

# Customer Targeting and Micro-Marketing in a Retail Supply Chain

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Submitted to the Department of Civil and Environmental Engineering and the Sloan School of Management in Partial Fulfillment of the Requirements for the Degrees of

Master of Business Administration  
and Master of Science in Civil and Environmental Engineering


In Conjunction with the Leaders for Manufacturing Program at the  
Massachusetts Institute of Technology  
June 2004

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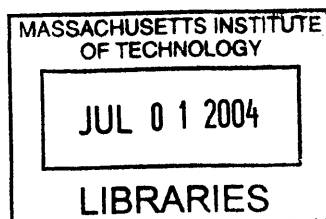
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**BARKER**



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## **Abstract**

As most companies in the consumer products space develop operational capabilities to produce and distribute high-quality low-cost products, leading firms in the industry continuously seek new ways to increase profitability and provide value to their retail partners and end consumers. While firms such as Procter & Gamble (P&G) have developed lean and flexible supply chains, this innovation has not had significant impact on the actual sale of product to the customer in individual stores.

Analysis shows that large differences in the level of consumer demand for specific products exist across retail chains. However, current practices typically treat all stores across a chain the same. This thesis presents methods to target store-level marketing levers, including product mix, promotions, pricing, distribution and inventory management levels, based on shopper demographics and past purchasing behavior. Specifically, a framework to divide large retail chains into smaller “virtual chains” and subsequently develop targeted micro-marketing strategies for these virtual chains is presented.

Research for this thesis was conducted during a six and a half month internship with P&G's Product Supply group at the Cosmetics division in Hunt Valley Maryland. The internship was affiliated with the Massachusetts Institute of Technology's Leaders for Manufacturing Program.

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## **Acknowledgements**

I would like to thank Procter & Gamble for sponsoring this work and the many people at P&G who made this project possible. In particular, I would like to thank Marc Pritchard and Carl Haney whose vision inspired this work. Bill Tarlton's daily guidance was invaluable throughout the project. Lori Ali's insights into cosmetics marketing were extremely helpful and Kelli Waldo and Aamir Mohatarem also provided invaluable assistance.

In addition, I would like to thank the Leaders for Manufacturing program for its support. In particular, I would like to acknowledge my thesis advisors Don Rosenfield and David Simchi-Levi for their insights and helpful comments.

I would like to thank my wife Amanda for her love and support throughout my time on this internship and at MIT. I've learned as much from her during this time as I have from school and work, and look forward to continuing to learn and grow together. Finally, I would like to thank my family and friends whose support sustained me throughout this project.



## Table of Contents

|  |           |
|--|-----------|
| <b>Abstract</b> .....  | <b>3</b>  |
| <b>Acknowledgements</b> .....  | <b>5</b>  |
| <b>Table of Contents</b> .....   | <b>7</b>  |
| <b>Chapter 1: Introduction</b> .....   | <b>9</b>  |
| 1.1 Project Background.....  | 9         |
| 1.2 Project Motivation .....   | 10        |
| 1.3 Project Overview .....   | 10        |
| 1.4 Background.....  | 11        |
| 1.4.1 The Procter & Gamble Company .....   | 11        |
| 1.4.2 Procter & Gamble Cosmetics.....  | 11        |
| 1.4.3 P&G Cosmetics Supply Chain.....  | 11        |
| 1.5 Thesis Organization .....  | 12        |
| <b>Chapter 2: Micro-Marketing Overview</b> .....                                   | <b>13</b> |
| 2.1 The Micro-Marketing Business Case.....   | 13        |
| 2.1.1 The Strategic Imperative of Value-Added Services .....                       | 13        |
| 2.1.2 Shopper Diversity is Increasing .....  | 14        |
| 2.1.3 Smart Customization is a Competitive Advantage .....                         | 14        |
| 2.1.4 Point-of-Sale Data is Becoming Widely Available .....                        | 16        |
| 2.2 Micro-Marketing Levers.....  | 16        |
| 2.2.1 Product .....  | 16        |
| 2.2.2 Price .....  | 17        |
| 2.2.3 Promotion.....   | 17        |
| 2.2.4 Place.....   | 18        |
| 2.3 Supply Chain Capabilities and Micro-Marketing.....                             | 18        |
| 2.3.1 Leveraging Supply Chain Capabilities to Create Value .....                   | 18        |
| 2.3.2 Supply Chain Evolution: A Comparison of the Retail and Auto Industries ..... | 19        |
| <b>Chapter 3: Identifying Virtual Chains</b> .....                                 | <b>25</b> |
| 3.1 Segmentation Strategies.....   | 25        |
| 3.1.1 Attribute-Based Clustering .....   | 25        |
| 3.1.2 Statistical Clustering.....  | 26        |
| 3.2 Cluster Analysis Overview .....  | 26        |
| 3.3 Cluster Analysis Example.....  | 27        |
| 3.4 Measuring the Distance between Objects .....                                   | 29        |
| 3.5 Choosing the Number of Clusters.....   | 30        |
| 3.6 Cluster Analysis Algorithm: The K-Median Integer Program .....                 | 33        |
| 3.7 Validation of Cluster Analysis Results .....                                   | 35        |
| <b>Chapter 4: Micro-Marketing Strategies</b> .....                                 | <b>39</b> |
| 4.1 Product Strategies .....   | 39        |
| 4.2 Price Strategies.....  | 42        |
| 4.3 Promotion Strategies.....  | 43        |
| 4.4 Place Strategies .....   | 46        |

|   |           |
|---|-----------|
| <b>Chapter 5: Procter &amp; Gamble Case Study .....</b>                     | <b>51</b> |
| 5.1 Case Study Introduction.....  | 51        |
| 5.2 Preliminary Analysis.....   | 51        |
| 5.3 Mass Retailer A Analysis.....   | 54        |
| 5.3.1 Three Cluster Scenario.....   | 54        |
| 5.3.2 Four Cluster Scenario .....   | 56        |
| 5.3.3 Ten Cluster Overview .....  | 57        |
| 5.3.4 Ten Cluster Performance Details.....                                  | 58        |
| 5.3.5 Ten Cluster Group Descriptions .....                                  | 58        |
| 5.4 Cluster Case Studies: Application of Micro-Marketing Strategies.....    | 69        |
| <b>Chapter 6: Influence of Store Attributes on Sales .....</b>              | <b>73</b> |
| 6.1 Retail Sales Drivers.....   | 73        |
| 6.2 Store Size .....  | 74        |
| 6.3 Store Location.....   | 76        |
| 6.4 Ethnicity.....  | 78        |
| <b>Chapter 7: Conclusions.....</b>  | <b>81</b> |
| 7.1 Hypothesis Revisited .....  | 81        |
| 7.2 Size of the Prize .....   | 81        |
| 7.3 Go-Forward Recommendations.....   | 82        |
| 7.3.1 Data Infrastructure .....   | 82        |
| 7.3.2 Product Mix Customization.....  | 82        |
| 7.3.3 Under-Performing Stores: In-Store Communications Recommendations..... | 83        |
| 7.3.4 Retail Inventory Management Policies.....                             | 84        |
| 7.4 General Conclusions .....   | 84        |
| <b>Appendix A – K-Median Cluster Analysis Example .....</b>                 | <b>85</b> |
| <b>Bibliography .....</b>   | <b>89</b> |



## Chapter 1: Introduction

### 1.1 Project Background

Procter & Gamble (P&G) has long been considered a leading innovator in the world of consumer packaged goods (CPG) supply chain management. In the mid-nineteen eighties, P&G and Wal-Mart popularized the concept of “channel partnerships”, an arrangement in which the consumer products manufacturer and retailer worked together to drive cost out of the supply chain and increase customer service levels to the benefit of each party.<sup>1</sup> At about the same time, P&G noticed the bull-whip effect and worked with retail partners to implement vendor managed inventory (VMI) processes and every day low pricing strategies to counter this phenomenon. In 1993, P&G redesigned its entire supply chain, a project credited with an annual savings of \$250M.<sup>2</sup> In recent years, P&G has pursued a variety of supply chain improvement initiatives both internally and within the greater retail value chain that are aimed at improving cost, lead time, flexibility, and quality.

A basic premise of each of these innovations is that, by looking at the supply chain for its products from a holistic viewpoint and focusing on improving the entire system, P&G and its supply chain partners can mutually benefit. This thesis attempts to extend this thinking to the management of individual retail locations.

Historically, consumer products manufacturers such as P&G have continuously striven to increase their shelf space in order to drive additional market share and sales within retail stores – the logic being that more space for P&G and less for competitors will allow more product(s) to be displayed and result in increased sales and market share. While shelf space is clearly an important factor in total sales to sales, obtaining additional space is a significant challenge because this space usually must be taken from other manufacturers who are following the same strategy. Given that seeking additional retail space can be a costly, time consuming, and

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<sup>1</sup> Buzzwell, Robert D. and Ortmeier, Gwen. *Channel Partnerships: A New Approach to Streamlining Distribution*. Cambridge, MA: Marketing Science Institute, 1994.

<sup>2</sup> Simchi-Levi, David, Philip Kaminsky, and Edith Simchi-Levi. *Designing and Managing the Supply Chain*. New York, NY: McGraw-Hill, 2000

potentially fruitless endeavor, consumer products manufacturers seek other methods to boost sales and profits by increasing the productivity of existing retail space.

One technique that has shown promise as a method to increase the productivity of retail space is micro-marketing. “Micro-marketing refers to the customization of price, promotion, product assortment, and service to the store-level, rather than adopting uniform marketing policies for all stores.”<sup>3</sup> The basic hypothesis of micro-marketing is that by better aligning marketing and supply chain strategies in stores with the particular market environment of that store, retailers and consumer products manufacturers can increase sales – a winning proposition for each. This thesis will discuss the use of such micro-marketing techniques in a retail supply chain and is based on research conducted at the cosmetics division of P&G.

## **1.2 Project Motivation**

For P&G’s cosmetics products, historical point-of-sale data shows that products and product lines sell at different rates in different stores throughout the United States. Many factors help explain this demand variation – shopper demographics such as age, ethnicity, and income level; geography, weather, and specific store location; retail channel type; and store size and traffic level are some explanations. Despite (increasingly) varying customer preferences, today the mix of P&G cosmetics sold in each retail chain is relatively homogenous across the chain. Micro-marketing provides a toolkit to customize marketing by store (or sub-set of stores) to maximize appeal to local shopper preferences in a way that will increase retail asset (space and inventory) productivity and ultimately sales and profits for both consumer products manufacturers and retailers.

## **1.3 Project Overview**

To achieve this objective, historical point-of-sale data, demographic data, and other store level data are analyzed to identify groups of similar stores within the larger chain that can be managed based on their unique shopper attributes. Having identified such a “virtual chain” within the larger retail chain, strategies to customize the product mix and merchandising activity for this

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<sup>3</sup> Montgomery, Alan L. "Creating Micro-Marketing Pricing Strategies Using Supermarket Scanner Data." *Marketing Science*, 16 (4), 1997: 315-337.

subset of stores are discussed. Next, the design of a micro-marketing pilot program and issues related to adopting these processes as standard business practices are described. Finally, a case study describing the application of these processes at Procter & Gamble is presented.

## **1.4 Background**

### **1.4.1 The Procter & Gamble Company**

Procter & Gamble is a \$43B manufacturer and marketer of consumer and household products. The company divides its operations into five business units including Baby and Family Care, Beauty and Feminine Care, Fabric and Home Care, Snacks and Beverages, and Health Care. In 2002, P&G conducted business in 160 countries and an estimated five billion customers used P&G products. Currently, the company's product portfolio includes thirteen brand which each boast over a billion dollars in sales per year, including such well-known brands as Bounty®, Charmin®, Crest®, Folgers®, Olay®, Pampers®, Pringles®, and Tide®.<sup>4</sup>

### **1.4.2 Procter & Gamble Cosmetics**

P&G's Cosmetics Division develops, manufacturers, and markets products under the Cover Girl and Max Factor brand names. Cover Girl is primarily a North American brand that includes a full line of beauty products for "women of all ages who want a clean, fresh and natural beauty look but don't want to spend a lot of time and money achieving it."<sup>5</sup> Max Factor is a global brand, has a strong association with the film industry, and is aimed at women who "want to look like a star."<sup>6</sup> Together, these brands comprise over a billion dollars in annual sales and maintain a US market share of over 20%. In the US, Procter & Gamble cosmetics products are sold in three primary retail channels including mass retailers such as Wal-Mart and Target, drug stores such as Walgreen's and CVS, and grocery stores such as H.E.B. and Albertson's.

### **1.4.3 P&G Cosmetics Supply Chain**

Procter & Gamble manufactures the majority of products sold in a single manufacturing facility in Maryland. The remainder of products, typically accessories that are not considered core

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<sup>4</sup> Procter & Gamble Corporate Website. P&G. 30 Oct. 2003 <<http://www.pg.com>>.

<sup>5</sup> Ibid

<sup>6</sup> Ibid

products, are outsourced to firms who specialize in whatever manufacturing technology might be required. Products are then distributed from single distribution center located in close proximity to the Maryland manufacturing. As previously alluded to, significant efforts have been made to develop more lean manufacturing and distribution operations within P&G's cosmetics business. Point-of-use deliveries of raw materials, change-over time reductions, preventive maintenance, quality initiatives, and increased investments in training human resources have reduced minimum batch sizes and consequently more than halved the manufacturing cycle time required to produce the full breadth of the cosmetics product lines. Whereas P&G previously shipped full cases of cosmetics products to retailer's distribution centers, advanced logistics systems today allow P&G to ship as a few as two units of a given product (often several weeks or more worth of store-level demand) in mixed cases destined for particular stores – enabling retailers to cross-dock P&G cosmetics and remove significant inventories from the system. These investments have paid off for P&G and their retail partners by drastically reduced the time and cost required to service customer demand. From a micro-marketing perspective, these systems provide the capabilities to cost effectively service the unique demand seen by individual stores.

### **1.5 Thesis Organization**

The rest of this thesis aims to provide an introduction to micro-marketing in the retail field and a discussion of the methods and strategies that can be employed. To begin, the strategic implications and business case for micro-marketing will be discussed to help explain the motivation for CPG firms to pursue such strategies. Next, a general overview of how firms can micro-market is provided and the importance of supply chain capabilities required to support such programs is discussed. Analysis methods used to analyze and understand shopper demand and marketing strategies that can be used to better serve that demand are then presented. Finally, case studies on the application of these methods at Procter & Gamble and lessons learned from these experiences are discussed.

## Chapter 2: Micro-Marketing Overview

### 2.1 The Micro-Marketing Business Case

There are several motivations for a retailer or consumer products manufacturer to micro-market. With the emergence of mass retailers such as Wal-Mart, the balance of power has shifted in the retail supply chain, therefore CPG firms must increasingly seek new ways to add value and defend their share of the retail pie. While the economies of scale and cost advantages of large firms such as P&G are an important advantage; CPG firms must also concentrate on meeting the needs of customers. Demographic data shows that the retail customer base is become increasingly diverse – leaving a fashion driven arena such as cosmetics open to competition from niche players that meet the needs of smaller market segments. P&G must sufficiently service these niches to fend off advances from these competitors and erosion of its market share. Finally, from a bottom line perspective, research on profitability shows that firms able to customize effectively are more profitable than those who do not.

#### 2.1.1 The Strategic Imperative of Value-Added Services

Viewed from a broader strategic perspective, the development of micro-marketing capabilities is an opportunity for CPG companies to provide value and services that will be difficult for large retailers and their private label brands to replicate. A recent estimate by *Private Label* magazine estimates that 40% of sales at Wal-Mart are private label products – a percentage that has been increasing steadily over the past decade as the quality of private label products has improved.<sup>7</sup> The growth of private label sales leads to the conclusion that the value of a brand name – the bread and butter for CPG firms such as P&G – is decreasing over time.

In order to maintain a strong strategic position in the retail value chain, CPG firms must continue to develop value-added services, such as vendor-managed inventory and quick-response programs, that benefit both the CPG firms and their retail partners. Micro-marketing provides a unique opportunity for CPG firms to leverage their intimate knowledge of product markets to

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<sup>7</sup> Feldman, Amy. "Riding the Wal-Mart Wave." *Money* Feb. 2004: 46.

both enhance the value of their brands and help develop and deliver products that will increase profits for both the firm's and their supply chain partners.

### 2.1.2 Shopper Diversity is Increasing

While a firm such as Procter & Gamble could historically produce cosmetics products targeting a Caucasian customer base and reach a larger percentage of the US population, census data and forecasts show that ethnically diverse customers are the fastest growing segment of the population – both as a percentage of the population and in terms of spending power. As shown in Figure 1, the US Hispanic population in particular is growing rapidly. As a whole, ethnic buying power increased 74% between 1990 and 1999 and a recent study of the ethnic skin care market predicts that the rate of ethnic spending on beauty care products will outpace inflation by 3% annually over the next 50 years.<sup>8</sup> If these trends play out as expected, cosmetics manufacturers would be foolish to ignore the unique requirements of these customers.

|                               | 1999 | 2050 |
|-------------------------------|------|------|
| <b>Hispanic</b>               | 11%  | 25%  |
| <b>African-American</b>       | 12%  | 14%  |
| <b>Asian/Pacific Islander</b> | 4%   | 8%   |

**Figure 1 - Ethnic Groups as a Percentage of US Population**

### 2.1.3 Smart Customization is a Competitive Advantage

A recent Booz Allen Hamilton study on “smart customization” evaluated different companies and their capability to serve fragmented demand. The study was conducted over six months with firms such as Unilever, Campbell Soup, Rohm & Haas, BP Castrol, Sprint, Ericsson, Time Warner, Hearst Magazines, Fleet, and Sun Trust.

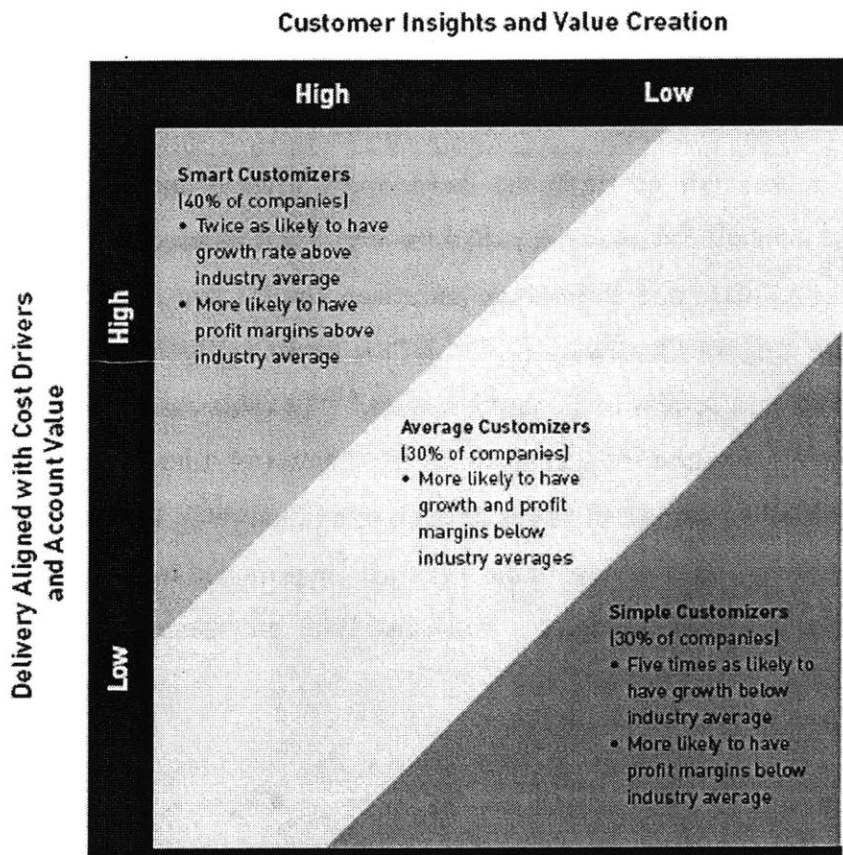
Within the group of firms studied, the authors found varying levels of sophistication with respect to the firm's ability to identify attractive market segmentation opportunities and deliver value to

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<sup>8</sup> US Census Bureau and Bitz, Karen. “The Ethnic Skin Care Market.” *Happi* Oct. 1999.

attractive segments. While they caution against undisciplined customization processes, stating that “few companies are successfully trading off the value of customization with the cost of complexity”, the authors found that firms able to customize “smartly” achieve better results. The most successful firms were able to both identify opportunities for customization and align fulfillment processes to serve these segments.

The study’s findings with regard to how companies were divided amongst the categories of “Smart Customizers”, “Average Customizers”, and “Simple Customizers” and the relative performance of each of these groups are described in Figure 2.<sup>9</sup>



**Figure 2 - Smart Customizers vs. Simple Customizers<sup>10</sup>**  
 (Source: Booz Allen Hamilton)

<sup>9</sup> Oliver, Keith, Leslie H. Moeller, and Bill Lakenan. “Smart Customization: Profitable Growth Through Tailored Business Streams.” *Strategy+Business Magazine* Spring 2004

<sup>10</sup> Ibid

#### **2.1.4 Point-of-Sale Data is Becoming Widely Available**

In terms of the information technology and data infrastructure required to implement a micro-marketing program, the widespread use of customer loyalty cards in the grocery chain has provided a significant amount of data that can be used to identify customer purchasing habits and design programs to better serve customer needs. Point of sale data for most retail chains is also available either from the retailers themselves or through information gathering and reporting firms such as IRI and AC Nielson. Indeed, studies of the retail channel show that most retailers have or are developing micro-marketing databases to track purchase, behavioral, and demographic data on customers.<sup>11</sup> The insight this data provides can be a key competitive advantage for firms who know how to analyze and use the information.

