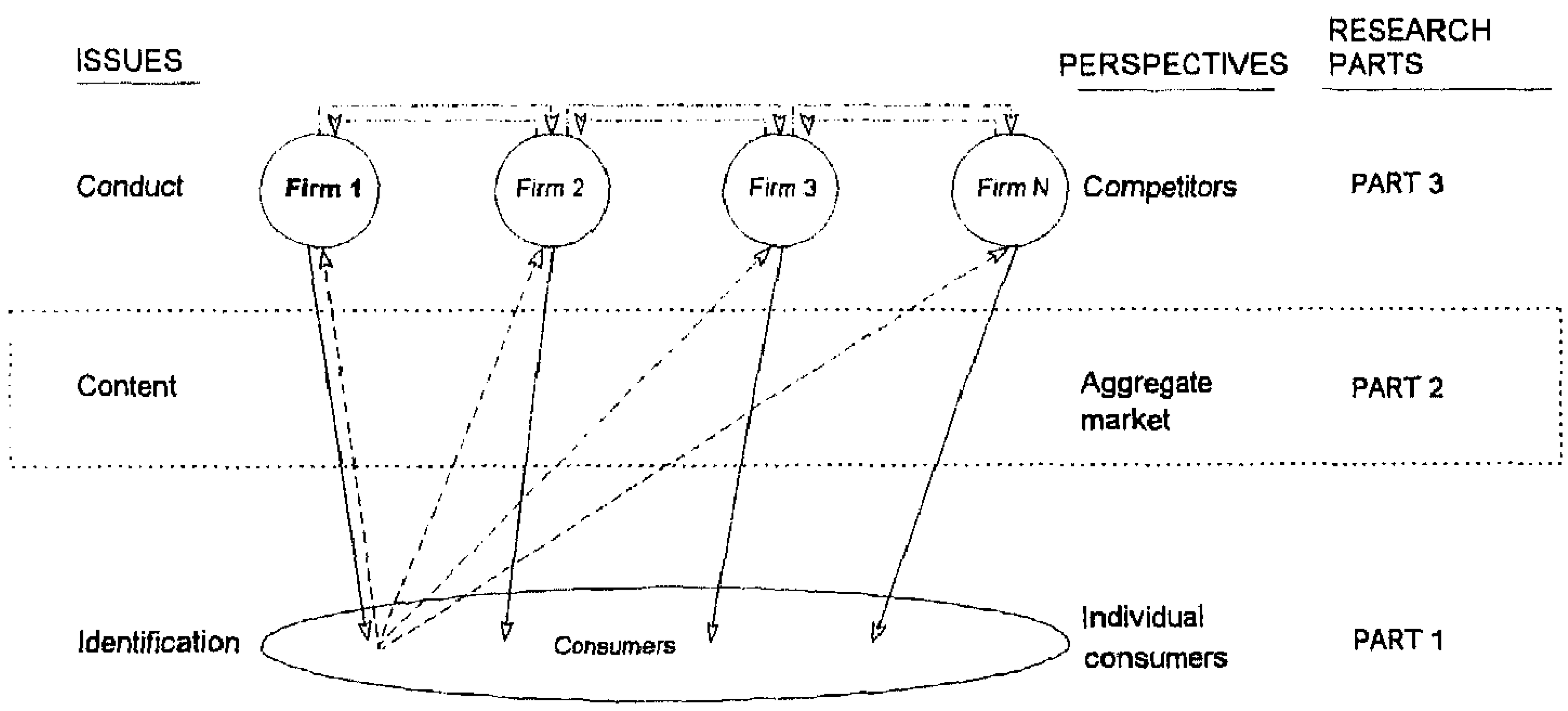
Part 2

The content of competitive links



3 Methods for analysing the content of competitive links

3.1 Introduction

The first part of this thesis was dedicated to the issue of the identification of competitive links. The focus was on tracing potential competitive links using consumer purchase data exclusively, that is without explicitly making use of marketing instrument data. Part 2 of this dissertation is devoted to the second aspect regarding competitive links, namely their *content*. It focuses on the actual cross-effects of marketing instruments from one brand to another. In analysing the content of competitive links, the perspective is from the *aggregate market level*. Typically, data are used concerning marketing instruments, brand sales and market shares.

To point out again what is meant by the content of competitive links, let us take the example of a marketing manager of a frequently purchased consumer good, say the marketing manager of Honig's Italian pasta's (macaroni, spaghetti, etc.). Suppose that in the market a few main competitors (Barilla, GranItalia, and Del Verde) offer a similar assortment of pasta. One way of identifying potential competitive links is by analysing the brands and types of products with respect to their mutual similarity and substitutability from the perspective of the consumers. The preceding chapter elucidated several ways for inferring this from the brand choice behaviour of consumers. Typically, after applying such methods, the manager knows which brands can be considered close to his Honig products (for instance, imagine Barilla's Macaroni proves to be very close to Honig's Macaroni) and which products are considered less close (e.g., GranItalia's tortellini may seem quite dissimilar to Honig's tortellini). If desired, this can be diagnosed per consumer segment, and, if applicable, variety-seeking elements can be accounted for.

The next question for the marketing manager is what the closeness of products implies in terms of the (cross)-effectiveness of marketing instruments. There are two aspects here. The first is what the impact will be of Honig's marketing activities on the performance of the competing brands. Here, the focus is on cross-effects from a focal brand on the competing ones. This information is relevant if, for example, the manager wants to assess the possibility of counter actions by the competitors. The second aspect works the other way round: how vulnerable are the Honig products to marketing activities by the competitors. Here, the focus is on cross-effects from competing brands on the focal brand. For instance, what will happen to Honig spaghetti's market share if Barilla lowers prices or increases advertising expenditures for certain paste products? This information is relevant for the manager because he may watch Barilla's activities more carefully and may try to safeguard his products beforehand if he knows that he is very vulnerable to such actions.

Accordingly, the *content* of a competitive link is viewed here as a composite construct and relates to the *cross-effects back and forth between a focal brand and a brand it is competitively linked with, concerning the effects of specific marketing instruments on each other's performances.* A brand usually has competitive links with several competing brands at the same time. The specific content of each competitive link becomes apparent in the mutual cross-effects of marketing activities.

The current part of this thesis contains two chapters devoted to the content aspect. The present chapter focuses on the main approaches found in the marketing literature with respect to analysing the content of competitive links. While recognising the fact that a long research tradition exists in investigating cross-effects of marketing instruments (cf. Kuehn, McGuire & Weiss, 1966; Kotler 1971; Lambin, Naert & Bultez, 1975; Hauser & Shugan, 1983; Cooper, 1988; Leeflang & Wittink, 1992; Russell & Kamakura, 1994), we have chosen to discuss two approaches in depth here, representing two very different 'schools' of analysing the content of competitive links.

The first 'school' is *econometric* and *inductive* in nature. This school approaches the problem by collecting and analysing actual sales and marketing instrument data (e.g., Nielsen data). Typically, the output of the analysis shows estimates of the (cross-)effects of marketing instruments as they have occurred in the market. This gives the manager a better view on what actually happened in his market, and provides information about the competitive impact of various marketing actions. While this 'school' of research has yielded a rich collection of models and methods (cf. Hanssens, Parsons & Schultz, 1990, Ch. 6), in this chapter we will focus on a method developed by Cooper (1988) and Cooper & Nakanishi (1988), called 'Competitive Maps'[1]. This particular method is selected because we consider it a prototype of econometric research specifically focusing on estimating competitive effects. In addition, the work incorporates and combines many elements of previous research, and it has had a substantial impact on further developments in the research field (Lilien, Kotler & Moorthy, 1992).

The second 'school' of analysing competitive links is *abstract-deductive* in nature. Basically, this school of research investigates competition questions by modelling the market and its underlying processes. Typically, the aim is to deduce 'optimal' marketing policies in a theoretical market framework setting. If the model is a good representation of actual market processes, it gives the manager a better understanding of 'why' effects occur in his market and how he can cope with this. An excellent example of this type of research is Hauser & Shugan's (1983) 'Defender model'. This is one of the first models in marketing explicitly modelling competition based upon a theoretical model of consumer choice behaviour. Moreover, the model has enough richness and external validity to be relevant for practical purposes. Inspired by the Defender model, a series of similar, but different deductive methods modelling competition were suggested (cf. Moorthy, 1988; Carpenter, 1989; Horsky & Nelson, 1992; Sudharsan, Kumar & Gruca, 1995). These are the reasons why the Defender model is selected

[1] Actually, the book published by Cooper & Nakanishi (1988) is entitled 'market share analysis'. This covers more than the concept of competitive maps, although that particular concept constitutes a substantial part of the book. In this thesis, we prefer to address the approach by Cooper & Nakanishi with 'Competitive Maps', because this better reflects the method in the context of competition. Moreover, the method is often referred to as 'competitive maps', which is reflected in Cooper's (1988) Management Science article on this method entitled: 'Competitive Maps: the structure underlying asymmetric cross elasticities'.

as the second 'prototype' approach in this chapter, next to Cooper & Nakanishi's 'Competitive Maps'.

Though the selected methods developed by Cooper & Nakanishi (1988) and by Hauser & Shugan (1983) represent different research schools, they are similar in the sense that they both aim to analyse the content of competitive links, i.e. they analyse the effects of marketing actions by a particular brand both on its own sales and market share, and on the sales and market shares of the competing brands. Also, both try to capture the competitive situations of brands in spatial representations. The models behind the approaches are completely different, though. Cooper & Nakanishi analyse asymmetric cross-elasticities from real data in a market share attraction model framework, while Defender model (Hauser & Shugan, 1983) analyses the (likely) effects of competitive actions if these actions take place in a (theoretical) consumer choice model framework. In the current chapter, we will discuss and compare the two selected methods in the perspective of the two schools of research for analysing the content of competitive links.

The second chapter devoted to the content of competitive links, Chapter 4, entitled *'Full-information maximum likelihood estimation of brand positioning maps using supermarket scanning data'*, forms a special section, elaborating on Shugan's (1987) Defmap method, which was developed for estimating the product locations in the Defender model from retail scanning data. In particular, in the next chapter, a number of extensions and improvements will be suggested on the proposed method by Shugan. The newly proposed method is illustrated by an application using supermarket scanning data on a specific category of frequently purchased consumer goods.

Cross-elasticities

Predominantly, in the economic literature cross-effects of firms' activities are studied by examining cross-elasticities, that is the relative effect of a change in a firm's marketing instrument (e.g., a price change) on the performances/sales of the competitors (e.g., the price cross-elasticity). The analysis of cross-elasticities has been common practice in (classical) economic theories for years. For example, it has been one of the criteria for developing the standard classifications of markets into different market forms, such as pure competition, monopolistic competition, homogeneous and heterogeneous oligopoly and monopoly. Even today, the 'cross-elasticity of demand' is still seen, by many economists, as a standard for analysing competition (Scherer & Ross, 1990; Lilien, Kotler & Moorthy, 1992).

Although the concept of 'cross-elasticity' is attractive from a theoretical point of view, there has always been much criticism by practitioners, mainly due to the alleged inapplicability of this measure in practice. The main objection is that the cross-elasticity at a certain point in time is a static measure and is difficult to estimate because the concept demands a general ceteris paribus condition: the other market circumstances should not change during the period of analysis. Yet, this is difficult to maintain in practice, especially when one has the idea that the performance dependencies to be measured can cause competitors to react to one another. The ceteris paribus condition will become a necessary prerequisite that will almost never hold in real markets. However, these problems can be circumvented by registering and controlling for changes in the market, which can be done by applying econometric methods (cf. Lambin, Naert & Bultez, 1975; Cooper, 1988; Cooper & Nakanishi, 1988). In this chapter, as mentioned before, we will discuss two different approaches for analysing the content of competitive links. We will start with an econometric method developed by Cooper (1988), and Cooper & Nakanishi (1988). We will postpone discussions about the methodology initiated by Lambin, Naert and Bultez (1975) to Chapter 5, because their methodology does not solely incorporate cross-effects on sales and shares, but also explicitly includes competitor responses, i.e. elements of the *conduct* regarding competitive links.

3.2 Cooper & Nakanishi's Competitive Maps

Cooper (1988) and Cooper & Nakanishi (1988) (hereafter C&N) have concentrated on the development of a general method, which analyses the content of competitive links through the estimation of (cross)-elasticities. Their point of departure is that every marketing plan should contain an instrument-by-instrument account of the actions to be taken. For example, it should address questions like what price-level should be selected, what should the advertising budget be, how much should be allocated to direct marketing activities, etc.? Marketing decisions should be based on the expected response in the market place of changes in each element of the marketing mix. The primary focus of C&N is on consumer response, and not on competitor response in the market place. C&N argue that elasticities can be used to provide this instrument-by-instrument account of market response.

C&N specify (cross-)elasticities, using market share attraction models (which we will introduce later), in order to estimate (i) *own* effects, which are the effects of marketing instruments on one's own product's market share, and (ii) *cross*-effects, which are the effects of the marketing instruments on the competing products' shares. An important feature of the C&N model is that cross-effects are allowed to be *asymmetric*, that is, the cross-effects can vary in strength towards each of the competing brands[2]. Further, an interesting distinction is made concerning the direction of the cross-effects: the '*clout*' and '*vulnerability*' of brands. The '*clout*' of a brand refers to the level of influence that a brand can exert on the competition with a particular marketing instrument. The '*vulnerability*' of a brand refers to the sensitivity of a brand for marketing activities by the competing brands. This allows, for instance, that a particular brand might be very effective with price reductions, thereby exerting large influence on certain competing brands, while the same brand might not be very sensitive to price reductions by the others.

The C&N approach builds upon a vast prior research avenue concerning market share analyses (cf. Weiss, 1968; Naert & Bultez, 1973; Nakanishi & Cooper, 1974; Bell, Keeney & Little, 1975; Nakanishi & Cooper, 1982; Leeflang & Reuyl, 1984; Naert & Weverbergh, 1985). Also, the method has inspired others to suggest extensions, improvements, and other directions (cf. Carpenter, Cooper, Hanssens & Midgley, 1988; Vanden Abeele, Gijsbrechts & Vanhuele, 1990; Russell, 1992; Russell & Kamakura, 1994; Foekens, Leeflang & Wittink, 1996). We will now discuss the content of the C&N approach.

[2] We point to the fact that 'asymmetry' in the context of attraction models is defined in the literature (cf. Vanden Abeele et al., 1990) as the property that a brand's cross-elasticities may differ towards different other brands. This allows that a brand can exert disproportionate strong or weak influence on some of the other brands. This type of 'asymmetry' must not be confused with another type of asymmetry, that is the notion that the cross-effects from brand i to brand j may be different from the effects from brand j to brand i. This second type of asymmetry relates to differences in the clout and the vulnerability of brands.

The C&N methodology works as follows. For a previously determined set of products, a time series is used containing market shares and marketing activity data (e.g., prices, advertising, promotions, etc.) for all brands[3]. For instance, C&N's application on the ground caffeinated coffee market uses data from a number of grocery chains in two cities over 78 consecutive weeks, covering shelf prices, newspaper features, in-store displays, and store-coupon activities and sales for all coffee brands.

The first step in the C&N analysis is the specification of models for describing sales and market share movements. C&N make use of standard attraction models to this end and extend them into several directions. We will briefly demonstrate their line of reasoning and modelling here. C&N start from a general structure of an attraction model:

$$s_{it} = \frac{A_{it}}{\sum_{j=1}^{m} A_{jt}} \quad ,$$

where s_{it} is the market share of brand i $(i, j=1,2..., m)$ in period t $(t=1,2...,T)$, A_{it} is the attraction of brand i in period t, and m is the number of brands. C&N use two different well-known attraction models (MCI and MNL) for relating the attraction of the brands to the marketing instruments of the brands. Firstly, the attraction component in a simple multiplicative competitive interaction model (MCI) is specified as (ignoring time-subscript t):

$$\text{MCI model:} \quad A_i = \exp(\alpha_i).\prod_{k=1}^{K} X_{ki}^{\beta_k}.\varepsilon_i \, ,$$

and secondly, the attraction component in a simple multinomial logit model (MNL) is specified as:

$$\text{MNL model:} \quad A_i = \exp(\alpha_i + \sum_{k=1}^{K} \beta_k . X_{ki} + \varepsilon_i)$$

[3] Clements and Selvanathan (1988) address the issue that a product set must be defined beforehand and that the estimated elasticities depend on the product set which the researcher uses. The authors suggest how one can make an explicit link between product set definition and model specification using the Rotterdam Model.

where

X_{ki} = the value of the k^{th} marketing instrument for brand i

K = the number of marketing instruments

β_k = a parameter to be estimated, describing the effectiveness of marketing instrument k

α_i = a parameter for the constant influence of brand i

ε_i = an error term

It is clear that, while both models relate the attractiveness of brands to the marketing instruments used, the models differ with respect to the expected form of the relationship between marketing instruments and brand attractiveness. The difference between the MCI and MNL model becomes more apparent when looking at the own market share elasticities for each model (C&N, p.34):

MCI model: $e_{si}^{(k)} = \beta_k(1 - s_i)$

MNL model: $e_{si}^{(k)} = \beta_k(1 - s_i)X_{ki}$

where $e_{si}^{(k)}$ is the own market share elasticity for brand i, regarding the k^{th} marketing instrument. The share elasticity in the MCI model declines monotonically as X_{ki} increases (assuming that the share increases as X_{ki} increases), while in the MNL model the share elasticities first increase to a certain point and thereafter decrease. C&N point out that both models can be a correct description of the actual share elasticity behaviour, depending on the specific marketing instrument. The MCI model is considered suitable for the price instrument, while the MNL model is suggested for modelling elasticities for advertising and promotions[4].

[4] Gruca & Sudharshan (1991) point out that when the MNL model is applied to firms having less than 50% market share, the result is that it would be optimal for these firms to increase their advertising expenditures as much as possible. They recommend to use the MCI model for advertising.

C&N extend the basic MCI and MNL models in two directions, thereby allowing the attraction models to be more flexible regarding the influence of brands on each other. Firstly, as they point out, the effectiveness of marketing instruments may differ over the brands. For instance, one brand can be very effective with advertising and not with price, while for another brand this can be just the other way around. C&N model this '*differential effectiveness*' phenomena by substituting the homogeneous parameter β_k into a brand specific (heterogeneous) parameter β_{ki}.

Secondly, *brand specific* cross-elasticities are introduced, summarising the effects that marketing instruments of one brand will have on each of the other brands' shares. In an attraction model with differential effects the (point) cross-elasticities are (ignoring superscript k):

MCI model: $e_{si.j} = -\beta_{kj} s_j$

MNL model: $e_{si.j} = -\beta_{kj} X_{kj} s_j$

where $e_{si.j}$ stands for the cross-elasticity of brand j exerting influence on the share of brand i (by means of marketing instrument k). In this model, the cross-elasticities of brand j to all other brands are equal, because in the right hand side of the latter equations only brand j is present. Again, C&N point out that this is not in line with observations in practice. Some brands have strong influence over each other, while other brands are practically immune from each others marketing activities. This phenomenon is a logical consequence of the differences in similarities between brands in the eyes of the consumers. After all, as was pointed out in the previous chapter of this dissertation, the closeness of brands in the eyes of the consumers should imply something about the influence the brands can exert on each other. C&N extend the differential effects model to accommodate brand specific cross-effects. This yields a so-called *fully extended attraction model* of the general form:

$$A_i = \exp(\alpha_i + \varepsilon_i) \prod_{k=1}^{K} \prod_{j=1}^{m} f_k(X_{kj})^{\beta_{kij}},$$

$$s_i = \frac{A_i}{\sum_{j=1}^{m} A_j}$$

where f_k is a monotone transformation of X_{kj} (yielding MCI or MNL models) and β_{kij} is the parameter for the differential cross-competitive effect of brand j's instrument k on brand i. The cross-elasticities of the fully extended attraction model are given by:

MCI model: $$e_{si.j} = \beta_{kij} - \sum_{h=1}^{m} s_h \beta_{khj}$$

MNL model: $$e_{si.j} = (\beta_{kij} - \sum_{h=1}^{m} s_h \beta_{khj}) X_{kj}$$

From the formulae for $e_{si,j}$, it is clear that the cross-elasticity towards a brand is moderated by the cross-effects towards all other brands. The β_{kij}'s allow the cross-elasticities to vary across brands and across marketing instruments, and allow the effect of brand i on brand j to be different from the other way around. These properties are essentially what we are looking for when studying the content of competitive links. This makes the C&N approach very relevant from the point of view of this part of the research.

Thus far, a brief overview of the model specification phase of the C&N approach has been given. In the next stage, the models are calibrated, i.e. the cross-elasticities are estimated, applying OLS and GLS regression analyses on log-transformed model specifications[5]. The result of the calibration of the model is a set of own-elasticities and cross-elasticities, averaged over time. A '*competitive map*' can be derived as a graphical representation of the elasticities, from which competitive relationships can be read.

[5] C&N provide ample discussions on the specific estimation procedures and tests for both the simple MCI and MNL attraction models as well as for the more complex differential-effects and fully extended attraction models. It goes beyond the aim of this chapter to elaborate on the specific estimation procedures, though. The reader is referred to discussions provided in Cooper (1988), Cooper & Nakanishi (1988), and Cooper (1993).

To illustrate how this works, consider an example provided by Cooper (1993) regarding the elasticities of a hypothetical six-brand market. Suppose the elasticities (on, say price) are as exhibited in Table 3.1.

Table 3.1 Hypothetical price-(cross-)elasticities for a fully extended attraction model[†]

(taken from Cooper, 1993)

brand	1	2	3	4	5	6
1	-1.2	1.0	0.2	0.2	0.3	1.2
2	0.9	-1.6	0.3	0.4	0.1	1.4
3	0.1	0.2	-0.4	0.6	0.2	0.2
4	0.2	0.3	0.0	-1.7	1.1	0.3
5	0.3	0.5	0.4	1.0	-1.8	0.3
6	0.9	1.0	0.3	0.1	0.2	-0.7

[†] The elasticities refer to the effects of a price change by a brand indicated by the column on the market share of a brand indicated by the row

Note that the cross-elasticities are asymmetric, meaning that the cross-elasticities from a brand toward each competing brands are different. Also, the cross-elasticities back and forth between two brands may not be identical. This allows, for instance, one brand to exert influence over another, but not the other way around (this is the case between brand 3 and 4, for example).

For interpretation purposes, Cooper (1993) suggests to graph the pattern of the elasticity matrix in the form of a 'competitive map'. In fact, the competitive map is nothing but a particular spatial representation of the elasticity matrix, which may be a more convenient way of showing competitive relations. For deriving the map, brands are thought of as vectors emanating from a fixed origin of a space, such that the stronger the cross-elasticity between two brands, the more correlated those brands' vectors are. The map is a joint-space, where each brand is represented by two vectors. One vector (c) indicates the 'clout' of a brand and the other vector (v) indicates its vulnerability. Cooper represents the cross-elasticities in the map as if they were the scalar products of the co-ordinates of the brands. Brands on the same c-vector from the origin exert similar pressure on competitors, while brands on the same v-vector are similarly vulnerable. The stronger the competition between two brands, the smaller the angle between the vectors for these brands. If the angle between the brands is more than 90°, brands are complementary to each other.

Figure 3.1 exhibits a two-dimensional competitive map inferred by Cooper (1993, p.290) from the elasticities in Table 3.1. The relative brand positions in Figure 3.1 represent the brands' clout and vulnerability. For instance, brand (C)2 exerts a large influence on brands 1 and 6, since they are (nearly) on the same vector. This is in agreement with the cross-elasticities in Table 3.1. Conversely, brands 1 and 6 exert large influence on brand 2. A similar competitive connection seems to exist between brands 4 and 5. However, there is little competitive influence between the two groups of brands {1, 2, & 6} and {4 & 5}, which is also consistent with the data in Table 3.1.

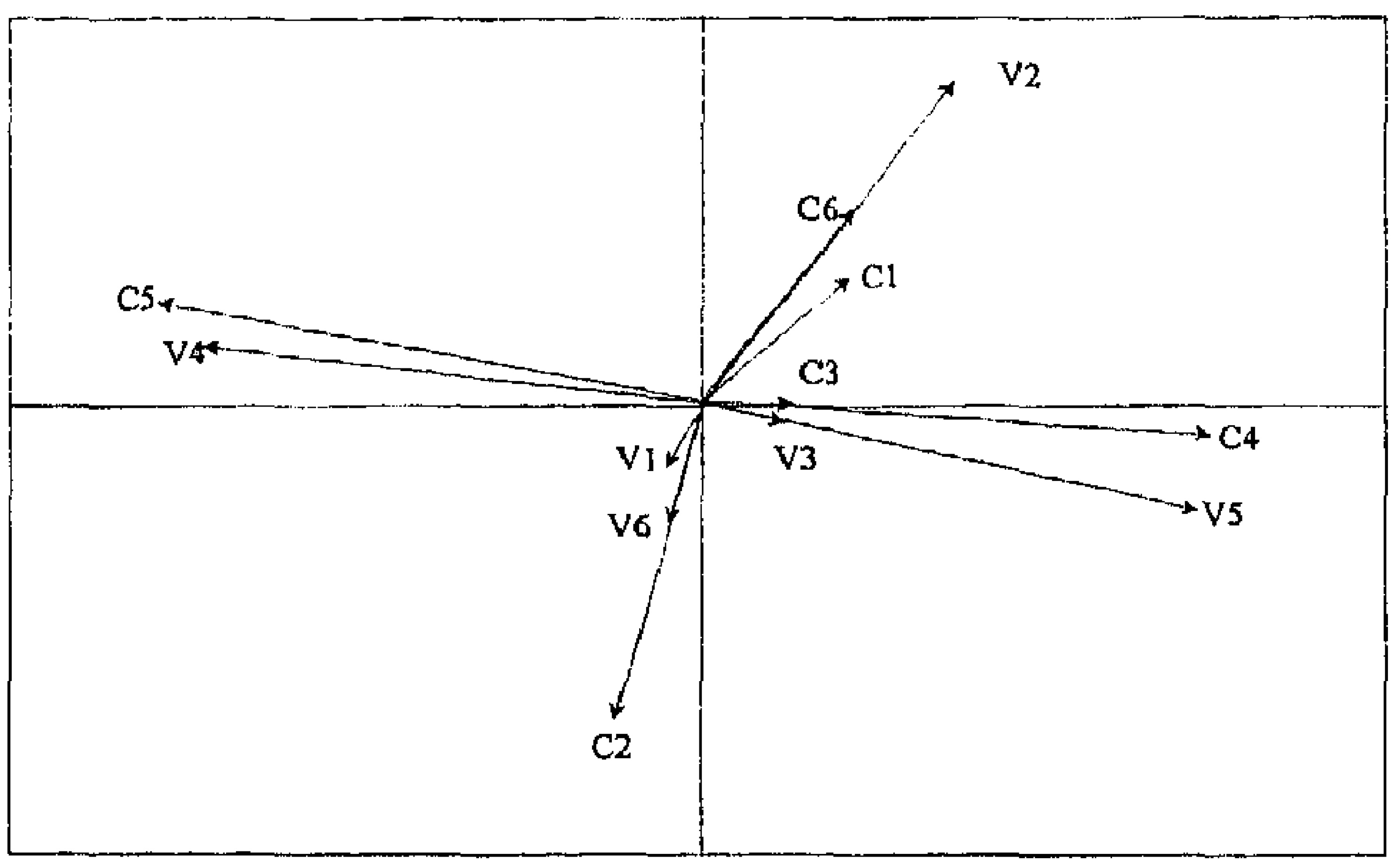


Figure 3.1 Competitive Map derived from the elasticities in Table 3.1
(taken from Cooper, 1993, p.290)

It is important to note that these multi-dimensional competitive maps are essentially different from 'usual' multi-dimensional product maps (e.g., the output of MDS-analyses). The latter generally give an overview of brand similarities in terms of locations of brands in a perceptual space with *product attributes* as dimensions. This does not necessarily have to be the case in the competitive maps of C&N, which deals with competitive links and competitive cross-effects. In fact, the brand positions in Figure 3.1 would probably be different if, instead of the shelf-price, another instrument of the marketing mix (say sales promotions) were used as focal instrument. Hence, for diagnosing the competitive situation in a market, one should draw up a separate competitive map for each marketing instrument. This is in line with the notion that price-competition may be different from non-price-competition.

The competitive map exhibited in Figure 3.1, is based on average elasticities, yielding a snapshot of the competitive positions. C&N state that for a clear grasp of the full story, it is useful to disaggregate the elasticities for different time periods in order to trace and follow changes in the competitive relations between the brands. Subsequently, the disaggregate set of elasticities needs to be further analysed in order for the decision maker to trace the most relevant signals. It is suggested that this be carried out with the help of three-mode factor analysis (cf. Kroonenberg, 1983; Cooper, Klapper & Inoue, 1996) where clout and vulnerability elasticities, and time (weeks) form a three-way array of the elasticities. The output of such analysis yields detailed information about competitive dynamics in the form of 3D-maps, depicting changes of the brands' clout and vulnerability over time, and about differences in competitive positions for various retail chains.

C&N (1988) and Cooper (1993) contain applications to the U.S. ground coffee market and the U.S. ketchup market, using retail scanner data. The results show detailed information of the effects of marketing instruments on own and other brands' market shares, particularised for different retail chains, for different time periods, and for different consumer segments. Though the 3D-competitive maps provided in these applications are not always easy to read and interpret, it is clear that the marketing decision maker can learn much from the output regarding what has happened on his market, what the effects have been of his own marketing actions and the actions of the competitors, how positions have changed over time, etc.

Restrictions and further developments

This concludes our description of the methodology of the approach of Cooper & Nakanishi (1988). As is shown, the C&N approach provides an interesting and rather intensive way of investigating the specific content of the competitive links between brands. It is meant to enable the marketing decision maker to have more insight in the actual market effects of his own actions and those of the competitors. Nevertheless, researchers have pointed to a number of drawbacks and restrictions. The first drawback concerns the quality of the parameter estimates. Hanssens & Parsons (1993) point out that, while attraction models have the desirable property of being logically consistent (i.e. market shares are constrained to the 0-1 interval and are summing to one), they are typically not very parsimonious in the number of parameters, and are therefore often 'overparameterised'. Blattberg (1989), Bucklin, Russell & Srinivasan (1993), and Russell & Kamakura (1994) mention the fact that the natural correlations in practice between price and promotion activities often produce unstable model parameters. For example, Bucklin, Russell & Srinivasan (1993), and Russell & Kamakura (1994) report applications in which more than one-third of the cross-price elasticities estimated using a cross-effects model have the wrong sign (negative instead of positive). Since the cross-effects model essentially is the only model of C&N rich enough to handle the diversity of the content of competitive links, this must be viewed as a serious drawback for using the C&N modelling[6].

The second important drawback, as remarked by C&N themselves, is the fact that the competitive maps are inherently *descriptive*, exhibiting and following competitive positions of brands in a competitive arena[7]. However, the dimensions of the arena are not labelled. Thus, the method does not prescribe or suggest anything about strategies for repositioning brands in order to avoid competitive pressures. To put it differently, though the C&N approach helps the manager to monitor competitive links with other brands as they existed during the observation period, it does not help him to understand '*why*' these links occurred, and it therefore does not help much for formulating strategies for improvements.

[6] In fact, C&N do address the aspect of model-induced collinearity which occurs when two marketing variables (e.g., couponing and in-store promotions) have many 'zeros' in common for the same observations (weeks). C&N discuss several possible remedies for this problem. However, they do not address another, 'real' collinearity problem, which occurs due to the fact that in practice marketing actions typically include more than one marketing instrument at the same time (e.g., a price-discount plus supporting advertising). As has been pointed out, this can cause unstable estimates and can cause wrong signs of the parameters.

[7] A related limitation of the use of elasticities for analysing competitive effects is the fact that elasticities are difficult to measure when marketing instruments vary infrequently or when changes are relatively small (cf. Lilien, Kotler & Moorthy, 1992). Where there is no variation, there are no elasticities to monitor. The fact that in that case no effects are registered does not imply, though, that brands are not in competition.

After the original publications of the C&N methodology, a number authors have proposed related methodologies, suggesting extensions and improvements. We will only briefly show the directions of the developments here. To start with, Carpenter, Cooper, Hanssens & Midgley (1988) use a similar, fully extended market share model, while extending and improving the C&N method in a number of directions. Firstly, they suggest improving the stability of the estimates by including only a subset of possible cross-effects in the model, thereby reducing the number of parameters to be estimated. Secondly, they explicitly model lagged effects of marketing instruments. For instance, the current effect of advertising of a brand is considered to be partly based on the current expenditure and partly on a declining portion of past expenditures. These properties are meant to improve the quality of the model and the stability of the estimates. In addition, Carpenter et al. (1988) derive conclusions about optimal marketing expenditures, assuming fixed strategies of competitors, which extends the methodology with a certain normative component.

Vanden Abeele, Gijsbrechts & Vanhuele (1990), and Foekens, Leeflang & Wittink (1996) propose other ways of reducing the number of parameters in the model. The former by specifying cluster-asymmetry market-share models, where brands are analysed in the context of a cluster of closely competing brands. The latter by analysing competition within and between brand partitions in a hierarchical market structure. The cost of reducing the number of parameters in these ways is that the methods require some sort of a priori structuring of competition, unlike the MCI and MNL models.

The interpretability of the structure of competition is addressed by Russell (1992). He focuses on the decomposition of a price elasticity matrix, by specifying two elements: a substitution index describing the strength of competition between brand pairs, and a brand specific coefficient describing the overall impact of a brand on its competitors.

Finally, Russell & Kamakura (1994) extend the research stream further by developing a method which combines micro (household level) data with macro (retail level) data. It uses household level purchase data to infer preference segments in the market. Next, cross-effects of marketing instruments are estimated per segment, using aggregate retail level data. This way, the marketing manager is able to monitor the content of competitive links in terms of both market segments and cross-elasticities.

To summarise, the original C&N methodology and much of the related work can be characterised as a 'monitor' approach for studying the content of competitive links between brands. Basically, it uses actual data and tries to infer and describe competitive effects from these data. Since data are becoming readily available from scanner panels, this type of analysis a gaining more attention from both marketing scholars as well as practitioners. After the original C&N methodology, further progress is being made along four dimensions: firstly, attempts are being made to improve the *quality* of the model and the estimates (cf. Carpenter et al., 1988; Vanden Abeele et al., 1990; Foekens et al., 1996); secondly, improvements are being suggested with respect to the *interpretability* of the competitive structures (cf. Russell, 1992); thirdly, macro-analysis is being combined with micro-analysis (cf. Kamakura & Russell, 1994), yielding a better *understanding* of competitive effects, and fourthly, further progress is being sought in deriving normative *managerial implications*, suggesting 'optimal' marketing policies (cf. Carpenter et al, 1988). Given the availability of the data and the emergence of fast high capacity computers, further progress in this type of analysis may be expected.

As was pointed out so far in this section, the C&N type of approach to studying competitive links is econometric and inductive in nature. In the next section, by contrast, we will discuss the Defender model, a method developed by Hauser & Shugan (1983) and Hauser & Gaskin (1984). The Defender model can be characterised as a prototype of a deductive way of approaching questions of competition. The model does not monitor actual marketing instrument cross-effects, but it provides a means to assess cross-effects within the framework of an analytical model of consumer choice behaviour. We will turn to the Defender model now.

3.3 Hauser and Shugan's Defender model

The *Defender* model (Hauser & Shugan, 1983; hereafter, H&S) is created for the situation that an incumbent brand in a product class has to devise a defensive marketing strategy against a new brand (attacker) introduced by a competing firm. It enables one to investigate the effects of various marketing actions that can be taken by a (defending) firm on its own sales and market shares as well as on the sales and shares of the competing brand, including the new one. Thus, the Defender model specifically looks into the content of competitive links between brands, in terms of own effects and cross-effects. The approach consists of two main elements:

(i) the specification of a consumer model that describes the brand choice of a consumer from the alternatives in the market, and

(ii) the derivation of optimal defensive marketing strategies for incumbent brands when an attacker has entered the market, given the consumer choice behaviour as assumed under (i).

The Defender approach is an interesting one because the consumer choice model is a virtual integration of consumer theory from economics (the Lancaster characteristics theory: cf. Lancaster, 1971) with a behavioural approach to consumer choice (multi-dimensional perception and preference modelling). The resulting model is surprisingly simple and elegant and leads to a number of clear-cut recommendations for marketing policy expressed in terms as: the optimal defensive price, the optimal defensive expenditures for advertising and distribution and the direction in which the incumbent brand should be repositioned in the case of a new brand entrance. These policy recommendations have been presented by H&S in the form of theorems for which algebraic proofs are given.

