Shelf Management and Space Elasticity

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Shelf management is a difficult task in which rules of thumb rather than good theory and hard evidence tend to guide practice. Through a series of field experiments, we measured the effectiveness of two shelf management techniques: "space-to-movement," where we customized shelf sets based on store-specific movement patterns; and "product reorganization" where we manipulated product placement to facilitate cross-category merchandising or ease of shopping. We found modest gains (4%) in sales and profits from increased customization of shelf sets and 5–6% changes due to shelf reorganization. Using the field experiment data, we modeled the impact of shelf positioning and facing allocations on sales of individual items. We found that location had a large impact on sales, whereas changes in the number of facings allocated to a brand had much less impact as long as a minimum threshold (to avoid out-of-stocks) was maintained.

Retailers can increase profits either by decreasing costs or increasing sales. The "cost reduction" opportunities are of an operational nature—they depend on efficient stock management, personnel management, and exploiting technology. The "sales increase" opportunities are market-driven, and can be divided into two categories: (1) out-of-store tactics; and (2) in-store tactics. With out-of-store tactics the retailer works to bring more consumers into the store, either by attracting new consumers or inducing current patrons to shop at their store versus the competition more often. With in-store tactics the retailer attempts to extract more surplus from consumers once they are in the store.

In this article, we focus on a subset of these in-store tactics. Specifically, we study how retailers (and manufacturers) can boost sales by better managing existing shelf-space through store-level shelf management, what is sometimes referred to a micro-merchandising. Instead of relying on a single chain-wide policy, micro-merchandising involves the implementation of store-specific merchandising and promotional tactics (Hoch, Kim, Montgomery, and Rossi 1995). Rapid developments in the efficient collection and analysis of sales data through UPC scanners make it economically feasible to measure and monitor heterogeneity in local

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area demand. The hope is that supermarket economies of scale and scope can be combined with the customization that "Mom and Pop" stores offer in order to more effectively meet the wants and needs of narrowly defined clienteles.

Indeed, one of the many challenges facing retailers is how to properly allocate shelf space to the multitude of products they sell. A typical large supermarket carries more than 45,000 different items or stocking keeping units (sku's) on an everyday basis. In 1992 there were 15,866 new grocery and health and beauty aid products introduced by manufacturers (*Marketing News* 1993). A typical chain may take on one-third of these new items each year. Each new product adoption is accompanied with uncertainty regarding the most appropriate location for its display and the optimal amount of shelf space to allocate.

Retail shelf space is valuable real estate. Store occupancy costs range from about $20/square foot for dry grocery shelf space to over $50/sq ft for dairy and $70/sq ft for frozen foods. Manufacturers expend considerable resources to secure this real estate: an improper location or an under-allocation of space might kill a product before it achieves full sales potential. And retailers work hard to maximize return on their investment: allocating too many facings is a waste, while allocating too few will result in lost sales due to out of stocks.

Most manufacturers are willing to pay significant premiums to obtain preferred retail locations on both a promotional and everyday basis. And retailers are more than willing to accommodate manufacturers for the right price. Manufacturers spend 45–50% of their promotional dollars on trade promotion, the vast majority used to secure feature advertising and temporary display space in the form of front-walls, end-caps, wings, and in-aisle gondolas. In many but not all product categories, retailers routinely charge slotting allowances when taking on new products. Although these fees help to defray the costs of adding (and deleting) an item from the system, they also cover the retailer's opportunity costs for allocating shelf space to one item over another. Some retailers supposedly even charge slotting fees to keep existing items on the shelf. In specialty categories, manufacturers provide free display racks, for example Hartz Mountain pet supplies, McCormick spices, and GE lighting. In exchange these manufacturers obtain exclusive or more prominent display privileges. In the cigarette category, all manufacturers sign long term "rent" agreements for space. The "lead" manufacturer pays higher rent and in return receives disproportionate shelf space.

The shelf space problem is quite different depending on whether we take the perspective of the manufacturer or the retailer. Manufacturers want to maximize the sales and profits of *their* products, and as such always want more and better space to be allocated to their brands. Retailers want to maximize *category* sales and profits, regardless of brand identity; they must allocate a fixed amount of shelf space in the best possible way.

After briefly reviewing prior research, we present the results of a series of shelf management experiments. We analyze the effects of changes in shelf space and location on sales and profits at two different levels: (1) the overall product category which is of greatest concern to the retailer; and (2) individual brands which is primary to the manufacturer. We then utilize the experimental data to parameterize a model that allows us to compute an upward bound on the returns that might accrue to an "optimal" shelf set. We use this model to evaluate whether better management of product location or product facings can provide greater returns to the retailer.

WHY SHOULD SHELF-SPACE MATTER?

Although everyone agrees that shelf-space matters, the viability of micro-merchandising depends on how much it really matters, that is the level of space elasticity. There are two distinct ways in which changes in shelf space can affect category and/or brand performance. First, changes in space influence the probability of being out-of-stock. Clearly, the retailer cannot sell something that is not in the store; this is purely an operational issue. We assume that store-level micro-merchandising will decrease out-of-stocks to some degree because shelf space is more closely allocated proportional to sales in comparison to a generic chain-wide shelf set. In the field test reported here, out-of-stocks did not appear to be a major problem because product displays generally were quite large and the shelves usually were restocked at least once a day. Second, changes in space can affect consumer attention; altering the visibility of a product through changes in location or number facings should influence the probability of purchase. The retailer potentially can improve performance by shifting consumers to higher margin items or by increasing the number of unplanned purchases on a given shopping occasion.

Three characteristics of grocery shopping behavior suggest that consumer attention in the store is both malleable and an important determinant of purchase behavior. First, the majority of consumer decision making occurs in the store, suggesting that consumer information processing is more bottom-up than top-down in nature (Hoch and Deighton 1989). Long-standing surveys of supermarket shopping behavior have found that only about 1/3 of purchases are specifically planned in advance of visiting the store (Dagnoli 1987). Second, consumers show a low level of involvement with most of these in-store decisions, making choices very quickly after minimal search (Hoyer 1984) and price comparison (Dickson and Sawyer 1990). This cursory level of information processing suggests that simply increasing the salience of products through better display could have significant effects on purchase behavior. Third, most consumers shop multiple stores each and every week. The average shopper visits a supermarket 2.2 times a week (Coca-Cola Research Council 1994). On average, however, shoppers visit each of their regular supermarkets 0.6 times a week. This means that, on average, consumers shop at 3 or 4 different supermarkets on a regular basis to satisfy their consumption needs.

In combination, these facts suggest that the total amount of dollars spent on any store visit is quite discretionary and therefore an elastic quantity. The goal of any given retailer then is to figure out how to increase the level of discretionary spending on each store visit; by doing so, they will effectively increase their share of the shopper's consumption requirements irrespective of total consumer spending. For example, Milliman (1982) found that a decrease in the tempo of background music slowed the pace of in-store traffic flow significantly. The slower pace in turn resulted in substantial increases in per capita expenditures in the store.

Another way in which retailers can increase per capita transactions is by doing a better job of attracting the consumer's attention to additional purchase opportunities through numerous temporary and permanent display characteristics. Clearly, temporary displays have the greatest potential for attracting attention; their large size and novelty make them much more intrusive. However, permanent displays can also be used to increase attention by manipulating: (1) the location of the product within a display; (2) the area (facings) devoted to the product; (3) product adjacencies; and (4) aesthetic elements such as size and color coordination and special signage. Consider how permanent display could be used to influence two types of unplanned or impulse purchases discussed by Stern (1962). Reminder purchases of frequently and habitually consumed products are sparked when the consumer sees the product in the store. The best reminder for a cigarette smoker is probably the package of their favorite brand; so when arranging the single-pack cigarette fixture at the express check-out line, the retailer can maximize reminders across consumers by placing the highest share brands in the most visible locations. Suggestion purchases usually involve less frequently purchased products and so in-store merchandising must provide a rationale for consumption. The suggestion factor can be increased by cross-merchandising of natural complements: turkeys and basters, white wine and fresh fish, toothpaste and toothbrushes, or laundry detergent and fabric softener.