### **2.2 Micro-Marketing Levers**

There are many marketing tools available to reach the increasingly diverse and segmented customer base. In this paper, the marketing framework called the 4 P's will be used to describe some of the strategies available. Product, Price, Promotion, and Place, the P's that provide the 4 P's framework with its name, are described by Philip Kotler as "the set of marketing tools that the firm uses to pursue its marketing objectives in the target market."<sup>12</sup> In some cases, the target market Kotler refers to may include an entire sales channel. In the context of micro-marketing, however, the target market is typically a sub-set of stores or even individual retail locations. To provide familiarity with this framework, an overview of the 4 P's will be provided in this section. A more in-depth discussed of the potential strategies a micro-marketer might employ will be provided in Chapter 4.

#### **2.2.1 Product**

The product variable of the marketing mix includes all aspects of the good or service being purchased by the end consumer. Product mix, variety, quality, design, features, brand, functionality, styling, packaging, sizes, services, and warranties all are part of the "Product"

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<sup>11</sup> Lewis, Len. "Micro-Marketing." *Progressive Grocer*. Nov 1996. Vol. 75, Iss. 11; pg. 18

<sup>12</sup> Kotler, Philip. *Marketing Management: Analysis, Planning, and Control*. Upper Saddle River, NJ: Prentice Hall, 1997.



marketing variable.<sup>13</sup> While retail chains ultimately control the end decision of what to stock on their shelves, consumer products manufacturers control the other aspects. On the most basic level, consumer product manufacturers must decide what to produce and which customers this product will be targeted to. On a more operational level, as channel partnerships become stronger, retailers and manufacturers have become much more collaborative with respect to tactical choices regarding display design, product presentation, and product mix.

### **2.2.2 Price**

The second marketing variable is the retail price of the product being offered.<sup>14</sup> While the selling price of a given product is typically set by the retailer making the sale, in many cases suggested retail price or wholesale price for a product has significant influence on the final price. The consumer products manufacturer also sets the wholesale prices for their products. Sometimes, as is the case with Procter & Gamble, the CPG manufacturer might provide different levels of service, for example full-case quantity shipments vs. mixed cases (for cross-docking). Historically the use of promotional wholesale prices has been prevalent in the retail industry. Depending on how wholesale prices are set, retailers are incentivized to take different courses of action.

### **2.2.3 Promotion**

The third marketing variable is promotional activity. Promotional activity includes all actions taken to communicate with the target consumers and induce customers to purchase a firm's products.<sup>15</sup> While retailers, especially in the drug and grocery channels, often promote products by advertising sales, in an environment with strong channel partnerships the development of promotional activities is often a mutual one. Additionally, in many cases the consumer products manufacturer's continued control of their brands and media advertising ensures that they still hold significant power with regard to the promotion of products.

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<sup>13</sup> Baker, Michael J.(ed.). *The IEBM Encyclopedia of Marketing*. London, UK: International Thomson Business Press, 1999.

<sup>14</sup> Kotler, Philip. *Marketing Management: Analysis, Planning, and Control*. Upper Saddle River, NJ: Prentice Hall, 1997.

<sup>15</sup> Ibid

#### **2.2.4 Place**

Place, the final marketing variable, describes all supply chain activities taken to make a product available in the marketplace. As previously mentioned, channel partnerships have led to better coordination of the manufacturer-retailer relationship, and the improvement of operational capabilities within each organization have increased the ability to deliver and manage small amounts of product at individual retail locations. Inventory management policies at each echelon of the supply chain are also included in the “Place” marketing variable.

### **2.3 Supply Chain Capabilities and Micro-Marketing**

A high degree of supply chain sophistication is required to control and execute a micro-marketing program. Consider a micro-marketing system in which each store stocks different products, has different inventory replenishment policies, and runs different promotions. The ability to manage both the complex flow of information and physical products is crucial in such a system.

#### **2.3.1 Leveraging Supply Chain Capabilities to Create Value**

In his Harvard Business Review article, “What Is the Right Supply Chain for Your Product?” Marshall Fisher emphasizes the importance of aligning supply chain capabilities with product and demand characteristics. Fisher states “one should recognize that a supply chain performs two distinct types of functions: a physical function and a market mediation function. A supply chain's physical function invokes the traditional definition of supply chain management and includes converting raw materials into parts, components, and eventually finished goods, and transporting all of them from one point in the supply chain to the next. Less visible but equally important is market mediation, whose purpose is ensuring that the variety of products reaching the marketplace matches what consumers want to buy.”<sup>16</sup>

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<sup>16</sup> Fisher, Marshall L. “What Supply Chain is Right for Your Product?” *Harvard Business Review* Mar/Apr97, Vol. 75 Issue 2: 105

Micro-marketing represents an attempt to leverage supply chain capabilities to perform the market mediation function. The customized nature of a micro-marketing program – especially with respect to the “product” and “place” marketing levers – almost ensures an increase in supply chain complexity. Therefore, companies attempting to pursue such a strategy must also develop supply chains with the “physical function” capabilities to enable such a program. Dell Computer is perhaps the ultimate example of a firm whose physical supply chain and market mediation strategies are well aligned. The web-based sales of Dell’s configurable personal computers allows Dell to shape demand by manipulating prices and promotions, and the short lead time of Dell’s assembly process allows the firm easily deliver on the configured computers promised to customers.

Fortunately, many of recent cost savings initiatives pursued in the retail supply chains, such as vendor-managed inventory, quick-response replenishment systems, cross-docking, and lean manufacturing, provide the flexibility and speed capabilities firms will need to enable micro-marketing. These capabilities allow firms to develop new products quickly and distribute and manufacture products in low volumes. Beyond cost savings, the trick for consumer products firms will be to use these capabilities to increase revenues. Micro-marketing provides a framework by which retailers and manufacturers can leverage these operational capabilities not just to cut costs, but to drive increased top-line sales volume.

### **2.3.2 Supply Chain Evolution: A Comparison of the Retail and Auto Industries**

The historical development of supply chain capabilities in the automobile industry provides an interesting parallel to the evolution of the retail supply chain. Many of the supply chain and manufacturing philosophies being applied today in retail supply chains – such just-in-time manufacturing – were first popularized in the automotive industry. In this section, the development of operational capabilities in the two industries and the potential future of retail supply chain evolution are discussed.

In the early days of the auto industry, craftsmen built individual cars in low volumes to custom specifications. Henry Ford soon realized that by taking advantage of massive economies of scale, he could produce comparatively high quality cars at an extremely low cost. When Ford unleashed these low-cost, acceptable quality cars on the market, prices fell dramatically and most craft production shops disappeared. While prices were lower, the disappearance of the craft production shop and rise of mass production also led to a marked decrease in the amount of variety available to customers. Henry Ford's famous quote that "you can get it in any color you want, as long as it's black" illustrates this point.

In a retail trend comparable to Fordism, Wal-Mart and other so called "big box" retailers have developed efficient supply chains and used huge economy-of-scale advantages to slash prices and dominate retail markets – driving many of their smaller "mom and pop" competitors, which were analogous in many ways to the craft production shops of the auto industry, out of business. "Historically, there has been a trend by retailers to consolidate stores into large national and regional chains. This move towards consolidation has been driven by the economies of scale associated with these larger operations." remarks Professor Alan Montgomery of the Carnegie Mellon Graduate School of Industrial Administration. However, similar to auto companies embracing Ford's version of mass production, Montgomery also notes that as they came to dominate the market "some of these large chains have lost the adaptability of independent neighborhood stores."<sup>17</sup>

As automobile buyers became used to the low-cost cars provided by Ford's mass production system, General Motors was eventually able to out compete Ford by combining Ford's massive production efficiencies with effective market segmentation strategies. The lineup of GM brands - Chevrolet, Pontiac, Oldsmobile, Buick, and Cadillac – was clearly based upon socioeconomic lines and allowed GM to capture market share in each segment. To maintain economies of scale, GM combined many functions involved in the design and delivery of these different product lines.<sup>18</sup>

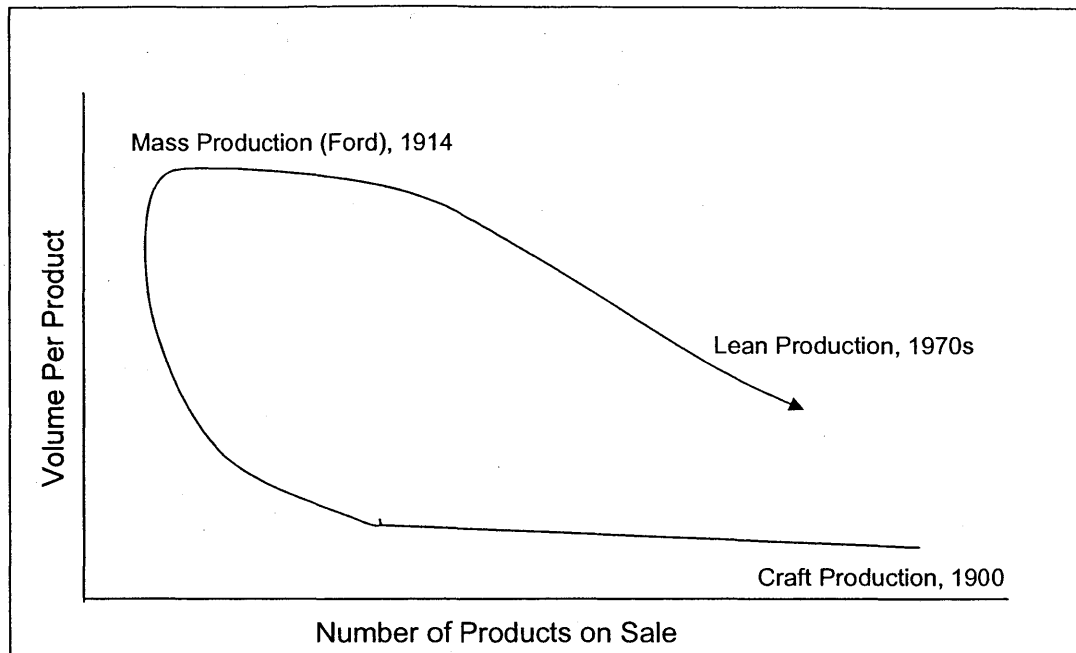
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<sup>17</sup> Montgomery, Alan L. "Creating Micro-Marketing Pricing Strategies Using Supermarket Scanner Data." *Marketing Science*, 16 (4), 1997: 315-337.

<sup>18</sup> Oliver, Keith, Leslie H. Moeller, and Bill Lakenan. "Smart Customization: Profitable Growth Through Tailored Business Streams." *Strategy+Business Magazine* Spring 2004

While GM's practiced a successful customer segmentation strategy, the firm's manufacturing strategy essentially retained the tenants of mass production. After the advent of Fordism and prior to the development and acceptance of Japanese manufacturing techniques, most American firms accepted the idea that trade-offs were an inherent part of production decisions - a choice had to be made between attributes such as quality, cost, variety and lead-time. However, as Japanese approaches such as Total Quality Management (TQM) and lean manufacturing were developed and popularized, firms began to realize that by looking at their problems differently, they could reduce or eliminate trade-offs.

These new strategies have allowed these auto companies to effectively meet the needs of smaller customer segments with increasingly customized products. To achieve these goals, a variety of techniques have been employed. From a design perspective, strategies such as postponement, the use of modular components, and design for manufacturability considered the production and inventory costs of a design up front and made efforts to eliminate this cost and increase manufacturing flexibility. In the realm of production, firms began to focus on identifying and removing constraints, as opposed to merely optimizing around them. By reducing set up costs and changeover times and reducing variability and uncertainty in production and logistics, firms were able to significantly reduce both inventories and lead times and be more flexible in meeting market demands. The end result, as depicted in Figure 3 is that auto firms using lean manufacturing techniques can cost effectively produce a wider range of products at lower volumes.

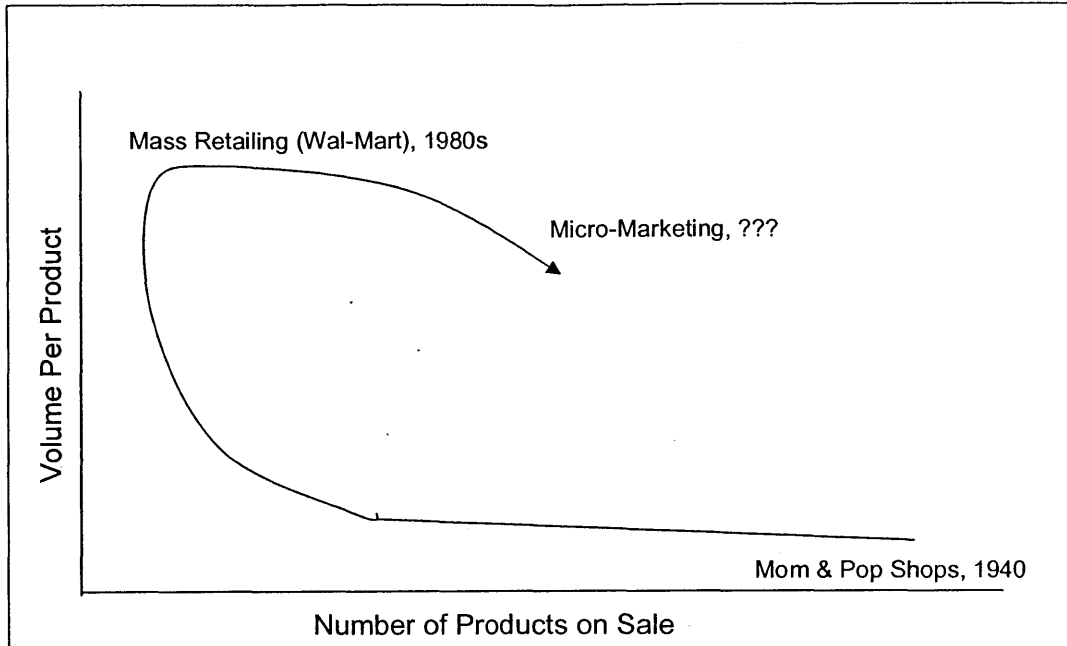


**Figure 3 - The Progression of Product Variety and Production Volume in the Auto Industry<sup>19</sup>**

Recent studies have found that, “Increasingly, as the retail environment is dominated by the largest and best managed firms, these competitors are reaching a high level of competitive parity.”<sup>20</sup> Just as the American automobile industry came to be dominated by giants such as GM, Ford, and Chrysler, so has the American retail industry transitioned from an era of locally-owned stores to an era of domination by giants such as Wal-Mart and Target. Many of the Japanese manufacturing, quality, and product development techniques developed in the automotive industry have successfully been used to reduce costs in the retail industry. But as depicted in Figure 4, the question remains open as to what non-dollar benefits these improvements will provide to consumers.

<sup>19</sup> Adapted from Womack, James P., Daniel T. Jones, and Daniel Roos, *The Machine that Changed the World*, New York: Harper Perennial, 1991. pg. 126.

<sup>20</sup> “Twenty Trends for 2010: Retailing in an Age of Uncertainty.” Columbus, OH: Retail Forward Inc. 2003



**Figure 4 - The Progression of Product Variety and Production Volume in the Retail Industry**

Keeping in mind the lessons learned in the auto industry, the case can be made that low costs will no longer be enough to win with retail consumers. This means that retailers will increasingly compete based on service, quality, product innovation, *and* cost. Just as improved capabilities in the auto industry heralded a return towards the product variety that had been available in the days of craft production, Montgomery notes that “Micro-marketing represents an interest on the part of managers to combine the advantages of these large operations with the flexibility of independent neighborhood stores.”<sup>21</sup>

<sup>21</sup> Montgomery, Alan L. "Creating Micro-Marketing Pricing Strategies Using Supermarket Scanner Data." *Marketing Science*, 16 (4), 1997: 315-337.





## **Chapter 3: Identifying Virtual Chains**

As described previously, micro-marketing attempts to customize marketing efforts at the individual store level. While micro-marketing strives to reach this ideal, in practice taking customization to this level of detail can be both impractical and unnecessary. While the expected benefits of a micro-marketing program are increased sales and profits, in most cases the increased complexity that results from managing stores individually results in the increased costs.

Fortunately, within most large chains, the sheer number of stores means that there will be many subsets of stores for which the demand of the customer base is similar from store to store. One of the first jobs of the micro-marketer therefore becomes identifying these clusters or “virtual chains” of similar stores within the larger chain. Having identified these virtual chains, the marketing manager can then apply the micro-marketing strategies discussed in the following chapter.

### **3.1 Segmentation Strategies**

Two general approaches are available to segment a retail chain into smaller virtual chains. Using the first method, attribute-based clustering, market researchers create groupings of stores based on store characteristics, such as demographic or geographic attributes, that are deemed to predict the sales patterns and preferences of the shopper base. The second method involves using statistical “Cluster Analysis” algorithms that look at historical demand and create groupings of stores that have experienced similar historical product demand profiles.

#### **3.1.1 Attribute-Based Clustering**

Attribute-based clustering has been a common practice in the retail industry for many years. Retail chains cluster stores based on shopper demographics, regional characteristics, weather patterns, and many other factors believed to influence consumer product demand. In cases where the attributes provide clear guidance on the types of products that should be offered, attribute based clustering has been used with great success. For example, a recent article in *Discount*

*Merchandise* magazine described an Ames Department Store strategy of stocking beach products near sea side locations and camping equipment at inland stores near popular camping vacation destinations.<sup>22</sup> In this case, high level shopper behavior could easily be predicted based on the store location.

### **3.1.2 Statistical Clustering**

While effective in circumstances such as the Ames example where the segmentation attributes and drivers of different shopper behaviors are easily identifiable, attribute based clustering methods are, by definition, less effective when the relevant attributes cannot be identified. In these circumstances, statistical clustering methods, which are exploratory in nature, can be an effective tool to segment the population.

When combined with analysis of the demographics and other factors of the clusters identified, statistical clustering methods provide a powerful exploratory tool to identify the attributes that drive differences in demand. Given the complexity present in the retail business – especially for fashion items such as cosmetics - statistical clustering methods were used in this project.

In most industrial applications of statistical clustering, commercial data mining software packages are used to conduct the analysis. Typically, these packages are designed for industry-specific applications and have interfaces designed to facilitate easy loading and analysis of data. However, even for the user of a commercial cluster analysis package, an understanding of the basic logic used to solve the clustering problem is useful. Therefore the remainder of this chapter explains the general steps and decisions involved in performing a cluster analysis. A relatively simple cluster analysis model that can be used for clustering stores in a retail chain based on historical sales is presented.

## **3.2 Cluster Analysis Overview**

Cluster analysis refers to a broad set of mathematical techniques used to accomplish what in marketing is typically referred to as segmentation. Clustering data is an inexact science; however

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<sup>22</sup> "Different strokes for different folks." *Discount Merchandise*. Bristol: Mar 1999. Vol. 39, Iss. 3; pg. 28

the mathematical approach of most algorithms is to minimize the variance within each cluster while maximizing the variance across groups to partition a set of data into distinct and relatively homogenous groups. Cluster analysis is not a specific mathematical procedure, but rather a range of different approaches ranging from statistically based heuristics to mathematical optimization techniques that all attempt to meet this objective.<sup>23</sup> While the exploratory nature of clustering results in the process being relatively iterative, the basic steps in cluster analysis are:

1. Identifying and measuring the difference between objects to be clustered
2. Choosing the number of clusters
3. Choosing and applying a cluster analysis algorithm
4. Validating the cluster analysis results

After a brief conceptual example of how cluster analysis might be applied in the retail industry, the remainder of this chapter will be spent discussing each of these steps.

### **3.3 Cluster Analysis Example**

As described previously, cluster analysis uses historical information to identify groups within a set of data. In a retail micro-marketing context, this typically involves using historical demand data to identify virtual chains of stores in a larger chain that have experience similar demand profiles. In the example presented here eight stores are divided into three different clusters based on the percent of sales for five different products. Without yet discussing the details of the cluster analysis algorithm, it is useful to understand the inputs and outputs of the analysis. A summary of the input data is presented in Figure 5.

