Planning Merchandising Decisions to Account for Regional and Product Assortment Differences

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The last decade has fundamentally changed the face of retailing. The genesis has been increased customer fragmentation, enabling technologies such as the internet and increased competition. In this era of "hypercompetition," retailers need to have a better understanding of the performance of individual stores so they can more accurately plan their merchandise assortments and set more realistic merchandising goals. In this paper, we determine the performance of retail outlets relative to the "best practice" set of outlets and demonstrate the importance of accommodating both regional and assortment differences. We empirically assess the performance of stores from a major Fortune 500 multinational retailing chain. Multiple inputs and outputs from 59 stores in three regions were used to determine sales goals for two different product categories. The results of three alternative models suggest that incorporating both assortment and regional differences significantly affects both performance and predicted sales volume estimates. Implications and avenues for future research are discussed.

The retail environment has become much more competitive over the past few decades. The growth of national specialty store chains (e.g., The Gap, Crate and Barrel) and category killers (e.g., Toys 'R' Us, Sports Authority) have significantly altered the retail landscape. These retailers have tended to take over their respective categories and consequently decimated many smaller, less efficient retailers.

There has also been an increase in customer fragmentation as smaller and smaller groups of customers demand products and services tailored to their individual needs (Bessen 1993; Blattberg and Deighton 1991; Kahn and McAllister 1997). Retailers are

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responding to these customer demands by embracing new technologies such as data base marketing and mass customization (Gilmore and Pine 1997). For example, made-to-measure Levi's are now available in some of their stores. Similarly, Custom Foot in Westport Connecticut can deliver a custom-made shoe from Italy in two weeks at mass-produced prices.

Another key driver of change in the structure of retailing is electronic commerce. For example, Dell and Gateway computers are each selling more than three million dollars every day on the Internet, whereas computer sales through traditional retailers have had flat to declining revenues (*Business Week*, March 23, 1998, p. 28–31).

All of these change drivers (e.g., category specialists, customer fragmentation, and technology) suggest that store-based retail chains must maintain cutting edge information systems to compete. In particular, they need to be able to accurately measure merchandise performance, predict the sale of merchandise categories, and identify and correct problems at the individual store level. For example, an automobile dealer may be a highly rated franchisee because its total sales of automobiles and light trucks are high. However, closer analysis might indicate that the proportion of light trucks sold is well below the norm, compared with similar dealers with similar locational properties. This type of performance information, along with a prediction of what the sale of light trucks should be, would provide a signal of potential problems. Further investigation might determine, for instance, that the sales of light trucks were low because of a poor inventory position, ineffective sales training, or poor promotions.

The previous example highlights the need to better understand the operations of individual stores so that their performance can be maximized. Unfortunately retailers typically rely on aggregate measures, such as sales per square foot, gross margin, inventory turnover, and GMROI, to plan and evaluate the performance of individual stores and departments within those stores. These measures are used to compare the performance of different stores, departments, as well the managers and buyers who run them. Unfortunately, as the car dealer example indicated, they can provide false signals for both planning and evaluating merchandising performance. Instead, we suggest that the planning and evaluation of merchandising activities be performed at a more disaggregate level using Data Envelopment Analysis (DEA). DEA allows managers to plan and evaluate the performance of similar operating entities. In essence apples are compared with other apples, rather than oranges.

The objective of this paper, therefore, is to demonstrate how to measure better the efficiency of a retail chain by dissagregating sales to consider certain characteristics that may effect a category's or a store's performance. In particular, we examine the effects of the disaggregation of two factors: regional and assortment differences. It is important for retailers to have a complete understanding of the efficiency of each outlet so they can distinguish between excellent and mediocre performers. Once the parameters of excellence are known, the mediocre stores can be modeled after the excellent ones. Also, because store managers' evaluations are based on the performance of their stores, it is important that their performance be evaluated in a fair and equitable fashion. Retailers also need to understand exactly why a store is performing the way that it is. For instance, are the successes or failures a result of managerial action, or an artifact of some environmental factor? In spite of the importance of the topic, the issue has not been extensively examined in the literature (see Kamakura, Lenartowicz, and Ratchford 1996).

There are three benefits to the proposed method. First, stores are evaluated against comparable "best practice" stores rather than the "average performers" traditionally used in mean-based analyses such as multiple regression. Not only is this type of evaluation more fair and accurate, but it also enables managers to determine how far they need to go to become a "best practice" store based on slack analyses. Second, performance is disaggregated at the category level, thus avoiding the potentially misleading and even inaccurate performance benchmarks inherent in using overall sales. Finally, regional differences are controlled because these differences can play a major role in determining the performance of a store.

We first examine the underpinnings of our approach to assortment planning. This discussion is followed by an examination of the concept of efficiency, and how retailers can utilize information on store efficiency in their merchandise planning process. Then, we illustrate the use of DEA for merchandise planning purposes. Specifically, the results of three analyses that test and assess the effects of assortment and regional differences on efficiency estimates and sales projections are reported. Finally, implications and avenues for future research are discussed.

ASSORTMENT AND REGIONAL PLANNING, AND STORE PERFORMANCE

The best retailers have learned to adjust their assortment by region to better meet the needs of customers. For example, Burdines, the Florida-based division of Federated Department Stores, carries a somewhat different assortment of goods than Macy's (although they are also owned by Federated). Because of the assortment differences, it would not be fair to compare the performance of a Burdines store with a Macy's store in Orlando, Florida. This situation is further complicated if regional effects are taken into consideration. Macy's roots are in New York, whereas Burdines is a Florida chain. Therefore, even if the stores were to carry exactly the same merchandise, the patronage of these stores would be somewhat dependent upon the number of "New York Transplants" shopping in Florida to the "Native Floridians." Therefore, the Macy's store in Orlando, Florida should not be directly compared with either a Burdines store in Orlando or a Macy's store in New York. The correct comparison would be another Macy's store in Florida.

