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Guest Satisfaction and Restaurant Performance

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This study demonstrates a methodology to quantify the links between customer satisfaction, repeat-purchase intentions, and restaurant performance. Using data from a national restaurant chain, the authors constructed a series of mathematical models that predict how the level of customer satisfaction with certain attributes of guests' dining experience affects the likelihood that they will come back. In turn, the model shows how guests' "comeback" scores and other variables affect restaurant performance (i.e., sales and entrée counts). Robust and statistically significant, the models showed that restaurants that pay attention to food quality, appropriate cost, and attentive service have the greatest chance to increase guests' intent to return. In turn, that intent to return is a chief driver of increased sales.

Keywords: customer satisfaction; restaurant performance; service-profit chain; guest intention to return

Companies and organizations in virtually every industry employ customer-satisfaction measures for the straightforward reason that satisfied customers are essential for a successful business. Despite what seems like agreement on the importance of customer satisfaction, however, there is little consensus on the details of what constitutes satisfaction or even how to quantify the difference customer satisfaction makes. Also in debate are how customer satisfaction should be measured, with what frequency, and at what level of aggregation, as well as how such measures are or should be linked with a firm's performance. What is more, some empirical evidence suggests that the relationships between customer satisfaction, customer loyalty (repeat business), and a firm's performance are tenuous at best.

The study described in this article attempts to address the key issue in customer satisfaction, namely, the relationships between customer satisfaction, customers' repeat-purchase intentions, and restaurant performance. Much research, both theoretical and empirical, has examined how customer satisfaction may be related to organizational goals and business performance. In this study, we employ a large data set from a national restaurant chain to construct models that describe the factors that influence customers' likelihood of repeat purchase. We then link this purchase likelihood, along with other variables, to restaurant sales.

Linking Customer Satisfaction with Performance

The relationships we study are part of a framework referred to as the service-profit chain (this concept was developed by Heskett et al. 2004). In this framework there are certain attributes of the dining experience that affect customer satisfaction. Next, higher customer satisfaction should lead to increased probability of repeat purchase, which in turn should result in greater restaurant sales. In this section, we review earlier work that measured the customer satisfaction and performance links in the restaurant sector.

The empirical literature on this topic with regard to restaurants dates from the past twenty years. A few studies were conducted in the late 1980s and the 1990s focusing mostly on attributes of the dining experience that determine customer satisfaction (see, e.g., Knutson 1988; Davis and Vollmann 1990; Dubé, Renaghan, and Miller 1994; and Kivela, Inbakaran, and Reece 2000). More recently, however, researchers started addressing the links between customer satisfaction and performance, emphasizing the way satisfaction affects customers' repeat purchases (examples of recent contributions include Sulek and Hensley 2004; Söderlund and Öhman 2005; and Cheng 2005). Next, we review the main findings on the drivers of customer satisfaction, the links between such drivers and repeat-purchase intentions, and the influence of customer satisfaction on restaurant performance.

Drivers of Customer Satisfaction

Many researchers have explored the underlying factors that result in customer satisfaction. Knutson (1988) discussed principles that managers should follow to meet or exceed customer expectations, such as employee greeting, restaurant atmosphere, speed of service, and convenience. Fitzsimmons and Maurer (1991) constructed a managerial tool to measure the attributes driving customer satisfaction. Other studies have identified numerous factors that influence customer satisfaction with a dining experience, including waiting time, quality of service, responsiveness of front-line employees, menu variety, food prices, food quality, food-quality consistency, ambience of the facilities, and convenience (Davis and Vollmann 1990; Dubé, Renaghan, and Miller 1994; Kivela, Inbakaran, and Reece 2000; Sulek and Hensley 2004; Iglesias and Yague 2004; and Andaleeb and Conway 2006).

Customer Satisfaction and Repeat-Purchase Intentions

Determining satisfaction is not sufficient, however, because one needs also to establish the link between satisfaction and repeat purchases, which are an important source of restaurants' profits. Thus, studies have addressed the links between customer satisfaction with various restaurant attributes and repeat-purchase intentions (for instance, see Sulek and Hensley 2004; Söderlund and Öhman 2005; and Cheng 2005). While these studies often find strong links, the importance of a particular attribute varies according to the type of restaurant and the type of customer (for a detailed analysis, see Cheng 2005). For instance, food quality is the critical attribute influencing repeat-purchase intentions in full-service restaurants, while waiting time is the most important attribute in quick-service restaurants (research focusing on full-service restaurants includes Sulek and Hensley [2004] and Clark and Wood [1998]; research on fast-food restaurants is from Davis and Vollmann [1990]). When

Kivela, Inbakaran, and Reece (2000) conducted an extensive survey of diners of various restaurants, they found that first and last impressions have the greatest impact on repeat-purchase intentions, followed by excellence in service and food quality. This literature concludes that different classes of restaurant businesses should implement different managerial strategies to compete and succeed (Cheng 2005). Most studies that show strong links between customer satisfaction and repeat-purchase intentions typically employ cross-sectional data. Nevertheless, marketing researchers argue that one should take into account the dynamic properties of such links (see, for example, Rust and Zahorik 1993; Bernhardt, Donthu, and Kennett 2000).

