Accounting Profits Versus Marketing Profits: A Relevant Metric for Category Management

Yuxin Chen • James D. Hess • Ronald T. Wilcox • Z. John Zhang
Leonard N. Stern School of Business, New York University, New York, New York 10012, ychen@stern.nyu.edu
College of Commerce and Business Administration, University of Illinois at Urbana-Champaign, Champaign, Illinois 61820, jhess@uiuc.edu
Graduate School of Industrial Administration, Carnegie Mellon University, Pittsburgh, Pennsylvania 15213, wilcox@andrew.emu.edu
Graduate School of Business, Columbia University, 3022 Broadway, New York, New York 10027-6902, zz25@columbia.edu

Abstract

Retailers have long recognized that some categories are more important than others in consumers' store choice decisions. The overall profitability of a store requires careful category-level merchandising decisions to draw the most desirable consumers into the store. However, the traditional accounting measure of category profits offers imperfect help making these decisions since it does not take into account the effect of merchandising one category on the profits of other categories in the store. A profit measure which takes into account these important cross-effects is the most relevant performance metric for category management. We call this new construct *marketing profits*, as it focuses on consumers and their store choice behavior, and is particularly pertinent to the calculus of marketing decision making.

Despite its practical importance, the total impact of merchandising a specific product category on a store's profitability is difficult to measure, and in practice managers can only rely on intuitive calibration of marketing profits in making many retailing decisions. The difficulty arises from the fact that to directly observe the marketing profits of a category, one has to know how consumer store shopping behavior would change and hence what a store's profit would be if the category were to disappear from the consumers' store choice decision. Furthermore, it is difficult to devise a demand structure that is rich enough to capture bundled purchases on the part of consumers in a reasonable manner, but is simple enough to allow estimation on the basis of commonly observed variables. These two technical difficulties explain the conspicuous lack of research that systematically examines how to quantify what we call marketing profits.

This paper builds a formal model of marketing profits. We start by formalizing shopper types, and then establish the implied relationship between accounting profits and marketing profits by examining shelf space allocations by a retailer. On the consumer side, we assume that some consumers pay attention to the assortments offered by different retailers when making their store choice decisions. This assumption allows us to establish the demand-side linkage between accounting profits and marketing profits. Consumer store choice decisions put pressure on the retailer to carry wide assortments in categories which are particularly critical to the store choice decisions of the most desirable consumers. Thus, the allocation of shelf space gives rise to the supply-side linkage between accounting profits and marketing profits. By examining the outcome of the supermarket's shelf space decision, we can merge these two linkages and determine the exact relationship between the accounting and marketing profits.

Central to our theoretical structure is our assumption on retailers' shelf space allocation decisions. Because of the well-documented pressure that retailers face in making shelf space allocation decisions, we assume that they are acting in a reasonably close-to-optimal fashion by using either an automated planogram or simply by trial-and-error. Optimization requires that returns on shelf space allocated to any category in the store must be identical on the margin and equate to the shadow price of shelf space. It is this outcome of shelf-space allocation that allows us to uncover the implied relationship between accounting and marketing profits.

This theoretical structure allows us to construct a measure of marketing profits which can be estimated with data commonly available to retailers. We demonstrate this measurement technique by using publicly available data, provided by Marsh Supermarkets, and show how marketing profits can improve merchandising decisions. In our particular application, we find many categories where the marketing profits of a category are very different from the traditional accounting profits. Further, we find that using this new marketing profits metric to make category-level feature advertising space decisions significantly improves the profitability of the retailer. The paper concludes by discussing how our measure of marketing profits might be improved by additional research, particularly if the researcher has data across many stores.
(*Category Management; Retailing; Management Decision Models*)

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1. Introduction

Retailers have long recognized that some categories are more important than others in consumers' store choice decisions. The overall profitability of a store requires careful category-level merchandising decisions to draw the most desirable consumers into the store. However, the traditional accounting measure of category profits offers imperfect help making these decisions. Why are the accounting profits imperfect?

Consider, for example, a grocery store manager who must allocate space in the *best-food-of-day* advertisement between the fresh produce category and the meat category (Blattberg and Neslin 1990, pp. 447–450). Some consumers come to the store primarily because of the fresh produce, although they also purchase meat. The store choice of these produce-focused consumers is dictated by the type, quality, selection, and price of fresh produce. Other consumers come to the store mainly to purchase meat, but buy produce as well. Likewise these meat-focused consumers consider only the attributes of the meat category in their store choice decision. If the grocer only has resources to properly feature one category in a large advertisement, which category should it be? To make the example concrete, Table 1 lists hypothetical purchasing patterns by the two types of consumers, produce-focused and meat-focused.

The uppercase letters (P and M) in Table 1 indicate the items which determine the consumers' store choices, while the lowercase letters (p and m) indicate purchases which do not affect store choice. In our example, the produce-focused consumer buys fresh produce that contributes $P = \$25$ but also purchases meat, which adds $m = \$35$ to profit, while the meat-focused consumer buys meat that contributes $M = \$35$ but also purchases fresh produce, which adds $p = \$5$ to profit. The accounting profits for a category are traditionally computed by aggregating over both consumer types in proportion to their representation in the population. In Table 1, the accounting profit is summed vertically: for produce it equals $P + p = \$30$ and for meat it equals $M + m = \$70$.

Table 1 **Profit Contributions**

	Produce	Meat	Marketing Profits
Produce-Focused Consumer	$P = \$25$	$m = \$35$	\$60
Meat-Focused Consumer	$p = \$5$	$M = \$35$	\$40
Accounting Profits	\$30	\$70	

If best-food-of-day advertisements were chosen on the basis of accounting profits, the grocer will feature meat in its advertisement. This seems reasonable because meat contributes \$40 more to profits than produce (\$70 − \$30 = \$40), and therefore can justify the extra promotional support.

This is wrong. It fails to recognize that a substantial part of meat sales, $m = \$35$, is made to produce-focused consumers. The manager arrives at a better understanding of the consumers by summing up profits horizontally in Table 1. We refer to the total profit of each category-focused consumer segment as *marketing profits* of the category. Through the lens of marketing profits, the manager now learns that meat-focused consumers make a contribution to profits of only \$40 ($M + p$) because these consumers do not buy much in the produce category, and produced-focused consumers bring to the store a profit of \$60 ($P + m$). Thus, it is more profitable to use best-food-of-day advertising to bring in produced-focused consumers, the most valuable customers.

For this reason, a profit measure that aggregates across different product categories for each type of consumer is the most relevant performance metric for category management. We call this new construct *marketing profits* as it focuses on consumers and their store choice behavior, and is particularly pertinent to the calculus of marketing decision making.

Despite its practical importance, the total impact of merchandising a specific product category on a store's profitability is difficult to measure, and in practice managers can only rely on intuitive calibration of marketing profits in making many retailing decisions (*Progressive Grocer* 1992b, 1996a, 1997a, Chiang and Wilcox 1997, Lal and Matutes 1994, Bliss 1988, Hess and Gerstner 1987). The difficulty arises from the fact that in order to directly observe the marketing profits of a category one has to know how consumer store shopping behavior would change and hence what a store's profit would be if the category were to disappear from the consumers' store choice decision.[1] Furthermore, it is difficult to devise a demand structure that is rich enough to capture bundled purchases on the part of consumers in a reasonable manner, but is simple enough to allow estimation on the basis of commonly observed variables. These two technical difficulties explain the conspicuous lack of research that systematically examines how to quantify what we call marketing profits.

To put it simply, the exact values of the entries in Table 1 are not easy to measure. The sum down the columns is regularly calculated by the accounting system, but this system cannot help sum across the rows to generate the marketing profits. How can we extract the latent marketing profits from the manifest accounting profits? A researcher could do primary marketing research to identify the customers who are produce-focused and measure the amount of contribution that they make to the retailer's profits, and fill in the main entries of the table. This would require substantial costs for data collection and analysis. We propose a simpler method using readily available data to infer the latent marketing profits. This inference requires that we supply some theoretical structure to the way that consumers shop and to the decisions retailers make in their assortment, in lieu new primary data. To flesh out this theory, consider Table 2 which modifies Table 1 by incorporating a simple theory of consumer shopping.

Just as before, in Table 2 consumers shop primarily for one focal category, either produce or meat. They purchase products in other categories, but their presence at the store is primarily driven by one category. The new facet of the theory is that the amount of shelf space allocated to their favorite category is an important element in drawing the category-focused consumers into the store. In Table 2, we spell this out with a logarithmic relationship between sales in each category to each consumer type. For example, the produce-focused consumers will shop at the store in proportion to $(1.5 + \log s_p)$, where s_p is the fraction of shelf space allocated to produce.

In addition, suppose that the store has allocated 60% of the shelf space to the produce category even though the accounting profit for the produce category is much smaller than the accounting profit for meat ($30 versus $70). Yet, the retailer is happy about the allocation and has no intention to change it any time soon. Stated more formally, the retailer has found, by hook or by crook, the allocation of shelf space that optimizes the store profit. The only explanation consistent with the shopping behavior and optimal shelf-space allocation in Table 2 is that the marketing profits differ from the accounting profits: $60 versus $30 for produce and $40 versus $70 for meat.

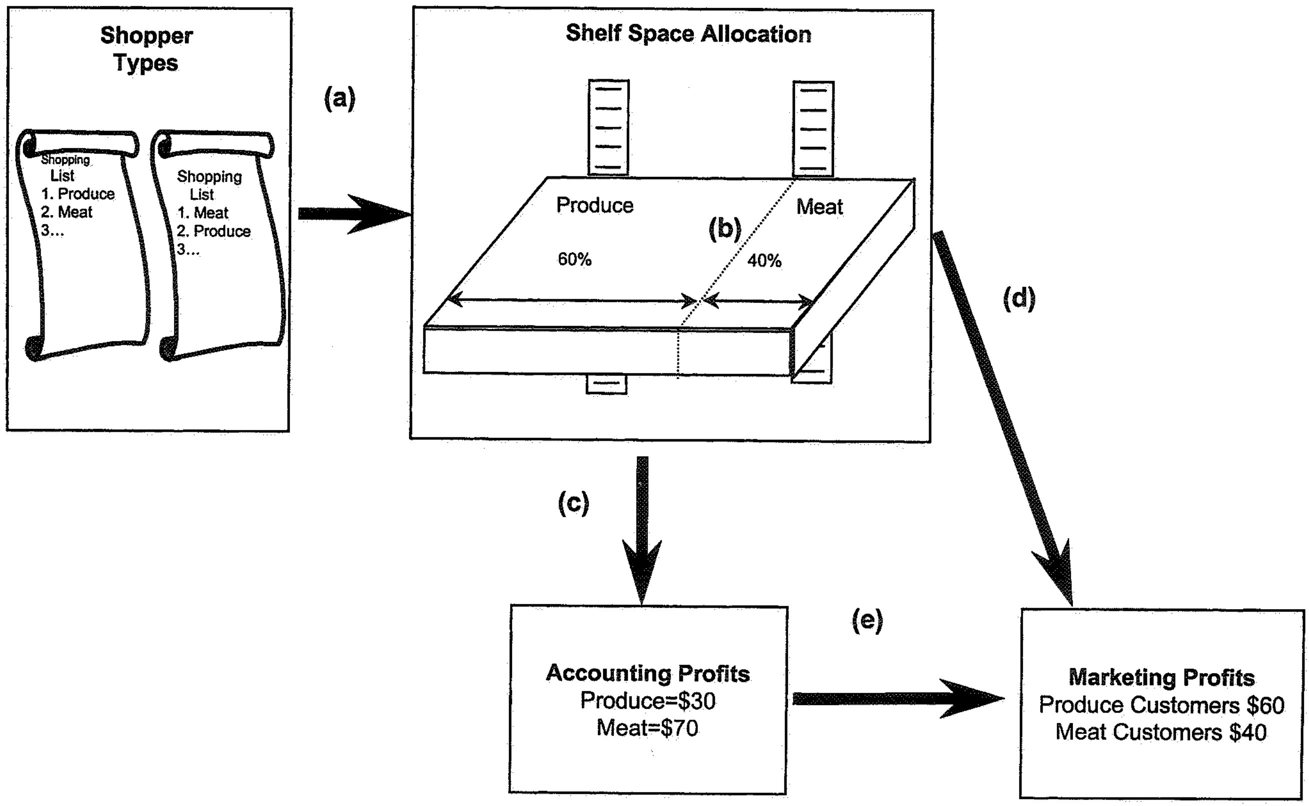
This paper builds a formal model that incorporates each element touched upon in Table 2: shopping for categories, shelf-space allocation, and the implied linkage between accounting and marketing profits (see Figure 1). The shoppers will be differentiated by the items that they place high on their shopping lists, a fact that gives rise to the demand-side linkage between accounting and marketing profits. Retailers recognize this (arrow (a)) and use it when experimenting with and optimizing their allotment of shelf space for each category (relationship (b)). This gives rise to the