The Defender model has its roots in a vast research stream on consumer behaviour (cf. Lancaster, 1971; Green & Rao, 1972; Einhorn, Kleinmuntz & Kleinmuntz, 1979; Lane, 1980; Hauser & Simmie, 1981; Rao & Gautschi, 1982). Various applications of the Defender model, addressing the validity of some of the assumptions, are provided in Hauser & Gaskin (1984), Hauser (1986), Calantone & di Benedetto (1990), and Wierenga & Waarts (1991). Based on more than 20 applications of the model all over the world, Hauser (1988, p.77) concludes that the Defender is a 'reasonable description of consumer behavior'.

After the original publication of the Defender model, a number of researchers have extended the Defender model or suggested related models, as will be shown later (cf. Shugan, 1987; Hauser, 1988; Hauser & Wernerfelt, 1988; Hauser & Wernerfelt, 1989; Carpenter, 1989;

Waarts, Carree & Wierenga, 1991; Horsky & Nelson, 1992; Sudharsan, Kumar & Gruca, 1995).

Let us now turn to the model and assumptions underlying the Defender model.
H&S mention four assumptions of the Defender model:

(i) Brands can be represented by their positions in a multi-attribute space. The position of a brand represents the amounts of attributes the consumer can obtain by spending one money unit (i.e. dollar) on that brand. In Figure 3.2 an illustration is given with a total of 4 brands (indicated by numbers), represented by their scores on two different attributes. The co-ordinates on the map are: attribute per dollar, obtained by buying the brand in question.

(ii) Each consumer chooses the brand that maximises his utility.

(iii) The utility function is linear (H&S actually use a somewhat more general formulation: 'utility is a concave function of a summary measure linear in the product attributes').

(iv) The effect of 'awareness' and 'availability' can be modelled by advertising and distribution response functions.

In the Defender model, the utility function of an individual consumer h for brand j can be written as (in a two-attribute situation):

$$u_{hj} = w_{h1}\, x_{1j} / p_j + w_{h2}\, x_{2j} / p_j$$

where u_{hj} refers to the utility of brand j for consumer h, w_{h1} and w_{h2} are the respective weight factors of consumer h for each of the two attributes, x_{1j} and x_{2j} represent the score of brand j on each of the two attributes, and p_j represents the price of the brand j. Referring to the graphical representation in Figure 3.2, it follows from assumption (ii) that only products (brands) on the 'north-east border' of the set of brands are efficient. A utility maximising consumer would never buy brand 4. Therefore, the line connecting the brands on the north-east border is called the *efficiency frontier* (the boldly drawn line in Figure 3.2). Brands such as brand 4 are called 'inefficient' and, if the market is fully transparent, this brand would not be chosen by consumers.

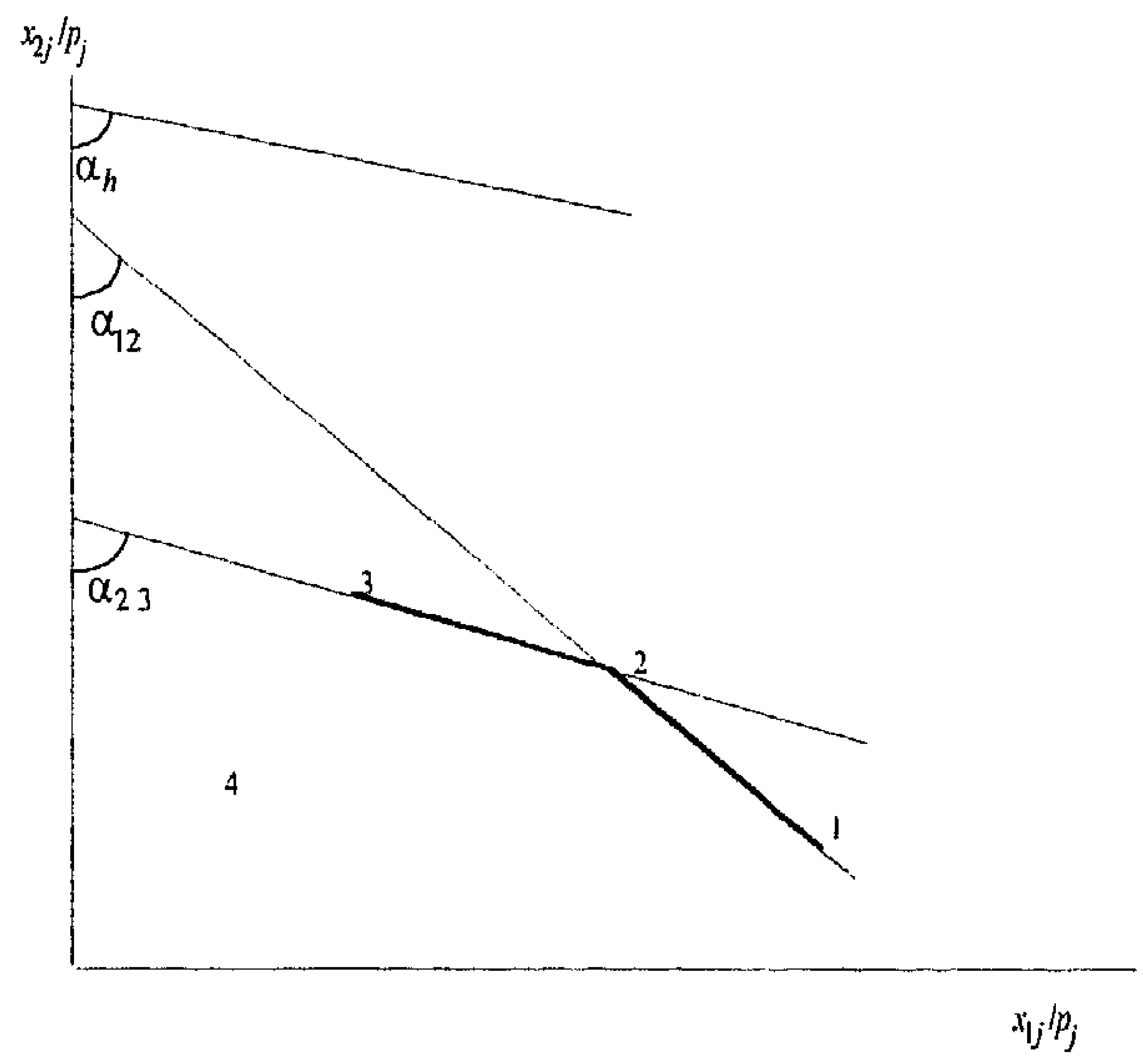


Figure 3.2 Graphical representation of the Defender multi-attribute space

Since the unit in which utility is expressed is arbitrary, only the ratio: w_{h2} / w_{h1} is important for the choice behaviour of consumers. It can be shown (H&S, p.328) that in the case of a linear utility function the iso-utility curves are straight lines. Each consumer h can be characterised by the angle which his iso-utility curve makes with the vertical axis. The tangent of this angle with the vertical axis, (α_h) is:

$$tg\ \alpha_h = w_{h2} / w_{h1}$$

As in standard micro-economics, the brand a particular consumer prefers can be found by moving his iso-preference curve in a parallel way in the direction of the efficiency frontier. The most north-east point of tangency is then the preferred brand. For example, in Figure 3.2 we have represented a consumer h by the angle of his iso-utility curve with the vertical axis α_h. From the diagram it is clear that this particular consumer would prefer brand 3.

The smaller the angle of the iso-utility curve with the vertical axis, the more weight a consumer puts on attribute 1, relative to attribute 2. In Figure 3.2, three sizes of the angle α are especially interesting. In the first place: $\alpha = \alpha_{23}$ (α_{23} is the size of the angle which the connection line of brand 3 and brand 2 makes with the vertical axis). All consumers with $\alpha > \alpha_{23}$ will prefer brand 3. Secondly, $\alpha = \alpha_{12}$ is interesting. All consumers having $\alpha < \alpha_{12}$ will prefer brand 1. All other consumers - those having $\alpha_{23} > \alpha > \alpha_{12}$ - prefer brand 2. It is clear that, given the locations of the brands in the multi-dimensional space, the distribution of α over consumers determines the market shares of the individual brands. Figure 3.3 shows a hypothetical distribution of α. The shaded region represents those consumers who will choose brand 2 in the situation of Figure 3.2.

With respect to the final choice, it is clear that a consumer can only choose a particular brand if he is aware of this brand and if the brand is available in a retail outlet where he can buy the product. This restricts the set of potential choice alternatives for an individual consumer. Moreover, often a consumer will only consider a subset of the brands he is aware of and which are available to him, as potential choice alternatives (evoked set). These refinements are included in the Defender model. So far, we have considered the basic Defender consumer model. We will now turn to some of the estimation issues.

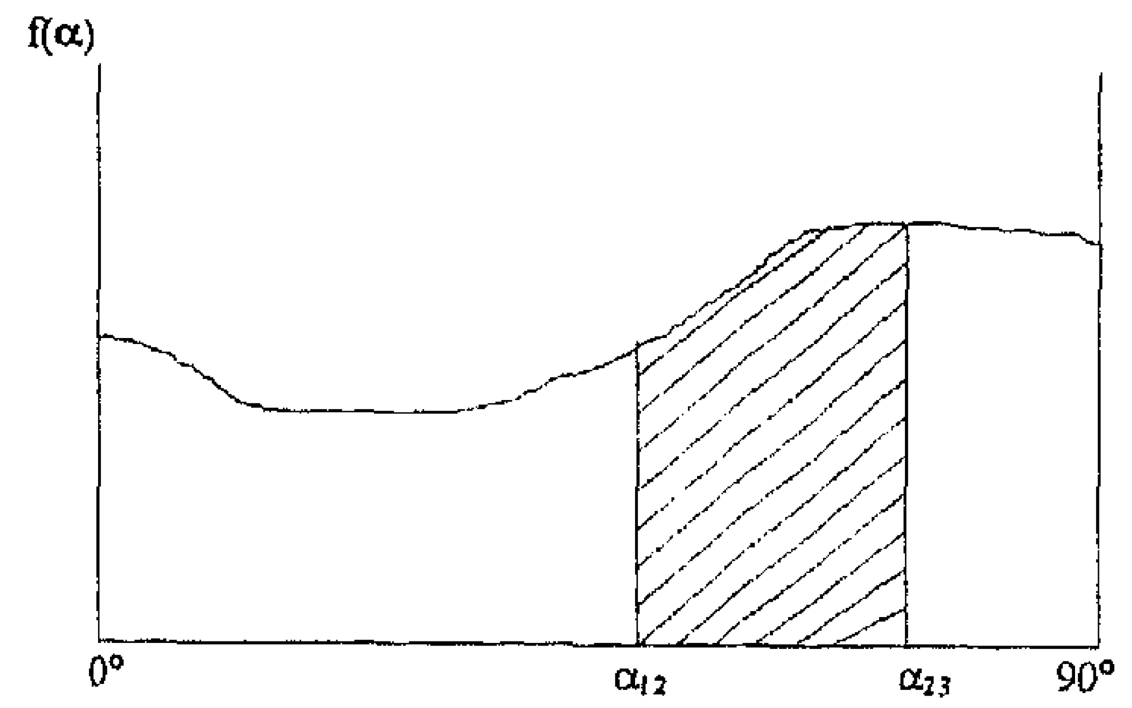


Figure 3.3 Hypothetical preference distribution

The first step in the Defender approach is the derivation of the Defender brand map. Assumption (i) states that brands can be represented by their position in a per dollar multi-attribute space. Of course, many studies are reported, confirming the existence of perceptual structures, using various analysis techniques. For the Defender model, though, one needs to obtain a homogeneous *per dollar* perceptual brand map, which implies additional complexity regarding rotation and anchoring. H&S and Hauser & Gaskin (1984) suggest using traditional attribute ratings on semantic scales, collected from a sample of consumers. Thereafter, the scores must be factor analysed to obtain the required dimensions and brand scores. To ensure that all brands have positive scores on all dimensions, zero-points must be set at or below the minimum value among brands along each dimension[8]. Hauser & Gaskin (1984) suggest anchoring the map to the worst product (i.e. the product having the lowest score) on each dimension.

Figure 3.4 gives an example of a two-dimensional Defender per-guilder brand map for a frequently purchased consumer good market with 13 brands, obtained from attribute perception data for a sample of Dutch consumers (Wierenga & Waarts, 1991). The map was derived using multi-dimensional scaling. Rotation was performed such that the horizontal axis

[8] Alternatively, one can use standard MDS-analysis on similarity data. In that case, rotation of the MDS-maps is a problem, because rotating has direct consequence for the per dollar brand positions, and, thereby on the predicted market shares. In order to be able to get the right map, the MDS map must be 'directed' by using external attribute data.

fitted with an expected general quality dimension. The map was anchored on the worst brand along each dimension (brands 9 and 10, respectively) as was suggested in Hauser & Gaskin (1984). The map shows the per guilder positions of the brands, their market shares (in brackets), and the efficiency frontier for the total market. As expected from the Defender model, the largest brands (brands 1, 2, 3, 4, and 13) are on or near the efficiency frontier. However, brand 8, a small brand (market share 1%) is on the frontier too, while there are also larger brands (e.g., brand 7 with market share 4%) quite a long distance from the frontier. In the Defender model this can be explained either by the preference distribution of the consumer population, or by the awareness and distribution levels of the brands (e.g., brand 8 proved to have very low levels in that respect).

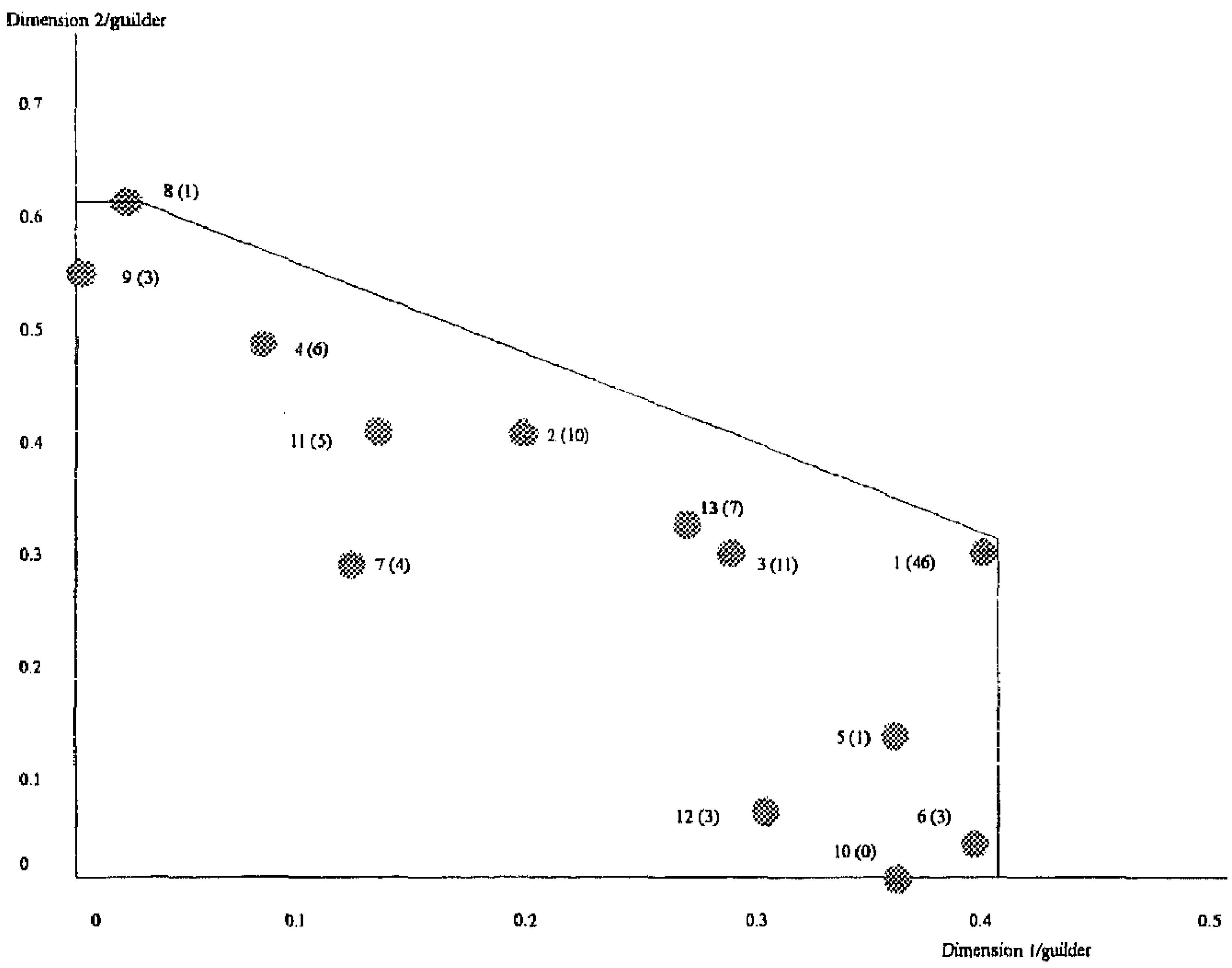


Figure 3.4 Example of a Defender map for a frequently purchased consumer good market with 13 brands (market shares in brackets, taken from Wierenga & Waarts, 1991)

The second major step in the Defender model is the estimation of the preference distribution. While H&S point to the fact that there are standard techniques for measuring preferences, they provide an alternative method by deriving the preference distribution from sales and positioning data. Recall the four brand map in Figure 3.2. As was pointed out, if one knows the per dollar positions and the preference distribution, the market shares can be calculated easily (as was shown in Figure 3.3).

H&S reasoning is that, conversely, if one knows the brand positions and the market shares, one can infer something about the preference distribution responsible for these shares. Because it is not possible to infer the exact form of the preference curve, H&S propose using a piece-wise uniform distribution as an approximation for the real distribution. This is illustrated in Figure 3.5. If we knew that the market share of say brand 2 is 30%, then the area under the preference curve between $\alpha=\alpha_{21}$ and $\alpha=\alpha_{32}$ should represent 30% of the total area under the curve[9].

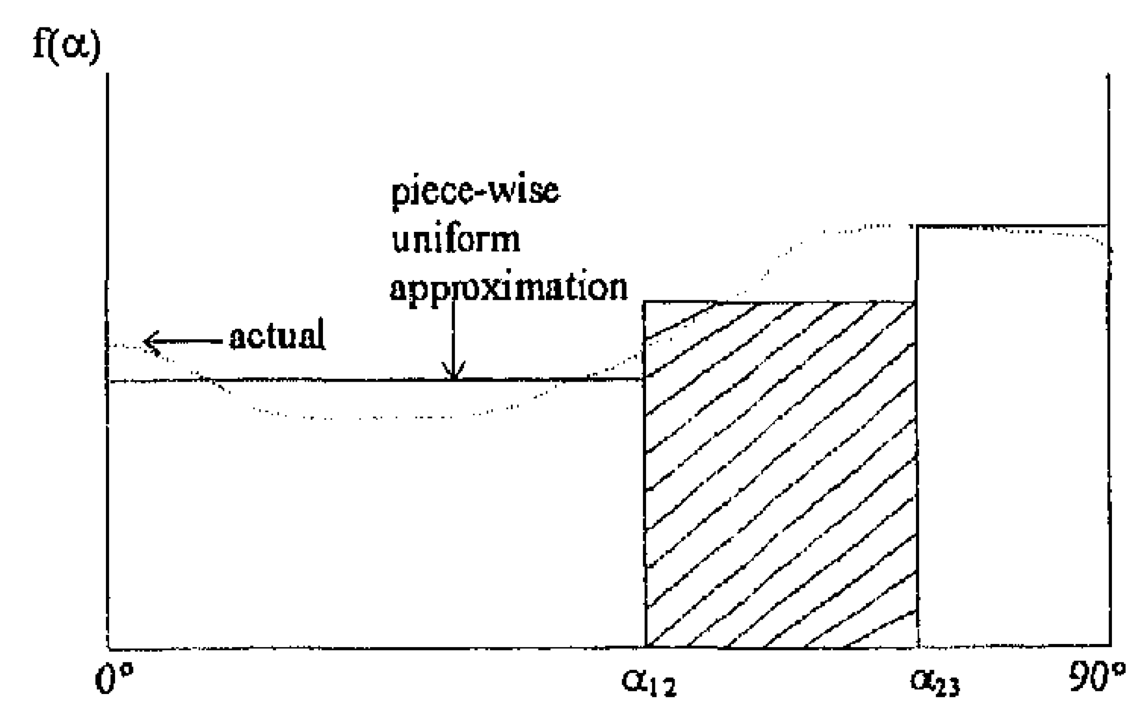


Figure 3.5 Piece-wise uniform preference distribution inferred from brand positions and market shares (adapted from Hauser & Shugan, 1983)

If the Defender model is filled with the necessary ingredients (the per dollar map, the current market shares, the evoked sets, and the estimated preference distributions), it is ready for predicting

[9] This holds under the assumption that every consumer has the same evoked set, evoking all (four) brands. H&S extend the procedure for the situation of heterogeneous evoked sets. In that case, for every possible evoked set the piece-wise uniform preference distribution is estimated and the aggregate distribution becomes the weighted sum of these distributions.

the effects of various changes of a brand's marketing instruments on the sales and shares of all brands. If, for instance, a brand decreases its price, that brand's position will shift further to the north-east (on the vector connecting the brand with the origin) on the map, and thus it will become more 'efficient'. Other conditions equal, that brand's market share will increase at the cost of the adjacent brands on the map. Recalculations within the Defender model will yield the magnitude of the effect on the acting brand and the sizes of the cross-effects on the other brands. Similar simulations can be performed for repositioning movements of brands, and for changing advertising and distribution levels. The Defender model provides estimates of the cross-effects of all marketing instruments on all other brands in that way. The Defender mechanism also allows that the cross-effects are not mutually identical. The clout of a marketing instrument (i.e. the impact of own instruments on others) can be different from the vulnerability to it (i.e. the impact of other brands' instruments on the own market share). This can be investigated via the Defender model.

These properties of the Defender model make it very suitable for investigating mutual dependencies between competing brands, and thus very suitable for analysing the content of competitive links. Actually, H&S proceed with using the Defender model to derive 'optimal' defensive marketing strategies for incumbent brands when an attacker has entered the market. For instance, they show that given the assumptions of the Defender model, it is always optimal to decrease awareness advertising, and, if the preference distribution is uniform, it is always optimal to decrease the price. These and other policy recommendations follow straight from the model. We will not embark on this element of the Defender model here, though, since such policy recommendations go beyond the scope of this research.

Restrictions and further developments

As has been demonstrated, the Defender model is an interesting way of analysing competitive effects in a framework which allows the decision maker to understand why these effects occur. Inspired by the original Defender model, a number of researchers have suggested improvements, refinements, and related models for analysing competitive effects. For instance, Shugan (1987) proposed an attractive alternative method for inferring a Defender brand map from aggregate scanning data. Shugan's method, called 'Defmap', searches for a Defender map by inferring the brand positions from a time series of observed prices and market shares, assuming a certain preference distribution (see also Waarts, Carree & Wierenga, 1991; Leeflang, 1993). Details concerning the method by Shugan (1987) will be given extensively in Chapter 4[10].

Another refinement relating to the Defender model was suggested by Pan & Lehmann (1993). They address the effects of a new brand's location on consumers' perceptions about the brand locations of the existing brands. For example, due to the 'range' effect, a new brand located at the end of an attribute scale will decrease the perceived differences between the other brands on that attribute. Also, if a new brand is located in between two other brands, this will cause the other brands to be perceived as being more dissimilar than before the entry, due to the 'frequency' effect. These 'autonomous' post-entry location shifts imply additional competitive effects due to brand entry or to brand repositioning.

Further, extensions are being suggested concerning Defender's conclusions about optimal marketing policies for the competing brands. The original model provides optimal policies for a defending brand given fixed positions of the other brands. Various attempts at relaxing this assumption have been made, so that optimal long-run marketing strategies can be inferred. Hauser (1988), Hauser & Wernerfelt (1988), and Hauser & Wernerfelt (1989) extend the normative conclusions of the Defender model regarding price and brand positions for the case where all competitors have full capacity to react to each other's actions. In addition, there is a stream of research which addresses the issue of optimal policies, using similar but different market models compared to Defender. To mention a few: Kumar & Sudharsan (1988) derive conclusions about optimal brand positions and prices for a model where price is not modelled as attribute-per-dollar, but within the utility function as in Lane (1980). Carpenter (1989) addresses optimal policies for all marketing instruments in a model restricted to two-brand situations with ideal point preferences in a two-attribute market. Horsky & Nelson (1992) determine optimal locations for an attacking new brand in case incumbents react with the price

[10] Waarts, Carree and Wierenga (1991) developed a procedure for simultaneously estimating both the Defender map *and the preference distribution* from aggregate data on the retail level. This enables to calibrate the total Defender model from aggregate market data, which makes it unnecessary to collect survey data. A full description of the proposed method can be found in Chapter 4 of this thesis.

instrument. VandenBosch & Weinberg (1995) derive equilibrium brand positions in a two-dimensional market using two-stage game theoretical analyses. Finally, Sudharsan, Kumar & Gruca (1995) look into defensible positions for brands located in market niches, considering the effects of future entrants on the market.

Summarising, the Defender model constitutes a clear-cut way of analysing competitive effects of new brand entries and of competitive actions by incumbent firms. Although the model is based on a number of assumptions, various applications of the model suggest that it is a reasonable description of consumer behaviour, which makes it suitable for investigating the content of competitive links between brands in a practical setting. The developments after the original Defender publications do suggest some refinements on the part of the model (e.g., Pan & Lehmann), but the mainstream of the related work has concentrated on optimisation of marketing policies both within the Defender framework and within similar market models.

We will now proceed by comparing the Defender model with the approach developed by Cooper & Nakanishi (1988), which was discussed in the preceding section.

3.4 Comparisons and conclusions

We conclude this chapter by elaborating on the value of the two previously discussed approaches used in analysing the content of competitive links. We defined the content of competitive links as a composite construct related to the cross-effects back and forth between a focal brand and another brand with which it is competitively linked, and, concerned with the effects of specific marketing instruments on each other's performances. The perspective is that of a marketing manager operating in a market together with similar brands. In deciding on marketing policies, the manager has to consider the effects of his actions on his own brand's sales. He also has to consider the effects of possible marketing actions by the competitors on his own brand.

In this chapter we have discussed two prototype methodologies belonging to two different 'schools' for investigating the content of competitive links: the approach developed by Cooper & Nakanishi (1988), resulting in competitive maps, and the Defender approach developed by Hauser

& Shugan (1983). As has been shown throughout this chapter, both approaches yield valuable insights into the content of competitive links, and both are useful in their own right for helping the manager conducting his marketing management.

It is also clear, though, that the methods differ considerably in a number of aspects. In Table 3.2 a comparison is given of the two methods. The fundamental difference between the methods is the general approach to the competition problem: the C&N approach belongs to the econometric and inductive 'school' of analysing competitive links. It is an inherently descriptive approach, monitoring in a convenient way the mutual dependency relationships between brands as they have actually occurred in the past. It does not explicitly go into the 'why' question concerning the mechanisms behind the observed phenomena. By contrast, the Defender model belongs to the abstract-deductive 'school'. It approaches the problem by modelling market mechanisms on the micro-level, and explores the content of competitive links between brands on the aggregate-level within the context of the particular market model. It focuses on optimal marketing policies, which makes it prescriptive in nature. These differences characterise the fundamental contrariety between the two approaches of analysing the content of competitive links.

Table 3.2 also exhibits the main differences between the two specific methods regarding the basic model, the type of data required, the calibration procedure, the applicability and the information provided to the marketing decision maker about the content of competitive links. The type of modelling underlying the methods is quite different, as has been pointed out before. C&N use macro-level, aggregate attraction models (MCI and MNL) for estimating cross-elasticities. The Defender model analyses aggregate cross-effects using the Lancaster characteristics model, which is essentially a micro-level model. Also, regarding the type of data, C&N requires aggregated data, i.e. a time series of marketing activities and sales data per brand, while the standard Defender model makes use of disaggregate data, i.e. various sorts survey data for deriving the brand map and the preference distribution (although it is also possible to use aggregate data to infer the Defender brand map and the preference distribution (cf. Shugan, 1987; Waarts, Carree & Wierenga, 1991; Leeflang, 1993)).

Table 3.2 Comparison of two approaches for analysing the content of competitive links (Cooper & Nakanishi (1988) versus Hauser & Shugan (1983))

	Cooper & Nakanishi (1988) *'Competitive Maps'*	*Hauser & Shugan (1983)* *'Defender Model'*
General approach	Inductive Descriptive Monitor History	Deductive Prescriptive Simulation Future
Model	Attraction models MCI/MNL Aggregate	Lancaster characteristics model Individual consumers
Type of Data	Macro data: marketing instruments and sales Retail scanner	Micro data: perceptions and preferences (macro data also possible) Survey (retail scanner also possible)
Calibration	OLS, WLS, (max. likelihood possible) Potential problems with collinearity	Direct measurement of positions and preferences Potential problems with rotation and anchoring
Applicability	Frequently purchased goods Analysis of existing brands	Frequently purchased goods (mature markets) Analysis of new brands possible
Content of Competitive links	Cross-effects estimated directly Clout and vulnerability differentiation Monitor of actual market dynamics No attribute related map provided No explanation of mechanism behind links No policy recommendations provided	Cross-effects assessed by simulations Clout and vulnerability differentiation No insight in actual market dynamics Attribute related brand map provided Explanation of mechanism behind links Policy recommendations provided

With respect to the calibration of the models, both approaches have their own procedures, which are briefly pointed out here and which are discussed in detail in the respective publications. Both have their own problems for yielding proper parameters. C&N has a serious potential collinearity problem, because, in practice, the marketing instruments strongly vary together. The Defender model does not have this problem, but has its main problem in finding the right Defender map (i.e. problems concerning the dimensionality, the rotation and anchoring of the map).

As to the practical applicability of the methods, C&N can handle all sorts of frequently purchased consumer good markets in all phases of the product life cycle, as long as enough data is available about marketing instrument variations and brand sales. The Defender model is more restrictive in that respect. It is primarily useful for analysing brands in mature markets. On the other hand, the Defender model is more flexible in the sense that it enables the manager to assess the effects of a new brand entering the market, which is impossible for the C&N method.

Finally, if a comparison is made from the viewpoint of yielding information about the content of competitive links, it is noted that both methods can do a good job in analysing (potential) cross-effects of specific marketing instruments on competing brands. Also, both are able to differentiate the effects according to the marketing instruments, according to the competing brands, and according to the direction of the effects (clout versus vulnerability). While C&N yield this type of information directly from the estimated elasticities, the Defender model must simulate the effects of all kinds of actions, which may be more cumbersome if many brands are present competing on various attributes with several marketing instruments. On the other hand, the Defender model enables the marketing manager to test the effects of various actions and suggestions are given for 'optimal' policies under certain market conditions, which is not provided by the C&N approach.

As has been demonstrated, although having their own limitations and difficulties, both the inductive and the deductive approach provide helpful means for highlighting parts of the content of competitive links. In that respect, the approaches must be viewed as complementary to each other rather than mutually exchangeable. We think that some cross-fertilisation between the approaches and models might be fruitful. After all, monitoring what has happened and understanding why these things have happened, are both vital aspects in marketing decision making. A first practical step in this direction might be to cross-validate estimated competitive effects, using both a C&N type of approach and a Defender type of model on the same market. This allows the researcher to 'tailor' a Defender model, for example, with response functions for specific advertising and distribution instruments, estimated using a C&N type of approach. A second way of linking the approaches, is to find ways to incorporate some of the 'real-life' value of the C&N type of approach into the abstract-deductive models, on the conceptual level. This may be achieved by estimating parts of the Defender model with the same type of data used in the C&N approach: retail scanner data. An example of how this can be done will be discussed in the next Chapter.

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4 Full-information maximum likelihood estimation of brand positioning maps using supermarket scanning data*

4.1 Introduction

In this chapter, we build on the idea put forward by Shugan (1987) to infer Defender product maps from scanning data. It is demonstrated that the actual estimation procedure used by Shugan has several methodological problems and may yield unstable estimates. An alternative estimation procedure is proposed, full-information maximum likelihood (FIML), which addresses the problems and yields significantly improved results. An important additional advantage of the procedure is that the parameters of the preference distribution can be estimated simultaneously with the brand co-ordinates. Hence, it is not necessary to assume a fixed (uniform) distribution of preferences. An empirical application is presented in which the outcomes obtained from Shugan's procedure are compared with those from the proposed procedure.

As has been pointed out in the previous chapter, the Defender model (Hauser & Shugan 1983) is a useful instrument for understanding the competitive positions of the various brands in a market, and serves as a useful framework for testing the effects of alternative competitive strategies. Using the model one can examine the implications of different brand positions as

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* This research part has been published as: Waarts, E., M. Carree, and B. Wierenga, 1991. Full-information maximum likelihood estimation of brand positioning maps using supermarket scanning data. *Journal of Marketing Research*, 28 (November), 483-90. The text in this chapter follows closely the text in the JMR-article. Slight adjustments are made, though, if desirable in the context of this thesis.

well as different pricing strategies for either current or new products. Results of the model show both the effects of actions on one's own market share and the effects on the market shares of competing brands.

One of the essential elements of the Defender model is the so-called 'per dollar multi-dimensional brand map'. The model needs information about the (perceived) locations of brands in a multi-dimensional product space to begin. The literature provides various ways for deriving per dollar multi-dimensional maps. Hauser and Gaskin (1984) demonstrate how such a map can be estimated by means of a perceptual mapping approach applied to cross-sectional survey data. An interesting development stems from work by Shugan (1986, 1987). Shugan proposes a procedure for direct estimation of the brand locations that uses a time series of aggregate price and market share data from supermarket scanning data. If one assumes that the Defender approach is valid, the idea is that only certain brand locations in a multi-dimensional space are consistent with price and share movements observed in the real market. The proposed method should enable one to infer the brand locations most likely to underlie the Defender mechanism that would explain the observed market dynamics.

Shugan's approach seems appealing. However, when applying the procedure to our own data we noticed certain methodological problems that inhibited proper estimation. These problems are inconsistent estimators, recursive estimation where a simultaneous procedure making full use of the information in the data would be better, frequent occurrence of dominated brands, and the exogenous assumption of the preference distribution. In addition, our empirical application revealed problems with the stability of the inferred brand locations over time.

We first address the methodological issues and then present an alternative estimation procedure. The procedure solves the estimation problems to a large extent, while allowing for relaxation of the (uniformity) assumption for the preference distribution. Finally, we report an empirical application of the two estimation procedures on a particular product category and compare their results.

The original recursive procedure

The Defender model infers market shares when given perceived brand locations, prices, and a preference distribution (corrected for awareness and distribution level, when appropriate[1]). Shugan (1987), reasoning the other way around, states that one must be able to find the unknown perceived brand locations given brand prices, market shares, and preference distribution. The locations of the brands cannot be inferred from a single period, but must be estimated by using a time series of price and share data.

One can specify a precise aggregate relationship between brand locations, brand prices, and brand shares, which directly follows from the Defender assumptions about consumer choices. Consider again, the four-brand market as was exhibited in Figure 3.2 (see Figure 4.1). The brands are ordered from the highest to the lowest value on the first per dollar dimension, x_1/p. The market share m_j of brand j depends on its per dollar position, the per dollar positions of the efficient adjacent brands, and the distribution of the consumer preference angles. Consumers with preference angles smaller than the angle α_{12} will choose brand 1, and consumers with angles larger than α_{23} will choose brand 3. Consumer h with $\alpha_{12} < \alpha_h < \alpha_{23}$ in Figure 4.1 will choose brand 2. Note that brand 4 is dominated by brands 2 and 3 and therefore will not be preferred by any consumer. Such a brand is called 'inefficient' or 'dominated'. Its market share will be zero (provided the other brands have full awareness and availability). The angle formed by the vertical axis and a line passing through both brands i and j (in time period t) is described as:

$$(1) \qquad \alpha_{ijt} = \arctan[(x_{1i}/p_{it}-x_{1j}/p_{jt})/(x_{2j}/p_{jt}-x_{2i}/p_{it})]$$

where:

i and j are efficient adjacent brands ($i < j$),

x_{dk} = the level of brand k on dimension d, and

p_{kt} = the price of brand k in time period t.

[1] The Defender model corrects for brand awareness and distribution levels, by inferring brand shares within each *evoked set* (defined as a set of products consumers consider in making a choice among brands). A brand may not be evoked if, for instance, consumers are not aware of the brand, or if the brand is not available when they shop. Brand share in the total category is calculated as the weighted average of the shares within the evoked sets.

