

**Modeling Supply Chain Benefits of Efficient Assortment**

by

**Marta Lew**

M.S., Economics (2004)

Warsaw School of Economics

Submitted to the Engineering Systems Division in Partial Fulfillment of the Requirements  
for the Degree of

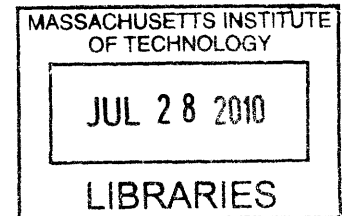
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## **ABSTRACT**

The recent developments in retail industry created a challenging environment for companies in the sector and their trade partners. Retailers' focus on recovering their financial results through eliminating unproductive inventory and reducing unnecessary complexity has led to an increased pressure on their suppliers. In order to adapt to the new market settings, a major manufacturer of consumer goods wanted to be able to look at its product portfolio through the perspective of its direct clients. This capability was established in form of a decision model which utilizes Point of Sales, operational, and financial data of the company's downstream partners to recommend assortment changes at item, category and cross-category levels, as well as to project results of these changes. The tool uses the input data and information on product variety to assess risk of lost sales and to quantify possible improvements in product availability, retailers' logistics costs, efficiency of their operations, utilization of supply chain assets, and—perhaps most importantly—their revenues and profits. The new decision model reinforced the manufacturer's competence to support objectives of clients while continuing to pursue its own goal of offering end-customers products which they need, trust and value.

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## 1. INTRODUCTION

My research on efficient assortment started as a thesis project proposed by a large global Consumer Packaged Goods Manufacturer which I will be calling “GoodsCo”. GoodsCo’s portfolio spans multiple consumer categories and well-known brands which can be found at the shelves of most stores offering personal care, household and healthcare items. The company’s products are popular across demographic segments on all continents. Quality, consistency and innovation differentiate GoodsCo’s brands from competitors’ and lead to customers’ loyalty.

In order to better manage the assortment of items offered to distribution channels and ultimately - to customers, GoodsCo wanted to be able to look at its product portfolio through the perspective of its retailers. Years of working partnerships with clients had given the manufacturer’s team a good understanding of what this perspective entailed. At the same time, the company knew that it could derive additional relevant insights from the Point of Sales (POS), operational and financial data which store operators were willing to share. The combination of relationship-based and analytical insights was going to enable GoodsCo’s team to take initiative in helping retailers achieve their goals.

Through proactively offering suggestions regarding assortments which support retailers’ goals and improve utilization of their supply chains, as well as proposing advice on shelf composition, GoodsCo was hoping to broaden the extent of their already close relationship with its downstream partners. In addition to information sharing, forecasting, inventory management, planning of promotions and product design, the company wanted to engage in the process of merchandising. GoodsCo expected that, while helping retailers’ objectives, such extended partnership would also help channel its funds and creativity to most popular products. The supplier was hoping that its involvement in the Efficient Assortment initiative would support

more successful product development, thus helping in retaining its portion of store shelves. At the same time, proactively managing the assortment would eventually allow the company to free its manufacturing and logistics network from servicing items that don't create much value to clients and customers.

Part of my role in GoodsCo's endeavor was to provide an unbiased perspective on trends present in the retail space, initiatives popular among companies in the sector and –most importantly—objectives driving their selection of products carried in stores. The other substantial part of the role consisted of capturing this perspective in a flexible, scalable decision model which GoodsCo could utilize to analyze sales, operational and financial data. These two elements were going to help the manufacturer see their products selection through the retailers' lens and structure its product portfolio so as to make it more attractive for its downstream partners.

The research addressed three of GoodsCo's product categories dubbed "Clean", "Fresh", and "Healthy", within two distinct retailers: a mass merchandiser and a drug channel. The scope was designed this way to ensure that the model was not tailored to the requirements of one particular merchant or customized for one product type and hence easy to adapt to another category-retailer setting. It was also important that the model could be scaled to larger datasets.

The following three sections outline the background of this research. Section 1.1 explains the general idea of efficient assortment. Section 1.2 discusses the relevant developments in the retail industry and explains the reasons why retailers are closely monitoring products offered to their customers. Finally, section 1.3 provides an overview of some of the challenges and opportunities which efficient assortment offers to manufacturers of consumer goods (1.3).

## 1.1. THE CONCEPT OF EFFICIENT ASSORTMENT

Thayer, W. (1997) defined efficient assortment as “an analytical evaluation tool that allows distributors and manufacturers to better understand what they are to provide to customers”. The author stressed that efficient assortment (EA) should not be seen as a simple SKU rationalization exercise performed by retailers. Instead, it should be implemented as a central element of category management which requires close cooperation between retailers and manufacturers as well as sharing of data and communicating strategies.

The process itself involves analyzing the trade-offs between financial performance of products (sales and profits), customer loyalty, and operational performance of supply chain. The collaborative analytical effort promises to improve the assortment’s efficiency: increase product turns, sales per square foot and GMROI (Gross Margin Returns on Investment), all while reducing the levels of inventory.

The engagement of vendors in EA typically occurs after the categories’ definitions, roles and strategies have been defined by retailer’s category managers. Knowing the category role and strategy is key to select the set of SKUs which will perform best in supporting the strategy. The category’s purpose affects its shelf space, number of SKUs offered and proportion between premium and economy products. It also determines the set of indicators which most accurately reflect the category assortment’s performance.

Finally, it should be noted here that efficient assortment is a process in which SKU evaluations should be performed at least quarterly. The repetitiveness of this exercise, together with the amount of information which needs to be processed in order to support relevant decisions, create the need for a tool which can automate the necessary analyses.

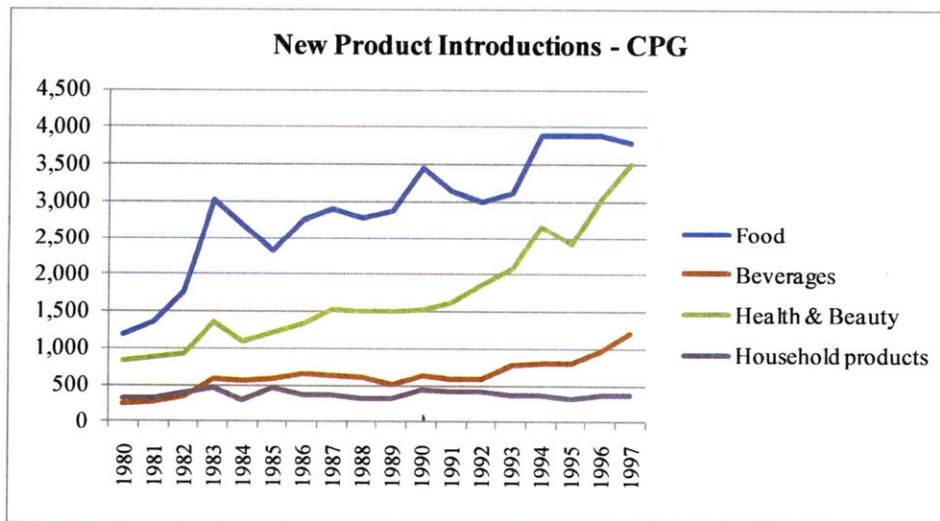
As it was mentioned in the Introduction, GoodsCo recognized that understanding the retailers' point of view was critical for the success of the EA initiative. The manufacturer appreciated the role of its distribution channels and the importance of understanding its downstream partners' challenges, some of which are outlined below.

## 1.2. DEVELOPMENTS IN RETAIL INDUSTRY AND THE NEED FOR EFFICIENT ASSORTMENT

Although efficient assortment is a cooperative effort, decisions regarding carried products belong to retailers, causing this research project to focus primarily on their perspective. This chapter talks about the recent and expected developments in the retail industry which make EA an attractive proposition for companies in the sector.

### 1.2.1. Proliferation of SKUs

Figure 1

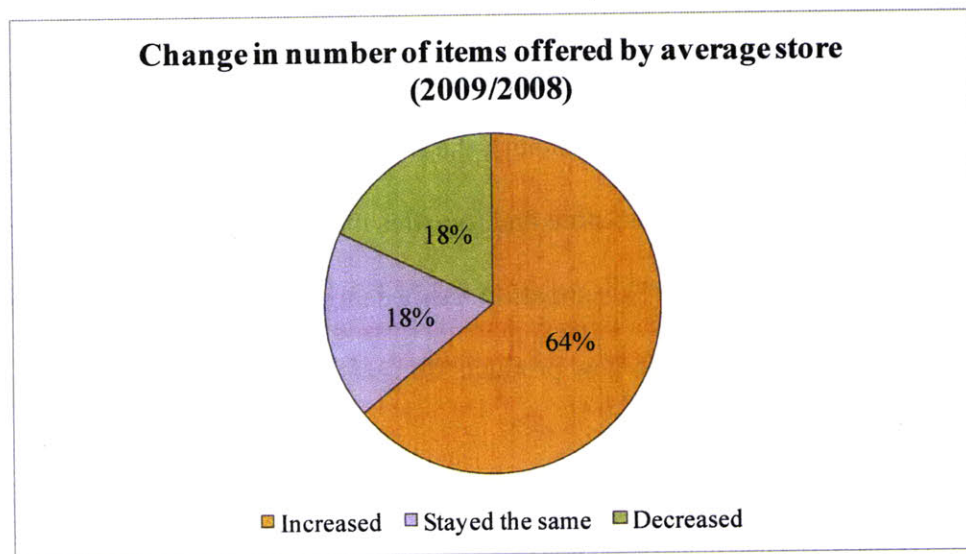


To appeal to new customers, CPG companies every year introduce multiple new product varieties.

Source: [www.allcountries.org/us Census/889\\_new\\_product\\_introductions\\_of\\_consumer\\_packaged.html](http://www.allcountries.org/us Census/889_new_product_introductions_of_consumer_packaged.html)

New products are the “lifblood of retailing” – they attract new customers, entice incumbent shoppers to return to a store, and give retailers the opportunity to capture a new portion of the market and incur sales growth. All these reasons were causing the number of new product launches to surge for long years before the recent weakening of consumers’ buying power (see Figure 1 for a comparison of several product categories).

**Figure 2**



SKU proliferation results from new items being added to store shelves without other items being eliminated.

Source: Consumer Goods Technology, AMR Research (2009)

At the same time, discontinuing existing products which represent known demand and client loyalty is a risk—for both the retailer and the manufacturer. As a result, many new products are introduced not in place of but next to the existing ones, creating an ever-growing array of brands, flavors and sizes. According to the Food Marketing Institute, a typical food retailer currently carries about 47,000 different products, which

represents a 50% increase, compared with 1996<sup>1</sup>. A recent report, Consumer Goods Technology, AMR Research (2009), shows that while 18% of CPG manufacturers maintained the same number of selling items in 2009 as they had in 2008 and another 18% reduced their product portfolio, as many as 64% of suppliers crammed additional items on their shelves (see Figure 2). Because retail space has not been expanding at an equal rate, this tendency to add products has made store shelves very cluttered and difficult to choose from.

Although product variety is one of the most important reasons for customers' preference of one store over another<sup>2</sup>, the recent proliferation of SKUs has been overwhelming for retailers, store and logistics managers, and—perhaps most importantly—shoppers. This situation has been a great concern for retailers, shifting their focus from expansion into new products, formats, and geographies over to category management activities.

### **1.2.2. Category Management**

Category management (CM) was developed in the early 1990s as a way of dealing with the soaring number of new product launches, erosion of margins, and range of customers' specific requirements. Within a few years it became an essential process for retailers. Through CM, retailers, with the help of their suppliers, decide on the best way to present a category of merchandise: which items should be carried in which stores, how

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<sup>1</sup> Ryan, T. (2009)

<sup>2</sup> Hoch, S.J., Bradlow, E.T., Wansink, B. (1999)

much of each SKU to carry, how to price them, which shelf to put them on, how much shelf space to allocate, whether and how to promote each item, etc.

As indicated in the previous paragraph, assortment decisions within category management are typically made for one category in isolation from others and with the assumption that shelf space dedicated to the category is predetermined. A category manager is typically responsible for maximizing profits from his or her category. Such approach, although common, does not optimize the store's or company's results and does not maximize the assortment's efficiency. If assortment decisions are made across categories, a portion space reserved for a less profitable category can be reassigned to a more profitable one. A cross-category analysis is also likely to suggest better utilization of logistic assets (e.g. storage rooms or trucks) and activities performed simultaneously for different types of products (picking, unpacking, shelving, monitoring etc.).

Adapting of assortment is often part of retailers' effort to attract a larger and more economically diverse shopper group. Retailers who look at their merchandise across categories and try to promote growing and profitable items can address customers' needs without expanding or even while reducing their product portfolios. In order to do this, they identify and group product categories which drive traffic to their stores and in which customers want to see more variety – the “destination categories”. On the other hand, they select products which should continue to be represented in stores (e.g. to maintain the status of a “one-stop shop”) but will not suffer from reduced selection. Such<sup>3</sup> category

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<sup>3</sup> The category groupings mentioned in this paragraph are two extremes; retailers typically define several intermediate classes of merchandise (Radhakrishnan, S. (2002)).

groupings represent varying objectives—they may be expected to attract a specific demographic segment, improve customer loyalty, drive traffic, generate profits etc.

The desire of retailers to satisfy their customers' requirements extends beyond offered assortment and can be described as store operators' quest for "shoppability".

### **1.2.3. Shoppability**

Shoppability—a concept which describes the “capacity of the shopping environment to transform consumer needs and desires into purchases”<sup>4</sup>—is a serious concern for retailers who are competing for positive impression and loyalty of shoppers. Although store operators are responsible for majority of the settings which may improve shoppability (most importantly: store layout, signage, atmosphere and service level), there are some initiatives where their vendors can provide considerable support. The most popular include, but are not limited to, sharing in the cost of displays, promotions, and marketing materials.

Reducing the overwhelming number of product varieties another way in which retailers can make their stores more “shoppable”. According to Hamstra, M. (2009), “supermarkets should be a filter between the supplier and the consumer, not a direct conduit”, they should simplify decisions for customers and to make their experience easier and more enjoyable.

Other methods of enhancing the shopping environment include: improving availability and presentation of items on shelves, ensuring that desired categories and popular brands are offered, giving customers access to product information, and allowing

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<sup>4</sup> Burke, R. R., Payton, P. E. (2006).

them to choose between classes of product (e.g. premium, regular or economy detergent). Additionally, it has been noted<sup>5</sup> that stores' flexibility to test new concepts, surprise shoppers, and always keep their offer current and attractive, is an important element of shoppability. Since this flexibility is partly constrained by stores' ability to remerchandise (change layout and composition of shelves), this consideration affects assortment and inventory decisions, providing directions and applying constraints to initiatives such as efficient assortment.

The growing popularity of club and discount stores is a sign that customers appreciate the ease of shopping and that many of them are ready to give up on wide product selection in return for a better understanding of the available options and ability to make their regular store visits shorter. Of course, customers' fondness of this store format is also strongly related with the difficult economy.

#### **1.2.4. Impact of Recession**

The recent economic downturn created a challenging environment for shoppers and—in turn—for retailers. For 15 years, the retail sector was growing at an average rate of 12%<sup>6</sup>, recording steadily growing revenues, profits and stock prices. In 2008, same-store sales began to decline, forcing retailers to suspend store openings, cut back store hours and—often—close some of their existing stores (Figure 3 illustrates the increase followed by decline in number of retail outlets operating in the USA from 2004 until 2009). To protect declining margins, retailers focused their attention on cost management. One of the areas which received most concern has been the size of systemic

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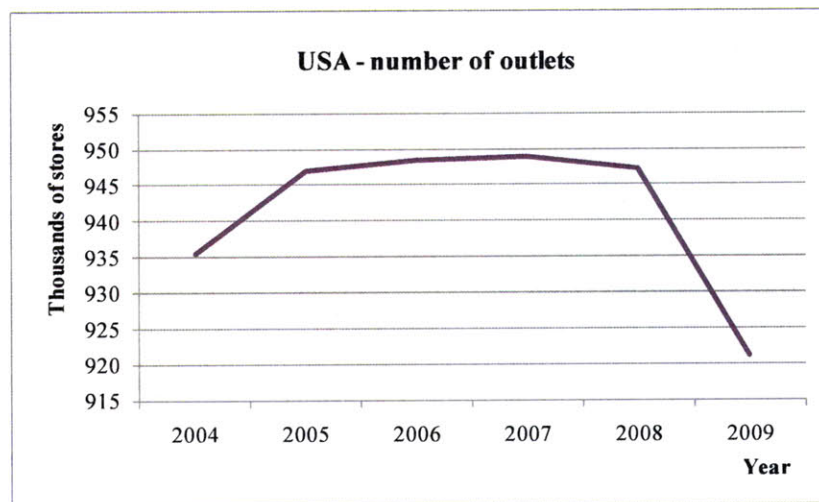
<sup>5</sup> Ibid.

<sup>6</sup> Favaro, K., Romberger, T., & Meer, D. (2009).

costs of complexity driven by uncontrolled product proliferation and unproductive inventory, both of which are directly related with product assortment.

Although SKU rationalization programs were being pursued by many retailers before the current recession began, the emphasis on cost reduction intensified in the last two years. The increased pressure on margins and omnipresent pursuit to reduce working capital added two more good reasons for retailers to look close at the performance of brands and SKUs.

**Figure 3**



After a period of steady growth in the retail industry, a dramatic decrease in consumer confidence caused by the recent economic downturn led many US retailers to stop expansion and close their stores.

Source: Consumer Goods Technology, AMR Research (2009).