[1]Econometricians typically handle this kind of counterfactual question by capturing the changes in the interested variable that occurred "before and after" (time-series analysis) or "with and without" (cross-sectional analysis) an exogenous stimulus while holding everything else constant. In the dynamic environment of retailing, such approaches are difficult to implement since it is difficult to maintain "everything else being equal."

Table 2 Marketing Profits and Shelf Space

	Shelf Space (s_i)	Produce	Meat	Marketing Profits
Produce-Focused Consumer	60%	$P = \$25\ (1.5 + \log s_p)$	$m = \$35\ (1.5 + \log s_p)$	$60
Meat-Focused Consumer	40%	$p = \$5\ (1.9 + \log s_m)$	$M = \$35\ (1.9 + \log s_m)$	$40
Accounting Profits		$30	$70	

Figure 1 **Road to Marketing Profits**



supply-side linkage between accounting and marketing profits for a category (arrows (c) and (d)). Thus, by examining the outcome of the supermarket's shelf-space decision, we can determine the relationship between the accounting and marketing profits (arrow (e)).

A meaningful estimate of the marketing profits can be made this way because of the well-documented pressure that retailers face in making shelf-space allocation decisions. Due to the high sensitivity of store profits to the space-allocation decision, retailers take great care with this decision and are behaving in a reasonably close-to-optimal fashion on shelf-space decisions by using computer planograms such as Apollo or SPACEMAN (Levy and Weitz 1998), or perhaps simply by trial and error (Dreze et al. 1994, Borin et al. 1994, Bultez and Naert 1988). Optimization requires that returns on the shelf space allocated to any category in a store must be identical on the margin and equal to the shadow price of shelf space. This allows us to establish the implied relationship between accounting and marketing profits mediated through retailing costs and shelf-space allocations, all of which but marketing profits are observable.

Is it necessary, though, to know category-level marketing profits in order to make better marketing decisions such as feature advertising, point of purchase displays, stocking, or price discounts? For instance, isn't it simpler to directly regress total store accounting profits on the category-level decision variables to measure response functions and then maximize total store profits with respect to those variables, thus skipping the step of measuring category marketing profits? We show in §6 that this seemingly simpler approach is actually impractical because it requires collecting a lengthy time series of data and solving an unwieldy constrained optimization problem. However, our measurement of category marketing profits requires only cross-sectional data and simplifies the optimization procedure.

In the rest of the paper, we will follow the roadmap laid out in Figure 1 to develop this measurement technique. We start by formalizing shopper types, and then establish the implied relationship between accounting profits and marketing profits by examining shelf-space allocations by a retailer. Finally, we demonstrate this measurement technique by using publicly available data, provided by Marsh Supermarkets[2], and show how marketing profits can improve merchandising decisions.

2. Consumer Shopping Behavior

2.1. Store Choice

In general, consumers choose both which store to visit and what items to buy. These are not always linked decisions and many store choice decisions are dominated by location or habitual behavior. However, some consumers, some of the time, reflect on the items they intend to buy and with those in mind, select the store to visit (Kahn and McAlister 1997, Bell et al. 1998). These are the consumers that retailers hope to influence by the assortment of goods and services they offer, along with other elements of the marketing mix, who are most responsive to retailers' marketing decisions, and hence are the focus of our analysis. However, our model is general enough to capture the aforementioned unplanned behavior, as discussed later.

Consider a representative consumer. On any shopping trip, we assume that this consumer has literally or figuratively created a shopping list, or an ordered market basket, out of the assortment of categories. Let $A = [1, 2, \ldots, n]$ denote the assortment of product categories carried by the retailer.[3] A market basket, B, is an element of the set of all subsets of the assortment. A shopping list, L, is any ordered vector formed from a market basket. The ordering, which distinguishes a shopping list from a market basket, reflects the observation that some products are more important to the consumer than others in the shopping decision. The first item on the shopping list is the most important item, the second the second most important, etc. We refer to the first item on the shopping list as the *lead category*.

As an example, suppose that there is a three category assortment $A = \{1, 2, 3\}$ and that the consumer is considering a market basket $B = \{1, 3\}$ with a shopping list $L = \{3, 1\}$. This consumer places primary importance on category 3, secondary importance on category 1, and has no purchase intention for category 2. Category 3 is the lead category.

We assume that there are specific brands which consumers prefer in each category on their shopping list L (where "brand" is shorthand for "brand-size-package-flavor" SKU since a consumer may prefer a particular size or shape of package or a particular flavor rather than a brand). The retailer may or may not carry the brand that the consumer prefers. Let p_j denote the probability, as assessed by the consumer, that their preferred brand in category j will be available at the store. We will discuss below how this perceived availability can be adjusted by the retailer.

Suppose that a given consumer has a shopping list $L = (I_1, \ldots, I_j, \ldots, I_J)$, where $I_j \in A$ is the jth item on the list. The consumer anticipates that all the favorite brands on the shopping list are available at the store with probability

$$\prod_{j=1}^{J} p_j. \tag{1}$$

However, this anticipation of complete satisfaction may not be relevant because category I_1 is more important to the shopper than category I_j. The shopper may be willing to take a big risk that the favorite brand in category I_j is not available if there is little risk that the favorite brand is missing from the most important category.

There are many ways in which the relative importance of items on the shopping list can be melded with the probabilities of finding the favorite brands to determine the overall attractiveness of a store to a consumer. We will take a dramatic approach to simplify the analysis: namely, the store choice will be made in direct proportion to the probability of finding the favorite brand of just the lead category. That is, for a consumer with I_1 topping the shopping list, we have

[2]Marsh Supermarkets is a large Midwestern grocery retailer headquartered in Indianapolis.

[3]A summary of the notation used in the theoretical model can be found in Appendix 1.

$$\text{Probability of Store Choice} = z_L * p_{I_1}, \tag{2}$$

where the coefficient z_L captures the impact of the marketing mix, such as prices and promotions on the store choice for a consumer with a shopping list L.

This assumption that the store choice does not depend on $p_{I_2}, \ldots, p_{I_J}$ is an extreme case of a more general model where

$$\text{Probability of Store Choice} = z_L * p_{I_1}^{\gamma_1} * p_{I_2}^{\gamma_2} * \cdots * p_{I_J}^{\gamma_J}, \tag{3}$$

where $\gamma_1 \geq \gamma_2 \geq \cdots \geq \gamma_J \geq 0$. Equation (1) represents the special case where all categories on the shopping list are of equal importance: $\gamma_1 = \gamma_2 = \cdots = \gamma_j = 1$, but we will only analyze the case where $\gamma_1 = 1$, $\gamma_2 = \cdots = \gamma_J = 0$.[4] This approach has the advantage in conceptual simplicity and clarity while still reflecting the reality that shoppers have priorities among categories. Thus, the only planning that our model assumes of shoppers is the selection of a lead category, either in mind or on paper.

For any realistic-sized assortment there exists a very large number of possible shopping lists, denoted by the set $\mathscr{L}$. Once a consumer has made a store choice, the purchases are made in each category on the shopping list. In particular, even if the favorite brand in a category is not available, the consumer chooses an alternative brand to avoid an additional shopping trip elsewhere. That is, none of the brands in our model are specialty goods that consumers would leave this store to find at other stores.

We assume that a fraction β_L of all consumers use shopping list $L \in \mathscr{L}$ on any given purchase occasion (where we normalize the size of the consumer population to equal one).[5] Implicit knowledge of the distribution of these different types of shopping lists among consumers is important to the retailer in many of the marketing mix decisions that they make since the distribution may change with these decisions. While we specify these fractions as we lay out the model, our measure for marketing profits will bypass the need to directly calibrate them.

Many shopping trips are unplanned; a Gallup study of over 4,000 shoppers found that 45% did not enter the store with a written shopping list (Shermach 1995). How can this be incorporated into the model? Our emphasis on a probability distribution over the collection of all shopping lists allows us to directly handle this situation. A totally unplanned shopping occasion can be conceptualized as a consumer who chooses shopping lists randomly according to some distribution (e.g. a uniform distribution). As we aggregate over all consumers, the impact of these unplanned shopping occasions are incorporated into β_L.

Let u_{iL} denote the number of units (packages, pounds, etc.) purchased on a shopping trip from category i by a consumer with a shopping list L that includes i. Consumers with the same shopping list are assumed to buy the same number of units. Then, the expected demand for category i is

$$D_i = \sum_{\{L \in \mathscr{L} \mid I_1 = i\}} u_{iL}\beta_L z_L p_i + \sum_{k \neq i} \sum_{\{L \in \mathscr{L} \mid I_1 = k, I_j = i \text{ for some } j > 1\}} u_{iL}\beta_L z_L p_k. \tag{4}$$

The first term is just the sum across all shopping lists where category i is the lead category of the probability of the list times the probability that the preferred brand is available in category i. The second term adds together the probabilities of buying i because category k is the lead category but i is on the shopping list. To simplify this notation, define

$$\alpha_{ii} = \sum_{\{L \in \mathscr{L} \mid I_1 = i\}} u_{iL}\beta_L z_L$$

and

$$\alpha_{ki} = \sum_{\{L \in \mathscr{L} \mid I_1 = k, I_j = i \text{ for some } j > 1\}} u_{iL}\beta_L z_L. \tag{5}$$

The expected demand for category i is then written more compactly as

$$D_i = \alpha_{ii} p_i + \sum_{k \neq i} \alpha_{ki} p_k. \tag{6}$$

The value of α_{ii} equals the potential sales of i because

[4] To analyze the case where $\gamma_1 = \gamma_2 = \cdots = \gamma_J = 1$, one needs to assume that all consumers have the same number of categories J in their shopping lists to maintain analytical tractability.

