Rocket Science Retailing:  
The 2006 Philip McCord Morse Lecture  

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Retailing is a huge industry. In the United States, retail business represents about 40% of the economy and is the largest employer. Retail supply chain management is still more art than science, but this is changing rapidly as retailers begin to apply analytic models to the huge volume of data they are collecting on consumer purchases and preferences. This industry-wide movement resembles the transformation of Wall Street that occurred in the 1970s when physicists and other “rocket scientists” applied their analytic skills to investment decisions.

The Consortium for Operational Excellence in Retailing (COER) (codirected by Ananth Raman, Harvard Business School, and myself) is a group of academics working with about 50 leading retailers to assess their progress towards rocket science retailing and to accelerate that progress through selected research projects.

After some brief comments on the current state of industry practice in retail supply chain management, this paper will describe examples of COER research in four areas: assortment planning, pricing, inventory optimization, and store execution.

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1. Introduction

My introduction to retailing began in 1995 with three formative projects with an apparel retailer, a cataloger, and a Dutch grocery retailer. My initial reaction was that retailing is a paradise for operations researchers for six reasons:

1. Retailers have clear goals, such as growing sales and gross margin.
2. They have well-defined decisions that directly influence those goals, like what assortment of products to carry, in what quantities, and at what prices.
3. Retailers are collecting consumer transaction data at a prodigious rate. Point of Sale (POS) scanners, customer loyalty cards, website click-through streams, radio-frequency identification (RFID) tags, and smart carts that track a consumer’s path through a grocery store are just a few of the new technologies that enable retailers to capture relevant data for understanding their customers. These data are giving retailers the ability to understand consumers more deeply, through analysis of what they buy, as well as their demographics and even the process by which they decide what to buy, through analysis of click stream or smart-cart data.
4. Compared with large manufacturing companies I’ve worked with, the pace of implementation of new ideas is much faster in retailing. It is relatively quick to implement on a trial basis a new algorithm for setting prices or inventory levels, and store-SKU POS data will reveal in a few weeks whether the new idea worked.
5. Retailing has always been a favorite context of our field, and many of our classic inventory optimization problems are described through the eyes of a retailer. Let us not forget that the newsvendor is a retailer.
6. Managing inventory is one of the most important things a retailer does, so a key intellectual activity of our field—inventory optimization—is also of central importance to retail CEOs.

There were some surprises, however. The biggest surprise was that, despite all the data that were available, the decision making of most retailers was still highly qualitative and judgment based. One vice president of merchandising we worked with during this period had a poster on her door that described the current state of affairs as “We are awash in data and starved for information.”

The results from decisions based almost exclusively on human judgment were less than stellar. One individual who was very helpful to my colleagues and me during this period was Jerome Fisher, a graduate of Wharton and the founder of Nine West. In describing the limitations of the current process for predicting demand and planning supply, he said, “Line up ten new shoes for the next season and ten
buyers and ask them, ‘Which of these will be the hot shoe next season?’ and you get ten answers.’

It seemed that this was a situation ripe for change. You had less than satisfactory results from the current system and many enablers of a new system, including the wealth of consumer data being generated and models and algorithms from academia that could be applied to this data. This was very similar to the investment world in the late 1970s, when Wall Street went through something called the Rocket Science Revolution, which transformed investment decision making from being more art than science to being more science than art. This transformation comprised four elements: (1) a large amount of useful data, such as stock ticker tape transactions; (2) models, mostly from academia, that could be applied to this data; (3) large-scale computing power to fuel the analysis of these models; and (4) the so-called “rocket scientists”—individuals with Ph.D.s in physics, operations research, and other technical disciplines who were hired by investment firms to staff this transformation.

These same conditions now exist in retailing. As discussed before, there are growing sources for consumer data, a wealth of models from academia, ample computing power and, although it is happening slowly, retailers are beginning to hire analytically trained individuals. As described in Fisher et al. (2000), retailing is slowly but surely gravitating from virtually all art to a well-balanced mix of art and science.

To better understand this phenomenon, over the last decade Ananth Raman of Harvard Business School and I have been leading a group of academics working with about 50 leading retailers to assess their progress towards rocket science retailing and to accelerate that progress through selected research projects and annual meetings. This group of academics and retailers is called the Consortium for Operational Excellence in Retailing (COER).

We began by taking stock of how well the current system was working. When a retailer buys inventory, there are only two things that can go wrong: they can have too much product at the end of a season.1

Figure 1. Department store markdowns as a percentage of sales: 1970–1997.

Source: National Retail Federation, Financial & Operating Results. After 1997 the NRF stopped reporting department store markdowns.

Table 1. 2000–2006 average gross margin and profit before tax as a percentage of revenue for four retail segments.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Gross margin (%)</th>
<th>Profit before tax (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jewelry</td>
<td>42</td>
<td>1.0</td>
</tr>
<tr>
<td>Consumer electronics</td>
<td>34</td>
<td>1.0</td>
</tr>
<tr>
<td>Apparel and accessory</td>
<td>39</td>
<td>2.9</td>
</tr>
<tr>
<td>Department stores</td>
<td>37</td>
<td>2.9</td>
</tr>
</tbody>
</table>

Source: S&P’s Compustat Industrial Annual Database accessed through Wharton Research Data Services (WRDS).

their inventory. Until recently, department stores shared and publicly reported their markdown data. As shown in Figure 1, department store markdowns increased from 7% in 1971 to average around 25% in the 1990s. This suggests a large number of instances in which department stores have too much product at the end of a season.1

With such a high level of markdowns, one might suspect that stockouts are infrequent, but a recent survey shows otherwise. Of the 70% of respondents to KSA’s Consumer Outlook Survey (Kurt Salmon Associates 1998) who said they enter a store with a clear idea in mind of an apparel item they wish to buy, 51% leave empty-handed because they cannot find what they came for. Not surprisingly, in-stock rate was listed as the biggest factor influencing store choice for respondents.

