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Promotion Induced Competitive Effects: Two Essays

Rajeev Airani
Old Dominion University

PROMOTION INDUCED COMPETITIVE EFFECTS: TWO ESSAYS

by

Rajeev Airani
M.B.A. May 1999, Karnatak University
B.E. September 1996, Karnatak University

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Approved By:

Kiran Karande (Chair)

John B. Ford (Member)

Larry Filer (Member)

ABSTRACT

PROMOTION INDUCED COMPETITIVE EFFECTS: TWO ESSAYS

Rajeev Airani
Old Dominion University, 2009
Chair: Dr. Kiran Karande

This dissertation focuses on the empirical generalizations related to retailer promotions. Two essays are developed addressing the generalizations. The first essay addresses the contradiction in the calculations of primary and secondary demand effects. A mathematical proof is developed to show that under Nested Logit modeling, competitors' gain assumption is violated. An alternative explanation is provided to calculate the primary and secondary demand effects. The second essay focuses on the empirical generalization of the neighborhood price effect. The effects of share and quality in shaping the neighborhood price effect are hypothesized and tested. Further, based on the evidence that neighborhood price effect and asymmetric share effect generally go together and contradict the market power notion, a related hypothesis is tested. This essay brings out new potential empirical generalizations.

Committee members: Dr. John B. Ford

Dr. Larry Filer

To my two year old son Hrishikesh, without his constant intervention
this dissertation would have been completed sooner.

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CHAPTER 1. Introduction

1.1 Sales Promotion Trends

Sales promotions are a diverse collection of incentive tools designed to simulate faster and/ or larger purchases of products or services by consumers or the trade (Kotler 1997, p664). Following are few of the important facts about sales promotion activities in US Consumer Products and Goods (CPG) industry:

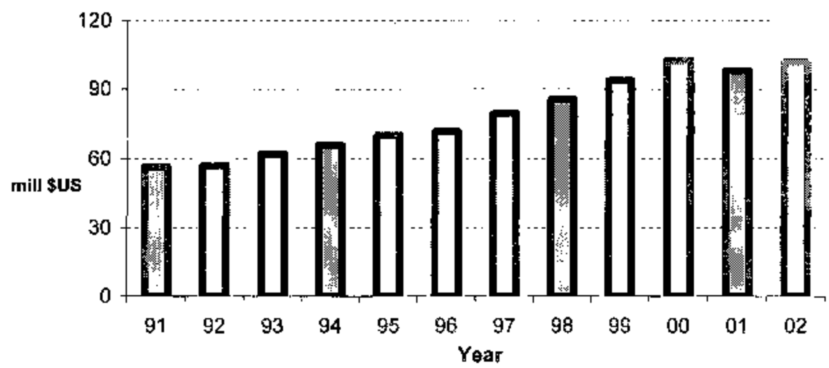
(1) According to the Annual Promotion Report 2003 of US markets by PROMO and PMA, more than 30% of the marketing budget is allocated to sales promotion activities, more than 52% of the companies involve top management for promotional planning and more than 50% of the time it is used as a tactical and strategic planning tool. This trend is increasing. (Graph 1).

(2) According to 2008 Information Resources Inc's (IRI) Times and Trends reports, around 70% of the CPG categories gain more than 30% of their volume on sales promotions. This trend has been consistent in the past few years.

(3) Also, consumers have been spending more per occasion/trip and consequently number of trips is decreasing over a period of time.

Apart from being effective in attracting customers, sales promotions also serve managers as 'easy to measure marketing actions' since they can be quantified with the metrics like change in sales (or market share/ brand switching / category related effects) to a corresponding promotion campaign. More importantly, sales promotions are also believed to be an important alternative to advertisement spending to build brands (Flanagan 1988). Thus, given the benefits and the recent thrust to measure the ROI of marketing functions, spending on sales promotions has been increasing. As a consequence of this trend, managers have much higher stake and need for prescriptive measures related to sales promotions than ever before (Bucklin and Gupta 1999).

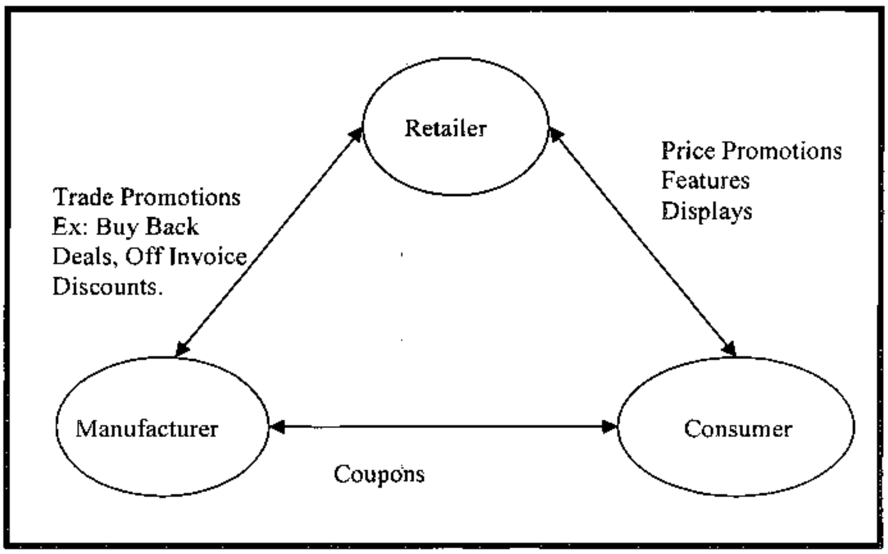
Graph 1. Sales Promotion Spending in US Market



1.2 Types of sales promotions

There are varieties of sales promotions offered by and targeted to different players in the market. Following framework depicts the different types of promotions between the players in the market (Figure 1). Manufacturers stimulate demand by direct marketing efforts like mailers and coupons directed towards consumers. They also provide incentives to increase their sales by offering trade promotions to retailers. Trade promotions are typically in the form of rebates and discounts to retailers. Third set of sales promotions are the promotions offered by Retailers to Consumers. These include price promotions/discounts, features and displays. These promotions are either initiated by retailers or these are passed on to consumers by retailers based on the trade promotions they get from the manufacturers. This dissertation focuses on Retailer to Consumer promotions and the empirical generalizations related to retailer promotions.

Figure 1. Sales Promotion Environment



Given the importance of retailer promotions, two decisive questions faced by the retail/marketing managers (Leeflang and Wittink 1996, Montgomery, Moore and Urbany 2005) in planning promotions are:

(1) What should be the optimum promotion mix policy to maximize profits, within the budget constraints, in terms of increase in sales or market share or percentage preference for the brand?

(2) What are the prescriptive measures against the promotion campaigns of the competing brands within the category?

Since, marketing managers, work around these decisions repetitively, many consulting and market research firms have provided standardized 'Market Response' decision support packages (Hanssens, Leeflang and Wittink 2005, Nair and Tarasewich 2003, Van Heerde, Leeflang and Wittink 2002, Cooper, Baron, Levy, Swisher and Gogos 1999, Silva-Risso, Bucklin and Morrison 1999). These packages help managers with the analysis of sales, competition, interaction and category related effects of promotions. However, these models do not encompass all the empirical generalizations that have been validated over a period of time in academic research. Among many other reasons, one of the important reasons for not incorporating the empirical generalizations validated in academia is that many of these generalizations have contradictory supports and few of them have little support across the categories or geographies.

1.3 Empirical Generalizations

The following discussion summarizes the academic findings that require further investigation due to little or contradictory evidence.

1.3.1 Proportion of primary and secondary demand

Empirical Generalization: Promoted brand gains more from the secondary demand than from the primary demand.

Explanation: When brands go for promotion they gain sales due to brand switching, increased category incidence and increased quantity buying. The gain from brand switching is known as secondary demand since this sale comes from other competing brands. The gain from increased category incidence and increased purchased quantity together is referred to as primary demand. Most of the studies interpret that gain from switching is more than the gain due to increased incidence and quantity buying. However, when the effects are measured in terms of unit sales under increased category incidence, gain from primary demand appears to be more than the secondary demand.

Evidence: Gupta (1988), Chiang (1991), Bucklin, Gupta and Siddarth (1998), Bell, Chiang and Padmanabhan (1999) conclude that gain from category expansion is 25% while gain from switching is 75%. They calculate primary and secondary demand effect based on the elasticity. However, Van Heerde, Gupta and Wittink (2003) show that when the impact is measured in terms of sales units the primary demand is 75% and the secondary demand is 25%. Following are the areas as indicated or implied by these studies which need further investigation.

(1) The calculations of Van Heerde, Gupta and Wittink (2003) study shows that competing brands gain due to increased incidence, when the target brand goes for promotion. Since nested logit model does not allow for simultaneous purchases, competing brands gaining under the promotion of a target brand misrepresents the promotion effects and thus needs investigation to explore under what conditions such an effect is observed.

(2) The Nested Logit (NL) models that address proportion of gain from primary and secondary demand implicitly assume that increased category incidence should be distributed to all the brands in proportion to their choice probability. Though, such an assumption is practically acceptable, from a theoretical point of view, since any brand(s) can increase incidence, only the brand(s) that contributes to the

incidence should benefit from it. Thus, it is required to develop the algebra as implied by the model to calculate the brand choice probability from the incidence.

Research Issues: Accordingly, the major issues addressed in this dissertation are:

(1) Under what conditions do competing brands gain/loose when a target brand goes for promotion?

(2) Developing the method (algebra) to calculate the brand choice probabilities from increased incidence as implied by the NL model.

1.3.2 Market share influence on neighborhood price effects

Empirical Generalization: Brands under promotion gain more from those competing brands which are nearer in price than from the competing brands that are farther away in price.

Explanation: Promotion effects exerted by a brand vary across competing brands. This empirical generalization crystallizes the idea. It states that brands have more competitive influence on the neighboring brands when ordered in terms of their price. It is an interesting generalization since, among many other factors like market share, quality and loyalty that may affect competition between the brands, it simplifies that competitive effects are mainly driven by price (the most important factor). However, given the understanding that multiple factors may influence competition between the brands under promotion, this generalization provides a starting point to explore the additional factors. This section elaborates on market share being an important factor that may define the competitive effects between the brands.

Evidence: Sethuraman, Srnivasan and Kim (1999) provide evidence that when price and share of the brands are correlated, brands under promotion gain more from the neighboring brands than the farther away brands in terms of price i.e. 'neighborhood price effect'. However, the sub-category level analyses demonstrated in the study of Wedel and Zhang (2004) shows that competition between the national and private label brands is more intense than the competition among the national or private label brands. In this study, prices of the national brands were closer to each other than to the private label brands and the private label shares in few instances were comparable to that of the national brands. Thus, these studies imply the following research issues:

(1) Since, the empirical study of Sethuraman, Srnivasan and Kim (1999) employs the data that has high correlation between price and share, neighborhood price effect might have come out as an important phenomenon. Thus, it is important to know if the neighborhood price effect still holds true when there is less/no correlation between the price and market share of the brands.

(2) It is important to study if there is anything similar to neighborhood share effect. As mentioned in the previous sections, market share influences competitive clout and vulnerability of the brands. Neighborhood effects of share will bring out better understanding of the competitive effects between the brands.

Research Issues: To validate the neighborhood price effects following research questions are explored in this dissertation:

(1) What is the influence of the market share on neighborhood price effects? If market shares shape the competitive strength/ vulnerability of the brands in gaining from the price neighbors?

(2) Is there "neighborhood share effect" i.e. do the brands that have similar market share gain more from each other under price promotions?

1.3.3 Quality influence on neighborhood price effects

Empirical Generalization: Brands under promotion gain more from those brands which are nearer in price than from the competing brands that are farther away in price.

Explanation: Promotion effects exerted by a brand vary across competing brands. This empirical generalization crystallizes this idea. It states that brands have more competitive influence on the neighboring brands when ordered in terms of their price. It is an interesting generalization since, among many other factors like market share, quality and loyalty that may affect competition between the brands, it simplifies that competitive effects are mainly driven by price (the most important factor). However, given the understanding that multiple factors may influence competition between the brands under promotion, this generalization provides a starting point to explore the additional factors. This section elaborates on quality being an important factor that may define the competitive effects between the brands.

Evidence: The study of Bronnenberg and Wathieu (1996) shows that, under promotion, both quality and positioning of the brands provide advantage to high quality tier brands to gain asymmetrically more from the low quality tier brands. In addition to this study, the work of Hardie, Johnson and Fader (1993) on consumer preferences also indicates that quality is an important explanatory variable in explaining the gain/loss under promotion.

However, the study of Sethuraman and Srinivasan (2002) does not account for the brand quality influence in generalizing the neighborhood price effects. Thus, quality influence on neighborhood effects still requires exploration. The research issues are:

(1) Empirical studies indicate that quality is an important factor that defines the competition between the brands. Thus, it is of importance to know the influence of quality on the neighborhood price effects.

(2) It is of significant importance to study if there is anything similar to neighborhood quality effect. As mentioned in this section, quality influences competitive effects between the brands. Neighborhood effects of quality will bring out better understanding of the price promotion effects between the brands.

Research Issues: The related research questions addressed in this dissertation are:

(1) What is the influence of quality on neighborhood price effects? Do quality differences between the price neighbor brands influence the neighborhood price effects?

(2) Is there "neighborhood quality effect" i.e. do the brands of comparable quality gain more from each other?

1.3.4 Market power notion

Empirical Generalization: High share brands gain more under promotion than the low share brands.

Explanation: High share brands have larger consumer base and have comparatively higher loyalty than the low share brands. High share brands also appear to be less deal elastic since they are more attractive and have higher competitive clout or strength. Under promotion due to larger consumer base high share brands pull more consumers towards them. In comparison low share brands do not pull comparable number of consumers when they go for promotion. This phenomenon of high share brands attracting more consumers is termed as market power notion. However, when the gains are expressed in terms of absolute cross effects (i.e. effects measured as the absolute dollar change in price relative to the category price), low share brands gain more from the high share brands than the reverse. The fact that low share brands gain more than the high share brands defies the idea of market power notion.

Evidence: Russell and Bolton (1988), show that high share brands gain more under promotion than the low share brands. This indicates that higher the share of a brand, it attracts more consumers and thus has higher market power (Kamakura and Russell 1989, Heilman, Bowman and Wright 2000, Anderson and Simester 2004). They draw this conclusion based on the market share attraction model. On the other hand, Sethuraman and Srinivasan (2002) based on the Bass, Jeuland and Wright (1976) model show that, when promotion effects are expressed in terms of absolute cross effects a low share brand gains more from the high share brand than the reverse. A low share brand gaining more under promotion i.e. "asymmetric share effect" questions the market power notion of high share brands. This study employs absolute cross effects since, share of the high share brands biases the results of the standard elasticity measure. Interestingly, this study also employs the data sets that are employed by Sethuraman, Srinivasan and Kim (1999). It should be noted that these studies employ different methodology. Market share attraction models are employed by the studies that propose market power notion, while asymmetric share model is based on brand choice model of Bass. Further, none of these studies account for the competitive interactions between the brands in drawing the conclusions. These studies lead us to the following research issue.

(1) It appears that whenever the neighborhood price effect holds true, the market power notion does not necessarily hold true and hence most likely asymmetric price effect holds true (given that Sethuraman and Srinivasan (2002) and Sethuraman, Srnivasan and Kim (1999) employ same data sets). Specifically, the research objective is to understand the conditions under which the market power notion or asymmetric share effect holds true based on the existence of the neighborhood price effect, when model accounts for competitive effects.

Research Issue: Accordingly, the major issues addressed in this dissertation are:

(1) To understand the conditions, under which market power notion or asymmetric cross effect holds true, based on the existence of neighborhood price effects employing a model that accounts for competitive effects.

1.4 Contributions of This Dissertation

1.4.1 Academic Contributions

As mentioned earlier the issues listed in the previous section demand attention, since there are contradictory and/or little supports to validate the empirical generalizations, following table lists the contributions.

1.4.2 Relevance to Practitioners

As listed in table 1, this study covers the empirical generalizations that have contradictory/little evidence. Once validated based on the results it is possible to include these generalizations in the Market Response models.

Table 1. Academic Contributions

Empirical Generalizations	*Academic Contributions*
1. Promoted brand gains more from secondary demand than from primary demand	1. Under what conditions the competing brands gain/loose when a target brand goes for promotion.
	2. Developing the method/algebra to calculate the brand choice probabilities from increased incidence as implied by the model
2. Brands under promotion gain more from those brands which are nearer in price than the brands that are farther away in price	The possibility of market share playing a major role in neighborhood price effects and if there exists neighborhood share effect.
3. Brands under promotion gain more from those brands which are nearer in price than the brands that are farther away in price	The possibility of quality playing a major role in neighborhood price effects and if there exists neighborhood quality effect.
4. High share brands gain more under promotion than the low share brands	This study evolves the conditions under which market power notion holds true.

1.5 Organization of the Manuscript

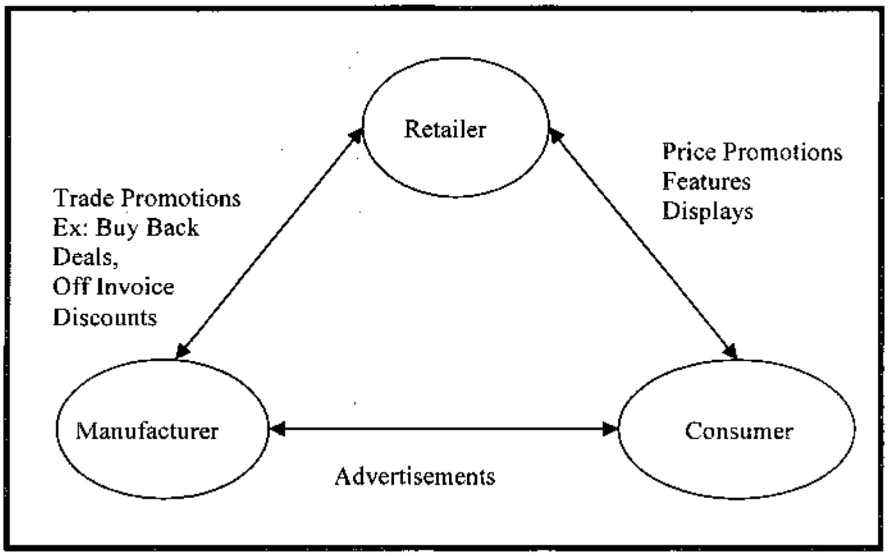
Following is the description of chapter wise details of the dissertation manuscript. The relevant literature related to sales promotions is discussed in Chapter 2. Theories are discussed briefly followed by the details of empirical generalizations. Literature is summarized in terms of their implications to model building. After which, two essays are written addressing the issues mentioned in table 1. Chapter 3 (essay 1) addresses empirical generalization 1 which explains the proportion of primary and secondary demand effects. Chapter 4 (essay 2) covers empirical generalizations 2, 3 and 4 that account for the research issues related to neighborhood price effects, market share and quality along with the implications on market power notion. Chapter 5 discusses the results and conclusions of both the essays.

CHAPTER 2. Literature Review

2.1 Introduction

In this chapter the relevant literature on sales promotions is discussed. Throughout this study by sales promotions is defined to mean *additional short-term incentives and benefits including price discounts and price cuts passed on to ultimate consumers either by manufacturer or retailer along with the basic product offering*. There are varieties of sales promotions offered by and to different players in the market. Following framework depicts different types of promotions between the different players in the market (Figure 2.1). The sales promotion literature can be divided based on the perspective or the relevance of the studies, (1) managerial/manufacturer perspective, (2) retailer perspective and (3) consumer perspective. This dissertation focuses on Retailer to Consumer promotions.

Figure 2. Promotion types between different players in the market



This chapter is organized as follows. The literature relevant to different types of promotions along with the summaries is discussed in first section 2.2. This includes trade deals, retailer to consumer promotions and manufacturer to consumer promotions which are discussed in sections 2.2.1, 2.2.2 and 2.2.3. In section 2.3, the econometric theories of sales promotions those explain the reasons for the existence of sales promotion practices are covered (Van Heerde 2001). These theories are discussed briefly under the subsection 'economic theories' of sales promotions.

Further, in section 2.4 relevant empirical generalizations focusing on sales effects of sales promotions are discussed. This is followed by the discussions that relates to the research issues addressed in the dissertation in section 2.5.

2.2 Literature Review on Sales of Promotions

Sales promotions can be classified into Trade Promotions, Retailer to Consumer Promotions and Manufacturer to Consumer Promotions. Following sections explain each of these types along with the findings and summary of important studies.

2.2.1 Trade (Manufacturer to Retailer) Promotions

Trade promotions or trade deals are the special discounts and benefits given by the manufacturer to the retailers like buy back deals, off-invoice rebates and scan back discounts. The literature related to trade deals is discussed under the sections of pass through effects, trade deal profitability, effect of bargaining power of the channel members on trade deal execution and normative models.

2.2.1.1 Retail Pass through

Pass through means, the extent of trade deal benefits provided by the manufacturers to retailers that are passed on to the ultimate consumers (Neslin 2002). Manufacturers provide deals to retailers so that they pass the benefits to consumers in the form of discounts or rebates. However, studies note that not all trade deals get the pass through (Walters 1989, Abraham and Lodish 1987). It appears that on an average brands get the pass through of less than 100%, though in some cases it may be as high as 200% (Besanko, Dube and Gupta 2005, Tyagi 1999). Retailers provide more than 100% pass through to adjust for their cost revenue benefits (Tyagi 1999). It is also observed that pass through varies by markets, categories and brands (Blattberg and Levin 1987, Besanco et al 2005).

Retailers have the objective of maximizing the category sales and profits. In doing so, they appear to provide better deal support to the high share or popular brands than to the low share brands (Besanko, Dube and Gupta 2005, Dube and Gupta 2008). Further, as a consequence of the retailer approach to trade deals, when low share brands are on trade deal benefits, high share brands also generally receive retailer promotions. This leads to cross brand pass through effects (Besanko et al 2005, McAlister 2007, Dube and Gupta 2008). In general it appears that, low share brands have an inherent disadvantage under the trade deals, because of low deal support, low pass through, cross brand pass through and when high share brands get pass through low share brands do not get high cross brand pass through (Pauwels 2007).

There are various other factors that affect the extent and executions of the trade deal pass through. Few studies indicate that pass through also depends on the type of a trade deal. If the trade deals are in the form of scan-backs, retailers generally pass maximum benefits to consumers, while if it is off-invoice then pass through is very low (Dreze and Bell 2003). Such a practice is observed since retailers' pass through execution is not accounted while providing the off-invoice trade benefits unlike for scan-back deals. However, retailers prefer off-invoice deals since it benefits them more in terms of forward buying and managing the inventory carrying costs (Neslin, Powell and Stone 1995). Retailers also tend to provide regular but low pass through to those brands that have strong loyal segments. This practice helps them maintain the store traffic for loyal customers as well as for the switchers (Agarwal 1996). Because of the loyalty effect, this practice also implies that high elasticity (low loyalty) brands may not necessarily get higher pass through (Tyagi 1999).

To add, it is also observed that the deals that involve low incentives to retailers do not get significant support and pass through (Walters 1989). If retailers have their own private labels then national brands need to provide very steep trade deals to get the pass through (Lal 1990). Retailer pass through also varies by seasonality and positioning of the brand (Meza and Sudhir 2006). Few studies also indicate that channel coordination by manufacturers in providing the pull promotions along with the trade deals affects the extent of pass through (Walters 1989, Kumar, Rajiv and Jeuland 2001, Moreau, Krishna and Harlam 2001). It is observed that due to regular trade deals, as part of the manufacturer policy, if consumers have the knowledge of trade deal periodicity then they tend to reduce their search costs and may switch stores. Thus, retailers prefer irregular trade deal pass through executions and also seek direct consumer promotions from manufacturers to benefit the store traffic (Kumar et al 2001, Moreau et al 2001).

2.2.1.2 Trade Deal Profitability

The most important factors that affect the profit of trade deals is the extent of pass through and its execution method. In turn, as described in the pervious section, both the extent of pass through and pass through execution depend heavily on positioning of the brand, type of deal, channel coordination and deal support.

Studies indicate that trade deal profitability mostly depends on the deal support provided by the manufacturers and retailers (Hardy 1986). In general, trade deals that are supported by sales force with consumer promotions appear to be more profitable (Walters 1989, Hardy 1986). The profitability also increases as manufacturers employ multiple push and pull promotions (Lucas 1996). The trade deals are referred to as push promotions and manufacturer provided consumer promotions (like rebates and discounts) are referred to as pull promotions. The combination of push and pull promotions appear to work profitable since it attracts price conscious consumers heavily (Gerstner and Hess 1991, 1995). Further, such combination of push and pull strategies make manufacturers to help retailers maintain regional monopoly. Since manufacturers can decide separate combination of push and pull promotions for each retailer, based on the promotion combination each store drives its own segments. This decreases store switching leading to regional retailer monopoly and thus higher trade deal profitability (Kim and Staelin 1999). Studies recommend that creating the synergy between push and pull promotions is the key for trade deal profitability (Cui, Raju and Zhang 2008, Bruce, Desai and Staelin

2005, Kim and Stealin 1999). Manufacturers can also increase trade deal profitability by combining advertisements with the trade deals and by appropriate channel coordination (Neslin, Powell and Stone 1995, Ailawadi, Beauchamp, Donthu, Gauri and Shankar 2009).

The length of the trade deals and the duration between the deals also affects the profitability (Walters 1989, Hardy 1986). Higher the frequency of the trade deals, lower is the pass through and deal support. This leads to lower profits. The positioning of the brand in the category or importance of the brand in the category and retailer margins on trade deals also drive the profits (Cui et al 2008, Walters 1989). High share/sales brands generate more profit during the trade promotions (Pauwels 2007).

Boatwright, McCulloch and Rossi (1999) study shows that hierarchical models employed for the analysis of the trade deal profitability indicate many more profit making areas other than the ones mentioned above. This article highlights the pitfalls in the analysis of regression models employed for trade deal analysis.

Study of Blattberg and Levin (1987) describes how retailers behave when trade promotions are offered. Retailers generally tend to forward buy inventory during trade deals and do not necessarily pass the benefits to consumers. This leads to loss in trade deals (Cui et al 2008). The characteristics of low positioning of a brand in a category and price premium of the brand appear to negatively affect the trade deal profits (Gomez, Rao and McLaughlin 2006, Haines 2007). Especially, low share brands have very high disadvantage (Pauwels 2007). Kim and Staelin (1999) also bring out an interesting aspect of side payments given by the manufacturers to retailers. In their study they note that, manufacturers pay additional money to retailers to implement their trade promotions to get more profit, though substantial portion of their payments go to the retailers' pockets.

2.2.1.3 Effect of the bargaining power of channel members on the execution of trade deals

There are a variety of possible channel interactions between manufacturers and retailers, based on which party holds the bargaining power. The theoretical literature has examined some of these effects on the trade deals.

Important theoretical research on the bargaining power in the channel structures is by Sudhir (2001). In this study the interactions between the manufacturers and retailers (Vertical Strategic Interaction) and competition between different manufacturer-retailer channels (Horizontal Strategic Interaction) are explored. This study notes that in general there is a shift in the bargaining power towards the retailers. This shift is observed since retailers can show change in the base line sales due to the promotions they offer to consumers (Sigue 2008). Important reasons are that manufacturer pull strategies (like advertisements) are fragmented and since most of the consumer decisions happen at the point of sales, trade deals loose their significance (Ailawadi et al 2009). In this context retailer promotions are crucial for the manufacturers to increase the baseline sales. Thus, from execution and profit perspective retailers appear to have greater control. Also, given the recent trend of nonexclusive retailing, retailers appear to get more bargaining power (Lal and Villas-Boas 1996).