[5] The probability of list L is assumed to be independent across shopping events. This precludes analyzing what Bucklin and Lattin (1992) call "indirect effects" of category marketing, where the decision to purchase an item in category i on any given shopping occasion impacts the probability that category i will be on the consumer's shopping list the next time he or she visits the store.

category i is the lead category on the shopping list. The value of α_{ki} equals the potential sales of i because k is the lead category on a shopping list that includes category i.

In our model, prices and other marketing mix variables affect the expected demand of a category in two different ways. First, they may affect the unit sales, u_{iL}. Second, they may affect the store choice probability though z_L (as suggested by Little and Shapiro 1980). Both these effects can be captured by assuming that α_{ij} is a function of marketing mix variables. As we will describe below, this will not change the measurement of marketing profits. For expositional simplicity we will suppress the dependence of α_{ij} on marketing mix variables.

2.2. The Impact of Shelf Space on Demand

Consumers have imperfect memories or experiences so they are not always absolutely certain that their favorite brand will be on the shelf when they shop. Mogelonsky (1998) reported that 34 new food products were introduced in the U.S. every day. The rapid turnover in SKUs in many categories creates uncertainties for consumers trying to find their favorite brands. Moreover, stores may carry a brand but be out-of-stock when the consumer does the shopping (Hess and Gerstner 1987, Balachander and Farquhar 1994). The likelihood that a consumer's favorite brand is perceived to be available depends on the shelf space allocated to the category. This follows because consumers' assessed probabilities of finding their preferred brand depends on the number of brands a store carries and the probability of stock-out for brands in this category. Both of these depend, everything else being equal, on the amount of shelf space the retailer allocates to the category.

This probability, p_i, also depends on other merchandising decisions, such as SKU assortment and stocking policies, but our primary objective is to infer the latent marketing profit from the fact that accounting profit per linear foot of shelf space varies across categories. These other variables, along with prices, could be used as control covariates in the empirical estimation of demand (if they are available), but are not essential to our measurement of marketing profits.

Denote the shelf space allocated to category i as s_i, and let $\mathbf{s} = (s_1, s_2, \ldots, s_n)$. If the retailer has consistently allocated significant shelf space to category i, then the consumers will perceive it more likely that they will find their preferred brand at the store. This means that $p_i = p_i(s_i)$. We will assume that $p_i(s_i)$ is a smooth monotonically increasing function of s_i. As s_i approaches 0 so does p_i, and as s_i approaches infinity p_i approaches 1. Therefore, we have

$$\frac{dp_i(s_i)}{ds_i} \geq 0, \quad \lim_{s_i \to 0} p_i(s_i) = 0 \quad \text{and} \quad \lim_{s_i \to \infty} p_i(s_i) = 1. \tag{7}$$

In previous studies (Corstjens and Doyle 1981, 1983) it was further specified that this probability function has a constant elasticity. We do not.

Thus, through modeling consumer store choice decisions, we have established the demand-side linkage between accounting and marketing profits for a category. This linkage is mediated through shelf-space allocation as illustrated by our roadmap (Figure 1).

3. Profit Calculations

3.1. Category Gross Profit Margins

We now establish the supply-side linkage between accounting and marketing profits for a category. The linkage is again mediated through shelf-space allocation. By examining a retailer's shelf-space allocation decisions, we can merge both demand and supply-side linkages to uncover the exact relationship between accounting and marketing profits for a category.

Let $\pi_i(\mathbf{s})$ denote accounting profits from the sales of category i, which obviously depend on category profit margins, demand, and retailing costs. Denote the gross profit margin, average shelf price minus wholesale price, for category i by m_i.[6] Our derivation takes retail margins as given regardless of whether or not they are competitively determined.[7] Incorporating pricing decisions in our model will simply add more first order

[6]In practice, m_i can be obtained by averaging retail margins across different brands in the same category, and is widely available.

[7]Apparently, retailers in general have little discretion or power in influencing the market prices for different categories. Grocery retailing profitability has been stable at about 1% of the sales between 1985 and 1992. See Messinger and Narasimhan (1995).

conditions which we do not need to use in deriving the expression for a category's marketing profits, as soon will be clear.

3.2. Shelf-Space Cost

A retailer typically incurs a wide array of merchandising costs to carry a product category, such as costs for restocking, lighting, refrigerating, etc.[8] We specify the following standard cost function:

$$C_i = t_i \frac{x_i D_i}{s_i} + h_i s_i. \tag{8}$$

The first term of the cost function captures the replenishment costs associated with merchandising the category, and the second term the costs associated with maintaining the shelf space for the category, such as lighting, refrigeration, tagging, etc., which change only with the amount of space allocated to the category, not with the number of items sold.[9]

Given the assumptions above, we can now write the accounting profit from category i as

$$\pi_i(\mathbf{s}) = \tilde{m}_i[\alpha_{ii} p_i(s_i) + \sum_{k \neq i} \alpha_{ki} p_k(s_k)] - h_i s_i \tag{9}$$

where $\tilde{m}_i = m_i - t_i x_i / s_i$ is the net contribution margin for category i, equal to the gross margin minus unit variable merchandising costs. The accounting profit of a category thus depends on the shelf space allocated to it (arrow (c) in Figure 1).[10] The total store profits similarly can be written as

$$\Pi(\mathbf{s}) = \sum_{i \in A} \pi_i(\mathbf{s}) = \sum_i \tilde{m}_i \left[\alpha_{ii} p_i(s_i) + \sum_{k \neq i} \alpha_{ki} p_k(s_k) \right] - \sum_i h_i s_i. \tag{10}$$

[8]For a detailed breakdown of different types of merchandising costs see the Food Marketing Institute's *The Direct Product Profitability Manual* (1986) and Borin and Farris (1990).

[9]Our notation follows that of the popular economic order quantity (EOQ) model of inventories: x_i is the linear shelf space occupied by a unit of category i, $x_i D_i$ the total linear shelf space required for the category to satisfy the demand for one week, $x_i D_i / s_i$ the frequency of restocking, and $t_i > 0$ the cost per restocking. Furthermore, h_i is the direct cost per linear foot.

[10]Although net margin is not explicitly written as a function of shelf space it does implicitly depend on this through the impact of shelf space on restocking costs.

4. Marketing Profits

4.1. Definition of Marketing Profits

The profit impact of a retailer's decision to merchandise a product category, or the marketing profit of a category, is the total profit a store makes from the consumers for whom the category is the lead category. In the notation of this paper, the marketing profits of category i are given by

$$\mathrm{MP}_i(\mathbf{s}) = \Pi(\mathbf{s}) - \Pi(\mathbf{s}_{-i}) - h_i s_i, \tag{11}$$

where MP_i denotes the total marketing profits from category i, and $\Pi(\mathbf{s}_{-i})$ the total store profits when all consumers with category i as the lead category on their shopping lists decide to shop elsewhere. In our model, one can easily derive $\Pi(\mathbf{s}_{-i})$ from $\Pi(\mathbf{s})$ by letting p_i approach 0 in Equation (10). Here we implicitly assume that the alternative to an actively merchandised category (which draws consumers with the category as their lead category into the store) is to have the category *perish on the shelf* in the sense that only consumers with some other category as their lead category may purchase from the category. A measure based on such a severely punishing alternative would highlight the importance and immediacy of proper category management and is thus more decision-relevant in today's supercompetitive retailing environment. Since the shelf space allocated to a category is only relevant to the shopping decisions of the consumers for whom the category is the lead category, the costs incurred in maintaining the shelf space ($h_i s_i$) should be entirely attributed to these consumers. Equation (11) establishes the linkage between marketing profits of a category and the allocation of shelf space as indicated by arrow (d) in Figure 1.

4.2. Relationship Between Shelf Space and Marketing Profits

The definition of marketing profits in Equation (11) would be incomplete if we did not incorporate a retailer's efforts to optimize its shelf-space allocation. Stores may be thought of simply as inventories of goods on display for consumers, so getting the display right is critical for a store's profitability. Therefore, our measure of marketing profits assumes that the retailer has solved the problem of shelf-space allocation. This means that the shelf space in Equation (11) is chosen by a retailer so that

$$\mathbf{s}^* = \arg \max_{(s_1, s_2, \ldots, s_n)} \Pi(\mathbf{s}) \tag{12}$$

$$\text{s.t.} \quad \sum_{i=1}^{n} s_i \leq \bar{S}. \tag{13}$$

That is, the shelf space occupied by each category is a result of the retailer's efforts to optimize the allocation of the total amount of shelf space available to the retailer, $\bar{S}$.

Why do we choose this particular decision as the basis for making inferences about marketing profits? First, in the face of a deluge of new products and the substantial profit opportunities available through slotting allowances, retailers have powerful incentives to make this decision correctly (Levy and Weitz 1998, *Progressive Grocer* 1996b, Dreze et al. 1994, Borin et al. 1994, Chu 1992, Bultez and Naert 1988). Second, the conditions under which the retailer makes this decision are considerably more stable than for some of the other necessary merchandising decisions. For example, the different co-op advertising allowances available to the retailer often shift dramatically from week-to-week and a retailer frequently wrestles with decision situations which he has never experienced before nor will ever experience again. In contrast, neither the total amount of shelf space available to the retailer, nor the basic composition of the different categories changes dramatically from week-to-week. Thus, we may reasonably expect that the retailer's shelf-space allocation is closer to optimal than many of his other more ephemeral decisions.

The optimal allocation of shelf space requires that $\mathbf{s}^*$ satisfy the first order conditions

$$\frac{\partial \pi_i}{\partial s_i} + \sum_{k \neq i} \frac{\partial \pi_k}{\partial s_i} = \lambda \quad \text{for } i = 1, 2, \ldots, n. \tag{14}$$

Here λ is the shadow price of the shelf space, the profit that the retailer can gain by increasing the total shelf space available by a unit, and it is also the opportunity cost of shelf space for the retailer. Equation (14) implies that marginal profit contributions from each category carried by a store must be the same if the shelf space is allocated optimally. The equation system (14) and shelf-space constraint (13) implicitly define the optimal allocation of shelf space $\mathbf{s}^*$ for the retailer. We will exploit the optimality of both direct impact, the first term in Equation (14), and indirect impact, the second term in Equation (14), on total profit to measure the marketing profits of a category from accounting profits that are traditionally measured.

Note that the fact that we do not incorporate retail price in consumer store choice decisions does not, as mentioned before, restrict the generality of our theoretical construct for marketing profits as defined in Equation (11). If we were to specify that α_{ii} is also a function of the retail price for the category, for instance, the retailer's efforts to optimize its pricing decisions would dictate that we have another set of the first order conditions, besides Equation (14), where the marginal profits with respect to any price change are set equal to zero. This additional set of first order conditions would help to determine the optimal retail prices. However, for the purpose of deriving marketing profits, we only need to use Equation (14), wherein the retail prices for each category are simply taken as given regardless of whether they are competitively set or determined by an optimizing retailer. For that reason, we subsume the prices in our derivations to simplify notation.