Although what we know about how consumers go shopping suggests that the returns to increasing consumer attention are high, the question is how easy it is to manipulate attention through better space management. The retailing environment is very noisy, with hundreds of competing stimuli vying for attention. Our expectation going into the research was that it would be difficult to increase salience in any significant way, so most changes in attention caused by shelf management were likely to be small in magnitude.

Previous Space Management Research

Evidence on the sales impact of space management is limited because of the high costs of implementing controlled experiments in the field. The existing work can be divided into three types: commercial applications, experimental tests, and optimization models. The commercial literature is composed of application oriented approaches where simplicity and ease of operation are the most important features. In the PROGALY model (Malsagne 1972), for instance, space is allocated in proportion to total sales. Cifrino (Chain Store Age 1963) and McKinsey (1963) assign space in relation to Direct Product Profit (DPP). Other models have focused on minimizing operating costs and reducing inventories and handling costs (*Chain Store Age* 1965). Today there are numerous PC-based shelf management systems available to retailers including Apollo (IRI) and Spaceman (Nielsen). Although each decision support system has "optimization" capabilities with the input of space elasticities, in out experience retailers use them mainly for planogram accounting purposes so as to reduce the amount of time spent on manually manipulating the shelves.

A number of experiments have been conducted to measure shelf space elasticities, usually focusing on a limited number of brands and only a few stores. An implicit assumption is that there are diminishing returns from additional shelf space. Brown and Tucker (1961) postulated three classes of products with respect to space changes: "unresponsive products," "general use products," and "occasional purchase products." They showed that space elasticity increased as one moved from one class to another. In the late 60s and early 70s, several controlled experiments investigated the effect of changes in product facings on unit sales (Cox 1970; Curhan 1972; Kotzan and Evanson 1969; Krueckenberg 1969). The average elasticity was about 0.2; that is, a doubling of facings led to a 20% increase in sales. Although this elasticity might seem sizable to a manufacturer, it is not clear how significant it is to a retailer given the likely within-category substitution that occurs.

Corstjens and Doyle (1981) focused on the optimization of shelf space for a chain of ice cream and candy stores. They considered both the supply and demand side by taking into account inventory and handling costs and own and cross space elasticities. Elasticities were estimated using OLS, yielding a mean own elasticity of .086 and cross elasticity of –.028. An interesting aspect of their work is that they do not constrain the interaction between categories to be symmetric and some of the products are complements and some substitutes. A constrained optimization indicated that profits can be increased from 3–20% depending on store size, though these results were not empirically validated. Bultez and Naert (1988) use an attraction model to represent the interaction between brands and apply it to space allocation for several product categories in Belgian and Dutch supermarkets. The attraction model implies perfect substitution between brands (a logical assumption since they work within rather than across categories); in their model, interactions are constrained to be symmetrical. As a result of their heuristic, each item is allocated space proportional to market share and contribution to category profits. They validate their work with some in-store implementations and find profit increases ranging from 6–33%. Bultez, Gijsbrechts, Naert, and Vanden Abeele (1989) extend this work by utilizing an asymmetric attraction model and incorporate multiple sizes of the same brand. Although progress slowly has been made, these methods typically have considered only small subsets of brands; moreover, they have not taken into account the position of each item.

OVERVIEW OF THE EXPERIMENTS

The purpose of our experiments was to investigate the sales and profit potential of micro-merchandising through better shelf-management. The tests were carried out at Dominick's Finer Foods (DFF), a leading supermarket chain in Chicago. Two different types of shelf management experiments were implemented: *space to movement* and *product reorganization*. In the space to movement (STM) tests, product allocations were customized to meet historical sales in specific demographic-based store clusters rather than the standard practice of a single chain-wide allocation for each category. The various reorganization schemes revolved around two central themes: complementary cross-merchandising and ease of shopping.

Sixty stores participated in the tests; each store was randomly assigned to a control or test condition (separately for each category). There was a warm-up period of about 4 weeks after the planogram changeover. The purpose was to allow shoppers to become more accustomed to the new shelf configuration, controlling for potential problems due to novelty, confusion, or any other reaction.

Auditors for the Graduate School of Business at the University of Chicago monitored the integrity of the planogram (spatial layouts of the category) bi-weekly. When problems arose (e.g., misplaced products or incorrect number of facings), they worked with store personnel to rectify the matter quickly. Both test and control planograms were monitored to eliminate differences in neatness or maintenance between old (control) and new (test) shelf sets. In general, when problems occurred, they happened early on after the reset (warm-up period). Therefore, we are confident that the implementation was of high quality. During the test period, changes in prices and promotion occurred as they would in the normal course of business.

Space-to-Movement Tests

Because it was not cost efficient to implement customized planograms for individual stores, we clustered the stores based on geo-demographic data, the assumption being that stores with similar customers would sell similar assortments of products. We performed a weighted k-means cluster analysis based on the following variables (in order of importance): household size, number of workers in family, household income, age of youngest child, race, home ownership, education, marital status, adult age, employment status. The analysis yielded four clusters: inner-city urban, blue collar urban, established suburbs, younger suburbs. These clusters form concentric half circles radiating from Lake Michigan.

For each of the four clusters, we computed average unit movement over the last 12 months for each sku. Lack of distinctive movement patterns for each of the four clusters justified a further reduction to two clusters of stores, one urban (22 stores) and one suburban (38 stores). With this cluster level movement data, planograms were jointly designed by the manufacturers and DFF using the Apollo and Spaceman decision support systems. As such, they represent "good faith" efforts using state-of-the-art technology to produce improved shelf sets. The new space-to-movement planograms resulted in: (1) increases and decreases in facings; (2) deletion of slow moving items; (3) changes in shelf height; and (4) some changes in product positioning. Allocating shelf space according to movement (i.e., proportional to market share) decreases the probability of out-of-stocks. Moreover, if we assume that the packages of products that people normally purchase (the higher share items) are more likely to attract attention than those that they do not regularly buy, it also effectively increases the level of attention across all consumers in a store.

All planograms retained their original size in terms of lineal feet. In essence, the size of the merchandising "box" remained constant—we manipulated only the assortment of items and where they were located inside the box. Figure 1 shows schematics of the urban and suburban planograms in the dish detergent category. The main difference here was the increase in automatic dish detergent in the suburban stores compared to the urban stores. The allocation of lineal footage at the category level is by itself an important issue to retailers that would benefit from more research. However, the costly logistic and operational side-effects (changing the size of one planogram affects the size of adjacent category planograms), make it a difficult topic to study with large scale experimentation.

