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Modeling the Dynamics on the Effectiveness of Marketing Mix Elements

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MODELING THE DYNAMICS ON THE EFFECTIVENESS OF MARKETING MIX ELEMENTS

BY

MALLIK GREENE

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

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ACCEPTANCE

This dissertation was prepared under the direction of the *MALLIK GREENE* Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Executive Doctorate in Business in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

MODELING THE DYNAMICS ON THE EFFECTIVENESS OF MARKETING MIX ELEMENTS

BY

MALLIK GREENE

August 06^{th,,} 2014

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The objective of this study is to conduct a marketing mix modeling to measure the effectiveness of past marketing activities on the product sales using a time-varying effect model (TVEM) approach. The longitudinal intensive data for this study has come from a large ice cream manufacturer in USA. Traditionally, static regression models have been used to measure the effectiveness of marketing mix variables to predict sales. And, these models used to find the time independent effect of the covariate on the dependent variable. On the other hand, a dynamic model such as time-varying effect model takes time into consideration. Researchers can model the changes in the relationship between dependent and independent variables over time using time-varying effect model. This is the first study, where a time-varying effect model approach has been used to measure the effectiveness of marketing mix elements in the ice cream industry. In addition, we have compared the predictive validity of both static and dynamic models using this data set.

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CHAPTER 1.0: INTRODUCTION

The objective of this study is to conduct marketing mix modeling to measure the effectiveness of past marketing activities on ice cream sales using a time-varying effect model (TVEM) approach. The study uses longitudinal intensive data from a large ice cream manufacturer in USA. The important questions we are trying to answer in this study are: Are premium ice cream and novelties brands in the ice cream market elastic or inelastic with respect to price? If elastic, how has the price elasticity changed over time? Can the company increase the price of its brands to gain value growth? What are the optimal price and distribution needed to achieve the desirable value growth? How can the company gain market share from its competitors?

Traditionally, static regression models have been used to measure the effectiveness of marketing mix variables to predict sales. In this study, we are using the time-varying effects model approach to measure the effectiveness of marketing mix variables. We will be comparing the results from both static-regression modelling and dynamic-time-varying effects modelling to see which model is able to predict outcomes closer to the actual values.

The objective of Chapter One is to provide an overview on the ice cream industry focusing mainly on the history, different products and sales, forces affecting sales, and briefly reporting on various marketing and advertising activities by several companies. In the second chapter, an overview on the selective marketing and marketing mix literature is reported. In the third chapter, the business problem, study research questions, and an explanation of the rationale for using the time-varying effect model are presented. In the fourth chapter, the study data variables and the study methodology is described. In the fifth chapter, static and time-varying effect models, data analysis, results and discussions are presented. In the sixth chapter, final study conclusions, recommendations to the industry, and the implications and limitations of this study are presented. The study references and appendixes are included in the seventh and eight chapters.

1.1 History

The origins of ice cream date back to second century B.C (Davis, Blayney, Yen, & Cooper, 2009). Alexander the Great used to enjoy snow and ice, flavored with honey and nectar. King Solomon was fond of iced drinks during harvesting. Nero Claudius Caesar in A.D. 54-86, used to enjoy snow with fruits and juices (Ice Cream, 2013). Officially, in 1774, a vendor in New York advertised in a newspaper that he was prepared to supply various products including ice cream (Davis, et al., 2009). In the 1800s, the technological advancements gave the support for large-scale production of ice cream. In the middle of 19th century, the commercial ice cream industry emerged in the U.S.A. The first wholesale ice cream industry was established in 1851, and in 1920s the introduction of continuous freezer continued the growth of the industry (Davis, et al., 2009). Between the 1950s and 1960s, the widespread establishment of supermarkets and specialty ice cream stores significantly changed the ice cream industry (Davis, et al., 2009). The easy availability of ice cream at home and on the road continues to affect the consumption of ice cream today (Manchester & Blayney, 1997).

1.2 U.S. Ice Cream

In 1984, President Ronald Reagan designated July as National Ice Cream Month, and the third Sunday of July as National Ice Cream Day (Ice Cream, 2013). Approximately nine percent of all the milk produced is used for the production of ice cream in U.S.A. The majority (66.7%) of the ice cream manufacturers in U.S., market their product regionally, around 16% market their ice cream nationally and less than 10% internationally. Of the available choices of ice cream products in the market, premium ice cream is preferred by 80% of Americans, with the next most popular choices being novelties such as ice cream sandwiches and fudge sticks (Ice Cream Industry Profile: United States, 2013).

The most popular flavors are vanilla, chocolate, cookies and cream, strawberry and chocolate chip mint. Vanilla flavor is very versatile; it mixes well with various types of toppings, drinks, and bakery desserts (International Dairy Foods Association Ice Cream Company Survey, 2012). In addition to these popular flavors, manufacturers regularly come up with new flavors or special seasonal flavors for their customers. Co-branding is another important trend for ice cream products. Generally, ice cream manufacturers partner with successful branded companion products to increase their co-market share (International Dairy Foods Association Ice Cream Company Survey, 2012). There are number of ice cream products that use ingredients from well-known products such as candy, cookie, fruits, coffee etc.

1.2.1 Definitions of Frozen Dessert Products

The U.S. Food and Drug Administration sets the standards for ice cream products so that consumers will get a consistent product, no matter what brand or type they buy. These federal standards follow the federal Nutrition Labeling and Education Act, which governs all food labeling (International Dairy Foods Association Ice Cream Company Survey, 2012). Each of the food items has its own definition, and many are standardized by federal regulations. The detailed list of definitions for different ice cream products is summarized in Appendix 8.1:

1.3 Market value

There are four different types of ice cream product segments in the USA. The majority (68.3%) of the market is from the take-home ice cream product segment (Ice Cream Industry Profile: United States, 2013). The other product segments comprise of impulse ice cream (13.6%), Artisanal ice cream (9.6%) and Frozen yogurt (8.5%). Segmenting the market geographically worldwide, the European ice cream market comprises of 42.1% of sales, Asia-Pacific has 27.8%, United States has 18.4% and the rest of the world has 11.7% (Ice Cream Industry Profile: United States, 2013). The detailed segmentation data is summarized in Table 1.

The ice cream market in the United States grew by 2.5% from 2010 to 2011 and reached a market value of $10.3 billion (Ice Cream Industry Profile: United States, 2013). The average annual growth rate from 2007 to 2011 was 1.8%. In 2011, total ice cream production reached a volume of 3.67 billion liters and the production volume continued increase from 2007 to 2011, with an average annual increase of 1.6% (Ice Cream Industry Profile: United States, 2013). The detailed ice cream market value and volume data is summarized in Table 2.

Table 1: Category segmentation in USA and Global geographic segmentation in Millions

Category	2011 (%)	Geography	2011 (%)
Take-home ice cream	$7,030.30 (68.3%)	Europe	$23,538.40 (42.1%)
Impulse ice cream	$1,402.40 (13.6%)	Asia-Pacific	$15,513.20 (27.8%
Artisanal ice cream	$990.00 (9.6%)	United States	$10,296.20 (18.4%)
Frozen yogurt	$873.50 (8.5%)	Rest of the World	$6,532.50 (11.7%)
Total	**$10,296.20 (100%)**	**Total**	**$55,880.30 (100%)**

Table 2: United States Ice Cream Market Value and Volume

Year	$ Million	% Growth	Million Liters	% Growth
2007	9,571.30	-	3,435.00	-
2008	9,748.10	1.8%	3,493.30	1.7%
2009	9,894.50	1.5%	3,551.10	1.7%
2010	10,045.30	1.5%	3,608.80	1.6%
2011	10,296.20	2.5%	3,666.00	1.6%

The four main companies that control more than half of the market share in the U.S.A., are Nestle S.A., Unilever, Blue Bell Creameries and Wells Enterprises (Table 3). The majority of the products are sold at supermarkets (66.4%) and specialist retailers (20.8%). A small percentage of ice cream products are sold at convenience stores (6.0%), service stations (3.4%), and other places (3.3%) (Ice Cream Industry Profile: United States, 2013).

Table 3: Ice Cream Market Share in USA in 2011

Company	% Share	Channel	% Share
Nestle S.A	21.3%	Supermarkets	66.4%
Unilever	19.6%	Specialist Retailers	20.8%
Blue Bell Creameries	9.6%	Convenience Stores	6.0%
Wells Enterprises	5.1%	Service Stations	3.4%
Other	44.4%	Other	3.3%
Total	**100%**	**Total**	**100%**

The global ice cream market is worth over $55 billion, and produces over 13 billion liters of ice cream each year (Global Ice Cream, 2013). There has been steady growth in the production of ice cream and the market value of the product in the last five years, and the overall global growth rate was much higher than in U.S.A. The detailed global ice cream market value and volume data is summarized in the Table 4.

Table 4: Global Ice Cream Market Value and Volume

Year	$ Million	% Growth	Million Liters	% Growth
2007	45,507.20	-	11,859.70	-
2008	49,457.30	4.1%	12,188.90	2.8%
2009	51,304.40	13.7%	12,505.90	2.6%
2010	53,599.30	4.5%	12,941.70	3.5%
2011	55,880.30	4.3%	13,315.20	2.9%

The top four companies that play a key role in the global ice market are Unilever (19.6%), Nestle S.A (13.1%), General Mills, Inc (2.1%), and Inner Mongolia Yili Industrial Group (2.1%) (Global Ice Cream, 2013). The rate (85%) of ice cream sold at supermarkets and various retail stores is similar in U.S.A and globally (Table 5).

Table 5: Global Ice Cream Market Share in 2011

Company	% Share	Channel	% Share
Unilever	19.6%	Supermarkets	37.8%
Nestle S.A	13.1%	Specialist Retailers	33.4%
General Mills, Inc.	2.1%	Independent Retailers	13.5%
Inner Mongolia Yili Industrial Group Co., Ltd.	2.1%	Convenience Stores	11.1%
Other	63.2%	Other	4.3%
Total	**100%**	**Total**	**100%**

1.4 Ice Cream Sales

According to data from Information Resources Inc, ice cream/sherbet category sales were up by 1.4% to $6.1 billion dollars and unit sales were up 2.7% to $1.6 billion dollars in the 52 weeks to October 2013 (Kennedy, 2014), while the frozen novelties category sales dropped by 3% to $4.5 billion dollars and unit sales fell 5% to $1.5 billion in same time period (Kennedy, 2014).

The sales were up 21.3% to $358.1 million, and unit sales were up 26.5% in the frozen yogurt segment (Kennedy, 2014). Among the top five frozen yogurt sales, Healthy Choice sales were up by 603% and the number of units increased by 483.4%. The sales were also up for the Ben & Jerry, and Kemps brands (Table 6). The total dollar sales were up 0.6% to $5.5 billion, and units were up 1.8% in the ice cream segment in 2013 (Kennedy, 2014). Even though private labels dominated the market, Haagen-Dazs had the highest growth, both in sales and units compared to other brands in the ice cream segment (Table 7).

Frozen novelties sales were hit harder than other products where dollars sales dropped 3% to $4.5 billion, and units fell 5% to 1.5 billion in October 2013 (Kennedy, 2014). Nestle Drumstick was the only brand in the category that had a positive sales increase compared to last year at 5.1%. Other brands saw a decrease in sales, such as Skinny Cow, sales down by 14.4%, and Wells Dairy Weight Watchers, down by 13%. Similarly, in the ice cream/ice milk desserts segment, dollars sales were down by 4.8% to $218.4 million, and units were down by 24.9%. Jon Donaire had some success with dollar sales up 5.2% and units up by 8.8%. However, for private labels and Carvel, dollar sales and unit sales were down compared to last year (Kennedy, 2014).

Table 6: Frozen Yogurt Sales in 2013

Frozen Yogurt	Dollar Sales (millions)	% change vs Year Ago	Unit Sales (millions)	% change vs Year Ago
Private Label	$63.3	8.3	20.8	15.6
Healthy Choice	$36.8	603.0	11.4	483.4
Ben & Jerry's	$33.3	48.0	9.5	45.2
Kemps	$29.5	21.2	7.8	21.0
Ben & Jerry's FroYo	$26.8	-2.3	6.8	-0.3
Total Category	$358.1	21.3	99.1	26.5

Table 7: Ice Cream Sales in 2013

Ice Cream	Dollar Sales (millions)	% change vs Year Ago	Unit Sales (millions)	% change vs Year Ago
Private Label	$1,131.9	-4.3	354.1	-3.2
Blue Bell	$596.6	5.8	155.8	3.8
Ben & Jerry's	$478.1	5.6	115.9	6.5
Breyers	$473.8	-7.8	134.1	-3.3
Haagen-Dazs	$406.1	14.3	97.5	17.6
Total Category	$5,557.5	0.6	1,520.8	1.8

Ice cream represented 54% of the total sales in the ice cream and frozen novelty market and its sales grew from $5.7 billion in 2011 to $5.9 billion in 2013. Frozen yogurt sales saw a 74% increase between 2011 and 2013 compared to 3.9% in the ice cream segment according to new research from Mintel (Frozen Yogurt Sales Grow Nearly 75%, 2013). The frozen yogurt sector grew from $279 million in 2011 to reach $486 million in 2013. Overall, sales of ice cream and frozen novelties grew 9% from 2008 to 2013 to $11.2 billion (Frozen Yogurt Sales Grow Nearly 75%, 2013).

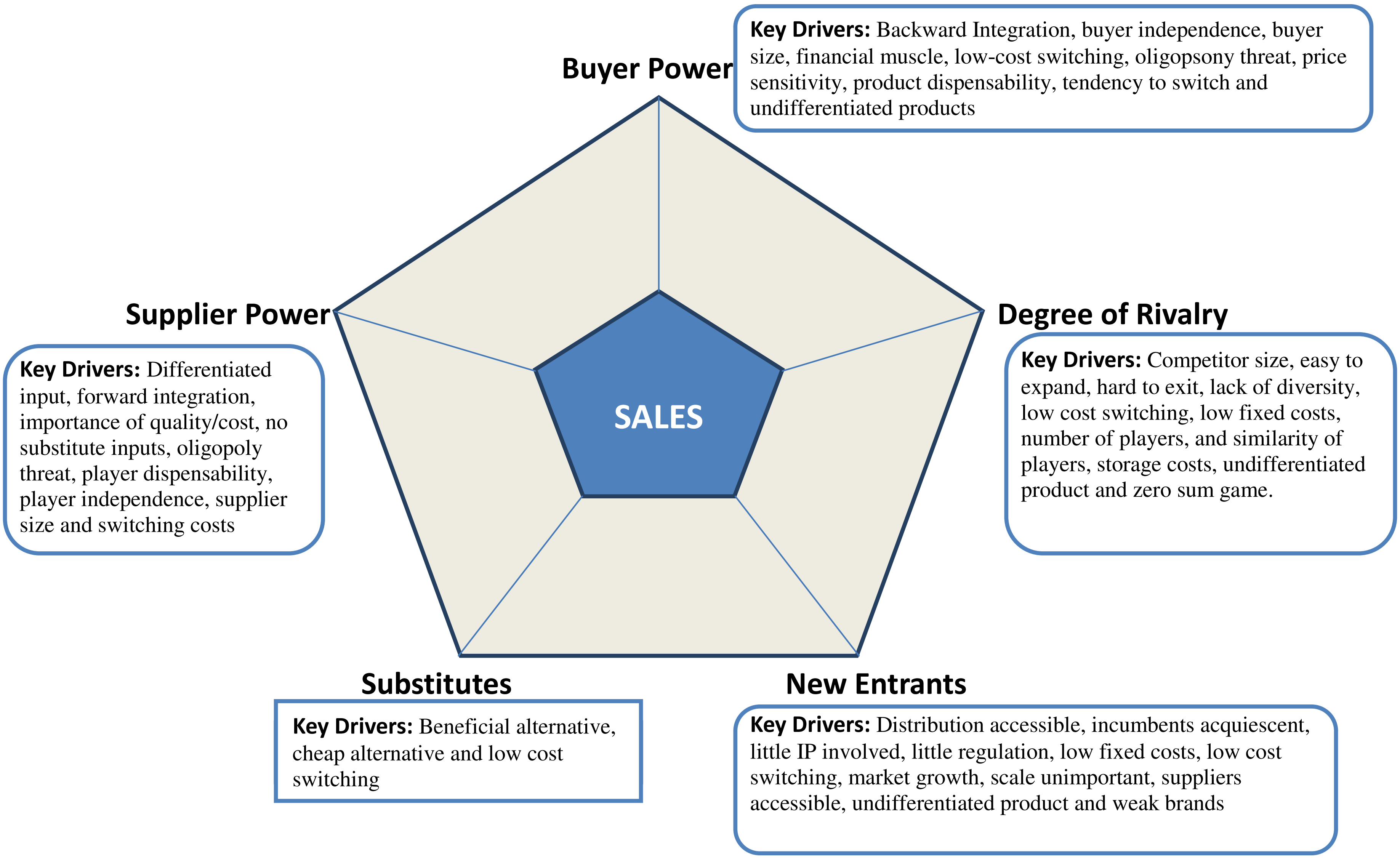
1.5 Porter's Five Forces Analysis

There are five marketing forces that drive the competition in the ice cream market in the United States (Ice Cream Industry Profile: United States, 2013). They are: buyer power, degree of rivalry, new entrants, substitution and supplier power. The impact of these five forces on ice cream sales is summarized in Figure 1.