With this introduction, we review the literature on assortment and regional planning for retailers. Retailers have traditionally varied their assortments to appeal to specific customer groups, provide variety to customers, and to cross-sell products and services. The merchandise assortment itself has become an effective method to attract and retain core customers. Harley Davidson has effectively used this strategy by combining lifestyle accessories in combination with their motorcycles. Range Rover has also successfully used this formula by redesigning their dealerships to teach customers how to drive Range Rovers as well as sell merchandise. Second, merchandise assortment strategies, such as scrambled merchandise, provide variety to customers and appeal to variety-seekers (Kahn 1995; Kahn and Lehmann 1991; Kahn and McAlister 1997). Finally, bundling products and services facilitates cross selling to larger segments (Yadav and Monroe 1993). For example, Best Buy sells a bundle consisting of a computer and an extended service contract to a segment that typically only bought computers and did not consider their service needs.

Retail chains are developing store formats that integrate regional differences to better meet customer needs. They realize, for instance, that more petite sizes are needed in areas where there is a high Hispanic or Asian population. Also, wider assortments of apparel should be found in smaller towns because there are usually fewer apparel outlets for customers than large towns offer. How do some stores fine-tune their assortments? Target's micromarketing efforts are based on age, climate, small-town community, and African American, Hispanic, or Asian heritage (Solomon 1994). These stores and others have found that having distinctive assortments tailored to specific customer groups is a viable method of developing a distinctive strategic competitive advantage. Unfortunately, these regional differences complicate the assortment planning process, and the methods used to achieve efficient regional assortments are not well defined in the literature.

RETAIL PRODUCTIVITY AND EFFICIENCY

Understanding and measuring the productivity and efficiency of retailers have been important issues in retailing research (e.g., Bucklin 1978; Donthu and Yoo 1998; Ingene 1982, 1984; Ratchford and Brown 1985; Ratchford and Stoops 1988). Past research has used and suggested the use of various measures and methods to assess retail efficiency. The majority of measures of outlet efficiency are input-output ratios, such as sales per square foot or sales per employee (Kamakura, Lenartowicz, and Ratchford 1996).

These traditional methods are problematic when a retail chain has multiple goals. Take, for example, a typical computer store that sells both products (e.g., computers, printers, etc.) and services (e.g., repairs, add-ons, etc.). They want to maximize the sales of both these outputs. Traditional methods would sum these two outputs, but would be unable to identify the optimal level of the individual outputs. Similarly, stores have both personnel and merchandise inputs. Traditional efficiency analysis methods would combine these two inputs into a single expenditure measure. These two inputs should, however, remain separate because they are not substitutable. Otherwise, the store might have great merchandise, but poor sales help, or vice versa. Using a combined input measure, management would not be able to delimit the problem.

Kamakura, Lenartowicz, and Ratchford (1996) and Donthu and Yoo (1998) identified a number of problems with traditional input/output measures. We highlight the following problems that are relevant for the purposes of this study:

1. Most retailing situations have multiple inputs and outputs that are not addressed in traditional analysis (Kamakura, Lenartowicz, and Ratchford 1996).
2. Most measures are sales management oriented (e.g., sales per hour) rather than measures of total retail productivity (Donthu and Yoo 1998).

3. Output is defined as a supply-side concept. The market conditions are normally not included in the analysis (Donthu and Yoo 1998, Ratchford and Stoops 1988).
4. Research that has used standard regression analysis used average store performance rather than the best performers (Chebat et al. 1994, Donthu and Yoo 1998).
5. Very few studies have examined the context of the efficiency of different outlets of a firm (Kamakura, Lenartowicz, and Ratchford 1996; Donthu and Yoo 1998).

This study examined the efficiency of outlets by using an efficiency frontier methodology called DEA that has started to be adopted in various marketing settings. Kamakura, Ratchford, and Agarwal (1988) examined brand efficiencies based on attribute data of brands and compared efficiencies with retail prices. Mahajan (1991) examined the efficiency of salespeople. Similarly, Boles, Donthu and Lohtia (1995) and Parsons (1990) used DEA to evaluate the performance and rank salespeople while using multiple input and outputs. Kamakura, Lenrtowiicz, and Ratchford (1996) evaluated bank-outlet performance and determined cost functions. Donthu and Yoo (1998) evaluated retail store performance and compared results with regression analysis. Murthi, Srinivasan, and Kalyanaram (1996) calculated the efficiency of firms relative to that of competing stores in a mature consumer goods market. Although some of these studies were in a retail setting, none have addressed the issues of calculating performance while accommodating regional and assortment differences.

There are four reasons why this methodology enables retailers to better plan their assortments. First, DEA accommodates multiple inputs and outputs, thus allowing for the disaggregation of total sales volume into individual product categories. This disaggregation process enables managers to better understand the assortment needs of each individual store. Second, the method allows for the inclusion of regional differences in retail outlets. Third, the method allows a comparison between individual stores with the best stores in the chain. Finally, DEA enables firms to predict what the sales of a store would be if it were performing as a best practice store. This sales prediction takes both regional and assortment differences of individual stores into consideration. This "best practice" prediction allows retailers to set more realistic and accurate goals based on the specific store profiles.