Shelf Reorganization Tests

Shelf reorganizations took two forms. In the first series of tests, planograms were rearranged to facilitate cross-category merchandising by increasing the proximity of natural complement products. We implemented this strategy in two categories: oral care and laundry care. In both categories, one subcategory is fully penetrated with an average interpurchase time of about 2 months (toothpaste and detergent) whereas the complement either is not purchased as frequently (4–6 months for toothbrushes) or has much lower penetration (65%

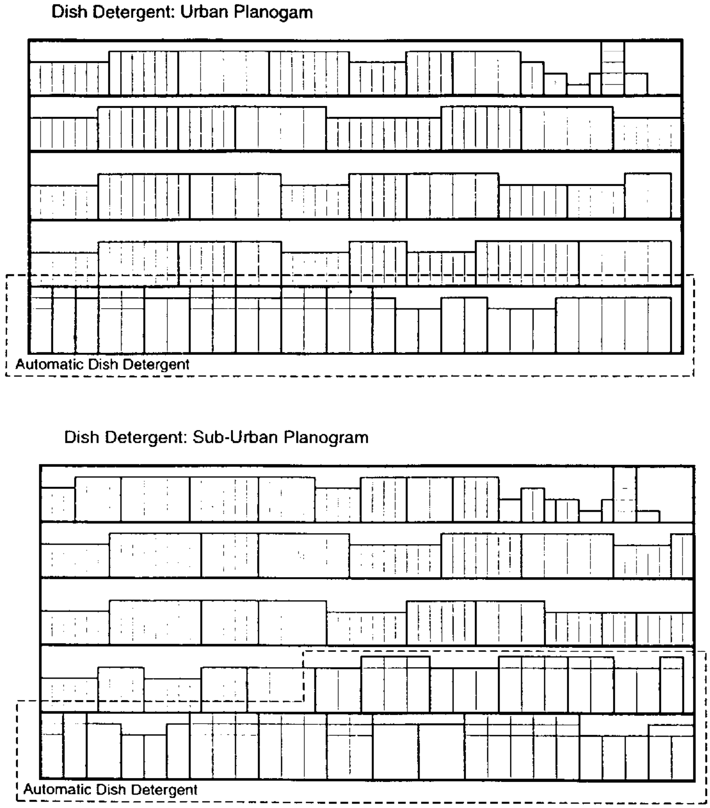

Figure 1. **This is a Reproduction of the Original Planograms. The names of the products have been omitted in order to make the picture easier to read.**

for fabric softener). Our goal here was to increase attention toward the less prominent subcategory at the time of purchase of the primary product. Toothbrushes were moved from the top shelf (72 inches above the floor) to a shelf that was at eye level (56 inches). The increased visibility of the toothbrushes was expected to have a positive impact on sales, while the toothpaste items moved to the upper shelf would suffer, but to a lesser extent since they were more likely to be a planned purchase. Similarly, laundry care originally had been vertically blocked, moving horizontally from liquid detergent to fabric softener. To enhance complementary purchase, we placed 8–12 feet of softeners in between the liquid and powder detergents where it was more likely to be noticed by buyers of both forms of detergent. This move was expected to benefit softener without affecting sales of detergents.

In the second series of tests, we tried to manipulate the ease of shopping. For example, in bath tissue we attempted to make it more difficult for consumers to make price comparisons. At the time of the test, quantity discounts for buying large sizes (packages of 12–24 rolls) were not substantial; in fact, smaller sizes (4 packs) often were cheaper because of more frequent promotions. Products were arranged by brand (all Charmin sizes displayed together) in the original planogram, facilitating intra-brand price comparisons. In the test, we reorganized the planogram by package size; by doing so, consumers had to walk 12–16 feet to make intra-brand price comparisons across size. In the ready-to-eat (RTE) cereal and condensed soup categories, our intent was to make it easier to shop by organizing the brands in what we and the manufacturers believed was a more logical fashion. Our thinking was that discretionary purchases could be increased by reducing the number of times that consumers give up looking for a particular brand or flavor variant. For condensed soup, where Campbell's represented over 95% of the category, we organized the flavors alphabetically (as in the spice section) rather than the quasi-random order characterizing the control set. For cereals, brands originally were organized by manufacturer (i.e., a Kelloggs block, a General Mills block, etc. . .). In the test planogram, brands were organized by three types of cereals—all family, kids, adults—and then further organized into subtypes such as raisin brans, fruit flavors, high fiber. This resulted in substantial changes in positions within the 50 lineal foot display.

CATEGORY-LEVEL RESULTS

We analyzed the effects of the experiments on both dollar sales and profits. Because profit margins for sku's within a category usually are quite similar, the profit results mimic the sales results. To simplify the presentation, we will focus our discussion on dollar sales except where the two sets of results diverge.

For each product category, we compared average weekly sales during the test period to sales in a pre-experimental baseline period. All sales, regular and promotional, were included in our performance measures. Baselines were computed over historical periods spanning 86 to 99 weeks depending on the category. Each experimental period lasted 16 weeks. We selected 16 weeks to balance off dual concerns about obtaining stable, steady-state results, and the reality that it would be difficult to maintain planogram integrity indefinitely, especially with the barrage of new product introductions in some categories. The results, however, appear robust to the exact length of the test (we were able to maintain planogram integrity for more than forty weeks in some categories).

Space-to-Movement Results

Customized planograms were developed separately for urban and suburban stores. Half of the urban (11) and half of the suburban (19) stores received the space-to-movement planograms; the other 30 stores received a chain-wide control planogram. Changes in sales and profits of the 30 space-to-movement test stores relative to the 30 stores in the chain-wide control group are reported in Table 1. Random assignment within urban and within suburban stores was carried out separately for each product category, meaning that any individual store had control planograms in some categories and space-to-movement planograms in other categories.

TABLE 1

Space-to-Movement Results

Category	*Category Change in $ Sales*	*Aggregate Change in Facings*	*p value*
Analgesics	8.4%	22%	0.0001
Bottled Juices	4.9	28	0.0001
Canned Soup	6.3	20	0.0001
Canned Seafood	-1.0	45	0.09
Cigarettes	7.2	25	0.02
Dish Detergents	-2.0	22	0.18
Frozen Entrees	4.4	22	0.0001
Refrigerated Juices	2.6	19	0.0001
Averages	3.9%	25%	

As can be seen in the second column, six out of the eight categories experienced sales and profit increases, all statistically significant. The other two categories, canned seafood and dish detergent, experienced non-significant sales declines. The average increase of 3.9% may seem small in the grand scheme of things, but it is important to keep in mind that these increases are made up of full margin sales, not the low margins obtained with promotional deals. Moreover, they represent long term incremental profits on a stable fixed cost base, and so constitute a more substantial improvement than is at first apparent. For example, for the 86 store supermarket chain in question, a 3% sales increase in a category generating sales of $2,000/week/store at a 25% gross margin would produce incremental profits of over $67,000 per annum. This increase in profit is at least an order of magnitude greater than the direct labor costs (probably less than $3,000/category) associated with designing the micro-market planograms. In-store labor costs for micro-market planograms would not be much greater because the planograms already are changed annually to accommodate all the new product introductions.

These sales increases for the STM planograms can also be compared to their respective changes in space allocation induced by customization. The last column of Table 1 displays the overall percentage difference in number of facings per sku between the urban and suburban versions of the space-to-movement planograms. The control stores (based on a chain-wide average) fell in between. These percentages were calculated as follows. For each sku we computed the difference in facings between the urban and suburban planograms. We then summed these differences across sku's and divided by the total number of facings in the set, that is:

$$\%\ \text{Change in facing} = \frac{\Sigma\,|\,\text{Urban}_i - \text{Suburban}_i\,|}{\text{Total Category Facings}}$$

This measure only captures aggregate changes in facings, with no regard to any changes in position. Keep in mind that the size of the planograms themselves remained unchanged. For each facing that was added to one item, a facing was removed from another item. For instance, the 22% difference between the urban and suburban planograms in the dish detergent category (Figure 1) is in main part a result of different space allocation to liquid detergents (e.g., Palmolive Green) versus automatic detergents (Cascade). In suburban stores, the space ratio of liquid to automatic was 65:35 and in urban stores it was 80:20. These allocations reflect the difference in market shares of liquid and automatic in the respective stores.

The level of customization varied dramatically by category, ranging from 17 to 46%. There is no clear correspondence, however, between changes in space and changes in sales at the category level. In the dish detergent category, the 22% change in facings had no significant impact on sales volume.

