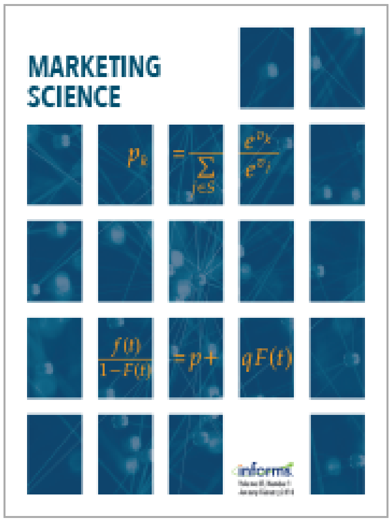

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Evaluating Promotions in Shopping Environments: Decomposing Sales Response into Attraction, Conversion, and Spending Effects

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Abstract

Retailers' marketing objectives can be classified into three broad categories: attraction effects that focus on consumers' store-entry decisions, conversion effects that relate to consumers' decisions about whether or not to make a purchase at a store they are visiting, and spending effects that represent both dollar value and composition of their transactions. This paper proposes a framework that incorporates all three of these effect categories and examines their influence on store performance. Specifically, store sales are broken down into four components: front traffic, store-entry ratio, closing ratio, and average spending. Using inexpensive and readily available infrared and video imaging technology, it is possible to measure these four components in a wide variety of retail environments, allowing retailers to obtain a richer understanding of the effectiveness of promotional activities on store sales.

A set of twelve hypotheses based on the economics of information and promotion literatures is proposed. These hypotheses relate the presence of various promotions (price, clearance, and new product), promotion scope, and the type of out-of-store communication vehicle used by retailers to each of the four store sales components. The proposed approach is then applied in two different empirical settings, both to test formally the hypotheses and to demonstrate more generally the richness of the information the approach can provide. The first application involves a Canadian apparel store that sells ladies' casual wear. The second application is based on a U.S. sporting-goods retail chain that sells a variety of sporting goods, including sportswear, sports shoes, and sports equipment.

A joint model of four simultaneous equations using front traffic, store traffic, number of store transactions, and store sales as the endogenous variables is then formulated for the applications. Promotional factors are used as explanatory variables, along with a number of additional control variables (including length of operation, day of week, holidays, seasonality, and weather). Seemingly unrelated regression is used to estimate the model efficiently. A comparison model that includes only store sales as the endogenous variable is estimated for comparison with the joint model.

Results from these applications indicate that the proposed framework provides more detailed information about promotional effectiveness than more traditional models of store performance. The effects of specific promotional decisions on store performance are described. Specifically, price promotions have little impact on front traffic, but positively affect store entry and likelihood that a consumer will make a purchase. The effect of price promotion on consumers' spending in a store is also significant, but varies in sign with the type of promotion employed. Second, while greater promotional scope enhances store entry, promotions with narrow scope seem to have negative impact on store traffic. The effects of promotion scope on store performance also seem to be moderated by the scope of merchandise carried by the retailer. Increased promotional scope appears to have a greater effect on store traffic and consumers' spending for a multicategory retailer than for a more focused seller. Third, clearance promotions have a weaker effect on store entry when compared to other multiple-category promotions, while new-product promotions have a positive impact on conversion. Finally, newspaper advertisements, when compared to targeted coupons, have a stronger effect on store attraction but a weaker effect on spending.

In addition to understanding the key drivers of store sales, retailers are also interested in determining whether or not their promotions affect store profitability. An assessment of the profit impact cannot be based on the change in overall store sales because promotions may affect various items or product categories inside a store differentially, and gross margins may not be the same for all items or categories. Although gross margin and item- or category-specific sales were not available for the two applications studied, the paper describes how such information can be integrated with the output of the proposed joint model to arrive at a richer understanding of how promotions affect overall store profitability.

Finally, managerial and academic implications of this work are described, and potential extensions of the joint model are suggested.

(*Retailing and Wholesaling; Marketing Mix; Promotion; Advertising and Media Research*)

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Retailers' marketing activities are designed with the objectives of drawing consumers into their stores, encouraging shoppers to make purchases, and influencing the types and quantities of items that consumers buy. These objectives can be classified into three broad categories: *attraction effects* that focus on consumers' store-entry or store-choice decisions, *conversion effects* that relate to consumers' decisions about whether or not to buy something at the store they are visiting, and *spending effects* that represent both the size (dollar value or units sold) and composition of their transactions (Dhebar et al. 1987, Mulhern and Padgett 1995, Kotler 1999). Historically, the ability of retailers to measure the effectiveness of their marketing activities has been limited by their inability to assess, accurately and economically, key performance measures such as store traffic, the number of transactions completed, and the composition of those transactions. However, developments in in-store technology have helped retailers overcome these barriers.

The introduction of scanners in the 1980s allowed grocers and other retailers to develop large transaction-specific databases. These databases, in turn, have permitted retailers to carefully investigate the effects of their marketing activities, such as promotions, on the number of transactions completed, product sales, and profitability. Food and drug retailers can typically assume that almost 100% of the consumers entering their stores will make purchases. Because the ratio of buyers to shoppers (the *closing ratio*) is typically close to one, these retailers are less concerned about managing conversion, and focus most of their attention on the attraction and spending effects of their marketing activities.

However, in the many retail settings that involve a significant amount of comparison shopping (e.g., apparel, jewelry, giftware), this emphasis is inadequate for studying the full response to a store or chain's marketing activities. In these retail environments, the number of transactions completed differs considerably from store traffic, and the closing ratio is variable and low—often less than 0.20 (Robins 1994). Recent advances in infrared and video-imaging technology have allowed retailers a means of tracking store traffic accurately and at low cost. They can record different kinds of traffic, including people walking along the front of the store (*front traffic*), people entering a store (*store traffic*), and people walking through an aisle inside the store (*aisle traffic*) (Robins 1994, Lam and Pearce 1997).[1] The availability of these traffic data enables retailers, particularly nonfood retailers, to analyze the attraction and conversion effects of their marketing activities more precisely.

Consider the case of a retailer who wants to assess the effectiveness of her feature advertising. Traditionally, she might look at the change in store sales following the advertisement's placement. If sales failed to increase, she would likely conclude that the advertising was not effective. However, partitioning sales response into attraction, conversion, and spending effects provides her with important insights. Traffic and transaction data might indicate that the feature advertising had increased store traffic, but that the closing ratio and average spending per transaction had declined compared to the preadvertising period. On this basis, the conclusion would be that the advertising had actually been effective in attracting shoppers, but the retailer had failed to convert the shoppers into buyers and encourage them to spend more money. This would point to problems with the retailer's merchandise assortment, store layout, staffing policies, or other in-store factors.

In this paper, we present a framework that incorporates attraction, conversion, and spending effects of marketing activities on store performance. Our analytical approach can be applied to a wide variety of shopping contexts, but is best suited to comparison-shopping environments where the conversion effects need to be considered in addition to the attraction and the spending effects. Most shopping mall and shopping district retailers fit into this category. Specifically, our framework breaks down store sales into four components: *front traffic, store-entry ratio, closing ratio,* and *average spending*. Based on these four sales components, we can identify which marketing variables affect store performance through attraction,

[1]A pair of infrared counters for a store entrance cost approximately U.S.$500 (Lam and Pearce 1997). The website http://www.storetraffic.com provides details about the technology and application of traffic counting in retail management.

conversion, or spending. While the ultimate goal continues to be the maximization of a store's sales and/or profits, our proposed framework permits a more detailed partitioning of sales response into different effects, leading to a better understanding of which marketing variables are and are not effective.

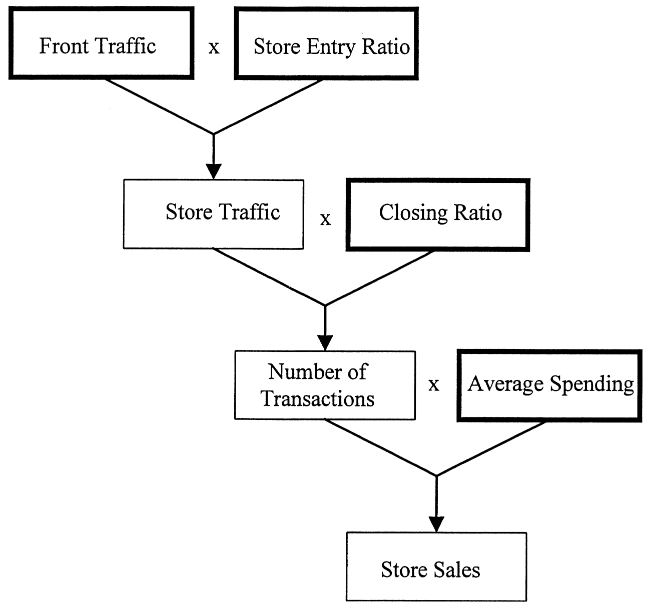
The remainder of this paper is organized as follows. In the next section, we outline our framework based on the partitioning of sales response into attraction, conversion, and spending effects. We then summarize various variables that may have these effects on store performance. In particular, based on economic theory and the existing promotion literature, we develop hypotheses about how price promotions exert multiple effects on store performance. We then develop a joint model to examine these effects, and demonstrate the usefulness of our model in two separate empirical studies of promotions—one for an apparel store and the second involving a sporting-goods retail chain. This is followed by a discussion of our studies' implications and limitations. We conclude the paper by suggesting other possible applications of our framework and summarizing the contributions of our research.