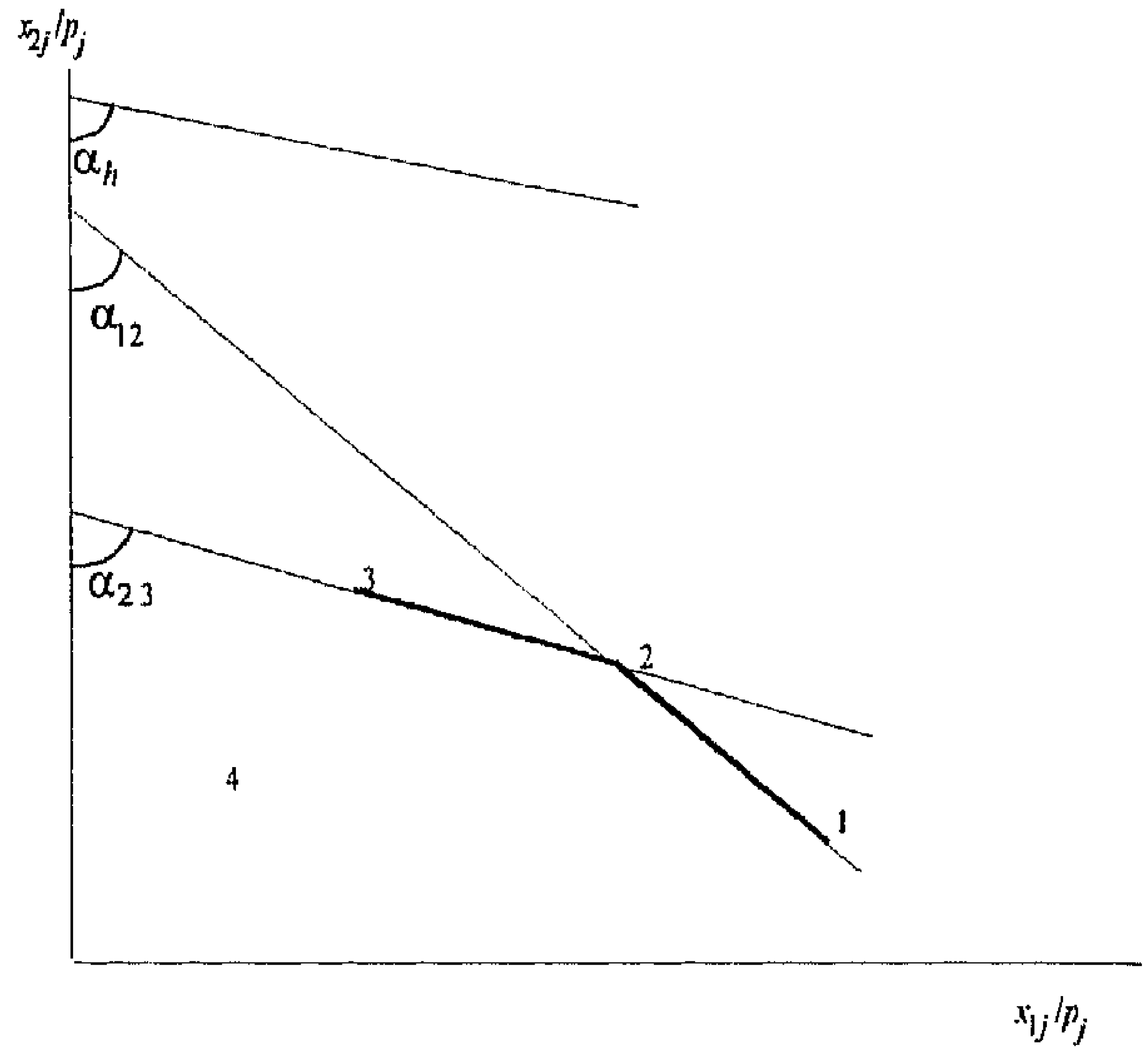

Figure 4.1 Graphical representation of the Defender multi-attribute space

The mathematical relationship between (i) market share in period t and (ii) per dollar brand locations in that period and the preference distribution is given by:

(2) $$m_{jt} = F(\alpha_{j,j+1,t}) - F(\alpha_{j-1,j,t})$$

where:

$j = 1,2,3....J$, ordered from high to low on the first dimension,
J = number of efficient brands in the market,
m_{jt} = market share of brand j in time period t, and
$\alpha_{01t} = 0°$ for all t ; $\alpha_{J,J+1,t} = 90°$ for all t,
$F(\tilde{\alpha})$= the cumulative distribution of the consumer preference angle $\tilde{\alpha}$.

The per dollar positions of the brands change over time as the brand prices vary. Combining (1) and (2) yields (3), which implies a procedure for inferring the positions of the brands from a series of prices and shares.

$$(3) \qquad \frac{p_{jt}}{p_{j-1,t}} = \frac{\left\{x_{1j} + x_{2j} \tan \mathrm{F}^{-1}\left[\left(\sum_{i=1}^{j} m_{it}\right)\right]\right\}}{\left\{x_{1,j-1} + x_{2,j-1} \tan \mathrm{F}^{-1}\left[\left(\sum_{i=1}^{j} m_{it}\right)\right]\right\}}$$

Shugan (1987) rewrites (3) into such a form that ordinary least squares regression analysis estimation is possible.

$$(4) \qquad \mathrm{PRATIO}_{j-1,j,t} = \beta_{jx} v_{jt} + \beta_{jy} w_{jt}$$

where:

$$\mathrm{PRATIO}_{j-1,j,t} = p_{jt} / p_{j-1,t}$$

$$\beta_{jx} = x_{1j}$$

$$\beta_{jy} = x_{2j}$$

$$v_{jt} = \left\{x_{1,j-1} + x_{2,j-1} \tan\left[\mathrm{F}^{-1}\left(\sum_{i=1}^{j-1} m_{it}\right)\right]\right\}^{-1}$$

$$w_{jt} = v_{jt} \tan\left[\mathrm{F}^{-1}\left(\sum_{i=1}^{j-1} m_{it}\right)\right]$$

The procedure does not allow for simultaneous estimation of the preference function F and the unknown parameters x_{1j-1} and x_{2j-1}; the preference distribution F must be measured separately in the marketplace, or a particular distribution must be assumed. Shugan starts by assuming a uniform preference distribution F.

One of the co-ordinates to be estimated must be fixed: x_{11}=1 (the scale of the map is arbitrary). For estimation of a two-brand map, (4), implying a constrained regression through the origin, is used with j=2. The co-ordinates of the two brands must then be found by iteration over x_{21} and selection of the value of x_{21} that maximises the R^2 of the regression.

Shugan estimates the multi-brand map by using regression equation 4 recursively. This means that estimates of $x_{1,j-1}$ and $x_{2,j-1}$ are substituted into the j^{th} regression. For every value of x_{21}, the co-ordinates of the other brands are estimated and the multiple R^2 is computed. The best solution is the set of co-ordinates that yields the highest multiple R^2 (which is equal to the minimal total sum of the squared errors).

The brands are assumed to be ordered from high to low on the first dimension. The ordering, however, is generally not known in advance. Therefore, regressions must be carried out for all possible orderings of the brands. The ordering that yields the best fit in terms of multiple R^2 is selected as the final best solution.

4.2 Methodological problems

The following methodological problems are related to the procedure just presented.

Inverse Causality

Though with (4) Shugan does not suggest that prices are caused by market shares, note that in (4) price ratios are used as dependent variables and market shares as explanatory variables. Theoretically, one would expect that market shares are caused by price ratios and other factors (represented by the disturbance terms). Hence, market shares should be the dependent variables. If in reality market shares are caused by price ratios and disturbances, the use of market shares as independent variables is flawed and will lead to inconsistent estimators. The reason is that the market shares will be correlated with the disturbances (Maddala 1977, p. 153).

Recursive Use of a Single-Equation Model

The procedure estimates (4) recursively. As a consequence, the information that parameters arise in two consecutive equations is not used optimally. By estimating x_{1j} and x_{2j} ($j \neq 1, J$) in the $(j - 1)^{th}$ equation and substituting the estimates into the j^{th} equation, we ignore the fact that the j^{th} equation provides information about the values of x_{1j} and x_{2j}.

Another point should be noted. In estimating the equations separately, one implicitly assumes that the disturbances of the equations are mutually uncorrelated. That assumption is questionable, however, because variables such as in-store promotion of the j^{th} brand in general influence all market shares. Especially the shares of the $(j\text{-}1)^{th}$ and the $(j+1)^{th}$ brand are expected to decrease as a result of promotional activities for the j^{th} brand.

Treatment of Dominated Brands

Shugan (1987, p. 4) states that his estimation procedure 'requires the assumption that every brand obtains a positive market share during every time period'. The reason is that equations (1) through (4) hold only for efficient brands. Though the assumption is necessary for accurate estimation, there is no guarantee that the estimated parameters produce predicted positive market shares for all brands in all the periods used in the estimation. Even with only positive market shares as data, the estimation procedure, searching for minimal error in price ratio fitting, allows for inferred product locations that imply zero (or negative) calculated market shares (dominated brands). We performed an application on a real prices-shares time series of a four-brand market with positive true market shares only. We found that one of the brands (average true share of 9%) was predicted to be dominated (and to have negative market share) in 39% of the periods involved in the estimation. In case of dominance, the brand should be ignored in the prediction stage and its market share set to zero. Equations (1) and (2) should be applied to the remaining efficient brands only. However, the information that the market share of a dominated brand should be set to zero *ex-post* is not used in the least squares regression procedure. That drawback causes a bias in the estimation.

Assumption of a Fixed (Uniform) Preference Distribution

As Shugan (1987, p. 13-14) points out, the preference distribution assumption limits the applicability of the procedure. He demonstrates that the shape of the preference distribution can have consequences for the derived locations of the brands and for the prediction of the market shares. The shape of the preference distribution therefore can be critical for policy recommendations following from a Defender application. With Shugan's method it is not possible to estimate the preference distribution directly, but a particular distribution must be assumed. One could, of course, estimate the model by using a large set of different assumptions about the shape of the preference distribution and then selecting the best one in terms of R^2. Shugan avoids this very cumbersome procedure and assumes a uniform distribution. Another possibility is to measure the preference distribution separately in the marketplace, but doing so would reduce the value of the proposed method.

4.3 Alternative procedure

The Shugan approach is an important development in the estimation of brand positions from scanning data. By overcoming the problems just mentioned, further progress can be made. We demonstrate that this can be done by specifying the model as a simultaneous equations model with the proper directions of causalities. Reduction of the dominance problem, and the possibility of estimating the preference distribution in one run with the product locations, improves the quality of the estimates and the applicability of the model.

A well-known econometric technique for estimating simultaneous equation models is the full-information maximum-likelihood (FIML) method. It is a 'system method' in which the parameters of all equations are estimated simultaneously, with all the information in the model (Maddala 1977 p. 486). We proceed by specifying a model that allows for estimation by the FIML technique. The model specification we propose is derived in the following steps.

Rewriting (3) as

$$\text{(5)} \qquad \left\{ x_{1j} + x_{2j} \tan\left[\mathrm{F}^{-1}\left(\sum_{i=1}^{j} m_{it} \right) \right] \right\} \frac{p_{j+1,t}}{p_{jt}} = x_{1,j+1} + x_{2,j+1} \tan\left[\mathrm{F}^{-1}\left(\sum_{i=1}^{j} m_{it} \right) \right],$$

and solving for $\sum_{i=1}^{j} m_{it}$, we get

$$\text{(6)} \qquad \sum_{i=1}^{j} m_{it} = \mathrm{F}\left(\arctan\left[\frac{x_{1,j+1} - x_{1j}\dfrac{p_{j+1,t}}{p_{jt}}}{x_{2j}\dfrac{p_{j+1,t}}{p_{jt}} - x_{2,j+1}} \right] \right),$$

$$j=1,\ldots,J\text{-}1;\ t=1,\ldots,T,$$

$$\sum_{i=1}^{J} m_{it} = 1,\ t=1,\ldots,T.$$

This relation implies the following system of nonlinear equations.

$$m_{1t} = \mathrm{F}\left(\arctan\left[\frac{x_{12} - x_{11}\dfrac{p_{2t}}{p_{1t}}}{x_{21}\dfrac{p_{2t}}{p_{1t}} - x_{22}} \right] \right)$$

$$\text{(7)} \qquad m_{2t} = \mathrm{F}\left(\arctan\left[\frac{x_{13} - x_{12}\dfrac{p_{3t}}{p_{2t}}}{x_{22}\dfrac{p_{3t}}{p_{2t}} - x_{23}} \right] \right) - \mathrm{F}\left(\arctan\left[\frac{x_{12} - x_{11}\dfrac{p_{2t}}{p_{1t}}}{x_{2j}\dfrac{p_{2t}}{p_{1t}} - x_{22}} \right] \right)$$

$$m_{3t} = \mathrm{F}\left(\arctan\left[\frac{x_{14} - x_{13}\dfrac{p_{4t}}{p_{3t}}}{x_{23}\dfrac{p_{4t}}{p_{3t}} - x_{24}} \right] \right) - \mathrm{F}\left(\arctan\left[\frac{x_{13} - x_{12}\dfrac{p_{3t}}{p_{2t}}}{x_{22}\dfrac{p_{3t}}{p_{2t}} - x_{23}} \right] \right)$$

$$\vdots$$

$$m_{Jt} = 1 - \mathrm{F}\left(\arctan\left[\frac{x_{1,J} - x_{1,J-1}\dfrac{p_{Jt}}{p_{J-1,t}}}{x_{2,J-1}\dfrac{p_{Jt}}{p_{J-1,t}} - x_{2,J}} \right] \right)$$

The x_{1j}'s and the x_{2j}'s are unknown parameters. It is clear that the m_{jt}'s do not change when both the x_{1j}'s and the x_{2j}'s are multiplied by some constant ξ. Therefore, following Shugan (1987, p.6) we assume x_{11}=1. Note that (5) through (7) are valid only if all J brands are efficient.

The full-information maximum likelihood (FIML) method is used to estimate the parameters x_{1j} and x_{2j} of this model. Adding disturbances U_{jt} and using x_{11}=1, we obtain the following model to be used for estimation.

(8)

$$m_{1t} = \mathrm{F}\left(\arctan\left[\frac{x_{12} - x_{11}\dfrac{p_{2t}}{p_{1t}}}{x_{21}\dfrac{p_{2t}}{p_{1t}} - x_{22}}\right]\right) + U_{1t}$$

$$m_{2t} = \mathrm{F}\left(\arctan\left[\frac{x_{13} - x_{12}\dfrac{p_{3t}}{p_{2t}}}{x_{22}\dfrac{p_{3t}}{p_{2t}} - x_{23}}\right]\right) - \mathrm{F}\left(\arctan\left[\frac{x_{12} - x_{11}\dfrac{p_{2t}}{p_{1t}}}{x_{2J}\dfrac{p_{2t}}{p_{1t}} - x_{22}}\right]\right) + U_{2t}$$

$$m_{3t} = \mathrm{F}\left(\arctan\left[\frac{x_{14} - x_{13}\dfrac{p_{4t}}{p_{3t}}}{x_{23}\dfrac{p_{4t}}{p_{3t}} - x_{24}}\right]\right) - \mathrm{F}\left(\arctan\left[\frac{x_{13} - x_{12}\dfrac{p_{3t}}{p_{2t}}}{x_{22}\dfrac{p_{3t}}{p_{2t}} - x_{23}}\right]\right) + U_{3t}$$

$$\vdots$$

$$m_{J-1,t} = \mathrm{F}\left(\arctan\left[\frac{x_{1,J} - x_{1,J-1}\dfrac{p_{Jt}}{p_{J-1,t}}}{x_{2,J-1}\dfrac{p_{Jt}}{p_{J-1,t}} - x_{2,J}}\right]\right) - \\ \mathrm{F}\left(\arctan\left[\frac{x_{1,J-1} - x_{1,J-2}\dfrac{p_{J-1,t}}{p_{J-2,t}}}{x_{2,J-2}\dfrac{p_{J-1,t}}{p_{J-2,t}} - x_{2,J-1}}\right]\right) + U_{J-1,t}$$

where the equation for m_{Jt} is left out because $\sum_{i=1}^{J} m_{it} = 1$ which implies $\sum_{i=1}^{J} U_{it} = 0$. The endogenous variables are $m_{jt}, j=1,\ldots,J-1$, and the exogenous variables are $p_{j+1,t}/p_{jt}, j=1,\ldots, J-1$. This is in accordance with the causality assumptions. The parameters to be estimated are x_{1j} and $x_{2j}, j=2,\ldots,J$, and x_{21}. To derive the likelihood function to be maximised, we introduce the following notation.

(9)
$$\mathbf{y}_t = (m_{1t}\, m_{2t} \ldots m_{J-1,t})'$$
$$\mathbf{z}_t = \left(\frac{p_{2t}}{p_{1t}} \frac{p_{3t}}{p_{2t}} \ldots \frac{p_{Jt}}{p_{J-1,t}}\right)'$$
$$\boldsymbol{\beta} = (x_{21}\, x_{12}\, x_{22} \ldots x_{2J})'$$
$$\mathbf{u}_t = (U_{1t}\, U_{2t} \ldots U_{J-1,t})'$$
$$\mathbf{f}(z_t, \boldsymbol{\beta}) = (f_1(z_t, \boldsymbol{\beta})\, f_2(z_t, \boldsymbol{\beta}) \ldots f_{J-1}(z_t, \boldsymbol{\beta}))',$$

where $f_j(z_t, \boldsymbol{\beta})$ stands for the systematic part of the right side of the j^{th} equation in (8). The concentrated log-likelihood function to be maximised is (see Appendix)

(10)
$$\mathbf{L}^*(\boldsymbol{\beta};\mathbf{y},\mathbf{z}) = \text{const.} - \frac{1}{2} T \log\left|\frac{1}{T}\sum_{t=1}^{T}\left[\mathbf{y}_t - \mathbf{f}(\mathbf{z}_t,\boldsymbol{\beta})\right]\left[\mathbf{y}_t - \mathbf{f}(\mathbf{z}_t,\boldsymbol{\beta})\right]'\right|.$$

This likelihood function is to be maximised with respect to $\boldsymbol{\beta}$, which means that the x_{1j}'s and the x_{2j}'s are estimated simultaneously. Numerical minimisation of -logL* with respect to $\boldsymbol{\beta}$ is performed by a comprehensive but standard quasi-Newton algorithm (routine E04JBF from the NAG Fortran Library), which yields an estimate $\hat{\boldsymbol{\beta}}$ of $\boldsymbol{\beta}$. The covariance matrix $\boldsymbol{\Omega}$ of the $\mathbf{u}_t$'s is estimated as

(11)
$$\hat{\boldsymbol{\Omega}} = \frac{1}{T}\sum_{t=1}^{T}\left[\mathbf{y}_t - \mathbf{f}(\mathbf{z}_t,\hat{\boldsymbol{\beta}})\right]\left[\mathbf{y}_t - \mathbf{f}(\mathbf{z}_t,\hat{\boldsymbol{\beta}})\right]'.$$

The asymptotic distribution of the maximum likelihood estimator $\hat{\boldsymbol{\beta}}$ is multivariate normal with mean $\boldsymbol{\beta}$ and covariance matrix $\boldsymbol{\Sigma}$. A consistent estimate of Σ is given by $\hat{\Sigma}$, where

$$(12) \qquad \hat{\boldsymbol{\Sigma}} = \left(\frac{-\partial^2 \mathbf{L}^*}{\partial \boldsymbol{\beta}\, \partial \boldsymbol{\beta}'} \right)^{-1} \text{ evaluated at } \boldsymbol{\beta} = \hat{\boldsymbol{\beta}}.$$

Note that this procedure allows for the introduction of a more general preference distribution. The parameters of this distribution function can be considered as additional elements of the parameter vector $\boldsymbol{\beta}$ and can be estimated simultaneously with the x_{1j}'s and the x_{2j}'s.

Local Optima and Starting Values

A problem with iterative estimation procedures such as FIML is the possible presence of local optima. Depending on the specific starting values of the parameters, the procedure could reach different 'optima'. Generally, this problem decreases with the number of observations, and therefore use of good starting points in combination with a fair number of observations is recommended.

Our applications of the FIML procedure to a real dataset confirm that local optima do occur in this model, and that starting values are critical for the produced solution. Only an exhaustive search process starting with many possible parameter values and many possible orderings can more or less guarantee finding the globally best solution, but such a search is difficult to carry out in practice. One could perform an extensive search process using the FIML method, but the computing costs rise considerably as the number of brands increases. Hence, the aim is to find a promising starting point for the estimation procedure. We recommend making use of the work that has been done already, and using the outcomes of the 'fast' Shugan procedure as 'reasonable' starting input values for the FIML procedure. Though there is no guarantee that we will find the global optimum in terms of likelihood, this procedure ensures that the quality of the estimates will at least be equal to, but probably surpasses, the quality of the initial configuration. Of course, one can do a sensitivity analysis afterward by taking alternative starting values and/or orderings.

If we want to estimate the preference distribution parameters simultaneously (e.g., using a beta-distribution), we can start with uniformity values (α and β of the beta distribution both equal one). When the values of α and β are estimated, we can easily test whether the produced parameter values differ significantly from the starting values.

On balance, we think the proposed model specification and the use of the FIML method provide several advantages over the original procedure proposed by Shugan. Our procedure makes maximal use of the information available in the data, specifies causalities in the right direction, uses simultaneous equations, and also allows for estimation of the preference distribution in one estimation with the location parameters. The procedure does not theoretically solve the dominance problem. The procedure still allows calculated shares to be negative, which of course should be set to zero afterward. However, as we show in the next section, our applications suggest that the new procedure circumvents the dominance problem to a large extent.

4.4 Empirical application

In our empirical application of the estimation procedures, we used a time series of price and sales data obtained from a scanner-equipped supermarket in a town near the Dutch capital, Amsterdam. The data consisted of a two year (1985-1986) series of weekly data on prices and sales of brands in a particular product class (frequently bought products in the food and beverage category). The exact product class and the brand names are disguised for confidentiality. Though the scanner database contains data on about 15 items in the product class, for our analysis we selected the two major national premium brands, a strong private label of the supermarket, and a cluster of smaller nationally distributed nonpremium brands (B-brands). Together these brands account for, on the average, an 84% share in the total product category.

We estimated a four-brand map using Shugan's 'recursive' procedure on the total 100-period time series. We then applied the FIML procedure, using as starting values the parameter values resulting from the Shugan procedure. We estimated the brand locations once assuming a uniform preference distribution and once assuming beta-distributed preferences. Results are reported in Table 4.1. As can be seen, our expectations are confirmed. In comparison with Shugan's solution, the FIML procedure produces different product locations that will affect predicted market shares under different price conditions. In the final solutions, we find that both brand 1 and brand 4 are located on the axes. This finding is somewhat surprising because we only restrict the co-ordinates to be non-negative. However, this finding is not an artefact of the FIML procedure. In a study with test data derived from a hypothesised brand configuration with known positive co-ordinates, FIML reproduced these (nonzero) co-ordinates exactly. Table 4.1 also shows that the FIML procedure yields substantially lower squared errors, even assuming a uniform preference distribution. The resulting sum of squared errors is reduced by 47% (the sign test on the equality of the squared errors renders a p-value of 0.000). Results also show that the percentage of periods in which one or more brands are predicted to be dominated (denoted in the table by '% of dominance') decreases from 39% to 1%, which reduces the dominance problem to minor proportions.

Table 4.1 Results of alternative procedures on four brands/100 periods

	Recursive procedure		FIML/uniform procedure		FIML/beta procedure	
brand	locations	S.E.	locations	S.E.	locations	S.E.
1	(1.000, .070)	[-,-]	(1.000,.000)	[-,-]	(1.000,.000)	[-,-]
2	(.962, .745)	[.15,.10]	(.841,1.179)	[.01,.10]	(.867,.812)	[.01,.18]
3	(.873, 1.063)	[.01,.03]	(.607,1.962)	[.02,.11]	(.659,1.262)	[.03,.26]
4	(.444, 1.195)	[.03,.02]	(.000,2.170)	[-,.09]	(.000,1.276)	[-,.26]

Results for parameters of the preference distribution,
residual sum of squared errors and percentage of dominance occurrence

	Recursive procedure	FIML/uniform procedure	FIML/beta procedure	
Alpha			.734	[.08]
Beta			.386	[.04]
RSS	2.381	1.248	1.113	
% of dominance	39	1	1	

The FIML solution can be improved further if we allow the preference distribution to be estimated freely. Our results show that for this application, the assumption of a uniform distribution cannot be confirmed (the Likelihood-ratio test on $\alpha = \beta = 1$ renders a p-value of 0.000). Our predictions are additionally improved by an 11% sum-of-squared-errors reduction if we specify a beta distribution (the sign test renders a p-value of 0.000). Figure 4.2 shows the estimated density function of the preference angles. The figure indicates a high preference density for products that score high on the second dimension.

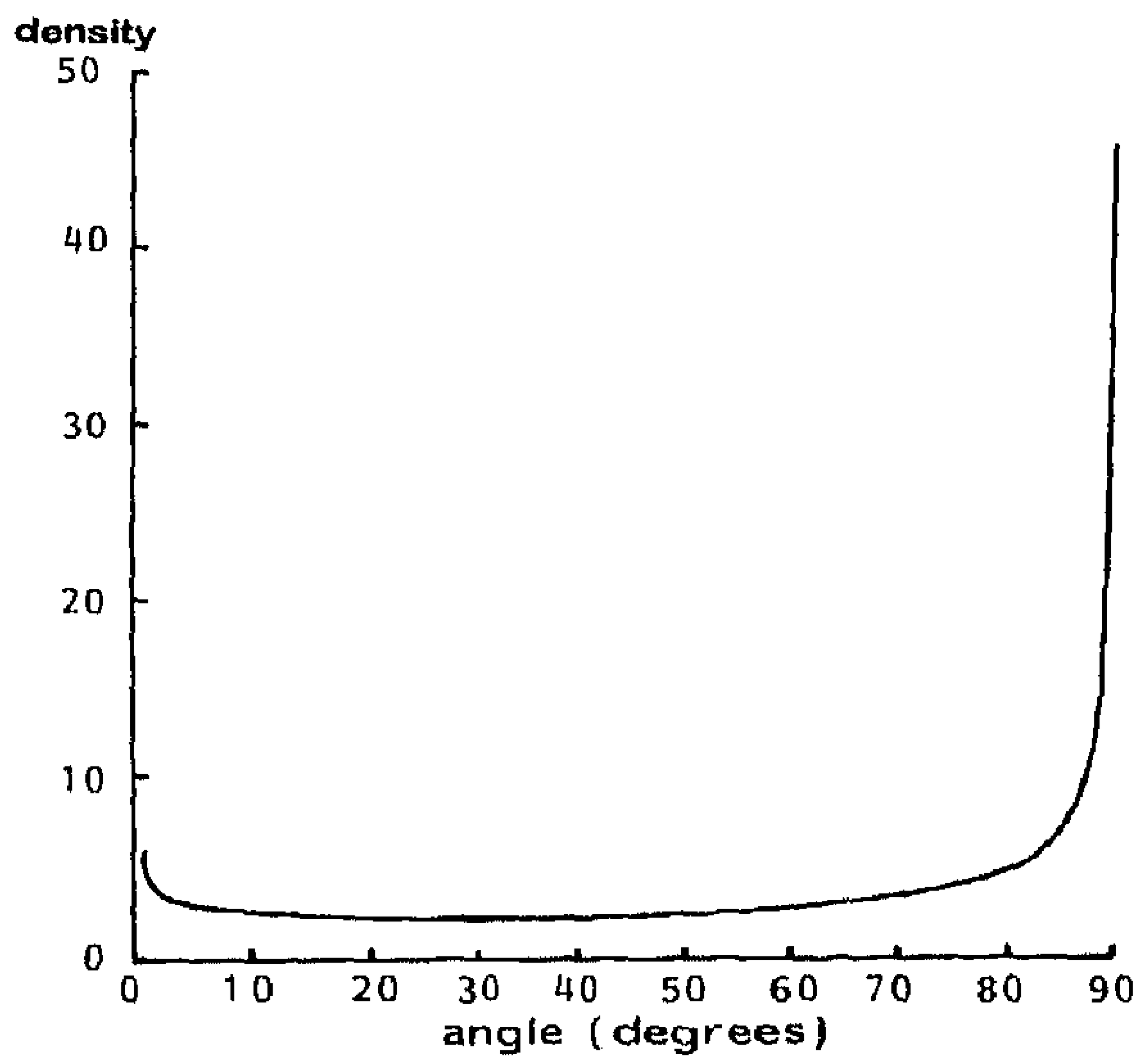

Figure 4.2 Distribution of preference angles

To compare the two estimation methods further, we explored the (in)stability of the estimated brand locations over 'shifting' periods in our two-year time series. We inferred a brand map for each of 50 consecutive 50-week periods (a map for period 1-50, one for period 2-51, and so on). Though the per dollar positions of a brand will vary from period to period, one expects the resulting 'absolute' locations to be reasonably stable over time because the brand map should reflect the perceptions of customers. To predict future market shares accurately, stability of perceptions is a requirement. Naturally, some instability of the estimations can be expected, not only because of stochastics, but also because of the limitations of the model itself, which only uses information about prices and shares.

Results of the analysis are shown in Figures 4.3 and 4.4, and Table 4.2. Figure 4.3 shows the quality of the predictions in terms of resulting squared errors (RSS) for each of the procedures. The FIML procedures yield stable and high quality predictions in comparison with the recursive method used by Shugan. Estimation of the (beta) preference distribution slightly improves the quality of the solutions. Table 4.2 summarises the means and variances of the estimated product locations and preference distribution parameters over the moving 50 periods. Because the periods overlap 98%, the variances should be used for comparison only. Note that the stability of the estimated locations improves with use of the FIML procedure; the variance of each of the estimated brand co-ordinates diminishes. Estimates of the (beta) preference parameters reveal that the distribution parameters are very stable and significantly different from one (uniformity). The results in Figure 4.4 show a slight upward trend in beta, meaning that the relative preference for the second dimension is decreasing over time. The stability of the co-ordinates on the first dimension increases when the beta distribution is used, and the stability on the second dimension seems to decrease somewhat.

4.5 Conclusions

Our study demonstrates that the recursive regression procedure, proposed by Shugan to estimate brand locations from scanning data, is a good starting point but has several problems: inconsistent estimators, no simultaneous estimation, dominated brands, and unstable estimates. Those problems can be solved (the dominance problem only partially) by using the full-information maximum likelihood method. In addition, that method makes it possible to estimate the parameters of the preference distribution simultaneously with the brand locations and to test for a specific distribution. Results of an empirical comparison of the two methods show significantly improved predictions in terms of resulting errors and stability of the parameters by using the proposed method.

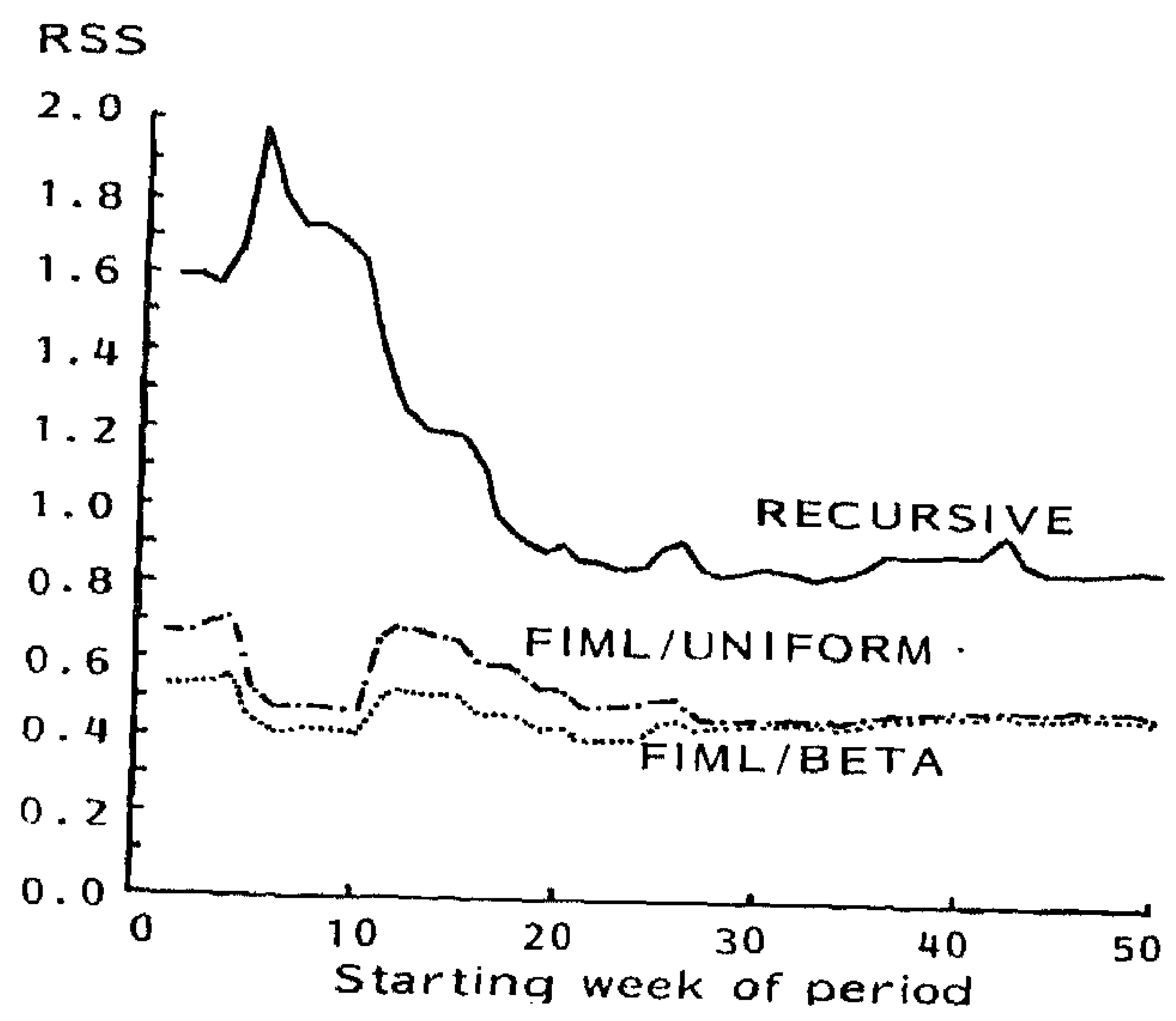

Figure 4.3 RSS for shifting 50-weeks periods

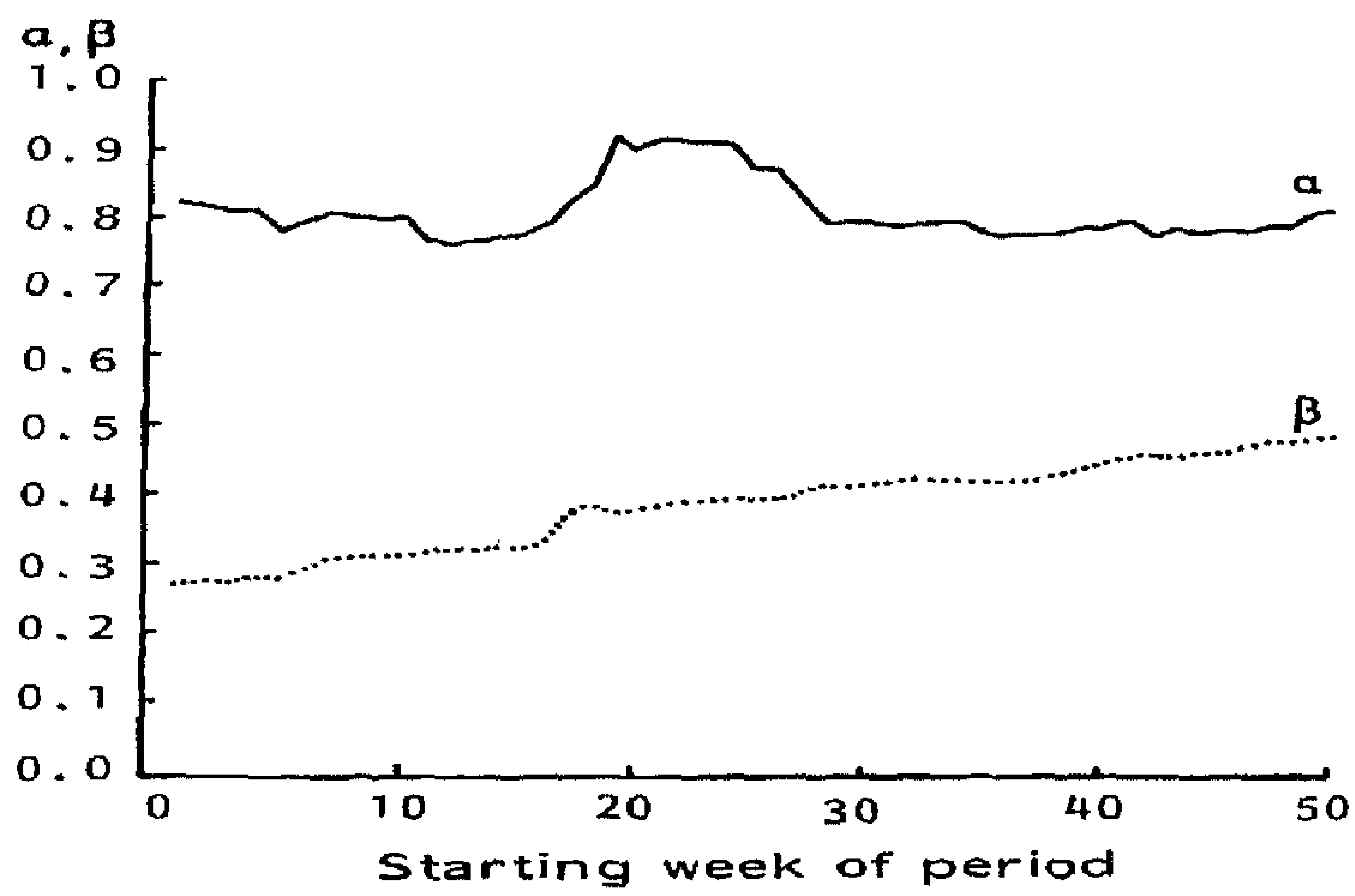

Figure 4.4 Beta-distributed preferences: α and β for shifting 50-weeks periods

Table 4.2 Product locations and preference distribution estimations over 50 consecutive 50-week periods (means and variances)