Even modest improvements in the match between supply and demand can have an enormous impact on a retailer’s profit. Retailing is a high-fixed-cost business; it costs a lot of money to maintain a store base, and that cost is the same, whether you sell $1 or $1 million in a store. This means that even small increases in sales from better in-stocks can result in large profit increases.

Table 1 shows average gross margins and before-tax profit for various retail segments. Note that gross margins are large relative to profit before tax, which means that even small increases in sales will have a big impact on profit before tax. For example, if a jewelry retailer can increase sales by 2.5%, the 42% gross margin for this segment implies an increase in profit before tax of 0.42 \times 2.5% = 1.05% of revenue, which would more than double profit before tax.

This scenario is not far fetched. In the 1990s, Bulgari,2 the high-end Italian jeweler and a member of COER, became concerned that they were losing sales because of high levels of stockouts in their stores. One hypothesis within the company was that these stockouts resulted in minimal lost sales because customers could be persuaded to substitute to another item if their first choice was stocked out. To better understand the situation, they began to monitor in a sample of stores the reaction of customers who came in asking for a specific item and were told that the item was stocked out. Based on this tracking, they concluded that about half of the time a customer encountered a stockout, a sale was lost.3 The other half of the time, the customer either bought another item or delayed purchase until their first choice was in stock. Thus it is reasonable to conclude that improving
in stocks by 5% would increase sales by 2.5% and double before-tax profit. Bigger in-stock improvements are needed in other segments to double profits, but in all cases, realistically achievable in-stock improvements can produce a dramatic improvement in profit.

Retailers face four important issues in managing their supply chains: determining what assortment of products to carry in each store at each point in time, at what prices and in what inventory quantities, and eliciting best efforts from store employees to achieve outstanding store execution. This paper describes a sample of COER research on these issues. This research has been or is being implemented by retailers as part of an accelerating adoption of analytic methods that has occurred over the last decade. For example, Googling “assortment planning” brings up more than a quarter-million references to analytic systems, several recent start-up companies have been based on analytic approaches to either markdown or initial pricing, I know of at least one retailer using highly sophisticated inventory optimization algorithms as a result of COER research, and many retailers now gather and analyze customer satisfaction survey data in an effort to improve store execution.

A much more extensive description of the research described in this paper in a format intended to be accessible to a managerial audience is in Fisher and Raman (2009). This paper is focused on COER research, and hence omits discussion of the growing body of outstanding work published by the many researchers focused on the retail context. The reader is referred to Agrawal and Smith (2009) for an excellent survey of recent retail research.

Retailing will always be a blend of art and science, with the relative proportions depending on the nature of the product. For example, apparel tends to have a greater proportion of art than categories like food and hardware. Over the last decade, the amount of science in this mix has been steadily increasing. We have seen the emergence of many successful analytic software companies, some started with the help of academics and based on their research, with a focus on areas like pricing, inventory management, and assortment planning. That said, it must be noted that retailers are by nature suspicious of fancy math, so implementation is always challenging. However, retailers care most about results, so any use of science that can demonstrate a significant improvement in results will get a serious look from retailers. I am personally optimistic that retailing will continue to evolve as a wonderful new application domain for our field.

2. Assortment Planning

Assortment planning involves determining the set of products a retailer will carry in each store at each point in time to optimize a specified profit function. Most retailers view assortment planning as a capital budgeting problem and blend analysis of history and human judgment to determine the amount of store space and buying dollars to allocate to each of their product categories. The choice of which specific SKUs (Stockkeeping Units) to carry in a category is usually left to a buyer who has few, if any, analytic tools to help them with this difficult decision. The decision of whether or not to carry a specific SKU is particularly challenging for products the retailer has not previously carried, and hence with which they have no sales experience.

Wharton Ph.D. student Ramnath Vaidyanathan and I have been working with three COER retailers to develop and test a new approach to assortment planning. The retailers span three different product segments: tires, convenience stores, and home furnishings. Our approach uses sales history to estimate the demand for all possible SKUs (including many SKUs not currently carried by the retailer) at each store and the likelihood a customer will substitute another SKU if their preferred product is not available. We then determine the profit-maximizing assortment for each store based on these estimates.

Our approach draws on an extensive literature in marketing that views a product as an aggregation of attribute values. The most relevant references are Bell et al. (2005) and Fader and Hardie (1996), who use an attribute-based approach to estimate demand. Several researchers have used stylized models to derive properties of an optimal assortment under different conditions, but little research has been done that would provide tools that would enable a retailer to choose a better assortment. The only decision-support research of which we are aware is Chong et al. (2001), Green and Krieger (1985), Kök and Fisher (2007), and Smith and Agrawal (2000), and among these only Kök and Fisher (2007) provide a method for estimating demand and substitution probabilities, crucial inputs to an assortment-planning algorithm. Other relevant references are given in Fisher and Vaidyanathan (2009). The key idea of our approach is to view an SKU as a collection of attribute values. For example, for a retailer selling bed sheets, a particular SKU might be a king-size, light blue, cotton, 400 thread count sheet. Although this retailer may never have carried this particular sheet, as long as they have sold king-size sheets, light blue sheets, cotton sheets, and 400 thread count sheets, we can use sales history for these attributes in a particular store to estimate the demand shares of these attributes in that store. We then estimate the demand share for a king-size, light blue, cotton, 400 thread count sheet as the product of the demand shares for king, light blue, cotton, and 400 thread count.

Clearly, this estimate is imperfect; for example, the color preferences of twin sheet buyers may differ from those of king sheet buyers, but in estimating the demand share for light blue we will have used the sales of light blue sheets in all sizes, fabrics, and thread counts. Nonetheless, in aggregate it is an accurate and highly useful assumption because the attribute decomposition it engenders enables an extremely powerful analysis that leads to interested insights, which can then be examined for correctness in light of the attribute decomposition assumption.
I will outline the details of this approach, using planning a tire assortment for an auto parts retailer as an example. An extensive description of this methodology is provided in Fisher and Vaidyanathan (2009).