An Expanded Store Performance Framework

Figure 1 presents an overview of our expanded framework for analyzing store performance. We expand the traditional measures used in assessing store performance by adopting actual shopper counts as traffic measures. Shopper counts are recorded by electronic traffic counters that can effectively exclude from their counting certain types of people not of interest to retailers, such as children.[2]

Few researchers have analyzed the attraction effects of retail marketing activities. Studies in this area have compared the attraction effects of different marketing activities by using the number of transactions com-

Figure 1 **An Expanded Framework for Analyzing Store Performance**



pleted as the store traffic measure (Walters and Rinne 1986, Walters 1988, Walters and McKenzie 1988, Mulhern and Leone 1990). However, researchers have not attempted to assess attraction effects in comparison-shopping environments, where the number of transactions falls well below actual store traffic.

We assess attraction influences by breaking store traffic down into two components: front traffic and store-entry ratio. This decomposition allows a distinction between different marketing activities in their attraction effects, and a more precise estimation of those attraction effects. Some retail marketing activities, such as newspaper advertising, may bring shoppers to a store, thus increasing both front traffic and the store-entry ratio. Other activities, such as storefront signage and display, may only have an effect of drawing people from front traffic into a store—that is, changing the store-entry ratio *without* significantly influencing front traffic. Furthermore, compared to front traffic and store traffic, the store-entry ratio may be less affected by seasonal factors, and hence be a better criterion variable for the measurement of attraction effects.

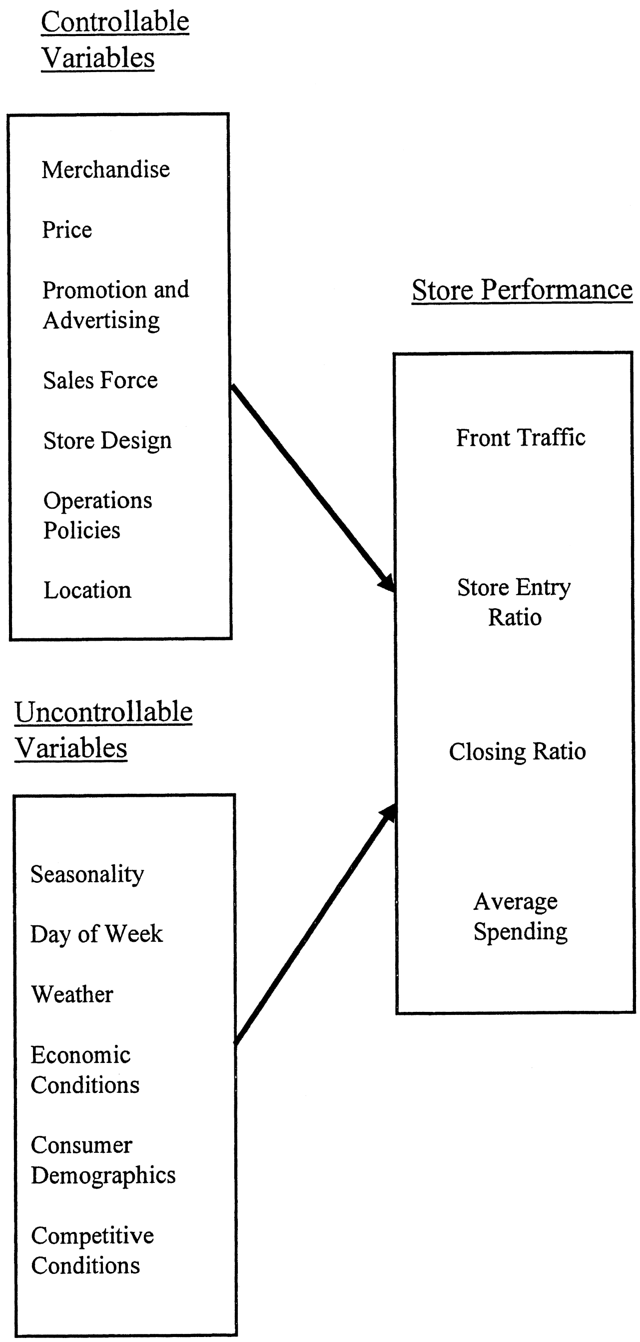
The closing ratio is related to the effectiveness of retailers' activities in converting shoppers to buyers. Use of a closing ratio to assess performance is an ac-

[2]The accuracy of store traffic counters has been well established. For example, Bunyar-Malenfant Store Traffic International, a maker of store traffic counters, showed that over a test period of 52 weeks, data provided by counters were at least 95% accurate.

cepted practice among retailers (Robins 1994). No empirical research to date has studied conversion effects at the store level, although several studies have investigated these effects at the product category or item level (e.g., Yalch and Spangenberg 1993, Wansink et al. 1998).

Numerous studies have investigated various spending effects of retail marketing activities, including the effects on sales and purchase quantities per transaction, and unit sales of substitutes and complementary items (e.g., Milliman 1986, Mulhern and Leone 1991, Mulhern and Padgett 1995, Wansink et al. 1998). In our framework, we employ average spending (per transaction) to assess the spending effects of marketing activities at the overall store level. This measure can be expanded to analyze the spending effects at item or category levels depending on data availability. Average spending can be expressed in dollar or unit terms, and is related to the composition of individual transactions completed at a store. Average dollar spending will increase if individual buyers purchase more products, or purchase products that have higher prices. Average unit spending will increase only when individual buyers purchase more items.

Figure 2 **Factors Influencing Store Performance**



Factors Influencing Store Performance: Hypotheses

A significant body of literature provides the theoretical arguments and some empirical support for the effects of various controllable and uncontrollable variables on front traffic, store-entry ratio, closing ratio, and average spending (e.g., Milliman 1986, Walters and MacKenzie 1988, Mulhern and Leone 1990). Figure 2 summarizes these variables at a general level and provides an organizing framework for studying the multiple impacts of these variables on store performance.

These variables may affect the four sales components differently. For example, out-of-store activity (e.g., newspaper advertising) would mainly affect front traffic and the store-entry ratio, whereas in-store activity such as the behaviors of salespeople and store atmospherics would mainly affect the closing ratio and average spending. The effects of these variables can be explained by economic and psychological theories. While a comprehensive account of all these effects is beyond the scope of this paper, we show here how the effects of several promotional variables studied in our empirical applications could be conceptualized based on the economics of information and promotion literatures.[3] Specifically, we develop hypotheses that relate the presence of price promotion, promotion scope, clearance promotion, new-product promotion, and the nature of the out-of-store communication vehicle employed to the four sales components. The economics of information perspective is particularly useful for developing these hypotheses because it considers how economic incentives (such as saving money) affect information search behavior—the essence of comparison-shopping. Previous studies applying the economics of information theory to marketing research have focused on explaining how personal variables, such as consumers' product knowledge and experience, affect search behavior (e.g., Punj and Staelin 1983, Srinivasan and Ratchford 1991). In contrast, our study investigates how marketing activity affects shopping decisions at an aggregate level.

Price Promotion

For many product categories (e.g., apparel, electronic appliances), consumers face considerable uncertainties about the price and quality of products sold by different retailers. The economics of information perspective describes the information search behaviors of these consumers (Stigler 1961, Moorthy et al. 1997). By visiting a store, consumers can ascertain their utility for the store's merchandise. Price is assumed to be one of the merchandise's attributes, so that the utility function measures utility net of price (Moorthy et al. 1997). To visit a store, consumers bear some search costs in terms of time, travel expenses, etc. Whether a consumer will visit a store is affected by the store's reservation utility—a summary measure of the value of getting information about the merchandise at a store, considering the perceived marginal utility and the costs of visiting the store (Moorthy et al. 1997). In turn, the perceived marginal utility depends on the utility distribution of the store's offering: the more positive the mean of the distribution or the wider the mean-preserved dispersion of the distribution, the higher the marginal utility. Various store activities can affect the mean and/or dispersion of this distribution. For example, price discounts offered by a store will increase the mean and consequently the reservation utility of the store. Because store visitation is essentially equivalent to the attraction effect studied here, we get the following hypothesis:

HYPOTHESIS 1. *Price promotions have a positive attraction effect on store performance.*

Consumers can ascertain the true utility of a store's merchandise once they visit the store. Various activities of the store can influence this assessment, which in turn affects consumers' probability of making a purchase at the store. For example, price discounts could increase the true utility by reducing the price paid by shoppers. In this case, use of a price promotion would lead to an increase in the closing ratio of the promoting store.[4]

HYPOTHESIS 2. *Price promotions have a positive conversion effect on store performance.*

It has been observed that during promotional periods, buyers often stockpile the promoted items (e.g., Litvack et al. 1985, Chakravarthi et al. 1996). Thus, for the promoting store, the average number of promoted items sold per transaction is likely to increase as a result of price promotion. Sales of nonpromoted items may also increase, although the existing evidence is mixed. For example, Walters (1988) found that promotions increased the sales of complementary purchases in one store, but decreased the sales of

[3]For a comprehensive account of all these effects, please refer to Lam (1998).