Kasulis, Morgon, Griffith and Kenderdine (1999) explore the optimal behavior of the channel members under alternative assumptions of manufacturer-retailer interactions.

This study recommends that if manufacturers have higher bargaining power then they should reduce the number of trade deals. If manufacturers and retailers have symmetric power then push and pull strategy should be adopted. However, in many cases it appears that manufacturers have a say on the total budgets for the trade deals, while retailers have the bargaining power to set the allocation of funds on different trade deals (Gomez et al 2007). Since retailers have to carry inventory costs and adjust for manufacturers' deal policies; they prefer off-invoice trade deals (Manning, Bearden and Rose 1998). Thus, as the bargaining power shifts towards retailers, off-invoice deals increase and scan-back or/and bill-back deals decrease. It also appears that manufacturers go with either absolute or percentage margins, while retailers only prefer percentage margin (Tyagi 2005).

Game theoretic approach is also employed in understanding the power of the channel members (Lal and Villas-Baos 1996, 1998, Kadiyali, Chintagunta and Vilcassim 2000). These studies provide empirical methods to measure the power of channel members and to understand the reasons for this power in terms of demand factors, cost factors and nature of channel interactions. The analysis in these studies is confined to pricing power in channels. In determining their optimal prices, manufacturers and the retailers account for how all the players in the channel choose their optimal prices. Also, these studies indicate that manufacturers usually sell their brands through common independent retailers.

2.2.1.4 Normative models

Abraham and Lodish (1987) discuss PROMOTER, a system and methodology for assessing manufacturers' trade promotions that may be combined with consumer promotions. The methodology includes ideas from expert systems to evaluate promotions on a mass scale with a minimum of analyst intervention. The system uses available data and contains a knowledge base for identifying and adjusting for data irregularities. The large potential biases in employing only factory shipment data for assessing promotions are investigated. This study supports that there is significant forward buying by retailers during the trade promotions. Kruger (1987) aptly points out that though the above model is attractive it involves lot of data massaging costs. Other important normative models are by Neslin et al (1995) and Silva-Risso, Bucklin and Morrison (1999). Both these model generate manufacturer calendars accounting for the repeat purchase and acceleration effects. These studies recommend that acceleration in consumption is an important effect. Not accounting for such an effect may need to biased calendars.

2.2.1.5 Summary of research related to trade deals

To summarize, literature in trade deals encompasses retailer pass through, trade deal profitability, effect of bargaining power of different channels on trade deal execution and normative models. However, as Neslin (2002) mentions the research still needs to focus on improving the accuracy of incremental sales estimation for trade promotions.

2.2.2 Retail Promotions

Retail promotions include price cuts, in store displays, in store feature advertisement, and other deals that the retailers pass to the consumers. This section covers the literature related to these promotions. To capture the essence of retailer promotions, following review focuses on promotion effectiveness and profitability, consumer reactions to promotions, promotion strategy and competitive effects, EDLP strategy and private labels and promotion effects.

2.2.2.1 Promotion effectiveness and profitability

One of the earlier studies of measuring promotion effectiveness employing experimental designs is by Miller and Strain (1970). As the research has grown over a period of time many such experimental studies measuring sales promotion effectiveness have been developed. For example, a replicated in-store factorial experiment is employed to measure the effect of in-store promotion and retail advertising on brand sales in the study of Bemmaor and Mouchoux (1991). Twelve national brands in six nonperishable consumer goods categories are examined in this study. The results show that the price elasticities are in the range of 2-11, with larger values for smaller brands. These elasticities increased from 20% to 180% when the retailers advertised the deals. The rates of elasticity increment are smaller for the leading brands. The price deal cross-elasticities of the higher priced brands are found to be smaller than those of the other brands i.e. in the range of 2-2.7. Significant and plausible effects are consistently found across the brands, empirically demonstrating that features and displays add significantly to the sales gains from price reductions.

To add, the study of Anderson and Simester (1998) offers an explanation for the effectiveness of sale signs. They argue that, sales signs inform customers about which products have relatively low prices and thus help customers decide whether to purchase now (purchase acceleration), visit another store (store switching) or perhaps return to the same store in the future (purchase delay). Their next study (Anderson and Simester

2004) analyzes sales sign data from a variety of sources. The analysis yields three conclusions: first, sales signs are less effective at increasing demand when more items use such signs. Secondly, total category sales are maximized when some but not all products have sale signs. Thirdly, placing a sale sign on a product reduces perceived likelihood that the product will be available at a lower price in the future, but the effect is smaller when more products have sale signs. The findings suggest that moderation of the sale sign effect is required in part, since when sales signs are used on more products they reduced credibility. On the other hand, Areni, Duhan and Kiecker (1999) examine point of sales features and show that point of sales features work when featured attribute is a salient attribute and has high purchase likelihood. Interestingly, study of Walters and Jamil (2002) finds that consumer responsiveness to features may also result in to cross category purchases.

As noted, promotion elasticities appear to be the most widely employed promotion effectiveness measures. Many empirical analyses in marketing and economics have estimated brand price elasticities for specific products in markets to measure effectiveness (Bolton 1989). The results of the studies show that price elasticities or effect seem to differ across brands, product categories, retail outlets, and regions. Bolton (1989) proposed few of the market characteristics that may be associated with differences in brand price elasticities for frequently purchased non-durables. Promotional price elasticities were estimated for national brands of frozen waffles, liquid bleach, bathroom tissue, and ketchup for 12 stores. A multivariate model was estimated that relates differences in the magnitudes of price elasticities to market characteristics. The results show that market characteristics such as brand market share, coupon activity, display activity and feature activity explain a considerable amount of the variation in promotional price elasticities. Further, the relationships between product category characteristics and average brand promotional elasticity within the category are also studied (Narasimhan, Neslin and Sen 1996). In the study of Narasimhan, Neslin and Sen (1996), three types of promotions and seven category characteristics are considered. One hundred and eight product categories are studied in total and data for the categories is compiled from weekly scanner data, scanner panel data, and survey data. The results indicate that promotional elasticities are higher for the categories that have relatively less number of brands, higher category penetration, shorter inter-purchase times, and higher consumer propensity to stockpile. No statistically significant relationship is found between promotional elasticity and either impulse buying behavior or private label market share.

The important research in the area of quantity promotions has been the flexible consumption by consumers. Ailawadi and Neslin (1998) show that promotion has strong impact on consumption and the consumption acceleration due to promotion depends on the category. Their study focuses on Yogurt and Ketchup categories and employs Monte Carlo simulation. Dada and Srikanth (1987) develop a model to explore the conditions under which manufacturers provide quantity discounts. They provide optimal pricing schemes which enable both sellers and buyers to save more. In another quantity discount model by Kohli and Park (1989), authors show that risk sensitivity and bargaining power both affect quantity discounts. Recent model developed by Allenby, Shively, Yang and Garratt (2004) models discrete quantity offerings of a brand. This study estimates econometric model to find primary and secondary demand. They find that the quantity promotions are beneficial.

Though most of the studies discussed above support the notion that variety of promotions are effective and profitable, study of Srinivasan, Pauwels, Hanssens and Dekimpe (2004) shows that, promotions neither necessarily benefit retailers nor do they benefit manufacturers in all the cases. However, in the specific circumstances like price promotions for the low share brand promotions may benefit manufacturers more. On the other hand retailers make benefits for impulse purchase categories that have shallow promotions. To add, though some results show that promotions do not hurt the brand evaluations by the consumers (Davis, Inman and McAlister 1992), there are other studies which show that promotions do have negative effects (Simonson, Carmon and O'Curry 1994). These studies support that higher the frequency of promotions lower is the consumer response and may lead to negative effects.

2.2.2.2 Consumer reaction to promotions

This section summarizes the studies that have investigated the effect of promotions on consumer buying patterns, switching behavior and expectations they form about the brand.

One of the important studies that describe consumer behavior under promotion is by Petty and Cacioppo (1986). This study proposes Elaboration Likelihood Model (ELM) to explain the consumer behavior in terms of route to persuasion. In this method the promotion signal is taken as a cue for a price cut. Data were collected from 155 undergraduates who shopped individually in a simulated grocery environment. They were motivated to consider the prices of the products. Subjects chose brands from 6 product categories, 3 of which received promotional manipulation. Results show that low need-for-cognition (NFC) individuals react to the simple presence of a promotion signal whether or not the price of the promoted brand is reduced. High NFC individuals react to a promotion signal only when it is accompanied by a substantive price reduction. The fact that the two groups responded differently to the real and signal-only promotion, suggests that, consumers traveling the peripheral route are affected by the presence of a simple promotion signal. Evidence suggests that some consumers react to promotion signals without considering relative price information. This is also supported by the study of Inman, McAlister and Hoyer (1990). The study of Lam, Vandenbosch, Hulland and Pearce (2001) decomposes the sales into attraction, conversion and spending effects. This study also accounts for shopping environment in store and shows that it is an important variable to gain sales.

The study of Mulhern and Padgett (1995) shows that, consumers do visit stores specifically because of promotions and are equally profitable to a store which receives the customers that visit during non promotion periods. Kaul and Wittink (1995) study supports that consumers' sensitivities to price changes are an important input to strategic and tactical decisions. It has been argued that price sensitivities depend on factors such as advertising. In this study, after analyzing the characteristics of the previous studies in marketing, a set of three empirical generalizations is generated. They are: (1) an increase in price advertising leads to higher price sensitivity among consumers, (2) the use of price advertising leads to lower prices, and (3) an increase in non-price advertising leads to lower price sensitivity among consumers. Results show that, manufacturers need to coordinate their advertising and pricing decisions to attain maximum profits. Kopalle, Mela and Marsh (1999) develop varying parameter sales response models. Their study indicates that: (1) if consumers are more price sensitive then promotions should be used frequently and (2) as the negative dynamic sales effect increases the deals should go down.

The study of Kahn and Louie (1990) also investigates the effect of retractions of price promotions on brand choice behavior for variety seeking and last purchase loyal customers. They find that in case of consumers that are last purchase loyal the retraction drops the sales and such is not the case if consumers are variety seekers. Another study by Kahn and Raju (1991) develop stochastic brand choice model accounting for the promotion effects. They find that the models that do not account for stochastic promotions effects tend give incorrect results. The main finding of this study is that, for the minor brands the gain is mostly from reinforced consumers than from the variety seekers. Dowling and Uncles (1997) study the customer loyalty programs. They argue that given the popularity of loyalty programs, they are surprisingly ineffective. In most cases, all that a customer loyalty program will do is cost money to provide more benefits to customers and not all of which will be seen as relevant to the brand's value proposition and/or positioning. To stand the best chance of success in tough market conditions, programs must enhance the overall value of the product or service and motivate loyal buyers to make their next purchase. The study of Sharp and Sharp (1997) discusses the potential of loyalty programs to alter the normal market patterns of repeat-purchase behavior which characterize competitive repeat-purchase markets. A large-scale loyalty program is evaluated in terms of its ability to change normal repeat-purchase patterns by generating 'excess loyalty' for brands in the program. Panel data were used to develop Dirichlet estimates of expected repeat-purchase loyalty statistics by each brand. These estimates were compared with the observed market repeat-purchase behavior. Only 2 of the 6 loyalty program participant brands showed substantial excess loyalty deviations. However, these deviations in repeat-purchase loyalty were observed for non-members of the loyalty program as well as members and appear likely to be at least partially the result of other loyalty efforts particular to these brands. Van Heerde, Leeflang and Wittink (2004) and Van Heerde and Bijmolt (2005) decompose promotional bump into loyalty program members vs common consumers. They find that it is the non-members that respond more to promotional discounts.

Study of Chintagunta, Jain and Vilcassim (1991) develop heterogeneous household elasticities. Their models find better fit than the homogeneous models. Study of Seetharaman (2004) also supports the idea that there are many state dependencies in the consumer brand choice decisions and ignoring such effects may not provide accurate promotion elasticities. Similarly, when Villas-Boas and Winer (1999) test for endogeneity of independent variables with the purchases, they find that not accounting for the endogeneity effects may give inaccurate results about the consumer promotion sensitivities. The empirical generalizations of the price elasticities as shown by Bijmolt, Van Heerde and Pieters (2005) indicate that heterogeneity does not affect the price elasticities much, as much as the endogeneity affects it. This study also mentions that the price elasticities have been getting larger compared to the earlier generalization by Tellis (1986).

Lattin and Bucklin (1989) focus on reference pricing implications on sales promotion effects. They find that reference price has significant impact on consumer responsiveness to promotions. The study of Greenleaf (1995) also shows that retailers should offer increased promotional activity sandwiched between two low promotion activities to exploit the reference pricing effects. The study of Jedidi and Zhang (2002) estimates the reservation price of consumers and then the promotion effectiveness based on the same. They develop conjoint experiment to study the effects. This study is unique in terms of employing reservation price effects on promotion, rather than the reference price effects.

The important implication of reference dependence has been the expectation of price from consumers. Kalwani, Yim, Rinne and Sugita (1990) develop price expectation model of brand choice. They find that consumers react strongly to price losses than to price gains i.e. loss aversion (Tversky and Kahneman 1991). They also find that expected price is not only dependent on the past price but also on frequency with which a brand is promoted, economic conditions, customer characteristics and the type of the store shopped. Another study of Kalwani and Yim (1992) also shows that consumer expectations to promotions are also asymmetric in the sense that losses loom larger than gains. The study of Krishna, Currim and Shoemaker (1991) also shows that consumers are good at predicting deal frequency and size. It is also seen that due to expectations or even otherwise, after sales promotions sales decrease (Van Heerde, Leeflang and Wittink 2000).

Further, Krishna (1992) shows that consumer price expectations are correlated with the perceived deal frequency than the actual. To add, the study of Swait and Erdem (2002) support the idea that when regular promotions are not happening consumer expectations decrease resulting into poor evaluation of the brands. Another perspective comes from the study of Assuncao and Meyer (1993). They develop inventory control model accounting for the consumer stock keeping and consumption. They show that as the promotion frequency remains stable consumer expectation of the deals also increases. These studies put together support that consumers do have promotion expectations and are good at predicting and using them for their purchases. However, based on the type of the deal the expectations may vary as indicated by Lichtenstein, Netemeyer and Burton (1995). Sun, Neslin and Srinivsan (2003) and Sun (2005) develop the consumption model based on the forward looking consumption and assert that consumption should be considered as endogenous. These studies develop structural model to provide behavioral explanation to promotion induced flexible consumption/brand switching due to (rational expectation) forward looking consumers.

2.2.2.3 Promotion strategies and competitive effects

Though, earlier studies (Rao, Arjunji and Murthi 1995) mention that competitive promotions are a mixed strategy, Kadiyali, Chintagunta and Vilcassim (2000) diagnose the nature and magnitude of competitive interactions among firms which is important for developing effective marketing strategies. A game-theoretic model of firm interaction is formulated to analyze the dynamic price and advertising competition among firms in a given product market. In this model firm (or brand) level demand functions account for the contemporaneous and carry-over effects of the marketing activities, and also allow for the effects of the competitor actions. The formulation enables one to quantify not only the direction and magnitude of the competitive reactions, but also identifies the underlying form of market conduct that generates the particular pattern of interaction. A fully structural econometric model is specified and estimated for three firms constituting a distinct sub-market within a personal-care product category. It is found that while firms seem to compete on advertising, they cooperate on pricing policy, thereby enhancing their price-cost margins.

Recent studies of Naik, Raman and Winer (2005), Montgomery, Moore and Urbany (2005) and Richards (2005) further this concept to develop the models that account for promotion interactions and competitor moves. They propose marketing mix strategies in the presence of promotion interactions and try to predict competitor moves. Demand sided characterization of the optimal promotional strategies is derived by Simester (1997). This study shows that products that are complimentary in nature generally tend to get deeper promotions. Shankar and Bolton (2004) provide specific retailer pricing strategies based on competitor interactions. They are based on price consistency, price promotion intensity, price promotion coordination and relative brand price. These dimensions are statistically related to (1) competitor deal and deal frequency, (2) category factors like storability and necessity, (3) chain positioning and size, (4) store size and assortment, (5) brand preference and advertising and (6) own price and deal elasticities. Another study by Steenkamp, Nijs, Hanssens and Dekimpe (2005) examines competitive reactions to promotions and advertising employing vector autoregression. They find the promotions and advertisements are countered with promotions and advertisements respectively. Surprisingly, they find that from long term perspective passive strategy i.e. no reaction at all, is rather a sound strategy. However, the study of Vindevogel, Van den Poel and Wets (2005) show that market basket analysis (cross category simultaneous purchases) does not help retailers develop the promotion strategy.

Raju, Srinivasan and Lal (1990) study the competitive promotional advantages among established national brands and new brands. The objective of this study is to examine how loyalties toward the competing brands influence firms' use of price promotions in a product category. The analysis predicts that a brand's likelihood of using price promotions increases with an increase in the number of competing brands in a product category. In the context of a market in which a brand with a large loyalty competes with a brand with a low brand loyalty, it is shown that, in equilibrium, the stronger brand promotes less frequently than the weaker brand. Results suggest that the weaker brand gains more from the price promotions. The analysis aids in understanding the discounting patterns in markets where store brands, weak national brands, or newly introduced national brands compete against strong, well-known national brands. When model predictions were compared with data on 27 different product categories taken from a major grocery chain, it was consistent with the main findings of the model.

Cotterill, Putsis and Dhar (2000) study finds that consumer response to price and promotion decisions and firm pricing behavior jointly determine observed market shares. It performs intra-category analyses using data on 6 individual categories, as well as a pooled analysis on a sample of 125 categories and 59 geographic markets. The estimates of the residual demand elasticities suggest that examination of partial demand elasticities alone may provide an incomplete picture of the ability of brands to raise price. In another related study, where the store elasticity was matched to the consumer elasticity of the store trading area, results show that around 67% of the elasticity could be matched (Hoch, Kim, Montgomery and Rossi 1995). Mace and Neslin (2004) also matched the store level pre and post promotion dips with consumer characteristics by category. They find that:

(1) post promotion dips are not significantly different for private labels but differ for the UPCs that have irregular promotion patterns and (2) stores with customers having more of the households with older members with cars tend to see high post promotion dips.

Ailawadi, Lehman and Neslin (2001) use Procter & Gamble's (P&G) value pricing strategy as an opportunity to examine consumer and competitor response to a major, sustained change in marketing-mix strategy. The study estimates an econometric model to trace how consumers and competitors react to such changes. For the average brand, the study finds that deals and coupons increase market penetration and surprisingly have little impact on customer retention as measured by share-of-category requirements and category usage. For the average brand, advertising works primarily by increasing penetration, but its effect is weaker than that of promotion. This study also finds that competitor response is related to how strongly their market share is affected by the change in marketing mix strategy. Another study by Kannan and Yim (2001) also elaborates on P&G's strategy and shows that promotions can actually redefine the submarket boundaries.

Grover and Rao (1988) have analyzed the market structure that shapes as a consequence of the promotions. In their study a technique for structuring markets based on a model of inter-purchase time is presented. A parameter of this model measures the substitutability for a pair of brands, and the matrix of these measures is analyzed for all pairs to determine the market structure. The method is then applied empirically to structuring the coffee market. The data employed for this study is provided by IRI which had purchases of 2,000 households from April 1980 to April 1982. The record for each purchase included the date, time, and quantity of purchase as well as binary codes that indicate whether the purchase was made during any of 4 types of promotions. These 4 types of promotions include: (1) manufacturer's coupon, (2) store coupon, (3) features, and (4) displays. Several tests are used to determine the robustness and validity of the model. They find that structuring the markets based on the promotions is important since promotions shape substitutability of brands. Mela, Gupta and Jedidi (1998) study shows that changes in promotional and advertising policy affect market structure over the long-term. The 8 and 1/4 years of scanner panel data used for the analysis indicate that brands in the analyzed product category tend to fall into premium or non-premium and attribute-base tiers. The differentiation between premium and non-premium brands has diminished during the period of the study (1984-1992). Increases in price promotions and reductions in advertising have led to decreased differentiation between brands. These findings suggest that shifts in marketing dollars from advertising to promotions have made national brands more vulnerable to store brands' marketing activity.

Few studies have focused on how retailers should employ promotions strategically. Feinberg, Krishna and Zhang (2002) elaborate on the targeted promotions and mention that retailers should be cautious in offering their segment wise promotions. Especially, when the stores are asymmetrically positioned high quality store should play on frequency of promotions, while low quality stores should employ magnitude cue for promotions (Rajiv, Dutta and Dhar 2002). On the extreme case retailers can offer one to one promotions to consumers (Shaffer and Zhang 2002). This study suggests that retailers should employ both offensive and defensive strategies to manage customer churn. Study of Subrahmanyan (2000) employs Bayesian updating and dynamic programming to help retailers set prices based on consumer seasonal responses. Another study by Lewis (2005) employs dynamic programming to develop CRM based pricing policies and Customer life time value (CV) based on retailer data.

On of the earlier studies, that investigates the decaying effect of promotions employing time series is that of Rao and Thomas (1973) and of Doyle and Saunders (1986). Recently, Leeflang and Wittink (1996) and Pauwels, Hanssens and Siddarth (2002) study the relationship between competitive reaction elasticities and own-market share elasticities employing time series technique. Prescriptions derived from economic theory indicate that the product of the reaction elasticity and the own market share elasticity equals the cross-market share elasticity, if managers aim to maintain their brands' market shares. A framework is developed that consists of all possible combinations of dichotomized cross-market share, competitive reaction, and own-market share effects. Managers can use this framework as a decision-making tool. It is argued that managers should react to changes in marketing activities for other brands only if those changes have nonzero effects on their own brands' market shares. It is shown that managerial practice deviates from these normative implications, resulting in under and over reaction. The empirical results suggest that over-reaction effects occur more frequently than under-reaction effects. Franses, Paap and Sijthoff (2007) and Foekens, Leeflang and Wittink (1999) have also employed dynamic promotion effects in time series to understand the self and cross elasticities. There are studies that have estimated the elasticity via nonparametric method leading to nonlinear elasticities (Abe 1998, Chintagunta, Jain and Vilcassim 1991). These results fit the data better than the traditional methods. Along these line studies of Dekimpe, Hanssens and Silva-Risso (1999) and Nijs, Dekimpe, Steenkamp and Hanssens (2001), Alvarez and Casielles (2005), Dawes (2004) measure the long-term impact of price promotions. They find that, though the long term impact at the category level is almost nil, short terms promotions do make an impact.

2.2.2.4 EDLP strategy

Studies have also focused on EDLP and HI-LO retailer promotion strategies. Experimental evidence suggests that a supermarket cannot obtain higher profits by merely setting constant low prices, leading to the question: exactly what makes EDLP successful? This question is of particular relevance to both academics and practitioners who have been intrigued by the success of this retailing strategy.

Study of Hoch, Dreze and Purk (1994) examines the viability of an "everyday low price" (EDLP) strategy in the supermarket industry. In two field experiments for 26 product categories conducted across 86-store grocery chain, it was found that 10% EDLP category price decrease led to a 3% sales volume increase, whereas a 10% Hi-Lo price increase led to a 3% sales decrease. Consumer demand did not respond much to the changes in everyday price, but for the large differences consumer responses were profitable. An EDLP policy reduced profits by 18% while Hi-Lo pricing increased the profits by 15%. In a third study, the frequency of shallow price deals were increased in the context of higher everyday prices and a 3% volume increase was found that translated into a 4% increase in profit.

Lal and Rao (1997) examine the EDLP differently. According to them, Every Day Low Pricing (EDLP) strategy has proved to be a successful innovation resulting in higher profits. EDLP helps better serve the time constrained consumers, while discouraging cherry pickers who seek promotions. However, it is unclear that such cost savings are being fully realized since EDLP stores also engage in price promotions. Further, this study investigates the factors contributing to EDLP's success by analyzing the competition between supermarkets through a game theoretic analysis of a market consisting of both time constrained consumers and cherry pickers. This research shows the condition under which retailers choosing different strategies (EDLP and Hi-Lo) reach a perfect Nash equilibrium. Study of Bolton and Shankar (2003) indicates that retailers should closely monitor the competitors' pricing and promotion decisions in the EDLP or Hi-Lo scenarios.

2.2.2.5 Private labels and promotions effects

Private labels offer unique blend to the competitiveness and store profitability. They also impact promotion effectiveness and profitability of the national brands. Following studies summarize the important findings.

Dhar and Hoch (1997) show how and why the performance of private label programs systematically varies across retailers. Although the analysis shows that the pull and push tactics of the national brands exert an important influence on store brand performance, a substantial part of the variation in market share comes from actions taken by the retailer, either independently as part of its overall marketing strategy or in response to manufacturer actions. Key insights include: (1) Overall chain strategy in the use of EDLP pricing, commitment to quality, breadth of private label offerings, use of own name for private label, a premium store brand offering, and number of stores consistently enhance the retailer's private label share performance in all categories. (2) Although an EDLP positioning helps the store brand, there are countervailing effects. A recent study by Ellickson and Misra (2008) shows that EDLP or Hi-Lo retailers have clusters of strategy based on the local conditions and rival retailers' actions.

Further, Hoch and Banerji (1993) investigate the profitability of private brands. According to their study, private labels or store brands are an important source of profits for retailers and a formidable source of competition for national brand manufacturers. However, market share of private labels varies dramatically across categories. A framework is proposed and tested to explain this variation in order to understand the determinants of private label success in the US supermarkets industry. It is found that private labels perform better in large categories offering high margins. Private labels also do better when competing against fewer national manufacturers who spend less on national advertising. Surprisingly, high quality is much more important than lower price.

Raju, Sethuraman and Dhar (1995) focus on store brands vs national brands to study the impact of retailer promotions. An analytical framework is presented for understanding the characteristics of the product category that makes it more conducive for the introduction of the store brands. This study also investigates market characteristics that help explain differences in store brand market share across the product categories. The findings suggest that the introduction of a store brand is likely to increase retailer's profits in a product category if the cross-price sensitivity among national brands is low and the cross-price sensitivity between the national brands and the store brand is high. The model predicts that the store brand share would also be high under these conditions. In addition, it is found that the introduction of a store brand is more likely to lead to an increase in category profits if the category consists of a large number of national. The models are compared with the data on 426 grocery product categories.

Other studies by Sethuraman (1995, 1996) shown that promotion of national brands have significant impact of private labels, while the converse does not hold true. Results show that in few cases low share private labels draw more from national brands when promotion effects are measured in terms of absolute effects (Sethuraman 1996).

2.2.2.6 Summary of literature on retail promotions:

As discussed the literature on retail promotions has focused on effectiveness of promotions, issues related to private and national brands, types of sales effects, competitive reactions and EDLP/HI-LO strategies. Though, most of the incremental sales questions are answered by the present research the questions still to be addressed are (Neslin 2002):

(1) Long term impact of sales promotions
(2) Conditions under which a brands gains because of competitive promotion deals
(3) Decision models, which include the observed sales effects and promotion phenomena.

2.2.3 Manufacturer to Consumer Promotions (Coupons and print Ads)

The promotions passed by the manufacturer directly to the consumers are known as consumer promotions. Coupons and free standing inserts happen to be the most popular consumer promotions. Following literature covers the studies related to them in the sections of coupon effectiveness and profitability, consumer reaction to coupons and other manufacturer promotions.