Tire attributes relevant to assortment planning are brand, mileage warranty, and size. This retailer offered several nationally advertised brands that they believed were viewed as equivalent by consumers, and three house brands of varying quality, which we denote House 1, House 2, and House 3, where House 1 is the highest quality and most expensive house brand, and House 3 the least. A couple dozen distinct mileage warranties were offered, but some of these varied only slightly and hence were believed to be equivalent to consumers. Therefore, we grouped the mileage warranties into three levels of high, medium, and low. It doesn’t make sense to sell a low-quality and low-price tire with a high-mileage warranty, or vice versa. Hence, we identified the following six brand-warranty combinations as representing the logical combinations: National High (NH), National Medium (NM), House 1 High (H1H), House 2 High (H2H), House 2 Medium (H2M), and House 3 Low (H3L). Sixty-four distinct tire sizes were offered, resulting in $64 \times 6 = 384$ distinct possible tire SKUs that could be offered. The retailer carried 122 of these 384 possible SKUs in at least one store, and an obvious question was whether any of the 262 tires not currently offered would have a high enough demand to warrant their being offered.

If a customer does not find their first choice in a tire, they might substitute another tire. It turns out it is possible to estimate the likelihood of substitution from sales history, although there is insufficient data to reliably estimate all possible substitution probabilities. Hence, we relied on management to tell us the most likely substitution patterns and focused on estimating those. Substitution across sizes is essentially nonexistent (for example, a 14-inch diameter tire cannot be used on a 15-inch wheel). Figure 2 depicts the qualitative likelihood of substitution from a given brand-warranty level to another as assessed by management. We let $\alpha_1$, $\alpha_2$, and $\alpha_3$ denote the least likely, likely, and most likely probabilities of substitution. We also asked management to rank order the given substitution alternatives for a given brand warranty, and we assume that if a customer substitutes, they substitute to the highest-ranked brand warranty carried in the assortment. Brand warranties are ranked for substitution in order of the likelihood of substituting, and where there are ties, the left-most brand warranty in the table is highest ranked.

Table 2 shows sales data for a particular store for a subset of sizes. We use this sales data to estimate for each store six brand-warranty shares, 64 size shares, and the three substitution probabilities. We employed maximum-likelihood estimation, an approach that finds parameter values that maximize the likelihood of observing the sales data being used to estimate the parameters. To further illustrate the use of this approach, Table 4 displays the likelihood function for the small example shown in Table 3, which is an extract of the larger example in Table 2. Note that in Table 3 all attribute combinations are represented except National High in size P175/80R13 and House 3 High in size P215/70R15. Customers who prefer these SKUs might substitute other SKUs. Per Figure 2, the probability of substitution from National High to House 2 Medium or House 3 Low is assumed 0 and can be ignored. As noted before, customers preferring House 3 Low may substitute to House 2 Medium with probability $\alpha_3$, and this possibility is included in the likelihood function.

### Table 2. Input data for a store are sales during the last six months of 2004 by size-brand-warranty level for SKUs that were offered.

<table>
<thead>
<tr>
<th>Size</th>
<th>National High</th>
<th>National Medium</th>
<th>House 1 High</th>
<th>House 2 High</th>
<th>House 2 Medium</th>
<th>House 3 Low</th>
</tr>
</thead>
<tbody>
<tr>
<td>P235/75R15</td>
<td>100</td>
<td>55</td>
<td>40</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P215/70R15</td>
<td>282</td>
<td>21</td>
<td>334</td>
<td>203</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P175/80R13</td>
<td>5</td>
<td>20</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P205/75R14</td>
<td>10</td>
<td>84</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P205/65R15</td>
<td>72</td>
<td>64</td>
<td>20</td>
<td>272</td>
<td>570</td>
<td></td>
</tr>
<tr>
<td>P225/60R16</td>
<td>56</td>
<td>97</td>
<td>285</td>
<td>763</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P215/60R16</td>
<td>10</td>
<td>16</td>
<td>70</td>
<td>76</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P195/70R14</td>
<td>7</td>
<td>33</td>
<td>157</td>
<td>377</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P205/70R15</td>
<td>10</td>
<td>272</td>
<td>524</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P185/65R14</td>
<td>39</td>
<td>225</td>
<td>568</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P225/70R15</td>
<td>8</td>
<td>100</td>
<td>73</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P185/70R14</td>
<td>8</td>
<td>95</td>
<td>223</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P195/65R15</td>
<td>152</td>
<td>298</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P215/65R15</td>
<td>144</td>
<td>221</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P205/75R15</td>
<td>8</td>
<td>200</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P175/70R13</td>
<td>436</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P185/60R14</td>
<td>101</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P195/60R14</td>
<td>115</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. A subset of sizes is shown.

Note: $\alpha_1 =$ somewhat likely substitution probability; $\alpha_2 =$ likely substitution probability; $\alpha_3 =$ most likely substitution probability.

### Table 3. Sample of sales data on which to demonstrate maximum likelihood.

<table>
<thead>
<tr>
<th>Size</th>
<th>National High</th>
<th>House 2 Medium</th>
<th>House 3 Low</th>
</tr>
</thead>
<tbody>
<tr>
<td>P235/75R15</td>
<td>100</td>
<td>55</td>
<td>40</td>
</tr>
<tr>
<td>P215/70R15</td>
<td>282</td>
<td>203</td>
<td></td>
</tr>
<tr>
<td>P175/80R13</td>
<td>5</td>
<td>20</td>
<td></td>
</tr>
</tbody>
</table>
Table 4. Maximum-likelihood function for the sample data.