1.5.1 Buyer power

The important buyers for ice cream products are supermarkets, hypermarkets, and convenience stores and the important suppliers for the ice cream production are suppliers of milk, fat, and emulsifiers (Ice Cream Industry Profile: United States, 2013). As the ice cream market is a high-volume sales and low-margin area, competitor rivalry tends to be high. Big supermarket chains have strong buyer power and may exert pressure on ice cream manufacturers for better deals (Ice Cream Industry Profile: United States, 2013). The manufacturers are able to obtain their key ingredients from a large number of suppliers to reduce the supplier power in the market. Given the presence of large brands in the ice cream industry, small scale manufacturers tend to struggle to be in the market.

Figure 1: Forces Driving Market Competition in the Global Ice Cream Industry(Global Ice Cream, 2013)



The key drivers of buyer power in the ice cream market are backward integration, buyer independence, buyer size, financial muscle, low-cost switching, oligopsony threat, price sensitivity, product dispensability, tendency to switch, and undifferentiated products (Ice Cream Industry Profile: United States, 2013).

Supermarkets account for approximately two thirds of the market's total value. The retail food industry is very disconnected, which means that key players can sell to a large number of diverse buyers (Ice Cream Industry Profile: United States, 2013). While the large buyers such as supermarkets, negotiate better deals with the manufacturers, and the smaller independent retailers have less negotiating leverage with the main players. The ice cream products are differentiated by their brand, flavor and calorie content, the key buyers offer a wide variety of products which tend to weaken their buyer power (Ice Cream Industry Profile: United States, 2013).

If the consumers are loyal to particular brands, the buyer power of the retailers is diminished (Ice Cream Industry Profile: United States, 2013). Some retail chains have tried to use backward integration where supermarkets have developed their own private label ice cream products with much lower prices than the branded products, putting the branded products under pressure (Ice Cream Industry Profile: United States, 2013). Some large ice cream producers have initiated selling the ice cream products directly to the consumers through licensed ice cream parlors to reduce the buyer power of retail chains. In addition, for retain chains where ice cream product sales are not part of the main business, the buyer power is limited (Ice Cream Industry Profile: United States, 2013).

1.5.2 Supplier power

The drivers of supplier power in the ice cream market are differentiated input, forward integration, importance of quality/cost, no substitute inputs, oligopoly threat, player dispensability, player independence, supplier size and switching costs (Ice Cream Industry Profile: United States, 2013). Ice cream, a flavored frozen food, is made up of milk fat or butterfat, milk solids, sweeteners, stabilizers, emulsifiers, and water. As long-term supply contracts are not routine, dairy products are usually purchased in the open market (Ice Cream Industry Profile: United States, 2013). Because of this approach, ice cream manufacturers have little control over the dairy prices. The larger ice cream manufacturers may have strong negotiating power, but due to a lack of long term supply contracts there is a regular switch of suppliers and the cost of switching supplier is generally very low (Ice Cream Industry Profile: United States, 2013).

The large dairy suppliers enhance the supplier power by selling milk fat and other bulk ingredients to large ice cream companies (Ice Cream Industry Profile: United States, 2013). However, maintaining the dairy product quality is the key to their brand equity in the long term. Some packaging supplier do enter into long-term contracts with the manufacturers, which in turn increases the supplier power (Ice Cream Industry Profile: United States, 2013). For some minor ingredients, substitution is possible, but for most of the main ingredients, such as milk and sugar, no satisfactory substitution exists (Ice Cream Industry Profile: United States, 2013). This also strengthens the supplier power.

1.5.3 New entrants

The factors influencing the likelihood of new entrants in the ice cream market in the United States in 2011 were distribution accessibility, incumbent acquiescence, little IP involved, little regulation, low fixed costs, low cost switching, market growth, scale unimportant, suppliers accessibility, undifferentiated product and weak brands (Ice Cream Industry Profile: United States, 2013).

Gourmet ice cream manufacturers attract customers by highlighting their natural ingredients and the high-quality of their products (Ice Cream Industry Profile: United States, 2013). Homemade ice creams can be sold at a higher price than the retail chain products, and the small-scale gourmet ice cream manufacturers are able to recoup their investments in raw materials, production equipment and personnel in a short period of time (Ice Cream Industry Profile: United States, 2013).

Another major limiting factor for the new entrants is the distribution channels. In general, fresh ice is difficult to transport and store, and the manufacturers need to distribute their ice cream in geographically large areas which involves channels such as supermarkets. The space in the retail store is limited and it may be difficult to persuade a retailer to allocate space for a new entrant when the competition is high from other established manufacturers (Ice Cream Industry Profile: United States, 2013).

Large ice cream manufacturers like Unilever and General Mills have opened up their own chains of ice cream parlors where they sell their products to the consumer directly (Ice Cream Industry Profile: United States, 2013). A smaller ice cream manufacturers cannot afford to open ice cream parlors and, therefore, must rely on supermarkets, specialist stores and other businesses to stock their products (Ice Cream Industry Profile: United States, 2013). Ice cream manufacturers differentiate their product quite strongly in the minds of customers. These manufacturers are willing to regularly push out old flavors and replace them with new and interesting flavors. The strong differentiation of products in the ice cream market makes it difficult for new entrants to attract retail buyers away from the existing manufacturers (Ice Cream Industry Profile: United States, 2013). Therefore, the likelihood of a new entrant into the market to play a key role is very low.

1.5.4 Threat of substitutes

The factors influencing the threat of substitutes in the ice cream market in the United States are beneficial alternatives, cheap alternatives and low-cost switching (Ice Cream Industry Profile: United States, 2013). From the consumer point of view, there are number of alternatives or substitutes for commercially available ice cream and these include frozen desserts, such as sorbets and gelato, confectionery, and smoothies (Ice Cream Industry Profile: United States, 2013). To meet the consumer demand, most retailers will stock up all kinds of ice cream and their substitutes. Even though the retail margin may be higher for substitute products the retail stores continue to sell ice cream products to meet the consumer needs, and the threat from substitutes is evaluated as low in this area (Ice Cream Industry Profile: United States, 2013).

1.5.5 Degree of Rivalry

The drivers that determine the degree of rivalry in the ice cream market are competitor size, ease of expansion, easy to exit, lack of diversity, low-cost switching, low fixed costs, number of players, similarity of players, storage costs, differentiation of product and the zero-sum game (Ice Cream Industry Profile: United States, 2013). The ice cream market in US is more concentrated than in other countries. The top four manufacturers hold more than half of the total market value. The larger the number of competitors in this market, the higher the rivalry among them. The retail stores can easily switch between different manufacturers' products, which leads to a higher degree of rivalry among the top players (Ice Cream Industry Profile: United States, 2013). The brand loyalty of consumers put pressure on retailers and it makes it difficult for them to ignore a popular branded product and replace it with a private-label product. The larger players own the majority of the factories, and the exit barriers are high. Therefore, leaving the ice cream market would require divestment of considerable fixed and specialized assets (Ice Cream Industry Profile: United States, 2013). Some players have diversified into other food businesses, which has reduced their rivalry by making them less reliant on ice cream sales. Overall, there is a strong degree of rivalry in the ice cream market (Ice Cream Industry Profile: United States, 2013).

1.6 Company Specific Marketing and Advertising Activities

In this section, a detailed list of the different types of marketing and advertising activities conducted by various companies in the ice cream industry is presented. All the different marketing and advertising activities are summarized into a table and included in Appendix 8.2.

1.6.1 Mars, Inc

Mars, Inc. is an American global food manufacturing company with US$30 billion in annual sales in 2012, and is ranked as the third largest privately held company in the United States (Mars Incorporated). Mars produces numerous popular ice cream products such as Snickers, Dove, Twix, Bounty, Galaxy, and Maltesers (Raising the Bar, 2012). Mars advertises their products on television, in print and online and uses special events to generate public relations buzz (Raising the Bar, 2012). In 2011, Mars organized a "Summer Movie Mania" promotion from June to August, offering consumers a chance to win movie tickets for a year. Mars also offered $9 in movie credit for consumers who purchased three Mars products, and the program was offered in clubs such as Sam's Club, convenience store, drug, grocery and mass channels (Raising the Bar, 2012).

During the summer, Mars sent ice cream trucks to Baltimore, Chicago and Minneapolis to promote their Ice Cream products (Raising the Bar, 2012). For loyal consumers, the trucks offered ice cream products along with massages and nail treatments for female adult consumers. Mars partnered with other retail stores such as Target and 7-Eleven and promoted their products by providing coupons and sweepstakes for grand prizes (Raising the Bar, 2012).

In 2012, Snickers Ice Cream sponsored the National Football League and was featured at the Super Bowl. A 2010 sweepstakes offered consumers a grand prize of a three-day trip to an NFL training camp and one-on-one time with a player (Raising the Bar, 2012). Other sponsored programs for Snickers Ice Cream consumers included Madden NFL 11 prize packs from EA Sports, Canon cameras and Visa prepaid debit cards. In order to capture health conscious consumers, Mars came up with ice cream novelties with 250 calories or fewer (Raising the Bar, 2012). The Dove Ice Cream Miniatures were 90 calorie novelties for snacking, and the marketing team used Facebook to communicate the healthy choice products to generate brand awareness among followers. Dove Ice Cream has its own website and a Facebook page with over 70,000 likes in the month of January in 2012. Mars Ice Cream continues to find ways to drive consumers to retailers' ice cream aisles by keeping the consumers engaged with the brand, through promotions, advertisements, online, television and print media, product development and brand extensions (Raising the Bar, 2012).

1.6.2 Pierre's Ice Cream Company

Alex Basset founded Pierre's Ice Cream Company in Cleveland in 1932. The company produces over 50 flavors of ice cream and 235 products in total, and the products are sold throughout U.S.A. (Pierre's Ice Cream Company). To support product marketing activities, the company actively promotes 30-second radio advertising, in-store specials, promotions, free-standing inserts, and it engages the consumers on social media sites like Facebook (Extending Its Reach, 2011). In addition, Pierre's supports local events and charities and has established good public relations with the community (Extending Its Reach, 2011). Matt Thornicroff, assistant marketing and communications manager at Pierre's Ice Cream said, "We like to participate in special events where we can coupon and have people experience our new products in a fun forum." Pierre's promotes sugar-free ice creams at the annual Juvenile Diabetes Research Foundation Walk to Cure Diabetes event in Cleveland. "We are also the presenting sponsor of a local event called Ice Cream Weekend held at Lake Metroparks Farmpark," says vice president of marketing Laura Hindulak (Extending Its Reach, 2011).

Pierre's has created separate pages for Pierre's, Hola Fruta, and Yovation on Facebook. "We view Facebook as a window into our company that you wouldn't otherwise have access to if you are not a fan," Hindulak says (Extending Its Reach, 2011). "We try to make it a casual, open forum for our fans. Customers can talk to us directly, post photos, share opinions, recipes and talk about ice cream in general. We post photos of initial runs of limited-edition flavors, alert customers to online coupons, upcoming F.S.I.S. We also provide sneak peeks at new flavors." The company uses social media sites and local community connections to promote and increase the awareness of their brands (Extending Its Reach, 2011).

1.6.3 Umpqua Dairy

Umpqua Dairy is the largest family owned dairy in Roseburg, Oregon providing ice cream, milk, and other dairy products(Umpqua Dairy History). Umpqua Dairy produces premium ice cream, premium lite ice cream, sherbet, non-fat frozen yogurt, sugar-free ice cream and university ice cream brands. Umpqua advertises their brands on television, radio, point-of-sale advertising and billboards. In addition, it also advertises on newspaper and in-store demonstrations (Carper, 2013). Tamara Osborne, Marketing Coordinator said "Advertising is becoming more expensive," and to make efficient use of its marketing budget, the company has produced more full-family advertisements to promote their ice cream products (Carper, 2013). Umpqua embraces Facebook and communicates their presence by printing the Facebook logo on the seal over its products. So that when a consumer removes the seal of the product, they can see the social media address under the seal. The company's YouTube channel features advertisements for their products and the Facebook page had nearly 2,200 likes in month of September in 2013 (Carper, 2013).

1.6.4 Graeter's

Graeter's is a national brand with a regional chain of retail stores offering ice cream in Cincinnati, Ohio. Being a small company with around $30 million annual revenue, the company is creative and strategic when comes to marketing and advertising (The Greater Good, 2011). Graeter's uses word-of-mouth, direct mail, public relations, social media campaigns, and limited advertising, as tactics for their brand awareness (The Greater Good, 2011). The company has a Facebook page with over 168,000 fan followers and Graeter's uses this medium to connect with loyal fans and to encourage them to share their love of the product. Graeter's ice cream products were mentioned on television by actress Susan Lucci on the Nate Berkus show and by Oprah Winfrey on Oprah show (The Greater Good, 2011). In addition, Graeter's is a major sponsor of "The Cure Starts Now Foundation," that is working to find a cure for pediatric brain cancer (The Greater Good, 2011). Graeter's says, "Community involvement is just part of being a good corporate citizen," and, "These are our neighbors; it's not a marketing ploy."

1.6.5 Turkey Hill Dairy

Turkey Hill Dairy is owned by the Kroger Company, and it manufactures and distributes more than 60 flavors of ice cream and frozen desserts throughout the United States and worldwide

(Turkey Hill). Turkey Hill ice cream flavors are sold at Kroger stores and at over 260 gas stations and convenience stores in Pennsylvania, Ohio and Indiana (Turkey Hill).

Turkey Hill spends about one-third of their annual marketing budget on sports sponsorships (Bair, 2009). The company sponsored the Philadelphia Phillies and developed several ice cream flavors in support of the team. The strategic partnership between the Philadelphia Phillies and Turkey Hill benefited both the parties. Similarly, the company partnered with the New York Yankees and developed two ice cream flavors–Bronx Bombers Sundae and Fudgy Cookie Swirl (Bair, 2009). The products are not only sold in the stadium when the teams are playing, but are also available in stores. Turkey Hill also sponsored the Philadelphia Eagles and produced an ice cream for the football team (Bair, 2009). In addition, the company has partnered with some minor league teams, including the Lancaster Barnstormers and the York Revolution to help promote their ice cream brands (Bair, 2009). “Brand identification is always important, particularly in food products. We want to continue to put that name out there,” Schuler said (Bair, 2009). “You need a blend of both community support and company support and I think you have to be sort of clear eyed about what those objectives are. You have to be realistic.”

1.6.6 Stonyfield Farm, Londonderry, Kraft Foods and Organic Valley

Ice cream companies are now using social media sites to introduce consumers to their ice cream products (Brands Update the Ice Cream Social, 2010). They are using popular social media sites such as Facebook, Foursquare, Flickr, Twitter, and YouTube to engage consumers with their brands. During the 2010 U.S. Open Tennis championship, Stonyfield Farm used social media tools extensively to promote their organic yogurts and other dairy products (Brands Update the Ice Cream Social, 2010). “The company wanted to bring the excitement consumers have for its products to the online world,” said Amy VanHaren, social media manager at Stonyfield Farm (Brands Update the Ice Cream Social, 2010). This marketing activity led to increased visits to the company website and its Facebook page, and more people were posting about the product on Twitter, and resulting in what VanHaren described as, “huge growth in engagement levels”.. Stonyfield Farm hired contractors to Tweet daily from the sports complex, and to upload pictures on social media sites and to engage consumers with their frozen yogurt brands (Brands Update the Ice Cream Social, 2010). These activities led to threefold increase in Facebook followers, and the views on Facebook page increased by 200%. “People like to interact,” and, “We gave them an outlet to engage,” VanHaren said.

Londonderry, a New Hampshire based dairy processor, conducted product sampling and sweepstakes contests at the U.S.T.A. Billie Jean King National Tennis Center in Queens, New York, in addition to social media presence (Brands Update the Ice Cream Social, 2010). Kraft Foods created a series of 90-second to two minute videos by comedian Anita Renfroe about breathing classes, raising children, chocolate, cool moms and other subjects, which were uploaded both to the company site and YouTube (Brands Update the Ice Cream Social, 2010). In these videos, they display Kraft Food logos and products in the background for consumer viewing. Through word-of-mouth, these videos created a buzz in daily newspapers, and on television (Brands Update the Ice Cream Social, 2010). Organic Valley took a two-week road trip and stopped at various college campuses in different states and documented the tour on a Facebook page with photos and links to news media coverage. As a result, Organic Valley brand awareness has increased significantly among college students and on social media (Brands Update the Ice Cream Social, 2010).