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<sup>23</sup> Everitt, Brian S., Sabine Landau, and Morvin Leese. *Cluster Analysis*. New York: Oxford University Press Inc., 2001.

| Store | Item 1 | Item 2 | Item 3 | Item 4 | Item 5 | ... |
|-------|--------|--------|--------|--------|--------|-----|
| 1     | 15%    | 2%     | 8%     | 8%     | 20%    |     |
| 2     | 8%     | 10%    | 15%    | 9%     | 15%    |     |
| 3     | 15%    | 3%     | 7%     | 10%    | 21%    |     |
| 4     | 2%     | 5%     | 6%     | 23%    | 10%    |     |
| 5     | 7%     | 12%    | 16%    | 9%     | 12%    | ... |
| 6     | 16%    | 3%     | 8%     | 9%     | 19%    |     |
| 7     | 10%    | 2%     | 9%     | 8%     | 20%    |     |
| 8     | 2%     | 6%     | 5%     | 24%    | 14%    |     |
| Avg   | 9.38%  | 5.38%  | 9.25%  | 12.50% | 16.38% |     |

**Figure 5 – Percent of Sales by Item by Store**

The cluster algorithm will identify three groups of stores that have the most similar demand profile. As shown in Figure 6, in this example the clusters are  $A = \{1, 3, 6, 7\}$ ,  $B = \{2, 5\}$ , and  $C = \{4, 8\}$ .

| Store | Item 1 | Item 2 | Item 3 | Item 4 | Item 5 | Group |
|-------|--------|--------|--------|--------|--------|-------|
| 1     | 15%    | 2%     | 8%     | 8%     | 20%    | A     |
| 2     | 8%     | 10%    | 15%    | 9%     | 15%    | B     |
| 3     | 15%    | 3%     | 7%     | 10%    | 21%    | A     |
| 4     | 2%     | 5%     | 6%     | 23%    | 10%    | C     |
| 5     | 7%     | 12%    | 16%    | 9%     | 12%    | B     |
| 6     | 16%    | 3%     | 8%     | 9%     | 19%    | A     |
| 7     | 10%    | 2%     | 9%     | 8%     | 20%    | A     |
| 8     | 2%     | 6%     | 5%     | 24%    | 14%    | C     |
| Avg   | 9.38%  | 5.38%  | 9.25%  | 12.50% | 16.38% | Avg   |

**Figure 6 – Store to Cluster Assignments**

In most cases, business decisions (which products to stock, how many facing to give each product, how much safety stock to hold, etc.) will be based on the average sales numbers for the entire chain. However, looking Figure 5, it is clear that there is a great amount of store to store variation that is not captured when average numbers are used. Figure 7, which shows the average demand profile by cluster, further illustrates this point. For example, Item 1, which represents 9.38% of sales for the overall chain, represents from 2 to 14% of cluster sales when the chain is broken into three clusters.

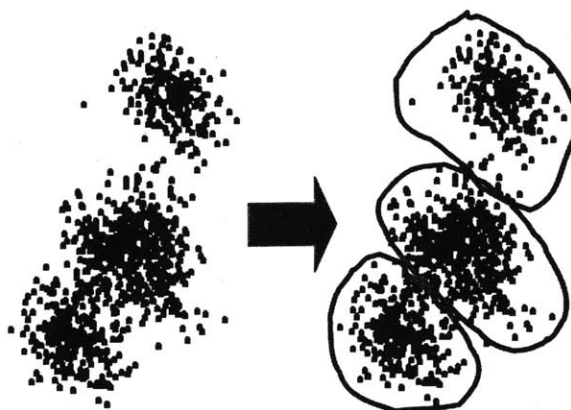
|         |     | Item 1 | Item 2 | Item 3 | Item 4 | Item 5 |
|---------|-----|--------|--------|--------|--------|--------|
| Group A | Avg | 14%    | 3%     | 8%     | 9%     | 20%    |
| Group B | Avg | 8%     | 11%    | 16%    | 9%     | 14%    |
| Group C | Avg | 2%     | 6%     | 5%     | 24%    | 14%    |
| Overall | Avg | 9.38%  | 5.38%  | 9.25%  | 12.50% | 16.38% |

**Figure 7 – Cluster Averages by Item**

Looking only at inventory management, the benefits of managing at more detailed level become apparent. If inventory levels are managed on a cluster basis, items with higher sales in a given cluster, such as item 2 in group B, will receive more inventory— thereby reducing lost sales and out of stocks. In other cases, such as item 1 in group C, managing at a cluster level will make the identification and removal of items that are not selling easier to identify.

### 3.4 Measuring the Distance between Objects

In a generic form, cluster analysis can be thought of as using a measure of “distance” of “difference” (typically denoted as  $d_{ij}$ ) between each pair of objects to create groupings.<sup>24</sup> In the previous example, this distance is based on the differences in the percent of sales between different stores. In the visual example in Figure 8, data is clustered into three groups based on the Euclidian distance between points.



**Figure 8 – Visual Clustering Example**

<sup>24</sup> Everitt, Brian S., Sabine Landau, and Morvin Leese. *Cluster Analysis*. New York: Oxford University Press Inc., 2001.

In cases in which multiple descriptive attributes are used to determine  $d_{ij}$ , the problem becomes how to weight the different attributes. A common approach is to weight each attributes by the inverse of some measure of variability in the attribute across all stores. The assumption in the approach, commonly referred to as “standardization”, is that the relative importance of each attribute from a clustering standpoint is inversely proportional to the variability of that variable. However, while common, it can also be demonstrated that in some cases this method actually results in poorer results than using simply the un-scaled data. Numerous other methods of weighting for multi-attribute cluster analysis have been proposed in the literature; however the choice of weights appears to be as much art as science at this point.<sup>25</sup>

### 3.5 Choosing the Number of Clusters

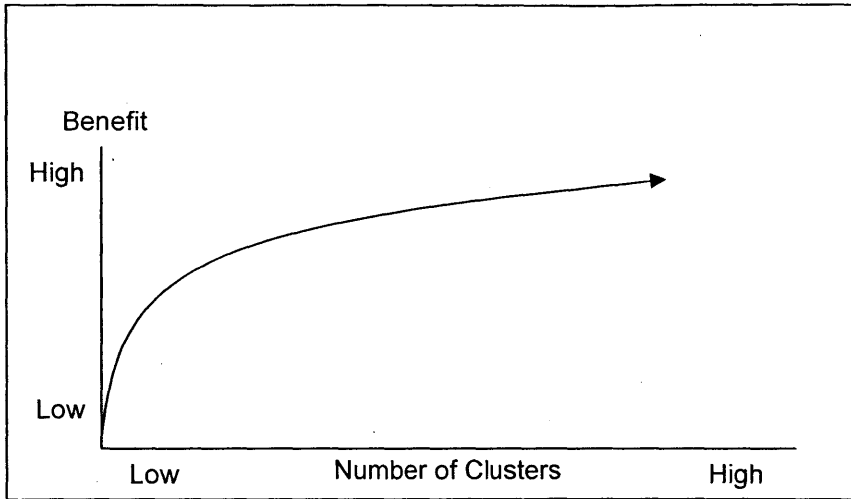
Having determined a distance matrix  $d_{ij}$ , the next step in a cluster analysis is to choose  $k$ , the number of clusters that will be created. The approach to this is often relatively informal. Typically, the clustering model will be solved for several values of  $k$ . The value of the objective function is then plotted versus  $k$  and “large” changes in the objective are taken as a suggestion that a particular number of groups are present in the data. In Figure 9, the “elbow” in the curve may represent a reasonable number of clusters. Everitt et al. are quick to note, however, that “this approach may be very subjective, with ‘large’ being often a function of the user’s prior experiences.”<sup>26</sup>

In most cases there is a trade-off associated with managing a larger number of clusters. In some cases, this trade-off can be quantified and evaluated analytically. Using the example of a retail chain, as more clusters are formed and each cluster becomes smaller and smaller, it would be expected that an increased sensitivity to local tastes would increase store sales. However, as depicted in Figure 9, it is expected that the most benefit will be derived with the first few clusters developed, and returns will be decreasing as the number of clusters  $k$  approaches the number of stores in the chain.

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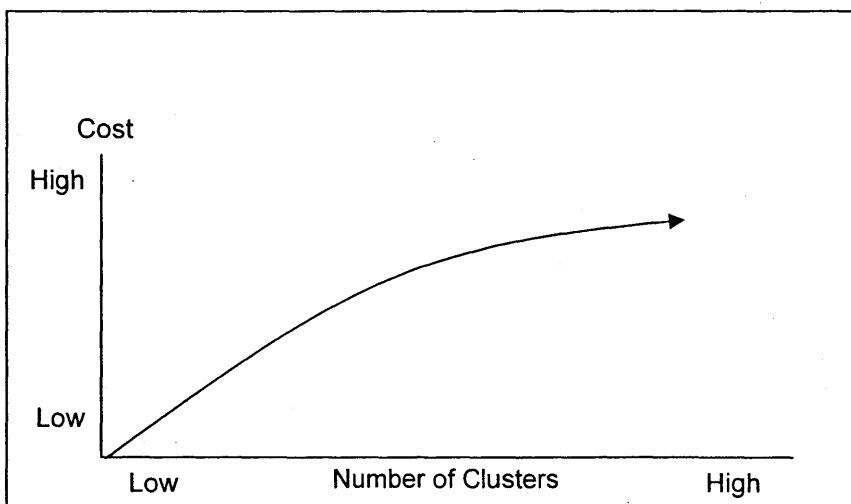
<sup>25</sup> Ibid

<sup>26</sup> Ibid



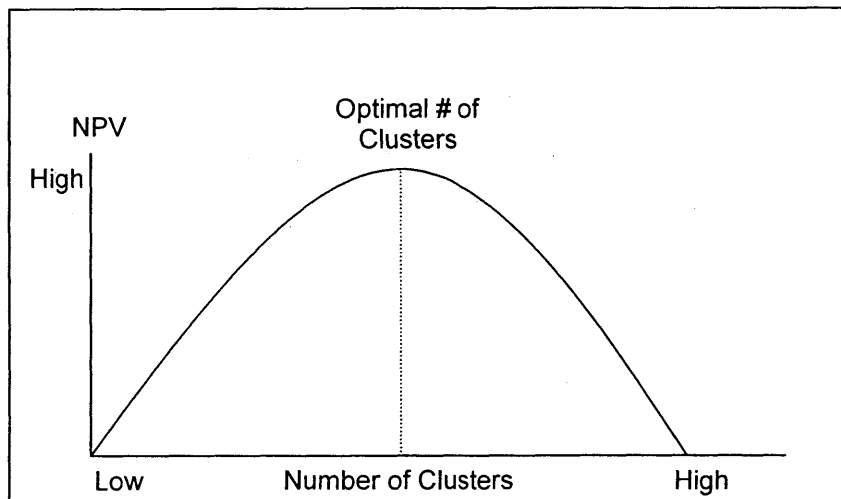
**Figure 9 – Expected Micro-Marketing Benefits as a Function of the # of Clusters**

Likewise, as the number of clusters increases, it would also be expected that the additional complexity added to the system will increase costs due to additional management required for each cluster of stores. However, when compared with the benefits, costs will also continue to increase, but in a more linear fashion with respect to the number of clusters. Figure 10 illustrates the expected relationship between costs and the number of clusters. The reason for the higher costs as the number of cluster increases is that customizing merchandising activities, planograms, and displays by cluster requires additional labor.



**Figure 10 – Expected Micro-Marketing Costs as a Function of the # of Clusters**

Given this relationship between costs, benefits, and the number of clusters, the optimal number of clusters can be calculated as depicted as in Figure 11. In essence, what this chart is saying is that looking at the extremes, while one marketing approach for all stores most likely leaves potential profit on the table, if a retailer was to manage each store completely individually the loss of economies of scale would remove any potential sales gains.



**Figure 11 – Cost / Benefit Optimization as a Function of the # of Clusters**

While analytically appealing, in the context of micro-marketing applications determining the optimal number of clusters may be both unrealistic and undesirable. Considering the feasibility of determining the optimal number of clusters, it is possible but extremely difficult to predict the profits and costs that will result based on micro-marketing to a given number of clusters  $k$ . But even if it is possible to determine the cost and benefit curves as a function of the number of clusters, there is a second and more meaningful reason not to spend the effort required to identify the optimal number of clusters. The reason for this is that while cost/benefit analysis typically assumes the costs and benefits will be applied to all stores in a chain, in a micro-marketing campaign there is no requirement that all stores or clusters must be customized.

For example, if a retail chain is divided into ten clusters of stores, the micro-marketer may identify three clusters where it is believed that a significant micro-marketing opportunity is present, make changes in stores in those clusters, and make no changes in the other seven clusters. In order to strictly evaluate the optimal number of clusters that a micro-marketer should



create all possible scenarios would have to be evaluated. Given that the retail forecasts that provide the basis for this analysis are typically quite uncertain to begin with, it may not be worthwhile to pursue this analysis. A more practical approach is to set a minimum cluster size that ensures some reasonable economies of scale within each cluster. For example, if the cost of developing different displays is a major cost driver, the minimum batch size in which displays can be ordered might be used as lower bound on the minimum number of stores that can be assigned to a single cluster.

For the reasons described above, the determination of the theoretically optimal number of clusters will not be discussed in this paper. However, readers interested in more information on this topic are encouraged to review the work of Fisher and Rajaram, who present an optimization model for choosing the optimal number of clusters for a slightly different problem involving the retail testing of fashion goods.<sup>27</sup>

Given the lack of sound analytical methods appropriate for identifying the correct number of clusters to be formed in a pure micro-marketing campaign, the marketing manager is left to the use of subjective approaches. The recommended method for is to set a minimum cluster size as previously described and then develop solutions for several values of  $k$ . The analyst can then evaluate how the groupings of stores change as the number of groups increases. Validating a cluster model will be discussed further in the next section and in the P&G case studies.

### **3.6 Cluster Analysis Algorithm: The K-Median Integer Program**

While a wide variety of cluster analysis methods are available, a relatively straightforward model that is appropriate for clustering a chain of retail stores will be discussed. This model uses a specialized integer program developed to solve what is known as the  $k$ -median problem.<sup>28 \*</sup>

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<sup>27</sup> Fisher, Marshall L. and Kumar Rajaram. "Accurate Testing of Fashion Merchandise: Methodology and Application". *Marketing Science*, Vol. 19, No. 3 266-278, 2000.

<sup>28</sup> Fisher, Marshall L. and Kumar Rajaram. "Accurate Testing of Fashion Merchandise: Methodology and Application". *Marketing Science*, Vol. 19, No. 3 266-278, 2000.

\* Please note that the cluster analysis performed at Procter & Gamble and presented in Chapter 5 of this thesis was completed using a commercial software package. While the specifics of this software package will not be discussed here, the  $k$ -median model is presented to help the reader understand the logic and mathematics used by software packages to perform cluster analysis.

The number of clusters to be created is an input parameter into the k-median clustering model. As described previously, the model is typically solved several times for different values of k (the number of clusters created) to evaluate different clustering options. In the example provided in Appendix A, three clusters were created.

A second input into the clustering model is historical retail point-of-sale (POS) data. For the sake of clustering stores, it is assumed that sales history is available for products comparable to those that will be sold in the future. If seasonality is of any concern, the POS data should be from period comparable to the time frame in which the micro-marketing activities will be implemented.

The mathematical model of the integer program is as follows:

K-Median Model Parameters

- k = the number of clusters
- n = the number of stores
- m = the number of products for which we have sales history
- I = (1,...n) = store index set
- P = (1,...m) = product index set
- $U_p$  = the per-unit cost of buying less than demand for product p
- $O_p$  = the per-unit cost of buying more than demand for product p

- $S_{ip}$  = the observed sales at store i for product p
- $S_p = \sum_{i=1, n} S_{ip}$  = the total sales of product p in all stores
- $w_i = \sum_{p \in P} S_{ip}$  = the total sales of all products in store i
- $B_{ip} = S_{ip} / \sum_{p \in P} S_{ip}$ ,  $i \in I$ ,  $p \in P$  = the percent of sales of product p in store i

$d_{ij} = \sum_{p \in P} [U_p \max(B_{ip} - B_{jp}, 0) + O_p \max(B_{jp} - B_{ip}, 0)]$  = the total “distance” between store i and store j for all products. This distance is calculated as the difference in the percent of sales between the two stores weighted by the cost of having too little or too much product on hand. This value is calculated for all store pairs prior to running the integer program. Note: the matrix  $D_{ij}$  is always symmetric with respect to the diagonal because the cumulative difference in percent of sales is always zero (i.e. if one product sells percentage-wise more in one store, it must follow that another product will sell percentage-wise less.)

Variables

- $y_j = 1$ , if store j is a cluster centroid; 0, otherwise
- $x_{ij} = 1$ , if store i is assigned to cluster j; 0, otherwise

### Integer Program

$$\text{Minimize } \sum_{(i \in I)} \sum_{(j \in I)} w_i * d_{ij} * x_{ij} \quad (1)$$

Subject to:

$$\sum_{(i \in I)} x_{ij} = 1, j \in I \quad (2)$$

$$\sum_{(j \in I)} y_j = k \quad (3)$$

$$0 \leq x_{ij} \leq y_j, i, j \in I \quad (4)$$

$$x_{ij} \text{ and } y_i \text{ are binary, } i, j \in I \quad (5)$$

The first constraint (2) ensures that each store  $i$  is assigned to one and only one cluster  $j$ . The second constraint (3) ensures that  $k$  stores are chosen as a cluster centroid – meaning that  $k$  clusters are created. The third constraint (4) ensures that store  $i$  is only assigned to a cluster with a centroid of store  $j$  if and only if store  $j$  is chosen as a cluster centroid.

The objective function seeks to minimize the total variation within the clusters, which is calculated as the percent of sales “distance” between each store  $i$  and the cluster centroid  $j$  weighted by the total sales of all products in store  $i$ .

The result of the  $k$ -median algorithm is  $k$  groups of stores each assigned to a one central “median” store. This result is especially useful if pilot program will be run, as the median store is the most representative of the other stores in the group and the preferred location for testing the effectiveness of micro-marketing strategies in the cluster.

### **3.7 Validation of Cluster Analysis Results**

Given that clustering algorithms will mathematically identify clusters even when none are truly present in the underlying data, validating the cluster model is a critical step in the analysis. As is likely clear at this point, while cluster analysis is a powerful tool for identifying patterns in data, there are few clear cut rules on the application of cluster analysis and, as Everitt, Landau, and Leese note, there “is no optimal strategy for either applying clustering or evaluating results.”<sup>29</sup>

The validation techniques presented aim to assure that the clusters identified are truly present in the underlying data and not merely results of algorithms searching for patterns where none exist.

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<sup>29</sup> Everitt, Brian S., Sabine Landau, and Morvin Leese. *Cluster Analysis*. New York: Oxford University Press Inc., 2001.

The first validation technique proposed focuses on determining whether the clusters identified in the data are stable using different clustering techniques. This method is called *split-sample* validation. In a split-sample validation, the sample data (stores) is first divided in two, and a cluster analysis is performed on one sample. Next, the centroids of each cluster ( $y_i = 1$  in the k-median model) are determined and the distances between the objects in the second sample and the centroids of each cluster are computed. The cluster centroid to which each object in the second group is closest is then recorded and the second sample of data is then clustered independently of the first. Finally, the two clustering solutions are compared for the second set of data to determine whether the cluster solutions remained fairly stable – meaning that most stores typically are placed in the same cluster regardless of the order.<sup>30</sup>

The second validation technique proposed evaluates the degree of cohesiveness present within each cluster. For a given cluster solution, this method compute the “tightness” of each cluster. This measure is essentially the average distance between each object in the cluster and the cluster’s centroid, using the notation from the k-median model previously discussed, for each cluster  $j = 1$  to  $k$ , compute the average tightness in cluster  $J = \sum(i \in I) d_{ij=j} * x_{ij=j} / \sum(i \in I) x_{ij=j}$ . Comparing the relative tightness of the different clusters gives a measure of the similarity of the objects within each group.

In the context of retail store clustering, perhaps the most useful validation feature typically available in commercial software packages is the ability to characterize clusters based on demographic data from the US census. In most cases, demographic data is attributed to each store based on the zip code in which the store resides. A statistical test comparing each cluster’s mean demographic attributes with the overall population mean values for factors such as ethnicity, income, family status, and education levels is used to identify which attributes that characterize each cluster. For example, a given cluster may be characterized as heavily Caucasian, urban, with residents who typically have high school education levels, and who earn lower than average income levels. In addition to demographic analysis, commercial clustering packages typically provide visual mappings of the stores in each cluster, which allow the user to easily identify the role that geography plays in the development of store clusters. Cluster

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<sup>30</sup> Ibid

demographic attributes and geographical information, clearly useful in the development of micro-marketing strategies, also provide another method to subjectively evaluate the cohesiveness and validity of clusters.



## **Chapter 4: Micro-Marketing Strategies**

Having identified a virtual chain of stores where a micro-marketing opportunity is available, the next decision to be made is which marketing mix variables can be manipulated to increase sales and profitability at these stores. The decision of which marketing lever to customize is often a subjective one, therefore the objective of this section is to outline some of the choices available. As described previously, the 4 P's of Marketing – Product, Price, Promotion, and Place – will be used as a general framework of the different options.

### **4.1 Product Strategies**

Within the product category, several options are available to the potential micro-marketer. Product mix, variety, design, styling, features, functionality, brand, packaging, and sizes all provide opportunities to customize the product offering to a local market.

Many of the opportunities to customize the Product variable result from improvements non-marketing functional areas of P&G. As manufacturing, distribution, and R&D organizations increase the flexibility and speed with which they can develop, introduce, and manufacture products, the costs and time required to introduce new products goes down. In a fashion driven business such as cosmetics, variety and “product freshness” are important sales drivers, therefore as the capability to handle a wider range of products is developed, product proliferation should be expected. Micro-marketing provides a framework to target this ever widening array of products to the right consumer.

#### *Product Mix*

Procter & Gamble currently produces on the order of 700 different cosmetics SKUs. This number will increase as P&G pursues a strategy of more frequent product introductions to maintain product freshness. A given mass market retailer will typically carry approximately 500 of these SKUs per store and a drug retailer may carry approximately 250 SKUs per store. This leads to the question of which SKUs should be carried at each store. Currently product mix decisions are made at a chain level, meaning that all stores in a given retail chain carry the same mix of products. However, the product mix demanded varies from store to store and region to

region, giving reason to believe that customizing the product mix by store may better meet the needs of local shoppers.