Industry journals published in 2009 reported a deluge of SKU rationalization programs. Virtually all non-specialty retailers—as well as several leading drug stores—engaged in such initiatives. Walmart, Walgreen, Supervalu, Rite-Aid<sup>7</sup>, Kroger<sup>8</sup>, Target,

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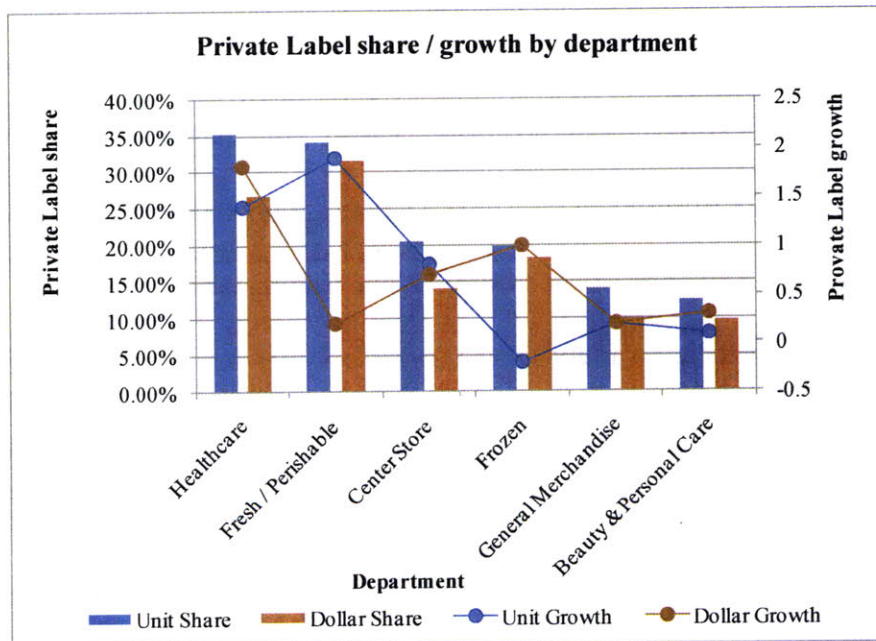
<sup>7</sup> Chain Drug Review (2009).

Safeway, Ahold, CVS, even Costco<sup>9</sup>--whose assortment has always been narrow--were among those which generated most interest with their ambitious goals in SKU count reduction. The recession has also led many retailers to redefine their category roles and begin to track product performance by adapted sets of measures.

Another side-effect of the tough economy of the last months is the growing popularity of private label products. The next subsection discusses its implications for assortment management.

### 1.2.5. Private Labels

Figure 4



Private label penetration and growth rates by retail department: consumers are most willing to accept store brands healthcare and perishable departments. National brands lead (and will continue to lead) in Beauty & Healthcare.

Source: IRI (2009).

<sup>8</sup> Thayer, W. (2009)

<sup>9</sup> Canning, K. (2009)

Growing popularity of Private Label products (see Figure 4 for penetration and growth rates by department) gives retailers another reason to carefully select which products to sell through their outlets. Store brands, which used to be merely cheaper alternatives for mainstream products, are now becoming recognizable trademarks with considerable brand equity. Many retailers are beginning to offer customers several differentiated private labels and invest in their marketing<sup>10</sup>.

Thanks to minimal advertising and R&D costs, store labels offer retailers much higher profit margins than national brands<sup>11</sup>. This advantage, together with growing consumers' acceptance for private labels in mainstream product categories, makes retailers protective their display space. National brand items with relatively low relevance or profitability are now subject to more strict scrutiny from stores which want to maximize the utilization of their greatest asset – the shelf. Considering the profitability and popularity of store brands, some retailers are observing that—for selected categories—an assortment consisting of one leading brand and private label SKU constitutes sufficient variety.

Although the market shares and of private label products in departments featuring GoodsCo's products are moderate and their growth is slower than 0.5% per year (see Figure 4), the manufacturer continues to monitor this strong trend in customers' and retailers' preferences.

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<sup>10</sup> Pinto, D. (2009).

<sup>11</sup> Information Resources, Inc. (2009) estimates the average size of the gap to be 31%. At the same time, there is a significant variability in margin between product categories: the difference between brands and private labels for Healthcare amounts to 46% and for Beauty & Personal Care - to 64%.

### **1.2.6. Variety of Store Formats**

The variety of store formats which have developed in the last two decades introduced new requirements for the portfolio of GoodsCo's products. Most of the manufacturer's clients, through various decisions including the types and locations of their stores, target a specific demographic group of shoppers. GoodsCo—and other large who sell their products through a variety of distribution channels—need to meet requirements of the strongly diversified collection of their clients' end-customers.

This situation makes product portfolio management very difficult for the manufacturers. On one side, consumer goods companies can benefit from being present in different channels (for prestige, advertising, to drive demand or margin etc). On the other side, the inconsistency of requirements across retailers—varying service levels, delivery schemes, packaging preferences, etc., as well as distinct assortments—makes it hard for GoodsCo to cater to such dissimilar clients. Retailers in separate sectors need different levels of variety (corresponding to their own set of goals, consumer expectations and needs) and often ask for different sets of products. Where a discount store carries three types of detergents—all in large formats—and offers them at an attractive price, a supermarket or drug store will charm the shopper by letting them choose from a full rack of detergents representing various brands, sizes and scents. A mass merchandiser oriented towards recurring shoppers will ask GoodsCo for a greater variety of family-size mouthwash while a drug store serving convenience customers may demand various sizes and flavors.

### **1.3. BRANDED GOODS MANUFACTURERS VS EFFICIENT ASSORTMENT**

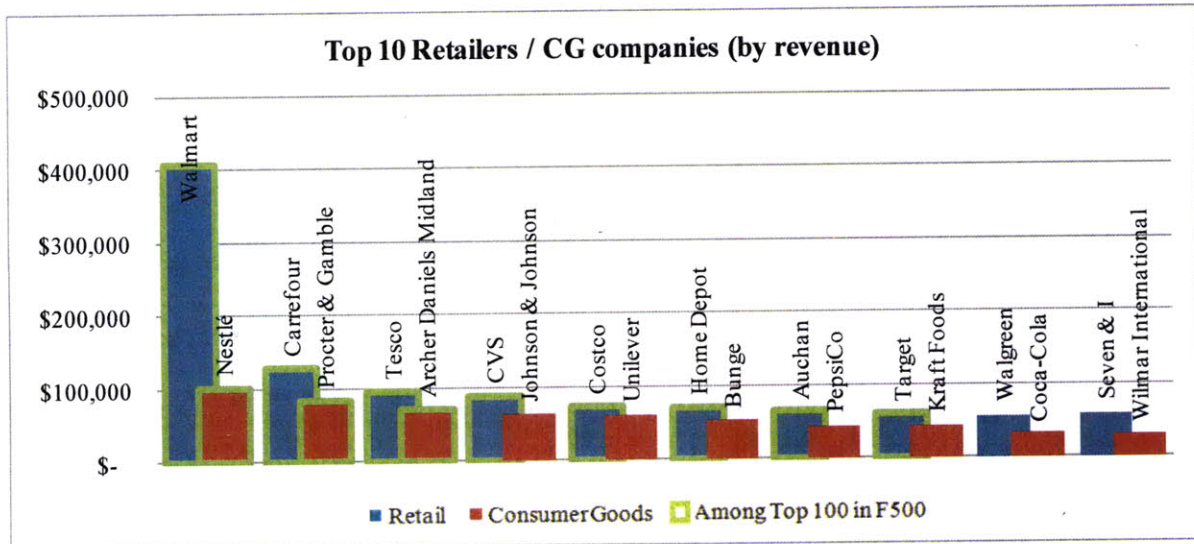
Growing popularity of SKU rationalization programs among retailers has led to increased pressure on manufacturers of branded goods. The strong financial position of retailers relative to that of their suppliers (see Figure 5 to compare the revenues of top 10 of Fortune 500 retailers with those of top 10 Consumer Goods companies) creates an imbalance of power between the trade and logistics partners.

Because of retailers' dominance, all manufacturers—including those who have traditionally been closely engaged in dealing with the stores that carry their products—are finding it increasingly difficult in the current environment to place additional items on retailers' shelves. Even owners of flagship brands now need to fight to retain their portion of the store shelf and convince store operators that the proposed additional product will appeal to shoppers and address previously unmet demand rather than cannibalizing sales of other brands.

While the value of SKU rationalization programs seems clear to most retailers (except perhaps for those who compete on selection of niche products), many manufacturers are naturally reluctant to eliminate variety and adapt their own goals to retailers' needs. According to Orgel, D. (2009), when asked about the most important initiatives that their suppliers should focus on, 70% of retailers pointed to SKU reduction, compared with only about half of supplier respondents who gave the same answer (sustainability and new product innovations were critical in their view). Although a 70% majority of suppliers declared that their overall ability to serve retailers' needs had improved in the previous two years, only 30% of retailers confirmed this opinion. This disproportion results largely from an asymmetry between the risks and objectives of the cooperating companies. The exposure to

risk of lost sales is greater for a manufacturer than for the retailer since shoppers are likely to find satisfying substitutes among competitors' brands. The retailer can potentially grow their profit by replacing national brands with private labels, while a company like GoodsCo will want to promote their own items.

**Figure 5**



Revenues of Fortune 500's top 10 retailers, compared with top 10 Consumer Goods manufacturers. Among F500's top 100, 8 belong to the retail and only 2 – to the CG industry.

Source: Own compilation, derived from "Fortune Global 500", 2009.

The new predicament of tighter SKU count control can be particularly challenging for niche manufacturers. With the growing popularity of private labels and smaller planograms<sup>12</sup>, specialty products which turn slower than mainstream items are facing a threat of being replaced. National brands seem to be in a better position, partly because of their velocity and profitability, partly because of their prestige and customer awareness. Some authors<sup>13</sup>,

<sup>12</sup> A planogram is a diagram of fixtures and products that illustrates how and where retail products should be displayed. This text uses the word "planogram" as synonym to "shelf composition"

<sup>13</sup> Johnsen, M. (2009)

however, argue that because of the low substitutability of niche products and high loyalty of their users, owners of leading brands may have more to lose than specialty suppliers.

While, as discussed above, both mainstream and niche manufacturers have reasons to view SKU rationalization as a threat for their sales and market shares, it needs to be noted here that they can also benefit from simplifications of product portfolio. The imperative to reduce variety can help a manufacturer eliminate extraneous complexity in manufacturing and logistics. Decreased inventories, better exposure of products on shelves, and improved management of out-of-stocks help not just retailers but also suppliers, especially if EA is performed across distribution channels. Reduced complexity can produce improvements in sales forecasts, lower the levels of inventory, and decrease transportation costs. Elimination of variety and tighter control of SKU proliferation can help Sales and Marketing departments prevent the dilution of brand power. Finally, reduced portfolio complexity can give the manufacturer's procurement an improved leverage and lower material costs.

## **2. LITERATURE REVIEW**

Based on my review of publications in several catalogues and databases of the Massachusetts Institute of Technology<sup>14</sup>, the term "efficient assortment" first appeared in print in King, R.P., Phumpiu, P.F. (1996). The paper elaborated on findings of the ECR Initiative and mentioned efficient product assortment as an element of the broader system characterized by "timely, accurate, paperless information flow and smooth, continual product flow matched to consumption". Inspired by the findings of the ECR Initiative, Thayer, W. (1997) focused on

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<sup>14</sup> In this review I focused on the following: Lexis Nexis Academic, Web of Science, Business Source Complete, and Barton.

efficient assortment, providing its definition and outlining a framework for the process – his framework provided a general guideline for this research.

Since Thayer's article, many practitioners and researchers have addressed different aspects of assortment management. Their works initially focused on consumer psychology and perceived variety and later centered on practical experiments testing possible outcomes of product variety reductions. At a more advanced stage of assortment-related research, publications began to describe complex mathematical models for assortment decision support, later including the element of cooperation between retailers and manufacturers. Many books and essays published during the period of growth in the retail industry discussed effects of desired product proliferation on undesired complexity of manufacturer operations. The recent downturn in economy brought retailers back into the spotlight of, resulting in a wave of articles talking about their ways of countering the contemporary difficulties.

The early stage of discussions around assortment management (soon after Thayer's publications) focused on research of consumers' cognitive perceptions regarding product variety. Broniarczyk, S.M., Hoyer W.D. and McAlister, L. (1998) quoted a number of studies which analyzed the effects of SKU reductions on customers' awareness of selection available in store. Defining the framework for thinking about variety and measuring the relative value of assortment variety was also the subject of Stephen J. Hoch, Eric T. Bradlow and B. Wasnik (1999). Amine, A. and Cadenat, S. (2003) talked about customers' sensitivity to offered assortment, its importance for store patronage and the methods to balance between overwhelming the shopper and not providing enough choice. Insights from these papers help in understanding that the trade-off between variety and sales is not straightforward. As shown through several experiments, the change in sales after eliminating products from shelves is

related not so much with the number of remaining products but rather with the variety that they represent. These insights on how understanding consumers' buying patterns can simulate demand transitions lead to including the element of transferring demand in the EA model which is discussed in subsection 3.3.1.

Essays describing practical studies on effects of category assortment reductions complement the extensive assortment-related research in the area of consumer psychology. One example which is particularly relevant to this research is provided by a study by Laurens M. Sloot, Dennis Fok and Peter C. Verhoef (2006). The authors assessed short- and long-term effects of a 25% item reduction on category sales, concluding that such assortment changes can result in an increase in perceived shopping efficiency without causing proportional sales decreases. Similar findings are described in Zhang, J., Krishna, A. (2007). A recent study (Chernev, A. Hamilton, R. (2009)) concluded that although customers generally prefer the choice offered by wide assortments, they consider a broad selection less attractive than a reduced one as long as the latter continues to include the items or product features they are personally interested in. This notion that product assortments should be defined by the variety of consumer needs satisfied, not the number of stock-keeping units, has inspired the idea to use key product attributes in defining incrementality of sales attributed to each SKU. Section 3.3.2 describes how the idea was implemented in building of the Efficient Assortment model.

Literature documents many attempts to derive mathematical models supporting assortment-related decisions<sup>15</sup>. Felipe Caro (2005) described a model built to suggest a policy for product portfolio decisions in the fast-fashion retail industry. D. Ramaheshan, N.R. Achuthan and R.

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<sup>15</sup> A more extensive review of the work published on the topic of assortment modeling can be found in Pentico, D. W. (2008))

Collinson (2008) proposed a decision support category management tool which suggests a number of facings to be displayed on the shelf for each considered product and indicates the optimal review period for each product. A. Gürhan Kök and Marshall L. Fisher (2007) developed an algorithmic process to help retailers compute the best assortment and product inventory levels for each store, accounting for cross-product substitution. Katia Campo and Els Gijbrecchts (2005) focused their research on three decision areas related to retailers' category management: assortment, shelf management and stockout management. Their paper discussed supply- and demand-based interdependencies and provided a framework for moderating consumer reactions to assortment changes. The authors list deficiencies of existing category management models and suggest areas of development, including dynamic modeling and incorporating "attribute effects of SKU elimination".

In addition to the shortcomings noted above, none of the models which I encountered in my research combined assortment decisions with operational benefits of handling fewer products at retailers' Distribution Centers and stores. I have found existing models to be built so as to maximize a single goal (usually the total net revenue). Their inflexible structure does not make them easy to adapt to multi-dimensional objectives. Users can't change the pre-defined dependent variables in order to apply the models to modified scenarios (e.g. a retailer who monitors sales volumes or inventory turns rather than revenues). The model created as part of this research applies elements of existing models, while at the same time addressing their reported deficiencies.

Some authors have tried to model the results of collaborative category management<sup>16</sup>. J. Tomás Gómez-Arias and José Méndez-Naya (2007) used game theory to model the theoretical effects of the adoption of category management strategies on manufacturers and retailers in a competitive environment and to examine the effect of the decisions made by all players on the industry. Jesper Aastrup, David B. Grant and Mogens Bjerre (2007) developed a model of retailers' benefits and losses from category management. The conclusion that "application of complementary information resources, improved coordination of tactical efforts, and an alignment of category strategies between manufacturers and retailers are all elements of improved value creation through Category Management" is an assumption that this research is trying to support.

While most of the literature referenced thus far considered the assortment problem as one related primarily to the field marketing and as a means to increase sales, some essays, theses and books recognize the consequences of an extended product portfolio on manufacturers' operations and logistics efficiencies and explore the implications of assortment management on supply chain. Marco Perona and Giovanni Miragliotta (2004) empirically investigated how complexity can affect the performance of a manufacturing company and its upstream supply chain partners. Michael George and Steven Wilson (2004) offered diagnostic tools for assessing the complexity and profitability of products, services and customers, along with advice on how to simplify, standardize or eliminate them altogether. Aaron Matthew Raphel (2005) analyzed the complexity that introducing new products adds to manufacturers' operations within an existing supply chain. John L. Marliotti (2008) provided several examples of companies who struggled with difficulties

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<sup>16</sup> In the context of this paper, "collaborative" will refer to efforts shared between partners in Supply Chain (primarily retailers and suppliers).

of expanding their product portfolios and suggested another framework to control the resulting complexity. This study employs insights on complexity costs to quantify operational efficiency gained by retailers thanks to assortment reductions (see section 3.3.7).

The most recent articles on the subject of efficient assortment appeared in business and industry publications and commented on current trends observed among retailers, their running initiatives and results of recently completed projects—a summary of these was presented in the Introduction.