In sum, our findings suggest that there are modest, but not trivial, gains to implementing customized space-to-movement planograms. The results in Table 1 most likely provide a lower bound on such gains because operational limitations constrained our store clustering scheme to be consistent across all categories. In more recent implementations, the retailer has moved to a category specific clustering of stores, where stores are grouped together based on historical data specific to the category under question. This ensures a higher degree of planogram customization because the store clusters are maximally different in terms of product movement for any particular category. In a follow-up test for the frozen entree category, we observed an additional 2% improvement by utilizing a category specific clustering of stores.

Complementary Merchandising Results

The two categories involved in the complementary merchandising tests, oral care and laundry care, experienced significant sales and profit increases as a result of the new shelf sets. Moving toothbrushes to eye level increased sales of toothbrushes by 8% and resulted in no change in toothpaste sales (see Table 2). The profit picture was even more encouraging because toothbrushes sell at twice the gross margin of toothpaste. Overall category (brush and paste) profits increased by 6% ($p < .05$). The laundry care category experienced a 4% increase in sales and profits ($p < .01$) after placing fabric softener in between liquid and powder detergents. Although our expectation was only that fabric softener would respond positively to the change in location, all three subcategories benefitted from the merchandising change.

Ease of Shopping Results

In the bath tissue category we physically separated different size packages of the same brand by about 12 feet in order to increase the difficulty of making price comparisons and possibly increase sales of higher margin big sizes. This merchandising scheme produced a 5% increase in category sales and profits compared to the brand blocked control planogram ($p < .001$). These results held up for a period of about 10 months before new product introductions necessitated a complete category reset.

TABLE 2

Ease of Shopping and Complementary Merchandising Results

Category	*Category Change in $ Sales*	*p value*	*Category Change in $ Profits*	*p value*
Oral Care (Complementary)				
Toothbrush	8%	0.05	11%	0.03
Toothpaste	1	0.06	1	0.15
Laundry Care (Complementary)				
Detergent	4	0.005	4	0.007
Fabric Softener	3	0.01	3	0.01
Bath Tissue (By Size)	5	0.001	5	0.001
RTE Cereals (By Type)	–5	0.08	–5	0.07
Canned Soup (Alphabetized)	–6	0.002	–1	0.11

Our intent with the RTE cereal "type" set and soup alphabetization was to organize items in a more user-friendly manner. Both test planograms had a substantial impact on sales. Alphabetizing soups decreased sales by 6% (see Table 2) and blocking different brands of cereals by their respective subcategories rather than by manufacturer decreased sales by 5%. Although it is possible that the shelf resets inadvertently confused consumers, we do not find this a likely explanation; the sales declines held up for over 6 months, long enough for consumers to learn the new scheme. Another possibility is that we made it too easy for consumers to find the items they were looking for and consequently reduced browsing and impulse purchases. We conducted in-aisle intercept interviews with 200 frequent shoppers in two control and two test stores. Consumers displayed virtually no knowledge of how each category was organized. They found both the control and test planograms confusing. Only about 10% of test store consumers reported any awareness that the category had been rearranged six months previously. Sommer and Aikens (1982) also found that consumers showed poor knowledge of product location in the interior aisles of the store. These sparse verbal reports, however, may underestimate consumer knowledge to the extent that shoppers possess store schemas in spatial as opposed to analytic form. We conclude that category shelf organization can have a substantial impact on performance but readily admit that we do not have an adequate explanation of these last two tests.

Where Do the Increased Sales Come From?

A reasonable question to ask at this point is why category sales increased at all? Did the altered planograms attract more customers into the Dominick's stores at the expense of competing stores? Did consumers increase their consumption of the category?

The answer to this question probably varies from one category to another, but it seems reasonably clear to us that we did not increase store traffic. Our changes were made in-store, without informing the public of the shelf manipulations. It is more likely that the increase in sales generated by the test planograms comes from consumers purchasing a higher share of their category requirements at Dominick's rather than the competition. It is not that DFF was able to steal consumers away from the competition with the new planograms, but it was able to increase its share of the total shopping experience. For the most part, DFF achieved this by being a better match to customers' immediate needs. Category expansion might, nevertheless, have occurred in the toothbrushes and fabric softener categories since these two categories are not fully penetrated.

BRAND-LEVEL SPACE AND LOCATION ELASTICITY

Thus far we have analyzed the experiments at the category level and considered how shelf reorganization and changes in assortment affect category sales and profits. These questions clearly are of tantamount importance to the retailer. The manufacturer (especially the market leader) also cares about category performance but is more concerned about understanding how their individual brands react to horizontal and vertical changes in shelf position and the addition or subtraction of facings. The category experiments, by virtue of injecting a substantial dose of independent variation into the normal course of business, provide good data for measuring brand level space and location elasticity.

To study the effect of shelf allocation on brand sales, we estimated a log-log model, using log of unit sales as the dependent variable and two sets of independent variables to capture space and location elasticity effects. We also included a set of control parameters.

Location Parameters

Retailers and manufactures believe that brand location has an important impact on sales. Eye-level often is seen as the best location. However, when pressed to be more specific about what is meant by eye-level, we found that experts were referring to any one of several shelves above the knees but below 6 1/2 feet. Manufacturers also profess preferences for particular positions along the horizontal plane. Some believe the middle is the focal position, but others prefer the edges in order to be first or last in the planogram. Since we lacked a complete theory on how location affects sales, we elected to model location effects in a fashion flexible enough to accommodate multiple phenomena that might vary by category.

The location of each sku was measured by the coordinates of the center of its facings relative to the lower left corner of the display as shown in Figure 2. We integrated these coordinates into the model using a polynomial function. We chose a second degree polynome for the horizontal coordinates (X_{ijk}). This formulation is flexible enough to model cases where the optimal position is in the middle of the aisle as well as cases where the optimal position is on one or both edges (entry points to the category). We chose a third degree polynome for the vertical coordinates (Y_{ijk}). The degree of the polynome is higher for the vertical dimension because we needed to accommodate special fixtures like the "well" in

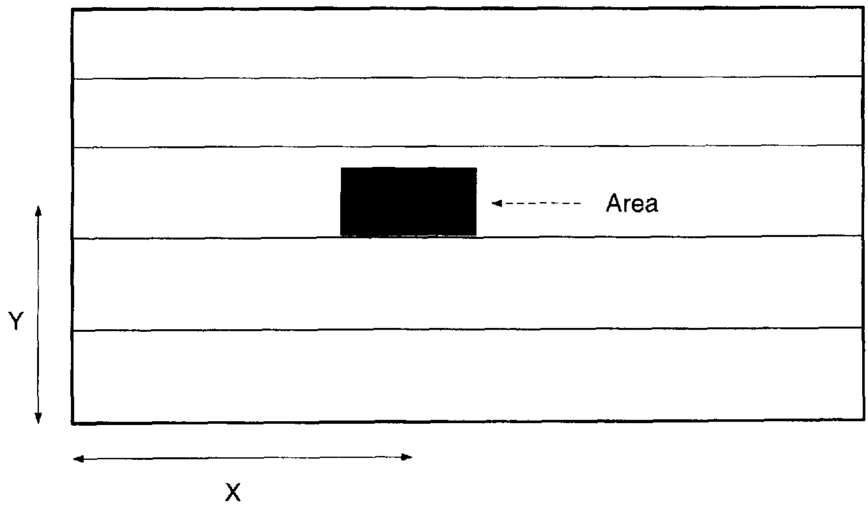

Figure 2.

refrigerated categories.[1] The results do not change materially if the vertical dimension is restricted to be quadratic. The location portion of the model is:

$$a_4X_{ijk} + a_5X_{ijk}^2 + a_6\,Y_{ijk} + a_7\,Y_{ijk}^2 + a_8\,Y_{ijk}^3 \tag{1}$$

Space Elasticity Parameters

We represented the amount of space allocated to an item by the actual cross-sectional area occupied by the product. For example, if there are two facings of an item whose package dimensions are 3" × 4", then it occupies a total space of 24 square inches. We experimented with a number of other measures, like shelf capacity or number of facings, but these measures have shortcomings. Capacity is more of an operational measure. It is important because of out-of-stocks, but in a system where shelves are re-stocked virtually every day, out-of-stocks are not that common. Number of facings is a good measure intuitively because it is easy to understand and communicate, however it is quite item dependent. One facing for a big item will not have the same effect as one facing for a small item. Holding constant other packaging factors, people are much more likely to visually acquire larger sized targets/products (Salvendy 1987).