[4]For some product categories (e.g., low-price grocery and toiletry products), even when consumers find that the true utility of the store they are visiting is not particularly high, they may be unwilling to travel to other stores because the dispersion of these products' utility distributions in a market may not be wide enough to warrant further search. In these cases, shoppers will be quite likely to make purchases at the store they visit initially. Thus, the closing ratio for stores selling these types of products (e.g., supermarkets, drugstores) would often be close to one, and appears to be unaffected by store activity. In contrast, for the comparison-shopping type of products investigated here, the closing ratio will typically be much lower than one.

complementary items in another store. Mulhern and Padgett (1995) found no significant differences in how much people spent on promoted items and nonpromoted items, whether shoppers came into the store specifically to purchase a price-promoted product or entered the store for other reasons.

Although the average dollar value per transaction may also be affected by price promotion, the direction of this effect depends on the tradeoff between the sales gain resulting from an increase in the quantity of goods sold and the sales loss due to the price reduction. Thus:

HYPOTHESIS 3. *Price promotions increase average unit spending.*

HYPOTHESIS 4. *Price promotions affect average dollar spending.*

Promotion Scope

Promotion scope is defined here as the number of product categories or items on discount. An increase in the number of promoted categories is likely to attract more consumers with different purchase needs to visit the promoting store. Similarly, an increase in the number of promoted items within a category will cause a positive shift in the mean of the utility distribution for this category, drawing more shoppers into the promoting store. In both cases, an increase in promotion scope results in a larger attraction effect.

HYPOTHESIS 5. *Greater promotion scope increases the attraction effect of price promotion.*

When more items or product categories are discounted, shoppers have a higher chance of finding a product that satisfies their utility requirements. Previous research based on consumers' verbal responses provides clear evidence that consumers assess the probability of getting a discount at a promoting store to be higher when a larger fraction of stock at the store is at a discount, and are therefore more likely to make purchases there (Dhar et al. 1999). Thus, we would expect that:

HYPOTHESIS 6. *Greater promotion scope increases the conversion effect of price promotion.*

Promotion scope may also increase the spending effects of price promotion, depending on how strongly promotion scope affects the quantity of goods bought by individual shoppers and the content of their ''purchase baskets.'' Offering price discounts in multiple categories may encourage shoppers to concentrate their purchases to the promoting store, thus increasing average spending in both unit and dollar terms.[5]

HYPOTHESIS 7. *Greater promotion scope increases the unit- and dollar-spending effects of price promotion.*

Clearance Promotion

Shoppers tend to hold poorer attitudes towards inventory clearance messages than towards other price discount messages (Bobinski et al. 1996). Such messages appear to lead to lower consumer utility perceptions for the store running the clearance event. Thus, shoppers will be less inclined to visit the promoting store during a clearance promotion than during other multiple-category price promotions.

HYPOTHESIS 8. *Clearance promotions, when compared to other multiple-category promotions, decrease the attraction effects of price promotion.*

Furthermore, during a clearance promotion, shoppers may have difficulty in finding products that match their sizes or preferences because the unsold merchandise may be deficient (e.g., wrong color, outdated style). Clearance events are often used to get rid of items that have not already been sold during previous promotion events, suggesting that such merchandise tends to be of lower utility for most consumers. Thus, compared to other multiple-category promotions, clearance promotions will result in smaller conversion effects because of the lower utility of the promoted items.

HYPOTHESIS 9. *Clearance promotions, when compared to*

[5]Mulhern and Leone (1990) showed that average dollar spending increased when the supermarkets under study changed their promotion strategy from offering many items on small discounts to offering fewer items on larger discounts. However, because they varied the depth of discount and promotion scope simultaneously, the study's results do not fully clarify the nature of the relationship between promotion scope and spending.

other multiple-category promotions, reduce the conversion effects of price promotion.

New Product Promotion

Retailers often promote new-product arrivals by displaying the new items in prominent store locations (e.g., shop windows). On one hand, this type of promotion may attract people who are looking for new items into the store. On the other hand, such promotion may also deter people seeking bargains from entering the store, because these people may infer from the display and signage that there is a smaller chance of finding bargains inside. Thus, it is not clear what effect new-product promotion will have on either front traffic or store entry.

In contrast, new-product promotion is likely to increase the closing ratio. Compared to older, unsold merchandise, new-product arrivals often provide shoppers with more choices in styles, colors, and sizes. Therefore, once in the store, shoppers are more likely to find items that match their preferences and are of sufficiently high utility to result in sales. Thus:

HYPOTHESIS 10. *New-product promotions have a positive conversion effect on store performance.*

To maximize profits, retailers selling seasonal goods often price the new items at a high level at the start of a season and then lower the price as time passes (Lazear 1986). This implies that consumers usually have to pay more to buy a new item than an old item. However, the quantity that they buy of the new items may also be smaller because of the higher price. Thus, it is unclear whether a new-product promotion will increase or decrease average spending.

Newspaper Advertisements Versus Targeted Coupons[6]

In addition to in-store display and signage, retailers often employ out-of-store communication vehicles to deliver their promotional messages to potential customers. These vehicles include various types of advertising and coupons. Past studies have shown that these vehicles help to increase store sales, store transactions, and the sales of promoted items (e.g., Walters and MacKenzie 1988, Bawa and Shoemaker 1989). In this section we consider the effects of newspaper advertising and targeted coupons on store performance.

Both newspaper advertisements and coupons can have substantial attraction effects on consumers. The attraction effects of out-of-store communication vehicles are positively related to their coverage—the number of potential customers in a retailer's target market exposed to the promotional message (Levy and Weitz 1998). As the coverage increases, more people are exposed to the promotion message and more shoppers with purchase needs are attracted to the promoting store, thus increasing the attraction effect. Because newspaper advertisements typically reach a much larger audience than targeted direct mail.

HYPOTHESIS 11. *Newspaper advertisements, when compared to targeted coupons, increase the attraction effect of store performance.*

In contrast, the relative impact of advertising versus coupons on conversion is not clear. On the one hand, coupons can have a large impact for the psychological effects that they exert on consumers (Shimp and Kavas 1984, Dhar and Hoch 1996). For example, compared to straight price-off messages, consumers often find coupon-supported discounts more convincing (Dhar and Hoch 1996). Furthermore, for coupons delivered by mail or hand to selected consumers, people receiving the coupons may value the promotional offer more highly because of the targeted nature of the promotion. Thus, although targeted coupons may have smaller coverage when compared to newspaper advertisements, one cannot tell whether or not targeted coupons will generally have smaller conversion effects than newspaper advertisements on store performance.

The impact of out-of-store communication vehicles on average spending is less ambiguous. Previous research provides evidence that direct mail coupons increase the purchase quantity of individual buyers (Bawa and Shoemaker 1989). In contrast, there is no reason a priori to expect newspaper advertising to affect average spending.

[6]Targeted coupons are defined here as coupons that are either hand delivered or mailed to a specific, targeted group of potential customers.

HYPOTHESIS 12. *Targeted coupons, when compared to newspaper advertising, increase the (unit and dollar) spending effects of store performance.*

Models

Following Figure 1, we formulate a joint model of four simultaneous equations using front traffic, store traffic, number of transactions (store transactions), and store sales as the endogenous variables (Equations 1–4). Store traffic is expressed as a product of front traffic and the store-entry ratio, store transactions as a product of store traffic and the closing ratio, and store sales as a product of store transactions and average spending.[7] Note that when average spending is expressed in dollars (units), the corresponding store sales will also be expressed in dollars (units) for consistency.

$$N_{1t} = f(\cdot) \tag{1}$$

$$N_{2t} = N_{1t}g(\cdot) \tag{2}$$

$$n_t = N_{2t}h(\cdot) \tag{3}$$

$$S_t = n_t j(\cdot) \tag{4}$$

where

N_{1t} : front traffic on day t;
N_{2t} : store traffic on day t;
n_t : store transactions on day t;
S_t : store sales on day t;
$g(\cdot)$: store-entry ratio;
$h(\cdot)$: closing ratio; and
$j(\cdot)$: average spending.