Despite the profusion of assortment-related publications, my review has not identified a paper describing the type of model that GoodsCo was hoping to use – one that would utilize Point of Sales data<sup>17</sup> to prioritize SKUs within a category according to the selected retailer's goals and provide recommendations regarding proportions between shelf space assigned to categories. However, many of the articles referenced here described the theoretical considerations of assortment decisions and threats of careless changes in the portfolio of products carried by stores. These insights were useful in structuring of this research, supported impartial focus on retailers' objectives, helped to identify their rationale and motivations for assortment management initiatives, all of which were fundamental for the underlying data-based decision model.

The next chapter provides more information about GoodsCo's motivation for this research project, discusses factors important for assortment reviews and describes how they can be quantified and used to support decisions inherent in assortment management.

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<sup>17</sup> GoodsCo, like a growing number of other manufacturers in the CPG industry, realizes the value of POS data they receive from cooperating retailers and wants to be able to use the data to gain insight into consumers and more effectively collaborate with their Supply Chain partners (see Henschen, D. (2009) and Balachandran, M., Morganstern, J. (2008).)

### 3. METHODS

GoodsCo enjoys a strong position in the market. The company owns multiple iconic brands, many of which have become so ubiquitous that their names function as synonyms for the type of product they represent. The manufacturer's history of partnerships with its clients—the retailers—is another powerful advantage over its competitors. The company has frequently been praised as one of the packaged-goods manufacturers who are most engaged in collaborating with retailers and most effectively eliminate costs in the pipeline that connects them with consumers. GoodsCo is one of the suppliers who value their relationships with retailers enough to organize its management in retailer-dedicated teams responsible for improve information sharing, order processing, promotion planning, sales and purchasing processes and merchandising. Instead of considering retailers as merely the channel through which its products reach customers, GoodsCo has a reputation of treating them as partners in its downstream supply chain.

Regardless of the strong market position, the evolution of the retail landscape (see section 1.2. for an overview of the most important tendencies) and engagement of GoodsCo's clients in assortment reduction programs exposed the company's relationships to a test and their product mix—to strict performance monitoring. As their financial results deteriorated, retailers increased focus on assortment management and began to demand that manufacturers justify introductions of new SKUs through elaborate business cases, including projections of financial results.

Industry developments, increasing requirements of retailers, as well as GoodsCo's objective to offer customers products which they need, trust and value, motivated the manufacturer to support its clients' endeavors through the Efficient Assortment program. Thanks to having closely cooperated with its downstream partners, GoodsCo knew their processes and was well aware of their objectives and concerns. To build on these strong foundations, its management

wanted to develop an in-house modeling capability and improve the quality and timeliness of assortment recommendations. They wanted to make sure that suggestions offered to clients were objective and accounted for a wide scope of relevant considerations of financial, operational, and strategic nature.

GoodsCo recognized that their advice regarding assortment should not be limited by the boundaries of traditional category management discussed in subsection 1.2.2. The manufacturer knew that in order to offer valuable recommendations, its insights on assortment needed to be based on a good understanding of the differences between positioning of categories at targeted retailers, and of its clients' logistics processes. It also acknowledged that, in addition to the different roles that a given category may play across retailers (e.g. dairy may be a destination category for a mass merchandiser but a convenience category for a drug store), retailers may also observe various basket structures and buying patterns and therefore insist on maintaining of specific products.

The manufacturer's team knew that the Efficient Assortment program should not focus exclusively on sales and price margins, but instead cover a variety of financial metrics which would help improve product and cash flow throughout the supply chain, leading to better results of the retailers. GoodsCo realized that in order for the initiative to be successful, it had to support its clients' objectives and insisted that results of recommended changes were viewed from its clients' point of view.

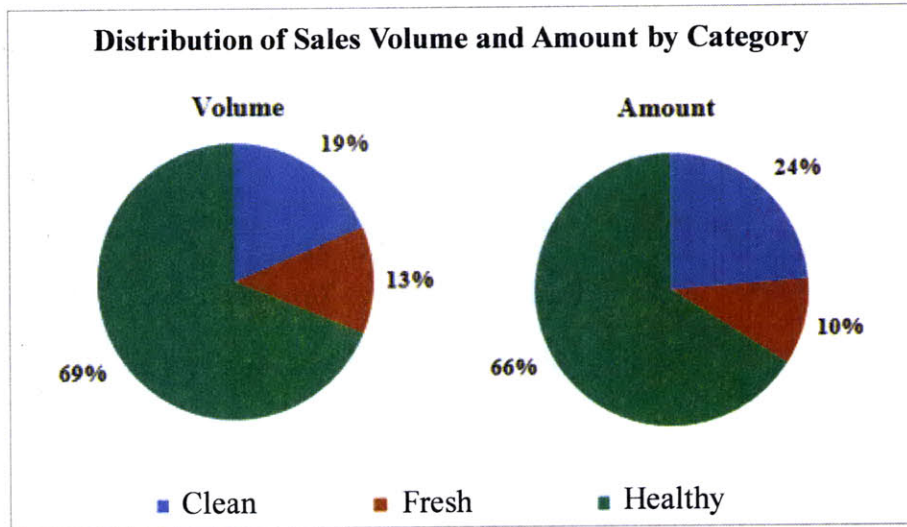
Because of the volume of information important for assortment decisions as well as the scale and repetitive nature of portfolio management activities, GoodsCo's Efficient Assortment effort required a decision model which could be fed with large datasets and configured to a specific retailer and category. The following five sections describe the decision model which was built as

part of this research. The description starts with an overview of the data that was provided by GoodsCo—the direct inputs which the model was expected to utilize and which determined the high-level shape of the tool. Section 3.2 provides an outline of the model’s structure and logic. The following three paragraphs discuss the quantitative, qualitative and strategic considerations for assortment decisions. Section 3.3 outlines how the data listed in 3.1 is processed into metrics and parameters which are further used to produce the final outputs. Section 3.4 explains the additional issues which—although difficult to express as metrics—need to be factored in SKU selections and shelf space allocations. Section 3.5 talks about some of the model’s parameters and built-in scenarios which make this tool applicable across retailers and categories. Finally, a summary of the models outputs is presented in section 3.6.

### **3.1. INPUT DATA**

In order to support its operational planning, GoodsCo maintains copious amounts of transactional data, including Point of Sales data (stores’ sales volume and amount by SKU) which the company receives from its retailers. In addition to POS data, clients often provide GoodsCo with indications of each product’s profitability as well as metrics reflecting their operational performance such as amount and volume of inventory of each SKU at every DC and store, recorded availability of SKUs at store shelves, as well as some other measures of efficiency tracked by the respective company (e.g. GMROI - Gross Margin Return on Investment).

**Figure 6**



Categories Clean, Fresh and Healthy differ in their contribution to retailer's total revenue and number of units sold.

Understanding that the value of all this information extends beyond demand forecasting and promotion planning, GoodsCo made portions of their POS, operational and financial data (limited to its own products) available for this research. The provided datasets comprised two years' worth of monthly sales information and average monthly operational efficiency measures. Table 1 provides an overview of the structure of input data for each Stock Keeping Unit<sup>18</sup>.

**Table 1: Input Data**

1	Retailers Stock Keeping Unit identifier (SKU #)
2	SKU description
3	Universal Product Code (UPC #)
4	Monthly Sales Volume
5	Monthly Sales Amount

<sup>18</sup> The model utilized information aggregated at the level of company (retailer). Sample datasets

<b>6</b>	Gross Margin %
<b>7</b>	Average monthly Gross Margin Return on Investment <sup>19</sup> (GMROI)
<b>8</b>	Total Inventory Volume at Retailers' Distribution Centers
<b>9</b>	Total Inventory Amount at Retailers' Distribution Centers
<b>10</b>	Total Inventory Volume at Retailers' Stores
<b>11</b>	Total Inventory Amount at Retailers' Stores

Each provided dataset contained the above information about one of three distinct merchandise categories:

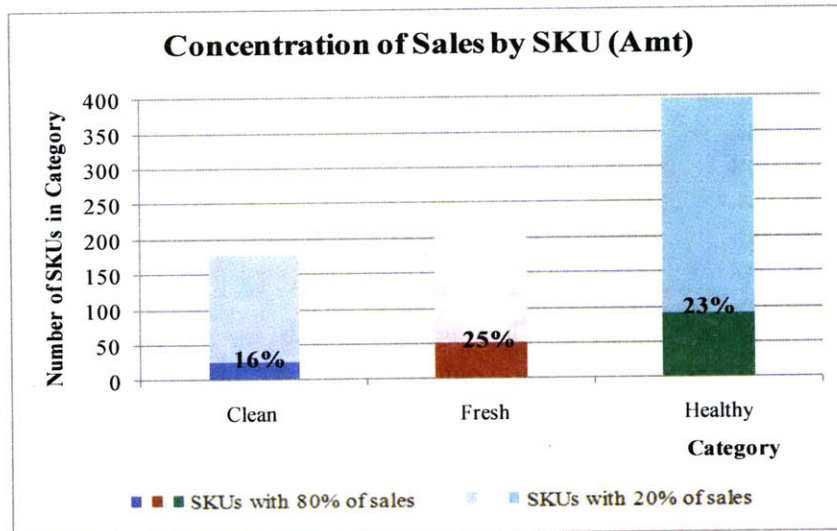
1. Category "Fresh";
2. Category "Clean";
3. Category "Healthy".

In addition to the input data listed in Table 1, GoodsCo provided necessary information about their retailers' distribution networks, replenishment methods and amount of shelf space dedicated to each of the categories listed above.

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<sup>19</sup> See 3.3.6.

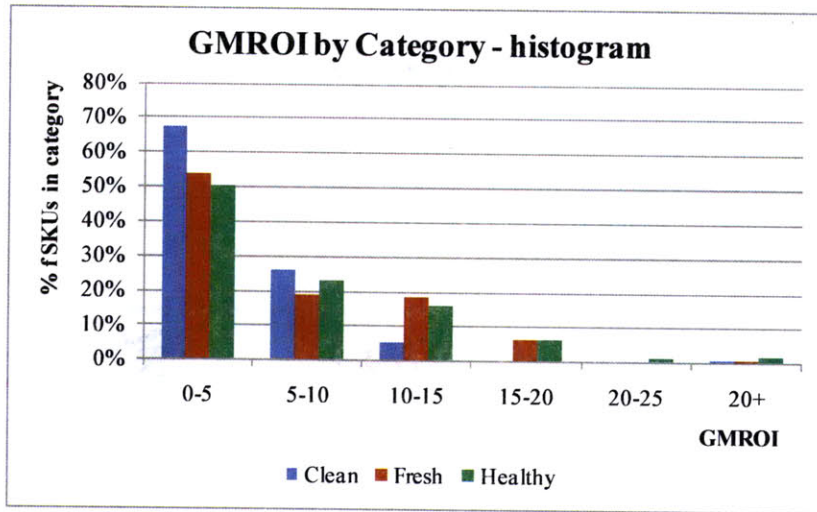
Figure 7



Categories covered by this research are characterized by varying count of SKUs as well as different concentration of sales among top SKUs.

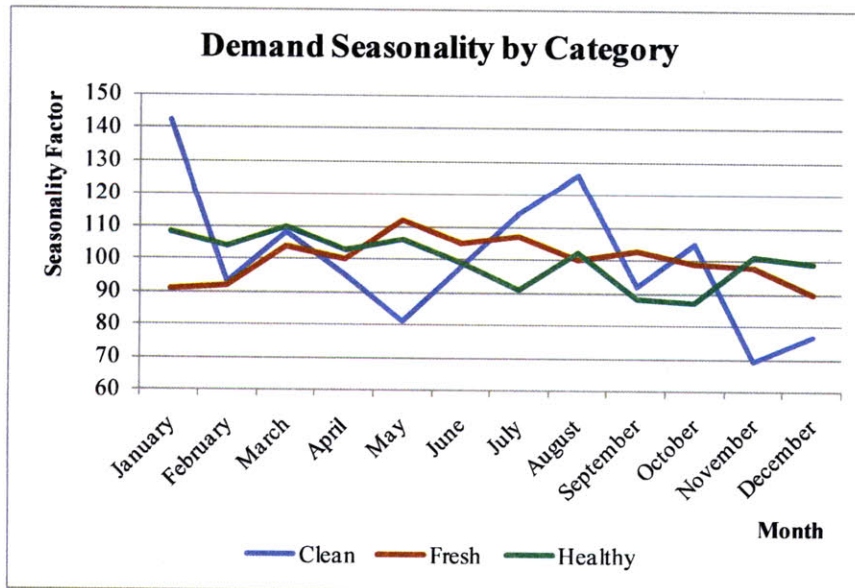
The three product groups were selected for this research with the intention to make the model robust and capable of handling datasets of different sizes and degrees of completeness. At the same time, these categories represent varying volumes, profitability, velocity, shelf space requirements, seasonality patterns, and demand concentration. All of these characteristics affect assortment decisions and had to be accounted for in the model. Figures 6, 7, 8, and 9 illustrate the distinct character of the three categories by presenting a few relevant summary statistics.

**Figure 8**



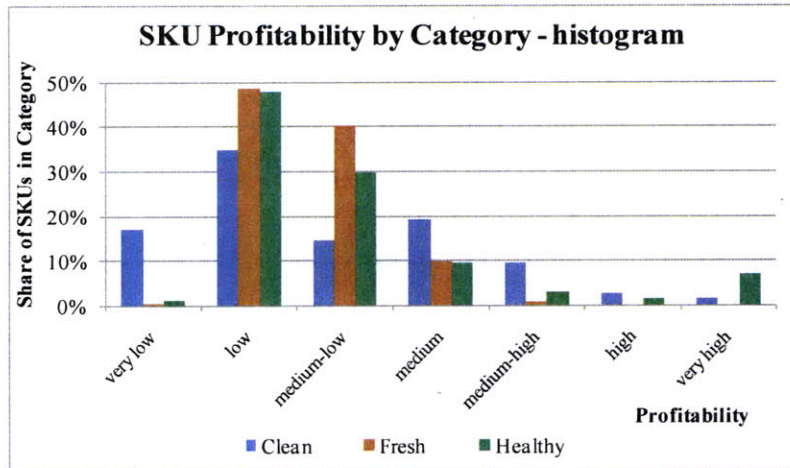
Gross Margin Return on Investment of category Clean is concentrated in the first two ranges. Distributions of GMROI values for products in category Healthy and Fresh are more flat.

**Figure 9**



Seasonality is one of the characteristics which differentiate product categories and introduce the need for flexible model adjustments (see 3.5.3.)

**Figure 10**



Profitability of SKUs in category Clean is distributed across the range. Products in category Fresh contribute mostly at the low and medium-low level. Category Healthy has the highest share of very profitable items.

The original datasets provided by GoodsCo (POS data as well as operational and financial performance information by category) were updated with additional product information. Values of attributes likely to drive purchase decisions for each category were populated for all SKUs based on their descriptions or other accessible sources. A list of product attributes which were updated in this step is presented in Table 2. (Subsections 3.3.2 and 3.5.4 discuss how these attributes were used in modeling of substitutability and transferable demand. Subsection 3.3.7 explains how SKU sizes and count of items per case helped in estimating of Cost to Shelf.)

**Table 2: Additional Input Data - Product Attributes**

Category / Attribute #	Fresh	Clean	Healthy
1	For Men / For Women	Application	Cause
2	Brand		
3	Sub-brand	Scent	Flavor
4	Format	Format	Format
5	Fresh A / Fresh B	Size <sup>20</sup>	
6	Size (oz)		
7	Items per case		

### 3.2. MODEL CONCEPT

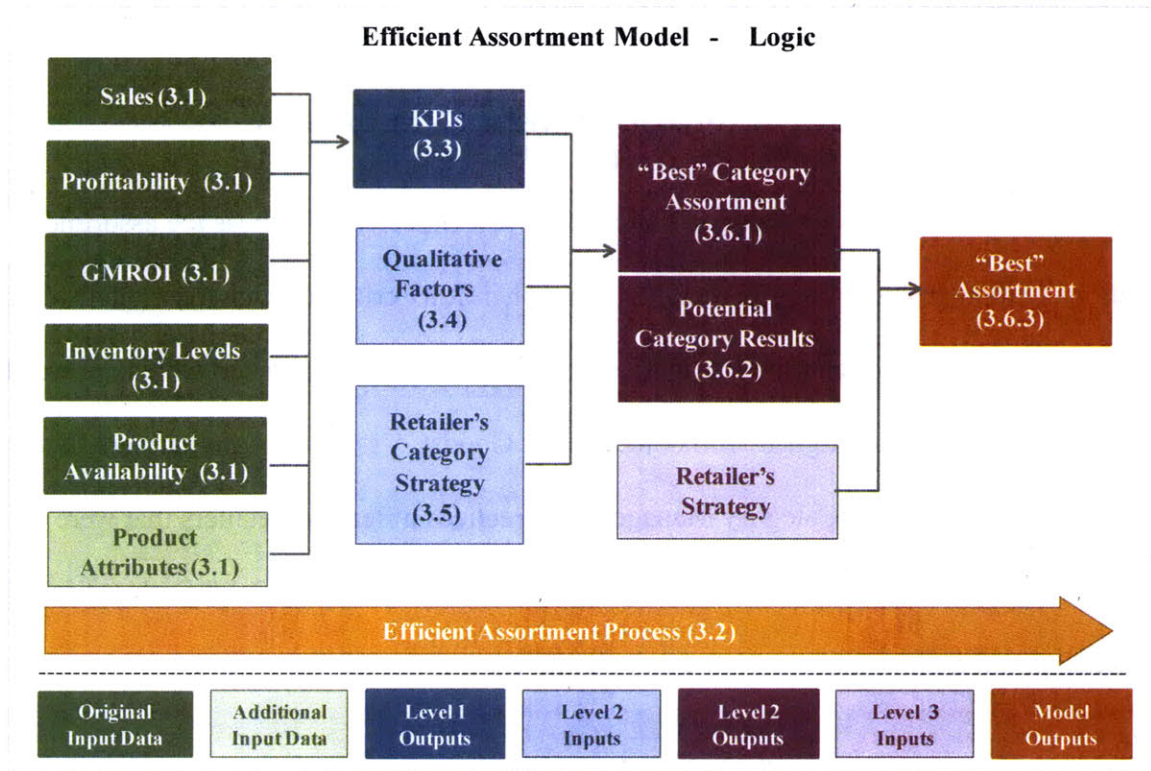
GoodsCo specified that the efficient assortment model should take the form of a spreadsheet, be relatively easy to use on the three pilot categories and lend itself to alterations allowing to apply it to categories outside the scope of this research. The model was expected to utilize all of the available information but—because of the inconsistency in the format of data<sup>21</sup> between retailers—it had to also be possible to use with incomplete inputs. Most importantly, the model had to be a good tool for defining efficient assortment - "the selection of category SKUs that most nearly optimize the retailer's objectives for the category in terms

<sup>20</sup> A descriptive attribute (“small” / “medium” / “large”) was used here. Actual size expressed in oz was used in Cost to Shelf calculations.