4.3. An Example

In the next section we will carry out a general analysis, but to fix the basic ideas let us begin with a simple example. Suppose there are three categories, $A = \{1, 2, 3\}$, and that only three shopping lists have positive probabilities: lists (1, 2), (2, 3), and (3, 1) with probabilities

$$\beta_{(1,2)} = \frac{1}{2}, \quad \beta_{(2,3)} = \frac{1}{3}, \quad \text{and} \quad \beta_{(3,1)} = \frac{1}{6}. \tag{15}$$

For simplicity assume that the margins for each item equal \$1, that all retailing costs are zero, that one unit is purchased in each category, and that the impact of other marketing mix variables on store choice is negligible. The profit earned by each category directly, what we call accounting profit, is

$$\pi_1 = \frac{1}{2} p_1 + \frac{1}{6} p_3, \quad \pi_2 = \frac{1}{2} p_1 + \frac{1}{3} p_2, \quad \text{and}$$

$$\pi_3 = \frac{1}{3} p_2 + \frac{1}{6} p_3. \tag{16}$$

The interpretation of π_1, to illustrate, is as follows. The accounting profits of category 1 are the sum of the profits from the sales of category made to the consumer with the shopping list (1, 2) and also with (3, 1). Half of the consumers have the shopping list (1, 2) and they will patronize the store with probability p_1, which is the perceived probability for the consumer to find the preferred brand in category 1, and purchase only one unit of category 1. Therefore, the expected profits that the store makes from the consumer with the shopping list (1, 2) by the sales of category 1 are $\frac{1}{2}p_1$. Similarly, $\frac{1}{6}$ of all consumers have the shopping list (3, 1) and will patronize the store with probability p_3 and contribute the expected profits of $\frac{1}{6}p_3$ to the category. The retailer's total profit is the sum of these category profits:

$$\Pi = \left(\frac{1}{2} + \frac{1}{2}\right)p_1 + \left(\frac{1}{3} + \frac{1}{3}\right)p_2 + \left(\frac{1}{6} + \frac{1}{6}\right)p_3. \quad (17)$$

The marketing profits of each category do not focus on the profits each of these categories make directly. Rather they focus on the total profits that the retailer makes from maintaining the visibility of any given category. In the context of our example, the marketing profits of each of the categories are given by

$$\mathrm{MP}_1 = \Pi - \Pi_{-1} = p_1, \quad \mathrm{MP}_2 = \Pi - \Pi_{-2} = \frac{2}{3}p_2, \quad \text{and} \quad \mathrm{MP}_2 = \Pi - \Pi_{-3} = \frac{1}{3}p_3. \quad (18)$$

The interpretation of MP_1 is as follows. If category 1 were to become invisible to the consumers for whom category 1 tops the shopping list, they would shop elsewhere (since they perceive $p_1 = 0$). In that case, the retailer would still make some profit (Π_{-1}). This profit would be derived from those individuals using the shopping lists (2, 3) and (3, 1). Specifically, the retailer would still earn $\frac{1}{6}p_3$ on category 1, $\frac{1}{3}p_2$ on category 2, and $\frac{1}{3}p_2 + \frac{1}{6}p_3$ on category 3. Notice that category 1 still contributes to profits even though it does not draw consumers to the store. Hence, if category 1 were to become invisible in the consumer store choice decision, the retailer would still earn $\Pi_{-1} = \frac{2}{3}p_2 + \frac{1}{3}p_3$. From our definition of marketing profits, we can calculate the profits from the consumer whose store choice decision critically hinges on the proper merchandising of category 1 as

$$\mathrm{MP}_1 = \Pi - \Pi_{-1} = \left(\frac{1}{2} + \frac{1}{2}\right)p_1 + \left(\frac{1}{3} + \frac{1}{3}\right)p_2 + \left(\frac{1}{6} + \frac{1}{6}\right)p_3 - \frac{2}{3}p_2 - \frac{1}{3}p_3 = p_1. \quad (19)$$

Here p_1 is simply the profits that the retailer would forego if none of the consumers who shop for category 1 as the lead category comes to the store, and hence it is also the total profit contribution to the store from the consumer for whom category 1 tops the shopping list.[11] MP_2 and MP_3 can be calculated in an analogous fashion.

Notice that the marketing profits of a category can be greater than, less than, or equal to its accounting profits depending on the probabilities of finding the preferred brands in each of the categories, which in turn depends on the shelf space allocated to the category. The sum of the marketing profits, however, equals the sum of the accounting profits.

The shelf space is not allocated arbitrarily and retailers have incentives to and do make efforts to optimize their shelf-space allocation. To reflect these efforts, we require that the observed shelf-space allocation is a result of optimization and must satisfy the following first-order conditions:

$$\frac{\partial \Pi}{\partial s_1} = \left(\frac{1}{2} + \frac{1}{2}\right)p_1(s_1)\left[\frac{p_1'(s_1)}{p_1(s_1)}\right] = \lambda, \quad (20)$$

$$\frac{\partial \Pi}{\partial s_2} = \left(\frac{1}{3} + \frac{1}{3}\right)p_2(s_2)\left[\frac{p_2'(s_2)}{p_2(s_2)}\right] = \lambda, \quad (21)$$

$$\frac{\partial \Pi}{\partial s_3} = \left(\frac{1}{6} + \frac{1}{6}\right)p_3(s_3)\left[\frac{p_3'(s_3)}{p_3(s_3)}\right] = \lambda. \quad (22)$$

By dividing both sides of Equation (20) by $p_1'(s_1)/p_1(s_1)$, Equation (21) by $p_2'(s_2)/p_2(s_2)$ and Equation (22) by $p_3'(s_3)/p_3(s_3)$, and then summing up both sides of the resulting three equations, we can express λ as

$$\lambda = \frac{\Pi^*}{\Sigma_j(p_j/p_j')}, \quad (23)$$

where Π^* is the optimal store profits (we will hereafter

[11]The consumer purchases one unit of category 1 with probability $\frac{1}{2}p_1$ and one unit of category 2 with the same probability, which amount to a total profit contribution of p_1.

use superscript * to indicate the optimal solution for a variable). As a direct result this implies

$$\mathrm{MP}_i = \Pi^* \left[\frac{p_i/p_i'}{\Sigma_j p_j/p_j'} \right]. \tag{24}$$

Thus, if we can measure the value of p_i'/p_i (the percentage increase in the probability that a consumer finds the favorite brand in category i when its shelf space is increased by one foot) for each category, which is a considerably easier task than to estimate the demand structure, Equation (24) allows us to express marketing profits as a function of observed direct profits Π^* (arrows (d) and (e) in Figure 1). In §5 we will illustrate how this quantity can be measured. Before we discuss this, we lay out, as promised, the general solution for our model.

4.4. General Solution

By performing the same optimization as in the previous example, we can derive the marketing profits for our general model as

$$\mathrm{MP}_i(\mathbf{s}^*) = \frac{\left(\sum_{i=1}^{n} \tilde{m}_i D_i - \sum_{i=1}^{n} \frac{\tilde{h}_i}{\phi_i}\right) \Big/ \left(\sum_{i=1}^{n} \frac{1}{\phi_i}\right) + \tilde{h}_i}{\phi_i} - h_i s_i^*. \tag{25}$$

The term $\tilde{h}_i$ is the cost per linear foot of expanding shelf space for category i and $\phi_i = p_i'/p_i$ is the percentage increase in the probability that a consumer finds the favorite brand in category i when its shelf space is increased by one foot. The definition of both terms, as well as a complete derivation of marketing profits, can be found in Appendix 2. Note that in Equation (25), the values of D_i, m_i, s_i^*, and x_i are commonly available from data while only t_i, h_i, and ϕ_i are parameters to be estimated. There are many possible approaches one can use to estimate those parameters depending on the specific nature of data. In the following section, we illustrate one such approach using readily available supermarket data.

5. An Empirical Study of Marketing Profits

5.1. Data

Before we describe our estimation procedure and results, we first provide some details about our data source. The measure of marketing profits described in Equation (25) is designed to be used with proprietary firm data, but the data source made available to us contained data at a higher level of aggregation. Naturally, access to proprietary data would allow us to reduce the number of makeshift adjustments in our empirical methods. However, rather than do nothing while waiting for proprietary data, we will illustrate our model using data on category-level margins, demand, and shelf-space allocation as well as a number of other category-level constructs obtained from Marsh Supermarkets. These measures, collected in 1990, were part of a large-scale effort by the retailer and *Progressive Grocer* to measure category performance and marketing costs. The data contained information on 199 grocery categories. The variables collected were aggregated and subsequently averaged over the five superstores in this retail chain (see *Progressive Grocer*, December 1992 and January 1993, for details). Thus, the measures we will use to demonstrate our methodology do not come from any single store, but rather represent averages taken over all stores. Specifically, the following measures are available:

- Margin (m) = a category's retail unit price net of unit wholesale price.
- Cost (C) = all costs, excluding wholesale price, associated with merchandising the given category. This cost is given on a per week basis.[12]
- Shelf space (s) = the average number of linear feet of shelf space allocated to a given category.
- Demand (D) = the average weekly unit sales in a category, where units are defined by the retailer.
- Size (x) = the average number of linear feet occupied by a unit in the given category.

Ideally, we would like to have store-specific data to estimate our model. In that case, the variations across stores for a given category would have allowed us to easily estimate the category-specific shelf-space parameter ϕ_i. However, our public data is restricted by its aggregate nature. To circumvent this problem and still illustrate our method, we grouped categories together into ten *supercategories*, using the original category observations as individual observations within a

[12]The costs included, among others, restocking costs, storage costs, average spoilage costs, costs associated with special shelf-space requirements (i.e. refrigeration), etc. A detailed explanation of these costs can be found in the *Direct Product Profitability Handbook*.

given supercategory and using the *IRI Marketing Factbook* (1995) to construct these supercategories. *The Factbook* groups all categories, except for meat and produce, into a series of supercategory aggregates. For instance, it specifies one supercategory called "health and beauty aids," which contains observations for categories such as shampoo, deodorant, analgesics, and other similar categories. We used the headings from *The Factbook* to construct eight of the ten supercategories. The remaining two, meat and produce, are not reported in this publication, but have very clear meanings.

5.2. Estimation Procedure

We now proceed to develop the estimation procedure for marketing profits. We show that, even with relatively sparse data, reasonable inferences can be made about marketing profits. We develop a set of assumptions that allows estimation within this type of data environment. As we lay out this procedure we will be careful to note where assumptions may be vacated if the retailer has access to store-level data across a sufficient number of stores.

To estimate marketing profits from observable data, we estimate ϕ_i, t_i, and h_i. Recall that $\phi_i = p_i'/p_i$ measures the percent increase in the probability of finding the favorite brand when shelf space is increased by one linear foot. The other two parameters are the costs of restocking the shelves and those of maintaining a foot of shelf space. To estimate ϕ_i, we need to estimate $p_i(s_i)$ first. Once the estimate of $p_i(s_i)$ is obtained, we can easily generate ϕ_i directly from its definition.

We can estimate $p_i(s_i)$ by using Equation (6), which we replicate below:

$$D_i = \alpha_{ii} p_i + \sum_{k \neq i} \alpha_{ki} p_k. \tag{26}$$

It is clear from Equation (26) that, as with almost any system of demand equations, some level of aggregation is necessary to perform this estimation. If we include all cross-category effects we would need to estimate at least 199^2 parameters, which is impossible given our limited data.