Researchers commonly express an equation in log-linear form when the dependent variable involves sales or frequency counts (Stevens 1996, Greene 1997).[8] Thus, we express the four sales components, represented by $f(\cdot)$, $g(\cdot)$, $h(\cdot)$, and $j(\cdot)$, as exponential functions of their explanatory variables. We then take logarithms on both sides of Equations 1–4, and obtain the following model:

$$y_{1t} = \beta_1' x_{1t} + \epsilon_{1t} \tag{5}$$

$$y_{2t} = y_{1t} + \beta_2' x_{2t} + \epsilon_{2t} \tag{6}$$

$$y_{3t} = y_{2t} + \beta_3' x_{3t} + \epsilon_{3t} \tag{7}$$

$$y_{4t} = y_{3t} + \beta_4' x_{4t} + \epsilon_{4t} \tag{8}$$

where

y_{1t}, y_{2t}, y_{3t}, and y_{4t} : log-transformed variables of front traffic, store traffic, store transactions, and store sales respectively;
β_i : a vector of parameters, including the intercept ($i = 1, 2, 3, 4$);
x_{it} : a vector of explanatory variables ($i = 1, 2, 3, 4$); and
ϵ_{it} : disturbance term, assumed to be normally and identically distributed with mean zero and constant variance ($i = 1, 2, 3, 4$).

By moving y_t, y_{2t}, and y_{3t} in Equations 6 to 8 to the left-hand side, we obtain a system of equations in which the right-hand side contains only the explanatory variables and the disturbance terms:

$$y_{1t} = \beta_1' x_{1t} + \epsilon_{1t} \tag{9}$$

$$y_{2t} - y_{1t} = \beta_2' x_{2t} + \epsilon_{2t} \tag{10}$$

$$y_{3t} - y_{2t} = \beta_3' x_{3t} + \epsilon_{3t} \tag{11}$$

$$y_{4t} - y_{3t} = \beta_4' x_{4t} + \epsilon_{4t} \tag{12}$$

Replacing $y_{2t} - y_{1t}$ with y^*_{2t}, $y_{3t} - y_{2t}$ with y^*_{3t}, and $y_{4t} - y_{3t}$ with y^*_{4t}, we simplify Equations 9 to 12 as follows:

$$y_{1t} = \beta_1' x_{1t} + \epsilon_{1t} \tag{13}$$

$$y^*_{2t} = \beta_2' x_{2t} + \epsilon_{2t} \tag{14}$$

$$y^*_{3t} = \beta_3' x_{3t} + \epsilon_{3t} \tag{15}$$

$$y^*_{4t} = \beta_4' x_{4t} + \epsilon_{4t} \tag{16}$$

Equations 13 to 16 constitute our proposed model.

[7]In the empirical portion of this paper, we define front traffic and store traffic as daily shopper counts (total number of shoppers recorded during the day), and store sales as daily dollar sales (net of sales tax) or daily unit sales.

[8]The log-linear formulation also seems to be appropriate for our joint model as the time-series plots of front traffic, store traffic, store transactions, and store sales in our empirical illustrations show that the variance of these variables increases as their overall levels increase.

In fact, the variables y_{2t}^*, y_{3t}^*, and y_{4t}^* represent the log-transform of the store-entry ratio, the closing ratio, and average spending, respectively, while y_{1t} represents the log-transform of front traffic. As the disturbance terms would be contemporaneously correlated and there are no endogenous variables on the right-hand side of Equations 13 to 16, we treat these equations as a model of four seemingly unrelated equations that are linked only by their disturbance terms.[9] For this type of model, we apply the seemingly unrelated regression (SUR) method for efficient estimation (Greene 1997). Note that for independent variables representing marketing activities, the coefficients of these variables (β_i's) represent the attraction, conversion, or spending effects of these activities.

To examine the usefulness of our joint model (13–16), we also formulate for comparison another model that includes only store sales as the endogenous variable (Equation 17). The latter model represents the traditional approach without the intermediate performance measures, and incorporates all the explanatory (exogenous) variables of our joint model.

$$y_{4t} = \beta_5' x_{5t} + \epsilon_{5t} \tag{17}$$

where

y_{4t} : log-transformed store sales;
β_5 : a vector of parameters;
x_{5t} : a vector of explanatory variables; and
ϵ_{5t} : disturbance term, assumed to be normally and identically distributed with mean zero and constant variance.

Empirical Illustrations

To demonstrate the usefulness of our expanded perspective, we use it to study the promotional activities of Lisa, an apparel store in Canada, and Sportsco, a sporting-goods retail chain in the United States.[10] Our objective is to test our hypotheses, and to examine whether our decomposed sales response approach can provide additional insights into the effects of retailers' promotional activities beyond those obtained using a traditional approach. We use data from the apparel and sporting-goods retail sectors because consumers typically undertake comparison shopping for these types of goods. Replicating our research across the Lisa and Sportsco samples allows us to examine the generalizability of our findings across different product categories and countries. Furthermore, compared to the Lisa data, the Sportsco data permit a more precise examination of the effects of promotion scope and type of communication vehicle employed. Finally, because the Sportsco study period is relatively short, the Sportsco results are less distorted by the effects of seasonality.

Data

Lisa focuses on selling ladies' casual wear, and is located in a well-established mall in a major Canadian city. The study period examined here ran from September 28, 1996 to March 31, 1997 (about 6 months long). The store used infrared counters to record front traffic and store traffic by hour. As the store's promotional activities did not vary within a day, the traffic data were aggregated to a daily level of analysis. In addition to the traffic data, Lisa provided information on retail transactions (including store sales in dollars), advertising and promotions, and trading hours. Lisa's store manager also recorded the daily total employee-hours and external events that might affect store performance, including the March school break and snowstorms.

Sportsco sells a variety of sporting goods, including sportswear, sports shoes, and sports equipment. The period studied for Sportsco ran from April 1, 1995 to June 24, 1995 (about 3 months long). Data were collected from 22 Sportsco stores in two states. Eighteen of the stores are located in malls. The studied stores recorded daily store traffic data using infrared counters. Sportsco had not installed front traffic counters, and hence front traffic data were not available. Other data that Sportsco provided were similar to the Lisa data already described. In addi-

[9]For the empirical examples described in the next section, correlations among the disturbance terms were found to be substantial, ranging from −0.358 to 0.103.

[10]At the request of the studied retailers, both are disguised in this paper.

tion, Sportsco provided both unit and dollar store sales.

Activities Under Investigation

Lisa. Lisa's study period covers three types of promotion: price promotion, special promotion, and new-product promotion. In turn, the price promotions can be classified into one of three groups: single-category, multiple-category, and clearance. Lisa ran three single-category promotions during the period from September 28 to November 20. Each of these promotions focused on one product category (jeans, vests, or dresses). The multiple-category promotions covered several product categories, and included a mid-season sale (October 21–30) and two Christmas promotions (November 25–December 31). Finally, the clearance promotions ran from January 2 to March 6. Lisa supported all of these promotions using signage and display both at the store's front and inside the store. The single- and multiple-category promotions were also supported by newspaper advertising. In terms of depth of discount, the clearance promotions were larger than the multiple-category promotions, and the multiple-category promotions were larger than the single-category promotions.

Lisa's special promotions consisted of a ''No Tax'' event and a ''Friends and Family'' promotion. During the ''No Tax'' event (November 21–24), shoppers were not required to pay sales tax (15% of sales) for all merchandise purchased at Lisa. For the ''Friends and Family'' promotion, Lisa's employees sent coupons to their friends and family, inviting them to visit the Lisa store on a specified date near the end of November. By presenting the coupons, invited customers received an additional 20% discount on any purchases made on that day, including products that were already on discount.

From February 24 to March 15, Lisa used new-product promotion to announce the arrival of 1997 spring items at regular prices. Lisa displayed these spring items, together with decorative posters, in the store windows.

Sportsco. Sportsco's price promotions can be classified into four groups:

1. Focused-ROP promotion: A price promotion supported by ROP advertising was undertaken for the Prince brand.
2. Category-ROP promotions: These were price promotions involving an entire category of merchandise (skates, shoes, fishing equipment) and supported by ROP advertising.
3. Storewide-insert promotions: Three price promotions (Spring, Memorial Day, and Father's Day) were undertaken. These promotions covered multiple categories and were supported by newspaper inserts.
4. Storewide-coupon promotion: Like Lisa, Sportsco undertook a targeted promotion—''Family Night.'' Sportsco's employees sent a limited number of coupons to their friends and family, inviting them to a ''Family Night'' event on June 4. By presenting the coupon, a visitor could obtain a 25% discount on items purchased.

Depth of discount did not differ substantially across the foregoing promotions undertaken by Sportsco, ranging in value from 20 to 35%. Thus, in the Sportsco case, we are able to separate the effects of promotion scope from those of depth of discount. All of the studied stores followed the same promotion schedule, except that the Prince promotion only took place in nine stores.