	Recursive procedure		FIML/uniform procedure		FIML/beta procedure	
parameter	mean	variance	mean	variance	mean	variance
x12	.95	.0001	.85	.0002	.86	.0001
x13	.89	.0016	.62	.0005	.65	.0002
x14	.48	.0057	0	0	0	0
x21	.19	.0236	0	0	0	0
x22	.53	.0646	1.12	.0196	.65	.0414
x23	.78	.1052	1.89	.0145	1.03	.0671
x24	.93	.1022	2.11	.0098	1.05	.0744
Alpha					.81	.0018
Beta					.38	.0042

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Appendix

Relation (8) can be written as

$$\mathbf{y}_t = \mathrm{f}(\mathbf{z}_t, \boldsymbol{\beta}) + \mathbf{u}_t \qquad t = 1,\ldots,T. \tag{13}$$

Assuming that the $(J-1)$-dimensional random vector $\mathbf{u}_t$ has a multivariate normal distribution with mean vector $\mathbf{0} = (0\ 0\ \ldots\ 0)'$ and covariance-matrix $\boldsymbol{\Omega}$, it follows that the joint density function of $\mathbf{u}_t$ is

$$h(\mathbf{u}_t) = (2\pi)^{-(J-1)/2} |\boldsymbol{\Omega}|^{-1/2} \exp\left\{-\frac{1}{2}\mathbf{u}_t'\boldsymbol{\Omega}^{-1}\mathbf{u}_t\right\} \tag{14}$$

Making use of the fact that the Jacobian of the transformation $\mathbf{u}_t \longrightarrow \mathbf{y}_t$ equals one, the joint density function of $\mathbf{y}_t$ is derived as

$$\mathrm{g}(\mathbf{y}_t) = (2\pi)^{-(J-1)/2} |\boldsymbol{\Omega}|^{-1/2} \exp\left\{-\frac{1}{2}[\mathbf{y}_t - \mathrm{f}(\mathbf{z}_t, \boldsymbol{\beta})]' \boldsymbol{\Omega}^{-1}[\mathbf{y}_t - \mathrm{f}(\mathbf{z}_t, \boldsymbol{\beta})]\right\}. \tag{15}$$

Hence, the log-likelihood function of the $\mathbf{y}_t$'s equals

$$L(\boldsymbol{\beta}, \boldsymbol{\Omega}; \mathbf{y}, \mathbf{z}) = \text{const.} - \frac{1}{2}T\log|\boldsymbol{\Omega}| - \frac{1}{2}\sum_{t=1}^{T}[\mathbf{y}_t - \mathrm{f}(\mathbf{z}_t, \boldsymbol{\beta})]' \boldsymbol{\Omega}^{-1}[\mathbf{y}_t - \mathrm{f}(\mathbf{z}_t, \boldsymbol{\beta})] \tag{16}$$

$$= \text{const.} + \frac{1}{2}T\log|\boldsymbol{\Omega}^{-1}| - \frac{1}{2}\mathrm{tr}\left\{([\mathbf{y}_1 - \mathrm{f}(\mathbf{z}_1, \boldsymbol{\beta})]\ldots[\mathbf{y}_T - \mathrm{f}(\mathbf{z}_T, \boldsymbol{\beta})])' \boldsymbol{\Omega}^{-1}([\mathbf{y}_1 - \mathrm{f}(\mathbf{z}_1, \boldsymbol{\beta})]\ldots[\mathbf{y}_T - \mathrm{f}(\mathbf{z}_T, \boldsymbol{\beta})])\right\}$$

$$= \text{const.} + \frac{1}{2}T\log|\boldsymbol{\Omega}^{-1}| - \frac{1}{2}\mathrm{tr}\left\{(\boldsymbol{\Omega}^{-1}[\mathbf{y}_1 - \mathrm{f}(\mathbf{z}_1, \boldsymbol{\beta})]\ldots[\mathbf{y}_T - \mathrm{f}(\mathbf{z}_T, \boldsymbol{\beta})])([\mathbf{y}_1 - \mathrm{f}(\mathbf{z}_1, \boldsymbol{\beta})]\ldots[\mathbf{y}_T - \mathrm{f}(\mathbf{z}_T, \boldsymbol{\beta})])'\right\}$$

Differentiating with respect to $\mathbf{\Omega}^{-1}$ (using the results $\partial \log|\mathbf{A}|/\partial\mathbf{A} = (\mathbf{A}')^{-1}$ and $\partial tr(\mathbf{AC})/\partial\mathbf{A} = \mathbf{C}'$, where $\mathbf{C}$ does not involve elements of $\mathbf{A}$) yields

(17)

$$\frac{\partial L}{\partial\mathbf{\Omega}^{-1}} = \mathbf{O} \Rightarrow \frac{1}{2}T\left(\left(\mathbf{\Omega}^{-1}\right)'\right)^{-1} - \frac{1}{2}\left(\left[\mathbf{y}_1 - \mathrm{f}(\mathbf{z}_1,\boldsymbol{\beta})\right]\ldots\left[\mathbf{y}_T - \mathrm{f}(\mathbf{z}_T,\boldsymbol{\beta})\right]\right)\left(\left[\mathbf{y}_1 - \mathrm{f}(\mathbf{z}_1,\boldsymbol{\beta})\right]\ldots\left[\mathbf{y}_T - \mathrm{f}(\mathbf{z}_T,\boldsymbol{\beta})\right]\right)' = \mathbf{O}$$

The (J - 1)×(J - 1)-matrix $\mathbf{O}$ is defined to have all elements equal to 0. Equation (17) gives

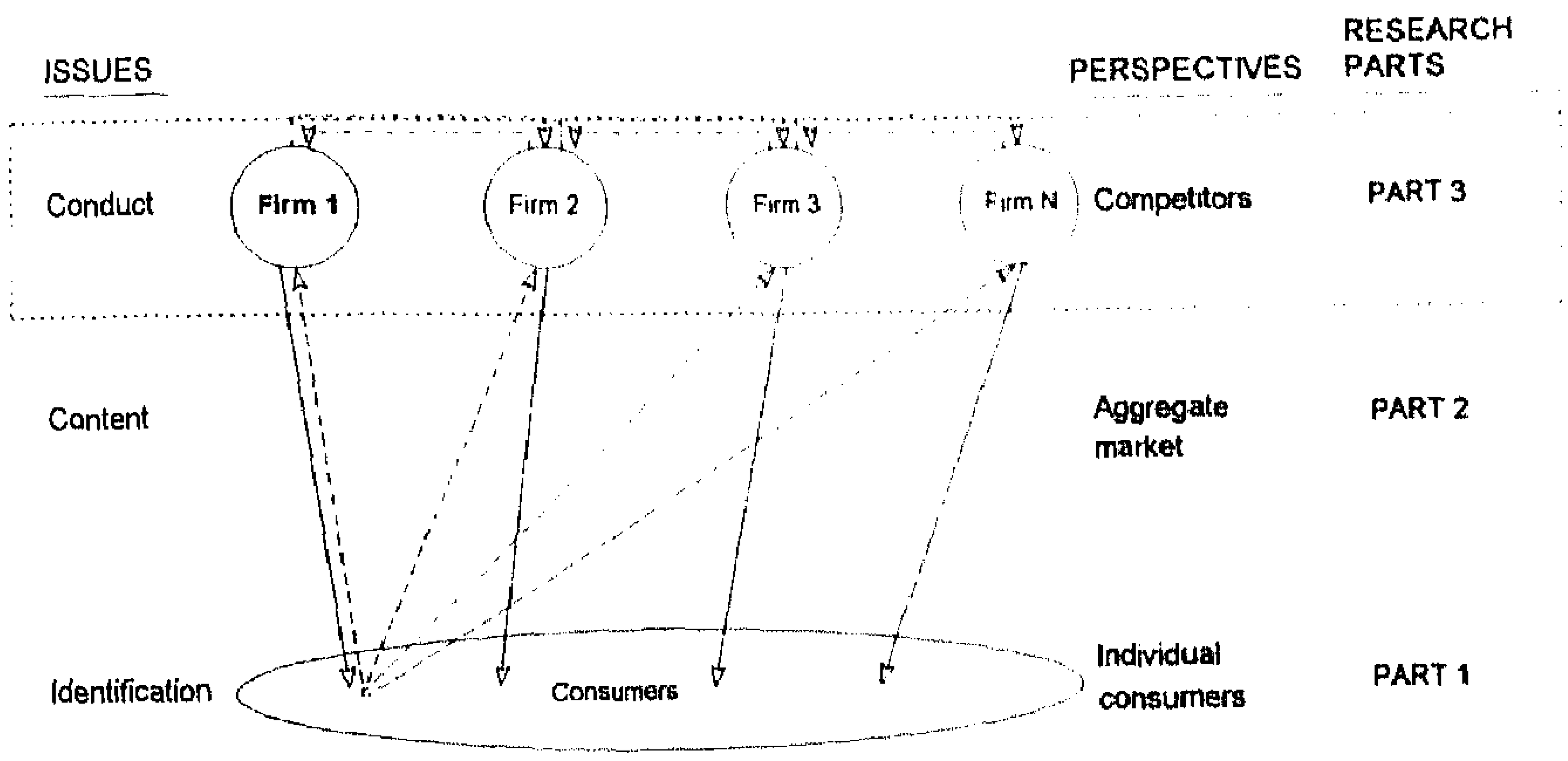
(18)

$$\hat{\mathbf{\Omega}} = \frac{1}{T}\left(\left[\mathbf{y}_1 - \mathrm{f}(\mathbf{z}_1,\boldsymbol{\beta})\right]\ldots\left[\mathbf{y}_T - \mathrm{f}(\mathbf{z}_T,\boldsymbol{\beta})\right]\right)\left(\left[\mathbf{y}_1 - \mathrm{f}(\mathbf{z}_1,\boldsymbol{\beta})\right]\ldots\left[\mathbf{y}_T - \mathrm{f}(\mathbf{z}_T,\boldsymbol{\beta})\right]\right)'$$
$$= \frac{1}{T}\sum_{t=1}^{T}\left[\mathbf{y}_t - \mathrm{f}(\mathbf{z}_t,\boldsymbol{\beta})\right]\left[\mathbf{y}_t - \mathrm{f}(\mathbf{z}_t,\boldsymbol{\beta})\right]'$$

Substituting (18) into (16) we get the concentrated log-likelihood function as in (10).

Part 3

The conduct regarding competitive links



5 Analysing the conduct regarding competitive links

5.1 Introduction

In the first two parts of this dissertation we focused on the issues of identification and content of competitive links, from the perspective of individual consumer choice behaviour and aggregate marketing cross-effects, respectively. In the preceding parts, an emphasis was put on the way consumers handle the choice between a set of alternative products, and how consumers and competitors are influenced by the focal firm's marketing activities. Results of these analysis give the marketing manager insights into two questions. First, with which other firms or brands are there competitive links? Second, to what extent do his marketing activities influence the performance of the competitors and, vice versa, to what extent is his own performance dependent on the activities of the firms he is competitively linked with?

In the third and final part of this thesis, we focus on the question of how the marketing manager is coping with these competitive links. We call the way firms behave in relation to competitive links, the *conduct* of firms regarding competitive links. In fact, due to the existence of competitive links with competitors, marketing actions by a focal firm will have an impact on the performance of the competitors, and might therefore provoke reactions. Thus, when deciding on which action to take, a marketing decision maker of the focal firm should not only consider the direct effects of an action on his own sales and profits and on the sales and profits of the competitors. He should also consider the indirect effects on his sales and profits, which occur due to reactions by competitors. After all, the effect of say a price reduction by a firm might cause a temporary shift in the firm's market share, but if the competitors react with similar actions, the overall result might be: no increase in share and decreasing profits. Therefore, from the perspective of the acting firm, the assessment of competitive reactions to an action is crucial for evaluating the overall effect on sales and profits.

In this thesis, we will concentrate on the issue of *reaction behaviour* as a response to competitive actions, which is an important aspect of competitive marketing conduct. Questions are: When do firms react to actions by competitors? If so, how strong are the reactions, how fast? Are there particular conditions affecting and explaining this reaction behaviour? The current research part contains two chapters devoted to this issue. The present chapter focuses on the various ways action-reaction behaviour has been studied in the marketing literature up to now. As Gatignon, Anderson & Helsen (1989, p.45) point out, "perhaps because of the difficulty of obtaining comprehensive data on competitive behavior, empirical research or competitive research is relatively sparse". Still, a number of notable contributions have been made, taking various approaches. Some researchers try to develop econometric methodologies for diagnosing competition (cf. Lambin, Naert & Bultez, 1975; Hanssens, 1980; Leeflang & Wittink, 1992, 1994). Others use modules of the PIMS data base (cf. Robinson, 1988; Bowman & Gatignon, 1995) or ad hoc survey data to analyse competitive conduct (cf. MacMillan, McCaffery & van Wijk, 1985; Heil & Walters, 1993; Lemmink & Kasper, 1994; Gatignon, Robertson & Fein, 1995). In this chapter, we will address these research avenues in terms of their general approach and their key findings about competitive reaction behaviour. A primary distinction will be made in this chapter between, on the one hand, econometric methods which focus on the development of a general methodology for diagnosing competition, and, on the other hand, empirically based studies which focus on describing and explaining actual competitive behaviour.

Chapter 6, the second chapter devoted to the conduct issue regarding competitive links, entitled '*Competitive marketing reactions to new product introductions*', contributes to the body of knowledge of competitive reaction behaviour. An empirical study will be reported which was carried out in The Netherlands, focusing on the actual marketing reaction behaviour of firms as a response to an introduction of a new product by a competitor. The empirical findings from this study are based on interviews held with 98 marketing managers responsible for a particular product(group) in various frequently purchased consumer good product categories.

5.2 The LNB-model

As was pointed out above, marketing scholars have tried to tackle the competitive conduct issue through various types of research. A main research avenue for analysing competitive marketing behaviour takes an econometric approach, using behavioural data on competitive actions and reactions. Exponent of this type of research is the so-called 'reaction matrix approach', also called the 'LNB-model approach', initiated by Lambin, Naert & Bultez (1975). It was further developed by, amongst others, Hanssens (1980), Gatignon (1984), Leeflang & Reuyl (1985), Plat & Leeflang (1988), and Leeflang & Wittink (1992). In this approach, a general econometric methodology is developed for measuring reactions and for assessing the net effect of marketing actions, while accounting for reactions by competitors.

The primary goal of the LNB-models is to observe and measure the state of rivalry in a market, and to use this information for further optimisation of marketing decisions (cf. Hanssens, 1980). The emphasis in the research avenue has been on the development of a general diagnosing methodology. The focus has not been on systematically applying the methodology in a large number of markets in order to better understand actual competitive reaction behaviour. Still, some empirical results are provided via the applications presented in the various papers meant to illustrate refinements in the methodology (cf. Hanssens, 1980; Gatignon, 1984; Leeflang & Wittink, 1992). In the current section, we will briefly discuss the structure of the original LNB-model and the extensions that have been suggested thereafter. We will address the question of what can be learned from the applications of these models with respect to the actual competitive behaviour of firms. In the subsequent sections we will address the key research findings from other research conducted on competitive reaction behaviour.

The original LNB-model

The original LNB-model (Lambin, Naert and Bultez, 1975) refers to an oligopolistic market where the market leader is the focal firm in the model and where all the other firms are considered to be followers. In fact, the model assumes that the market consists of only two parties: the leading firm and the aggregate of all other following firms. The model's goal is to estimate the overall effects of marketing instruments on the sales of a brand. To this end, the model decomposes the overall sales effects into different components.

A first distinction is made between *size-effects* (the effects on the total industry sales) and *share-effects* (effects on the brand's market share). This is done because marketing actions, for instance a major advertising campaign, might cause the total market to grow, while at the same time it might also cause the brand's market share to increase.

A second distinction is made between direct and indirect effects. *Direct effects* refer to the impact of an action on industry sales and on the focal brand's market share, assuming competitors would not react. *Indirect effects* are the effects on industry sales and on the focal firm's market share resulting from reactions by competitors. The incorporation of indirect effects is typical for all LNB-type models.

A third distinction is made regarding the type of competitive reaction. Reactions can either be *simple* if the same instrument is used to react (e.g., a price cut by the leader is followed by a price cut by the followers), or *multiple* if reactions take place on other marketing instruments (e.g., a price cut by the leader is followed by an increase in the advertising budget of the followers). The decomposition of the effects in the original LNB model is shown in Figure 5.1.

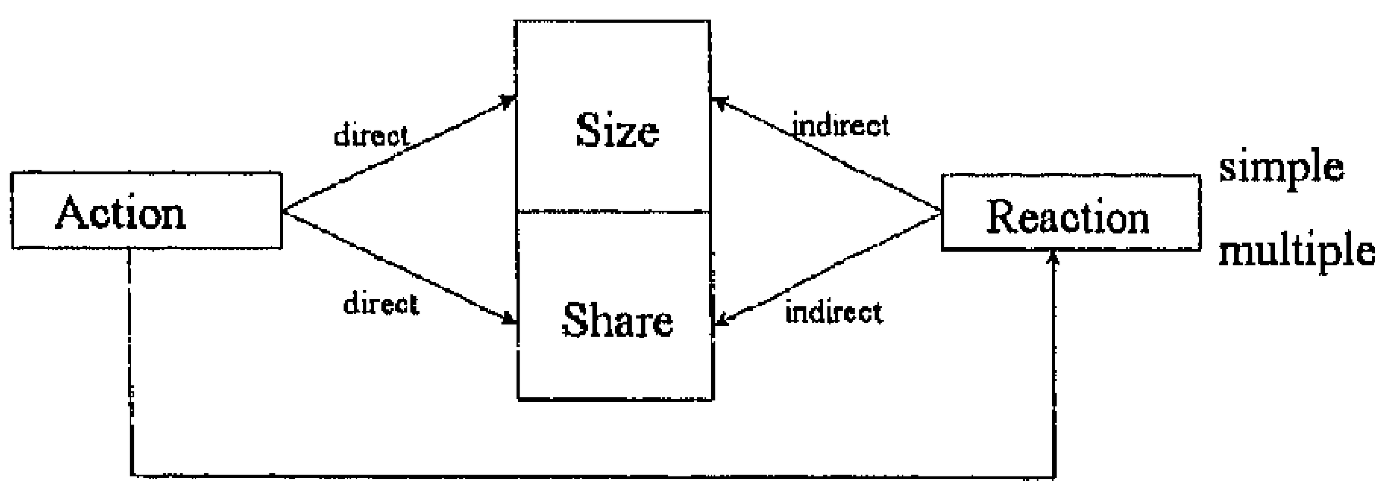


Figure 5.1 Decomposition of marketing instrument effects in the original LNB-model

The LNB-model is specified in terms of decomposing sales-elasticities (Lilien, Kotler & Moorthy, 1992, p.542) as:

(1) Sales-elasticity = share-effect + size-effect

(2) Share-effect = direct effect + (indirect) competitive response effect

(3) Size-effect = direct effect + (indirect) competitive response effect

The (indirect) competitive response effects are captured in the LNB-model by *reaction-elasticities*, which summarise to what extent a change in a marketing instrument by the leading brand is followed by a change in the same or another marketing instrument by the competing brands. The reaction-elasticities are put into a matrix, called a *reaction-matrix*, R. The diagonal elements of R refer to the simple reactions, while the off-diagonal elements refer to the multiple reactions. For illustration, an elementary LNB reaction-matrix R, for a leader (l) and a group of followers (f) competing on price (p) and advertising (a) is specified as:

$$R = \begin{bmatrix} e_{p_f,p_l} & e_{a_f,p_l} \\ e_{p_f,a_l} & e_{a_f,a_l} \end{bmatrix},$$

where the cells in the matrix denote the reaction-elasticities of the marketing instruments of the followers, with respect to the marketing actions by the leader (i.e. the percentage change in a marketing instrument of the follower relative to the percentage change in a marketing instrument of the leader)[1].

Based on the decomposition of total sales effects into the various components as in (1), (2), and (3), the LNB-model uses the following relationship, constituting the fundamental LNB-theorem[2]:

(4) $E_{q,u} = [I,R] \, . \, [E_m + E_{QT}]$,

[1] The notion that reactions do not always occur instantaneously can also be incorporated in the LNB-models. Reactions are then allowed to occur after a time lag.

[2] Cf. Lambin, Naert & Bultez (1975), Hanssens (1980), and Plat (1988).

where

$E_{q,u}$ $= [e_{q,u_1}, e_{q,u_2}, \ldots, e_{q,u_k}]'$, the vector of (overall) sales-elasticities for the leader regarding its marketing instrument $u_i (i = 1 \ldots k)$,

I = identity matrix (k x k),

R = the matrix of reaction-elasticities $(k \times k)$,

E_m $= [e_{QT,u_1}, e_{QT,u_2}, \ldots, e_{QT,u_k}, e_{QT,U_1}, e_{QT,U_2}, \ldots, e_{QT,U_k}]'$, the vector of market share-elasticities for both the instruments u_i of the leading firm and U_i of the followers, and

E_{QT} $= [e_{m,u_1}, e_{m,u_2}, \ldots, e_{m,u_k}, e_{m,U_1}, e_{m,U_2}, \ldots, e_{m,U_k}]'$, the vector of size-elasticities for both the marketing instruments u_i for the leading firm and U_i for the followers.

To see the decomposition of effects clearly, Equation (4) can be rewritten as:

(5) $$E_{q,u} = E_{m,u} + R.\ E_{m,U} + E_{QT,u} + R.E_{QT,U},$$

which equals the decompositions in (1), (2), and (3) in terms of adding the direct share effect ($E_{m,u}$), the indirect share effects ($R.E_{m,U}$), the direct size effect ($E_{QT,u}$), and indirect size effects ($R.E_{QT,U}$). In estimating the model, use is made of a time-series of data regarding sales and marketing instruments of all brands. Originally, LNB-models were calibrated on bi-monthly or monthly data. An example of the output of an LNB application will be given in the section below.

Extensions of the original LNB-model

Without question, the LNB-model has laid the foundation for a vast research avenue, inspiring many researchers to extend and apply the methodology. One extended LNB-model stems from Hanssens (1980). He proposed extending the original model in two ways.

Firstly, Hanssens (1980) specified the model in such a form that the competition is not seen anymore as one bunch of followers, as was the case in the original model. Instead, each competitor is considered separately. This can be useful if, in a market, a small number of competitors operate and if one is interested in differences with respect to their reaction behaviour[3].

[3] Also Leeflang & Reuyl (1985) specified an extended LNB-model, where each competitor is considered separately.

The second extension Hanssens (1980) put forward is the incorporation of *joint marketing decision making*, that is 'the possibility that levels of one marketing instrument affect or are affected by levels of other marketing instruments within the same firm'. This is a useful refinement of the model, since in practice one can frequently observe that several instruments of the marketing mix vary together. For instance, a price decrease might be accompanied by an increase in supporting advertising. As a result, the estimation of the parameters in the standard model becomes troublesome due to collinearity problems (the same problem was pointed out in Chapter 3 in relation to the Cooper & Nakanishi (1988) methodology). Hanssens (1980) proposes solving the problem by including *intrafirm* reaction-elasticities into the reaction matrix, describing the change in one instrument in relation to the change in another instrument within the same firm.

Hanssens (1980) shows an application to a domestic two-city air travel market, where three major carriers (1,2 and 3) compete with two instruments: advertising expenditure (A) and number of flights per week (F). Public quarterly data were collected over the years 1965-1974, concerning advertising, number of flights per week and passenger sales per carrier. Total sales-elasticities were decomposed according to the principles described above. Results showed significant primary demand (size) effects for two firms' number of flights, but it revealed no size effects of advertising expenditure. In addition, only one significant market share effect was detected: firm 2's number of flights showed a positive effect on that brand's share of passenger sales. This particular firm was also the only one showing intrafirm reaction of the number of flights with advertising.

Table 5.1 shows the complete reaction matrix R, resulting from the Hanssens (1980) application. Although only four non-zero elasticities were found, they point to a clear pattern of competitive reaction behaviour. For instance, it shows that firm 1 reacts to firm 3's number of flights actions ($e_{f1,f3}$ =.34), but not the other way around. Furthermore, firms 1 and 3 tend to react to firm 2's advertising expenditure.

Table 5.1 Reaction-matrix for a three firm airline market competing on advertising (A) and number of flights (F)[†]. (adapted from Hanssens, 1980)

	F1	A1	F2	A2	F3	A3
F1	1	0	0	0	0	0
A1	0	1	0	0	0	0
F2	0	0	1	0	0	0
A2	0	.37	.17	1	0	.37
F3	.34	0	0	0	1	0
A3	0	0	0	0	0	1

[†]Cell-numbers reflect significant reaction-elasticities referring to the reaction of the column firm as a response to actions by the row firm

After the development of the an extended model by Hanssens (1980), Gatignon (1984) and Plat & Leeflang (1988) extended the LNB-model further by decomposing the total competitive effects into effects occurring in different market segments. Alsem, Leeflang & Reuyl (1989) and Alsem (1991) use the LNB-models to investigate the forecasting accuracy of market share models. Finally, Leeflang & Wittink (1992, 1994) specify an extended LNB-model for diagnosing competitive reactions using retail scanner data. Their model includes the notion that competitive effects may occur due to actions by manufacturers as well as by retailers.

Obviously, the original LNB-model has gone through an evolutionary process over the past two decades. Figure 5.2 shows the elements which have been incorporated in the LNB-models. Compared to the original model (exhibited in Figure 5.1), the current extensions of the original LNB-model incorporate much of the real-life complexity of competitive action-reaction behaviour. Figure 5.2 illustrates (i) the inclusion of *joint decision making* within the acting firm, (ii) the incorporation of *multiple competitors* separately, (iii) the inclusion of *single* and *multiple* reactions, (iv) the incorporation of different *market segments*, and (v) the specification of *retailers* as an acting party.

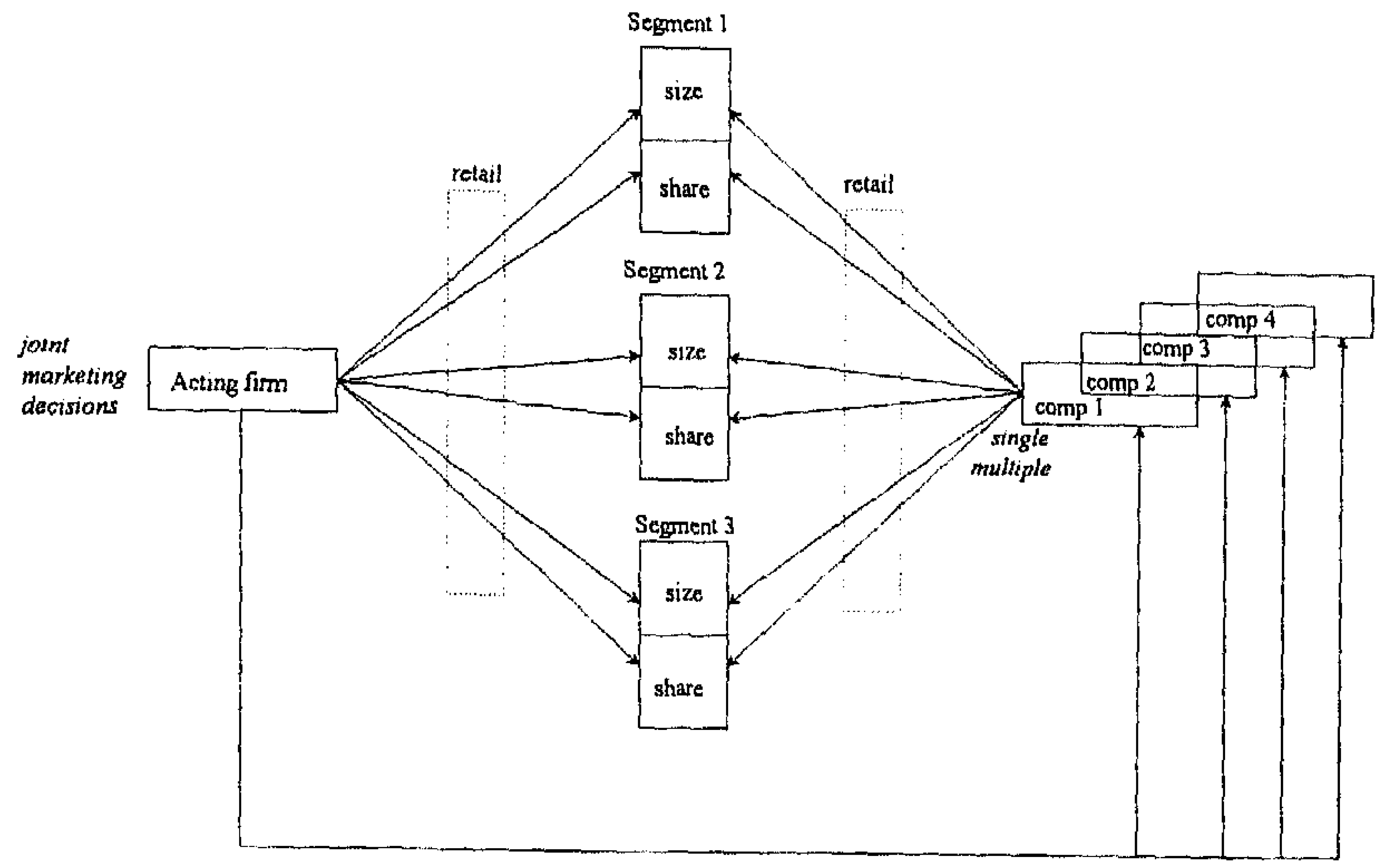


Figure 5.2 Illustration of the extensions of the LNB model, including joint decision making, multiple competitors, single and multiple reactions, multiple segments, and retailers

Findings of the LNB-approach regarding competitive reaction behaviour

It has been pointed out already that the primary goal in this type of research is the development of a methodology for diagnosing competition. Undoubtedly, LNB-models are a useful means for doing so. Question is, though, to what extent this research avenue has provided generalisable knowledge about competitive reaction behaviour. In the respective publications the models are tested ad hoc on one or two markets, with an emphasis on testing. The models are not (yet) utilised systematically for generating comprehensive knowledge about actual competitive conduct in markets. Therefore, only some tentative conclusions about competitive behaviour can be drawn from the empirical findings of the LNB-applications. As Ramaswamy et al. (1994, p.46) put it: 'in general, these empirical findings indicate that firms do not all react in the same way to a competitor's action'. Although true, this is a bit short on what can be inferred from the LNB-applications. For example, the various LNB-applications show proof of the fact that reactions by competitors can influence the net effect of marketing actions. Also, the applications show that various types of reactions may occur: simple and multiple reactions, intrafirm reactions, instantaneous and lagged reactions, retailer and manufacturer reactions. One conclusion from Leeflang and Wittink (1992, p.55) is 'that *simple* marketing reactions functions fail to capture systematic effects due to other marketing variables. At the same time, simple reactions do account for a disproportionate number of reaction effects. Importantly, the competitive reactions appear to be very complex'.

While the LNB-model approach has emphasised the development of a methodology for diagnosing competition based on registration of observed competitive marketing behaviour, a number of researchers have performed studies that focus on contributing to the *explanation* of competitive action-reaction behaviour. We will discuss these studies in the next section.

5.3 Explanatory studies on competitive reaction behaviour

Table 5.2 exhibits and describes the main explanatory studies on competitive marketing action-reaction conduct published over the past ten years. We will refer to the content of the table throughout this section. As can be seen, the frequency of publications in this field has increased substantially in the most recent two years, especially due to the work of Gatignon et al. (Ramaswamy, Gatignon & Reibstein, 1994; Bowman & Gatignon, 1995; Gatignon, Robertson & Fein, 1995). Although all reported studies have competitive action-reaction behaviour as common research issue, the approach and specific focus of the studies varies.

Table 5.2 shows how researchers have investigated various aspects of reaction behaviour as response to different competitive actions, using different types of data. The second column of Table 5.2 indicates the various types of *competitive actions* that have been used in the studies for analysing reactions to those initiating actions. Though the type of competitive actions varies across the studies, predominantly they are related to new products or new firms entering a market. This type of event is usually quite distinct and visible in markets, and therefore relatively easy to observe and analyse.

Table 5.2 Explanatory studies on competitive marketing action-reaction behaviour

	Competitive Action	*Dependent Reaction Variable (X=included)*					*Type of Data*	*Key Findings*
		# of Reactions	*Strength*	*Speed*	*Marketing Instruments*	*Success*		
MacMillan, McCaffery & van Wijk, 1985	new product introduction			X			Interviews Three competing banks	Faster reactions if action has high impact and if organisational inertia is low
Robinson, 1988	firm entry	X	X				SPI N=115 Start-up businesses	Stronger reactions if action is innovative, reacting firm is market dependent, and market has high growth
Gatignon, Anderson, & Helsen, 1989	firm entry				X		Nielsen data OTC & Airline	Firms react with their most effective marketing instruments, and cut down their ineffective ones
Chen, Smith, & Grimm, 1992	various actions	X		X			Content analysis U.S. Airline	More reactions if more firms are affected; less and slow reactions if action is strategic vs. tactical
Heil & Walters, 1993	new product introduction		X				Mail survey N=106 Broad range	Stronger reactions if action signals hostility and huge consequences to competitors
Lemmink & Kasper, 1994	quality improvement	X	X	X			Mail survey N=206 Industrial markets; durable goods	Generally, reactions occur with single marketing instruments. Less strong reactions in declining markets
Heil, Morrison & Walters, 1994	price reduction		X		X		Primary data Broad range	Stronger reactions if action signals aggressiveness and commitment
Ramaswamy, Gatignon & Reibstein, 1994	price and sales force				X		PIMS (N=90) Industrial markets	Retaliatory reactions more likely in low concentrated markets, growth markets, and for commodities
Bowman & Gatignon, 1995	new product introduction			X			PIMS (N=101) Broad range	Faster reactions in growth markets, and by highly flexible firms having relatively high market shares
Gatignon, Robertson, & Fein, 1995	new product introduction					X	Mail survey N=346 Broad range	Reactions are more successful in growth markets; if action is not very innovative, if the reaction comes fast and if it uses a single marketing instrument, but not price
Robertson, Eliashberg & Rymon, 1995	new product announcements	X					Mail survey N=346 Broad range	More reactions if announcement is more hostile and incumbent has high fixed commitment; more aggressive reactions if signal has more credibility

There is also variety in the specific aspect of the reaction behaviour that is being studied. This becomes apparent in the different dependent variables the various studies use in explaining competitive reactions (see the centre-columns of Table 5.2). Apart from studying the intensity of reactions in terms of the *number of reactions* and the *strength* of reactions (cf. Robinson, 1988; Lemmink & Kasper, 1994; Robertson et al., 1995), there are also studies focusing on the specific *marketing instruments* used (cf. Gatignon et al., 1989; Heil et al., 1994; Ramaswamy et al., 1994), *speed* of reactions (cf. MacMillan et al., 1985; Chen et al., 1992; Lemmink & Kasper, 1994; Bowman & Gatignon, 1995), and the *success* of reactions (Gatignon et al., 1995).