<table>
<thead>
<tr>
<th>Size</th>
<th>National High</th>
<th>House 2 Medium</th>
<th>House 3 Low</th>
</tr>
</thead>
<tbody>
<tr>
<td>P235/75R15</td>
<td>NH × A/T</td>
<td>H2M × A/T</td>
<td>H3M × A/T</td>
</tr>
<tr>
<td>P215/70R15</td>
<td>NH × B/T</td>
<td>(H2M + αH3L)B/T</td>
<td></td>
</tr>
<tr>
<td>P175/80R13</td>
<td>H2M × C/T</td>
<td>H3M × C/T</td>
<td></td>
</tr>
</tbody>
</table>

Notes. NH = probability a customer buys National High; H2M = probability a customer buys House 2 Medium; H3L = probability a customer buys House 3 Low; A = probability a customer buys size P235/75R15; B = probability a customer buys size P215/70R15; C = probability a customer buys size P175/80R13; α3 = probability a customer whose preferred brand warranty is H3L is willing to substitute to H2M; T = probability a customer buys something = 1 − (1 − α3)H3L × B; Likelihood of the observed sales = (NH × A/T)100 × (H2M × A/T)25 × (H3L × A/T)25 × (NH × B/T)50 × (H2M × A + α3H3L × B)/T25 × (H2M × C/T)25 × (PL × C/T)100.

To find parameter values that maximize the likelihood function, we take the log to obtain a separable function and apply a gradient method. It is easy to find examples that demonstrate that the likelihood function is not in general concave, so we apply the gradient method repeatedly from randomly generated starting points. Once demand shares are estimated, it is straightforward to estimate unit demand for each possible SKU by multiplying the demand shares times an estimate of total demand equal to total demand for each possible SKU. Estimation results.

Table 5.

<table>
<thead>
<tr>
<th>Brand warranty</th>
<th>Sales share (%)</th>
<th>Estimated demand share (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>National High</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>National Medium</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>House 1 High</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>House 2 High</td>
<td>26</td>
<td>24</td>
</tr>
<tr>
<td>House 2 Medium</td>
<td>45</td>
<td>5</td>
</tr>
<tr>
<td>House 3 Low</td>
<td>24</td>
<td>61</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Substitution probabilities</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>α1</td>
<td>2%</td>
</tr>
<tr>
<td>α2</td>
<td>6.1%</td>
</tr>
<tr>
<td>α3</td>
<td>45%</td>
</tr>
</tbody>
</table>

These results are that the demand share estimate for House 3 Low is much higher than its sales share, and for House 2 Medium, much lower than its sales share. The reason for this is that this retailer offered House 3 Low in only 15 of the 64 sizes, but as shown in Table 6, in the 9 sizes where House 3 Low is offered with House 2 Medium, it is strongly preferred. The retailer offered House 3 Low in few sizes because they preferred to sell the higher-priced House 2 Medium and believed their sales staff could convince customers to trade up to this tire. The substitution estimate of 45% shows that many customers did in fact trade up, and this explains the high sales share for House 2 Medium relative to its demand share. However, the 55% of the 61% of customers preferring House 3 Low who did not substitute represents more than 33% of demand that was being lost when House 3 Low is not offered in a size, suggesting that there was substantial opportunity to increase sales by reassorting.

To further confirm the validity of our results, we plot in Figure 3 the share of House 3 Low versus median income in the zip code in which the store is located, and find, as one would expect, lower demand for the least expensive tire in higher-income neighborhoods.

Figure 3. Share of the low-price tire correlates with income.
We used a greedy heuristic applied to our demand, substitution, and pricing estimates to determine optimized assortments. To choose an assortment of \( N \) SKUs to maximize profit, we choose the first SKU to be the SKU that would maximize profit if that were the only SKU in the assortment. We continue to select additional SKUs, choosing each to maximize the increase in profit given the earlier selections, until we have chosen \( N \) SKUs.

We first apply this greedy heuristic to generate an assortment for each store individually, and an assortment for the entire chain. In generating the chain assortment, we use the demand and substitution estimates unique to each store, but assume that all stores carry the same assortment. This produces both a chain-wide preferred assortment if the retailer wants to use the same assortment in all stores, and the preferred store-specific assortment if the retailer is willing to use a unique assortment for each store. Most retailers are reluctant to have a unique assortment for each store because of the high administrative costs, but they also want to use more than one assortment for the chain to enable some catering to local tastes.

Suppose the retailer is willing to support \( K \) assortments. We have two alternative heuristics for generating \( K \) assortments from the assortments created thus far: a forward heuristic and backwards heuristic. In the forward heuristic, we make the chainwide assortment the first assortment, identify the store for which the difference is greatest between the profit this store generates using its store-specific assortment and using the chain-wide assortment, and make this store’s specific assortment the second assortment. We assign all stores to whichever of these two assortments produces the greatest profit and then reapply greedy to each of the two store clusters, aggregating profit across the stores in the cluster when making greedy choices, to create assortments tuned to the demand for each store cluster. This process continues until we have created \( K \) assortments.

In the backwards heuristic, we choose two stores to cluster together. The criterion for which stores to cluster can be either least loss in profit or greatest overlap between the two store-specific assortments. Then we apply the greedy heuristic to generate an assortment for this two-store cluster. We continue to join pairs of stores or store clusters until we have exactly \( K \) assortments.

Figure 4 shows results for the tire assortment example. In this application we optimize revenue, since exact profit margin data were not available but the retailer believed that profit percentages were similar across products.

The estimated revenue increase shown in Figure 4 is remarkably large, so it is worth examining the changes in the assortment that produce this increase. We will focus on the case of a single assortment for the chain, for which the estimated revenue lift is 46%. The assortment is defined by the number and composition of brand warranties offered in each size. Table 7 shows the number of brand warranties offered in each size under the current and new assortments, where we define the current assortment as the 122 SKUs carried in at least one stage and the new assortment as the SKUs chosen by the greedy heuristic for \( N = 122 \). Note that the new assortment offers the most brand warranties for the sizes with the highest estimated revenue, whereas this is not consistently the case for the current assortment.