Models and Variables

Lisa. We conduct our analysis based on our joint model (Equations 13–16) and the comparison sales model (Equation 17), and compare the results. The three price promotion groups, the two special promotions, and the new-product promotion are represented by separate dummy variables. The nonpromotion days from March 16 to 31 are used to establish the baseline. Hypothesis testing is then performed by examining the significance of the parameter estimates for these promotional variables and comparing these estimates using contrast tests.

The two models also incorporate several independent variables for control purposes. These covariates include day of week, Christmas days, length of operation, external events (March school break and snowstorms), and seasonality.[11] Some of these variables, such as day of week and the March school break, represent the temporal change in the volume and consumer composition of front traffic. For example, many full-time workers tend to shop on weekends, and as a result both front traffic and the proportion of full-time workers shopping in a store rise during weekends. Furthermore, full-time workers have higher time opportunity costs, and hence higher search costs when compared to other shoppers. Therefore, they are more likely to make purchases at a store they are visiting and to concentrate their purchases in that store. The rise in the proportion of full-time workers near the weekend thus implies that the closing ratio and average spending of a store would increase near the weekend. The day-of-week covariates account for such changes.

Search costs are also related to weather. Under adverse weather conditions (e.g., snowstorms, extreme heat or cold), search costs increase, and shoppers often prefer to wait for better weather conditions. Consequently, front traffic drops under bad weather conditions. Furthermore, shoppers inside a store are likely to be less inclined to visit other stores because of the high search costs, leading to increases in the closing ratio and average spending within the store.

For the day-of-week variable, pilot runs on the two models indicate no significant difference among Monday, Tuesday, and Wednesday. Thus, these three days are taken as the reference category and each of the other days is represented by dummy variables. Variation in the sales components on a number of days around Christmas were also examined in the preliminary runs. Significant parameter estimates were found for dummy variables representing some of these days. These dummy variables are included in the final model specification to control for the holiday effects. External events, including the March school break and snowstorms, are represented by dummy variables. The length of store operation, represented by the log-transformed value of the trading hours, is included in the front-traffic submodel because front traffic is expected to be positively related to the length of operation.

Seasonality is modeled as a Fourier series—a series of sinusoidal functions of various harmonics (Makridakis et al. 1983, DeLurgio 1998). Starting from the lowest harmonic, sinusoidal functions are successively added to the joint and comparison models until the parameter estimate of the additional function is insignificant at the 0.05 level (see the Appendix for details of the seasonality treatment).

Sportsco. As we do not have front traffic data in the Sportsco sample, we use only Equations 14–16 in our joint model and exclude front traffic from the store traffic submodel. The exclusion of the front traffic variable implies that the parameters in the store traffic submodel represent the combined effects of the explanatory variables on front traffic and the store-entry ratio. Because we have store sales data in terms of both dollars and units, we can examine the spending effects in both dollar and unit terms by estimating the joint model twice—first, by using average dollar spending as the dependent variable in Equation 16, and second, by replacing it by average unit spending. As in the Lisa case, we employ Equation 17 as the comparison sales model, using dollar sales as the dependent variable.

We introduce four dummy variables to represent the four groups of promotion—''focus-ROP,'' ''category-insert,'' ''storewide-insert,'' and ''storewide-coupon''—in both the joint and comparison models. As in the Lisa case, hypothesis testing is performed by examining the significance of the parameter estimates of these promotion variables and comparing these estimates using contrast tests. The covariates included in these models are essentially the same as those used in the Lisa analysis. The length of operation is not included in the Sportsco case, as this variable was

[11]We also tried including a staffing variable, because service availability may affect shoppers' information search and processing inside a store, and hence the closing ratio and average spending. Because the trading hours varied across the study period, we divided the daily total employee-hours by the daily trading hours to obtain an average staffing level. The staffing variable was operationalized as the inverse of the average staffing level to ensure that its effects on the store-entry and closing ratios were bounded between zero and one. However, preliminary runs of the models yielded nonsignificant parameter estimates for this variable, and deleting it did not alter the regression results substantially. Thus, we excluded staffing from all subsequent model estimations.

found to be perfectly correlated with the day-of-week variables. Similar to the Lisa analysis, we take into account the effects of several holidays (Easter, Memorial Day, and Father's Day) by conducting an intervention analysis on a number of days around these holidays. Those days associated with significant changes in the sales components are included in the models as dummy variables. As the study period is relatively short and we do not find a seasonal pattern in the time-series plots of the sales components, we do not include seasonal terms in the specification. To control for store-specific variation, dummy variables representing individual stores were also included.

Results

The Lisa regression results are reported in Table 1, while those for Sportsco are shown in Table 2. These results clearly demonstrate the greater richness of information provided by the joint model versus the traditional (comparison model) approach. Both sets of results also clearly show that the different components in the joint model are affected differentially by the promotional variables and the covariates. Particularly in the Lisa case, the parameter estimates for the average spending submodel are opposite in sign to the corresponding estimates for the store-entry ratio and closing ratio submodels. Furthermore, in both the Lisa and Sportsco cases, the incremental sales resulting from many of the promotions seem to come primarily from increases in the store-entry ratio or store traffic. In contrast, variations in front traffic seem to be related primarily to external factors beyond retailers' control rather than to the promotional variables. Below we examine more fully the effects of price promotion, promotion scope, clearance promotion versus multiple-category promotion, new-product promotion, newspaper advertising versus targeted coupons, and the covariates on the joint model elements.

Price Promotion. Evidence for an attraction effect due to price promotion appears to vary with promotion type. For the Lisa sample, the front traffic results do not provide support for the positive attraction effects of price promotion hypothesized in Hypothesis 1. Most of the parameter estimates for the studied promotions are nonsignificant, and contrary to expectation, the estimate for the clearance promotion suggests that this type of promotion decreases front traffic significantly. In contrast, the store-entry ratio results provide strong support for Hypothesis 1, with the results showing that both price and special promotions generally have a positive and significant effect on store entry. In the Sportsco case, the store traffic results provide mixed evidence about the effect of price promotion on store traffic. The category-ROP and storewide-insert promotions appear to have increased store traffic significantly, whereas the focus-ROP promotion actually led to significantly decreased store traffic.

The conversion effects of price promotion described in Hypothesis 2 are well supported by the closing-ratio results for the Lisa sample. All of the parameter estimates for price promotion and special promotion are positive, and most are significant. The closing-ratio submodel results for the Sportsco sample also provide some support for the hypothesized conversion effect. The estimates for the effects of price promotion on the closing ratio are all positive, although only the effect of the storewide-insert promotion is significant.

The average unit-spending results from the Sportsco sample provide mixed evidence for Hypothesis 3, which predicts that price promotion increases the average number of units sold per transaction. The storewide-insert and storewide-coupon promotions appear to increase the average number of units sold significantly as expected, but contrary to expectation, the focus-ROP promotion appears to decrease this number significantly.

The average dollar-spending results for the Lisa sample provide strong support for Hypothesis 4. The estimated average spending coefficients for price promotion and special promotion are all significant, and all but one is negative. The Sportsco results also strongly support Hypothesis 4 because most of the average spending (dollar) coefficients for price promotion are significant.

Promotion Scope. Both the Lisa and Sportsco results provide support for Hypothesis 5, which anticipates that greater promotion scope will increase the attraction effect of price promotion. In the case of

Table 1 Regression Parameter Estimates—The Lisa Sample

	Joint Model[a]				
Submodels	Front Traffic	Store-Entry Ratio	Closing Ratio	Average Spending	Comparison Model[a]
Intercept	8.55***[b]	−3.13***	−2.15***	3.87***	7.73***
Price Promotion					
Single category	−0.123	0.464***	0.248**	−0.236**	0.406*
Multiple category	−0.101	0.548***	0.265***	−0.308**	0.385*
Clearance	−0.239**	0.234*	0.226**	−0.462***	−0.279
Special Promotion					
No tax	−0.892	0.414***	0.373*	−0.421**	0.250
Friends and family	−0.0771	0.113	0.131	0.503**	0.650*
New Product Promotion	−0.137	−0.0675	0.338***	−0.309***	−0.293*
Length of Operation	0.298*	–	–	–	0.0573
External Events					
School break	0.228***	0.0143	0.108	−0.282***	0.0856
Storm	−0.233***	−0.00870	−0.147	−0.0433	−0.432**
Day of Week					
Thursday	0.0839***	−0.0146	0.0581	0.0753*	0.226***
Friday	0.199***	0.0568	0.0332	0.0480	0.331***
Saturday	0.399**	0.292***	0.118*	0.0907**	0.860***
Sunday	−0.0111	0.248***	0.167**	0.0227	0.242
Christmas[c]					
Dec. 23	0.421***	–[d]	–	–	0.907***
Dec. 26	–	0.391**	–	–	–
Dec. 27	–	–	–	−0.311*	–
Dec. 28	−0.389***	–	–	−0.458**	−0.862**
Dec. 29	−0.256*	–	–	–	–
Seasonality[e]					
Sin_1	−0.0870[f]	0.136**	–	−0.0240	0.0620
Cos_1	0.198***	0.0235	–	−0.0168[g]	0.217**
Sin_2	−0.0734***	−0.0598*	−0.0608	0.0553	−0.171***
Cos_2	0.0707***	0.0737***	0.146***	−0.152***	0.128***
Sin_3	−0.0871***	0.0695**	–	−0.123***	−0.130**
Cos_3	0.0485***	0.0811***	–	−0.0516**	0.102**
Sin_4	−0.0238	–	–	–	–
Cos_4	0.0548***	–	–	–	–
Sin_5	−0.0348*	–	–	–	–
Dependent Variable					
Mean	9.18	−2.72	−1.86	3.58	8.19
Standard deviation	0.290	0.245	0.255	0.239	0.556