In the previously mentioned example of product mix customization at Ames Department Stores, the store-level product mix was customized based on a store's geography and location. For example, stores located near sea-side resort locations sell products such as swim suits and beach toys later in the summer than do other stores, stores near popular camping spots carry a wider array of outdoor items, and in the fall stores near colleges carry more of house ware items typically purchased by students. This micro-marketing appears to have paid off at Ames; while comparable store sales increased 6% in 1998, stores involved in the resort micro-marketing program increased sales by an additional 3% during the same period.<sup>31</sup>

### *Variety*

While product line proliferation provides a wider range of options for the product mix, the number of product lines displayed becomes an important decision. For example, given a planogram with 100 spots, should 10 products from 10 different product lines be displayed or 5 products from 20 product lines?

### *Design and Styling*

Beyond simple product line proliferation, improved manufacturing flexibility may provide the ability to customize the design and packaging of a product. An example of this is seen in the beverage industry, where cans or bottles are often customized with artwork for sports teams or cultural events that is targeted at a specific market.

### *Features and Functionality*

While the customization of features and functionality are often not relevant marketing levers in the consumer products industry, in other industries such attributes are critical marketing strategies. A clear example is automotive industry, where the variety of optional features

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<sup>31</sup> "Different strokes for different folks". *Discount Merchandiser*. Bristol: Mar 1999. Vol. 39, Iss. 3; pg. 28



typically available for any given make of automobile is a key method of targeting the needs of different customers and raising profits.

### *Brand*

Similar to the GM strategy of creating different automobile brands (Chevy, Pontiac, Oldsmobile, Buick, and Cadillac) targeted at customers of different socio-economic statuses, a micro-marketing program might involve the development of different brands targeted at different shoppers. In P&G's case, Cover Girl and Max Factor, while sharing manufacturing processes and research and development, are clearly focused on different sub-segments of the cosmetics market. If a sub-segment, such as the Hispanic market, is sufficiently large, the development of another brand specifically focused on this market may be the appropriate action.

### *Packaging and Sizing*

In addition to design and styling, another packaging consideration is the amount of product offered and the bundling of multiple products. The sizing and packaging of products sold at bulk discount stores such as Sam's and Costco versus the packaging of the same products sold by drug retailers illustrates this point. For a consumer products manufacturer, there is a clear tradeoff between the variety of packaging options offered and the inventory and manufacturing costs associated with doing so. However, as manufacturing and distribution flexibility increases, the possibility of targeting packaging to smaller markets becomes feasible.

### *Location in Store/Position on Shelf*

P&G and other firms with retail interests have conducted considerable research into the impact of shelf location on product sales. While the availability of a product in a given store is important, the location of the shelf itself and the individual products position on the shelf have a dramatic impact on unit sales. Intuitively this makes perfect sense, if a product is placed in a prominent location – say at eye-level in a end of row display – the product will most likely sell at a higher rate. There is something of a chicken-and-egg dilemma here, as it can be difficult to assess the inherent desirability of a given product and the sales volume that should be attributed

to product position in a store, but needless to say, research on potential impact of shelf location on product sales should be considered in display design.

One final piece of guidance with respect to a product's position on the shelf is that the impact of position on sales can vary depending on the type of product being sold. Some products, such as nail polish remover, may be "destination" items – items which shoppers purchase because they visit a store intending to buy the product. In this case the position on the shelf may have little impact on product sales. Other items, such as seasonal lipsticks, may be "impulse" purchases – items that are sold almost exclusively as a result of a customer noticing the product while browsing for something else. When determining where a product should be placed on the shelf, planners should consider whether the item is a destination or impulse item and position the product appropriately.

## **4.2 Price Strategies**

The demand curves of introductory micro-economics tell us that, for most goods, the amount of product sold is a function of the price at which it is sold. While this relationship between demand and price is true both in the sale of products to retailers and in the sale of products to end consumers, this paper the discussion will focus on the retail price charged to customers.

Price based micro-marketing is an attractive option to retailers because of the low cost associated with implementing such a program. In fact, in contrast with other forms of Product and Promotion micro-marketing, most retailers today do practice Price-based micro-marketing. The practice is known as "zone" pricing and essentially follows the logic described in this paper – stores are grouped into clusters and prices are set on the cluster level.<sup>32</sup> These prices are typically adjusted based on readily available consumer price index information.

Because retail prices are typically beyond the control of manufacturers and price micro-marketing in clusters is already a common practice, this topic will not be discussed in greater detail here. Additionally, significant research has already been performed in this area with respect to price micro-marketing at the store level. Readers interested in learning more about this

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<sup>32</sup> Montgomery, Alan L. "Creating Micro-Marketing Pricing Strategies Using Supermarket Scanner Data." *Marketing Science*, 16 (4), 1997: 315-337.

topic are recommended to read Alan Montgomery's *Marketing Science* article entitled, "Creating Micro-Marketing Strategies Using Supermarket Scanner Data."

As a final word on Price-based micro-marketing, it is important to note that the "challenge for the retailer in implementing micro-marketing pricing strategies is to retain a consistent image while altering prices that adapt to neighborhood differences in demand."<sup>33</sup> The experiences of online retailer Amazon.com illustrate this caution. In 2000, Amazon initiated a program in which movies being sold online were priced differently to different customers. Given the wealth of data an online retailer can collect about a regular customer's purchasing habits, it is easy to imagine a system designed to evaluate a customer's price sensitivity, determine the likelihood that a customer will make a purchase for given dollar amount, and price products to maximize the retailer's profits. However, when customers learned of this practice, a massive outcry ensued over the "unfairness" of the practice and Amazon dropped the program.<sup>34</sup>

### 4.3 Promotion Strategies

Promotional activity includes all advertising or merchandising actions a firm might take to communicate with the target consumers and promote purchase of a firm's products.<sup>35</sup> Often, responsibility for the development and implementation of promotional programs is shared between retailers and product manufacturers. From a manufacturer's perspective, it is important to be involved to ensure that the appropriate brand image is maintained. The attractiveness of promotional activities in micro-marketing is that promotions can be relatively low-cost investments while yielding significant increases in sales.

#### *Coupons and Targeted Advertising*

Focusing advertising spending on media or events where target customers are likely to view and respond to the advertising is hardly a new concept. Cosmetics advertising is plentiful in health and beauty magazines read by female audiences, new bands promote their CDs in the pages of music magazines, and tobacco manufacturers promote NASCAR races. However, recent

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<sup>33</sup> Montgomery, Alan L. "Creating Micro-Marketing Pricing Strategies Using Supermarket Scanner Data." *Marketing Science*, 16 (4), 1997: 315-337.

<sup>34</sup> Krugman, Paul "What Price Fairness?" *New York Times*. 4 October 2000: A35.

<sup>35</sup> Ibid

advances in technology have made it possible to target advertising on an even more detailed level.

On the internet, websites such as Amazon.com maintain detailed sales histories and continually suggest products that will appeal to customers based on their sales histories. Kraft Foods has worked with cable television providers to develop software that will target cable television advertising so that viewers in two different households in the same market may see different commercials simultaneously. The ultimate vision for Kraft's program is that viewers in different rooms in the same household might see different advertising, for example a viewer in the kitchen might see advertising for food products while a viewer in the living room might see advertising for a new stereo.<sup>36</sup> In each of these cases, as the cost of targeting a message to a specific customer gets smaller, the ability to promote products to smaller segments of the population becomes more realistic.

Coupons present an extremely interesting micro-marketing opportunity because, unlike prices, coupons allow retailers and CPG companies to segment the market without lowering prices to all customers. Coupons, can take many forms including price discounts or product bundling discounts, can either be distributed nationally or regionally via mass media channels such as newspapers and magazines – allowing price conscious consumers to self select – or can be targeted specifically at individual consumers. In the previous example about Amazon.com, it is easy to imagine online coupons being customized to appeal to individual customers.

One example of coupon targeting follows from the previously discussed cable television targeted advertising programs being developed by Kraft. Eventually, when addressable cable television boxes are common, Kraft is considering programs to send coupons or recipes to these cable boxes based on a customer's viewing habits.<sup>37</sup>

Another firm that does an incredibly effective job targeting specific customers with promotional materials is Harrah's Entertainment. Harrah's has instituted a customer loyalty program that tracks the activity of regular Harrah's customers. Combining gambling history with demographic data gathered when customers sign up, Harrah's is able to identify the promotional strategies that

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<sup>36</sup> Pollack, Judann. "Coupons Over Cable." *Advertising Age*. 13 April 1998, Vol. 69 Issue 15.

<sup>37</sup> Ibid

work best with different customer groups. For example, for a particular group of highly profitable customers, Harrah's found that "these customers typically did not stay in a hotel but visited a casino on the way home from work or on a weekend night out. At the same time, we found that our target customers often responded better to an offer of \$60 of casino chips than to a free room, two steak meals, and \$30 worth of chips because they enjoyed the anticipation and excitement of gambling itself."<sup>38</sup> Such analysis allowed Harrah's to both lower the cost of promotions and increase promotional effectiveness (as measured by customer visits) through the use of quantitative models.

### *In-Store Communications*

Retailers increasingly rely on CPG manufacturers regarding the design of in-store signage and display materials. These in-store communications provide an attractive opportunity with respect to micro-marketing because there is often a clear-cut reason for developing different signage based on the attributes or locations of given stores. For example, P&G's cosmetics business has recently been experimenting with bi-lingual signage in stores located in heavily Hispanic areas. It is easy to image displays showing ethnic models in stores in diverse neighborhoods or the inclusion of bilingual product educational materials in displays in areas where cosmetics usage is low. Given the relative ease of identifying heavily ethnic stores and proof from previous research on the effectiveness of these approaches, in-store communications can often be a cost effective approach to developing a better connection with shoppers and increasing sales.

### *Bundling and Buy-One-Get-One Free Promotions*

Another promotional strategy is the use of buy-one-get-one free (BOGO) promotions. This technique can be used simply to drive increased consumption of a given product line and is also effective as a way of driving trial usage of new products. BOGO promotions can be managed in a variety of ways including packaging coupons, direct mail coupons, media coupons, or through direct packaging of free products with the product that must be purchased.

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<sup>38</sup> Loveman, Gary. "Diamonds in the Data Mine." *Harvard Business Review* May 2003, Vol. 81 Issue 5: 109

#### **4.4 Place Strategies**

The “Place” marketing variable in the 4 P’s framework refers to the supply chain functions associated with making a product available to consumers. As discussed earlier in this paper, channel partnerships and supply chain improvements by both retailers and consumer product manufacturers have increased the ability to deliver and manage small amounts of product at individual retail locations. In the context of micro-marketing, the challenge is to leverage these improved capabilities to drive increased sales. While supply chain execution may not directly drive additional sales in retail stores, in the end effective logistics systems are a critical component to ensuring that the right products are available to customers when they need them. Therefore some of the supply chain capabilities that must be developed to support micro-marketing will be presented.

##### *Replenishment Batch Sizes*

In a low-volume retail segment such as cosmetics, where SKU level demand can be on the order of several pieces per store per year, it is critical that the supply chain be able to deliver small replenishment quantities. Micro-marketing, which can require product-line proliferation and product mix customization on a store-level, makes the ability to deliver small replenishment batch sizes even more important. In addition to the development of cross-docking capabilities with important retail customers, P&G’s cosmetics business has also developed advanced technology in their distribution centers that is capable of picking and shipping mixed cases of product. These mixed cases, which can contain as many as 50 different SKUs, enable P&G to supply product in a micro-marketing system without significantly increased costs or complexity for either the retailer or the manufacturer.

##### *Inventory Management Policies*

While some sophisticated chains managed inventory policies at the store-level, most retail chains currently set in-store inventory management policies – review or shipment periods, order points, order-up-to or order quantities – on a chain level. Depending on the retailer and product line, these policies are set at either by SKU or product line. In either case, however, the management of inventory policies based on chain-level data results in policies that are not well aligned with

the demand in individual stores. This misalignment results in significant out-of-stocks and missed sales opportunities.<sup>39</sup>

In her paper, “Supply Chain Optimization in a Retail Environment” Stephanie Hsu describes the systemic effects of uniform inventory management policies at large retailers. In an audit of retail stores, Hsu found that store-level out-of-stock rates varied widely across chains as shown in Figure 12.

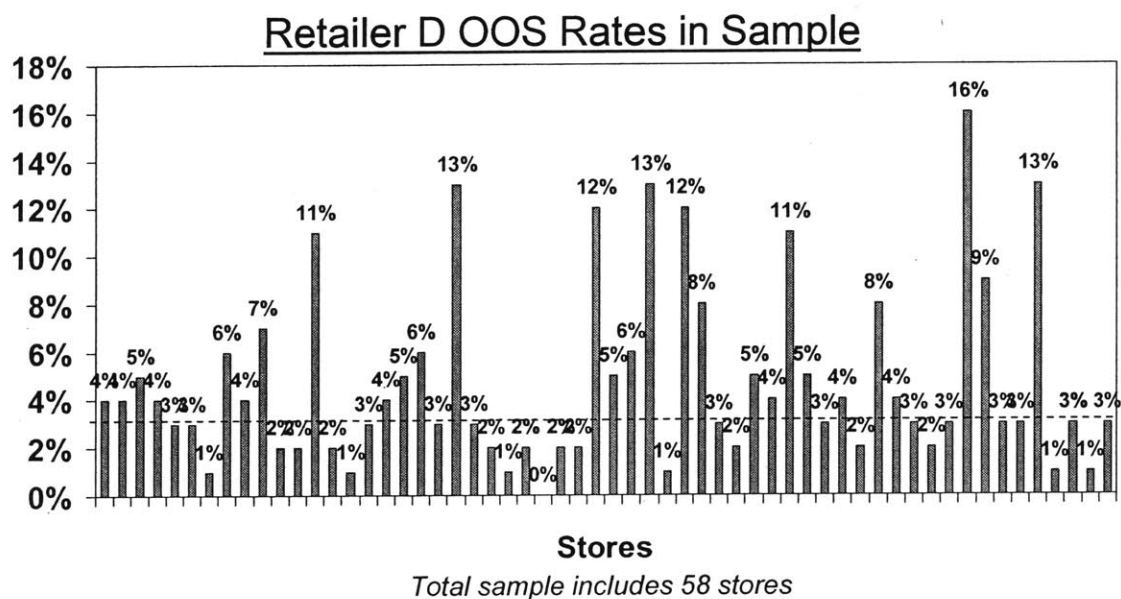
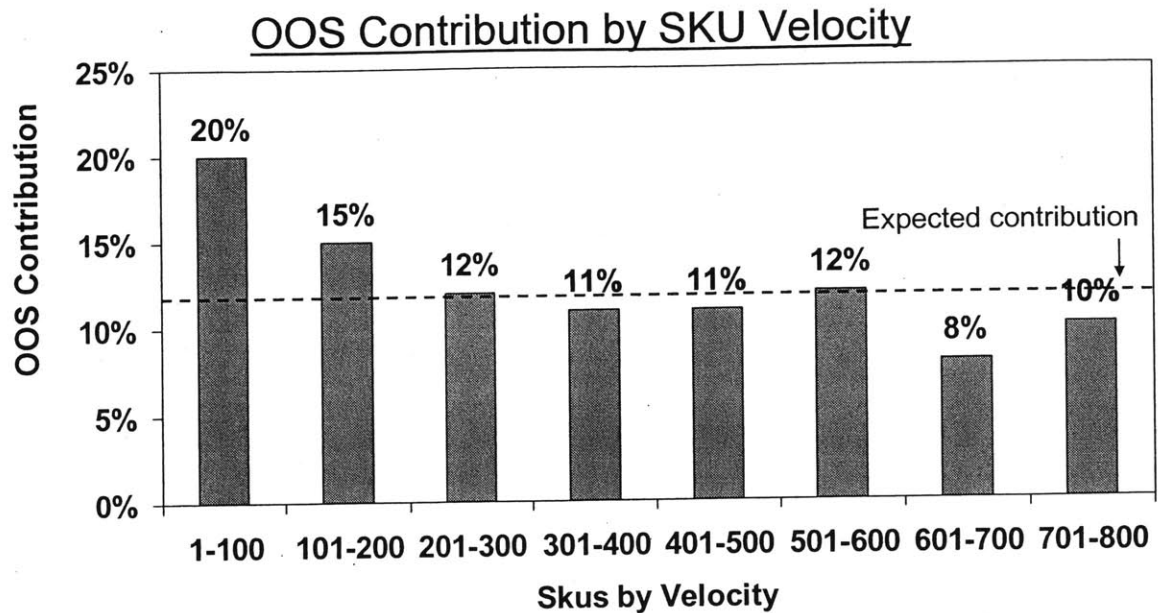


Figure 12 – Observed Store-Level Out-of-Stock Variation<sup>40</sup>

As shown in Figure 13, Hsu also found that (as expected) out-of-stock rates varied widely from SKU to SKU within stores, with high velocity (sales) SKUs out-of-stock much more often than slow moving items.

<sup>39</sup> Hsu, Stephanie. “Optimizing the Retail Supply Chain.” LFM Thesis. MIT. 2003

<sup>40</sup> Ibid



**Figure 13 – Out-of-Stock Rates as a Function of SKU Velocity<sup>41</sup>**

Micro-marketing provides a logical framework in which to address the concerns raised by Hsu’s research. Cluster analysis identifies groups of stores with a similar demand profile which provides a logical basis for the development of cluster-level inventory policies. Often the differences in cluster-to-cluster sales can be drastic. For example, one P&G cosmetics product had average annual sales per store of approximately 8 units across an entire mass retail chain. However, when the stores were clustered, it was discovered that average unit sales per year for this product were below 6 in most clusters while sales in one cluster were 31 units per year. Implementing the same inventory strategy across the entire chain for this product will result in both out-of-stocks and excess inventory, while implementing cluster specific policies will reduce costs in slow moving stores and better serve demand in high volume stores.

In the previously discussed Ames example of micro-marketing, customizing inventory management parties is described as a critical component of the micro-marketing program. “In Wells, ME, for example, a store sold 1,400 boogie boards last summer, says Denis T. Lemire,

<sup>41</sup> Hsu, Stephanie. “Optimizing the Retail Supply Chain.” LFM Thesis. MIT. 2003



executive vice president of merchandising. 'If we weren't focused on that store, we would have sold our usual 100 or 200.' <sup>42</sup>

### *Display and Planogram Logistics*

While most attention is paid to product logistics, designing and implementing a flexible supply chain for displays and planograms is critical to the ability to customize. In Chapter 3 of this paper, the trade-off between costs and benefits as a function of cluster size are discussed. The basic idea of this trade-off is that as a greater number of clusters are formed, the cost of complexity associated with the management of these clusters eventually overwhelms the benefits realized by the increased customization. If product mix or display customization is the micro-marketing strategy employed, the design and implementation of customized displays and planograms are major drivers of this cost increase. Therefore, before these strategies can be employed on a broad basis, it is critical to continue current work aimed at developing flexible, low-cost planograms and display design and implementation processes.

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<sup>42</sup> "Different Strokes for Different Folks." *Discount Merchandiser*. Bristol: Mar 1999. Vol. 39, Issue 3: pg. 28



## **Chapter 5: Procter & Gamble Case Study**

### **5.1 Case Study Introduction**

As mentioned in the introduction to this paper, consumer products manufacturers have traditionally sought additional retail space as a means to drive increased sales. Given the tremendous efforts required to both obtain and defend the space allotted to Procter & Gamble products with top retailers, senior management in P&G's cosmetics division began to look for methods to increase sales within P&G's existing space – and therefore the P&G value proposition to retailers. Following this line of thinking, the original hypothesis of this project was to develop method to customize the product mix and planogram design in specific retail stores to better suit customer preferences and drive increased sales and profits. As the project proceeded, however, the team's thinking expanded to consider the variety of other options that have been mentioned. In this chapter, the analysis performed to validate the project and develop preliminary conclusions will be discussed.