Since availability of data is a major problem in studying competitive action-reaction behaviour (Weitz, 1985), researchers have used various types of data in this field, as can be observed from the *Type of Data* column in Table 5.2. Most studies use survey data, sometimes using existing databases on action-reaction behaviour (e.g., the SPI/PIMS databases used by Robinson, 1988; Ramaswamy, Gatignon & Reibstein, 1994; Bowman & Gatignon, 1995), sometimes using ad hoc surveys (e.g., MacMillan, McCaffery & Helsen, 1985; Heil & Walters, 1993; Robertson, Eliashberg & Rymon, 1995).

The final column of Table 5.2 shows the main findings on competitive behaviour resulting from each of the studies. We will now discuss the key aspects and findings of the studies mentioned in Table 5.2. We will first describe the studies in chronological order, and thereafter we will integrate the key findings in overview diagrams.

MacMillan, McCaffery & van Wijk (1985)

MacMillan, McCaffery & van Wijk (1985) studied the speed of competitor response to easily imitated new products (e.g., a high interest savings account) introduced in commercial banking. They interviewed the product managers of one bank responsible for the 11 selected new product introductions, to collect information about the reactions by two competing banks. The new products were described by a number of characteristics (e.g., visibility, strategic pressure, complexity), assessed by a independent expert in the banking industry. Main conclusions based on this rather small sample of events are:

- faster reactions occur if the introduction exerts high *strategic pressure* on the reacting firms,
- faster reactions occur if the reacting firms' *organisational inertia* is low.

Robinson (1988)

Robinson (1988) used the SPI (Strategic Planning Institute) start-up business database (a PIMS satellite database) for investigating reactions by the main competitors as a response to market entry by start-up businesses. Robinson's study resulted in one of the first comprehensive publications on competitive reactions covering a broad range of markets. The SPI database contains information provided by managers of start-up businesses (i.e. less than seven years old businesses). One of the issues respondents have to report on is the marketing mix reaction of the three main competitors in the market during the first two years of the start-up business.

Table 5.3 reports the findings of Robinson (1988), showing the percentages of *aggressive* reactions (which are defined as reactions making entry more difficult) per marketing instrument[4]. As can be seen, such reactions are relatively infrequent during the first year, and are predominantly on price and marketing expenditures. During the second year, reactions are more common, and cover all marketing instruments, although relatively low on distribution. Robinson further analysed the strength of the reactions (defined as the number of marketing instruments reacted with) with respect to a number of explanatory variables concerning the type of entry, the type of market, and the type of competitors.

Robinson's (1988) key findings are:

- stronger reactions occur against *innovative entries,* especially in the second year after entry,
- stronger reactions occur if the market is *strategically important* for the incumbents,
- stronger reactions occur if *market growth* is higher.

[4] By contrast, Robinson defined *accommodating* reactions to make entry easier. In fact, very few accommodating reactions were observed in Robinson's study.

Table 5.3 Aggressive marketing mix reactions to start-up entry (taken from Robinson, 1988)

N=115	(Aggressive) reactions Year 1[†]	(Aggressive) reactions Year 2[†]
Incumbent Reactions on		
Product	4%	20%
Distribution	3%	7%
Marketing Expenditures	10%	18%
Price	15%	24%
No reaction	72%	54%

[†] Percentage of entrants encountering an aggressive reaction by any of the three leading incumbents in the first, resp. the second year after entry.

Gatignon, Anderson & Helsen (1989), and *Chen, Smith & Grimm (1992)*

In subsequent studies (reported in Table 5.2) performed by Gatignon, Anderson & Helsen (1989) and Chen, Smith & Grimm (1992), competitive behaviour is analysed in a few selected markets. Both studies analysed parts of the U.S. domestic airline market, using public information about prices, flight frequencies, number of passengers, etc. In addition, Gatignon et al. (1989) also used Nielsen data for analysing the OTC-market (i.e. over-the-counter medical products). While Gatignon et al. focused on incumbent marketing mix reactions to a specific event (a new firm entry), Chen et al. studied competitive reactions to changes in various marketing instruments. The fact that these studies were performed in specific market situations, though, may limit the generalisability of the findings of these studies (cf. Leeflang & Wittink, 1996b). Gatignon et al.(1989) conclude the following:

- incumbents tend to react to new entrants with their most *effective marketing 'weapons'* (i.e. those instruments having relatively high cross-elasticities), and they tend to cut down in expenses for their less effective marketing weapons.

The key findings of Chen, Smith & Grimm (1992) are:

- the number of reactions increases if the *number of incumbents affected* by an event increases,

- the number of reactions is relatively high if the action is *tactical* as opposed to strategic,
- speed of reaction is low if the action is *strategic*, if the action requires substantial *implementation efforts* from the actor, or if it poses a *strong threat to the key market* of a competitor.

Heil & Walters (1993), and *Heil, Morrison & Walters (1994)*

Another notable contribution was made by Heil & Walters (1993). They used a mail survey to collect data from a broad array of firms (net sample size 106; response rate 14%). The idea was to let respondents reflect on a recent new product introduction by a major competitor, concerning their perceptions regarding that introduction and the strength of their reaction to it. Heil & Walters use a 'signaling' approach, which takes the premise that competitors view new product introductions as a bundle of signals from the introducing firm toward the competitors. Each competitor may evoke different signals for the same introduction. The notion that competitors have their own perceptions of the market, competitors and competitive events, and that signals are used in communication between competitors has received much attention in the marketing literature recently (cf. Eliashberg & Robertson, 1988; Heil & Robertson, 1991; Chapman Moore, 1992; DeChernatony, Daniels & Johnson, 1993; Chapman Moore & Urbany, 1994; Heil & Langvardt, 1994; Johnson & Russo, 1994; Clarke & Montgomery, 1996). Heil & Walters (1993) distinguished between three types of new product signals: hostility, commitment and consequences. In a more recent study (Heil, Morrison & Walters, 1994) the same signaling approach is used for analysing competitive responses to *price reductions*.

The main conclusions from Heil & Walters (1993) and Heil, Morrison & Walters (1994) are:

- stronger reactions occur if a new product introduction signals higher level of *hostility*,
- stronger reactions occur if a new product introduction signals more severe *consequences*,
- stronger reactions occur if a price reduction signals a higher level of *hostility* and *commitment*.

Lemmink & Kasper (1994)

Next, Lemmink & Kasper (1994) report a study concerning competitive reactions to quality improvements in products and services. Use was made of mail survey results from a net sample of 206 Dutch companies operating in industrial markets with durable products. Response rate was 20%. The dependent variable was reaction strength, which was calculated as in Robinson (1988), as the number of different instruments used by the competitors in their reactions.

Their key findings are:

- in 70% of the cases, the quality improvements resulted in a reaction by the main competitor, typically with the marketing instrument product,
- stronger reactions occur if quality improvements are *common practice*, if the *number of competitors* is relatively large, and if the initiating firm's *profit increase* was expected to be more substantial,
- weaker reactions occur if the market is in the *decline* phase.

Ramaswamy, Gatignon & Reibstein (1994)

The publication by Ramaswamy, Gatignon & Reibstein (1994) is based on PIMS data. Ramaswamy et al. analysed 90 SBU's that operate in industrial markets, regarding their action-reaction behaviour with the marketing instruments price and sales force. They attempt to explain variance in *aggressive*, retaliatory behaviour and *co-operative* behaviour across competitors with explanatory variables concerning the market (e.g., market growth and market concentration), and the competitors (e.g., cost position and company image rating).

Key findings of Ramaswamy et al. (1994) are:

- aggressive reactions occur more frequently in *concentrated* markets (i.e. markets having high C4-ratios), *growth* markets, and if products on the market are relatively *standardised*,
- aggressive reactions are less likely if the acting firm has a *cost advantage* over its largest competitor.

Bowman & Gatignon (1995)

Bowman & Gatignon (1995) focused on explaining the *speed of reactions* to competitive new product introductions. They used a part of the PIMS data containing reported information by a broad spectrum of 101 SBU's, on the question 'how long did each of your leading competitors take to respond in a manner visible to your immediate customers?'. Explanatory variables in this study relate to the market (e.g., growth and concentration), the threatening firm (market share and capacity utilisation), and the reacting firm (e.g., strategic importance and organisational abilities of the SBU). Their main findings are:

- faster reactions occur if the *market growth* is high and customer *switching costs* are low,
- faster reactions occur if the reacting firm has high *market share*, if the *development time* of new products is short, and if the rate of *technology change* is high,
- faster reactions occur if the introducing firm has a low *market share*.

Robertson, Eliashberg & Rymon (1995), and *Gatignon, Robertson & Fein (1995)*

Finally, Robertson, Eliashberg & Rymon (1995), and Gatignon, Robertson & Fein (1995) reported the results from a net sample of 346 firms in various markets, using a mail survey (response rate 21%). While Robertson et al. (1995) focused on explaining the frequency and nature of reactions to new product announcements using the concept of signaling, Gatignon et al. (1995) focused on explaining the *success* of reactions to new products.

Key findings reported from Robertson et al. (1995) are:

- the probability of a reaction by incumbents increases if the new product announcement signals a higher level of *hostility* and *commitment*,
- aggressive (i.e. not-accommodative) reactions are more likely to occur if the new product announcement has a higher level of signal *credibility*.

Gatignon et al. (1995) report the following main findings:

- reactions are considered more successful if the *speed of reaction* is high,
- reactions are considered more successful if *number of reaction* instruments used is limited,

- reactions are considered more successful in fast *growing* markets, and in *non-high-tech* markets,
- reactions are considered more successful if the *competitive threat* posed by the new entry on the reacting firm, is greater.

This concludes our overview of the main findings resulting from the studies on competitive action-reaction behaviour. We will now turn to the general findings and conclusions with respect to the current body of knowledge on competitive reaction behaviour, which has emerged from the research performed so far. In this section, we have reviewed the main explanatory studies on competitive action-reaction behaviour, describing and explaining the actual ways competitors react to certain actions. Table 5.2 gave an overview of the explanatory studies regarding (i) the focal competitive action (new entrant, new product, price reduction, etc.), (ii) the variable to be explained (yes or no reaction, the strength, the speed, the marketing instruments used, and the success of reaction), (iii) the type of data used (broad versus narrow market focus; PIMS versus ad hoc survey, etc.), and (iv) the key findings from the studies.

It is clear that the studies are rather diverse in approach and focus. Therefore, one should be careful in comparing and merging the findings. Nevertheless, some general, though tentative, conclusions can be drawn regarding the *intensity*, the *speed* and the *success* of actual marketing reaction behaviour by firms confronted with a competitive event. We will now summarise the findings regarding these aspects.

Figure 5.3 summarises the key findings regarding the *intensity* of response a firm can encounter when performing a competitive action. The *reaction-intensity*, as specified in the various studies, reflects either the number of marketing instruments reacted with by competitors (e.g., Robinson, 1988; Lemmink & Kasper, 1994) or the strength of reactions relative to industry practice (Heil & Walters, 1993; Heil, Morrison & Walters, 1994). The findings of the studies suggest that the reaction-intensity is dependent on four groups of explanatory variables, related to: (i) the *market conditions* of the market in which the action has taken place (e.g., market growth, supplier concentration, product standardisation); (ii) the *action* itself (e.g., the level of innovation, the impact on competitors), (iii) the *actor*, i.e. the acting firm (e.g., relative cost (dis)advantage, level of commitment), and (iv) the *reacting firm* (e.g., the importance of the market, the level of threat encountered, the level of organisational inertia). The factors in Figure 5.3 are leading to a higher level of reaction intensity.

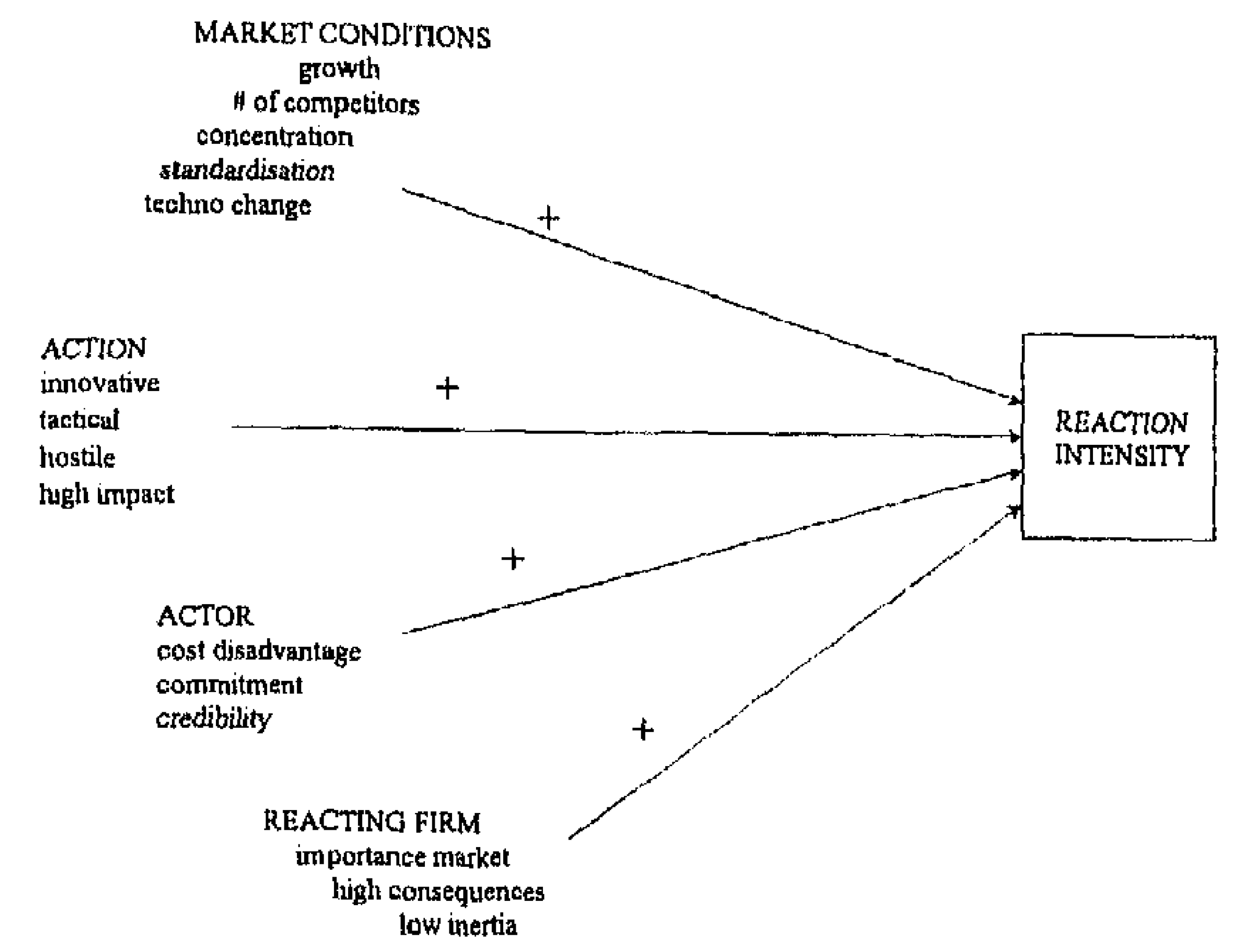


Figure 5.3 Summary of key groups of variables explaining the *<u>intensity</u>* *of competitive reactions (overall conclusions derived from the studies reported in Table 5.2)*

Based on the findings exhibited in Figure 5.3, acting firms can assess the probable intensity of competitors' reactions to their actions. For instance, heavy response can be expected if a strong and heavily committed firm takes an innovative, tactical, hostile and high impact action, in a high growth market with many competitors and many technological changes. Reactions can especially be expected from those competitors for which the market is important, those which feel heavily threatened by the action, and those which are flexible enough to respond.

In addition to explaining the reaction-intensity, research work has also focused on explaining the *speed* of the reactions, as one element of the reaction strategy of firms. Generally, the speed of reaction is defined as the number of days (or weeks) between the particular competitive event and the first response by the competitors. The main blocks of variables explaining the speed of reactions are the same as those explaining the reaction-intensity: the market conditions, the competitive action, the actor (the lower market share of the actor, the faster the reactions), and the reacting firm. The key variables significantly explaining the speed of reaction in the studies reported thus far, are summarised in Figure 5.4.

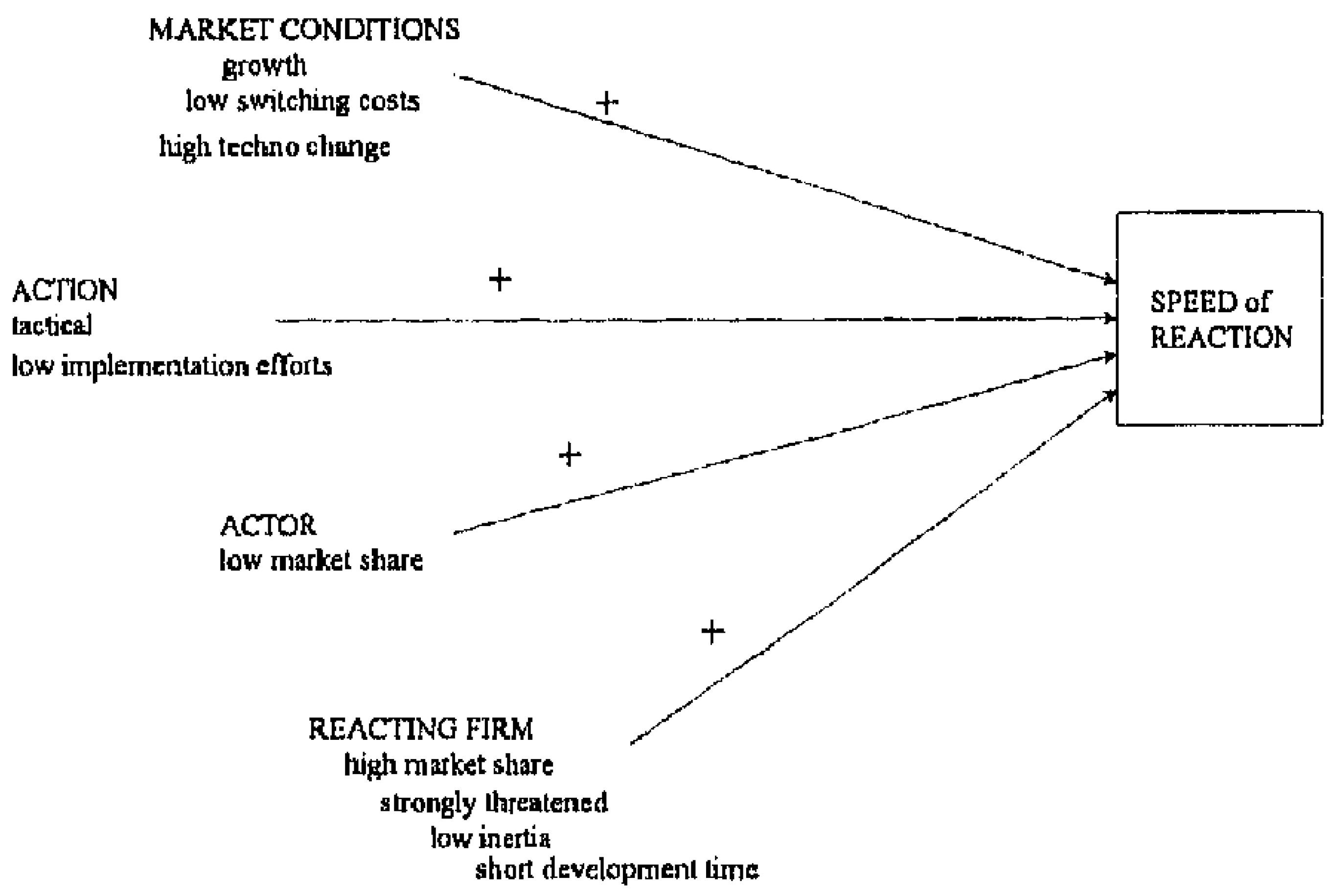


Figure 5.4 Summary of key groups of variables explaining the <u>speed</u> of competitive reactions (overall conclusions derived from the studies reported in Table 5.2)

Finally, the *success* factors of competitive reactions has been studied by Gatignon et al. (1989, 1995). The findings from these studies are exhibited in Figure 5.5. In general, the level of success seems to be determined by certain market conditions (high growth and low-tech), and, importantly, also by the reaction strategy pursued: successful reactions are speedy, are narrow focused, and are executed with the most effective marketing instruments only.

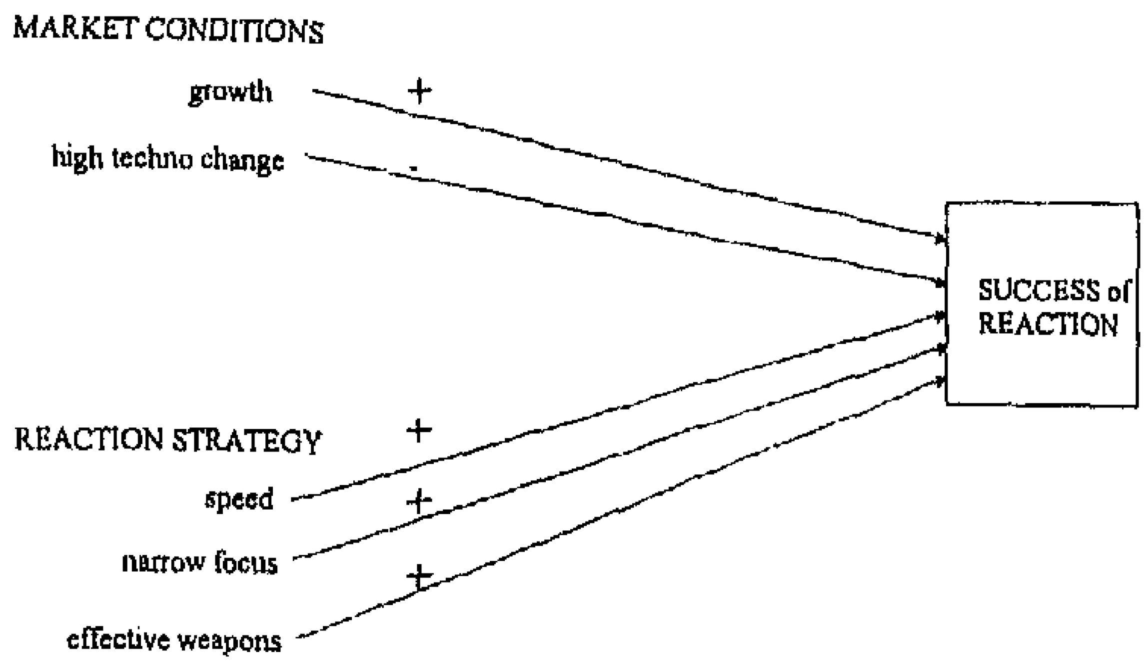


Figure 5.5 Summary of key findings explaining the success of competitive reactions (based on Gatignon et al., 1989 and 1995)

5.4 Conclusions

In this chapter we have described the approaches and the main findings of the studies in marketing devoted to the analysis of competitive action-reaction behaviour in markets. Section 5.2 demonstrated the use of generalised LNB-models to analyse the effects of reactions by competitors on the net effect of a marketing action by a focal firm. The LNB-approach is basically aimed at developing a general methodology for diagnosing competition. Though the LNB-models have not yet been applied systematically in various markets in order to understand actual competitive reaction behaviour, one conclusion from that type of research is that, in general, reactions by competitors do have an impact on the net effect of a marketing action by a focal firm. Furthermore, it is shown that in practice, usually a complex reaction pattern does occur, which makes it difficult for acting managers to make conjectures about possible reactions by their competitors.

Also, as has been demonstrated in Section 5.3, the explanatory research on reaction behaviour performed so far is rather sparse and scattered with respect to the approach and focus. Nevertheless, it has provided some tentative conclusions about the intensity, speed and successfactors in the context of competitive response. The primary blocks of explanatory variables seem to have been identified. More work has to be done, though, to fully grasp competitive response behaviour. For instance, a more detailed analysis of the relation between the type of competitive action, the type of acting firm, the interpretations of competitive decision makers, and the type of reaction, might provide deeper understanding of competitive reaction behaviour. In the next chapter, we will report such a study, using primary data from a N=98 sample of Dutch marketing managers of frequently purchased consumer goods.

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6 Competitor reactions to new product introductions*

6.1 Introduction and overview

In the previous chapter, an overview was given concerning the current body of knowledge about competitive reaction behaviour. One conclusion is that research on this topic has been quite sparse and the existing studies are rather scattered with respect to the research focus. Only some tentative conclusions can be drawn about groups of factors explaining reaction behaviour. In the present chapter, an empirical study will be presented aimed at further explaining reaction behaviour by studying the process behind the reaction decisions. This is done in a specific competitive setting: marketing mix reaction by incumbents as a response to new product introductions in frequently purchased consumer good markets. The central question is: what are the determining aspects of the reaction behaviour of competitors as a response to new product introductions? Our specific focus is on the relationship between reaction behaviour on the one hand, and characteristics of the new product introduction event on the other hand. The research is carried out by performing structured, computerised interviews with 98 responsible marketing decision makers, who were asked (i) to reflect on their reactions to a recent competitive new product introduction on their market, and (ii) to perform a conjoint analysis task concerning the introduction of a new product, judging various 'profiles' of new product introductions.

* This research part builds on an earlier publication: Waarts, E., 1995. Reactions to new product introductions: a decision making perspective. 24th EMAC conference proceedings, M.Bergadaà (ed.), 1291-1312.

We concentrate on reaction behaviour taking place in *frequently purchased consumer good markets*, which is the type of market we have been primarily focusing on throughout this thesis. An advantage of this choice is that the research is carried out in a relatively homogeneous market context. We focus on *new product introductions* as the focal competitive action in response to which competitors might react, following previous studies (cf. MacMillan, McCaffery & van Wijk, 1995; Heil & Walters, 1993; Bowman & Gatignon, 1995; Gatignon, Robertson & Fein, 1995; Robertson, Eliashberg & Rymon, 1995). This type of competitive action is especially interesting, since introducing a new product is one of the most important actions a marketing manager takes. In addition, the results of the action usually are quite uncertain, partly due to the reactions the focal firm might encounter by competing firms (Lynn, 1987; Robinson, 1988; Scherer and Huh, 1992; Heil and Walters, 1993). For instance, some time ago Kimberly-Clark tried to penetrate into the Dutch disposable diaper market by introducing 'Huggies', a new type of disposable diapers for nearly trained little children. The incumbent competitors responded rapidly by introducing similar products: Procter & Gamble introduced 'Trainers', and Mölnlycke launched 'Libero Up & Go'. Besides these matching introductions both P&G and Mölnlycke defended their positions in the regular diaper segments by reducing consumer prices. These reactions will certainly have had an impact on the performance of Kimberley-Clark products. Competitive reactions can even destroy a new product. This was demonstrated by Procter & Gamble's marketing war against Unilever's self-proclaimed revolutionary detergent Omo Power (Riezebos & Waarts, 1994).

As has been pointed out in the previous chapter, it is not uncommon that competitors react to an action by a focal firm. Schelling (1960) already remarked that, in general, the success of a competitive action often depends on the actor's apparent commitment to it and the opponent's likelihood of retaliation. Thus, from the perspective of a marketing manager deciding on an action, for example a new product introduction, the assessment of likely reactions by competitors is important, because it may influence his decision whether or not to launch, or it may alter the introduction strategy. But how can a decision maker assess the likely reactions by his competitors? A number of theoretical studies exist concerning how firms *should* behave in terms of reactions to new product introductions. For instance, the Defender model (Hauser and Shugan, 1983), discussed in Chapter 3, provides a number of normative recommendations of how to react if an attacker enters the market. Also other researchers provide recommendations for similar situations (e.g., Carpenter, 1986; Kumar & Sudharsan, 1988, Carpenter, 1989; Horsky & Nelson, 1992; Sudharsan, Kumar & Gruca, 1995). Whether these recommendations are also followed in actual practice is hard to tell, because empirical research in this field is still scarce, as has been shown in the preceding chapter.

The present study contributes to the empirical knowledge of competitive behaviour, by investigating the factors influencing actual reaction behaviour of competitors and the managerial decision process behind that behaviour. The central concept in our research is '*Expected Competitive Impact*'. We will deal with the meaning of this concept and its measurement. We will show that (i) the 'Expected Competitive Impact' of a competitive new product entry is a relevant concept for explaining defending managers' competitive reaction decisions and that (ii) the 'Expected Competitive Impact' can be predicted by the characteristics of the introduction event, as perceived by defending managers.

Hereafter, we will (1) develop a theoretical framework for studying competitive reactions to new product introductions, (2) formulate hypotheses, (3) empirically test the hypotheses by using primary data from a field study performed with marketing managers and (4) draw conclusions about how managers interpret product introductions and decide on their reactions to such events.

6.2 Theoretical framework

Our specific focus in this study is concerned with the relationships between the characteristics of a new product introduction event and the reaction behaviour of competitors. In the preceding chapter, a number of studies were reviewed examining several aspects of the reaction behaviour of competitors (see Table 5.2). While some of the studies specify a broad range of explanatory variables for explaining competitive reactions (e.g., Robinson, 1988; Ramaswamy et al., 1994; Bowman & Gatignon, 1995; Gatignon et al., 1995), Chen, Smith and Grimm (1992) explicitly focused on investigating the relationship between action characteristics and competitive response. In fact, their goal was to demonstrate that competitive responses may be predicted based on the characteristics of the initial action. For example, one of their findings was that strategic actions (e.g., expansion into new markets), as opposed to tactical ones (e.g., price cuts), reduce the number and delay the timing of rivals' counter-actions. In a theoretical sense, they used the stimulus-response model to link competitive actions to reactions (as exhibited in Figure 6.2.1). The model was tested using public information data on the U.S. domestic airline industry. Chen et al. (1992) conclude that it is fruitful to use the stimulus-response model for predicting reactions, and appeal for future studies exploring the effect of other characteristics, especially characteristics of the acting firm. Furthermore, they also make a plea for investigating the process by which competitors decide to respond, because such research may open the 'black box' of the stimulus-response model and may yield better explanations and predictions of reactions.

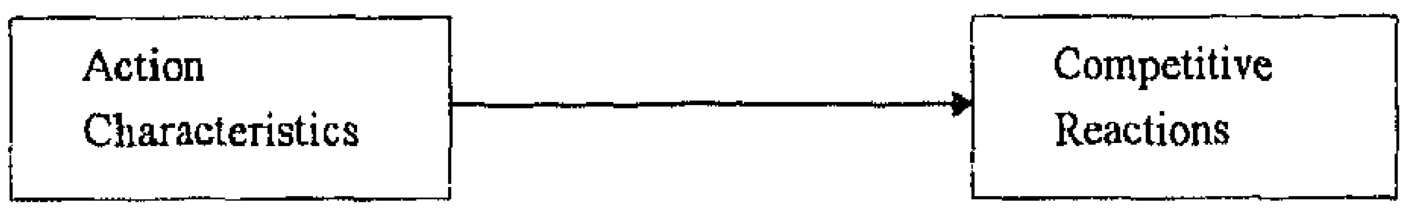

Figure 6.2.1 Stimulus-response research framework used by Chen et al.(1992)

The present study responds to the suggestions made by Chen et al.(1992) in two ways: firstly, by both including characteristics of the action as well as characteristics of the acting firm in the research model, and secondly, by trying to further explain competitive reactions by modelling the decision making process of managers confronted with a competitive new product. Regarding the first issue, since the design and findings of the study by Chen et al. may be specific for the U.S. Airline industry (cf. Leeflang & Wittink, 1996b), in our study we will propose using a different set of variables, suitable for analysing competitive reactions in frequently bought consumer good markets. Regarding the latter issue, the traditional stimulus-response model as used by Chen et al. (1992) does not explicitly include the notion that stimuli have to be interpreted by subjects before they respond. But, as Katona (1975) already pointed out, there is always the 'organism' (i.e., the manager) in between the stimulus and the response. There is a difference between subjective perception and actual 'reality'. Thus, the same stimulus can provoke different levels of 'alarm' depending on the interpretation of the stimulus by the various subjects. Similarly, a manager faced with a competitive event, e.g., a new product introduction by a competitor, has to process and interpret various informational stimuli related to the event before he decides on counter-actions. This is also the reasoning in the studies performed by Heil & Walters (1993), and Heil, Morrison & Walters (1994), who state that actual reactions to new product introductions are the output of a decision making process in which signals, perceptions, and interpretations of the defending firms' managers play a crucial role. Our research basically integrates the approaches of Chen et al. (1992) and Heil & Walters (1993) and Heil, Morrison & Walters (1994).

Figure 6.2.2 shows the core of our research framework, which contains three main elements: the '*Perceived Event Characteristics*' of the new product introduction (referring to the perceptions of the manager of both the new product *action* itself and the *actor* behind the action), the '*Expected Competitive Impact*' defending managers attribute to the introduction (referring to the interpretation of the event by the manager) and the '*Competitive Reaction*' executed by these managers as a response to the competitive new product.

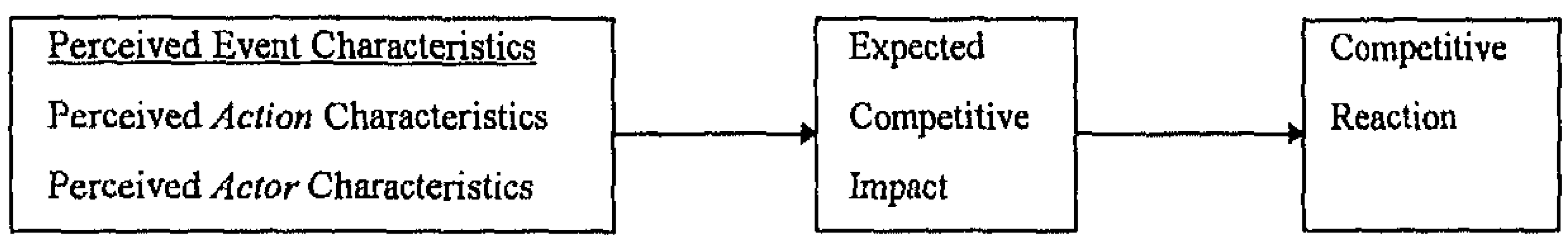

Figure 6.2.2 Conceptual model regarding competitive reactions to new products

The model exhibited in Figure 6.2.2 assumes the following decision making process by defending managers deciding on their reactions to a competitive new product. Firstly, a manager confronted with a particular new product introduction by a competitor, will form his own perception about the event in terms of certain characteristics (Perceived Event Characteristics) related to this new product and to the acting firm behind it (e.g., the manager perceives the new product to be innovative, and thinks the introducing company has an excellent reputation regarding the introduction of new products). Next, the manager's perception of the new product event forms the basis for his assessment of the impact this event would have on his own products' market performance, which is called the Expected Competitive Impact. Basically, this sets the 'state of alarm' of the manager. Finally, the expected competitive impact drives the manager's decisions about whether or not to react and how to react (Competitive Reaction). The basic assumption here is that a manager's primary motive to react to competitive events is to counter a drop in market performance that is expected if he wouldn't react.

Compared to the model of Chen et al. (1992) in Figure 6.2.1, the most fundamental differences are that competitive reactions are not *directly* explained by *actual* characteristics of the competitive action. Instead, it is postulated that *perceived* characteristics related to the action (and the actor) explain competitive reactions *indirectly*, via the assessment by the manager regarding the expected competitive impact of the event. The fact that in our model we use *perceived* characteristics instead of actual, observable characteristics, is in conformity with the approach of Heil & Walters (1993) and Heil, Morrison & Walters (1994).

In the preceding chapter, we have identified four key blocks of variables (see Figure 5.3) which summarise the main explanatory variables used in the various previous studies of competitive response. In this research, our primary focus will be on the blocks concerning the 'action' and the 'actor'[1]. We will now elaborate on each of the main elements and variables, starting with the Perceived Event Characteristics.

Perceived Event Characteristics

The first element in the research model as exhibited in Figure 6.2.2 focuses on the perception managers have about the characteristics of a competitive new product event. Our vantage point is the notion that managers, like all humans, do not necessarily take decisions based upon 'true' characteristics, but that they take decisions based upon their own perceptions and subjective interpretations about reality (cf. Heil & Walters, 1993; Johnson & Russo, 1994; Chapman Moore & Urbany, 1994).