Traditional methods of evaluating store performance typically use aggregated sales data. The problem with using aggregated data is that it leads to optimistically large sales target goals that may be unrealistic and unreachable because it ignores a particular store's advantage in selling a particular product category over another. Also, in a traditional aggregate level analysis, some stores are likely to be regarded as successful or efficient stores simply because they are in better regions or locations.

Using DEA, sales can be disaggregated by product category and by region. Stores will be evaluated against "best practice" stores in the same region and with similar assortments. To illustrate how the analysis using disaggregated sales data works, consider three stores that all carry category "A" and "B" and all have identical inputs.

The first store sold seven units of "A" and seven units of "B." The second store sold 5 units of "A" and 15 units of "B." The third store sold eight units of "A" and eight units of "B." Using aggregated sales, the second store is efficient with 20 units sold, and stores one and three are inefficient. With disaggregated data, both the second and third stores are efficient because the second store sold the most of category "B" and the third store sold the most of category "A." Importantly, if the first store sold only one more each of products "A" and "B," it too would be efficient. Yet, using aggregated data, the first store would be in third place, and would have to increase aggregate sales by at least six units to make it efficient. The use of aggregated sales data may therefore obfuscate reality and erroneously penalize stores carrying categories "A" and those carrying both "A" and "B."

Model Development

A fundamental assumption behind DEA analysis is that if a given store-A, is capable of y_A units of outputs (e.g., sales) with x_A inputs, then other stores should also be able to do the same if they were to operate efficiently. Similarly, if store-B is capable of y_B units of outputs with x_B inputs, then other stores should also be capable of the same performance.

DEA also assumes that stores A, B, and others can be combined to form a composite store with composite inputs and composite outputs. Because this composite store may not necessarily exist, it is typically called a virtual store. [11] The heart of the analysis lies in finding the "best" virtual store for each real store. If the virtual store is better than the store being evaluated by either accomplishing more outputs with the same inputs or having the same outputs with less inputs, then the original store is inefficient.

The procedure for finding the best virtual store can be formulated as a linear program. Analyzing the efficiency of N stores is then a set of N linear programming problems. The efficiency frontier defines the maximum combinations of outputs that can be posted for a given set of inputs.

The DEA literature proposes several different types of models that have been developed for a variety of different goals. The description of these models and their differences are beyond the scope of this paper. We restrict our attention to describing the model suggested for calculating (technical) inefficiencies (see, Banker and Morley 1986a, 1986b) of stores in an output formulation: one in which we focus on considering the estimation of the extent to which outputs could be increased without requiring additional inputs. This particular model is appropriate for the evaluation of retail stores because one of the primary objectives of most retail chains is to maximize sales and market share.

Suppose $output_{rj}$, $r \in \{1,...,S\}$ and $input_{ij}$, for $i \in I = \{1,...,M\}$ are the observed output and input values for $j = 1,...,N$ stores. The linear programming problem that helps estimate the output technical inefficiency measure for *store x* is as follows:

$$Maximize\ score + \epsilon(\sum_{r=1}^{S} excess_r + \sum_{r=1}^{M} slack_i)$$

Subject to:

$$\sum_{j=1}^{N} \lambda_j input_{ij} + slack_i = \mathrm{input}_{ix}, i \in \{1,...,M\}$$

$$\sum_{j=1}^{N} \lambda_j output_{rj} - excess_r = \text{score*output}_{rx}, r\epsilon\{1,...,S\}$$

$$\sum_{j=1}^{N} \lambda_j = 1$$

$$score, \lambda_i, excess_r, slack_i \geq 0$$

The first constraint set indicates that the weighted sum of inputs of the virtual store is set equal to at most the input of the store under investigation. The slack $slack_i$ can take positive values when the virtual store does not need to use inputs at the same level. The second set of constraints indicates that corresponding to using these levels of inputs, the virtual store is capable of producing outputs at the level score * $output_{rx}$ where $score \geq$ 1and ϵ is an infinite by small, positive number.

DEA determines a store to be efficient only when comparisons with other relevant stores do not provide evidence of inefficiency in the use of any input or output. An efficient store has a score of 1, and has $slack_i = 0$ for each input i, i.e., it is on the efficiency frontier. The closer the score is to 1, the more efficient the store is considered to be. In output oriented models, scores are greater than or equal to 1. This is in contrast to input-oriented models, in which scores vary from 0 to 1. The reasons that we use inefficiency scores that are greater or equal to one, is that the scores are an indication of the factor improvement in output of specific decision making units (DMUs) to make them efficient.

For an inefficient store, the adjustments needed in each of its outputs to render it technically efficient is given by:

$$output'_{rx} = excess_r + score*output_{rx} \, for \; r = 1,...,S.$$

Simultaneously, inefficient scores must decrease their input levels by $slack_i$. In other words, slack analysis helps retail outlets allocate resources more efficiently and improve their performance. Also, slack analysis enables managers to identify their store's potential.

EMPIRICAL ILLUSTRATION

The efficiency of 59 retail outlets of a Fortune 500 retailing and manufacturing firm is calculated using DEA. To empirically demonstrate the effect of assortment and regional differences on individual store assessments, "best practice" based performance analysis is calculated on an aggregate basis, an assortment basis, and on a regional assortment basis. The results are then compared with a regression-based analysis.