<sup>21</sup> Inconsistency between the format of retailers’ POS data is one of the persisting barriers in using the data in a wider range of operations planning applications (Henschen, D. (2009))

of target consumer needs fulfillment, overall retail portfolio strategic alignment and financial returns<sup>22</sup>.

**Figure 11**



The scheme illustrates section 3.2 by explaining how the Efficient Assortment model described throughout chapter 3 processes POS, financial and operational data to arrive at the best assortment across categories.

The high-level logic of the model is illustrated in Figure 11 which shows four stages of decision-making and helps navigate through this chapter. The first stage of the process involves using data outlined in 3.1 to calculate KPIs listed in 3.3. In the second stage, the KPIs are weighed to emphasize the retailer’s strategic objectives (see 3.5) and combined into a comprehensive score which, together with relevant qualitative factors (3.4), defines the “best” assortment in a given Category (3.6.1). Results of this suggested assortment—sales,

<sup>22</sup> Frozen Food Age (1997).

profits, turns etc—which are produced at this stage of modeling (3.6.2) are then used to define the composition of store shelves which most strongly supports the retailer’s strategic objectives.

### 3.3. CRITERIA FOR SKU AND ASSORTMENT EVALUATION

As it has already been mentioned, the model was expected to address the assortment rationalization problem through retailers’ lens. Therefore, criteria which the model would apply to determine which products to discontinue, which to maintain and which are worth investing in, had to be aligned with objectives of GoodsCo’s downstream partners. The eleven KPIs typical for Category Management practices of leading retailers that were included in the model are introduced in Table 2 (subsections 3.3.1 – 3.3.8 further discuss the meaning, importance and method of calculating each of the KPIs).

**Table 3: SKU Evaluation Criteria**

<b>Criterion</b>	<b>Description</b>
<b>Annualized Recorded Sales Volume</b>	Potential volume of sales if SKU maintained in assortment (annualized and net of out-of-stocks)
<b>Demand Trend</b>	A score which reflects the potential of a given SKU (growing / level / decreasing share in category sales)
<b>Annualized Recorded Sales AMT</b>	Potential amount of sales if SKU maintained in assortment (annualized and net of out-of-stocks)
<b>Average Unit Margin</b>	Average margin realized by a retailer per unit of given SKU
<b>Annualized Profit</b>	Profit realized by a retailer from sales of given SKU (annualized)
<b>Margin Net Cost to Shelf</b>	Profit realized by a retailer from sales of given SKU net additional cost-to-shelf from DC to store (holding, handling and transportation)
<b>GMROI</b>	Average General Margin / Return on Investment per SKU

<b>Criterion</b>	<b>Description</b>
<b>GMROI Trend</b>	Year-to-year trend displayed by GMROI
<b>Incrementality</b>	Percentage of SKU sales accounting for demand which had previously not been captured by any product from the assortment
<b>Shelf Space Productivity</b>	Margin per linear foot of retail space
<b>Inventory Turns</b>	Number of times inventory is sold over a period of one year

GoodsCo’s team agreed that the KPIs listed above represented the repertoire of retailers’ assortment objectives but stressed that these objectives differ between companies and categories, change in time and are often expressed by a combination of several goals of which some may be more critical than others. Considering these concerns, the model was structured so that the user can define relative importance of evaluation criteria specific to the retailer whose assortment is being analyzed by assigning weights to modeled KPIs. A combined score is then calculated for each SKU using equation 1:

$$(Eq. 1) \quad SCORE_{SKU} = \sum_i \left( KPI_{SKU,i} \times \frac{weight_i}{\sum_i weight_i} \right)$$

Based on this compound score, SKUs are then ranked from best to worst and those with bottom ratings<sup>23</sup> are indicated as candidates for elimination – for more information about the automated elimination process see section 3.6.1.

### **3.3.1. Sales Volume and Amount**

Sales figures –amount and volume per SKU—were available from the POS data.

Although the dataset available for this project contained full years’ worth of information for each category, the model can be run on datasets which cover periods

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<sup>23</sup> The number of eliminated SKUs depends on the initial count of products in assortment and the targeted SKU reduction.

shorter or longer than 12 months. By entering the beginning and end date of the period covered in the dataset and selecting the pattern of seasonality<sup>24</sup>(see subsection 3.5.3), the user lets the model scale the available range of data to annual results.

Because revenue and volume represent key objectives of most retailers, it was important that the model reflects changes in sales figures resulting from reducing of the assortment. At the same time, it was important that the changes in sales are not limited to zeroing the figures for products marked for elimination. Instead, the model had to account for positive effects of reducing assortment such as customers' enhanced shopping experience or improvements in managing of out-of-stocks.

#### **3.3.1.1. Improved management of out-of-stocks**

Out-of-stocks (oos) occur mostly due to mismatches between demand and supply at the outlet (under-forecasted demand and insufficient orders) or due to operational inefficiency of Distribution Center and store operators (product present in the supply chain but not available at the shelf). Regardless of the reason, the absence of product on the shelf often results in lost sales for the manufacturer, the store or even the retailer.

With fewer products to manage, more shelf and storage space can be dedicated to the well-performing SKUs, monitoring of product availability throughout the supply chain becomes more accurate and replenishment - more frequent. Moreover, there is a chance for improvements in demand forecasting, not just at the aggregate level but also for each individual product. As a result, availability of products in the reduced

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<sup>24</sup> In addition to the option of selecting between predefined seasonality patterns, the spreadsheet allows users to define new schemes of demand peaks and troughs. This will make the model easily adaptable to categories other than those which it was built for.

assortment is expected to improve, which—*ceteris paribus*—translates to improved sales. This improvement was quantified based on a set of data showing store-in-stock rate<sup>25</sup> per SKU per store. As shown in Figure 12, number of carried products and store in-stock-availability (SISA) showed a statistically significant relationship ( $R^2 = 0.6833$ ), described by equation 2:

$$(Eq. 2) \quad SISA = -0.007 \times \#SKUs + 1.5184.$$

Based on this finding, it was assumed that with each product removed from the assortment, the individual store-in-stock rate of other products improves by 0.7 percentage point compared to their average recorded availability. The relationship was used in modeling of improved store-in-stock rates in the following fashion:

$$(Eq. 3) \quad SISA_{SKU, ra} = SISA_{SKU, oa} + 0.007 \times (\#SKUs_{oa} - \#SKUs_{ra}),$$

where “oa” – original assortment, as per received dataset, “ra” – rationalized assortment.

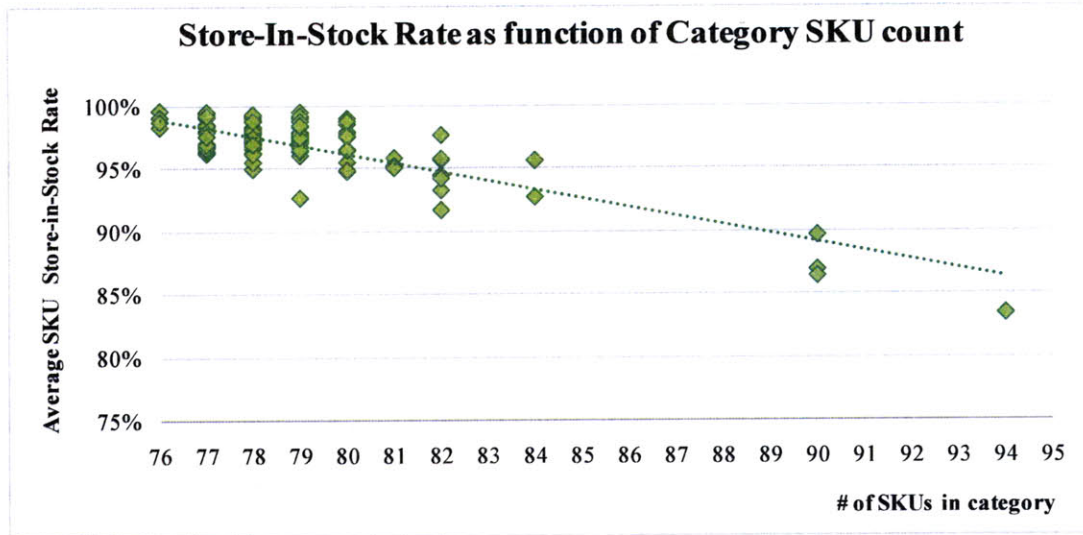
Consequently, expected sales of each SKU improve by:

$$(Eq. 4) \quad \Delta Sales_{SKU} = \left( \frac{SISA_{SKU, ra}}{SISA_{SKU, oa}} - 1 \right) \times Sales_{SKU, oa}.$$

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<sup>25</sup> Store-in-stock availability = 1 – out-of-stock

Figure 12



The relationship between product availability and the number of SKUs which a store manages was based on a sample of data representing sales and in-stock rates per SKU-store combination.

### 3.3.1.2. Transferrable demand

In addition to reduced out-of-stocks, the model had to also simulate the expected rearrangements of sales between similar products to reflect realistic reactions of customers facing the new assortment<sup>26</sup>.

The concept of “similar products” was captured through the use of product attributes (for a list of these, see section 3.1). Based on values of their attributes, SKUs were grouped into sets of substitutes<sup>27</sup>. The number of substitutes within each of these groups determined how inter-exchangeable these products were for an average

<sup>26</sup> Relevant behavioral experiments were discussed in Sloot et al (2006).

<sup>27</sup> For more information about the definition of substitutes and relevant settings, please refer to 3.5.4.

shopper and how transferable their individual demand was<sup>28</sup>. For example, if customers can currently choose between ten similar products then if one becomes unavailable, majority of them will still choose among the remaining nine.

Transferability of demand will be high, dictating that a high percentage of the removed item's sales shift to other items. However, if one of two similar products gets eliminated, customers are more likely to notice the change in available assortment and look for alternatives among other brands. Transferability of demand will be close to zero - almost all of the item's sales will be lost for GoodsCo. In modeling this effect, it was assumed that transferability of demand:

- is equal to zero if the product in question has no functional substitutes;
- is equal to 100% if there are “many”<sup>29</sup> substitutes;
- increases between 0 and 100% for counts of substitutes between zero and “many” (the assumed shape of the demand transferability curve is presented in Figure 13);
- does not occur between groups of substitutes<sup>30</sup>.

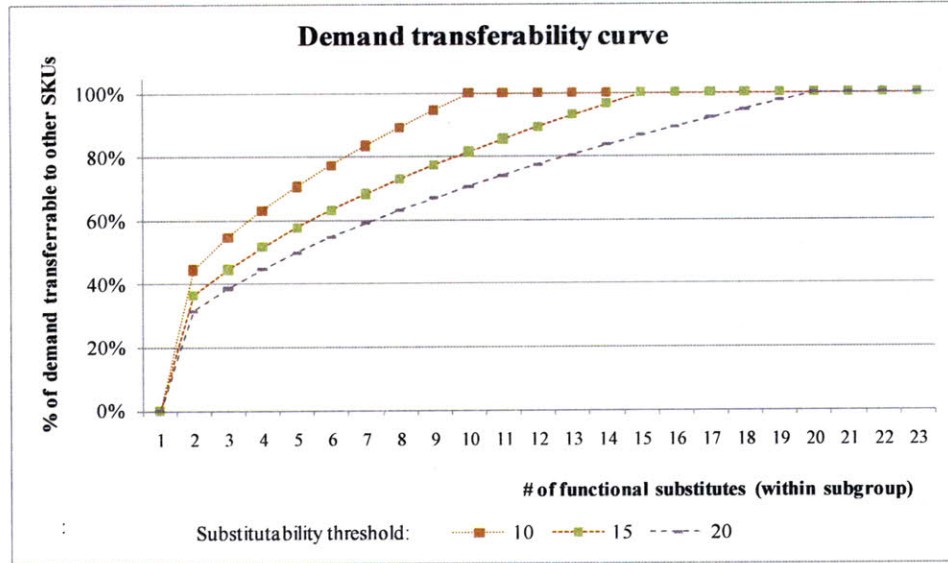
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<sup>28</sup> Transferability of demand is the percentage of shoppers who buy a similar product if their preferred choice is not available.

<sup>29</sup> The number of substitutes which makes the shopper effectively indifferent is set up as a model parameter and can be set arbitrarily, depending on the category and targeted channel.

<sup>30</sup> This assumption can be modified through selection of attributes which define substitutes – see 3.5.4 for details.

Figure 13



Modeling of demand transferability was based on expert judgment and assumed that proliferation of functional substitutes makes customers more indifferent to the available variety. Substitutability threshold—the number of products described with identical values of attributes at which entire demand is assumed to transfer to other functional substitutes—is a parameter of the EA model.

### 3.3.2. Incrementality

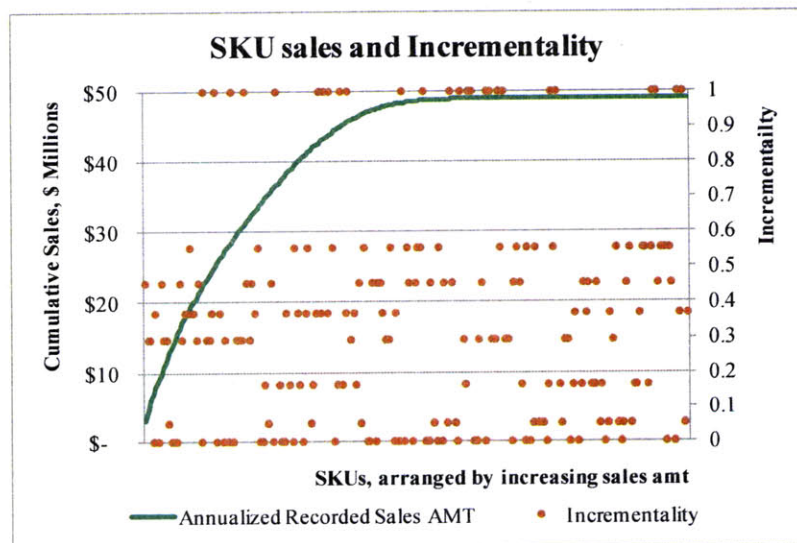
The effect of some SKUs' demand being less transferable to other SKUs described in the previous paragraph is closely tied with "incrementality"<sup>31</sup> which quantifies the strength of each product's individual contribution to its category sales. Incrementality of a SKU is not equivalent or even related to its share in the category's sales. In fact, products with high sales are often characterized with low incrementality and vice-versa (Figure 14 illustrate this observation for one of the categories). The metric shows how much of the SKU's sales would not have materialized if this product had not been introduced. When looked at from the perspective of assortment rationalization,

<sup>31</sup> Incrementality is understood as the percentage of a SKU's sales which did not result from cannibalization of another SKU in the same category.

incrementality can be used as an indicator of how much of a given SKU's sales are not expected to transfer to other products if it was removed from the shelf. Therefore, while it seems this characteristic is not yet widely used in retailers' category management decisions, incrementality has been included among KPIs guiding SKU elimination decisions.

Incrementality of a product depends on the context in which it exists, the assortment of products against which it competes. The model was structured so as to look for the proposed solution in multiple iterations, each time updating the value of incrementality<sup>32</sup> and simulating demand migrations based on the current assortment.

Figure 14



Ranking SKUs based on their annual revenues can lead to elimination of products described with high incrementality indexes.

<sup>32</sup> Incrementality was calculated as complement of demand transferability.

### **3.3.3. Demand Trend**

Demand trend was introduced as one of the KPIs to promote products which have been becoming more popular and demote those whose demand has been declining. Depending on the range of available data, the indicator of whether demand for a given product has been increasing or declining can be calculated as:

- a ratio of annual sales recorded in two consecutive years (if complete sales data is available for two full years or if accessible information is sufficient to estimate demand for both years<sup>33</sup>),
- a year-to-year sales ratio for a selected month (if sales data is available for a period covering more than 12 consecutive months),
- a ratio of the share that the product holds in the sales of complete category portfolio at the end of the considered period vs. the same share at the beginning of the period (or the first period after the product was introduced).

### **3.3.4. Product Profitability**

Gross margin generated through product sales is the most popular measure of a product's profitability. However, it does not consider the volume of sales, account for how much inventory needs to be held in order for profit to be made or show the product's actual effect on overall profit contribution. Because of these shortcomings, gross margin is considered as a starting point rather than sufficient basis for conclusions in the analysis of retail profit (Varley, R. (2001)).

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<sup>33</sup> Fragmentary demand information can be scaled to reflect annual demand if seasonality of considered product's sales is known.

