A THEORY OF RETAILER PRICE PROMOTION USING ECONOMIC FOUNDATIONS: IT'S ALL INCREMENTAL

By

Kurt Alan Jetta

BS, Statistics, North Carolina State University

MBA, The Fuqua School of Business, Duke University

RESEARCH DISSERTATION

SUBMITTED IN FULFILMENT OF THE REQUIREMENT FOR THE DEGREE OF DOCTOR OF PHILOSOPHY IN THE DEPARTMENT OF ECONOMICS

FORDHAM UNIVERSITY

Bronx, New York

April, 2008

ACKNOWLEDGEMENTS

As I crawl to the finish line of the Ph. D. attainment process, there are many people that I would like to thank for helping me get to this point. First and foremost is my wife Nancy who exercised great patience and support during the three years of the program. Not only was I trying to complete my course requirements – which became exponentially harder each semester – but I was trying to run my consulting business and manage 13 employees. Nancy also has served as my chief proofreader. I also want to thank my children Connor (17), Susie (15) and Cami (12) for their support and encouragement during this time, as well.

Academically, I want to thank Dr. V. Kumar of the University of Connecticut that referred me to the Fordham University program, which is one of the few Ph.D. programs that can accommodate full-time professionals. During my first two years in Fordham, I always had the feeling that I made the wrong choice by pursuing Economics rather than my field of expertise, Marketing. It was largely due to Dr. Dominick Salvatore, however, who was able to stimulate the idea of tying together Economics and Marketing. I had always assumed that there would be a great deal of co-integration of these two fields, but my review of the literature suggests otherwise. If nothing else comes out of this paper, at minimum, I hope to validate Dr. Salvatore's strong belief that theory is supremely important and is the driver of true practical innovation. Dr. Salvatore has served as a reader on my committee, and has definitely pushed me to make sure that I am fully proficient on the theoretical material in this paper.

Special thanks go to my advisor Dr. Erick Rengifo who provided a consistent level of encouragement and support. He also showed me the way to make the most efficient use of my efforts in the dissertation process so that I could complete this project by this semester (May 2008). The other two members of my committee – Dr. Vinod and Dr. Praveen Kopalle – have also been greatly supportive of my efforts. Both of these gentlemen always made sure to provide timely and insightful feedback. Dr. Vinod

was the one who originated the idea of adding the section on Hysteresis (Section VIIE), and it has turned out to be an extremely important topic which provides a certain amount of closure to the topic. Dr. Kopalle has gone out of his way to be helpful to me even though he is not a Fordham professor. I only met Dr. Kopalle once at a conference, and it would have been very easy for him to beg off of this project. Dr. Kopalle, thank you for being a part of this process.

It is my intention to provide important empirical and theoretical content to both the Marketing and Economics fields, and stimulate a greater intellectual co-ordination between these two fields. I think this paper can act as a first step to that end.

Kurt Jetta
Fordham University, 2008

PERSONAL BIOGRAPHY

Kurt Jetta, 46, is a third year Ph. D. Student in the Department of Economics at Fordham University. His specialty is Consumer Demand Theory. Mr. Jetta is officially a part-time student in the program, but he has taken a full-time course load at the same time as he has been running his marketing research and consulting company, TABS Group.

Kurt Jetta founded TABS Group in 1998 to provide quality service to clients in the Consumer Products industry through innovative analytical methods. Since its inception, the company has grown revenue by 40% per year, as an increasing number of companies embrace the analytical innovations introduced by Mr. Jetta. TABS Group now consists of 14 employees and over 40 regular clients.

Prior to starting TABS Group, Kurt was Chief Executive Office of Binky-Griptight, Inc., a supplier of baby feeding products and pacifiers. In that capacity, Mr. Jetta grew revenue by 75% within 18 months and narrowed the operating loss by 50%. Based on the growth generated in the Binky brand, the company was sold to his former company, Playtex Products. At Playtex, Kurt worked in both Sales and Marketing positions, with his last job as Director, Trade Marketing. In 1993 he invented the Pay-for-Performance retailer promotion program on the company's largest and profitable business, Playtex Tampons. The program was instrumental in growing the brand sales by over $20MM (+15%) and profits by nearly that much. This program was cited as the biggest contributor to company growth in the company's Initial Public Offering in 1994. It was the success of this program many years ago that gave rise to his interest in a formal theoretical proof to explain why it was so successful. This inquiry eventually lead to his return to the academic world after 20 years in industry.

Mr. Jetta has an M.B.A. from The Fuqua School of Business at Duke University (1986) and a B.S. in Statistics from North Carolina State University (1983). Mr. Jetta has been married for 18 years to Nancy Price Jetta from Stamford, CT. They have three children: Connor (17), Susanne (15) and Camille (12). Kurt currently resides in Shelton, CT where he has lived for the last 15 years. In his spare time – what little there is of it – Kurt is an avid fan of Duke Blue Devil Basketball as well as an avid viewer of independent films. He also vows to start back to playing tennis with his wife once the Ph. D. process is over.

TABLE OF CONTENTS

TABLES AND FIGURES

Research Abstract

This dissertation offers a theory of retailer price promotions*. The theory is based on a desire to understand theoretically the tens of thousands of in-market observations that I have seen empirically over 20 years in the Consumer Packaged Goods Industry. Specifically, the theory states that incremental retail sales generated by reduced price promotions from retailers exhibits a Complete Category Expansion Effect (CCEE). That is, sales are entirely incremental to the retailer and the promoting manufacturer: there is no post-period reduction in sales ("dip") either in the short or long-term, nor is there a reduction in sales from competing brands, nor is there a reduction of sales for the promoted item in competing retailers. To develop this theory, the research will be divided into several sections. First (Section IV) , there will be a discussion of why aggregated point-of-sale data at the chain level is an easier, cheaper and more extendable method of analyzing retailer promotions. Section V uses aggregated data to develop a more accurate and robust baseline model (sales in the absence of price promotion) using Dynamic Linear Models. This new model will be tested against the industry standard model on three measures of performance. We shall use this dynamic modeling technique to measure post-period sales effects. Section VI tests the model with over one thousand empirical examples. The examples will demonstrate the presence of the in-market effect of retailer price promotions with significant *and* sustained price discounts and no detectable reduction in post-period baseline sales. Section VII will explain why these empirical findings, as well as the theory, are consistent with the foundations of consumer demand theory. It will also provide insight on optimum profit conditions using the theory of hysteresis (Dixit – 1992) and demonstrate why not all sectors of the consumer economy can take advantage of the Theory of Retailer Price Promotion. Finally, Section VIII will discuss the managerial and academic implications of these findings along with suggestions for future research.

* Retailer Price Promotion is defined as a temporary price reduction at a retailer for fixed amount of time. It is accompanied by some form of communication about the reduced price, usually through Feature Advertising, In-Store Signage. In this paper "Promotion," "Price Promotion," and "Retail Price Promotion" will be used synonymously, unless otherwise noted.

II. Introduction

Authors Note: This paper will use dozens of terms that are jargon particular to the consumer packaged goods industry. Readers that are unfamiliar with these terms are encouraged to consult the Glossary of Terms that can be found in Appendix I on Page118. Additionally, this paper will use the term "incrementality" quite frequently although it is not a word recognized in any dictionary. Most marketing practitioners commonly use this term to mean, "the degree to which sales increases from marketing activities are incremental." E.g. a brand line extension that sourced almost its entire volume from the base brand exhibited low <u>*incrementality*</u>*.*

IIA. Dissertation Overview

In the United States, the Consumer Packaged Goods industry (CPG) accounts for over $500 Billion in annual retail sales according to A.C. Nielsen. If we project the industry out to the entire world, this industry posts well in excess of $1 Trillion annually. Furthermore, it is well-documented that retailer price promotions (defined as a temporary reduction in retailer price for a specific set of products for a specific set of time) account for the largest share of CPG firms' marketing budget (Source: Cannondale 2007), and that percentage has grown consistently over time. Industry estimates (TABS Group - 2008) peg the amount of annual spending on retailer price promotions at about $50-75B annually in the U.S. (about 15-20% of factory sales according to Accenture) and over $100B worldwide.

It is fortunate indeed that this industry has perhaps the most extensive information infrastructure of any industry. Most U.S. retail outlets in the Food, Drug and Mass Merchandiser channels (excluding Wal-Mart) are able to track the sales of virtually every product that is sold in the store with the use of scanners. These scanners can read the UPC (Universal Product Code) on each product, and the UPC is matched to information that describes dozens of characteristics about the product: manufacturer, brand, product type, flavor, weight, count size, etc… The in-store scanner data is augmented by household-level scanning data (aka panel data) from over 100,000 homes, and it is used to generate even more granular information on the consumer purchasing process. Two major firms, Information Resources and Nielsen Company, have created a multi-billion dollar industry by collecting much of this information and selling it to manufacturers, retailers and other interested parties.

Armed with this information, manufacturers, retailers and academics have the ability to develop extraordinarily detailed models to measure the effectiveness of promotions and most other marketing vehicles like consumer advertising, price changes and public relations. This technology has been in wide use since the late 1980's, so 20 years later it is easy to imagine an industry with a well-defined understanding of the optimal use of their marketing budgets. Given this understanding, we might expect the academic community to have moved on to other areas of inquiry.

But alas, imagination is all it is; the vision of the use of this data infrastructure has not been realized. Despite all of the resources available and the amount of money at stake, the fundamental issues surrounding the largest portion of the marketing budget, retailer price promotion, are still mired in controversy or outright misconception. A review of the academic literature on the topic of promotions yields a bewildering array of conflicting results. Consider this summary of results from Koppalle, Mela and Marsh (1999) on the issue of price sensitivity of promotions over time:

> "Evidence regarding the dynamic price sensitivity effect is mixed. Blattberg et al. (1995) suggest that increased promotions reduce the discount spike. Conversely, Zenor et al. (1998) find that increased promotions amplify the discount spike. Bolton (1989) finds no effect. Boulding et al. (1994) find the effect the effect varies by brand. Narasimhan et al. (1996) indicate the effect may be category-specific."

Five studies on one issue yield five different results. This is not an anomaly; in fact, most of the issues surrounding retailer price promotion are still controversial in many respects. Another example would be Pauwels, Hanssens and Siddarth (2002) discussing research about the long-term effects of promotions.

> "Any study of long-term effects needs to carefully define and operationalize the long run. In this respect, academic research has proceeded along three research streams, each with different methodologies and findings." (Underline added for emphasis)

In particular, there are eight issues that regularly surface among practitioners and academics concerning the expected results of retailer price promotion:

1. What is the short-term (immediate) effect of price promotion?
2. What are the intermediate effects of promotion? Specifically, is there a "dip" in sales for the weeks immediately following a promotion?
3. What is the long-term effect on sales of promotion?
4. What is the long-term effect on more qualitative aspects of brand choice (e.g. reference price, brand preference, brand image, etc…)?
5. What are the estimates of specific promotional tactics?
6. What is the effect of promotion at other, non-promoting retailers?
7. What is the source of the volume from increased sales from promotion?
8. What effect do specific promotional strategies (e.g. depth of discounts, frequency of execution) have on short and long-term brand sales?

These eight issues can be group under the general heading of **sales promotion decomposition research**. They are all centered on gaining an understanding of what happens to sales when brands are promoted. Of the eight issues, only one - the immediate effects of price promotion - can be considered resolved beyond dispute. Blattberg, Briesch and Frisch (1995) cited numerous articles that identified a dramatic increase in retail sales (aka "lift") the week of a promotion. This effect has been documented dozens of times since then.

The discrepancies in academic conclusions on the other fundamental issues are so profound, however, that another empirical study – no matter how statistically robust – will not resolve anything, and will only compound the confusion. This paper will seek to bring some consensus to these issues by offering a theoretical economic basis around which future results can be evaluated. Additionally, it will investigate two deeply held analytical paradigms that could be the source of the empirical discrepancies that are found throughout the literature.

The first analytical paradigm involves the data sources used for promotional research. A clear majority of academics use only store-level or household-level data (i.e. disaggregated data) rather than chain-level or market-level data (aggregated data) to conduct sales decomposition research of promotions. Nijs et al (2001) and Song and Chintagunta (2006) are two of a small group of articles on promotion to use aggregated data. Section IV will provide an evaluation of the issue of models using disaggregated vs. aggregated data. There are obvious disadvantages of disaggregated data in terms of costs, time and data availability, and is it not clear that this data – contrary to what the literature suggests – will yield results that are more accurate or unbiased that those from aggregated data. In fact, Christen et al (1997) state that if marketing variables are implemented homogeneously, there are no biases in parameter estimates from aggregated data. Section IV will demonstrate that the majority of marketing variables, and the most important ones, are implemented homogeneously. Furthermore, there will be an explanation as to why consideration of parameter bias is irrelevant for baseline sales estimation.

The second analytical paradigm addresses two models that are considered to be the industry and academic standard for estimating baseline sales: Scan*Pro (Wittink et al – 1988) and PromotionScan (Abraham and Lodish – 1993). These two models are very similar (Bucklin and Gupta – 1999) in that they take a log linear regression of sales against price and promotional activity. Numerous papers, e.g. Kopalle et al (1999) and Christen et al (1997), use this model as the foundation for their particular research into retailer price promotion. Section V will offer numerous examples of how these models are flawed in that they yield "phantom" spikes in baseline sales.

There will be an explanation of the theoretical and intuitive reasons why baseline sales are supposed to be relatively stable estimates of expected sales in the absence of promotional activity. Pauwels et al (2002) provided empirical proof of long-term stationarity in brand sales trends. Under the assumption of stationarity, there the expected deviation in weekly sales should be zero. Section V will discuss an alternative modeling technique, DLM (Dynamic Linear Modeling), compared against the existing model in terms of weekly baseline volatility and correlation of baseline with promotional activity. The DLM is a Bayesian estimation technique where sales in week *t* are conditional on all prior information. The model is based on a similar DLM from Ataman and Van Heerde (2007).

After we establish the optimal data source (aggregated rather than disaggregated) and the better baseline model (dynamic rather than log linear), Section VI will conduct empirical testing in three areas: 1) tests to validate the long-term stationarity (ergodicity) of brand trends, 2) tests to determine the superiority of the DLM baseline, and 3) tests to prove the CCEE. The tests will be conducted in two categories: Desserts and Beverages. The tests for the CCEE will test for post-promotion sales dips, brand switching and retail channel migration. A literature search of promotional studies identified only two other instances, Walters (1991) and Dawes (2004), where the authors took this comprehensive view of sales promotion decomposition. Most often, researchers fail to consider cross channel effects, but many others – particularly ones using panel data – are likely to ignore the timing effects of sales decomposition.

The hypotheses to be tested are to provide statistical validity to conclusions that appear to be obvious from a cursory inspection of the data. In Figures 1 and 2, even a casual observer would make the following conclusions:

- There is no post-promotion dip. There is no adverse long-term effect from promotions.
- There is no wear out from promotions, either from deal depth or deal frequency.

- The absence of promotion doesn't help improve the baseline sales.
- There appears to be no limit to the frequency with which promotions can be executed. In Figure 1 there are significant promotional lifts in 49 out of 104 weeks.

FIGURE 1
Weekly Sales: Dessert Brand D
Southeastern Grocery Chain

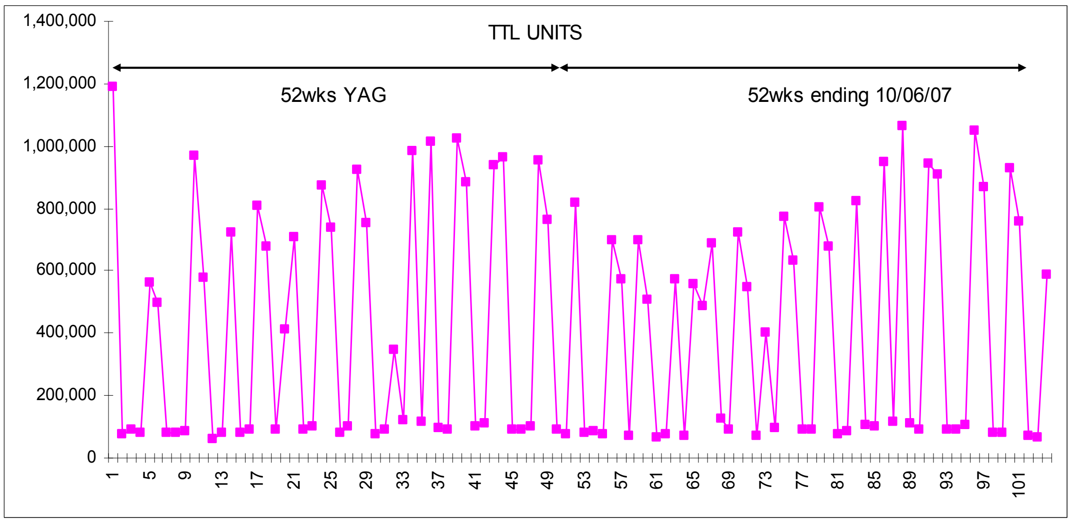
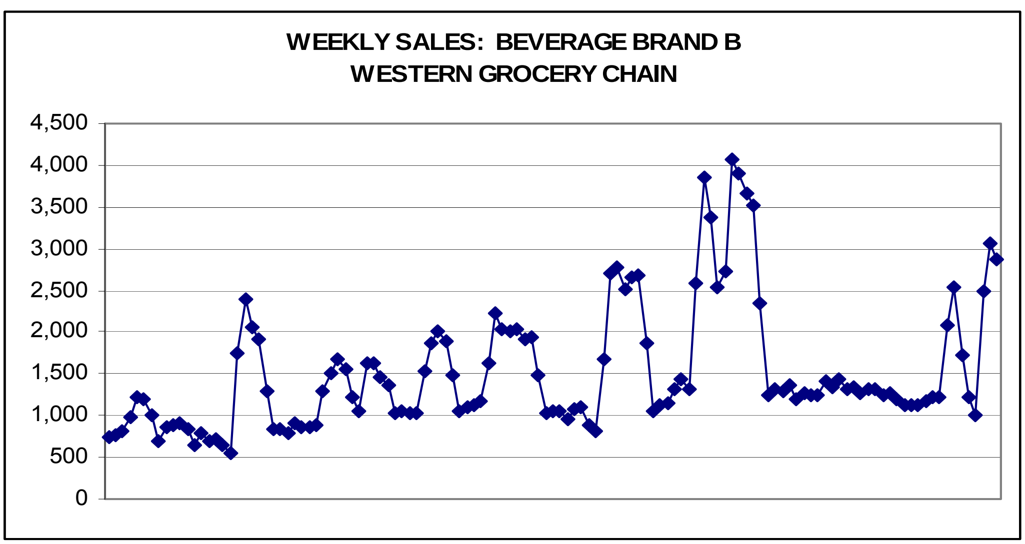


FIGURE 2



The academic paradigm has been for researchers to be trained not to believe their eyes. Because there were early studies based on flawed methods and shaky data sources that concluded that the above effects could not be real, fifteen years of research has been dedicated to validating those early studies. This paper will conclude that seeing is believing, and the ultimate proof is that the obvious trends in the data can be confirmed with robust statistical tests and are explained by microeconomic theory.

Section VII, then, will use microeconomic theory to explain and support the results that were derived in Section VI. Conversely, the empirical results derived in Section VI can be viewed as compelling support for the classical economic theories discussed in Section VII. Specifically, the work from such venerated theorists as Slutsky, Hicks, Marshall, Cournot, Pareto and Samuelson will be used to affirm that the empirical results from Section VI are, in fact, consistent with consumer demand theory.

Three cornerstones, in particular, will be discussed at length. **Slutsky's Fundamental Equation of Value Theory** (1915) provides the first formal equation for the Law of Demand. It proves a downward sloping demand curve; that is, quantity demanded for good x increases as price for good x decreases, all other prices staying constant. Further, Slutsky decomposed the effect on sales into two effects: a Substitution effect and an Income Effect. The Substitution effect is the component which aligns with the marketing concept of brand switching, and is therefore vital in explaining the Complete Category Expansion Effect (CCEE). Specifically, Slutsky offers a precise *mathematical* definition for identifying cross-substitution between Good x and Good y. For two products to be substitutes, the equation $\frac{\partial y}{\partial p_x} > 0$ must hold. That is, there must be an empirically measurable change in the quantity demanded of Good y for a change in the price of Good x and the change must be in the same direction as the change in price.

Hicks' Composite Good Theorem (1946) identifies the source of the substitution effects when no switching (or substitution) are evident within the category. The Composite Goods Theorem permits all other goods to be considered as one composite good as long as their relative prices are constant. With a 2-product structure, the third element, **Cournot's Aggregation Condition** (Henderson and Quandt – 1980), is easy to calculate. It will show that the cross elasticity for any given product in the substitution basket is effectively zero except for promoted products that a) account for a very high percentage of the consumer's budget constraint *and* b) have and extremely high price elasticity. Several scenarios will be run to demonstrate that there are virtually no plausible scenarios of budget/elasticity combinations for a CPG product that can generate an observable cross-elasticity effect.

Section VII will also consider the entire profitability of promotions under an assumption of the existence of the CCEE. There will be a proof that even in scenarios with a very high likelihood of generating positive economic profits, a condition of hysteresis will exist because of uncertainty in the manufacturer/retailer value chain needed to pass through price promotions. For durable goods, it will be shown that promotions in most instances cannot be profitable due to limitations in the value chain margin percentage and the price elasticity of higher ticket goods. Dixit (1992) called hysteresis the "theory of optimal inertia." Assuming that structural barriers can be addressed, it will be shown that there exists arbitrage opportunities for products with high margin consumer products with high and predictable promotion responsiveness.

Section VIII will summarize the findings and conclusions of the research, offer managerial and academic implications and offer areas of future research. The desired outcome of this research is not so much to definitively prove the Theory of Retailer Price Promotions. The more important goal is to initiate a new approach to marketing research, whereby marketing scientists are obliged to reconcile their results and conclusions with economic theory.

IIB. Interest and Importance in the Dissertation Topic

As noted in Section IA, there is a lot of money at stake in this particular marketing tactic. Some $50-100 Billion per year is spent in the U.S. from CPG manufacturers on promotions. This spending not only effects the specific manufacturers and retailers that are implementing these programs, but there is a large residual effect on suppliers of other forms of marketing programs, such as advertising agencies, television networks, consumer promotion agencies and many others. Should spending increase with retailers, there is the real potential of reduced spending levels for other marketing programs. The reverse is true, as well: the advertising industry, in particular, would like nothing more than to prove the ineffectiveness of spending on retailer promotions in order to have marketing dollars reallocated towards them.

Taking a cue from industry, academic researchers have also shown a heightened interest in this issue. This paper alone cites almost 100 articles dealing with various aspects of retailer price promotions. There are probably five times those amounts that have been written since Gupta's 1988 paper ignited the strong interest in the topic. From an academic standpoint, research in this area is interesting because data is in abundance, the effects to be measured are immediate (as compared to advertising which is longer term and harder to measure), and the research involves an econometric as well as behavioral component.

Research in the field of consumer packaged goods is inherently interesting because everyone has direct experience with these types of products: deodorant, soft drinks, candy, frozen dinners, etc… With these personal experiences, potential readers of the material are much more likely to be engaged in the topic and are able to understand the fundamental issues of the research ("How important is promotion on this dessert product to me and how does that compare to the results in the research?").

The primary importance of this research is that is one of the very few papers to explicitly create an intersection between marketing research and classical microeconomic theory. Marketing academics can no more ignore the laws and theories of economics than a mechanical engineer can ignore the laws of physics. There are few examples of economic principles being incorporated in marketing research, and the practice has not been embraced into the mainstream of most literature. Even the ones that have made the link between economics and marketing (e.g. Song and Chintagunta – 2007) appear to use economics as a modeling tool rather than a theoretical framework for explaining empirical results. Section VII will also show several examples of where marketing literature invokes economic theory incorrectly or incompletely. Therefore, the importance of the topic is not as much in the theory, but in the philosophy of incorporating economic principles into marketing literature.

On the empirical side, this paper proposes to make several important modeling contributions to the field. First, a better baseline estimate will help managers make better spending decisions on their promotion budgets. Second, the baseline method will be extendable to a broader section of retailers to include Club Stores, Category Killers (like Home Depot and Staples) and many other retailer channels. Third, the baseline model can reach hundreds, if not thousands, of small-to-mid sized manufacturers that cannot afford the significant investment required to purchase baseline estimates from the major syndicated data suppliers. Fourth, the DLM approach is very new in marketing applications, and this paper will add to the body of knowledge of this useful tool in econometric analysis.

IIC. Research Approach

By now it should be obvious that I am setting out to challenge several aspects of academic research into retailer price promotions: the type of data used, the estimates of non-promoted sales, and the conclusions about the effects of promotions on future weeks, competitive brands and other retailers. Having laid out these challenges now places me in the seemingly untenable position of having to support arguments within this research with citations from articles and authors with whom there is fundamental disagreement on their basic conclusions. An extreme example of the conflict comes in the discussion of baseline models. A considerable amount of space is dedicated to an unfavorable critique of the rationalization by Van Heerde et al (2002) of the current baseline model only to offer a superior alternative whose primary inspiration is (who else?) Van Heerde (Ataman and Van Heerde - 2007). It should be noted, though, that disagreements with the major elements of an author's work do not mean that there is disagreement with *all* of the elements of his work. More importantly, the final arbiter of the truth will be the economic theory used as substantiation of the Theory of Retailer Price Promotion.

Upon reviewing the literature on this topic in chronological order – starting in the early 1980's, when data was scarce, until now, when data is abundant - it is clear that the level of higher order calculus and econometrics has increased dramatically over the years. This paper will not meet those standards. In some cases – as in the discussion of aggregated vs. disaggregated data - I will use simple summary statistics to support a thesis. In others, I will use somewhat more complex models, but they will all be relatively simple compared to the prevailing literature on comparable topics. Analysis of Variance, Ordinary Least Squares and Unit Root testing will be the standard testing procedures. While it may desirable to demonstrate academic gravitas by use of such mathematical calculations, the topic does not require it to make the point. The data is straight-forward, the statistics required to analyze the are fairly standard, the conclusions to be derived from the analysis are obvious, and the theory used to reinforce the conclusions is universally accepted.

This approach has several advantages: first, the lack of heavy calculus should make this information comprehensible to a wide audience of both academics and practitioners; second, the research should be easy to replicate; third, it is easy to explain and teach should the conclusions withstand scrutiny from other academics.

While the literature over time has been increasingly technical, the content has become much less theoretical. It was not uncommon twenty years ago to find papers on marketing topics without math or statistics. Authors used the tools of logic, theory, analogy and critique to make their points. This approach was the one advocated by the godfather of economics, Alfred Marshall. This paper will be much in that same spirit.

Before proceeding, however, it is important to note that this research is based on several fundamental premises and assumptions:

A. <u>The aggregated market view – whether it be national, regional, market or chain – is the standard of reality that marketing research should be structured to explain</u>. This seemingly obvious premise is not internalized in the mainstream promotional literature. We regularly see papers which try to reconcile conflicting results seen in aggregated data to prior research done with disaggregated data. Van Heerde et al (2000) commented that, "Researchers expect to find a postpromotion dip because analyses of …panel data indicate that consumers tend to accelerate their purchases in response to a promotion." Chen and Yang (2007) propose a Bayesian method for estimating disaggregated choice models using aggregate data. In both instances the paradigm runs contrary to the intuition. Managers gauge their success on *aggregate* level results, and the information tools and research should trying to predict and explain those results, not the disaggregated results.

B. <u>Syndicated Scanner Data in the CPG Industry is the Standard of Measurement for sales results throughout the industry, and it is assumed to be accurate</u>.

This assumption precludes the rejection of results or conclusions based on the rationale of "bad data."

C. Brand Switching in Marketing terms is the analagous concept to the Substitution effect (Hicks, Allen, Slutsky – 1915, 1934, 1936) in microeconomic terms. Furthermore, if a specific brand-switching effect can be empirically identified, it can be concluded that the Substitution effect occurs for intrinsically similar products (intercategory). Conversely, if no intercategory brand switching can be found, then it follows, that there must be another source for the Substitution effect.

While the main goal of this paper is to establish the TRPP on theoretical grounds, there will be some empirical work as well. The work will proceed as follows:

1. Statistical testing of unit roots for all distinct "dataclasses." A dataclass is all sales observations associated with a specific retailer for a specific product at a specific market level (within retailer or competitive market).

2. Create a model to generate an endogenous dummy variable for promotional activity. The model will look exclusively at unit sales levels and volatility to generate this variable.

3. Use the promotional dummy variable to generate a baseline sales model for each dataclass.

4. Conduct statistical testing to compare this new baseline model to the industry-standard model. Specifically we will conduct two tests: first, a test of volatility using the standard deviation of the log of weekly sales differences. A better baseline model minimizes volatility. Second will be a test of covariance between baseline sales and promotional activity. A better baseline model should have no covariance between a baseline sales estimate and the presence of promotional activity.

5. Use the baseline model to conduct statistical testing of sales decomposition effects of promotion. These effects are post-promotion dips for Own Brand, Competitive Brand and Competitive Retailer.

With respect to the theoretical aspects of this paper, the goal is not to break ground on any major stream of microeconomic theory. Rather, it will be a straightforward exercise in applying Ph.D.-level consumer demand theory to a real world issue. Given the limited amount of classical economic theory in the marketing research literature, this approach is not only helpful in appealing to a broad audience of readers, it is *necessary* as a starting point for economic foundations to be a standard component of marketing research literature

The discussion on hysteresis and break-even profitability for price promotions offers a simple, but very powerful, derivation of the equilibrium conditions for optimizing promotions. This set of formulas can be used to explain which industries can and cannot use price promotions to generate incremental profits and even for the ones that can, there are structural barriers in the price promotion value chain that prohibit a significant expansion in the strategy.

Theoreticians often lament the difficulty of finding real world applications for their work, and empiricists are often dismissive of theory as impractical and removed from reality. It is hoped that this paper will demonstrate that microeconomic theory holds a treasure trove of insights that can be applied to real world marketing problems.

IID. Hypotheses to Test

Empirical work will be focused on testing individual elements of the CCEE (Note: CCEE – Complete Category Expansion Effect and TRPP – Theory of Retailer Price Promotion will be used interchangeably from here on). Sales decomposition analysis seeks to identify the source of incremental volume in several dimensions:

- Intertemporal Effects (When): Sales lifts can be generated from consumers switching the timing of their purchases either by Acceleration (moving their purchases up) or Stockpiling (loading household inventory and reducing future purchases). These effects would manifest themselves in pre- or post-promotional "dips" or declines in sales below baseline levels.

- Switching Effects (Who): Incremental sales can be sourced from other brands that are either within the category or from other categories. Most prior research has focused on within category switching, but many others have acknowledged the potential for switching across category (see Walters – 1991 and Kirk – 1996).

- Spacial Effects (Where): Consumers can switch the outlets where they buy due to the existence of a promotion (store substitution).

These effects in isolation appear to be relatively easy to address. However, there is difficulty once we account for overlapping effects between these effects. For example, there may be intertemporal brand switching effects or store substitution *and* brand switching effects. As noted previously, none except for Walters (1991) and Dawes (2004) have studies all of these effects together. Table 1 provides an accounting of these effects and illustrates the research gaps in the most influential papers on the price promotion issue.

Store Substitution is seen in the column dimension: Within Channel and Cross Channel. Nested under that are intertemporal effects: Immediate (Week 1), Adjustment (Weeks 2-8) and Permanent (Weeks 9+). The Switching Effects is seen in the row dimension; sales come either from Own Brand, Within Brand, Competitive Brand or Category Expansion (switch from other categories)..