Confidentiality requirements do not allow for the identification of the products or regions. However, the firm is an automobile parts retail chain. The retail outlets sell two non-substitutable categories (A and B) and the majority of their sales come from these two categories. The retail stores are located in three geographical regions (1, 2, and 3). The locational profiles of stores within a region were similar. The first region, in the Northeast, is characterized by cold winters with snow. The average per-capita income within a 3-mile radius of each store was $25,177. The second region, in the Midwest, has very cold winters with large amounts of snow. The average per-capita income within a 3-mile radius of each store was $26,538. Finally, the third region, on the west coast, has a temperate climate. The average per-capita income within a 3-mile radius of each store was $22,389. Also, because one region is more rural than the others, its residents use a larger proportion of light trucks, compared with automobiles. As a result, the demand for certain auto products, such as batteries, tires, and coolants vary dramatically across regions.

Determination of Inputs and Outputs

Researchers have suggested that to evaluate stores, the input factors should include store specific factors (see Donthu and Yoo 1998). Store specific factors can include those pertaining to the square footage of the store, inventory levels or investment, technology, service levels, number of employees, operating hours, operating expenditures, etc. (Bucklin 1978; Lusch and Serpkenci 1990). The store specific input factors used in this study were selected based on management input and previous literature (e.g., Boles, Donthu and Lohtia 1995; Lusch and Jaworski 1991; Kamakura, Lenartowicz and Ratchford 1996). They are:

- *Store Operating Expenses* include all operating costs including salary and benefits, store supplies, and utilities, but exclude inventory costs and other corporate costs such as national advertising;
- *Square Footage* represents the size of the store; and
- *Inventory* represents the level of product availability of a specific product and can be viewed as a proxy of reducing buyers' waiting time.

The factors of store operating expenses and inventory were under the control of management. There was high variance in these inputs and the proportion of maximum/minimum was 6.9 for store operating expenses, 4 for square footage, and 4.4 for inventory.

The key output factor is typically sales volume in either dollars or units (Bucklin 1978; Ratchford and Stoops 1988). The output factor used in this study was sales volume in units. The unit cost and retail prices for all SKUs within a category in this case are similar. Thus, the results would be the same if either unit or dollars sales were used.

The purpose of the first study was to determine the aggregate efficiency of individual stores. The single output was sales volume of both products A and B. The purpose of the second analysis was to disaggregate the sales of the two product categories to specifically take assortment differences into consideration. Therefore, two outputs – unit sales of Product A and Unit sales of Product B were used in the analysis. Finally, the third analysis, included the regional factor as a control input variable.

As suggested earlier, we use DEA to determine the performance of retail outlets. Specifically, we calculate the following:

1. Inefficiency Score that is greater than or equal to 1.
2. Sales goals that is equivalent to projected sales of product(s) for the retail outlets to be efficient. This is calculated by adding excess and the product of the present sales and the inefficiency score.
3. Slack in percentage that is calculated by (Sales goals-Current Sales)/(Current Sales). This figure provided outlets with an indication of the sales increase necessary to become efficient.

ANALYSES

Three analyses were performed in this study, each with a different level of data aggregation. Each analysis used three inputs (store operating expenses, square footage and inventory) and one or two outputs (sales volumes of product category A, B, or combined). The first analysis provides a measure of each store's relative efficiency based on aggregated sales data. The second analysis uses the same input variables as the first analysis, but disaggregates the output sales data into the two separate major product categories (A and B) and used sales of each product category as different outputs. We will show that disaggregating the sales data provides a better understanding of the role that product assortment plays in the evaluation of a store's performance.

The third analysis is similar to the second, except the comparison is limited to stores from the same region. Specifically, instead of using all 59 stores in one analysis, three different sets of analyses were performed, one for each region. This further refinement allows for the examination of regional differences. For example, suppose the two regions are the greater Sacramento, California area and the greater New York City area. It would be inherently unfair to aggregate the two areas and compare Sacramento stores against those in New York, because the New York stores may be more efficient due to the greater population concentration.

Controlling for a region can be succinctly accomplished by altering the linear program by inclusion of categorical control variables (see Banker and Morey 1986a). Alternatively, the same results are found if one were to run the analysis for each of the three regions separately. Limiting the analysis to a particular region restricts the linear program even further than in the second analysis. This has the effect of generating an even lower inefficiency score for any given store than was possible in the first two analyses. A lower score means that a store will be closer to "efficient" than would be the case without parceling the data into regions and disaggregating by product category. Also, restricting the analysis into regions will result in more conservative estimated sales goals.

RESULTS

The inefficiency scores as well as the projected sales volumes at the efficient levels for the 59 retail stores from the three geographic regions are presented in Table 1.

Role of Dissagreggating Overall Sales to Account for Product Assortment

The comparison of the results of Analysis 1 versus Analysis 2 provides a test of the role of disaggregating sales volume using multiple outputs as opposed to a single summated output. The results reported in Table 1 indicate that 10 stores are classified as efficient in Analysis 1, whereas the number increases to 14 in Analysis 2. Thus by considering the efficiency of the two product categories separately, more stores are rated as being efficient. Furthermore, the overall average inefficiency declines from 1.39 in Analysis 1 to 1.29 in Analysis 2. The decline in efficiency is significant (Table 2: $t = 4.96$, $p < .001$). Additionally, the projected sales also decline ($t = 5.29$, $p < .001$).

Role of Regional Differences

The comparison of the results for Analysis 2 versus Analysis 3 provides a test of the role of regional differences (i.e., using three analyses to assess the role of the regions versus a single analysis where the data are pooled). The results reported in Table 1 indicate that 14 stores are classified as efficient in Analysis 2, whereas the number increases to 30 in Analysis 3. Furthermore, the overall average inefficiency declines from 1.29 (Analysis 2) to 1.08 (Analysis 3). The decline in inefficiency is significant (Table 2: $t = 6.72$, $p < .001$). Additionally, the projected sales also decline ($t = 9.02$, $p < .001$).