To see the impact this has on revenue, consider the six sizes with revenue ranks 6 and 60 thru 64. The current assortment carries a single brand warranty in each of these sizes, and while not shown in the table, that brand warranty was House 2 Medium. By contrast, the revised assortment carries six brand warranties for the size ranked 6 and none for the sizes ranked 60 thru 64. Hence, the new assortment captures 100% of the 4.8% of revenue for size 6 and none of the revenue for sizes 60–64, for a total revenue of 4.8%. By contrast, the current assortment captures 5 + 0.45 * 61 + 0.02 * (24 + 4) = 33% of the total revenue of 4.94% for sizes 6 and 60–64 for a total revenue of 1.63%. Hence, the revenue lift in this instance is more than 290%. Although this is an extreme case, it shows that revenue is highly sensitive to the number of brand warranties offered in each size.

The principle of offering more choices in the most popular sizes is such an intuitive concept that one might wonder why the retailer was not doing this already. One answer is that the assortment offered distorts the true demand patterns so that raw sales present a murky picture. Also shown in Table 7 is the rank of each size based on actual revenue. Note that the size ranked 6 on true demand ranked only 18 on actual revenue. This is because offering only one brand warranty in this size reduced revenue from its potential.

Table 8 shows the number of sizes in which each brand warranty is offered. Note that the new assortment substantially reduced the number of House 2 Medium offered and increased the number of House 2 High and House 3 Low offered, the two brand warranties with highest estimated demand.
Consider the impact of these changes. With 64 sizes and 105 SKUs on average per store, on average 1.6 brand warranties are offered in each size, so a typical case is offering 2 brand warranties. The most common pairs offered under the current assortment were House 2 Medium paired with either House 3 Low or House 2 High. The most common pair offered under the new assortment was House 2 High and House 3 Low. We can compare the revenue of this with the revenue of the pairs commonly offered in the current assortment. The average price of House 2 High was 1.2 times the price of House 2 Medium and the average price of House 3 Low, 0.84 times the price of House 2 Medium.

For simplicity, consider a size with total unit demand of 100 units, and assume prices of $120, $100, and $84 for House 2 High, House 2 Medium, and House 3 Low. These assumptions simplify explanation without affecting the conclusions. Then the revenue of House 2 Medium and House 3 Low is $100(5 + 0.02*(24+4)) + $84*61 = $5,680, of House 2 Medium and House 2 High is $100(5 + 0.45*61 + 0.02*4) + $120(24 + 0.06*4 + 0.02(3+4)) = $6,178.60, and of House 2 High and House 3 Low is $120(24 + 0.02*(4+3) + 0.06(4+5)) + $84*61 = $8,085.60. The changes in brand warranties offered under the new assortment in these two cases produce revenue increases of 42% and 31%, respectively.

Thus, we see by careful examination of the types of changes made in the assortment that a revenue increase of 46% is quite plausible.

### 3. Pricing

One of the great things about retailing is that you can do experiments. In this section we review research reported in Gaur and Fisher (2006) to conduct an experiment to measure price elasticity. Of course, there is a vast marketing literature on measuring price elasticity. Tellis (1988) summarizes findings from a number of papers in this literature. Also relevant to this section is a literature on the effect of price on perceived quality. Lichtenstein and Burton (1989) investigate this effect for 15 durable and nondurable product categories. Other relevant references are given in Gaur and Fisher (2006).
Table 9. Test prices and purchase costs.

<table>
<thead>
<tr>
<th>Prices ($)</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
<th>Purchase cost ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product B</td>
<td>24.99</td>
<td>29.99</td>
<td>34.99</td>
<td>18</td>
</tr>
</tbody>
</table>

Fisher and Rajaram (2000) describe a structured method for conducting a retail test. Gaur and Fisher (2006) apply that methodology at Zany Brainy, an innovative toy retailer, to test alternative prices for three different toys. We used the approach described in Fisher and Rajaram (2000) to create three matched panels of six stores each. We identified low, medium, and high prices for each of the toys, as listed in Table 9, and charged one of these prices in each of the three panels. The prices were assigned so that each panel had one toy each at a low, medium, and high price. Figure 5 shows sales at each of these prices over a six-week test period.

Product C is surprising in that sales are much higher at the medium price than at the low or high price. We concluded that this was because customers were using price as an indicator of quality. Product C was an unbranded walkie-talkie, and there was no way the customer could objectively evaluate the quality of the electronics. On the other hand, product A was a branded product with known quality, and produce B was a block set whose features were readily observed by customers.

A preference for paying a higher price is related to the concept of conspicuous consumption made popular by Thorstein Veblen, and is rooted in the fact that “the utility derived from a unit of a commodity employed for the purpose of conspicuous consumption depends not only on the inherent qualities of that unit, but also on the price paid for it” (Leibenstein 1950). Simonson and Tversky (1992) have also noted that consumer choice is influenced by context, and that the attractiveness of an option is diminished if it is the lowest or highest price. We do not know the price of other walkie-talkies offered by this retailer, but it may be that at the Low price, it was the lowest price of all walkie-talkies, diminishing its attractiveness to consumers.

For products A and B, we fit a demand curve (Figure 6 shows the demand curve for product B) and found optimal prices, as shown in Figure 7. The profit increase of 3% for product A was considered significant.

4. Inventory Optimization

Inventory optimization is one of the most heavily studied topics in operations research, and there is a vast literature on the subject. This literature is potentially applicable to retail inventory optimization, although usually one finds

Figure 6. Demand curve estimation for product B.

Figure 5. Total unit sales for the three test products at each of the three price levels.

Figure 7. Finding an optimal price.
that the classic models studied in the literature do not quite fit the nuances of a real problem, so much of our research has focused on adapting classic models to the greater complexity of real situations.

One differentiating feature of inventory optimization models is the assumed planning horizon, which ranges from so short as to allow only a single purchase in the newsvendor model, to infinite in the order-up-to model. Of course, reality is usually somewhere between these two extremes.

I will describe an inventory model that is similar to the newsvendor model, except that two buys are allowed rather than one. The second buy is made after observing some sales, which allows updating to a more accurate forecast. This model was first developed and reported in a supplier context in Fisher and Raman (1996) and later applied with a catalog retailer as reported in Fisher and Raman (1999) and Fisher et al. (2001). The description here closely follows Fisher and Raman (1999).