As can be seen in Table 1, none of the prominent articles on sales decomposition considered the cross retailer effects of promotions. Additionally, neither Van Heerde et al (2003) nor Gupta (1988) considered the specific intertemporal effects.

TABLE 1: SALES DECOMPOSITION COMPARISON

UNIT SALES EFFECTS PER 100 UNITS OF INCREMENTAL PROMOTION LIFT

	WITHIN CHANNEL				CROSS CHANNEL				TOTAL MARKET			
JETTA (2008)	WK1	WK2-8	WK9+	TOTAL	WK1	WK2-8	WK9+	TOTAL	WK1	WK2-8	WK9+	TOTAL
PROMOTIONAL LIFT	100	0	0	100	0	0	0	0	100	0	0	100
REDUCTION EFFECT	0	0	0	0	0	0	0	0	0	0	0	0
OWN-BRAND	0	0	0	0	0	0	0	0	0	0	0	0
WITHIN BRAND	0	0	0	0	0	0	0	0	0	0	0	0
COMPETITIVE BRAND	0	0	0	0	0	0	0	0	0	0	0	0
CATEGORY EXPANSION EFFECT	100	0	0	100	0	0	0	0	100	0	0	100

	WITHIN CHANNEL				CROSS CHANNEL				TOTAL MARKET			
GUPTA (1988)	WK1	WK2-8	WK9+	TOTAL	WK1	WK2-8	WK9+	TOTAL	WK1	WK2+	WK9+	TOTAL
PROMOTIONAL LIFT	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	100
REDUCTION EFFECT	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	-100
OWN-BRAND	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	-16
WITHIN BRAND	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
COMPETITIVE BRAND	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	-84
CATEGORY EXPANSION EFFECT	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	-100

NOTE: Reduction Effects by Period and by Channel were ambigous in the research.

	WITHIN CHANNEL				CROSS CHANNEL				TOTAL MARKET			
PAUWELS, et al (2002)	WK1	WK2-8	WK9+	TOTAL	WK1	WK2-8	WK9+	TOTAL	WK1	WK2-8	WK9+	TOTAL
PROMOTIONAL LIFT	NA	NA	NA	NA	NA	NA	NA	NA	100	0	0	100
REDUCTION EFFECT	NA	NA	NA	NA	NA	NA	NA	NA	-25	-13	0	-38
OWN-BRAND	NA	NA	NA	NA	NA	NA	NA	NA	0	-13	0	-13
WITHIN BRAND	NA	NA	NA	NA	NA	NA	NA	NA	0	0	0	0
COMPETITIVE BRAND	NA	NA	NA	NA	NA	NA	NA	NA	-25	0	0	-25
CATEGORY EXPANSION EFFECT	NA	NA	NA	NA	NA	NA	NA	NA	75	-13	0	62

NOTE: Reduction Effects by Channel were ambiguous in the research. Also, effects in the research were reported in terms of elasticities not actual unit changes, therefore, intertemporal effects not exactly aligned with the article.

	WITHIN CHANNEL				CROSS CHANNEL				TOTAL MARKET			
VAN HEERDE, et al (2003)	WK1	WK2-8	WK9+	TOTAL	WK1	WK2-8	WK9+	TOTAL	WK1	WK2-8	WK9+	TOTAL
PROMOTIONAL LIFT	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	100
REDUCTION EFFECT	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	-67
OWN-BRAND	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	-34
WITHIN BRAND	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
COMPETITIVE BRAND	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	-33
CATEGORY EXPANSION EFFECT	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	33

NOTE: Reduction Effects by Period and by Channel were ambigous in the research.

The other three authors drilled into the intertemporal effects further by identifying post period sales declines either due to Stockpiling or Purchase Acceleration. This study will not attempt to do that, as the analysis can only be done with household panel data. More importantly, the issue is irrelevant for proving the CCEE because the CCEE theorizes that there are no intertemporal sales effects to analyze.

Although not as influential as the other works, Walters (1991) has received a considerable number of citations, and therefore is worth noting. Walters considered brand substitution, complementary purchases within store and cross-outlet substitution due to promotion. The net results were strong evidence of immediate Own Brand lifts, "modest support" for of brand substitution, "modest support" for complementary purchases and "low to modest support" for interstore (or cross outlet) substitution. Walters did not specifically test for intertemporal effects, and he also did not quantify category expansion effects as a percentage of the immediate sales lift. Based on the aggregate of the two conclusions of relatively modest substitution effects, however, it can be inferred that Walters (1991) was the first study to find a significant category expansion effect due to promotion.

With regards to category expansion effects – the main focus of the CCEE - Pauwels et al (2002) was the first one to definitively conclude that there were no permanent effects on brand sales from promotion, and, therefore there was a significant category expansion effect in the short-term. Specifically the authors stated,

> " …permanent effects of promotions on aggregate sales components are the exception rather than the rule…the general absence of permanent effects reassures practitioners that promotional activity does not structurally damage any of the three sales components [category incidence, brand choice or purchase quantity]...As long as the immediate and adjustment effects are profitable, playing the promotional game appears better than staying out of it."

Adding further support to the presence of a category expansion effect, Van Heerde et al (2003) noted, "Our results suggest that promotions are more attractive for managers than has been assumed thus far."

The Theory of Retailer Price Promotion goes much further than the other two studies in attributing the sales increase to category expansion. Indeed, the theory suggests that 100% of the increase is due to category expansion. To prove this empirically, though, only a subset of the most meaningful effects will be tested. We will test at the points where the effects are assumed to be most pronounced if, in fact, they exist. E.g. if there is zero immediate brand switching from a promotion, there is little likelihood of brand switching occurring intertemporal or spatially. Similarly, if store-substitution for Own Brand does not occur in during the promotion week, there is no reason to think that it would occur in future weeks. This logic is inspired by

Lancaster's Characteristic Theory (1966) that proposes "to operate with the minimum number of characteristics that give sufficient explanatory power." This approach would suggest that the effect of brand switching occurring in future weeks and competitive retailers measured by Dawes (2004) is implausible given that we are measuring deviations in three characteristics (choice brand, time and store) instead of just one (choice brand within a specific store at a specific time).

Theory: Incremental sales generated from retailer price promotions exhibit a Complete Category Expansion Effect. That is, the sales are entirely incremental to the brand and category at both the promoting retailer and competing retailers.

Hypotheses to Test the Theory

A. Tests for Long-Term Stationarity of Brand Sales

H0: *Brand sales exhibit ergodicity, which implies no adverse long-term effect from promotions.*

$E[L(S)_{ir}] - E[L(S)_{jr}] = 0$, L(S) is the one week natural log difference in sales (S) at week *i* and week *j* within retailer *r*, i=j+1. It is expected that the null hypothesis will be accepted.

B. Tests for Improved Baseline Model

H1: *Weekly sales variability during non-promoted weeks is equal to or greater than weekly sales variability of non-promoted weeks.*

$\sigma_{L(NONPROMO)} \geq \sigma_{L(PROMO)}$, where L(..) is the *natural log* differences of sales for NONPROMO vs. PROMO weeks. It is expected that the null hypothesis will be rejected.

H2: *The proposed baseline model has volatility that is equal to or greater than the existing baseline model.*

$\sigma_{L(Bn)} \geq \sigma_{L(Be)}$, where L(Bn) is the natural log differences of sales for the New Model (n) and L(Be) is the natural log differences of sales for the existing Model (e). It is expected that the null hypothesis will be rejected.

H3: *The Expectation of baseline sales during the promotion week are equal to the expectation of baseline sales during non-promotion weeks.*

$E(B_{PROMO}) = E(B_{NONPROMO})$, where B is Baseline sales. The test will be conducted on both the new and existing models. It is expected that the null hypothesis will be rejected for the existing baseline.

C. Tests for the Incrementality of Promotional Lifts

H4: *Within a retailer, Post-promotional sales for Own Brand are equal to or greater than Own Brand baseline sales for weeks before and during a promotional event.*

$S_{0ir} \geq S_{0jr}$, where S_{0ir} are sales for Own Brand (0) in week *i* at retailer *r* and S_{0jr} are baseline sales for Own Brand (0) in week *j* at retailer *r*. *i*=weeks 1...8 after a promotion and *j*=-8...-1 weeks prior to a promotion (j=0 is the promotional week). It is expected that the null hypothesis will be accepted.

H5: *Within a retailer, the actual sales of a non-promoting competitor during an Own Brand promotion are equal to or greater than the sales of the non-promoting competitor when Own Brand is not being promoted.*

This is a test for cross-effects (switching) between brands when one brand is promoted and the other is not. The test $S_{cirp*} \geq S_{cjrp}$, where S_{cir} are actual unit sales for Competitive Brand (c) in week *i* at retailer *r*. These sales are compared for weeks when Own Brand is promoted (p*) and non-promoted (*p* in week *j*). It is expected that the null hypothesis will be accepted. It is assumed that any potential cross-effects will be most pronounced during the specific promotional weeks. Therefore, there is no need to test for residual effects: if no effect is found in week *i*, then no effect would be found in week i+1, i+2, ... Conversely, if the hypothesis is rejected is week i, there is no need to carry the test through to future weeks.

H6: *Total Market Sales for Own Brand should increase sales at an equal to or greater level than the increase in the promoting retailer.*

This is a test for cross-outlet effects when a brand is promoted at one retailer, but not necessarily others in the same market. The equation to be tested takes the form $S_{0iM*} - B_{0iM*} \geq S_{0ir*} - B_{0ir*}$, where S_{0iM*} are actual unit sales and B_{0iM*} baseline sales for Own Brand (0) in week *i* in Market *M.* M* and r* designate promotional activity for week *i*. This increase is compared to the sales lift in the promoting retailer: Sales and Baseline sales of Own Brand (*0)* in week *i* and retailer *r* . It is expected that the null hypothesis will be accepted. Similar to H4, it is assumed that any cross-effects will be most pronounced during the specific promotional weeks. Therefore, there is no need to test for residual effects: if no effect is found in week *i*, then no effect would be found in week i+1, i+2, ... Conversely, if the hypothesis is rejected is week *i*, there is no need to carry the test through to future weeks.

For the CCEE to hold, hypotheses H4-H6 must *all* be accepted.

III. Literature Review

There are three literature streams that are relevant to understanding the background of this topic: Empirical Marketing Research (plentiful), Consumer Demand Theory in Economics (plentiful), and Marketing Theory (extremely thin). It is striking that despite the existence of a massive amount of data (or perhaps because of it), very little has been written about Marketing Theory, and the amount of discussion of economic theory as a foundation to marketing theory is virtually non-existent. While there are hundreds of articles and books on both Marketing Research on Price Promotion and Consumer Demand Theory, there are a dozen that provide a solid overview of the specific issues that have been explored.

IIIA. Empirical Marketing Research

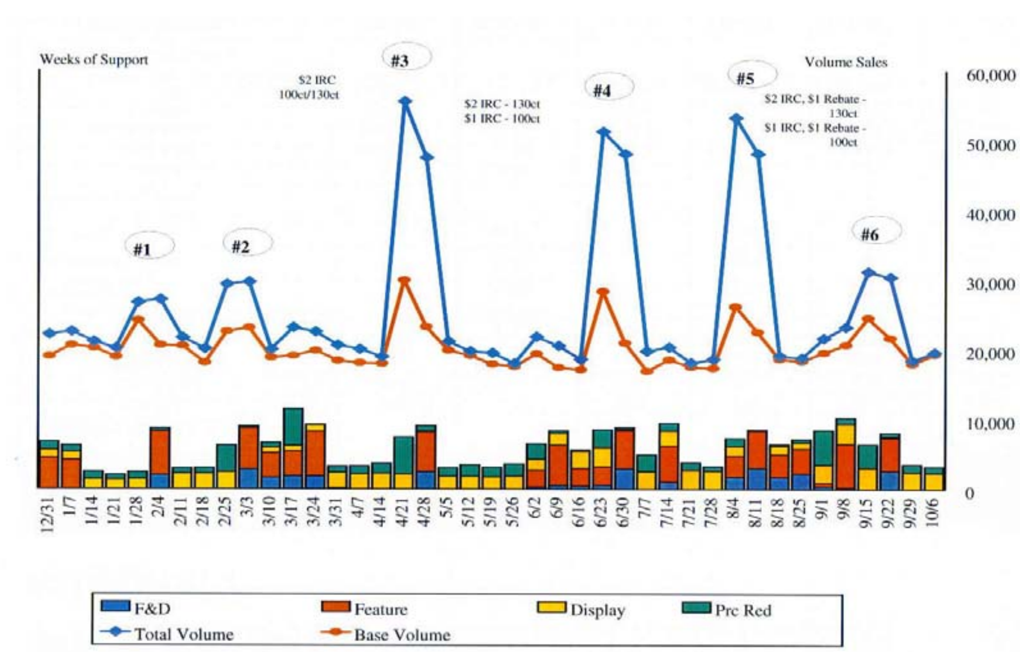
1. Gupta (1988): The seminal article, *"Impact of Sales Promotions on When, What and How Much to Buy,"* in the Journal of Marketing Research (JMR) is the most cited article on the topic of retailer price promotions according to the EBSCO Host Academic database. The research was important from several perspectives: first, it used household panel data, which was a relatively untapped database for academic research. Second, it was the first article to attempt a decomposition of the source of volume for price promotions. Third, the topic had a very high interest level, as the decomposition of sales from marketing tactics had significant practical implications for managers. Finally, the research pioneered the use of logit brand choice modeling in marketing research.

   The article focused on the Coffee category using panel data from one relatively rural market. The results that the source of volume from promotions are 84% derived from Brand Switching, 14% from Purchase Acceleration and 2% from Stockpiling are still cited nineteen years later. Unfortunately, the results were never consistently replicated and were ultimately invalidated by Van Heerde, Sachin Gupta and Wittink (2003) who demonstrated that Gupta (1988) failed to account for category growth in his calculations.

2. Wittink et al (1988) and Abraham and Lodish (1993): Scan*Pro (Wittink et al.) and PromotionScan (Abraham and Lodish) were developed by the two major suppliers of syndicated point-of-sale data: AC Nielsen and Information Resources (aka IRI). Both models provide estimates of baseline sales (i.e. sales in the absence of retailer promotional activity) and sales response to specific promotional vehicles like price discounts, feature ads and displays. Both models are fundamentally similar (Bucklin and Gupta – 1999; Hanssens, Parsons, Schultz - 2000) in that they are log-linear regressions of unit sales as a function of retailer price and in-store causal variables like display and feature ad activity.

   While there are no academic challenges to the validity and accuracy in the model, it is generally recognized by most practitioners and consultants that these baseline models are flawed. This generalization will be demonstrated with numerous examples in Section V and then proven in Section VI. Figure 3 shows one of these examples.

FIGURE 3 – BASELINE EXAMPLE



Another important aspect of these works is that they establish the paradigm of analyzing promotions on a store-level (or disaggregated) basis. Several future researchers worked to substantiate this approach (most notably Christen et al. – 1997). Conversely, there has been no challenge in the literature to the need to construct promotional lift models using disaggregated data.

3. Blattberg, Friesch and Fox (1995): "*How Promotions Work*," was a highly readable article that took the measure of the state of knowledge about Retailer Price Promotion through 1995. At that time, scanner data was widely available for at least five years, so there was sufficient time for the academic community to digest this information and develop empirical generalizations about the effects of promotions on sales. The most interesting aspect of the article is not so much what was known at that point, but what issues were still controversial, or "Key Issues with Conflicting Empirical Results." In fact, there are three closely related issues that will be tested in this dissertation because 12 years later there are still conflicting results.

    a. *"There is a Trough After the Deal*." *The* authors explicitly state that, "This effect has been surprisingly difficult to find…examination of store-level POS data for frequently purchased goods rarely reveals a trough after a promotion." Over the next dozen years, numerous other researchers would express a similar level of confusion over the lack of an obvious "dip" in sales in the weeks immediately following a promotion.

    b. *"The Majority of Promotional Volume Comes from Switchers."* According to Blattberg et al, "This was the conclusion of Gupta (1988), Totten and Black (1987), and Kumar and Leone (1988). However other research – Vilcassim and Chinagunta (1992) and Chintagunta (1993) showed that the majority of volume *did not* source from switchers."

c. *"There is a Negative Long Term Effect to Promotions."* The authors declare this to be "probably the most debated issue in the promotional literature."

4. Mela et al (1997-1999): These three years marked an extremely prolific stretch for the author as he published five papers during that period. All five addressed the challenge laid out by Blattberg et al. in 1995 about the need to resolve the long-term effects of promotions. Each one touched on a variant of these effects: e.g. the effect on baseline sales (Kopalle, Mela and Marsh – 1999), the effect on consumer price judgments (Alba, Mela, Shimp and Urbany – 1999), and the effect on stockpiling behavior (Mela, Jedidi and Bowman – 1998). While some variations were noted, the overarching conclusion in each article was that promotion had a negative effect on long-term sales.

5. Bell, Chiang and Padmanabhan (1999): Second only to Gupta (1988) in the number of citations within promotion-related research, the authors sought to replicate the Gupta (1988) study with a more extensive database of categories, specifically 173 brands across 13 categories. In general, the results appeared to be very close to Gupta: source of volume was 74% (Switching)/11% (Acceleration)/14% (Stockpiling) vs. 84%/14%/2% for Gupta. In fact, many later researchers interpreted the results to be a validation of the Gupta results. A closer inspection of the data, however, shows there was little convergence between the two studies.

   First, the coffee results were significantly different. Bell et al. showed the decomposition to be 52/3/45 vs. 84/14/2. The variance was brushed aside with the dubious assertion that, "we have newer and different data." The 45% vs. 2% difference in the Stockpiling component, however, seems much too large to brush aside unless it can be conclusively shown that there was a structural change in the category that could have caused such a dramatic shift.

Second, the authors were in the position of having to reconcile their conclusions with the recently published article by Ailawadi and Neslin (1998) that proved the theoretical possibility of expanding category sales through increase consumption. The authors explicitly considered the category expansion effect, and found that this effect in some categories was offset by stockpiling effects in others. They appeared uncomfortable with this conclusion as they commented, "we use the label 'No Effect' with some caution."

6. Dekimpe et al (1999), Nijs et al. (2001), Pauwels et al (2002): Three separate papers used traditional econometric modeling techniques (VAR, Unit-Root testing, etc…) to demonstrate a long-term stationary trend (ergodicity) in brand and category sales after a promotion. In other words, the long-term effect of promotions is neutral. These conclusions were derived through a variety of data sources (scanner and panel), markets (US and Netherlands) and time periods (1980's and 1990's) which suggest robust results. However, there has been no empirical documentation of ergodicity using time-series methodologies independent of Dekimpe or Hanssens.

   The papers refuted the results of the Mela (1997-1999) articles that found negative long-term effects. More recently Del Vecchio (2006) and Graham (2007) also found similar results to the Dekimpe/Hanssens research stream, but with different techniques. Del Vecchio et al. (2006) developed a meta-analysis to conclude, on average, no long-term effects, while Graham (2007) also found long-term stationary trends in the vast majority of brands in the UK market over seven years. Given the conclusions of these papers, it can be inferred that a consensus has developed about the long-term effects of promotion being neutral, but that there are still some notable disagreements.

   One area of ambiguity that still exists from both Nijs et al. (2001) and Pauwels et al. (2002) is their finding of a significant post-promotional dip in sales in the Intermediate Period (defined as up to eight weeks after a promotion) in a meaningful number of instances. It is ambiguous in that many studies have had a difficult time identifying this effect. Consider the following:

- Blattberg, Briesch and Fox (1995): "This effect has been surprisingly difficult to find."

- Van Heerde, Leeflang, and Wittink (2000): "At first it might be expected that the acceleration effects in timing and quantity evident at the household level would translate directly into a postpromotion dip in weekly store-level sales data. <u>However, postpromotion dips are rarely detected in visual (or traditional) statistical analyses of store data</u>." (Underline added)

- Hendel and Nevo (2003): "One of the puzzles of store-level scanner data is the lack of a dip in the quantity sold in the weeks following a promotion."

- Mace and Neslin (2004): "It is surprising that early attempts to measure the dips were not successful."

Undeterred by the obvious evidence of no dip, all of the above authors (except Blattberg et al) go on to proposed more "advanced" models that detect the post-promotion dip. The ambiguity then is not so much in the final conclusions, but in why the "Adjustment effects" are not obvious.

7. <u>Van Heerde, Leeflang and Wittink (2003)</u>: In their award winning article, "Is 75% of the Promotion Bump Due to Brand Switching? No, Only 33% Is," the authors identify a flaw in the interpretations of Gupta (1988) and Bell et al. (1999), which by inference points out the flaws of the methodology. Simply put, Gupta (1988) and Bell et al. (1999) developed elasticity estimates for the decomposition of sales which failed to incorporate a possibility for category expansion. As noted by Van Heerde et al, "this interpretation is correct only if category volume is held constant when the cross-brand effect is assessed."

   The authors then use the data from the previously mentioned studies to recalculate the sales decomposition using unit sales, not brand choice probability, as the numerator in the elasticity calculations. While several authors had previously demonstrated the theoretical and empirical existence of category expansion effects, this paper carried particular importance because it restated conclusions using the data from existing research that had been particularly influential.

There are dozens of other papers that have been written on the issue of retailer price promotions, but the seven research streams listed above exemplify several key issues with respect to empirical research on this issue:

- Despite the immense amount of information available the knowledge base has been very slow to evolve. Indeed, 15 years transpired between Gupta (1988) work and the time when it was effectively refuted by Van Heerde et al (2003). In the interim period, Van Heerde et al (2003) enumerates 19 major studies that use the Gupta study as a cornerstone of their research.

- The most influential papers are devoid of marketing or economic theory. In the rare instances where authors invoke any type of theory it is based on either behavioral theory (as in Gupta - 1988 or Pauwels et al - 2002) or some general mathematical or statistical theory.

- Conflicting results are the norm vs. an exception. Again, we would not expect this result in an area with such data abundance. The lack of any clear theoretical framework, however, leaves open the possibility of these conflicts because there is no objective standard to evaluate their validity.

IIIB. The State of Academic Consensus Around the Key Issues of Promotion

Given that there are more controversies than consensus in the field. It is helpful to establish the current state of knowledge surrounding the eight key issues identified in Section IIA.

1. **Immediate Effects of Promotion** – No controversy. Numerous papers - Blattberg, Wisniewski (1987), Bolton (1989), Narasimhan, Neslin and Sen (1996) and Van Heerde, Leeflang and Wittink (2001), to name a few - established the immediate, temporary increase of sales from promotion.

2. **Intermediate Effects of Promotion –** This is perhaps the most controversial issue surrounding the issue of retailer price promotions. The sentiment among most academics clearly seems to believe that a post-promotion reduction right after a promotion ("dip") should be evident based on various aspects of behavioral theory. Additionally, expectations of a postpromotion dip appear to be driven by the early conclusions derived from Gupta (1988) from panel data about the source of volume from purchase acceleration and stockpiling.

3. **Long Term Effects of Promotion** – There now appears to be a consensus on this issue of neutral long-term effect. Dekimpe, Hanssens, and Silva-Risso (1999), Nijs et al (2001), and Pauwels et al (2002) all traditional econometric modeling techniques (VAR, Unit-Root testing, etc…) to determine a long-term stationary trend in brand and category sales after a promotion. These conclusions were derived through a variety of data sources, markets and time periods. A potential shortcoming of these papers is the common authorship of Hanssens.

4. **Long Term Effect on Qualitative Factors Effecting Brand Sales** – This is another area of significant controversy in the literature. As recently as 2006, DelVecchio, Henard and Freling stated that,"scholastic opinion on whether promotions help or hinder a brand in subsequent choice periods is mixed." Their meta-analysis of 51 empirical studies found that *on average*, sales

promotions do not affect post-promotion brand preference. They did leave open the possibility that in certain instances – and quite a few of them – promotions could either help or hinder post-promotion preferences. This study was not quite the definitive study that would suggest an end to the controversy on this issue. The general conclusion however (no long-term effect, on average), is consistent with the econometric literature. Therefore, these two research streams would seem to point to a consensus that the long-term effect of promotions is that the brand returns to steady-state.

5. **Specific Effects of Promotional Tactics** – This issue indirectly addresses the accuracy of the current models used to measure promotional response. Both Scan*Pro (Wittink et al – 1988) and PromotionScan (Abraham and Lodish, 1988 and 1993) are used among practitioners and academics to determine the immediate increase in sales of such in-store tactics as temporary price reductions, displays and feature advertising. While there are no academic challenges to the validity and accuracy in the model, it is generally recognized by most practitioners and consultants that the baseline models, are flawed. This generalization of practitioners has not been proven in a formal sense; it is based on my discussions with analysts from 10 major CPG manufacturers. This generalization will be formally tested in Section VI.

   A closely related issue to the baseline accuracy is the use of aggregated (market or chain level) vs. disaggregated (store level) scanner data. Christen et al (1997) and Van Heerde, Leeflang and Wittink (2002) both argue that disaggregated store level data is needed to create baseline sales models. Their primary rationale is that parameter bias can occur when aggregating non-linear response functions linearly across a heterogeneous set of stores. There has been no explicit challenge to the use of disaggregated data, and the majority of the work on promotional effects continues to be done with store-level data.

6. **The Effect of Promotions on Competing Retailers –** Only a handful of papers could be found that explicitly address this very important issue.

Walters and Rinne (1986), V. Kumar and Leone (1988), Walters (1991), and Dawes (2004). In general, these studies have found weak store-substitution effects due to promotion. Dawes found the improbable result that the only effect of price promotion was a post-period effect of competing brands at competing retailers. His study found no effect on own-brand sales in any period at any retailer, nor was there an adverse affect on sales of competitive brands at the promoting retailer.

7. **The Source of Volume from Price Promotion** – This is the area receiving the most amount of attention in the literature. Gupta (1988) released his seminal research on this issue with "Impact of Sales Promotions on When, What and How Much to Buy." Among the 50+ articles sourced for this thesis, Gupta's work is the most often cited in EbscoHost database. The end result was a decomposition of the increased sales from promotion: 84% from brand switching, 14% from purchase acceleration and 2% from consumer stockpiling. Subsequent work from Ailawadi and Neslin (1998), Bell, Chiang and Padmanabhan (1999), Pauwels et al (2002) and Van Heerde, Leeflang and Wittink (2003) all approached the source of volume issue with the same decomposition approach. Of the five major works on the issue, none of the results were replicated by any of the others on the most important component, brand switching. Ailawadi and Neslin (1998) established the theoretical possibility of category expansion through promotion via Monte Carlo simulations. Pauwels et al (2002) and Van Heerde, Leeflang and Wittink (2003) then were the first ones to quantify a Category Expansion effect empirically. However, their estimates on this effect differed significantly (62% for Pauwels et al (2002), 33% for Van Heerde et al - 2003). All of these papers, with the exception of Pauwels et al (2002), did not specify the timing of these effects; they were all in the ambiguous future. Pauwels et al (2002), by contrast, established a logical timing framework for source of volume effects into Immediate (the promotion week), Adjustment (short-term effects up to 8 weeks after the promotion) and Permanent (long-term effects from the promotion). The study concluded that while the overall sales effect was

positive for the promoting brand, the strong gains from the Immediate effects were somewhat offset by negative Adjustment effects

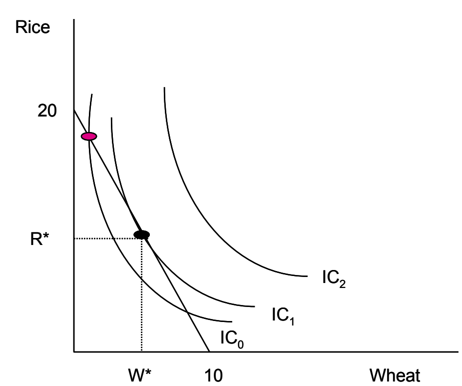
8. **The Effects of Specific Promotional Strategies on Short- and Long-Term Sales** – Blattberg, Friesch and Fox (1995) contend there to be a consensus in the literature with respect to the adverse effect of deal frequency both in terms of changing the reference price of consumers and lowering the magnitude of the deal spike. Alba et al (1999) extends the analysis to measure a mix of frequency and price discount strategies on consumers' reference prices. The results are ambiguous, at best, and many of them conflict with prior Alba et al (1994) results on a similar issue. This issue will not be addressed in this paper.

IIIC. Consumer Demand Theory

The lack of discussion of economic theory in marketing literature, in general, and promotional literature, in particular, cannot be attributed to a lack of theoretical output related to consumers and consumer demand. In fact, the last 100+ years of classical economic theory has a rich assortment of material that could be used in the better understanding of marketing phenomenon. Listed below are the authors most relevant to an understanding of consumer demand theory. These will be expanded upon in Section VII when the empirical results of Section VI are explained by microeconomic theory.

1. Marshall (1890): Marshall's *Principles of Economics* is the "standard treatise on economics" (Sorley – 1891) and provides the foundation of all future work in economics. In this work Marshall dedicated an extensive amount of the text to the concept of utility maximization of consumers and the concept of marginal utility, which was defined as the level of satisfaction a consumer received from consumer a good or service. The utility concept is central to understanding how a consumer makes purchase decisions. He identified the fundamental relationship that consumer equilibrium is reached at the point where marginal utilities for all commodities purchases are proportional to their prices.

FIGURE 4
INDIFFERENCE CURVE EXAMPLE*



2. Pareto (1909): The father of the famous Pareto Optimization (80/20 rule), Pareto's primary contribution to consumer theory was translating Marshall's concept of marginal utilities of single goods into indifference maps which laid out preferences between two goods. All of the properties associated with the basic indifference curve (like the one shown in Figure 4) were developed by Pareto. He demonstrated that these curves were convex and negatively sloped, which

* Source: Cornell University, John Abowd, Economics Dept.

represented the diminishing marginal utility of each product as quantity increased. Each curve represented a fixed level of utility, and each curve moving away from the origin represented a higher level of utility. Importantly, he introduced the concept of ordinal utility, rather than Marshall's idea of utility being a measurable concept (cardinal utility). With utility as a scale of preferences rather than a fixed value, the door was opened to much broader questions of consumer demand theory, because, as Hicks (1946) explained, "a quantitative concept of utility of not necessary to explain market phenomena." In summary, all initial instruction in consumer theory are framed by the work of Pareto, and in this paper Pareto's work is the foundation for the consideration of Hicks' Composite Goods Theorem (CGT). As will be shown, the CGT is the primary microeconomic theory explaining the CCEE.

3. <u>Slutsky-Hicks-Allen (1915, 1934, 1936)</u>: Slutsky (1915) derived the Fundamental Equation of Value Theory to decompose the dynamic effects of demand resulting from price changes. Hicks and Allen (1934) discovered the work of Slutsky, and introduced it to a broader audience. Slutsky's Equation is now the canonical formula in consumer demand theory. His decomposition of sales changes into Substitution and Income Effects were widely adopted in all disciplines within economics, not just consumer demand. The concept of brand switching is derivative of the Slutsky equation which included a component for measuring cross-brand effects. The cross-brand component is also used for identifying whether two products are substitutes, complements or independent based on their movement in sales concurrent with a price change of another product. Proof of the Complete Category Expansion Effect rests on whether a cross-brand effect in sales can be measured for a product in the same category as a promoted brand.

4. <u>Samuelson (1938, 1948)</u>: Samuelson proposed the concept of Revealed Preference which theorized that consumers purchase preferences can be inferred by observing different combinations of goods combinations at various

relative prices. He later developed a mathematical methodology to derive a consumer's specific indifference curve based on Revealed Preference. Another interpretation of Samuelson's work is that empirical observation and measurement is the foundation for determining specific effects related to the Slutsky equation.