Comparison of Regression-Based Approach to DEA-Based Approach

As mentioned earlier, regression-based sales estimates compare an individual store to the average performer, whereas the DEA approach compares an individual store to the best-performers. Thus, the regression-based approach is likely to provide more conservative sales estimates. To examine this issue, a regression model was run with the same variables as in the first DEA analysis – the independent variables were variable expenses, square footage, and inventory); whereas the dependent variable was sales. The resulting sales estimates from the regression analysis were compared to the Analysis 1 projections. As expected the DEA projections were larger (Table 3: $t = 22.42$, $p < .001$).

TABLE 1

Efficiency and Total Target Sales Estimates

	Experiment 1		*Experiment 2*				*Experiment 3*				
Store	*Inefficiency*	*Total Target Sales*	*Inefficiency*	*Category A Target Sales*	*Category B Target Sales*	*Total Target Sales*	*Region*	*Inefficiency*	*Category A Target Sales*	*Category B Target Sales*	*Total Target Sales*
1	1.09	16687	1.09	1239	15329	16568	1	1.03	1254	14546	15800
2	1.39	18085	1.3	1625	15222	16847	1	1	1253	11740	12993
3	1.48	19378	1.44	1973	16880	18853	1	1	1366	11685	13051
4	1.15	22417	1.15	1493	20878	22371	1	1	1298	18151	19449
5	1.46	19682	1.46	1547	18097	19644	1	1.11	1254	13767	15021
6	1.81	19907	1.8	1430	18380	19810	1	1.42	1254	14529	15783
7	1.2	23367	1.15	2164	20307	22471	1	1.07	2008	18841	20849
8	1.05	24861	1	2644	21019	23663	1	1	2644	21019	23663
9	1.16	24861	1	2213	19262	21475	1	1	2213	19262	21475
10	1.15	22887	1.06	2280	18942	21222	1	1	2142	17799	19941
11	1.21	22890	1.17	2109	19977	22086	1	1.07	1926	18241	20167
12	1	15962	1	1254	14708	15962	1	1	1254	14708	15962
13	1.35	17805	1.05	1484	13522	15006	1	1	1415	11737	13152
14	1.87	17645	1.55	1619	12994	14613	1	1	1043	8371	9414
15	1.21	24817	1.16	2176	21697	23873	2	1.01	1890	18850	20740
16	1.46	18987	1.45	1459	17439	18898	2	1.19	1202	14372	15574
17	1	17965	1	1490	16475	17965	2	1	1490	16475	17965
18	1.19	19548	1.12	1583	16831	18414	2	1.02	1440	15314	16754
19	1.14	24861	1.12	1826	22728	24554	2	1.05	1706	21230	22936
20	1.81	14761	1.02	1323	10649	11972	2	1	1293	6851	8144
21	1	13840	1	951	12889	13840	2	1	951	12889	13840
22	1.42	17210	1.42	1525	15648	17173	2	1.05	1130	11590	12720
23	1	24861	1	1544	23317	24861	2	1	1544	23317	24861
24	1.71	15100	1.56	1597	12189	13786	2	1	1021	7793	8814
25	1.6	15120	1.6	1157	13902	15059	2	1.21	874	10501	11375
26	1.28	19157	1.28	1649	17474	19123	2	1.07	1379	14615	15994
27	1.44	18714	1.44	1663	17004	18667	2	1.18	1362	13925	15287
28	1	10592	1	521	10071	10592	2	1	521	10071	10592
29	1.54	21325	1.39	2323	17179	19502	2	1.2	2017	14638	16655

30	1.55	20458	1	2085	11134	13219	2	1	2085	11134	13219
31	1.24	19272	1.23	1740	17360	19100	2	1.04	1480	14773	16253
32	1.14	21503	1.10	2165	18482	20647	2	1	1974	16855	18829
33	1.25	18770	1.04	2153	15837	17990	2	1	2060	12944	15004
34	1.09	22695	1.09	1690	20833	22523	2	1.04	1611	19857	21468
35	1.08	21239	1.04	2051	18417	20468	2	1	1976	17744	19720
36	1	13157	1	917	12240	13157	2	1	917	12240	13157
37	1.36	14671	1.36	1093	13578	14671	2	1	796	9980	10776
38	1.25	16130	1.05	1469	12100	13569	2	1.04	1453	11971	13424
39	1.42	14203	1.2	1310	11781	13091	2	1	1092	8934	10026
40	1.23	17797	1.09	1619	14136	15755	2	1.04	1542	13464	15006
41	1.6	17560	1.3	1700	14276	15976	2	1.14	1488	10977	12465
42	1.14	15329	1	1352	12121	13473	2	1	1350	12102	13452
43	2.04	17560	1.63	1450	15219	16669	3	1.24	1107	10596	11703
44	1.36	16048	1.11	1244	14451	15695	3	1	1122	10652	11774
45	1.58	22310	1.26	2344	16321	18665	3	1	1855	12302	14157
46	2.27	18462	2.27	1437	17002	18439	3	1.49	1447	11171	12618
47	1.82	13849	1.82	960	12889	13849	3	1.33	849	9426	10275
48	1	8401	1	398	8003	8401	3	1	398	8003	8401
49	2.03	20982	2.01	1390	19589	20979	3	1.15	1378	11228	12606
50	1	7263	1	681	6582	7263	3	1	681	6582	7263
51	1.65	19755	1.47	1947	15549	17496	3	1.09	1582	11544	13126
52	1.83	19440	1.81	1609	17686	19295	3	1.17	1509	11372	12881
53	2.45	21139	2.42	1392	19639	21031	3	1.42	1498	11492	12990
54	2.18	11991	2.17	908	11083	11991	3	1.44	710	7370	8080
55	1	12936	1	1715	11221	12936	3	1	1715	11221	12936
56	1.27	10387	1.26	900	9487	10387	3	1	624	7552	8176
57	1.35	10798	1.29	1411	9387	10798	3	1.29	1411	9387	10798
58	1	6631	1	819	5812	6631	3	1	819	5812	6631
59	2.04	19392	1.73	1799	14568	16367	3	1.35	1508	11431	12939