The example I will use concerns a set of women’s apparel sold by a cataloger. Their challenge is to determine supply quantities for these products in support of a particular catalogue. Typically, a team of expert merchants will forecast the life-cycle sales of each item prior to their introduction and prior to any sales experience. The left graph in Figure 8 shows these forecasts. Each dot corresponds to a particular apparel style and color and shows the forecast developed by the expert merchants and the actual demand for this product.

The average forecast error for this example is 55%, which is typical of other short life-cycle products. Generally, I have found that expert forecasts like these made in advance of any sales information have average errors ranging from 50% to 100%. The right most graph shows life-cycle forecasts for the same products, developed by a simple extrapolation of the first two weeks of demand. This cataloger has found that in the first two weeks after a catalog is issued they typically receive 11% of the eventual life-cycle orders. Thus, if a product sells 11 units in the first two weeks, we would predict sales of 100 over its life cycle.

This simple extrapolation of a small amount of early sales provides forecasts that are dramatically more accurate than the initial forecasts, in this case having an average forecast error of just 8%. This is one of the most robust empirical findings in our work on short life-cycle products. In all cases, we have found that the initial judgmental forecasts are quite inaccurate, whereas forecasts developed from intelligent interpretation of a small amount of initial sales data are dramatically more accurate.

This suggests a strategy for managing supply. There is no way to avoid the need to position initial supply based on the inaccurate expert forecasts. However, after a brief period (two weeks) to read the market based on early sales, we can order additional quantities as warranted based on the highly accurate early demand forecasts. Replenishment quantities arrive after a lead time. The shorter this lead time, the greater the proportion of demand that can be supplied based on the accurate forecasts, and the better we can match supply with demand over the life of the products.

The initial order $Q_1$ should ideally be big enough to cover the expected initial demand over the “read” period and the replenishment lead time, but not so large that we have leftover inventory at the end of the catalog’s life. $Q_1$ depends on two costs, $C_u$, the per-unit cost if demand exceeds supply and we stock out, and $C_v$, the per-unit cost if supply exceeds demand and we are forced to dispose of excess inventory at a loss. As illustrated in Figure 9, the problem of determining $Q_1$ is similar to the newsvendor model, except that we are exposed to underage and overage in different periods. Analogous to the newsvendor solution, we can choose $Q_1$ so that the expected net profit on the $Q_1$st unit we buy is 0. This expected net profit equals $C_u p_1 + C_v p_2$, where $p_1$ is
Figure 9. The initial buy should minimize the cost of stockouts and closeouts.

<table>
<thead>
<tr>
<th>Initial buy</th>
<th>Rebuy</th>
<th>Rebuy received</th>
<th>End of life</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial demand</td>
<td>Life-cycle demand</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

is the probability of demand exceeding $Q_1$ during the initial react period (the area to the right of $Q_1$ under the initial demand density) and $p_2$ is the probability that total life-cycle demand is less than $Q_1$ (the area to the left of $Q_1$ under the life-cycle demand density). Unlike the newsvendor solution, this choice of $Q_1$ is not in general optimal, except for special cases as shown in Fisher et al. (2001), but it is a reasonable heuristic. This approach does not lead to a closed-form expression for $Q_1$, but the requisite value of $Q_1$ can be found using a search algorithm.

To determine the initial and life-cycle demand densities, we followed the approach in Fisher and Raman (1996) and asked four expert buyers for this product category to independently predict life-cycle demand for each product. Figure 10 shows that there is a high correlation between the standard deviation of these four forecasts and the error of a forecast equal to the average of the individual predictions. We therefore used for the life-cycle demand density a Gamma with mean equal to the average of the four buyer predictions and a standard deviation equal to the standard deviation of the four predictions, scaled so that the average fitted standard deviation equals the average standard deviation of forecast errors in prior seasons. Fisher et al. (2001) describes how to derive the initial demand density from the life-cycle demand density.

Figure 11 shows that this process can have a significant financial impact. Compared to the process that was being followed by this cataloger to determine supply quantities, the process we have just described added an amount equal to 3.5% of revenue to total gross margin, enough to increase bottom-line profit by at least 50%. This increase resulted from additional gross margin earned on incremental sales generated by reducing stockouts of some items and by reducing the loss on overstocks of other items. The figure also shows the value of lead-time reduction. The graph was developed by rerunning our model on demand history for different assumed lead times. We have found this analysis to be very useful to companies that otherwise have trouble quantifying the value of lead-time reduction.

Figure 10. Forecast error is highly correlated with the committee standard deviation.

Figure 11. Impact.
5. Store Execution

I will report early results of a project being conducted with Serguei Netessine of the Wharton School, Nicole DeHoratius of the University of Chicago, and Wharton Ph.D. student Jayanth Krishnan. We are working with four leading retailers to determine the links between store execution, customer satisfaction, and sales.

This project is motivated in part by the many researchers who have reported on various execution and data accuracy problems that arise in retail stores, including Corsten and Gruen (2003), DeHoratius and Raman (2003, 2008), Ton and Raman (2004), Raman et al. (2001a, b), and Salmon (1989). I will summarize early results from this project, based on analysis of a large data set from one retailer and reported in Fisher et al. (2006).

This retailer wondered, of the many events that occur within the four walls of a store, which have the greatest impact on sales and customer satisfaction. To address this question, we assembled the data listed in Table 10, comprising monthly sales for 17 months at about 500 stores, as well as data on various factors that might be expected to influence sales. The data on potential sales drivers include operational variables and the results of customer satisfaction surveys that ask customers to rate various aspects of a store visit. The operational variables include book in stock (the percentage of SKUs in a store at the end of a month that have positive book inventory as recorded on the retailer’s computer), planned and actual payroll for associates and managers, the number of terminations for associates and managers, and the percentage of sales from items in a deep discount category called clearance. Payroll could vary either because of variation in pay rate or in the number of people working in a store. The variation in our data was almost completely due to the latter.