### **5.2 Preliminary Analysis**

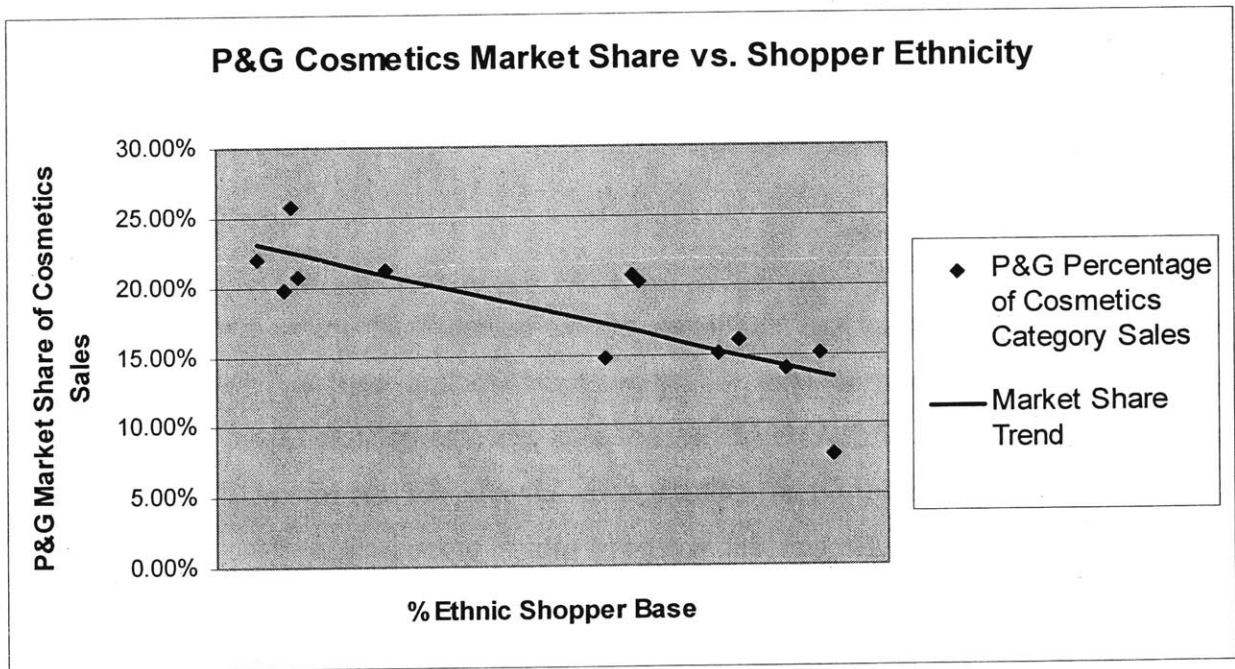
In order to provide a first-pass validation of the potential for micro-marketing in P&G's cosmetics division, a subset of stores selling cover girl products were analyzed. To perform this analysis, a year's worth of SKU-level point-of-sale data was collected from approximately 25 different drug and mass retail stores in Chicago, IL, Lincoln, NE and Miami, FL. These locations were chosen to represent a demographic and geographical cross-section of the retail chains being analyzed.

The characteristics for the average shopper at each store were approximated using the store's zip code and data from the 2000 US census. Store characteristics such as shopper ethnicity, age, and income were analyzed. The data was then analyzed to identify sales trends and determine whether trends can be explained by customer or store attributes.

The information shared here is a brief overview of the insight gained via the preliminary analysis. This sample of findings represents some of the key takeaways from the preliminary

analysis and presents some initial hypotheses on how a micro-marketing program could benefit P&G and their retail partners.

In Chapter 2, the increasing diversity of the US population was discussed; Figure 14 shows market share of P&G's cosmetics products as a function of shopper ethnicity in the stores evaluated in the preliminary analysis. The sharp drop off in market share that P&G experiences as diversity increases gives reason for concern given the demographic trends predicted in the United States – both in the short and long term. A micro-marketing program – which would allow the products and marketing message in each store to be customized to the local shopper base – is one method a large manufacturer such as P&G can use to better serve such a diverse marketplace.



**Figure 14 – P&G Cosmetics Market Share vs. Shopper Ethnicity**

Having identified customer diversity as one factor that impacts the total volume of sales, the data is then evaluated to determine whether there is reason to believe that customization can make a difference. The following two charts evaluate whether the product mix sold changes as a function of shopper diversity. Figure 15 shows this relationship for the P&G cosmetics product segments (accessory, eye, face, lip, and nail products). In Figure 16, the “Eye” product segment

is evaluated in finer detail – evaluating the product mix sold by specific product lines within this segment.

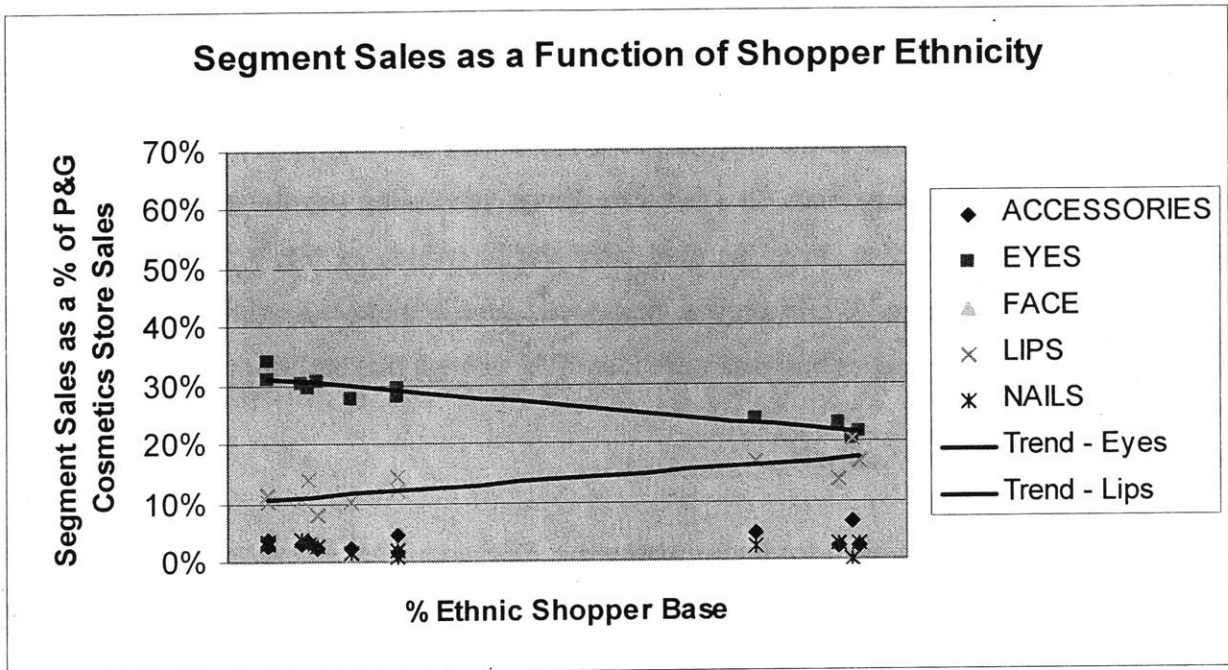


Figure 15 – Segment Sales as a Function of Shopper Ethnicity

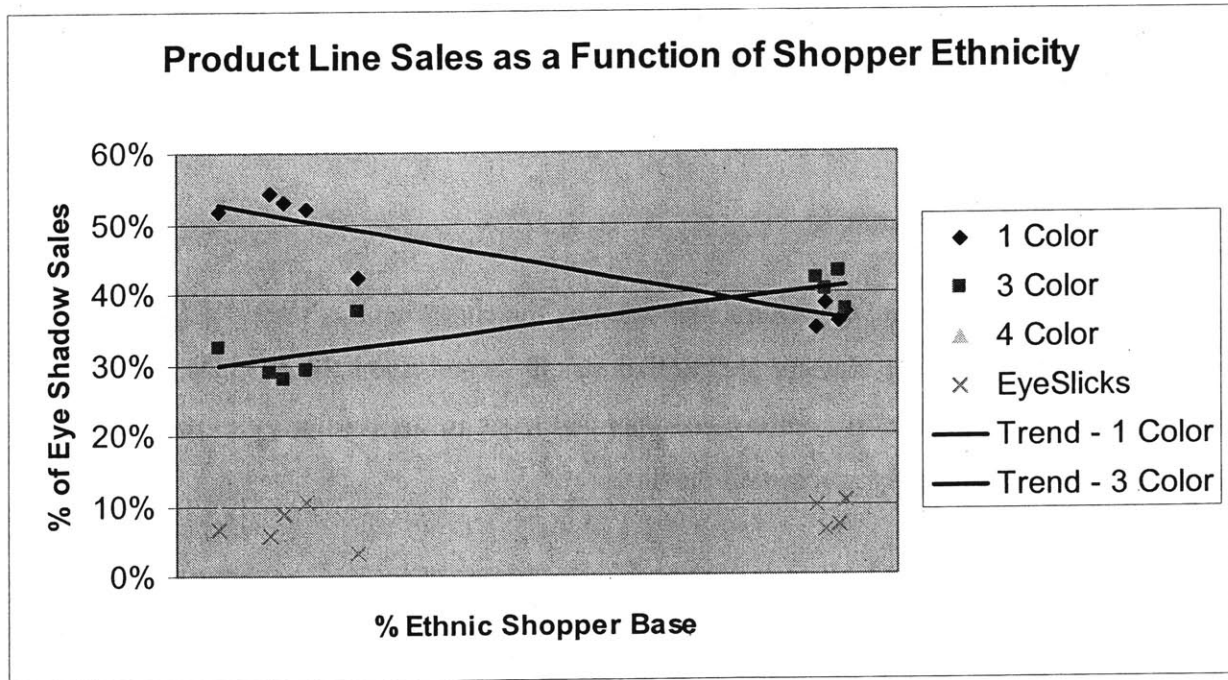


Figure 16 – Product Line Sales as a Function of Shopper Ethnicity

Although limited in scope, in each of these cases, the analysis showed that as the ethnicity of the shopper base changed, the mix of products purchased also changed. From a micro-marketing perspective, this gives reason to believe that potential exists. For example, in a store where a given product is relatively popular, it makes sense to stock similar products that are also likely to be popular. Product popularity can also be capitalized upon in advertising or other promotional activities. A straightforward example of this is the bundling products in a buy-one-get-one free promotion to drive customer trials. In a less direct way, promoting popular products targeted to the local audience can also drive increase aisle traffic, which is likely to lead to impulse purchases on other items. While only a first look, several potential applications of micro-marketing in P&G's cosmetics business were identified through this preliminary analysis.

### **5.3 Mass Retailer A Analysis**

To further explore the potential for micro-marketing, POS data from stores in a mass retail chain was gathered and analyzed. A year's worth of POS data for 48 P&G cosmetics product lines representing almost 500 SKUs was used to cluster the stores in the retail chain. The results of cluster analyses creating three, four, and ten clusters are presented. To start, a brief overview of each scenario is presented to show the evolution of the groups as the number of clusters is increased. The ten cluster scenario will then be discussed in greater detail. Potential micro-marketing strategies for the ten cluster results will be presented.

#### **5.3.1 Three Cluster Scenario**

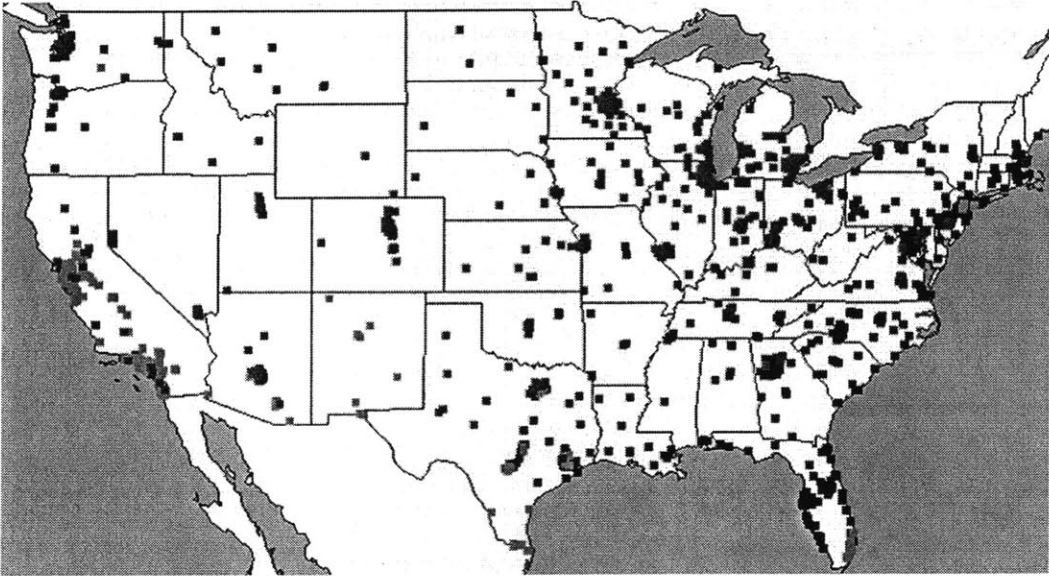
In the three cluster scenario, the groups identified by the cluster analysis are defined primarily by geography. Given that the clusters are created strictly based upon the POS demand profile in each store, the appearance of a strong geographical basis in the results gives reason to believe there is an underlying pattern present in the data.

Stores in Group 1 (colored blue\* in Figure 17), is primarily located on the eastern seaboard. Group 2 (green\*) consists primarily of stores located in southern Florida, the Southwest from California to Texas, and in New York City. Store Group 3 (red\*) is located primarily in the

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\* When printed in black-and-white, blue is black, green is light gray, and red is medium gray.

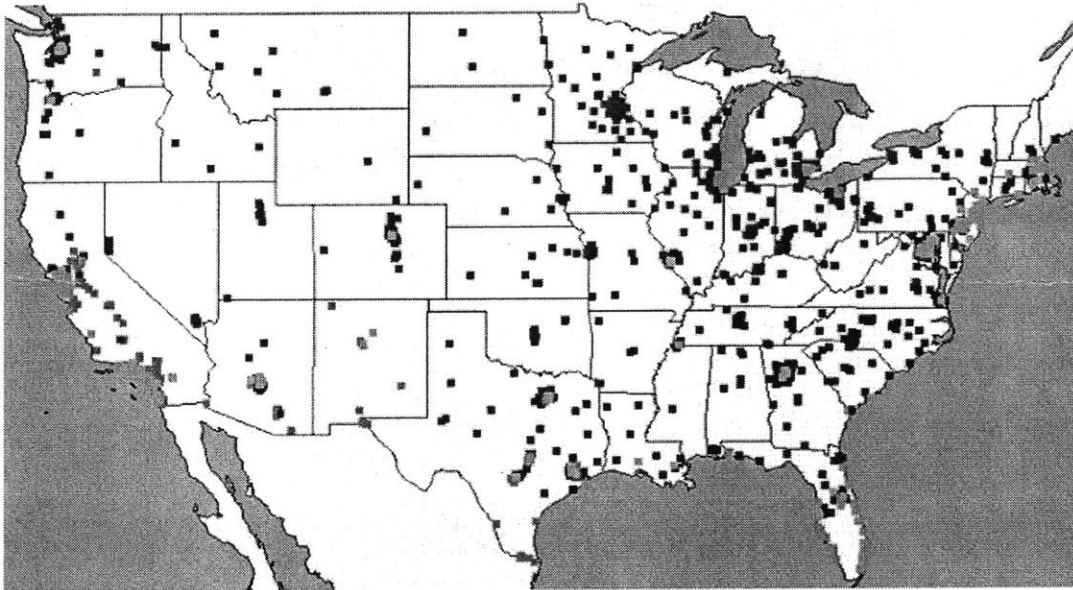
upper Midwest, Great Plains, and Northwest. When compared with US census data, the shopper base in Groups 1 and 3 was not significantly different than US national averages. Group 2, with a large percentage of Hispanic shoppers and non-native English speakers, is the only group to differ from the overall US population.



**Figure 17 – Retailer A Three Cluster Analysis**

### 5.3.2 Four Cluster Scenario

In the three cluster scenario, geography continues to play an important role in the creation of clusters. Groups 1 (blue\* in Figure 18) and 3 (red\*) still consist primarily of stores on the Eastern seaboard and Midwest/Great Plains/Northwest, respectively. Group 3 (green\*) continues to be a primarily Hispanic group, however the cluster no longer contains stores in the Southeast and the shopper base is now primarily of Mexican Hispanic heritage. The new Group 4 (light blue\*) includes primarily stores in urban locations including the Hispanic stores in the Southeast that were previously in Group 3, a large portion of the stores in New York City that were previously in Group 1.



**Figure 18 – Retailer A Four Cluster Analysis**

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\* When printed in black-and-white, light blue is the lightest shade of gray, green is the next lightest shade, red is the darkest shade of gray, and blue is black.



### 5.3.3 Ten Cluster Overview

Figure 19 shows the clusters created in the analysis of the ten cluster scenario. As before, the geographical basis for the clusters is clearly identifiable. The demographic descriptions for each cluster are provided on the following pages.

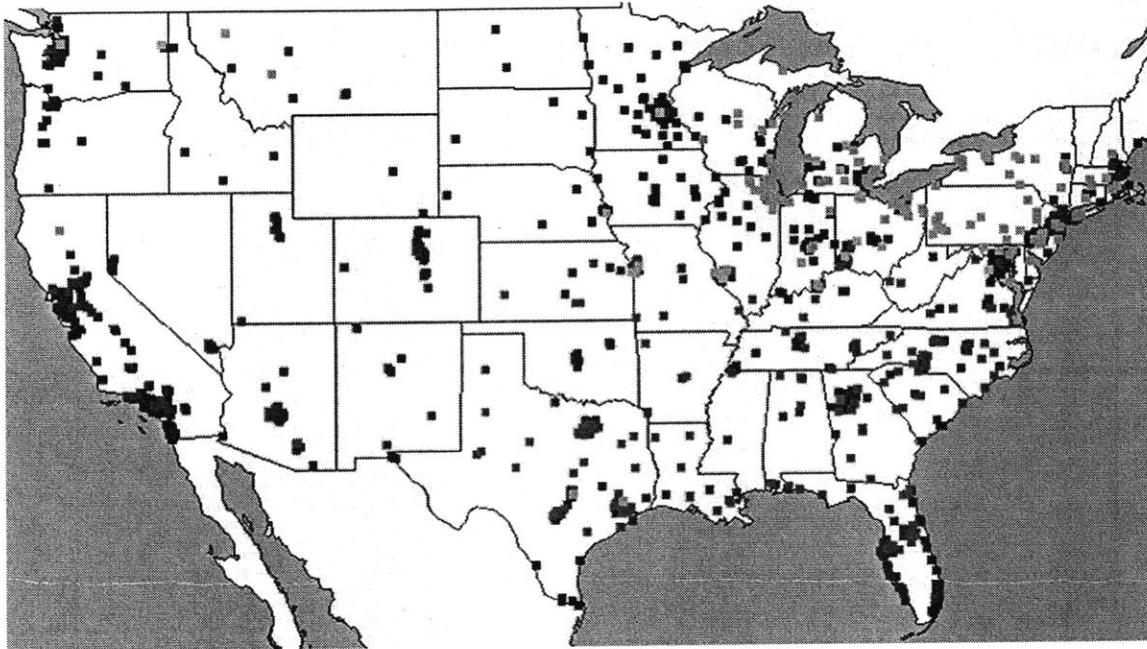


Figure 19 – Ten Cluster Scenario Map

### 5.3.4 Ten Cluster Performance Details

A summary of sales performance in each cluster as well as cluster averages for store attributes and in-stock metrics is presented in Figure 20. The clusters, which are fairly similar in terms of the number of stores assigned to each, have a wide range of average unit sales per store - from 7,808 units/store/year in cluster 5 to 17,057 units/store/year in cluster 3. The next step in the analysis is to identify the attributes that distinguish each cluster.

|          | % of Stores | Unit Sales / Store / Yr (Index vs. Average) | In-Stock % <sup>1</sup> | Avg. PoG Width | ~ % African American <sup>2</sup> | ~ % Hispanic <sup>2</sup> |
|----------|-------------|---|-------------------------|----------------|-----------------------------------|---------------------------|
| Group 1  | 8.6%        | 107%  | 96.2%                   | 19.5           | 11%                               | 7%                        |
| Group 2  | 8.0%        | 111%  | 95.1%                   | 19.3           | 8%                                | 51%                       |
| Group 3  | 8.6%        | 145%  | 95.8%                   | 18.8           | 4%                                | 5%                        |
| Group 4  | 9.3%        | 100%  | 96.1%                   | 19.1           | 15%                               | 25%                       |
| Group 5  | 8.0%        | 66%   | 96.7%                   | 19.3           | 14%                               | 10%                       |
| Group 6  | 10.2%       | 97%   | 96.3%                   | 19.2           | 14%                               | 6%                        |
| Group 7  | 10.0%       | 98%   | 95.9%                   | 18.6           | 5%                                | 4%                        |
| Group 8  | 11.1%       | 113%  | 95.0%                   | 18.9           | 5%                                | 19%                       |
| Group 9  | 11.8%       | 77%   | 96.0%                   | 19.1           | 17%                               | 10%                       |
| Group 10 | 14.3%       | 95%   | 96.2%                   | 19.1           | 9%                                | 5%                        |
| Total    | 100.0%      | 100%  | 95.5%                   | 19.1           | 10%                               | 13%                       |

**Figure 20 – Mass Retailer Group Summary**

### 5.3.5 Ten Cluster Group Descriptions

In addition to performance data, each cluster was also characterized based on demographic data from the US Census. Each cluster was compared with US national averages and significant differences were noted. Cluster averages were based on the zip codes for the stores in each and age, ancestry, commute mode, education level, family size, home ownership levels, home size, income level, labor force participation, language, marital status, occupation type, place of birth population density, race, rent or mortgage rates, and vehicle ownership attributes were evaluated for each cluster. The following pages list key attributes that describe each cluster of stores.