We modeled the effect of space on sales using the Gompertz growth model. It is S-shaped, characterized by non-linear parameters, and a flexible form because it is not symmetric around the point of inflection. The general form of the Gompertz growth model is:

$$\omega = \alpha\theta^{-\beta\theta^{-k\,\mathrm{Area}}} \tag{2}$$

It implies decreasing space elasticity as allocated area increases. We experimented with other models of the area effect, for example logarithmic models of width and height or total surface area. On the basis of fit, it is difficult to justify one particular specification of area over another. We settled on the Gompertz specification because it mixes well with the rest of model, yielding a reasonable estimation procedure, and it exhibits the following two characteristics:

1. *Bounded unit sales*: one can argue that there must be a level at which incremental space allocations stop having an impact on consumers because they are unable to process the change, if for no other reason than the additional space is outside the visual field. In the extreme, imagine an entire store full of only one item. Clearly, there is a limit to how much a one-item store can sell.
2. *Concave in the vicinity of the origin*: this feature is desirable because if the function is convex over its entire domain, then there would be no benefits to lumping together two facings of the same product. One would always be better off displaying each facing in a different part of the display. Conversely, if the function is concave near the origin, it will only pay off to split the display when a large number of facings is involved. In such a case it would make sense to sell the same item in more than one location in the store. Multiple locations in the store undoubtedly result in increased item sales, e.g., end-of-aisle promotional displays, but it is not a practice that retailers typically endorse on an everyday basis, mainly for reasons of operational control.

Since we use a log-log model, we need to take the natural logarithm of sales (ω):

$$\log(\omega) = \log(\alpha) - \beta e^{-k\mathrm{Area}} \tag{3}$$

$\mathrm{Log}(\alpha)$ can be incorporated in the model's constant, and so the space elasticity portion of our model becomes:

$$a_g\, e^{-k*A_{ijk}} \tag{4}$$

Control Parameters

We included control parameters to account for the heterogeneity across brands and across stores. Individual brands have different baseline sales and specific stores have different store traffic. Hence, we have (in addition to the constant) a dummy for each brand (B_i), one for each store (S_j), and a price coefficient (P_{ijk}) to account for changes in price over time (within items):

$$a_0 + a_{1i}\, B_i + a_{2j}\, S_j + a_3 \log(P_{ijk}) \tag{5}$$

where i is a brand index, j a store index, and k a week index.

Complete Model

The complete formulation of our model comes from the merging of Equations 1, 4, and 5:

move
unit sales

$$\log(U_{ijk}) = a_0 + a_{1i}B_i + a_{2j}S_j + a_3 \log(P_{ijk}) + a_4 X_{ijk} + a_5 X_{ijk}^2$$

$$+ a_6 Y_{ijk} + a_7 Y_{ijk}^2 + a_8 Y_{ijk}^3 + a_9 e^{-k*A_{ijk}} + \varepsilon_{ijk} \quad (6)$$

The model accounts for: (1) heterogeneity across brands; (2) heterogeneity across stores; (3) category level price elasticity; (4) variation in the amount of space allocated to each sku; and (5) variation in the location of each sku. The model does not account for: heterogeneity in brand and store level price elasticities; trends (seasonality, category expansions, . . .); or packaging attributes other than size. Moveover, we do not explicitly model interactions between brands, whether due to relative positioning (two brands together or apart) or relative number of facings.

Description of the Brand Level Data

In addition to the sku level weekly scanner data for each of the 60 stores involved in the previously described experiments, we used a set of planograms describing the position, the number of facings, and the package dimensions of each sku. A pictorial representation appears in Figure 1. Each category had multiple planograms. For the analysis we selected a total of 32 weeks of data, 16 weeks before planograms were changed and 16 weeks after. Because we were interested in understanding space elasticity for permanent display space, we removed all promotional sales from the dataset. There were several reasons for this choice. First, promotion sales are usually accompanied with special displays (gondola, end-cap,. . .). In such cases we are unable to determine whether an item was picked up from the temporary or the regular display area. Second, promotions are usually accompanied by special signage, drawing attention to the product and the promotion. This effect of the extra signage is different from the location and facing effects we are after. Third, promotions are often accompanied with more frequent restocking of the shelves. Promoted items in the refrigerated juice section are restocked up to three times a day, while non-promoted items are restocked during the night. Fourth, we are interested in steady-state consumer reaction to changes in everyday space allocations. We should say, however, that for each of the categories we studied it does not make any difference empirically whether we estimate the model with or without promotional sales. The substantive conclusions are virtually identical.

We focused on 8 category data sets where we had complete planogram information, ranging in size from 20,000 to 150,000 observations (mean = 66,000). The average category contained 115 items, from a low of 27 in bath tissue to a high of 235 in analgesics.

Empirical Results

The model fits the data quite well (see Table 3). The average R^2 was 67%, ranging from 53% for bottled juices to 86% for analgesics. The order of importance of the variables was consistent across categories. Based on the proportion of variance explained, the most important determinants of sales were the brand and store dummies, followed by price and

TABLE 3

Estimated Parameters From Complete Model

			Area		*Location*				
Category	R^2	*Price*	a_9	k	X	X^2	Y	$Y2$	Y^3
Analgesics	86%	–0.98**	–367.39**	0.9827**	–0.0028**	0.000014*	–0.001	0.0005*	–0.00001**
Bath Tissues	55	–5.512**	0	0	0.0047**	–0.000015**	2.93**	–0.091**	0.00083**
Bottled Juices	53	–3.13**	–0.4363**	0.02588**	0.0052**	–0.000041**	–0.034**	0.00067**	–0.0000034**
Canned Seafood	69	–2.16**	–5.716**	0.39158**	0.00055	–0.000005	0.0544**	–0.0014**	0.0001**
Canned Soup	71	0.65**	–1.651**	0.00192**	–0.00018	–0.0000024	0.055**	–0.0011**	0.0000075**
Cereals	63	–2.93**	–32350**	0.3666**	0.0014**	–0.00001**	0.03288**	–0.00094**	0.00001**
Refrigerated Juices	73	–3.48**	–0.543**	0.0272**	–0.00093**	–0.000002	–0.047**	0.002**	–0.000027**