5. Hicks (1946): Hicks' *Value and Capital* (1946) became the canonical economic text for generations. One of the more important contributions to consumer theory was his notion of the composite good which stated that in the absence of price changes, the entire market basket of goods can be collapsed into a single dimension relative to a focus good. This greatly facilitated utility analysis in a two-dimensional context. With respect to the CCEE, this theorem is the most important theoretical piece in its support because it explains why we might not expect a measurable change in sales of intercategory products when products are promoted.

6. Lancaster (1966): Lancaster's Characteristic Theory of Consumer Demand declared that goods have no utility in and of themselves; it is the characteristics contained in goods that have utility. Furthermore, characteristics are not necessarily ones that are perceived to be intrinsic to a particular good. E.g. Bottled Water could be a Substitute for Perfume among consumers that perceive Luxury to be a characteristic of both. Some have interpreted Lancaster's work as the theoretical basis for why substitution effects must come from intrinsically similar products. Section VIID will address the points made from Lancaster's important advance in consumer demand theory, and will show why his theory can be reconciled with the CCEE.

7. Lucas (1975): The Lucas Critique proposed that optimal economic decision rules must be based on the deep structural parameters of a model, not variables that are created endogenously by those parameters. While initially developed as a critique for fiscal policy, the approach has been adapted to virtually all aspects of economics under the umbrella of "microeconomic

> foundations." Within the context of marketing research, it is not enough to understand consumer demand as the locus of points of price and quantity. Rather, decision rules should be based on the structural parameters that comprise a consumer's utility function. This paper was inspired by this work because of its application to all disciplines within economics. Marketing is no different from monetary policy or international trade in its requirement that phenomenon should be explained in terms of their microeconomic foundations.

As can be seen from these authors, the foundations for understanding promotional response in the context of economic theory are readily available.

IIID. Marketing Theory

Marketing is a field that has been in existence for decades; it has hundreds of thousands of practitioners and thousands of academics. As noted earlier, billions of dollars are spent each year in various marketing endeavors. Despite all of this time, effort and money in the field of marketing the record of actual marketing theory is lacking. Only two pieces of literature stand out as actual 'marketing theory:' 1) *The General Theory of Marketing* (Bartels – 1968) and 2) *Foundations of Marketing Theory* (Hunt – 2002).

Bartel's General Theory was not actually a proposed theory, but rather a journal article that laid out a blueprint on how such a General Theory should be developed and what marketing-related issues should be incorporated into the General Theory. Hunt's text was originally written in 1976 and revised three times through 2002. The monograph sought to incorporate a variety of marketing theories into a single-source. It appears that the author does not lay out one general theory, and instead attempts, "to explore systematically some of the basic methodological issues underlying marketing research."

Hunt draws heavily from the philosophy of science in his text. Early in the first chapter he explains,

> "…the analytical methods to be developed and employed will be drawn from the tool kit of critical pluralism and scientific realism, with insights from logical empiricism, critical rationalism (falsificationism), and pragmatism where appropriate. Numerous other tool kits exist in the philosophy of science: classical empiricism, phenomenalism, rationalism, instrumentalism, logical positivism, conventionalism, relativism, constructivism, and, recently, "Weltanschauungen-ism."

Notably missing from the tool kit is *economics*. In fact, the minimal commentary Hunt dedicates to the topic (less than ½ page out of 287) suggests a field of academia that is not only uncomfortable with economics as a means to explain marketing phenomenon, but even whether marketing itself is a scientific field of endeavor. Consider these telling quotes in his book:

> "There is a real reason, however, why the field of marketing has been slow to develop a unique body of theory. It is a simple one: marketing is not a science (underline added). It is rather an art or a practice, and as such much more closely resembles engineering, medicine and architecture than it does physics, chemistry, or biology." – Hutchinson, 1952.

> "Perhaps many in marketing have reacted (overreacted?) to certain perceived deficiencies in economic theory…Economic theory is often perceived to be unrealistic and divorced from the real world (underline added)." – Hunt, 2002, pg. 29

> "Is Marketing a science? Differing perceptions of the scope of marketing have been shown to be a primary factor in the controversy over this questions." – Hunt, 2002, Pg. 19.

What Hunt tends to overlook throughout the text is the more substantial role of psychological and behavioral factors in shaping the theoretical framework of marketing. Gupta (1988), for example, justifies his Brand Choice model because "it is based on a behavioral theory of utility." The economic theory was ignored completely in the paper. Pauwels et al (2002) use three *behavioral* theories and no economic theories to explain the post-period effect of promotion.

Johnson (2006) formally quantified this lack of cross-pollination between Marketing and Economics, and the bias of Marketing towards Psychology by looking at the number of cross-citations in academic journals from 2004. In the study he found less than 5% of the journal citations in the three main Marketing journals – *Journal of Consumer Research, Journal of Marketing Research and Marketing Science* – were from the top four economics journals. He also found that the Journal of Consumer Research was almost twice as likely to cite Psychology journals as other Marketing journals.

A summary of citations in Neslin (2002) yields similar conclusions about the lack of cross-referencing between economics and marketing. Neslin's book, *Sales Promotion,* is generally considered the most complete synthesis of academic literature on sales promotion. From Table 2 we can see that 88% of the citations were from marketing journals with over half from the Top 3 – Marketing Science, Journal of Marketing Research and Journal of Marketing. Only 5% (13) of the citations were from economic journals, and only one – an economic textbook – could be considered an article about classical economic theory as it relates to marketing.

TABLE 2
SUMMARY OF CITATIONS – NESLIN (2002)

SOURCE	NUMBER	PCT
MARKETING SCIENCE (1)	80	31.1%
JOURNAL OF MARKETING RESEARCH	45	17.5%
WORKING PAPER (MARKETING)	25	9.7%
JOURNAL OF MARKETING	21	8.2%
TEXTBOOK (MARKETING)	14	5.4%
JOURNAL OF CONSUMER RESEARCH	10	3.9%
JOURNAL OF RETAILING	8	3.1%
INTERNATIONAL JOURNAL OF RESEARCH IN MARKETING	6	2.3%
JOURNAL OF ADVERTISING RESEARCH	6	2.3%
MARKETING LETTERS	6	2.3%
AMERICAN MARKETING ASSOCIATION	3	1.2%
OTHER MARKETING	3	1.2%
Subtotal Marketing	**227**	**88.3%**
AMERICAN ECONOMIC REVIEW	3	1.2%
ECONOMETRICA	2	0.8%
JOURNAL OF BUSINESS AND ECONOMIC STATISTICS	2	0.8%
QUARTERLY JOURNAL OF ECONOMICS	2	0.8%
JOURNAL OF ECONOMETRICS	1	0.4%
TEXTBOOK (ECONOMICS)	1	0.4%
JOURNAL OF ECONOMICS AND MANAGEMENT	1	0.4%
JOURNAL OF ECONOMIC THEORY	1	0.4%
Subtotal Economics	**13**	**5.1%**
OTHER SOURCES (2)	17	6.6%
TOTAL CITATIONS	**257**	

(1) Includes presentations given at the Marketing Science Conference
(2) Periodicals, reports and business journals.

While there are very few works on general marketing theory, there are quite a few papers relating to a theory of trade promotions. Blattberg and Levin (1987), Gerstner and Hess (1991) and Dreze and Bell (2003) all consider trade promotion theory by including off-invoice allowances, which are not relevant to the theory outlined in this paper. All three authors document how only a fraction of the allowance from these manufacturer discounts to the retailer are passed through to the consumer. This paper develops the theory and the implementation guidelines with the assumption of scanback promotions, which are assumed to have no market frictions.

In other literature on promotional theory, Raju (1988) takes a game theoretic approach where competitive considerations are the primary determinants of promotional activity. Blattberg, Eppen and Lieberman (1981) view promotions as a mechanism for economic to transfer inventory carrying costs: manufacturer to retailer to consumer. In none of these works were there references to microeconomic principles. Additionally, none of these works address the issue of the incrementality of retailer price promotions. Finally, these works were predominantly focused on firm dynamics (manufacturer vs. retailer or competitor A vs. competitor B) rather than on consumer behavior towards retailer price promotion.

Much more common in the marketing literature than theory are "empirical generalizations." Hunt dedicates a substantial amount of space towards rationalizing the use of these generalizations in the behavioral sciences that may "potentially qualify as lawlike in marketing." The problem with this rationale is that – as has already been documented – there are far too many conflicting results in marketing's empirical work. Without some foundations of theories laws there is no way to rationalize all of the conflicting results.

IV. Aggregated vs. Disaggregated Data for Promotion Models

IVA. Introduction

A firmly entrenched research paradigm within promotional analysis is the notion that only disaggregated data should be used for model estimation. Indeed the paradigm has taken such extremes that Chen and Yang (2007) developed a model that translates aggregated data – which is readily available - into a disaggregated equivalent so that the proper modeling could take place. Since the disaggregated standard was established by Wittink et al (1988) and Abraham and Lodish (1993) there has been no critical challenge to it.

Numerous authors – Christen et al (1997), Foekens et al (1994), Van Heerde, Leeflang and Wittink (2002) - have conceded that the use of aggregated data holds several appealing properties in the areas of cost, availability, modeling flexibility, processing time and overall compliance and acceptance by practitioners. However, the initial research on the issue maintained that there was a significant risk of parameter estimation bias by using aggregated data in non-linear models (Scan*Pro and PromotionScan are log linear). With this bias, for example, the estimate of the percentage increase in sales from display activity might be overstated using aggregated data.

Christen et al (1997) suggest a debiasing procedure that can be used for market-level data. That had nothing to say, however, on the more important issue of chain-level aggregation. Therefore, there has been no use of the debiasing procedure in other literature, and the conventional wisdom remains that disaggregated data is always optimal for modeling. Acceptance by other researchers of this conclusion has presented a practical barrier to more robust research that would include examination of chain-wide effects of retailers with thousands of stores. Currently an inordinate amount of the promotional literature uses the Dominick's database, which only consists of 30 stores in the Chicagoland market.

An issue not discussed relative to the data aggregation issue is a consideration for the standard of management accountability. Specifically, sales and marketing managers are most interested in aggregated levels of performance, and therefore, the research tools should be developed to predict and explain results at that level. The disaggregation paradigm also carries over to panel data where researchers analyze the behavior of individual households to gauge marketing effects rather than analyzing results for a group of individuals.

In concept, it is similar to Hicks' (1946) comment in Value and Capital,

> "But economics is not, in the end, much interested in the behaviour of single individuals. Its concern is with the behaviour of groups. A study of individual demand is only a means to the study of market demand."

While there is clearly a role for the use of disaggregated data, the initial discovery process should occur at the group (aggregated) level to determine the total effects of programs in which managers are most interested. Unfortunately, the disaggregation paradigm means that many, if not most, marketing researchers have overlooked aggregated effects entirely.

IVB. Practical Shortcomings of Disaggregated Scanner Data

This paper is only addressing the shortcomings of disaggregated scanner data, but many of these shortcomings - primarily in cost and standards of accountability – carry over to disaggregated panel data. Even if the quantitative rationale for disaggregated data is sound, there are still several large problems with this data source that would seem to call out the need for a better way to conduct research. The key practical shortcomings of using disaggregated scanner data are as follows:

1. **Computing capacity requirements are huge.** Most of the models in the literature are built on manageable store counts, usually 30 or less. Even then, a Dynamic Linear Model (DLM) may take weeks to run (Ataman, Van

Heerde – 2007). This would then preclude any consideration of running a model against a 5000+ store chain like CVS or Walgreens for a typical business or academic application.

2. **The data required to conduct store-level analysis is extremely difficult and expensive to get**. Very few parties have access to this data currently. In the academic world, there are only two databases - University of Chicago Dominick's Database and the Stanford Basket Dataset – with this information. The static universe of data for research limits the opportunity for robust results. Additionally, these restrictions on the data make the conclusions that result from this data source difficult to replicate by academicians and difficult to embrace by practitioners.

3. **Store-level data does not align with the standard of business accountability in the CPG environment, which is usually chain level performance**. Sales managers are evaluated based on their ability to effect sales at the aggregated chain level. Therefore, informational tools should be aligned to measure aggregated performance.

IVC. Quantitative Deficiencies of Disaggregated Scanner Data

In addition to problems with cost, availability and managerial alignment there are several deficiencies with disaggregated data from a purely quantitative standpoint. The two major issues are:

1. **The primary rationale for disaggregated data is not a factor for the majority of promotional applications, particularly in the US and Canada**. Van Heerde, Leeflang and Wittink (2002) state that the primary reason for using disaggregated data is to ensure there is no estimation bias of parameters when the independent variables are heterogeneous. From a practical standpoint, most chains execute Ads and Price Reductions, homogeneously. That is, every store within a chain receives the same marketing stimulus. For

the Dessert category studied in this paper, 86% of the 17,881 weeks with some level of Feature activity had ACV (All Commodity Volume) percentages of 80% or more.

According the primary advocates of disaggregated data; as long as marketing activity is implemented homogenously there is very little risk of biased estimation. Furthermore, even with heterogeneous marketing activity the magnitude of the bias depends on the percentage of stores promoted; the bias increases as the percentage gets lower (Van Heerde el al – 2002). See Table 3 from Christen et al (1997) which summarizes the bias issues.

TABLE 3
AGGREGATION BIAS – Christen et al (1997), pg 323

	HOMOGENEOUS MARKETING ACTIVITY	HETEROGENEOUS MARKETING ACTIVITY
HOMOGENEOUS PARAMETERS	No Bias	No Bias (Linear) Bias (Non-Linear)
HETEROGENEOUS PARAMETERS	No Bias (Linear) Small Bias (Non-Linear, Logit)	Bias (Linear under certain conditions) Bias (Non-Linear)

In addition to in-store marketing vehicles, external marketing programs like advertising and couponing are also implemented homogeneously across an entire market, much less a retailer. In-store displays are the only marketing program that is seldom implemented homogeneously. However, displays are typically of secondary importance in most promotional plans and are only consistently available to the largest brands in a given category. Given all of the other vehicles that are implemented homogeneously, this suggests that bias in display effect estimation is an insufficient rationale to steer an entire research protocol. It should be noted that some industry experts feel that feature advertising in Europe is also implemented heterogeneously by several major retailers and disaggregated data would more appropriate in those instances. This does not affect, however, the issue for North American analyses.

2. **Parameter estimation bias is irrelevant for the first and most important part of promotional analysis, baseline development.** According to Abraham and Lodish (1993), the first step in their Promotional Productivity system is to estimate the baseline sales. *"The first [step] is the baseline procedure used to estimate short-term within store incremental sales due to promotions run by retailers. The second part relates these short-term incremental sales to the causal factors – features, displays and price cuts."*

   Intuitively, bias in model parameters is unimportant when developing a baseline model estimate since the only measurement we are trying to derive is whether the parameter is significantly different from zero. Accuracy in the estimation of, say, a 30% Off Feature has no importance in the development of a baseline sales estimate.

   Response parameter estimation is only as good as the estimate of baseline; if the baseline is off, then estimates of promotion response will be flawed. No authors have suggested that disaggregated data is a necessary component of baseline estimation. Section VI will test the accuracy of the current log linear baseline models to expose an even more problematic bias in the parameter estimation than whether parameters or marketing activities are homogeneous or not. Namely, it can be shown that there is a significant correlation between the baseline estimate and promotional activity which distorts the lifts estimates of promotions.

In summary, disaggregated data contains severe practical and quantitative limitations that preclude it from being the sole or even primary source of marketing research data. Particularly given the homogeneity of most marketing stimulus, aggregated chain-level data is appropriate for many more applications than is being used currently.

V. An Improved Baseline sales Estimation

VA. Baseline Model Introduction

Fundamental to all promotional analysis – or analysis of the effectiveness of any marketing program – is the concept of baseline sales. In order to determine if a causal variable generated some effect on sales, the analyst needs a reasonable estimate of what sales what would have been without the existence of the causal variable. That is the definition of Baseline sales: an estimate of sales in the absence of specific marketing activity for a specific period of time.

A Baseline sales estimate can range in sophistication from the rudimentary, back-of-the-envelope "guess" to complex, econometric models that require a lot of data input and computer processing power. In the CPG industry, there are two models that have wide use by academics and practitioners alike. Scan*Pro (Wittink 1988) and PromotionScan (Abraham and Lodish, 1993) were developed by the two major suppliers of syndicated point-of-sale data: AC Nielsen and Information Resources (aka IRI). Both models are fundamentally similar (Bucklin and Gupta – 1999; Hanssens, Parsons, Schultz - 2000) in that they are log-linear regressions of unit sales as a function of retailer price and in-store causal variables like display and feature ad activity.

Van Heerde, Leeflang and Wittink (2002) lay out the original version of the Scan*Pro model that was developed in 1988.

$$q_{kjt} = \left[\sum_{r=1}^{n} \left(\frac{p_{krt}}{p_{kr}} \right) \beta_{rj} \sum_{1}^{3} \gamma_{lrj}{}^{D_{lkrt}} \right] \left[\sum_{t=1}^{T} \delta_{jt}{}^{X_t} \right] \left[\left[\sum_{k=1}^{K} \lambda_{kj}{}^{Z_k} \right] \right] e^{u_{kjt}} \text{ , k=1,...,K, t=1,...,T}$$

where: q_{kjt} is unit sales for brand j in store k, week t

p_{krt} is unit price for brand r in store k, week t

$\overline{p}_{kr}$ is the median regular unit price (in non-promoted weeks) for brand r in store k

D_{1krt} is a Dummy variable for feature advertising: 1 if brand r is featured (but not displayed) by store k, in week t; 0 otherwise.

D_{1krt} is a Dummy variable for feature advertising: 1 if brand r is featured (but not displayed) by store k, in week t; 0 otherwise.

D_{2krt} is a Dummy variable for display: 1 if brand r is displayed (but not featured) by store k, in week t; 0 otherwise.

D_{3krt} is a Dummy variable for the simultaneous use of feature and display: 1 if brand r is featured and displayed by store k, in week t; 0 otherwise.

X_t is a Dummy variable (proxy for missing variables and seasonal effects): 1 if the observation is in week t; 0 otherwise.

Z_k is a Dummy variable for store k: 1 if the observation is from store k; 0 otherwise.

β_{rj} are price discount elasticities ($r=j$ own brand, $r \neq j$ cross brand)

γ_{lrj} are feature only (l=1), display only (l=2) and feature and display (l=3) multipliers.

δ_{jt} is the seasonal multiplier for week t for brand j

λ_{kj} is store *k's* regular (base) unit sales for brand j if the actual price equals the regular price and there are no promotion activities for any of the brands r, $r=1,\ldots,n$

u_{kjt} is the disturbance term

n is the number of brands in the competitive set

K is the number stores in the sample

T is the number of weeks.

This model is non-linear, hence the authors' concern about parameter bias. Taking the natural log of this model provides the opportunity to conduct normal OLS regression on the data. The authors imply that the model is simple, as it was the first step in an evolutionary model building process. The complexity of this first generation model can be seen in the high parameter count for interaction effects, store effects and promotional response effects.

The authors did not address the significant cost to collect and incorporate all of the causal inputs into the model. In fact, well over $50MM per year is spent by IRI and Nielsen combine to gather this data (Sources: IRI Annual Report, 2003; Nielsen Annual Report, 1999). This presents a very high barrier to categories and retailers not currently included in the IRI/Nielsen infrastructure. Retailers not included in this infrastructure account for over 60% of the retailers in the Top 50 in the U.S. (source: MVI), including the largest one, Wal-Mart.

The authors extended this model over time to include four weeks of leads and lags in order to "accommodate the illusive post-promotion dip" (author's words). The incorporation of eight weeks of leads and lags expands the model parameters dramatically. Overfitting in time-series models can be a primary source of such problems as multi-collinearity and autoregression (Brooks – 2002).

The authors dedicate little time in explaining the methodology for calculating baseline sales – the foundation of the log linear model (Abraham and Lodish -1993). Since the model incorporates cross-brand promotional effects from numerous brands it would appear that there would be considerable difficulty in the modeling of a precise (stable) baseline estimate. In fact, the authors contend that baseline sales are dynamic and show a graphic example where the baseline estimate shows several sharp dips and spikes. Within one 10 week period the baseline deviates by +/- 12% around the median level for the period. They contend that this dynamic effect is "consistent with expectation" since promotional lifts tend to reduce post-period baseline sales ("the illusive post-promotion dip"). This conclusion of a dynamic baseline runs contrary to findings of sales being trend stationary, which should show no consistent deviation in weekly baseline sales.

Van Heerde et al (2002) enumerate 15 major findings derived from the Scan*Pro model. Several of these results will be tested in this paper. It is the thesis that a prior cause of the flawed paradigms in the literature is due to flaws in the baseline methodology.

1. Temporary price cuts product strong effects.

2. Display and feature multipliers show similar average magnitudes in parametric models.

3. Multipliers are strongly biased upward in a nonlinear model applied to linearly aggregated data; the magnitude of the bias depends upon the proportion of stores promoting the item.

4. **The effects of promotion are asymmetric; a promotion for brand i may have an effect on brand j's sales while j's promotion does not affect brand i's sales.**

5. The higher the frequency of promotion, the lower the price discount elasticity.

6. The deeper the most recent price discount, the lower (toward zero), the price discount elasticity.

7. **Promotions create both lagged and lead effect, consistent with the idea that consumers engage in stockpiling and anticipate future promotions.**

8. **The dynamic effects of promotions are substantial: shifts in the timing of purchases of the promoted brand account for up to 25 percent of the current sales effect.**

9. There is a threshold effect: discounts below 10 percent often generate sales levels that differ little from baseline sales.

10. There is a saturation effect: discounts above 25 percent often provide minimal sales increases relative to sales obtained at a 25 percent discount.

11. The shape of the deal effect curve for a brand depends on associated promotion signals.

12. Deal effect curves for different supports may intersect; for example, the feature-only deal curve may show less discount sensitivity than the display-only curve.

13. **The unit sales effect of a promotion for a brand can be decomposed into different effects: one attributable to other brands, another attributable to stockpiling, and a third attributable to category expansions.**

14. **A promotion for one SKU may reduce sales of other SKU's belonging to the same brand.**

15. **The category expansion effect in a store or chain can be decomposed into a store-switching effect and a within-store effect attributable to other categories.**

Sixe of the 15 major conclusions (#4, 7-8, 13-15) derived from Scan*Pro are in direct contradiction with the Theory of Retailer Price Promotion. Another two, #5 and #10 about the frequency and discount saturation effects, will not be formally tested but the conclusion does not appear to be supported by even a cursory inspection of the data. Wittink was a co-author of all 15 of these conclusions across 1994-2002. While Van Heerde is the lead author on this summary article, it is ironic that his pioneering work in DLM models for marketing will be used as the foundation to test the validity of these Scan*Pro-based conclusions.

Other models have been used in the literature to calculate baseline sales, but none has been offered as an alternative to the industry-standard log linear models. Nijs et al (2001) developed an alternative baseline model using a VARx where baseline sales are implied from the sales forecast for time t. They then use Impulse Response functions for each promotion to gauge the incremental effects for periods t, t+1, t+2, … Ataman, Mela and Van Heerde (2007) used a Dynamic Linear Model (DLM) to estimate Baseline sales in a model for decomposing the effects of various marketing mix elements in new brands. Both of these models are confined to specific academic applications.

Bucklin and Gupta (1999) make an important point about the baseline sales measure: many practitioners believe the measure to be an actual number, when, in fact, it is a modeled measure. A modeled measure presents difficulties in determining whether the measure is accurate, since there is never any actual data to validate against. The first benchmark of measurement is intuition and judgment. As noted in the introduction, it is a widely held view that the baseline models used by the syndicated data suppliers are flawed. Figure 5 shows an example of this flaw.

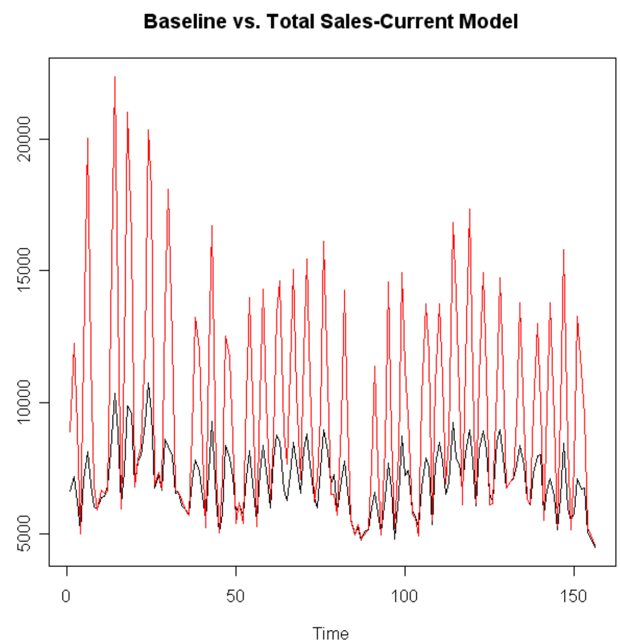
From this graph the following dynamics are obvious:

1. Given the extreme sales lifts, the promotional timing is obvious without requiring any exogenous information about promotional activity.

2. Equally obvious are weeks when the product is not on promotion.

3. Sales during the off promotion weeks are remarkably similar and, therefore, predictable.

FIGURE 5
BASELINE EXAMPLE - DESSERT



4. Sales during non-promoted weeks do not drop significantly below the level seen for prior promotion weeks. Similar to the observations of other authors, there is no obvious post-promotion dip (below baseline). In fact, despite an extraordinarily regular and responsive promotional cycle, weekly sales never drop below 5,000 units per week during the entire three year period.

5. Given that sales for non-promoted weeks fall into a very narrow and predictable range, the "eyeball" method discussed previously would be roughly equal to the average of the sales in non-promoted weeks immediately before and after the promotion (S_{t-1}, S_{t+1}).

6. The modeled baseline sales from the syndicated data supplier are vastly different from the stable baseline that would be expected from the "eyeball" method. In fact, there is no reason to expect there to be a high degree of volatility in this baseline estimate.

7. Similarly, we see that baseline sales estimates exhibit "phantom spikes" concurrent with promotional activity. There is no reason to expect the two variables – baseline sales and promotional activity – to exhibit any covariance except in cases where manufacturers consistently executed other marketing

programs during those promotion weeks. Instances where manufacturers are able to do this *consistently* are rare.

VB. Validity Standards for Baseline Models

It is proposed that – contrary to Van Heerde, Leeflang and Wittink (2002) – baseline sales *are not* dynamic and that, theoretically, they should be stable estimations of weekly, non-promoted sales. The specific propositions are that baseline sales should have a) minimal weekly volatility and b) no correlation with promotional activity. There are several empirical and theoretical explanations for this:

1. We can test for the relative level of variance in sales between weeks with and without promotion. A visual inspection of the data leads to an expectation that there is a significant difference between these two classes of weekly data.

2. Should we identify a low level of variability in weekly sales for non-promoted weeks, this would be evidence of a steady-state sales equilibrium, which, by definition, is non-dynamic.

3. Nijs et al (2001) and Pauwels et al (2002) determined that brand and category sales were trend-stationary. Given this finding the expectation for the deviation in weekly sales for any given week or any class of weeks (like promoted weeks) should be zero.

VC. Ataman, Van Heerde DLM Baseline Model (2007)

While Ataman and Van Heerde have not offered their baseline model as a superior alternative to the log-linear models, it has several elements which suggest a DLM (Dynamic Linear Model) is a better alternative to the current standard.

1. It does not rely on an expensive infrastructure to gather causal measurements.

2. It can implicitly incorporate the effect of distribution build – or any other structural change to baseline - over time. Distribution, in particular, is a measure that is missing from the current regression models. Mace and Neslin (2004) incorporate total category distribution levels (measured by UPC count) into the model, but Van Heerde, Leeflang, and Wittink (2002) did not. Neither, however, incorporate the number of own brand SKU's into the model.

3. The model does not need to include any independent variables; therefore it is independent of potential data collection issues associated with the causal inputs. *Its primary benefit is that it can be applied to any retailer that has scanner data without requiring a major data collection infrastructure..*

4. Visually, their baseline estimates appear to be free of the volatility and phantom spikes we see in the log-linear models.

DLM is a modeling technique pioneered by West, Harrison and Migon (1985) to address time series problems. The technique uses a recursive Bayesian approach to provide probability parameters to each observation in a time series. Each parameter estimate for an Observation equation is based on the conditional probabilities of the State equation of prior periods. As more time periods are added to the model, the parameters are recursively refined to minimize the forecasting error.

From a marketing modeling perspective, Ataman and Van Heerde (2007) offer the following advantages of DLM:

- It has greater statistical efficiency with parameter evolution and explanation in one step.

- There is no need for pre-steps (like unit root testing) or assumptions on the distribution of error terms. This gives DLM an advantage over Kalman Filters (another recursive time series technique), which require the assumption of normally distributed error terms.

- Parameters update immediately as new data becomes available.

- Missing data is accommodated relatively easy by using estimates from prior periods for imputation in the missing data.

- The technique allows for subjective information. Prior expectations can be overridden to accommodate anomalies in the data.

- The model accommodates longitudinal as well as cross-sectional heterogeneity.

The disadvantages of DLM offered by Ataman and Van Heerde (2007) involve the implementation of the model rather than any weaknesses statistically. Specifically they note that DLM's are extremely processing intensive, where models can take days – even weeks – to run. They also note that few software packages include a DLM module and that the process is very coding intensive.

The reason for the process intensity is their assumption that disaggregated data must be used in the model. In their discussions at the Marketing Dynamics Conference they mentioned a study using DLM with less than 50 stores, and even that took several weeks to run the model. This approach would preclude any consideration of modeling against a 6,000 store chain like Walgreens or CVS without the most powerful hardware. Section IV, however, addressed that issue by concluding that aggregated data was acceptable baseline estimate and promotion modeling. With this vast simplification, DLM becomes an attractive alternative for baseline development, assuming the appropriate level of programming expertise.

Even on that front, the programming for novice programmers is difficult, but not insurmountable. This paper uses R – a free, open-source language - to program the DLM. Programming time from start to finish of a first working model (prior to inclusion of error checks and other tweaks) was approximately 20 man-days. Subsequent model modifications for other categories took less than one day. R and MATLAB, matrix language software, are in widespread use a variety of academic and business fields.

The Ataman/Van Heerde model is, as follows:

$$Sales_t = Baseline_t + \beta_t{*}PIndex_t + v_t \qquad \text{Equation V.C.1.}$$

$$\text{where, } Baseline_t = \lambda{*}Baseline_{t-1} + \omega_t \qquad \text{Equation V.C.2.}$$

$$\beta_t = \beta_{t-1} + \varepsilon_t \qquad \text{Equation V.C.3.}$$

Observed sales for a given week are a function of a dynamic baseline component at time t and a dynamic promotion response evolution defined by β at time t. It is the evolution of the baseline that Abraham and Lodish (1993) identify as the first step in promotional response analysis. Immediately evident is a model that is more parsimonious than the Scan*Pro model. They, of course, leave open the possibility of additional exogenous variables, but as a first-generation model it is much simpler.