2.2.3.1 Coupon effectiveness and profitability

Krishna and Zhang (1999) mention that US firms collectively spend over $65 billion annually on coupon promotions and are becoming increasingly concerned with their profitability. FSI (free-standing-insert) data shows that coupon duration varies across brands. It is also shown in many studies that coupon duration can affect coupon profitability. In this study answers are provided for some empirical observations on coupon duration. It is explained, for example, why: (1) coupon duration will vary across firms, such that large market share firms will give short-duration coupons and small market share firms will give long-duration coupons; (2) longer coupon duration for one brand will increase redemption for coupons of that brand and of a competing brand, and (3) coupon duration will affect coupon profitability.

The earliest study on coupon is by Reibstein and Travar (1982). This study examines if one could accurately predict the rate of coupon redemption and if the direct costs of a specific promotion could be easily calculated. With the assistance of a consumer goods company that utilizes coupon as a major promotional device, a model was developed to discover the relative importance of a number of factors on the redemption rate of past coupon efforts for a specific brand and to predict subsequent redemption rates. Variables included in the model were: (1) distribution variables, (2) normalized coupon value, (3) normalized ratio of coupon value to price, (4) intensity of distribution, and (5) normalized market share. This model provides a method for quantifying the relationship between a variety of dimensions in the coupon decision and costs associated with it.

To understand the coupon effects better, Neslin and Clarke (1987) posit that managers must consider not only the costs of coupon, but they must also measure the benefits of coupon. This study measures the coupon benefit by determining the amount of incremental sales the coupon is inducing. An experiment was conducted using a coupon book, distributed either by mail or by consumer request, followed by a telephone survey to determine brand-use profiles of various products. It was discovered that coupon programs for low-share brands were more effective than for high-share brands. Coupons prompted more purchasing among occasional users and new category buyers. Other findings from the experiment are: (1) while low-share brands should receive the bulk of the coupon budget, coupon programs for high-share brands that are targeted toward non-loyal users can be effective. (2) consumer-request distribution vehicle should be utilized more extensively, (3) very short expiration dates on coupons should be avoided (4) coupon effectiveness differs across geographies and (5) higher redemption rates may yield unfavorable brand-use profiles.

Inman and McAlister (1994) provide further insights that, coupon providers should temporally limit their financial liability by using expiration dates. Traditionally, coupon redemptions are greatest in the period immediately following the coupon drop and then decline monotonically. Using regret theory, it is predicted that expiration dates induce a 2nd mode in the redemption pattern just prior to the expiration data. This prediction is tested by extending an existing coupon redemption model to incorporate an expiration effect and then estimating both the existing and the expiration models using weekly coupon redemption data for spaghetti sauce from AC Nielsen panels in two cities. Results are consistent with the prediction.

Another study of Leclerc and Little (1997) examines packaged goods. Accordingly, packaged goods manufacturers distribute cents-off coupons in free-standing inserts (FSI) in newspapers. Using two laboratory experiments and a separate analysis of coupon measurements from scanner panels, this study investigates whether the content of the print advertisement influences the effectiveness of the coupon. Theoretical arguments suggested that the impact on consumer attitudes would depend on the executional cues of the copy, the brand loyalty of the consumers and the consumer's involvement with the product category. The results support this theoretical framework and suggest that it is possible to make FSI coupons more effective by choosing appropriate executional cues for their advertising copy.

In Neslin's (1990) study, an econometric market response model for measuring the effect of coupon promotions on market share is formulated. The model is a multi-equation, simultaneous estimation method and employs scanner panel data provided by the Test Marketing Group. In addition to the own couponing efforts of a target brand, the proposed model also accounts for retailer promotions for the brand and competitive couponing activity. The results indicate that coupons have a significant effect on market share, but the effect varies from brand to brand and may not be strong enough for some brands to be profitable in the short run. This research reinforces the emerging understanding that coupons are a major tool for achieving market share. Kumar and

Swaminathan (2005) measure elasticity of coupons employing a decay model at store level. This study shows that if the face value of the coupon is doubles then increase in elasticity is more than twice. This also implies how coupons can be employed to increase market shares.

Another study in the same lines is that of Dhar and Raju (1998). This study focuses on cross-ruff coupons. Cross-ruff coupons are obtained at the time of purchase of a carrier brand and may be redeemed at a later date on a target brand. These coupons therefore have the ability to link consumer purchases across different brands as well as shopping trips. The effects of cross-ruff coupons on consumer choice behavior and derive the conditions under which cross-ruff coupons can lead to higher sales and profits than other types of package coupons. An empirical analysis is conducted using data from 195 different cross-ruff coupon campaigns observed in grocery stores in a major US city over a three-month period. The model provides insights into the selection of appropriate carrier and target brands. It also shows that how the choice of an appropriate carrier or a target brand is affected when the brand categories that are demand complements or substitutes.

Leone and Srinivasan (1996) mention that, although much research has examined the impact of coupons on redemption rates, incremental sales, and market share, only a few studies have addressed the impact of coupons on brand profitability. One possible reason is the lack of readily available profitability data. In the absence of such data, researchers have used managerial judgments (Neslin and Shoemaker 1983) and experiments to investigate the profitability of coupons. It is also seen that immediately after the couponing period sales go down (Neslin and Shoemaker 1989). Thus they develop an integrative framework for evaluating the impact of coupon face value on brand profitability and have implemented the model employing the readily available scanner data. The research reveals that when a manufacturer optimizes the market-level profitability from a coupon program, profit for individual chains in the market could be sub-optimal.

Chiang (1995) develops a model that accounts for simultaneous coupon activity by competitors. This is again based on consumer utility maximization. This study examines the category expansion effects of coupons and concludes that coupons do not increase category sales/purchase acceleration.

2.2.3.2 Consumer reaction to promotions

Study by Neslin, Henderson and Quelch (1985) shows that coupons accelerate quantity purchases by the consumers, which is similar to advertising and price cut effects.

One of the earlier studies of Bawa and Shoemaker (1987) examines the effects of a direct mail manufacturer's coupon on consumer brand choice behavior. The level of coupon redemption and changes in brand choice behavior after coupon redemption are analyzed as the functions of: (1) prior probability of purchasing the coupon brand, (2) probability of purchasing a favorite competitive brand, and (3) coupon face value. The coupon redemption decision is modeled using a cost-benefit model that analyzes 3,808 households. The results indicate that coupon redemption rates are much higher among households that have purchased the brand regularly in the past. Data on consecutive purchase behavior suggest that most households that have not used the coupon brand regularly will revert to their regular brand immediately after redeeming the coupons. Partial support was found for the hypothesis that the redemption rate will increase with coupon face value. In another study (Bawa and Shoemaker 1989), analyze the household characteristics that respond better to coupons. They find that the responsiveness to coupons varies across demographic segments.

Further, Raghubir (1998) has hypothesized that consumers use the value of a coupon to estimate price, and this hypothesis is tested with a series of studies. First study shows that higher the percentage discount, higher is the perceived price. Second study demonstrates the same effect with cents-off coupons. Third study then demonstrates that the effect is contingent on whether alternate sources of information are available to consumers and examines the consequences of such information on deal evaluations and purchase intentions.

Raju, Dhar and Morrison (1994) study proposed a stochastic choice model and provides empirical analyses to understand the effect of package coupons on brand choice. Package coupons can be broadly classified into three types: peel-off coupons, on-pack coupons, and in-pack coupons. This model helps understand the relative impact of these types of coupons on market share. The results reveal that on-pack coupons may lead to a higher market share than peel-off coupons. While the benefit of a peel-off coupon is realized immediately, the consumer has to wait until the next purchase occasion to cash in the benefit of an on-pack coupon. The key predictions of the model are compared with the data collected from a series of in store quasi-experiments. The data are consistent with the model's predictions. Silva-Risso and Bucklin (2004) provide similar understanding by developing coupon effectiveness with panel choice model.

In the study of Zhang, Krishna and Dhar (2000), front and rear loaded incentives are investigated to understand the key factors that influence a firm's decision whether to use front-loaded or rear-loaded incentives based on the consumer response. Consumers obtain an immediate benefit upon purchase of a front-loaded incentive, when using price packs, direct mail coupons, FSI coupons or peel-off coupons. When buying products with in-pack coupons or products affiliated with loyalty programs, however, promotion incentives are obtained on the next purchase occasion or later, i.e. a rear-loaded incentive. Analysis shows that the innate choice process of consumers in a market is an important determinant of the relative impact of front-loaded and rear-loaded promotions. It is shown that in markets with high variety-seeking it is more profitable for a firm to employ rear-load couponing, and in markets with high inertia it is more profitable to employ front-loaded coupons. Consistent with these findings, other studies by d'Astous and Jacob (2002) and d'Astous and Landreville (2003) reveal that when a premium promotion is offered to consumers they respond more to the immediate premium offers than the delayed premiums. Laroche, Pons, Zgolli, Cervellon and Kim (2003) compare coupons with two-for-one promotions. They evaluate the similarities between these promotions based on the cognitive-affective-behavioral pattern.

2.2.3.3 Other manufacturer promotions

Rossi, McCulloch and Allenby (1996) study proposes model for direct marketing activities. This study takes the stand that an important aspect of marketing practice is the targeting of consumer segments for differential promotional activity. The premise of this activity is that there exist distinct segments of homogenous consumers who can be identified by readily available demographic information. A study is presented whose goal was to assess the information content of various information sets available for direct marketing purposes. Information on the consumer is obtained from the current and past purchase history as well as demographic characteristics. New econometric methods to implement a random coefficient choice model in which the heterogeneity distribution is related to observable demographics are developed. Results indicate that there exists a tremendous potential for improving profitability of direct marketing efforts by more fully utilizing household purchase histories.

Fox, Reddy and Rao (1997) investigate effects of print ads on the purchases for different segments. They find that responses to print ads, varies based on the segments. Another interesting study of Zinkhan (2002) explores internet promotion and recommends nine new ways of promotions. Bawa and Shoemaker (2004) have also explores the free sampling effect on repurchase. They find that acceleration, expansion and cannibalization effects vary widely based on the nature of the free sample promotions.

2.2.3.4 Summary of manufacturer to consumer promotions

The literature related to consumer promotions reveals that (Neslin 2002):

(1) Coupons appear to be in decline over a period of time. More research is needed to understand this trend.

(2) The research should also focus on understanding the implications of reward programs, rebates and targeted promotions.

2.3 Sales promotion theories

Econometric theories of sales promotions can be classified based on their orientation for sellers and customers. Seller oriented theories are that of Blattberg, Eppen and Lieberman (1981), Narasimhan (1988), and Blattberg and Neslin (1990) [1]. Customer oriented theories are proposed by Varian (1980), Narasimhan (1984), Jeuland and Narasimhan (1985) and Hann, Hui, Lee and Png (2005). Following is the brief description of each of the theories.

The theory proposed by Blattberg, Eppen and Lieberman (1981) takes the approach that sellers offer promotions to reduce their inventory holding costs and pass them to consumers. Thus, sellers benefit by reducing their holding costs, and consumers benefit by stockpiling for the increased or future consumption. If the holding cost of customers is not lesser than that of the retailers or sellers then promotions are not offered. Narasimhan (1988) proposes the theory that accounts for competitive reactions among sellers. If a seller offers regular discounts then competitors can match the deals to offset the net benefits. On the other hand, if sellers offer promotions randomly then the unexpected promotions may yield profits. Blattberg and Neslin (1990) take the approach of 'Prisoners' Dilemma' to explain a game theoretic model of sales promotions. According

[1] Though Blattberg and Neslin (1990) include theory of demand uncertainty of Lazear (1986) as one of the sales promotion theories (van Heerde 2001), it is not discussed here since our focus is on short term promotions. According to this theory under demand uncertainty firm offers high price initially for a period and then lowers the price to exploit the consumer reservation price to maximize the profits. Also, this section is intended to explain the existence of sales promotions and hence market equilibrium conditions are not discussed. Interested readers can refer to Varian (1980), Narasimhan (1984,1988) and Blattberg and Neslin (1990).

to this theory, promotions offered by a seller triggers counter promotions by competitors and subsequently everyone settles for a sub optimal solution.

Varian's (1980) theory of promotion is based on differential information among consumers. All the consumers do not have information about promotions offered due to search costs. Firms can offer promotions in occasional intervals so that informed consumers can buy and uninformed consumers have a disadvantage. Thus, firms can offer unexpected promotions to increase sales as consumers are looking for such promotions to minimize their search costs. The theories of Narasimhan (1984), and Jeuland and Narasimhan (1985) are based on price discrimination. It divides the consumers into low elastic and high elastic segments, which have low and high response functions to promotions respectively. Thus, firms can maximize profits by offering different prices to two different segments. Hann et al (2005) propose a general sales promotion theory. This is the extension of Varian's theory as it accounts for differential information and tests the assumption of customer acquisition. This study posits that if customers are acquired before setting price then the equilibrium is asymmetric else it is symmetric.

2.4 Empirical Generalizations

Empirical generalizations are: 'a pattern or a regularity that repeats over different circumstances and that can be simply described by mathematical, graphical, or symbolic methods' (Bass 1995, pg.G7). Empirical generalizations are covered under the headings of 'who gains from promotions?', 'from whom they gain?' and 'how they gain?' to imply their relevance to the decision makers.

2.4.1 Who gains from promotions?

It is widely known that promotions increase sales. However, to explore further insights as to which brands gain and to what extent, the relevant generalizations are discussed below.

2.4.1.1 Price-quality tiers exist and switching between them is asymmetric favoring high price-quality brands

This generalization is based on an agreement that brands belonging to a product-category can be classified into different price-quality tiers. By asymmetry of switching we mean, consumers' switching from low tier brands to a promoted high tier brand is more compared to switching from high tier brand to a promoted low tier brand (Blattberg, Briesch and Fox 1995). Blattberg and Wisniewski (1989) analyze product categories of Flour, Margarine, Bathroom tissue, Tuna based on 48 week UPC scanner data. They employ OLS regression for exponential function as implied by their model. It is one of the earlier studies to document such a phenomenon.

Krishnamurthi and Raj (1988, 1991) study frequently purchased product categories (Not mentioned) comprising of three major brands. They employ the data of 375 families over 7000 purchases of ADTEL diary panel. They analyze the data with MNL choice and 2-stage Least Squares for quantity. There study also supports that high price brands gain more from promotions than the low price brands. Other important studies are that of Cooper (1988), Kamakura and Russell (1989). These two studies indicate the existence of market power notion as an explanation for asymmetry. This means a brand with high market share has relatively higher power in comparison with a low share brand in attracting sales under discounting.

Table 2. Studies supporting price-quality tiers and asymmetric effect

Study	*Product category*	*Data*	*Methodology*
Blattberg and Wisniewski (1989)	Flour, Margarine, Bathroom tissue, Tuna	48 week UPC scanner data	OLS regression for exponential function form implied by their model
Krishnamurthi and Raj (1988)	Frequently purchased product categories (Not mentioned). Three major brands.	375 families over 7000 purchases of ADTEL diary panel	Combined model of MNL for choice and 2-stage LS for quantity.
(1991)	Frequently purchased product category and Ground coffee	BURKE panel data 52 weeks for households buying more than 15 times, and IRI UPC data of 105 weeks for households buying more than 20 times.	Combined model of MNL for choice and 2-stage LS for quantity.
Cooper (1988)	Ground caffeinated Coffee data	IRI BahaviorScan data from two cities for 18 months.	Regression and three mode factor analysis
Kamakura and Russell (1989)	Not mentioned	IRI data 78 weeks and 585 households	MNL for choice, LC for segmentation
Walters (1991)	Boxed cake mix, ready-to-serve frosting, Boxed spaghetti, ready-to-serve spaghetti sauce	Store level scanner data 26 weeks	OLS regression
Allenby and Rossi (1991)	Margarine	AC Nielsen ERIM scanner panel data. 9196 purchases 517 households.	Varying marginal substitution choice model (similar to nested logit)
Bemmaor and Mouchoux (1991)	Sparkling wine, Regular ground coffee, Liquid cleanser, Disposable diapers, Hair lacquer, Cat litter	Total of 144 observations.	Factorial Experimental design. Semi log and double log OLS estimates relating sales units with treatments.
Mulhern and Leone (1991)	Cake mix and Frosting	Store level scanner data 104 weeks	Regression of negative exponential function.
Vilcassim and Jain (1991)	Saltine crackers	IRI scanner data with 399 households and 4790 observations	Developed MLE for exponential hazard function proposed in the model.
Grover and Srinivasan (1992)	Ground coffee purchases	IRI scanner panel data for 450 households and two years.	MNL and Nested Logit
Sethuraman (1996)	Fabric Softener sheets	IRI scanner data 104 weeks between 1991-1993	Linear and non-linear seemingly unrelated regression

Table 2. Continued

Study	*Product category*	*Data*	*Methodology*
Bronnenberg and Wathieu (1996)	Chilled orange juice, Peanut butter	Secondary data, 3745 purchase occasions for orange juice, and 3758 choices for peanut butter	MNL
Sivakumar and Raj (1997)	Ketchup, Soup, Yogurt and Crackers	IRI scanner data 104 weeks	Nested Logit
Sethuraman, Srinivasan and Kim (1999)	19 grocery product categories	Meta analysis of earlier studies employing same data sets.	Regression of semi-log, double log and logit
Nowlis and Simonson (2000)	Different categories	399 students as subjects for survey	Factorial design of experiments
Wathieu, Muthukrishnan and Bronnenberg (2004)	Correction Pen category	172 respondents for the first and third experiments and 89 respondents for the second experiment.	Design of experiments

Walters (1991) and Allenby and Rossi (1991) employ quality as another important factor in explaining asymmetry. Allenby and Rossi (1991) build a varying marginal substitution model to accommodate asymmetry using the data of Margarine of AC Nielsen ERIM scanner panel data with 9196 purchases of 517 households.

Other important studies, which have also documented asymmetric effect, are Bemmaor and Mouchoux (1991), Mulhern and Leone (1991), Vilcassim and Jain (1991), Grover and Srinivasan (1992), Sethuraman (1996), Bronnenberg and Waithieu (1996), Sivakumar and Raj (1997) and Sethuraman, Srinivasan and Kim (1999). These studies have either employed the asymmetry of promotion effects in explaining their proposed theories or added one more support using a new product category. Table 2 summarizes these studies.

2.4.1.2 There exists synergy between different types of promotions and different price-quality tiers favoring low price-quality tiers

Earlier research had contradictory evidence about the signs of the interaction effects (i.e. if they are additive or subtractive) (Wilkinson, Mason and Paksoy 1982, Kumar and Leone 1988, Bemmaor and Mouchoux 1991). However, Lemon and Nowlis (2002) research clarifies that different promotions definitely have synergetic effects but differ based on the price-quality tiers. For example, studies have explored the interaction effects of price discounts, displays and end of aisle feature advertisements (Wilkinson, Mason and Paksoy 1982, Lemon and Nowlis 2002). In accordance with the generalization of asymmetry, low price-quality brands employing a single promotion gain less than the high price-quality brands. However, promotions employed simultaneously benefit low price-quality brands more than the high price-quality brands, there by offsetting the disadvantage of isolated single promotion offerings. Specifically synergies favor low price-quality brands (Bemmaor and Mouchoux 1991). In conclusion, high price-quality brands are better off with 'one promotion at a time' plan, while low price-quality brands gain comparable advantage by offering 'more than one promotions' simultaneously. Table 3 summarizes the relevant studies that have documented this phenomenon. However, none of these studies address simultaneous promotions of competing brands and how such scenarios may affect promotion elasticity estimates.

Table 3. Studies Supporting Synergy Between Promotions

Studies	*Product category*	*Data*	*Methodology*
Wilkinson, Mason and Paksoy (1982)	Camay soap, White house apple juice, Mahatma Rice, Piggly-Wiggly peas	In-store factorial experiment for 80 weeks in 5 stores of one city	ANOVA and ANCOVA

Table 3 Continued

Studies	*Product category*	*Data*	*Methodology*
Gupta (1988)	Ground coffee	IRI scanner panel data, 2000 households for two years	Erlang-2 for purchase timing, MNL for choice and ordered regression or cumulative logit for quantity
Kumar and Leone (1988)	Disposable diaper	Scanner data of 60 weeks and 10 stores	OLS regression for pooled data
Bemmaor and Mouchoux (1991)	Sparkling wine, Regular ground coffee, Liquid cleanser, Disposable diapers, Hair lacquer, Cat litter	Total of 144 observations.	Factorial design of experiments, conducted over 5 weeks. Semi log and double log OLS estimates relating sales units with treatments.
Papatla and Krishnamurthi (1996)	Detergents (powder and liquid form)	Ac Nielsen scanner data for Sioux Falls, South Dakota. 138 week panel, 1397 households and 14,082 purchases	Covariance probit with heteroskedastic variance and covariances
Lemon and Nowlis (2002)	Saltine crackers	IRI data 1984-85 of Williamsport, Midland and Rome, total of 27,768 observations for 2057 households	MNL
	Batteries, Ice cream, Ketchup and Portable Stereos	378 subjects	Factorial experiment. Logit model
	Batteries, Camera film, Ketchup and Toasters	491 subjects	Factorial experiment on the internet. Logit model

2.4.1.3 High market share brands are less deal elastic

Intuitively, this generalization means that high share brands are relatively less vulnerable to self and cross promotional effects than the low share brands. However, high share brands affect low share brands more than the reverse exhibiting the notion of 'market power' (Russell and Bolton 1988). This occurs due to low self / cross elasticity of high share brands (competitive clout) and high self / cross elasticity of low share brands (vulnerability) (Kamakura and Russell 1989). Further, the recent study on how consumers evolve their preferences (Heilman, Bowman and Wright 2002, Anderson and Simester 2004) also shows that consumers prefer the high market share popular brands more when they are new to the market. This reaffirms the market power notion.

On the other hand, if effects are measured in sales units then low share brands gain more sales from high share brands than vice versa. This phenomenon is termed as 'asymmetric share effect' (Sethuraman and Srinivasan 2002)[2]. In conclusion, studies imply that higher the market share of a brand, lesser the promotion gains it experiences and vice versa. This study questions market power notion of high share brands. This issue is addressed in chapter 4. Other important studies are Vilcassim and Jain (1991), Bemmaor and Mouchoux (1991), and Sethuraman and Srinivasan (2002).

Table 4. Studies Linking Low Promotion Effects to High Market Share

Studies	*Product category*	*Data*	*Methodology*
Kamakura and Russell (1989)	Not mentioned	IRI data 78 weeks and 585 households	MNL for choice, LC for segmentation
Bolton (1989)	Frozen waffles, liquid bleach, Bathroom tissue and Ketchup	IRI data 75 weeks of two cities and 12 stores	Weighted least squares estimation
Vilcassim and Jain (1991)	Saltine crackers	IRI scanner data with 399 households and 4790 observations	Developed MLE for exponential hazard function proposed in the model.
Bemmaor and Mouchoux (1991)	Sparkling wine, Regular ground coffee, Liquid cleanser, Disposable diapers, Hair lacquer, Cat litter	Total of 144 observations.	Factorial design of experiments, conducted over 5 weeks. Semi log and double log OLS estimates relating sales units with treatments.

[2] It is difficult to give a numerical example without introducing underlying mathematical equations. Thus, example is discussed in Chapter 2. These calculations will clarify that there is no contradiction with the notion of 'market power' according to this model, as the authors of the study claim.

Table 4. Continued

Studies	*Product category*	*Data*	*Methodology*
Chnitagunta, Jain and Vilcassim (1991)	Saltine Crackers for brands Sunshine, Keebler, Nebisco and Private Labels	IRI panel data for 135 panelists. Modeling purchases were 1736 and validation purchases were 1542.	Random Coefficient Logit Model
Sethuraman and Srinivasan (2002)	19 product categories, 280 brands	72 data sets for meta analysis	Dirichlet-multinomial choice model, tested with binary logit

2.4.2 From whom do promoted brands gain?

This subsection lists the empirical generalizations that imply which brands loose when a competing brand is promoted. These generalizations hold true when one or more of the brands offer promotions.

2.4.2.1 Brands that are closer in terms of price-quality, affect each other more than the brands that are farther apart:

The above generalization summarizes observed degree of substitution between brands when they are promoted. Specifically, brands that are deemed to be the close substitutes in terms of price and/ or quality affect each other more (Bronnenberg and Wathieu 1996). This is known as 'neighborhood price effect' (Sethuraman 1996). The Sethuraman, Srinivasan and Kim (1999) study reports a meta-analysis of neighborhood price effects and this phenomenon holds true when effects are measured both in terms of elasticity (elasticity calculations account for percentage change in sales to percentage change in price) and absolute effects (absolute effects account for unit change in sales to unit change in price). An important implication of this generalization is that promoted brands gain more switching from the competing brands that are in the same price-quality tier, than from those in different price-quality tiers. The details of each of these studies along with their data and analysis are described in table 5

However, note that in the study of Sethuraman, Srinivasan and Kim (1999), the price and market share of brands are highly correlated. Thus, it still remains a question, when correlation between price and share does not hold true, do the neighborhood price effects still hold true (Wedel and Zhang 2004). This also calls for investigating the effect of market share on neighborhood price effects.

Table 5. Studies supporting neighborhood effect

Studies	*Product category*	*Data*	*Methodology*
Rao (1991)	None	Conceptual, Assumed values	Game theory
Bronnenberg and Wathieu (1996)	Chilled orange juice, Peanut butter	Secondary data, 3745 purchase occasions for orange juice, and 3758 choices for peanut butter	MNL
Sethuraman (1996)	Fabric Softener sheets	IRI scanner data 104 weeks between 1991-1993	Linear and non-linear seemingly unrelated regression
Sethuraman, Srinivasan and Kim (1999)	19 grocery product categories	Meta analysis of earlier studies employing same data sets.	Regression of semi-log, double log and logit

To add, Bronnenberg and Wathieu (1996) show that both quality and positioning of the brands provides advantage to high quality tier brands to gain asymmetrically more from promotion than the low quality tier brands. In addition to this study, Hardie, Johnson and Fadher (1993) study on consumer preferences, also indicates that quality is an important explanatory variable in explaining the gain/loss under promotion. However the study of Sethuraman, Srinivasan and Kim (1999) does not account for the quality effects in concluding the neighborhood price effects. Thus, quality influence on neighborhood price effects has little evidence and still requires exploration. The research issues of effect of market share and quality on neighborhood price effects is explored in chapter 4 of this dissertation.

2.4.2.2 Promotions affect sales in complementary and competitive categories

Research on consumer 'purchase basket' shows that consumer spending across the complementary and competitive categories can be assumed to be constant for a considerable period of time (Manchanda, Ansari and Gupta 1999). As a consequence, brands under promotion attract sales from competitive or substitute categories due to their increased utility. The sales of the complementary categories also increase in a relatively smaller magnitude. Hence, competitive categories loose sales, resulting into category expansion i.e. increased sales for the category to which the promoted brand belongs, along with benefiting complementary categories. Walters and McKenzie (1988), Mulhern and Leone (1991) and Walters (1991) also provide support that there is some gain from cross- category effects.

Table 6. Studies supporting effect of promotions on complementary and competitive categories

Studies	*Product category*	*Data*	*Methodology*
Walters and McKenzie (1988)	Most available in grocery chain. Broad categories examples are: Rolls and Buns, Baking supplies, Paper products, prepared foods, coffee, carbonated soft drinks, laundry detergent and condiments	131 weeks of data from mid-western grocery retail chain.	MLE to estimate equations proposed by the model.