CHAPTER 2.0: INTRODUCTION TO MARKETING MIX ELEMENTS

The objective of this section is to provide an overview of the marketing mix elements and the factors that impact marketing. Even though there are several factors that impact marketing, we are restricting ourselves here only to pricing, distribution, and advertising. The rationale for presenting only the above three topics is that in our study we are able to test the impact of these three variables on product sales. There is a significant lack of literature from the marketing perspective on the ice cream industry. Therefore, wherever possible, general retail marketing specific literature was substituted for ice cream marketing literature.

2.1 Marketing Mix Elements

Marketing is essential for the growth of a company and annually in US companies spend over $285 billion on advertising (Gupta & Steenburgh, 2008). Marketing managers are regularly under pressure to show their investment decisions are yielding a better return on investments(Gupta & Steenburgh, 2008). Allocating resources in marketing is a complex process in a continuously changing environment. To keep up with the evolving new technology, there has been a significant shift in how the marketing resources are allocated. Companies must now market their products across multi-channels, including television, print, radio, direct mail, and public relations(Kumar, 2008).

Marketing practitioners across industries are under increased pressure to measure and maximize the return on marketing investment to improve the value of their firms (Venkatesan, Kumar, & Bohling, 2007). This has increased the importance of identifying the marketing assets in which to invest, and of understanding how the assets provide potential for sustained profits in the long run (Rust, Lemon, & Zeithaml, 2004). Customers are considered a critical element of a firm's marketing assets, and the effective management of customer assets can be expected to affect a firm's profits (Bolton, Lemon, & Verhoef, 2004). In this context, the emphasis has shifted toward measuring the value of customer assets, understanding the impact of marketing expenditure on customer value, and actively using marketing actions, such as contacts through various channels, including salespeople and direct mail, to maximize customer and, company value (Venkatesan, et al., 2007; Webster Jr, 1992).

Increasingly, competitive stores (e.g., Procter & Gamble acquiring Gillette, and Wal-Mart acquiring ASDA in the United Kingdom) are making some manufacturers add new product categories and others to narrow or consolidate their product categories (e.g., Unilever reducing more than 1,600 brands to about 500, and the K-Mart and Sears, Roebuck & Company merger consolidating their products) (Chen & Green, 2009). If these companies and their products can differentiate themselves from their competitors they will be successful in the markets they serve (Chen & Green, 2009). According to Walter Landor, products are created in the factory, but brands are created in the minds of customers (Trout, 2005). Therefore, brands must have the right marketing mix of – product, price, place and promotions, to enhance the product positioning strategy in the minds of target customers, in comparison to the competing brands (Chen & Green, 2009).

Marketing mix is defined as “a systematic function and as a sequence of processes for originating, conveying and transporting importance to the clients and for taking care of customer associations with means which help the company and its stockholders" (Chelliah, Chin Kok, Annamalah, & Munusamy, 2013). Marketing managers can control the marketing tools of product, price, place and promotion, in order to best satisfy their customers in the target market. The approach of marketing mix involves the four major areas of decision making in the marketing process that are mixed together to achieve the results desired by the company, to fulfill their customer needs (Chelliah, et al., 2013).

Marketing Mix Modeling uses statistical analysis on a product/s sales and marketing time series data to evaluate the effect of several marketing strategies on sales. It then forecasts the effect on future sets of strategies. Marketing mix approach uses past information to quantify the sales impact of several marketing strategies. It evaluates the value of each of the marketing tactics in terms of its contribution to sales volume, effectiveness, efficiency, and return on investment. The findings from the analysis are then incorporated to modify marketing tactics, and strategies, and to improve the marketing plan and forecast sales (Russell & Cohn, 2012).

Customer markets have evolved significantly since Smith's (Smith, 1956) and McCarthy's (McCarthy, 1960) research on market segmentation, when marketing mix concepts were initially discussed. For example, Wal-Mart has evolved from a small store in Rogers, Arkansas, in 1962, to a largest retailer in the world with revenues over $470 billion, 8,500 stores, and over two million employees in over 15 countries (Daniel, 2010). The strategy for Wal-Mart's success was based on the company's understanding of customer expectations from a retailer. This understanding translated into convenience, one-stop shopping, competitive pricing, and adapting to a changing customer market (Chen & Green, 2009).

During tough economic times, marketing managers feel the need to make changes to their marketing mix. According to a survey conducted by Mckinsey & Co, 96% of the marketing managers had made changes to their marketing mix during the global economic crisis (McKinsey&Co, 2009). The most common form of making changes to the marketing mix was the reduction of marketing support for the company brands (Deleersnyder, Geyskens, Gielens, & Dekimpe, 2002; Srinivasan, Rangaswamy, & Lilien, 2005). During the economic crisis, global advertising expenditure dropped by 10.8% and in the United States it fell by 15.8% (Harald J. Van Heerde, Gijsenberg, Dekimpe, & Steenkamp, 2013). In order to offset company losses, many marketing managers increase their product prices during an economic crisis to balance the revenue losses caused by reduction in sales volume (Marn, Roegner, & Zawada, 2003). This type of lay-man's response to a market situation may be counterproductive in the short term (Deleersnyder, et al., 2002; Lamey, Deleersnyder, Dekimpe, & Steenkamp, 2007), but it leaves marketing managers with questions on how to successfully develop longer term strategies that can address the issue with an scientific approach rather than a lay-man's approach (Harald J. Van Heerde, et al., 2013).

2.2 Price

The monetary cost of a product is defined as the price of the product and other measures that are associated with price are price premiums, quality of the product, fee method, brand loyalty, and product branding (Anselmsson, Johansson, & Persson, 2007; Chen & Green, 2009; Munnukka, 2006; Peterson, 1970; Sethuraman & Cole, 1999). According to Sethuraman and Cole (Sethuraman & Cole, 1999), women are more willing to pay higher price premiums compared to men in a grocery product study. Their willingness to pay higher prices is purely based on a customer's perceived quality of the product. In addition, the price of a product provides a hint of the product quality and brand loyalty of the customers (Chen & Green, 2009).

Marketing researchers and practitioners have long acknowledged that price response functions need not be monotonic and symmetric (Pauwels, Srinivasan, & Franses, 2007). Generally, customers respond less to shallow price discounts, and they, therefore, have under-proportional effects on market performance, compared to deep-price discounts (Gilbride & Allenby, 2004; Hruschka, 2000; Pauwels, et al., 2007). Simultaneously, customers respond very strongly to even minor price increases, therefore, increase in price of the product and decrease in sales leads to a saturation effect (Pauwels, et al., 2007; Harald J Van Heerde, Leeflang, & Wittink, 2001).

Marketing managers would like to predict the sales and profit impact of different levels of price increases and decreases, and to identify the category and brand characteristics that affect price elasticity thresholds (Han, Gupta, & Lehmann, 2002). Marketing managers generally evaluate price threshold effects through simple methods, but a more robust evaluation is necessary for better predictions (Pauwels, et al., 2007). While complex price threshold effects have been discussed previously, those price thresholds often escaped explicit modeling and pragmatic observation (Pauwels, et al., 2007). From the academic research perspective, there are two robust approaches to the problem of estimating price thresholds (Pauwels, et al., 2007). They are individual product-level analyses and robust data-driven analyses. Individual product-level analyses shows unbalanced price thresholds around a reference price with an area of insignificance, such that changes in product price within this area produce no changes in customer perception (Pauwels, et al., 2007), although their focus remained restricted to the customer behavioral phenomenon of interest, such as historical or competitive reference prices and assimilation/contrast effects or saturation effects (Han, et al., 2002; Pauwels, et al., 2007).

Robust data-driven estimation of the effect curve may offer a more flexible estimation approach to capture a wide variety of price threshold phenomena (Pauwels, et al., 2007). A complete data-driven estimation of the effect curve may offer a better estimation approach to capture a large selection of price phenomena (Kalyanam & Shively, 1998; Harald J Van Heerde, et al., 2001). However, this type of data-driven estimation comes at the expense of severe data requirements and sometimes it is difficult to interpret the results (Pauwels, et al., 2007).

The current marketing literature lacks the information on the usefulness of brand price thresholds and kinked demand curves across various product categories in retail markets (Pauwels, et al., 2007). Retail pricing managers, in particular, must need information on factors that impact price elasticity at the high level, for the products that they have to set prices on, and their actions give them accountability for sales results (Pauwels, et al., 2007). Therefore, a comprehensive comparison across various brands/products and categories is important to uncover realistic generalizations, offer proper guidelines for pricing managers, and identify areas for future scientific research (Shugan, 2003).

2.2.1 Characteristics of Price Thresholds

There are two types of assumptions in which customers use benchmarks for price comparisons (Briesch, Krishnamurthi, Mazumdar, & Raj, 1997). First, historical price comparisons in which customers remember the prices of their past purchase decisions, and second, a competitive price comparison between different brands, in which a price comparison has occurred across various brands on the shelves of a retail store (Briesch, et al., 1997). This type of price distinction is very important for pricing managers to set prices in retail stores (Pauwels, et al., 2007). Historical benchmark pricing conveys that pricing managers should be aware of their own past product price discounting, and that they compare that with the current or proposed pricing of their products (Pauwels, et al., 2007). Conversely, competitive benchmark pricing requires pricing managers to focus on current competitive prices of other brands at the local level and to price them accordingly (Mazumdar & Papatla, 2000; Rajendran & Tellis, 1994). There are several research papers that have analyzed both historical and competitive benchmark prices of products, and they have found that both types of benchmarks matter in pricing a product. However, the current literature does not provide guidance on which type of price benchmark is needed to be considered when it comes to price setting (Kumar, Hurley, Karande, & Reinartz, 1998; Mazumdar & Papatla, 2000; Rajendran & Tellis, 1994).

For pricing managers, an understanding of the implications of threshold-based price elasticity is important (Pauwels, et al., 2007). Price thresholds less than 15% are considered as assimilation effect in customer price perception and encoding (Kalyanaram & Winer, 1995). For larger price thresholds greater than 15%, customers assume better deals may come in the future and will wait until then (Mela, Jedidi, & Bowman, 1998). Additionally, price threshold size can be asymmetric to both gains and losses (Kalyanaram & Little, 1994) (Pauwels, et al., 2007). According to a study by Han et al. (Han, et al., 2002) in the coffee product category, larger thresholds were found for gains versus losses and it was not clear whether a similar response can also be expected in other product categories. In general, customers may react more to perceived price losses than to price gains, and the magnitude of elasticity difference plays an important role (Greenleaf, 1995; Kalyanaram & Winer, 1995; Krishnamurthi, Mazumdar, & Raj, 1992). In the past, researchers have shown there is a leeway of price acceptance, suggesting a strengthening of price elasticity beyond a certain threshold (Pauwels, et al., 2007). However, current research shows that there is a possibility of saturation effects, suggesting a weakening of price elasticity beyond a threshold (Harald J Van Heerde, et al., 2001). This particular distinction between the findings is essential for pricing managers to plan product pricing appropriately (Pauwels, et al., 2007).

2.2.2 Expensive Products vs Price

Price changes in expensive product categories may draw more customer attention compared to less expensive product categories (Pauwels, et al., 2007). Customers are more likely to remember the past prices of expensive products in comparison to prices of less expensive categories. Therefore, any price increase will stand out in the minds of customers (Pauwels, et al., 2007). Therefore, historical benchmark pricing is very important for pricing managers to consider when pricing a product in this category (Mazumdar & Papatla, 2000).

For expensive products, larger price discounts would bring in more customers than smaller price discounts (Pauwels, et al., 2007). Significant price reductions on expensive products will enable budget conscious customers to shop and enjoy high quality or prestige products (Chandon, Wansink, & Laurent, 2000). Therefore, larger price discounts allow more customers to buy the expensive products and should yield more negative price elasticity than smaller discounts. This type of price effect is less likely to occur for cheaper products because of their affordability by a larger customer population (Pauwels, et al., 2007).

2.2.3 Historical Price Benchmarks

Customers will make an effort to remember past prices of products and use them as benchmarks when shopping for new products (Pauwels, et al., 2007). As this requires some effort from the customers, they may not conduct this exercise for every product. However, they will track old prices for products in high-volatile categories, due to regular promotional fluctuation activity (Mazumdar & Papatla, 2000). Whereas in lower-price-volatile products, memory-based price benchmarks are easily accessible and noticeable by customers (Briesch, et al., 1997) (Pauwels, et al., 2007).

Customers are used to seeing high levels of promotional activity and significant price discounts in high-price-volatile products. Therefore, when the promotional activity is reduced or stopped, customers will stop or reduce buying that product until the promotional activity resumes (Pauwels, et al., 2007). For this type of products, more negative price elasticity is seen once the promotion crosses the gain threshold (Kopalle, Mela, & Marsh, 1999; Mela, et al., 1998).

2.2.4 Planned vs Impulse Purchases

Customers who regularly engage in planned purchases, generally conduct active price searches across various products and memorize them before the actual purchase event happens (Mazumdar & Monroe, 1990). Because of this behavior, customers recall historical price benchmarks in planned purchase product categories (Mazumdar & Papatla, 2000). As these customers are planning on buying in large volumes to stock up their house, or they are buying for an event, there is little concern on small increases in price. Small price increases may be nullified by large volume purchases (Pauwels, et al., 2007).

Impulse buying customers are generally more price sensitive about products and competitor products in the same store, when they make a purchase decision (Hausman, 2000). Therefore, small price gains or reductions will impact the customers decision to purchase the product (Chandon, et al., 2000). Impulse buying customers do not generally buy products in large quantities. As the purchases are not planned ahead, the product may not be on top of their priority list (Wertenbroch, 1998). Even in the case of higher price increases, few customers may still buy the product due to the desire to purchase. However, the percentage of these customers is generally smaller than regular and planned purchase customers (Pauwels, et al., 2007).

2.2.5 Storable Products vs Price

Customers who are looking for products to stock up at home are generally looking for a better price deals. Even a small price gain will affect their decision to purchase a product because these customers are not in a hurry to make a transaction (Pauwels, et al., 2007). They do not mind waiting for a while until the prices are within their range. These customers are generally waiting for the great deals and buy the products in large quantities (Pauwels, et al., 2007).

2.2.6 Price Spread and Purchase Cycles vs Price

In the high price spread category, there is a strong product differentiation, which makes it easier for the customer to memorize prices of a specific brand. In the low price spread category, there is not much product differentiation, and customers do not remember the past prices of the products (Pauwels, et al., 2007). Therefore, the recalling of historical price benchmarks for high price spread products is common and pricing managers need to take this into consideration when pricing a product (Briesch, et al., 1997).

There are two types of purchase cycles that customers routinely engage shorter purchase cycles and longer purchase cycles. In shorter purchase cycles, customers purchase products regularly and they have a good memory of the product prices and the information can be easily accessible from their previous purchases (Pauwels, et al., 2007). In longer purchase cycles, customers purchase products after long periods of time, and their recall of the previous prices of products is less clear. Therefore, their understanding of price gains or reductions is limited (Briesch, et al., 1997).

2.2.7 National Brands and Store Brands vs Price

National brands generally spend a significant amount of dollars and time on advertising and product differentiation. Therefore, loyal customers understand the brand quality and prefer to be loyal to that brand (Pauwels, et al., 2007). Even slight increases in prices of national brands are tolerated by loyal customers. In general, store brands mimic the national brands in packaging, taste, and the type of product. Store brands barely spend any amount of dollars in promoting their product (Pauwels, et al., 2007). The only differentiating factor for the store brand is lower prices than the national brand. Therefore, a slight increase in the store brand price will attract customer attention and may lead to negative price elasticity (Gupta & Cooper, 1992). In addition, the national brands have high market share, and they provide a larger amount of customer experience with a brand. Therefore, they operate on a flat portion of the price demand curve (Pauwels, et al., 2007). A smaller price hikes in national brands have limited sales elasticity compared to store brands (Blattberg, Briesch, & Fox, 1995).

2.3 Distribution

2.3.1 Demand signaling and screening in channels of distribution

Product distribution is the key for a brand or a company to succeed in today's competitive environment. Product manufacturers' fight for the limited shelf space available at retail stores and the stores assess which of the new products out of thousands available will really recover their carrying costs and generate some profits (Chu, 1992). In demand signaling, when a manufacturer becomes aware of the demand for their product, it launches an extensive advertising campaign and increases the wholesale price of the products to convince retailers that their product will sell (Chu, 1992).

According to signaling model, an ice cream manufacturer has the power to offer a take-it-or-leave it wholesale price to the retailer (Chu, 1992). The bargaining power of an ice cream manufacturer may come from tits ability to mediate rewards or punishment to the retailer, the desirability of the product to the retailer, the availability of other retailers to distribute the product, market knowledge and marketing expertise of the manufacturer (Etgar, 1976; Gaski, 1984).

According to the screening model, first the retailer sets the slotting allowances, and secondly the manufacturer sets the wholesale price for the product (Chu, 1992). Finally, the retailer sets the retail price of the ice cream, based on wholesale price. The slotting allowance is a fee charged by a retailer or a supermarket to the ice cream manufacturers in order to place their product on their shelves (Chu, 1992). The fee varies greatly depending on the manufacturer, location, and the market demand. The slotting fee can be anywhere from between a few thousand dollars in a regional cluster of stores to a million dollars in high demand markets.