Notes: *$p < 0.05$
**$p < 0.01$

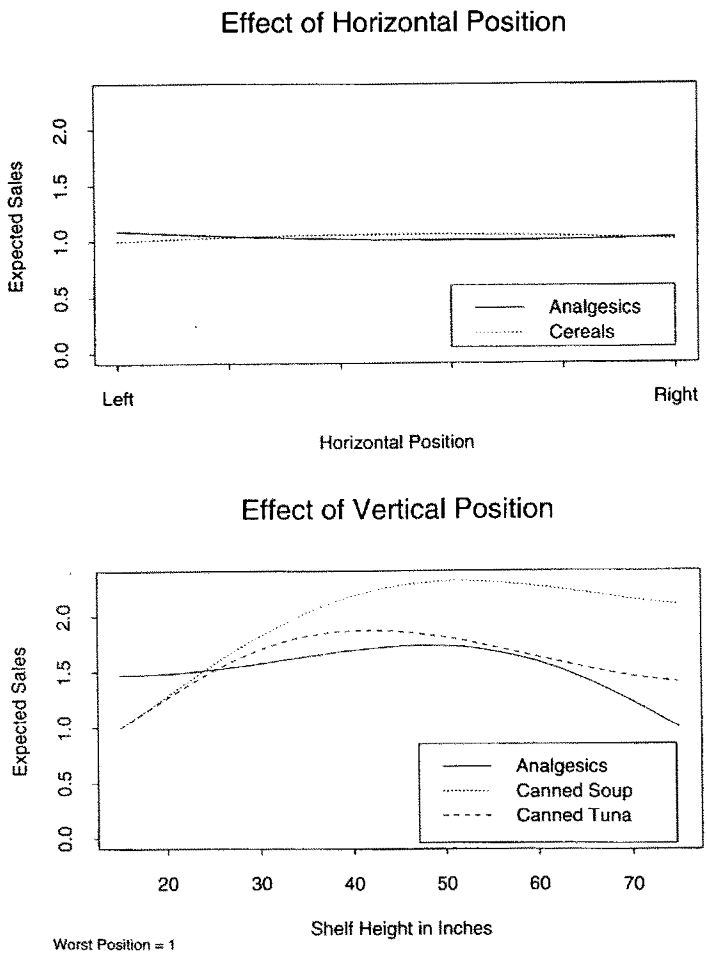

Figure 3.

shelf location, with area trailing behind. Since the control variables are not of direct interest, we focus our discussion on location and area.

Location: Location was a statistically significant construct in all categories. On the horizontal axis, there was no consensus on whether it is better to be located on the edges or in the center of a set; half of the categories favored the edges, the other half favored the center (see the top half of Figure 3). The results for the vertical dimension were more consistent. A central location is most desirable, on average an elevation of 51–53 inches off the floor (see the bottom half of Figure 3). This matches well with ergonomic research on the natural resting position of the eye. The standard rule is that the preferred viewing angle lies 15 degrees below the horizontal (Eastman Kodak Co. 1983). The average eye height for U.S. females is 59" and U.S. males 64". If we assume that shoppers stand about four feet away

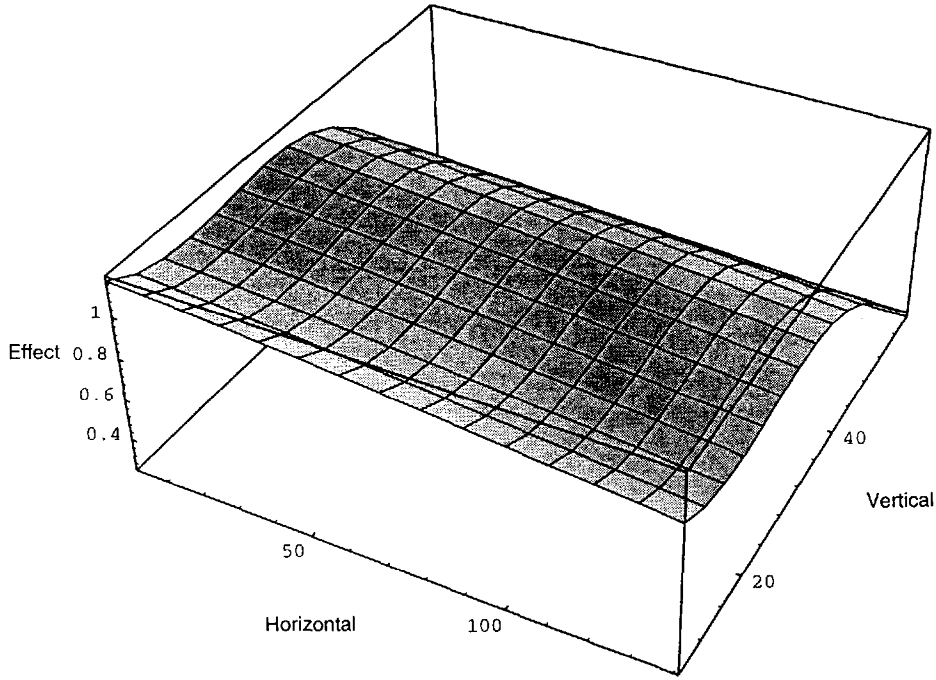

Figure 4. **Refrigerated Juice: Position Effect**

from the shelves, this would imply average resting positions of 49" and 55". The one exception was in the refrigerated juice category where the well was more valuable. Figure 4 displays the combined horizontal and vertical effects for refrigerated juice.

Being statistically significant, however, is not enough. It also should be the case that the impact of location on sales is large enough to matter to retailers and manufacturers. Using the parameters estimated in the model, we found the best and worst positions (maxima and minima of the polynome over the shelf domain) and then computed the expected differences in sales between these two positions (see Table 4). We decomposed the location effect into its horizontal and vertical components. By moving from the worst to the best horizontal position, a brand could increased sales by 15% on average. In contrast, the difference between the worst and best vertical position was 39% on average, more than 2.5 times the difference for horizontal location. The combined effect resulted in a 59% increase. The largest horizontal effect occurs in the bath tissue category. Canned soup showed no horizontal sensitivity, possibly because the planogram was only 8 lineal feet. On the vertical dimension, cereals show tremendous sensitivity, possibly due to the important role that children play in this category.

One can question whether the position effect might be confounded with the brand effect (i.e., the best brands are in the best positions and the small brands are out of sight). There are three pieces of information that lead us to believe that this is not a problem. First, the

TABLE 4

Expected Increase in Brand-Level Sales When Moving from the Worst to the Best Location

Category	*Horizontal Effect*	*Vertical Effect*	*Combined Effect*
Analgesics	11%	19%	32%
Bath Tissues	52	18	79
Bottled Juices	27	41	79
Canned Seafood	3	54	59
Canned Soup	2	28	32
Cereals	5	100	112
Refrigerated Juices	22	69	108
Average	15%	39%	59%

model has individual brand dummies. Hence, the position coefficients would be nonsignificant if position and brands were confounded. Second, in the canned soup category, the biggest sellers were located on the bottom shelves (for logistic purposes), and the model still estimated that location to be the worse one. Last, in the refrigerated juice category, one test involved explicitly switching the items in the well with the items on the second shelf. The effect measured matches the model prediction.

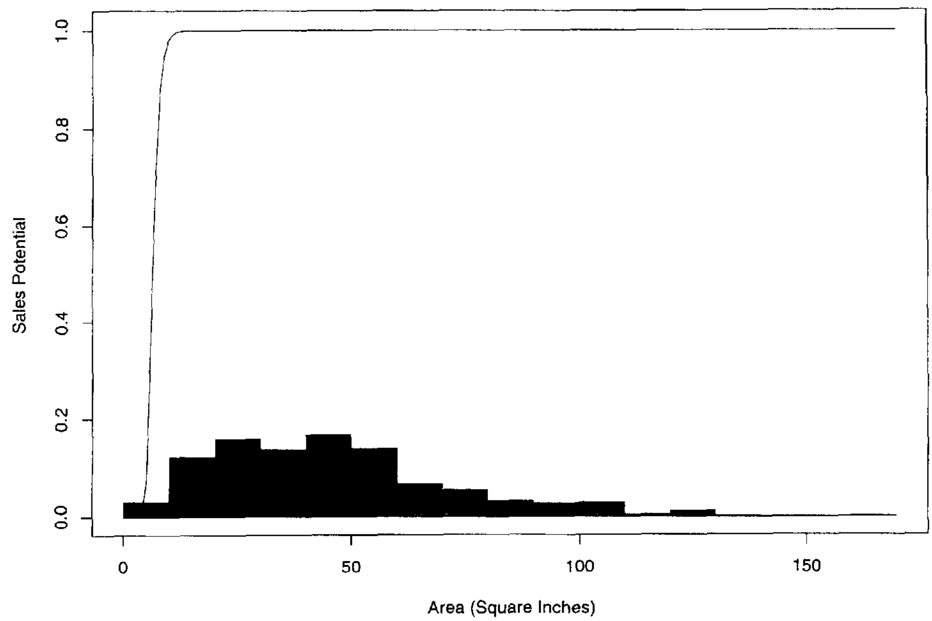

Figure 5. **Analgesics**

Area: The area effect modeled through the Gompertz function was statistically significant ($p > .01$) in all but one category. As for location, we must measure the actual economic impact of area on sales. One way to look at this is to plot on the same graph the impact of area on sales, and the current distribution of products across area. Figure 5 shows such a graph for analgesics.