[a]System weighted R-square of the joint model = 0.891; R-square of the comparison model = 0.821. The dependent variables of the submodels are represented by the log-transform of front traffic, store-entry ratio, closing ratio, and average spending, respectively.
[b]*, $p < 0.05$. **, $p < 0.01$. ***, $p < 0.001$.
[c]No significant parameter estimates were found for December 24. The store was closed on Christmas.
[d]For the Christmas and seasonality factors, dummy variables with insignificant parameter estimates ($p > 0.05$) were excluded from the final specification of the joint model.
[e]For any integer k, $Sin\_k = sin[(2B*k/185)*t]$ and $Cos\_k = cos[(2B*k/185)*t]$, where t is the time index ($t = 1$ for Sept. 28, 96; $t = 2$ for Sept. 29, 96; $\ldots$; $t = 185$ for Mar. 31, 97). The lowest harmonic terms of the closing ratio seasonality are *Sin_2* and *Cos_2* since the fundamental frequency for this seasonality is $2B*2/185$.
[f]For the lower harmonic terms, we include an insignificant sinusoidal term in the model when the other term at the same frequency is significant. The time series and economic forecasting literature does not indicate whether the insignificant term should be dropped in such a situation. However, examples of Fourier series modeling usually show the sinusoidal terms in pairs (Madridakis et al. 1983, DeLurgio 1998). The results change little even if the insignificant term is dropped.
[g]The parameter estimates of *Cos_1* terms are significant at 0.05 level when the higher harmonic terms are absent.

Table 2 Regression Parameter Estimates—The Sportsco Sample[a]

	Joint Model[b]				
Submodels	Store Traffic	Closing Ratio	Average Spending (Dollar)	Average Spending (Unit)	Store Sales (Comparison Model)[b]
Intercept	6.72***[c]	−1.54***	3.59***	0.452***	8.46***
Price Promotion					
Focus-ROP	−0.0847**	0.0629	−0.0167	−0.0520**	−0.120***
Category-ROP	0.0698***	0.0303	0.0212*	−0.00534	0.115***
Storewide-Insert	0.259***	0.0561***	0.0484***	0.0384***	0.348***
Storewide-Coupon	−0.0372	0.0384	0.0822*	0.115***	0.0900
Weather—Precipitation (Reference: Clear)					
Overcast	0.0490***	−0.0670***	−0.0188	0.00411	0.0349
Rain	0.0675***	−0.0521*	−0.0244	0.0180	0.0242
Weather—Temperature (Reference: 60–80°F)					
Below 15°F	0.0234	0.0472*	0.0109	0.0264*	−0.0363
15–40°F	−0.0230	−0.0596	−0.0581	−0.0526	−0.158**
40–60°F	−0.0176	−0.0773***	−0.00542	−0.0191	−0.0972***
Above 85°F	0.0778**	−0.0299	−0.0562*	−0.00676	0.0249
Day of Week					
Friday	0.217***	0.206	0.0108	0.0314**	0.236***
Saturday	0.693***	−0.0311	0.101***	0.0724***	0.761***
Sunday	0.228***	−0.0437	0.158***	0.0532***	0.330***
Holiday					
Easter (Day after)	0.278***	−0.185**	–	–	0.213**
Memorial Day	0.577***	–[d]	0.126***	–	0.529***
Father's Day	−0.143**	0.175*	−0.0889*	–	–
Dependent Variable					
Mean	6.69	−1.43	3.64	0.563	8.90
Standard deviation	0.593	0.335	0.182	0.148	0.600

[a]To save space, the estimates for the dummy variables that identify individual stores are not shown. Most of these estimates are significant at 0.001 level.
[b]System weighted R-square of the joint model = 0.832; R-square of the comparison model = 0.806. The results of the store traffic and closing ratio submodels relate to the estimation using average spending (dollars) as a dependent variable. For the case of the estimation using average spending (units), the results of the two submodels differ only slightly from the results shown and hence are not reported here.
[c]*, $p < 0.05$. **, $p < 0.01$. ***, $p < 0.001$.
[d]For the holiday factor, dummy variables with insignificant parameter estimates ($p > 0.05$) were excluded from the final model specification.

Lisa, the store-entry ratio estimate for multiple-category promotion is larger than that for single-category promotion, although a contrast test does not reject the equality of these parameters at the 0.05 level. Stronger evidence for a relationship between promotion scope and the attraction effect is found in the case of Sportsco. Comparing the focus-ROP, category-ROP, and storewide-insert promotions, the parameter estimates in the store traffic submodel increase monotonically with growing promotion scope. A joint contrast test rejects the equality of these parameters (F = 129; $p < 0.001$). Furthermore, specific pairwise contrasts indicate that the storewide-insert promotions lead to a significantly larger attraction effect than the category-ROP promotions, and the category-ROP promotions lead to a significantly larger attraction effect than the focus-ROP promotion (F = 140 and F = 22.0, respectively; $p < 0.001$ in both cases).[12]

[12]One should be cautious not to overinterpret these results. In ad-

The Lisa and Sportsco results do not provide strong support for the impact of promotion scope on the conversion effects of price promotion (Hypothesis 6). For the closing-ratio submodel, contrast tests conducted on both the Lisa and Sportsco samples do not reject the equality of the parameters estimated for promotions with different scope.

Promotion scope appears to increase average spending (both units and dollars) in the Sportsco case, a finding consistent with Hypothesis 7. The parameter estimates for the average dollar spending and the average unit spending submodels exhibit an upward trend across the focus-ROP, category-ROP, and storewide-insert promotions. Furthermore, a joint contrast test rejects the equality of these parameters for both average dollar spending (F = 5.40; $p < 0.01$) and average unit spending (F = 13.6; $p < 0.001$). More specific pairwise contrasts found that, compared to the focus-ROP and category-ROP promotions, the storewide-insert promotion has both larger dollar-spending effects (F = 7.04, $p < 0.01$ and F = 4.34, $p < 0.05$, respectively) and larger unit-spending effects (F = 15.7 and F = 13.0, respectively; $p < 0.001$ in both cases). In contrast, the Lisa average dollar-spending results do not provide evidence of any significant difference.

Clearance Promotion and New-Product Promotion. Examining the Lisa store-entry ratio and closing-ratio submodel results, we observe that the clearance promotion yields smaller parameter estimates compared to the multiple-category promotions. These parameters are significantly different in the case of the store-entry ratio submodel (F = 6.79; $p < 0.01$), but not in the case of the closing-ratio submodel. Thus, Hypothesis 8, which states that clearance promotions should have smaller attraction effects than other multiple-category price promotions, is supported, but Hypothesis 9 (conversion effects) is not. Counter to expectations, the coefficient estimate of the clearance promotion in the front traffic submodel is negative and significant. Perhaps during the clearance promotion, the large clearance signage displayed in front of the Lisa store deterred some shoppers from approaching the store.

A positive and significant parameter estimate in the closing-ratio submodel is noted for the Lisa new-product promotion, providing empirical support for Hypothesis 10. Interestingly, a negative and significant parameter estimate is observed for this type of promotion in the average spending model. Because new items usually have higher prices than old items, this negative estimate suggests that during the new-product promotion period, consumers buy fewer items per store visit than during the nonpromotion baseline period.

Newspaper Advertisements Versus Targeted Coupons. The results obtained from the Sportsco data can be used to test Hypothesis 11 and Hypothesis 12. These hypotheses predict that newspaper advertisements, when compared to targeted coupons, will lead to higher attraction effects (Hypothesis 11) but lower average spending (both unit and dollar) effects (Hypothesis 12). The parameter estimates in the store traffic submodel are consistent with Hypothesis 11. Whereas the targeted coupon promotion (storewide-coupon) does not have a significant effect on store traffic, both the category-ROP and storewide-insert promotions have a significant positive effect. The difference between the storewide-coupon promotion and the storewide-insert promotion was also significant (F = 30.1; $p < 0.001$).