Shelf space productivity is a key indicator of profitability for assortment management. Much like the information about marginal profits helps manufacturers split their production capacity between product lines, profit per unit of shelf space is a useful indicator in retail shelf space allocation. If space allocation is based solely on expected gross margins, the retailer may decide to stock products which yield high individual margins but consume a bigger portion of the shelf than the high margin would justify. For example, when choosing between two products: A, which requires 0.2 linear ft of space and yields a profit of \$2 per unit and B, which yields unit profits of \$5 but takes 1 linear ft of space, the seemingly more profitable decision could lead to worse results. Instead of using the linear foot of space for one product B and earning \$5, the retailer should use the same space for five A's, generating an income of \$10. To account for such trade-offs, Shelf Space Productivity was calculated for each KPI (see Equation 5):

$$(Eq.5) \text{ Shelf Space Productivity}_{KPI} = \frac{\text{Average Annual Profit per Store}}{\text{Linear footage per unit of SKU}}$$

As discussed above, shelf space productivity is a very pragmatic measure of product profitability in a retail setting. However, it does not take into account two important considerations: the amount (and cost) of inventory required for this expected profitability and frequency of sales.

To address the deficiencies of gross margin and shelf space profitability, inventory turns and GMROI (Gross Margin Return on Investment) were introduced as complementing KPIs.

### 3.3.5. Inventory Turns

Retailers hold inventory to be able to sell products to their clients. At the same time, if a product is held in stock but clients are not interested in buying it, rather than being a welcome asset, inventory becomes a costly liability. To determine which products are worthwhile investments that quickly turn to profits, it is helpful to calculate inventory turns (equation 6).

$$(Eq. 6) \quad \textit{Inventory turns}_{SKU} = \frac{\textit{Annual Cost of Goods Sold}_{SKU}}{\textit{Average Inventory}_{SKU}}$$

The higher the ratio, the more times in a year a product earns its margin. Also, the faster products turn, the easier it is for a retailer to keep their assortment current and remain attractive to customers. However, inventory turns alone do not promote products which earn higher margins. A metric which ties both the profitability and the inventory turnover is Gross Margin Return on Investment.

### 3.3.6. Gross Margin Return on Investment

Gross Margin Return on Investment (GMROI) takes into account the cost of holding inventory and allows for comparing of SKUs across brands, categories and departments. This measure is becoming popular among retailers (Timme, S.G. (2007)) and is therefore proposed as one of KPIs used for evaluating the performance of SKUs. Equation 7 shows how GMROI is calculated:

$$(Eq. 7) \quad \textit{GMROI}_{SKU} = \frac{\textit{Annual Sales}_{SKU} \times \textit{Gross Margin}_{SKU}}{\textit{Average Inventory}_{SKU}}$$

For reasons similar to those described in 3.3 3, the average value of GMROI is complemented with an additional index evaluating the improvement or decrease in performance for each SKU.

Gross margin calculations rarely take into account all costs related with storing and handling of the product. To address this gap, another profitability measure was introduced in the model: the “Profit Net Cost to Shelf”.

### **3.3.7. Profit Net Cost to Shelf**

Cost to Shelf was computed to assess those expenses which retailers have to bear after a product is purchased from GoodsCo and before it is sold through one of their outlets. Profit Net Cost to Shelf is a concept close to that of Direct Product Profitability<sup>34</sup> that was introduced by McKinsey (General Foods Corporation (1963)) and which is based on a similar principle as Activity Based Costing<sup>35</sup> proposed by Cooper, R., Kaplan, R.S. (1988).

Because GoodsCo’s retailers typically calculate margins as the simple difference between retail price and purchase price, Profit Net Cost to Shelf was expected to quantify the disparity between reported profitability of a SKU and its actual impact on the retailer’s bottom line. Embedding Profit Net Cost to Shelf in the model helped show that changes in assortment affect profitability not just by eliminating low-margin products but also by improving the efficiency of operations at DC and store.

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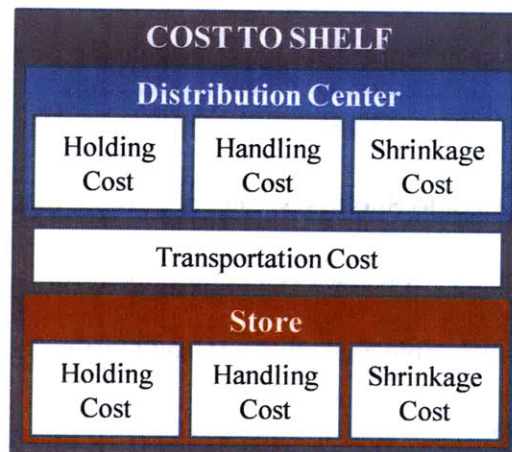
<sup>34</sup> Direct Product Profitability reduces the profitability suggested by a product’s gross margin by costs incurred through the supply chain, including transportation, warehousing and storage and handling costs.

<sup>35</sup> The difference between DPP and ABC is that the first method considers only direct charges while the latter accounts also for indirect costs (e.g. cost of procurement).

“Cost to Shelf” is estimated as a sum of three groups of components (see Figure 15):

1. costs incurred at the DC level: cost of holding inventory, cost of handling products, cost of shrinkage<sup>36</sup>;
2. costs related to transportation between DCs and stores;
3. costs incurred at the store level: cost of holding inventory, cost of handling products, cost of shrinkage.

**Figure 15**



Cost to Shelf estimated in the EA model includes elements of logistics at the store and DC level as well as cost of transportation.

### 3.3.7.1. Carrying Cost

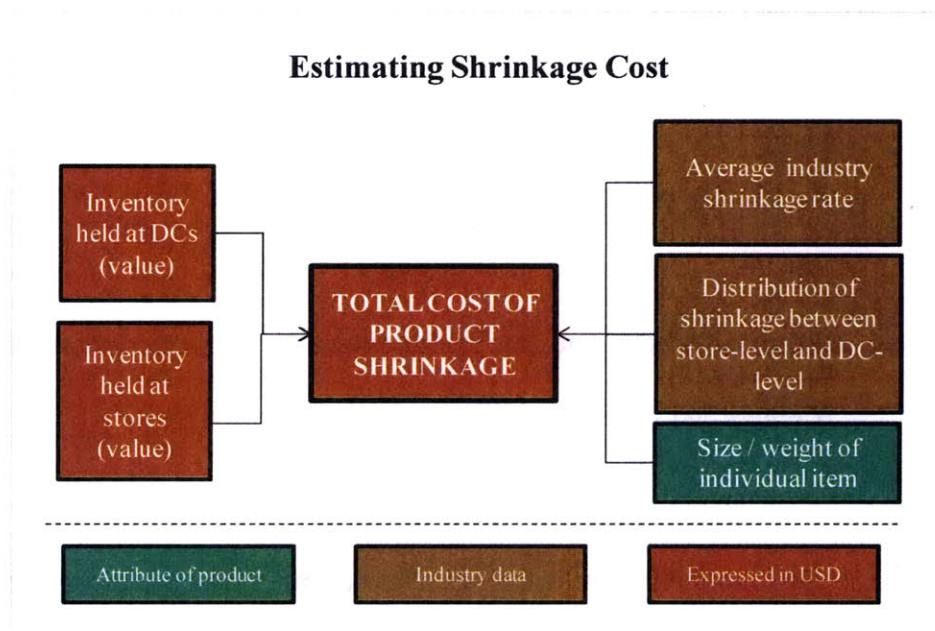
Carrying cost—cost of holding inventory—was approximated as a portion of the SKU’s average inventory value reflecting the cost of capital tied in product,

<sup>36</sup> Varley, R. (2001) defines shrinkage “stock that is removed from a retail outlet without any payment being made to the retailer”.

obsolescence, insurance and taxes<sup>37</sup>. The same method was used for products held at DCs and stores. In addition to Carrying Cost, the element of Shrinkage Cost was introduced to account for shoplifting losses, employee theft, supply chain losses and loss-prevention costs.

### 3.3.7.2. Shrinkage Cost

Figure 16



Cost of product shrinkage was estimated based on total value of inventory held at DCs and stores, and average industry statistics. SKU count reductions were assumed to improve shrinkage management (shrinkage decreases linearly as SKU count is reduced).

Cost related to product shrinkage from Distribution Centers and stores was assumed to be (on average) proportional to the product value. At the same time, to reflect that a smaller number of products managed by DCs and stores can be better monitored, the rate of shrinkage was expressed a decreasing function of the

<sup>37</sup> Cost of capital, like many other values in the model, is a parameter and can be easily changed to reflect altering business conditions.

size of category's assortment, starting with the baseline rate (when assortment is unchanged relative to the input data). The baseline rate in each analyzed category was set at the level quoted by the Center for Retail Research in their annual report, the "Global Retail Theft Barometer" (Chain Store Age (2009)). Shrinkage rate appropriate to the size of analyzed assortment is applied to the value of inventory at the DC and value of merchandise at the store. The mechanism is illustrated in Figure 16.

### **3.3.7.3. Handling Cost**

Cost of product handling was estimated with the use of DC and store activity models. Each of these models specified the durations of activities performed on every case, item, tote, stack of totes or SKU during replenishment of Distribution Centers and stores, respectively.

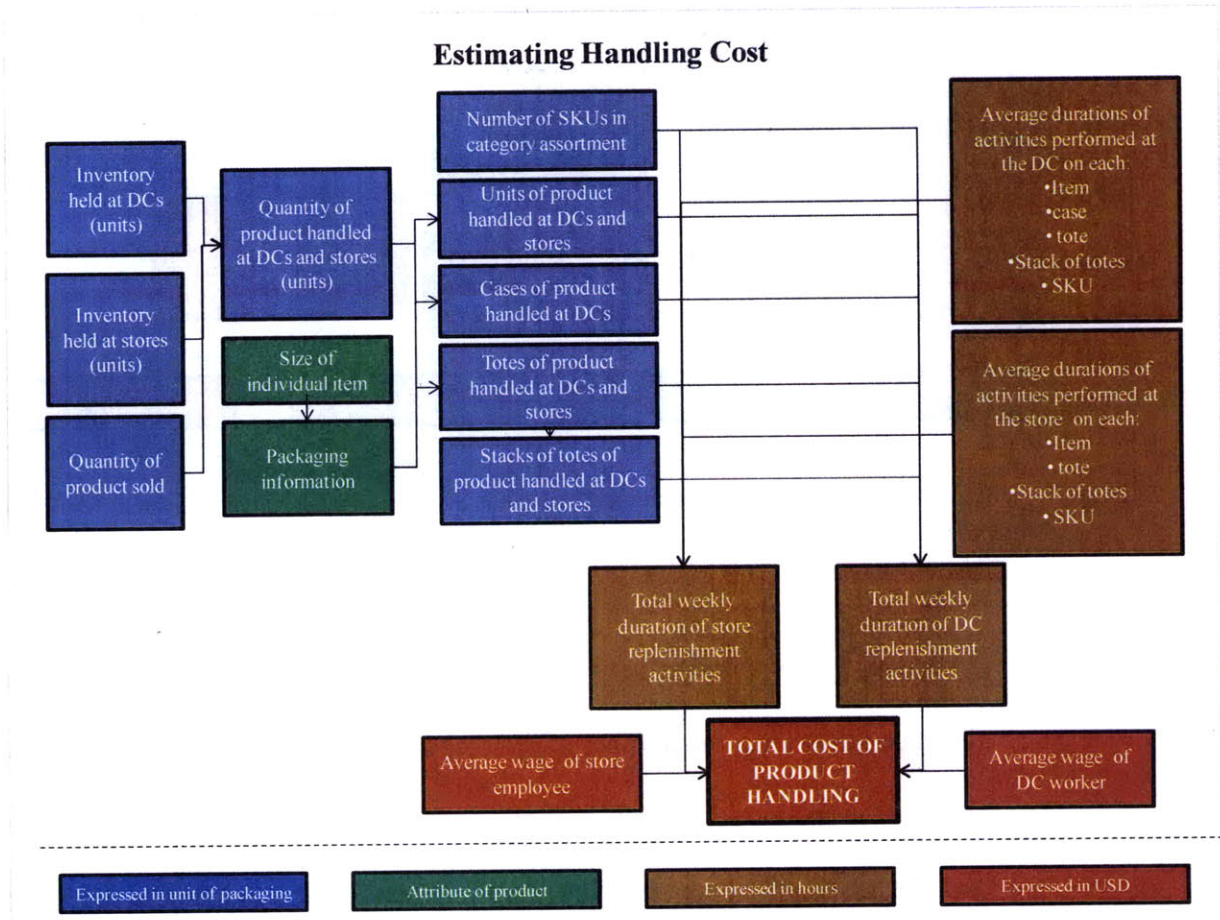
The total volume of product (number of items) handled weekly by Distribution Center workers and store employees was assumed to be equal to the average quantity of product moved weekly between DCs and stores. The numbers of cases, totes and stacks of totes corresponding to the handled volume were approximated taking into account sizes of individual items. Next, the estimated average cost of handling each product was calculated by multiplying average quantities of handled products expressed in the appropriate unit, i.e. case, item, tote, stack of totes or SKU, by the total duration of activities performed on each such unit and by the hourly rate typical for warehouse and store labor<sup>38</sup>. A

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<sup>38</sup> Labor rates at the DC and store level are defined as changeable parameters. The Cost to Shelf estimated by this research was calculated using median hourly wages available from the Occupational Employment Statistics

scheme of the methodology used to estimate each product's handling cost is presented in Figure 17.

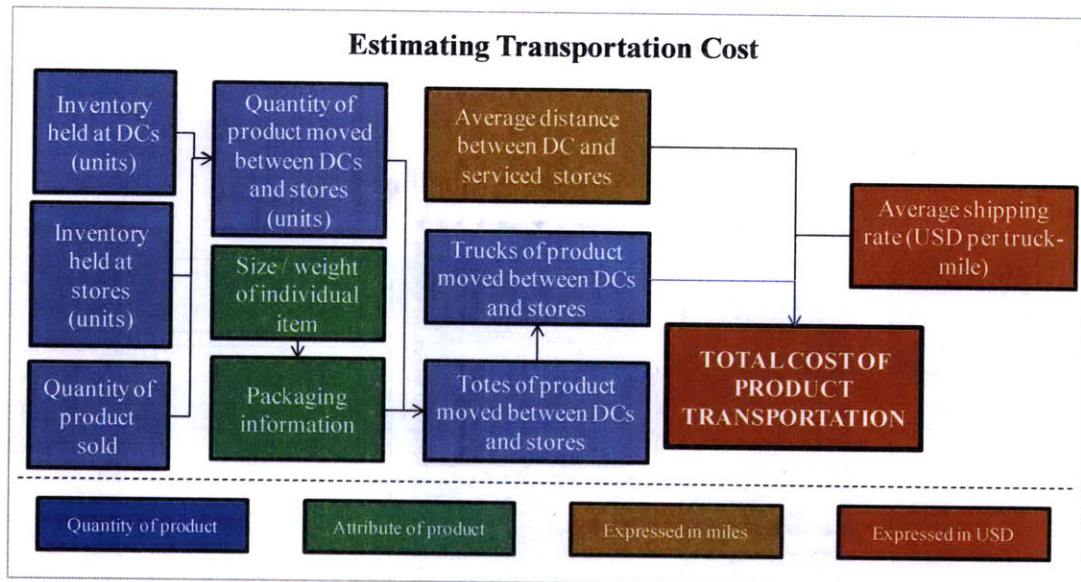
Figure 17



Total cost of product handling includes cost of replenishment activities at the Distribution Center and store level: picking, packing, unpacking, counting, monitoring of availability, ordering, shelving tagging etc. Factors which were assumed to affect cost of unit handling included items size, units per case / tote and replenishment procedure specific for retailer.

### 3.3.7.4. Transportation Cost

Figure 18



Cost of product transportation was estimated using the average quantity moved between Distribution Centers and stores and the average distance of a shipment.

Cost of transportation between DCs and stores, although linked to volume and distance rather than the number of different products that are moved<sup>39</sup>, has been included in the model to provide a reasonable approximation of the Cost to Shelf and the actual profit generated by a unit of each SKU in the revised category. The key product characteristic at this step was the physical volume of each item which dictates the number of items per tote and—in turn—per truck, thus determining the per-mile cost of shipping each item. Because the exact quantities shipped from each Distribution Center to each store were not available for each SKU, the distance traveled by each item was assumed to be the same and equal to the

<sup>39</sup> However, depending on the distribution and replenishment system, the number of SKUs may have an effect on the size of shipment (e.g. if each product variety needs to be sent to stores in a separate tote).

approximated average distance between DCs and stores, weighed with the amount of product which is moved on each of the routes. While not exact, the method illustrated in Figure 18 was accepted as reasonable for a project which does not aspire to reorganize the distribution network or to optimize transportation costs.

### **3.4. SHOPPING BASKET EFFECT AND OTHER QUALITATIVE CONSIDERATIONS**

Some of the retailers who have recently embarked on initiatives involving SKU rationalizations (see Introduction, section 1.2.4) have reportedly made the mistake of ignoring the market basket effect<sup>40</sup>. Focusing on each product's individual attractiveness (measured through its profitability, sales or level of differentiation), retailers removed from their shelves many products which—as it later appeared—had a strategic importance. After these products were eliminated, sales of other items began to drop as many customers turned away from their previously favored stores. As proven by the examples of retailers who lost customers through hasty SKU reductions, it is important that, while maintaining focus on their “destination categories”, retailers also analyze shoppers' baskets and try to understand shopping patterns in order to identify which items are critical for the patronage of profitable customers.