**Group #1**

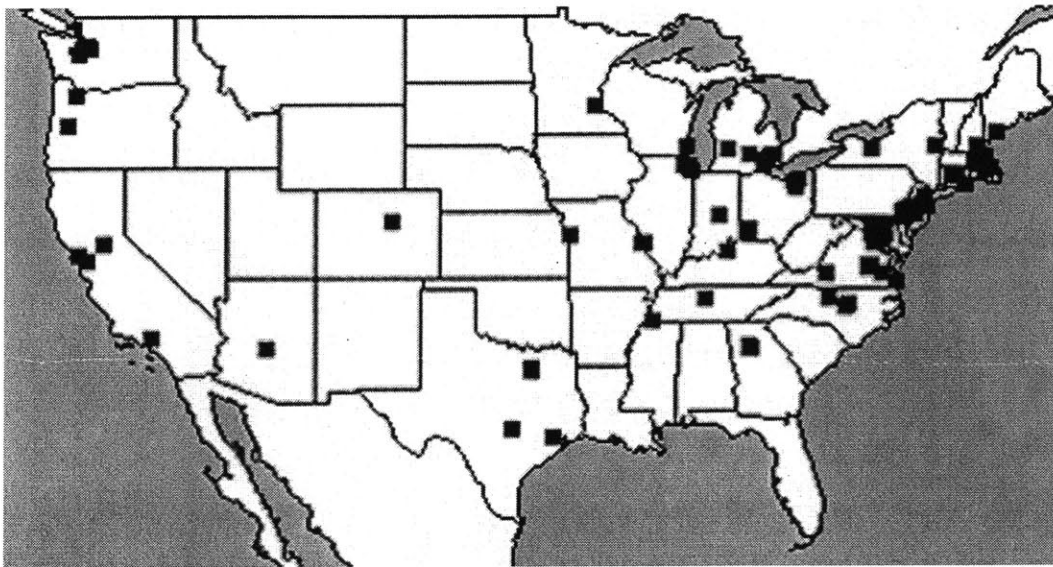
% of Stores: 8.6%

Annual unit sales per store index: 107%

Distinguishing characteristics:

Slightly higher than the US average in terms of:

- Education
- Income per capita
- Professional occupation
- Mid-Atlantic location



**Figure 21 – Group 1 Map**

**Group #2**

% of Stores: 8.0%

Annual unit sales per store index: 111%

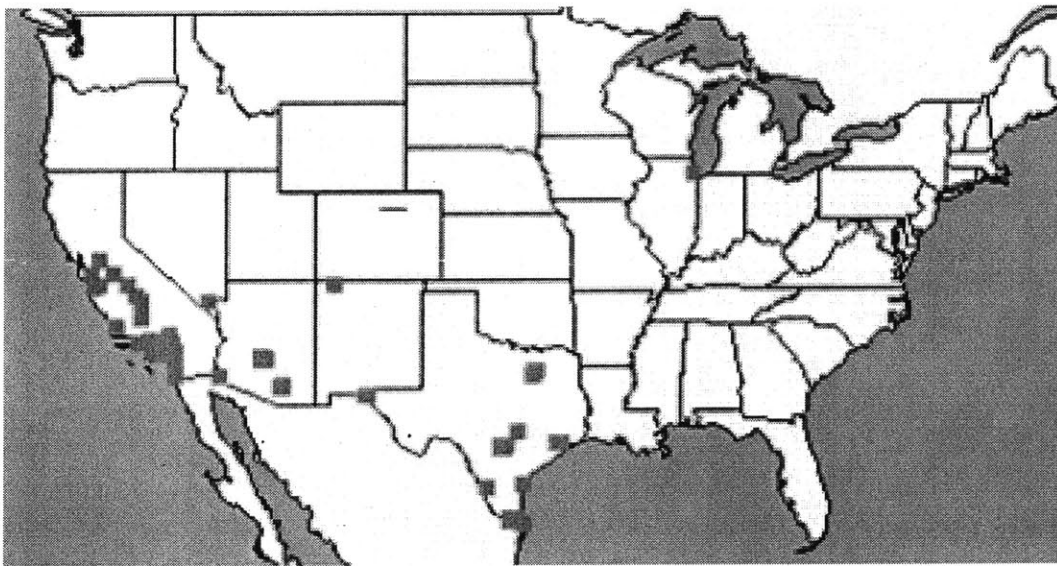
Distinguishing characteristics:

Much higher than the US average in terms of:

- Ethnic diversity
- Hispanic/Mexican background
- Spanish language
- Family size

Lower than the US average in terms of:

- Income per capita



**Figure 22 – Group 2 Map**

**Group #3**

% of Stores: 8.6%

Annual unit sales per store index: 145%

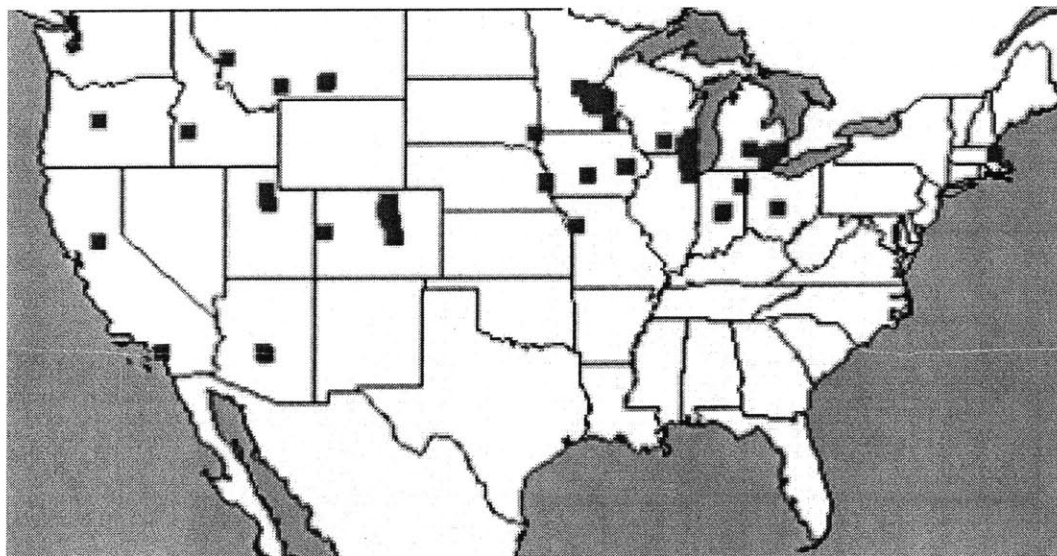
Distinguishing characteristics:

Much higher than the US average in terms of:

- Scandinavian ancestry

Slightly higher than the US average in terms of:

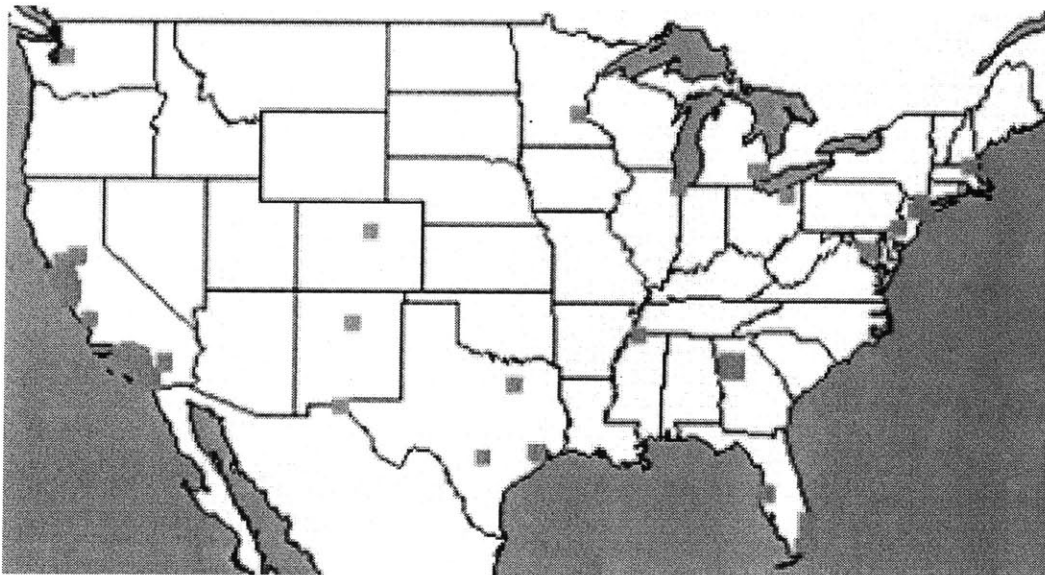
- Income per capita
- Percent of family HH



**Figure 23 – Group 3 Map**

**Group #4**

|   |
|---|
| % of Stores: 9.3%   |
| Annual unit sales per store index: 100%   |
| Distinguishing characteristics:<br>Much higher than the US average in terms of: <ul style="list-style-type: none"><li>• Large city environment</li><li>• Ethnic diversity</li><li>• Asian/Hispanic/Hawaiian background</li><li>• Home language not English</li></ul> Slightly higher than the US average in terms of: <ul style="list-style-type: none"><li>• Income per capita</li><li>• Cost of living</li><li>• Population density</li></ul> |



**Figure 24 – Group 4 Map**

**Group #5**

% of Stores: 8.0%

Annual unit sales per store index: 66%

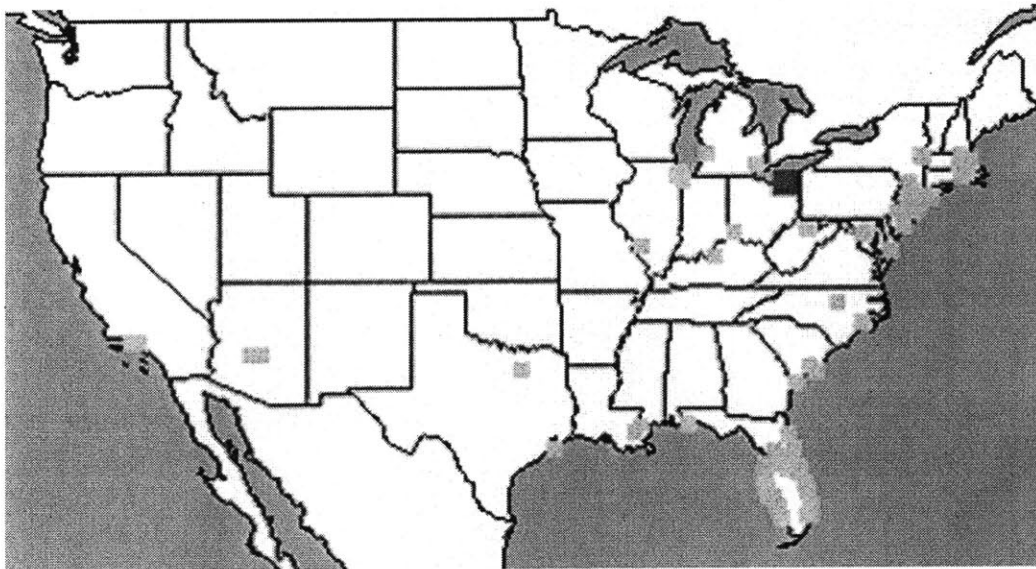
Distinguishing characteristics:

Much higher than the US average in terms of:

- East coast location

Higher than the US average in terms of:

- Puerto Rican and West Indian ethnicity



**Figure 25 – Group 5 Map**

**Group #6**

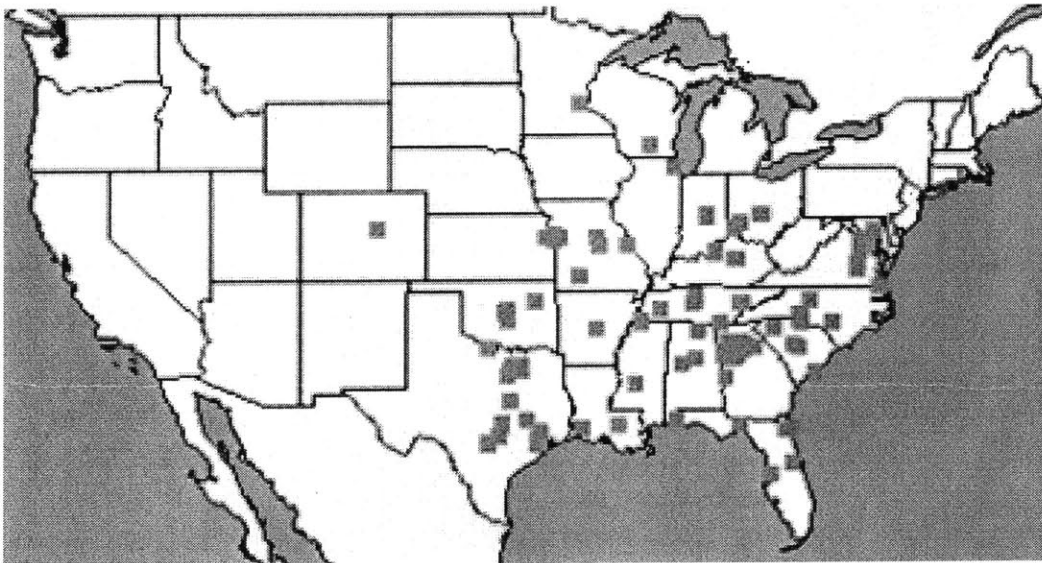
% of Stores: 10.2%

Annual unit sales per store index: 97%

Distinguishing characteristics:

Slightly higher than the US average in terms of:

- US ancestry
- Education
- Southeast location



**Figure 26 – Group 6 Map**



**Group #7**

% of Stores: 10.0%

Annual unit sales per store index: 98%

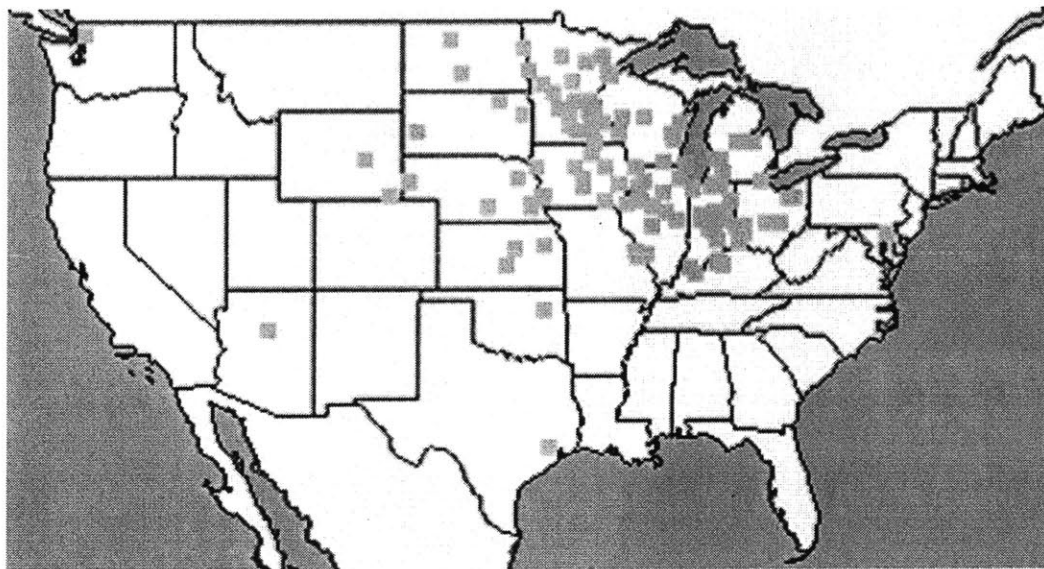
Distinguishing characteristics:

Slightly higher than the US average in terms of:

- US born
- English-only language
- Midwest location

Slightly lower than the US average

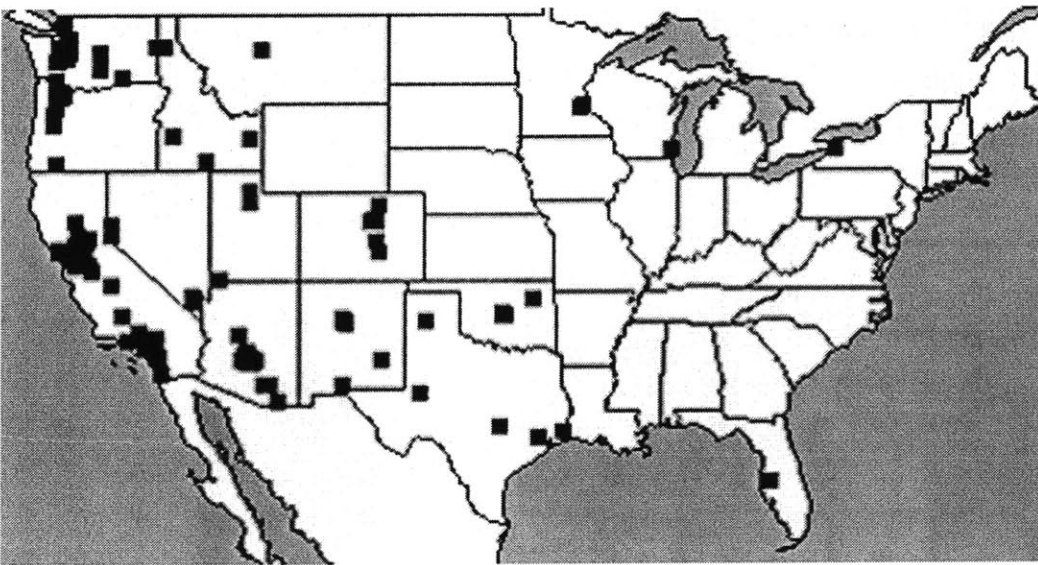
- Cost of living
- Education levels



**Figure 27 – Group 7 Map**

**Group #8**

|   |
|---|
| % of Stores: 11.1%  |
| Annual unit sales per store index: 113%   |
| Distinguishing characteristics:<br>Slightly higher than the US average in terms of: <ul style="list-style-type: none"><li>• Mixed ethnicity</li><li>• West location</li></ul> |



**Figure 28 – Group 8 Map**

**Group #9**

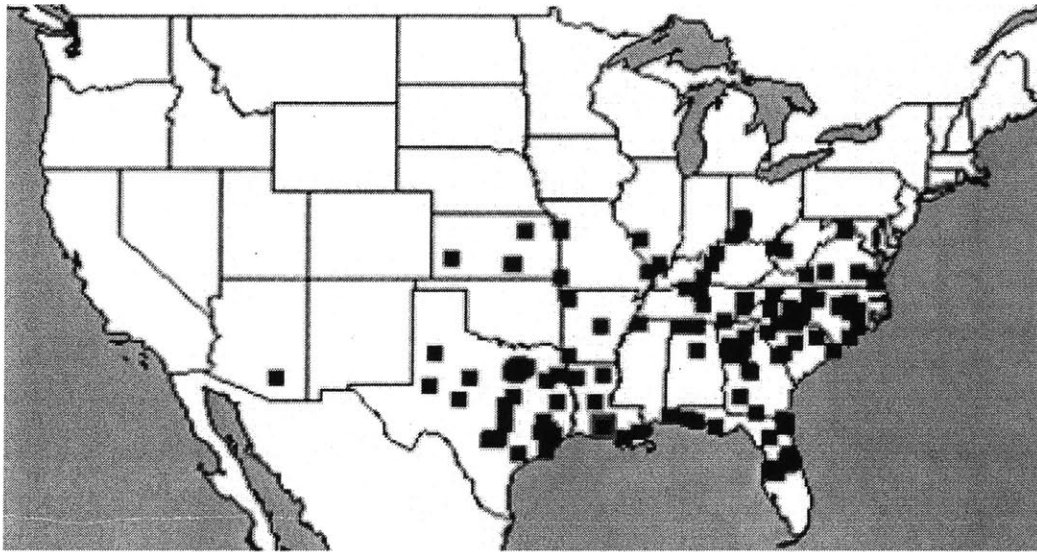
% of Stores: 11.8%

Annual unit sales per store index: 95%

Distinguishing characteristics:

Slightly higher than the US average in terms of:

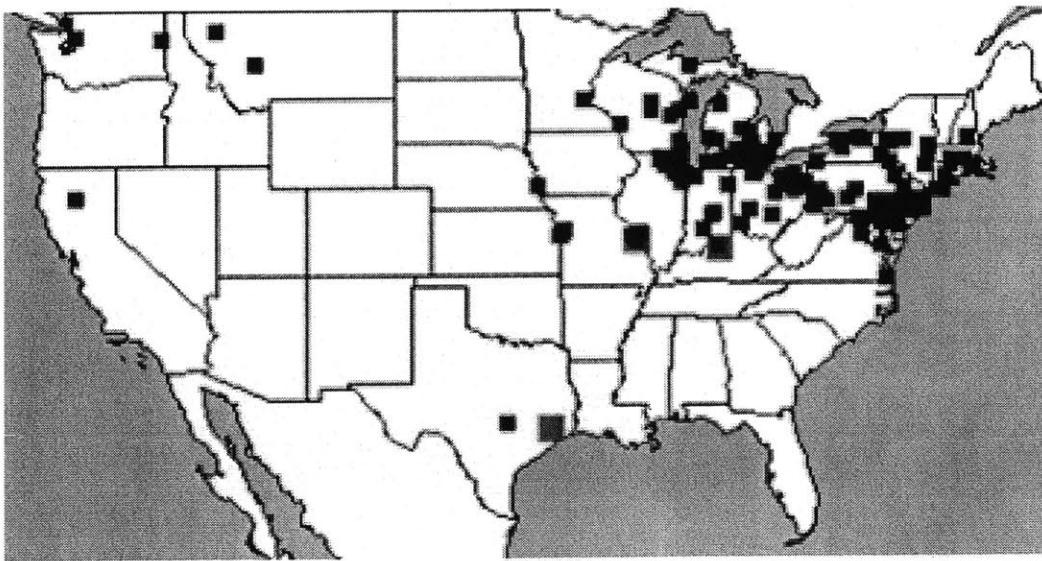
- US ancestry
- Southeast location



**Figure 29 – Group 9 Map**

**Group #10**

|  |
|--|
| % of Stores: 14.3%   |
| Annual unit sales per store index: 95%   |
| Distinguishing characteristics:<br>Slightly higher than the US average in terms of: <ul style="list-style-type: none"><li>• European ancestry</li><li>• Northeast location</li></ul> |



**Figure 30 – Group 10 Map**

## 5.4 Cluster Case Studies: Application of Micro-Marketing Strategies

In this section, several case studies showing how the results of cluster analysis can be used to develop micro-marketing strategies will be presented. To protect proprietary information, these cases are based on a different analysis than the case studies previously presented, however the logic followed would be the same in either case.