When a customer buys something in a store at this retailer, a toll-free 800 number is printed at the bottom of their receipt, and they are invited to call this number and answer several questions about their visit, using an automated voice response system. If they do so, they are entered in a lottery for a prize. (There is clearly a self-selection bias, in which customers elect to take this survey, over which we had no control and may have affected the results.) The questions include rating their overall satisfaction with the visit on a 10-point scale, as well as a number of factors that might have influenced their satisfaction.

A store is an interesting blend of a factory and a sales office. Factory functions include receiving deliveries into the back room, moving product to the shelves, making sure the aisles are clear, and manning the checkout registers. Sales office functions include greeting customers, asking them if they need help, and providing information as needed. The data available to us on the quality with which these factory and sales execution tasks were performed were the answers to the questions under the customer survey data column of Table 10. The question “Employees Knowledgeable?” asked respondents to rate the knowledge of the store associate they interacted with on a 10-point scale. All other questions were yes-or-no questions. We converted the many survey responses received during a month for a store into single monthly variables by taking the average of 10-point ratings and the percentage of yeses on yes-or-no questions.

All of the data listed in Table 10 could reasonably be expected to impact sales and customer satisfaction, but our challenge was to identify those few variables that have the greatest impact and on which this retailer could focus its energies. For this, we employed linear regression. However, this was not straightforward.

For example, you might want to know whether increasing payroll increases sales. It turns out there is a very high correlation between payroll and sales, but there are causal mechanisms between payroll and sales working in both directions. One causal mechanism is that the retailer staffs in proportion to their estimate of future sales. If they could perfectly predict sales and they always set payroll to 10% of predicted sales, there would be a 100% correlation between payroll and sales, but it would tell you nothing about the impact of increasing payroll on sales. In this situation, one might be tempted to raise payroll 20% in 10% of the stores, lower it 20% in another 10% of the stores, and see what happens to sales. It turns out that this experiment is done naturally by the retailer because they never perfectly match actual payroll with what they plan. Lack of labor availability can cause actual payroll to be below plan. When this happens, the store can “bank” those hours for future months, which causes actual payroll to be above plan in those months. This random, exogenous deviation between actual and planned payroll creates a natural experiment that we exploit by using the residual of actual relative to planned payroll as our independent payroll variable.

We also tried to remove every source of correlation among the data that was due to mechanisms that we were not interested in, such as seasonality. To do this we first deseasonalized the data on each variable by computing monthly seasonality factors equal to the average value of that factor for the chain that month, divided by the average value for the chain for the year. We then divided each store-month variable by the seasonality factor for that month.

<table>
<thead>
<tr>
<th>Table 10. Data obtained from retailer alpha.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Operational variables</strong></td>
</tr>
<tr>
<td>Book in stock</td>
</tr>
<tr>
<td>Planned associate payroll</td>
</tr>
<tr>
<td>Planned manager payroll</td>
</tr>
<tr>
<td>Actual associate payroll</td>
</tr>
<tr>
<td>Actual manager payroll</td>
</tr>
<tr>
<td>Associate terminations</td>
</tr>
<tr>
<td>Manager terminations</td>
</tr>
<tr>
<td>Clearance</td>
</tr>
<tr>
<td><strong>Customer survey data</strong></td>
</tr>
<tr>
<td>Did you find everything?</td>
</tr>
<tr>
<td>(Customer in stock)</td>
</tr>
<tr>
<td>Aisles clear?</td>
</tr>
<tr>
<td>Quick checkout?</td>
</tr>
<tr>
<td>Were items out of reach?</td>
</tr>
<tr>
<td>Sales office functions</td>
</tr>
<tr>
<td>Employees knowledgeable?</td>
</tr>
<tr>
<td>Were you greeted?</td>
</tr>
<tr>
<td>Assistance provided if needed?</td>
</tr>
<tr>
<td>Found prices?</td>
</tr>
</tbody>
</table>

associate they interacted with on a 10-point scale. All other questions were yes-or-no questions. We converted the many survey responses received during a month for a store into single monthly variables by taking the average of 10-point ratings and the percentage of yeses on yes-or-no questions.
Table 11. Regression results.

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Customer in stock</th>
<th>Customer satisfaction</th>
<th>Sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall customer satisfaction</td>
<td>0.202***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Customer in stock</td>
<td>0.399***</td>
<td>0.176***</td>
<td></td>
</tr>
<tr>
<td>Book in stock</td>
<td>0.218***</td>
<td>0.483***</td>
<td></td>
</tr>
<tr>
<td>Associate payroll</td>
<td>-0.02</td>
<td>0.018***</td>
<td></td>
</tr>
<tr>
<td>Manager payroll</td>
<td>0.032***</td>
<td>-0.008</td>
<td>0.040***</td>
</tr>
<tr>
<td>Associate terminations</td>
<td>-0.005</td>
<td>0.006</td>
<td></td>
</tr>
<tr>
<td>Manager terminations</td>
<td>0.002</td>
<td>-0.01</td>
<td></td>
</tr>
<tr>
<td>Clearance</td>
<td></td>
<td>0.043***</td>
<td></td>
</tr>
<tr>
<td>Aisles clear</td>
<td>-0.005</td>
<td>-0.003</td>
<td></td>
</tr>
<tr>
<td>Quick checkout</td>
<td></td>
<td>0.064***</td>
<td></td>
</tr>
<tr>
<td>Were items out of reach</td>
<td>-0.003</td>
<td>-0.002</td>
<td></td>
</tr>
<tr>
<td>Employees knowledgeable</td>
<td>0.597***</td>
<td>0.571***</td>
<td></td>
</tr>
<tr>
<td>Were you greeted</td>
<td></td>
<td>0.032***</td>
<td></td>
</tr>
<tr>
<td>Assistance provided if needed</td>
<td>-0.021***</td>
<td>-0.005</td>
<td></td>
</tr>
<tr>
<td>Found prices</td>
<td>0.031***</td>
<td>-0.018***</td>
<td></td>
</tr>
<tr>
<td>Assoc payroll: Book in stock</td>
<td>-0.056***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Assoc payroll: Employees knowledgeable</td>
<td>0.041***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R² (%)</td>
<td>71</td>
<td>94</td>
<td>75</td>
</tr>
</tbody>
</table>