VD. Improvement to Ataman/Van Heerde

While Equations V.C.1.-3. provide a good starting point for a general baseline model, the inclusion of the Price Index variable presents some potential problems in maximizing the accuracy of the forecast. The price is prone to measurement error: some retailers deduct promotion discounts off of the entire shopping order and do not assign them to a specific product. Additionally, many promotional vehicles like In-Ad Coupons, Rebates and Loyalty Card discounts have a history of tracking difficulties. From a retailer perspective, some stores may lower prices on a local basis for competitive reasons without the typically promotional support like shelf tags. Other retailers have non-traditional methods of handling Buy One/Get One Free consumer deals. Often both items will be scanned at full revenue with some other code denoting the BOGO offer. To be sure, there is no evidence of systematic problems with price tracking in the syndicated data (except for a few isolated retailers). However with so many potential shortcomings even for Own Brand promotion response, using the Price Index as an exogenous variable does not appear to be optimal.

The Price Index variable would have even greater shortcomings at the market level. The market will tend to reflect an average retail price with modest weekly deviations.

A promotion at a smaller retailer in the market may have a significant impact on incremental sales, but only a modest impact on price. Conversely, a large retailer can move the weighted average price, but have a limited impact on incremental sales with a weak promotion. Therefore, the Price Index has minimal value for baseline creation at higher levels of aggregation than retailer.

One other deficiency of the Ataman/Van Heerde model is that they do not reflect an evolutionary parameter for the lift parameter (β). Including this parameter permits the opportunity to test for promotional wearout effects over time. Table 4 provides a comparison of the two models. The structure of the Ataman/Van Heerde model is preserved in the Jetta (2008) model. The inclusion of the endogenous promotional variable (P) adds an additional processing step.

TABLE 4
DLM BASELINE MODEL COMPARISON

Ataman/Van Heerde (2007)	**Jetta (2008)**	**Comments**
$Sales_t = \alpha_t + \beta_t{*}PIndex_t + v_t$	$Sales_t = \alpha_t + \beta_t{*}P_t + \gamma_{ti}I_t + v_t$	Observation Equation: Sales for week t is a function of Baseline sales (α_t), Promotional Activity (P_t) and other exogenous variables.
$\alpha_t = \lambda_t * \alpha_{t-1} + \omega_{1t}$	$\alpha_t = \lambda_t * \alpha_{t-1} + \omega_{1t}$	State Equation: Baseline evolution
$\beta_t = \beta_{t-1} + \omega_{2t}$	$\beta_t = \varphi_t * \beta_{t-1} + \omega_{2t}$	State Equation: Lift parameter. Replace PIndex (exog) with Promo dummy variable, P, (endog). Include possibility of evolution.
	$\gamma_t = \rho_t * \gamma_{t-1} + \omega_{3t}$	State Equation: Category-specific dummies for special seasonal dips/spikes
	$P_t = f(Sales_t, \alpha_{t-1})$	Endogenous Variable Creation: Endogenous variable to create the Promo dummy is a function of current week sales and prior forecast of Baseline sales.

The endogenous variable is calibrated to flag any observation week where there is an abnormal deviation in weekly sales change or where the absolute sales level is significantly above the overall average. The model runs through several iterations to refine this variable in order to minimize the model standard error. Exhibit 1 provides the algorithm for the Jetta (2008) model.

Ataman and Van Heerde (2007) advocate 200 Gibbs samples with back and well as forward filtering. Gibbs sampling is an algorithm to generate a sequence of samples from the joint probability distribution of two or more random variables (Casella and George – 1992). In the case of baseline model, each sequence will generate samples for the Observation and the State Equations. By filtering both back and forth, we reduce the forecasting errors for the first several weeks of the time series. From a practical standpoint, the primary objective is to make the most recent forecast as precise as possible; it is not a major problem if model parameters for weeks more than 100 weeks ago have an undue amount of variability or bias. Therefore, this model will conduct 100 iterations of forward filtering. The burn-in step is replaced by the endogenous variable estimation.

The endogenous variable, the PROMO dummy, was compared to the Percent of Units on Promotion provided by the data supplier. This measure is currently the industry accepted standard for detecting the presence of meaningful promotional activity. The Percent of Units on Promotion measure was divided into four equal quartiles of promotional levels: 0-24.9%, 25.0%-49.9%, etc... Cross-tabulations were run again the PROMO dummy by GEOLEVEL (Chain vs. Market) and BRAND. The results are summarized below in Table 5 for Beverages.

TABLE 5: VALIDITY TEST FOR ENDOGENOUS VARIABLE ESTIMATION

BEVERAGES: ALL BRANDS

% OF UNITS ON ANY PROMO — ENDOGENOUS EST

CHAIN	NON-PROMO	PROMO	% of All Wks	NON-PROMO	PROMO
0-24.9%	8,360	1,957	67%	81%	19%
25.0-49.9%	910	426	9%	68%	32%
50.0-74.9%	505	796	8%	39%	61%
75.0%+	301	2,174	16%	12%	88%

COMP MKT	NON-PROMO	PROMO	% of All Wks	NON-PROMO	PROMO
0-24.9%	6,499	1,681	54%	79%	21%
25.0-49.9%	2,210	1,227	23%	64%	36%
50.0-74.9%	734	1,834	17%	29%	71%
75.0%+	69	996	7%	6%	94%

BEVERAGE: BRAND A1

ENDOGENOUS EST

CHAIN	NON-PROMO	PROMO	% of All Wks	NON-PROMO	PROMO
0-24.9%	3,339	268	42%	93%	7%
25.0-49.9%	1,495	536	24%	74%	26%
50.0-74.9%	568	1,155	20%	33%	67%
75.0%+	108	1,156	15%	9%	91%

RTD: BRAND A2

COMP MKT	NON-PROMO	PROMO	% of All Wks	NON-PROMO	PROMO
0-24.9%	3,664	1,857	90%	66%	34%
25.0-49.9%	138	164	5%	46%	54%
50.0-74.9%	27	86	2%	24%	76%
75.0%+	37	159	3%	19%	81%

BEVERAGE BRAND B

ENDOGENOUS EST

CHAIN	NON-PROMO	PROMO	% of All Wks	NON-PROMO	PROMO
0-24.9%	3,585	544	54%	87%	13%
25.0-49.9%	747	377	15%	66%	34%
50.0-74.9%	350	645	13%	35%	65%
75.0%+	177	1,161	18%	13%	87%

RTD: BRAND C

COMP MKT	NON-PROMO	PROMO	% of All Wks	NON-PROMO	PROMO
0-24.9%	4,271	969	63%	82%	18%
25.0-49.9%	740	576	16%	56%	44%
50.0-74.9%	294	744	12%	28%	72%
75.0%+	48	694	9%	6%	94%

For the most part we can see that there is a high level of convergence between the two measures of promotional activity, particularly for the first and last quartiles. There is no consistent measurement bias depending on the geography measured. (Chain vs. Trading Area).

When brands are considered, however, we see significant measurement errors for the endogenous variable for Brand A2 at the lower range of promotional activity (we give the presumption of greater accuracy to the syndicated data measure). This brand (Brand A2, a size variation of Brand A1) had lower promotional levels in terms of depth and frequency than the other brands. Therefore, this flags one potential weakness in the revised baseline model. An inaccurate PROMO variable will also have an impact on the statistical tests in Section VI.

The most notable feature of Dessert promotional activity (Table 6) is the extraordinarily high promotional activity on the major brands (Brands F and H). The Top 2 brands had 67% of their weeks with at least half of the units sold on a promotion. The most lightly promoted brand of Dessert was promoted more than the most promoted brand of Beverages, and Beverage promotional activity is typical of most categories. We see once again that the endogenous PROMO variable tracks very closely to the syndicated values, particularly in identifying the occurrence of activity.

TABLE 6: VALIDITY TEST FOR ENDOGENOUS VARIABLE ESTIMATION (DESSERTS)

DESSERT

% OF UNITS ON ANY PROMO — ENDOGENOUS EST

CHAIN	NON-PROMO	PROMO	% of All Wks	NON-PROMO	PROMO
0-24.9%	22,153	4,925	44%	82%	18%
25.0-49.9%	2,967	1,781	8%	62%	38%
50.0-74.9%	2,051	2,606	8%	44%	56%
75.0%+	2,749	22,680	41%	11%	89%

COMP MKT	NON-PROMO	PROMO	% of All Wks	NON-PROMO	PROMO
0-24.9%	5,555	1,190	11%	82%	18%
25.0-49.9%	8,379	4,761	22%	64%	36%
50.0-74.9%	7,801	14,083	36%	36%	64%
75.0%+	1,721	17,244	31%	9%	91%

ICE CREAM: BRAND D

ENDOGENOUS EST

NON-PROMO	PROMO	% of All Wks	NON-PROMO	PROMO
5,258	1,366	31%	79%	21%
1,802	1,481	16%	55%	45%
1,199	3,126	20%	28%	72%
564	6,370	33%	8%	92%

ICE CREAM: BRAND E

NON-PROMO	PROMO	% of All Wks	NON-PROMO	PROMO
1,827	784	39%	70%	30%
725	460	18%	61%	39%
405	900	19%	31%	69%
134	1,490	24%	8%	92%

DESSERT: BRAND F

NON-PROMO	PROMO	% of All Wks	NON-PROMO	PROMO
4,372	415	23%	91%	9%
1,878	294	10%	86%	14%
2,076	1,409	17%	60%	40%
1,166	9,455	50%	11%	89%

ICE CREAM: BRAND G

NON-PROMO	PROMO	% of All Wks	NON-PROMO	PROMO
1,577	532	43%	75%	25%
460	336	16%	58%	42%
195	636	17%	23%	77%
103	1,030	23%	9%	91%

ICE CREAM: BRAND H

ENDOGENOUS EST

NON-PROMO	PROMO	% of All Wks	NON-PROMO	PROMO
4,390	429	23%	91%	9%
1,645	372	10%	82%	18%
2,133	1,891	19%	53%	47%
982	9,014	48%	10%	90%

ICE CREAM: BRAND I

NON-PROMO	PROMO	% of All Wks	NON-PROMO	PROMO
6,130	1,350	36%	82%	18%
1,828	1,489	16%	55%	45%
868	3,232	20%	21%	79%
402	5,557	29%	7%	93%

DESSERT: BRAND J

NON-PROMO	PROMO	% of All Wks	NON-PROMO	PROMO
2,586	964	17%	73%	27%
2,552	1,986	22%	56%	44%
2,309	5,081	35%	31%	69%
886	4,492	26%	16%	84%

ICE CREAM: BRAND K

NON-PROMO	PROMO	% of All Wks	NON-PROMO	PROMO
1,568	275	29%	85%	15%
456	124	9%	79%	21%
667	414	17%	62%	38%
233	2,516	44%	8%	92%

As a side note we can see that Desserts is an extreme example of promotional activity, and this level of activity provides prima facie evidence refuting contentions of long-term negative effects on brands from price promotion. If this were, in fact, the case we would expect to see the major dessert brands with non-promoted sales levels approaching zero after three *years* of bi-weekly promotions.

With 90% accuracy in capturing high levels of promotional activity, the endogenous promotional calculation provides viable substitute for the expensive causal measure infrastructure. So with confidence in the validity of the endogenous promotional dummy, PROMO, we can proceed to conduct empirical testing for the CCEE.

VI. Empirical Testing

VIA. Description of the Data

Aggregated data at the retail chain level was gathered for two categories: Desserts and Beverages. Data is gathered from a major syndicated data supplier. The data is fairly recent, so for confidentiality reasons, there will be a considerable level of data masking. The specifications of the data are as follows:

Categories: Desserts and Beverages. Average everyday retail pricing in each category is in the \$3.00-\$7.00 range, so they are both somewhat more expensive than the typical Food category.

Products: Brand-Sizes that Account for at least 80% of the category dollar sales on a Total US basis. There are four brand-sizes for Beverages: three brands and one additional size of the leading brand. There are eight brands for Desserts, with only the most predominant size for each brand. The Dessert brand splits are: Private Label, four large national brands and three significant regional brands. Since the regional brands often do not have full distribution in their markets they will not be tested for cross-outlet effects since often only one retailer in a market stocks these brands.

Periods: 120 Individual Weeks Beverage, 156 Individual Weeks for Desserts

Markets: At Least 20 major retail chain buying points per category. Additionally, data for the Trading Area (aka Competitive or Comp Market) is available for all chains except a Mass Merchandiser chain. The Comp Markets is the entire geography for a specific chain within a specific trade channel (e.g. Food or Drug).

Measures: Unit Sales is the primary measure used for modeling. However, causal measures such as Average Price, Promotional Activity and Baseline sales are used for model validation purposes. Two exogenous seasonal factors were incorporated into the Beverage model to account for a significant dip in sales during Thanksgiving and Christmas weeks and the significant increase in sales the following week as sales return to regular rates.

The primary analytical group is a identified as a dataclass, which is a specific retailer within a specific geography (Chain or Comp Market). There are 247 dataclasses in Beverages and 799 for Desserts. This is the number of baseline models that will be created (1,046) and unit root tests conducted. All Trading Area data for a brand where Chain-level sales for that market were not significant were excluded from the analysis. Additionally, dataclasses with sales consistently below 100 units per week were excluded from the analysis. These dataclasses accounted for less than 0.1% of the total sales across both categories.

The Dessert database is more robust than Beverages as it includes more weeks (156 vs. 125), more measures (including baseline sales), more brand-sizes (8 vs. 4) and much greater promotional activity. This particular dessert category is among the most frequently and aggressively promoted categories in the entire CPG industry. It is not uncommon to see 50% Off sales for more than half the weeks in a particular dataclass over a three-year period. The extreme promotional nature of the category makes it desirable for analysis into the effects of promotion on future sales and promotional effectiveness. By contrast, Beverage promotional activity is average relative to other categories in the store. The results in this category would be relevant to a greater number of categories.

VIB. Ergodicity Hypothesis

In their review of the long-term category demand effects of Retailer Price Promotion, Nijs et al (2001) concluded, "Category demand is found to be predominantly stationary around a fixed mean or deterministic trend." Their net conclusion for price promotion is that "their long-term impact is essentially zero." These authors established the ability to make conclusions about long-term effectiveness of marketing variables with multivariate time series techniques like Unit Root Testing and Vector Autoregressive models. Pauwels et al (2002) used similar econometric techniques to address long-term stationarity around brands, and found very similar results. They found long-term persistence in only 5% of the sales measures reviewed, and only one case could be attributed to price promotion. "The most common competitive scenario in our data is business as usual."

All of the half dozen econometric studies on the issue of the long-term effectiveness of promotion have had Dr. Dominique Hanssens as a co-author. There is value to validating these results using similar econometric techniques independent of Hanssen's co-authorship. A positive conclusion of stationarity can also be used in the development of the endogenous promotional variable in the baseline model. Stationarity will motivate some basic OLS procedures from which we can derive initial parameter estimates for the DLM. More importantly, acceptance of either level or trend stationarity of brand sales implies that the expectation for any specific class of weekly observations is zero either in logs or log differences.

Each dataclass was tested for both level and trend stationarity. In total there were 1,046 dataclasses across two categories (799 Dessert and 247 Beverage). R-software was used to conduct unit root tests for the weekly sales for each of the 1,046 dataclasses across the two categories. The natural log of sales was differenced to the previous week (first difference), with the log difference of the first week of each dataclass set to a value of 0.000.

Augmented Dickey-Fuller Unit Root tests were conducted on each dataclass for the two stationarity tests:

H0a: $S_{ir} - S_{jr} = 0$, where S_{ir} and S_{jr} are Sales (S) at week *i* and week *j* within retailer *r*, $i \neq j$

H0b: $L(S)_{ir} - L(S)_{jr} = 0$, L(S) is the one-week natural log difference in sales at week *i* and week *j* within retailer *r*, $i \neq j$

The unit root testing results show that retail sales data is a trend stationary process, as 99.8% of the dataclasses did not have a unit root. By contrast 68% of the tests conducted on sales without differencing had a unit root at a 90% confidence level. Table 7 provides the summary of results.

TABLE 7: AUGMENTED DICKEY-FULLER TEST RESULTS FOR STATIONARITY

DESSERTS

		p-value				
TYPE	**MEASURE**	**[0-.05)**	**[.05-.10)**	**[.10-.20)**	**[.20-1.00]**	**TOTAL**
LEVEL	WKLY OBS	426	101	56	216	799
	%	53.3%	12.6%	7.0%	27.0%	
	Cum %	53.3%	66.0%	73.0%	100.0%	
TREND	OBS	797	0	1	1	799
	%	99.7%	0.0%	0.1%	0.1%	
	Cum %	99.7%	99.7%	99.9%	100.0%	

BEVERAGES

		p-value				
TYPE	**MEASURE**	**[0-.05)**	**[.05-.10)**	**[.10-.20)**	**[.20-1.00]**	**TOTAL**
LEVEL	WKLY OBS	156	32	18	41	247
	%	63.2%	13.0%	7.3%	16.6%	
	Cum %	63.2%	76.1%	83.4%	100.0%	
TREND	OBS	247	0	0	0	247
	%	100.0%	0.0%	0.0%	0.0%	
	Cum %	100.0%	100.0%	100.0%	100.0%	

COMBINED CATEGORIES

		p-value				
TYPE	**MEASURE**	**[0-.05)**	**[.05-.10)**	**[.10-.20)**	**[.20-1.00]**	**TOTAL**
LEVEL	WKLY OBS	582	133	74	257	1,046
	%	55.6%	12.7%	7.1%	24.6%	
	Cum %	55.6%	68.4%	75.4%	100.0%	
TREND	OBS	1,044	0	1	1	1,046
	%	99.8%	0.0%	0.1%	0.1%	
	Cum %	99.8%	99.8%	99.9%	100.0%	

The null hypothesis is confirmed for trend stationarity (H0b), but rejected for level stationarity (H0a). These findings validate the conclusions of Nijs et al (2001) and Pauwels et al (2002) of the lack of a long-term effect from price promotions. They are also consistent with DelVecchio et al (2006) in their meta-analysis of the long-term effects of promotion on brand choice.

Having established the ergodicity of weekly retail sales we can use the first difference to conduct statistical testing for identifying significant deviations in the weekly sales trends. In this first generation model, these deviations will fall into one of four classifications: a promotion week (sales spike up), the week after a promotion (sales drop back down), the week of a special holiday (sales swing either up or down depending on the holiday), and the week after a specific holiday (sales swing back the other way). We can also use this ergodicity to test the accuracy of the existing and new baseline models.

VIC. Improved Baseline Hypotheses

The proposition is that baseline sales should be a relatively stable estimate over time. This proposition is initially based on the intuition which can be derived from a visual inspection of the data. The hypothesis is strengthened by the conclusion from Section VIB showing a stationary sales trend for brands over time. Based on these two factors, an improved baseline estimate will exhibit the characteristics of low variability week-to-week and no correlation between baseline sales and promotional activity. These characteristics can be operationalized into three hypotheses tests:

H1: *Weekly sales variability during non-promoted weeks is equal to or greater than weekly sales variability of non-promoted weeks.*

$\sigma_{L(NONPROMO)} \geq \sigma_{L(PROMO)}$, where L(..) is the natural log differences in sales for NONPROMO vs. PROMO weeks. It is expected that the null hypothesis will be rejected.

H2: *The proposed baseline model has volatility that is equal to or greater than the existing baseline model.*

$\sigma_{L(Bn)} \geq \sigma_{L(Be)}$, where L(Bn) is the natural log differences of sales for the New Model (n) and L(Be) is the natural log differences of sales for the existing Model (e). It is expected that the null hypothesis will be rejected.

H3: *The Expectation of the Log Difference in baseline estimate of the first promotion week equals zero.*

$Lnd(B_{PROMO}) = 0$, where Lnd(B) is the natural log difference in baseline sales for the first promotion week of each promotional event The test will be conducted on both the new and existing models. It is expected that the null hypothesis will be rejected for the existing baseline; there is no prediction for the new baseline.

If H1 is rejected, it will provide proof that lack of weekly volatility in the baseline estimate is, indeed, a desirable property. H2 then tests to determine whether the new baseline has reduced the level of weekly sales volatility. H3 is the test motivated by the proof of ergodicity from H0. Specifically, we will test to determine whether there is a consistent bias in the baseline estimates for promotion weeks.

H1 Hypothesis Test (Weekly Sales Volatility for Low Promotion Weeks)

For H1, each weekly observation within each dataclass was divided into one of four Classes based on the percentage of units on any promotion that week: Class 1 (0-25.0%), Class 2 (25.1-50.0%), Class 3 (50.1-75.0%) and Class 4 (75.1%+). The percentage of units on promotion is a measure directly pulled from the data supplier with no other manipulation to the figures. Table 8 provides the Analysis of Variance Results for Geography Level by Category.

TABLE 8: TEST OF VARIANCE OF FOR NON-PROMOTED VS. PROMOTED WEEKS

		DESSERT			BEVERAGE		
CHAIN	% UNIT on PROMO	OBS	Estimate	Std. Error	OBS	Estimate	Std. Error
CLASS1	0-25.0%	26,367	15,505	644.2	10,317	1,235	21.7
CLASS2	25.1-50.0%	4,677	25,427	1,667.8 **	1,336	1,986	64.1 **
CLASS3	50.1-75.0%	4,924	34,828	1,681.6 **	1,301	2,215	64.9 **
CLASS4	75.1%+	27,174	49,166	925.7 *	2,475	2,476	49.4 **

		DESSERT			BEVERAGE		
COMP MKT	% UNIT on PROMO	OBS	Estimate	Std. Error	OBS	Estimate	Std. Error
CLASS1	0-25.0%	6,416	46,007	1,442.6	8,180	1,101	32.7
CLASS2	25.1-50.0%	13,025	73,847	1,795.0 *	3,437	1,464	71.1 **
CLASS3	50.1-75.0%	22,702	104,254	1,710.7 *	2,568	1,400	75.1 **
CLASS4	75.1%+	19,683	144,999	1,017.1	1,065	1,184	80.8 **

* Significantly different from Class 1 at the 90% confidence level.

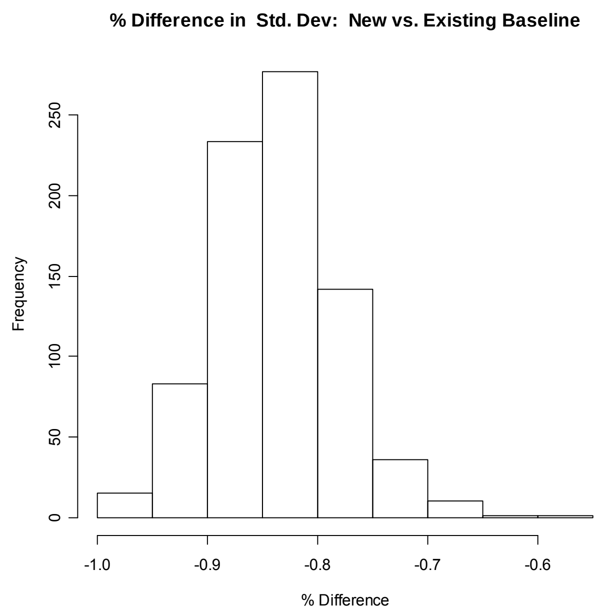
** Significantly different from Class 1 at the 95% confidence level.

In three of the four cases, and both the most important cases (Chain-Level data), F-testing concludes that the Standard Error of unit sales for low promotion weeks are significantly less than the Standard Error for weeks with higher promotion levels. In just one case – Dessert Comp Market –the relationship did not hold. Since we are most interested in accurate Baseline estimates for Chain-level data - the aggregation level that most aligns with managerial accountability - these results provide sufficient evidence that sales during promotion weeks should have relatively low levels of volatility. H1 is rejected.

H2 Hypothesis Test (Comparison of Baseline sales Volatility)

Baseline data was only available for the Dessert category, hence that is all that can be tested. Within Desserts, however, there are 799 separate dataclasses, which encompass a wide cross-section of retailers, trading areas and brands within those geographies. Within each dataclass, the natural log difference in sales was created. The standard deviation for the log differences within each dataclass was calculated, and the standard deviations were compared for New vs. existing Baseline. Figure 6 shows the results of the comparison. We can see a dramatic reduction (over 80%, on average) in the variability in weekly baseline sales estimate. The differences in these standard deviations are significant at the 99+% confidence level. Thus as expected, we reject H2 that the volatility of the New baseline is greater than or equal to the existing baseline.

FIGURE 6



H3 Hypothesis Test (Correlation Between Baseline and Promotional Activity)

The test for estimation bias for the baseline estimate (H3) is the most important of the baseline tests. First, the consistent deviation in weekly sales during promotional weeks appears to be the major source of the volatility in the existing baseline measures we saw in H2. Second, there are considerable managerial implications to these “phantom spikes” during promotional weeks. An erroneous spike in baseline sales will cause erroneous estimates of sales lifts due to promotions. In fact, the bias caused by these non-stationary effect ("phantom spikes") may outweigh any bias in parameter estimates using aggregated data. The converse of this issue also applies. Just as promotional lifts are understated, baseline sales are overstated with "phantom spikes." Baseline sales are viewed by many in the industry as the gauge of the underlying health of a brand, so its accurate estimation has significant management implications.

To conduct this test, the natural log differences in the weekly baseline sales were created for all weeks. Each weekly observation was coded into three factors: Non-Promotional, First Week of Promotion and Other Promotion Week. An analysis of variance was conducted by regressing the Log Difference of baseline sales against the Promotion Class factor within each Geography Level. Table 9 provides the results of

TABLE 9: TEST OF NON-STATIONARITY FOR SPECIFIC CLASSES OF PROMOTION WEEKS

EXISTING BASELINE

DESSERTS		**OBS**	**Estimate (1)**	**Std. Error**	**T-stat**	**p-value**	**% Diff vs. zero**
CHAIN	NON-FIRST WK	30,079	-0.06250	0.00083	-75.03	0.0000	-6.06%
	1ST PROMO WK	10,545	0.17837	0.00165	146.06	0.0000	19.53%
	OTHER PROMO WK	22,518	0.00570	0.00129	52.89	0.0000	0.57%
COMP MKT	NON-FIRST WK	23,866	-0.03823	0.00126	19.33	0.0000	-3.75%
	1ST PROMO WK	10,298	-0.15680	0.00202	-46.74	0.0000	-14.51%
	OTHER PROMO WK	27,662	-0.06445	0.00132	-1.47	0.1408	-6.24%

NEW BASELINE

		OBS	**Estimate**	**Std. Error**	**T-stat**	**p-value**	**% Diff vs. zero**
CHAIN	NON-FIRST WK	30,079	0.00008	0.00013	0.59	0.5600	0.01%
	1ST PROMO WK	10,545	-0.00163	0.00026	-6.54	0.0000	-0.16%
	OTHER PROMO WK	22,518	0.00062	0.00020	2.65	0.0082	0.06%
COMP MKT	NON-FIRST WK	23,866	-0.00002	0.00019	-0.51	0.6100	0.00%
	1ST PROMO WK	10,298	-0.00061	0.00031	-2.16	-0.0310	-0.06%
	OTHER PROMO WK	27,662	0.00009	0.00020	0.06	0.9600	0.01%

(1) Parameter estimate reflects difference from the Base Scenario -- Chain, Non-First Week

NEW BASELINE

BEVERAGE		**OBS**	**Estimate (1)**	**Std. Error**	**T-stat**	**p-value**	**% Diff**
CHAIN	NON-FIRST WK	9,595	-0.00025	0.00014	-1.79	0.0719	-0.02%
	1ST PROMO WK	1,682	-0.00188	0.00036	-5.22	0.0000	-0.19%
	OTHER PROMO WK	4,152	0.00099	0.00025	3.96	0.0009	0.10%
COMP MKT	NON-FIRST WK	9,304	-0.00065	0.00020	-3.25	0.0011	-0.06%
	1ST PROMO WK	1,852	-0.00039	0.00046	-0.85	0.3967	-0.04%
	OTHER PROMO WK	4,094	-0.00021	0.00030	-0.71	0.4770	-0.02%

(1) Parameter estimate reflects difference from the Base Scenario -- Chain, Non-First Week

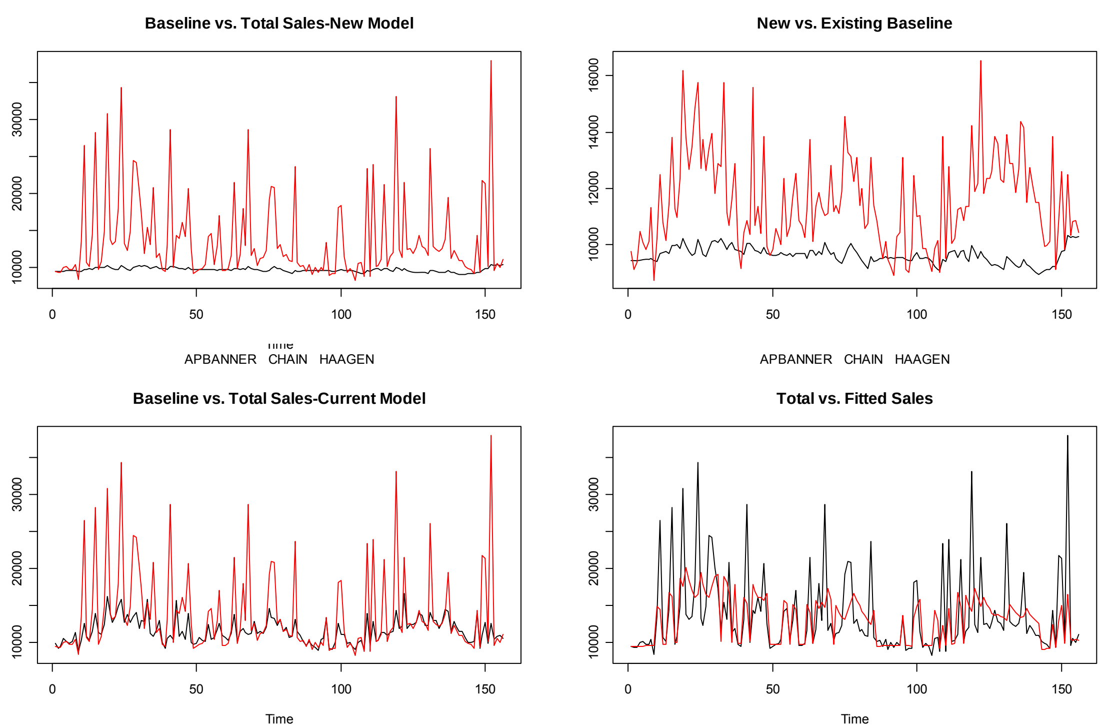
each baseline model for Desserts.

The existence of non-stationarity is evident throughout the current baseline model. For Chain-Level data, the baseline spike is an unacceptably high 20% in the first week of the promotion relative to a zero deviation expectation. We see the opposite effect for Comp Market data where baseline sales during the first promotional week actually dip 15%. The new Baseline model also has non-stationary conditions but all of the deviations are extremely small, and analytically trivial.

We can see the comparisons graphically in the Figure 7. In these graphs we can see: 1) actual Sales vs. New Baseline (upper left), 2) existing Baseline vs. New Baseline (upper right), 3) actual Sales vs. existing Baseline (lower left), and 4) actual Sales vs. Fitted Sales from DLM.

We can see visually what was proven analytically: the existing Baseline is more volatile than the new one, and it covaries with actual sales. <u>Both H3a and H3b are rejected</u>.

FIGURE 7
Results of New vs. existing Baseline



The new baseline model is missing some crucial seasonal variance that understates baseline sales and overstates lifts. This failure to pick up structural shifts in baseline also appeared to be an issue in instances when a brand had a major increase in distribution that increased overall sales. The overall fit of the new model, in general, appears good. Importantly, the DLM process facilitates the inclusion of additional variables to improve its accuracy. Future generations of this model will require a seasonal trend to be included.