Targeted coupons have a greater impact than newspaper advertising on the average unit-spending model, supporting Hypothesis 12. Specifically, the average number of units purchased during the targeted coupon promotion is significantly higher than the average number during the baseline period. In contrast, although storewide-insert advertising also has a significant positive impact on average unit spending, this effect is much weaker than that observed for the coupon promotion. A contrast test revealed that the coupon-supported promotion has marginally larger spending effects in unit terms than the insert-sup-

dition to promotion scope, the category-ROP and storewide-insert promotions also differ by the type of communication vehicle used (ROP versus insert). Thus, the effects of the two factors are confounded in the Sportsco case.

Table 3 Summary of Hypotheses and Results

Variable	Hypothesis	Sales Effect	Anticipated Sign	Data Sources	Results
Price Promotion	H_1	Attraction	+	Lisa and Sportsco	Mixed evidence. Effects on front traffic are negligible, but effects on store entry support the hypothesis. (Lisa and Sportsco)
	H_2	Conversion	+	Lisa and Sportsco	Supported. (Lisa and Sportsco)
	H_3	Unit spending	+	Sportsco	Mixed evidence. Results depend on promotion type. (Sportsco only)
	H_4	Dollar spending	+ or −	Lisa and Sportsco	Supported. (Lisa and Sportsco)
Promotion Scope	H_5	Attraction	+	Lisa and Sportsco	Supported. Evidence is weak for Lisa, stronger for Sportsco.
	H_6	Conversion	+	Lisa and Sportsco	Not supported.
	H_7	Spending (unit or $)	+	Lisa and Sportsco	Mixed. No support in Lisa case but supported by Sportsco results.
Clearance Promotion	H_8	Attraction	−	Lisa	Supported.
(versus Multiple-Category Promotion)	H_9	Conversion	−	Lisa	Not supported.
New Product Promotion	H_{10}	Conversion	+	Lisa	Supported.
Newspaper Advertisements	H_{11}	Attraction	+	Sportsco	Supported.
(versus Targeted Coupons)	H_{12}	Spending (unit or $)	−	Sportsco	Mixed. Support found for unit effect but not dollar effect.

ported promotion ($F = 3.49$; $p < 0.1$).[13] While these results are interesting, they are not replicated in the average dollar-spending submodel results. In this latter case, there is no significant difference between the two communication vehicles' effects on average dollar spending.

The Covariates. The parameter estimates of the covariates provide some support for our conceptual thinking about factors affecting store performance and the nomological validity of the sales components. For example, in the Lisa case, the substantial decrease in front traffic during snowstorms supports the idea that adverse weather conditions increase search costs, leaving consumers to wait for better weather before shopping. The significant change in the four sales components near the weekend is also consistent with the notion that store performance is affected by customer composition, which varies with day of the week. The sinusoidal variables used to control for seasonality in the Lisa sample indicate that seasonal factors were present across all sales components. Given the pattern of the significant parameters, seasonal variation seems to be more prevalent in the attraction and spending submodels.

[13]Given that the targeted coupon promotion lasted only one day, a significance level at $p < 0.1$ is noteworthy.

Summary. Both the hypotheses advanced earlier and the results obtained from the Lisa and Sportsco analyses are summarized in Table 3. Although the evidence to support the various hypotheses is in some cases mixed, we believe that use of the joint model enriches our understanding about the effects of the studied promotion variables on store performance. We explore this issue more fully in the next section.

Discussion

Effects of Price Promotion and Individual Promotional Elements

Our modeling approach, particularly when applied to comparison shopping contexts, examines the effects of retail marketing activity more thoroughly than traditional models of store performance. For example, a manager using the traditional model to evaluate price promotions at Lisa would conclude that only the single-category and multiple-category promotions significantly affected sales. However, the joint model results show that all of the price promotions have a significant impact on attraction, conversion, and spending.

Price Promotion. The joint model results indicate that price discounts could have both positive and negative effects on store performance. Specifically, the results suggest that while many of the studied promotions attract shoppers to the promoting store and help convert store visitors to buyers, these promotions also decrease the buyers' expenditures. Because of the interplay between these opposite effects, the impact of price discounts on overall store sales may appear to be negligible or even negative. For example, the Lisa comparison model results show a negative effect of clearance promotion on store sales, and the retailer may therefore think that this promotion is not worth undertaking. However, the joint model results indicate that this type of promotion can improve performance by attracting more people in the front traffic to enter the store and converting more visitors into shoppers.

Using the relevant parameter estimates from the joint model results, we can estimate the resultant impact of price promotion due to the attraction, conversion, and spending effects, and examine the tradeoffs among them. Referring to Table 1 (which is expressed in logarithmic terms), the resultant impact of clearance promotion equals the sum of −0.239, 0.234, 0.226, and −0.462, or −0.241. Converting this sum to the original data domain, the overall impact amounts to $[exp(-.241) - 1]\cdot 100\%$—a 21.4% decrease in store sales. In other words, ceteris paribus, the undertaking of clearance promotion is expected to decrease store sales by 21.4%. In this case, the positive effects of the clearance promotion on both the store-entry and closing ratios cannot compensate for its negative effects on average spending and front traffic. To overcome this, Lisa's management might decide to run alternative promotions that increase front traffic concurrently with its clearance promotions.

It should be noted that we found significant attraction effects due to price promotion, whereas Walters and his coauthors observed no such impact of price promotions on store traffic in their supermarket studies (Walters and Rinne 1986, Walters and MacKenzie 1988). We attribute this difference to two factors. First, the studies completed by Walters and his colleagues were done in supermarkets, where weekly price promotions are the norm. In contrast, our studies compare intensive promotional periods to periods with very low levels of promotional activity. Second, Walters and Rinne (1986) and Walters and MacKenzie (1988) represent store traffic by the number of transactions completed. Thus, the ''traffic effect'' that they report is actually a combination of the attraction and conversion effects explored here. In contrast, our studies measure store traffic by the actual number of people entering a store.

Individual Promotional Elements. Apart from price promotion, the joint model results also provide three additional insights into the effects of specific promotional elements on store performance. First, the effects of promotion scope on store performance, particularly the attraction and spending effects, are more distinct for the Sportsco sample than for the Lisa sample. One potential explanation for this may be differences in the breadth of merchandise offered by the two retailers. Sportsco sells a wide variety of sporting-goods merchandise, encompassing many different product categories, whereas Lisa focuses on selling ladies' casual wear. Thus, Sportco's merchandise breadth is considerably larger than Lisa's. The extent to which consumers can make purchases across multiple categories at a particular store depends on the breadth of that store's merchandise. Therefore, the relationship between promotion scope and the store attraction effect, and between promotion scope and the spending effect, should be stronger for a store with a wide breadth of merchandise versus a store with a narrower breadth.

This is precisely what the results summarized in Table 3 show. For Lisa, the single- and multiple-category promotion effects do not differ significantly from one another. In contrast, the Sportsco results clearly demonstrate that the attraction and spending effects are positively related to promotion scope.

Thus, breadth of merchandise appears to moderate both the relationship between promotion scope and the attraction effect and between promotion scope and the spending effect. Interestingly, the Sportsco focused-ROP promotion resulted in decreased store traffic. Perhaps the Prince line highlighted in this promotion might not have widespread appeal to consumers. Thus, when the store display and out-of-store advertisements focused exclusively on the Prince line, a number of shoppers who were not interested in this brand became less inclined to visit Sportsco, and consequently, store traffic decreased. Thus, retailers need to be particularly careful about managing focused promotions, perhaps choosing only those brands or products that have widespread consumer appeal.

Second, in both the Lisa and Sportsco cases, targeted coupons appear to have larger spending effects but smaller attraction effects when compared to newspaper advertisements. This suggests that although coupons are more convincing than price-off offers (Dhar and Hoch 1996), the limited distribution of the coupons has a negative influence on attraction. Third, the smaller attraction effects of the clearance promotion, when compared to other multiple-category promotions, are consistent with the notion that shoppers hold a poorer attitude towards an inventory clearance message as a rationale for price discounts versus other rationales (Bobinski et al. 1996).

Other Issues. In addition to the specific results highlighted above, two of the findings in our analyses warrant further comment. First, for the Lisa sample, almost no promotion had an impact on front traffic. Though this can be expected in shopping mall environments where the target retailer has only a small store, these results have implications for the promotional strategies employed by such retailers. For example, they suggest that because out-of-store advertising does not greatly affect mall traffic, any promotion needs to be accompanied by significant advertising and display activity at the storefront to encourage store entry.

Second, the promotional elements studied here tended to have a greater impact on attraction (particularly store entry) than conversion. These results persisted even though many of the promotional events incorporated a price-off component. Conversion is influenced by various in-store activities, including product assortment and quality, service level, and store layout. Thus, retailers need to carefully study how these in-store marketing elements can be used to enhance store performance, particularly conversion and spending.