*** Statistically significant at the 1% level.

and variable. This left us with a 17-month time series for each store and variable. For each data element, we subtracted the average of this time series and divided by its standard deviation. This normalized the data for store size and allowed us to pool the data. Note that deseasonalized store sales plays the same role as planned payroll in providing a benchmark against which to measure actual sales to gauge whether sales in a store month is higher or lower than we would have expected, and using the scaled residual of actual sales versus average deseasonalized sales as our dependent variable is analogous to using the residual of actual to planned payroll as an independent variable.

Table 11 shows the results of two-stage least-squares regression applied to this data to estimate equations for customer in stock, customer satisfaction, and sales. Because of our data normalization, the coefficients in this regression can be directly compared as indicators of the importance of variables. In the Customer in-stock regression, we included interaction terms between Assoc Payroll and Book in stock.

Figure 12. Sales path analysis.

Figure 13. Increase in monthly sales for a one-dollar increase in associate payroll.

and between Assoc Payroll and Employees Knowledgeable, because the presence of inventory alone may not result in better product availability, unless there are associates to help the customer find the product and those associates are knowledgeable. Coefficients for these interaction terms are shown in the last two rows of Table 11.

I have highlighted those coefficients that are highly significant and greater than 0.1. Figure 12 depicts the relationships among these most important variables. Those factors the retailer can control that have the greatest impact on sales and customer satisfaction are associate payroll, employee knowledge, and book in stock.

Let us look more closely at associate payroll. The coefficient of 0.483 from associate payroll to sales means that if we increase the payroll in a store by one standard deviation of its variation in that store, sales increases by 0.483 of the sales standard deviation in that store. Thus, the dollar increase in sales from a $1 increase in payroll equals 0.483 times the ratio of the sales standard deviation to the payroll standard deviation. Because these standard deviations are store specific, the sales lift from a $1 payroll increase will vary by store.

Figure 13 is a histogram that shows the frequency of occurrence of different sale lifts and shows that these values vary considerably across stores, ranging from $4 to $28. To understand the cause of this variation, we investigated the shape of the sales versus payroll function. Figure 14 shows this function for a particular store. The concave increasing shape of this function is intuitive in that one would expect diminishing returns.

Figure 14. Sales vs. payroll for one store shows diminishing returns.
Figure 15. Sales vs. payroll for all stores motivates the difference in payroll sales lifts.

diminishing returns as employees are added to a store. The sales lift we calculate for incremental payroll in a store is essentially the slope of this curve at a point equal to the stores’ current payroll level. Clearly, these sale lift values will vary depending on where on the revenue versus payroll curve a store is located. A store with a relatively low level of staffing will have a higher lift than one that is more heavily staffed. Figure 15 shows average monthly payroll and sales for all stores. Those stores to the right in this curve are the ones with lower sales lift per payroll dollar, and vice versa.

These data allow us to discover sales- and profit-enhancing interventions. For example, the 236 stores with the lowest lifts had total monthly payroll of $5,375,052, versus a nearly equal value of $5,384,640 for the remaining 201 stores with highest lift. Increasing monthly payroll by 25% (an amount we judged to be within the range of approximate linearity on the concave sales versus payroll curve) for the 201 stores with highest lift and lowering payroll by 25.05% for the remaining stores would leave total chain payroll unchanged and, based on our estimates of the increase in revenues for an increase in payroll, increase sales by 2.6%, an amount that is significant relative to the usual sales increases reported by retailers for existing stores. This retailer earned gross margin of 40%, so a 2.6% sales increase with no additional expense would generate an increase in net profit equal to more than 1% of revenue, an increase that is highly significant.

6. Conclusions

Retailing is an industry in transition from decision making almost exclusively based on art to a well-balanced blend of art and science. This transformation resembles the rocket science movement that started on Wall Street in the 1970s, and just as academic finance was a major contributor to Wall Street’s rocket science, our field has an enormous opportunity to play an equally pivotal role in the retail rocket science movement. I hope that the few examples chronicled here will be viewed as a useful start in that direction and will inspire others to pursue this wonderful opportunity for our field.

Endnotes

1. The retailer take two types of markdowns—promotional markdowns, intended to create excitement in the store and further stimulate sales of products that may already be selling well, and forced markdowns, taken to clear inventory that is left over at the end of a season. Figure 1 reports both types, but of course only forced markdowns are a marker of leftover inventory. Nonetheless, there is no evidence that the relative proportions of these two types are changing, so the data suggest a significant increase in forced markdowns. Of course, this can be due to many factors, not the least of which is the increased sourcing from Asia, with longer lead times. However, the fact remains that the gap between supply and demand appears to have grown over time.
2. This description is based on discussions in 1999–2000 with Arrigo Berni, then Vice President, Global Supply Chain, Bulgari Group.
3. This is consistent with Corsten and Gruen (2003), who found that 40% of the time a stockout results in a lost sale to the retailer.
4. The careful reader might object that if stockouts were concentrated in items with a slower sales rate, then a 5% increase in in-stock rate would not result in 5% more customers finding an item they were looking for in stock. However, my general experience is that most retailers have
their highest in-stock rates on slow movers. Excepting food, most retail products have a slow sales rate; an average sales rate of one per store-SKU month is typical. Thus, the minimum amount of inventory to fill a fixture in a store represents a very large amount of safety stock for a slow mover and results in a high in-stock rate.

5. Actual demand was known by this cataloger even if they stocked out of a product, because customers usually back ordered a stocked-out product.

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References