Some retailers also charge manufacturers for promotional activities in addition to stocking their products. Some small retail chains may earn more profit from placing a manufacturer's product than actually selling the product in their stores to consumers (Slotting Fee, 2013). And for some retailers this fee helps them to efficiently allocate limited retail shelf space and to help balance the risk of new product failure between manufacturers and retailers (Slotting Fee, 2013).

Retailers request slotting fees, especially in three different cases, which make economic sense for the retailer and supplier if they select to participate (Slotting Fee, 2013) (a) when a brand wants a preferred positioning in a retail store, (b) when the product price is higher than other brands, and (c) when a new brand is trying to shelve their product among a vast variety of other brands. The slotting fee discourages small-scale manufacturers who do not have the same level of cash flow to compete with large manufacturers (Slotting Fee, 2013). Therefore, it is tough to compete with larger manufacturers nationally. According to Sullivan (1997), in U.S.A. companies spent anywhere between $5 to $8 billion dollars annually (Sullivan, 1997).

The slotting allowances are effective to reduce the risk of loss from low-demand products, when a manufacturer is confident of generating enough demand to recover the high fixed cost of the slotting allowance(Chu, 1992). At the right balance, the manufacturers product demand exceeds the slotting allowance, so that both the retailer and manufacture are able to make profit out of it (Chu, 1992).

The screening model assumes that a retailer has the power to make a take-it-or-leave-it slotting allowance deal (Chu, 1992). The emergence of slotting allowances in consumer packaged goods can be attributed to the retailers' increased power in distribution channels which, in turn, can be attributed to the consolidation of major retailers, the substitutability of manufacturers' products, retailers' increasingly competent use of sales data, and managerial sophistication (Bucklin & Schmalensee, 1987).

2.3.2 Signaling or screening

The bargaining power of manufacturers' is through advertising and wholesale price. Manufacturers benefit from offering take-it-or-leave-it offer to retailers, rather than vice versa. Manufacturers are able to profit directly in the short run through advertising and wholesale price rather paying slotting allowances to retailers (Chu, 1992). The recent developments in paying slotting allowances and take-it-or-leave-it offers from retailers show that the bargaining power has shifted from manufacturers to retailers. The wholesale price is dependent on the product advertising by the manufacturer, whereas the slotting allowances are lump sum payments made by the manufacturer to the retailer, and the marginal effect of payment on demand is zero. Therefore, slotting allowances are a costless way of signaling demand (Chu, 1992).

It is possible for the manufacturer to signal demand by incorporating a return policy and to compensate the retailer for the stocking fee for the failure of the product (Chu, 1992). This approach would be efficient, as would cost nothing to signal. However, the retailer has no incentive to put any extra effort into selling the product, as it will be reimbursed if the product fails the demand expectations of the manufacturer (Chu, 1992). Also, in some instances, the retailer may abuse the approach by simply profiting from the failure fee they receive from manufacturers (Chu, 1992).

2.4 Social Media Advertising

The top global social media sites in terms of active users are Facebook with over one billion users, the video-sharing platform, YouTube, with 800 million users, the microblog Twitter, with 200 million users, the business network, LinkedIn, with over 187 million and finally the social network, Google+, with 135 million users (Aichner & Perkmann, 2013). Other international social media sites include the Chinese social network, Qzone, with 600 million users, the Russian social network, VZ, with 100 million users and the Brazilian social network, Orkut, have 52 million active users (Aichner & Perkmann, 2013).

Social media users in the 50 to 64 years age group jumped from 4% in August 2006 to 57% in August 2012 (Schlinke & Crain, 2013). Similarly, the social media adoption rates among those aged 65 years or more has climbed from 1% to 38% within the same timeframe. However, the youngest adults, aged between 18 to 29 years, are the most likely (92%) to use social media (Schlinke & Crain, 2013). More than 20% of all adult Internet users visit LinkedIn and 70% of professionals have LinkedIn pages (Schlinke & Crain, 2013). LinkedIn is much more business oriented among the big three social media platforms (Facebook, LinkedIn and Twitter). Unlike LinkedIn, Facebook is more of a social place for showcasing the culture and community of a brand.

In the last decade, social media has reshaped the existing digital media landscape, and has changed the way companies disseminate marketing messages to consumers (Lipsman, Mudd, Rich, & Bruich, 2012). Social media sites provide an easily accessible platform for a brand to inform and educate its consumers (Schlinke & Crain, 2013). The main difference between a static web presence and the social media platform is the ability of consumers to interact with a brand and to spread brand awareness to a broader population (Schlinke & Crain, 2013). Instead of pushing one-way communication from brands such as newsletters, ads, and web-sites, powerful social media platforms, such as Facebook, engages the consumer community together on the brand. In order to be successful on the social media sites, the brand should have a good strategy of developing content that is relevant and interesting to consumers. In addition, the brand social media sites should nurture the growth of consumers by providing them with dependable and reliant information (Schlinke & Crain, 2013).

In the last decade, Facebook has emerged as a powerful social media marketing and advertising platform (Lipsman, et al., 2012). Facebook is the number one social networking site with a monthly audience of approximately 160 million in U.S., accounting for 90 percent of all time spent on social networking sites, and about three in every four Internet users visit the site on a daily basis. Many American iconic brands such as Coca Cola, Starbucks, and Disney have been able to build up more than 20 million fans on Facebook, as of July 2011, (Lipsman, et al., 2012).

Facebook has simplified two unique consumer experiences of interest to brand marketers (Lipsman, et al., 2012) First, the ability of consumers to identify brands of their interest. Connecting with them directly on Facebook has enabled new ways of sharing information between brands and consumers. Due to this, brands and their consumers are now sharing two-way information and developing relationships between them (Lipsman, et al., 2012). Second, Facebook has facilitated loyal consumers to share information on brands with their friends (Lipsman, et al., 2012), and Facebook encourages and accelerates the sharing of information on brands to a broader population. Most of the brands, whether they are a service industry or product manufacturer, are now able to spread their wings widely on social media sites, such as Facebook, to reach out to their consumers. The Top 100 Advertisers (companies) on *Advertising Age* have established Facebook pages for their brands. According to a *Harvard Business Review* study, only 12 percent of companies surveyed had effectively used social media and only 7 percent were able to incorporate social media into their marketing activities (Lipsman, et al., 2012).

Social media sites are able to provide the opportunity for companies to deliver brand impressions, brand awareness, favorability, purchase intent, conversion, long-term loyalty and lifetime value. The ability to measure and show the impact of these brand impressions, in terms of traditional marketing metrics, can help brands realize the true value of social media as an essential component of their overall marketing mix (Lipsman, et al., 2012). Building a long-lasting consumer relationship that is beneficial to both consumers and the brand is an important way to create a competitive advantage in a crowded marketplace (Clark & Mashburn, 2013). Social media sites fill this gap by forming a bridge between the brand and consumers by providing a platform for consumers, and brands to share their voice about their brands (Clark & Mashburn, 2013).

Good social media strategy focuses on building consumer trust and loyalty, and communicating clear and relevant information to the consumer about a brand. In addition to simply providing information on the brand, social media marketing should also focus on building a mutually beneficial relationship between the consumer and the brand (Clark & Mashburn, 2013). The majority of marketers and brand managers agree that the ability to engage a dialogue with consumers is one of the best benefits of social media marketing (Clark & Mashburn, 2013).

CHAPTER 3.0: MODEL FRAMEWORK

In this section, a brief overview of the business problem, research questions, study hypothesis, and a detailed description of the time-varying effect model and its superiority over the static model is presented.

3.1 Business Problem

The data for this study was obtained from a large ice cream manufacturing company in U.S.A. that has been selling ice cream products for over 100 years. Each year, the ice cream manufacturer spends millions of dollars in various forms of marketing-related. So far, in the history of this large ice cream manufacturing company, no scientific methodology has ever been used to allocate resources to various marketing-related activities to support the brand. They have been using their experience and immediate market need as a base to allocate resources. The new generation leadership team at the company now understands the importance and the need for marketing mix modeling to guide the company in better allocating their resources, so that they can obtain a better return on their investments.

Marketing decisions based on return on investment are important for the company, because it will provide a practical and scientific approach for distributing resources effectively to yield a better return on investment (Kumar, 2008). The current marketing mix modeling study will use all the marketing mix elements that are available from the company and will involve a robust analysis and simulated marketing scenarios for the company products. Through analysis and simulation, the marketing department can rearrange its budget in various scenarios and see the direct impact on its sales or value. With this approach, the marketing department may able to optimize its budget by allocating their funds to support tactics which yield a high return on their investments.

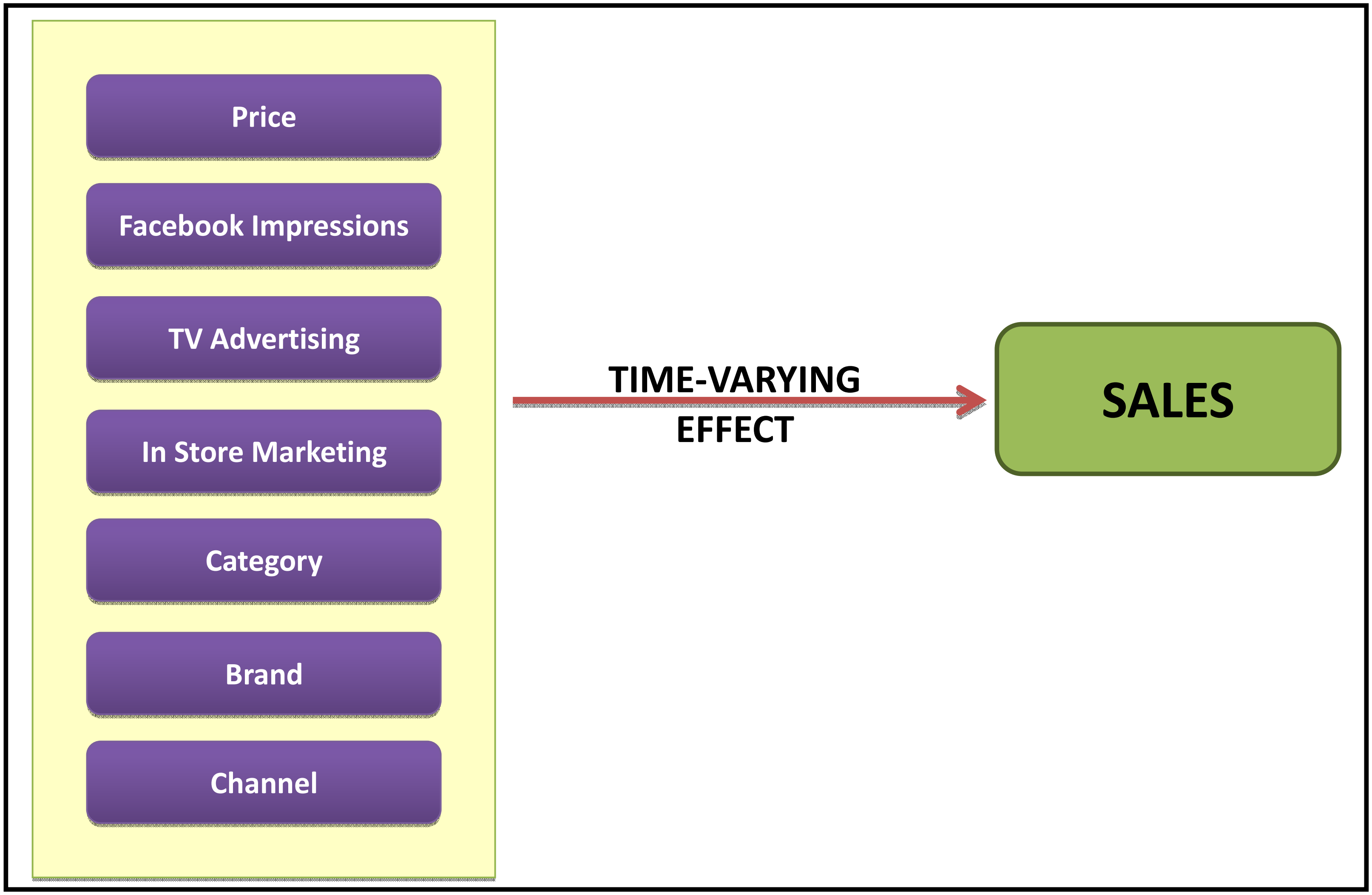
3.2 Research Questions

The important questions for the company are: Are the Premium ice cream brands and Novelties in the ice cream market elastic or inelastic with respect to price? If elastic, how has the price elasticity changed over time? Can the company increase the price of its brands to gain value growth? What prices and distribution tactics are needed to achieve the desirable value growth?

The questions raised above are the most fundamental questions any marketer could ask when managing a brand/s. The literature has shown that if a brand/s has significant brand awareness and brand loyalty, a slight increase in price would have no impact on the brand sales. In this case, the company's brands have been in the market for over 100 years. Therefore, its brand awareness and brand loyalty must be very good.

To scientifically answer these marketing mix questions, we developed a time-varying effect model research framework by measuring elasticities, investigating the pricing, distribution, and the advertising strategies for achieving the desired value growth for the company's brands. The entire research frame work model is depicted in the Figure 1. Therefore, the purpose of the study is to conduct marketing mix modeling, using the existing company marketing data, by simulating various scenarios that can predict key marketing variables, and by applying the time-varying effect approach to capture the dynamic effect of marketing mix elements on sales. In addition, we have compared the time-varying effect model analytical data with static-regression model has the better predictive power.

Figure 2: Time-Varying Effect Model Research Frame Work



3.3 Study Hypothesis and Rationale

Based on the identified research questions, the following study hypothesis was developed for testing using the TVEM frame work in a large ice cream manufacturer's intensive longitudinal data set. The study hypothesis is summarized in the Table 8.

3.3.1 Price Elasticity

The large ice cream manufacturer's products have been in the market for over 100 years. Therefore, a significant brand loyalty might have developed over those years. With strong brand awareness, a slight change in the brand price will not affect the purchase decisions of the loyal customers. Over time, as consumers prefer a product and develop brand loyalty, they become less price sensitive in their choices (Krishnamurthi & Raj, 1991).

H1: The price elasticity decreases over time

3.3.2 Social Media

As consumers engage with the brand more on social media, the brand awareness and brand loyalty improves, which leads to an increase in sales over time. In the last decade, social media has reshaped the existing digital media landscape and has changed the way companies disseminate marketing messages to consumers (Lipsman, et al., 2012). Social media sites provide an easily accessible platform for a brand to inform and educate its consumers (Schlinke & Crain, 2013). Instead of pushing one-way communication from brands, such as newsletters, ads, and web sites, powerful social media platforms, such as Facebook, engage the consumer community together on the brand.

H2: The effect of social media on sales increases over time

3.3.3 Television Advertising

Television is still a powerful medium and an important brand builder. Despite the changing advertising media landscape, the basic principle of communication of brands through television has remained the same for the last 30 years (Turner & Lester, 2007). Since TV advertising serves as an information medium, there is no mediating mechanism. As a result, more TV advertising tomorrow does not mean even more sales in the future. Therefore, the effect of TV advertising on sales is expected be constant.

H3: The effect of TV advertising on sales will be constant over time

3.3.4 In-Store Marketing

Impulse buying customers generally react to prices of products and competitor products that are shelved in the same store when they make purchasing decisions (Hausman, 2000). Therefore, small price increases or reductions will impact the customers' decision to purchase a product (Chandon, et al., 2000). Even in the case of higher price increases, some customers may still buy the product due to their desire to purchase (Chandon, Hutchinson, Bradlow, & Young, 2009). As in-store marketing is repeatedly conducted over time, consumers tend to expect it to be happening at all times. Therefore, its effect on sales will not vary over time

H4: The effect of in-store marketing on sales will not vary over time

3.3.5 Time-varying Effect Modeling (TVEM)

TVEMs are a natural extension of linear-regression models. In a linear-regression model, a single estimate of each covariate's effect is provided, but with TVEM, the coefficients can vary over time. In general, intensive longitudinal data captures information on temporal changes in a process, so not only the outcome might change over time, but the relationships among the covariates and the outcome might also change (Tan, Shiyko, Li, Li, & Dierker, 2012). Therefore, TVEMs are designed to analyze whether, and how, the effects of covariates change over time, and to embrace the complex relationships over time and their impact on the outcome.

H5: Time-varying effect model has a better predictive ability than static regression model

Table 8: Study Hypothesis and Rationale

Number	Study Hypothesis	Estimated Effect	Rationale
H1	The price elasticity decreases over time	+	As consumers build more brand loyalty, their price elasticity decreases over time.
H2	The effect of social media on sales increases over time	+	As consumers engage with the brand more on social media, the brand awareness and brand loyalty improve, which lead to increase in sales over time.
H3	The effect of TV advertising on sales	+	Since TV advertising serves as an information medium, there is no mediating mechanism. As

	will be constant over time		a result, more TV advertising tomorrow does not mean even more sales in the future. Therefore, the effect of TV advertising on sales is expected be constant
H4	The effect of in store marketing on sales will not vary over time	+	As in-store marketing is repeatedly conducted over time, consumers tend to expect it to be happening at all times. Therefore, its effect on sales will not vary over time
H5	Time-varying effect model has a better predictive ability than static regression model	+	TVEM embraces complex relationships over time and their impact on the outcome.