Three popular methods which help identify the SKUs that keep consumers coming back include: 1) tracking of switching across product characteristics to determine substitutability levels and consumer loyalty for each SKU in the category; 2) estimating exclusivity of items (percentage of a user base which uses only a specific brand, size, format, etc.) and 3) “worth

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<sup>40</sup> A frequently quoted example of this effect is the correlation of demand for diapers and diapers. Another illustration cited in Nishi, D. (2005) is that of olive oil: if only few sell consistently, a manager might consider eliminating the remaining poor performers. But an analysis of market basket might reveal that these usually sell with other high-margin items.

calculations” showing the total amount of a category purchased by shoppers of a specific segment<sup>41</sup>. Products showing high consumer loyalty or exclusivity, items from baskets of frequent valuable customers and those characterized with low substitutability represent high risk when removed from the shelf.

The scope of this research did not include analyses of loyalty and exclusivity or worth calculations. However, in order to help GoodsCo avoid making incorrect recommendations, the model had to allow for inputs from such analyses. This way, some items could be immune from elimination, even if their performance score was low. As a resolution, the model allows the user to mark a strategically important SKU and protect it from being removed. This feature will be useful for the following:

- “loss leaders” – popular products sold at cost or below cost to stimulate other, more profitable sales;
- products which on their own are not highly attractive for the retailers but are frequently featured in baskets of profitable customers;
- products to which customers are so loyal that they would switch to another retailer in order to find them;
- new products which have little history representing their performance;
- products which have been designed specifically to the requirements of a retailer, e.g. packaged in “ready to display” cases or multipacks designed for efficient replenishment of shelves.

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<sup>41</sup> Frozen Food Age (1997).

### **3.5. MODEL SETTINGS**

In order for the Efficient Assortment model to support recommendations adequate for different products and retailers, its users had to be able to manipulate several variables and parameters. The following four subsections describe the model settings which help define how inputs should be processed into decisions depending on the client for which the assortment is tailored (3.5.1), the category classification (3.5.2), category seasonality (3.5.3) and attributes determining incrementality of the type of products (3.5.4).

#### **3.5.1. Retailer**

Assortment decisions differ between retailers. Even those who compete in the same market and whose stores are direct competitors are likely to adapt their decisions to different demographic groups and make their product selections based on diverse sets of criteria.

Because of this disparity between retailers' assortment evaluation methods, as well as to address the differences in replenishment methods, the model requires that the user selects one of the retailers for which the model was configured<sup>42</sup>. Selecting a retailer provides the model with an indication of which Category Classes it should make available for the subsequent menu and lets the model use the appropriate DC and store logistics scheme to estimate the Cost to Shelf.

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<sup>42</sup> The model was initially configured only for the Mass Merchandiser and Drug Channel but can be easily expanded to other channels.

### **3.5.2. Category Classes and Assortment Evaluation Schemes**

After selecting the retailer, the user is asked to indicate the category class appropriate for the currently rationalized group of products.

Despite the common general guidelines which were briefly mentioned in 1.2.2, most retailers create and use their own definitions of category classes. Grouping of categories into classes helps them manage and monitor performance of their merchandise. Each class is typically expected to contribute to the retailer's overall performance in a different way – e.g. some products are put on shelves to generate traffic, others are carried because of their high profitability. The element of category class was configured in the model in order to help manage the objectives that a category is supposed to be achieving. Selecting the class determines the set of weights which the model automatically assigns to each SKU performance metric.

Because—depending on the company's position and current strategic direction—the taxonomy of categories is subject to change in time, the category was not firmly assigned to each of the analyzed product types. Instead, users can select the currently appropriate category class each time a category rationalization is run. They are also given the option of modifying the existing category classes or creating new ones.

### **3.5.3. Seasonality**

Demand for many categories of consumer goods is subject to seasonal fluctuations. Products which were covered in scope of this research are not such extreme examples as sunscreen or cold medicine but also display some seasonal demand fluctuations (see Figure 9).

If assortment decisions were made within a category, it could then be assumed that demand for all compared products follows a similar seasonality pattern and that the effect of seasonality is not relevant for the EA model. However, because retailers plan their assortments across categories, it was important that sales are correctly scaled to reflect annual demand. Unless demand is evenly distributed across the year, scaling of demand proportionally to the length of period which the input dataset covered could produce incorrect projections. For example, if the input dataset for category “Ice Cream” covered June, July and August, scaling it to 12 months by multiplying the summer sales by four would lead to significant overestimation of annual revenues. To avoid this effect, demand was scaled proportionally to the recorded period’s expected share of annual category demand. The user helps the model scale the projected results by selecting the seasonality pattern<sup>43</sup> which most accurately describes the category’s demand.

#### **3.5.4. Product Substitutability**

The mechanics of the Efficient Assortment model allow users to select which of the captured attributes (see list in section 3.1) should be used for grouping SKUs into sets of functional substitutes.

The fact that two products are “functional substitutes” means that when one is unavailable, the probability that an average client will switch to the other is greater than zero. At the same time, demand was assumed to stay within groups of functional substitutes - switching between two products from separate groups was not modeled. If demand is known to be transferable across a specific attribute, this attribute should not be

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<sup>43</sup> Like with category classes, the model user can easily modify and define new seasonality patterns.

used for grouping of functional substitutes. For example, if shoppers are known to frequently switch between brands, the attribute “brand” should not be selected as product differentiator. However, because the likelihood of a man switching to women’s cosmetics is very low, the “Men’s / Women’s” attribute should be used to separate substitutes. All selected attributes are assumed to be equally important for the customer.

Selecting attributes to identify substitutes sets direction for two decisions simulated by the model. First, it indicates how much of the demand represented by historical sales of eliminated items is expected to materialize despite the fact that it is being removed (see discussion about transferrable demand in 3.3.1.2). Second, it defines which of the remaining products should receive this portion of transferred demand<sup>44</sup>, thus contributing to the assortments’ simulated results.

### **3.6. MODEL OUTPUTS**

This section discusses the three direct outputs which the Efficient Assortment model can generate, depending on the selected settings:

- 1) A ranking of SKUs according to the strategy which their category is meant to be supporting;
- 2) A projection of category results, reflecting the potential of the entire category to support a retailer’s strategy;
- 3) The suggested proportions of shelf space which can further enhance the retailer’s results.

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<sup>44</sup> All items from the same grouping of functional substitutes are assumed to receive an equal portion of the transferred demand.

### **3.6.1. SKU Performance Assessment and Recommendations for Portfolio**

#### **Rationalization**

The model can either eliminate the worst-performing SKUs from original portfolio, based on their composite scores and a SKU reduction parameter<sup>45</sup>, or allow the user to manually indicate SKUs for discontinuation.

If the user wishes to use the model to objectively identify the worst-performing products in a category, the model uses the process illustrated in Figure 11 and produces a list of the products which should be considered for elimination.

If the user wants to use the model to project results of a predefined scenario, they may either manually eliminate the SKUs from their scenario or indicate a group of products by selecting their common attributes (e.g. to project the results of eliminating all lavender-scented liquid detergents)

In all cases—with automatic selection, user’s selection by SKU, and user’s selection by attribute—the model produces a summary of the reduced portfolio’s results and a comparison with results of the entire category.

### **3.6.2. Category Results**

In parallel to the category portfolio rationalization, the model generates a comparison of results (Figure 19 demonstrates how they are presented in the model) between the entire portfolio and its reduced subset. Results are evaluated and the change caused by elimination of SKUs is quantified in terms of the following:

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<sup>45</sup> The SKU reduction parameter indicates what share (%) of the current SKU count GoodsCo is looking to eliminate from their retailer’s category assortment.

- # of maintained SKUs,
- Annual Sales Volume and Amount,
- Average Store-In-Stock Ratio,
- Average Unit Margin,
- Annual Profit,
- Average Unit Margin Net Cost-to-Shelf,
- Annual Profit Net Cost to Shelf,
- Average GMROI,
- Average Inventory Turns,
- Average Incrementality,
- Average Shelf Space Productivity.

Numbers shown in Figure 19 were based on disguised financial data but are illustrative of the results predicted by the model. The example shows that, when done right, eliminating the 10% worst-performing SKUs can lead to only a slight decrease in sales, and some reduction of unit margins while significantly improving other KPIs: product availability, assortment profitability, shelf space productivity, turns and GMROI.

Figure 19

**Complete and Rationalized Portfolio – Comparison of Results**

PORTFOLIO INFORMATION - BASELINE EVALUATION (1/2)					
# of SKUs	Annualized Recorded Sales Volume	Annualized Recorded Sales Amt	AVG Store In-Stock Rate	AVG Unit Margin	TOTAL Annualized Profit
100	5,000,000	\$ 20,000,000	50%	\$ 1.00	\$ 4,000,000

EVALUATION OF RATIONALIZED PORTFOLIO (1/2)					
# of SKUs	Annualized Recorded Sales Volume	Annualized Recorded Sales Amt	AVG Store In-Stock Rate	AVG Unit Profit	TOTAL Annualized Profit
90	4,999,212	\$ 19,996,739	56%	\$ 0.92	\$ 4,256,829
↓ -10.0%	↓ -0.02%	↓ -0.02%	↑ 12.49%	↓ -7.99%	↑ 6.42%

PORTFOLIO INFORMATION - BASELINE EVALUATION (2/2)					
AVG Profit Net Cost to Serve	TOTAL Profit Net Cost to Serve	AVG Shelf Space Productivity	AVG GMROI	AVG Inventory Turns	AVG Incrementality
\$ 0.90	\$ 3,000,000	\$ 60.00	2.00	5.00	20.0%

EVALUATION OF RATIONALIZED PORTFOLIO (2/2)					
AVG Profit Net Cost to Serve	TOTAL Profit Net Cost to Serve	AVG Shelf Space Productivity	AVG GMROI	AVG Inventory Turns	AVG Incrementality
\$ 0.86	\$ 3,105,907	\$ 63.85	2.23	5.57	20.9%
↓ -4.76%	↑ 3.53%	↑ 6.42%	↑ 11.48%	↑ 11.44%	↑ 4.67%

Figure 19 illustrates effects of Efficient Assortment as they are presented in the decision model.

While ABSOLUTE NUMBERS WERE DISGUISED, trends shown in the figure are representative of the actual changes in retailers' results.

**3.6.3. Suggested Shelf-Space Allocation**

As discussed in the previous two subsections, selecting which SKUs to carry is a key assortment decision which—if done correctly—can help retailers drive improvements in results of a category. Another major decision which has a great impact on whether a

retailer is successful in pursuing their strategy is the allocation of available shelf space between carried categories.

Depending on the possible results of assortment in each category, the retailer may expand the space of one category while reducing others. If additional shelf space becomes available, the retailer can split it across several categories, dedicate the space to the most successful category, set up additional facings of the best performing products or dedicate the shelf space to new brands or varieties. All these decisions should not be made without a careful consideration of the gained or lost “assortment efficiency”.

As shown in Figure 11, potential results of several categories’ assortments which were discussed in subsection 3.6.2 are the output of the third stage of the modeled decision process and at the same time an input to the ultimate decision about the shape and composition of the entire product portfolio.

KPIs discussed in 3.3 were revisited to identify factors relevant not only for category management but also for management of assortment across categories. Because most of the criteria applicable to product evaluation should be managed within rather than across categories, the Efficient Assortment Model uses the standard measures of sales and profitability to optimize shelf space composition. These two results were expressed in terms of rates per unit of shelf space (sales and profits per linear foot of shelf) and applied as parameters for a linear optimization model which treated the linear footage of shelf space for each category as the decision variable. Two constraints were applied on the variables:

- 1) Sum of space assigned to all categories could not exceed available linear footage (the model allows to model shelf space changes);
- 2) A minimum amount of space was assigned to each category to ensure that all product types which the retailer wants to offer are represented on shelves.

The structure of the optimization problem is described by Equation 8:

$$(Eq. 8) \quad \textit{Annual Result of Assortment} = \sum_i (\textit{Result per Lin. Ft}_{cat.i} \times \textit{Shelf Space}_{cat.i}),$$

$$\text{where } \sum_i \textit{Shelf Space}_{cat.i} \leq \textit{Total Available Shelf Space} \times \textit{Shelf expansion coefficient}$$

$$\text{and } \textit{Shelf Space}_{cat.i} \geq \textit{Min Shelf Space}_{cat.i}$$

The model returns the suggested linear footage of shelf space which should be dedicated to each product category as well as the expected results of assortment: sales, revenue and profitability. An example of how shelf restructuring can impact results is shown in Figure 25 on page 78.

#### 4. ANALYSIS AND FINDINGS

Some of the individual KPIs calculated as part of the model can provide insight and directions for GoodsCo's portfolio management decisions. Two such revealing metrics are Profit Net Cost to Serve and Incrementality. Interpretations and implications of analyses of these two KPIs are discussed in sections 4.1 and 4.2.

In addition to these two KPIs, many types of fairly complex decisions can be supported by the three outputs of the model: the SKU selection best supporting category objectives, the expected category results, and the recommended shelf composition. The final sections of this chapter discuss three areas of questions which can be answered by modeling relevant what-if scenarios in the model: 1) product variety management, 2) planogram reconfigurations, and 3) changes in category strategy.

#### **4.1. MANAGEMENT OF LOGISTICS COSTS**

As discussed in 3.3.7, servicing products from the moment they are received at merchandisers' Distribution Centers to the moment they land in shoppers' bags generates considerable logistics effort and cost on part of the retailer. Comparing the cost to shelf per unit of each SKU with its gross profitability and assessing the total costs of logistics for alternative product portfolios can help GoodsCo manage their offer in a way that ensures sustainable financial results.

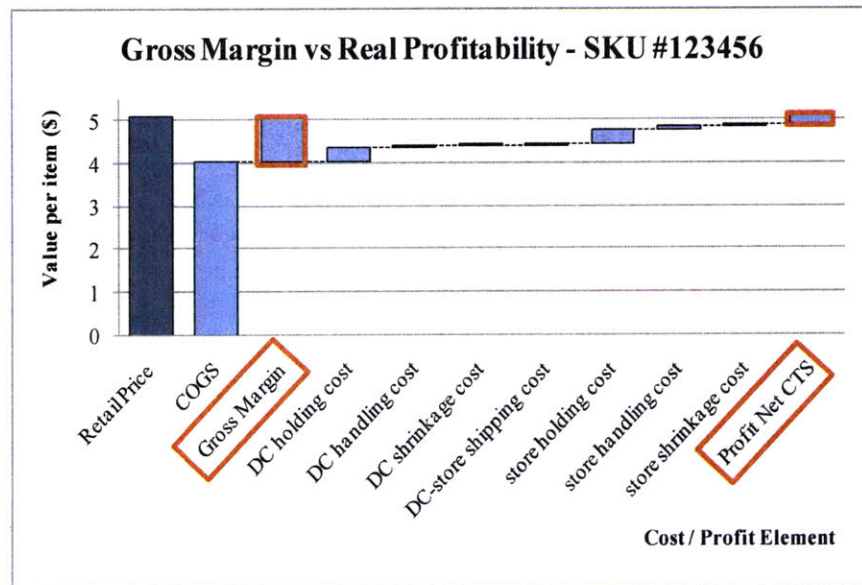
##### **4.1.1. Unit Profit Net Cost to Shelf**

The Profit Net Cost to Shelf factor calculated for each SKU which was introduced in subsection 3.5.7 can help determine which products are indeed most profitable for a selected retailer. As discussed in chapter 3, the most easily available and widely used measures of product profitability do not accurately reflect the impact of each SKU on a retailer's bottom line.

Gross margin (the unit profitability measure used by the mass merchandiser and drug channel considered in this research) realized through product sales is used to cover costs of storing, handling and shipping of goods, as well as costs of managing of assortment at store level.

Depending on the products' characteristics—e.g. unit value, volume, dimensions, packaging, velocity and variability of sales, as well as the structure of the distribution network—the actual profitability of goods with similar gross margin levels may differ significantly. Some products are handled efficiently and contribute high percentages of

**Figure 20**

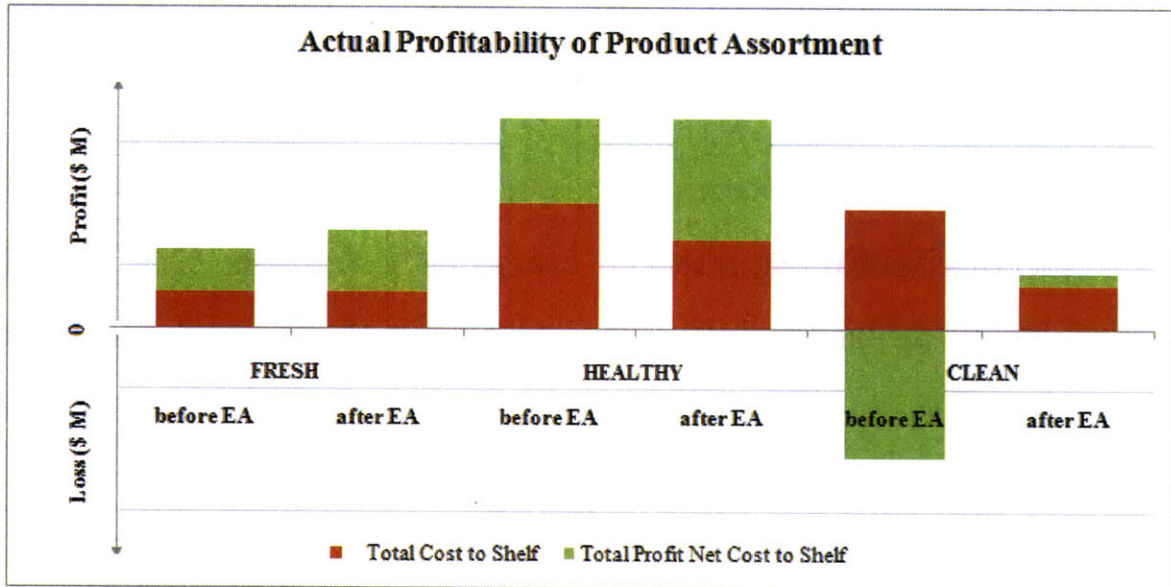


An example showing how the gross margin of a product can be consumed before the product is sold to the customer.

gross margin to retailers' total income while others—although apparently profitable—are so costly to carry that their impact on bottom line is marginal or even negative. An example of this effect of logistics' costs on product profitability is pictured in Figure 20.