Table 6. Continued

Studies	*Product category*	*Data*	*Methodology*
Mulhern and Leone (1991)	Cake mix and Frosting	Store level scanner data 104 weeks	Regression of negative exponential function.
Walters (1991)	Boxed cake mix, ready-to-serve frosting, Boxed spaghetti, ready-to-serve spaghetti sauce	Store level scanner data 26 weeks	OLS regression
Manchanda, Ansari and Gupta (1999)	Laundry detergent, Fabric softener, Cake mixing and Cake frosting	AC Nielsen Data for 120 weeks from large metropolitan western chain	MCMC, hierarchical bayes

2.4.3 How do promoted brands gain?

According to research, promotion sales gain is composed of primary and secondary demand (Gupta 1988). Primary demand includes sales gain because of category expansion and increased purchase quantity. Secondary demand occurs due to switching. These generalizations describe the proportion of secondary demand in comparison with the primary demand and factors that influence the proportions.

2.4.3.1 Majority of the promotion gain comes from switchers i.e. secondary demand is more than the primary

As stated, secondary demand or gain due to switching from substitute brands is more (around 75%) than the gain due to category expansion or increased quantity (around 25%) (Bell, Chiang and Padmanabhan 1999). This effect is supported by many studies listed in table 7. Specifically, these studies have empirically shown that elasticity of switching is more than the category elasticity plus the purchase quantity elasticity and thus conclude that gain from switching is more (Sivakumar 2000).

On the other hand, decomposing the sales gain in terms of unit sales finds that secondary demand is relatively less important compared to the primary demand (Van Heerde, Gupta and Wittink 2003). Table 8 illustrates the example considered in Van Heerde, Gupta and Wittink (2003). According to their calculations unit sales gain due to switching from other brands is lower than the unit sales gain due to category expansion. The implication is that brands, when promoted, do not gain 75% of the unit sales from competing brands, though switching elasticity is around 75 %. However we argue that, for brand promotion decisions secondary demand would still be an important factor. We illustrate this point by extending the example of Van Heerde, Gupta and Wittink (2003). Following is the description of the calculations.

Table 7. Studies supporting secondary demand effect

Studies	*Product category*	*Data*	*Methodology*
Gupta (1988)	Ground coffee	IRI scanner panel data, 2000 households for two years	Erlang-2 for purchase timing, MNL for choice and ordered regression or cumulative logit for quantity
Chiang (1991)	Ground caffeinated coffee	IRI scanner panel data, 24 weeks 253 households	Nested logit for choice and MNL for 'how much to buy?'
Chintagunta (1993)	Yogurt	Ac Nielsen scanner panel data, 100 households, 5976 observations for estimation and 6780 for validation	Non-linear constrained programming for consumer basket, MNL for choice and non-linear equation developed in the model for quantity
Dillon and Gupta (1996)	Paper Towels	Survey data of 2500 households	Poisson purchase rate, multinomial quantity purchase and consideration choice set choice model.

Table 7 Continued

Studies	*Product category*	*Data*	*Methodology*
Walters and Bommer (1996)	302 brand across 89 categories	52 week scanner data	Multiple Regeression
Arora, Allenby and Ginter (1998)	Food item	Survey data	Hierarchical Bayes
Bucklin, Gupta and Siddarth (1998)	Yogurt	Ac Nielsen scanner panel data, 300 households, 30791 observations	MNL for choice, Nested Logit for incidence and Poisson regression for quantity
Bell, Chiang and Padmanabhan (1999)	Bacon, Margarine, Butter, Ice-cream, Paper towels, Sugar, Liquid detergents, Coffee, Soft drinks, Bath tissue, Potato chips, Dryer softeners and Yogurt.	IRI scanner panel data, 250 households, 78 weeks	Generalized Least Squares approach to meta analysis

Table 8. Comparison of promotion effects

Effects	*Before promotion*	*Product category expansion due to the promotion of focal brand (Calculations of Van Heerde et al 2003)*
Focal brand sales	36 units (18%)	45.2 units (21.8%)
Competing brands' sales	164 units (82%)	161.8 units (78.2%)
Category sales	200 units (100%)	207 units (100%)

Consider a brand under promotion, with its promotion elasticity decomposed into switching, category expansion (incidence) and quantity (Gupta 1988). Let the values for three elasticities be 0.210, 0.034 and 0.004 respectively. Total promotion elasticity adds up to 0.248. Thus, the secondary demand elasticity is 0.210/0.248 = 0.84 and primary demand elasticity is (0.034+0.004)/0.248=0.16. This means, if the brand goes for a 1%

change in a promotion mix variable, then it will increase its sales by 24.8%, out of which 84% comes from brand switching and 16% comes though category expansion and increased purchase quantity. This interpretation is consistent with Gupta (1988). Let the probability of selecting the focal brand be 18% and category sales be 200 units (Van Heerde, Gupta and Wittink 2003). The shares expressed in number of sales units are given in column-2 of table 8. Since quantity elasticity is very low, it was not included in the calculations of Van Heerde et al (2003). If the brand offers promotion, then it gains sales through primary and secondary demand. The probability of choosing the focal brand increases to 21.8%, which is (18% + 0.21 x 18%). Thus, the probability of choosing other brands in the category adds up to (100%- 21.8%) = 78.2%. Category sales increase to (200+ 0.034 x 200) = 207 units. The split of sales units when the brand goes on promotion are given in column-3 of table 8. Note that due to promotion, the increase in sales for the focal brand is (45.2-36) = 9.2 units. On the other hand the decrease in sales for rest of the brands in the category is (164-161.8) = 2.2 units. The gain of the focal brand due to promotion can be split as follows.

Gain in sales units = Gain due to category sales increase + Gain from switching. (1)

$$9.2 \quad = \quad 7 \quad + \quad 2.2$$

Van Heerde (2003) interpret the gain from switching as revealed by the above equation as: "The net decline is 24.3% of the 9.2 unit sales increase..". That is, 2.2 units decrease in the competing brands (i.e. other brands in the product category) sales accounts for the net secondary demand gain for the promoted brand, and it is 24.3% of its total gain of 9.2 units. Thus, the gain from switching is not 84% as interpreted by Gupta (1988), but is only 24.3% (Van Heerde et al. 2003). The Calculation of Van Heerde et al. (2003)

account for the simultaneous effect of category expansion on unit sales change unlike Gupta's interpretation.

2.4.3.2 Brand elasticities of promotion are influenced by category factors, brand factors and consumer factors

As mentioned earlier, promotional gains result due to switching increased purchase incidence and purchase quantity. Though secondary demand is more than the primary in terms of elasticity or potential unit sales, the proportion of secondary to primary demand depends on category factors, brand factors and consumer characteristics. Studies reveal that category factors explain most the variation in elasticities, followed by the brand factors and least by the consumer characteristics. Most influential category factors are amount spent on category or share of consumer budget, and storability of products (Bolton 1989; Bell, Chiang and Padmanabhan 1999).

Brand factors that influence the elasticities are price variability of brands within the category and brand loyalty. Consumer characteristics have negligible influence (Bell, Chiang and Padmanabhan 1999). Table 9 summarizes these studies. This generalization gives an idea to decision makers about the factors that may influence their promotion efforts, though managers may not be in control of category factors. Note that, the low elasticity of promotional efforts estimated by the Market Response models can be attributed to category and brand factors and might not be the limitation of models themselves.

Table 9. Studies supporting effect of category, brand and consumer factors on brand elasticities of promotion

Studies	*Product category*	*Data*	*Methodology*
Bolton (1989)	Frozen waffles, liquid bleach, Bathroom tissue and Ketchup	IRI data 75 weeks of two cities and 12 stores	Weighted least squares estimation
Fader and Lodish (1990)	331 different grocery product categories	IRI data for 20,000 households for one year from 12 different markets	Factor and cluster analysis for grouping category / promotion. DA for category influence
Fader and McAlister (1990)		200 panelists for 45 weeks	EBA and disaggregate MNL
Raju (1992)	27 categories	25 weeks from one grocery chain store	Linear and multiplicative regression
Narasimhan, Neslin and Sen (1996)	108 categories	Store level scanner data, panel data and survey data	Regression analysis
Bell, Chiang and Padmanabhan (1999)	Bacon, Margarine, Butter, Ice-cream, Paper towels, Sugar, Liquid detergents, Coffee, Soft drinks, Bath tissue, Potato chips, Dryer softeners and Yogurt.	IRI scanner panel data, 250 households, 78 weeks	Generalized Least Squares approach for meta analysis

2.5 Summary and Implications to Model Building

The following table summarizes the above discussion on empirical generalizations related to 'who gains?', 'from whom do promoted brands gain?' and 'how do promoted brands gain?' As discussed in chapter 1, following table links the anomalies in the empirical generalizations as brought out in chapter 2 with the respective essays.

Table 10. Summary of Research Issues and Implications on Model Building

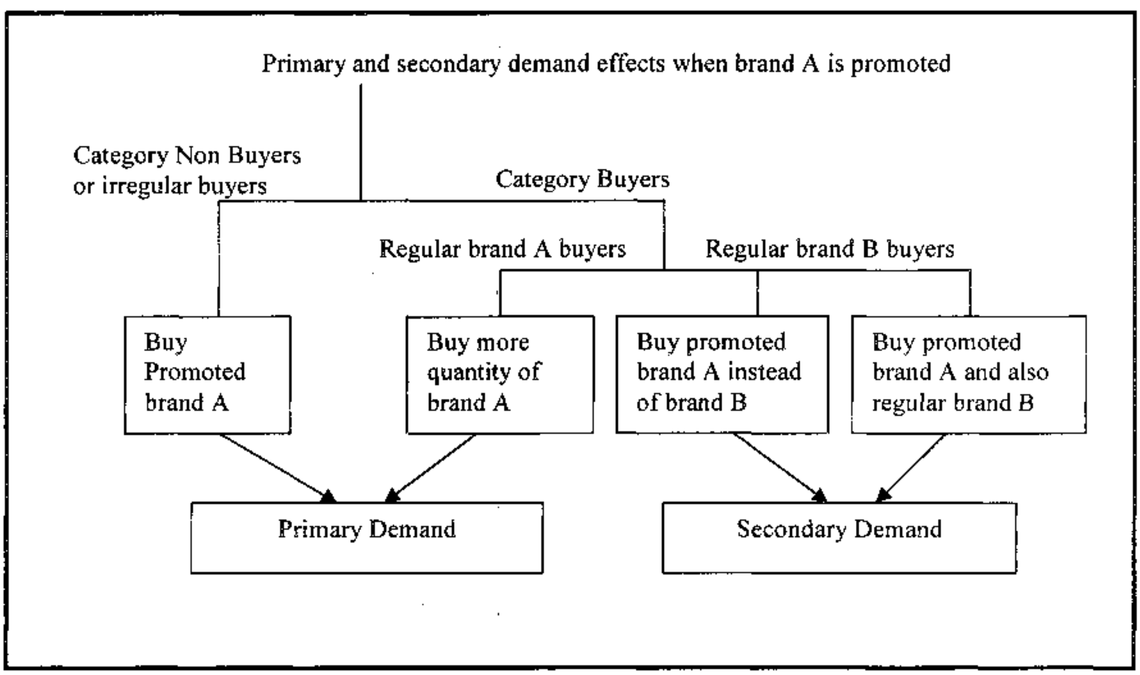
Who gains?	*From whom do promoted brands*	*How do promoted brands gain?*
• Simultaneous purchases • Market power notion • Asymmetric share effect	• Gain is more from those brands which are nearer in terms of price • Gain is mainly from relatively lower price-quality tiers than the higher	• Proportion of primary and secondary demand Conditions under which competing brands gain when target brand is under promotion are to be explored
	Implications on model building	
• Simultaneous brand choice model is adopted similar to Russell and Peterson (2000) • Covariance heterogeneity (CovHEV) model is adopted (Hensher 1994).	• The effect of market share and quality are expressed. • Modeling requires that either an HEV MNL (to overcome IIA) and/or CovHEV	• Algebra to calculate primary and demand effect
	Corresponding Chapters	
• Chapter 3 • Chapter 4	• Chapter 4	• Chapter 3

Chapter 3. Composition of Brand Switching and Increased Category Incidence Under Promotion Induced Competition

3.1 Introduction

Research shows that gains due to sales promotion come from increase in the category incidence, stockpiling and brand switching (Van Heerde, Gupta and Wittink 2003, Neslin 2002, Bell, Chiang and Padmanabhan 1999, Chintagunta 1993, Chiang 1991, Gupta 1988, Krishnamurthy and Raj 1988, 1991, Papatla and Krishnamurthy 1996, Bucklin, Gupta and Siddarth 1998). In marketing, an important issue of investigation has been the proportion of sales gain that comes from increased category incidence, increased quantity buying (together referred to as primary demand) and brand switching (i.e. secondary demand). Following figure depicts the primary and secondary demand effects.

Figure 3. Primary and Secondary Demand Effects



Let us assume that there are only two brands i.e. brand A and B. Diagram 1 depicts the purchase behavior of the consumers when a given brand, say brand A is promoted. Note that primary and secondary demand stem from various sources. Primary demand is composed of increase in the incidence due to non category buyers or irregular buyers buying brand A, along with the increased quantity bought by the brand A buyers. The secondary demand comes from brand switching, i.e. brand B buyers under the promotion of brand A find it more attractive than brand B and thus buy the promoted brand A. In addition to that, secondary demand is also contributed by the simultaneous purchases of brand A and B. For example, this may be happening because of the income effect (Allenby and Rossi 1991).

The dominant conclusion in marketing literature related to the sales gain under promotion has been that when measured in terms of elasticity, the secondary demand contributes more (75%) than the primary demand (25%). This conclusion follows from Gupta's (1988) work, which is further generalized by Bucklin, Gupta and Siddarth (1998) and Bell, Chiang and Padmanabhan (1999). Note that, purchase incidence and brand choice models are independent in Gupta's (1988) study. In contrast, Bucklin, Gupta and Siddarth (1998) employ nested logit for incidence & choice and Poisson regression for quantity. In this model choice is dependent on the incidence. However, the conclusion remains the same that secondary demand contributes 75% to brand sales gain, while primary demand contributes only 25%. On the contrary, Van Heerde, Gupta and Wittink (2003) employing Bucklin, Gupta and Siddarth's (1998) model to show that when the gains are expressed in terms of unit sales, the gain from secondary demand happens to be only 33%. Although, their calculations provide interesting insights on the promotion effects, the drawback in their calculation is the assumption that if a target brand is promoted, then its competing brands gain sales proportional to their choice probabilities due to the increased category incidence.

Such an analysis of primary and secondary demand effects is extremely important to marketers to manage promotional tactics and competitive effects. As discussed, though many studies have investigated this issue, there is still confusion surrounding the exact interpretation and the composition of sales gain under sales promotion. This study focuses on the following two research issues related to the composition of brand switching and increased category incidence:

(1) Do competing brands gain sales in the presence of the promotion of a focal brand?

The interpretations of Van Heerde, Gupta and Wittink (2003) follow from the nested logit specification. However, such an assumption of competing brands gaining under the promotion of a focal brand misrepresents the promotion effects, since this model does not account for the simultaneous brand purchases/choices in the category. Under the promotion of a focal brand, due to budget allocation/constraints or greater utility, consumers may buy more from the same category and this may benefit the competing brands. One possible reason is that, consumers buy more than one brands under the price promotion of a focal brand since they can afford to buy more in the category for the same budget due to the income effect (Allenby and Rossi 1991). However, such simultaneous choices are not explicitly accounted in the nested logit model of Bucklin, Gupta and Siddarth (1998). Thus, the calculations that follow from such a model as employed by Van Heerde et al (2003) do not capture the simultaneous choice effects. As Van Heerde, Gupta and Wittink (2003) mention (pp:489) "...(T)there is an opportunity to study whether and under what conditions non-promoted brands experience sales increases when a competing brand is promoted." On this account the interpretation of the proportion of primary and secondary demand needs further investigation and remodeling.

(2) What is the correct proportion of gain from brand switching and increased category incidence in terms of unit sales?

In the study of Van Heerde, Gupta and Wittink (2003), category incidence benefits every brand in proportion to its probability of choice due to nested logit specification. This study finds that for the couple of categories (Ice cream and Butter), the secondary demand (switching effect) is negative. The reasoning provided for the negative switching effect is that the extent of category expansion benefit for the competing brands is so high that it overcomes their switching losses to the focal brand.

However, note that, total utility of the category incidence is composed of brand utilities and category level variables. Now, in case of the nested logit specification under promotion, if utility of one of the brands increases then this leads to increase in the utility of incidence. Thus, increase in the choice of any one of the brands leads to the increased incidence. Accordingly, if the category expands it does not necessarily imply that such an increase is due to the increased probability of choice of all the brands in the category[3], since under promotion only the utility of the promoted brand increases. In conclusion, due to the promotion of a target brand if there is increased category incidence, then such an increase need not necessarily benefit all the brands in the category. Accordingly, the proportion of primary and secondary demand is miscalculated in the study of Van Heerde et al (2003). Thus, in accordance with the nested model, it is required to recalculate the proportion of primary and secondary demand effects.

This essay is organized as follows. Second section discusses the dominant conclusions in the literature related to the primary and secondary demand effects and elaborates on the research issues. Based on which the mathematical models and alternative explanation are discussed in the third section. The underlying assumptions of the existing models are hypothesized. Methodology is discussed in section four to test the hypothesis. Thereafter, the last section discusses the expected results and the contributions.

3.2 Measuring the Primary and Secondary demand effects under sales promotion

Sales S_j of a given brand j in the product category can be written as the product of category incidence probability p_c, probability of choice $p_{j/c}$ for brand j conditional on the category incidence, and quantity bought per purchase occasion Q_j (Van Heerde et al 2003). Thus, we have sales for brand j as:

$$S_j = p_c p_{j/c} Q_j \qquad (1)$$

The above model has the following assumptions:

(1) The brand choice decision is dependent on the category incidence decision i.e. $p_{c/j} = 1$ for $\forall j \in c$. Conceptually, this implies increase in the choice probability of any of the brands (not necessarily all the brands) in the category

[3] It is an implicit assumption that categories under investigation are not evolving and are stationary. Thus,

increases incidence probability. Conversely, since $p_{j/c} \neq 0$, for some $j \in c$, model implies that, there is certain probability with which each brand's choice may increase because of the increased category incidence.

(2) Also, as Van Heerde et. al. (2003) mention, cross quantity promotion effects are zero (For example studies of Bell, Chiang and Padmanabhan 1999, Chintagunta 1993, Chiang 1991 and Gupta 1988 assume the same) i.e. for the promotion of brand j the variation in the quantity bought for the other brands is zero. This follows from the fact that simultaneous purchases are not accounted in the nested logit specification.

Now, the sales elasticity of promotion d_{lj} can be written as follows:

$$\frac{\partial S_j}{\partial d_{lj}} \cdot \frac{d_{lj}}{S_j} = \frac{\partial p_c}{\partial d_{lj}} \frac{d_{lj}}{p_c} + \frac{\partial p_{j/c}}{\partial d_{lj}} \frac{d_{lj}}{p_{j/c}} + \frac{\partial Q_j}{\partial d_{lj}} \frac{d_{lj}}{Q_j}$$

$$\text{i.e.} \qquad \eta_s = \eta_c + \eta_{j/c} + \eta_Q \qquad (2)$$

Here, primary demand elasticity is $PD_e = \frac{\eta_c + \eta_Q}{\eta_s}$ and $SD_e = \frac{\eta_{j/c}}{\eta_s}$ is the secondary demand elasticity.

3.2.1 Calculations of Van Heerde et al (2003)

Now, from equations (1) and (2) the following assumption is evident. If the category incidence accelerates due to promotion d_{lj} of brand j, then from the total increased category incidence, every brand gains proportional to its choice probability $p_{k/c}$ $(k \in J$, where J is the total number of brands in the category $c)$. To illustrate this point, let us consider the numerical example discussed in Van Heerde et al (2003).

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increase in the incidence is solely due to the increased utilities of the promoted brands.

For Folgers 16(oz) coffee, η_s=0.248, $\eta_{j/c}$=0.210, η_c=0.034 and η_Q=0.004. Thus PD_e=0.16 SD_e= 0.84 (Gupta 1988). Initially, p_c=0.20 and purchase quantity Q_j per occasion is 1. Thus for 1000 purchase occasions there will be category sales of 200 units. Thus, if the Folgers market share is 18%, then their total sales units are 36. Now during the promotion the secondary demand would yield (0.21)*36= 7.6 units, leading the total unit sales of Folgers to 43.6. Other brands will have the share of (1-0.18(1.21))*200= 156.4 units. During this time category expands to (1.034)*200=207 units. Of those 7 units, the promoted brand will gain 1.6 units and the other brands will gain (1-0.218)*7=5.4 units. Thus, after the promotion total sales for Folgers would be around 45 units, while for the other brands it will be 162 units. Thus, the net unit sales gain for the promoted brand from secondary demand is only 2 units.

Above calculations are based on the assumption that category expansion due to promotion benefits all the brands in the category, in proportion to their choice probability (Van Heerde et al 2003). Let us refer to this assumption as "competitors' gain" assumption.

3.2.2 Illustration of the misrepresented effect due to competitors' gain assumption of nested logit model: The following example illustrates the misrepresentation of primary and secondary demand effects because of the "competitors' gain" assumption that is based on the nested models (assumption 1). Now, consider the following purchase history from table 11. If incidence occurs then it is considered as 1 else 0. Choice is represented by the name of the brand i.e. A or B. The final row represents the promotion variable, where 'Y' stands for promotion and 'N' for no promotion.

Table 11. Example of Purchases

Week	1	2	3	4	5	6	7	8	9	10
Incidences	1	0	1	0	1	2	0	1	3	0
Choice	A	-	A	-	A	B	-	A	A	-
Promotion	N	N	N	N	N	Y	N	N	Y	N

Note that, in nested logit model simultaneous purchases are not explicitly modeled. Thus, in such a model, secondary demand comes only from the switching effects. Thus, to keep the explanation intact, in the following example either brand A or brand B is purchased for a given incidence, but not both. Also it is assumed that quantity bought per occasion is one unit. While modeling the category incidence, the data considered takes the finite value for incidences and 0 for no incidence (row two). Under promotion (refer to row four), if there is category expansion and/or acceleration in incidence then it will be reflected in the elasticity measure of the incidence since the number of incidences increase. For instance, during the occasions 6 and 9 there is promotion event and incidence increases to 2 and 3. This increased incidence happens because of the increased acceleration in purchases i.e. due to more number of visits to the store to buy the promoted brand. At the same time note that, wherever there is incidence, it is translated into choice of either brand A or B (refer to row three) since both A and B are never bought together. Now for the occasions 6 and 9 incidence has increased only because of brand B and brand A respectively. Thus, if one were to decompose the incidence elasticity, it need not necessarily benefit both brands A and B whenever the incidence increases.

However, in the calculation of Van Heerde et al (2003), category incidence increases under the promotion and changes to 207 from 200. Also according to the nested specification, model is interpreted on 207 incidences that benefit all the brands according to the choice probabilities of the brands. As mentioned in assumption (1) of the nested modeling, this leads to "competitors' gain assumption". However, all the brands in the category would gain if and only if the category itself was evolving i.e. there are more consumers tunneling to the current market from the potential market (more non-buyers buying in the category). However, under sales promotion, category attraction increases only due to the increased utility of the promoted brand. Since, increased incidence need not stem from all the brands in the category, decomposing increased incidence to benefit all the brands in the category under sales promotion misrepresents the primary and secondary demand effects. In such cases, the incidence effect should be decomposed based on the increase/decrease in the utilities of all the brands in the category.

3.2.3 Effect of the simultaneous purchases on competitor's gain assumption: Under simultaneous purchases it is possible for the consumers to buy more than one brands in a given occasion. Thus, if the model were built to account for the simultaneous purchases then it would accommodate both the sources of secondary demand as mentioned in diagram 1. Further, if such a model were employed then the competitors' gain assumption may hold true for few brands, since the cross elasticity under such cases need not necessarily be always negative (Russell and Petersen 2000).

3.3 Alternative Explanations

In this section the two research issues of competitors' gain assumption and exact calculation of primary/secondary demand are addressed. The first research issue of testing the competitors' gain assumption is addressed in three different models. First explanation is based on the unconditional brand choice, second one is based on the nested logit model i.e. conditional choice and the third one is explained based on the simultaneous choice model. After which the exact calculation of primary and secondary demand are addressed.

3.3.1 Testing the competitors' gain assumption

Three alternative explanations are provided to test competitors' gain assumption. Table 12 summarizes the methods.

Table 12. Alternative Models

Method	*Mathematical Proof*	*Empirical Proof*
Unconditional brand choice	Yes	No
Conditional brand choice	Yes	Yes
Simultaneous brand choice	Yes	Yes

By "unconditional brand choice" it is meant that brand choice does not depend on the category incidence, but rather it is viewed that incidence and choice occur simultaneously. In this case multinomial logit (MNL) is employed. Conditional choice means choice is viewed as conditional on incidence. Here, nested logit model is employed. Finally, for the simultaneous choices the nested logit is employed, but the alternatives are the combination of choices from the available alternatives. Note that, unconditional model is proposed for the purpose of theoretical explanation alone. Estimation of such model would require specifying the no choice option, which biases the results (Haaijer 1999). Thus the empirical proof is provided only for the conditional and simultaneous choice models.

3.3.1.1 Unconditional brand choice

This section explains the competitors' gain assumption based on the unconditional brand choice. Now, based on equation (1) it is evident that p_c and $p_{k/c}$ (where $k = 1..J$), are built on the same purchases since brand choice and category incidence occur simultaneously. To account for simultaneity, p_c and $p_{j/c}$ should be considered together in deriving the elasticity equation. This can be stated as:

$$\frac{\partial S_j}{\partial d_{lj}} . \frac{d_{lj}}{S_j} = \frac{\partial p_c p_{j/c}}{\partial d_{lj}} . \frac{d_{lj}}{p_c p_{j/c}} + \frac{\partial Q_j}{\partial d_{lj}} . \frac{d_{lj}}{Q_j}$$

$$= \frac{\partial p_j}{\partial d_{lj}} . \frac{d_{lj}}{p_j} + \frac{\partial Q_j}{\partial d_{lj}} . \frac{d_{lj}}{Q_j} \qquad (3)$$

Note that, $p_c p_{j/c} = p_{c/j} p_j = 1.p_j = p_j$, which is the unconditional probability of brand j, that can be considered as being modeled based on the no-choice option calibrated to the purchase data or conditional on the store visits (Chib, Seetharaman and Strijnev 2004, Bucklin, Gupta and Siddarth 1998, Chintagunta 1993). Note that, $\frac{\partial p_j}{\partial d_{lj}}$, contains both category incidence acceleration and brand switching effects. We have:

$$p_o + p_c = \sum_{\substack{k=1 \\ k \neq j}}^{J} p_k + p_j + p_o$$

$$1 = \sum_{\substack{k=1 \\ k \neq j}}^{J} p_k + p_j + p_o$$

$$0 = \sum_{\substack{k=1 \\ k \neq j}}^{J} \frac{\partial p_k}{\partial d_{lj}} + \frac{\partial p_j}{\partial d_{lj}} + \frac{\partial p_o}{\partial d_{lj}} \tag{4}$$

In this case, $p_c = \sum_{k=1}^{J} p_k$, where J is the total number of brands, and p_o is the probability of no-incidence. Thus, marginal change in the category incidence can be found using the following relationship:

$$\frac{\partial p_c}{\partial d_{lj}} = \sum_{k=1}^{J} \frac{\partial p_k}{\partial d_{lj}}$$

$$= \sum_{\substack{k=1 \\ k \neq j}}^{J} \frac{\partial p_k}{\partial d_{lj}} + \frac{\partial p_j}{\partial d_{lj}} \tag{5}$$

For the promotion d_{lj} of brand j, the expected sign of the term $\sum_{\substack{k=1 \\ k \neq j}}^{J} \frac{\partial p_k}{\partial d_{lj}}$ will be negative, while the term $\frac{\partial p_j}{\partial d_{lj}}$ will be positive. This formalization clearly indicates that if the category incidence accelerates then the promoted brand gains while the competing brands loose. This happens since category incidence is expressed in terms of the additive composition of the brands. Also, category incidence is expected to be positive since $\frac{\partial p_o}{\partial d_{lj}}$, the change in the probability of no-choice option or no-category incidence will most likely be negative i.e. category non-buyers may buy under the promotion of any one of the brands in the category as explained in figure 3.