In these examples, stores are divided into five clusters. Figure 31 show the locations of these stores in four major cities. Basic descriptions of these clusters are as follows:

- Cluster 1: Northeast-based, diverse ethnicities, immigrants
- Cluster 2: Southeast, Hispanic, Spanish speaking
- Cluster 3: Urban, highly educated, professional occupations
- Cluster 4: Northeast-based, Caucasian, suburban
- Cluster 5: Suburban/rural, blue-collar professions

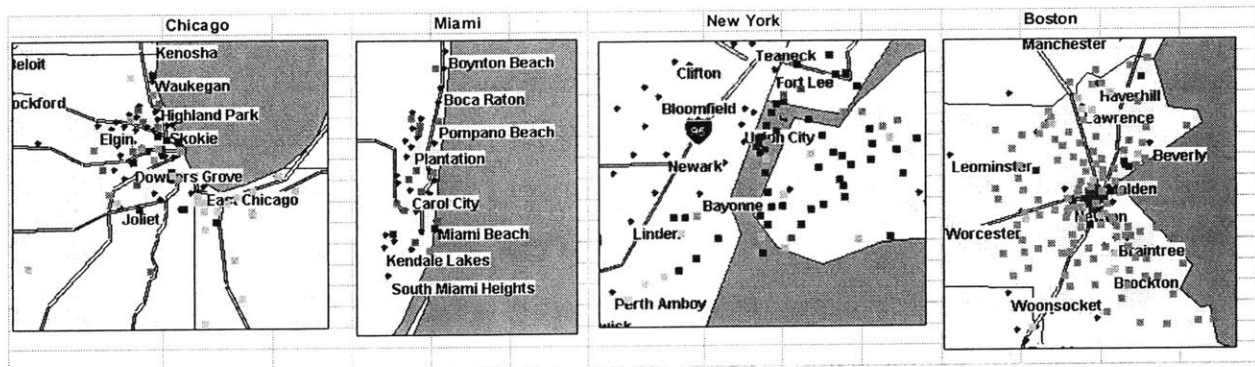


Figure 31: Micro-Marketing Strategies Store Map

*Case Study #1: Lipstick Product Line X*

|  | All Stores | 1     | 2     | 3    | 4    | 5    |
|--|------------|-------|-------|------|------|------|
| % of Cover Girl Sales                    | 9.5%       | 10.3% | 18.1% | 8.0% | 9.4% | 8.5% |
| Index vs. All Stores                     |            | 108%  | 191%  | 84%  | 99%  | 89%  |
|  |            |       |       |      |      |      |
| Annual Unit Sales / Facing <sup>43</sup> | 7.3        | 7.7   | 9.0   | 7.1  | 8.0  | 4.1  |
| Index vs. All Stores                     |            | 105%  | 122%  | 97%  | 109% | 56%  |

**Figure 32: Lipstick X Sales by Cluster**

Situation: While Lipstick X sales are 9.5% of sales among all stores, the product line’s sales in Group 2 are 18.1% of sales. However, while sales are higher on percentage terms in Group 2, the annual unit sales per facing are only slightly higher than other stores.

Conclusion: While Lipstick X sells relatively well in Group 2, other products appear to be selling poorly.

Micro-Marketing Strategies:

1. Capitalize on the popularity of Lipstick X in Group 2: Maximize sales for this product line. Give space from under performing properties to Lipstick X – carry as many shade of Lipstick X as possible.ble.
2. Cross-Promote Other Products in Group 2: Develop merchandising activity to capitalize on Lipstick X’s popularity. For example, physically bundle or offer a buy-one-get-one promotion including a new product with Lipstick X to drive trial of the new item.
3. Bilingual Advertising or Display in Group 2: Considering that sales are lower as a whole in Group 2

<sup>43</sup> A facing is a single slot on the wall of product.

*Case Study #2: Mascara Type Y*

|                            | All Stores | 1    | 2    | 3    | 4    | 5    |
|----------------------------|------------|------|------|------|------|------|
| % of Cover Girl Sales      | 1.1%       | 1.1% | 0.7% | 1.7% | 1.0% | 0.7% |
| Index vs. All Stores       |            | 98%  | 65%  | 158% | 88%  | 63%  |
| Annual Unit Sales / Facing | 18.1       | 16.5 | 7.4  | 31.0 | 18.9 | 6.8  |
| Index vs. All Stores       |            | 91%  | 41%  | 171% | 104% | 38%  |

**Figure 33: Mascara Y Sales by Cluster**

Situation: Both percent of store sales and unit sales are significantly higher for Mascara Type Y in Group 3. Sales volumes for the same product are much lower than average in Groups 2 and 5.

Conclusion: Mascara Type Y is a strong seller among urban, educated, professionals (Group 3). The product does not sell as well to Hispanic shoppers and blue-collar workers.

Micro-Marketing Strategies:

1. Ensure that Mascara Type Y is included in all planograms for the Group 3 demographic. Consider removing the product from stores fitting the Group 2 and 5 demographics if a replacement product is available.
2. Set inventory levels to cover higher demand in Group 3 and, if the product remains available to Groups 2 and 5, lower inventory levels for these groups.
3. Give stores in Group 3 the highest supply priority since stock-outs in these stores are most likely to result in a lost sale.

Case Study #3: Concealer Z

|                            | All Stores | 1    | 2    | 3    | 4    | 5    |
|----------------------------|------------|------|------|------|------|------|
| % of Cover Girl Sales      | 1.7%       | 1.4% | 1.1% | 2.2% | 1.8% | 1.4% |
| Index vs. All Stores       |            | 80%  | 64%  | 127% | 103% | 80%  |
| Annual Unit Sales / Facing | 19.0       | 14.0 | 7.3  | 26.1 | 23.1 | 8.9  |
| Index vs. All Stores       |            | 74%  | 39%  | 137% | 122% | 47%  |
| Rank Among Face Properties | 9          | 10   | 9    | 4    | 7    | 11   |

**Figure 34: Concealer Z Sales by Cluster**

Situation: Annual unit sales per facing for Concealer Z range from 7.3 in Group 2 to 26.1 in Group 5. Among Face products, this product line is the 9th most popular product line overall, but is the product line is 4th most popular within Group 3.

Conclusion: Concealer Z is extraordinarily strong in Group 3. However, among all stores, the product line is not a particularly popular face product.

Micro-Marketing Strategies:

1. Include property in Group 3 planograms with a higher priority than properties ranked ahead of this property based on national sales.
2. Set inventory levels to cover higher demand in groups 3 and 4 and give these stores the highest supply priority since stock-outs in these stores are most likely to result in a lost sale.



## Chapter 6: Influence of Store Attributes on Sales

### 6.1 Retail Sales Drivers

Ideally in a micro-marketing program, an analyst would be able to forecast the sales of each SKU in each store under a variety of conditions and then assemble the product and marketing mix that will maximize sales across the chain. However, in practice this is extremely complicated because of a multitude of factors that influence sales. It is also quite difficult to quantify many of the factors that drive sales. Figures 35 and 36 below show several of the factors identified in discussions with P&G's marketing and sales departments as sales drivers.

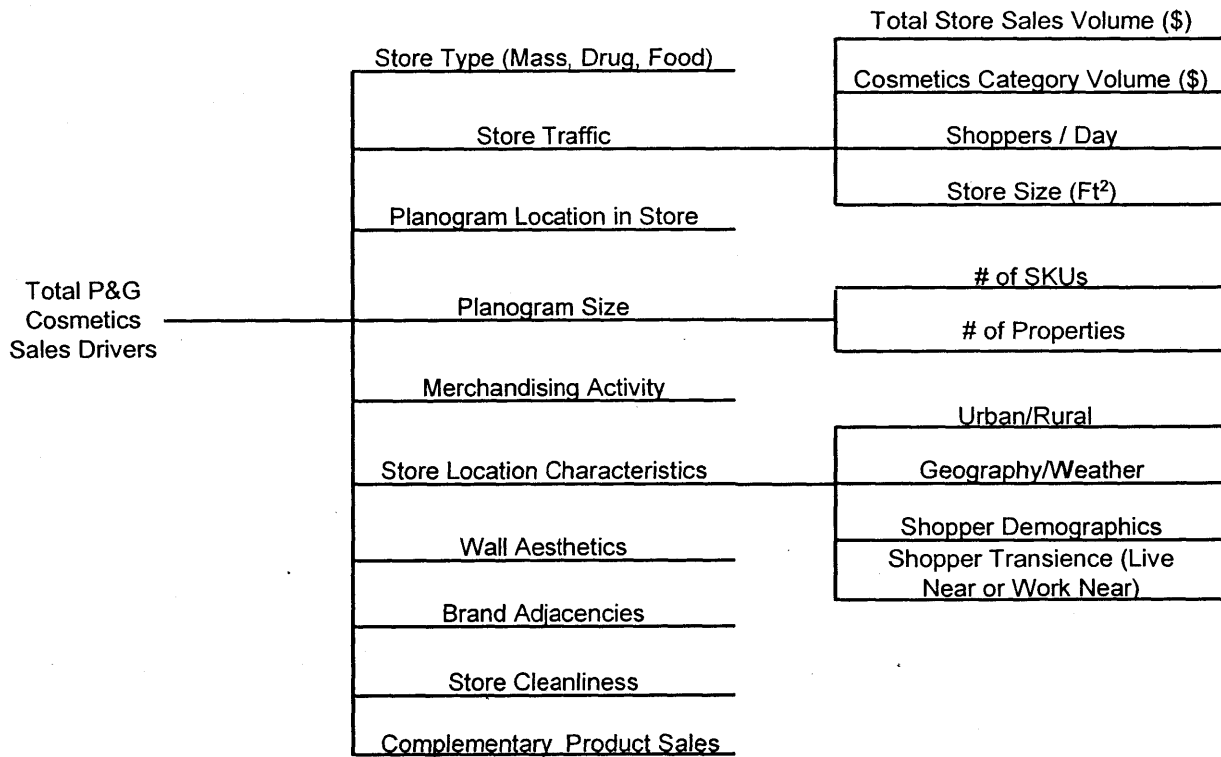
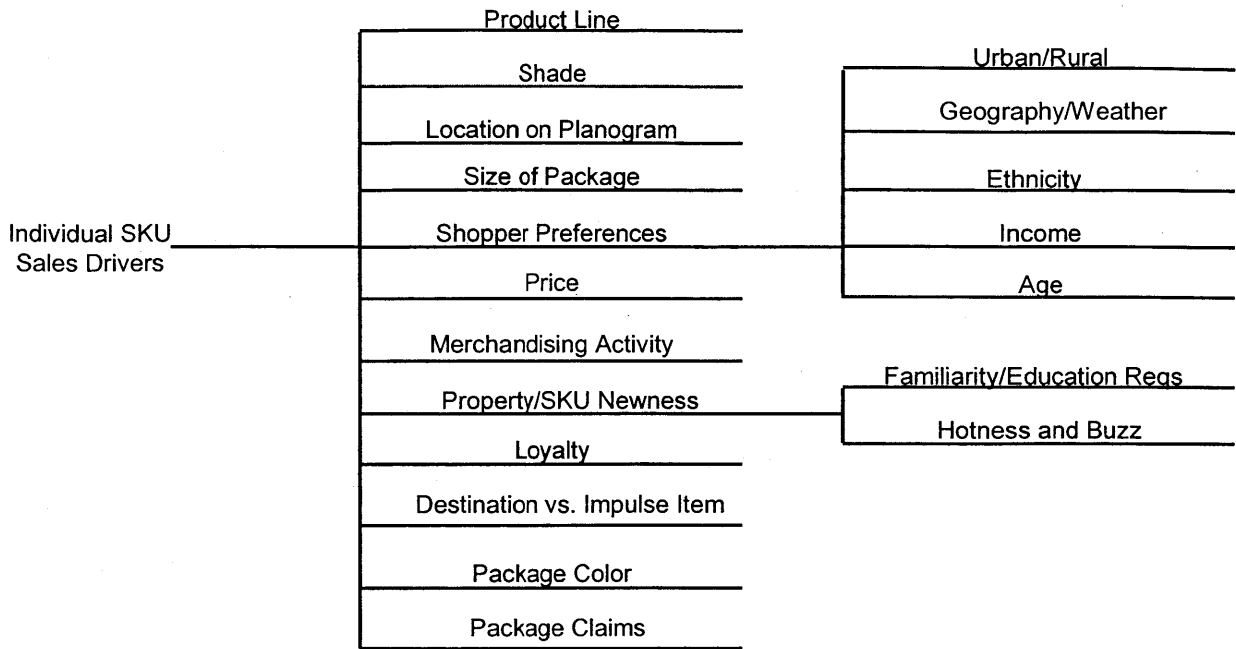


Figure 35 – Sales Drivers that Impact Total Store-Level P&G Cosmetics Sales



**Figure 36 – Sales Drivers that Impact SKU Store-Level Sales**

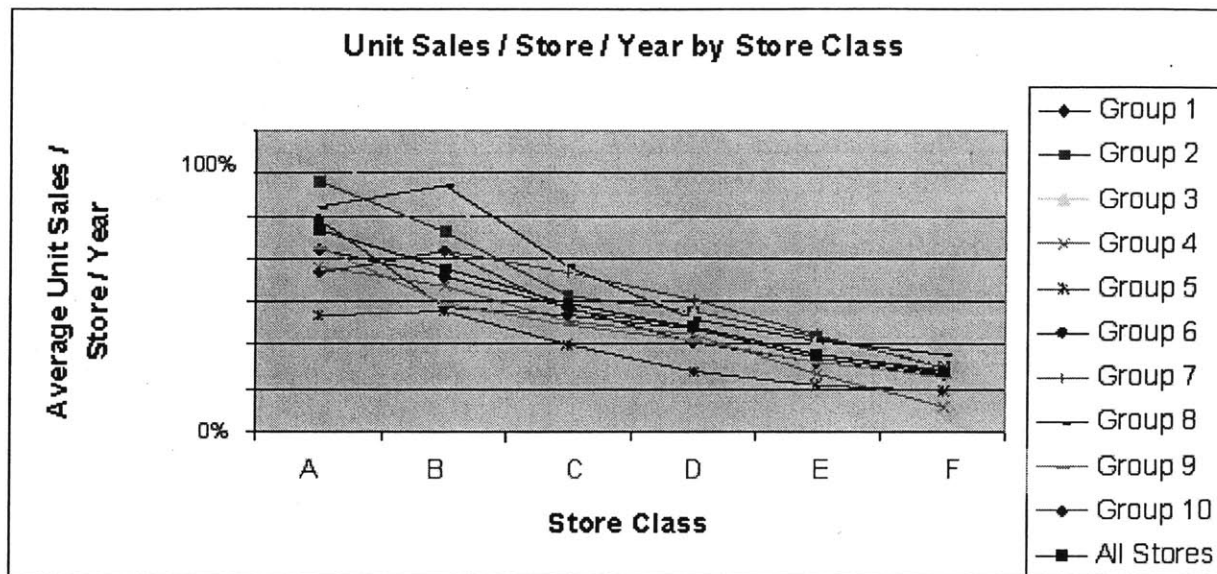
The inherent complexity in marketing and selling a fashion product to a fickle shopper base makes it impossible to develop equations to predict shopper behavior based on the variables described above. It is, however, a useful exercise to explore the impact that these factors have on product sales. In the course of the analysis three factors – store size, store location, and shopper ethnicity were found to clearly impact total sales. The remainder of this chapter will describe the relationships found between these variables and total store sales. If nothing else, these insights provide some important insights into sales and demand from a market research perspective.

## 6.2 Store Size

In most retail chains, a variety of store sizes exist throughout the chain. In the data shown in Figure 37, sales data for six different store classes<sup>44</sup>, ranging from A, the largest, to F, the smallest, are shown. In this chart, average annual unit sales by store are shown for the ten clusters of stores discussed in Section 5.3.3. A clear relationship is shown between the store class and total cosmetics sales is shown in Figure 37. It is also interesting to note that, while the clusters of stores were created based on the demand profile in each store, stores in clusters with

<sup>44</sup> *Store class* is a general store categorization scheme used by the retailer that represents a combination of store traffic, physical size, and total sales.

high sales (example, Groups 3 and 8) tend to sell better across all classes of stores, and vice versa.



**Figure 37 – Unit Sales / Store / Year by Store Class**

One reason it is important to understand the factors that influence sales is to enable a fair comparison of the performance of two different groups. For example, earlier in this paper, the average total sales by cluster for the 10 cluster scenario were discussed. However, given that the average store size might differ significantly from cluster to cluster, it is not a fair comparison to look at these raw sales numbers. The first column in Figure 38 lists the actual annual unit sales per store for the ten clusters. The second column is a prediction of what would have been expected from that cluster based on the size of the stores in the cluster. For example, if “large” stores sold 2,000 units / year on average and “small” stores sold 1,000 units / year on average, a cluster of two large stores and two small stores would be expected to average 1,500 units / store / year.

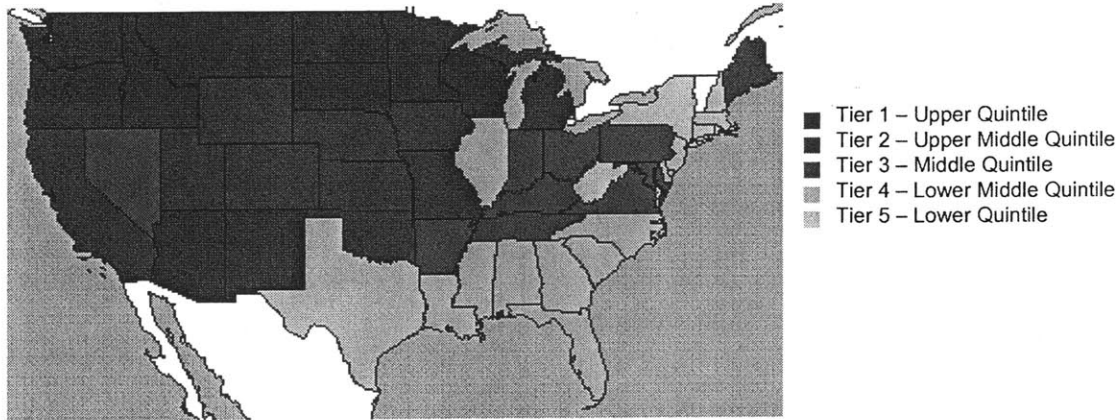
|          | <b>Actual Unit Sales / Store / Yr Index</b> | <b>Unit Sales / Store / Yr Index Normalized by Store Class</b> | <b>Index: Actual vs. Normalized</b> |
|----------|---|--|-------------------------------------|
| Group 1  | 107%  | 116%   | 93%                                 |
| Group 2  | 111%  | 98%  | 114%                                |
| Group 3  | 145%  | 116%   | 125%                                |
| Group 4  | 100%  | 115%   | 87%                                 |
| Group 5  | 66%   | 104%   | 63%                                 |
| Group 6  | 97%   | 103%   | 94%                                 |
| Group 7  | 98%   | 81%  | 120%                                |
| Group 8  | 113%  | 95%  | 119%                                |
| Group 9  | 77%   | 88%  | 88%                                 |
| Group 10 | 95%   | 95%  | 100%                                |
| Total    | 100%  | 100%   | 100%                                |

**Figure 38 – Actual and Normalized Sales by Cluster for the 10 Cluster Scenario**

A comparison of Groups 6 and 7 in the table above is a clear example of why it is important to consider the impact of store size. Looking at the raw data, these clusters had approximately the same total sales. However, when the size of the stores in each cluster are factored in, Group 6 is actually performing worse than would be expected for the size of the stores in the group while Group 7 is performing significantly better than would be expected for the size of the stores in the group.

### **6.3 Store Location**

The second factor that was evaluated was the impact of location on store level sales. Figure 39 shows the relative sales performance (normalized to remove the effects of store size) of stores in each state for one mass retailer.



**Figure 39 – P&G Cosmetics Sales Performance by Store**

In this simple analysis, a clear relationship between the region of the country in which the store is located and the average sales at the store level emerges. Dividing the states into quintiles, the following tiers emerge.

| <b>Tier</b> | <b>Region</b>                 | <b>Sales Index vs. National Average<sup>45</sup></b> |
|-------------|-------------------------------|--|
| 1           | Upper Great Plains            | 127%   |
| 2           | Lower Great Plains            | 114%   |
| 3           | Eastern Midwest, Mid-Atlantic | 92%  |
| 4           | Southeast                     | 83%  |
| 5           | Northeast                     | 76%  |

**Figure 40 – Regional Performance Indices**

Given the drastic differences that appear from region to region, further investigation into performance in different regions is warranted. From a micro-marketing perspective, it is worth investigating whether the marketing strategies being used across the entire chain are geared more towards the market in the first two tiers and whether more effective strategies can be developed for the regions where P&G is currently less successful.