#### 4.1.2. Actual Profitability of Product Assortment

Figure 21



Depending on the efficiency of baseline category assortment, SKU rationalization can help reduce its aggregate Cost to Shelf. The example shows that profits generated by category Fresh can increase through a change of product mix although Cost to Shelf will not be significantly impacted. Category Healthy will generate a comparable cumulative gross margin after rationalization as before but will be less costly to handle and therefore more profitable. Finally, EA can transform category Clean which is currently carried despite its negative financial results to one which generates a modest profit.

As indicated in subsection 4.1.1., actual profitability of product assortment depends on the selection of products. If a retailer chooses to carry goods whose handling consumes little of the earned gross margins, their net earned profits will be preserved.

At the same time, some aspects of logistics complexity are related not so much with the characteristics as with the count of products in the portfolio. For example, picking goods from Distribution Centers and assembling them into shipments is likely to take longer if a retailer carries many products. Similarly, monitoring of product availability

and replenishment of DCs and stores is more complicated and time-consuming if the count of carried SKUs is high.

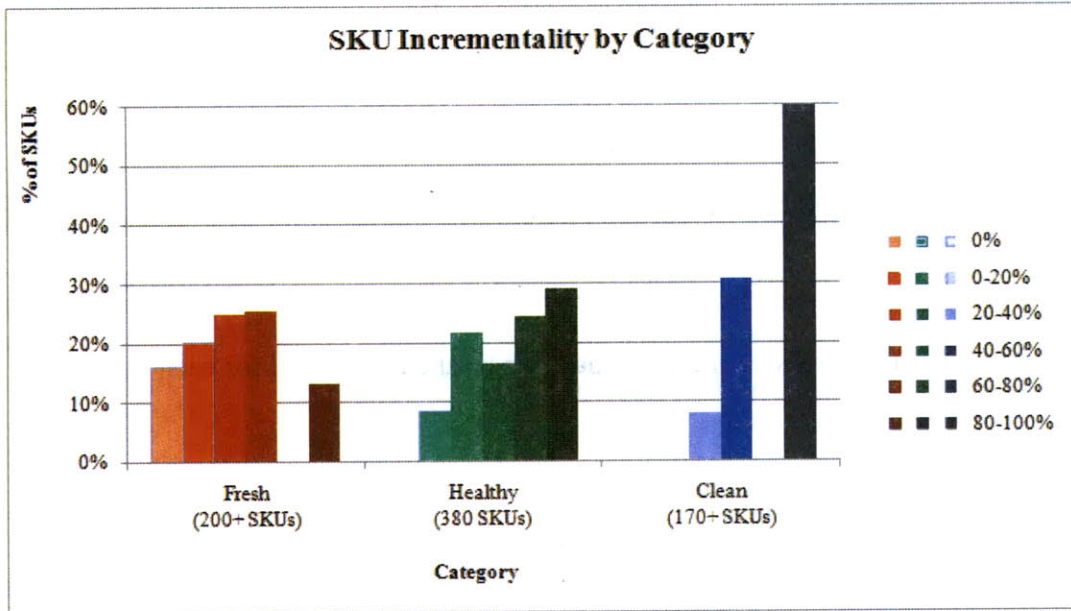
Analyses of projected results, such as those illustrated in Figure 21, help to understand the difference between total profit and profit net cost-to-shelf for each category. Based on the model outcomes, GoodsCo can understand upfront how much impact Efficient Assortment can have on total cost-to-shelf for each category.

#### **4.2. INCREMENTALITY OF SKUS IN CATEGORY**

Analyses of the incrementality metric which was introduced in subsection 3.3.2—the quantitative measure of the strength of each SKU’s individual contribution to its category sales—can also lead to interesting insights and help category managers.

Products with low incrementality should be the first ones to consider in SKU rationalization initiatives. In fact, products which are easy to substitute (both for retailers and end-customers) are a better elimination target than those which generate higher sales or margins. GoodsCo realizes that whenever it decides to stop offering products with high incrementality, a portion of sales is given away to their competitors. Although it may seem that products with high incrementality but low unit margin or low sales are less attractive than those with high sales and profits but low incrementality, the results projected by the model support the opposite conclusion.

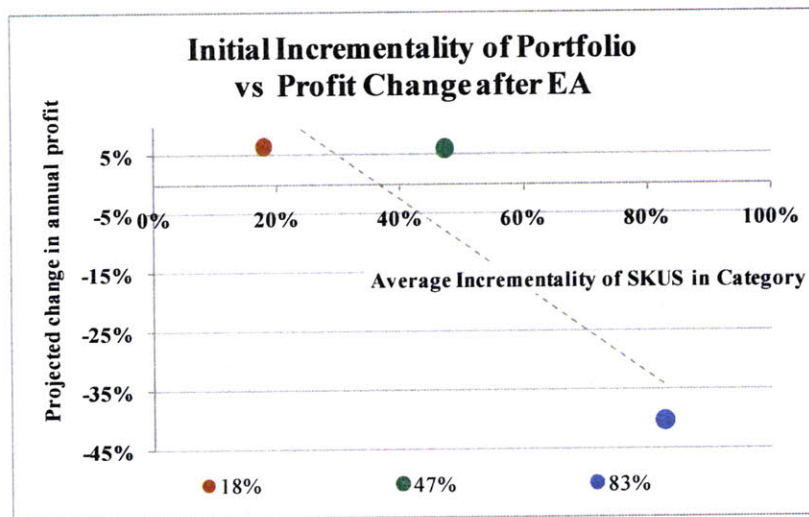
Figure 22



Incrementality of items in category Clean is very high – reductions of the category assortment will likely draw GoodsCo’s customers to competitors’ products.

An analysis of how product incrementality is distributed in a category can help managers decide whether to pursue category reductions or expansion. Comparing of product incrementality across categories can help select the category which will profit most from SKU reduction activities. For example, based on Figure 22, there are more functional duplicates (low incrementality) in Category Fresh than Categories Healthy and Clean. Although Category Healthy has twice as many SKUs, reductions of variety in this category are more likely to result in demand transferring to products offered to GoodsCo’s competitors or even in shoppers moving their baskets to another retailer. Sample results presented in Figure 23 confirm this understanding: indeed, elimination of 10% of category “Clean”, dominated by SKUs with very high incrementality factors, is associated with very high risk. The other two categories are much better SKU rationalization targets.

Figure 23



Both categories described with relatively low incrementality can benefit from a data-driven SKU rationalization program. Incrementality of sales in Category Clean is very high and elimination of products is likely to result in lost sales.

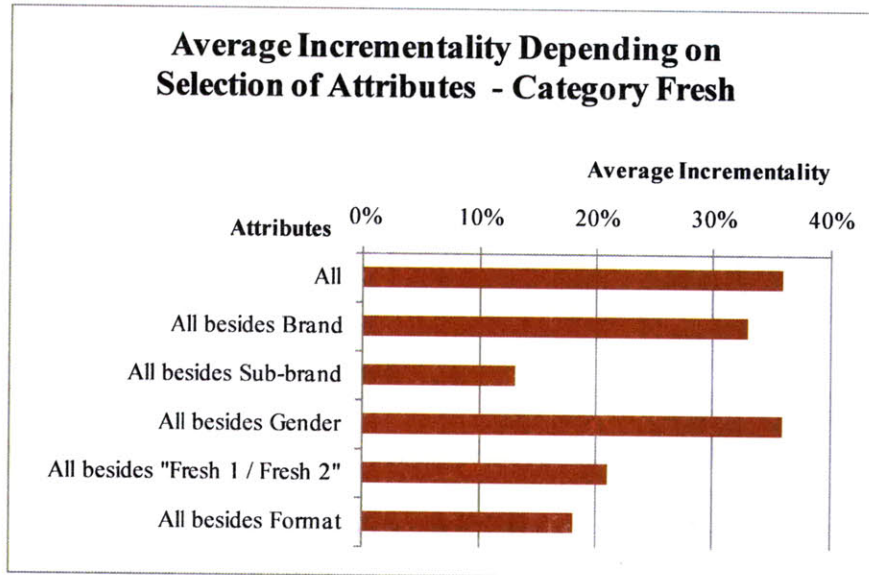
#### 4.3. MANAGEMENT OF PERCEIVED PRODUCT VARIETY

Incrementality depends on the variety of products. The higher the differentiation within a product portfolio, the lower the cannibalization of demand between SKUs and the higher the overall sales.

The Efficient Assortment model allows one to project results of reducing the variety within a category. The user can select an attribute or set of attributes (e.g. “Color” and “Type of fabric”) and indicate the values which don’t seem popular among customers (e.g. ”red” and “cotton”). In response, the model will generate an estimate of the expected results and compare it against the baseline of entire portfolio. The expected change will be presented as it was illustrated in Figure 19 on page 68. The projected difference in profits can then be

compared against the cost of maintaining the group of products and potentially support the decision to eliminate it.

**Figure 24**



Because sales incrementality is a function of perceived product variety, its value depends on attributes used in product differentiation. The observation can be applied in marketing of GoodsCo's products.

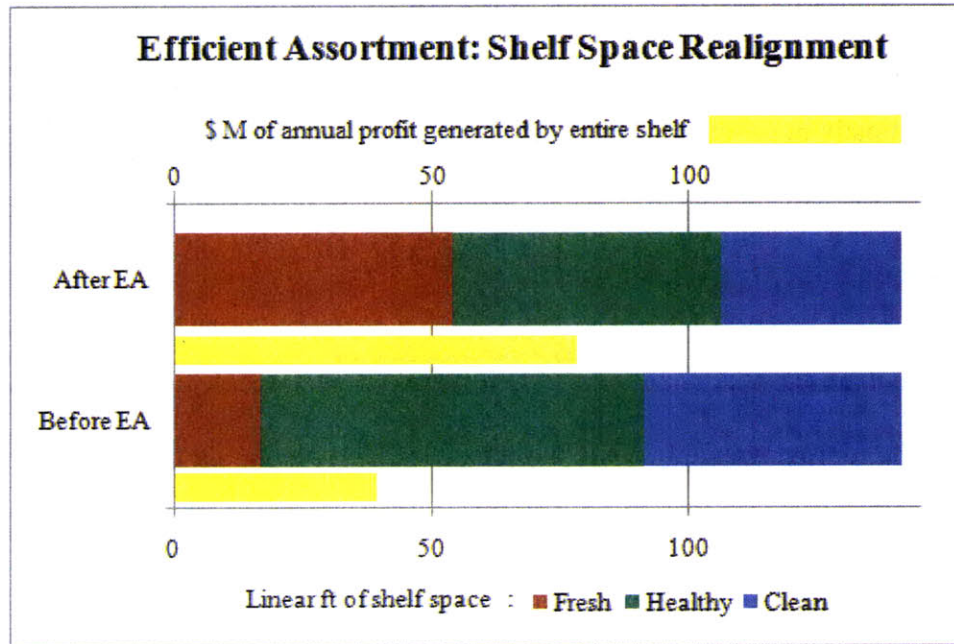
In addition to providing insights regarding the expected changes in results yielded by the reduced portfolio, the Efficient Assortment model can help GoodsCo understand which product features should be promoted in their advertising campaigns<sup>46</sup>. Similarly, it can help set direction to the subsequent new product development initiatives. Figure 24 illustrates an example of how GoodsCo could potentially use the tool to understand the value of adding and emphasizing each of product features. As can be read from the chart, sub-brand, binary attribute "Fresh 1 / Fresh 2" and format should continue to be used as product differentiators.

<sup>46</sup> See comments in subsection 5.5.2.

#### 4.4. SHELF SPACE ADJUSTMENTS

Section 3.6.3 described how the model processes the outputs of category assortment modifications into the suggested shelf space allocation. While recommending a shelf

Figure 25



According to the EA model, if a portion of shelf space previously dedicated to categories Healthy and Clean is reassigned to category Fresh, the retailer will observe increases in sales volume and profits.

structure, the model also makes projections regarding the increase in sales, revenues and profits which are expected to result from reassigning of shelf space among available categories (projected results can also be calculated for a scenario created outside of the model). An example of such recommendation and its anticipated outcomes in terms of volume and income is illustrated in Figure 25.

One of the decisions which projections indicated by the tool can help with is whether a considered mid-year planogram reconfiguration scheme is justified by the increased utilization of shelf space.

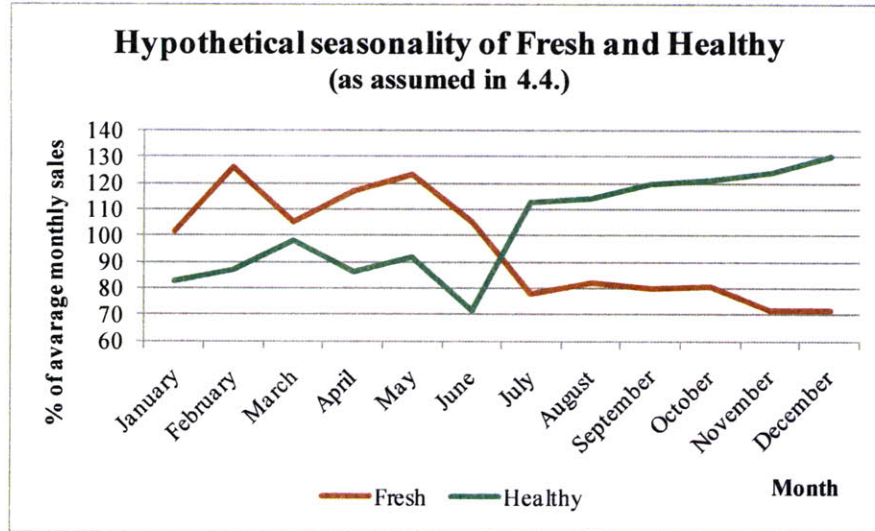
Products with strong seasonality effect typically ensure high utilization of shelf space in periods when demand peaks and record low profitability per shelf space unit outside of the season. If demand patterns of two categories are showing alternating peaks (e.g. one category is sold mostly in summer and another – in winter), it may be desirable to change composition of the shelf and use most of it for the category which is more in demand, depending on the current season.

Although seasonality patterns of neither two of the modeled categories complement each other, the following example will assume that SKUs belonging to Fresh sell better in the first half of the year, while those in category Healthy record higher revenues in the second half of the year, following seasonality pictured in Figure 26.

Three possible options which a retailer may consider in such situation are:

- 1) To maintain the current shelf configuration where the linear footage reserved for Healthy and Fresh does not change throughout the year and avoid costs of biannual remerchandising;
- 2) To change the shelf composition permanently as per indications of the EA model;
- 3) To change the shelf composition in January and July, reserving substantially more space to Fresh in the first two quarters and to Healthy in quarters 3 and 4.

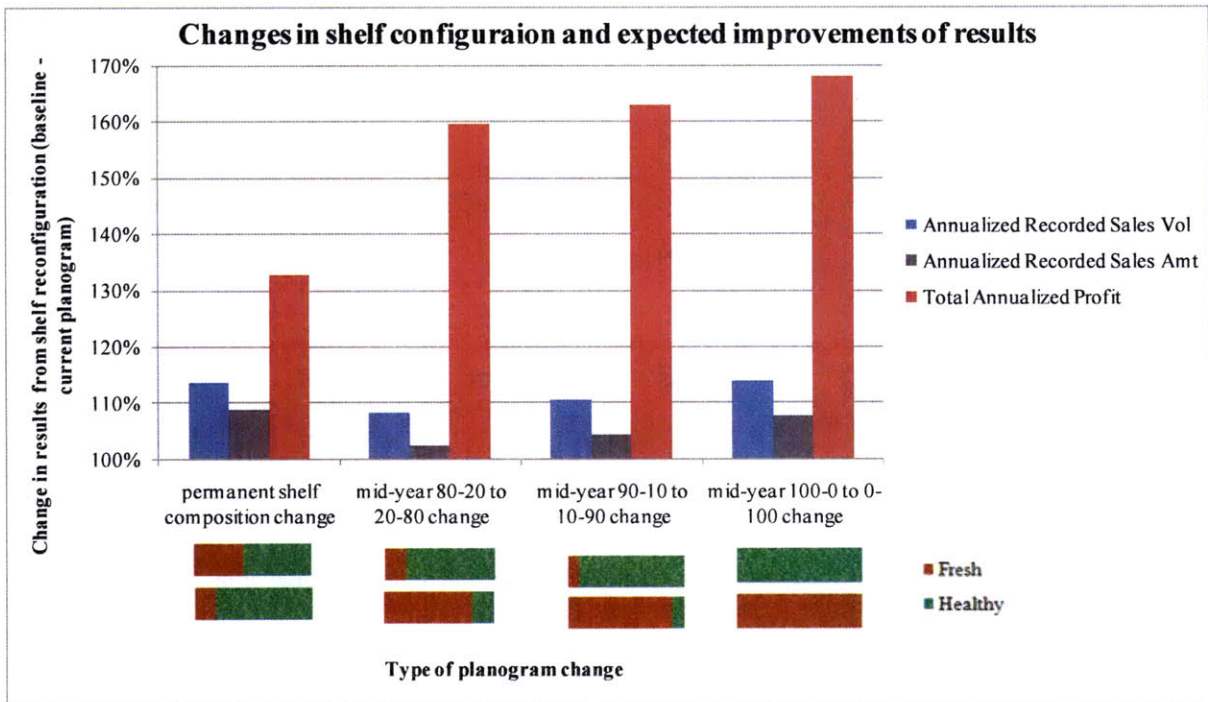
Figure 26



To present a scenario in which the model helps determine the value of mid-year planogram reconfigurations, category Fresh was assumed to record higher sales in Q1 and Q2, Healthy – in Q3 and Q4.