We need to make three assumptions to allow this demand structure to be tractable for estimation. First, we assume that for all categories i, j in the same supercategory c, $\alpha_{ii} = \alpha_{jj} = \alpha_c$. This means that the sales potential of each category from those consumers who use this category as the lead item on their shopping list is the same across all categories within a supercategory. Thus, the sales potential of tomatoes from tomatoes-focused consumers is the same as that of lettuce from lettuce-focused consumers. This assumption may be relaxed if cross-store data is available.

Second, we assume that $\alpha_{ki} = \alpha_{kj}$ for all $k \neq i, j$ if i and j belong to the same supercategory. In other words, the potential sales of categories i or j in the same supercategory to a consumer for whom category k is the lead category are the same. Thus, for instance, the potential sales of tomatoes and lettuce to the consumers who have shampoo as the lead category on their shopping lists are the same.

These assumptions allow us to write the demand for categories i and j in the supercategory c as

$$D_i = \alpha_c p_i + \sum_{m \neq i,j} \alpha_{mi} p_m + \alpha_{ji} p_j, \tag{27}$$

$$D_j = \alpha_c p_j + \sum_{m \neq i,j} \alpha_{mj} p_m + \alpha_{ij} p_i. \tag{28}$$

Notice that the only difference between these two expressions is in the $\alpha_{ji} p_j$ and $\alpha_{ij} p_i$ terms since $\alpha_{mi} = \alpha_{mj}$ from our second assumption. The effect of the common $\Sigma_{m \neq i,j}\, \alpha_{mi} p_m$ term, a summation over 197 categories in our application, will far outweigh the effect of the final $\alpha_{ji}\, p_j$ term. The practical implication of this is that we can treat $\Sigma_{m \neq i,j}\, \alpha_{mi} p_m + \alpha_{ji} p_j$ as constant, b_c, within a supercategory. Thus, the demand for category i can be closely approximated by

$$D_i = \alpha_c p_i + b_c. \tag{29}$$

Third, to facilitate our estimation, we assume that $p_i(s_i)$ takes the functional form

$$p_i(s_i) = \exp(-w_i/s_i). \tag{30}$$

We can verify that such a functional form has all the desirable properties as a probability function, $dp_i(s_i)/ds_i \geq 0$, $\lim_{s_i \to 0} p_i(s_i) = 0$, and $\lim_{s_i \to \infty} p_i(s_i) = 1$, and also exhibits the desired property of decreasing elasticity as the shelf space allocated to a category increases. This allows us to rewrite Equation (29) as

$$D_i = \alpha_c \exp(-w_i/s_i) + b_c. \tag{31}$$

Finally, in order to generate the variation in the data needed for estimation, we assume that w_i is constant within a supercategory. This implies that the shelf-space allocation decision for any category within a given supercategory affects consumers' shopping behavior in fundamentally the same way. Retailers with sufficient store-level data need not make this assumption. Conceptually, it is also possible to model w as a function of marketing mix variables as well as category-specific characteristics. However, we do not adopt this approach due to the aggregate nature of our data.

These assumptions allow us to estimate the following demand specification for each supercategory c as

$$\log D_{ci} = \log[b_c + \alpha_c \exp(-w_c/s_{ci})] + \epsilon_i \tag{32}$$

where $i \in c$. The log-log transformation is used because demands are all positive. We then estimate w_c from this nonlinear model, using the category-level observations within each supercategory, via the SAS NLIN procedure (a nonlinear regression estimator).[13]

Estimation of t_i and h_i proceeds directly from the cost specification in Equation (8). By assuming t_i and h_i are constant within a supercategory, for reasons mentioned previously, we can estimate t and h from the following linear model for each supercategory:

$$C_i = t\,\frac{x_i D_i}{s_i} + h s_i + v_i. \tag{33}$$

Notice that even though we have restricted w, t, and h to be the same within a supercategory this does not prevent us from obtaining marketing profit measures for each individual category. Since s_i, x_i, and D_i vary across categories, we can assign a unique MP value for each category.

5.3. Results

Table 3 reports the results from estimating w, t, and h.[14] All the parameter estimates have the expected signs except for the estimated h for bakery, which is highly insignificant. While these are intermediate constructs which will ultimately be used to calculate marketing profits, they are interesting in their own right. Our estimates suggest, for instance, that cost involved in one full restocking of the category Health and Beauty Aides is much more expensive than that of the category Meat for the retailer ($302.43 for HBA versus $10.05 for Meat). This is because the supercategory HBA has a large number of SKUs with diverse packaging. However, maintaining a linear foot of shelf space for Meat is much more expensive than maintaining the same length of shelf space for Health and Beauty Aides ($2.80 versus $0.29) since meat requires refrigeration.

The above intermediate constructs, in conjunction with observed category sales and margins allow us to compute marketing profits for each supercategory as well as each of the 199 categories by applying Equation (25). In Table 4 we provide the marketing and accounting profits for the supercategories, normalized by the number of linear feet allocated to the relevant supercategory. The supercategory Produce clearly dominates the others in terms of the marketing profits it generates. Our analysis suggests that heavy merchandising of products in this supercategory is very important in generating profits for the store. Given that survey results have indicated that produce quality is second only to neatness of store and competitive prices in determining store choice (*Progressive Grocer* 1997b), this result is particularly reassuring. Our analysis also suggests that four of the ten supercategories examined, Dairy, Meat, Deli, and Bakery, have negative marketing profits, while all but Bakery have positive accounting profits. Negative marketing profits can arise when the consumers who are attracted to the store by a category spend little on anything else or spend a lot on the items that are not profitable to the retailer, and yet the cost involved in maintaining the category is quite high. These categories make sizable accounting profits because they are on many people's shopping lists and they are add-ons to the retailer. Bakery is one supercategory that has both negative accounting and marketing profits. This is one supercategory that the retailer ought to take a hard look at to see if there are

[13]The demand data provided is measured in units. Since the unit used is different for different categories even within a supercategory (i.e. ounces for shampoo and "counts" for some analgesics), it is thus necessary to normalize the unit data using the average size of a unit within a category.

[14]The range of the R^2 fit statistic for Equation (32) (used to estimate w) is 0.47 to 0.99 with a mean of 0.77. The range of the R^2 statistic for Equation (33) (used to estimate t and h) is 0.66 to 0.95 with a mean of 0.83.

Table 3 Data Description and Results of Estimated Model

Supercategory	Number of Categories	Mean Dollar Sales	Demand Parameter (w)	Stocking Cost (f)	Shelf Maintenance Cost (h)
Health and Beauty Aides	23	378.02	24.58	302.43	0.29
		(371.80)	(5.87)	(66.95)	(0.06)
General Merchandise	11	433.10	86.51	21.21	0.67
		(278.40)	(124.98)	(24.74)	(0.06)
Edible Dry Grocery	34	2389.47	187.09	14.47	1.73
		(2680.71)	(31.68)	(51.65)	(0.16)
Nonedible Dry grocery	9	3058.35	276.71	85.49	2.00
		(3630.34)	(25.17)	(230.58)	(0.57)
Dairy	12	2398.28	104.60	31.21	6.24
		(3037.41)	(73.99)	(24.12)	(1.80)
Frozen Foods	22	1071.35	49.27	30.16	1.21
		(1144.81)	(15.13)	(22.75)	(0.22)
Deli	12	1554.35	64.25	160.20	1.38
		(1510.08)	(33.19)	(47.21)	(2.56)
Bakery	8	611.25	33.66	128.44	−5.34
		(468.56)	(33.84)	(23.43)	(5.79)
Meat	8	2844.13	17.85	10.05	2.80
		(2171.12)	(39.21)	(2.93)	(1.88)
Produce	60	347.45	6.30	24.24	4.59
		(509.73)	(0.66)	(2.73)	(0.33)

Note: Standard deviations in parentheses.

Table 4 Marketing and Accounting Profits of Supercategories

Supercategory	MP/Foot	AP/Food
Produce	$17.94	$3.98
Health and Beauty	$10.15	$1.41
Frozen Foods	$4.55	$4.11
General Merchandise	$2.27	$1.34
Edible Dry Grocery	$1.21	$2.41
Nonedible Dry Grocery	$.86	$2.12
Dairy	−$1.84	$9.10
Meat	−$2.96	$11.85
Deli	−$4.51	$6.77
Bakery	−$18.63	−$6.62

any other strategic reasons to continue carrying these products.

Interestingly enough, based on the feature fliers we collected from the chains Met Food Markets in New York, Schnucks Markets, Dierbergs, and National Supermarkets in St. Louis, and Giant Eagle and Shop-N-Save in Pittsburgh for the week of December 15, 1997, none of the six grocery retailers in three geographically distinct cities promoted bakery products. We further measured the square centimeters of feature ad space allocated to each supercategory in each of the feature flyers, and for each supermarket chain we ranked the supercategories by ad space allocated (since the feature flyers contained different amounts of overall ad space). We then ranked each supercategory by its estimated accounting profitability and marketing profitability.[15] The Spearman rank correlation between the total accounting profits of each supercategory and feature flyer ad space is $R = -0.37$, and is significant at the $p = 0.01$ level. The analogous measure for marketing profits is $R = 0.34$ and is also significant at the $p = 0.01$ level. Considering the fact that feature flyer advertising also depends on many other factors, for instance, the availability of trade promotions, the positive correlation found between the estimated

[15]These measures were not normalized by the number of feet allocated to the supercategory. This seems to be the more natural measure to use here.

marketing profits and feature advertising frequency and the negative correlation between accounting profits and ad frequency is quite remarkable and reassuring. This is by no means a test of our model, but it does seem to offer prima facie evidence that these retailers are emphasizing the products that our model suggests are important in generating marketing profits.

Table 5 provides the estimated marketing profits and accounting profits for several of the categories examined in this study. Instead of reporting these estimates for all 199 categories we chose instead to report the results for the most extreme categories. In particular, we report the five categories which had the highest estimated marketing profits as well as the five which had the lowest. Our results reveal that the retailer in our study will have a totally different perspective about a category depending on whether he/she evaluates the category by the accounting or marketing profits. Cosmetics, for instance, has the highest marketing profits of all categories examined, yet its accounting profits are quite modest. Salads appears to be a much more a lucrative category using traditional accounting profits than when we examine it through the lens of marketing profits. Snacks is one category that has both relatively high marketing and accounting profits.[16]

[16]The Pearson correlation between the category-level MP and AP is 0.25 and is significant. In 112 categories the sign of the accounting profits was the opposite of that of the accounting profits. This number is inflated by the fact that many of these reversals represent very small differences in absolute magnitude.