The S-shaped line is the estimated Gompertz function. It shows that below 3 square inches, sales potential is virtually non-existent, and then increases sharply between 3 and 15 square inches, and levels off to full potential above 15 square inches. At 10 square inches of display, a brand would reach about 98% of its potential. The histogram at the bottom of the graph shows the distribution of items across the size of displays. About 2.5% of the items have less than ten square inches of display, 12% have between 10 and 20 square inches, and 85.5% have more than 20 square inches (with one percent that have more than 150 square inches). As one can see, most of the items have a number of facings that put them on the flat portion of the S curve, indicating that adding or removing a facing would not affect their sale.

The situation represented in Figure 5 is characteristic of most of the other categories as well. This suggests that in many situations manufacturers may receive a low return on investment from their efforts to secure more shelf space. In fact, in these tests the return from better shelf location was greater. Only in refrigerated juices and canned soups did we find a situation where a significant portion of the items are on the upward segment of the Gompertz function. In refrigerated juice (see Figure 6), more than 70% of the items had less than 150 square inches of display (beginning of the flat portion of the curve). Some of these items would gain up to 50% in sales if they enjoyed more display space. In the canned soup category

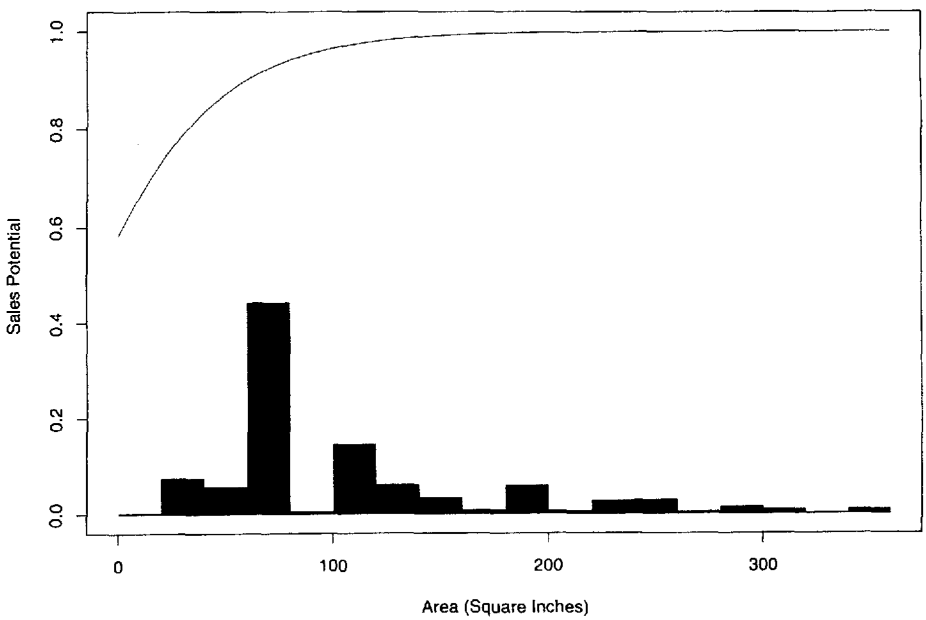

Figure 6. **Refrigerated Juice**

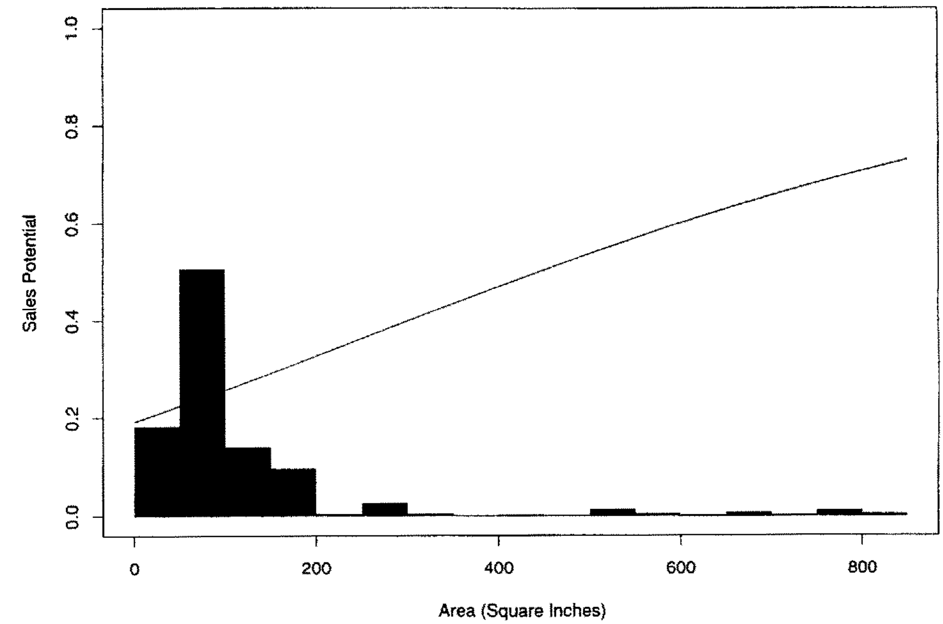

Figure 7. **Canned Soup**

(see Figure 7), there seemed to be an almost linear relationship between space and sales potential, suggesting significant opportunities for improving performance. One possible explanation for this linear relationship is that Campbell's dominates the category, and from a distance, all red and white Campbell's cans look alike. Hence one has to read each label individually in order to find the soup one desires, making the probability of being chosen directly proportional to a brand's space allocation.

OPTIMIZATION OF SPACE

In this section we attempt to utilize the empirically estimated parameters from our experiments as input to an optimization routine. It was not our intention to develop a complete model of shelf allocation and stock replenishment. Others, notably Bultez et al. (1988), have produced detailed work in the area. Instead, we conducted this optimization exercise as a means of better appreciating the upside potential of improved location and space allocations. We attempted to build a reasonable facsimile of the consumer side of shelf management, and used this model to better understand the potential of shelf management as a part of micro-marketing.

Optimizing shelf space allocations for our model is a difficult problem for which we do not pretend to have a complete solution. In an ideal world, not only would we want to allocate the appropriate amount of space and location to each item, we would also want to determine the optimal number of shelves and the optimal height of each shelf given that a product can be displayed on its side of turned upside down. The problem can be made easier to solve by imposing a few reasonable assumptions.