Repeat-Purchase Intentions and Sales Performance

The general conclusion of these studies is that higher levels of customer satisfaction lead to an increase in customers' repeat purchases and improved financial performance (Mittal and Kamakura 2001). However, evidence regarding the link between customer satisfaction and a restaurant's performance remains ambiguous. Anderson, Fornell, and Rust (1997), for instance, found no correlation between customer satisfaction and productivity in service firms as a group or among restaurants in particular. In contrast, Bernhardt, Donthu, and Kennett (2000) employed data from a national chain of quick-service restaurants and found a positive association between changes in customer satisfaction and changes in sales performance. They argued that researchers and managers should take into account the dynamic properties of this link because there is a time horizon for the influence of customer satisfaction on restaurant performance. Söderlund and Öhman (2005) found another dimension in addition to time. They concluded that the correlations between (1) repeat-purchase intentions and customer satisfaction and (2) repeat-purchase intentions and actual repeat purchases are sensitive to the particular measure of repeat-purchase intentions employed. Overall, the restaurant literature calls for further empirical research on the links between customer satisfaction and firm performance (Söderlund and Öhman 2005).

In the study described in this article, we address at the same time all three elements of the link between customer satisfaction and performance, namely, customer satisfaction, repeat-purchase intentions, and firm performance. Our model considers the dynamic nature of the aforementioned relationships and identifies the lag structure among the three constructs. Finally, our study fills a gap in the empirical literature that focuses on the restaurant sector by linking customer satisfaction to restaurant performance.

Study Goals and Data Sources

We set out to determine the principal drivers of customer satisfaction in a restaurant chain and, subsequently, to determine how customer-satisfaction data can be most effectively used to improve the chain's performance. In particular, our goals were the following: (1) to identify the customer-experience attributes that cause customers to come back to a restaurant; (2) to prioritize those customer experience attributes in terms of their effect on customers' likelihood to come back; and (3) to identify the relationships between likelihood to come back, and guest count or restaurant sales, and quantify the effect of changes in "come-back" scores on restaurant performance.

We acquired a large data set from a national restaurant company that has more than three hundred outlets in locations covering roughly one-half of the United States. This company's three restaurant divisions record total sales of approximately $1,000,000 per day. This rich data set contained several distinct parts. First, we had data from more than eighty thousand guest surveys regarding guests' detailed and overall restaurant experience spanning the period September 2005 to April 2006. Second, the data set also contained detailed information on various indices of daily individual restaurant performance, such as guest counts, sales, and margin. Third, we collected data on a series of restaurant characteristics to refine our analysis for the three restaurant concepts, including number of restaurant seats, lot square footage, and building square footage. Fourth, we measured the available marketing activity during the time that our guest-satisfaction survey was conducted. Included here were weekly data on TV and radio advertising by market, direct marketing activity, number of free-standing inserts (FSIs), and outdoor marketing activity. Although we attempted to gather monthly data on unemployment rates, Consumer Price Index, and hourly wage rates, these data are not available at a level that coincides with the restaurants' locations, except forthe unemployment rate. Unemployment data are available by zip code from the U.S. Department of Labor, Bureau of Labor Statistics.

Analysis and Interpretation

We constructed two separate models. The first explores the relationship of guest satisfaction with twenty-one distinct attributes of the dining experience, defined by the guest-satisfaction survey, and guests' overall intention to return to the restaurant. This is done both at an aggregate level for five major attribute groups and at a more detailed level for the entire list of fifteen attributes. The second model captures the relationship between restaurant performance (number of entrées sold) and customers' reported likelihood to return for a repeat visit (which we term the "comeback score"), along with several additional control variables described below.

Model 1: Intention to Come Back

The goal of this model is to quantify the relationship between guests' perception of each of the twenty attributes of their current dining experience and their intention to return (that is, to come back) to this restaurant in the subsequent thirty days. Data for this model were obtained from the guest-satisfaction survey. The variables in the model are defined in Exhibit 1.

We treat intention to come back as the dependent variable. Since this variable takes only two values (0 or 1), we employed logit models for analysis. "Model 1 Overall" uses the overall ratings of the five major attributes as explanatory variables, while "Model 1 Detailed" uses the fifteen detailed attributes within each of the five major attributes as explanatory variables. (See Appendix A for the technical details of the model and its estimation procedures.)