[1] The two other explanatory variable blocks in Figure 5.3 'Market conditions' and 'Reacting firm' are not specified in our core model, because in this study we are specifically interested in the relationships between the (perceived) action and actor characteristics, expected competitive impact, and competitive reactions. We will specify a number of variables relating to the 'Market conditions' and the 'Reacting firm', though, in order to investigate the possible moderating influence of these variables on the hypothesised relationships in our model.

Figure 6.2.3 gives an illustration of this process if a manager is faced with a new product introduction by a competitor. From the literature on information processing and perception formation, it is known that managers use 'cues' from various information sources to form their own cognitive structure of the reality they are operating in (cf. Brunswik, 1952; Engel, Blackwell & Miniard, 1995). Indeed, marketing managers continuously make use of various sources and types of information, obtained from retailers, from the sales force, from market monitors, from pre-announcements by competitor, and so on, to stay informed about the market developments. At a certain moment, this market 'radar system' will spot a (coming) new product event on his market. Next, the manager might collect more information and must transform all this information into a manageable picture of the event.

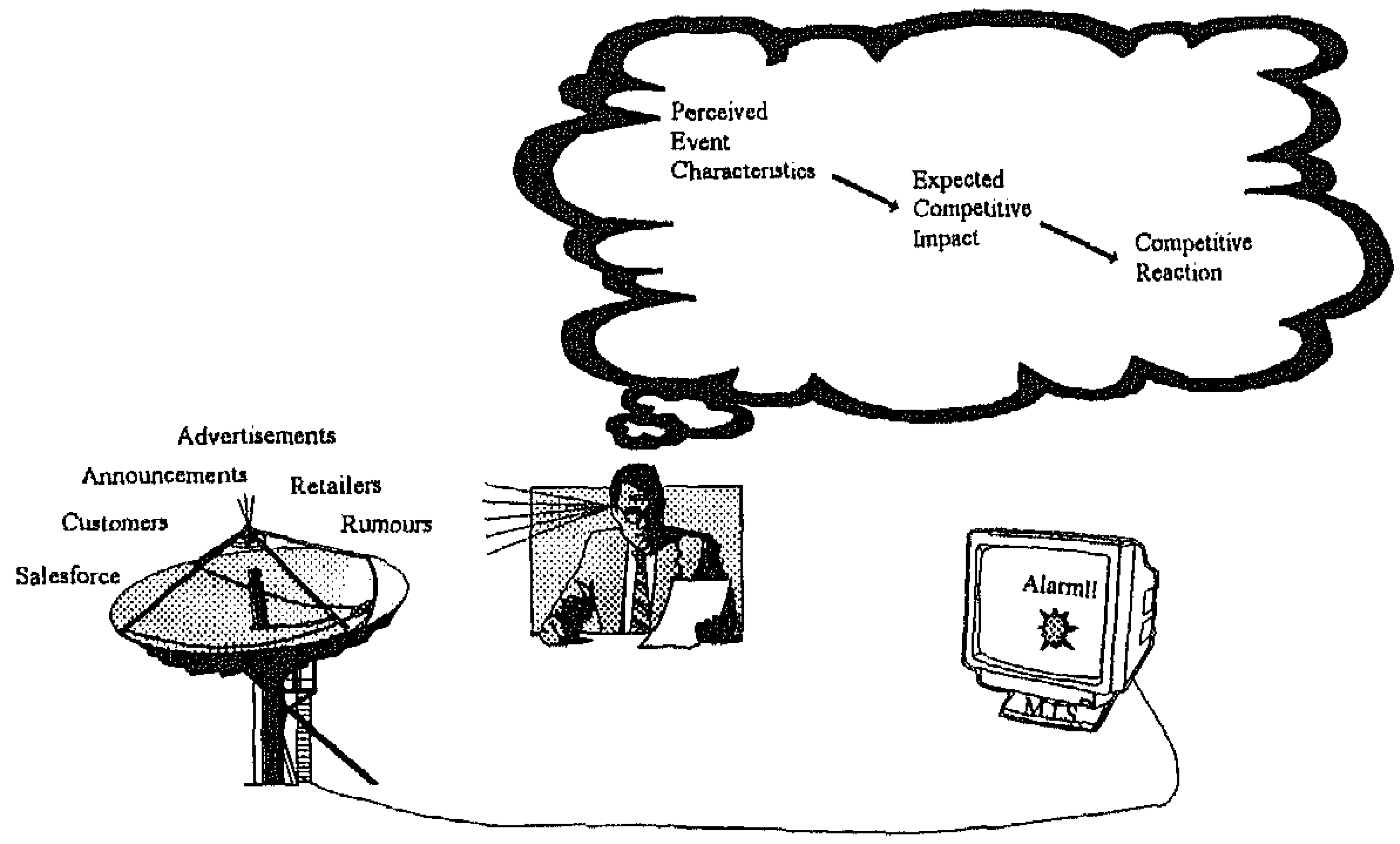

Figure 6.2.3 Illustration of information processing and the decision making process by managers faced with a competitive new product introduction

In the model, we assume that this picture -that is a manager's perception of the new product event- can be described by a set of *perceived event characteristics*. These are the characteristics of a competitive new product event *as perceived* by the defending manager[2]. For instance, a manager may perceive a new product as being closely positioned to his own products, whether it is true or not. We point again to the fact that the perceived event characteristics used in this study are conceptually different from the 'action characteristics' used in Chen et al. (1992). While these authors specify directly observable 'true' action characteristics as independent variables (e.g., a price discount on a flight destination), in our model we assume that managers decide on their reactions based upon the characteristics they, subjectively, attribute to the new product event. We argue, in line with Heil & Walters (1993), Johnson & Russo (1994), and Chapman Moore & Urbany (1994), that competitive reactions can be explained better by using the perceptions of managers rather than taking the 'true' characteristics as the point of departure. After all, although a manager's perception may be distorted or false, his decisions are based upon these perceptions (cf. Leeflang & Wittink, 1996a).

Perceived Action and Actor characteristics

Two sets of perceived event characteristics concerning a new product event are distinguished, which serve as explanatory variables for the dependent variable 'expected competitive impact'. On the one hand we specify a number of characteristics related to the new product action itself, which we will call *'perceived action characteristics'*. On the other hand, as was suggested by Chen et al. (1992), we specify a number of *'perceived actor characteristics'*, related to the firm behind the new product. We briefly describe each of the specified characteristics in our model below. Further specifications and operationalisations are given in subsequent sections.

Four potentially relevant perceived *action* characteristic variables are specified:

1) the perceived *level of innovation* of the new product,

2) its *intended brand position* (the perceived closeness of the new product to our own products),

3) the perceived *introduction strategy* (low/highly priced and little/heavily supported), and

[2] It is realized that, in general, complex transformation processes exist from informational stimuli managers are exposed to, towards resulting perceptions (e.g., Brunswik, 1952; Newell and Simon, 1972, Chapman Moore & Urbany, 1995). In the present study we do not explicitly address this transformation process. Instead, we are primarily interested in the resulting perceptions of a manager and the effects of these perceptions on the manager's assessment of the expected competitive impact and his reaction decisions.

4) the anticipated *market size effect* caused by the new product (the expected effect of the new product on total market sales).

In addition, five perceived actor characteristic variables are specified:

1) whether the introducing company is seen as an *incumbent or* as a *new entrant,*
2) whether or not the actor is viewed as the current *market leader,*
3) the perceived *success reputation* of the introducing company in terms of its success regarding previous introductions,
4) the perception about the actor's *aggressiveness reputation* of doing business, and
5) the assessment about the *stakes involved* for the introducing company.

These proposed variables have their support in the literature. Regarding the *action* characteristics, we specify the 'Level of Innovation', which refers to Robinson's (1988) finding that highly innovative new entries provoke relatively frequent reactions by incumbent competitors (see Table 5.2 and Figure 5.3)[3]. The 'Intended Brand Position', the 'Introduction Strategy' and the expected 'Market Size Effect' follow directly from Hauser & Shugan (1983). In their Defender model, these variables form key factors determining the impact of a product introduction on the existing brands' market shares and sales. With respect to the *actor* characteristics, we have specified the variables 'Incumbent or New Entrant' and 'Market Leader or Not', which are referred to in Bowman & Gatignon (1995) and Scherer & Ross (1990). The latter variable is in conjunction with the concept of cost advantage in Figure 5.3, as in Ramaswamy et al. (1994). Finally, the actor's 'Aggressiveness Reputation', 'Success Reputation', and 'Stakes Involved' are related to the concepts of hostility, credibility, and commitment as in Heil & Walters (1993), Heil, Morrison & Walters (1994), and Robertson et al. (1995).

[3] Figure 5.3 also shows the variables 'tactical', 'hostile', and 'high impact'. We did not include the variable 'tactical vs. strategic' here since we focus on different characteristics of a certain class of actions; 'hostility' will be dealt with as a variable relating to the actor; and 'impact' is treated in our model as an intermediate variable to be explained by the perceived event characteristics, rather than as an explanatory characteristic variable itself.

Expected Competitive Impact

The central element in our research model is the '*Expected Competitive Impact*' (ECI) of a new product event. Chen et al. (1992), referring to Schelling's (1960) work on decision making in conflict situations, point out that the most important thing for predicting reactions to a competitive move is to determine its competitive impact for the firms confronted with it. Firms are most likely to respond to an action if that action is believed to affect their own performance directly and pervasively. Following this argument we assume that defending managers assess the impact of a competitive new product predominantly in terms of the effect this new product is believed to have on the market performance of the own company's products. We call this assessment: the *Expected Competitive Impact*. In the present study, we assume that managers use market share as a primary performance indicator for assessing the expected competitive impact. This seems a reasonable assumption, because generally marketing managers are used to thinking in terms of market shares[4]. Expected Competitive Impact, thus, refers to a defending manager's assessment of the effect a particular new product event - with certain perceived event characteristics- would have on his product's market share.

If this assumption is correct, then defending managers must assess the Expected Competitive Impact of a new product introduction, in order to decide on their reaction. In line with general expected value principles - which include values and probabilities - we further assume that the Expected Competitive Impact of a new product has two components:

- the *Expected Consequences*, i.e. the expectation of a manager regarding the pressure the new product would exert on his market share if that new product would prove successful, and
- the *Success Probability*, i.e. assessment of the manager regarding the probability that the new product actually will prove a success and, thus, the expected consequences would become reality.

[4] Alternatively, one may use ROI, ROS or some other profit indicator as a judgment criterion regarding the expected competitive impact. However, since marketing managers are more used to thinking in terms of market share than in terms of profit (cf. Armstrong & Collopy, 1996; Leeflang & Wittink, 1996), the former is used here.

In an expected value sense, the 'Expected Competitive Impact' then is the multiplication of the 'Expected Consequences' and the assessed 'Success Probability'. If both the Expected Consequences and the Success Probability of an introduction are perceived to be high, the 'Expected Competitive Impact' will be high, and firms are assumed to be highly inclined to react. The elements of the research model we have just described are exhibited in Figure 6.2.4, which provides an overview of the key blocks and main variables in the model.

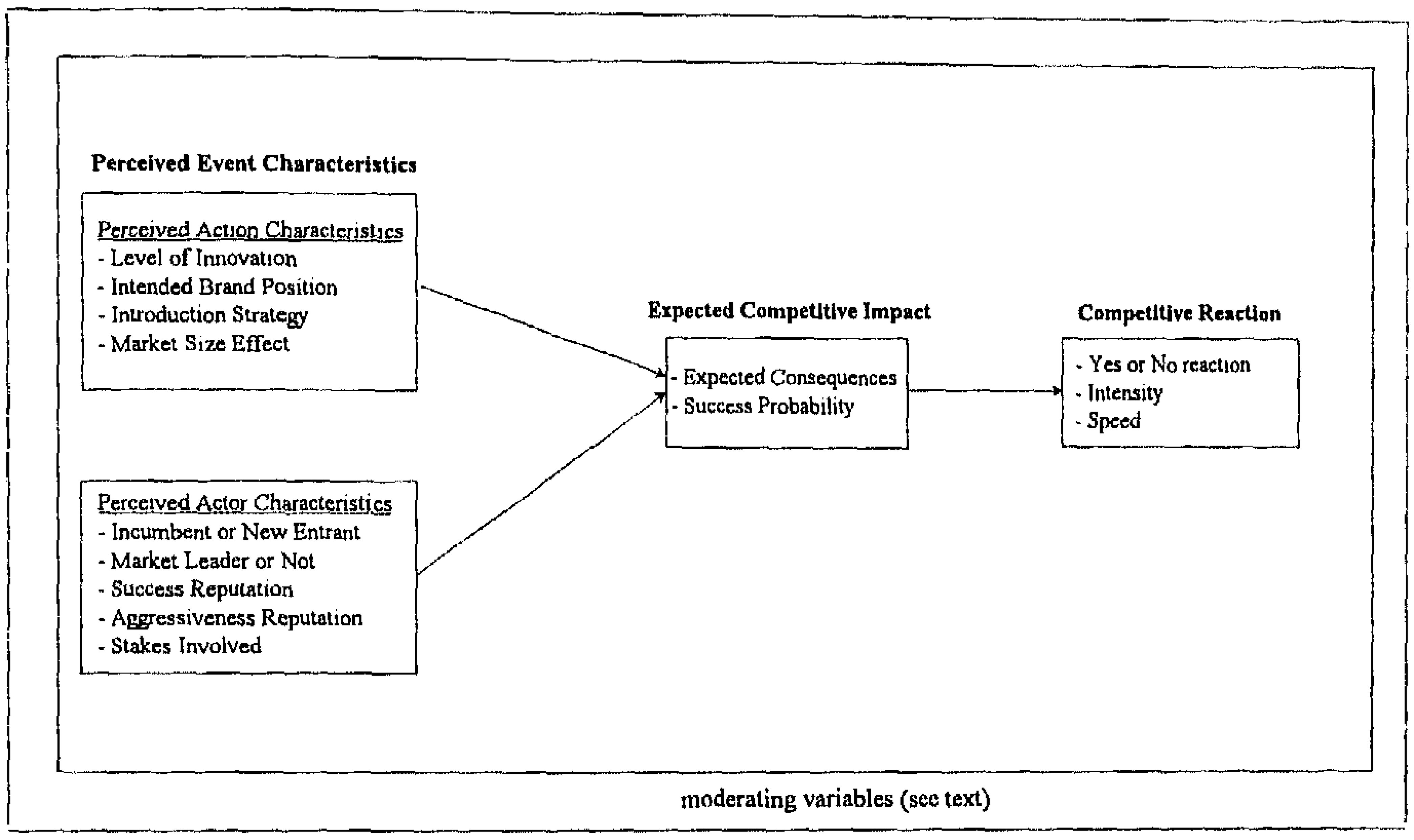

Figure 6.2.4 Conceptual model for explaining competitive marketing reactions to new product introductions

Competitive Reaction

The final main element in our research model is the *Competitive Reaction.* As exhibited in Figure 6.2.4, reactions are described in this study on three dimensions: '*Yes or No*' reaction, the strength or '*Intensity*' of the reaction and the '*Speed*' of the reaction, These dimensions can also be found in Robinson (1988), Chen et al. (1992), Heil & Walters (1993), and Lemmink & Kasper (1994). 'Yes or No' reaction refers to the basic decision by defending managers to react in some way or not to react at all. 'Intensity' points to the decision about the strength of the reaction ranging from minor adjustments of one of the marketing instruments, to fierce responses relative to industry practice. 'Speed' refers to the moment when a firm places its first reaction, relative to the moment that a coming new product introduction has first been detected by the defending manager. The moment of first detection is used as a benchmark here (instead of the moment of actual introduction), because many of the planned introductions are spotted by competitors before the actual launch. Sometimes new products are even deliberately pre-announced by the introducing companies (Eliashberg & Robertson, 1988; Robertson, Eliashberg & Rymon, 1995).

Moderating variables

In Chapter 5, an overview was provided in Figure 5.3, showing four main blocks of variables used across various studies for explaining various aspects of competitive behaviour. As pointed out before, in our model we concentrate on the two main blocks which relate to the *action* and to the *acting firm*. This is done because our research is specifically focused on the relationships between the perceived action and actor characteristics, expected competitive impact, and competitive reaction. Two other blocks of variables were identified in Figure 5.3, concerning the *market conditions* and the *reacting firm*. In this research, we assume that such variables do not have a direct effect on reaction behaviour, but we assume that they may have a moderating influence on the relationships between perceived characteristics, expected competitive impact and competitive reaction. Examples of such moderating influences will be given below. In order to investigate the moderating effects, a number of variables relating to the market conditions and reacting firm are specified.

Market Conditions

Although our research takes place in the relatively homogeneous market environment of frequently purchased consumer goods, different competitive conditions may occur in different market segments, which might influence the relationships in the model. For example, in fast growing market segments new products might cause relatively small expected competitive impact compared to new products in mature market segments, due to the greater pressure on competitors' sales in mature markets (Robinson, 1988). Also, firms operating in high rivalry market segments might generally be more inclined to react than firms operating in low rivalry markets, irrespective of the level of expected competitive impact of an event, because they are more used to frequent interactions with competitors. We have distinguished five potentially moderating variables concerning 'market conditions', which describe the structural competitive conditions of a market: *market growth*, *concentration* (i.e. the number of firms in a market and the market share distribution), *rivalry*, *contestability* (i.e. the 'openness' of a market), and *strategic uncertainty* of the firms (Daems and Douma, 1990)[5].

Reacting Firm variables

Regarding the influence of variables concerning the reacting firm, one can imagine that if the market under attack is strategically very important to a defending firm, the probability of a reaction may be high, even if the expected competitive impact in terms of market share is relatively small. We have distinguished three potentially moderating 'Reacting firm' variables: the defending firm's current *market position*, the *strategic importance*, and the *financial importance* of market under attack for the defending firm, which directly relate to the variables 'importance market' and 'high consequences' which were identified in Figure 5.3[6]. We expect that the latter two variables may be moderating factors especially where the relationship between expected competitive impact and competitive reaction is concerned. Of course, other factors may also influence the competitive reaction behaviour of defending managers. For instance, one could think of the culture of the defending firm, the firms' reaction flexibility, the personality of the manager, etc. However, for reasons of parsimony not all potentially relevant factors are included in the research model.

6.3 Hypotheses

Following the core elements of our research model, the study can be divided into two separate research parts to formulate the hypotheses. Firstly, we consider the relationships between the perceived event characteristics and managers' assessment of the expected competitive impact. Secondly, we consider the relationships between the expected competitive impact and the defending firms' competitive reactions.

[5] The concepts of 'standardisation' and 'technological change' (which are exhibited in Figure 5.3) were not specified as market condition variables here, because of the relative homogeneity of the markets under study with respect to these aspects. In addition, the '# of competitors' variable is not included as such, but it is implicitly incorporated in the concept of concentration.
[6] We did not incorporate the concept of internal 'inertia' (Figure 5.3) in the research for reasons of parsimony.

Expected relationships between Perceived <u>Action</u> Characteristics and Expected Competitive Impact

Four action characteristics were specified in our model. First the action characteristic '*<u>level of innovation</u>*' of the introduction is considered. In many markets, the majority of the events concern relatively minor changes in existing products and only a small part can be considered really new or 'new-to-the-world'. Firms facing a really innovative event will probably expect greater competitive impact than firms facing just another relaunch. Two opposite effects might play a role here. Innovative new products could draw a large number of customers away from existing products, thereby enlarging the expected consequences of such a product introduction. On the other hand, the assessed probability that a highly innovative new product actually becomes a success may be relatively low, due to uncertainties in consumer adoption and market diffusion. There is not much empirical evidence about the net effect yet. Only Robinson's (1988) preliminary findings suggest that innovative introductions generally are seen as a bigger threat, resulting in (slightly) more frequent reactions in the first year after the event has taken place. Given these results, we expect that

> ***H1a:** the higher the perceived level of innovation of a new product, the greater the expected competitive impact.*

The second action characteristic refers to the '*<u>intended brand position</u>*' of the new product. A manager probably will expect greater competitive impact from an introduction very closely positioned to his own products, than from new products positioned far away from his own product. This also follows from normative research on defensive strategies, e.g., from Hauser and Shugan's Defender model (1983): brands adjacent to the attacker's brand position are more vulnerable to lose share than non-adjacent brands, because consumers are more likely to switch between close substitutes than between two very different products. So we expect

> ***H1b:** the closer a new product is perceived to be positioned to the defending firm's own products, the greater the expected competitive impact.*

The third action characteristic concerns the '*introduction strategy*' regarding the new product, in terms price and support. Following Hauser and Shugan's Defender model again, low-priced and heavily supported new products -as compared to high-priced and little supported ones- will draw more customers away from the existing brands and therefore cause greater impact on the market performance of competitors. Therefore, the next hypothesis is formulated as

H1c: low priced/heavily supported new product introductions cause greater expected competitive impact than highly priced/little supported ones.

The fourth and last action characteristic -'*market size effect*'- refers to whether or not the entry event is believed to create a market impulse, that is an extra increase of the total market sales. If the defending manager's perception is that the new product would not enlarge total market sales, then the new product's share inevitably has to be obtained at the cost of existing brands, thus putting more pressure and imposing far-reaching consequences on the incumbent firms. If the market is expected to be stretched as a result of the introduction, then pressure would be lower. So we expect that

H1d: the larger the perceived market size effect of a new product, the smaller the expected competitive impact.

Expected relationships between Perceived Actor Characteristics and Expected Competitive Impact

The first actor characteristic in our model is the current position of the actor in terms of *incumbent or new entrant*. The question is whether the introducing company is already active on this market (incumbent) or does not have any products on this market yet (new entrant). Everything else being equal, 'new entrant' events generally could be considered more 'shocking' for the industry than a product introduction by one of the current competitors: new entrants usually add production capacity and raise industry output, thereby putting pressure on competitors (Scherer & Ross 1990, p.374). If it is an introduction by one of the incumbents, consequences may be less pervasive. On the other hand, though, Porac, Thomas & Baden-Fuller (1989) find that incumbent firms tend to have a myopic view of their business and tend to underestimate the effects of events coming from outside the industry. In this view, the possibility of introductions by new entrants would cause small alarm on the part of the incumbents. We argue that if an introduction actually occurs on a market, the current competitors will expect greater impact if it is launched by a new entrant because of the additional capacity and increasing supply. Thus, we formulate our hypothesis

***H2a**: new products introduced by new entrants cause greater expected competitive impact than new products introduced by incumbents.*

Next, the current market position (if any) of the introducing company is considered. When the introducing company is perceived to be the *market leader*, then defending firms probably expect stronger consequences and assess higher success probability of the new product, than when the acting company does not have a market leader position. So, our hypothesis is that

***H2b**: new products introduced by market leaders cause greater expected competitive impact than new products introduced by non-market-leaders.*

The third actor characteristic relates to the perceived credibility of the acting company. For assessing the probability that the new product will become a success, an obvious characteristic is the '*success reputation*' of the acting company with respect to previous new product introductions. Another trial by a firm which has failed in the past again and again may well be considered to have a lower probability of success than a launch by a company which has proven to be very successful with new product introductions. A higher success probability is assumed to lead to greater expected competitive impact, so our next hypothesis states that

***H2c**: the stronger the success reputation of the introducing company, the greater the expected competitive impact of the new product.*

The fourth actor characteristic concerns the reputation of the introducing company regarding its level of *aggressiveness* in doing business. Some companies embrace a co-operative introduction strategy, in the sense that they do not seek to win market share at the cost of others, but instead try to create win-win situations aiming at a better market situation for all players (cf. Ramaswamy, Gatignon & Reibstein, 1994). Contrary, the main goal of aggressive competitors is to win market share, if necessary at the expense of other firms. Price wars and aggressive take-overs, for instance, are not uncommon when an aggressive new entrant tries to penetrate into a market. Following this reasoning we formulate the hypothesis

> ***H2d:** new products introduced by companies with an aggressive reputation cause greater expected competitive impact than new products introduced by companies having a co-operative reputation.*

The fifth and final actor characteristic concerns the ***stakes involved*** for the company introducing the new product. Stakes refer to the consequences of failure as compared to the consequences of success for the firm behind the new product. If the stakes are high, so must be the commitment of the company to make the action successful. This is expected to lead to greater expected competitive impact by defending firms. Thus we hypothesise

> ***H2e:** the higher the stakes involved for the introducing company, the greater the expected competitive impact.*

Expected relationships between Expected Competitive Impact and Competitive Reaction

The first reaction variable specified in our model is the '*Yes or No*' reaction variable. Sometimes defending firms decide to react in some way or another, in other cases firms decide to do nothing. As outlined before, we expect that whether or not a firm decides to react to an introduction depends on the assessment by the decision maker of the expected competitive impact due to the new product. If a manager does not expect any share consequences or he believes the new product will not survive, he will probably decide not to react. If the manager evokes a great expected competitive impact, a reaction becomes more probable. We therefore formulate

H3a: The greater the expected competitive impact of a new product, the higher the probability that a defending firm reacts.

Having decided to react, the defending manager's next decision will how and when to react. The second reaction variable in our model - *Intensity* - refers to the strength of the competitive reaction. It could vary from a small adjustment of just one marketing instrument (e.g., a minor increase in advertising expenditure) to very forceful reactions with a number of marketing instruments simultaneously. It is expected that greater expected competitive impact of a new product leads to the decision to react more strongly. Thus

H3b: The greater the expected competitive impact of a new product, the higher the reaction intensity.

The third reaction dimension concerns the *speed* of the response. Speed refers to the time between the detection of the competitive event and the firm's first reaction with a marketing instrument. In practice, we see many early, even pre-emptive reactions, either in order to be the first on the market with a similar new product or to deter the entrant beforehand. In other cases, however, firms seem to wait somewhat longer before they respond. We expect that managers are likely to respond more quickly, in cases of great expected competitive impact, than in cases of small expected competitive impact, because the urge to react to highly pervasive events may be greater. Hypothesis 3c, concerning the speed of reactions, is formulated as

H3c: the greater the expected competitive impact of a new product, the higher the speed of reaction.

6.4. Method

Overview

To collect the data necessary for testing the hypotheses, interviews were held with (defending) managers responsible for the marketing of products in frequently purchased consumer good markets. The interviews were performed using a pre-structured questionnaire containing two different data collection methods: (i) a '*reflection approach*', where respondents were asked to recall the most recent competing new product introduction on their market and to reflect on the characteristics of that introduction, its expected competitive impact and the firm's reactions to this introduction, and (ii) a *conjoint analysis* study, in which respondents were asked to evaluate different 'profiles' of new products.

The sample consisted of managers responsible for the marketing of a specific product(group) in The Netherlands: they were either product managers, product group managers, brand managers or marketing managers. This type of respondents (instead of e.g., top executives) was chosen because our interest is in reaction decision making in an operational marketing environment of the company, for which it is essential that respondents are able to recall enough detail about a specific product introduction by a competitor. The sampling procedure started with the selection of 31 frequently purchased consumer good categories (e.g., coffee, deserts, snacks, detergents), in which one or more new products were introduced during the past two years[7]. Next, within each selected product category, all companies supplying one or more products in the product category were approached for contributing to this study. In total 225 managers were contacted for allowing an interview, resulting in 98 completed and usable interviews, implying a response rate of 44%.

Nonresponse was mainly due to unwillingness to co-operate with any interview; due to refusing to allow an interview given the subject of the questionnaire and time constraints. In spite of the difficulties of contacting and making appointments with the managers, the response can be considered quite good, given the delicacy of the subject. We have no reason to believe that the nonresponse biases our findings in any systematic way. The types of new product introductions the respondents reflected on are exhibited in Table 6.4.1.

[7] The product categories in the sample were selected from a standard classification of fast moving consumer product categories as provided by Trade Service Netherlands and the Centraal Bureau Levensmiddelenhandel (the Dutch Central Bureau for Provision Trade). The selection of the product categories in the sample was based upon information about new product introductions published in a weekly retail journal (Distrifood).

Table 6.4.1 Types of new product introductions reflected on (n=98)

improvements of existing products	12%
line extensions	32%
brand extensions	27%
new brand introductions	18%

The majority (70%) of these new product events had occurred within one year prior to the interview. On average the managers had five years' experience in marketing and about two years' experience in the specific product category. The companies involved varied from small- or medium-sized independent national manufacturers to large multinationals. We consider it safe to conclude that the sample is a good reflection of marketing managers operating in the Dutch frequently purchased consumer goods industry.

Questionnaire, measurement and scaling

As mentioned above, the interviews were held using pre-structured questionnaires, containing two different data collection methods: (i) a 'reflection approach' and (ii) a conjoint analysis study. The 'reflection approach' has been used by a number of other authors for studying competitive reaction behaviour (e.g., MacMillan et al., 1985; Heil & Walters, 1992; Lemmink & Kasper, 1994). The 'reflection approach' section of our questionnaire embodied questions regarding the respondents' reflections concerning:

1. the perceived action and actor characteristics of the most recent competitive product introduction the respondent was confronted with in his market,
2. the expected competitive impact of this new product event,
3. the firm's reactions as a response to the introduction in terms of 'yes or no' reaction, the reaction intensity and the speed of reaction.

In addition, the questionnaire included sections regarding the 'market conditions' and the 'reacting firm' variables. Precise descriptions of the measures and scales used in this section of the questionnaire will be reported below.

The conjoint analysis study embodied a section in which the respondents had to perform a conjoint analysis task focusing on their assessment of the expected competitive impact of various pre-defined new product event 'profiles'[8]. There were two main reasons for including a conjoint analysis task. The first reason deals with the possible occurrence of 'hindsight bias' in the data resulting from the 'reflection approach'. Respondents' current knowledge about the actual results of a past introduction might distort their perceptions about their reaction decision processes at the time of the introduction. The advantage of adding a conjoint analysis study is that this does not suffer from hindsight bias, and, at the same time, it enables us to cross-validate the results with the 'reflection data'. The second reason for including a conjoint analysis study is that in that case all respondents are faced with the same set of stimuli, which makes the results more comparable over all respondents, and which makes it also possible to perform analyses *per respondent.*

The complete questionnaire was built using Sawtooth's CI3-software. This allows for building a flexible structure of the questionnaire. Furthermore, the use of CI3 made it possible to include an adaptive conjoint analysis (ACA) task. The questionnaire was copied onto diskettes for interviewing. The computerised questionnaire was pretested, using five expert opinions (the author's colleagues) and five managers' evaluations about the clarity of the questions and the structure and length of the questionnaire. The pretest results were used to improve the questionnaire. The computerised questionnaire was filled out by the respondents in the presence of two graduate students, for assistance purposes[9]. The average time required for completing the computerised interview was about 30 minutes.

[8] Precise descriptions and results of this part of the study will be reported separately, in section 6.6.

[9] 17 respondents preferred to fill out a paper version of the questionnaire, for various reasons. This paper version was a straight print out of the computerised one, thus containing identical questions. The only difference was that for these respondents the adaptive conjoint task had to be skipped.

Full descriptions of all relevant measures and scales used in the questionnaire are given in the Appendix. Respondents' perceptions about the most recent product introduction were measured using item scales regarding each of the event characteristics mentioned in the research framework. Some of the concepts were measured using multiple-item scales (as indicated in the Appendix). For example, the concept 'Stakes Involved for the introducing company' was measured on a two-item scale. One item focused on the financial stakes involved with the new product; the other item measured the stakes involved regarding the market reputation of the company. Cronbach's standardised item alpha for the two items was .77, indicating a fair internal consistency of the scale. For the three-item scale 'Strategic Importance' factor loadings were used to compute the factor scores on the compounded scale.

The construct 'Expected Competitive Impact' was operationalised, by using items referring to the two underlying components: the 'Expected Consequences' of the new product for the firm's own market share and the 'Success Probability' (see the Appendix). Because pretests revealed that managers were very reluctant to give any numbers and percentages in the interviews, both components were measured on item scales: the 'Expected Consequences' if the new product would be a success was measured on a single 4-point item scale referring to the pressure the new product would put on the market shares of the own products; the assessed 'Success Probability' was measured on a single 5-point item scale. The compounded variable 'Expected Competitive Impact' (ECI) was computed afterwards, as the multiplication of the scores on the 'Expected Consequences'-scale and the 'Success Probability'-scale[10].

With respect to the nature of the reactions, a number of items were specified. The first item related to whether or not the firm actually had reacted with marketing instruments to the introduction at hand: the 'Yes or No' reaction question. Out of the 98 respondents reflecting on a specific product introduction, 28 scored a 'Yes' here, resulting in a 29% reaction percentage. Only these 28 respondents were asked further questions about the intensity and speed of their reaction. The

[10] Alternatively, it is possible to operationalise the Expected Competitive Impact construct by using an additive two-item scale, straightly adding the scores on the expected consequences and the success probability scales. Actually, reliability analysis shows that the additive two-item scale is fairly reliable (Cronbach's alpha .66). It also turns out, though, that the additive two-item scale is strongly correlated with the multiplicative ECI-scale (R^2=.90). We prefer to use the multiplicative ECI-scale in this study from a theoretical expected value point of view.

intensity of the response was measured on a two-item scale. One of these items measured the perceived strength of the reaction relative to industry practice (as in Heil & Walters, 1993). The other item focused on the number of marketing instruments used to react, as a second indicator of the reaction intensity (Robinson, 1988; Lemmink & Kasper, 1994). Cronbach's standardised item alpha for the two indicators was .63, which is fairly good for a two-item scale. The two items were combined into the constructed scale 'Intensity'.

The timing of a reaction (the first, if any) was measured on a single 7-point intervalscale, ranging from more than three months before to more than three months after the introduction had actually taken place. Respondents were also asked to indicate (on a similar scale) when the introduction had first been detected by the firm. For those who did react, the 'Speed' of the reaction was calculated as the time (in weeks) between first detection and first reaction. Table 6.4.2 shows a summary description of the results regarding the main variables in our model.

Table 6.4.2 Summary descriptives of the key model variables

Variables	*Min.*	*Max.*	*Mean*	*Std. Dev.*
Level of Innovation	1	3	1.79	0.65
Intended Brand Position	1	4	2.22	0.93
Introduction Strategy	1	4	2.32	1.07
Market Size Effect	1	3	1.50	0.58
Incumbent (1) or New Entrant (0)	0	1	0.81	0.39
Market Leader (1) or Not (0)	0	1	0.39	0.49
Success Reputation	1	5	3.62	1.00
Aggressiveness Reputation	1	5	3.78	0.97
Stakes Involved (factor scores)	-2.5	1.78	0.00	1.00
Expected Consequences	1	4	1.55	0.71
Success Probability	1	5	3.19	1.05
Expected Competitive Impact (ECI)	1	20	5.34	3.84
Yes (1) or No (0) Reaction	0	1	0.29	0.46
Intensity (factor scores)	-1.64	1.69	0.00	1.00
Speed	0	24	7.88	6.38

6.5 Findings

Brief overview of the analysis procedure

In this section we only show results from the data concerning respondents reflections about recent competitive new product introductions. Results from the conjoint analysis study will be presented in the next section. We start by analysing the relationships between the perceived event characteristics and the expected competitive impact. This is done applying OLS regression. We will investigate the moderating influence of market conditions and reacting firm variables using moderated regression models and subgroup analysis. Next, the relationships between the expected competitive impact and the reactions will be investigated performing t-tests and logistic regression. Finally, the complete model will be estimated using LISREL path analysis. Precise descriptions of the procedures and findings are reported subsequently.

Relationships between Perceived Event Characteristics and Expected Competitive Impact

Hypotheses 1a-d and 2a-e focus on the relationships between the Perceived Event Characteristics and the manager's assessment of the Expected Competitive Impact of the introduction. These hypotheses are tested simultaneously by standard OLS regressions. Firstly, the compounded Expected Competitive Impact scale (ECI) was specified as the dependent variable. The four perceived action and five perceived actor characteristics were specified as independent variables. The results are shown in the second main column of Table 6.5.1. To investigate the underlying effects, also OLS regressions were carried out using each of the components of ECI as dependent variables: the 'Expected Consequences' (see the third main column of Table 6.5.1) and the 'Success Probability' (see the fourth main column of Table 6.5.1).

As can be seen from the signs of the beta estimates (second main column of Table 6.5.1.), for seven of the nine event characteristics the direction of the effects on the ECI-scale is in line with our expectations (Level of Innovation, Intended Brand Position, Introduction Strategy, Incumbent or New Entrant, Success Reputation, Aggressive Reputation and Stakes Involved). The variables 'Market Size Effect', and 'Market Leader or Not' show opposite signs to what was expected, but their beta's are close to zero and non-significant.