Summary of Test for Baseline Model

These three tests provide compelling empirical evidence of the superiority of the extension of the Ataman/Van Heerde DLM model compared to the existing industry models. First, it was demonstrated that non-promotion week should show a lower level of sales variability than promotion weeks, particularly for chain-level data. Next, it was demonstrated that the New DLM Baseline Model greatly reduced the level of volatility in the weekly baseline estimates. On average, the reduction in variability was 80%. Finally, it was demonstrated that the existing Log Linear Baseline Model exhibited unacceptably high weekly sales deviations during promotion weeks (+20%) for Chain-level data. The New DLM Baseline Model has very slight negative deviations in baseline estimates during the first promotional weeks. Additionally, it does not appear to adequately evolve with structural shifts in baseline sales like seasonality. In summary, the first generation DLM baseline has substantial room for improvement, but is significantly better than what is currently available. In addition to the quantitative benefits of this model, it also has the advantage of not being reliant on an expensive data-gathering infrastructure for causal measures. Additionally, the model can be extended to any retailer and trade class which gathers weekly point-of-sale data.

VID. <u>Complete Category Expansion Effect (CCEE) Hypotheses</u>

The final stage of empirical tests uses the DLM baseline model developed in Section VIC as well as actual sales to test the CCEE. The theory expects the tests to show that the immediate effects from price promotion are entirely incremental to the brand, retailer and category. In particular, a variety of tests will be conducted to identify the existence of any negative effects to immediate or future sales of a promoting brand or competitive brand.

<u>H4</u>: *Within a retailer, Post-promotional sales for Own Brand are equal to or greater than Own Brand sales for weeks before and during a promotional event.*

$S_{0ir} \geq S_{0jr}$, where S_{0ir} are sales for Own Brand (0) in week *i* at retailer *r* and S_{0jr} are sales for Own Brand (0) in week *j* at retailer *r*. *i*=weeks 1...8 after a promotion and *j*=-8...-1 weeks prior to a promotion (j=0 is the promotional week). <u>It is expected that the null hypothesis will be accepted.</u>

<u>H5</u>: *Within a retailer, the actual sales of a non-promoting competitor during an Own Brand promotion are equal to or greater than the sales of the non-promoting competitor when Own Brand is not being promoted.*

This is a test for cross-effects (switching) between brands when one brand is promoted and the other is not. The test is $S_{cirp*} \geq S_{cjrp}$, where S_{cir} are actual unit sales for Competitive Brand (c) in week *i* at retailer *r*. These sales are compared for weeks when Own Brand is promoted (p*) and non-promoted (*p* in week *j*). <u>It is expected that the null hypothesis will be accepted.</u> It is assumed that any potential cross-effects will be most pronounced during the specific promotional weeks. Therefore, there is no need to test for residual effects: if no effect is found in week *i*, then no effect would be found in week i+1, i+2, ... Conversely, if the hypothesis is rejected is week *i*, there is no need to carry the test through to future weeks.

H6: *Total Market Sales for Own Brand should increase sales at an equal to or greater level than the increase in the promoting retailer.*

This is a test for cross-outlet effects when a brand is promoted at one retailer. The test $S_{0iM} - B_{0iM} \geq S_{0ir*} - B_{0ir*}$, where S_{0iM} are actual unit sales and B_{0iM} baseline sales for Own Brand (0) in week *i* in Market *M*. *r** designates promotional activity for week *i*. This increase is compared to the sales lift in the promoting retailer: Sales and Baseline sales of Own Brand (*0)* in week *i* and retailer *r* . It is expected that the null hypothesis will be accepted. Similar to H4, it is assumed that any cross-effects will be most pronounced during the specific promotional weeks. Therefore, there is no need to test for residual effects: if no effect is found in week *i*, then no effect would be found in week i+1, i+2, ... Conversely, if the hypothesis is rejected is week *i*, there is no need to carry the test through to future weeks.

H4 Results: Post-Promotional Dip

Each weekly observation was classified in two ways: the number of weeks prior to the next week promotional observations, and the number of weeks after the last weekly promotional observation (WEEKCLASS). This was done because a specific non-promotion week both precedes one promotional event and follows another. WEEKCLASS values ranged from 1 to 8 for both Before and After Promotion, with another value "9" as a placeholder for all values greater than 8. The eight week period aligns with the Adjustment period (aka Dust settling) in Pauwels et al (2002) where a post-promotional dip was identified.

The mean unit sales value for each WEEKCLASS was calculated within each BRAND and GEOLEVEL (Chain or Trading Area). WEEKCLASS values were grouped to ensure symmetric timing around the PROMO observation (2 weeks Pre grouped with 2 weeks Post, 3 Pre with 3 Post, etc...). An Analysis of Variance was run for the eight Before WEEKCLASS values and the 8 After WEEKCLASS values.

Across 12 different brands (4 Beverage, 8 Dessert) there was no consistent or statistically discernible negative sales effect either pre- or post-promotion. Figures 8 and 9 show the average weekly trends for the largest brand in each category.

FIGURE 8 – Promotional Dip Analysis
Average Unit Sales by WEEKCLASS – Brand 1A (Beverage)

		WK 8	WK 7	WK 6	WK 5	WK 4	WK 3	WK 2	WK 1
BRAND 1A	BEFORE	3,864	3,837	4,000	4,195	4,595	4,780	4,495	4,763
	AFTER	3,783	3,978	4,164	4,301	4,404	4,860	4,707	5,089

Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Row 1	8	34,529	4,316	153,318
Row 2	8	35,286	4,411	200,562

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	35,816	1	35,816	0.2024	0.6597	4.6001
Within Groups	2,477,160	14	176,940			
Total	2,512,976	15				

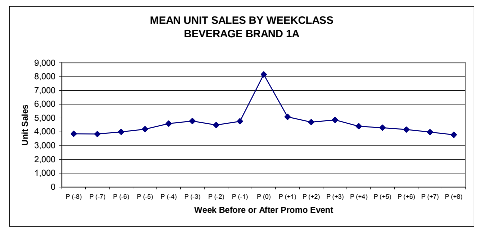


FIGURE 9 – Promotional Dip Analysis
Average Unit Sales by WEEKCLASS – Brand F (Dessert)

		WK 8	WK 7	WK 6	WK 5	WK 4	WK 3	WK 2	WK 1
BRAND F	BEFORE	17,250	18,657	18,432	17,881	17,792	18,858	18,544	18,371
	AFTER	16,896	18,329	17,988	18,687	17,840	19,254	18,805	18,020

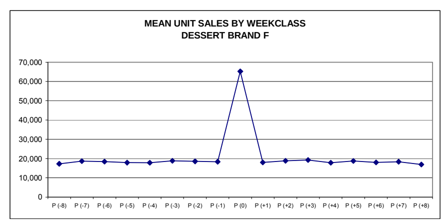
Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Row 1	8	145,785	18,223	287,094.4
Row 2	8	145,819	18,227	518,873.7

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	72	1	72	0.0002	0.9895	4.6001
Within Groups	5,641,777	14	402,984			
Total	5,641,849	15				



The detailed data for the "dip effect" are provided in Exhibits 2A and 2B. For Desserts, there was significant drop in sample size after four weeks surrounding a promotion because the brands are promoted so frequently. Additionally, the regional brands (E, G and K) saw quite a few instances of structural shifts in baseline sales that likely affected the results of this test. For Beverages, we see a couple of instances (Brands 1B and C) where there are signs of the pre and post promotion dips. However, these were also the two instances where there was the greatest deviation between the promotional activity comparisons. Therefore, the dips are likely due to variation in the endogenous promotional variable than from actual pre and post promotional sales dips.

H4 is accepted. The conclusion from these tests is that there is no intertemporal brand substitution due to promotion, either from stockpiling or purchase acceleration.

This conclusion conflicts with the conclusions reached by both Mace and Neslin (2004) and Van Heerde, Leeflang and Wittink (2000). Both studies, using the same methodology but different data sources, found there to be both Pre-and Post-Promotional dips prior to promotions. Both studies found the net incremental gain in UPC-level sales was roughly 67% at the product level. There are several points to be made about this lack of convergence:

1. The strongest evidence of the lack of promotional dips come from Desserts where the promotional activity is predictable, frequent and aggressive. Mace and Neslin (2004) conclude that postpromotion dips "are greater for higher-priced, frequently promoted, more mature, higher-share UPC's; smaller for UPCs that promote steeply or more predictably." It is hard to determine from their conclusions what results would be expected by the major Dessert brands: they fit both classifications exactly. The authors conjecture that the positive relationship between promotional frequency and promotion dips might be explained by behavioral learning. In summary, there is nothing in their conclusions that are supported by the evidence in the frequently promoted Dessert category or in the Beverage category, for that matter.

2. Both studies were based on disaggregated data. As stated in Section IV, aggregated data is the standard of reality that must be explained and predicted. If the conclusions derived from disaggregated do not conform to the reality of aggregated results then they must be rejected unless there is a compelling theoretical basis to accept them.

3. These two studies, however, are typical of most promotional research in that they are atheoretical. There is no overriding theme of what results should be expected and why based on either consumer psychology or microeconomic theory. Consequently the results conflict with prior research, have weak "theoretical rationale," or are implausible from an economic standpoint. One example of

conflicting results is the comment by Mace and Neslin (2004) about the relationship between demographics and deal-proneness, "...the inconsistency has been in determining which particular demographics are key. It is rare to find two studies with the same findings." The authors also cite numerous inconsistencies in their results from Bell et al (1999) and with Van Heerde et al (2000). In both instances, a difference in data sources is cited as a possible source of the discrepancy. If data sources accounted for conflicting results, then the conclusions can hardly be characterized as robust or generalizable.

From a theoretical standpoint, it is difficult to understand how promotion predictability would lead to *less* promotional dips due to stockpiling. If we accept stockpiling to be evident (with the emphasis on *if*), then the presumption of rational consumer expectations would predict a significant increase in stockpiling, not decrease.

4. The authors in both studies use the Scan*Pro baseline as the benchmark for identifying promotional dips. Section V demonstrated that baseline estimates have several problems in terms of excess volatility and correlation with promotional activity. Therefore, any conclusion based on these measures is suspect, particularly in the absence of a solid theoretical approach.

In contrast to a paper with conflicting results and ambiguous theoretical support, this paper's results for the hypothesis test of "no-dip" are based on a solid theory whose foundations are proven microeconomic principles. The results support the theory, and the deviations from the theory seen in Beverages are explainable.

H5 Results: Cross-Brand Effects

Pair-wise comparisons between brands within a specific geography were made. For a focus brand (Own Brand), each weekly observation was classified into one of four classes: 1=No Promotion for either Own Brand or Competitive Brand, 2=Promotion on Own Brand, but not Competitive Brand, 3=Promotion on Competitive Brand, but no Own Brand, and 4=Promotion on both Own and Competitive Brand. These are groups will be called PROMOCLASS.

For Beverages there were six cross-effects tests run across the two largest brands. For Desserts, Cross-effects were only run for the top two brands against eight brands in the competitive set (one being Private Label). There were 13 cross-effects measured. Analysis of variance testing was conducted for each competitive pair against chain-level data only.

There were no cross-brand effects found at statistically significant levels for any of the 13 brand combinations. While some coefficients had negative signs, indicating some level of negative cross-brand effects, p-values for these were always very high...above 0.5. Additionally, there were as many promotion/non-promotion coefficients that had positive signs, and p-values were very high for these, as well. The cross-effects were effectively zero.

H5 is accepted. This test provides empirical support that intrinsically similar products are not necessarily close substitutes. The result finds that there is no brand switching that occurs due to promotion.

H6: Cross Outlet Effects

For each promoted brand, sales lifts during the promoted week were compared to the sales lifts generated at the market level during the same week. The market is defined as the geographic area that aligns with the exact trading area of the retailer, so we are fortunate to have a relatively precise definition of cross-outlet effects from promotion. The null hypothesis is for the market-level lifts to be equal to or greater than the lifts generated at the account level. Conversely, a rejection of the hypothesis – market lifts less than retailer lifts - would suggest evidence of channel switching effects due to promotion. Again, the test assumes that the most measurable cross-channel effect will occur for promoting brands during the week of the promotion. Therefore, the tests will isolate on just those weeks. In Table 11, we see no evidence of negative effects due to promotional activity. In both categories, all market-levels effects were greater than retailer level.

TABLE 10
Cross-Outlet Switching Tests

BEVERAGES

CROSS-OUTLET EFFECTS
Difference Between Sales Lifts (Market vs. Chain) when Chain Promotes

BRAND	Estimate	Std Error	t-value	p-value
BRAND A1	235	17.76	13.23	0.00001
BRAND A2	172	15.95	10.78	0.00001
BRAND B	2,858	146.57	19.50	0.00001
BRAND C	131	13.44	9.75	0.00001

NULL HYPOTHESIS: Difference in Lift between Market and Chain >= 0

DESSERTS

CROSS-OUTLET EFFECTS
Difference Between Sales Lifts (Market vs. Chain) when Chain Promotes

BRAND	Estimate	Std Error	t-value	p-value
BRAND D	10,312	387.09	26.64	0.00001
BRAND F	35,956	1596.90	22.52	0.00001
BRAND H	41,244	1528.30	26.99	0.00001
BRAND I	9,536	374.20	25.48	0.00001
BRAND J	24,689	834.46	29.59	0.00001

NULL HYPOTHESIS: Difference in Lift between Market and Chain >= 0

<u>H6 is accepted</u>, and therefore, we can complete the loop on an empirical proof of the Complete Category Effect. There was no post-promotion dip (H4), no brand switching (H5) and no cross-channel effects (H6).

These results are not too different from Walters (1991) except that are more pronounced conclusions. Whereas Walters (1991) found inconsistent or "modest" evidence of brand substitution or store substitution from promotion, this study finds none. Additionally, while the empirical work of Walters (1991) – and most marketing researchers – is atheoretical, Section VII will demonstrate the consistency between the TRPP, the empirical results in Section VI and consumer demand theory.

VII. Economic Foundations of Price Promotions

VIIA. <u>The Link Between Marketing and Economics</u>

Having run all the empirical tests, the final steps is to create the linkage between microeconomic theory and marketing research. As noted in the Section III there is a very limited record of cross-referencing between the marketing and economics fields. The majority of those in the marketing field ignore economic theory in the pursuit of their research goals. Except for the fairly regular invocation of the need to have price elasticities coefficients "properly signed" there are no recurring themes of consumer demand theory which have been absorbed into the marketing literature. The reverse seems to be true, as well: economists do not look to marketing academics for insight into the consumption function in their macroeconomic models. Friedman (1976) illustrated this lack of regard of economists for marketing when he stated, "economic theory proceeds largely to take wants as fixed...The economist has little to say about the formation of wants; this is the province of the psychologist." With all due respect to the late Dr. Friedman, it is actually the province of the marketer to explore the formation of consumer wants. The marketer is the person that synthesizes both economics and psychology to gain insights into consumer behavior. It is not even clear that economists view marketing as a field of economics. A search of Economics on Wikipedia yielded fourteen sub-categories of Economics such as Agricultural Economics, Environmental Economics, and Industrial Organization. Marketing was not one of the fourteen.

With such minimal interdisciplinary efforts, one might wonder if it is even appropriate to apply economic theory to marketing issues. Hunt (2002) called out the controversy among marketing theoreticians of whether marketing was a science. Even if marketing is a science, the second part of the question would be if marketing is a scientific discipline within economics. Both questions can be answered if there is a positive answer to the issue of marketing being a discipline within economics.

It is helpful to start with some definitions of marketing and of economics to see if these definitions can provide answers to the questions posed above. Here are a few typical definitions:

Marketing Definitions

"Marketing is the process of planning and executing the conception, pricing, promotion, and distribution of ideas, goods, services, organizations and events to create and maintain relationships that will satisfy individual and organizational objectives." *Contemporary Marketing Wired* (1998) Boone and Kurtz. Dryden Press.

"Marketing is a societal process that is needed to discern consumers' wants; focusing on a product/service to those wants, and to mold the consumers toward the products/services. Marketing tends to be seen as a creative industry, which includes advertising, distribution and selling." Wikipedia (2007)

"Marketing is the activity, set of institutions, and processes for creating, communicating, delivering, and exchanging offerings that have value for customers, clients, partners and society at large." *American Marketing Association Website (2007)*

Economics Definitions

"The social science that studies the production, distribution and consumption of goods and services." Douglas Harper, Online Etymology Dictionary – Economy (2001).

"Economics examines that part of individual and social action which is most closely associated with the attainment and with the use of the material requisites of wellbeing." Alfred Marshall (1890).

"Economics is defined as the social science concerned with analyzing and describing the production, distribution, and consumption of wealth." Robbins

Certainly there are several common threads to these definitions that would suggest a formal link between marketing and economics. First, is the focus on the consumer and consumption; second is the orientation towards social science and society, and third is the importance of goods and services. In addition to these elements, there is a larger common element to the two fields: pricing is a fundamental consideration in each field. Many use the term Price Theory interchangeably with Microeconomics.

In Marketing, Price is one of the "4 P's" pillars of marketing interventions, and pricing research is one of the largest areas of marketing research.

Without belaboring the point, there is ample evidence that marketing is, in fact, a branch of economics despite the dearth of co-integration between the two fields. The lack of this intellectual cross-pollination is evidence is several marketing articles that fail to reconcile apparent contradictions with microeconomic theory. Some noteworthy examples are provided in Table 11.

TABLE 11
Comparison of Marketing Research Conclusions with Economic Theory

Authors	**Conclusion or Hypothesis**	**Apparent Contradictions with Microeconomic Theory**
Allenby and Rossi (1991)	Hypothesized that asymmetric switching between high and low priced brands within a category was due to the Income effect.	Slutsky Equation suggests that Income Effect is virtually zero for groups of products accounting for a very small proportion of a consumer's budget.
Allenby and Rossi (1991), Blattberg and Wisniewski (1989) and Kamakura and Russell (1989), many others	Each documented asymmetric switching between high priced (quality) and low priced (quality) brands within a category.	Asymmetric switching needs to be reconciled with two issues: 1) is low quality synonymous with an inferior good as opposed to a normal good? This would affect conclusions about gross substitution, as income effects can be evident in inferior goods, 2) the Slutsky equation shows that cross-brand effects in two commodity space are symmetric.
Bolton (1989), Neslin (2002), many others	Promotional Elasticities Exceed Price Elasticities	Given the temporary nature of promotion, the conclusion implies a fundamental change in a consumer's utility function depending on whether the price offering is promoted or everyday price. It is theoretically impossible for a utility function to switch in this manner. The empirical results need to be reconciled with a consumer's utility function.

Authors	**Conclusion or Hypothesis**	**Apparent Contradictions with Microeconomic Theory**
Van Heerde, Dekimpe and Putsis (2005)	They suggest that the Lucas Critique would not help researchers predict consumer response to a historically unobservable promotional pricing policy (e.g. a 50% price reduction when 20% had been the lowest observed discount)	The Lucas Critique challenges researchers to focus on the deep structural parameters effecting policy change. Under that guideline, there is no reason that researchers cannot predict the response to a new promotional pricing policy given that the structural parameters of the consumer's utility function (his scale of preferences) are assumed to be constant in the short-term.
Walters (1991), Kirk (1996), many others	Identified cross category substitution effects from price promotion	The Cournot Aggregation Condition for all plausible ranges of own price elasticity and a product's household budget share suggest that any effect would be very difficult to detect unless sample sizes were very high.
Gupta (1988), Bell et al (1999), many others	Concluded that the source of volume from promotional spikes was entirely sourced within a category of intrinsically identical products. The effects were primarily brand switching (cross-brand effects).	Results would imply an implausible scenario of a weakly separable and weakly additive utility function where products were grouped entirely by intrinsically identical properties. Using the Slutsky Equation, this implies that the cross-partials for combinations of within-category and outside-category products are zero.

In summary, we have established that a) marketing is a science (taken as a given), b) marketing is a scientific discipline within economics, c) there has been little cross-referencing of economic principles within marketing literature and vice-versa, and d) lack of consideration of microeconomic principles in marketing have yielded some seemingly incorrect or incomplete conclusions derived from empirical results. Having established theses premises, we can now turn our attention to exposing the specific aspects of microeconomic theory that would help us understand the dynamics of retailer price promotion.

VIIB. <u>Utility Maximization and Indifference Curves</u>

Classical economic theory, as introduced by Alfred Marshall in the late 1800's, places the consumer and his utility squarely at the forefront of economic understanding. It was Marshall that pioneered the concept of utility as a measure of total consumer satisfaction, and he also established that the marginal utility of each incremental unit consumer provides a diminishing level of marginal utility. Utility maximization occurs within a consumer's budget constraint. The concept of diminishing marginal utility is the foundation of all future work in consumer demand theory. Marshall established the important relationship that to maximize utility between two goods their marginal utilities must be proportional to their prices.

After Marshall, Vilfredo Pareto (1909) provided what Hicks (1946) termed, "the other classical treatment of the theory of consumer's demand from which all modern investigation must begin." Pareto's major contributions were in proving utility to be an ordinal rather than a cardinal (measurable). The ordinal scale of preferences was a significant methodological breakthrough as researchers were no longer concerned with the measurability of utility.

More important, Pareto translated marginal utility into indifference curves, which is a graphical depiction of utility for two different goods. Pareto built the basic shape of the negatively sloped, convex utility function. He also demonstrated that consumers maximize utility for a two-good universe at the point where the marginal rate of substitution is equal to the slope of the consumer's budget constraint. It is not important to provide any excessive treatment of these concepts other than to note that indifference curves like the one in Figure 4 (pg 37) will be fundamental towards an understanding of the consumer trade-offs that occur when purchasing a promoted product.

VIIC. <u>The Substitution effect and the CCEE</u>

Slutsky Equation

Eugen Slutsky (1915) was the first to provide a full treatment of the law of consumer demand with a derivation of a negatively sloped demand curve given a certain consumer's utility function and budget constraint. Slutsky's Fundamental Equation of Value Theory decomposed a consumer's demand for a good into three components: Own Price Effects, Cross Price Effects (from other goods) and Income Effects. From an initial 2-good utility function and budget constraint, Slutsky derives a comparative static approach to determine the change in quantity demanded for Good *x* in the event of perturbations in each of the three effects. The equation is derived as below starting with the LaGrangian function. The derivation follows Henderson and Quandt (1980).

Maximize V $$f(x,y) + \lambda(M - p_x x - p_y y), \tag{1}$$

where $f(x,y)$ is a 2-commodity space utility function, M=income and λ is the Lagrangian multiplier, which will also be the marginal utility of money. p_x is the price of x and p_y is the price of y.

First Order Conditions
$$\begin{aligned} \frac{\partial V}{\partial x} &= f_x - \lambda p_x = 0 \\ \frac{\partial V}{\partial y} &= f_y - \lambda p_y = 0 \\ \frac{\partial V}{\partial \lambda} &= M - p_x x - p_y y = 0 \end{aligned} \tag{2a-2c}$$

In order to ensure a maximum solution the first as well as second-order conditions must be satisfied. Fully differentiating (2a-2c) produces the following, which must be positive. Set up the Bordered Hessian
$$\Omega = \begin{bmatrix} f_{xx} & f_{xy} & -p_x \\ f_{yx} & f_{yy} & -p_y \\ -p_x & -p_y & 0 \end{bmatrix} > 0 \tag{3}$$

Calculate the determinant
$$2f_{xy}p_xp_y - f_{xx}p_y^2 - f_{yy}p_x^2 > 0 \tag{4}$$

The total differentiation of (2a-2c) expands to

$$\begin{aligned} &f_{xx}dx + f_{xy}dy - p_x d\lambda = \lambda dp_1 \\ &f_{yx}dx + f_{yy}dy - p_y d\lambda = \lambda dp_2 \\ &-p_x dx - p_y dy = -dy + xdp_x + ydp_y \end{aligned} \qquad \text{(5a-5c)}$$

Rearrange for dx,dy

$$dx = \frac{\lambda\Omega_{11}dp_x + \lambda\Omega_{21}dp_y + \Omega_{31}(-dM + xdp_x + ydp_y)}{\Omega} \qquad \text{(6a)}$$

$$dy = \frac{\lambda\Omega_{12}dp_x + \lambda\Omega_{22}dp_y + \Omega_{32}(-dM + xdp_x + ydp_y)}{\Omega} \qquad \text{(6b)}$$

Ω is the determinant from equation (3), and Ω_{ij} are the cofactors for the element in row *i*, column *j*.

If we isolate just on Own Demand for *x* and hold price on *y* constant (dp_y=0), we can rewrite 6a as follows:

$$\frac{dx}{dp_x} = \frac{\Omega_{11}\lambda}{\Omega} + x\frac{\Omega_{31}}{\Omega} \qquad \text{(7)}$$

By assumption we know that Ω is positive (from equation 3) and we know that λ, the marginal utility of money, is positive. Therefore, the sign of the substitution effect on direct demand is dependent on Ω_{11}, which is $-p_y^2$. Since this term is unambiguously positive then Ω_{11} is negative. This part of the equation is known as the compensated demand function, where the consumer is compensated by an income change concurrent with a price change in order to leave him on the same indifference curve. This is the proof of a negatively sloped demand curve.

A compensated demand function in two-commodity space can be characterized by the rate of substitution between *x* and *y* equal to zero (equation 8). Recall that Marshall established that marginal utilities were proportional to their prices. Pareto modified this principle to state that the rate of marginal substitution is proportional to the prices of the two goods (equation 9)

$$dU = f_x dx + f_y dy = 0 \tag{8}$$

$$\frac{f_x}{f_y} = \frac{p_x}{p_y} \tag{9}$$

Substitute (9) in (8) $$p_x dx + p_y dy = 0 \tag{10}$$

Substitute (10) into (5c) $$0 = -dy + xdp_x + ydp_y \tag{11}$$

Equation (11) eliminates the second term on the RHS (Right Hand Side) of Equation (7). We are, therefore, left with:

$$\frac{dx}{dp_x} = \frac{\Omega_{11}\lambda}{\Omega}\bigg|_{U=const} \tag{12}$$

If we then hold p_x and p_y constant for (6a) we have $\frac{\partial x}{\partial M} = -\frac{\Omega_{31}}{\Omega}$, (13)

which is the change in *x* with respect to a change in income.

Combining (12) and (13) $$\frac{\partial x}{\partial p_x} = \left(\frac{\partial x}{\partial p_x}\right)_{U=const} - x\left(\frac{\partial x}{\partial M}\right)_{price=const} \tag{14}$$

From the second term on the RHS of (14) it can be inferred that the income effect for products accounting for a small portion of a consumer's budget yields an income effect that converges to zero. This is affirmed by Hicks (1946) and projected to the market as a whole when he says,

> "The group income effect will usually be negligible if the group as a whole spends a small portion of its total income on the commodity in question...*It is therefore a consideration of great importance that this unreliable income effect will be of relatively little importance in all those cases where the commodity in question plays a fairly small part in the consumer's budget; for it is only in these cases…that we have an unequivocal law of demand."*

This is a vitally important consideration since almost every CPG category, and most consumer categories in general, fit the criteria of accounting for a small portion of the group's total income. This basic microeconomic principle undermines the argument of Allenby and Rossi (1991) that explains asymmetric brand switching behavior in terms of income effects. Rather than incorporate the income effect into our explanation of the CCEE we can ignore it altogether.

We can then focus on the kernel of the entire microeconomic rationale for the CCEE, namely the Substitution effect. As noted earlier, researchers that specify brand switching effects within a category are implicitly assuming that there is a substitution effect occurring among intrinsically similar products. The validity of the TRPP rests upon proving that these close substitution effects do not exist. A review of the canonical consumer demand theory literature reveals that while close substitutes are consistently implied or hypothesized throughout the writings of Hicks, Lancaster, Marshall and others, there has been no formal proof that products with intrinsically similar properties *must* be close substitutes.

Henderson and Quandt (1980) also try to create an informal definition of substitution by analogy, but ultimately yield to the more rigorous, empirically derived definition.

> "Two commodities are substitutes if both can satisfy the same need of the consumer; they are complements if they are consumed jointly in order to satisfy some particular need. These are loose definitions, but everyday experience may suggest some plausible examples. Coffee and tea are most likely substitutes, whereas coffee and sugar are most likely complements. <u>A more rigorous definition of substitutability and complementarity is provided by the cross-substitution term of the Slutsky equation.</u>" (Underline added for emphasis)

The extensive empirical findings from Section VI provide support for the lack of a cross-substitution effect within a specific category. Going back to the Slutsky derivation, we can isolate on the specific element that determines the sign of the cross effects between brands.

Recall (7), but for cross effects $$\frac{dx}{dp_y} = \frac{\Omega_{12}\lambda}{\Omega} + y\frac{\Omega_{31}}{\Omega} \tag{7b}$$

For two brands to exhibit brand switching (i.e. substitution), (7b) must be positive, a decrease in the price of *x* will decrease the demand for Good *y*. For the

LHS to be positive, the first term of the RHS must be positive (the second term is zero). By symmetry with Equation (14), (7b) becomes

$$\frac{\partial x}{\partial p_y} = \left(\frac{\partial x}{\partial p_y} \right)_{U=const} - y(\frac{\partial x}{\partial M})_{prices=const} \tag{15}$$

This implies that for brands to be substitutes the cross-partial of the utility function between *x* and *y* must be positive. The empirical data suggests that the cross-partial is zero, which, in turn, implies that consumers have utility functions that are separable and additive across all physical commodities. From a broader perspective we can conclude that identification of brands as substitutes is a concept that must be empirically derived rather than manifestly evident because of their intrinsically similar properties. This is a concept consistent with Samuelson's Revealed Preference Theory (1948), which theorizes that the nature of a utility function can be deduced by the observed choices of consumers.

Composite Goods Theorem

Thus far it has been established that the sales change in the promoted product can only be as a result of the substitution effect since the income effect is negligible. We have also established that the determination of substitute products for the promoted product is empirically derived. However, the empirical results demonstrate that the other brands in the category were *not* substitutes for the promoted brand. This leads to the obvious question: where did the cross-substitution effects come from?

The most reasonable explanation is provided by the Composite Goods Theorem of Hicks (1946). Henderson and Quandt (1980) summarize the theorem as follows: "if the prices for a group of *m (<n)* commodities always change in the same proportion in *n*-commodity space, the aggregate demand for the *m* commodities behaves as if they were a single commodity." In his own conversational style, Hicks explained,

> "A collection of physical things can always be treated as if they were divisible into units of a single commodity so long as their relative prices can be assumed to be unchanged…So long as the prices of other consumptions goods are assumed to be given, they can be lumped together into one commodity 'money' or 'purchasing power in general.'"

Hicks also offers the notion that substitution need not necessarily reflect a trade-off of two physical commodities. He argues that the geometrical argument for indifference maps can be expanded to any two concepts where a consumer makes trade offs within a constraint. E.g. bread can be substituted with purchasing power or work can be substituted with leisure. Macroeconomics quite regularly views dimensions on the indifference maps on a time dimension to determine substitution between two periods (intertemporal substitution). Hicks stated,

> "Similarly, so long as the terms on which money can be converted into other commodities are given, there is no reason why we should not draw up a determinate indifference system between any commodity X and money (that is to say, purchasing power in general)."

Within a short-term, finite time horizon all non-promoted goods behave as the composite good, consistent with Hicks (1946). The Composite Goods Theorem provides the most reasonable explanation of the lack of a visible cross-brand effect in Section VI: increased category expenditures are being funded at the expense of discretionary income or Money.