3.4 Time-varying Effect Model

The effectiveness of marketing variables on sales can be measured using statistical models. A static model, such as regression, is used to find the time-independent effect of the covariate on dependent variables. On the other hand, a dynamic model, such as the time-varying effect model (TVEM) takes time into consideration.

Over two decades ago, the time-varying effect model was first introduced by Hastie and Tibshirani (Hastie & Tibshirani, 1993). Researchers are able to apply TVEM on longitudinal data to observe and predict change over time, in the variables that influence an outcome. Researchers can model the changes in the relationship between dependent and independent variables over time, under certain circumstances (Tan, et al., 2012). TVEM allows researchers to answer new and existing questions with greater clarity than the existing models that are available in the public domain (Tan, et al., 2012).

In order to use TVEM, the data must be longitudinal and with multiple data points available through the duration of the data. If we are trying to model a number of variables and their complex relationship between each other, it is valuable to have intensive longitudinal data. The more frequent the number of observations throughout the data set, the better the outcome will be.

Covariates are variables that may impact an outcome of interest, and these can be constant or changing. For example, television advertising share, and Facebook impressions can change over time and impact an outcome. The variables such as the brand and the channel of distribution may impact an outcome, but are highly unlikely to change during the study observation period. Both time-varying effects and time-in-varying effects can be incorporated in the TVEMs (Tan, et al., 2012).

The standard model that is commonly used to study intensive longitudinal data is the growth curve model. There are many valuable applications for growth curve models. The advantage of intensive longitudinal data is it can contain a number of variables with complex inter-relationships and processes. These complex relationships and processes are ignored by the existing growth curve model. TVEM embraces these complex relationships over time and their impact on the outcome (Tan, et al., 2012).

TVEMs are a natural extension of linear-regression models. In a linear-regression model, a single estimate of each covariate's effect is provided, but in TVEM the coefficients can vary over time. In general, intensive longitudinal data captures information on the temporal changes in a process, so not only the outcome might change over time, but the relationships among the covariates and the outcome might also change over time (Tan, et al., 2012). Therefore, TVEMs are designed to analyze whether, and how, the effects of covariates change over time.

In this study, we used TVEM as a novel approach to evaluate intensive longitudinal data to study the course of change and the impact of various variables on the outcomes of interest. This is the first time this model has been used to study the marketing mix elements in the ice cream industry. TVEM provides an ideal medium for assessing the relationship between marketing mix elements and incorporating time as a third dimension in the model (Tan, et al., 2012).

Although TVEM has not been previously used in marketing mix modeling research in the ice cream industry, its potential is evident now. In general, intensive longitudinal data are frequently used in marketing mix modeling and the analysis conducted, to quickly see the changing phenomena. The variables included in marketing mix modeling change on a momentary basis, but their influence on each other may also change over time (Tan, et al., 2012). TVEM studies this change as a function of time. In particular, the TVEM does not assume any specific pattern of the relationship, and the underlying nonparametric nature allows any longitudinal shapes to be accommodated (Tan, et al., 2012).

CHAPTER 4.0: RESEARCH METHODOLOGY

In this section, the study data and key variables are described in detail.

4.1 Data Description

The data for the study comes from a large ice cream manufacturing company in the United States. The company sales represented 5% of the annual ice cream market share in U.S.A. in 2011 (Ice Cream Industry Profile: United States, 2013). The company sells a broad variety of ice cream products across all the states in the United States under the product categories of premium ice cream and novelties. Premium ice cream tends to have low overrun and higher fat content than regular ice cream, and the manufacturer uses higher-quality ingredients. Novelties are separately packaged single-servings of a frozen dessert, such as ice cream sandwiches, fudge sticks, and juice bars that may or may not contain dairy ingredients. Under each product category, there are numerous products that are sold as different brand names in various flavors, shapes, and sizes, in order to meet the customer demand.

The data for this study comprises of marketing mix variables and product specific information. All the data was available at a national level on a weekly basis, from August 2010 to August 2013. The total number of data points that were available on a weekly basis during the study period was 156. The company advertising data comprises of television, digital online, radio, digital search, public relations, and print media advertising. The television advertising data includes both national and regional advertising data on a weekly basis, along with target rating points for each event (TRPs). The company's television advertising, not only targets the general population and kids, but also focuses on some ethnic groups, such as Hispanic Americans.

The television advertising expense data are for both the focal company and its competitors. Moreover, the company regularly conducts several in-store marketing activities, such as coupon machines, checkout coupons, aisle coupons, shelf signs, floor signs, and product sampling to promote their product sales. The print media and digital online search data is available on a weekly basis, along with gross rating points (GRPs) for both national and regional advertising. The company also sponsors regularly banners, videos and search results on the Yahoo search engine.

The company's public relations department periodically publishes paid articles in newspapers, magazines, television, radio, and internet, and the data contains detailed information, including dates, types of activity, location, and measures (GRPs / TRPs / impressions). The company conducts regular in-store marketing activities, such as coupon machines, checkout coupons, aisle coupons, shelf signs, floor signs, and sampling to promote their product sales. In addition, the company regularly conducts sampling tours all over the U.S.A. The detailed data related to in-store marketing activities and sampling tours were included in the data set. The company's detailed sales data was provided in the data set and the data was categorized, based on the channel and the product. Finally, the product price information was provided by the company according to the type of channel.

The company has a big presence in social media such as Facebook, Twitter and blogs. The company's Facebook page has over 677,000 likes and contains information on several brands and sponsored events along with customer interaction. The social media data contains weekly information on total impressions (measured in millions) from Facebook.

The company's detailed sales data was provided in the data set and the data was categorized based on the channel and the product. Finally, the product price information was provided by the company, according to the types of brand and sales channel.

4.2 Key Variables

The initial data set from the company had several variables that have not been used in the study, due to lack of complete data throughout the study period. We decided to include only those variables that have complete information during the entire 156 weeks analyzed in the study. Therefore, a limited number of variables were used in the study for testing the TVEM and static-regression models.

This study uses the log-transformed sales (ln(sales)) as a dependent variable. Because sales depend on a variety of factors, this study controlled for key marketing mix independent variables, including product price (Price), ratio of the company's television advertising expense against the competitors' total television advertising expenses (TVadshare), log-transformed in-store marketing expenses (ln(instoremkt)), and Facebook impression (FBimp), which measures the number of times the company's Facebook content was displayed on user's news feeds. We also included three interaction variables to find the interaction effect between TVadshare and log-transformed in-store marketing cost (TV×ln(instore)), interaction between product category and log-transformed in-store marketing cost (Cat×ln(instore)), and interaction between product category and product price (Cat×Price). We have log-transformed the dependent variable and in-store marketing cost variable in order to compress the variance and for ease of interpretation.

In addition to the marketing mix variables, we have included product specific binary variables. Product category (Cat) equals 1 for premium ice cream that has higher quality ingredients, and 0 for single-serving ice creams. There are four different company brands considered in the data set. Brand 1 (Br1), brand 2 (Br2), and brand 3 (Br3) are 1 for respective brands and 0 otherwise. Moreover, we also included retail channel variables. Channel 1 (Ch1) and channel 2 (Ch2) are 1, for respective channel and 0 otherwise. Finally to control for seasonality, we added a seasonality variable (Season) which equals 1 for peak seasons (Memorial weekend through Labor weekend) and 0 otherwise.

CHAPTER 5.0: RESULTS AND DISCUSSION

In this section, a detailed model description, study data analysis, results and discussion of static and dynamic models are presented.

5.1 Model Specification

The effectiveness of the marketing variables on sales can be measured using statistical models. A static model, such as regression, is used to find the time-independent effect of the covariate on dependent variables. On the other hand, a dynamic model, such as the time-varying effect model (TVEM), takes time into consideration. In the following sections, we analyze the static-regression model and the dynamic time-varying effect model, which measures the time-varying effects of the marketing mixes and the time-constant effects of seasonality, product categories, brand, and retail channel variables.

5.2 Static Model - Regression

A static-regression method is used to study the contemporaneous relationship between the covariates and log-transformed sales. We decided to log-transform the dependent variables because the log specification estimates how the level changes in independent variables effects the percentage change in dependent variables. Equation (1) shows the static regression model we estimated.

Equation 1: Static Regression Model

$$
\begin{aligned}
(1) \qquad ln(Sales)_t = \beta_0 + \ & \beta_1 FBimp_t + \beta_2 Price_t + \beta_3 TVadshare_t \\
& + \beta_4 \, ln(instore)_t + \beta_5 (TV \times ln(instore))_t \\
& + \beta_6 (Cat \times ln(instore))_t + \beta_7 \, (Cat \times Price)_t + \alpha_1 Cat \\
& + \alpha_2 Br1 + \alpha_3 Br2 + \alpha_4 Br3 + \alpha_5 Ch1 + \alpha_6 Ch2 + \alpha_7 Season \\
& + \varepsilon_t
\end{aligned}
$$

Table 10 presents the parameter estimates from static regression, represented in Equation (1). All variables except Cat×ln(instore) are statistically significant at 1% level.

Online Facebook impression (FBimp) and television advertising share (TVadshare) both have significantly positive effects on log sales. The share of television advertising expenses is expected to increase sales by 105%. However, increasing TVadshare against other competitors is very costly to implement. On the other hand, an increase in Facebook impression, which is measured in millions, increases sales by 0.21%. Thus, investing in social media, such as increasing Facebook impressions, may be more cost effective than investing in an increase in the share of television advertising.

In addition, the estimated elasticity of sales with respect to in-store marketing costs is 0.229 ($p<0.01$). Thus, holding other effects constant, a 1% increase in in-store marketing increases the overall sales by 0.22%. The interaction of variables between TVadshare and in-store marketing costs suggests that the effect of in-store marketing is augmented with an increase in shares in television advertising. Moreover, in-store marketing seems more effective for premium ice creams (Cat×ln(instore)).

Interestingly, price has a positive effect on sales ($p<0.01$). As revenues are a function of price and sales quantity, the percentage increase in product prices does not impact the purchase quantity as much. Thus, revenue and price has a positive relationship. Moreover, the changes in ice cream price are only by a few tenths of a cent. Thus, a minimal price increase does not influence the purchase decision as much. Also, this ice-cream brand is very popular nationwide, so high brand preference may make the price less elastic. In addition, the interaction of variables between product category and price (Cat×Price) provides further explanation of the effect of price on sales. This effect of price is more positive for single serving ice creams compared to premium ice creams.

The parameters α_1 through α_6 represent the difference in intercept between the respective product specific binary variables. The premium ice creams (Cat=1), brand 1 (Br1=1), and the first two channels (Ch1=1 and Ch2=1) all have higher intercept compared to the single-serving ice creams (Cat=0) and other brands and channels, respectively. Based on the results, brand 2 (Br2=1) and brand 3 (Br3=1) both have negative parameter values (α_3=-1.38, $p<0.01$; α_4=-0.26, $p<0.01$). Finally, the intercept is higher during the peak season (Season=1). As ice cream is consumed more during summer, the results are consistent with the expectation.

Table 9: Parameter estimates of static regression model

Variable	Parameter Estimate		Standard Error
Intercept	-4.74230	***	0.02601
FB_impressions	0.20866	***	0.02154
Price	1.87011	***	0.02881
TVadshare	1.05376	***	0.09719
Ln(instore)	0.22858	***	0.0145
TVadshare x Ln(instore)	0.15805	***	0.02994
Cat x Ln(instore)	0.03194		0.02004
Cat x price	-0.33236	***	0.03555
Cat	1.99786	***	0.14724
Br1	1.02647	***	0.06257
Br2	-1.38305	***	0.08585
Br3	-0.25667	***	8.28E-02
Ch1	1.77424	***	6.26E-02
Ch2	2.16910	***	0.06259
Seasonality	0.79469	***	0.12864
Adjusted R-sq: 0.9207			
Notes: * p < 0.10; ** p < 0.05; *** p < 0.01.			

5.3 Dynamic Model - Time-Varying Effect Model

In this paper we will use the time-varying effect model (TVEM) suggested by Tan et al.(Tan, et al., 2012). In order to identify the time-varying effect of marketing mixes on sales given time-constant effects of product specific variables (Cat, Br1, Br2, Br3, Ch1, and Ch2) and seasonality, the following model is estimated:

Equation 2: Dynamic - Time-Varying Effect Model

$$\begin{aligned}
\ln(Sales_{imkj}) = {} & \beta_0(t_{imkj}) + \beta_1(t_{imkj})FBimp_{imkj} + \beta_2(t_{imkj})Price_{imkj} \\
& + \beta_3(t_{imkj})TVadshare_{imkj} + \beta_4(t_{imkj})ln\,(instore_{imkj}) \\
& + \beta_5(t_{imkj})(TV \times \ln\,(instore))_{imkj} \\
& + \beta_6(t_{imkj})(Cat \times \ln(instore))_{imkj} \\
& + \beta_7(t_{imkj})(Cat \times Price)_{imkj} + \alpha_1 Cat + \alpha_2 Br1 + \alpha_3 Br2 \\
& + \alpha_4 Br3 + \alpha_5 Ch1 + \alpha_6 Ch2 + \alpha_7 Season + \varepsilon_{imkj}
\end{aligned}$$

where, $\ln(Sales_{imkj})$: log-transformed sales for category i , brand m, channel k measured at time j.

$\beta_0(t_{imkj})$: time-varying intercept function for category i , brand m, channel k, marketing mix covariate measured at time j.

$\beta_p(t_{imkj})$: time-varying coefficient for category i , brand m, channel k, marketing mix covariate measured at time j.

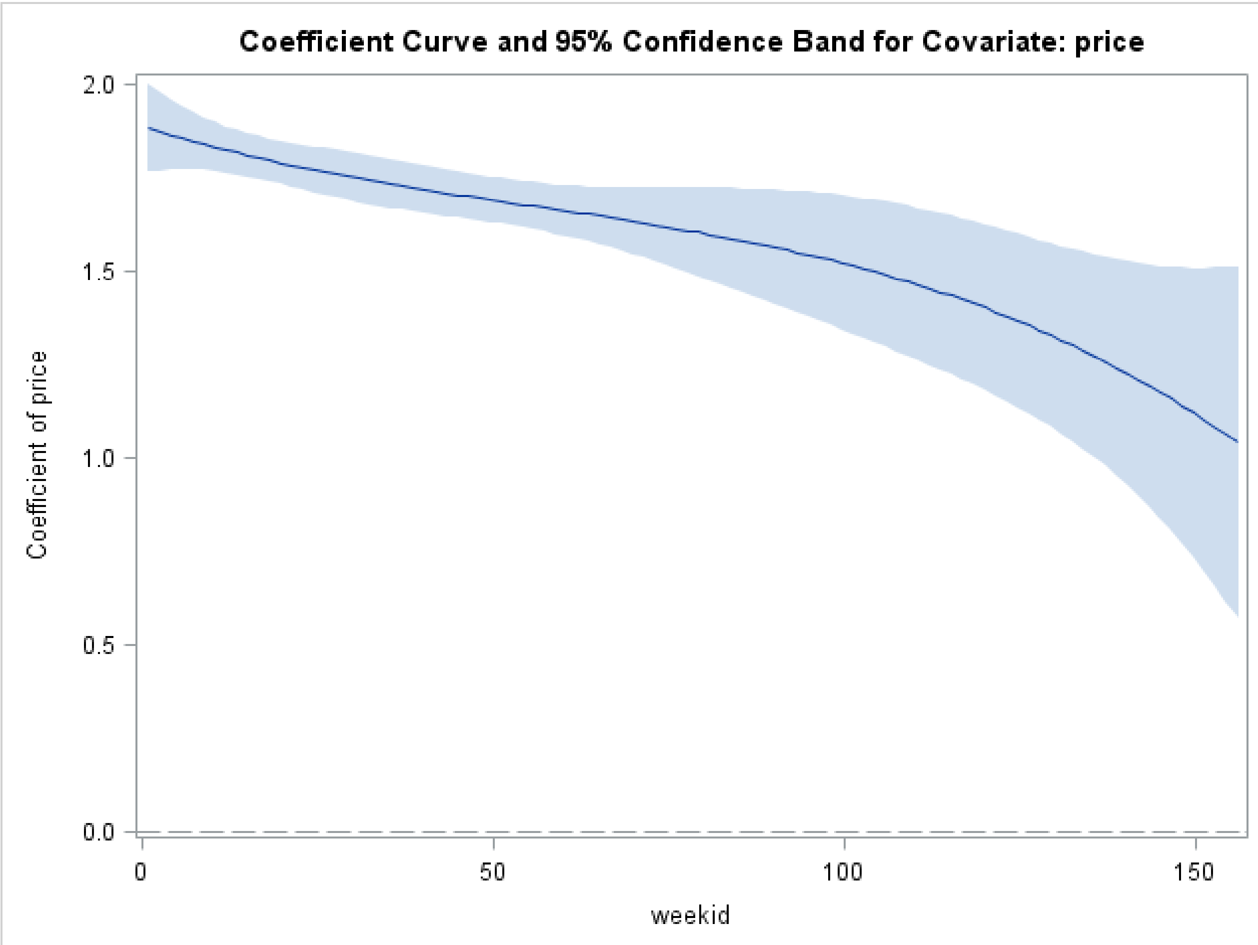
α_p: time-invariant coefficient for categorical variables

ε_{imkj} : random errors for category i , brand m, channel k measured at time j, and are assumed to be normally and independently distributed.