Profit Impact

In addition to understanding the key drivers of store sales, retailers are also interested in determining whether or not promotions affect store profitability. An assessment of the profit impact cannot be based on the change in overall store sales because promotions may affect various items or product categories inside a store differentially, and gross margins may not be the same for all items or categories. Furthermore, store promotions may attract people whose purchase behaviors are different from those shopping in a nonpromotion period, such as "cherry-picking" consumers who buy only promoted items (Mulhern and Padgett 1995). Thus, price promotions may increase the sales of promoted items and possibly their complements, have little effect on unrelated merchandise, and decrease the sales of substitute items (Walters 1988, Walters and MacKenzie 1988). It is therefore necessary to estimate sales and profit changes for the promoted, substitute, complement, and unrelated items separately.

Because our data do not include information about gross margins and sales volumes of individual items, we are unable to examine the profit impact of the promotional variables under study. However, to illustrate how this analysis might be conducted, we assume gross margin and sales volume numbers for two types of promotion. First, consider Lisa's new product promotion. Based on previous experience or consumer judgments, Lisa's management could classify all nonpromoted merchandise into three groups: substitutes, complements, and unrelated items. The joint model approach could then be used to separately estimate the sales impacts of the new-product promotion for promoted items, substitutes, complements, and unrelated items. Because the sales components in the joint model were originally developed for overall sales analysis, they need to be adapted to estimate the sales impact at a less aggregate level. Front traffic and store traffic would be defined as before, because it is generally not possible to distinguish between those who have purchase needs for the different merchandise groups. However, the number of transactions completed and the resulting sales dollars can be noted for each group separately, allowing the closing-ratio and average spending values to be determined at the merchandise group level.

To provide a tangible example of this approach, suppose that, relative to the nonpromotion period, the impact of the new-product promotion on sales is a 30% increase for promoted items, a 15% increase for complements, a 20% decrease for substitutes, and a 3% increase for unrelated items. Using sales figures for the nonpromotion (baseline) period, these percentages can be converted into dollar terms. For example, if average daily sales during the nonpromotion period are $3,000 for promoted items, $2,000 for substitutes, $2,500 for complements, and $1,000 for unrelated items, then the corresponding sales changes due to the promotion would be a $900 increase for promoted items, a $300 decrease for substitutes, a $500 increase for complements, and a $30 decrease for unrelated items.

To derive the incremental gross profit due to the new-product promotion, one needs to know gross margins for individual items or categories. Returning to the previous example, suppose (for the sake of simplicity) that these margins do not differ substantially within each group. Because the new-product promotion did not involve price discounts, these margins would not change, and the gross margins from the nonpromotion period can be used directly to calculate the incremental gross profit. For example, if the gross margins are 50% for promoted items, 35% for substitutes, 40% for complements, and 40% for unrelated items, the corresponding changes in gross profit would be $450, −$105, $200, and $12. In this case, the total daily incremental gross profit generated by the new product promotion would be $557.

The foregoing procedure for estimating gross profit change can also be applied to price promotions, except that the change in gross margin due to price discounts now has to be taken into account. A price promotion on jeans, for example, may cause the gross margin on jeans to decrease from 50% to 30%. Furthermore, it is likely that the sales impact of the promotion on the various merchandise groups will be different than in the case of the new-product promotion. Whether the promotion increases or reduces gross profit will depend largely on how the sales volume increase of the promoted items (and possibly complements) counteracts the reduction in the gross margin of the promoted items, along with any loss in the sales of substitutes.

Limitations and Future Research

By being able to partition store sales into its subelements, our modeling framework can be used to assess a wide variety of retail marketing activities such as TV/radio advertising, media-delivered coupons, store design, product assortment, and personal selling. Activities that may have "countereffects" on performance deserve particular attention. For example, in the case of Lisa we noted that some promotions have negative effects on front traffic and average spending. These effects would be a concern to retailers, since they may nullify the beneficial effects of promotion, such as an increase in the store-entry ratio. Future research designed to jointly consider the effects of various marketing activities on attraction, conversion, and spending will help to better illuminate these tradeoffs. Furthermore, an increase in store traffic resulting from an effective promotion could have implications for other activities undertaken by retailers, such as inventory planning and staff scheduling (Lam et al. 1998). These implications are also worth investigating.

The attraction and conversion effects of retail marketing activity may also vary with the type of store location involved. The stores investigated in this study were largely located in malls. For mall-based stores, a large proportion of people included in the front traffic measure are likely to be people on their way to other stores in the mall, and a large proportion of the store traffic may be "browsers"—people who are interested in a product category but do not have a current intent to buy (Bloch et al. 1986). In these cases, marketing activities that increase conversion (e.g., personal selling, price promotion, attractive merchandise assortments and displays) need to be carefully considered. In contrast, for stores in stand-alone locations, a very high proportion of the front traffic and store traffic will comprise people with specific purchase needs who have already decided to visit these retailers. For these stores, determining which marketing activities lead to a higher attraction effect will be critical to their overall success. Future research examining differences in these effects across in-mall versus stand-alone locations would be valuable.

Our store performance framework can also be directly applied to e-commerce or Web shopping-mall environments. In these Internet shopping environments, the front traffic variable would be Web mall traffic, and store traffic would be the number of hits on a specific store page. The number of transactions and spending variables could be measured directly. Because traffic is more easily tracked and experimentation more easily conducted over the Internet, our modeling framework could be quite useful in planning and evaluating e-commerce marketing programs.

Although the retailers in our empirical illustrations did not systematically vary their retail marketing activities within or across stores, the store performance model developed here provides a good basis for experimentation. In fact, a true experimental design would be able to remove any seasonality confounds that may be present. In spite of the application of the Fourier series method, there still remains a risk of over- or underadjusting for the seasonality. If studied stores could be randomly assigned to either a "no promotion" (control group) or "promotion" (experimental group) condition, a comparison of the performance observed for both groups in the *same* time period could help separate out the effects of promotional activities and seasonality.

In our empirical studies, some of the promotional elements covaried or were otherwise confounded with one another. As a result, it is difficult to relate some of our results to specific elements. An experimental design could be used to isolate the effects of specific promotional elements, such as semantic cues and storefront display (Dhar and Hoch 1996, Wansink et al. 1998). For example, several versions of storefront signage with different semantic cues can be produced and randomly assigned to the studied stores in the same time period. By tracking the store-entry ratios of these stores over time, we could tell which semantic cue helps attract more customers to enter a store.

Conclusion

The primary objective of this paper is to present a store performance model useful to researchers and managers in comparison-shopping environments. Our model is based on a framework that partitions sales response into attraction, conversion, and spending effects, which relate to consumers' decisions in their comparison shopping process. The availability of electronically tracked traffic data and the combined use of these data and transaction data make it possible and economical to study these effects. Compared with a traditional approach to looking at store sales, we offer a more comprehensive view on store performance and provide further insights into the effectiveness of retail marketing variables. We believe that the application of our modeling framework will allow researchers and managers to better understand the determinants of store performance in comparison-shopping environments.

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Appendix: Modeling Seasonality

The Fourier series method uses a series of sine and cosine functions of different harmonics to simulate seasonal variation. Other methods of modeling seasonality, such as multiplicative decomposition and differencing, cannot be applied here because the period under study is not sufficiently long. The Fourier series method begins by identifying the fundamental frequency of the series—the frequency of the lowest harmonic:

$$f_0 = 2B \cdot k_0/185$$

where

f_0 : fundamental frequency; and
k_0 : number of peaks (or number of troughs) identified from the time series plot of the variable under study.

Note that 185 is the number of days in the study period. The time-series plots of the four sales components indicate that there is one peak for both front traffic and the store-entry ratio, two peaks for the closing ratio, and one trough for average spending. Thus, for the front traffic, store-entry ratio, and average spending seasonality, the fundamental frequency is $2B\cdot 1/185$, whereas for the closing-ratio seasonality the fundamental frequency is $2B \cdot 2/185$. The seasonal variation of a sales component is then modeled as a series of sine and cosine terms, including the lowest harmonic, $\sin(f_0t)$ and $\cos(f_0t)$, and the higher harmonics—$\sin(2f_0t)$ and $\cos(2f_0t)$, $\sin(3f_0t)$ and $\cos(3f_0t)$, $\sin(4f_0t)$ and $\cos(4f_0t)$, etc.

These terms are included in our model as covariates. In other words, the seasonal terms compete with other explanatory variables in the model for explanatory power. A concern about this simultaneous estimation is whether the correlation between the seasonal terms and other explanatory variables would lead to a multicollinearity problem. However, our regression results show no signs of multicollinearity—the standard errors of parameter estimates are not particularly large, the majority of the promotion variables are statistically significant, and the sign of the parameter estimates for many variables conforms to our hypotheses.

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