Table 6.5.1 **Relationships between Perceived Event Characteristics and Expected Competitive Impact (OLS-regression estimates, N=96)**

Dependent variables Independent variables (Perceived Event Characteristics)	Expected Competitive Impact (ECI-scale) (low → high)		Expected Consequences (weak → strong)		Success Probability (low → high)	
	Beta	Sig. T (p-value)	Beta	Sig. T (p-value)	Beta	Sig. T (p-value)
Perceived Action Characteristics						
Level of Innovation (low → high)	.12	.26	.10	.33	.14	.16
Intended Brand Position (far away → close)	.24	.02	.33	.00	.02	.84
Introduction Strategy (modest → heavy)	.12	.21	.11	.27	.13	.17
Market Size Effect (no-slight-strong)	.08	.40	.00	.97	.26	.01
Perceived Actor Characteristics						
Incumbent or New Entrant (dummy; incumbent=1)	-.00	.99	.04	.66	-.03	.70
Market Leader or Not (dummy; market leader=1)	-.07	.50	-.20	.07	.09	.39
Success Reputation (weak → strong)	.23	.03	.15	.17	.32	.00
Aggressiveness Reputation (co-operative → aggressive)	.16	.12	.15	.16	.20	.05
Stakes Involved (low → high stakes)	.18	.06	.15	.13	.09	.34
Multiple R Square	.37		.36		.43	

When looking at the significance levels of the parameters, three of the characteristics show significant effects ($p<.10$) on the ECI-scale: Intended Brand Position ($p=.02$), Success Reputation ($p=.03$), and Stakes Involved ($p=.06$). Firstly, it shows that the closer the intended brand position of a new product to the own product, the greater a manager's assessment of the expected competitive impact of that new product. This result was anticipated in H1b, reasoning that close attacks are generally considered more pervasive than attacks happening far away. As can be seen from the third and fourth column of Table 6.5.1, this effect is mainly due to a significant (p=0.00) effect on the Expected Consequence component of ECI.

Secondly, results show that the stronger the perceived Success Reputation of the initiating company, the greater the Expected Competitive Impact. This is in accordance with hypothesis H2c. This effect proves to be due to a significant (p=.00) effect on the Success Probability component of ECI[11]. Thirdly, the effect of the variable Stakes Involved for the initiating company shows a relationship which is conform hypothesis H2e, suggesting that the higher the stakes involved for the introducing firm, the greater the expected competitive impact managers assess to the event. The effect is significant on the compounded ECI-scale, while both the underlying effects are weakly significant.

We point to the fact that the latter two event characteristics (Success Reputation and Stakes Involved) both are perceived *actor* characteristics. This supports the suggestion of Chen et al. (1992), that one should not look solely at characteristics of a competitive action itself, but one should also consider features of the firm behind the action.

It is interesting to observe again the non-significant impact of Market Size Effect on ECI (p=.40). Hypothesis H1d expected a negative effect of this variable on the expected competitive impact due to an anticipated lower competitive pressure if markets would expand as a result of a product introduction. Results reveal, though, that there is no significant relationship between Market Size Effect and Expected Consequences (beta=.00; p=.97), indicating that managers do not expect that the additional growth of the market would diminish the pressure on their own product's market shares. However, there is a significant effect (p=.01) on the Success Probability component of ECI, indicating that if managers consider a competitive new product to have the potential to stimulate total market sales, they assess a relatively high success probability of that new product. On balance, the Market Size Effect characteristic does tend to be positively related to the compounded ECI-scale (beta= .08, p=.40), which is contrary to our expectations formulated in H1d.

[11] The fact that we find different effects on the expected consequences and success probability component of ECI, supports our proposition that both components should be incorporated into the expected competitive impact construct.

Moderating effects of market conditions and reacting firm variables

Above, we investigated the relationships between Perceived Event Characteristics and Expected Competitive Impact. The results showed a number of interesting effects on ECI. The next step in the analysis is to investigate whether these effects hold for all market conditions and reacting firms, or that there are factors moderating these effects. As we postulated before, one might for instance assume that in high growth markets the effects of event characteristics on the expected competitive impact is different from the effects in low growth markets.

We tested the moderating influence was of the five Market Conditions variables (*market growth, concentration, rivalry, contestability,* and *strategic uncertainty*), and the reacting firm's 'Market Position' variable[12] on each of the three significant relationships between the perceived event characteristics and the compounded ECI-scale.

Possible moderating effects were investigated in two ways: (i) by estimating regression models with multiplicative interaction terms consisting of the characteristics and the moderating variables[13], and (ii) by performing subgroups analysis (cf. Slater and Narver, 1994). For the subgroups analysis, partial correlation coefficients were estimated for each of the three significant Characteristic-ECI relationships, under Hi and Lo environmental conditions[14].

Table 6.5.2. shows the coefficients and standard errors for the multiplicative interaction terms. As is shown in the table, only one of the coefficients for the multiplicative interaction terms proves statistically significant: Market Growth moderates the effect of Stakes Involved for the introducing company on the Expected Competitive Impact (coefficient .51). This indicates that if market growth is low, the effect of the perceived Stakes Involved of the acting company on the Expected Competitive Impact is relatively high. In fast growing markets, the stakes involved of the acting

[12] We only specify the Market Position of the reacting firm as a possible moderating 'reacting firm' variable regarding the relationship between the perceived event characteristics and the expected competitive impact. It is more probable that the other two reacting firm variables - the financial and strategic importance of the market for the reacting firm- are moderating the relationship between expected competitive impact and competitive reaction.

[13] For instance, the moderating effect of Market Growth on the relationship between ECI and the Intended Brand Position was analysed by including the interaction term Intended Brand Position x Market Growth in the regression equation.

[14] The splits into Hi and Lo conditions were made by selecting the cases scoring high resp. low on the respective scales, while excluding the cases scoring on the midpoint(s).

firm seem to be less important in assessing the competitive impact of the event. When looking at the results of the subgroup analyses, the direction of this effect is confirmed, although the difference between the partial correlation coefficients is not significant. In fact, for none of the other subgroup analyses did the differences in partial correlation coefficients prove to be statistically significant. This might, however, be due to the limited cell observations we have in our sample for the various Hi and Lo conditions.

Table 6.5.2 Tests for moderating effects of Market Conditions and Market Position on the significant relationships between Perceived Event Characteristics and Expected Competitive Impact.
Regression Coefficients (Standard Errors) - Partial Correlation Coefficients[†]

	Intended Brand Position - Expected Competitive Impact			Success Reputation - Expected Competitive Impact			Stakes Involved - Expected Competitive Impact		
	Multiplicative Interaction term	Subgroups Analysis LO	HI	Multiplicative Interaction term	Subgroups Analysis LO	HI	Multiplicative Interaction term	Subgroups Analysis LO	HI
Market Growth	.15 (.14)	.17	.09	.18 (.09)	.29	.19	.51[1] (.27)	.54[1]	-.03
Concentration	-.19 (.17)	n.a.[1]	n.a.	-.07 (.15)	n.a.	n.a.	-.14 (.19)	n.a.	n.a.
Rivalry	.00 (.22)	.14	.14	-.04 (.13)	.46	.34	-.01 (.38)	-.39	.10
Contestability	-.19 (.19)	.28	.15	-.09 (.11)	.01	.52[1]	-.14 (.41)	.36	.41
Strategic Uncertainty	.18 (.17)	.20	-.61	.11 (.11)	.14	.53	.36 (.44)	.32	.75
Market Position of defending firm	-.06 (.11)	.33	.24	-.02 (.08)	-.01	.08	-.13 (.29)	.39	.15

[†] differences in partial correlation coefficients were tested employing Fisher's Z-test (Jaccard, Turrisi & Wan, 1990); no significant differences (at $p<.10$) were found.
[1] coefficient significant at $p<.05$
[1] no coefficients estimated due to lack of cell observations

Conclusions about the relationships between the Perceived Event Characteristics and ECI

The analyses up till now focused on the relationships between the Perceived Event Characteristics and the Expected Competitive Impact. Analyses were performed using the data describing the respondents' reflections on the most recent competitive new product on their market. At this point, we conclude the following:

- We have statistically significant evidence for three of our hypotheses:
  - H1b: the closer the perceived *Intended Brand Position* of the new product to the defending firm's own products, the greater the expected competitive impact.
  - H2c: the stronger the perceived *Success Reputation* of the introducing company, the greater the expected competitive impact of the new product.
  - H2e: the higher the perceived *Stakes Involved* for the introducing company, the greater the expected competitive impact of the new product.
- For four of our hypotheses concerning *Level of Innovation* (H1a), *Introduction Strategy* (H1c), *Incumbent or New Entrant* (H2a) and *Aggressiveness Reputation* (H2d), the signs of the relationships confirm our expectations, but the evidence is not statistically significant.
- For H1d (*Market Size Effect*) some evidence has been found pointing at an effect opposite to what was expected: the larger the perceived market size effect of a new product, the greater rather than the smaller the expected competitive impact. This is due to the effect that managers think that new products have a higher success probability if extra market growth would be created due to the new product.
- With respect to hypothesis H2b (*Market Leader or Not*), no relationship was detected concerning the Expected Competitive Impact. A significant effect was detected, though, on the Expected Consequences component, suggesting that new products introduced by non-market leaders are expected to exert higher pressure on defending firms' market shares than new products introduced by market-leaders.
- Some evidence has been found regarding the existence of a moderating effect of *market growth* on the relationships between perceived Stakes Involved and the Expected Competitive Impact. This suggests that in low growth markets (e.g., biscuits, marmalade) the effect of the stakes involved for the introducing company is relatively large.

Relationships between the ECI and Competitive Reaction

We will now focus on the right hand side of the research model, concerning the relationship between Expected Competitive Impact and Competitive Reaction. H3a states that the greater the expected competitive impact regarding a new product introduction, the more likely firms react. If the hypothesis is correct, a higher fraction of the firms in our sample giving high scores on the Expected Competitive Impact-scale should have reacted to a new product as compared to firms giving low scores on that scale.

T-tests were performed to statistically test differences between the two groups (group 1: No reaction; group 2: Yes reaction) with respect to the mean scores on the ECI-scale and both underlying components. Results (see Table 6.5.3, upper part) show significant differences between the mean scores of the reacting and non-reacting firms on both the ECI-scale as well as on the underlying components. The directions of the means differences support our hypothesis. On average, reacting firms assess greater expected competitive impact of a new product than non-reacting firms. Similar results are found (see Table 6.5.3) for the underlying components of ECI: reacting firms both assess greater expected consequences, i.e., higher pressure on market shares, and anticipate a higher success probability of the new product.

Table 6.5.3 Relationship between Expected Competitive Impact and Yes-or-No Reaction
T-tests: differences in means between group 'Yes' and group 'No' reaction (N=96)

	Reaction to introduction			
Expected Competitive Impact	group 1 YES	group 2 NO	t-Value	Sign.
ECI-scale (higher score = greater competitive impact)	8.17	4.17	-5.25	.000
Expected Consequences (1=very weak; 4=very strong)	2.07	1.33	-5.20	.000
Success Probability (1=very low; 5=very high)	3.75	2.95	-3.57	.001

To investigate the relationship between ECI and the Yes-or-No reaction variable further, logistic regression was carried out of ECI on the Yes-or-No reaction variable. Results confirmed the existence of a strongly significant relationship (b=.30, p=.000, R=.34, % correct predictions=73%, Goodness-of-Fit[15]=92.2)[16].

Intensity

Our next hypotheses, H3b and H3c, concern managers' decisions about the intensity and the speed of their reactions. It is important to note at this point, that these hypotheses can only be tested on the 28 cases in our sample that included a Yes-reaction decision. This sample size is quite small. H3b assumed a positive relationship between the expected competitive impact of a reacting firm and the intensity of the reaction: the greater the expected competitive impact, the stronger the reactions. Regression results (see Table 6.5.4) do not provide strong support for this hypothesised relationship. Although the bivariate regression model (Table 6.5.4, model 1) shows that the sign of the relationship was as expected, indicating that a higher ECI-score is associated with stronger reactions, it proved not to be significant (p=.28). Also bivariate regression models using the underlying components of the ECI-scale (Table 6.5.4, models 2 and 3) did not show a significant relationship. Although the lack of explanation might be due to the limited sample size, we must conclude that hypothesis H3b is not significantly confirmed by the data[17].

Table 6.5.4 Relationships between expected competitive impact and the Intensity and Speed of reactions. Bivariate regressions (N=28)

Model:	Intensity				Speed			
	b	T	Sig.T	R^2	b	T	Sig.T	R^2
1) ECI-scale	.03	.72	.47	.02	-.46	-1.81	.08	.33
2) Expected Consequences	.19	.82	.42	.03	-3.08	-2.32	.03	.17
3) Success Probability	.23	.99	.33	.04	.11	.07	.94	.00

[15] The Goodness-of-Fit statistic compares the observed probabilities to those predicted by the model.
[16] Further logistic regressions were performed to check for moderating effects of environmental factors on the ECI-Reaction relationship. No significant effects were found.
[17] Further analyses were performed to check for moderating effects of environmental factors on the ECI-Intensity relationship. No significant effects were found.

Speed

Hypothesis 3c focused on the speed of reaction. It was argued that managers are likely to react faster the greater the expected competitive impact of a new product introduction. The average detection moment of an introduction in our sample was about 2.5 months *before* the introduction actually had taken place. Hypothesis H3c is formulated in terms of speed of reaction, defined as the time between the firm's first detection of the new product and its first marketing reaction. Bivariate regression results (see right hand part of Table 6.5.4) show a significant (p=.08), negative relationship between the ECI-score of a new product and the firms' reaction-time. This implies that firms react faster the greater the new product's expected competitive impact. The regression results using the underlying components of the ECI-scale show a significant negative correlation between the Expected Consequences and the Speed of reaction (p=.03). In other words, firms tend to react faster the greater the expected pressure on their market share due to the new product. This is in line with H3c[18].

Conclusions about the effect of ECI on Competitive Reaction

We summarise our findings regarding the relationships between the Expected Competitive Impact posed by a competitive new product and defending firms' reactions as follows:

- Greater expected competitive impact of new product introductions increases the probability of reactions by competitors, in line with hypothesis H3a.
- Although the sign of the relationship between the expected competitive impact and the intensity of the reactions was as expected, the relationship did not prove statistically significant. Hypothesis H3b can therefore not be confirmed.
- Greater expected competitive impact, i.e. greater expected consequences of new products leads to faster reactions by competitors, in line with hypothesis H3c.

[18] Further analyses were performed to check for any moderating effects of environmental factors on the ECI-Speed relationship. No statistically significant effects were found.

Testing the Perceived Event Characteristics - ECI - Competitive Reaction model

In the previous sections, we addressed a number of hypothesised relationships between the three main components of our research model: perceived event characteristics, expected competitive impact and competitive reaction. We focused separately on relationships between (1) perceived event characteristics and expected competitive impact and (2) between expected competitive impact and competitive reaction decisions. This was done, because from a decision making perspective a logical sequence would be: managers translate perceived event characteristics into the expected competitive impact the new product would have on their own market performance, which in turn motivates them to react in a particular way. One could wonder, however, whether also direct relationships exist between perceived event characteristics and competitive reactions and whether or not the model is improved by incorporating the concept of expected competitive impact into the model.

Path analyses were carried out using the LISREL 8 computer programme (Jöreskog and Sörbom, release 8.03, 1993) in order to analyse whether any direct relationships exist between the perceived event characteristics and the competitive reactions and to check whether the specification of the expected competitive impact concept enriches and improves the model. In the path analyses both the nine event characteristics (x-variables), the ECI-scale (y-variable) and the Yes-or-No reaction variable (y-variable) are specified as manifest variables. The Intensity and Speed variables were left out because of the limited sample size. LISREL 8 was used to estimate the models. After omitting the non-significant (at .10) x-variables, the overall end model was estimated, which is shown in Figure 6.5.1. This model fits the data quite well (chi-square=1.76; p=.62; GFI=.99; AGFI=.96; CFI=1.00) The squared multiple correlation for the Yes-or-No Reaction variable in this model was .27, indicating that the model accounts for 27% of the variance[19].

The path analyses showed that:

- The significant effects of the perceived event characteristics on the expected competitive impact (ECI), largely confirm the previous findings from the OLS-regression models. The variables

[19] The goodness of fit of the model is indicated by the Goodness of Fit index (GFI), the Adjusted Goodness of Fit Index (AGFI, adjusted for the degrees of freedom), and the Comparative Fit Index (CFI) for small samples (cf. Jöreskog and Sörbom, 1993). Additional logistic regression showed a percentage of correct predictions by the model of 80%.

Intended Brand Position and Success Reputation show significant effects both in the OLS estimations as well as in the LISREL path analyses. The variables Aggressiveness Reputation and Stakes Involved showed somewhat higher significant effects using the LISREL model as compared to the estimates obtained from the OLS model. Summarising, one can argue that these four perceived event characteristics are all used by defending managers for assessing the expected competitive impact of a competitive new product.

- The ECI-variable has a significant effect on the Yes-or-No Reaction variable, which is in agreement with the previous findings. The conclusion seems justified that the greater the expected competitive impact of a new product introduction the more likely defending managers will decide to react.

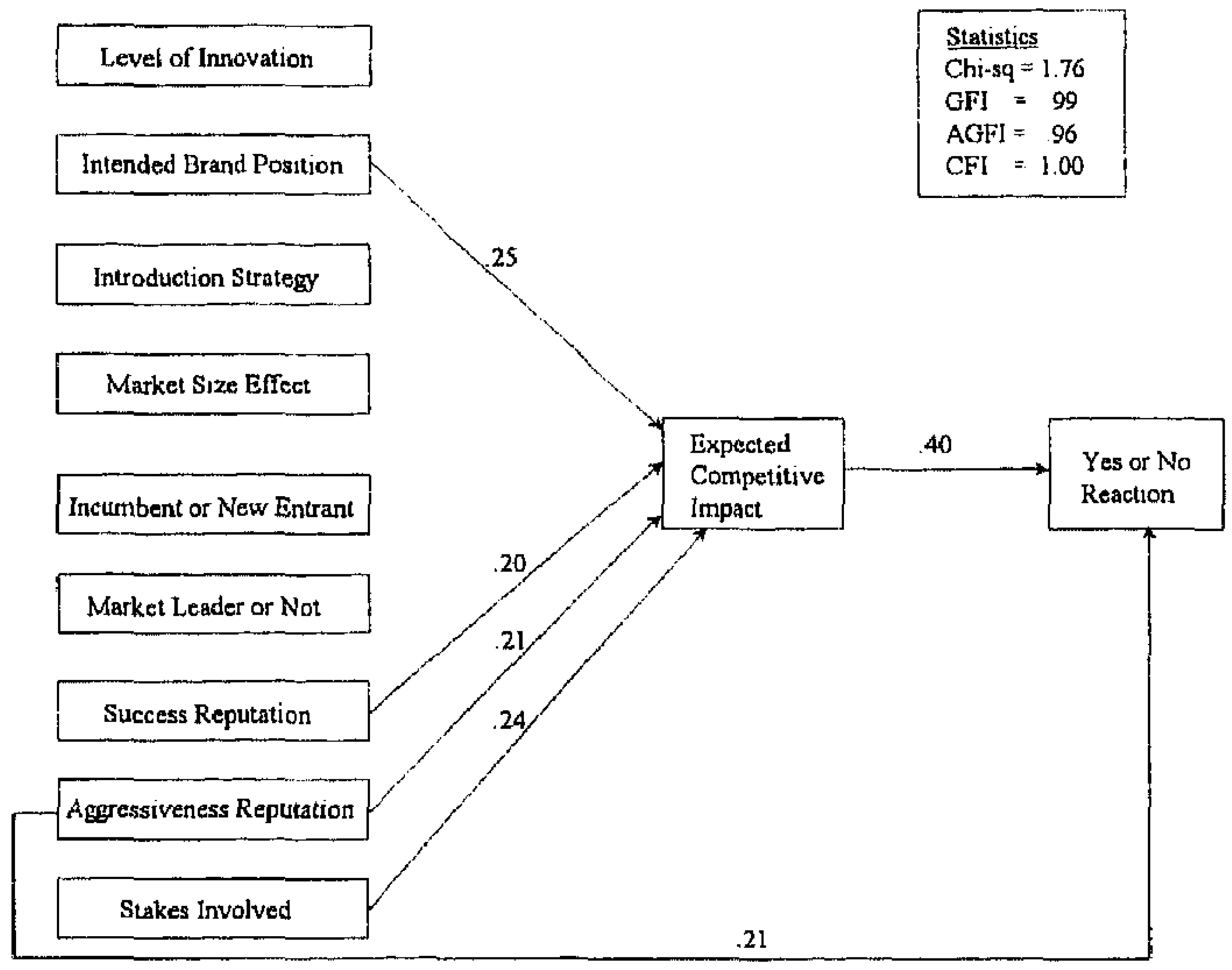

Figure 6.5.1 Summary of the path analysis results for the hypothesised model (N=96) (standardised solutions; significant (p<.10) effects only)

- The four significant event characteristic variables have an *indirect* effect on the reaction decision, via the ECI-variable. The only event characteristic that also has a direct effect on the reaction decision is the Aggressiveness Reputation of the initiating company[20]. This indicates that managers are relatively likely to react to introductions by companies having a aggressive reputation, due to two reasons. First, introductions by aggressive companies lead to greater expected competitive impact, which leads to a higher probability of competitive reactions. Second, the mere existence of an aggressive reputation tends to increase the probability of a reaction, irrespective of the expected competitive impact of the actual new product. Apparently, managers have a general tendency to react to a new product if the introducing firm has a reputation of being aggressive.

To investigate whether the model improves by including the ECI-variable as compared to excluding it from the model, additional path analysis was carried out omitting the ECI-variable. Results showed a squared multiple correlation coefficient for the Yes-or-No reaction variable for the model *excluding* the ECI-variable of .18, a substantial reduction compared to the .27 squared multiple correlation for the model *including* the ECI variable[21]. Based on these findings and our finding that the characteristic effects are predominantly *indirect*, via the ECI variable, we conclude that incorporating the Expected Competitive Impact improves the competitive reaction model as compared to a straight 'stimulus-response' model of perceived event characteristics towards competitive reactions.

General conclusions based on managers' reflections on real product introductions.

Summarising our findings, we conclude that the hypothesised model following the structure Perceived Event Characteristics → Expected Competitive Impact → Competitive Reaction is a fruitful one for explaining competitive reaction behaviour. We have found (partly) support for most of our hypotheses regarding relationships between the perceived actor and action characteristics, expected competitive impact and competitive reaction. Table 6.5.5 provides a summary overview of the hypotheses and our findings based on the sample of respondents reflecting on a recent new product introduction by a competitor. As can be seen from the table, we have (partly) support for

[20] This was verified by applying logistic regression of the event characteristics on the Yes-or-No reaction variable. In line with the findings of the LISREL analysis, the only effect that proved significant was the Aggressiveness Reputation of the acting firm.

[21] Results from logistic regression revealed that the percentage correct predictions reduces from 80% (including ECI) to 72% (excluding ECI). The chi-square difference test renders a p-value of 0.00.

nine of our hypotheses. Regarding H1d (Market Size Effect) the effect tends to be opposite to what was expected. For two hypotheses (H2a and H2b) no relationships were detected. Before elaborating further on the implications of these findings, though, we will first present the results of the conjoint analysis study, which formed a part of our research methodology.

Table 6.5.5 Summary of hypotheses and findings based on defending managers' reflections on real product introductions

HYPOTHESES	FINDINGS
H1a: the higher the perceived level of innovation of a new product, the greater the expected competitive impact.	Some support. The sign of the relationship is as expected, but the parameters are not statistically significant.
H1b: the closer a new product is perceived to be positioned to the defending firm's own products, the greater the expected competitive impact.	Strongly supported. A closer positioned new product leads to greater expected competitive impact as assessed by competitors.
H1c: low priced/heavily supported new product introductions cause greater expected competitive impact than highly priced/little supported ones.	Some support. The sign of the relationship is as expected, but the parameters are not statistically significant.
H1d: the larger the perceived market size effect of a new product, the smaller the expected competitive impact.	Not supported. On the contrary, the perceived market size effect of a new product shows a weakly significant *positive* relationship with the expected competitive impact.
H2a: new products introduced by new entrants cause greater expected competitive impact than new products introduced by incumbents.	Not supported. No relationship detected.
H2b: new products introduced by market leaders cause greater expected competitive impact than new products introduced by non-market-leaders.	Not supported. No relationship detected.
H2c: the stronger the success reputation of the introducing company, the greater the expected competitive impact of the new product.	Strongly supported. A stronger perceived success reputation of the acting company leads to greater expected competitive impact as assessed by competitors.
H2d: new products introduced by companies with an aggressive reputation cause greater expected competitive impact than new products introduced by companies having a co-operative reputation.	Supported. A more aggressive reputation of the acting company leads to greater expected competitive impact of the new product. In addition, a more aggressive reputation also directly provokes more frequent reactions by competitors.
H2e: the higher the stakes involved for the introducing company, the greater the expected competitive impact of the new product.	Supported. Higher stakes for the attacking firm leads to greater expected competitive impact as assessed by competitors. The effect is relatively large in low growth markets.
H3a: the greater the expected competitive impact of a new product, the higher the probability that a competing firm reacts.	Strongly supported. Greater expected competitive impact as assessed by defending firms leads to more frequent reactions by these competitors.
H3b: the greater the expected competitive impact of a new product, the higher the reaction intensity.	Some support. The sign of the relationship is as expected, but the parameters are not statistically significant.
H3c: the greater the expected competitive impact of a new product, the higher the speed of reactions.	Supported. Greater expected competitive impact as assessed by competitors leads to faster reactions.

6. 6 Conjoint analysis

The findings reported up to now were based upon information collected via the 'reflection approach', i.e. reflections by managers on a particular competitive new product introduction they were actually confronted with in their market. We call the data generated in this way: the 'reflection data'. As mentioned before, a conjoint analysis section was also included in our field study, specifically focusing on the relationships between perceived event characteristics and expected competitive impact. The reasons for the inclusion of a conjoint analysis study were (i) to be able to cross-validate the findings from the reflection data, which might suffer from hindsight bias, and (ii) to analyse the effects by confronting respondents with the same set of hypothetical, pre-defined new product event 'profiles'. This constitutes a homogeneous set of stimuli as compared to the rather heterogeneous set of competitive events respondents reflected on. In addition, a conjoint analysis study also allows us to analyse the size and direction of the effects per respondent, and to investigate possible heterogeneity in the effects across respondents.

Design and procedure

The computerised questionnaire contained a special section in which managers had to perform a conjoint analysis task. This conjoint analysis study was carried out within the computerised questionnaire, and used the Sawtooth Adaptive Conjoint Analysis software (ACA)[22]. Adaptive Conjoint Analysis is a widely used and recommended conjoint analysis technique, having advantages in flexibility and immediate availability of the data and results on the computer (Wittink et al., 1994). The Sawtooth's ACA-software can easily be integrated in a computerised questionnaire built with standard CI3-software.

Table 6.6.1 shows the design of the conjoint analysis study. The attributes used in the design refer to two action-, and three actor-characteristics. The specification was restricted to five attributes (with two or three levels each), for practical purposes. Pretests of the questionnaire showed that this was the maximum feasible size given the difficulty of the task and the total length of the

[22] As mentioned before, 17 respondents filled out a paper version of the questionnaire, and thus were not able to perform the ACA task. Instead, these respondent were asked to perform an alternative version of the conjoint task. However, for comparability purposes we only use the data of the 81 respondents having completed the ACA task for further analysis.

questionnaire. We chose the following characteristics, which were *a priori* assumed to be important attributes managers use for evaluating competitive new products: Level of Innovation (Robinson, 1988), Intended Brand Position (Hauser & Shugan, 1983), Incumbent or New Entrant (Scherer & Ross, 1990), Success Reputation, and Aggressiveness Reputation (Heil & Walters, 1993; Robertson et al., 1995). The respondents were given full descriptions of the attributes and the levels.

Table 6.6.1 Design of the Conjoint Analysis study

Attributes	Levels	Descriptions
Action characteristics		
Level of Innovation	high	the new product has strong innovative features
	medium	the new product has some innovative features, but can not be considered a real innovation.
	low	the new product does not have any innovative features.
Intended Brand Position	close	the brand position of the new product is similar to (one of) your own products.
	far away	the brand position of the new product is dissimilar to (one of) your own products.
Actor characteristics		
Incumbent or New Entrant	incumbent	the company is a competitor already operating on your market.
	new entrant	the company was not operating on your market before.
Success Reputation	strong	the company was frequently successful with previous new product introductions.
	medium	the company was sometimes successful and sometimes not successful with previous new product introductions.
	weak	the company was frequently not successful with previous new product introductions.
Aggressiveness Reputation	aggressive	the company is known for gaining sales at the cost of competitors (win-lose strategy).
	co-operative	the company is known for gaining sales without fighting competitors (win-win strategy).

Cross-validity of the measurement scales

The respondents were asked to imagine that a new product with a given set of characteristics was actually introduced onto their own market, and they were asked to evaluate such a new product introduction. The criterion for evaluating the profiles was '*the perceived level of threat you would attribute to a product introduction with the specified characteristics on your market*'. This description of the evaluation criterion was used as a proxy for the 'expected competitive impact' construct discussed in the previous section. To examine the cross-validity of the conjoint analysis evaluation criterion and the expected competitive impact, the following check was made. For each respondent, we know from the reflection data the perceived characteristics he/she attributed to the new product actually encountered (e.g., high level of innovation, closely positioned, etc.), and we know his/her assessment of the expected competitive impact (ECI). For the same respondent we know from the conjoint analysis study 'his/her' part-worths for each attribute level (e.g., high level of innovation: 0.346; closely positioned: 0.402, etc.). So, for each respondent's actual encountered product introduction, the corresponding sum of the estimated part-worths for this introduction can be calculated (e.g., 0.346 + 0.402, + ...). This calculated sum of the part-worths serves as an indicator for the 'perceived level of threat' (i.e. the conjoint analysis evaluation criterion) posed by that event for the responding manager. We computed this level of threat indicator for all 81 cases (the total sample-size in the conjunct analysis study, see footnote 17). Next, the correlation coefficient was computed between the calculated perceived level of threat indicator (following from the conjoint data) and the actual reported Expected Competitive Impact (following from the reflection data). Results showed a significant (p=.02) correlation coefficient of .27. This result gives support for the validity of the evaluation criterion used in the conjoint analysis. We can also conclude that the two measures are fairly comparable, and, thus, that it is justifiable to compare the results.

Results

The ACA-software provides the data and estimations immediately after the interview has finished. Table 6.6.2 shows the basic results of the ACA-study. The column 'Average Part-worths' shows the relative contribution of each of the attribute levels to the evaluation criterion. Larger part-worths must be interpreted as leading to a higher perceived level of threat. For example, if a new product is considered to be highly innovative, this would on average add .248 points to the level of threat evaluation criterion. As can be seen from Table 6.6.2, the 'event profile' constituting the highest level of threat has these characteristics: a highly innovative and closely positioned product, introduced by an incumbent competitor with a strong success reputation and an aggressive reputation of doing business. The Average Part-worths reported in Table 6.6.2 show that, on average, for four of the attributes, the directions of the effects of the event characteristics on the evaluation criterion are in line with our expectations; the higher the level of innovation of a new product, the closer the intended brand position, the stronger the success reputation of the introducing company and the more aggressive its reputation of doing business, the higher the perceived level of threat.

Table 6.6.2 Conjoint analysis results regarding the contribution of Event Characteristics to the Perceived Level of Threat as assessed by defending managers (N=81)

	Average Part-worths	Average Relative Attribute Importance	Percentage of respondents for which the attribute level leads to the highest perceived level of threat
Level of Innovation		0.23	
high	0.248		53%
medium	-0.053		27%
low	-0.287		20%
Intended Brand Position		0.20	
close	0.334		79%
far away	-0.395		21%
Incumbent or New Entrant		0.15	
Incumbent	0.160		69%
New Entrant	-0.221		31%
Success Reputation		0.25	
strong	0.506		88%
medium	-0.077		6%
weak	-0.521		6%
Aggressiveness Reputation		0.17	
aggressive	0.229		77%
co-operative	-0.290		23%

The only attribute showing an effect different from what was expected is whether the introducing company is an 'Incumbent or New Entrant'. Contrary to what was hypothesised in H2a, on average, respondents evaluate Incumbent events as exerting a higher level of threat than New Entrant events. This attribute did not show a significant effect in the reflection data. We will come to a possible explanation for these diverging findings later.

The third column of Table 6.6.2 shows the Average Relative Attribute Importance. To obtain these average importances, first, for each respondent, the relative importance of each of the attributes was calculated by dividing the part-worth range of an attribute by the total part-worth range. Next, the individual relative importances were averaged over all respondents. The results clearly show that, in line with our previous findings, the attributes Intended Brand Position and Success Reputation indeed are important event characteristics managers use for evaluating the level of threat, i.e. the expected competitive impact of a new product introduction. It also shows that the Level of Innovation is the second most important attribute. This is a surprising result because this particular attribute showed no significant effect in the reflection data analysis. A possible explanation for the diverging findings will be given below. The attributes Aggressiveness Reputation and Incumbent or New Entrant are the least important ones.

The final column in Table 6.6.2 shows the heterogeneity among respondents regarding the effect of the attributes. In particular, it reports the percentages of respondents for which a particular attribute level gives the highest contribution to the perceived level of threat. For example, it shows that slightly more than half of the respondents (53%) view highly innovative new products as yielding the highest level of threat, whereas the other respondents think that either medium (27%) or low innovative new products (20%) exert the highest level of threat. Apparently, managers think differently about the threat posed by new products having new features.
This phenomenon also holds for the attribute 'Incumbent versus New Entrant', which on average showed an effect contrary to what was expected. 69% of the respondents view incumbent new product events as exerting a higher level of threat than new product introduced by new entrants. The other 31% of the respondents have the opposite view: in their view new entrant events are supposed to cause a higher level of threat than incumbent events.

Since a part of the respondents view highly Innovative new products and New Entrant events as exerting the highest perceived level of threat, one might say that there is support for the hypothesised effects of these attributes in this data, but it only holds for a limited fraction of the sample. The result of the heterogeneity among respondents is that the reported average part-worths over all respondents yield a substantial underestimation of the real effect on the individual respondent level[23]. The fact that, especially for the characteristics Level of Innovation and Incumbent or New Entrant, the direction of the effects varies across respondents, might explain why no significant relationships were found regarding these characteristics using the OLS-regressions on the respondents' reflection data[24].

Table 6.6.2 shows that the agreement among the managers is the greatest for the attributes Success Reputation, Intended Brand Position and Aggressiveness Reputation, for which more than 75% of the respondents think in the same direction. Note that these attributes also did show significant effects on the Expected Competitive Impact, when performing the OLS regressions on the reflection data. For these three attributes, the results from both types of data are consistent.

Summing up the results of the conjoint analysis, there is strong support for the hypotheses H1b (Intended Brand Position), H2c (Success Reputation) and H2d (Aggressiveness Reputation). A vast majority of the responding managers have the view that the closer the intended brand position of new products, the stronger the success reputation of the introducing firm and the more aggressive its reputation, the higher the level of threat posed by the new product event. There is partial support for H1a (Level of Innovation), which only holds for a small majority of the

[23] To illustrate this, suppose, for instance, that one manager views highly innovative new products as yielding the highest level of threat (suppose, for example, that the estimated part-worths are .30; .00 and -.30 respectively) and suppose that another manager conversely thinks that 'low' innovative new products contribute the highest to the level of threat (suppose the estimated part-worths are -.30; .00 and .30 respectively). Then, although for both managers the level of innovation of a new product affects their assessments about the level of threat substantially, the effect when looking at the average part-worths would be non-existent (.00; .00 and .00 respectively). In general, if heterogeneity among respondents occurs, the average part-worths yield an underestimation of the real contribution to the evaluation criterion.

[24] In order to investigate whether this explanation is valid, the sample was split into subsamples corresponding with the direction of the attribute effects resulting from the conjoint analysis. So, for example, we selected a subsample consisting of those respondents thinking that a low Level of Innovation would yield a high perceived level of threat, and a second subsample of respondents thinking the opposite. Next, for each subsample, correlation coefficients were calculated between the specific attribute (i.e. Level of Innovation) and the Expected Competitive Impact. Results showed that, for the attribute Level of Innovation, the signs of the coefficients were as expected, but not significant. However, for the attribute Incumbent or New Entrant, we indeed found significant effects in the subsamples. These results support the 'levelling out' explanation for not finding significant effects in the total sample.

respondents. This also holds for Hypothesis H2a, concerning Incumbent versus New Entrant events, although in this case the majority of the managers depart from our expectations by viewing incumbent new product events as yielding a higher level of threat than new products introduced by new entrants.