The plots of time-varying coefficients $\beta_p(\cdot)$ show how the link between sales and each marketing mix changes over time. Figures 2 to 8 present the estimated coefficient functions for time-varying marketing mix variables.

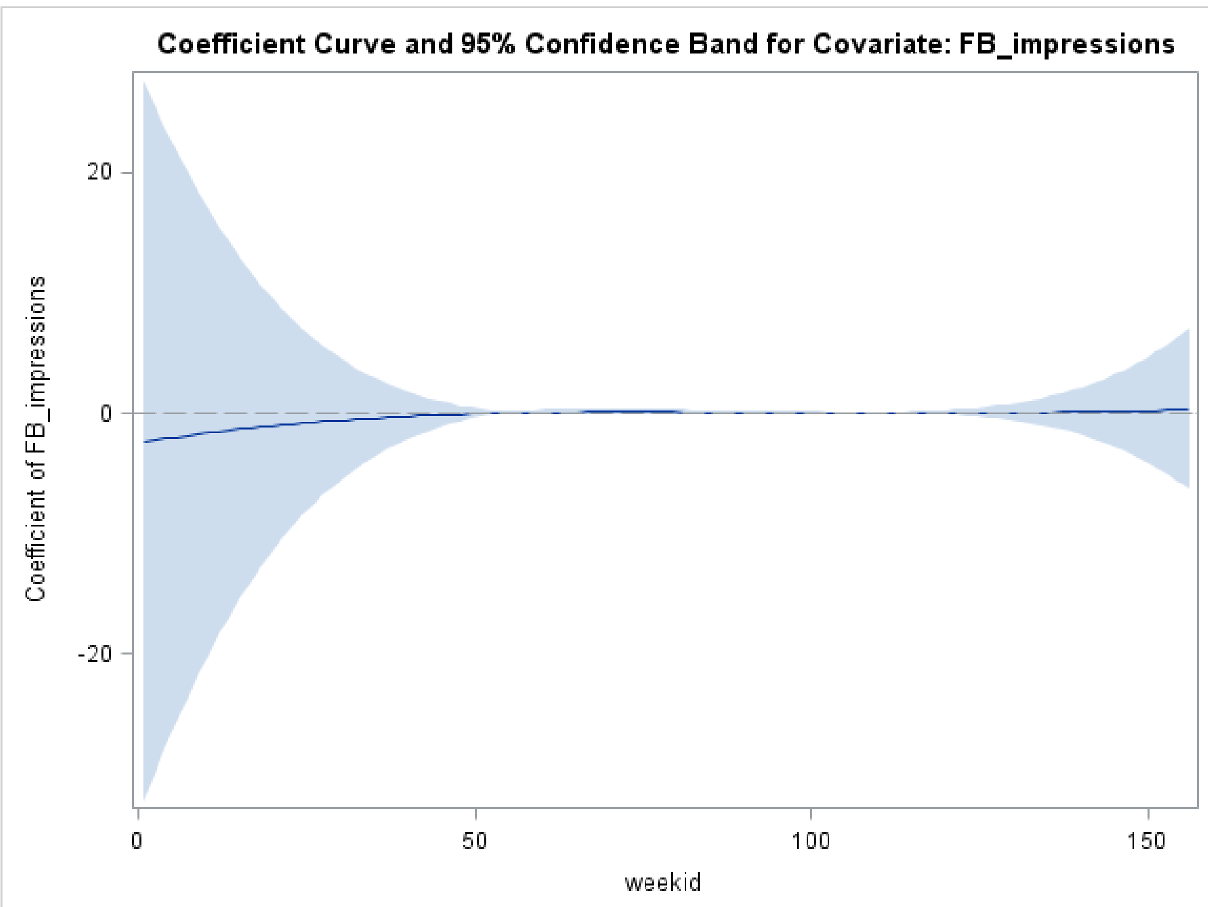
H1 assumes the price elasticity decreases over time (Figure 3). As predicted, the price elasticity of the products decreased over time during the study period. The company products were in the market for over 100 years. Therefore, a significant brand loyalty has been developed over those years. With strong brand awareness and brand loyalty, a slight change in the brand price will not affect the purchase decisions of the loyal customers. As consumers prefer the product and build brand loyalty, they become less price sensitive in their choices (Krishnamurthi & Raj, 1991). Consistent with the prior research, the slope function of the effect of price on sales decreases over time. These findings were consistent with our H1, where we predicted that the price elasticity will decrease over time.

Figure 3: Coefficient Curve and 95% Confidence Band for Covariate Price



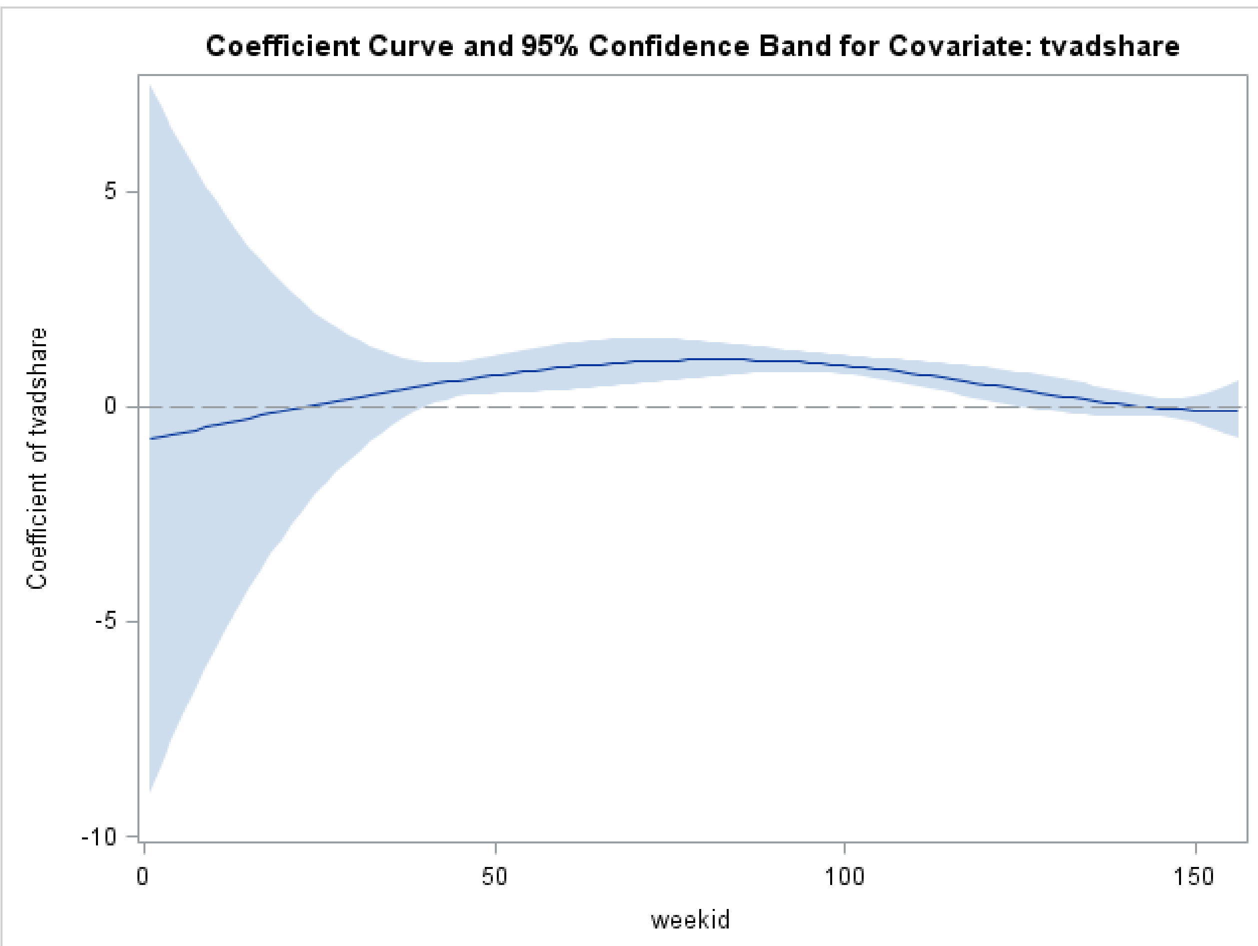
H2 specified that the effect of social media on sales increases over time. The slope function $\beta_1(\cdot)$ shows that a temporal pattern of the relationship between the Facebook Impression value and sales is almost constant, or only marginally increasing, over time (Figure 4). This result is consistent with the recent report by Gallup. Inc. (Swift, 2014). Based on a Gallup study, more than 70% of adults in the United States use social media often several times a day. However, in the survey 62% of the participants reported their purchasing decisions are not affected by the company sponsored social media pages. Consumers are not visiting the company social media pages to engage with the brand, but rather to engage with the people in their social network (Swift, 2014). Thus, the impact of social media on sales is only slightly positive over time. Also, the social media marketing concept is new to customers and the industry. It may take some more time before it can show a significant impact on the sales.

Figure 4: Coefficient Curve and 96% Confidence Band for Covariate Facebook Impressions



The share of television advertising expense (TVadshare), exhibits an increasingly positive effect on sales and peaks at around week 82. However, the effect decreases and then increases again from week 148 onwards. These results prove that our H3 assumption was accurate. Figure 5 shows that the effect of in-store marketing cost is oscillating over time, but, consistently exhibits a positive impact on sales.

Figure 5: Coefficient Curve and 95% Confidence Brand for Covariate Television Advertising Share



H4 assumes the effect of in-store marketing increases over time. The coefficient functions of the interaction variables show that the effect of in-store marketing is slightly increasing over time as the television advertising share is increasing (Figure 6). The combined effect of television advertising and in-store marketing has a positive impact on ice cream sales (Figure 7). The interaction variables against the product category (Cat×ln(instore)) indicates that the effect of in-store marketing is increasing over time for premium ice creams (Figure 8). Moreover, the Cat×Price variable shows that the effect of price is decreasing over time for premium ice creams (Figure 9).

Figure 6: Coefficient Curve and 95% Confidence Band for Covariate Log of In-Store Marketing

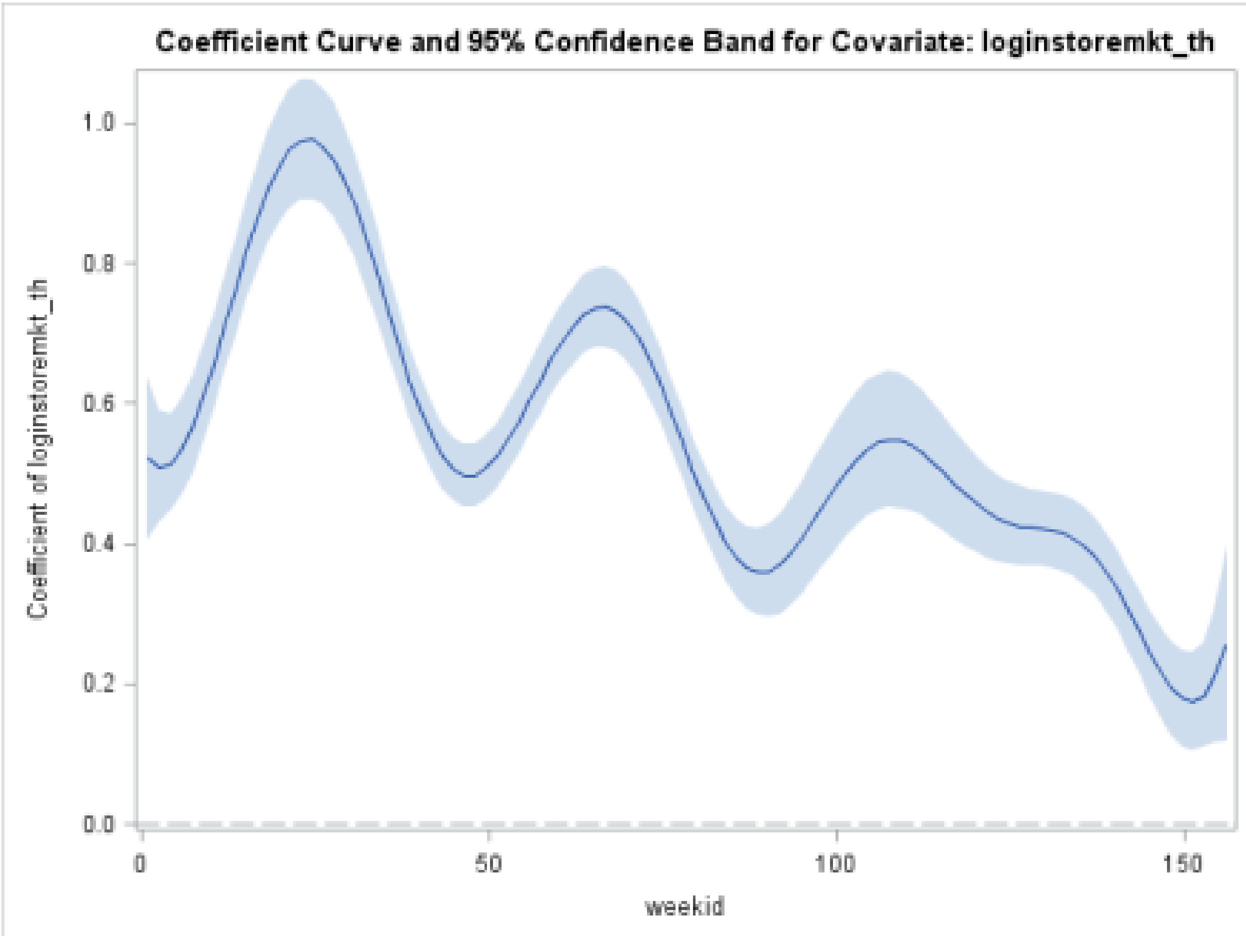


Figure 7: Coefficient Curve and 95% Confidence Band for Covariate Television Advertising Share and Log of In-Store Marketing

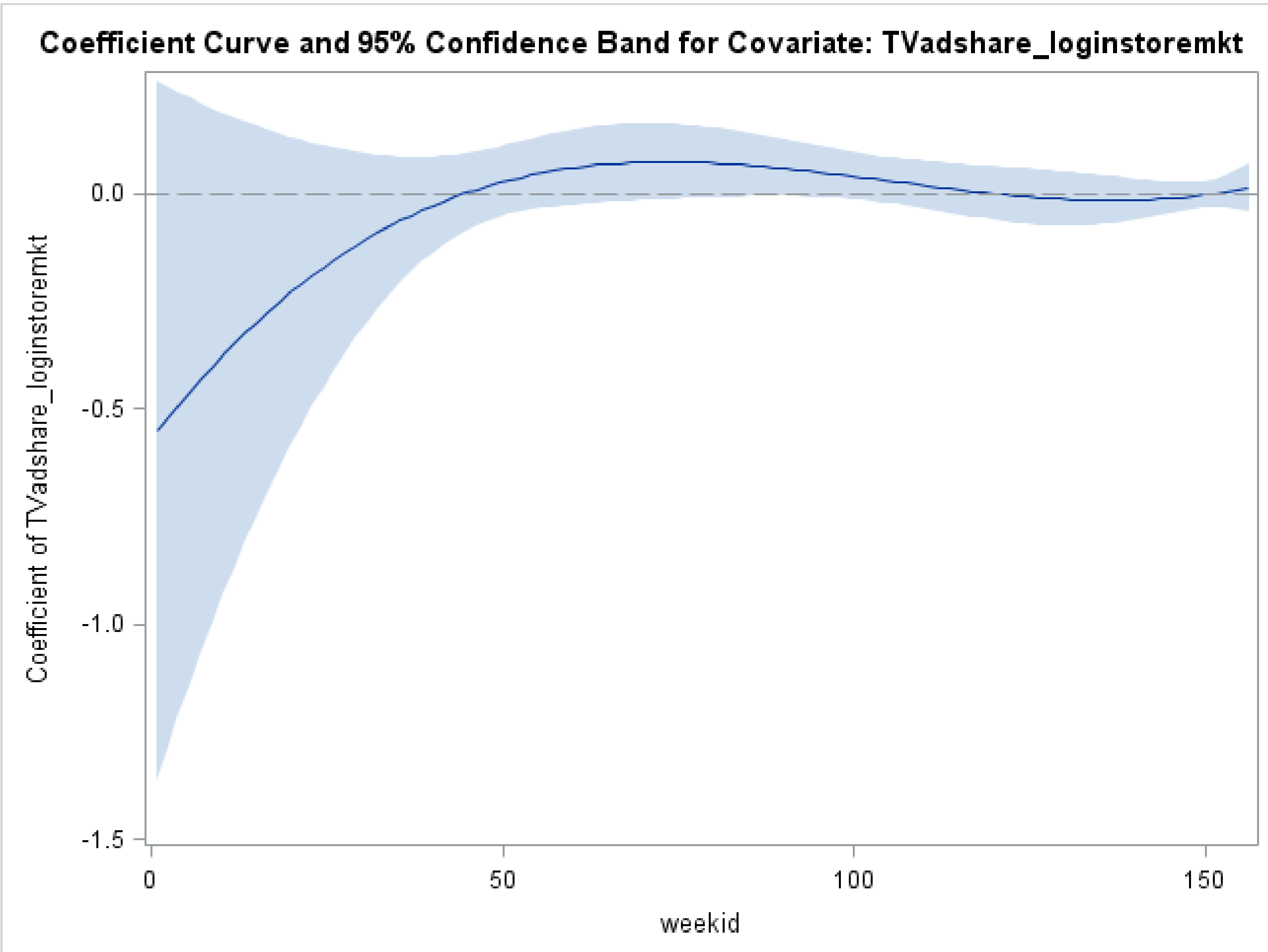


Figure 8: Coefficient Curve and 95% Confidence Band for Covariate Category log of In-Store Marketing