<sup>45</sup> Normalized for to remove the effects of store size

## 6.4 Ethnicity

The final sales driver that will be discussed is the ethnicity of the shopper base. Figures 41 and 42 show the relationship between average annual store sales volume for P&G cosmetics products and the percent of African-Americans and Hispanics in the shopper base, respectively.

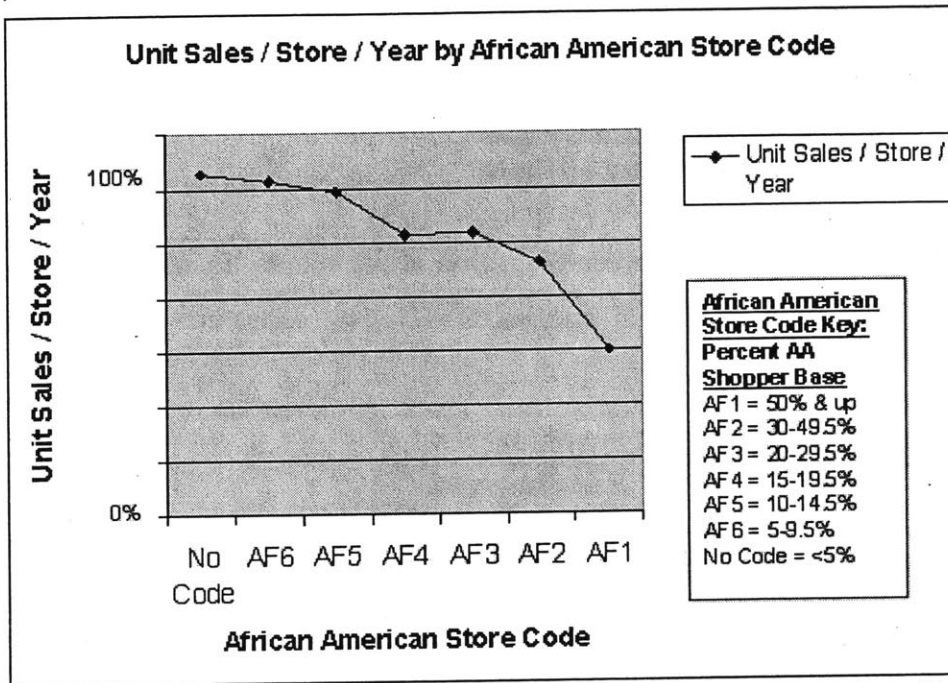


Figure 41 – Sales Performance as a Function of African-American Shopper Base

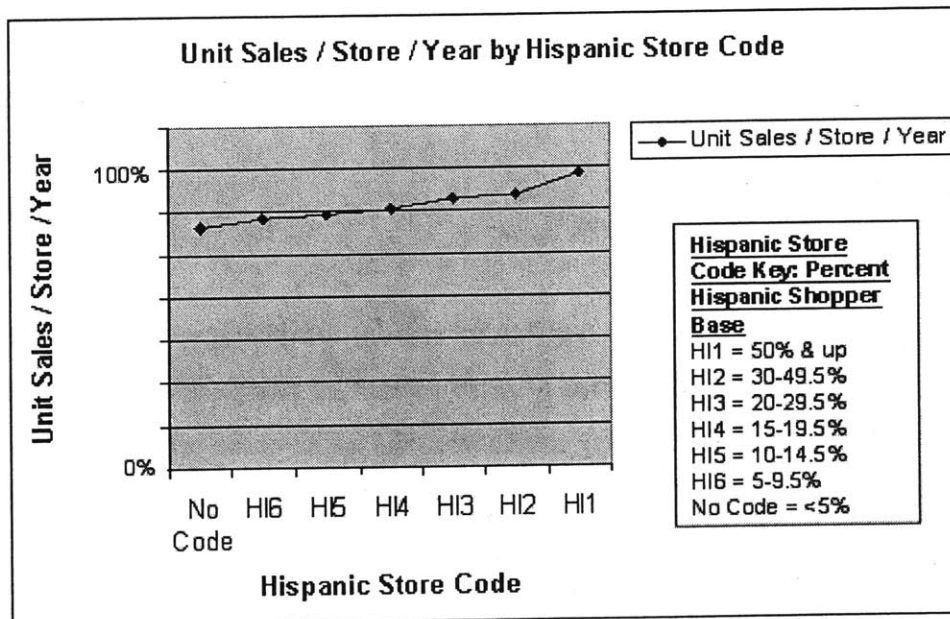


Figure 42 – Sales Performance as a Function of Hispanic Shopper Base

In each of these cases, a clear and relatively stable trend appears with respect to P&G's sales to each ethnic group. Examining these trends highlights the effectiveness of P&G's total marketing package to each ethnic group. With regard to micro-marketing, the analysis shows a potential opportunity to do a better job reaching African-American customers and provides some evidence that current efforts to focus on the Hispanic market are succeeding.





## **Chapter 7: Conclusions**

### **7.1 Hypothesis Revisited**

The original hypothesis of this project focused on varying the product mix and planogram design in specific retail stores to better suit customer preferences as a method of increasing sales and profits. As the project evolved, analysis showed that, even in stores serving different shopper bases, the product mix sold typically did not vary to the degree that mix customization would result in large changes in the mix offered. These results, and the fact that a large percentage of sales are generated through trial product use, lead to the belief that the customization of other micro-marketing strategies such as customized inventory management policies, targeted promotion and communications may be a more effective method of increasing sales than customizing product mix.

The general conclusion of this project is that significant potential exists in the area of store-level micro-marketing. Customization of store-level communications is believed to be the easiest strategy to implement. In some cases, such as those highlighted in Section 5.4, product mix customization may also offer some promise. However, additional analysis and validation through store pilots is necessary before broad conclusions can be made. This document provides a brief project background, describes general conclusions and opportunities available, and provides recommendations on how to implement pilot programs to evaluate these opportunities.

### **7.2 Size of the Prize**

Sales of Cover Girl products in the US vary greatly from store to store within retail chains and the analysis identified several under-performing groups of stores. Targeted efforts to better serve these shoppers and geographies have the potential to increase sales considerably. While the use of more advanced micro-marketing tools will be an effective strategy long-term, in the near future perhaps the biggest contribution of a micro-marketing program and the analysis involved will be to provide clearer insights into the performance of products in the field. Being able to identify weak and strong selling products and establish a better understanding of where and to

whom these products are selling well is valuable in terms of focusing marketing efforts at both a micro and macro level.

This analysis will provide a better method of identifying the regions and shoppers that are being underserved and provide the business case to develop strategies to more effectively meet the needs of these shoppers. While it is difficult to quantify the sales potential resulting from a micro-marketing program, micro-marketing analysis makes it much easier to see the gaps in performance between different groups of stores, between different product lines, and in serving different customer groups. As an example of the sales potential, in the ten cluster example discussed in Section 5.3.3, improving the performance of the three clusters with the lowest average store sales (~350 stores) to the sales / store level in comparably sized stores in the three highest selling clusters holds a net outside sales potential on the order of \$5MM for Procter & Gamble.

### **7.3 Go-Forward Recommendations**

Four work streams have been identified to continue the initial analysis described in this thesis.

#### **7.3.1 Data Infrastructure**

Creating a micro-marketing program is a data intensive affair. In order to gain an understanding of store-level demand and customer preferences, point of sale data must be available. While there is a cost with gathering such data, POS information has many uses beyond micro-marketing – marketing, sales, and supply chain personnel can benefit from improved knowledge of store operations and demand. However, given improvements in information technology, there is little reason that such information is not readily available.

#### **7.3.2 Product Mix Customization**

Stores in clusters that show drastic differences in the demand profile should be considered candidates for evaluating changes in product mix. Cluster #2 in the Mass Retailer A analysis, consisting primarily of stores in California and Texas serving a heavily Hispanic, Spanish-

speaking population, is one such cluster where the product mix sold varied greatly from national numbers. Implementing such a program will involve:

1. Development of planograms for the clusters based on the product mix that sold in these stores.
2. Implementation of a pilot program to test the updated product mix.
3. Measurement of sales in pilot and control stores.
4. Evaluation of results and reapplication of lessons learned.

### **7.3.3 Under-Performing Stores: In-Store Communications Recommendations**

The recommended strategy for increasing sales in the vast majority of under-performing stores where product mix is not an obvious driver is to test the impact of targeted in-store communications. This strategy is appropriate for both mass and drug channels.

Given the vast number of factors that appear to drive low sales, for simplicity's sake, the recommended approach is to choose a group of stores based on one store attribute that has been associated with low sales and focus efforts on this group. For example, stores in the Southeast region or stores in heavily African-American zip codes should be targeted.

A cross-functional team including marketing, market research, sales, and supply chain members will be required to conduct the analysis to better understand these underserved markets and develop the in-store communications strategies. It is important to leverage other work being done in this area when developing these strategies<sup>46</sup>; therefore the inclusion of a wide range of team members is critical. Promotion and in-store signage and display design are strategies that should be considered.

Once strategies are chosen and developed, a pilot program, similar in nature to the pilot program discussed for evaluating product mix changes, should be developed, implemented, and evaluated. If possible, this pilot should be run in parallel to a product mix pilot to allow comparison of the two methods.

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<sup>46</sup> For example, current tests of Spanish language signage will provide valuable information on the effectiveness of this strategy.

#### **7.3.4 Retail Inventory Management Policies**

A final area that should be investigated is the effectiveness of current retail inventory management systems. Figure 13 shows evidence from Stephanie Hsu's analysis of retail out of stocks detailing the high likelihood that high volume SKUs are out of stock. However, even this analysis may understate the true extent of the problem because "SKU velocity" is based on average product sales.

In the second micro-marketing case study presented in Section 5.4, demand for the mascara being studied ranged from 7 units per store per year in once cluster to 31 units per store per year in another. While out-of-stock information for these clusters was not available, inventory policies set at a chain level will clearly not account for the differences in demand experienced by these different groups of stores. Given these concerns, further investigation of retail inventory management policies is warranted.

#### **7.4 General Conclusions**

While the analysis of micro-marketing presented in this thesis is provided from the perspective of a consumer products manufacturer, the lessons learned are broadly applicable in the retail industry and beyond. As discussed in Chapter 2, the business world is moving to place where quality products and low costs are not sufficient to maintain and grow market share. The importance of focusing on operational excellence has been popularized by firms such as Toyota and a more widespread understanding of methods to improve operational performance has led to most firms having the ability to product high-quality, low-cost products. In order to compete, firms must now find ways to leverage these capabilities not only to cut costs but to grow revenues. In a world where success is increasingly defined by a firm's ability to provide excellent service and meet individual customer's specific needs as well as provide high-quality, low-cost products, micro-marketing provides a method to translate supply chain capabilities into such an advantage.

## Appendix A – K-Median Cluster Analysis Example

The following simple example illustrates the use of the k-median model for a fictional chain of eight stores that carry ten products. For example purposes, demand for the ten products is used to cluster eight stores into three clusters. Underage/overages costs of \$2 and \$1 were chosen based on average margins achieved on cosmetics products.

Sp – Total unit sales by product

|  | Product |       |       |       |       |       |       |       |       |       |
|--|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
|  | Item1   | Item2 | Item3 | Item4 | Item5 | ItemA | ItemB | ItemC | ItemD | ItemE |
|  | 167     | 124   | 208   | 260   | 328   | 185   | 119   | 201   | 213   | 288   |

Sip – Unit sales by product by store

|       | Product |       |       |       |       |       |       |       |       |       |
|-------|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Store | Item1   | Item2 | Item3 | Item4 | Item5 | ItemA | ItemB | ItemC | ItemD | ItemE |
| 1     | 25      | 6     | 25    | 25    | 64    | 16    | 28    | 37    | 21    | 28    |
| 2     | 19      | 23    | 35    | 21    | 35    | 23    | 5     | 21    | 19    | 47    |
| 3     | 35      | 7     | 16    | 23    | 49    | 44    | 35    | 47    | 29    | 62    |
| 4     | 6       | 14    | 17    | 65    | 28    | 6     | 16    | 19    | 73    | 32    |
| 5     | 30      | 51    | 68    | 38    | 51    | 14    | 6     | 14    | 17    | 23    |
| 6     | 20      | 4     | 10    | 11    | 12    | 38    | 5     | 20    | 20    | 50    |
| 7     | 29      | 6     | 26    | 23    | 58    | 28    | 5     | 14    | 16    | 17    |
| 8     | 4       | 13    | 11    | 53    | 31    | 16    | 20    | 30    | 18    | 30    |

Bip – Percent of sales by product p in store i

|       | Product |       |       |       |       |       |       |       |       |       |
|-------|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Store | Item1   | Item2 | Item3 | Item4 | Item5 | ItemA | ItemB | ItemC | ItemD | ItemE |
| 1     | 9%      | 2%    | 9%    | 9%    | 23%   | 6%    | 10%   | 13%   | 8%    | 10%   |
| 2     | 8%      | 9%    | 14%   | 8%    | 14%   | 9%    | 2%    | 8%    | 8%    | 19%   |
| 3     | 10%     | 2%    | 5%    | 7%    | 14%   | 13%   | 10%   | 14%   | 8%    | 18%   |
| 4     | 2%      | 5%    | 6%    | 24%   | 10%   | 2%    | 6%    | 7%    | 26%   | 11%   |
| 5     | 10%     | 16%   | 22%   | 12%   | 16%   | 4%    | 2%    | 4%    | 6%    | 8%    |
| 6     | 10%     | 2%    | 5%    | 6%    | 6%    | 20%   | 3%    | 11%   | 11%   | 26%   |
| 7     | 13%     | 3%    | 12%   | 10%   | 26%   | 12%   | 2%    | 6%    | 7%    | 8%    |
| 8     | 2%      | 6%    | 5%    | 23%   | 14%   | 7%    | 9%    | 13%   | 8%    | 13%   |

Overage and underage costs

|      | Product |       |       |       |       |       |       |       |       |       |
|------|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
|      | Item1   | Item2 | Item3 | Item4 | Item5 | ItemA | ItemB | ItemC | ItemD | ItemE |
| Up = | \$2     | \$2   | \$2   | \$2   | \$2   | \$2   | \$2   | \$2   | \$2   | \$2   |
| Op = | \$1     | \$1   | \$1   | \$1   | \$1   | \$1   | \$1   | \$1   | \$1   | \$1   |

w<sub>i</sub> – Total unit sales by store

| Store |     |
|-------|-----|
| 1     | 276 |
| 2     | 248 |
| 3     | 346 |
| 4     | 276 |
| 5     | 310 |
| 6     | 190 |
| 7     | 223 |
| 8     | 226 |

d<sub>ij</sub> – Percent of sales “distance” between stores

| Store | 1      | 2      | 3      | 4      | 5      | 6      | 7      | 8      |
|-------|--------|--------|--------|--------|--------|--------|--------|--------|
| 1     | 0.0000 | 0.7330 | 0.4944 | 1.1240 | 0.8968 | 1.0382 | 0.5327 | 0.6743 |
| 2     | 0.7330 | 0.0000 | 0.5989 | 1.1343 | 0.6735 | 0.8030 | 0.6926 | 0.8088 |
| 3     | 0.4944 | 0.5989 | 0.0000 | 1.1847 | 1.1801 | 0.5663 | 0.8067 | 0.6258 |
| 4     | 1.1240 | 1.1343 | 1.1847 | 0.0000 | 1.2730 | 1.3382 | 1.2838 | 0.6001 |
| 5     | 0.8968 | 0.6735 | 1.1801 | 1.2730 | 0.0000 | 1.4170 | 0.7633 | 1.1276 |
| 6     | 1.0382 | 0.8030 | 0.5663 | 1.3382 | 1.4170 | 0.0000 | 1.0326 | 1.1247 |
| 7     | 0.5327 | 0.6926 | 0.8067 | 1.2838 | 0.7633 | 1.0326 | 0.0000 | 1.0804 |
| 8     | 0.6743 | 0.8088 | 0.6258 | 0.6001 | 1.1276 | 1.1247 | 1.0804 | 0.0000 |

d<sub>ij</sub> \* w<sub>j</sub> – Percent of sales “distance” weighted by total store sales

| Store | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|
| 1     | 0   | 202 | 136 | 310 | 247 | 286 | 147 | 186 |
| 2     | 182 | 0   | 149 | 281 | 167 | 199 | 172 | 201 |
| 3     | 171 | 207 | 0   | 410 | 409 | 196 | 279 | 217 |
| 4     | 311 | 314 | 328 | 0   | 352 | 370 | 355 | 166 |
| 5     | 278 | 209 | 366 | 395 | 0   | 439 | 237 | 350 |
| 6     | 197 | 152 | 107 | 254 | 269 | 0   | 196 | 213 |
| 7     | 119 | 154 | 180 | 286 | 170 | 230 | 0   | 241 |
| 8     | 152 | 183 | 142 | 136 | 255 | 254 | 244 | 0   |

### Decision Variables

Y<sub>j</sub> – Binary variable determining whether store j is a cluster centroid

|                |   |   |   |   |   |   |   |   |                        |   |
|----------------|---|---|---|---|---|---|---|---|------------------------|---|
| Y <sub>j</sub> | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | Sum(Y <sub>j</sub> ) = | 3 |
|                |   |   |   |   |   |   |   |   | =                      |   |
|                |   |   |   |   |   |   |   |   | K =                    | 3 |

$X_{ij}$  – Binary variable determining whether store  $i$  is included in cluster  $j$

| Store | Cluster |   |   |   |   |   |   |   | Row_Sum | = | RHS |
|-------|---------|---|---|---|---|---|---|---|---------|---|-----|
|       | 1       | 2 | 3 | 4 | 5 | 6 | 7 | 8 |         |   |     |
| 1     | 0       | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1       | = | 1   |
| 2     | 0       | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1       | = | 1   |
| 3     | 0       | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1       | = | 1   |
| 4     | 0       | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1       | = | 1   |
| 5     | 0       | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1       | = | 1   |
| 6     | 0       | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1       | = | 1   |
| 7     | 0       | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1       | = | 1   |
| 8     | 0       | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1       | = | 1   |

$w_i * d_{ij} * X_{ij}$  – Objective function values

| Store | 1 | 2 | 3   | 4   | 5 | 6 | 7   | 8 |
|-------|---|---|-----|-----|---|---|-----|---|
| 1     | 0 | 0 | 136 | 0   | 0 | 0 | 0   | 0 |
| 2     | 0 | 0 | 149 | 0   | 0 | 0 | 0   | 0 |
| 3     | 0 | 0 | 0   | 0   | 0 | 0 | 0   | 0 |
| 4     | 0 | 0 | 0   | 0   | 0 | 0 | 0   | 0 |
| 5     | 0 | 0 | 0   | 0   | 0 | 0 | 237 | 0 |
| 6     | 0 | 0 | 107 | 0   | 0 | 0 | 0   | 0 |
| 7     | 0 | 0 | 0   | 0   | 0 | 0 | 0   | 0 |
| 8     | 0 | 0 | 0   | 136 | 0 | 0 | 0   | 0 |

Objective solution minimizing the  
 $\text{Sum}(i,j) w_i * d_{ij} * X_{ij} =$

765

### Solution

| Group | Store | Product |       |       |       |       |       |       |       |       |       |
|-------|-------|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
|       |       | Item1   | Item2 | Item3 | Item4 | Item5 | ItemA | ItemB | ItemC | ItemD | ItemE |
| A     | 1     | 9%      | 2%    | 9%    | 9%    | 23%   | 6%    | 10%   | 13%   | 8%    | 10%   |
| A     | 2     | 8%      | 9%    | 14%   | 8%    | 14%   | 9%    | 2%    | 8%    | 8%    | 19%   |
| A     | 3     | 10%     | 2%    | 5%    | 7%    | 14%   | 13%   | 10%   | 14%   | 8%    | 18%   |
| B     | 4     | 2%      | 5%    | 6%    | 24%   | 10%   | 2%    | 6%    | 7%    | 26%   | 11%   |
| C     | 5     | 10%     | 16%   | 22%   | 12%   | 16%   | 4%    | 2%    | 4%    | 6%    | 8%    |
| A     | 6     | 10%     | 2%    | 5%    | 6%    | 6%    | 20%   | 3%    | 11%   | 11%   | 26%   |
| C     | 7     | 13%     | 3%    | 12%   | 10%   | 26%   | 12%   | 2%    | 6%    | 7%    | 8%    |
| B     | 8     | 2%      | 6%    | 5%    | 23%   | 14%   | 7%    | 9%    | 13%   | 8%    | 13%   |

### Average Demand Profile for Each Cluster

| Group | Product |       |       |       |       |       |       |       |       |       |  |
|-------|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|--|
|       | Item1   | Item2 | Item3 | Item4 | Item5 | ItemA | ItemB | ItemC | ItemD | ItemE |  |
| A     | 9%      | 4%    | 8%    | 8%    | 14%   | 12%   | 6%    | 12%   | 9%    | 18%   |  |
| B     | 2%      | 6%    | 6%    | 24%   | 12%   | 5%    | 8%    | 10%   | 17%   | 12%   |  |
| C     | 12%     | 10%   | 17%   | 11%   | 21%   | 8%    | 2%    | 5%    | 7%    | 8%    |  |





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