Explaining heterogeneity in the attribute effects

One may wonder why the above mentioned differences in the contributions of the attribute levels to the perceived level of threat exist and whether these differences can be explained by the market conditions and the characteristics of the reacting firm. This is an explorative research subject, of which we did not specify any hypotheses. We focused our investigation on the two attributes showing the largest heterogeneity among the respondents: 'Level of Innovation' and 'Incumbent or New Entrant'. To investigate possible effects, first for both attributes and for each respondent, we classified the respondents into groups according to the attribute level having the highest part worth. For instance, a respondent whose highest part worth on the Level of Innovation attribute was on level 'low', was classified in group 1; if it was on level 'medium' he/she was classified in group 2; if it was on level 'high' the respondent was classified in group 3. A similar classification was made for the attribute Incumbent versus new Entrant. Next, it was investigated whether group membership could be explained by the variables concerning the 'Market conditions' and 'Reacting firm' variables. This was done using (multiple) discriminant analysis.

The results of the analyses showed only two statistically significant relationships between the environmental variables and the group membership. First, the group membership of the Level of Innovation was significantly related (p=.07) to the level of *rivalry* that takes place in the market. The results imply that in high rivalry markets (e.g., detergents, soft drinks, dairy products), respondents tend to think that highly innovative new products add the most to the level threat. In a market with relatively low rivalry (e.g., biscuits, teas), respondents tend to 'fear' low innovative new products. This finding seems intuitively plausible, since in many high rivalry markets managers tend to be strongly competitor-oriented, and might therefore be very sensitive to innovative actions by competitors.

The second significant effect (p=0.01), again concerned the influence of the level of rivalry, but now on the group membership regarding the attribute Incumbent versus New Entrant. It shows that respondents operating in high rivalry markets, tend to think that introductions by incumbents add the most to the level of threat. Respondents operating in low rivalry markets tend to fear new products introduced by new entrants. This finding seems to be in line with findings by Porac, Thomas & Baden-Fuller (1989), who found that managers operating in a high rivalry market were strongly focused on internal competition (i.e., competition within a product category) rather than external competition.

6.7 Conclusions, limitations, managerial implications and future research

The study reported in this chapter was aimed at contributing to understanding marketing reaction behaviour of defending firms as a response to actions by competitors. Compared with studies published earlier on this research area, this study takes a specific approach with respect to (i) the research model, (ii) the use of two different data collection methods (a 'reflection approach' and a conjoint analysis study), (iii) the choice of the competitive action (i.e. a new product introduction), and (iv) the type of market (i.e. frequently purchased consumer goods). The primary purpose of this research was to develop and test a model for explaining competitive reaction behaviour. Following on the work by Chen et al. (1992) and Heil & Walters (1993), we take a decision-making and an information-processing approach, in which the 'expected competitive impact' of a new product constitutes a key concept. Our model assumes that defending managers' competitive reactions are essentially driven by the impact they expect from the new product on their own products' market performances. The model further assumes that managers base their assessments about the expected competitive impact primarily on their perceptions about certain characteristics of the new product introduction and about certain characteristics of the company introducing it.

The results of the analyses on both types of data (reflection and conjoint analysis) are put together in Table 6.7.1, which summarises the main findings regarding the hypotheses formulated in the present study.

The findings from our research point to the following main methodological conclusions:

Table 6.7.1 Summary of the main findings regarding competitor reactions to new product introductions

VARIABLE	FINDINGS
Level of Innovation	Important attribute for assessing the expected competitive impact of a new product event. About half (53%) of the respondents views highly innovative new products as causing the highest level of threat, i.e. the greatest expected competitive impact. Especially in high rivalry markets, more managers tend to fear highly innovative new products. In low rivalry markets, low innovative new products are feared the most.
Intended Brand Position	Important attribute for assessing the expected competitive impact of a new product event. A vast majority (79%) of the managers believes that a closer positioned new product leads to greater expected competitive impact.
Introduction Strategy	No significant effect detected on the expected competitive impact (findings based on reflection data only).
Market Size Effect	A larger perceived market size effect of a new product does not lead to smaller expected competitive impact. It does lead, though, to a higher assessed success probability of the new product (findings based on reflection data only).
***Incumbent or* New Entrant**	Attribute of limited importance. The majority (69%) of the respondents views new products introduced by incumbents as causing greater expected competitive impact than new products from new entrants. Especially as the internal rivalry in a market increases, introductions by incumbent competitors are viewed as being increasingly threatening.
Market Leader or Not	No significant effect detected on the expected competitive impact (findings based on reflection data only).
Success Reputation	Important attribute for assessing the expected competitive impact. Almost all (93%) respondents view new products introduced by highly successful companies as causing great expected competitive impact.
Aggressiveness Reputation	Attribute of moderate importance for assessing the expected competitive impact. The majority (77%) of the respondents views an aggressive reputation of the introducing company as leading to greater expected competitive impact. In addition, the more aggressive the reputation of a company, the more likely competitors react to introductions by this company, irrespective of the expected competitive impact posed by a new product introduced by that company.
Stakes Involved	The higher the stakes involved for the introducing firm, the greater the expected competitive impact (findings based on reflection data only).
Yes or No reaction	The greater the expected competitive impact of a new product event, the more likely competitors react to it (findings based on reflection data only).
Intensity	No significant effects detected (findings based on reflection data only).
Speed	The greater the expected competitive impact of a new product event, the faster competitors react (findings based on reflection data only).

1. Empirical evidence provided by this study, confirms the validity of our model. The explanation of competitive reaction behaviour improves by including the concept of Expected Competitive Impact as an intermediate variable between the characteristics of the event and the reaction behaviour of defending firms. This is an improvement in comparison to the stimulus-response approach as used by e.g., Chen et al. (1992).

2. The use of a conjoint analysis study in addition to e.g., a 'reflection approach' is very productive for explaining competitive reaction behaviour, since it reveals heterogeneity among respondents regarding their interpretation of competitive events. Different interpretations of the same event by different managers can lead to different reaction behaviour. Moreover, heterogeneity in attribute effects among individual respondents has been shown to lead to underestimations of the average attribute effects on the aggregate level. This phenomenon can even cause aggregate effects to be non-significant, while individual effects are significant indeed.

Besides these *methodological* conclusions, the findings from our research point to the following *substantive* conclusions about competitive reaction behaviour:

3. With respect to the relationship between Expected Competitive Impact and competitive reaction behaviour we find that:
   * The greater the expected competitive impact, the *more likely* defending firms react,
   * The greater the expected competitive impact, the *faster* defending firms react,
   * We can *not* conclude, however, that the greater the expected competitive impact, the *stronger* firms react.

4. The expected competitive impact of product introductions can be explained by the characteristics of the event, as perceived by defending managers. It proves useful to include both *action* and *actor* characteristics in the model. The most substantial effects relate to the *Level of Innovation* and the *Intended Brand Position* of the new product, and the *Success Reputation*, the *Aggressive Reputation*, and the *Stakes Involved* for the acting company.

5. Regarding the heterogeneity among managers with respect to the attribute effects, most importantly we find that while most managers (53%) fear highly *innovative* products the most, other managers think that medium innovative (27%) or low innovative ones (20%) exert the highest level of threat. The latter managers tend to operate in low-rivalry markets. Also, heterogeneity exist among managers regarding the perceived threat posed *by Incumbents*

versus *New Entrants*. Most managers (63%) fear new products introduced by incumbent the most, especially those managers operating in high-rivalry markets.

Limitations of this study

The results of this study are subject to a number of constraints that should be borne in mind when interpreting the results of this study. Firstly, the sample was drawn from managers operating in frequently purchased consumer good markets. This type of market constitutes a special kind of market with special kinds of marketing strategies and executions. With respect to product introductions, although many are introduced, many of them are extensions of existing brands and product lines and cannot be viewed as real innovations and technological breakthroughs. This limits our results to this type of new products, and to this type of markets. It particularly restricts our findings about the specific attribute effects. In industrial markets and service markets the important attributes might differ from those observed in the frequently purchased consumer good markets (e.g., in industrial markets the implied switching costs of a new product might be a very important attribute). However, in our view the basic decision-making process and the mere concept of the expected competitive impact is generalisable to other types of markets.

A second limitation concerns the sample size. We have a rich database containing information about a fair number (N=98) of actual new product events and we do have additional insightful information resulting from the conjoint analysis study. These data have provided us with sufficient information for testing the basic model. On the other hand, the number of cases for which an actual reaction and its speed and intensity was reported, is limited to twenty-eight. Although some of the hypotheses about intensity and speed are supported by the data, a number of hypothesised relationships showed to be statistically insignificant. This can either be due to the lack of statistical power, given the limited subsample size, or due to a true lack of relationship.

Managerial implications

Notwithstanding these limitations, the findings imply that firms planning to introduce a competitive new product into a market should be alert on the impact competitors will expect from the new product. The expected impact of a new product forms a driving factor for competitors to counteract. The expected impact seems to be based on the defending managers' perceptions about certain characteristics related to the new product and of to the company behind it. Findings from this study can be used by acting companies to make conjectures about the likely reaction behaviour of the competitors. Companies planning to introduce a new product may even try to influence competitive response by influencing the perceptions of the defending managers. There are many communication instruments suitable for such purposes (Eliashberg & Robertson, 1988; Robertson, Eliashberg & Rymon, 1995). For instance, one could communicate to competitors about the intended brand position of the new product by using pre-announcements, or stress the fact that the company tries to operate co-operatively and does not primarily seek to score at the expense of other companies. Such communications can even be tailored to specific competitors. The recent case of Omo Power (Riezebos & Waarts, 1994) proves that an aggressively announced new product with high stakes involved for the introducing firm, aimed at a very important market for the major competitor, is likely to provoke fierce competitive reactions.

Future research

There are various interesting avenues for further research. To mention a few, first, the model can be adjusted and extended to other types of competitive events and markets. More extensive conjoint designs might be helpful for studying the effects of various event characteristics on the evaluation of an event by defending managers. Secondly, as in this study we had a relatively small 'reaction sample', future studies may focus more on the characteristics of actual reactions, such as the specific instruments used, the success of the reaction, rebound actions, etc. For example, the recent study by Gatignon, Robertson & Fein (1995) on the success of reactions is a valuable contribution to this field of research. Another very interesting extension would be to further explore the perception-formation process in depth. Such research would focus on how managers' perceptions about a competitive new product are being formed. From a managerial point of view it is of paramount importance to know more about the different types of information managers use for forming a picture of a competitive introduction. Knowing more about, for instance, the sources of information, the assessed credibilities of these sources, etc., may yield fruitful insights for the communication a firm could apply regarding a new product, especially targeted at the competitors' intelligence-systems (Chapman Moore & Urbany, 1994). This may be studied formally by making use of information-processing theories.

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Appendix Summary of measures and scales

Scales:	Cronbach Alpha
Perceived Event Characteristics of the most recent competitive new product introduction	
Level of Innovation of the new product	
. 3-pnt item (low - moderate - high level of innovation)	
Intended Brand Position of the new product	
. 4-pnt item (very dissimilar - very similar position as compared to the own products)	
Introduction Strategy of the new product	
. 4-pnt item (high/low priced and heavy/little marketing support)	
Market Size Effect of the new product	
. 3-pnt item (no - slight - strong additional market growth)	
Incumbent or New Entrant	
. 2-pnt item (incumbent - new entrant)	
Market Leader or Not (regarding the position of the introducing company)	
. 2-pnt item (market leader - non-market-leader)	
Success Reputation of the introducing company	
. 5-pnt item (very weak - very strong)	
Aggressiveness Reputation of the introducing company	
. 5-pnt item (very co-operative - very aggressive)	
Stakes Involved for the introducing company	.77
1) financial importance of the new product for the acting company (5-pnt item: very low - very high)	
2) importance of new product for the market reputation of the acting company (5-pnt item: very low - very high)	
Expected Competitive Impact of the most recent competitive new product introduction	
Expected Consequences	
. expected pressure on market share if the new product would be successful (4-pnt item: very weak - very strong)	
Success Probability	
. assessed probability of success of the new product (5-pnt item: very low - very high)	
Competitive Reactions to the most recent competitive new product introduction	
Yes or No reaction	
. did the company react to new product introduction? (yes - no)	
Intensity	.63
1) reaction's strength relative to industry practice (3-pnt item: less strong-normal-stronger)	
2) number of marketing instruments reacted with (0-5)	
Speed	
. time of detection of the introduction relative to the actual introduction date (7-pnt item: >3 months before - >3 months after)	
. time of reaction to the introduction relative to the actual introduction date (7-pnt item: >3 months before - >3 months after)	

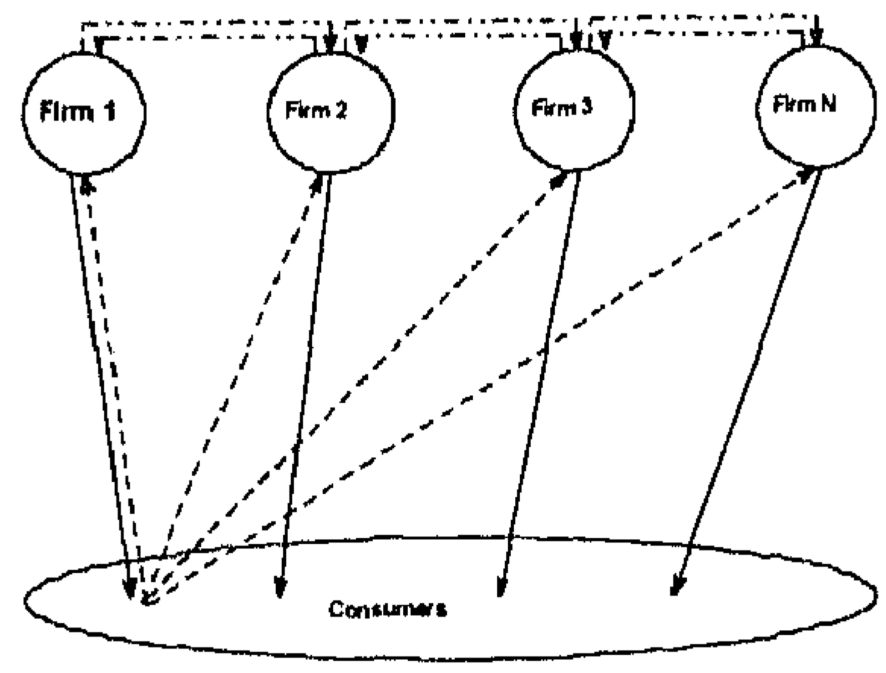
Appendix Summary of measures and scales (continued)

Scales:	Cronbach Alpha
Market Conditions relating to the product category in question	
Market Growth	
. 5-pnt item (>10% annual growth - >5% annual decline)	
Concentration	
. C4-index categories (<25% ; 25-<50 ; 50%-<75% ; >75%)	
Rivalry	
. 5-pnt item (very strong - very weak internal rivalry)	
Contestability	
. 6-pnt item (almost impossible to enter - very easy to enter)	
Strategic Uncertainty	
. uncertainty respondents feel about future marketing activities of the competitors (5-pnt item: very little uncertainty - very much uncertainty)	
Reacting Firm variables	
Financial Importance of the product category for the total company	.91
1) company sales on this market relative to total company sales (5-pnt item: <10%; 10-25%; 25-50%; 50-75%; >75%)	
2) company profits on this market relative to total company profits (5-pnt item: <10%; 10-25%; 25-50%; 50-75%; >75%)	
Strategic Importance of the product category for the total company	.68
1) importance of the market from product mix perspective (5-pnt item: very important - not important at all)	
2) importance of the market from technical know-how perspective (5-pnt item: very important - not important at all)	
3) importance of the market from market reputation perspective (5-pnt item: very important - not important at all)	
Market Position in the product category	
. (2-pnt item: market leader - non-market-leader)	
. (5-pnt item: market share <10%; 10-25%; 25-40%; 40-60%; >60%)	

Epilogue

About ten years ago, Barton Weitz wrote his editorial introduction for the special issue of the *Journal of Marketing Research* devoted to competition in marketing (Weitz, 1985). At that time he concluded that " Most research on competition in marketing simply describes the results of competitive activities but provide little insight about why these outcomes occur." (Weitz, 1985, p.234). At the end of this thesis, it is useful to look back and to see what has been achieved in the research field of competition in marketing. We will first address the developments in the research field in general, and thereafter reflect on the specific research in this thesis. The aim of this epilogue is not to enumerate again the findings resulting from the three parts of this thesis. This has already been done separately in each of the research parts.

We will start with some observations regarding the general developments in the research field. We structure the research on marketing and competition along the basic research framework we have used throughout this thesis. This framework is exhibited again below.



The framework reflects the essential working of marketing competition, at least at the tactical level of marketing. The focus is on the situation where a marketing manager offers a brand to a group of customers, where alternative brands are also available. In practice, dealing with this type of competition is daily reality for marketing managers. They use their marketing instruments primarily to influence the potential buyers of their own brands, but are continuously confronted with competitors doing the same. In this thesis, we have used the framework to structure research in marketing competition, along three levels of perspective: (i) the individual consumers perspective, (ii) the aggregate market perspective and (iii) the competitor perspective.

At the time Weitz put the provoking statement cited at the start of the epilogue, a large part of the research on competition had been devoted to the question of market structuring. It was predominantly aimed at developing methods for identifying competitive links, i.e. for analysing levels of competition among a set of brands. The perspective used to identify market structures was essentially connected with the first level of perspective: the individual consumers. In addition, some pioneering research on competition had been connected with econometric modelling, i.e. the market share attraction model approach (basically connected with the second level of perspective), and the reaction matrix approach developed by Lambin, Naert & Bultez (1975) and Hanssens (1980), which was aimed at providing a methodology for diagnosing competitive response (connected with the third level of perspective). Indeed, these pioneering research avenues were describing and diagnosing competition rather than explaining it. When, back in 1983, Hauser & Shugan published their Defender model, a model that explicitly modelled the mechanisms underlying competition, this was considered a major breakthrough. Since then, research on competition has been accelerating, triggered by changing economic conditions, e.g., a slack in world economic growth, deregulations and globalisation of markets, which forced many firms to face the fact of competition. Research followed practice here. Without question, also the work of Michael Porter has had a catalytic effect on the research devoted to competition. After the *JMR* special issue on competition (1985), many articles in this area have been published in the scientific marketing and management journals. Today, many aspects of competition are being covered. The pioneering 'diagnosing' research avenues, i.e. market structuring and econometric modelling are still flourishing, even more than ever before, due to the availability of data and of high capacity computer equipment. Also Hauser & Shugan's Defender model has inspired many others to include competitive effects in analytical marketing models (cf. Kumar & Sudharsan, 1988; Horsky & Nelson, 1992; VandenBosch & Weinberg, 1995). But, besides these 'analytical' approaches of competition, new research issues in competition have emerged, that predominantly focus on *managerial* aspects of competition. Such research is essentially connected with the third level of perspective: the competing manager. The question here is how and why managers deal with competition when performing their marketing management. Examples of such research areas are:

- Competitive reaction behaviour (cf. Robinson, 1988; Gatignon, Anderson & Helsen, 1989; Chen, Smith & Grimm, 1992; Heil & Walters, 1993; Bowman & Gatignon, 1995),
- Competitive information systems and competitive intelligence (cf. Fuld, 1988, 1995; Ghoshal & Westney, 1991; Zajac & Bazerman, 1991; Gulid, Gordon & Sudit, 1993; Johnson & Russo, 1994; Chapman Moore & Urbany, 1994),
- Competitive signaling (cf. Heil & Robertson, 1991; Chapman Moore, 1992),
- Mental models of competition (cf. Thomas & Soldow, 1988; Porac, Thomas & Baden-Fuller, 1989; Porac & Thomas, 1990; Ginsberg, 1994),
- Competitive pioneering advantage and entry-timing (cf. Lambkin, 1988; Lilien & Yoon, 1990; Lambkin, 1992; Golder & Tellis, 1993; Brown & Lattin, 1994; Huff & Robinson, 1994).

One might say that research on competition in marketing has become more balanced in terms of analytical versus managerial approaches and in terms of the three levels of perspective. The shift to studying more managerial aspects of competition can also be seen as an answer to the plea of Weitz (1985) for research devoted to the 'why' of marketing competition.

Having addressed some observations about the general developments in the research field of competition in marketing, we will proceed by reflecting on the specific research in this thesis, using again the three-level framework.

In this thesis, we have used the framework - following the three levels of perspective - to address methods and knowledge related with three general questions managers usually pose with respect to marketing competition: (i) who are our (main) competitors?, (ii) how dependent are we on the actions of our competitors and vice versa?, and (iii) how will our competitors react to our marketing activities, respectively how should we react to theirs? We have structured our research in line with these three questions, using the concept of 'competitive link' as a general umbrella.

Although on the face of it, the question 'who are our (main) competitors?' might seem to be a rather trivial one, in most markets it certainly is not. Especially in markets where new brands enter and existing brands leave, where new products features are being introduced, and new customer-needs are being fulfilled, the competitive structure of a market changes all the time. In the first part of this thesis we have focused on reviewing the methods and techniques a marketing researcher might use for analysing the competitive structure of a market. While there are various avenues of analysing, we limited ourselves to investigating the long standing tradition of analysing the competitive structure of markets based on the brand purchase behaviour of consumers. Having reviewed the methodologies originating from this tradition, we observe that though many techniques have been developed over the past twenty-five years, most of them will only be useful in specific, rather *static* market circumstances. *Dynamic* markets do not fit well with this type of analysis. Moreover, little is known yet about the practical value of the methods, because published applications have been scarce. The emphasis has been on the development of sophisticated techniques, of which many exist today. Since in many markets getting the data is no bottle-neck any more, we think there is a need for aiding the researcher to choose the right method under the right conditions, and to help the manager to understand the managerial implications of the research outcomes.

The second part of our thesis focused on the question 'how dependent are we on the actions of our competitors and vice versa?'. In our research, we observe an interesting divergence between two 'schools' of analysing this issue. On the one hand, there is the econometric school, which aims at developing tools for diagnosing competitive effects of marketing activities, using time series of actual aggregate market data. On the other hand, there is the abstract-deductive 'modelling' school, which tries to assess aggregate competitive effects by building theoretical models which are assumed to describe the market mechanisms of the process behind the effects. Both schools have been developing in the level of sophistication over the past few decades, and both schools provide useful tools and theories for investigating the mutual dependencies between brands. The econometric school tends to dive into more and more data to analyse, while the modelling school is taking pains in developing more and more sophisticated theoretical models. It seems, though, that in the latter case, the number of assumptions grow, of which the external validity is not always proven[1]. From the point of view of using realistic assumptions in theoretical models, the use of the econometric methods can be fruitful. In chapter 4 of our thesis we have elaborated on one specific method, constituting a linkage between an abstract-deductive model and an econometric estimation method.

The final part of this dissertation was concerned with the third question managers pose: 'how will our competitors react to our marketing activities, respectively how should we react to theirs?' The first part of this question refers to predicting competitive response to marketing actions. Up till now, marketing science has produced (i) a general methodology for diagnosing competitive response in a market, i.e. the reaction-matrix approach (Lambin, Naert & Bultez,

[1] For example, the recent model of VandenBosch & Weinberg (1995) studies 'optimal' product and price competition under conditions of: (i) only two brands; (ii) vector model preference curves, negative for price; (iii) uniformly distributed preferences, and (iv) zero marginal cost and no fixed costs. The authors frankly admit that the their results probably are quite dependent on the specific restrictions and assumptions of the model. They propose to develop the model further by relaxing some of these restrictions and assumptions.

1975), and (ii) several explanatory studies trying to build theories and find factors explaining competitive reaction behaviour. While the reaction-matrix approach has already advanced a long way on the life-cycle, the second type of research has started only very recently, in the late nineteen-eighties. As it stands, research in this area has produced some general factors associated with competitive response behaviour. However, there is still a lack of theories and evidence about the driving forces behind this behaviour. In the chapter 6 of this thesis, we reported an empirical study which takes a managerial decision making perspective as the point of departure. The findings of this research give us the confidence that this is a fruitful way of investigating reaction behaviour and useful for developing and testing theories. It also serves to provide the marketing manager with practical implications for management.

This leaves us the second part of the final question, i.e. how should we react to our competitors? In this thesis, we did not explicitly go into that question. Although game theory and marketing science have some valuable things to say about this - think in that respect of the recommendations following from the Defender model, we are inclined to comply with the statement of Moorthy (1993) that it is still too early for providing 'optimal' solutions for competitive reactions, because "...optimal competitive strategies must necessarily be situation specific. And the dimensionality of the 'situation-space' is large" (Moorthy, 1993, p.186). To put it even stronger, because marketing basically is a multi-player, multi-period, non-zero sum game with uncertain pay-offs, real optimal solutions will probably not exist at all. Still, marketing science can provide the manager with general factors and rules which are associated with *better* reaction decisions. Game-theory and social dilemma theory may be of help in this respect (cf. Armstrong & Collopy, 1996; McAfee & McMillan, 1996). Also the recent research on successful defence strategies for incumbent firms, performed by Gatignon, Robertson & Fein (1995), is an illustration of how marketing science can help managers making better competitive decisions.

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Samenvatting (Summary in Dutch)

"Analysing competitive links in marketing: a three-level perspective"

Eric Waarts

Erasmus Universiteit Rotterdam

Faculteit der Bedrijfskunde

Postbus 1738

3000 DR Rotterdam

E-mail: ewaarts@fac.fbk.eur.nl

Het in deze dissertatie beschreven onderzoek gaat over marketingconcurrentie tussen aanbieders van consumentenproducten. In het eerste hoofdstuk wordt het onderzoeksveld afgebakend en worden de doelstellingen van deze studie geformuleerd. We beschouwen in deze studie de concurrentiesituatie die ontstaat wanneer meerdere aanbieders producten aanbieden aan een groep consumenten, waarbij die producten vanuit de afnemer gezien weliswaar verschillend, doch min of meer uitwisselbaar zijn. Ieder van de aanbieders tracht met marketing activiteiten het koopgedrag van consumenten te beïnvloeden. Het gevolg van deze situatie is dat de prestaties van een aanbieder, bijvoorbeeld in termen van marktaandelen of winst, niet alleen afhankelijk zijn van het effect van de eigen marketing activiteiten, maar ook van de marketing activiteiten van de overige aanbieders. Immers, indien een concurrent bijvoorbeeld een prijsverlaging doorvoert of een nieuwe spaaractie start, zal dat een bepaald effect hebben op de verkopen van de andere aanbieders. Wij duiden deze prestatie afhankelijkheid aan met de term '*competitive link*' ('concurrentiële verbinding'). Indien twee aanbieders concurrentieel met elkaar verbonden zijn, houdt dat dus in dat beide aanbieders een bepaalde mate van invloed kunnen uitoefenen op elkaars resultaten, via het koopgedrag van consumenten. Deze studie behandelt een drietal aspecten van deze vorm van concurrentie, die elk centraal staan in de drie respectievelijke delen van dit boek: *identificatie, inhoud en gedrag*.

Deel 1, hoofdstuk 2, gaat in op de kwestie van de *identificatie* van concurrenten. Het hoofdstuk heeft als doel na te gaan op welke manieren kan worden vastgesteld welke producten als concurrerend met elkaar kunnen worden beschouwd, en heeft het karakter van een state-of-the-art overzicht. We concentreren ons hierbij op de verzameling van methoden en technieken die in de marketingliteratuur bekend zijn om marktstructuren af te leiden uit gegevens over het feitelijk koopgedrag van consumenten. Met behulp van dergelijke methoden worden eventuele concurrentiële verbindingen tussen aanbieders beschouwd en geanalyseerd vanuit het perspectief van de individuele consumenten. We constateren dat in de praktijk van het marketing management steeds meer gegevens beschikbaar komen over de aankopen van individuele consumenten. Tevens wordt geconstateerd dat in de afgelopen vijfentwintig jaar een scala van technieken en methoden is ontwikkeld, uiteenlopend met betrekking tot de benodigde data, de methodologie en de toepasbaarheid, waarmee dergelijke gegevens kunnen worden geanalyseerd. In hoofdstuk 2 worden deze technieken in kaart gebracht, worden de ontwikkelingslijnen geschetst en wordt een taxonomie opgesteld, van waaruit de eigenschappen van de verschillende methoden en technieken met elkaar kunnen worden vergeleken. We besluiten hoofdstuk 2 met een aantal conclusies ten aanzien van de bruikbaarheid en de beperkingen van deze klasse van methoden om concurrerende producten te identificeren.

Deel 2 van deze dissertatie behandelt het aspect van de *inhoud* van de concurrentiële verbindingen tussen aanbieders. Het gaat daarbij in de kern om de vraag in hoeverre de marketing instrumenten van de verschillende aanbieders kruis-effecten naar elkaar vertonen. Bijvoorbeeld, wat is het effect van een prijsverlaging of een sales promotion door de ene aanbieder op de verkopen van de overige aanbieders? Deel 2 van dit boek omvat een tweetal hoofdstukken. Hoofdstuk 3 behandelt de manieren waarop in de marketingliteratuur kruis-effecten worden bestudeerd. Een onderscheid wordt gemaakt tussen (i) de econometrische benadering, waarbij kruis-effecten worden geschat op basis van gegevens over de feitelijke inzet van marketing-instrumenten en de feitelijk gerealiseerde afzetten van een verzameling aanbieders, en (ii) de abstract-deductieve 'model' benadering, waarmee kruis-effecten kunnen worden voorspeld door het modelleren van de mechanismen waarlangs de kruis-effecten totstandkomen. Geconstateerd wordt dat de twee benaderingen verschillende bijdragen kunnen leveren tot het verkrijgen van inzicht in de inhoud van de concurrentiële verbindingen tussen aanbieders.

In hoofdstuk 4 wordt een verbeterde en meer uitgebreide versie ontwikkeld van een methode die, althans voor een specifieke toepassing, beide bovengenoemde benaderingen bijeenbrengt. Er wordt gebruik gemaakt van een econometrische methode waarmee tegelijkertijd meerdimensionale productlocaties en consumentenpreferenties zijn af te leiden uit een tijdreeks van prijzen en afzetten. De geschatte productlocaties en consumentenpreferenties kunnen vervolgens worden gebruikt als ingrediënt in een marktmodel, waarmee de kruis-effecten van marketing instrumenten kunnen worden voorspeld. De voorgestelde methode wordt geïllustreerd en toegepast in een bepaalde categorie van frequent gekochte consumenten producten.

In het derde deel van deze dissertatie staat het *gedrag* van aanbieders centraal in de context van de concurrentiële verbindingen met andere aanbieders. Specifiek wordt de vraag gesteld op welke wijze concurrerende aanbieders op elkaars activiteiten reageren. Bijvoorbeeld: hoe reageert aanbieder Y op een prijsverlaging of een productintroductie door concurrent X? Deel 3 omvat eveneens een tweetal hoofdstukken. Hoofdstuk 5 geeft een overzicht van de huidige kennis omtrent het reactiegedrag van concurrenten. We bespreken daarbij (i) een specifieke econometrische methodologie, de zgn. reactie-matrix benadering, die gekarakteriseerd kan worden als een instrument voor reactiviteitsdiagnose, en (ii) de bevindingen van de onderzoeken die verricht zijn naar verklaringen van het reactie-gedrag van concurrenten. We constateren dat de huidige kennis omtrent concurrentieel reactie-gedrag in de marketing beperkt is. De reactie-matrix benadering is weliswaar als diagnose-instrument reeds ver ontwikkeld, echter het instrument is nog niet op systematische wijze ingezet om reactie-gedrag onder verschillende condities te analyseren. Tegelijkertijd zijn pas de afgelopen jaren enkele studies verricht die reactie-gedrag trachten te verklaren. Deze onderzoeken zijn tamelijk divers van aard voor wat betreft het te bestuderen reactie-aspect en de verklarende variabelen. We kunnen stellen dat op dit moment slechts een beperkt aantal generieke factoren is geïdentificeerd die het reactie-gedrag van concurrenten kunnen verklaren. Er is een manco voor wat betreft de ontwikkeling van theorieën en empirische toetsing daarvan, die gericht zijn op het begrijpen van de onderliggende processen inzake reactie-gedrag.

In hoofdstuk 6 wordt verslag gedaan van een in het kader van deze dissertatie uitgevoerd empirisch onderzoek, waarbij het reactie-gedrag van concurrenten wordt bestudeerd vanuit het perspectief van de besluitvormingsprocessen van de daarbij betrokken managers. Het onderzoek richt zich specifiek op het reactie-gedrag van marketing managers, dat zich voordoet naar aanleiding van een productintroductie door een van de concurrenten. Er wordt een besluitvormingsmodel ontwikkeld waarin wordt verondersteld dat de reactie op een productintroductie primair verklaard kan worden door de impact die de reagerende manager daarvan verwacht op het marktaandeel van zijn eigen producten. Tevens veronderstelt het model dat de verwachte concurrentiële impact door de managers wordt ingeschat op basis van een aantal door hem/haar aan de introductie geattribueerde eigenschappen. Daarbij wordt een onderscheid gemaakt tussen eigenschappen van het geïntroduceerde product en eigenschappen van de onderneming die het product introduceert. Het model wordt getoetst op basis van gegevens die verkregen zijn door middel van interviews met 98 marketing managers van frequent gekochte consumenten producten. Een adaptieve conjuncte analyse maakt deel uit van het onderzoek. De resultaten bevestigen het model. Daarbij wordt geconstateerd dat er heterogeniteit bestaat onder de respondenten met betrekking tot de richting van het effect van bepaalde eigenschappen van een productintroductie op de verwachte concurrentiële impact daarvan. Deze heterogeniteit blijkt overigens een verklaring te vormen voor het feit dat die betreffende variabelen op geaggregeerd niveau een niet-significant effect vertonen.

In het laatste hoofdstuk, 'epilogue', worden de ontwikkelingen in het onderzoeksveld 'marketingconcurrentie' in bredere zin belicht. We observeren een groeiende belangstelling voor het onderzoeksveld, waarbij diverse aspecten van concurrentie aan de orde komen. Naast de traditionele 'analytische' onderzoekstrajecten, zoals marktstructuuranalyse, econometrische modellen van concurrentie en analytische modellen met concurrentie-aspecten, wordt de laatste jaren ook aandacht geschonken aan meer 'managerial' aspecten van concurrentie. Te denken valt hierbij aan onderzoek naar reactie-gedrag van concurrenten; de ontwikkeling van concurrentie informatie systemen en competitive intelligence; onderzoek naar concurrentie-signaling; het toepassen van mentale modellen inzake concurrentie; en onderzoek naar aspecten van market-pioneering en entry-timing. We constateren daarbij een verschuiving van beschrijvend onderzoek naar meer conceptueel theorievormend en verklarend onderzoek op het gebied van marketingconcurrentie.

Curriculum Vitae

Eric Waarts (1958) werd geboren te Den Haag. In 1976 behaalde hij het gymnasium-β diploma aan het Dr. W. A. Visser 't Hooft lyceum te Leiden. In hetzelfde jaar begon hij zijn studie Bedrijfseconomie aan de Erasmus Universiteit te Rotterdam. Hij studeerde af in 1983 met als specialisaties kwantitatieve bedrijfseconomie en commerciële beleidsvorming. In de periode 1981-1983 was hij student-assistent bij de sectie Marketing van de voormalige Interfaculteit Bedrijfskunde te Delft, alwaar hij in 1983 werd aangesteld als universitair docent. Sinds 1985 is hij verbonden aan de Faculteit Bedrijfskunde van de Erasmus Universiteit te Rotterdam, vakgroep Marketing Management. Zijn onderzoeksinteresses gaan vooral uit naar concurrentieanalyse en concurrentiestrategie, strategisch marketing management en de marketing van nieuwe producten.

Eric Waarts (1958) was born in The Hague, the Netherlands. In 1976 he obtained the gymnasium-β certificate at the Dr. W. A. Visser 't Hooft lyceum at Leiden. In the same year he started his study business administration at the Erasmus University Rotterdam. He graduated in 1983 with the specialisations quantitative business administration and marketing management. From 1981 to 1983 he was research assistant at the marketing department of the former Interfaculteit Bedrijfskunde (Graduate School of Management) at Delft, and was appointed there as assistant professor of marketing in 1983. Since 1985 he joins the Marketing Management department at the Rotterdam School of Management of the Erasmus University Rotterdam. His current research interests are in competitive analysis and competitive strategy, strategic marketing management, and marketing of new products.

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