Table 5 **Categories with the Most Extreme Marketing Profits**

	Total Marketing Profits	Total Accounting Profits
Highest MP		
Cosmetics	\$9,378	\$76
Potatoes	\$5,510	\$590
Apples	\$2,852	\$574
Frozen Entrees	\$1,912	\$666
Snacks	\$1,799	\$2,155
Lowest MP		
Muffins	−\$384	−\$1,573
Fresh Bread	−\$468	−\$22
Ground Beef	−\$755	−\$551
Salads	−\$955	\$158
Doughnuts	−\$2,197	−\$135

The implied shadow price of shelf space/linear foot, λ, is \$1.23 (from Equation (53) in Appendix 2) with a standard deviation of 0.34.[17] This can be a very useful number for the retailer. If the retailer has information on the costs of expanding shelf space, the shadow price can help the retailer to determine whether further expansion of its store size is advisable.

6. Marketing Profits and Retail Decision Making

The concept of marketing profits and their measurement are important not only because they provide a retail manager with a different perspective on the profitability of a category, but also because they embody the management philosophy that focuses on customer profitability rather than direct product profitability. When Alfred Zeien, the chairman and CEO of Gillette, is asked about the secret of Gillette's success, he says: "We do not sell more units or raise prices; we earn more from each customer" (Koselka 1994). Such a customer focus is the key to the success of many manufacturers and retailers alike. However, a customer focus is actionable only if customer profitability can be measured. That is why, as Zeien intimates, "I keep that number in the upper right-hand drawer of my desk. It is my favorite statistic" (Koselka 1994). Indeed, as we will show in this section, it ought to be the favorite statistic of all retail managers as well if they seek to maximize a store's overall profits.

Our MP approach can be used in a number of decision-making situations by retailers. For example, the MP approach provides a more accurate measure of the performance of various categories, allowing retailers to develop better compensation plans for different departmental managers. It also provides retailers with information on the value of their shelf space (the shadow price of shelf space). This can be a useful statistic in slotting allowance negotiations. Finally, a retailer may use this information to better allocate his

[17]We used a Taylor expansion to compute the standard deviation of λ. Details are available from the authors upon request.

promotional resources such as feature advertising space.

Consider again the issue of allocating feature space among competing categories by a retailer. In the Introduction, we have addressed the issue of which category to feature briefly through a simple example. Let us now revisit this example to see how marketing profit helps allocate feature space between these two categories when both are featured.

Let f_p denote the total feature space allocated to produce and f_m the feature space allocated to meat. Considering for the moment only the produce category, the accounting profits (AP) and marketing profits (MP) for produce are given by

$$\mathrm{AP}_p = P(f_p) + p(f_m), \tag{34}$$

$$\mathrm{MP}_p = P(f_p) + m(f_p).$$

Many retailers delegate authority to category managers and provide them with accounting profit data for their respective categories. Note that the accounting profit does not account for the impact of feature advertising on the sales of meat since it is an artificially compartmentalized metric. The produce category manager, with the parochial interest of the category's profitability in mind, may naturally believe that feature advertising f_p only impacts sales through $P(f_p)$ and that the indirect effect $p(f_m)$ is essentially random and can be approximated with historic averages. If feature advertising for meat is typically at a level f_m^H, then the produce manager may treat the indirect sales as a constant, $p(f_m^H)$. Given that there has been some variation in the historical feature advertising, the produce manager who uses accounting profits as his metric for category profitability would believe that the marginal impact of changes in the feature advertising of produce on produce profitability is

$$\frac{d\mathrm{AP}_p}{df_p} = P'(f_p), \tag{35}$$

while if he uses marketing profits he would deduce the marginal impact to be

$$\frac{d\mathrm{MP}_p}{df_p} = P'(f_p) + m'(f_p). \tag{36}$$

Results for the meat category manager can be derived in a completely analogous manner.

Suppose the produce and meat category managers entered into a debate involving how best to allocate this best-food-of-the-day feature advertising space, the size of which we normalize to one, between the two categories. If they were using accounting profits, the debate would lead to the solution of the two equations

$$P'(f_p) = M'(f_m) \quad \text{and} \quad f_p + f_m = 1. \tag{37}$$

If instead these managers were using marketing profits, this would lead to the solution of the two equations

$$P'(f_p) + m'(f_p) = M'(f_m) + p'(f_m)$$

$$\text{and} \quad f_p + f_m = 1. \tag{38}$$

Naturally, using the marketing profits to make the feature space-allocation decision leads to the global optimum, while using the accounting profits lead to suboptimal feature advertising decisions.

The same logic applies to the general model. To see this, let f_i denote the fraction of feature advertising space allocated to category i. Feature advertising has the effect of either drawing more people to the store who put the category on top of their shopping list or increasing the purchases of the existing consumers who focus on the category. Recall from Equation (5) that α_{ik} represents the potential sales of k because i is the lead category on a shopping list which includes category k. Thus, in the context of our model, the short-term effect of feature advertising category i can be captured by a change in α_{ik}, i.e. $\alpha_{ik} = \alpha_{ik}(f_i)$, where $d\alpha_{ik}(f_i)/df_i > 0$, $d^2\alpha_{ik}(f_i)/d_i^2 < 0$ and $i, k = 1, \ldots, n$.[18]

If a retailer considers the full impact of featuring a product category from the perspective of consumer profitability, i.e. allocating feature space to maximize the sum of each category's marketing profits, it solves the following optimization problem (total feature space is normalized to one):

$$\max_{(f_1, \ldots, f_n)} \sum_{i=1}^{n} \left\{\tilde{m}_i \alpha_{ii}(f_i) p_i(s_i^*) + \left(\sum_{k \neq i} \tilde{m}_k \alpha_{ik}(f_i)\right) p_i(s_i^*) - h_i s_i^*\right\}, \tag{39}$$

[18] Since α_{ik} and $p_i(s_i)$ always appear together in our demand formulation, we can also interpret the effect as enhancing the awareness of the category's availability among those consumers who focus on the featured category.

$$\text{s.t.} \sum_{i=1}^{n} f_i \leq 1 \text{ and } f_i \geq 0 \quad \text{for } i = 1, \ldots, n.$$

The solution to the problem determines the optimal allocation of feature space $\mathbf{f}^{MP} = (f_1^{MP}, \ldots, f_n^{MP})$ and the corresponding store profits $\Pi(\mathbf{f}^{MP})$.

A category manager focusing on the accounting profit of the category under his supervision will learn from Equation (9) that

$$\pi_i(\mathbf{s}, \mathbf{f}) = \tilde{m}_i[\alpha_{ii}(f_i)p_i(s_i^*) + \sum_{k \neq i} \alpha_{ki}(f_k)p_k(s_k^*)] - h_i s_i^*. \quad (40)$$

Notice that the terms inside the summation include the response function $\alpha_{ki}(f_k)$, but not $\alpha_{ik}(f_i)$. Category i is given accounting profits when category k has feature advertising f_k and draws customers to the store who also buy in category i. The category manager who need not and does not think across product categories will naturally treat the indirect effects $\Sigma_{k \neq i}\alpha_{ki}(f_k)p_k(s_k^*)$ as essentially random and approximate them with historic averages. If feature advertising is typically at a level f_k^H, then the category i manager may treat the indirect sales as a constant,

$$\sum_{k \neq i} \alpha_{ki}(f_k^H)p_k(s_k^*) \equiv q_i^H. \quad (41)$$

In this case, a retailer using accounting profits may resolve the feature advertising problem by solving

$$\max_{(f_1, \ldots, f_n)} \sum_{i=1}^{n} \{\tilde{m}_i\alpha_{ii}(f_i)p_i(s_i^*) + q_i^H - h_i s_i^*\} \quad (42)$$

$$\text{s.t.} \sum_{i=1}^{n} f_i \leq 1 \text{ and } f_i \geq 0 \quad \text{for } i = 1, \ldots, n.$$

Denote the solution to this problem by $\mathbf{f}^{AP} = (f_1^{AP}, \ldots, f_n^{AP})$. If the market place is in equilibrium, then the historic values equal the solution, i.e. $f_i^{AP} = f_i^H$, and the corresponding store profits are $\Pi(\mathbf{f}^{AP})$.

Although the retailer is correct in tabulating the profits of each category in both cases, the allocation based on compartmentalized accounting profits in the second case always leads to a lower overall profit for the store than the allocation based on marketing profits, i.e. $\Pi(\mathbf{f}^{AP}) \leq \Pi(\mathbf{f}^{MP})$. Indeed, even if a retailer is sophisticated enough to pay attention to the linkages among categories, he can still benefit from this paradigm shift. We show in Appendix 3, that as long as the retailer does not fully account for the indirect effects, $\Sigma_{k \neq i}\alpha_{ki}(f_k)p_k(s_k^*)$, in allocating its feature space, its allocation is always suboptimal. Since only marketing profits can guarantee the full consideration of the indirect effects, it pays for a retailer to measure and focus on marketing profits.

Marketing profits are important not only because they embody the right managerial perspective on category profitability, but also because they provide both the right measurements for trade-off analysis and an actionable statistic for retail decision making. We can see this clearly if we let $\alpha_{ij}(f_i)$ take on the specific logarithmic functional form

$$\alpha_{ij}(f_i) = \alpha_{ij}\left[1 + \mu \frac{\log(1 + \omega f_i)}{\log(1 + \omega)}\right]. \quad (43)$$

In Equation (43), $\alpha_{ij}(f_i)$ converges to the constant α_{ij} if no feature space is allocated to category i, and μ is the maximum possible percentage increase in $\alpha_{ij}(f_i)$ if all feature space is allocated to category i. For $0 < f_i < 1$, Equation (43) exhibits all the desirable properties as a response function: $\partial\alpha_{ik}(f_i)/\partial f_i > 0$ and $\partial^2\alpha_{ik}(f_i)/\partial f_i^2 < 0$. The responsiveness of $\alpha_{ij}(f_i)$ to the change in f_i depends on the scaling factor $\omega \in [0, \infty)$. If $\omega = 0$, the percentage increment in $\alpha_{ij}(f_i)$ is directly proportional to the increment in f_i, i.e. $\partial\alpha_{ij}(f_i)/\partial f_i = \alpha_{ij}\mu$. As ω becomes larger, $\alpha_{ij}(f_i)$ becomes less responsive to the change in f_i, i.e. $\partial^2\alpha_{ij}(f_i)/\partial f_i\partial\omega < 0$. However, the effect of ω on the responsiveness is very gradual. For instance, to reduce $\partial\alpha_{ij}(f_i)/\partial f_i$ from $\alpha_{ij}\mu$ when $\omega = 0$ to one half of the magnitude, ω needs to be about 200,000.[19] Thus, for all practical purposes, ω can be treated as a very large number.

With the specific response function (43), we can provide an explicit solution to (39). Our analysis shows that to allocate feature space optimally, a retailer should never assign any feature space to a category that earns zero or negative marketing profit excluding fixed shelf maintenance costs, $\mathrm{MP}_i + h_i s_i^* \leq 0$, regardless of the magnitude of its accounting profit (see Appendix 4). For any other category, the optimal allocation of feature space is given by

[19]This estimation assumes $f_i = 0.1$. For $f_i < 0.1$, which is typically the case, the number becomes even larger.

$$f_i^* = \frac{N_1 + \omega}{\omega} \frac{\mathrm{MP}_i + h_i s_i^*}{\sum_{i=1}^{N_1} \mathrm{MP}_i + h_i s_i^*} - \frac{1}{\omega}, \tag{44}$$

where N_1 is the total number of categories satisfying $\mathrm{MP}_i + h_i s_i^* > 0$. Note that $(N_1 + \omega)/\omega$ in Equation (44) is approximately 1 and $1/\omega$ approximately zero when ω is very large. Thus, for any practical application, feature space can be allocated based on the following formula:

$$f_i^{\mathrm{MP}} = \frac{\mathrm{MP}_i + h_i s_i^*}{\sum_{i=1}^{N_1} (\mathrm{MP}_i + h_i s_i^*)}. \tag{45}$$

This formula provides a very intuitive rule for allocating feature space on the basis of marketing profits: allocate feature space to a category in relation to its marketing profit relative to that of all categories having positive contribution to store profit, excluding any shelf-maintenance costs.