3.3.1.2 Conditional brand choice i.e. nested logit specification

In this section, the explanation for competitors' gain assumption is addressed based on the nested logit specification as employed by Van Heerde et al (2003).

Let us assume that, increased incidence during the promotion d_{lj} of brand j affects all the brands in the category. The increased incidence attributable to brand $k \in c$, is the change in the incidence due to change in the probability of choice of brand $k \in c$, multiplied by the change in the choice probability of brand $k \in c$, under the promotion d_{lj} of brand j. Mathematically, change in the incidence I due to brand k, under the promotion d_{lj} of brand j is:

$$I_{kj} = \frac{\partial p_c}{\partial p_{k/c}} \cdot \frac{\partial p_{k/c}}{\partial d_{jl}}$$

Here, $p_c = \dfrac{\exp(\boldsymbol{\gamma}\mathbf{Z} + \gamma_{IV} IV)}{1 + \exp(\boldsymbol{\gamma}\mathbf{Z} + \gamma_{IV} IV)}$, $p_{k/c} = \dfrac{\exp(\boldsymbol{\beta}^T \mathbf{D}_k)}{\sum_{j=1}^{J} \exp(\boldsymbol{\beta}^T \mathbf{D}_j)}$, and $IV = \ln\{\sum_{j=1}^{J} \exp(\boldsymbol{\beta}^T \mathbf{D}_j)\}$.

Here IV is the sum of the utilities of all the brands in the category.

$$\frac{\partial p_c}{\partial p_{k/c}} = \frac{\dfrac{\partial p_c}{\partial \exp(\beta^{\mathrm{T}} \mathbf{D}_k)}}{\dfrac{\partial p_{k/c}}{\partial \exp(\beta^{\mathrm{T}} \mathbf{D}_k)}} = \gamma_{IV} \cdot \frac{p_c(1 - p_c)}{(1 - p_{k/c})} = \gamma_{IV} \cdot \frac{p_c p_o}{(1 - p_{k/c})}$$

$$\frac{\partial p_{k/c}}{\partial d_{lj}} = -\beta_l p_{k/c} p_{j/c} \text{ and } \frac{\partial p_{j/c}}{\partial d_{lj}} = \beta_l p_{j/c}(1 - p_{j/c})$$

$$=> \quad I_{kj} = \gamma_{IV} \cdot \frac{p_c p_o}{(1 - p_{k/c})} \cdot (-\beta_l p_{k/c} p_{j/c})$$

$$= -\gamma_{IV} . \beta_l \frac{p_o p_j p_{k/c}}{(1 - p_{k/c})}$$

$$I_{kj} = -\gamma_{IV} . \beta_l \frac{p_o p_j p_k}{(p_c - p_k)} \tag{6}$$

$$\text{and } I_{jj} = \gamma_{IV} . \beta_l p_c p_o p_{j/c} = \gamma_{IV} . \beta_l p_o p_j \tag{7}$$

$$\text{Thus, } I_{kj} = -I_{jj} . \frac{p_{k/c}}{(1 - p_{k/c})} \tag{8}$$

The effect from switching for brand k under the promotion is d_{lj} of brand j is:

$$B_{kj} = \frac{\partial p_k}{\partial d_{lj}} - I_{kj} \tag{9}$$

Based on the alternative explanation provided for the marginal change in the category incidence due to the change in the brand choice probability, the proposed hypothesis is that:

H0: $I_{kj} = -\gamma_{IV} . \beta_l \frac{p_o p_j p_k}{(p_c - p_k)} \geq 0$, for promotion d_{lj} of brand j,

$\Rightarrow$ H1: $I_{kj} = -\gamma_{IV} . \beta_l \frac{p_o p_j p_k}{(p_c - p_k)} \leq 0$ is the alternative hypothesis.

Intuitively the null hypothesis states that change in the category incidence contributed by the change in the probability of choice of a competing brand is positive.

3.3.1.3 Simultaneous brand choices in the category

This section explores the competitors' gain assumption employing simultaneous purchase choice i.e. multivariate choice model. The multi-category purchase model of Russell and Peterson (2000) is employed. This model is based on the Besag's (1974) spatial model which states that given the full conditional distributions of the random variables, their joint distribution can be determined uniquely, provided the uniqueness criteria are satisfied. Russell and Peterson (2000) employ multivariate logit formulation of full conditional probability of the categories. They exploit Besag's (1974) theorem to derive the multivariate logit formulation of the multi-category purchases. This model is better than the models of McAlister (1979) and Harlam and Lodish (1995), since it has the capability to uniquely determine the joint distribution since it is built on the full conditional distributions. Russell and Peterson (2000) model is applied to multiple brand choices. All the non-empty simultaneous choices are nested under the category incidence. The empty set is considered as the no incidence option similar to Russell and Peterson (2000).

Thus, if there are J brands in the category then there are (2^J-1) non-empty combinations of choices. Each of these combinations is treated as an alternative while specifying the MNL choice model. The utility of each such alternative b for the occasion t for household h is:

$$U_{bt}^{h} = \sum_{J} \beta^{\mathrm{T}} \mathbf{X}_j I_j + \sum_{j<i} \theta_{ij} I_i I_j \tag{10}$$

Here, X_j is the vector of marketing mix variables of brand j, $\theta_{ij} = \delta_{ij} + \phi SIZE^h$, and $I_j = 1$ if j^{th} alternative is present in the combination b else is 0. The $SIZE^h$ is the size loyalty variable calculated from the calibration period. This remains same for all the alternatives across all the occasions for a given household h. The term δ_{ij} captures the association between the brands, which is symmetric to satisfy the Besag's (1974) criterion to determine the joint distribution uniquely. If more than one brand are chosen then

θ_{ij} appears in the utility. Based on the utility function and following the MNL framework the probability of choice for the combination of choices b is:

$$p_{b/c} = \frac{\exp(\boldsymbol{\beta}^T \mathbf{X}_b + \sum_{i<j} \theta_{ij} I_i I_j)}{\sum_{2^J-1} \exp(\boldsymbol{\beta}^T \mathbf{X}_b + \sum_{i<j} \theta_{ij} I_i I_j)} \tag{11}$$

Here, $p_{b/c}$ is the probability of choosing a combination of choices b given the incidence c.

The probability of choosing a brand k is: $\frac{\sum_{\forall b \in \text{brand } k} U_{bk}^h}{\sum_{\forall b} U_{bk}^h}$. It can be easily shown that even in this case the derivative $\frac{\partial p_c}{\partial p_{k/c}}$ is $\gamma_{IV} \cdot \frac{p_c p_o}{(1 - p_{k/c})}$. However, based on the cross and self elasticities (Russell and Peterson 2000) the marginal changes are:

$$\frac{\partial p_{k/c}}{\partial d_{lj}} = \beta_l p_{j/c} p_{k/c} \left(\frac{p_{kj/c}}{p_{j/c} \cdot p_{k/c}} - 1\right) \text{ and } \frac{\partial p_{j/c}}{\partial d_{lj}} = \beta_l p_{j/c} (1 - p_{j/c}) \tag{12}$$

Thus,

$$I_{kj} = \frac{\partial p_c}{\partial p_{k/c}} \cdot \frac{\partial p_{k/c}}{\partial d_{jl}} = \gamma_{IV} \cdot \frac{p_c p_o}{(1 - p_{k/c})} \cdot \beta_l p_{j/c} p_{k/c} \left(\frac{p_{kj/c}}{p_{j/c} \cdot p_{k/c}} - 1\right) \tag{13}$$

And

$$I_{jj} = \frac{\partial p_c}{\partial p_{j/c}} \cdot \frac{\partial p_{j/c}}{\partial d_{jl}} = \gamma_{IV} \cdot \frac{p_c p_o}{(1 - p_{j/c})} \cdot \beta_l p_{j/c} (1 - p_{j/c}) \, . \tag{14}$$

Equation (13) will be employed to test the assumption of competitors' gain. Note that the cross elasticity in this case is need not necessarily be always negative. Based on the explanation provided for the marginal change in the category incidence due to the change in the brand choice probability, the proposed hypothesis is that:

H0: $I_{kj} = -\gamma_{IV} \cdot \beta_l \frac{p_c p_o}{(1 - p_{k/c})} \cdot p_{j/c} p_{k/c} \left(\frac{p_{kj/c}}{p_{j/c} \cdot p_{k/c}} - 1\right) \geq 0$, for promotion d_{lj} of brand j,

$\Rightarrow$H1: $I_{kj} = -\gamma_{IV} \cdot \beta_I \frac{p_c p_o}{(1-p_{k/c})} \cdot p_{j/c} p_{k/c} (\frac{p_{kj/c}}{p_{j/c} \cdot p_{k/c}} - 1) \leq 0$ is the alternative hypothesis.

Intuitively the null hypothesis states that change in the category incidence contributed by the change in the probability of choice of a competing brand is positive.

3.32 Calculation of increased category incidence and brand switching effects

3.3.2.1 For conditional brand choice

The summation of equation (6) for all the competing brands along with equation (7) provides the total primary effect. The self elasticity will give the secondary demand effect.

3.3.2.2 For simultaneous choice

The summation of equation (13) for all the competing brands along with equation (14) provides the total primary effect. The self elasticity will give the secondary demand effect.

3.4 Data, Estimation and Results

3.4.1 Data description

IRI panel data for margarine category (includes spreads and butter blends as well) is employed. Data has 52 weeks of initialization period from January to December 2005 and 52 weeks of modeling period from January to December 2006. Following table summarizes the data. In this category, one pound is the prominent brand size and accounts for 82% of the category share[4]. The top 5 brands in this size are selected, which make up for 65.66% of the 1lb total share. Data are analyzed for 100 randomly selected

[4] The size of 0.9375 LB is combined with 1 LB since there is hardly any price difference between these sizes. Totally this size accounts for 82% of the category share.

panelists from Eau Claire, Wisconsin area who constitute 1098 purchase occasions across 5 stores. This method of selecting the brands and panelists is consistent with the research method followed in marketing. For example Chintagunta (1993) and Bucklin, Gupta and Siddarth (1999) follow the similar method. Table 2 summarizes the data.

Table 13. Data Description

*Brand**	*Market Share (%) From modeling data*	*Avg. Price per Unit($) From modeling data*	*Probability of incidence*
1	32.15	1.5977	0.19
2	28.69	0.7069	
3	21.31	1.2667	
4	4.74	1.3493	
5	13.11	1.7781	

3.4.2 Variables employed in the model

The variables considered are similar to that of Bucklin, Gupta and Siddarth's (1998) study. They are:

1. Brand Loyalty (BL_k): This variable is calculated based on the initialization period. The market share of the brand for a household during the initialization period stands for BL_k for brand k. This variable remains constant for a household across the modeling time period.
2. Last Brand Purchased (LBP_{kt}): LBP_{kt} indicates the brand purchased during the last occasion t. This remains same across all the alternatives for a given occasion for a given household.
3. Price ($PRICE_{kt}$): This variable is the shelf-price of the brand k on occasion t, which also includes discounted prices.

4. Promotion ($PROMO_{kt}$): This variable takes the value 1 if there is feature or display otherwise is equal to 0. This varies across the brands across the occasions.

The incidence level variables are:

5. Consumption rate (CR): This remains same for the household across the modeling period. This is calculated based on the total volume of product bought for the 61 weeks of initialization period.
6. Inventory (INV_t): This variable captures the inventory level of the household on the purchase occasion t.
7. IV: This is the inclusive value variable that captures the total utility of all the brands in the nest.

Thus, the deterministic component of the utility of brand k is for a given household h is:

$$\beta^T \mathbf{x}_j = u_{ks} + \beta_{s1} BL_{kt}^h + \beta_{s2} LBP_{kt}^h + \beta_{s3} PRICE_{kt}^h + \beta_{s4} PROMO_{kt}^h \tag{16}$$

The errors are assumed to be extreme value type- IIDs. This leads us to:

$$p_{kt/c}^h = \frac{\exp(\beta^T \mathbf{X}_k)}{\sum_{j=1}^{J} \exp(\beta^T \mathbf{X}_j)} \tag{17}$$

The deterministic part of the incidence utility is:

$$U_{ct}^h = u_{cs} + \gamma_{s1} CR_t^h + \gamma_{s2} INV_t^h + \gamma_{IV} IV_t^h \tag{18}$$

The probability of incidence is:

$$p_{ct}^h = \frac{\exp(U_{ct}^h)}{1 + \exp(U_{ct}^h)} \tag{19}$$

The quantity is also modeled similar to Bucklin, Gupta and Siddarth (1998). The probability that household h buys q_j quantity of brand j at time t is given by:

$$P(Q^h{}_{jt} > q_{jt}) = \frac{\exp(-\lambda_{jt}) \lambda_{jt}^{q_{jt}}}{(1 - \exp(-\lambda_{jt})) q_{jt}!} \tag{20}$$

Here, $\lambda_{jt} = \exp(\theta_{j0} + \theta_{j1} BL + \theta_{j2} PROMO + \theta_{j3} PRICE + \theta_{j4} INV + \theta_{j5} PR)$ (21)

The model of Van Heerde, Gupta and Wittink (2003) and Bucklin, Gupta and Siddarth (1998) employ latent class estimation of the incidence, choice and quantity. Since the objective of this step is to test the assumption for the same model, the log-likelihood function for one segment model MLE results into nested logit MLE (Gupta and Chintagunta 1994, Bucklin, Gupta and Siddarth 1998). This holds true for the simultaneous choice model as well. The objective is to test if the competitors' gain assumption holds true and thus only one segment nested logit case is analyzed.

3.4.3 Estimation

The log-likelihood for the proposed model is:

$$LL_1 = \sum_{h=1}^{H}\sum_{t=1}^{T}\{\delta_i[\gamma^T \mathbf{Z} - \ln(1+e^{\gamma^T \mathbf{Z}})] - (1-\delta_i)\ln(1+e^{\gamma^T \mathbf{Z}})\} \tag{22}$$

$$LL_2 = \sum_{h=1}^{H}\sum_{t=1}^{T}\sum_{j=1}^{J}\{\delta_j[\beta^T \mathbf{x_j} - \ln(\sum_{j=1}^{J} e^{\beta^T \mathbf{x_j}}) - \lambda_j + q_j \ln \lambda_j - \ln(1-e^{-\lambda_j}) - \ln(q_j!)]\} \tag{23}$$

$$LL = LL_1 + LL_2 \tag{24}$$

Following table summarizes the estimates:

Table 14. Estimated Coefficients for conditional choice

Choice Model									
Coefficient	*LBP*	*BL*	*PROMO*	*PRICE*	*u1*	*u2*	*u3*	*u4*	*u5*
Estimate	3.027	0.929	0.398	-0.95	0.69	-0.44	-0.19	-0.51	0.75
Std. Error	0.001	0.008	0.039	0.005	0.003	0.009	0.012	0.025	0.001

Table 14 Continued

Incidence Model										
Coefficient	*Uc*	*CR*	*IV*							
Estimate	-1.967	0.487	0.091							
Std. Error	0.231937	0.047098	0.088765							
Model Fit										
Brand	*1*	*2*	*3*	*4*	*5*					
Actual Probability	0.3215	0.2869	0.2131	0.0474	0.131					
Predicted Probability	0.357	0.279	0.167	0.048	0.149					
Incidence	Yes	No								
Actual Probability	0.19	0.81								
Predicted Probability	0.191	0.809								
LL -Model	-4451.9									
LL0	-12511.8									
Pseudo ρ^2	0.6441									

Table 14 demonstrates that actual and predicted probabilities for choice and incidence are very close with McFadden's R^2 of 0.64. This demonstrates that model has excellent fit. The quantity model is not relevant for the study and thus the coefficients are not reported[5]. For the simultaneous choice model table 15 summarizes the results. Note that in this model fit 0.466 is slightly lower than the conditional choice model. All the combinations of the five brands are considered, which makes up for 31 brands. These are listed in column four of table 15 along with the actual and predicted probabilities for the choice and incidence model.

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[5] Additionally, the quantity model was calibrated for λ's without the exponent of the variables, unlike equation (21). However, given the model fit it appears that model may not change much even with the exponential correction.

Table 15. Estimated Coefficients for conditional simultaneous choice

Choice Model			*Model Fit*				
Coefficient	*Estimate*	*SE*	*brand*	*Actual probability*	*Predicted probability*	*Actual Probability of incidence*	*Predicted probability of incidence*
b1	-2.69552	0.0005	1	0.30080	0.34401	0.19	0.18
b2	-3.29941	0.0047	2	0.27040	0.30156		
b3	-3.48888	0.0018	3	0.21060	0.14915		
b4	-3.90649	0.0040	4	0.04550	0.03648		
b5	-2.52992	0.0008	5	0.13090	0.15306		
b12	2.786477	0.0051	12	0.02370	0.00270		
b13	1.95288	0.0040	13	0.00850	0.00152		
b14	-2.21512	0.0013	14	0.00090	0.00091		
b15	-1.8979	0.0008	15	0.00090	0.00285		
b23	0.419349	0.0092	23	0.00000	0.00131		
b24	1.729162	0.0028	24	0.00190	0.00080		
b25	0.907866	0.0022	25	0.00280	0.00249		
b34	2.174253	0.0054	34	0.00090	0.00047		
b35	1.66366	0.0062	35	0.00190	0.00148		
b45	1.564865	0.0077	45	0.00000	0.00091		
LBP	1.066988	0.0033	123	0.00000	0.00004		
BL	3.619673	0.0157	124	0.00000	0.00002		
promo	0.444607	0.0022	125	0.00000	0.00007		
price	-0.55043	0.0065	134	0.00000	0.00001		
Incidence Model			135	0.00000	0.00004	*Fit diagnostic*	
Coefficient	*Estimate*	*SE*	145	0.00000	0.00003	LL-Model	-4542
C	-1.63514	0.0017	234	0.00000	0.00001	LL0	-8507.586
CR	0.477571	0.0042	235	0.00000	0.00004	Pseudo R^2	0.466124
IV	0.071134	0.0234	245	0.00000	0.00002		
			345	0.00000	0.00001		
			1234	0.00000	0.00000		
			1235	0.00000	0.00000		
			1245	0.00000	0.00000		
			1345	0.00000	0.00000		
			2345	0.00000	0.00000		
			12345	0.00000	0.00000		

3.4.4 Results

Based on the above coefficients the elasticities for incidence are calculated using the equations (6) and (7) for the conditional choice model and equations (12) and (13) are used for the simultaneous choice models. Table 16 lists all the marginal effects of incidence and the net elasticity for the incidence along with the change in unit sales for price promotion.

Table 16. Deal Effects and Elasticities for Price

Conditional Choice					
Brand	*1*	*2*	*3*	*4*	*5*
1	0.0048	-0.0021	-0.0012	-0.0004	-0.0011
2	-0.0019	0.0037	-0.0009	-0.0003	-0.0008
3	-0.0010	-0.0007	0.0022	-0.0001	-0.0004
4	-0.0002	-0.0002	-0.0001	0.0006	-0.0001
5	-0.0008	-0.0007	-0.0004	-0.0001	0.0020
Net Marginal Effect	0.0009	0.0001	-0.0004	-0.0002	-0.0004
Incidence Elasticity	0.0075	0.0003	-0.0025	-0.0015	-0.0036
Unit sales change per 1000 units	39.2986	1.3170	-13.0125	-7.6027	-18.7639
Conditional Simultaneous choice					
Brand	*1*	*2*	*3*	*4*	*5*
1	0.0022	-0.0012	-0.0006	-0.0002	-0.0005
2	-0.0011	0.0020	-0.0005	-0.0002	-0.0005
3	-0.0004	-0.0004	0.0010	-0.0001	-0.0002
4	-0.0001	-0.0001	-0.0001	0.0003	-0.0000
5	-0.0004	-0.0004	-0.0002	-0.0001	0.0010
Net Marginal Effect	0.0001	-0.0001	-0.0003	-0.0001	-0.0003
Incidence Elasticity	0.0008	-0.0003	-0.0024	-0.0010	-0.0031
Unit sales change per 1000 units	4.4790	-1.7153	-13.4991	-5.8642	-17.2084

The value 0.0048 in column two and row three of table 6 indicates the marginal incidence change due to the promotion of brand 1. The ninth row indicates the net marginal change in incidence under the promotion of brand 1. The tenth and eleventh rows give total incidence elasticity and change in the unit sales if category sales were 1000 units under the promotion of brand 1. . The incidence elasticity is 0.0075. The value 38.29 indicates that under the promotion of brand 1 the net change in the incidence is 38.39 units if the total category sales were 1000 units. Further, it is evident from the rows four to seven of the column two that none of the marginal changes in the incidence because of the competing brands is positive. Similar interpretations hold true for conditional brand choice model. Note that the joint probability of occurrence of any pair of brands is not so high as to increase sales of the competing brands under the promotion of a focal brand. Since, based on the test of proportions P-value for the competing brands greater than or equal 0 is almost 0 the hypothesis that competing brands gain under the promotion of a focal brand is not supported for both the conditional and simultaneous choice models. Thus for the given category competitors' gain assumption does not hold true.

3.5 Implications and discussions

3.5.1 Academic contributions

This dissertation focuses on the increased category incidence and brand switching effects under promotion. The method of calculating the incidence change under the promotion of a given brand in the category is developed. Two alternative methods are employed to test if the competing brands gain under the promotion of a focal brand as employed in the calculations of Van Heerde, Gupta and Wittink (2003). Results indicate that, for the given category of margarine such an assumption does not hold true.

The incidence elasticities for different brands provide several interesting insights. Firstly, note that for the brands three, four and five the net unit sales change is negative. Accordingly, the incidence elasticities are also negative for the low share brands indicating that category utility decreases when low share brands go for promotion. This happens since, high share brand consumers switch to promoted brand and as a consequence high share brands do not attract the same level of consumers from outside the category. Further, the results also contradict the competitors' gain assumption as employed by Van Heerde, Gupta and Wittink (2003) in two aspects. They are, (1) the category elasticity does not benefit all the brands in the category when any of the brands in the category is promoted and (2) increase in the incidence for the promoted brand accounts for the incidences attributed to switching (which otherwise would have gone for the competing brands) and incidences from non-buyers. First aspect clearly demonstrates the violation of competitors' gain assumption. While the second aspect brings out the fact that even though net category increment is positive, competing brands do not necessarily benefit from it.

Secondly, when the simultaneous conditional choice model is employed, the competing brands may gain because of the incidence under the promotion of a focal brand if the joint probability of the competing brand with the focal brand p_{ij} is significantly high, i.e. $p_{ij} > p_i\, p_j$. If this condition is not satisfied then competing brands do not gain from the incidences under the promotion of a focal brand. Thirdly, if the joint probability for a set of brands is observed then the elasticities implied by the simultaneous choice models is different than that of the conditional choice model for these brands. For example brands 1 and 2 have quite a few simultaneous choices with the other brands. Their elasticities for the incidence according to table 6 are different for the simultaneous choice case than that of the conditional choice. However, for the other brands i.e. 3,4 and 5 the elasticities are comparable.

3.5.2 Managerial Implications

The results of this study have several interesting managerial implications. Most important among them is the observation that category elasticity decreases under the promotion of a low share brand. Interestingly, this explains why retailers practice cross-brand pass through (Besanco, Dube and Gupta 2006). When low share brands get trade deals retailers pass through the benefits to consumers, but at the same time they also promote the high share brands in the category, leading to cross-brand pass through. Given the empirical evidence in this study, it appears that retailers indeed loose category sales if they do not promote high share brands along with the low share brands. This implies that low share brand managers do not benefit much because of the trade deals.

Second important implication is that, if the low share brand is positioned in the category so that it gets tagged with the high share brands during the simultaneous purchases then it benefits from the promotion of a high share brand. In the analyzed category around 4% of the sales are because of the simultaneous purchases. These simultaneous purchases include either brand 1 or brand 2 in the maximum number of cases. Thus, when the simultaneous choice model is estimated, the category elasticity does not benefit the high share brands of 1 and 2 as much as it does when only the conditional model is estimated, while it does not alter the category benefits for the low share brands of 3, 4 and 5. Thus it is best for the managers to promote their brands when high share brands are under promotion or the low share brands should be positioned in a way that the positioning encourages the simultaneous purchases with the high share brands.

3.6 Limitations and future research directions

The above results hold true only for the analyzed category of margarine. Thus, further investigation is required to find out if the competing brands gain due to the increased incidence under the promotion of a focal brand when the simultaneous choice condition holds true for the other categories. Also, the causal drivers are to be investigated to understand why brands in a category experience simultaneous choices from their positioning perspective. This helps understand and develop positioning for the brands or brand variants in a way that synergizes the promotion effects.

Note that, in this dissertation the periodic strategic promotions offered by the manufacturers or retailers are not considered in the modeling. As the marketing literature indicates an approach that includes such effects may largely change the coefficients (Sun, Neslin and Srinivasan 2003) and thus the incidence effects. Inferences from such modeling will also provide much legitimate understanding of the incidence effects.

Chapter 4. Investigating the Effects of Share and Quality on Neighborhood Price Effect: Implications on market power notion

4.1 Introduction

Marketing literature has heavily focused on the brand switching effects of sales promotions. Important brand switching effects are:

(1) Asymmetric promotion effect: When a high price-quality tier brand goes for promotion it gains more from the low price-quality tier brand than the reverse (Cooper 1988, Krishnamurthi and Raj 1988, Bolton 1989, Blattberg and Wisniewski 1989, Bemmaor and Mouchoux 1991, Mulhern and Leone 1991, Allenby and Rossi 1991, Vilcassim and Jain 1991, Walters 1991, Grover and Srinivasan 1992, Bronnenberg and Wathieu 1996, Sivakumar and Raj 1997, Wedel and Zhang 2004) ,

(2) Neighborhood price effect: Under price promotions, the brands that are nearer to each other in terms of price, gain more from each other than from the farther away brands (Sethuraman, Srinivasan and Kim 1999),

(3) Market power notion: High share brands gain more from the low share brands under the promotion than the reverse (Kamakura and Russell 1989, Russell and Bolton 1988), and

(4) Asymmetric share effect: Low share brands gain more from the high share brands than the reverse when the promotion effects are measured in terms of absolute cross effects (Sethuraman and Srinivasan 2002).

This study focuses on the neighborhood price effects.

The study of Sethuraman, Srinivasan and Kim (1999) explores the neighborhood price effect that was earlier revealed by the studies of Rao (1991) and Sethuraman (1996). Following table summarizes all the studies that support neighborhood price effect.