Table 2

Role of Assortment and Regional Differences

Paired sample t-*test: Test for Assortment Differences*				
Analysis	*Mean Efficiency*	*n*	t-*value*	p-*value*
Analysis 1	1.39	59		
Analysis 2	1.29	59	4.96	.000

Paired sample t-*test: Test for Assortment Differences*				
Analysis	*Mean Sales Volume Estimate*	*n*	t-*value*	p-*value*
Analysis 1	17,854	59		
Analysis 2	16,939	59	5.29	.000

Paired sample t-*test: Test for Regional Differences*				
Analysis	*Mean Efficiency*	*n*	t-*value*	p-*value*
Analysis 2	1.29	59		
Analysis 3	1.08	59	6.72	.000

Paired sample t-*test: Test for Regional Differences*				
Analysis	*Mean Sales Volume Estimate*	*n*	t-*value*	p-*value*
Analysis 2	16,939	59		
Analysis 3	14,391	59	9.02	.000

Slack Analysis

The slack analysis is provided in addition to the sales goals in Table 4. Recall that the sales goal of Product A and B are calculated as the projected sales for the retail outlets to be efficient. We calculated the slack as a percentage of current sales, i.e., percentage increase of current sales volume required to transform an inefficient outlet into an efficient outlet. The results on individual stores as well as the averages are presented in Table 4. The slack for both products A and B sales in Analysis 1 was 39.66% and in Analysis 2 was 32.52% ($t = 5.01$; $p < 0.001$). The slack percentage for Analysis 3 for both products A and B was 9.26%, significantly different from Analysis 1 and Analysis 2 ($t = 8.87$ and 7.58, respectively; $p < 0.001$). The slack percentage was significantly different in Analysis 2 and Analysis 3 for Product A (32.84% and 8.71%, respectively, $t = 7.44$; $p < 0.001$) and Product B (30.84% and 16.59%, respectively, $t = 6.59$; $p < 0.001$). Therefore, the results of comparing slacks from the three analyses were similar to the results of the efficiency analysis.

IMPLICATIONS AND AVENUES FOR FUTURE RESEARCH

The implications for evaluating performance at a more disaggregate level using a "best practice" methodology such as DEA are in two major areas. First, the method illustrates

TABLE 3

Regression-based Versus DEA-Based Estimates

Analysis	*Mean Sales Volume Estimates*	*n*	t-*value*	p-*value*
Analysis 1 (DEA)	17,854	59		
Regression	13,454	59	22.42	.000

Paired sample t-test: Test for Differences Based on Methodology.

a method of goal setting and assortment planning that is superior in many ways to more traditional methods. Second, the results of the process provide directions for enhancing the overall performance of the retail chain. These issues and avenues for future research are discussed next.

Goal Setting and Assortment Planning

The issues of evaluation, goal setting and assortment planning are becoming more important for retailers because of the increase in competition and changing retail paradigms. For example, research on store evaluation and retail productivity has been prolific as seen by the special issues of *Journal of Retailing* in 1984 and 1997 (e.g., Achabal, Heineke and McIntyre 1984; Ingene 1984), and *International Journal of Research in Marketing* in 1997. The traditional measures of efficiency or retail productivity (i.e., a ratio of a single output to a single input) have made the evaluation of retail outlets in different regions that carry different assortments very difficult. In this paper, we presented a method of obtaining efficiency measurements (using multiple inputs and outputs) that compare individual outlets with "best practice" outlets located in the same region.

Retail chains recognize that regional idiosyncrasies should be included in the store evaluation process. Yet, traditional evaluation methods do not allow for these differences. Retail firms typically classify their stores into A, B, and C level stores based on sales of the store and the markets in which they operate. This ABC typology is carried through to the evaluation of categories. The DEA methodology used in this paper provides a more accurate assessment of the productivity of stores than the ABC approach because it controls for regional and assortment differences. For instance, the accumulated goodwill and familiarity of Nordstrom's in the Seattle area should lead to higher levels of performance and productivity than the new store in Denver, because Nordstrom's was founded in and has had several stores in Seattle for many decades. Thus, using traditional analyses, the performance of the A store in Denver would be unfairly compared directly with an A store in Seattle. In this study, store 20 in region 2 was rated as being extremely inefficient (score of 1.81) in the aggregate analysis, but was considered to be efficient when regional and assortment differences were taken into consideration. Thus, using a traditional aggregated analysis, store 20 and its manager could be unfairly penalized.