Similarly, we can derive the corresponding formula for allocating feature space on the basis of accounting profits. It is given by

$$f_i^{\mathrm{AP}} = \frac{\tilde{m}_i \alpha_{ii} p_i(s_i^*)}{\sum_{i=1}^{N_2} \tilde{m}_i \alpha_{ii} p_i(s_i^*)}, \tag{46}$$

where N_2 is the number of categories that satisfy $\tilde{m}_i \alpha_{ii} p_i(s_i^*) > 0$.

Since our estimation in the previous section provides all necessary information to use Formulas (45) and (46), we can easily assess Marsh Supermarkets's profit gain from allocating feature space based on marketing rather than accounting profits. Table 6 lists the allocations based on the two formulas and corresponding profits for the ten supercategories. The incremental profit gain from using marketing profits instead of accounting profits to make feature advertising allocation decisions is 23% when $\omega = 1.5$ million and 36% when $\omega = 50{,}000$.[20] Our analysis has shown that a retailer can substantially improve profitability by allocating feature space based on marketing rather than accounting profits.

This example also shows the benefit of our theoretical approach in simplifying this allocation decision for practitioners. With our approach, a retailer can first estimate marketing profits for each category, which is possible with even very sparse data as we have shown, and then simply apply the proportional rule in Equation (45). If one were to follow a more conventional approach, namely first regressing total store profit against the feature space allocations of each category and then carrying out the constrained optimization, the task would be formidable. There are three major problems with this approach. First, it requires a long time-series to generate accurate and stable estimates of even a simple specification. Second, the coefficients in a macro-level regression model are likely to be correlated since consumers' response to feature advertising is correlated across categories (Ainslie and Rossi 1998). Ignoring this correlation will reduce the efficiency of the estimation, which is particularly troublesome given the data limitations that retailers are likely to face. Finally, even if a response fuction is estimated, the constrained optimization problem is still unwieldy.[21] Our MP approach circumvents these problems for practitioners.

7. Conclusion

One-stop shopping and the large grocery superstores have reinforced the notion that assortments are important in consumer store choice decisions and that the sales of all products in the store are interrelated. The retail assortment contributes directly and indirectly to profits because consumers make their purchase decisions in two stages: first, which store to shop at, and second, what items to buy. The direct profit focuses primarily on the second stage, measuring the total purchases of a category of merchandise. The indirect profit focuses more on the first stage, trying to gauge how much of all sales in the store were attributed to store-draw power of one category.

[20]The percentage increase in incremental profits was calculated by $(\Pi(f^{\mathrm{MP}}) - \Pi(f^{\mathrm{AP}}))/(\Pi(f^{\mathrm{AP}}) - \Pi(f = 0))$ where $\Pi(f = 0)$ indicates the baseline case of no feature advertising. We calculated the profits for the case where $\mu = 0.01$ and $\mu = 0.05$. The results were insensitive to this change in the parameter value.

[21]The authors have performed a simulation to compare different macro-level regression approaches to the MP approach presented here. These results are available from the authors upon request.

Table 6 **Allocating Feature Space by Marketing and Accounting Profits**

Supercategory	f^{MP}	f^{AP}	MP(f^{MP})		MP(f^{AP})	
Produce	29.7	.9	13,606	13,670	13,290	13,422
Health and Beauty	20.1	2.7	11,686	11,716	11,517	11,588
Frozen Foods	13.8	9.3	6,537	6,571	6,510	6,551
General Merchandise	4.3	1.6	1,987	2,000	1,974	1,990
Edible Dry Grocery	19.9	37.6	5,070	5,124	5,083	5,134
Non-Edible Dry Grocery	6.5	24.9	1,236	1,252	1,257	1,269
Dairy	3.8	9.7	−829	−817	−820	−811
Meat	1.5	1.0	−787	−782	−792	−786
Deli	0.4	12.1	−1,966	−1,964	−1,979	−1,980
Bakery	0.0	0.1	−3,763	−3,763	−3,767	−3,768

Note: Profits are calculated based on $\mu = 0.05$; $\omega = 50{,}000$ (the first column in MP) and $\omega = 1{,}500{,}000$ (the second column in MP). Feature advertising allocations are given as a percent of the total feature space available.

The concept of marketing profits for a category incorporates both direct and indirect profits, while the more traditional accounting profits paint only part of the picture by concentrating on direct product profit. The marketing profits provide category managers with better information to make merchandising decisions than accounting profits, but marketing profits are not easily calibrated. When a purchase is made, the only information recorded is that a particular unit was sold at a particular price. The motive of that consumer, at this store, buying that particular item is latent and unrecorded. For example, it is possible that all the sales of salad dressing and croutons would never have occurred had the store not carried an excellent assortment of fresh produce for salads, so the whole basket should really count as sales of "augmented" fresh produce. But who would know that except the consumer?

Without explicit knowledge of the plan that the shopper had for selecting a store and buying items at the store, a degree of guesswork is always involved in measuring marketing profits. Our method for calculating the marketing profits of product categories substitutes the observed sales per unit of shelf-space for the unobserved shopping list under the assumption that the store manager has taken great care and/or has been disciplined by the market competition to allocate scarce shelf space toward those categories whose total contribution to store profits is largest. However, they do so intuitively, without knowing precisely what are direct and indirect profits of a category, much in the same way that a consumer can intuitively maximize utility without knowing the calculus of constrained optimization. We are implicitly assuming that the shelf-space problem is slowly changing so that the retailer can adjust toward the optimal allocation that we model formally.

While shelf-space allocation decisions may be closer to being optimal than not, the same cannot be said about promotional decisions as ample trade press would testify. This is because (1) promotional opportunities come and go due to manufacturers' initiatives; (2) promotional decisions are short-term decisions that typically involve a lower level of management and are decentralized; (3) consumer's preference at the category level is much less fickle than at the brand level; and (4) it is much harder to disentangle any promotional effect when many things are compounded. Thus, for promotional decisions, intuition is harder to develop and is less of a guide as circumstances frequently change. Knowing precisely what each category will bring to a store when the category is merchandised is managerially important and necessary for promotion and other decisions. This is where our measure of marketing profits can help.

The approach we are taking is that the stable, long term, category-level decision of shelf-space allocation helps us to pin down the implied marketing profits, which can in turn guide a retailer's short-term and transitory decisions such as feature advertising, and help to institutionalize the perspective of customer focus. Our method of measuring marketing profits does not require additional marketing research to discover the pattern of shopping lists used by consumers. It only requires commonly available information like sales, shelf-space allocation, and merchandising costs.

The method can be improved with additional research. The data that we used to demonstrate the measurement of marketing profits was data that is readily available, but it forced us to pool categories into supercategories in order to have sufficient variation to perform the estimation. The shortcoming of the data also restricts us from using more general functions for estimating demand response functions. Other scholars, and certainly supermarket chains, have access to data across many stores and would not have to aggregate this way; they would have variability in shelf space within the chain of stores. In fact, others may want to carry out an analysis at a level of aggregation below that of the category (brand level). Other researchers may choose to measure marketing profits by other methods, such as consumer surveys of shopping lists.

Our research began with a simple model of shopping lists and store choice. It was simple because we were using it as a means to an end. Additional research on prioritized shopping lists and store choice is just one of many issues that we hope will be sparked by our effort at practical measurement of marketing profits.[22]

Appendix 1

Table 1A **Notation**

A	The assortment of product categories carried by the retailer
B	A market basket
L	A shopping list—an ordered vector formed from a market basket
$\mathcal{L}$	The set of all possible shopping lists
l_j	The jth item on the shopping list
β_L	The fraction of consumers who use shopping list L on a given purchase occasion
p_j	The consumer's subjective probability that their preferred brand j will be available at the store
z_L	Coefficient measuring the impact of the marketing mix on store choice for a consumer with shopping list L
u_{iL}	The number of units purchased on a shopping trip from category i by a consumer with shopping list L
D_i	The expected unit demand for category i
α_{ii}	The potential sales of i because category i is the lead category on the shopping list
α_{ki}	The potential sales of i because k is the lead category on a shopping list that includes category i
s_i	The shelf spacee allocated to category i
$\mathbf{s}$	A vector of all shelf-space allocations $(s_1, s_2, \ldots, s_n)$
$\bar{S}$	The total shelf space available to the retailer
$p_i(s_i)$	A smooth monotonically increasing function which maps the shelf space allocated to category i to the consumer's subjective probability of their preferred brand's availability
m_i	Category i's retail gross margin
$\tilde{m}_i$	The net contribution margin for category i
C_i	The total cost of merchandising category i
x_i	The linear shelf space occupied by one unit of category i
t_i	Category i's cost per restocking
h_i	The cost associated with maintaining one linear unit of shelf space, net of restocking costs, for category i
$\tilde{h}_i$	The cost per linear foot of expanding shelf space for category i
MP_i	The total marketing profit of category i
$\Pi(\mathbf{s})$	The total store profit given some space allocation $\mathbf{s}$
$\Pi(\mathbf{s}_{-i})$	The total store profits when all consumers with category i as their lead category decide to shop elsewhere
λ	The shadow price of shelf space

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Appendix 2

Equation (10) can be rewritten as

$$\Pi(\mathbf{s}) = \sum_i \pi_i(\mathbf{s}) = \sum_i p_i(s_i)\Big[\tilde{m}_i\alpha_{ii} + \sum_{k\neq i} \tilde{m}_k\alpha_{ik}\Big] - \sum_i h_i s_i. \tag{47}$$

To simplify notation, we define

$$\tilde{h}_i = h_i - \frac{t_i x_i D_i}{s_i^2}, \tag{48}$$

$$\phi_i = \frac{dp_i(s_i)/ds_i}{p_i(s_i)}. \tag{49}$$

Then the optimization of shelf-space allocation implies

$$\Big(\tilde{m}_i\alpha_{ii} + \sum_{k\neq i} \tilde{m}_k\alpha_{ik}\Big)p_i(s_i^*)\phi_i - \tilde{h}_i = \lambda \tag{50}$$

for all $i = 1, 2, \ldots, n$. From Equation (50), we further have

$$\Big(\tilde{m}_i\alpha_{ii} + \sum_{k\neq i} \tilde{m}_k\alpha_{ik}\Big)p_i(s_i^*) = \frac{\lambda + \tilde{h}_i}{\phi_i}. \tag{51}$$

Summing up both sides of Equation (51) and using Equation (6), we get

$$\sum_i \tilde{m}_i D_i = \sum_i \frac{\lambda + \tilde{h}_i}{\phi_i}. \tag{52}$$