Cournot

It is less than satisfactory to end the discussion of identifying the location of the substitution effect with an invocation of the Composite Goods Theorem. Considering the position of a retailer, there is value to quantifying the expected cross-substitution effects on any particular set of products. There is some empirical work that suggests the promotions have a weak effect on complementary categories (Walters – 1991 and many others) and other research suggests promotions can have a noticeable effect on store substitution (Kumar and Leone – 1988). Section VI could find no substitution effect within category at other retailers; therefore we can isolate the cross-substitution effect to other categories.

The Cournot Aggregation Condition (CAC) is a theorem for identifying the cross-price elasticity for the composite good. The required inputs are the Own Price Elasticity and percentage of Total Income for the promoted good. The derivation of the CAC follows the work of Sullivan (2005).

Assume in the short-term $dM=dp_2=0$, p_2 is the price of the composite commodity and M is income. Both are assumed to be invariant in short increments of t, where t is in one-week increments. Given these assumptions we can take the total differential of the budget constraint to be:

Start with the budget constraint from (1)

$$M = p_x x + p_y y \tag{16}$$

Differentiate with respect to p_x dM, $dp_y=0$

$$x + p_x \frac{\partial x}{\partial p_x} + p_y \frac{\partial y}{\partial p_x} = 0 \tag{17}$$

Multiply by $\frac{p_x}{M}$

$$\frac{p_x x}{M} + p_x \frac{\partial x}{M \partial p_x} p_x + p_y \frac{\partial y}{M \partial p_x} p_x \tag{18}$$

Multiply 1 to each term (x_i/x_i)

$$\frac{p_x x}{M} + \frac{p_x x}{M} \frac{p_x \partial x}{\partial p_x x} + \frac{p_y y}{M} \frac{p_x \partial y}{\partial p_x y} = 0 \tag{19}$$

Substituting elasticity terms and letting $\alpha_x = p_x x/M$ or the share of Good *x* of the total budget we get:

$$\boxed{\alpha_x \cdot \varepsilon_{xx} + \alpha_y \cdot \varepsilon_{yx} = -\alpha_x} \tag{20}$$

Equation (20) can be used to determine if we can expect any meaningful cross-substitution effects from the composite good for plausible ranges of the consumer's budget share (α) and own price elasticity (ε_{xx}). Recall that CPG products carry a very low retail price, and consequently, in developed economies constitute a very low percentage of the typical household income. Even if all promotional goods in a given week were aggregated and compared to the composite good of non-promoted merchandise, the share of promoted goods would still be relatively low.

In the simulations below (Table 12), we see an extremely low cross-price elasticity for the composite good even in instances of hyper-price sensitivity (ε_{11} = -20.0) and a relatively high assumption of the proportion of income spent on the promoted commodity. While the first simulation is an extreme example, it is plausible if we assume a product with very high price elasticity (e.g. desserts) and a household (albeit an unhealthy one) that spent a sizeable percentage of their income – in this case 1.0% - on that commodity.

TABLE 12
Promotional Simulations of Cross Effects

% of Income (M) spent on commodity 1	Own Price Elasticity of Good 1	% of Income (M) spent on Composite Commodity	Calculate Cross-Price Elasticity of Good 2
α_1	ε_{11}	α_2	ε_{21}
1.000%	-2.0	99.000%	0.0101
1.000%	-5.0	99.000%	0.0404
1.000%	-10.0	99.000%	0.0909
1.000%	-15.0	99.000%	0.1414
1.000%	-20.0	99.000%	0.1919
0.500%	-2.0	99.500%	0.0050
0.500%	-5.0	99.500%	0.0201
0.500%	-10.0	99.500%	0.0452
0.500%	-15.0	99.500%	0.0704
0.500%	-20.0	99.500%	0.0955
0.100%	-2.0	99.900%	0.0010
0.100%	-5.0	99.900%	0.0040
0.100%	-10.0	99.900%	0.0090
0.100%	-15.0	99.900%	0.0140
0.100%	-20.0	99.900%	0.0190

Taking the extreme assumption of very high budget allocation for Commodity 1 and very high price elasticity of that commodity, only then do we motivate a result that could have meaningful effect on the composite commodity and would enable use to reliably measure cross-category effects. Even in that instance the percentage discount would need to be pretty significant (30% or more) to have an observable effect. In the extreme case, a 50% price discount would decrease demand for Commodity 2 by 9.5%.

The more plausible examples, however, can be found in Table 13. Here we see typical budget allocations for any give product less than 0.1%, and price elasticities in the -2.0 to -10.0 range, with -5.0 being the norm.

TABLE 13: COURNOT AGGREGATION SIMULATION

% CHG IN SALES TO COMPOSITE GOOD AS A FUNCTION OF DISCOUNT PERCENT, PRICE ELASTICITY AND SHARE OF INCOME TO PROMOTED GOOD

	25% Discount				50% Discount			
Share	**-2.0**	**-5.0**	**-10.0**	**-20.0**	**-2.0**	**-5.0**	**-10.0**	**-20.0**
0.01%	0.00%	0.01%	0.02%	0.05%	0.01%	0.02%	0.05%	0.10%
0.05%	0.01%	0.05%	0.11%	0.24%	0.03%	0.10%	0.23%	0.48%
0.10%	0.03%	0.10%	0.23%	0.48%	0.05%	0.20%	0.45%	0.95%
0.20%	0.05%	0.20%	0.45%	0.95%	0.10%	0.40%	0.90%	1.90%
0.50%	0.13%	0.50%	1.13%	2.39%	0.25%	1.01%	2.26%	4.77%
1.00%	0.25%	1.01%	2.27%	4.80%	0.51%	2.02%	4.55%	9.60%

Under these conditions we would require an extremely high sample size to discern any cross-category effects from a decrease in the price of *x*. The calculations assume proportional cross-product affects across all other potential product options. This assumption is valid in light of the failure to identify cross-effects among intrinsically similar products. Therefore, there is no basis to assume any particular bias in cross-commodity effects. This result supports the point made in Section VIIA about the implausibility some empirical conclusions that purported to identify cross-category effects from promotion.

VIID. Other Microeconomic Considerations

Initial reaction to the Theory of Retailer Price Promotion seems to center on two questions: 1) If the results are so obvious, why aren't the multi-billion dollar CPG firms doing something about it, and 2) How can this theory be correct since it is so counterintuitive? While there appears to be compelling empirical and theoretical support for the CCEE, it is necessary to rationalize the theory to address the previous questions as well as rationalize it in terms of other elements of microeconomic theory. Specifically, consideration must be given to the Rational Expectations of Consumers, the Rational Behavior of Firms, the reconciliation of the CCEE with Lancaster (1966) and a separate section to address the supply-side of the equation since it has been ignored entirely up to this point. There is also a role for discussing the role of organizational behavior and group psychology in shaping the conventional wisdom about this important marketing topic, but will not be addressed in this paper. Section VIIE is presented with the objective of laying out hypotheses and ideas rather than offering full empirical treatment to the issues above.

Rational Consumers

The assumption of rational, forward-looking consumers would predict that they would adapt their purchasing behavior based on predictable pricing patterns. Certainly, the Dessert category demonstrates evidence of highly predictable, regular and aggressive price discounting. We would expect a rational consumer to engage in either stockpiling or purchase acceleration to take advantage of these semi-weekly deals. However, the empirical evidence across almost 800 dataclasses is unambiguous; consumers – in the aggregate – are not exhibiting the expected forward-looking behavior.

We can reject any notion of irrational consumers and focus on plausible explanations of why stockpiling or acceleration is not evident. Based on the patterns of the data, it appears that consumers readjust their budget decisions every week, which is the unit of time for promotions. If their planning horizon were longer we would see evidence of intertemporal switching.

There is also some insight to be gained by decomposing the utility function for consumers. The relatively predictable level of promotional lifts suggests stable utility functions and demand curves for the representative consumer. We can safely assume household income changes are neglible week-to-week. and we can also establish a stable scale of preference during such a short time horizon. In fact, every parameter within the utility function from t-1 to t (one week) can be assumed constant except information about the consumer offer and the depth of the offer (which affects the budget constraint). There is no controversy in the dozens of articles about how various promotions (TPR vs. Ad, for instance) produce different level of responses. Given that we see relatively predictable lifts over time for identical promotional programs and a significant variance in lifts when programs are changed, it strongly suggests that an information parameter is affecting the demand curve. This explanation is consistent with consumer demand theory. By contrast, authors that advance a theory of difference in price elasticity vs. promotional price elasticity are not considering the structural parameters of the consumer's utility function.

Finally, it is important to have an unrestricted view of utility. Most of the literature uses the term consumption synonymously with "own use." Even if we accept this restriction, Ailawadi and Neslin (1998) provide formal proof that promotion can increase category consumption, primarily by reducing out-of-stocks between purchasing cycles. There is no need to restrict the definition of utility, however, as there are many sources of potential utility that can be derived from a purchase of a promoted good. Neslin (2002) discusses transaction utility ("the thrill of the deal") as a potential source of utility. It is not too difficult to think of other reasons why consumers can derive utility. Convenience utility (multiple locations of a product for easier access) and gift utility (purchasing for a friend or relative) are two of the most plausible sources.

Lancaster's New Approach to Consumer Theory (1966)

Lancaster's new approach to consumer theory is based on the theory that goods have no intrinsic utility in and of themselves; it is the characteristics that they contain that give them utility. The new approach evaluates consumer demand in terms of accumulating bundles of characteristics within a budget constraint rather than a bundle of goods. The primary application of the theory is to evaluate consumer reactions to changes in quality or introduction of new products. Lancaster argues that traditional demand theory has nothing to say on either of these two issues.

Lancaster was among the first to identify substitution of goods in terms of intrinsically similar properties. There are many passages in this article that can be interpreted as supporting a requirement for substitution effects for intrinsically similar products. Take, for example, this passage in the introduction:

> "In spite of the denial of the relevance of intrinsic properties to the pure theory, there has always been a subversive undercurrent suggesting that economists continue to take account of these properties. Elementary textbooks bristle with substitution examples about butter and margarine, rather than about shoes and ships, as though the authors believed that there was something intrinsic to butter and margarine that made them good substitutes and about automobiles and gasoline that made them somehow intrinsically complementary. Market researchers, advertisers and manufacturers also act as though they believe that knowledge of (or belief in) the intrinsic properties of goods are relevant to the way consumers will react to them."

Lancaster seems to imply that there is an inherent, structural relationship between substitution and product similarities, as he mentions all of the various economic agents that are acting according to that principle. In another passage, Lancaster uses a specific example to contrast consumer choice in terms of classical vs. his new demand theory.

> "It is clear that only by moving to multiple characteristics can we incorporate many of the intrinsic qualities of individual goods. Consider the choice between a gray Chevrolet and a red Chevrolet. On ordinary theory these are either the same commodity (ignoring what may be a relevant aspect of the choice situation) or different commodities (in which case there is no a priori presumption that they are close substitutes). Here we regard them as goods associated

> with satisfaction vectors which differ in only one component, and we can proceed to look at the situation in much the same way as the consumer ... would look at it."

Lancaster proceeds to give formal respectability to *intrinsic commodity groups* as a means where substitution can occur only within products with an identical taxonomy. Further, price changes outside the group will have no effect on the intrinsic commodity group.

It is important to note, however, that while Lancaster provides a theoretical justification for substitution for products with similar characteristics, there is nothing in the theory that requires it. The definition of an intrinsic commodity group are highly restrictive, "If, further, the activities in question require a particular set of goods which are used in no other activities...then we can regard the goods as forming an *intrinsic commodity group."*

There are many areas of the paper where the author implicitly acknowledges that substitution can and does occur across products that *are not* intrinsically similar. For example, he describes a meal as a good possessing nutritional characteristics as a single good, but possessing aesthetic and social characteristics at a dinner party. He also recognizes that goods within a commodity group can have interactions that are partly complementary and partly substitution. What is not mentioned is the fact that consumer products (CPG, in particular) in a complex economy are usually differentiated to some degree; even just a brand name is a point of differentiation. He also fails to acknowledge the composite good concept and discretionary spending as a source of cross-effects with a particular good. In summary, it is reasonable to interpret Lancaster's new approach to demand theory as one that <u>does not require</u> cross product effects to occur among intrinsically similar products. However, it is one that would predict that the most measurable substitution effects would come from intrinsically similar products. It can also be used explain how, theoretically substitution that may occur among these types of products.

Rational Firms

With all the money invested in acquiring and analyzing scanner data, why have firms with vast resources not already identified the CCEE? This legitimate question has several aspects worthy of response. First, it is well documented in the literature that CPG firms are increasing their spending on retailer price promotions, and this spending is capturing a greater share of the marketing budget. The fact that this growth is steady over time, and not just an abrupt reaction, suggests that profit-maximizing firms are adapting their decisions to observable market responses. That could be seen as rational behavior.

Second, rational behavior is not synonymous with perfect information or perfect decisions. This paper has spent a considerable amount of space documenting flawed paradigms, conflicting results, and incorrect conclusions in a research topic where lack of information and data is *not* one of the problems. If this situation exists in academia - where the level of diagnostic ability is much higher - there is every reason to believe the faulty situation exists in industry, as well. Empirical support for this hypothesis can be found in Bucklin and Gupta (1999) who compared commercial vs. academic uses of scanner data. Of 18 key business issues addressed by scanner data, they found that only 3 of 18 (17%) showed consensus in results between industry and academia. One of the issues considered "Unresolved" was Baseline sales.

The third, and final, point to be made concerning rational firms is the enormous importance that the "market share" paradigm has had in shaping attitudes towards issues around category structure, brand switching and category expansion. In the 1940's Arthur Nielsen began the industry of market tracking by conducting in-store audits of inventory at shelf. Deviations in inventory counts, after adjusting for inventory received by the store, every two months were used as a proxy for sales. The results were reported in terms of market share. This has been, and continues to be, the standard of business performance in the CPG industry.

This approach institutionalizes two significant paradigms that still shape attitudes towards price promotion. First, all meaningful market fluctuations for a brand took place within the context of a pre-defined "category," a group of intrinsically similar products. There was no consideration of related categories and how they might affect sales of the category of interest. This precluded examination of the effect of Cookie sales on Cake or Tea sales on Coffee. The second paradigm was the notion of market share, which implicitly assumes a zero sum game. Minimal consideration is given to brand growth in the context of category growth; the key measure of performance is whether share is up or down.

We can see this paradigm carried over to the first 10-15 years of promotional research – none of the most influential papers accounted for category growth in their sales decomposition work. It was not until 2001, with Nijs et al (2001) did we see a full accounting for category expansion effects resulting from promotion. This expansion effect has been confirmed by Pauwels et al (2002), Van Heerde, Leeflang and Wittink (2003) and Mace and Neslin (2004). The magnitude of that effect is what is unresolved.

Even if we assume perfect information with optimal decision making and full acceptance of the CCEE, neither the manufacturer nor the retailer has complete control over the price promotion process. As will be discussed in more detail in the next section, there are some structural barriers that preclude a dramatic shift in marketing policy towards retailer price promotion.

In summary, any argument against the existence of the Complete Category Expansion Effect based on the supposition of rational firms making optimal decisions is undermined by the empirical evidence we can see in the marketing literature. Clearly, the information for making optimal decision is less than perfect. Even if there was perfect information, there were structural barriers in the price promotion process that prevent acting in an optimal manner.

VIIE. Supply Considerations and Hysteresis

Up until now the sole focus of the Theory of Retailer Price Promotions has been on the demand side of the microeconomic equation. It is desirable to develop a thorough economic model that incorporates supply considerations as well. Primarily we want to know whether firms can take advantage of the CCEE to maximize profits. We will consider this question with the assumption of full acceptance of the CCEE.

Manufacturers are allocating more towards promotions which suggests some level of acceptance of the positive benefits of this activity as compared to other investment alternatives. In general, though, there has been a great deal of uncertainty about the post-period costs of promotion either through a sales dip or erosion in brand imagery (no different than in academic work). This paper has documented the considerable areas of controversy and ambiguity surrounding the issue of promotions. There seems to be a greater sentiment on the manufacturer side that retailer promotions are more of a necessary evil than a worthwhile business building activity (Cannondale, 2006). Similarly, 95% of CPG companies do not believe that the significant expense in promotion - whose share of the marketing budget continues to grow - is profitable for their company (Source: Accenture). Clearly, manufacturers are not acting in a manner that suggests anywhere near total acceptance of the CCEE principle.

Even if manufacturers and retailer did accept did the CCEE, it must be recognized that the incremental units from promotion may not be profitable units. In generating incremental sales, the manufacturer does not have complete control over the components of profitability. *Retailers* control the price discount, the retail margin (manufacturer subsidy) requirement, the communication vehicle, the timing of the promotion, and the qualitative factors of the promotion (e.g. front page, ad size, display support, etc...). Obviously, with so much money at stake manufacturers are not totally powerless over the use of the funds, and the absolute dollar commitment to a retailer is a significant point of leverage they have in order to ensure compliance with optimal promotion execution. Srinivasan et al (2004) found that promotions are predominantly positive for generating incremental revenue for manufacturers, but the effect on retailers revenues are mixed. This fundamental conflict in performance suggests that retailers will try to move promotions to more favorable terms. Given that retailers have the last say on promotions; their involvement in the process presents a source of profit uncertainty and constraint for the manufacturer.

In addition to uncertainty about longer-term effects and uncertainty about profitability, one final area uncertainty is the variability in the immediate effects of promotions, an effect for which there is no controversy. We have documented the flawed baseline models that exist in the industry currently. In particular, a baseline that has a high covariance with the existence of promotions will have see a spike in baseline sales and a commensurate decline in incremental sales. Even with a high predictable promotion response, manufacturers that use the baseline for profit analysis will undervalue these promotions. Promotion response, however, tends to see a lot of variability due to qualitative factors that can effect payout. While models can be developed to provide accurate response parameters within a fairly tight confidence interval, it is possible that the confidence interval may still be too broad to justify a greater investment in an activity that generates only marginal profits.

Dixit (1992) addresses the concept of investment under uncertainty, and contends that firms require payout hurdle rates that are well in excess of the Marshallian criterion of investing when an activity has a positive expected net worth. In the case of retailer price promotion, it is likely that the level of uncertainty combined with the relatively low marginal contribution of promotions for manufacturers make it unattractive for them to significantly increase their investment. This is the concept of hysteresis. There is a substantial lag in behavior even when the cause of certain activity is fairly obvious. Dixit calls this “a theory of optimal inertia.”

The objective is to determine whether there is something inherent in the process of retailer price promotion that will maintain the condition of hysteresis. Other articles have explored the price promotions process from the perspective of off-invoice deals compared to scanback promotions (Dreze and Bell – 2003) or the level to which manufacturer allowances are passed through, in general (Pauwels – 2007). However, there is no formula available that structures the profit maximizing conditions for both retailer and manufacturer for a scanback program, where we can assume no market inefficiencies (Dreze and Bell – 2003).

In this derivation we will use the "Marshallian criterion" of an expected normal return (Dixit – 1992) where we can assume no uncertainty in the sales lift from a particular promotional strategy. We will also assume full acceptance of CCEE. The first step is to build a model to identify the conditions – sales elasticity, price discount, promotional vehicle, spending rates - required for a positive promotional ROI. Our interest is not whether promotions *have* been profitable, but whether they *could* be profitable. If we can develop a profit maximizing solution, Step #2 is to identify anything in the solution that presents a barrier to implementation (a cause of hysteresis). If there is no profit-maximizing solution, then CCEE turns out to be only of academic interest, since it would be irrational for firms to pursue a policy of increased or sustained promotions.

Derivation of Break-Even Conditions for Retailer Price Promotions

The profitability of promotion can be evaluated in any given week for exactly the time of its duration (time = t, t+1...); there is no need to consider a post-period adjusment due to the CCEE. This time subscript will be omitted for brevity as will the subscript (x) denoting Brand X. Further, this version of the model assumes all variables are known at time t-1 to eliminate uncertainty. It also assumes risk neutral economic agents so that there is no loss function that produces an asymmetric utility function for decision-makers (Friedman and Savage, 1948). This assumption will be used later in the model when we include some level of variability in the key model inputs. Finally, it is assumed that – consistent with the proof of Dreze and Bell

(2003) - there are no additional costs from forward-buying and excess retail inventory due to the promotion.

Variable Definitions

X = Baseline Unit Sales of Brand X.

F = Factory Price of Brand X

C = Marginal Cost of Brand X.

We assume both F and C are fixed. Therefore, $F_x = \overline{F}_x, C_x = \overline{C}_x$.

P = Retailer Price of Brand X

D = Retail Price Discount Offered to the Consumer when Promoted

B = Billback Allowance per unit sold of X provided by the manufacturer to the retailer to subsidize the Retail Price Discount (D)

d = Discount Percentage for Promoted Product (D/P)

g = Percentage increase in sales when the brand is promoted. (aka lift)

Profit Equations – Non-Promoted

Manufacturer:	X·(F-C)	(1)
Retailer:	X·(P-F)	(2)

Profit Equations – Promoted

Manufacturer:	X·(F-C-B) ·(1+g)	(3)
Retailer:	X·(P-F-D+B) ·(1+g)	(4)

- The manufacturer makes their normal profit (F-C) less the Billback allowance per unit (B). To offset the lower margin, he sells X ·(1+*g*) units. Again, *g* is known.
- The retailer makes their normal profit (P-F) less the Discount to the Consumer (D), but it is somewhat offset by the Billback allowance (B) from the manufacturer. He also sells X ·(1+*g*) units at a new (likely lower) margin. There are no constraints on B relative to D, but for practical purposes, B is typically ≤ D.

Indifference Point

For *both* manufacturers and retailers to be indifferent to promotions vs. normal priced sales, both conditions must hold: (1)=(3) and (2)=(4). We can simplify this system of equations as follows:

Mfr indifference	$X \cdot (F-C) = X \cdot (F-C-B) \cdot (1+g)$	(5)
which simplies to	$F-C = F - C - B + gF - gC - gB$	(6)
eliminating terms	$B = gF - gC - gB$	(7)
Retailer indifference	$X \cdot (P-F) = X \cdot (P-F-D+B) \cdot (1+g)$	(8)
which simplies to	$P - F = P - F - D + B + gP - gF - gD + gB$	(9)
eliminating terms	$D - B = gP - gF - gD + gB$	(10)
Adding (7) + (10)	$D = gP - gD - gC$	(11)
Dividing by P	$(D/P) = d = g - gd - g(C/P)$	(12)
Simplifying	$d = g \cdot (1 - d - v)$, where v is the ratio of marginal cost of production to the consumer retail price. Will refer to this as the *value cost ratio* and the equation *1-v* as the *value differential.* It is the percentage of the retail price that has been marked up in the value chain.	(13)
Rearranging	$\boxed{\frac{g}{d} = \left\lvert \frac{\partial x / x}{\partial p / p} \right\rvert = \lvert \varepsilon \rvert = \frac{1}{1 - v - d} \quad \text{, where } d \leq v}$	(14)

Equation (14) states that total profit throughout the value chain is break-even between the promoted and non-promoted options at the point where the absolute value of the price elasticity is equal to the inverse of the *value differential (1-v)* less the consumer discount (*d*). This, however, is the equation to ensure that the entire system remains at break-even levels. We now need a formula to determine the allocation of the consumer price reduction (D) that will be required between manufacturer (B) and retailer (D-B) to ensure that both parties remain break-even.

Rework (7) and (10)	$B + gB = gF - gC$	(7a)

$$B\cdot(1+g) = g\cdot(F - C) \tag{7b}$$

$$D - B = g\cdot(P - F) - g\cdot(D-B) \tag{10a}$$

$$(D - B)\cdot(1+g) = g\cdot(P - F) \tag{10b}$$

(7b) divided by (10b) $$\frac{B}{D-B} = \frac{F-C}{P-F} \tag{15}$$

This is the relative weight of manufacturer to retailer in the consumer discount (D). To convert to a share of the total discount we can divide both sides by the sum of manufacturer weight and the retailer weight (=1).

Convert to share $$\frac{\frac{B}{D-B}}{\frac{B}{D-B}+\frac{D-B}{D-B}} = \frac{\frac{F-C}{P-F}}{\frac{F-C}{P-F}+\frac{P-F}{P-F}} \tag{16}$$

Eliminate terms $$\frac{\frac{B}{D-B}}{\frac{D}{D-B}} = \frac{\frac{F-C}{P-F}}{\frac{P-C}{P-F}} \tag{17}$$

Reduce to a share $$\boxed{\frac{B}{D} = \frac{F-C}{P-C} = \alpha} \tag{18}$$

Equation (18) states that the percentage of the manufacturer discount subsidy should be equal to the share of the manufacturer's margin in the overall value chain. This can be re-entered into the profit conditions to obtain the equilibrium points for each party in the process.

<u>Manufacturer</u>

Let $B=\alpha D$, sub in (7b) $$\alpha D\cdot(1+g) = g\cdot(F - C) \tag{7c}$$

Isolate g $$g(F - C - \alpha D) = \alpha D \tag{19}$$

Divide by P $$g\cdot\left(\frac{F}{P}-\frac{C}{P}-\frac{\alpha D}{P}\right) = \frac{\alpha D}{P} \tag{20}$$

v, d from (12) & (13) $$\boxed{g\cdot(1-m-v-\alpha d) = \alpha d} \tag{21}$$

m is the retailer margin percentage and *1-m* is the ratio of factory price to retail price.

Solve for *g/d* $$\frac{g}{d} = |\varepsilon_m| = \frac{\alpha}{\left(1 - m - v - \alpha d\right)} \tag{22}$$

1-*m*-*v* is the manufacturer's share of the total value chain, after subtracting out the retailer's "cut" (*m)* and the production cost. Subtracted from that is their subsidy percentage (α*d*).

<u>Retailer</u>

Sub $B=\alpha D$, sub in (10b) $$(D - \alpha D) \cdot (1+g) = g \cdot (\mathrm{P} - \mathrm{F}) \tag{10c}$$

Isolate g $$g(P - F - D + \alpha D) = D - \alpha D \tag{23}$$

Divide by P $$g \cdot \left(\frac{\mathrm{P}}{\mathrm{P}} - \frac{F}{P} - \frac{D}{P} + \frac{\alpha D}{P}\right) = \frac{D}{P} - \frac{\alpha D}{P} \tag{24}$$

v,d from (12) & (13) $$g \cdot \left(1 - (1 - m) - d + \alpha d\right) = d - \alpha d \tag{25}$$

Rearranging $$g \cdot \left(m - d(1 - \alpha)\right) = d(1 - \alpha) \tag{26}$$

Solve for g/d $$\boxed{\frac{g}{d} = |\varepsilon_r| = \frac{1 - \alpha}{\left(m - d(1 - \alpha)\right)}} \tag{27}$$

So the total equilibrium condition, assuming no Advertising costs, is

$$\boxed{\frac{g}{d} = |\varepsilon_m| = |\varepsilon_r| = \frac{\alpha}{\left(1 - m - v - \alpha d\right)} = \frac{1 - \alpha}{\left(1 - d(1 - \alpha)\right)}} \tag{28}$$

where α is the manufacturer's share of the consumer discount they will subsidize, which, in turn, is their share of the profit in the overall value chain.

<u>Addition of Advertising Allowances</u>

Retailers usually require some type of advertising investment in conjunction with running a feature advertising insert in their Advertising vehicle. Up until now, the formulas assumed a TPR (Temporary Price Reduction) with no fixed cost component in the profit function. The addition of this fixed cost effects the break-even levels in two ways: first, it adds an additional hurdle for manufacturers in order for promotional events to be profitable, and second, it adds a conditional expectation on the sales gain from the consumer discount (*d*). Trade Ads (aka Features) typically can increase the promotional sales lift dramatically vs. a TPR only (Neslin – 2003). We can incorporate this feature into the description of price elasticity, which now becomes: $E[\varepsilon \mid d^A] \sim (0,\sigma_\varepsilon^2)$, where the absolute value of the price elasticity (ε) is conditional upon the consumer discount level for promotional vehicle A. The random variable is distributed with errors terms of mean zero and some variance (σ_ε^2). Note that we are using ε and *d* in absolute terms rather than as negatively signed.

We now restate the manufacturer profit function with the additional advertising cost, *A*, included. The retailer profit function will stay the same as we assume that the incremental advertising funds, *A*, are used to defray the actual out-of-pocket cost of producing the ad vehicle as well as subsidize ongoing retailer operations. This equation will consider *A* to be a "cost of doing business" with the retailer, with an offsetting benefit of increasing the sales lift *g*. The manufacturer fully absorbs *A*.

Restating (5) $$X\cdot(F\text{-}C) = [X\cdot(F\text{-}C\text{-}B)\cdot(1+g)] - A \tag{29}$$

Reworking (16) $$B = g\cdot(F - C - B) - \frac{A}{X} \tag{30}$$

Adding (10) + (17) $$D = gP - gD - gC - \frac{A}{X} \tag{31}$$

Divide by P $$d = g - gd - g\cdot\frac{C}{P} - \frac{A}{PX} = g - gd - gv - \frac{A}{R}\text{ , where} \tag{32}$$

R=Retail Dollars (P·X)

Divide by d $$1 = \varepsilon(1 - v - d) - \frac{A}{dR} \tag{33}$$

Solving for ε $$\varepsilon = \frac{1+\dfrac{A}{dR}}{1-v-d} \tag{34}$$

Add Expectations $$E\left(\mid \varepsilon \mid d^A \mid\right) = \frac{1+\dfrac{A}{d^A E(R)}}{1-v-d^A} \tag{35}$$

Equation (35) is the new break even level in the manufacturer/retailer value chain. Compared to the TPR model, we now have an additional Advertising cost factor as a percentage of the discount times retailer revenue. An expectations operator has also been added to the retail revenue component (*R)* because there is some variability around the value of X. Therefore, E(R) = P·E(X) since we assume P to be exogenous and known by all parties. We assume *d* to be fixed as an equilibrium condition. While there may be some uncertainty by the manufacturer as to how much of the discount will actually be passed to the consumer, the expectation based on a game theoretic approach is for there to be only one retailer deviation from an agreed upon program before manufacturer sanctions are imposed.

There are different equilibrium conditions for the manufacturer and retailer since the manufacturer absorbs the entire cost of *A*. This will place a higher hurdle rate on the manufacturer, and therefore, the retailer, as well, since they need the co-operation of the manufacturer to execute these promotions. Equation (22) can be modified to reflect the additional cost.

Restating (29)
$$X \cdot (F-C) = [X \cdot (F-C-B) \cdot (1+g)] - A \tag{29}$$

Isolating g
$$g(F-C-B) = B + \frac{A}{X} \tag{36}$$

Dividing by P
$$g\left(\frac{F}{P} - \frac{C}{P} - \frac{\alpha D}{P}\right) = \frac{\alpha D}{P} + \frac{A}{PX} \tag{37}$$

Restated as
$$g(1-m-v-\alpha d^A) = \alpha d^A + \frac{A}{E(R)} \tag{38}$$

Solve for g/d
$$\boxed{\frac{g}{d} = E(|\varepsilon_m \mid d^A|) = \frac{\alpha + \dfrac{A}{d^A E(R)}}{1-m-v-\alpha d^A}} \tag{39}$$

This shows that Equation (35) is subordinate to Equation (39) since it is only the manufacturer's equilibrium point that will determine an optimal outcome. Again, the retailer's break-even point stays the same in either scenario, but the manufacturer has a higher hurdle rate when advertising costs are involved.