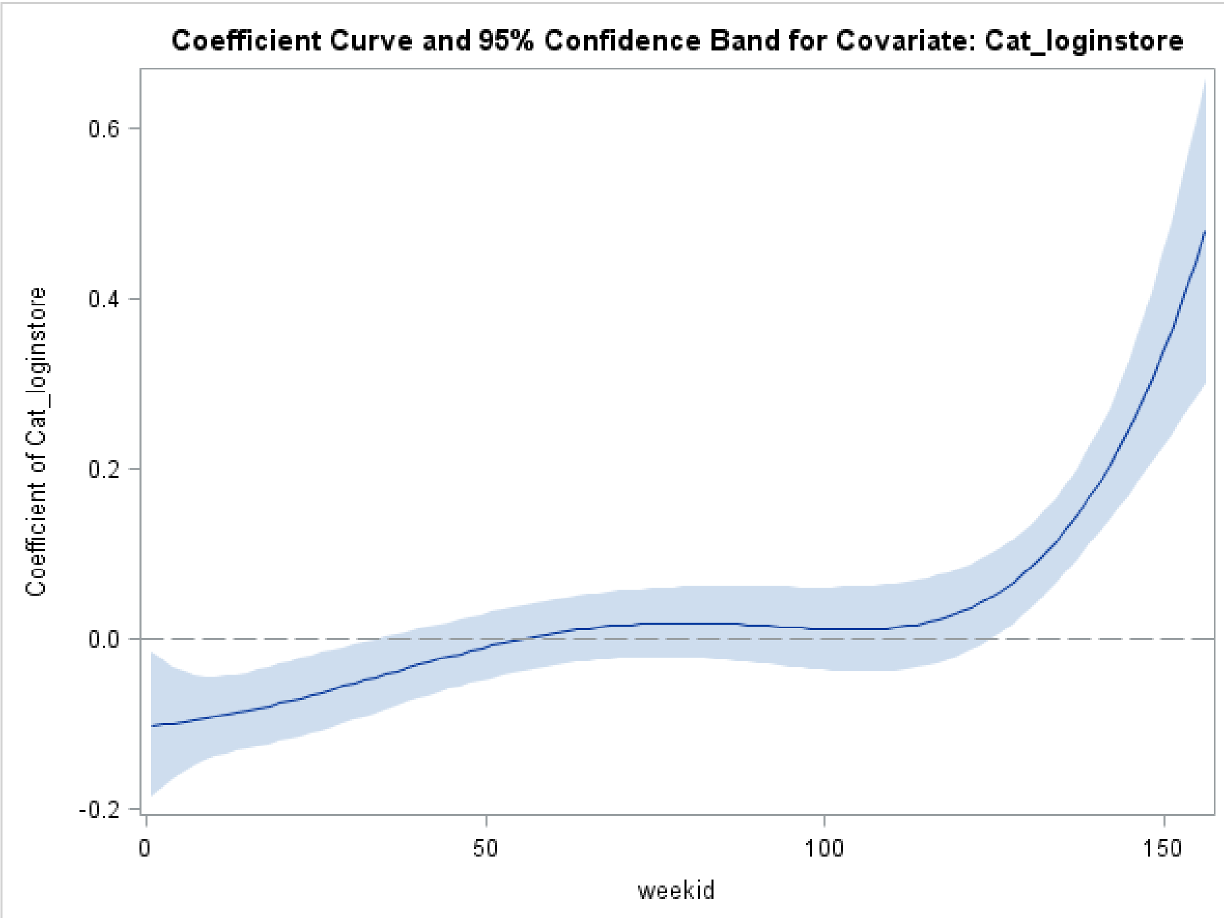


Figure 9: Coefficient Curve and 95% Confidence Band for Covariate Category Price

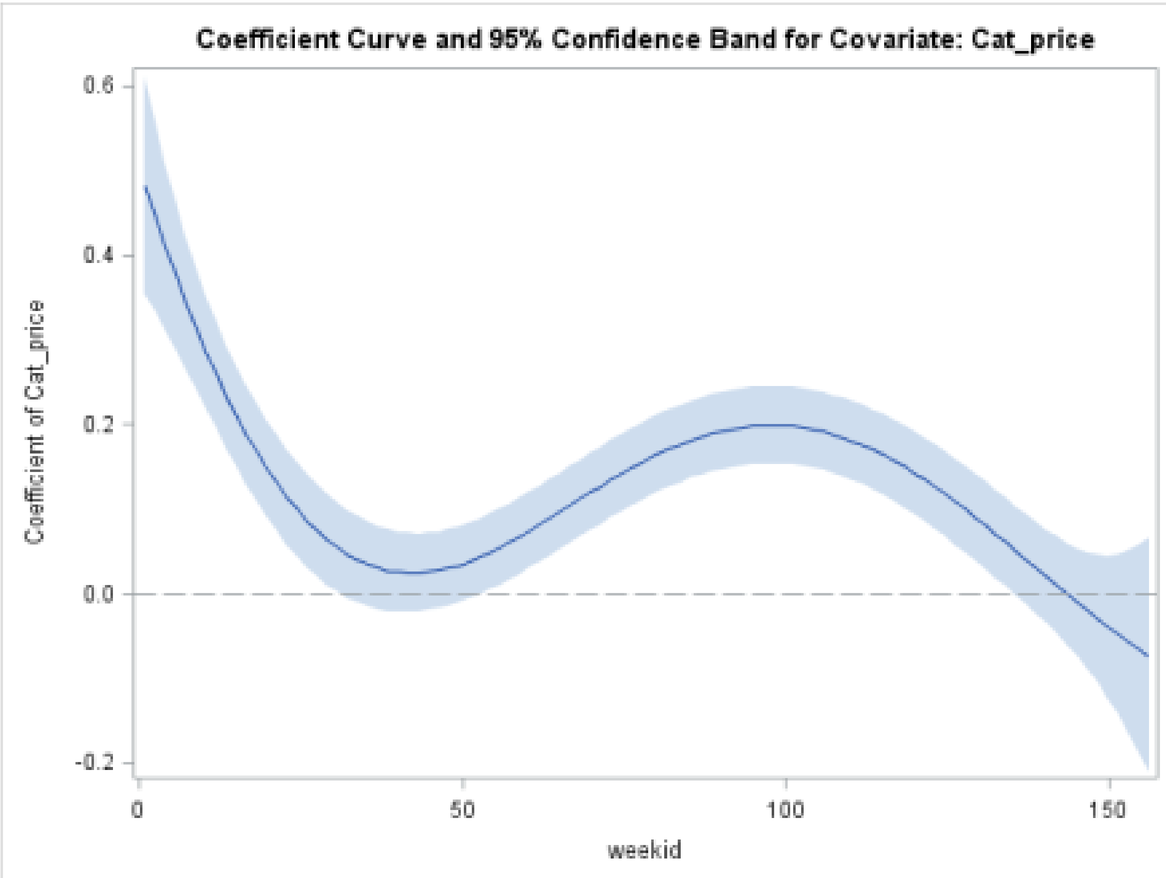


Table 10: Parameter estimates of Time-Varying Effect Model for time-invariant covariates

Variable	Parameter Estimate		Standard Error
Cat	0.31621	***	0.04271
Br1	1.1127	***	0.04271
Br2	-0.91023	***	0.0565
Br3	0.04488		0.0565
Ch1	0.59194	***	0.04271
Ch2	1.01616	***	0.04271
Season	0.00155		0.03849
Notes: * p < 0.10; ** p < 0.05; *** p < 0.01.			

Equation (2) includes time-invariant covariates for product specific variables and seasonality, whose effect remains static over time. The parameter estimates for time-invariant variables are summarized in Table 10. Compared to the static regression parameter estimates, in which all covariates are time constant, the time-invariant parameter estimates of TVEM are smaller or insignificant. The product category (Cat), channel effects (Ch1 and Ch2), and seasonality (Season) variables had lower parameter estimates than the static-regression results. As for brand variables all three brands had more positive parameter estimates than those of the static regression. Finally, brand 3 and seasonality were statistically insignificant, even at 10% level.

The plots of coefficient functions (Figures 2 to 8) provide visual representations of how the effects of variables are not static, but changing over time. Compared to the static-regression model, the dynamic model, such as the time-varying effect model, better illustrates the relationship between the covariates and dependent variables.

5.4 Predictive Validity

In order to validate the superiority of the dynamic TVEM model, we provide the predictive accuracy of the TVEM model against the static-regression model. We used the first 140 weeks of data to obtain the parameter estimates of both static and dynamic models. As for the time-varying covariates in Equation (2), we used the parameter estimate values at week 140. We then used the estimates to predict sales for the following 16 weeks. Finally, we compared the predicted sales to the actual sales. We computed the mean absolute percentage error (MAPE) [1] and the mean absolute deviation (MAD)[2] for both regression and the time-varying effect model to compare the prediction accuracy of both models (Table 11).

Table 11: Predictive Accuracy by Model Types

Predictive Measure	Static Regression Model	Time-varying Effect Model
Mean Absolute Percentage Error	0.59	0.22
Mean Absolute Deviation	2.23	1.06

The MAPE and MAD can be calculated as follows:

[1] Mean Absolute Percentage Error (MAPE)= $\frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{Actual\ Sales_t - Predicted\ Sales_t}{Actual\ Sales_t}\right|$

[2] Mean Absolute Deviation (MAD)= $\frac{1}{n}\sum_{t=1}^{n}|Actual\ Sales_t - Predicted\ Sales_t|$

Mean Absolute Percentage Error (MAPE) = $\frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{Actual\ Sales_t - Predicted\ Sales_t}{Actual\ Sales_t}\right|$

Mean Absolute Deviation (MAD) = $\frac{1}{n}\sum_{t=1}^{n}|Actual\ Sales_t - Predicted\ Sales_t|$

H5 predicts that TVEM has the better predictability than the static-regression model. Based on the regression model, the mean absolute percentage difference between actual sales and predicted sales was around 58% (MAPE) and MAD was 2.23, which is on average $9,303 absolute deviation in sales. However, TVEM was superior to regression in accurately predicting sales. The MAPE of the time-varying effect model was 22%, which is less than half of the regression model's MAPE. Moreover, MAD was 1.06, which is on average $2,906 absolute deviation in sales. The results in Table 11 provide strong evidence supporting H5 that the time-varying effect model has better predictive power than the regression model.

CHAPTER 6.0: CONCLUSIONS

In this section, the study conclusions based on the results, recommendations to the industry, implications of the study findings, and finally the study limitations are presented in detail.

6.1 Conclusions:

It is the first study that has conducted marketing mix modeling using a large ice cream manufacturing company in the USA. It is also the first study to use time-varying effects model to capture the dynamic effects of marketing mix elements on sales in the Ice Cream Industry. Similar to the findings in the literature, the price elasticity to the brands were decreasing over time during the study period. This effect is mainly due to customer brand awareness and brand loyalty, and in course of time, they become insensitive to slight changes in the prices of the brands.

The effect of Facebook media on sales has a marginal improvement over time. One of the main possible reasons for this result would be the saturation of the advertising through Facebook for ice cream products from this large manufacturer. As the cost of advertising and maintaining Facebook will be minimal compared to other major advertising spending, a marginal improvement in sales over time should translate into a higher return on investment. The impact of television advertising on the company's brands has a significant positive impact on sales. However, the impact of television advertising on sales will be constant over time.

The effect of in-store marketing cost fluctuated over time, but consistently exhibited a positive impact on sales. TVEM is an excellent model to study the relationship between various factors on the outcome in intensive longitudinal data set studies. It adds a third dimension to the model, which is time. The MAPE and MAD of the time-varying effect model was less than half of the regression model's MAPE and MAD. Therefore, the time-varying effect model has better predictive power than the static-regression model

6.2 Recommendations:

The impact of social media on sales is slightly positive over time. Given the cost of advertising and maintaining Facebook pages is lower than other advertising expenses, it is advised to continue to invest in social media marketing for ice cream products in U.S.A. The effect of in-store marketing for premium ice cream on sales is increasing over time. Therefore, continued investment in the in-store marketing activities for premium ice cream will lead to a higher return on sales in the long run.

Generally, during off-peak sales time and competition from big players in the market, marketing managers recommend a decrease of brand prices to boost their sales. Given that the fundamental goal of the company is to increase value growth of their brands, and the price elasticity decreased over time in this study, therefore, decreasing the price of the brand is not recommended. As the company products were in the market for a long time and brand loyalty to company products was high, a slight increase in the price of the products may not impact the sales. The other marketing activities such as television advertising, in-store marketing and social medial advertising helps the build brand awareness and loyalty and will decrease the price elasticity to the product over time.

6.3 Implications:

This study enhanced our understanding of varying marketing mix elements on ice cream sales. It also contributed to the literature by investigating the effects of various marketing mix elements on ice cream sales using the time-varying effects model. The predictive validity of the time-varying effects model is twice that of the static-regression model. Therefore, using the time-varying effects model to study marketing mix elements, in comparison to the traditional static-regression model is very valuable to the ice cream industry. Further research should be conducted, comparing the time-varying effects model with other types of models to determine its superiority in intensive longitudinal data set studies.

The ice cream market is a high-volume sales and low-margin area. Therefore, competitor rivalry tends to be high. The big supermarket chains, generally, have strong buyer power and may exert pressure on ice cream manufacturers for better deals (Ice Cream Industry Profile: United States, 2013). If the manufacturer has a better brand awareness and brand loyalty, the negotiating power of big supermarket chains will reduce. Based on the study findings, a slight increase in the price of a brand(s) will not impact the overall sales, if the brand has good brand awareness and brand loyalty. In addition, the company can increase its brand price, even though there is competitive rivalry among various ice cream manufacturers and high negotiating power from big supermarket chains. Conducting marketing mix modeling regularly, to measure the effectiveness of past marketing activities, will be a better approach than allocating resources purely based on the demand from the respective department within the company.

The effect of in-store marketing of a particular brand increases over time. Therefore, if the manufacturer of a brand has good in-store marketing plans in place, it can increase the impulse purchases made by customers. In addition, it can increase the brand awareness through multi-channel advertising and marketing, and reduce the big supermarket negotiating power. These activities should increase the brands' overall sales.

6.4 Limitations:

We could use for the first 148 weeks of data to predict sales for the next 16 weeks. If we had a longer data set for the hold up, that is more than 16 weeks, to compare our estimates, it would have been valuable, to assess the predictive validity of the model. This is the first time a TVEM has been used to conduct marketing mix modeling. Further studies in this area are required to validate the model's real-world usability. The TVEM needs to be compared with other types of models to validate its predictability.

CHAPTER 7.0: REFERENCES

Aichner, T., & Perkmann, U. (2013). Social media: opportunities and risks for regional market research. [Opinion]. *International Journal of Market Research, 55*(5), 609-610. doi: 10.2501/ijmr-2013-055

Anselmsson, J., Johansson, U., & Persson, N. (2007). Understanding price premium for grocery products: a conceptual model of customer-based brand equity. *Journal of Product & Brand Management, 16*(6), 401-414.

Bair, J. (2009). Firms sponsor major teams to dish out branding success. [Article]. *Central Penn Business Journal, 25*(16), 1.

Blattberg, R. C., Briesch, R., & Fox, E. J. (1995). How promotions work. *Marketing Science, 14*(3 supplement), G122-G132.

Bolton, R. N., Lemon, K. N., & Verhoef, P. C. (2004). The theoretical underpinnings of customer asset management: a framework and propositions for future research. *Journal of the Academy of Marketing Science, 32*(3), 271-292.