Solving for λ, the shadow price of shelf space, from (52) we get

$$\lambda = \Big(\sum_i \tilde{m}_i D_i - \sum_i \frac{\tilde{h}_i}{\phi_i}\Big)\Big/\Big(\sum_i \frac{1}{\phi_i}\Big). \tag{53}$$

From our definition for $\mathrm{MP}_i(\mathbf{s}^*)$ in Equation (11), we have

$$\begin{aligned}\mathrm{MP}_i(\mathbf{s}^*) &= \Pi(\mathbf{s}^*) - \Pi(\mathbf{s}^*_{-i}) - h_i s_i^* \\ &= \Big(\tilde{m}_i\alpha_{ii} + \sum_{k\neq i} \tilde{m}_k\alpha_{ik}\Big)p_i(s_i^*) - h_i s_i^*, \end{aligned}\tag{54}$$

which from Equation (51) implies

$$\mathrm{MP}_i(\mathbf{s}^*) = \frac{\lambda + \tilde{h}_i}{\phi_i} - h_i s_i^*. \tag{55}$$

By combining Equations (53) and (55), we can express marketing profits in terms of D_i, $\tilde{m}_i$, $\tilde{h}_i$, h_i, s_i^*, and ϕ_i as

$$\mathrm{MP}_i(\mathbf{s}^*) = \frac{\left(\sum_{i=1}^{n} \tilde{m}_i D_i - \sum_{i=1}^{n} \frac{\tilde{h}_i}{\phi_i}\right) \Big/ \left(\sum_{i=1}^{n} \frac{1}{\phi_i}\right) + \tilde{h}_i}{\phi_i} - h_i s_i^*. \tag{56}$$

We can show that

$$\sum_i \mathrm{MP}_i = \sum_{i=1}^{n} \pi_i.$$

First note that

$$\sum_i \mathrm{MP}_i = \sum_i \left(\frac{\lambda + \tilde{h}_i}{\phi_i} - h_i s_i\right).$$

By substituting in λ from Equation (53), we have

$$\begin{aligned}
\sum_{i=1}^{n} \mathrm{MP}_i &= \sum_{i=1}^{n} \left(\frac{\dfrac{\sum_{i=1}^{n} \tilde{m}_i D_i - \sum_{i=1}^{n} \frac{\tilde{h}_i}{\phi_i}}{\sum_{i=1}^{n} \frac{1}{\phi_i}} + \tilde{h}_i}{\phi_i} - h_i s_i \right) \\
&= \sum_{i=1}^{n} \tilde{m}_i D_i - \sum_{i=1}^{n} \frac{\tilde{h}_i}{\phi_i} + \sum_{i=1}^{n} \frac{\tilde{h}_i}{\phi_i} - \sum_{i=1}^{n} h_i s_i \\
&= \sum_{i=1}^{n} (\tilde{m}_i D_i - h_i s_i) \\
&= \sum_{i=1}^{n} \left[m_i D_i - \left(\frac{t_i x_i}{s_i} D_i + h_i s_i \right) \right] \\
&= \sum_{i=1}^{n} (m_i D_i - C_i) = \sum_{i=1}^{n} \pi_i. \quad \text{Q.E.D.}
\end{aligned}$$

Appendix 3

Define the following optimization problem:

$$\begin{aligned}
\max_{(f_1, \ldots, f_n)} \sum_{i=1}^{n} \Bigg\{ &\tilde{m}_i \alpha_{ii}(f_i) p_i(s_i^*) + \left(\sum_{k \neq i} \tilde{m}_k \alpha_{ik}(f_i)\right) p_i(s_i^*) - h_i s_i^* \\
&+ \delta \sum_{k \neq i} \tilde{m}_k [\alpha_{ik}(f_i^{\mathrm{AP}}) - \alpha_{ik}(f_i)] p_i(s_i^*) \Bigg\},
\end{aligned} \tag{57}$$

$$\text{s.t.} \sum_{i=1}^{n} f_i \leq 1,$$

where $0 \leq \delta \leq 1$. Let $\mathbf{f}^\delta = (f_1^\delta, \ldots, f_n^\delta)$ denote the solution to the problem and $\Pi(\mathbf{f}^\delta)$ the corresponding profits. By definition, we have $\Pi(\mathbf{f}^0) = \Pi(\mathbf{f}^{\mathrm{MP}})$ and $\Pi(\mathbf{f}^1) = \Pi(\mathbf{f}^{\mathrm{AP}})$. For any given $1 \geq \delta \geq 0$, we have $\Pi(\mathbf{f}^{\mathrm{MP}}) \geq \Pi(\mathbf{f}^\delta)$. This is shown below:

$$\begin{aligned}
\Pi(\mathbf{f}^\delta) &= \sum_{i=1}^{n} \Bigg\{ \tilde{m}_i \alpha_{ii}(f_i^\delta) p_i(s_i^*) + \left(\sum_{k \neq i} \tilde{m}_k \alpha_{ik}(f_i^\delta)\right) p_i(s_i^*) - h_i s_i^* \\
&\quad + \delta \sum_{k \neq i} \tilde{m}_k [\alpha_{ik}(f_i^{\mathrm{AP}}) - \alpha_{ik}(f_i^\delta)] p_i(s_i^*) \Bigg\} \\
&= (1 - \delta) \left[\sum_{i=1}^{n} \left\{ \tilde{m}_i \alpha_{ii}(f_i^\delta) p_i(s_i^*) + \left(\sum_{k \neq i} \tilde{m}_k \alpha_{ik}(f_i^\delta)\right) p_i(s_i^*) - h_i s_i^* \right\} \right] \\
&\quad + \delta \left[\sum_{i=1}^{n} \left\{ \tilde{m}_i \alpha_{ii}(f_i^\delta) p_i(s_i^*) + \left(\sum_{k \neq i} \tilde{m}_k \alpha_{ik}(f_i^{\mathrm{AP}})\right) p_i(s_i^*) - h_i s_i^* \right\} \right] \\
&\leq (1 - \delta) \left[\sum_{i=1}^{n} \left\{ \tilde{m}_i \alpha_{ii}(f_i^{\mathrm{MP}}) p_i(s_i^*) + \left(\sum_{k \neq i} \tilde{m}_k \alpha_{ik}(f_i^{\mathrm{MP}})\right) p_i(s_i^*) - h_i s_i^* \right\} \right] \\
&\quad + \delta \left[\sum_{i=1}^{n} \left\{ \tilde{m}_i \alpha_{ii}(f_i^{\mathrm{AP}}) p_i(s_i^*) + \left(\sum_{k \neq i} \tilde{m}_k \alpha_{ik}(f_i^{\mathrm{AP}})\right) p_i(s_i^*) - h_i s_i^* \right\} \right]
\end{aligned} \tag{58}$$

$$\begin{aligned}
&\leq (1 - \delta) \left[\sum_{i=1}^{n} \left\{ \tilde{m}_i \alpha_{ii}(f_i^{\mathrm{MP}}) p_i(s_i^*) + \left(\sum_{k \neq i} \tilde{m}_k \alpha_{ik}(f_i^{\mathrm{MP}})\right) p_i(s_i^*) - h_i s_i^* \right\} \right] \\
&\quad + \delta \left[\sum_{i=1}^{n} \left\{ \tilde{m}_i \alpha_{ii}(f_i^{\mathrm{MP}}) p_i(s_i^*) + \left(\sum_{k \neq i} \tilde{m}_k \alpha_{ik}(f_i^{\mathrm{MP}})\right) p_i(s_i^*) - h_i s_i^* \right\} \right] \\
&= \sum_{i=1}^{n} \left\{ \tilde{m}_i \alpha_{ii}(f_i^{\mathrm{MP}}) p_i(s_i^*) + \left(\sum_{k \neq i} \tilde{m}_k \alpha_{ik}(f_i^{\mathrm{MP}})\right) p_i(s_i^*) - h_i s_i^* \right\} = \Pi(\mathbf{f}^{\mathrm{MP}}).
\end{aligned} \tag{59}$$

Inequality (58) comes from the fact that $\mathbf{f}^{\mathrm{MP}}$ and $\mathbf{f}^{\mathrm{AP}}$ are, respectively, the solutions to optimization problems (39) and (42) in the text. Inequality (59) comes from the fact that $\mathbf{f}^{\mathrm{MP}}$ is the optimal solution to problem (39). $\Pi(\mathbf{f}^{\mathrm{MP}}) > \Pi(\mathbf{f}^\delta)$ holds strictly if $0 \leq \delta < 1$. Q.E.D.

Appendix 4

Let λ_i be the Kuhn-Tucker multipliers for nonnegativity constraint, where $i = 1, \ldots, n$, and λ_0 is feature space constraint. Then, the first-order conditions for a solution to (39) are given by

$$\left[\tilde{m}_i \frac{\partial \alpha_{ii}}{\partial f_i} + \sum_{k \neq i} \tilde{m}_k \frac{\partial \alpha_{ik}}{\partial f_i}\right] p_i(s_i^*) + \lambda_i - \lambda_0 = 0, \tag{60}$$

$$\lambda_i \geq 0 \text{ for all } i \text{ and } \lambda_i = 0 \text{ if } f_i^{\mathrm{MP}} > 0, \tag{61}$$

$$\lambda_0 \geq 0 \text{ and } \lambda_0 = 0 \text{ if } \sum_{i=1}^{n} f_i^{\mathrm{MP}} < 1. \tag{62}$$

Since feature space will always be fully allocated, we must have $\lambda_0 > 0$ and $\Sigma_{i=1}^n f_i^{\mathrm{MP}} = 1$. Furthermore, from (60) and (61), any category that has positive allocation of feature space ($f_i^{\mathrm{MP}} > 0$) must satisfy the condition

$$\left[\tilde{m}_i \frac{\partial \alpha_{ii}}{\partial f_i} + \sum_{k \neq i} \tilde{m}_k \frac{\partial \alpha_{ik}}{\partial f_i}\right] p_i(s_i^*) > 0,$$

since $\lambda_0 > 0$. By using (43) and the definition of MP in the text, we can reduce the condition to $\mathrm{MP}_i + h_i s_i^* > 0$.

Thus, for all categories with $\mathrm{MP}_i + h_i s_i^* > 0$, we must have

$$\frac{\mu\omega}{(1 + \omega f_i^{\mathrm{MP}}) \log(1 + \omega)} [\mathrm{MP}_i + h_i s_i^*] - \lambda_0 = 0, \quad (63)$$

$$\sum_{i=1}^{N_1} f_i^{\mathrm{MP}} = 1. \quad (64)$$

From Equation (63), we get

$$\frac{\mu\omega}{\lambda_0 \log(1 + \omega)} [\mathrm{MP}_i + h_i s_i^*] = 1 + \omega f_i^{\mathrm{MP}}. \quad (65)$$

Summing up both sides of Equation (65) for all categories with $\mathrm{MP}_i + h_i s_i^* > 0$ and using Equation (64), we can solve for λ_0 as

$$\lambda_0 = \frac{\mu\omega}{(N_1 + \omega) \log(1 + \omega)} \sum_{i=1}^{N_1} [\mathrm{MP}_i + h_i s_i^*].$$

Substituting λ_0 back into (65), we can solve for f_i^{MP} as Equation (44) in the text. Q.E.D.

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