We placed three restrictions on the space management problem. First, we decided beforehand the number of shelves and shelf height. Second, we simplified the problem by ignoring the horizontal position and assumed that only the vertical dimension matters. Last our analysis ignores *slotting allowances*. The use of slotting allowances varies greatly across categories and retailers. The reasons for the emergence of slotting allowances during the last decade are not known with certainty (Sullivan 1994). It seems that except for categories with exclusive distribution (e.g., greeting cards or spices) or rental arrangements (e.g., cigarettes), there is no direct link between the acceptance of a new product by a retailer and the existence of a slotting allowance (Rao and McLaughlin 1989). Retailers claim (Freeman 1991, *Supermarket News* 1984) that slotting allowances are used to defray the administrative and logistic costs associated with the introduction of new items rather than to *buy* a certain amount of shelf space. In this light, we will carry out the rest of our analysis ignoring the existence of slotting allowances. We acknowledge however that for categories such as those mentioned above, slotting allowances could play an important role in planogram development.

If we accept these three restrictions, the problem can be written as:

$$\text{Max} \sum_{i=1,N} \text{Profit}_{ijk} * \text{Usage}_{ijk}$$

$$\text{st:} \sum_{j=1,J} \sum_{k=1,K} \text{Usage}_{ijk} = 1 \qquad i = 1,N$$

$$\sum_{i=1,N} \sigma_{j=1,J}\, \text{Usage}_{ijk} * \text{Size}_{ij} \leq 1 \qquad k = 1,K$$

where:	$i =$	item index (N items in the category)
	$j =$	number of facings (maximum of j facings per item)
	$k =$	shelf (K shelves)
	$\text{Profit}_{ijk} =$	the profits accruing to j facings of item i if displayed on shelf k
	$\text{Usage}_{ijk} =$	1 if item i is displayed on shelf k with j facings, and 0 otherwise
	$\text{Size}_{ij} =$	proportion of the total width of the shelf used in j facings of i are displayed on that shelf.

Because Profit_{ijk} is non-linear in j and k, we first compute all possible Profit_{ijk} in advance and then feed the values into an optimization routine. Given that the sales matrix already exists, and linear optimization package (LINDO, LINGO) is able to find the optimal solution in a reasonable amount of time.

We ran this optimization on six categories analyzed in the previous section. Table 5 displays the results. The first column shows the expected improvement in profits for the optimal shelf set compared to the existing planogram. The next two columns provide the profit improvement that would be expected if we optimized either location or facings while

TABLE 5

Increases in Profits When Optimizing on Both Area and Location, Area Only, and Location Only

Category	*Both*	*Area*	*Location*
Analgesics	9%	1%	6%
Bottled Juices	25	1	20
Canned Seafood	15	1	12
Canned Soup	27	14	10
Oral Care	7	1	6
Refrigerated Juices	8	3	5
Average	15%	3%	10%

holding the other dimension constant. Specifically, to obtain an estimate of the profit improvement uniquely attributable to optimal positioning of the products, we reran the optimization routine while holding constant the allowable area allocated to each product. Each sku was allocated the exact number of facings it had in the control planogram of our experiments. Similarly for area, we optimized on facings while holding constant the shelf on which the product was displayed (the control shelf).

In examining Table 5, we observe that in all cases the estimated category profit improvement from the optimal shelf set is greater than that observed in our category experiments. For example, while we observed a 2.6% increase in performance after moving to space-to-movement planograms for refrigerated juice, expected profit from the optimal planogram is 8%. A big part of this difference comes from the fact that we have calculated an optimal planogram for each individual store, whereas in the experiment we were constrained to developing planograms for only two clusters of stores. Because developing and maintaining individual planograms is not operationally feasible for most retailers, our optimization results probably represent an upward bound on the returns from better space management.

From the second and third columns of Table 5, we can see that in most of the categories position optimization is more important than facing optimization. These category-level results corroborate those found at the brand level, where we also found that location of the product was more important than the number of facings. One difference between the results is the absolute magnitude of the effects. For any individual brand, the improvement that accrues to better location and more facings is much greater than when we look at the overall category. The reason obviously is substitution. Only one brand can occupy any given position and similarly more facings for one particular brand imply fewer facings for other brands.

This analysis highlights the tension between manufactures and retailer goals mentioned at the outset. Although manufacturers can experience substantial brand-level gains from securing better shelf locations and modest gains from increased facings, the attendant category-level benefits to the retailer are more modest. Thus it is crucial for both retailers and manufacturers to consider the other party's interests when negotiating for space and location.

CONCLUSION

We found that a retailer can increase sales (and profits) by better managing existing shelf space. We explored two different ways to increase profits: customized space-to-movement planograms; and product reorganization intended to influence cross-merchandising and ease of shopping. Each method produced different results. Customized space-to-movement led to changes in sales and profits ranging from –2% to 8%, whereas product reorganization produced changes in sales of 5–6%.

We then developed a model to measure the effect of changes in product location and shelf space allocations on sales of individual brands within the category. On the whole, we found that the majority of products were over-allocated in terms of shelf space. Contrary to popular belief, the number of facings allocated to a product was one of the least important success factors. A product must, of course, be displayed in order to sell, but the return from additional shelf space declined quickly, and above a certain threshold (different for each category), the benefits from additional facings were non-existent. Position was far more important than the number of facings. A couple of facings at *eye level* did more for a product than five facings on the *bottom shelf*. Although there was no consensus about the best position on the horizontal axis (categories were split evenly between the center of the aisle or the edges as being the best location), two positions were clearly favored as far as the vertical axis is concerned: the well in the refrigerated section; and slightly below eye level in the other categories.

After several years of shelf management experience, it is our belief that most supermarket retailers should expect only modest gains in category sales, probably 4–5%, from better product positioning and space allocation. This estimate represents only 1/3 of the 15% potential increase suggested by our optimization results. There are several reasons why the retailer will not be able to realize all this potential. First, they do not have the personnel to manage individual store planograms in more than a handful of the 300 categories that they sell. Second, our optimization is a static representation of a very dynamic world. With multiple new product introductions and changes in demand for individual brands, sizes, flavors, and entire categories, the optimal shelf set would be outdated before it could ever be implemented.

We do not mean to imply that there are no circumstances under which good shelf management might not lead to more substantial sales gains. Our results come from only one retailer at one point in time; moreover, most of the stores were large (> 45,000 sq. ft). In the U.K., by contrast, where land and building costs often are an order of magnitude greater than in North America, supermarkets average about 1/3 the selling space per retail sales dollar. In such cases where space is very tight, correct in-store inventory levels will be much more crucial to avoid out-of-stocks and at the same time maintain reasonable restocking cycles. Similarly, convenience stores, like 7–11, may observe a larger payback from improved shelf management.

It also should be kept in mind that our assessment of the value of shelf management focused solely on the consumer demand side of the question. We took the size of a category planogram and the general assortment of items as given, and then attempted to increase sales through changes in brand-level product placements and space allocations. It is likely that there are sizable gains on the operations side from "effective" shelf management. If the low space elasticities that we encountered were to hold up, retailers could cut costs substantially by reducing the overall space allocated to a category. Smaller category shelf sets would lead to operational costs savings by reducing in-store inventories. By narrowing the assortment and/or carrying fewer items, retailers could reduce administration and handling costs and simplify warehouse inventory along the lines of the mass merchandisers and warehouse clubs. The freed-up space could be allocated to new value-added services or non-traditional product categories that might better benefit from the installed base of customers that currently traffic the store. However, additional research is needed in this area because little or nothing is known about how consumers would react to the cuts in breadth and depth of assortment that would accompany shrinkage of the planogram.

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NOTES

1. A standard refrigeration case is L-shaped. Most of the shelves are vertically stacked in a fashion comparable to the rest of the store. The well is the bottom of the L. It is a special horizontal bin at the bottom of refrigeration cases, about 2 feet above floor level, where consumers must lift the product up rather than pull it off the shelf.

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