A key diagnostic benefit of the DEA methodology is the slack analysis. In particular, in this study we concentrate on output-oriented slack analysis. As mentioned earlier, the

TABLE 4

Slack Analysis

	Analysis 1	*Analysis 2*			*Analysis 3*		
Stores	*Percentage Slack For Products A and B*	*Percentage Slack For Products A and B*	*Percentage Slack For Product A*	*Percentage Slack For Product B*	*Percentage Slack For Products A and B*	*Percentage Slack For Product A*	*Percentage Slack For Product B*
1	9.35	8.57	8.57	8.59	3.54	3.02	9.90
2	39.19	29.66	29.66	29.69	0.00	0.00	0.00
3	48.48	44.46	44.46	44.44	0.00	0.00	0.00
4	15.26	15.02	15.02	15.02	0.00	0.00	0.00
5	45.97	45.68	45.69	45.67	11.40	10.83	18.08
6	80.51	79.63	79.63	79.65	43.12	42.00	57.54
7	19.70	15.11	15.11	15.11	6.80	6.80	6.81
8	5.06	0.00	0.00	0.00	0.00	0.00	0.00
9	15.77	0.00	0.00	0.00	0.00	0.00	0.00
10	14.77	6.42	6.42	6.44	0.00	0.00	0.00
11	21.18	16.93	16.93	16.91	6.77	6.77	6.76
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13	35.38	14.10	15.21	4.88	0.00	0.00	0.00
14	87.43	55.23	55.23	55.23	0.00	0.00	0.00
15	21.08	16.48	16.48	16.49	1.19	1.19	1.18
16	45.68	45.00	45.00	45.03	19.50	19.50	19.48
17	0.00	0.00	0.00	0.00	0.00	0.00	0.00
18	19.02	12.12	12.12	12.11	2.01	2.01	1.98
19	13.71	12.30	12.30	12.30	4.90	4.90	4.92
20	81.25	47.00	55.44	2.32	0.00	0.00	0.00
21	0.00	0.00	0.00	0.00	0.00	0.00	0.00
22	42.06	41.75	41.75	41.73	4.99	4.99	5.02
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	71.32	56.41	56.41	56.42	0.00	0.00	0.00
25	60.25	59.61	59.61	59.59	20.56	20.56	20.55
26	28.23	28.01	28.01	28.03	7.06	7.06	7.07
27	43.88	43.52	43.52	43.49	17.53	17.53	17.52
28	0.00	0.00	0.00	0.00	0.00	0.00	0.00
29	54.10	40.93	41.25	38.60	20.36	20.36	20.35
30	54.76	0.00	0.00	0.00	0.00	0.00	0.00
31	23.87	22.77	22.76	22.79	4.47	4.47	4.45
32	14.20	9.66	9.65	9.68	0.00	0.00	0.00
33	25.10	19.90	22.35	4.51	0.00	0.00	0.00
34	9.45	8.62	8.62	8.61	3.54	3.54	3.53
35	7.70	3.79	3.79	3.80	0.00	0.00	0.00
36	0.00	0.00	0.00	0.00	0.00	0.00	0.00
37	36.15	36.15	36.05	37.31	0.00	0.00	0.00
38	25.16	5.28	5.28	5.30	4.16	4.16	4.16
39	41.66	30.57	31.87	19.96	0.00	0.00	0.00
40	22.89	8.79	8.79	8.80	3.62	3.62	3.63
41	59.93	45.50	47.65	29.67	13.52	13.53	13.50
42	13.95	0.16	0.16	0.15	0.00	0.00	0.00
43	103.67	93.33	96.83	62.92	35.73	37.04	24.38
44	36.30	33.30	35.66	10.87	0.00	0.00	0.00

TABLE 4 CONTINUED

	Analysis 1	*Analysis 2*			*Analysis 3*		
Stores	*Percentage Slack For Products A and B*	*Percentage Slack For Products A and B*	*Percentage Slack For Product A*	*Percentage Slack For Product B*	*Percentage Slack For Products A and B*	*Percentage Slack For Product A*	*Percentage Slack For Product B*
45	57.59	31.84	32.67	26.36	0.00	0.00	0.00
46	126.86	126.58	126.57	126.66	55.05	48.87	128.23
47	82.39	82.39	82.07	86.77	35.32	33.15	65.18
48	0.00	0.00	0.00	0.00	0.00	0.00	0.00
49	102.67	102.64	101.45	120.99	21.76	15.47	119.08
50	0.00	0.00	0.00	0.00	0.00	0.00	0.00
51	65.42	46.51	46.51	46.50	9.91	8.77	19.04
52	82.60	81.24	81.25	81.19	20.99	16.54	69.93
53	144.52	143.27	142.46	155.41	50.26	41.88	174.86
54	117.82	117.82	117.02	128.14	46.78	44.31	78.39
55	0.00	0.00	0.00	0.00	0.00	0.00	0.00
56	27.04	27.04	25.62	44.23	0.00	0.00	0.00
57	34.98	34.98	35.93	28.98	34.98	35.93	28.98
58	0.00	0.00	0.00	0.00	0.00	0.00	0.00
59	104.41	72.52	72.52	72.48	36.39	35.37	44.58
Average	39.66	32.52	32.84	30.84	9.26	8.71	16.59

Slack Percentage = 100* (Target Sales - Current sales)/(Current Sales)

slack analysis (provided in Table 4) would allow the chain to understand what percentage increase in sales volume is required to transform an inefficient retail outlet to an efficient retail outlet. For example, in Analysis 3, store 6 (inefficiency rating of 1.42) would need to increase its target sales by 42% for product A and 57.4% for product B to transform it from an inefficient retail outlet to an efficient retail outlet.