Brands Update the Ice Cream Social. (2010). [Article]. *Dairy Foods, 111*(12), 10-12.

Briesch, R. A., Krishnamurthi, L., Mazumdar, T., & Raj, S. P. (1997). A comparative analysis of reference price models. *Journal of Consumer Research, 24*(2), 202-214.

Bucklin, R. E., & Schmalensee, D. H. (1987). *Viewpoints on the changing consumer goods distribution scene: summary of a Marketing Science Institute conference, May 19 and 20, 1987*: The Institute.

Carper, J. (2013). That's how you sell milk. [Article]. *Dairy Foods, 114*(10), 66.

Chandon, P., Hutchinson, J. W., Bradlow, E. T., & Young, S. H. (2009). Does In-Store Marketing Work? Effects of the Number and Position of Shelf Facings on Brand

Attention and Evaluation at the Point of Purchase. [Article]. *Journal of Marketing, 73*(6), 1-17. doi: 10.1509/jmkg.73.6.1

Chandon, P., Wansink, B., & Laurent, G. (2000). A benefit congruency framework of sales promotion effectiveness. *The Journal of Marketing*, 65-81.

Chelliah, S., Chin Kok, K., Annamalah, S., & Munusamy, J. (2013). Does Marketing Mix Still Relevant? A Study on Herbal Coffee in Malaysia. [Article]. *International Journal of Management & Innovation, 5*(1), 31-45.

Chen, H.-C., & Green, R. (2009). Marketing mix and branding: competitive hypermarket strategies. *International Journal of Management and Marketing Research, 2*(1), 17-34.

Chu, W. (1992). Demand signalling and screening in channels of distribution. *Marketing Science, 11*(4), 327-347.

Clark, M. N., & Mashburn, K. P. (2013). Consumer Motivation to Engage in Social Media Communications. [Article]. *Society for Marketing Advances Proceedings, 25*, 172-173.

Daniel, F. (2010). Head of Wal-Mart tells WFU audience of plans for growth over next 20 years Retrieved November 10th, 2013, from http://www.journalnow.com/business/article_5ad539d5-d616-55ba-ab27-aeaf45b06074.html

Davis, C., Blayney, D., Yen, S., & Cooper, J. (2009). An analysis of at-home demand for ice cream in the United States. *Journal of dairy science, 92*(12), 6210-6216.

Deleersnyder, B., Geyskens, I., Gielens, K., & Dekimpe, M. G. (2002). How cannibalistic is the Internet channel? A study of the newspaper industry in the United Kingdom and the Netherlands. *International Journal of Research in Marketing, 19*(4), 337-348.

Etgar, M. (1976). Channel domination and countervailing power in distributive channels. *Journal of Marketing Research*, 254-262.

Extending Its Reach. (2011). [Article]. *Dairy Foods, 112*(10), 59.

Frozen Yogurt Sales Grow Nearly 75%. (2013). [Article]. *Nutraceuticals World, 16*(9), 14-14.

Gaski, J. F. (1984). The theory of power and conflict in channels of distribution. *The Journal of Marketing*, 9-29.

Gilbride, T. J., & Allenby, G. M. (2004). A choice model with conjunctive, disjunctive, and compensatory screening rules. *Marketing Science, 23*(3), 391-406.

Global Ice Cream. (2013). [Article]. *Ice Cream Industry Profile: Global*, 1-36.

The Greater Good. (2011). [Article]. *Dairy Foods, 112*(8), 95.

Greenleaf, E. A. (1995). The impact of reference price effects on the profitability of price promotions. *Marketing Science, 14*(1), 82-104.

Gupta, S., & Cooper, L. G. (1992). The discounting of discounts and promotion thresholds. *Journal of Consumer Research*, 401-411.

Gupta, S., & Steenburgh, T. (2008). Allocating Marketing Resources. In R. Kerin & R. O'Regan (Eds.), *Marketing Mix Decisions: New Perspectives and Practices*. Chicago: American Marketing Association.

Han, S., Gupta, S., & Lehmann, D. R. (2002). Consumer price sensitivity and price thresholds. *Journal of Retailing, 77*(4), 435-456.

Hastie, T., & Tibshirani, R. (1993). Varying-Coefficient Models, 757.

Hausman, A. (2000). A multi-method investigation of consumer motivations in impulse buying behavior. *Journal of consumer marketing, 17*(5), 403-426.

Hruschka, H. (2000). Specification, Estimation, and Empirical Corroboration of Gutenberg's Kinked Demand Curve *Theory of the Firm* (pp. 153-168): Springer.

Ice Cream. (2013) Retrieved November 24th, 2013, from http://en.wikipedia.org/wiki/Ice_cream

Ice Cream Industry Profile: United States. (2013). [Article]. *Ice Cream Industry Profile: United States*, 1-36.

International Dairy Foods Association Ice Cream Company Survey. (2012) Retrieved November 24th 2013, from http://www.idfa.org/

Kalyanam, K., & Shively, T. S. (1998). Estimating irregular pricing effects: A stochastic spline regression approach. *Journal of Marketing Research*, 16-29.

Kalyanaram, G., & Little, J. D. (1994). An empirical analysis of latitude of price acceptance in consumer package goods. *Journal of Consumer Research*, 408-418.

Kalyanaram, G., & Winer, R. S. (1995). Empirical generalizations from reference price research. *Marketing Science, 14*(3 supplement), G161-G169.

Kennedy, S. (2014). Frozen yogurt melts the competition. [Article]. *Dairy Foods, 115*(1), 44-44.

Kopalle, P. K., Mela, C. F., & Marsh, L. (1999). The dynamic effect of discounting on sales: Empirical analysis and normative pricing implications. *Marketing Science, 18*(3), 317-332.

Krishnamurthi, L., Mazumdar, T., & Raj, S. (1992). Asymmetric response to price in consumer brand choice and purchase quantity decisions. *Journal of Consumer Research*, 387-400.

Krishnamurthi, L., & Raj, S. P. (1991). An empirical analysis of the relationship between brand loyalty and consumer price elasticity. *Marketing Science, 10*(2), 172-183.

Kumar, V. (2008). Optimal Allocation of Marketing Mix Resources. In R. Kerin & R. O'Regan (Eds.), *Marketing Mix Decisions: New Perspectives and Practices*. Chicago: American Marketing Association.

Kumar, V., Hurley, M., Karande, K., & Reinartz, W. J. (1998). The impact of internal and external reference prices on brand choice: the moderating role of contextual variables. *Journal of Retailing, 74*(3), 401-426.

Lamey, L., Deleersnyder, B., Dekimpe, M. G., & Steenkamp, J.-B. E. (2007). How business cycles contribute to private-label success: evidence from the United States and Europe. *Journal of Marketing*, 1-15.

Lipsman, A., Mudd, G., Rich, M., & Bruich, S. (2012). The Power of" Like": How Brands Reach (and Influence) Fans through Social-Media Marketing. *Journal of advertising research, 52*(1), 40.

Manchester, A. C., & Blayney, D. P. (1997). Structure of Dairy Markets: Past, Present, Future: United States Department of Agriculture, Economic Research Service.

Marn, M. V., Roegner, E. V., & Zawada, C. C. (2003). Pricing new products. *McKinsey Quarterly*(3), 40-49.

. Mars Incorporated.   Retrieved February 4th, 2014, from www.wikipedia.org

Mazumdar, T., & Monroe, K. B. (1990). The effects of buyers' intentions to learn price information on price encoding. *Journal of Retailing*.

Mazumdar, T., & Papatla, P. (2000). An investigation of reference price segments. *Journal of Marketing Research*, 246-258.

McCarthy, E. J. (1960). Basic marketing: a managerial approach. Homewood, IL: Richard D. Irwin: Inc.

McKinsey&Co. (2009). The Crisis: A New Era in Management. *McKinsey Quarterly, 45*(1), 1-156.

Mela, C. F., Jedidi, K., & Bowman, D. (1998). The long-term impact of promotions on consumer stockpiling behavior. *Journal of Marketing Research*, 250-262.

Munnukka, J. (2006). Pricing method as a tool for improved price perception. *Journal of revenue and pricing management, 5*(3), 207-220.

Pauwels, K., Srinivasan, S., & Franses, P. H. (2007). When Do Price Thresholds Matter in Retail Categories? [Article]. *Marketing Science, 26*(1), 83-100.

Peterson, R. A. (1970). The price-perceived quality relationship: experimental evidence. *Journal of Marketing Research, 7*(4), 525-528.

Pierre's Ice Cream Company. Retrieved February 4th, 2014, from www.wikipedia.org

Raising the Bar. (2012). [Article]. *Dairy Foods, 113*(2), 53-56.

Rajendran, K. N., & Tellis, G. (1994). Contextual and temporal components of reference price. *Journal of Marketing, 58*, 22-34.

Russell, J., & Cohn, R. (2012). *Marketing Mix Modeling*: Lennex Corp.

Rust, R. T., Lemon, K. N., & Zeithaml, V. A. (2004). Return on marketing: using customer equity to focus marketing strategy. *Journal of Marketing*, 109-127.

Schlinke, J., & Crain, S. (2013). Social Media from an Integrated Marketing and Compliance Perspective. [Article]. *Journal of Financial Service Professionals, 67*(2), 85-92.

Sethuraman, R., & Cole, C. (1999). Factors influencing the price premiums that consumers pay for national brands over store brands. *Journal of Product & Brand Management, 8*(4), 340-351.

Shugan, S. M. (2003). Editorial: Defining interesting research problems. *Marketing Science, 22*(1), 1-15.

Slotting Fee. (2013) Retrieved November 24th, 2013, from http://en.wikipedia.org/wiki/Slotting_fee

Smith, W. R. (1956). Product differentiation and market segmentation as alternative marketing strategies. *The Journal of Marketing, 21*(1), 3-8.

Srinivasan, R., Rangaswamy, A., & Lilien, G. L. (2005). Turning adversity into advantage: does proactive marketing during a recession pay off? *International Journal of Research in Marketing, 22*(2), 109-125.

Sullivan, M. W. (1997). Slotting Allowances and the Market for New Products 1. *The Journal of Law and Economics, 40*(2), 461-494.

Swift, A. (2014). Americans Say Social Media Have Little Sway on Purchases Retrieved June 26th 2014

Tan, X., Shiyko, M. P., Li, R., Li, Y., & Dierker, L. (2012). A time-varying effect model for intensive longitudinal data. *Psychological methods, 17*(1), 61.

Trout, J. (2005). Branding can't exist without positioning. *Advertising Age, 14*, 2005.

Turkey Hill. Retrieved February 4th, 2014, from www.wikipedia.org

Turner, C., & Lester, R. (2007). TV ads still top the ratings. (cover story). [Article]. *Marketing Week, 30*(45), 22-25.

Umpqua Dairy History. Retrieved February 4th, 2014, from www.umpquadairy.com

Van Heerde, H. J., Gijsenberg, M. J., Dekimpe, M. G., & Steenkamp, J.-B. E. M. (2013). Price and Advertising Effectiveness over the Business Cycle. [Article]. *Journal of Marketing Research (JMR), 50*(2), 177-193.

Van Heerde, H. J., Leeflang, P. S., & Wittink, D. R. (2001). Semiparametric analysis to estimate the deal effect curve. *Journal of Marketing Research*, 197-215.

Venkatesan, R., Kumar, V., & Bohling, T. (2007). Optimal customer relationship management using Bayesian decision theory: an application for customer selection. *Journal of Marketing Research*, 579-594.

Webster Jr, F. E. (1992). The changing role of marketing in the corporation. *The Journal of Marketing*, 1-17.

Wertenbroch, K. (1998). Consumption self-control by rationing purchase quantities of virtue and vice. *Marketing Science, 17*(4), 317-337.

CHAPTER 8.0: APPENDIX

APPENDIX 8.1: Definitions of Frozen Dessert Products

- **Ice Cream** consists of a mixture of dairy ingredients such as milk and nonfat milk, and ingredients for sweetening and flavoring, such as fruits, nuts and chocolate chips. Functional ingredients, such as stabilizers and emulsifiers, are often included in the product to promote proper texture and enhance the eating experience. By federal law, ice cream must contain at least 10% milk fat, before the addition of bulky ingredients, and must weigh a minimum of 4.5 pounds to the gallon.
- **Frozen Custard** or **French Ice Cream** must also contain a minimum of 10% milk fat, as well as at least 1.4 % egg yolk solids.
- **Sherbets** have a milk fat content of between 1% and 2%, and a slightly higher sweetener content than ice cream. Sherbet weighs a minimum of 6 pounds to the gallon and is flavored either with fruit or other characterizing ingredients.
- **Gelato** is characterized by an intense flavor and is served in a semi-frozen state that is similar to "soft serve" ice cream. Italian-style gelato is more dense than ice cream, since it has less air in the product. Typically, gelato has more milk than cream and also contains sweeteners, egg yolks and flavoring.
- **Sorbet** and **Water Ices** are similar to sherbets, but contain no dairy ingredients.
- A **Quiescently Frozen Confection** is a frozen novelty such as a water ice novelty on a stick.
- **Frozen Yogurt** consists of a mixture of dairy ingredients such as milk and nonfat milk which have been cultured, as well as ingredients for sweetening and flavoring.

- **Novelties** are separately packaged single servings of a frozen dessert -- such as ice cream sandwiches, fudge sticks and juice bars -- that may or may not contain dairy ingredients.
- **Reduced fat ice cream** contains at least 25% less total fat than the referenced product (either an average of leading brands, or the company's own brand).
- **Light ice cream** contains at least 50% less total fat or 33% fewer calories than the referenced product (the average of leading regional or national brands).
- **Low-fat ice cream** contains a maximum of 3 grams of total fat per serving (½ cup).
- **Nonfat ice cream** contains less than 0.5 grams of total fat per serving.
- **Super-premium ice cream** tends to have very low overrun and high fat content, and the manufacturer uses the best quality ingredients.
- **Premium ice cream** tends to have low overrun and higher fat content than regular ice cream, and the manufacturer uses higher quality ingredients.
- **Regular ice cream** meets the overrun required for the federal ice cream standard.
- **Economy ice cream** meets required overrun and generally sells for a lower price than regular ice cream.

APPENDIX 8.2: Company Specific Various Marketing and Advertising Activities

Company Name	Products	Traditional Marketing Activities (TV, Print, Radio etc)	Non-Traditional Marketing Activities (Social Media, Digital online, etc)	Unique Marketing Activities
Mars, Inc	Snickers, Dove, Twix, Bounty, Galaxy and Malteser	Television, Print, coupons at Target and 7-Eleven.	Dove ice cream has own Facebook page with over 70K likes	– Summer Movie Mania – Movie Voucher for year, and $9 coupon in movie cash program in clubs, c-stores, drug stores, grocery stores and mass channels. – Summer Ice Cream Trucks - massages and nail treatments for female adult loyal consumers. – Sponsored National Football

				League and featured at Super Bowl. – Sponsored trips to NFL
Pierre's Ice Cream Company	Pierre, Hola Fruta and Yovation	Radio advertising, in-store specials, promotions and free-standing inserts	Facebook page	– Participates in local events and charities and provides free sampling and couponing – Promotes sugar free ice cream during Juvenile Diabetes Research Foundation Walk to Cure Diabetes – Ice cream weekend event
Umpqua Dairy	Umpqua premium ice cream, lite ice cream, sherbet, non-fat frozen yogurt, no-sugar	Television, Radio, Point of Sale advertising, Billboards, Newspaper and In-Store demonstrations.	– Facebook page and facebook logo printed on the product seal.	

	added ice cream and university ice cream		– YouTube channel	
Greater's	Black Raspberry Chocolate Chip, Sorbet, Oregon Field Strawberry, Summer Peach, Caramel Truffle and Chocolate Chip	– Word-of-Mouth, direct mail and public relations – Products were promoted on TV shows	Facebook and Twitter	Major sponsor of "The Cure Starts Now Foundation"
Turkey Hill Dairy	Premium Ice Cream, Stuff'd, All Natural, Light Ice Cream, No Sugar Added, Sherbet, and Frozen Yogurt			– One third of the marketing budget spent on sports sponsorships – Sponsored Philadelphia Phillies and developed ice cream flavor in the name of the team

				– Partnered with New York Yankees and developed Bronx Bombers Sundae and Fudgy Cookie Swirl – Sponsored Philadelphia Eagles – Partnered with minor league teams too
Stonyfield Farm	After Dark Chocolate, Crème Caramel, Gotta Have Java, Gotta Have Vanilla, Minty Chocolate Chip, Vanilla Fudge Swirl		Facebook, Foursquare, Flickr, Twitter and YouTube	– Sponsored US Open Tennis Championship – Hired contractors to tweet daily from the sports complex, upload pictures on social media sites and engaged customers about frozen brands

- Product sampling and sweepstakes at USTA Billie Jean King National Tennis Center, New York
- Created YouTube videos with Anita Renfroe
- Road Trip and stopped at college campuses and documented the tour on Facebook daily