Table 17. Studies supporting neighborhood effect

Studies	*Product category*	*Data*	*Methodology*
Rao (1991)	None	Conceptual, Assumed values	Game theory
Sethuraman (1996)	Fabric Softener sheets	IRI scanner data 104 weeks between 1991-1993	Linear and non-linear SUR
Sethuraman, Srinivasan and Kim (1999)	19 grocery product categories	Meta analysis of earlier studies	Regression of semi-log, double log and logit

Neighborhood price effect means, under price promotions brands gain more from the competing brands those are adjacent to them in price, than from the farther away brands (Sethuraman, Srinivasan and Kim 1999). Simply put, brands have more competitive influence on the neighboring brands when ordered in terms of their price. This study reveals that neighborhood price effect holds true for both the measures of cross-price elasticities and absolute cross-price effects. Cross price elasticity is measured based on the percentage change in the price of the focal brand while absolute cross-price effect is measured based on the absolute dollar/cents change in the price of the focal brand. The meta-analysis result reported by Sethuraman, Srinivasan and Kim (1999), employs the grocery data for 19-categories that has positive correlation between price and market share. This meta-analysis lends strong support to the neighborhood price effects.

The empirical generalization of neighborhood price effect crystallizes the idea that promotion effects exerted by a focal brand vary across its competing brands. This is an interesting generalization since it simplifies that, switching effects under price promotions are mainly explained by the price differences (the most important factor). However, given the understanding that multiple factors may influence switching between the brands under price promotion, this generalization provides a starting point to explore the additional factors.

For example, there is a limited but convincing proof from the other studies that, the high price national brands and the low price private brands, though being farther away from each other in terms of price, compete with each other more intensely than competing among themselves (Sethuraman 1996, Wedel and Zhang 2004). This intense competition between the high price national brands and low price private brands cannot be attributed to neighborhood price effects. It appears that whenever price-share continuum is broken, i.e. share of the high price brands is not higher than the share of the low price brands, neighborhood effect vanishes (Sethuraman 1996:p 404 table 4). Thus, share is an important factor that appears to mediate neighborhood price effects and is worth investigating.

Secondly, studies have shown that high quality tier brands gain more from low quality tier brands under promotion than the reverse (Allenby and Rossi 1991, Heath and Chatterjee 1995). It is also observed that loss aversion for quality is more than for the price (Hardie, Johnson and Fader 1993, Heath and Chatterjee 1995, Heath, Ryu, Chatterjee, McCarthy, Mothersbaugh, Milberg and Gaeth 2000). To add, value of the brand (quality/price) plays an important role in the consumer choice process (Heath et al 2000). Thus, it is interesting to see how do two price neighbor brands that significantly differ in their quality, gain/loose to each other under price promotions. According to the literature, a higher quality brand should not loose significantly to its price discounted lower quality price neighbor and lower quality brand should gain more from those brands that have comparable quality irrespective of the price differences. On this account it is important to explore the effect of quality on neighborhood price effect.

Thirdly, it appears that neighborhood price effect has important implications on the market power notion and asymmetric share effects. Closer look at the inferences of few of the studies shows that whenever neighborhood price effect exists, asymmetric share effect mostly holds true and market power notion does not (Sethuraman 1996:p 404 table 4, Bronnenberg and Wathieu 1996:p388-389 table 3 and table 4). On the other hand, whenever market power notion holds true neighborhood price effect does not exist (Bronnenberg and Wathieu 1996:p388 table 3).

To summarize, switching effects influenced by the factors like market share or quality might have significant impact on the existence of neighborhood price effects. Further, existence of neighborhood price effect has important implications on the asymmetric share effect and market power notion. Accordingly, this study extends the empirical generalization of the neighborhood price effect by examining the influence of market share and quality in sections 2.1 and 2.2. Further, based on the existence of the neighborhood price effects, its implications on market power notion and asymmetric share effects are also explored in section 2.3. In section 3 a new model is proposed to test the hypotheses. Section 4 discusses the data, estimation and results. Last section discusses the conclusions.

4.2 Investigating the effects of share and quality on neighborhood price effects

4.2.1 Importance of market share in understanding the neighborhood price effects

The study of Sethuraman (1996) provides the detailed analysis of the impact on private labels (low price brands) when national brands (high price brands) are promoted. This study employs the data for Fabric Softener category. From the data employed in this study it appears that, as long as price and share are correlated i.e. price-share continuum exists, neighborhood price effect is observed. Important conclusion is that, when high price national brands go for discount they attract sales mainly from the neighboring national brands (Sethuraman 1996:p403 table 2 and p404 table 4). For the fabric softener category, it holds true for the national brands of Bounce and Downy. But in few cases it appears that national brands compete more with private labels than the price neighboring national brands. For example, Snuggle competes more with the private labels than with Downy or Arm & Hammer. Further, Arm & Hammer under promotion only affects Downy which is not its price neighbor. To add, private labels affect Downy, a national brand, more than their price neighbor Arm & Hammer. This might be happening since Arm & Hammer, a national brand with niche positioning, has lesser market share compared to its price neighbors (Snuggle or Private Labels). This clearly brings out the importance of market share in explaining the switching effects under price promotion.

Another study of Wedel and Zhang (2004) also investigates the switching effects between high price national brands and low price private labels for Orange Juice category. This study investigates the promotion effects at the sub-category level. In this category, private label brands have comparable market shares with that of the national bands, while national brands are priced higher than the private label brands. This study supports that, though not being price neighbors, competition between the national and private label brands is more than the competition among the nation brands or among the private label brands. Further, the competition among the national brands is more than the competition among the private label brands. This study is based on only one product category, but questions if the neighborhood price effect indeed holds true for all the categories. Similar conclusion can be drawn from the study of Bronnenberg and Wathieu (1996). In this study Orange Juice and Peanut butter categories are investigated. The cross price elasticities and cross price effects do not exhibit neighborhood price effect since in both the cases price-share continuum does not exist.

These studies imply the following research issues:

(1) Since, the empirical study of Sethuraman, Srnivasan and Kim (1999) employs the data that has positive correlation between price and share, neighborhood price effect might have come out as an important phenomenon. Thus, it is of importance to know if the neighborhood price effect still holds true when there is less/no correlation between price and market share of the brands. The research hypothesis is:

H1: Neighborhood price effect is observed under price promotions, if and only if price neighbor brands are also share neighbors in the same order.

The above hypothesis can be explained with the following example. Consider three brands A, B and C. To observe the neighborhood price effects it is required that, if their respective prices P_a, P_b and P_c are in the order of $P_a > P_b > P_c$, then their shares should also be in the order of $S_a > S_b > S_c$.

(2) Also, it is of significant importance to study if there is anything similar to neighborhood share effect. As the corollary of H1, the related hypothesis is:

H2: Under price promotions, if neighborhood price effect holds true for a set of brands then neighborhood share effect also holds true.

Here, neighborhood share effect means, under price promotions brands gain more from the neighboring share brands than from the farther away brands.

4.2.2 Importance of quality in understanding the neighborhood price effects

Blattberg and Wisniewski (1989), mention that, task complexity of choosing between the brands is compounded by the perceived quality differences by the consumers and the degree of importance attached by them to these differences. Later studies by Allenby and Rossi (1991), Hardie, Johnson and Fadher (1993), Heath and Chatterjee (1995), Bronnenberg and Wathieu (1996), Heath et al (2000) have explored the impact of quality on promotion related switching effects. These studies have revealed a number of important quality related implications on brand switching under promotion. Following discussion illustrates the implications of quality related switching effects on neighborhood price effect. Since it is generally observed that high quality brands have higher price, in the following discussion the same is assumed unless otherwise mentioned.

Bronnenberg and Wathieu (1996) study reveals that for the categories of Orange juice and Peanut butter, gain under promotion induced switching need not always favor high quality brands. This implies that under price promotions though high price brands have high quality they may still loose to their low price-quality neighbors. This leads to the possibility that neighborhood price effect may hold true irrespective of the quality differences between the price neighbor brands. Concept of diminishing returns also implicitly hints at neighborhood effects being prominent i.e. first dollar difference between the brands hurts (pleases) more under loss (gain) (Hardie, Johnson and Fader 1993). However, other studies indicate that, high quality brand offers high resistance to loose to the low quality promoted brand (Allenby and Rossi 1991, Heath and Chatterjee 1995, Heath et al 2000). Heath et al (2000) provide an explanation for such a phenomenon under dominance effects.

According to the study of Heath etal (2000), a high quality brand gets more switching from low quality brand by reducing the price since it increases the overall value. Its value increases since before promotion high quality brand would be under price disadvantage. By decreasing the price it overcomes the disadvantage and thus dominates the low quality brand. However, when a low quality brand reduces its price it does not fetch much switching from the high quality brands since it is just improvising on its advantage. On the other hand the reverse would happen if low quality brand would improve its quality i.e. it would gain more from the high quality brand than the reverse. This clearly questions if a low quality price neighbor offering discounts gains more from its higher price higher quality neighbor than those competing brands that have lower quality than itself (the promoted brand). Since it is also observed that loss aversion is high for quality than for the price (Hardie et al 1993, Heath and Chatterjee 1995, Heath et al 2000), high quality high price customers may not switch to low quality low price brand when low price brand offers price discounts.

Given these alternative explanations it is interesting to know in what way quality influences neighborhood price effect. The research issues are:

(1) Empirical studies indicate that quality is an important factor that defines the competition between the brands due to loss aversion. Given the contradictory evidence that quality may favor either high price-quality brand or low price-quality brand to gain under price promotions, it is important to know the influence of quality on the neighborhood price effects. The related research hypothesis is:

H3: Neighborhood price effect is observed under price promotions, if and only if price neighbor brands are also quality neighbors in the same order.

The above hypothesis can be explained with the following example. Consider three brands A, B and C. To observe the neighborhood price effects it is required that, if their prices P_a, P_b and P_c are in the order of $P_a > P_b > P_c$, then their quality should also be in the order of $Q_a > Q_b > Q_c$. If this hypothesis is rejected it means that, irrespective of the quality order or quality difference between the brands neighborhood price effect is observed. However if it is accepted then it means that apart from being price neighbors, brands also should be quality neighbors to observe the neighborhood price effects under price promotions.

(2) Also, it is of significant importance to study if there is anything similar to neighborhood quality effect. As the corollary of H3, the related hypothesis is:

H4: Under price promotions if neighborhood price effect holds true for a set of brands, then neighborhood quality effect also holds true.

Here, neighborhood quality effect means, under price promotions brands gain more from the neighboring quality brands than from the farther away brands.

4.2.3 Implications of neighborhood price effects on market power notion

High share brands affect low share brands more than the reverse, exhibiting the notion of 'market power' (Russell and Bolton 1988). This occurs due to higher competitive clout of the high share brands (Kamakura and Russell 1989). Further, the recent study that investigates, how consumers evolve their preferences when they are new to a category, (Heilman, Bowman and Wright 2002, Anderson and Simester 2004) shows that consumers prefer high market share popular brands more to the low share brands. This reaffirms the idea of market power notion. On the other hand, Sethuraman and Srinivasan (2002) based on the Bass, Jeuland and Wright (1976) model show that, when promotion impacts are expressed in terms of absolute cross effects, low share brands gain more from high share brands than the reverse. Interestingly, this study also employs the same data set that is employed in the study of Sethuraman, Srnivasan and Kim (1999). According to this study, low share brands gaining more under promotion i.e. "asymmetric share effect" questions the market power notion of high share brands.

Now, according to the dominance theory (Heath et al 2000), for a brand to draw more switching from its price neighbors, it should be asymmetrically dominating the price neighbors more than the other brands. This would lead to neighborhood price effects. However, for the asymmetric share effects to hold true, low share or low price brand should dominate the high share or high price brand more than the reverse. Since the data set employed in the study of Sethuraman and Srinivasan (2002) exhibits positive correlation between market share and price, a high (low) price brand would also mean high (low) share brand. Thus, in both the cases of neighborhood price effect and asymmetric share effect, a focal brand draws more from the high share/price neighbor brand, than from the non-neighbor low share/price brands. Thus, there is a high probability that whenever the neighborhood price effect is observed asymmetric share effect also holds true. Following is the empirical illustration.

A closer look at the study of Sethuraman (1996) brings out interesting insights. In the Fabric Softener category the top three price-share neighbor brands Bounce (BO), Downy (DO) and Snuggle (SS) exhibit descending price and share order. The deal effects show that neighborhood price effect indeed holds true for these three brands. BO gains more from DO, while DO gains more from BO and SS gains more from DO. Interestingly asymmetric share effect also holds true for these set of brands i.e. what DO gets from BO is more than what BO gets from DO. Same phenomenon holds true between SS and DO, but not between SS and BO. Now, if the bottom three price share brands of Snuggle (SS), Arm & Hammer (AH) and Private Label (PL) were considered then neighborhood effect does not hold true for them. As discussed in section 2.1 this may be happening because price and share orders do not match for this set of brands. To note, asymmetric share effect also does not hold true for this set of brands. The SS brand and PL compete with each other more than with their neighbor AH brand. Also, SS draws more from low share PL than the reverse. The study of Bronnenberg and Wathieu (1996) also reports cross price effects for Orange Juice and Peanut Butter categories. In their study it is evident that neighborhood effect does not hold true. The results reveal that asymmetric share effect is observed only between 7 pairs of brands out of 60 pairs. This also means market power notion holds true for 53 out of 60 pairs of brands. These studies lead us to the following research issue.

a. It appears that whenever neighborhood effect holds true market power notion does not necessarily hold true, and hence most likely asymmetric price effect holds true (given that Sethuraman and Srinivasan (2002) and Sethuraman, Srinivasan and Kim (1999) employ same data sets). Specifically, the research objective is to understand the conditions under which the market power notion or asymmetric share effect holds true based on the existence of the neighborhood price effect, when model accounts for competitive effects. The research hypothesis is:

H5: If a set of brands display neighborhood price effects then for the majority of pairs of these brands, asymmetric share effect is significant.

If this hypothesis is accepted then it means that market power notion is significant for a set of brands that do not display neighborhood price effects. Otherwise it means that market power notion does not depend on the neighborhood price effects.

4.3 Proposed Model

The research issues that are discussed in the previous section relate neighborhood price effects to market share and quality. Implications of neighborhood price effects on market power notion and asymmetric cross effects are also discussed. Each of these research issues is considered one after the other to develop the model.

To begin with, since the research issues relate to switching effects under short term promotion, discrete choice model is deemed appropriate. However, as Sethuraman et al (1999) bring out, multinomial logit (MNL) choice model leads to symmetric substitution apart from the fact that it suffers from independence from irrelevant alternatives (IIA) property. Nested Logit models also suffer from IIA within each nest. On the other hand multinomial probit (MNP) leads to symmetric competition between a pair brands since correlation between a pair of brands is same i.e. correlation between brands A and B or between B and A are the same. Though heteroscedastic extreme value (HEV) model can be employed, it rests on the assumption that sources of variation essentially come from the random components (Louvier, Hensher and Swait 2000). To overcome the limitation of HEV, covariance heterogeneity extreme value model is employed (CovHEV). With CovHEV, each of the alternatives can have their specific source of variations and reduces to MNL like closed form (Louviere, Hensher and Swait 2000). This model is derived by assuming the dummy nests for all the alternatives, where scale parameter varies for each of them (Hensher 1994, Hensher and Greene 2002). The scale parameter can be defined based on the alternative specific characteristics to define the covariance heterogeneity.

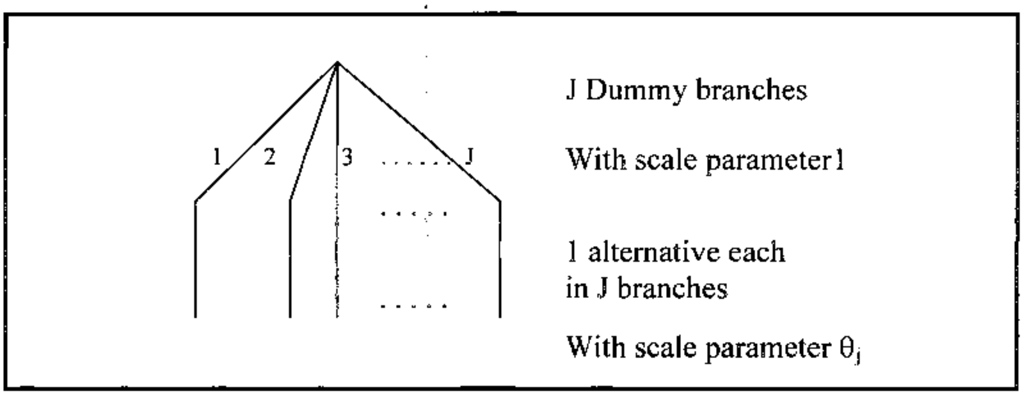
4.3.1 Derivation of the model

Consider a set of brands J in a given category, with each alternative j having the utility structure of $U_j = V_j + \varepsilon_j$. Here V_j is the deterministic component of the utility and ε_j is the random error. It is assumed that ε_j follows Gumbel distribution. Then the probability of choosing brand i, based on the standard MNL choice model has the form (Ben-Akiva and Larman 1985):

$$p_i = \frac{\exp(v_i)}{\sum_{j=1}^{J} \exp(v_j)} \tag{1}$$

Now, if the J alternatives were represented in J dummy nests, with each having only one alternative, then following is the structure.

Figure 4. Dummy Nesting



Given the utilities for the alternatives as $U_{1/j} = V_{1/j} + \varepsilon_{1/j}$ within each nest, the branch level utility is $U_j = \theta_j \ln \sum_{a \in j} \exp(V_j) = \theta_j V_j = \theta_j \beta^T X_j$, since there is only one alternative per nest (Hensher 1994). This is equivalent to specifying the Random Utility Model 1 (RUM1) of Nested Logit (Hensher and Greene 2002). Thus, the probability of choosing an alternative i (branch i) is:

$$p_i = \frac{\exp(\theta_i \beta^T X_i)}{\sum_{j=1}^{J} \exp(\theta_j \beta^T X_j)} \tag{2}$$

4.3.2 Modeling the source of heterogeneity (scale parameter)

The deterministic utility component is the linear additions of the product of the attributes and their sensitivities of that brand. All these attributes are generally objective in nature and do not depend on consumer perceptions. However, quality on the other hand is the consumer perception of the set of objective measures. Zeithaml (1988) discusses these issues in detail. Given that quality is perception of the consumers, it is not appropriate to model for it like every other objective measure, since:

(1) Research has employed consumer reports for the quality indicators. Thus, quality associated with a given brand is the consumer perceived (objective) rating (Zeithaml 1988) and thus is not an absolute objective measure like the other attributes of price or feature or display.

(2) Secondly, though earlier research has employed quality along with the price as the ratio scaled measure to evaluate brand positioning (Bronnenberg and Wathieu 1996), any conventional metric/distance measurement does not reflect the true difference in the quality between the brands as it is a measure of consumer perception. Since, brands are chosen based on the relative utilities in discrete choice framework, employing quality ratings themselves as part of the utility might not be appropriate.

Instead, it is best to state that quality rating is a distribution around the actual rating reported by the consumers. To make the quality measure more objective the perceived value of the brand, i.e. quality/price is employed. Without loss of generality, it is assumed that consumer perceived value (Q/P) is normally distributed with mean Q/P and variance σ_p^2. Since, quality rating does not change often for a brand it is assumed that the variation in the perceived value is explained by the variance of the price σ_p^2.

Further, in order to develop a measure for the difference in the price quality (perceived value) positioning between the brands, it is required to employ a metric that measures the value positioning differences and the direction of the difference. However, mathematically every metric is symmetric, i.e. distance between A and B is same as distance between B and A. These conventional metrics inherently bias the model since, due to symmetric nature they would undermine the true difference in the perceived values experienced by the consumers. Note that, perceived value difference between brands need not be symmetric i.e. consumers do not always experience equal loss or gain for the equal increase or decrease in the value for the given quality and price of the brands. Secondly, metrics are also always positive. This also biases the perceived value difference since value difference need not always translate in to benefits. For example, when consumers switch to a low value brand then the value difference should be negative.

To address the asymmetric perceived value differences, the Kullback-Leibler (KL) divergence measure of distance between the distributions is employed. This divergence measure is always positive, but need not be symmetric. Thus, if two brands have normally distributed perceived values of $v_i(x) = N(\frac{Q_i}{p_i}, \sigma_{p_i}^2)$ and $v_j(x) = N(\frac{Q_j}{p_j}, \sigma_{p_i}^2)$ then the KL divergence is:

$$D_{ij} = \int_{-\infty}^{\infty} v_i(x) \log \frac{v_i(x)}{v_j(x)} dx = \frac{1}{2}[\log(\frac{\sigma_j^2}{\sigma_i^2}) + \frac{\sigma_i^2}{\sigma_j^2} + \frac{(\frac{Q_j}{p_j} - \frac{Q_i}{p_i})^2}{\sigma_j^2} - 1] \tag{3}$$

The KL- divergence is the popular method to measure the distance between the distributions and has applications in the fields of information science, physics and biostatistics. Note that, KL divergence is not always symmetric but is always positive. Thus, to bring in the directional and diminishing returns sense to the distance, the KL divergence between the brands is weighted by their price difference factor $(p_i - p_j)$. For a given occasion t to capture the choice complexity for an alternative i, the perceived value difference between the focal brand and all the other brands is considered as its scale parameter. The scale parameter θ_{it} is opertaionalized as:

$$\theta_{it} = \sum_{\substack{j=1 \\ j \neq i}}^{J} \lambda_{ij} D_{ij} (p_i - p_j) \tag{4}$$

Here λ_{ij} are the coefficients for the perceived value difference between the brands. Substituting equation (4) in to (2), choice model takes the following form:

$$p_i = \frac{\exp(\sum_{\substack{j=1 \\ j \neq i}}^{J} \lambda_{ij} D_{ij} (p_i - p_j) \beta^T X_i)}{\sum_{j=1}^{J} \exp(\sum_{\substack{k=1 \\ k \neq j}}^{J} \lambda_{jk} D_{jk} (p_j - p_k) \beta^T X_j)} \tag{5}$$

Following are the important implications of Tversky and Kahneman (1991) study on the operationalization of the scale parameter.

(1) Reference point changes from one purchase to the other as implied by Tversky and Kahneman (1991) study (Hardie, Johnson and Fader (1993). Though, Bass, Jeuland and Wright (1976) have also shown that even the zero order processes are good enough to model consumer purchases, recent studies have shown that consumer decision does depend on the past purchases (Heath et al 2000). Accordingly, the value of σ_p^2 is calculated based on the calibration period for the first purchase. It is updated after each purchase for each consumer, since the price observed by every consumer may differ.

(2) Secondly, Tversky and Kahneman (1991) theory strongly supports loss aversion phenomenon, i.e. losses are more than the gains for the equal change in the perceived value. Note that, KL divergence is asymmetric between the brands, but it does not distinguish between the gains and losses. In the scale parameter this distinction is brought in by the factor $(p_i - p_j)$. However, if the loss aversion indeed holds true then it will be captured in the coefficients of λ_{ij}. In other words if loss aversion holds true then, for the reference brand *i*, between brands *i* and *j*, if $(p_i - p_j) > 0$, then $\theta_{ij} < \theta_{ji}$ should hold true.

4.4 Data, Estimation and Results

4.4.1 Data Description

IRI panel data for Margarine (includes Spreads and Butter blends also) category is employed. The modeling data is for 52 weeks from January to December 2006 and the calibration data is also for 52 weeks from January to December 2005. In this category, one pound is the prominent brand size and accounts for 82% of the category share[6]. The top 5 brands in this size are selected, which make up for 65.66% of the 1lb total share. Data are analyzed for 100 randomly selected panelists from Eau Claire, Wisconsin area who constitute 1098 purchase occasions across 5 stores.

Table 18. Data Description

*Brand**	*Market Share (%) From modeling data*	*Avg. Price per Unit($) From Calibration data*	*Quality*	*Variance of Avg. Price From calibration data*
1	32.15	1.49	2.50	0.20
2	28.69	0.56	2.50	0.08
3	21.31	1.15	2.33	0.15
4	4.74	1.30	2.33	0.09
5	13.11	1.75	3.00	0.09

This method of selecting the brands and panelists is consistent with the research method followed in marketing. For example Chintagunta (1993) and Bucklin, Gupta and Siddarth (1998) follow the similar method. Table 18 summarizes the data.

4.4.2 Variables employed in the model

The following variables are employed:

(1) Brand Loyalty (BL): This is the share of the brands bought during the calibration period for each panelist. This remains constant throughout the modeling period for each panelist.

(2) Last Brand Purchased (LBP): This is the indicator variable which takes the value 1 if the brand was bought in the last occasion, else it is 0.

[6] The size of 0.9375 LB is combined with 1 LB since there is hardly any price difference between these

(3) Promotion (PROMO): This is the variable indicating the promotional activity which takes the value 1 in the presence of either a display or a feature activity, else it takes the value 0.

(4) Price (PRICE): This is the actual price reported by the panelists.

The variables of BL, LBP, PROMO and PRICE are operationalized similar to Bucklin, Gupta and Siddarth (1998).

(1) Scale Parameter Theta (θ_j): This variable captures the scale parameter for the alternatives as described in equation (4). This variable consists of three parts: λ's, D_{ij}'s and the price differences. The KL divergence between a pair of brands i and j i.e. D_{ij} is calculated by considering the mean price, quality and variance of the price for the pair of brands i and j using the formula (3). The mean and variance of the price for all the brands are calculated from the calibration data across all the panelists. Table 2 describes the mean price, variance of price and quality for the brands that are used for calculating the KL divergence. The value D_{ij} remains the same for a pair of brands throughout the modeling period. For each successive occasion during the modeling period D_{ij} is multiplied by the price differences between the brands that are observed for that occasion. The coefficients λ's are estimated which provide weighting to the product of the KL divergence and price difference between a pair of brands.

(2) Quality (Q): Consumer Reports (2002) ratings are used as the proxy for quality. The quality ratings for the various brands that are available in different forms are

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sizes. Totally this size accounts for 82% of the category share.

averaged. For example, brand 1 is has two variants with the quality ratings of 3 and 2. This is averaged and the quality rating for brand 1 is considered as 2.5

4.4.3 Estimation

The log-likelihood of the proposed model is:

$$LL = \sum_{h=1}^{H}\sum_{t=1}^{T}\sum_{i=1}^{J}\delta_i[\theta_i\boldsymbol{\beta}^T\mathbf{X}_i - \ln\sum_{j=1}^{J}e^{(\theta_j\beta^T\mathbf{x}_j)}] \tag{6}$$

The model is estimated in SAS. The multinomial logit (MNL) model was estimated as the first step. These values were employed as the initial values for model optimization. Following table 19 summarizes the final estimates.

Table 19. Estimated Coefficients (Betas β's)

Coefficient	*LBP*	*BL*	*PROMO*	*PRICE*
Estimate	2.37637	8.90459	1.099783	-1.18331
Std. Error	0	0.011149	0	0.050564
Actual Probability	0.3215	0.2869	0.2131	0.0474
Predicted Probability	0.381106	0.290847	0.194265	0.050039
LL -Model	-699.55			
LL0	-1767.16			
Pseudo ρ^2	0.604139			

From table 19, it is evident that model has excellent fit with McFadden's R^2 of 0.60. Also as indicated in rows 4 and 5 of table 19, actual and predicted probabilities are very close and follow the same order. Table 20 lists the λ's, coefficients for the scale parameter. Although, few of these coefficients have high standard error, most of them have low standard error. All of these coefficients are employed to calculate the deal effects and elasticities.