There are three points of hysteresis in the retailer price promotion process. First, *v*, the value cost percentage, is unknown by the retailer, but known by the manufacturer. This structural uncertainty into the model places inherent barriers to a significant expansion in trade promotion activity even if all the other components can be predicted within some acceptable range of certainty. Until there is some broad level of regular and accurate information sharing between retailers and manufacturers about the manufacturer's share of *v* then we would not expect any dramatic movement in the investment levels behind retailer price promotions, *even with full acceptance of the CCEE.*

The second structural barrier is the higher hurdle rate required by manufacturers with the inclusion of Advertising. This condition significantly reduces the number of brands where promotion is a viable option. A high value of $\frac{A}{d^A E(R)}$ would make the elasticity requirement unobtainable for smaller manufacturers that want to use aggressive promotion as a profitable investment opportunity.

Equation (39) also explains why some retailer promotions will never be optimal. A break-even profitability requires a significant margin in the entire value chain (*v*), and consumer packaged goods categories seem to be at the high end of these values. Based on publicly available information, *v* for automobiles, for example, have *v* levels of well under 0.5, whereas CPG categories are generally 0.7 and above. Based on discussions with experts in the consumer products industry, margins on durable goods appear to be much lower than those in CPG

If there is a restriction on *v*, there is an even greater restriction on *d*, the consumer discount. The value of *d* is what drives the big promotional lifts, especially when combined with A. Though not formally proven, the empirical evidence from this study suggests that the elasticities increase with *d*. In addition to restrictions on ε due to restrictions on *d*, it can also be hypothesized that elasticities for durable goods are lower than elasticities for CPG products at identical levels of *d*. This is because durable goods will account for a higher percentage of income and require a greater trade off of other goods. The Cournot Aggregation formula can be used to predict this effect. A product accounting for 5.0% of a household's annual income would create a 5.26% reduction in expenditures of the composite good (discretionary income) assuming a -5.0 elasticity and 25% discount. At a 50% discount (assuming $v>0.5$), the cross-effects double to 10.53%. Intuitively, we can assume the tradeoffs with the composite good become non-trivial at that point, and therefore, fewer consumers are willing to respond to the price promotion on these bigger-ticket products.

The third barrier is a legal barrier that applies to the U.S. market, for sure, and likely many other countries. The Robinson-Patman Act prohibits price discrimination from manufacturers towards different retailers. All discount subsidies and co-op advertising allowances are considered to be part of the net price charged to retailers. Therefore, retailers which have a higher level of promotional responsiveness will receive higher allowances and, therefore, a lower price. A lower average price due to high scanback allowance is a violation of Robinson-Patman.

VIIF. <u>Arbitrage Opportunity Condition</u>

While Equation (39) explains why it is difficult for all and impossible for some to implement a profitable promotional strategy, the equation does hold out the possibility of arbitrage under certain conditions. To capture this opportunity, which we will call AOC (Arbitrage Opportunity Condition), the following conditions must be met:

- v is known by both parties. Therefore, manufacturers may need to share sensitive margin information with retailers. Without that information, however, it is relatively easy to obtain a solid estimate of the manufacturer's cost.
- The product is highly promotion elastic, even at the lower bound of the range of expected response (99% confidence interval) for $g^{A}_{.01}$.
- The assumption of zero market friction in scanbacks is maintained (Dreze and Bell – 2003). That means that neither manufacturer nor retailer actually ever have to invest money or tie up capital with these promotions. All vendor subsidies (*B & A*) are transferred at the completion of the promotion. By that time, the retailer has been compensated by their customers.
- Baseline sales are known within a very narrow confidence range.
- Baseline sales are sufficiently high such that that Advertising Cost ratio $\left(\dfrac{A}{d^{A}E(R)}\right)$ is relatively low, typically under 25%.
- Assume Robinson-Patman does not apply, as all retailers in a specific market receive the same pricing and discount subsidies.

Table 14 below provides one actual example in the Dessert category for a Southeastern Food retailer that promotes Brand F very frequently. We can determine if the AOC holds.

Over the last three years, this retailer executed 26 Buy One/Get One Free promotions on Dessert Brand F. The median lift (*g)* was 12.6 and the lowest value was 6.3.

TABLE 14: ARBITRAGE OPPORTUNITY CONDITION
Example Based on Real Data

Inputs

REGULAR PRICE	$5.00	v	25%
FACTORY PRICE	$3.50	d	50%
COGS	$1.25	m	30%
PROMO PRICE	$2.50	MFR SHARE (	60%
AD COST	$100,000	B/E elasticity	7.1
		A/dR	47%

RETAILER	**NON-PROMO**	**PROMO**	**DIFF**
UNITS	86,000	391,333	305,333
DOLLARS	$430,000	$978,333	$548,333
COST	$301,000	$1,369,667	$1,068,667
MARGIN	$129,000	-$391,333	-$520,333
SUBSIDY		$587,000	$587,000
TOTAL PROFIT	$129,000	$195,667	$66,667
DISCOUNT		-$978,333	-$978,333
MANUFACTURER			
FACTORY	$301,000	$1,369,667	$1,068,667
COGS	$107,500	$489,167	$381,667
NET	$193,500	$880,500	$687,000
SUBSIDY		-$587,000	-$587,000
AD COST		-$100,000	-$100,000
CONTRIBUTION	$193,500	$193,500	$0

In summary, in an environment with full acceptance of the CCEE, we would still predict a condition of hysteresis in the short-term. For CPG firms, the uncertainty by retailers in the value of *v* (the value chain margin) will limit profitable co-operation between retailer and manufacturer. Second, the higher break-even hurdle rates faced by manufacturers when retailer ad dollars are required will prohibit many manufacturers from participating in these programs. Finally, the Robinson-Patman Act will act as a constraint to a rapid expansion of promotion even if the other barriers are addressed. For other consumer products manufacturers (especially durables), it is unlikely that a break-even profitability condition can exist due to low values of either v or ε. However, if the structural barriers can be addressed, there exists real arbitrage opportunities with retailer price promotions for both retailers and manufacturers.

VIII. CONCLUSIONS AND FOLLOW-UP RESEARCH

VIIIA. Summary of Empirical Findings

To summarize the empirical results, the research has tested and accepted the following:

1. Aggregated, chain-level data can be used for promotional modeling.

2. A Bayesian DLM baseline model using aggregated, chain-level data is a better, cheaper and more extendable way to derive a stable and accurate baseline sales estimate.

3. The conclusions of Dekimpe and Hanssens (1999), Nijs et al (2001) and Pauwels et al (2002) that the sales after a promotion return to trend stationarity in the long-term are confirmed. In other words, there are no long-term effects of promotions.

4. There is no post-promotion sales dip for the promoting brand in the intermediate weeks.

5. There is no brand switching due to price promotions.

6. Competing retailers do not see a decline in sales due to promotions.

7. Results #4-6 are validation of the Complete Category Expansion Effect (CCEE) from retailer price promotion, which, in turn, is validation of the Theory of Price Promotion.

8. The CCEE is consistent with microeconomic theory that explains this effect via the Composite Goods Theorem and the Cournot Aggregation Condition. There is no proof that intrinsically similar product *must* be substitutes. Substitution between two products can only be proven if it is derived empirically.

9. There are structural barriers to wide implementation of the CCEE, even with its full acceptance. These barriers center around asymmetric margin information between retailers and manufacturers (manufacturers have more than retailers),

unattainable hurdle rates of profitability relative to a non-promotional strategy in the form of ad costs, low margins or low price elasticity, and legal barriers that require fair and equal pricing treatment to all retailers in a market.

10. There are, however, certain arbitrage opportunities in price promotion assuming legal and informational barriers are addressed. Brands in categories with high margins (most CPG categories), high and predictable elasticity and sufficient sales levels can produce riskless profits for both retailers and manufacturers.

VIIIB. Discussion of Results

Despite having demonstrated the CCEE with a considerable amount of empirical data and analysis, it must be recognized that these results conflict with many other studies. E.g. Pauwels et al (2002), using very powerful econometric techniques, found a dip in intermediate period sales due to promotion. Mela, in several works from 1997-99, used advanced modeling techniques to demonstrate a long-term negative effect from promotions. As discussed in Section VI, both Van Heerde et al (2000) and Mace and Neslin (2004) found evidence for both pre and postpromotion dips.

As you read these works, particularly in the discussion of results, there is the consistent sense that these are empirical endeavors in a anchorless search for a theory to explain them. The words “might explain...,” “may be due to...,”, “seems to suggest that...,” serve to notify the reader that the authors are uncertain about their conclusions even after an impressive level of work. Not once in any of the most cited pieces in this article were findings explained in the context of microeconomic theory, and when any theory was invoked, the majority were based on behavioral or psychological theory.

So how do we reconcile these outcomes? I would suggest that the work whose conclusions are grounded in formal theoretical framework, and even more so in a microeconomic framework, takes precedence over those that are not. Second, the benefit of the doubt must go to results based on aggregated data, because that is the reality that we seek to explain through our research. This is not to say that the results in this document are definitive. Rather, the claim is that the burden of proof for resolving conflicting results lay with those that would dispute this work as opposed to the other way around.

Further, future conflicting results that seem to discredit the results in this paper are an insufficient proof to invalidate the conclusions herein. Certainly it has been documented that conflicting empirical results in marketing science are the norm rather than the exception. Any contrary evidence must be combined with a firm economic rationale. In fact, an economic rationale alone could be sufficient proof to undermine the thesis of the CCEE.

The narrow topic of the incrementality of retailer price promotions is certainly important, and if the CCEE is validated it has the potential to have a material effect on the results on CPG manufacturers and retailers to whom they sell. The broader and more long-lasting implication of this research, however, is an attempt to catalyze a new approach to marketing research by imposing the consideration for the theories of microeconomics into the literature.

VIIIC. Managerial Implications

The proposition that retailer price promotion lifts are entirely incremental to the business is one that will surely meet with a lot of resistance because of such deeply held paradigms about their effects ("undermining our brand," "mortgaging the future," etc...). Section VIIE also documented several structural limitations to broad expansion of promotional activity, even if there was full acceptance of the CCEE. Assuming the structural barriers are addressed, there is the potential, in certain categories, for the CCEE to have a profound affect on sales and profits. Importantly to other marketing interests, like advertising agencies, a major increase in these promotions <u>does not</u> have to come at the expense of other marketing investment. While the *share* of spending for promotion may increase, there is no reason that all marketing spending should not increase in an environment where promotions are profitable for the manufacturer. Assuming scanbacks are the predominant form of executing these promotions, they represent an arbitrage opportunity for the participants in this policy.

To ensure profitability, however, managers must set up management controls to ensure retailer subsidies conform to the AOC found in Equation (39). It appears from the Cannondale 2006 report that much of the distaste for these promotions has as much to do with lack of spending control than what these promotions do for retail sales in the short and long-term.

The improved baseline model has the potential for a more immediate impact on retailer performance since it removes most limitations to which companies can have access to a reliable baseline estimate. Currently retailers like Staples, Toys ‘R Us, Sports Authority, Best Buy, and many other non-Food/Drug/Mass retailers have no reliable means to estimate baseline sales for the entire retail portfolio. Smaller manufacturers also will have a more cost-effective option to gauge the success of their promotional investment.

VIIID. Suggestions for Follow-Up Research

Given the CCEE presents such a dramatic departure from the conventional wisdom concerning price promotions, there is a need to validate these results by other researchers using different data sources over a variety of categories. These results would need to be tied to a specific theoretical framework.

The DLM baseline model developed in Section V is just a first generation model. Although it tested favorably against the existing log-linear models, there are still areas for improvement. The primary issue is to improve the responsiveness of the baseline evolution to structural changes like seasonality or distribution changes.

Finally, here is an opportunity for a more expansive discussion about the microeconomic foundations (as opposed to just the economic foundations) of the TRPP and of marketing effects other than promotions. It is hoped that those with more experience and expertise can add to the literature that ties the marketing and economics disciplines together.

APPENDIX I
GLOSSARY OF TERMS

1. Acceleration: The process where consumers purchase a product earlier than what they intended or what they would have typically have done due to a retailer promotion. Similar to stockpiling, Acceleration is another potential source of short-term incremental sales not resulting from increased consumption.

2. ACV (All Commodity Volume): A standard of measurement of distribution used by the syndicated data suppliers. Rather than measure a product's distribution by the percent of stores stocking or selling it, ACV weights the relative size of each store that carries the product. The weighting is done by a store's All Commodity Volume. As an example, a product could be carried in 5 stores of a 10 store chain (50% of stores selling). However, if those stores account for 80% of the total chain's sales, the "ACV Distribution" (or ACV) is said to be 80%.

3. Aggregated Data: Scanner or panel data that reflects a combination of sales of disaggregated entities (chain level for scanner, total market for panel).

4. Brand: A Brand is any group of products with the same trade name and similar characteristics with respect to product formulation, marketing program and distribution profile. This would *exclude* products that license a brand name into a separate category of products. E.g. Gerber Life Insurance, Gerber Baby Food and Gerber Baby Bottles are three separate brands.

5. Baseline sales: Baseline sales are expected sales during a given period of time that would have occurred in the absence of any promotional activity. This is a modeled measure, *not* an actual one.

6. Brand-Size: A Brand-Size is a group of products within a specific brand that carry common characteristics with respect to either product configuration (i.e. size), price point or promotional strategy. Brand-Size is typically the basic unit of measure for promotional analysis. Gupta (1988) and Guadagni and Little (1983) defined these groupings to be a Brand for ease of naming, and this paper will use the same convention, except where noted. Brand-Size will also be synonymously referred to as Own Brand.

7. Category Expansion: The phenomenon of generating incremental sales from increased purchases in the category due to price promotion.

8. Causal Measure: Any variable (or measure) that is believed to cause a change in sales. The most common Causal Measures used in promotional modeling are the promoted price, the promotional price discount and the level of feature advertising.

9. CPG (Consumer Packaged Goods): aka FMCG (Fast-Moving Consumer Goods) is the industry characterized by products sold with the following profile: a) packaged (rather than bulk), b) fast-moving, meaning purchased multiple times per year by the typical consumer, c) relatively low retail pricing, the vast majority of items are under $10.00, and d) mass market distribution, meaning Food, Drug, Mass Merchandiser, Convenience or Club. CPG refers not only to the companies that manufacture and distribute the products, but the retailers that sell them and the suppliers that service them. (ad agencies, consultants, marketing researchers).

10. Cross Brand: Cross Brand is all other products within a specific category not within a certain brand. Cross Brand is also referred to as "Competitive Brand" or the "Competitive Set."

11. Disaggregated Data: Individual Store-level data for scanner data and household-level data for panel data.

12. Feature Advertising (Ad): Feature is a general term for any Price Promotion that is communicated in a vehicle other than on-shelf communication. This would include Newspaper Ads or Circulars, Window Banners, Coupon Books or other similar vehicles.

13. Incremental Sales: Incremental Sales are the difference between actual Sales and Baseline sales for a given period of time.

14. Lift: A meaningful, short-term increase in sales via price promotion. It is often used synonymously with Incremental Sales. E.g. If Baseline sales are 100 and Sales during the Promotion Week are 200, the Brand-Size saw a 100 unit Lift (or 100% Lift) in sales.

15. Panel Data: Panel Data is household-level transactional data. The data is gathered from panelists who agree to either record every purchase that they make. This data is often aggregated up to the category or market level, however, the methodology does not ensure complete sales coverage of the particular market.

16. Rebate: Any Price Promotion that is advertised as a reduced price to the consumer, but the consumer can only get that price by sending in a proof of purchase to a third party clearing house. The discounted value is the refunded (or rebated) back to the consumer.

17. Retailer Promotion: Promotions offered to retailers by consumers (*Blattberg et al – 1995).* This paper will use a somewhat tighter definition of retailer promotion, and one that aligns with a more conventional understanding of retailer promotions. First, retailer promotions must offer some type of price promotion; this would exclude displays without reduced price, sweepstakes, and similar forms of non-price promotion. Second, the price promotion must have a one-to-one relationship

between the consumer offer (i.e. lower price) and the specific purchase of a product. This would eliminate programs that offer incentives for multiple purchases over time. Retailer Promotions are subclasses of Trade Promotions.

18. Retailer Price Promotion: Any temporary price reduction offered to the consumer. There are several types of price promotions: TPR's, Features, and Rebates. Price Promotion is a subclass of Retailer Promotion. This paper is focusing entirely on these types of promotions. All references to sales promotion, promotion, price promotion or trade promotion can be assumed to mean Retailer Price Promotion.Sales Promotion: A generic term for any type of promotion used to stimulate short-term sales. It is not synonymous with retailer promotion. However, for brevity there will be instances within this paper, where the two terms will be used interchangeably.

19. Sales Decomposition: The process of decomposing observed sales levels for a given period of time into it component parts. The typical decomposition occurs at two levels: first, decomposing actual Sales into Baseline and Incremental Sales, and second, decomposing Incremental Sales for the source of the extra sales (e.g. Acceleration, Stockpiling, Switching, Category Expansion, etc…).

20. Scanner Data: This is perhaps the most misused term in the literature. Scanner Data is a primary data source for almost all of the literature on retailer promotions. Most authors, however, are not using the term correctly. Scanner data is a form of Syndicated Data. It is data gathered from Point-of-Sale data in-store and aggregated at some meaningful level for analysis: Store-Level, Chain Level or Market-Level. *Scanner Data is not household level transactional data that is captured by scanner either through in-store or at-home scanners. This type of data is Panel Data*. Most of the early literature on Retailer Promotions was developed using Panel Data even though it was referred to as Scanner Data. It is vital that these two terms – Scanner and Panel Data – be distinguished because the conclusions derived from each data source have yielded very different conclusions.

21. Stockpiling: Stockpiling is the concept of a consumer purchasing a product at levels that exceed his normal level of household inventory. It is used in the context of explaining the potential sources of incremental sales from promotion not directly as a result of extra consumption. The common term for this by practitioners is "pantry-loading;" a term which never seems to appear in the literature. For our purposes, the two terms are synonymous.Trade Promotion: Promotions offered to retailers by manufacturers (*Blattberg et al – 1995).* Retailers have discretion as to whether to pass these promotions through to consumers. These promotions are not addressed in this paper.Within Brand: All products within a specific brand *not* included in a specific Brand-Size. E.g. 12ct, 12oz Pepsi is a Brand-Size; all of the other package configurations – 6ct, 12oz, 2-Liter Bottles, etc… - are considered *Within Brand*. Brand-Size + Within Brand = Total Brand

22. Switching (Brand Switching): The process of generating incremental sales from sourcing sales on a Brand-Size either from Within Brand or Cross Brand consumers. It is concept closely related, but not identical to, substitution.

23. Syndicated Data: In general terms it is any dataset that has a standardized structure and is sold to multiple parties. In the literature, however, syndicated data is used in the context of point-of-sale data gathered *from major markets, regions or total country* and projected to those geographies. It is also narrowly defined to be just the scanner data used to track consumer packaged goods products in Food, Drug and Mass Merchandiser outlets. Information Resources, Inc. (IRI) and AC Nielsen (ACN) are the only two suppliers of this syndicated data in the world.

24. Trade Promotion: Promotions offered to retailers by manufacturers (*Blattberg et al – 1995).* Retailers have discretion as to whether to pass these promotions through to consumers. These promotions are not addressed in this paper.

APPENDIX II

SPECIFIC DATA FROM A SINGLE RETAILER

EXHIBIT 1

IMPROVED BASELINE ALGORITHM

1. Data Setup

 1.1. Assign a dataclass for each brand/geography combination

 1.2. Input exogenous variables (if needed)

 1.3. Read in and clean up unit sales.

 1.4. Within each dataclass create additional measures

  1.4.1. LnSales for each week

  1.4.2. Diff(LnSales) for each week (Week 1=0)

2. Generate Promotional Dummy Variables

 2.1. *Iteration #1 (Iterate within Dataclass)*

  2.1.1. Flag any week as PROMO (=1) where either (LnSales > Avg(LnSales) + SD(LnSales)) or (LnDiff > SD(LnDiff)

  2.1.2. Flag any week as POST-PROMO where 2.1.1. criteria not met, but Week t-1 is a PROMO (=1).

  2.1.3. Flag any week as NON-PROMO where neither 2.1.1. or 2.1.2. are valid.

  2.1.4. Run Regression of LnDiff against PROMO, POST-PROMO and exogenous variables

  2.1.5. Capture Residuals of the Regression

  2.1.6. Calculate SD (Std Dev) of Residual of each Factor (PROMO, POST-PROMO, NON-PROMO from 2.1.1.-2.1.3.)

  2.1.7. Calculate mean(LnSales) by Factor

  2.1.8. Calculate and Capture Model Error (Std Dev of Residuals)

  2.1.9. Flag all observations where Residuals are +/- 1 SD of the applicable factor for that observation

 2.2. *Additional Iterations*

2.2.1. If observation not flagged from 2.1.9. test, carry over Factor from last iteration.

2.2.2. For POST-PROMO and NON-PROMO factor observations, if Resid > 1 SD of Factor, then change Factor to PROMO

2.2.3. Capture POST-PROMO observations similar to 2.1.2.

2.2.4. Repeat 2.1.4 to 2.1.9. for all iterations.

2.3. Capture initial parameter estimates for Dynamic Model

2.3.1. After all iterations complete, identify the iteration for each dataclass with the minimum Standard Error

2.3.2. Keep the PROMO values associated with the minimum Standard Error iteration.

3. Generate Dynamic Parameter Estimates for the Observation Equation (each Dataclass)

3.1. Regress LnSales against PROMO (from 2.3.2.) and any exogenous variables and Capture key estimators.

3.1.1. Capture the Coefficients and Std Error estimates for Alpha (Intercept), Beta (Lift) and Gamma (exog parameter)

3.1.2. Capture the model Standard Error

3.2. Initialize the DLM model

3.2.1. Initialize the State Mean estimates with the coefficients from 3.1.1. Call this vector θ_t.

3.2.2. Initialize the State Variance estimates with the Variances from 3.1.2. (SD^2) . Call this vector ω_t.

3.2.3. Initialize the model variance with the Variance from 3.1.2. ($\sigma_t^2 = SE^2$)

3.3. *For first iteration, update weekly parameter estimates*

3.3.1. Update LnSales forecast ($E(S_t) = \theta_t \times X_t$)

3.3.2. Update model variance (Model + State var)

3.3.3. Calculate adjustment factor to apply to θ_t and ω_t. This will be the ratio of the State Variance vs. Model Variance. Call this A.

3.3.4. Update θ. Prior State Mean + ($A * [S_t - E(S_t)]$)

3.3.5. Update ω. Prior State Var – ($A^2 * \sigma_t^2$)

3.4. *Additional DLM iterations (Gibbs Samples)*

3.4.1. Use parameter estimates from prior model

3.4.2. If PROMO = 0 (nonpromo) and Forecast deviation > 1.5 SD for σ_t then PROMO = 1

3.4.3. If PROMO = 1 (promoted) and Forecast deviation < 1.5 SD for σ_t then PROMO = 0

3.4.4. Rerun 3.3.1.-3.3.5.

Identify the iteration with the minimum variance and select the parameter estimates from that model for θ, PROMO and E(S).

EXHIBIT 2
ANALYSIS OF VARIANCE OF INTERTEMPORAL EFFECTS

EXHIBIT 2A
MEAN UNIT SALES BY WEEKCLASS
BEVERAGES

WEEKCLASS defined as number of weeks either before or after a promotional week.

									PROMO								
BRAND	**P (-8)**	**P (-7)**	**P (-6)**	**P (-5)**	**P (-4)**	**P (-3)**	**P (-2)**	**P (-1)**	**P (0)**	**P (+1)**	**P (+2)**	**P (+3)**	**P (+4)**	**P (+5)**	**P (+6)**	**P (+7)**	**P (+8)**
BRAND 1A	3,864	3,837	4,000	4,195	4,595	4,780	4,495	4,763	8,150	5,089	4,707	4,860	4,404	4,301	4,164	3,978	3,783
BRAND 1B	801	851	888	852	822	799	697	676	1,005	759	736	805	810	850	867	857	816
BRAND B	793	801	755	677	682	703	656	680	1,718	720	672	664	662	662	719	718	695
BRAND C	1,073	1,054	1,028	984	1,000	970	918	888	1,335	941	936	982	1,009	1,021	1,061	1,061	1,020

		WK 8	**WK 7**	**WK 6**	**WK 5**	**WK 4**	**WK 3**	**WK 2**	**WK 1**
BRAND 1A	BEFORE	3,864	3,837	4,000	4,195	4,595	4,780	4,495	4,763
	AFTER	3,783	3,978	4,164	4,301	4,404	4,860	4,707	5,089

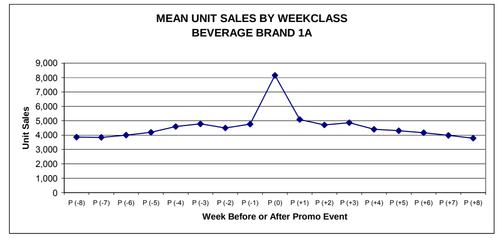
Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Row 1	8	34,529	4,316	153,318
Row 2	8	35,286	4,411	200,562

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	35,816	1	35,816	0.2024	0.6597	4.6001
Within Groups	2,477,160	14	176,940			
Total	2,512,976	15				



		WK 8	WK 7	WK 6	WK 5	WK 4	WK 3	WK 2	WK 1
BRAND 1B	BEFORE	801	851	888	852	822	799	697	676
	AFTER	816	857	867	850	810	805	736	759

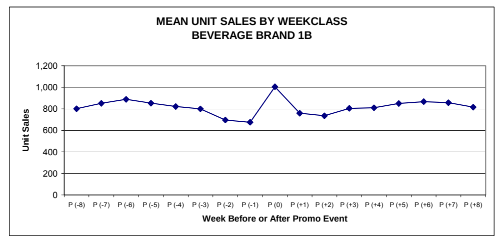
Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Row 1	8	6,386	798	5,642.2
Row 2	8	6,500	813	2,163.7

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	812	1	812	0.2081	0.6552	4.6001
Within Groups	54,642	14	3,903			
Total	55,454	15				



		WK 8	**WK 7**	**WK 6**	**WK 5**	**WK 4**	**WK 3**	**WK 2**	**WK 1**
BRAND B	BEFORE	793	801	755	677	682	703	656	680
	AFTER	695	718	719	662	662	664	672	720

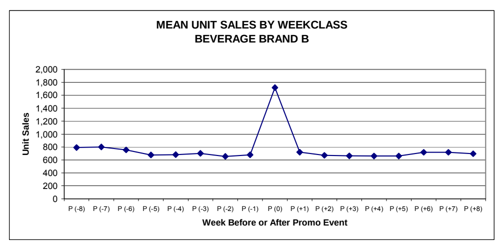
Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Row 1	8	5,747	718	3,196.0
Row 2	8	5,512	689	730.0

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	3,452	1	3,452	1.7583	0.2061	4.6001
Within Groups	27,482	14	1,963			
Total	30,933	15				



		WK 8	WK 7	WK 6	WK 5	WK 4	WK 3	WK 2	WK 1
BRAND C	BEFORE	1,073	1,054	1,028	984	1,000	970	918	888
	AFTER	1,020	1,061	1,061	1,021	1,009	982	936	941

Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Row 1	8	7915	989.375	4078.55
Row 2	8	8031	1003.88	2306.41

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	841	1	841	0.26343	0.61578	4.60011
Within Groups	44694.8	14	3192.48			
Total	45535.8	15				

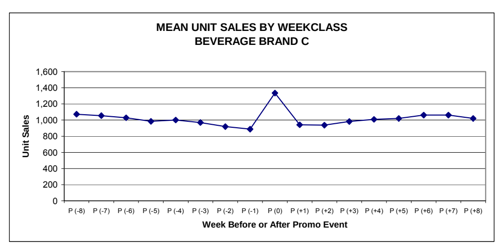


EXHIBIT 2B
MEAN UNIT SALES BY WEEKCLASS
DESSERTS

WEEKCLASS defined as number of weeks either before or after a promotional week.

BRAND	P (-8)	P (-7)	P (-6)	P (-5)	P (-4)	P (-3)	P (-2)	P (-1)	PROMO P (0)	P (+1)	P (+2)	P (+3)	P (+4)	P (+5)	P (+6)	P (+7)	P (+8)
BRAND D	9,420	9,581	9,584	9,733	9,980	10,740	10,951	11,280	20,144	11,445	10,998	10,896	10,400	9,726	9,499	9,574	9,365
BRAND E	7,089	7,039	8,383	8,774	9,646	10,922	12,103	12,412	22,998	12,352	12,271	11,358	9,839	8,942	8,720	7,455	7,081
BRAND F	17,250	18,657	18,432	17,881	17,792	18,858	18,544	18,371	65,261	18,020	18,805	19,254	17,840	18,687	17,988	18,329	16,896
BRAND G	2,004	2,138	2,319	2,369	3,379	4,378	6,195	8,548	17,444	8,427	6,458	4,431	3,267	2,461	2,441	2,117	2,158
BRAND H	16,078	20,442	20,060	20,110	19,198	18,650	17,629	18,688	65,101	18,633	17,733	19,253	19,635	20,893	21,596	21,877	20,834
BRAND I	9,642	10,145	10,075	10,506	10,495	11,253	11,365	11,465	19,037	11,460	11,405	11,353	10,376	10,700	10,308	10,252	10,301
BRAND J	26,485	32,533	29,025	32,771	32,761	33,927	39,628	42,064	62,753	42,096	40,276	35,376	34,227	33,531	31,347	34,108	28,740
BRAND K	3,472	4,285	4,548	5,162	5,951	7,896	9,292	10,962	65,598	10,455	9,766	8,526	6,713	5,824	4,789	4,462	2,951

		WK 8	WK 7	WK 6	WK 5	WK 4	WK 3	WK 2	WK 1
BRAND D	BEFORE	9,420	9,581	9,584	9,733	9,980	10,740	10,951	11,280
	AFTER	9,365	9,574	9,499	9,726	10,400	10,896	10,998	11,445

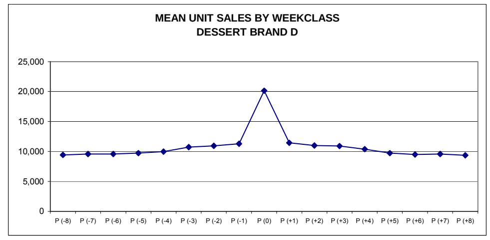
Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Row 1	8	81,269	10,159	520,830.3
Row 2	8	81,903	10,238	643,563.8

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	25,122	1	25,122	0.0432	0.8384	4.6001
Within Groups	8,150,759	14	582,197			
Total	8,175,881	15				



		WK 8	WK 7	WK 6	WK 5	WK 4	WK 3	WK 2	WK 1
BRAND E	BEFORE	7,089	7,039	8,383	8,774	9,646	10,922	12,103	12,412
	AFTER	7,081	7,455	8,720	8,942	9,839	11,358	12,271	12,352

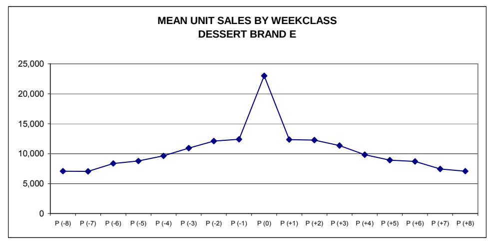
Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Row 1	8	76,368	9,546	4,418,004.6
Row 2	8	78,018	9,752	4,260,534.2

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	170,156	1	170,156	0.0392	0.8459	4.6001
Within Groups	60,749,772	14	4,339,269			
Total	60,919,928	15				



		WK 8	WK 7	WK 6	WK 5	WK 4	WK 3	WK 2	WK 1
BRAND F	BEFORE	17,250	18,657	18,432	17,881	17,792	18,858	18,544	18,371
	AFTER	16,896	18,329	17,988	18,687	17,840	19,254	18,805	18,020

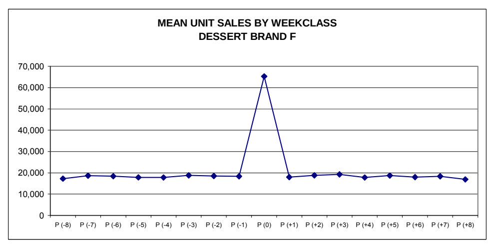
Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Row 1	8	145,785	18,223	287,094.4
Row 2	8	145,819	18,227	518,873.7

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	72	1	72	0.0002	0.9895	4.6001
Within Groups	5,641,777	14	402,984			
Total	5,641,849	15				



		WK 8	WK 7	WK 6	WK 5	WK 4	WK 3	WK 2	WK 1
BRAND G	BEFORE	2,004	2,138	2,319	2,369	3,379	4,378	6,195	8,548
	AFTER	2,158	2,117	2,441	2,461	3,267	4,431	6,458	8,427

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Row 1	8	31,330	3,916	5,558,817.6
Row 2	8	31,760	3,970	5,441,942.6

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	11,556	1	11,556	0.0021	0.9641	4.6001
Within Groups	77,005,322	14	5,500,380			
Total	77,016,878	15				

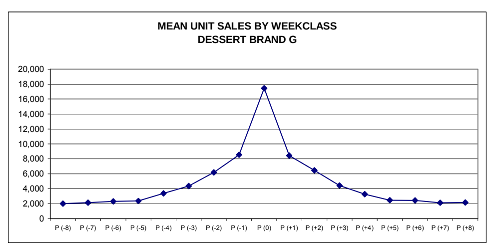
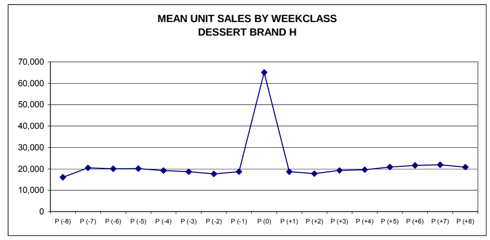


EXHIBIT 2B
MEAN UNIT SALES BY WEEKCLASS
DESSERTS

WEEKCLASS defined as number of weeks either before or after a promotional week.