Alternatively, using an input-oriented slack analysis, the retail chain could try and assess what percentage reduction in inputs would help transform an inefficient retail outlet to an efficient outlet. An input-oriented DEA analysis suggests that store 15 would need to reduce operating expenses by 13.68%, square footage by 22.06%, and inventory by 17.73% to become efficient. Note, however, that a reduction in operating expenses and inventory are more controllable in the short term compared with square footage.

Another strength of the DEA methodology is that it can calculate a fair and realistic sales target for specific merchandise categories based on the region in which a particular store operates. For example, retailers know that it would not be fair to compare the sales of truck tires of a dealer in Wyoming with one in the greater New York City area. Yet, using traditional methodologies, retailers have no accurate basis of setting sales goals between regions.

DEA allows retailers to predict target sales for any unit of analysis from the SKU to the store level based on the “best practice” SKUs, categories, or stores in similar locations. Although regions were used as the basis of analysis in this application, other criteria, such as trade areas, or stores whose customers are psychographically similar could also be used.

DEA is very useful for determining merchandise budgets fairly. Because it predicts what sales should be for a particular category in a given store using the slack analysis, it provides accurate information to buyers and store managers about how particular categories are performing compared with what they should be doing. For instance, a traditional analysis would base the sales targets for two K-Mart swimwear departments in St. Petersburg and Clearwater Florida on past sales. Instead of using a backward measure like past sales, the DEA analysis looks forward into what sales should be. Suppose the DEA analysis identifies the Clearwater store as efficient, and the St. Petersburg store as inefficient. Because they are "comparable" stores, the DEA analysis would suggest that the St. Petersburg store sales predictions should be based on the efficient Clearwater store information.

Another problem with traditional methods that forecast future sales using a percentage increase of last year's sales is that it penalizes the better performers while giving below average stores an advantage. Consider again the two stores in St. Petersburg and Clearwater. St. Petersburg has sales this year of $50 million, whereas Clearwater has $80 million. Traditional planning may suggest a 10% increase for both stores, forecasting sales of $55 million and $88 million, respectively. A DEA analysis may show that St. Petersburg is operating at 50% efficiency and needs to improve to 80% efficiency, setting a goal of $80 million. On the other hand, Clearwater may have an efficiency of 100%, requiring a modest increase to $82 million. The DEA analysis, therefore, rewards the Clearwater store for doing well in the past by giving it a moderate increase, whereas raising the hurdle for the St. Petersburg store.

Directions for Enhancing the Overall Performance of the Retail Chain

Competition in retailing is increasingly being regarded as an information contest. Retailers, such as Wal-Mart, are admired more for their prowess in the information arena than for their ability to pick merchandise or locate stores. In fact, information has become so critical that Wal-Mart accused and sued Amazon.com for stealing their IT talent. Amazon.com and other virtual retailers are being viewed by Wall Street with intense optimism. Price/earnings ratios on these firms are astronomical.

Retailers have advanced information systems for everything from procuring merchandise to locating stores. They have invested millions in sophisticated data warehouses. For example, Wal-Mart has developed a 24-tetrabyte data warehouse. Sears and Kmart have 14- and 8-tetrabyte warehouses, respectively (Zimmerman 1998). The degree to which retailers are able to harness this information is expected to determine their success in the future.

The proposed methodology can be used to enhance the retail performance by examining and propagating 'best practice' skills. Once the DEA methodology identifies 'best practice' stores, top management should examine two aspects of their behaviors. First, they should determine what the more successful store managers and buyers "DO" when they face everyday situations. At a deeper level, they should determine how the more successful store managers and buyers "THINK" about stores and customers. The first exercise develops behavioral guidelines for the managers and buyers, whereas the second exercise develops cognitive or thinking guidelines about customers and stores.

Behavioral guidelines are broad lessons that store managers and buyers have learned from good and bad situations (i.e., what to do and what not to do). Previous research and experience have shown that the best way to learn behavioral guidelines is through story-telling, i.e., case studies of successful and unsuccessful situations (Klein 1998). The best retailers, e.g., Home Depot, JCPenney, and Wal-Mart, are known to disseminate this type of information during weekly meetings, closed circuit satellite broadcasts, and in-house publications. Some, e.g., Nordstrom, encourage innovative and heroic service efforts by having employees tell about their activities and giving awards for the best ones.

Cognitive guidelines provide inputs into how store managers should think about their stores and customers. Research suggests that in a store identified as a 'best practice' store, managers and their employees will classify and interact with their customers differently than those managers and employees in mediocre performing stores (c.f., Klein 1999). The way these managers and employees think is referred to as their knowledge structures. To enhance performance, organizations have found it useful to disseminate "knowledge structure" information from best practice managers and key employees (c.f., Klein 1998). In short, behavioral guidelines will lead store managers to understand that "behaviors 'x' and 'y' work with our customers", and cognitive guidelines will refine that understanding to determine what type of behaviors to use with different types of customers.

Avenues for Additional Research

The results of the paper suggest areas for additional research. First, the selection of standardized or similar inputs and outputs across stores are proposed. This would make it easier to compare chains. Although our selection of inputs and outputs were based on management input and past research, future studies should explore different input and output measures. Similarly, it is important to determine what factors are associated with 'best practice' stores, e.g., characteristics of target market, geographical similarities. Once known, managers can attempt to clone their best performers through organizational learning-based research. Finally, we chose to examine the effects of region and assortment on the merchandise planning process. Other factors, such as type of location or demographic/psychographic makeup of the trade area, may be equally important in other research settings. In the future, researchers should attempt to determine which are the most important factors to consider for various retail formats.

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NOTES

1. Virtual stores is a term used in DEA analysis and does not refer to an Internet-based store.

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