Table 20. Estimated Scale Parameter Coefficients (Lambdas λ's)[7]

Brand	*1*	*2*	*3*	*4*	*5*
1	-	0.009049 (2.63)	-1.02004 (0.03)	0.697287 (0.00)	-1.2405 (0.00)
2	0.009753 (15.85)	-	-0.02086 (6.38)	0.005134 (35.64)	-0.00763 (75.26)
3	0.46915 (0.00)	0.005746 (0.93)	-	-1.19697 (0.00)	-0.65976 (0.00)
4	-11.9273 (0.00)	-0.00005 (0.55)	0.966389 (0.00)	-	-34.6823 (0.011)
5	2.463912 (0.00)	0.012137 (0.00)	2.490053 (0.032)	-44.0041 (0.005)	-

4.4.4 Results

Based on the coefficients the deal effects and Elasticities are calculated. The self and cross-elasticities for the proposed model are:

$$\eta_{ii} = (1 - p_i)(\beta_k \theta_i + \lambda_i^T D_i \boldsymbol{\beta}^T \mathbf{x}_i) x_p \tag{7}$$

$$\eta_{ij} = -p_j(\beta_k \theta_i + \lambda_i^T D_i \boldsymbol{\beta}^T \mathbf{x}_i) x_p \tag{8}$$

Here, λ_i and D_i are the coefficients and product of the KL divergence and price difference vectors of the modeled scale parameter for brand i. Table 21, summarize the deal effects and the elasticities for price.

[7] Standard Errors are reported below the coefficients

Table 21. Deal effects and elasticities for price

	Deal Effects						Elasticities				
	1	*2*	*3*	*4*	*5*		*1*	*2*	*3*	*4*	*5*
1	-0.52	-0.25	0.05	1.48	0.13	*1*	-0.83	-0.41	0.08	2.22	0.19
2	0.18	-0.94	0.04	1.14	0.10	*2*	0.12	-0.66	0.02	0.64	0.05
3	0.12	-0.13	-0.44	0.76	0.06	*3*	0.15	-0.17	-0.51	0.87	0.07
4	0.03	-0.03	0.01	1.54	0.02	*4*	0.04	-0.05	0.01	2.00	0.02
5	0.05	-0.06	0.02	0.33	-0.83	*5*	0.09	-0.10	0.03	0.57	-1.45

Similar to Sethuraman, Srinivasan and Kim (1999) the average neighborhood deal effects for the brands below the focal brands price and above the focal brands price are calculated. Similar calculations are done for the share and quality neighbors. Table 22, summarizes these calculations. In this table, k stands for the rank of the neighbor i.e. k=1 indicates the first neighbor, k=2 indicates the second neighbor and so on. Since, there are five competing brands the maximum neighbors are going to be 4.

In table 22, column three, the value for the high price brands effect on the low price neighboring brands is listed. This is calculated by taking the average of the deal effects of all the brands on their first lower priced neighbor. The average first neighbor value is 0.2387 = ¼ * (0.0303 + 0.0396 + 0.7592 + 0.1256). Similar calculations are done for the other neighbors. Also, since no coefficients for the neighborhood price effects are generated directly from the model like Sethuraman, Srinivasan and Kim (1999), the calculated average deal effects determine if the neighborhood effects are indeed true for the analyzed category.

Table 22. Neighborhood Effects[8]

		Average Price Effects		*Average Share Effect*		*Average Quality Effect*	
K	*Observations*	*High-Priced brands effect on Lower-priced brand*	*Low-Priced brands effect on Higher-priced brand*	*High-share brands effect on Lower-share brand*	*Low-share brands effect on Higher-share brand*	*High-quality brands effect on Lower-quality brand*	*Low-quality brands effect on Higher-quality brand*
1	4	0.2387	0.4204	0.0852	0.1722	0.0656	0.6794
2	3	0.4236	0.1376	0.0615	0.3023	0.1108	0.1721
3	2	0.1201	0.1375	0.0281	0.6311	--	--
4	1	0.0959	0.0566	0.0303	1.4894	--	--

Table 23. Nearest Neighbor Rankings Based on Price, Share and Quality

Nearest Price Rankings						*Nearest Share Rankings*						*Nearest Quality Rankings*					
brands	*1*	*2*	*3*	*4*	*5*	*brands*	*1*	*2*	*3*	*4*	*5*	*brands*	*1*	*2*	*3*	*4*	*5*
1	-	3	2	2	1	*1*	-	1	3	4	4	*1*	-	1	2	2	1
2	4	-	4	4	4	*2*	1	-	1	3	3	*2*	1	-	2	2	1
3	3	1	-	1	3	*3*	2	2	-	2	1	*3*	2	2	-	1	3
4	2	4	1	-	2	*4*	4	4	4	-	2	*4*	2	2	1	-	3
5	1	2	3	3	-	*5*	3	3	2	1	-	*5*	4	4	4	4	-

In the given data the correlation between the share and price of the brands is -0.31 and correlation between price and quality is 0.50. Table 23 provides the neighbor rankings of all the brands with all other brands. For example, row three and column three has the value 3. This means for brand 2, the third neighbor is brand 1. Similar interpretations

[8] Absolute values of the deal effects are considered while calculating the average deal effects. This is done since the neighborhood effects signify the degree of impact rather than the direction of the impact.

hold true for share and quality neighbor rankings. Now, apart from correlation to test the hypothesis table 23 is employed. A closer look at the table 22 provides following insights:

(1) Hypothesis one states that, neighborhood price effect is observed under price promotions, only if price neighbor brands are also share neighbors in the same order. Now, from table 23, out of 20 neighborhood rankings only 2 rankings between price and share neighbors match. The matched rankings are: brand 4 is the fourth ranked neighbor for brand 2 both in terms of price and share, and brand 4 is the second ranking neighbor for brand 5 both in terms of price and share. To find if price neighbor brands are also share neighbor brands, it is hypothesized that at least 50% of the neighborhood rankings for price and share should match. The test of proportions is done, where observed proportion is 10%. This gives the P-value of less than 0.00003 and thus the null hypothesis that there is at least 50% match between the rankings based on the price and share neighbors is not supported i.e. it is true that price neighbors are not the share neighbors in the given category. From table 22, column three it is evident that for the high priced brands neighborhood price effects are not observed, since the effect on the second nearest neighbor (0.4326) is more than that of the first neighbor. Thus, not observing the neighborhood price effect when price neighbors are not the share neighbors in the given category supports H1. However, from column four of table 22, low priced brands' effect on the higher priced brands exhibits neighborhood price effect. Thus. For low price brands H1 is not supported. In conclusion

considering columns 3 and 4 of table 22 it appears that H1 is supported for high price brands and is rejected for low price brands.

(2) The hypothesis two (H2) states that, under price promotions, if neighborhood price effect holds true for a set of brands then neighborhood share effect also holds true. Again as mentioned, column three of table 22 does not indicate neighborhood price effects while column four does. Accordingly, column five should not indicate neighborhood share effects and column six should display neighborhood share effect. However, as observed, column 5 exhibits neighborhood share effect while column 6 displays exactly the opposite. These observations clearly do not support hypothesis two. Thus H2 is not supported for this category.

(3) Further, similar observations can be drawn for the hypotheses H3 and H4. The third hypothesis states that neighborhood price effect is observed under price promotions, only if price neighbor brands are also quality neighbors in the same order. For the margarine category correlation between price and quality is 0.5. Based on the test of proportions from table 23 there are 9 out of the 20 rankings between price and quality neighbors that get a match. The P-value for the hypothesized 50% match is again less than 0.00003 and thus it appears that price neighboring brands are not the quality neighbors. Accordingly, neighborhood price effect should not hold true. The third column does not exhibit neighborhood price effect and thus H3 is supported for high priced brands. However, based on

column four neighborhood price effects are observed for low priced brands. This does not support H3.

(4) Also, as observed neighborhood quality effects do not hold true for high quality brands (column seven) and neither the neighborhood price effects (column three). Secondly, for the low quality brands neighborhood quality effects hold true (column eight) and so do the neighborhood price effects (column four). These two observations support H4.

(5) The low share brands gaining more from the high share brands or from the farthest neighbor brands signify asymmetric share effect. Thus, for the low price brands neighborhood price effects hold true (column four) and so do the asymmetric share effects (column four). This further supports the idea that probability of observing the asymmetric share effect is higher if the neighborhood price effects are observed. Thus H5 is supported.

To summarize, hypotheses H4 and H5 are supported for both the high priced and low priced brands. Hypotheses H1 and H3 are supported for the high priced brands and are not supported for the low priced brands. The hypothesis H2 has no support from either the high price or the low price brands.

4.5 Implications and discussion

4.5.1 Academic Contributions

The analysis provides few interesting findings. Firstly, it appears that the neighborhood price effect may hold true for only a part of the entire category. In the above study neighborhood effects appear to hold true for lower price brands, and not for the higher price brands. Thus it appears that positioning of the brand in the category in terms of price makes a significant impact on the type of effects observed. Secondly, the explanation of Sethuraman and Srinivasan (2002) which states that "high share brands have larger pool of consumers to loose from their share" appears to hold true. In both the cases of higher and lower share brands, the highest share competing brands appear to loose more based on the cross deal effects. This implies that when a high share brand goes for price promotions it displays neighborhood share effect, while lower share brands display "farthest neighbor share effect". Thus, positioning of the brand in the category in terms of share is also an important factor.

Thirdly, according to the dominance theory, if a low quality brand goes for price promotion it should not gain more from the higher quality brands since it is not improvising on its disadvantage i.e. quality (Heath et al 2000). However, in the given category it appears that low quality brands under discount gain more from the immediate quality superiors, than the gain of high quality brands from the low quality brands. These observations bring out the limitation of the dominance theory in explaining the price quality effects under promotion. However, for the high quality brands price promotions do overcome their disadvantage and attract more sales from the low quality brands. This is consistent with the dominance theory (Heath et al 2000). This phenomenon of high quality brands gaining more from the farthest neighbors requires further proof from the other categories.

To add based on the neighborhood quality effects it appears that consumers may not have higher loss aversion for quality compared to price. This conclusion can be drawn from the fact that low quality brands attract sales from the higher quality neighbor brands under price promotions more than the higher quality brands gaining from the lower quality brands.

4.5.2 Managerial Insights

The analysis also provides few interesting insights for the practitioners. First of all, the long held notion that high share brands have an inherent advantage under promotion i.e. market power notion, does not hold true. Thus, managers cannot take their share for granted if they are leading in the category, since other brands can significantly gain from them under promotions. It is in fact the low share brands that have an advantage. Secondly, note that, though low quality brands do not improvise on their disadvantage of quality by promoting price, they can still gain from their neighbors. Thus, it appears that, the low quality national brands are not at a complete disadvantage and they can still gain from price promotions. On the other hand, it also means that low quality private labels can also gain from the lower quality national brands when they are promoted. To extend this implication for the private labels, it is best for the retailers to position their brands at least in par with the lowest quality national brand to ensure gain in market share. However, the national brands will have to continuously improve their quality to distance themselves from the private labels to avoid share erosion.

4.6 Limitations and Future research directions

To generalize the findings, further investigation with different categories is required. Important direction for the future research are to explore if the neighborhood effects of price, share and quality hold true for only a part of the category or for the entire category.

Second important direction is to generalize if "farthest neighbor effect". This extends the existing concept of asymmetric share effect (Sethuraman and Sriunivasan 2002), in providing the order of such an effect. Similar effect of farthest neighbor may hold true for high quality brands. It appears that when high quality brands promote they draw more from the farthest neighbor.

Another important area of research can be the applications of divergence measures to find the differences between the brands. The current multi-dimensional scaling techniques and clustering techniques can be improvised employing divergence measures, since they offer natural extension of the distance measures to distributional variables and do not suffer from the limitations of symmetry of the regular metrics.

CHAPTER 5. Summary

This dissertation focuses on the empirical generalizations related to retailer promotions. Two essays are developed addressing the following generalizations.

(1) Promoted brand gains more from secondary demand than from the primary demand.

The above generalization follows from the study of Bell, Chiang and Padmanabhan (1999), when the promotion impact is measured in terms of elasticity. On the other hand, Van Heerde, Gupta and Wittink (2003) show that when the promotion impact is measured in terms of sales units the primary demand is 75% and the secondary demand is 25%. In their calculation they assume that increased category incidence under promotion benefits all the brands in the category. The first essay addresses this issue by developing a mathematical proof that under Nested Logit model specification, such an assumption is violated. An alternative explanation is provided to calculate the primary and secondary demand effects.

(2) Neighborhood price effect, Market power notion and Asymmetric share effect.

The second essay focuses on the empirical generalization related to the neighborhood price effect (Sethuraman, Srinivasan and Kim 1999). The effects of share and quality in shaping the neighborhood price effect are hypothesized. Further, based on the evidence that neighborhood price effect and asymmetric share effect generally go together and contradict the market power notion, it is hypothesized that asymmetric share effect holds true only when neighborhood price effect is observed. The covariance heterogeneity (CovHet) logit model (Hensher 1994) is formulated to test the hypotheses where, brand specific scale parameters are explicitly modeled based on the Kullback-Leibler (K-L) divergence measure.

BIBLIOGRAPHY

Abe, Makaoto (1998), "Measuring Consumer, Non-Linear Brand Choice Response to Price", *Journal of Retailing,* 74 (4), p.541-568

Abraham, Magid M. and Leonard M. Lodish (1987), "PROMOTER: An Automated Promotion Evaluation System", *Marketing Science,* 6 (Spring, 2), p.101-123

Agarwal, Deepak (1996), "Effect of Brand Loyalty on Advertising and Trade Promotions: A Game Theoretic Analysis with Empirical Evidence", *Marketing Science,* 15 (1), p.86-108

Ailawadi, Kusum L., Bary A. Harlam, Jacques Cesar and David Trounce (2006), "Promotion Profitability for a Retailer: The Role of Promotion, Brand, Category and Store Characteristics", *Journal of Marketing Research,* 43 (November), p.518-535

Ailawadi, Kusum L., Donald R. Lehmann and Scott A. Neslin (2001), "Market Response to a Major Policy Change in the Marketing Mix: Learning from Procter & Gambel's Value Pricing Strategy", *Journal Marketing*, 65 (January, 1), p.44-61

Ailawadi, Kusum L., J. P. Beauchamp, Navin Donthu, Dinesh K. Gauri and Venkatesh Shankar (2009), "Communication and Promotion Decisions in Retailing: A Review and Directions for Future Research", *Journal of Retailing,* 85 (1), p.42-55

Ailawadi, Kusum L., and Scott A. Neslin (1998), "The Effect of Promotion on Consumption: Buying More and Consuming it Faster", *Journal of Marketing Research,* 35 (August, 3), p.390-398

Allenby, Greg M. and Peter E. Rossi (1991), "Quality Perceptions and Asymmetric Switching Between Brands", *Marketing Science,* 10 (Summer, 3), p.185-204

Allenby, Greg M., Thomas S. Shively, Sha Yang and Mark J. Garratt (2004), "A Choice Model for Packaged Goods: Dealing with Discrete Quantities and Quantity Discounts", *Marketing Science,* 23 (Winter, 1), p.95-108

Alvarez, Begona Alverez and Rodolfo Vazquez Casielles (2005), "Consumer Evaluations of Sales Promotion: The Effect on Brand Choice", *European Journal of Marketing,* 39 (1/2), p.54-70

Anderson,Eric T. and Duncan I. Simester (1998), "The Role of Sale Signs", *Marketing Science,* 17 (2), p.139-154

Anderson,Eric T. and Duncan I. Simester (2004), "Long-Run Effects of Promotion Depth on New Versus Established Customers: Three Field Studies", *Marketing Science,* 23 (Winter, 1), p.4-20

Areni,Charles S.,Dale F. Duhan and Pamela Kiecker (1999), "Point-of-Purchase Displays, Product Organization, and Brand Purchase Likelihoods", *Journal of the Academy of Marketing Science,* 27 (Fall, 4), p.428-441

Assuncao, Joao L. and Robert J. Meyer (1993), "The Rational Effect of Price Promotions on Sales and Consumption", *Management Science,* 39 (May, 5), p.517-535

Bass, Frank M. (1995), "Empirical Generalizations and Marketing Science: A Personal View", *Marketing Science*, 14 (3), G6-G19.

Bass, Frank M., Abel Jeuland and Gordon P. Wright (1976), "Equilibrium Stochastic Choice and Market Penetration Theories: Derivations and Comparisons", *Management Science,* 22 (June, 10), p.1051-1063

Bawa, Kapil and Robert W. Shoemaker (1987), "The Effect of a Direct Mail Coupon on Brand Choice Behavior", *Journal of Marketing Research,* 24 (November, 4), p.370-376

Bawa, Kapil and Robert W. Shoemaker (1989), "Analyzing Incremental Sales from a Direct Mail Coupon Promotion", *Journal of Marketing,* 53 (3), p.66-78

Bawa, Kapil and Robert W. Shoemaker (2004), "The Effects of Free Sample Promotions on Incremental Brand Sales", *Marketing Science,* 23 (Summer, 3), p.345-363

Bell, David R., Jeongwen Chiang and V. Padmanabhan (1999), "The Decomposition of Promotional Response: An Empirical Generalization", *Marketing Science,* 18 (4), p.504-526

Bemmaor, Albert C. and Dominique Mouchoux (1991), "Measuring the Short-term Effect of In-Store Promotion and Retail Advertising on Brand Sales: A Factorial Experiment", *Journal of Marketing Research,* 28(May, 2), p.202-214

Ben-Akiva, Moshe E. and S. Lerman (1985), "Discrete Choice Analysis: Theory and Application to Travel demand", *Cambridge, Mass, MIT Press*

Besag, Julian (1974), "Spatial Interaction and the Statistical Analysis of Lattice Systems", *Journal of the Royal Statistical Society B,* 36, p.192-236

Besanko, David, Jean-Pierre Dube and Sachin Gupta (2005), "Own-Brand and Cross-Brand Retail Pass-Through", *Marketing Science,* 24 (Winter, 1), p.123-137

Bijmolt, Tammo H.A., Harald J. Van Heerde, and Rik G. M. Pieters (2005), "New Empirical Generalizations on the Determinants of Price Elasticity", *Journal of Marketing Research,* 42 (May), p.141-156

Blattberg, Robert C. and Alan Levin (1987), "Modeling the Effectiveness and Profitability of Trade Promotions", *Marketing Science,* 6 (Spring, 2), p.124-146

Blattberg, Robert C., Gary D. Eppen and Joshua Lieberman (1981), "A Theoretical and Empirical Evaluation of Price Deals for Consumer Non-durables", *Journal of Marketing*, 45 (Winter), 116-129.

Blattberg, Robert C. and Kenneth J. Wisniewski (1989), "Price-Induced Patterns of Competition", *Marketing Science*, 8 (4), p.291-309

Blattberg, Robert C., Richard Briesch and Edward J. Fox (1995), "How Promotions Work", *Marketing Science*, 14 (3, 2/2), p.120-132

Blattberg, Robert C. and Scott A. Neslin (1990), *Sales Promotion: Concepts, Methods and Strategies*, Engle Wood Cliffs, NJ: Prentice-Hall, Inc.

Boatwright, Peter, Robert McCullock and Peter Rossi (1999), "Account-Level Modeling for Trade Promotion: An Application of a Constraint Parameter Hierarchical Model", *Journal of American Statistical Association*, 94 (December, 448), p.1063-1073

Bolton, Ruth N. (1989), "The Relationship Between Market Characteristics and Promotional Price Elasticities", *Marketing Science*, 8(Spring, 2), p.153-169

Bolton, Ruth N. and Venkatesh Shankar (2003), "An Empirically Derived Taxonomy of Retailer Pricing and Promotion Strategies", *Journal of Retailing*, 79, p.213-224

Bronnenberg, Bart J. and Luc Wathieu (1996), "Asymmetric Promotion Effects and Brand Positioning", *Marketing Science*, 15 (4), p.379-394

Bruce, Norris, Preyas S. Desai and Richard Staelin (2005), "The Better They are the More They Give: Trade Promotions of Consumer Durables", *Journal of Marketing Research*, 42 (February), p.54-66

Bucklin, Randolph E. and Sunil Gupta (1999), "Commercial Use of UPC Scanner Data: Industry and Academic Perspectives", *Marketing Science*, 18 (3), p.247-273

Bucklin, Randolph E., Sunil Gupta and S. Siddarth (1998), "Determining Segmentation in Sales Response Across Consumer Purchase Behaviors", *Journal of Marketing Research*, 35 (May), p.189-197

Chiang, Jeongwen (1991), "A Simultaneous Approach to the Whether, What and How Much to Buy Questions", *Marketing Science*, 10 (Fall, 4), p.297-315

Chiang, Jeongwen (1995), "Competing Coupon Promotions and Category Sales", *Marketing Science*, 14 (Winter, 1), p.105-122

Chintagunta, Pradeep K. (1993), "Investigating Purchase Incidence, Brand Choice and Purchase Quantity Decisions of Households", *Marketing Science,* 12 (Spring, 2), p.184-208

Chintagunta, Pradeep K. (2002), "Investigating Category Pricing Behavior at a Retail Chain", *Journal of Marketing Research,* 39 (May, 2), p.141-154

Chintagunta, Pradeep K., Deepak C. Jain and Naufel J. Vilcassim (1991), "Investigating Heterogeneity in Brand Preferences in Logit Models for Panel Data", *Journal of Marketing Research,* 28 (November, 4), p.417-428

Cooper, Lee G. (1988), "Competitive Maps: The Structure Underlying Asymmetric Cross Elasticities", *Management Science,* 34 (June, 6), p.707-723

Cooper, Lee G., Penny Baron, Wayne Levy, Michael Swisher and Paris Gogos (1999), "PROMOCAST: A New Forecasting Method for Promotion Planning", *Marketing Science,* 18 (3), p.301-316

Cotterill, Ronald W., William P. Putsis Jr. and Ravi Dhar (2000), "Assessing the Competitive Interaction Between Private Labels and National Brands", *Journal of Business*, 73 (1), p.109-137.

Cui, Tony Haitao, Jagmohan S. Raju and Z. Jon Zhang (2008), "A Price Discrimination Model of Trade Promotions", *Marketing Science,* 27 (September-October, 5), p.779-795

Dada, Maqbool and Srikanth K.N. (1987), "Pricing Policies for Quantity Discounts", *Management Science,* 33 (October, 10), p.1247-1252

d'Astous, Alain and Isabelle Jacob (2002), "Understanding Consumer Reactions to Premium-Based Promotional Offers", *European Journal of Marketing,* 36 (11/12), p.1270-1286

d'Astous, Alain and Valerie Landreville (2003), "An Experimental Investigation of Factors Affecting Consumers' Perceptions of Sales Promotions", *European Journal of Marketing,* 37 (11/12), p.1746-1761

Dawes, John (2004), "Assessing the Impact of a Very Successful Price Promotion on Brand, Category and Competitor sales", *Journal of Product and Brand Management,* 13 (5), p.303-314

Dekimpe, Marnik G., Dominique M. Hanssens and Jorge M. Silva-Risso (1999), "Long-Run Effects of Price Promotions in Scanner Markets", *Journal of Econometrics,* 89, p.269-291

Devis, Scott, J., Jeffrey Inman and Leigh McAlister (1992), "Promotion Has a Negative Effect on Brand Evaluations- Or Does It? Additional Disconfirming Evidence", *Journal of Marketing Research,* 29 (February, 1), p.143-148

Dhar, Sanjay K. and Jagmohan S. Raju (1998), "The Effect of Cross-Ruff Coupons on Sales and Profits", *Management Science,* 44 (November, 1/2), p.1501-1516

Dhar, Sanjay K. and Stephen J.Hoch (1997), "Why Store Brand Penetration Varies by Retailer", *Marketing Science,* 16 (3), p.208-227

Dowling Grahame R. and Mark Uncles (1997), "Do Customer Loyalty Programs Really Work?", *Sloan Management Review,* 38 (Summer, 4), p.71-82

Doyle, Peter and John Saunders (1986), "Measuring the Profitability of Sales Promotions", *The Journal of the Operational Research Society,* 37 (October, 10), p.955-965

Dreze, Xavier and David R. Bell (2003), "Creating Win-Win Trade Promotions: Theory and Empirical Analysis of Scan-Back Trade Deals", *Marketing Science,* 22 (Winter, 1), p.16-39

Dube, Jean-Pierre and Sachin Gupta (2008), "Cross-Brand Pass-Through in Supermarket Pricing", *Marketing Science,* 27 (May-June, 3), p.324-333

Ellickson, Paul B. and Sanjog Misra (2008), "Supermarket Pricing Strategies", *Marketing Science,* 27 (September-October, 5), p.811-828

Feinberg, Fred M., Aradhna Krishna and Z. Jon Zhang (2002), "Do We Care What others Get? A Behaviorist Approach to Targeted Promotions", *Journal of Marketing Research,* 39 (August, 3), p.277-291

Flanagan, Joseph P. (1988), "Sales Promotion: The Emerging Alternative to Brand-Building Advertising", *The Journal of Consumer Marketing,* 5 (Spring, 2), p.45-48

Foekens, Eijte W., Peter S.H. Leeflang and Dick R. Wittink (1999), "Varying Parameter Models to Accommodate Dynamic Promotion Effects", *Journal of Econometrics,* 89, p.249-268

Fox, Richard J., Srinivas K. Reddy and Bharat Rao (1997), "Modeling Response to Repetitive Promotional Stimuli", *Journal of the Academy of Marketing Science,* 25 (Summer, 3), p.242-255

Franses, Philip Hans, Richard Paap and Philip A. Sijthoff (2007), "Modeling Potentially Time-Varying Effects of Promotions on Sales", *Erim Reoprt Series Research in Management,* ERS-2001-05-MKT, p.27

Gerstner, Eitan and James D. Hess (1991), "A Theory of Channel Price Promotions", *The American Economic Review,* 81 (September, 4), p.872-886

Gerstner, Eitan and James D. Hess (1995), "Pull Promotion and Channel Coordination", *Marketing Science,* 14 (Winter, 1), p.43-60

Gomez, Miguel I., Vithala R. Rao and Edward W. McLaughlin (2007), "Empirical Analysis of Budget and Allocation of Trade Promotions in the U.S. Supermarket Industry", *Journal of Marketing Research,* 44 (August), p.410-424

Greenleaf, Eric A. (1995), "The Impact of Reference Price Effects on the Profitability of Price Promotions", *Marketing Science,* 14 (Winter, 1), p.82-104

Grover, Rajiv and Vithala R. Rao (1988), "Inferring Competitive Market Structure Based on a Model of Interpurchase Intervals", *Journal of Marketing,* 62 (2), p.46-59

Grover, Rajiv and V. Srinivasan (1992), "Evaluating the Multiple Effects of Retail Promotions on Brand Loyal and Brand Switching Segments", *Journal of Marketing Research,* 29 (February, 1), p.76-89

Gupta, Sachin, Pradeep K. Chintagunta (1994), "On Using Demographic Variables to Determine Segment Membership in Logit Mixture Models", *Journal of Marketing Research,* 31, February, p.128-136

Gupta, Sunil (1988), "Impact of Sales Promotions on When, What and How Much to Buy", *Journal of Marketing Research,* 25 (November, 4), p.342-355

Haaijer, E. Marinus (1999), *Modeling Conjoint Choice Experiments with the Probit Model*, Dissertation of the Faculty of Economics, University of Groningen, Groningen, NL

Haines, Doudlas C. (2007), "Manufacturer and Retailer Power in Retailer Response to Trade Discounts", *The Journal of the Academy of Marketing Science,* 11 (2), p.1-18

Hann, Il-Horn, Kai-Lung Hui, Sang-Yong T. Lee and I.P.L. Png (2005), "Sales and Promotions: A More General Model", *University of Southern California, Working Paper.*