If the Efficient Assortment model is fed with data representing January-June for Fresh and July –December for Healthy, it automatically annualizes their results. If, however, the end date of the covered period is manually changed to December 31st, the model displays results of the respective six months. Next, the model converts these annual or semi-annual results into dollars / units per linear foot of shelf and returns possible total annual revenue, sales volume and profit in each scenario. Possible improvements in results are illustrated in Figure 27. GoodsCo can use the estimated additional profits generated by the mid-year change to verify whether the additional income justifies the costs of seasonal remerchandising for the retailer.

**Figure 27**



Results of four scenarios involving different shelf structures are compared to the current planogram in terms of annual sales volume, revenue and profit under the assumptions illustrated in Figure 26.

#### 4.5. CHANGE IN CATEGORY STRATEGY

By manipulating the category strategy parameters (see 3.5.2) GoodsCo can determine how much its current product portfolio is robust against the changes in category classification and definition of category objectives.

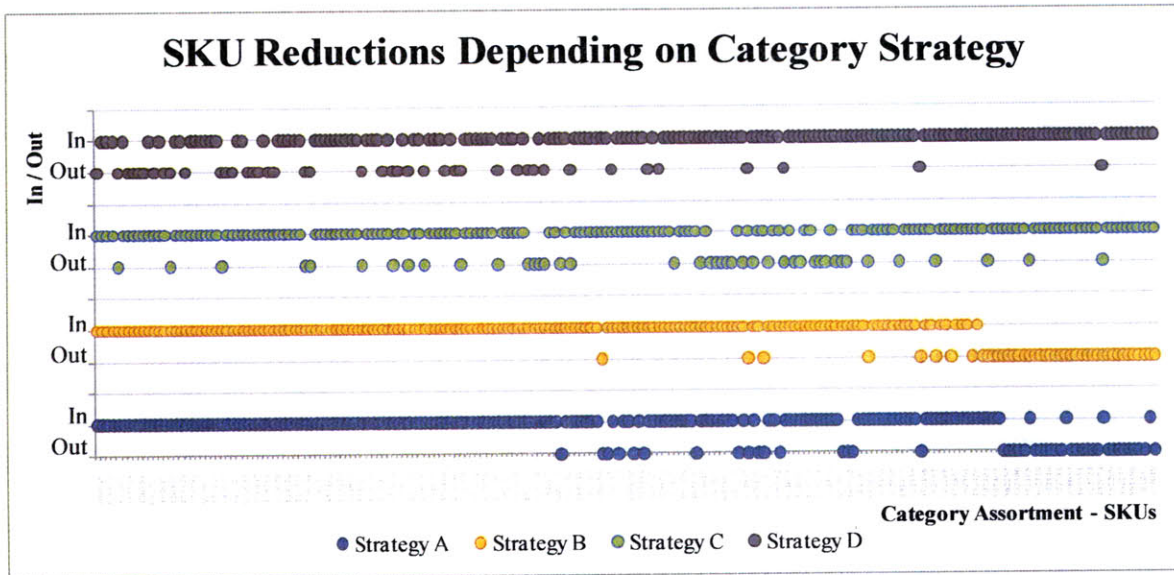
Changing the category class settings by assigning different weights to selected KPIs and observing the simulations of subsequent SKU reduction can identify products which are most suitable for long-term investments such as marketing campaigns or customized packaging. On the other hand, it can determine SKUs which do not support the known strategies of retailers and are therefore safe to eliminate.

**Table 4: Possible Category Strategies**

<b>Criterion</b>	<b>Category A</b>	<b>Category B</b>	<b>Category C</b>	<b>Category D</b>
<b>Annualized Recorded Sales Volume</b>	X			
<b>Demand Trend</b>	X			
<b>Annualized Recorded Sales AMT</b>		X		
<b>Average Unit Margin</b>			X	
<b>Annualized Profit</b>				
<b>Unit Margin Net Cost to Shelf</b>				X
<b>Profit Net Cost to Shelf</b>				
<b>GMROI</b>			X	
<b>GMROI Trend</b>			X	
<b>Incrementality</b>				
<b>Shelf Space Productivity</b>				
<b>Inventory Turns</b>				
<b>Annualized Recorded Sales Volume</b>	X			

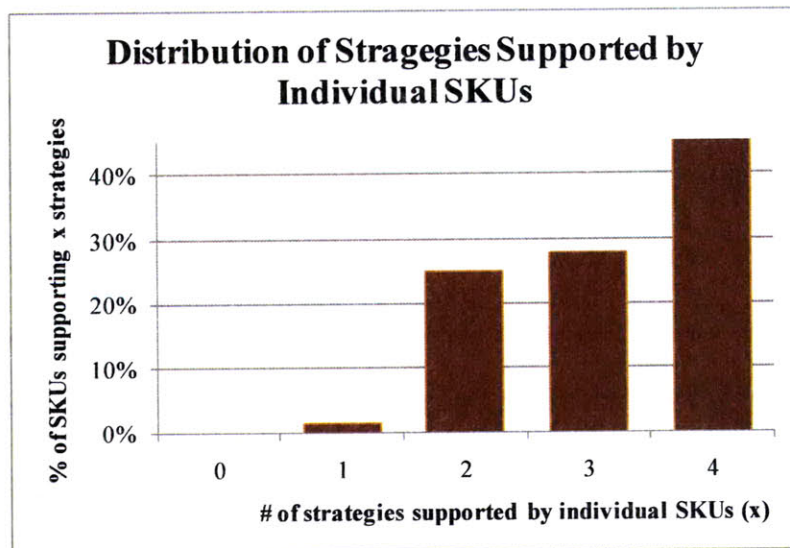
Figure 28 provides an illustration of the problem. The same set of SKUs (Category Fresh) was subject to evaluation and rationalization under four different strategies described in Table 4. The same reduction factor of 20% was used for all four scenarios. As shown in Figure 28, the bottom 20% of the portfolio consisted of different products under each scenario. In fact, only 43% of analyzed SKUs were retained under all considered scenarios - these would be the ones which GoodsCo can invest in, regardless of the robustness of retailers' strategy. Even more surprisingly, none of the SKUs were eliminated under all of the scenarios. The distribution of the number of strategies supported by each SKU, presented in Figure 29, proves how strongly category strategy can affect assortment decisions.

Figure 28



The decision to keep or eliminate a SKU depends on the goals which the company has defined for the category. A retailer will select a different subset of the category portfolio depending on which of the four strategies outlined in Table 4 it applies to the category.

Figure 29



Results of only 40% of SKUs in this category are strong enough to make them relevant to the retailer regardless of the strategy.

## **5. POSSIBLE MODEL EXTENSIONS**

As explained in the Introduction, the scope of this research covered three categories and two retailers. The main rationale of including several product types and different merchandisers was to motivate a broader analysis of retailers' needs and inspire a strategic approach to assortment modeling, which had to reach beyond one company and category.

Another important reason for such broad scope was GoodsCo's intention to use the research's findings and—perhaps most importantly—the model to analyze a variety of other categories from its portfolio and to apply it to retailers other than the two retailers covered in this pilot.

This chapter describes how this latter requirement was met, how the tool can be modified to answer additional questions and how it can be further refined to provide more accurate results.

### **5.1. ADDITIONAL RETAILERS**

As per GoodsCo's specifications, the original model was configured for two of their major clients: a mass merchandiser and a drug channel. However, adding new retailers is a fairly straightforward modification.

As described in section 3.5., the model determines two sets of variables based on the selected retailer: the range of category classes and the settings reflecting the approximate structure of the selected retailer's replenishment processes. Two modifications are required to extend the model to support additional clients of GoodsCo. First, category strategies specific for these new clients need to be defined (the idea of category class and strategy was introduced in 3.5.2). Second, the user should define the structure of retailers' operations by

adjusting several parameters and thus specifying: durations of logistics processes, average distances between replenishment DCs and stores, as well as labor and transportation rates.

## **5.2. ADDITIONAL CATEGORIES**

The scope of the research covered three product categories: Fresh, Clean and Healthy. Similarly as in case of retailers, the decision model can accommodate multiple other product groups.

Features which enable such flexibility include:

- 1) The model's scalability: the spreadsheet is currently set up to process raw datasets up to 20,000 lines (number of SKUs x number of periods covered) and analyze categories containing up to 1,000 SKUs. If larger datasets need to be processed, modifying several pre-defined data ranges can increase the size of input dataset to over 1,000,000 lines;
- 2) The model's robustness: through error-proofing and macros which restore original settings, the model can work with incomplete data and is easy to manage without the necessity to rewrite formulas in case they get overwritten or corrupted;
- 3) The shelf space model's capacity to determine the best allocation of linear footage across up to twenty product categories.

Thanks to the above, the model can be used to analyze any category. The two inputs which require updating are the POS, operational and financial data (as per Table 1) and attributes appropriate for the new category (analogous to those listed in Table 2).

### **5.3. COMPETITORS' PRODUCTS**

Because of GoodsCo commitment to data confidentiality, all datasets provided for this research and used in creating of the model represent only products manufactured by GoodsCo. However, including information about products of other manufacturers in the input dataset can help GoodsCo determine how its retailers view their items compared with those offered by GoodsCo's competitors.

Features listed in section 5.2 make it fairly easy to use the model to evaluate the entire category. Once information about GoodsCo's and GoodsCo's rivals' products are entered in the tool's input sections, the manufacturer can better predict the result that product eliminations may have on their market share, determine which of their products should be subsidized, which deserve a more aggressive promotion campaign etc.

### **5.4. STORE-LEVEL DECISIONS**

As explained in section 3.1, the three datasets used as inputs to the model represented monthly sums and averages for each SKU across all stores in which a given SKU was represented. The only set of data representing SKU-store combinations was the sample which was used to determine realistic dependency between number of carried SKUs and out-of-stock levels. Because most stores cater to their local demand, they also carry different numbers and selections of products. Therefore, each of the three main datasets covered more of GoodsCo's SKUs than any store would need to manage in the respective category.

For these reasons, recommendations discussed in chapter 4 were limited to the level of retailer. Rather than defining the subset of SKUs which should be put on shelves, the Efficient Assortment model helps reduce GoodsCo's entire portfolio of SKUs in each

category. Similarly, instead of projecting stores' results, it estimates the possible results of the entire company.

At the same time, the decision model can be easily adjustable to provide indications of store-level decisions, e.g. if the product proliferation problem is particularly acute in selected stores. By simply replacing the list of all category SKUs with only those which are carried by that store (the concept of “protecting” SKUs was introduced in section 3.4), the user can reduce the scope of elimination so that it is aligned with the store assortment.

## **5.5. FURTHER ANALYSES AND MODEL ENHANCEMENTS**

This section suggests two studies which could potentially enhance the model and improve the accuracy of its results. First, an analysis of consumer switching patterns would help verify the underlying assumptions regarding demand transferability and product incrementality. Second, a closer examination of retailers' logistics would provide more accurate inputs for the Cost to Shelf calculations.

Results of these studies can be fed into the Efficient Assortment model without the need for major modifications of its structure.

### **5.5.1. Incrementality and Switching Patterns**

As discussed in 3.3.2 and 3.5.2, the incrementality calculations used for simulating of sales' transfers were based on several assumptions. The shape of the demand transferability curve shown in Figure 14 and the selection of attributes used to determine the sets of substitutes were stipulated using the intuitive understanding of consumer decision-making process.

Additional market research or analysis of sales data including loyalty program information<sup>47</sup> would help verify and better define what constitutes a set of substitutes in each studied category. Such effort would help understand which product characteristics are evaluated when shoppers are selecting among variety of goods in a category and check whether there is a hierarchy of requirements. If the research reveals that some attributes are more important for shoppers than others then the mechanics of demand cross-attribute transferability modeling should be modified. Specifically, the portion of migrating demand should depend not only on the count of substitutes but also on the strength of the differentiating attribute. An analysis of switching patterns would also help more accurately describe the relationship between the number of substitutes and transferability of demand.

### **5.5.2. Retailers' Replenishment Processes and Cost to Shelf**

The framework used for approximating Cost to Shelf was based on GoodsCo's extensive knowledge of their clients' logistics infrastructure and processes, and supported by analysis of available publications discussing distribution operations of major retailers.

At the same time, the analysis used several assumptions. The precise duration of replenishment activities, hourly labor and per-mile transportation rates, as well as distances at which products are shipped were based on approximations. A closer survey of retailers' operations, preferably one performed in cooperation with the retailers logistics teams would help refine the above listed parameters and bring the results reported by the EA model closer to reality.

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<sup>47</sup> Loyalty program information was not provided within category datasets and analyses of demand switching patterns were not included in the scope of this research.

## 6. SUMMARY AND CONCLUSIONS

Adjustments in product selection can bring significant operational improvements to both the retailers and their suppliers, justifying the label of “Efficient Assortment”. The table below summarizes the nature of such improvements, indicating whether each benefit is realized entirely by the retailer, entirely by the manufacturer, or shared between the parties, and whether the effect has been captured in the Efficient Assortment model<sup>48</sup> described in chapter 3.

**Table 5: Supply Chain Benefits of Efficient Assortment**

#	Benefit	Retailer’s benefit?	Benefit modeled?	Manufacturer’s benefit?
1	Optimized inventory levels	Direct	Partly	Direct
2	Lower inventory carrying costs	Direct	Yes	Direct
3	Increased inventory turns	Direct	Yes	Direct
4	Lower operating costs	Direct	Yes	Direct
5	Improved fill rate	Direct	Yes	Direct
6	Reduced out of stocks	Direct	Yes	Direct
7	Improved category shoppability	Direct	Yes	Indirect
8	Increased sales	Direct	Partly	Indirect
9	Better utilization of logistics assets	Direct	Partly	Direct
10	Better utilization of shelf space	Direct	Yes	Indirect
11	Better return on investment in shelf space	Direct	Yes	Indirect
12	Better labor productivity	Direct	Yes	Direct

<sup>48</sup> Because of GoodsCo’s request that the research should focus on the retailers’ perspective, “yes” indicates that the benefits were quantified for the retailer, not for the manufacturer.

Table 6 presents a fairly exhaustive list of the benefits which efficient assortment is expected to bring to retailers and their suppliers. There is, however, another party which will enjoy the results of this initiative - the shared customers of both partners. Instead of getting all the choice they need and more (as it has been the case for several years), shoppers will now actually need and appreciate the selection they are getting.

While efficient assortment can be highly advantageous for the manufacturer, its retailers, and customers of both, it is also a very challenging initiative.

First, in order for the potential benefits of EA to be reflected in the bottom line of either of the partners, the changes that it involves need to be accepted and supported at several levels:

- 1) across functions, within both companies;
- 2) between the two affected trading partners;
- 3) among the ultimate stakeholders – the shoppers.

Lack of buy-in from Sales, Marketing, Finance, or Logistics on part of either the retailer or the manufacturer can put the results of efficient assortment at stake. Poor understanding, miscommunication or misalignment of objectives between the two companies can not only lead to abandoning of the initiative but even damage the existing partnership. Finally, even if assortment changes are a product of consensus across functional departments, as well as between the supplier and retailer, they can still hurt both companies in case customers find themselves deprived of their favorite items or dissatisfied with the reduced selection. Considering the risks, it is vital that partners engaging in such endeavors trust one another and are equally dedicated to the shared goal of serving the customer.

Second, uneasy as finding a solution which satisfies the needs of all involved parties may be, realizing all benefits listed in Table 6 requires implementing changes across the chain linking manufacturing plants with stores and consumer baskets. While some of the required changes may be fairly simple, others are complex and require time and effort.

Some of the short term adjustments involve discontinuing low-performing products from selected retailers and indicating items which should fill their shelf space so that the customers' perception of variety is unaffected and stores' results - improved. The Efficient Assortment model can help GoodsCo and its retailers select products worth carrying through analyses such as those outlined in section 3.6.

In the mid-term, retailers' assortment management process should be adapted to account for the engagement of the manufacturer's representatives. This stage may potentially involve a refinement of category strategies and a reconsideration of the processes by which the shelf space is divided between products. By using the model to evaluate scenarios such as the one discussed in 4.4, GoodsCo can help its clients improve their profitability. Analyses similar to that presented in section 4.1 can help GoodsCo identify categories which incur high logistics costs.

Collaboration with retailers in the area of assortment management can lead to changes in the way products are handled throughout the supply chain. Discussions based on insights such as those outlined in 4.2 and 4.3 can provide the vendor with ideas regarding the direction of innovations which its partners would desire.

In the long term, once efficient assortment has addressed multiple retailers, the manufacturer should examine its product portfolio in a similar fashion as it was presented in section 4.5, to

determine which products it should not only stop delivering to selected clients but which should not be further manufactured.

As shown through this research, data-driven assortment rationalization can reduce the risk of lost sales and introduce improvements in product availability, retailers' logistics costs, efficiency of their operations, and utilization of supply chain assets. The decision model built as part of the project reinforced the manufacturer's competence to support objectives of clients while continuing to pursue its own goal of offering end-customers products which they need, trust and value.

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