BRAND	P (-8)	P (-7)	P (-6)	P (-5)	P (-4)	P (-3)	P (-2)	P (-1)	PROMO P (0)	P (+1)	P (+2)	P (+3)	P (+4)	P (+5)	P (+6)	P (+7)	P (+8)
BRAND D	9,420	9,581	9,584	9,733	9,980	10,740	10,951	11,280	20,144	11,445	10,998	10,896	10,400	9,726	9,499	9,574	9,365
BRAND E	7,089	7,039	8,383	8,774	9,646	10,922	12,103	12,412	22,998	12,352	12,271	11,358	9,839	8,942	8,720	7,455	7,081
BRAND F	17,250	18,657	18,432	17,881	17,792	18,858	18,544	18,371	65,261	18,020	18,805	19,254	17,840	18,687	17,988	18,329	16,896
BRAND G	2,004	2,138	2,319	2,369	3,379	4,378	6,195	8,548	17,444	8,427	6,458	4,431	3,267	2,461	2,441	2,117	2,158
BRAND H	16,078	20,442	20,060	20,110	19,198	18,650	17,629	18,688	65,101	18,633	17,733	19,253	19,635	20,893	21,596	21,877	20,834
BRAND I	9,642	10,145	10,075	10,506	10,495	11,253	11,365	11,465	19,037	11,460	11,405	11,353	10,376	10,700	10,308	10,252	10,301
BRAND J	26,485	32,533	29,025	32,771	32,761	33,927	39,628	42,064	62,753	42,096	40,276	35,376	34,227	33,531	31,347	34,108	28,740
BRAND K	3,472	4,285	4,548	5,162	5,951	7,896	9,292	10,962	65,598	10,455	9,766	8,526	6,713	5,824	4,789	4,462	2,951

		WK 8	WK 7	WK 6	WK 5	WK 4	WK 3	WK 2	WK 1
BRAND H	BEFORE	16,078	20,442	20,060	20,110	19,198	18,650	17,629	18,688
	AFTER	20,834	21,877	21,596	20,893	19,635	19,253	17,733	18,633



Anova: Single Factor

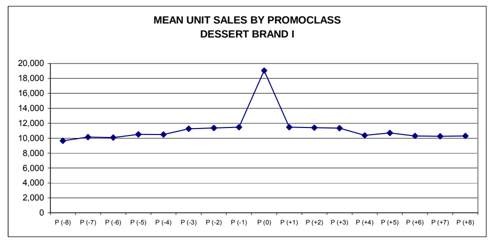
SUMMARY

Groups	Count	Sum	Average	Variance
Row 1	8	150,855	18,857	2,135,422.7
Row 2	8	160,454	20,057	2,176,685.4

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	5,758,800	1	5,758,800	2.6710	0.1245	4.6001
Within Groups	30,184,756	14	2,156,054			
Total	35,943,556	15				

		WK 8	WK 7	WK 6	WK 5	WK 4	WK 3	WK 2	WK 1
BRAND I	BEFORE	9,642	10,145	10,075	10,506	10,495	11,253	11,365	11,465
	AFTER	10,301	10,252	10,308	10,700	10,376	11,353	11,405	11,460



Anova: Single Factor

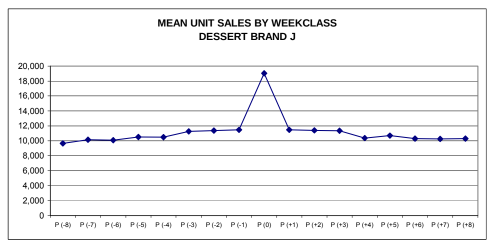
SUMMARY

Groups	Count	Sum	Average	Variance
Row 1	8	84,946	10,618	453,924.2
Row 2	8	86,155	10,769	297,296.6

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	91,355	1	91,355	0.2432	0.6295	4.6001
Within Groups	5,258,545	14	375,610			
Total	5,349,900	15				

		WK 8	WK 7	WK 6	WK 5	WK 4	WK 3	WK 2	WK 1
BRAND J	BEFORE	26,485	32,533	29,025	32,771	32,761	33,927	39,628	42,064
	AFTER	28,740	34,108	31,347	33,531	34,227	35,376	40,276	42,096



Anova: Single Factor

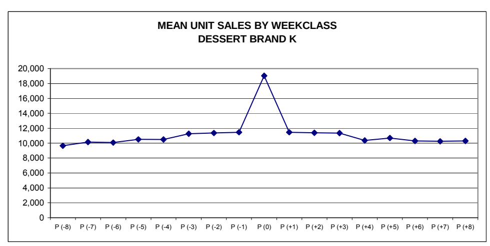
SUMMARY

Groups	Count	Sum	Average	Variance
Row 1	8	269,194	33,649	26,021,015
Row 2	8	279,701	34,963	19,200,394

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	6,899,816	1	6,899,816	0.3052	0.5894	4.6001
Within Groups	#########	14	22,610,704			
Total	#########	15				

		WK 8	WK 7	WK 6	WK 5	WK 4	WK 3	WK 2	WK 1
BRAND K	BEFORE	3,472	4,285	4,548	5,162	5,951	7,896	9,292	10,962
	AFTER	2,951	4,462	4,789	5,824	6,713	8,526	9,766	10,455



Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Row 1	8	51,568	6,446	7,086,736.3
Row 2	8	53,486	6,686	7,188,020.5

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	229,920	1	229,920	0.0322	0.8601	4.6001
Within Groups	99,923,298	14	7,137,378			
Total	#########	15				

EXHIBIT 3
ANALYSIS OF VARIANCE: BRAND SWITCHING

EXHIBIT 3A
MEAN UNIT SALES BY PROMOCLASS
DESSERTS

PROMOCLASS defined as level of promotional activity between two competitive brands

ESTIMATE

		BRAND A1 NO-PROMO	BRAND A1 PROMO	BRAND B NO-PROMO	BRAND B PROMO
BRAND A1	NO-PROMO	---	---	787	1,810
	PROMO	---	---	687	1,622
BRAND A2	NO-PROMO	3,602	6,504	781	1,150
	PROMO	4,105	5,510	674	1,264
BRAND B	NO-PROMO	4,250	7,368	---	---
	PROMO	5,907	9,853	---	---
BRAND C	NO-PROMO	4,053	7,497	771	1,572
	PROMO	5,068	6,839	614	1,526

STANDARD ERROR

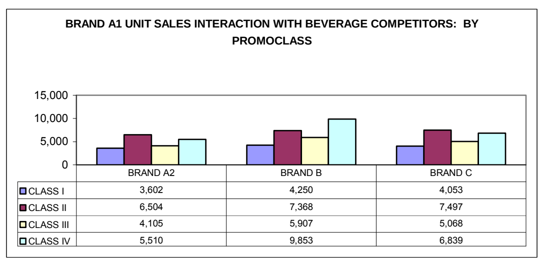
		BRAND A1 NO-PROMO	BRAND A1 PROMO	BRAND B NO-PROMO	BRAND B PROMO
BRAND A1	NO-PROMO	---	---	43.7	86.2
	PROMO	---	---	80.9	87.9
BRAND A2	NO-PROMO	301.8	475.3	48.9	88.9
	PROMO	46.8.6	642.7	81.7	102.8
BRAND B	NO-PROMO	258.7	510.3	---	---
	PROMO	478.9	520.0	---	---
BRAND C	NO-PROMO	241.7	441.2	42.5	79.2
	PROMO	447.7	472.0	75.5	89.8

OBSERVATIONS

		BRAND A1 NO-PROMO	BRAND A1 PROMO	BRAND B NO-PROMO	BRAND B PROMO
BRAND A1	NO-PROMO	---	---	2,010	695
	PROMO	---	---	828	661
BRAND A2	NO-PROMO	1,181	781	1,316	571
	PROMO	837	334	736	385
BRAND B	NO-PROMO	2,010	695	---	---
	PROMO	828	661	---	---
BRAND C	NO-PROMO	1,961	841	1,928	779
	PROMO	807	697	893	555

	BRAND A2	BRAND B	BRAND C
CLASS I	3,602	4,250	4,053
CLASS II	6,504	7,368	7,497
CLASS III	4,105	5,907	5,068
CLASS IV	5,510	9,853	6,839

CLASS I = NEITHER BRANDS PROMOTE
CLASS II = BRAND A1 PROMOTES ONLY
CLASS III = COMPETITOR PROMOTES ONLY
CLASS IV = BOTH BRANDS PROMOTE



	BRAND A1	BRAND A2	BRAND C
CLASS I	787	781	771
CLASS II	1,810	1,150	1,572
CLASS III	687	674	614
CLASS IV	1,622	1,264	1,526

CLASS I = NEITHER BRANDS PROMOTE
CLASS II = BRAND B PROMOTES ONLY
CLASS III = COMPETITOR PROMOTES ONLY
CLASS IV = BOTH BRANDS PROMOTE

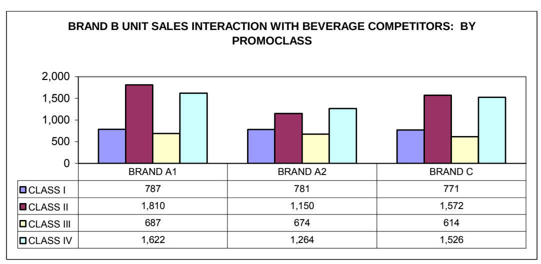


EXHIBIT 3B
MEAN UNIT SALES BY PROMOCLASS
DESSERTS

PROMOCLASS defined as level of promotional activity between two competitive brands

CROSS-EFFECTS WITH BRAND F

FOCUS BRAND	COMP BRAND	PROMO-CLASS	EST (Deviation)	NEWEST	STD ERR	T-VALUE	COUNT
1 - BRAND D	3 - BRAND F	I	0	10,314	783.0	0.000	2,789
		II	269	10,583	1,207.0	0.223	2,029
		III	11,288	21,602	1,134.0	9.954	2,545
		IV	8,794	19,108	1,066.0	8.250	3,272
3 - BRAND F	1 - BRAND D	I	0	17,219	2,617.0	0.000	2,789
		II	58,200	75,419	4,033.0	14.431	2,029
		III	2,287	19,506	3,789.0	0.604	2,545
		IV	41,760	58,979	3,562.0	11.724	3,272
2 - BRAND E	3 - BRAND F	I	0	8,867	2,155.0	0.000	774
		II	1,697	10,564	2,955.0	0.574	879
		III	14,013	22,880	2,924.0	4.792	921
		IV	12,812	21,679	3,059.0	4.188	763
3 - BRAND F	2 - BRAND E	I	0	19,585	3,778.0	0.000	774
		II	26,501	46,086	5,180.0	5.116	879
		III	1,291	20,876	5,125.0	0.252	921
		IV	23,808	43,393	5,362.0	4.440	763
4 - BRAND G	3 - BRAND F	I	0	4,340	2,067.0	0.000	632
		II	981	5,321	2,988.0	0.328	580
		III	15,511	19,851	3,154.0	4.918	476
		IV	11,141	15,481	3,080.0	3.617	518
3 - BRAND F	4 - BRAND G	I	0	17,935	8,075.0	0.000	632
		II	89,830	107,765	11,672.0	7.696	580
		III	1,698	19,633	12,319.0	0.138	476
		IV	49,982	67,917	12,031.0	4.154	518
5 - BRAND H	3 - BRAND F	I	0	18,450	2,648.0	0.000	2,076
		II	-327	18,123	3,423.0	-0.096	3,092
		III	58,612	77,062	3,396.0	17.259	3,216
		IV	27,306	45,756	3,735.0	7.311	2,097
3 - BRAND F	5 - BRAND H	I	0	20,296	3,038.0	0.000	2,076
		II	65,915	86,211	3,928.0	16.781	3,092
		III	-3,042	17,254	3,897.0	-0.781	3,216
		IV	17,485	37,781	4,286.0	4.080	2,097
6 - BRAND I	3 - BRAND F	I	0	10,168	909.0	0.000	2,735
		II	-116	10,052	1,333.0	-0.087	2,376
		III	9,405	19,573	1,308.0	7.190	2,557
		IV	7,260	17,428	1,277.0	5.685	2,813
3 - BRAND F	6 - BRAND I	I	0	17,287	2,659.0	0.000	2,735
		II	54,136	71,423	3,900.0	13.881	2,376
		III	2,401	19,688	3,825.0	0.628	2,557
		IV	45,311	62,598	3,734.0	12.135	2,813
7 - BRAND J	3 - BRAND F	I	0	37,012	2,575.0	0.000	2,163
		II	2,111	39,123	3,569.0	0.591	2,348
		III	32,357	69,369	3,352.0	9.653	3,115
		IV	17,438	54,450	3,414.0	5.108	2,855
3 - BRAND F	7 - BRAND J	I	0	16,370	2,995.0	0.000	2,163
		II	62,286	78,656	4,151.0	15.005	2,348
		III	2,522	18,892	3,898.0	0.647	3,115
		IV	36,002	52,372	3,970.0	9.069	2,855
8 - BRAND K	3 - BRAND F	I	0	9,092	4,138.0	0.000	837
		II	-1,099	7,993	5,779.0	-0.190	881
		III	76,876	85,968	5,774.0	13.314	884
		IV	18,109	27,201	6,906.0	2.622	469
3 - BRAND F	8 - BRAND K	I	0	19,320	6,661.0	0.000	837
		II	132,239	151,559	9,301.0	14.218	881
		III	708	20,028	9,293.0	0.076	884
		IV	55,344	74,664	11,115.0	4.979	469

EXHIBIT 3B
MEAN UNIT SALES BY PROMOCLASS
DESSERTS

PROMOCLASS defined as level of promotional activity between two competitive brands

CROSS-EFFECTS WITH BRAND H

FOCUS BRAND	COMP BRAND	PROMO-CLASS	EST (Deviation)	NEWEST	STD ERR	T-VALUE	COUNT
1 - BRAND D	5 - BRAND H	I	0	10,579	829.0	0.000	2,496
		II	-299	-299	1,195.0	-0.250	2,311
		III	11,053	11,053	1,145.0	9.653	2,746
		IV	8,763	8,763	1,119.0	7.831	3,029
5 - BRAND H	1 - BRAND D	I	0	18,285	2,418.0	0.000	2,496
		II	49,233	67,518	3,488.0	14.115	2,311
		III	792	19,077	3,342.0	0.237	2,746
		IV	44,980	63,265	3,266.0	13.772	3,029
2 - BRAND E	5 - BRAND H	I	0	8,992	2,015.0	0.000	792
		II	2,000	10,992	2,783.0	0.719	873
		III	12,673	21,665	2,816.0	4.500	832
		IV	13,619	22,611	2,855.0	4.770	787
5 - BRAND H	2 - BRAND E	I	0	17,563	2,771.0	0.000	792
		II	26,019	43,582	3,827.0	6.799	873
		III	-2,021	15,542	3,871.0	-0.522	832
		IV	20,039	37,602	3,925.0	5.105	787
3 - BRAND F	5 - BRAND H	I	0	20,296	3,038.0	0.000	2,076
		II	65,915	86,211	3,928.0	16.781	3,092
		III	-3,042	17,254	3,897.0	-0.781	3,216
		IV	17,485	37,781	4,286.0	4.080	2,097
5 - BRAND H	3 - BRAND F	I	0	18,450	2,648.0	0.000	2,076
		II	-327	18,123	3,423.0	-0.096	3,092
		III	58,612	77,062	3,396.0	17.259	3,216
		IV	27,306	45,756	3,735.0	7.311	2,097
4 - BRAND G	5 - BRAND H	I	0	3,614	2,011.0	0.000	698
		II	2,499	6,113	3,062.0	0.816	530
		III	16,153	19,767	3,060.0	5.279	531
		IV	14,727	18,341	3,451.0	4.267	359
5 - BRAND H	4 - BRAND G	I	0	19,380	4,566.0	0.000	698
		II	55,975	75,355	6,951.0	8.053	530
		III	-3,236	16,144	6,947.0	-0.466	531
		IV	56,049	75,429	7,836.0	7.153	359
6 - BRAND I	5 - BRAND H	I	0	10,883	899.0	0.000	2,818
		II	-326	10,557	1,330.0	-0.245	2,374
		III	10,338	21,221	1,322.0	7.820	2,425
		IV	6,370	17,253	1,256.0	5.072	2,967
5 - BRAND H	6 - BRAND I	I	0	17,995	2,276.0	0.000	2,818
		II	51,412	69,407	3,366.0	15.274	2,374
		III	1,520	19,515	3,346.0	0.454	2,425
		IV	43,661	61,656	3,178.0	13.739	2,967
7 - BRAND J	5 - BRAND H	I	0	36,457	2,584.0	0.000	2,168
		II	4,253	40,710	3,593.0	1.184	2,320
		III	30,649	67,106	3,385.0	9.054	3,026
		IV	22,076	58,533	3,412.0	6.470	2,914
5 - BRAND H	7 - BRAND J	I	0	18,069	2,611.0	0.000	2,168
		II	53,070	71,139	3,632.0	14.612	2,320
		III	575	18,644	3,421.0	0.168	3,026
		IV	40,469	58,538	3,449.0	11.734	2,914
8 - BRAND K	5 - BRAND H	I	0	9,172	4,109.0	0.000	844
		II	-1,264	7,908	5,761.0	-0.219	874
		III	80,670	89,842	5,844.0	13.804	825
		IV	18,544	27,716	6,623.0	2.800	528
5 - BRAND H	8 - BRAND K	I	0	15,019	5,268.0	0.000	844
		II	99,089	114,108	7,386.0	13.416	874
		III	1,391	16,410	7,493.0	0.186	825
		IV	52,210	67,229	8,492.0	6.148	528

NAME INDEX

BIBLIOGRAPHY

Abraham, Magid and Leonard Lodish (1993) “An Implemented System for Improving Promotion Productivity Using Store Scanner Data,” *Marketing Science*, **12**(3). 248-269

Ailawadi, Kusum and Scott A. Neslin (1998), “The effect of promotion on consumption: buying more and consuming it faster”, *Journal of Marketing Research*, Vol.35, pp. 390-8.

Alba, Joseph, Susan Broniarczyk, Terence Shimp, and Joel E. Urbany (1994), “The Influence of Prior Beliefs, Frequency Cues and Magnitude Cues on Consumers’ Perceptions of Comparative Price Data,” *Journal of Consumer Research*, Vol 21 (Sep), 219-235.

Alba, Joseph, Carl Mela, Terence Shimp, and Joel E. Urbany (1999), “The Effect of Discount Frequency and Depth on Consumer Price Judgments,” *Journal of Consumer Research*, Vol 26 (Sep), 99-114.

Allen, R.G.D. (1936), “Professor Slutsky’s Theory of Consumers’ Choice,” *The Review of Economic Studies*, Vol. 3 (2), 120-129.

Allenby, Greg and Peter Rossi (1991) “Quality Perceptions and Asymmetric Switching Between Brands,” *Marketing Science,* Vol. 10 (3), 185-204.

Ataman, Berk, Carl Mela, and Harald Van Heerde (2007), “Building Brands,” *Working Paper, Marketing Dynamics Conference, University of Groningen*.

Bartels, Robert (1968), “The General Theory of Marketing,” *Journal of Marketing*, Vol. 32, 29-33.

Bell, David R., Jeongwen Chiang, and V. Padmanabhan, (1999), “The decomposition of promotional response: an empirical generalisation”, *Marketing Science*, Vol. 18 No. 4, pp. 504-26

Blattberg, Robert , Gary Eppen and Joshua Lieberman (1981), “A Theoretical and Empirical Evaluation of Price Deals for Consumer Nondurables,” *Journal of Marketing Research,* Vol. 45, 116-129.

Blattberg, Robert C. and Alan Levin (1987), “Modelling the Effectiveness and Profitability of Trade Promotions,” *Marketing Science,* Vol. 6 (2), 124-146.

Blattberg, Robert and Kenneth Wisniewski (1989). “Price-Induced Patterns of Competition,” *Marketing Science*, **8**(Fall): 291-309

Blattberg, Robert, Richard Briesch, and Edward J. Fox (1995), “How Promotions Work,” *Marketing Science*, Vol. 14 (3), G122-G132.

Bolton, Ruth N (1989). “The Relationship Between Market Characteristics and Promotional Price Elasticities,” *Marketing Science*, **8**(Fall): 291-309

Brooks, Chris (2002), *Introductory Econometrics for Finance*, Cambridge University Press, Cambridge UK.

Bucklin, Randolph and Sunit Gupta (1999), “Commercial Use of UPC Scanner Data: Industry and Academic Perspectives,” *Marketing Science*, Vol. 18 (3), 247-273.

Casella, George and Edward I. George (1992) "Explaining the Gibbs sampler," *The American Statistician*, Vol. 46, 167-174.

Chen, Yuxin and Sha Yang (2007), "Estimating Disaggregate Models Using Aggregate Data Through Augementation of Individual Choice," *Journal of Marketing Research*, Vol. XLIV, 613-621.

Chintagunta, Pradeep (1993), "Investigating Purchase Incidence, Brand Choice and Purchase Quantity Decisions of Household," *Marketing Science*, Vol. 12, No. 2 (Spring 1993). 184-208.

Christen, Markus, Sachin Gupta, John C. Porter, Richard Staelin, and Dick R. Wittink, "Using Market-Level Data to Understand Promotion Effects in a Nonlinear Model," *Journal of Marketing Research*, Vol. XXXIV (Aug), 322-334.

Dawes, John (2004), "Assessing the impact of a very successful price promotion on brand, category and competitor sales," *The Journal of Product and Brand Management*, Vol. 13 (4/5), 303-314.

Dekimpe, Marnik G., Dominique Hanssens, and Jorge M. Silva-Risso (1999), "Long-run effects of price promotions in scanner markets," *Journal of Econometrics*, Vol. 89, 269-291.

DelVecchio, Devon, David H. Henard, and Traci H. Freling (2006), "The effect of sales promotion on post-promotion brand preference: A meta-analysis," *Journal of Retailing*, Vol. 82 (3), 203-213.

Dixit, Avinash, "Investment and Hysteresis," *The Journal of Economic Perspectives*, Vol. 6 (1), 107-132.

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

Foekens, Eijte W., Peter S.H. Leeflang, and Dick R. Wittink (1994), "A Comparison and Exploration of the Forecasting Accuracy of Nonlinear Models at Different Levels of Aggregation," *International Journal of Forecasting*, 10, 245-61.

Friedman, Milton (1976), "*Price Theory*," Aldine Publishing Company, New York, NY.

Friedman, Milton and L.J. Savage (1948), "The Utility Analysis of Choices Involving Risk," *Journal of Political Economy,* Vol. 56, 279-304.

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

Graham, Charles (2007), "How Stationary is Stationary? Loyalty and Brand-Share Dynamics in the Longer-Term," *Working Paper Presented at the Marketing Dynamics Conference,* August 2007.

Guadagni, Peter M. and John D.C. Little (1983) "A Logit Model of Brand Choice Calibrated on Scanner Data," *Marketing Science*, **2**(3). 203-238

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

Hanssens, Dominique, Leonard J. Parsons, and Randall L. Schultz (2000), *Market Response Models: Econometric and time series analysis*. International Series in Quantitative Marketing, Norwell, MA.

Hendel, Igal and Aviv Nevo (2003). "The Post-Promotion Dip Puzzle: What do the Data Have to Say?" *Quantitative Marketing and Economics*, Vol 1, 409-424.

Henderson, James and Richard Quandt (1980), Microeconomic Theory: A Mathematical Approach. Economics Handbook Series, McGraw-Hill, New York, NY.

Hicks, J.R. and R.G.D. Allen (1934), "A Reconsideration of the Theory of Value. Part I. A Mathematical Theory of Individual Demand Functions," *Economica*, Vol. 1 (1), 52-76.

Hicks, J.R. (1946), Value and Capital, Second Edition. Oxford University Press, Oxford, UK.

Hunt, Shelby D. (2002), Foundations of Marketing Theory, M.E. Sharpe, Armonk, NY.

Jedidi, Kamel, Carl F. Mela, and Sunil Gupta (1999), "Managing Advertising and Promotion for Long-Run Profitability," *Marketing Science*, Vol. 18 (1), 1-22.

Johnson, Eric (2006), "Things That Go Bump in the Mind How Behavioral Economics Could Invigorate Marketing," *Journal of Marketing Research,* **Vol. XLIII** (Aug 2006), 337-340.

Kirk, George A., (1996), "Price Promotions and Retail Store Profitability: The Influence of Direct Substitutes, Close substitutes and Complementary Goods," *Ph. D. Dissertation*, Texas Tech University.

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) 317-332.

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) 178-185

Lancaster, Kelvin (1966), "A New Approach to Consumer Theory," *The Journal of Political Economy,* Vol. 74 (2), 132-157.

Lucas, Robert E. (1976), "Econometric Policy Evaluation: A Critique," in *The Phillips Curve and The Labour Market, Carnegie-Rochester Conference Series on Public Policy*, Vol. 1, Karl Brunner and Allan H. Meltzer, eds. Amsterdam: North Holland, 19-46.

McAlister, Leigh and Michael J. Zenor (1992), "The Impact of Retailer Differences on Promotional Response: The Link Between Unusual Levels of Support and Unusual Levels of Response," *working paper.*

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

Marshall, Alfred (1920), Principles of Economics, London: Macmillan and Co. Ltd. Eighth edition, first published in 1890.

Mela, Carl, Sunil Gupta, and Donald R. Lehmann (1997), "The long-term impact of promotion and advertising on consumer brand choice", *Journal of Marketing Research*, Vol. 34, pp. 248-61.

Mela, Carl, Kamel Jedidi, and Douglas Bowman (1998), "The long-term impact of promotions on consumer stockpiling behavior", *Journal of Marketing Research*, Vol.35, pp. 250-62.

Narasimhan, C., Scott A. Neslin, and Sen S. (1996), "Promotional Elasticities and Category Characteristics," *Journal of Marketing*, Vol. 60, 17-30.

Neslin, Scott (2002), <u>*Sales Promotion*,</u> Relevant Knowledge Series, Cambridge, MA: Marketing Science Institute.

Nijs, Vincent R., Marnik G. Dekimpe, Jan-Benedic E.M. Steenkamp, and Dominique Hanssens (2001), "The category-demand effects of price promotions", *Marketing Science*, Vol. 20 No. 1, pp. 1-22.

Pareto, Vilfredo (1907), <u>*Manuel d'economie politique*.</u>

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

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

Raju, Jagmohan Singh (1988), "A Theory of Price Promotions," *Ph. D. Dissertation*, Stanford University, Graduate School of Business.

Samuelson, Paul (1938), "The Empirical Implications of Utility Analysis," *Econometrica*, Vol. 6 (4), 344-356.

Samuelson, Paul (1948), "Consumption Theory in Terms of Revealed Preference," *Economica*, Vol. 15 (60), 243-253.

Slutsky, Eugen (1915), "On the Theory of the Budget of the Consumer," *Giornale degli Economisti,* Vol. LI, 1-26.

Song, Inseong and Pradeep Chintagunta (2007), "A Discrete-Continuous Model for Multicategory Purchase Behavior of Households," *Journal of Marketing Research*, Vol. XLIV, 595-612.

Srinivasan, Shuba, Koen Pauwels, Dominique Hanssens, and Marnkik G. Dekimpe (2004), "Do Promotions Benefit Manufacturers, Retailers, or Both?" *Management Science*, 50 (5), 617-29.

Sullivan, Timothy (2005), "Constrained Optimization with Several Choice Variables," *Lectures Notes,* Southern Illinois University, Department of Economics

Totten, J. and M. Block (1987), *Analyzing Sales Promotion: Test and Cases,* Chicago, IL: Commerce Communications.

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), 383-95.

Van Heerde, Harald J., Peter S.H. Leeflang, and Dick R. Wittink. (2001), "Semiparametric Analysis to Estimate the Deal Effect Curve," *Journal of Marketing Research*, Vol XXXVIII (May), 197-215.

Van Heerde, Harald J., Peter S.H. Leeflang, and Dick R. Wittink (2002), "How Promotions Work: Scan*Pro-Based Evolutionary Model Building," *Schmalenbach Business Review*, Vol 54 (Jul), 198-220.

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

Van Heerde, Harald J., Carl F. Mela, and Puneet Manchanda (2004), "The Dynamic Effect of Innovation on Market Structure," *Journal of Marketing Research*, 41 (May), 166-83.

Van Heerde, Harald J., Marnik G. Dekimpe, and William P. Putsis (2005)," Marketing Models and the Lucas Critique," *Journal of Marketing Research,* XLII (February), 15-21.

Vilcassim, Naufel and Pradeep Chintagunta (1992), "Investigating Retailer Product Category Pricing From Household Scanner Panel Data," *Journal of Retailing*, Vol. 71 (2), 103-128.

Walters, Rockney and Rinne H.J., "An Empirical Investigation into the Impact of Price Promotions on Retail Store Performance," *Journal of Retailing*, Vol. 62 (3), 237-266.

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

West, Mike, Jeff Harrison and Helio Migon (1985), "Dynamic Generalized Linear Models and Bayesian Forecasting," *American Statistical Association*, Vol. 80, 77-83.

Wittink, Dick R., Michael Addona, William Hawkes, and John C. Porter (1988), "SCAN*PRO: The Estimation, Validation and Use of Promotional Effects Based on Scanner Data," working paper, ACNielsen.