Hanssens, Dominique M., Peter S.H. Leeflang and Dick R. Wittink (2005), "Market Response Models and Marketing Practice", *Applied Stochastic Models in Business and Industry,* 21, p.423-434

Hardie, Bruce G.S., Eric J. Johnson and Peter S. Fader (1993), "Modeling Loss Aversion and Reference Dependence Effects on Brand Choice", *Marketing Science,* 12 (Fall, 4), p.378-394

Hardy, Kenneth G. (1986), "Key Success Factors for Manufacturers' Sales Promotions in Packaged Goods", *Journal of Marketing Research,* 50 (July, 3), p.13-23

Harlam, Bari A. and Leonard M. Lodish (1995), "Modeling Consumers' Choices of Multiple Items", *Journal of Marketing Research,* 32 (November), p.404-418

Heath, Timothy B. and Subimal Chatterjee (1995), "Asymmetric Decoy Effects on Lower-Quality Versus Higher-Quality Brands: Meta-Analytic and Experimental Evidence", *Journal of Consumer Research,* 22 (December, 3), p.268-284

Heath, Timothy B., Gangseog Ryu, Subimal Chatterjee, Michael S. Mccarthy, David L. Mothersbaugh, Sandra Milberg and Gary J. Gaeth (2000), "Asymmetric Competition in Choice and the Leveraging of Competitive Disadvantages", *Journal of Consumer Research,* 27 (December, 3), p.291-308

Heilman, Carrie M., Douglas Bowman and Gordon P. Wright (2000), "The Evolution of Brand Preferences and Choice Behaviors of Consumers New to a Market", *Journal of Marketing Research,* 37 (May), p.139-155

Hensher, David A. (1994), "Stated preference Analysis of Travel Choices: The State of Practice", *Transportation,* 21 (May, 2), p.107-133

Hensher, David A. and William H. Greene (2002), "Specification and Estimation of the Nested Logit Model: Alternative Normalizations", *Transportation Research: Part B* , 36, p.1-17

Hoch, Stephen J. and Shumeet Banerji (1993), "When Do Private Labels Succeed?", *Sloan Management Review,* 34 (Summer, 4), p.57-67

Hoch, Stephen J., Byung-Do Kim, Alan L. Montgomery and Peter E. Rossi (1995), "Determinants of Store-Level Price Elasticity", *Journal of Marketing Research,* 32 (February), p.17-29

Hoch, Stephen J., Xavier Dreze and Mary E. Purk (1994), "EDLP, HI-LO and Margin Arithmetic", *Journal of Marketing,* 58 (October, 4), p.16-27

Inman, Jeffrey J., and Leigh McAlister (1994), "Do Coupon Expiration Dates Affect Consumer Behavior?", *Journal of Marketing Research,* 31 (August, 3), p.423-428

Inman, Jeffrey J., Leigh McAlister and Wayne D. Hoyer (1990), "Promotion Signal: Proxy for a Price Cut?", *Journal of Consumer Research,* 17 (June, 1), p.74-81

Jedidi, Kamel and Z. John Zhang (2002), "Augmenting Conjoint Analysis to Estimate Consumer Reservation Price", *Management Science,* 48 (October, 10), p.1350-1368

Jeuland, Abel P. and Chakravarthi Narasimhan (1985), "Dealing-Temporary Price Cuts-by Seller as a Buyer Discrimination Mechanism", *Journal of Business*, 58 (3), p.295-308

Kadiyali, Vrinda, Pradeep Chintagunta and Naufel Vilcassim (2000), "Manufacturer-Retailer Channel Interactions and Implications for Channel Power: An Empirical Investigation of Pricing in a Local Market", *Marketing Science*, 19 (Spring, 2), p.127-148

Kahn, Barbara E. and Jagmohan S. Raju (1991), "Effects of Price Promotions on Variety-Seeking and Reinforcement Behavior", *Marketing Science*, 10 (Fall, 4), p.316-337

Kahn, Barbara E. and Therese A. Louie (1990), "Effects of Retraction of Price Promotions on Brand Choice Behavior for variety-Seeking and Last-Purchase -Loyal Consumers", *Journal of Marketing Research*, 27 (August, 3), p.279-289

Kalwani, Manohar U. and Chi Kin Yim (1992), "Consumer Price and Promotion Expectations: An Experimental Study", *Journal of Marketing Research*, 29 (February,1), p.90-100

Kalwani, Manohar U., Chi Kin Yim, Heikki J. Rinne and Yoshi Sugita (1990), "A Price Expectations Model of Customer Brand Choice", *Journal of Marketing Research*, 27 (August, 3), p.251-262

Kamakura, Wagner and Gary J. Russell (1989), "A Probabilistic Choice Model for Market Segmentation and Elasticity Structure", *Journal of Marketing Research*, 26 (November, 4), p.379-390.

Kannan, P.K. and Chi Kim (Bennett) Yim (2001), "An Investigation of the Impact of Promotions on Across-Submarket Competition", *Journal of Business Research*, 53, p.137-149

Kasulis, Jack J., Fred W. Morgan, David E. Griffith and James M. Kenderdine (1999), "Managing Trade Promotions in the Context of Market Power", *Journal of the Academy of Marketing Science*, 27 (Summer, 3), p.320-332

Kaul, Anil and Dick R. Wittink (1995), "Empirical Generalizations about the Impact of Advertising on Price Sensitivity and Price", *Marketing Science*, 14 (3), p.151-160

Kim, Sang Yong and Richard Staelin (1999), "Manufacturer Allowances and Retailer Pass-Through Rates in a Competitive Environment", *Marketing Science*, 18 (1), p.59-76

Kohli, Rajeev and Heungsoo Park (1989), "A Cooperative Game Theory Model of Quantity Discount", *Management Science*, 35 (June, 6), p.693-707

Kopalle, Praveen K., Carl F. Mela and Lawrence Marsh (1999), "The Dynamic Effect of Discounting on Sales: Empirical Analysis and Normative Pricing Implications", *Marketing Science*, 18 (3), p.317-332

Kotler, Phillip (1987), *Marketing Management*, 9th ed, Upper Saddle River, NJ: Prentice Hall

Krishna, Aradhna (1992), "Effect of Dealing Patterns on Consumer Perceptions of Deal Frequency and Willingness to Pay", *Journal of Marketing Research,* 28 (November, 4), p.441-451

Krishna, Aradhna and Z. John Zhang (1999), "Short- or Long-Duration Coupons: The Effect of the Expiration Date on the Profitability of Coupon Promotions", *Management Science,* 45 (August, 8), p.1041-1056

Krishna, Aradhna, Imran S. Currim and Robert W. Shoemaker (1991), "Consumer Perceptions of Promotional Activity", *Journal of Marketing,* 55 (April, 2), p.4-16

Krishnamurthi, Laxman and S.P. Raj (1988), "A Model of Brand Choice and Purchase Quantity Price Sensitivities", *Marketing Science,* 7 (Winter, 1), p.1-20

Krishnamurthi, Laxman and S.P. Raj (1991), "An Empirical Analysis of the Relationship Between Brand Loyalty and Consumer Price Elasticity", *Marketing Science,* 10 (Spring, 2), p.172-183

Kruger, Michael W. (1987), "Steps Toward Mastering Trade Promotions", *Marketing Science,* 6 (spring, 2), p.147-149

Kumar, Nanda, Surendra Rajiv and Abel Jeuland (2001), "Effectiveness of Trade Promotions: Analyzing the Determinants of Retail Pass Through", *Marketing Science,* 20 (Fall, 4), p.382-404

Kumar, V. and Robert P. Leone (1988), "Measuring the Effect of Retail Store Promotions on Brand and Store Substitution", *Journal of Marketing Research,* 25 (May, 2), p.178-185

Kumar, V., and Srinivasan Swaminathan (2005), "The Different Faces of Coupon Elasticity", *Journal of Retailing,* 81 (1), p.1-13

Lal, Rajiv (1990), "Manufacturer Trade Deals and Retail Price Promotions", *Journal of Marketing Research,* 27 (November, 4), p.428-444

Lal, Rajiv and J. Miguel Villas-Boas (1996), "Exclusive Dealing and Price Promotions", *Journal of Business,* 69 (April, 2), p.159-172

Lal, Rajiv and J. Miguel Villas-Boas (1998), "Price Promotions and Trade Deals with Multiproduct Retailers", *Management Science,* 44 (July, 7), p.935-949

Lal, Rajiv and Ram C. Rao (1997), "Supermarket Competition: The Case of Every Day Low Pricing", *Marketing Science*, 16 (1), p.60-80

Lam, Shun Yin, Mark Vandenbosch, John Hulland and Michael Pearce (2001), "Evaluating Promotions in Shopping Environments: Decomposing Sales Response into Attraction, Conversion and Spending Effects", *Marketing Science,* 20 (Spring, 2), p.194-215

Laroche, Michel, Frank Pons, Nadia Zgolli, Marie-Cecile Cervellon and Chankon Kim (2003), "A Model of Consumer Response to Two Retail Sales Promotion Techniques", *Journal of Business Research,* 56, p.513-522

Lattin, James M. and Randolph E. Bucklin (1989), "Reference Effects of Price and Promotion on Brand Choice Behavior", *Journal of Marketing Research,* 26 (August, 3), p.292-310

Leclerc, France and John D.C. Little (1997), "Can Advertising Copy Make FSI Coupons More Effective?", *Journal of Marketing Research*, 34 (November, 4), p.473-484

Leeflang, Peter S.H. and Dick R. Wittink (1996), "Competitive Reaction Versus Consumer Response: Do Managers Overreact?", *International Journal of Research in Marketing,* 13, p.103-119

Lemon, Katherine N. and Stephen Nowlis (2002), "Developing Synergies Between Promotions and Brands in Different Price-Quality Tiers", *Journal of Marketing Research,* 39 (May), p.171-185

Leone, Robert P. and Srini S. Srinivasan (1996), "Coupon Face Value: Its Impact on Coupon Redemptions, Brand Sales, and Brand Profitability", *Journal of Retailing,* 72 (3), p.273-289

Lewis, Michael (2005), "Research Note: A Dynamic Programming Approach to Customer Relationship Pricing", *Management Science,* 51 (June, 6), p.986-994

Lichtenstein, Donald R., Richard G. Netemeyer and Scott Burton (1995), "Assessing the Domain Specificity of Deal Proneness: A Field Study", *The Journal of Consumer Research,* 22 (December, 3), p.314-326

Louvier, Jordan J., David A. Hensher and Joffre D. Swait (2000), "Stated Choice Methods: Analysis and Application", *Cambridge University Press, Cambridge, U.K.*

Lucas, Anthony (1996), "In-Store Trade Promotions-Profit or Loss?", *International Journal of Retail and Distribution Management,* Autumn, p.13-15

Mace, Sandrine and Scott A. Neslin (2004), "The Determinants of Pre- and Postpromotion Dips in Sales of Frequently Purchased Goods", *Journal of Marketing Research,* 41 (August), p.339-350

Manchanda, Puneet, Asim Ansari and Sunil Gupta (1999), "The Shopping Basket: A Model for Multicategory Purchase Incidence Decisions", *Marketing Science*, 18 (2), 95-114

Manning, Kenneth C., William O. Bearden and Randall L. Rose (1998), "Development of a Theory of Retailer Response to Manufacturers' Everyday Low Cost Programs", *Journal of Retailing,* 74 (Spring, 1), p.107-137

McAlister, Leigh (1979), "Choosing Multiple Items from a Product Class", *Journal of Consumer Research,* 6, December, p.213-224

McAlister, Leigh (2007), "Cross-Brand Pass-Through: Fact or Artifact?", *Marketing Science,* 26 (November-December, 6), p.876-898

Mela, Carl F., Sunil Gupta and Kamel Jedidi (1998), "Assessing Long-Term Promotional Influences on Market Structure", *International Journal of Research in Marketing*, 15, p.89-107

Meza, Sergio and K. Sudhir (2006), "Pass-Through Timing", *Quantitative Marketing and Economics,* 4, p.351-382

Miller, Bill R. and Charles E. Strain (1970), "Determining Promotional Effects by Experimental Design", *Journal of Marketing Research,* 7 (November, 4), p.513-516

Montgomery David B., Marian Chapman Moore and Joel E. Urbany (2005), "Reasoning About Competitive Reactions: Evidence from Executives", *Marketing Science,* 24 (Winter, 1), p.138-149

Moreau, Page, Aradhna Krishna and Bari Harlam (2001), "The Manufacturer-Retailer-Consumer Triad: Differing Perceptions Regarding Price Promotions", *Journal of Retailing,* 77, p.547-569

Mulhern, Francis and Daniel T. Padgett (1995), "The Relationship Between Retail Price Promotions and Regular Price Purchases", *Journal of Marketing,* 59 (October, 4), p.83-90

Mulhern, Francis J. and Robert P. Leone (1991), "Implicit Price Bundling of Retail Products: A Multiproduct Approach to Maximizing Store Profitability", *Journal of marketing,* 55 (October, 4), p.63-76

Naik Prasad A., Kalyan Raman and Russell S. Winer (2005), "Planning Marketing-Mix Strategies in the Presence of Interaction Effects", *Marketing Science,* 24 (Winter, 1), p.25-34

Nair, Suresh K. and Peter Tarasewich (2003), "A Model and Solution Method for Multi-Period Sales Promotion Design", *European Journal of Operation Research,* 150, p.672-687

Narasimhan, Chakravarthi (1984), "A Price Discrimination Theory of Coupons", *Marketing Science*, 3 (2), p.128-147

Narasimhan, Chakravarthi (1988), "Competitive Promotional Strategies", *Journal of Business*, 61 (4), 427-449

Narasimhan, Chakravarthi, Scott A. Neslin and Subrata K. Sen (1996), "Promotional Elasticities and Category Characteristics", *Journal of Marketing,* 60 (April, 2), p.17-30

Neslin, Scott A. (1990), "A Market Response Model for Coupon Promotions", *Marketing Science,* 9 (Spring, 2), p.125-145

Neslin, Scott A. (2002), *Sales Promotion,* Marketing Science Institute, Cambridge, MA

Neslin, Scott A. and Darrel G. Clarke (1987), "Relating the Brand Use Profile of the Coupon Redeemers to Brand and Coupon Characteristics", *Journal of Advertising Research*, 27 (February-March, 1), p.23-32

Neslin, Scott A. and Robert W. Shoemaker (1983), "A Model for Evaluating the Profitability of Coupon Promotions", *Marketing Science,* 2 (Fall, 4), p.361-388

Neslin, Scott A. and Robert W. Shoemaker (1989), "An Alternative Explanation for Lower Repeat Rate After Promotion Purchases", *Journal of Marketing Research,* 26 (May, 2), p.205-213

Neslin, Scott A., Caroline Henderson and John Quelch (1985), "Consumer Promotions and the Acceleration of Product Purchases", *Marketing Science,* 4 (Spring, 2), p.147-165

Neslin, Scott A., Stephen G. Powell and Linda Schneider Stone (1995), "The Effects of Retailer and Consumer Response on Optimal Manufacturer Advertising and Trade Promotion Strategies", *Management Science,* 41 (May, 5), p.749-766

Nijs, Vincent R., Marnik G. Dekimpe, Jan-Benedict E. Steenkamps and Dominique M. Hanssens (2001), "The Category-Demand Effects of Price Promotions", *Marketing Science,* 20 (Winter, 1), p.1-22

Papatla, Purushottam, and Lakshman Krishnamurthi (1996), "Measuring the Dynamic Effects of Promotions on Brand Choice", *Journal of Marketing Research*, 33 (February, 2), p.20-35

Petty R. E. and J. T. Cacioppo (1986), "The Elaboration Likelihood Model of Persuasion", *Advances in Experimental Social Psychology*, 19, p.123-205

Pauwels, Koen (2007), "How Retailer and Competitor Decisions Drive the Long-Term Effectiveness of Manufacturer Promotions for Fast Moving Consumer Goods", *Journal of Retailing,* 83 (3), p.297-308

Pauwels, Koen, Dominique M. Hanssens and S. Siddarth (2002), "The Long-Term Effects of Price Promotions on Category Incidence, Brand Choice and Purchase Quantity", *Journal of Marketing Research,* 39 (November, 4), p.421-439

Raghubir, Priya (1998), "Coupon Value: A Signal for Price?", *Journal of Marketing Research*, 35 (August, 3), p.316-324

Rajiv, Surendra, Shantanu Dutta and Sanjay K. Dhar (2002), "Asymmetric Store Positioning and Promotional Advertising Strategies: Theory Evidence", *Marketing Science,* 21 (Winter, 1), p.74-96

Raju, Jagmohan S., Raj Sethuraman and Sanjay K. Dhar (1995), "The Introduction and Performance of Store Brands", *Marketing Science*, 41 (6), p.957-978

Raju, Jagmohan S., Sanjay K. Dhar and Donald G. Morrison (1994), "The Effect of Package Coupons on Brand Choice", *Marketing Science,* 13 (Spring, 2), p.145-164

Raju, Jagmohan S., V. Srinivasan and Rajiv Lal (1990), "The Effects of Brand Loyalty on Competitive Price Promotional Strategies", *Management Science,* 36 (March, 3), p.276-304

Rao, Ram C. (1991), "Pricing and Promotions in Asymmetric Duopolies", *Marketing Science,* 10 (Spring, 2), p.131-144

Rao, Ram C., Ramesh V. Arjunji and B. P. S. Murthi (1995), "Game Theory and Empirical Generalizations Concerning Competitive Promotions", *Marketing Science,* 14 (2), p.89-100

Rao, Vithala R. and L. Joseph thomas (1973), "Dynamic Models for Sales Promotion Policies", *Operational Research Quarterly,* 24 (September, 3), p.403-417

Reibstein, David J. and Phillis A. Traver (1982), "Factors Affecting Coupon Redemption Rates", *Journal of Marketing*, 46 (4), p.102-113

Richards, Timothy J. (2005), "A Nested Logit Model of Strategic Promotion", *American Agricultural Economics Association Annual Meeting.*

Rossi, Peter E., Robert E. McCulloch and Greg M. Allenby (1996), "The Value of Purchase History Data in Target Marketing", *Marketing Science*, 15 (4), p.321-340

Russell, Gary J. and Ann Petersen (2000), "Analysis of Cross Category Dependence in Market Basket Selection", *Journal of Retailing,* 76 (3), p.367-392

Russell, Gary J. and Ruth N. Bolton (1988), "Implications of Market Structure for Elasticity Structure", *Journal of Marketing Research,* 25(Aug), 229-241

Seetharaman, P.B. (2004), "Modeling Multiple Sources of State Dependence in Random Utility Models: A Distributed Lag Approach", *Marketing Science,* 23 (Spring, 2), p.263-271

Sethuraman, Raj (1995), "A Meta-Analysis of National Brand and Store Brand Cross-Promotional Price Elasticities", *Marketing Letters,* 6 (4), p.275-286

Sethuraman, Raj (1996), "A Model of How Discounting High-Priced Brands Affects the Sales of Low-Priced Brands", *Journal of Marketing Research,* 33 (November, 4), p.399-409

Sethuraman, Raj, and V.Srinivasan (2002), "The Asymmetric Share Effect: An Empirical Generalizations on Cross-Price Effects", *Journal of Marketing Research,* 39 (August), p.379-386

Sethuraman, Raj, V.Srinivasan and Doyle Kim (1999), "Asymmetric and Neighborhood Cross-Price Effects: Some Empirical Generalizations", *Marketing Science,* 18 (1), p.23-41

Shaffer, Greg and Z. Jon Zhang (2002), "Competitive One-to-One Promotions", *Management Science,* 48 (September, 9), p.1143-1160

Shankar, Venkatesh and Ruth N. Bolton (2004), "An Empirical Analysis of Determinants of Retailer Pricing Strategy", *Marketing Science,* 23 (Winter, 1), p.28-49

Sharp, Byron and Anne Sharp (1997), "Loyalty Programs and Their Impact on Repeat-Purchase Loyalty Patterns", *International Journal of Research in Marketing,* 14 (5), p.473-486

Sigue, Simon Pierre (2008), "Consumer and Retailer Promotions: Who is Better Off?", *Journal of Retailing,* 84 (4), p.449-460

Silva-Risso, Jorge M. and Randolph E. Bucklin (2004), "Capturing the Effect of Coupon Promotions in Scanner Panel Choice Models", *Journal of Product and Brand Managament,* 13 (6), p.442-452

Silva-Risso, Jorge M., Randolph E. Bucklin and Donald G. Morrison (1999), "A Decision Support System for Planning Manufacturers' Sales Promotion Calendars", *Marketing Science,* 18 (3), p.274-300

Simester, Duncan (1997), "Note. Optimal Promotion Strategies: A Demand-sided Characterization", *Management Science,* 43 (February, 2), p.251-256

Simonson, Itamar, Ziv Carmon and Suzanne O'Curry (1994), "Experimental Evidence on the Negative Effect of Product Features and Sales Promotions on Brand Choice", *Marketing Science,* 13 (Winter, 1), p.23-40

Sivakumar, K (2000), "Price -Tier Competition: An Integrative Review", *Journal of Product and Brand Management,* 9 (5), p.276-290

Sivakumar, K., and S.P. Raj (1997), "Quality-Tier Competition: How Price Changes Influence Brand Choice and Category Choice", *Journal of Marketing*, 61 (July), p.71-84

Srinivasan, Shuba, Koen Pawels, Dominique M. Hanssens and Marnik G. Dekimpe (2004), "Do Promotions Benefit Manufacturers, Retailers or Both?", *Management Science,* 50 (May, 5), p.617-629

Steenkamp, Jan-Benedict E.M., Vincent R. Nijs, Dominique M. Hanssens and Marnik G. Dekimpe (2005), "Competitive Reactions to Advertising and Promotion Attacks", *Marketing Science,* 24 (Winter, 1), p.35-54

Subrahmanyan, Saroja (2000), "Using Quantitative Models for Setting Retail Prices", *Journal of Product and Brand Management,* 9 (5), p.304-315

Sudhir, K. (2001), "Structural Analysis of Manufacturer Pricing in the Presence of a Strategic Retailer", *Marketing Science,* 20 (Summer, 3), p.244-264

Sun, Baohong (2005), "Promotion Effect on Endogenous Consumption", *Marketing Science,* 24 (Summer, 3), p.430-443

Sun, Baohong, Scott A. Neslin and Kannan Srinivasan (2003), "Measuring the Impact of Promotions on Brand Switching When Consumers Are Forward Looking", *Journal of Marketing Research,* 40 (November), p.389-405

Swait, Joffre and Tulin Erdem (2002), "The Effects of Temporal Consistency of Sales Promotions and Availability on Consumer Choice Behavior", *Journal of Marketing Research,* 39 (August, 3), p.304-320

Tellis, Gerard J. (1986), "Beyond the Many Faces of Price: An Integration of Pricing Strategies," *Journal of Marketing*, 50 (October, 4), 146-160

Tversky, Amos and Daniel Kahneman (1991), "Loss Aversion in Riskless Choice: A Reference-Dependent Model", *The Quarterly Journal of Economics,* November, p.1039-1061

Tyagi, Rajeev K. (1999), "A Characterization of Retailer Response to Manufacturer Trade Deals", *Journal of Marketing Research,* 36 (November, 4), p.510-516

Tyagi, Rajeev K. (2005), "Do Strategic Conclusions Depend on How Price is Defined in Models of Distribution Channels?", *Journal of Marketing Research,* 42 (May), p.228-232

Van Heerde, Herald J. (2001), *Models for Sales Promotion Effects Based on Store-Level Scanner Data,* Dissertation of the Faculty of Economics, University of Groningen, Groningen, NL.

Van Heerde, Harald J. and Tammo H.A. Bijmolt (2005), "Decomposing the Promotional Revenue Bump for Loyalty Program Members vs Nonmembers", *Journal of Marketing Research,* 42 (November), p.443-457

Van Heerde, Harald J., Peter S.H. Leeflang and Dick R. Wittink (2000), "The Estimation of Pre- and Postpromotion Dips with Store-Level Scanner Data", *Journal of Marketing Research,* 37 (August, 3), p.383-395

Van Heerde, Harald J., Peter S.H. Leeflang and Dick R. Wittink (2002), "How Promotions Work: SCAN*PRO- Based Evolutionary Model Building", *Schmalenbach Busines Review,* 54 (July, 4), p.198-220

Van Heerde, Harald J., Peter S.H. Leeflang and Dick R. Wittink (2004), "Decomposing the Sales Promotion Bump with Store Data", *Marketing Science,* 23 (Summer, 3), p.317-344

Van Heerde, Harald J., Sachin Gupta and Dick R. Wittink (2003), "Is 75% of the Sales Promotion Bump Due to Brand Switching? No, only 33% Is.", *Journal of Marketing Research,* 40 (November), p.481-491

Varian, Hall R. (1980), "A Model of Sales", *American Economic Review*, 70 (4), p.651-659

Vilcassim, Nauffle J. and Deepak C. Jain (1991), "Modeling Purchase-Timing and Brand-Switching Behavior Incorporating Explanatory Variables and Unobserved Heterogeneity", *Journal of Marketing Research,* 28 (February, 1), p.29-41

Villas-Boas, Miguel J. and Russell S. Winer (1999), "Endogeneity in Brand Choice Models", *Management Science,* 45 (October, 10), p.1324-1338

Vindevogel, Bernd, Derk Van den Poel and Geert Wets (2005), "Why Promotion Strategies Based on Market Basket Analysis Do Not Work", *Expert Systems with Application,* 28, p.583-590

Walters, Rockney and Maqbul Jamil (2002), "Measuring Cross-Category Specials Purchasing: Theory, Empirical Results, and Implications", *Journal of Market-Focused Management,* 5(March, 1), p.25-42

Walters, Rockney G. (1989), "An Empirical Investigation into Retailer Response to Manufacturer Trade Promotions", *Journal of Retailing,* 65 (Summer, 2), p.253-272

Walters, Rockney G. (1991), "Assessing the Impact of Retail Price Promotions on Product Substitution, Complementary Purchase, and Interstore Sales Displacement", *Journal of Marketing,* 55 (April, 2), p.17-28

Walters, Rockney G. and Scott B. MacKenzie (1988), "A Structural Equations Analysis of the Impact of Price Promotions on Store Performance", *Journal of Marketing Research,* 25 (February, 1), p.51-63

Wedel, Michel and Jie Zhang (2004), "Analyzing Brand Competition Across Subcategories", *Journal of Marketing Research,* 41 (November), p.448-456

Wilkinson J. B., J. Barry Mason and Christie H. Paksoy (1982), "Assessing the Impact of Short-term Supermarket Strategy Variables", *Journal of Marketing Research,* 19 (Febraury), p.72-86

Zeithaml, Valarie A. (1988), "Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence", *Journal of Marketing,* 52 (July, 3), p.2-22

Zhang, John Z., Aradhna Krishna and Sanjay K. Dhar (2000), "The Optimal Choice of Promotional Vehicles: Front Loaded or Rear Loaded Incentives?", *Management Science,* 46 (March, 3), p.348-362

Zinkhan, George M. (2002), "Promoting Services via the Internet: New Opportunities and Challenges", *The Journal of Services Marketing,* 16 (5), p.412-431

VITA

Rajeev Airani.

College of Business and Public Administration, Constant Hall, Old Dominion University.

PhD	2009	Old Dominion University, Virginia, USA.
M.B.A.	1999	Karnatak University, Dharwad, India.
B.E.	1996	Karnatak University, Dharwad, India.