Model validity. The key metric for model validation here is the face validity of estimated attribute effects. We expect to see positive effects on "comeback" of each of the major attributes in Model 1 Overall, and each of the detailed attributes in Model 1 Detailed. Thus, each of the estimated model parameters is expected to be positive. We also assess statistical significance of each of the estimated parameters at the 5 percent level.

Interpretation of effects. First, we define an attribute's score as the percentage of surveys in the sample that rate the attribute positively. Similarly, we define the comeback score as the percentage of surveys in the sample that are positive with respect to their intention to come back in the succeeding thirty days.

Exhibit 1:
Guest Satisfaction Survey Questions and Variable Names for Model of Comeback
(Response Categories: Yes or No)

Question Number	*Question Text*	*Short Text*	*Variable Name*
1	When you arrived, were you greeted promptly and made to feel welcome?	Greeting: overall	G0
2	Was the greeting you received cheerful, friendly and attentive?	Greeting: cheerful friendly attentive	G1
3	And did we seat you at your table as quickly as possible?	Greeting: seated quickly	G2
4	Overall, were you pleased with the level of your service?	Service: overall	S0
5	Was the food served in a timely manner?	Service: food served in timely manner	S1
6	Was the server attentive to your needs and did they check back with you often?	Service: attentive	S2
7	Was your server's appearance neat and clean?	Service: server appearance	S3
8	Did a server approach your table promptly and offer to take your order?	Service: prompt approach and take order	S4
9	Was your server friendly?	Service: friendly	S5
10	Were you completely satisfied with the quality of your food?	Food: overall	F0
11	Was the food served exactly as you ordered it?	Food: accurate order	F1
12	And the food, was it delicious?	Food: delicious	F2
13	Was your food served at the proper temperature?	Food: temperature	F3
14	Was the presentation of the meal appealing?	Food: presentation	F4
15	Do you feel that you received a good value for the money you spent?	Value: overall	V0
16	Was the total cost appropriate for the food and service you received?	Value: cost appropriate	V1
17	Were the menu prices too high?	Value: prices too high	V2
18	Were you pleased with the amount of food you were served?	Value: food portion	V3
19	Was the interior of the restaurant clean, comfortable and inviting?	Restaurant: overall	R0
20	Was your table clean and dry?	Restaurant: table clean and dry	R1
21	Did your visit make you want to come back again soon?	Comeback	CB

We use the elasticity of the comeback score with respect to an attribute score as the measure of how large is the effect of changes in an attribute score on the comeback score. Needless to say, whether the attribute score improves or deteriorates determines whether the elasticities are positive or negative. We distinguish between an "up elasticity" and a "down elasticity." An up elasticity of an attribute is the change in the comeback score when the attribute score improves by 1 percentage point, all other attributes remaining unchanged. For example, if the current comeback score is 94 percent, and the food overall score is 92 percent, an up elasticity of .30 for food overall means that if the food overall score increases to 93 percent, the comeback score is predicted to increase to 94.3 percent. A down elasticity is defined analogously as the predicted impact on comeback score of a 1 percentage point decrease in the attribute score. Up and down elasticities are computed by simulation, separately for each attribute. Elasticities can be compared across attributes to assess the relative importance of attributes' effects on comeback.

Model 2: Restaurant Performance and Comeback

Next we develop a model to assess the impact of the comeback score on restaurant performance. The performance of each restaurant is measured using weekly guest counts, that is, the number of entrées sold on each business day, summed within each week. Comeback score is computed as the average score within each restaurant for each week, to make the data comparable with guest counts. To illustrate, a comeback score for a particular restaurant equaling 90 percent would mean that 90 percent of the respondents in a particular week reported that they intended to come back in the following thirty days.

We considered the following key issues in developing the model:

1. We expect that the guest count in any restaurant-week is affected by the comeback scores in the same restaurant-week, as well as in several recent weeks. The number of prior weeks that is relevant depends on the intervisit frequency of restaurant guests, which is not known from these data files. After some trial and error, we concluded that up to seven prior weeks of comeback scores may influence the guest count in any week. It is possible that comeback scores older than seven weeks might also affect guest counts, but a longer time-series of data than were available to us would be needed to model such effects reliably.

   We aggregate the lagged comeback scores (that is, the scores in prior weeks) into two variables, as follows. The average comeback score over the current week (call it week t) and the past three weeks (weeks t-1, t-2, and t-3) is called lag_comeback_1. The average comeback score over the four weeks preceding week t-3 (namely, weeks t-4, t-5, t-6, and t-7) is called lag_comeback_2. These two variables are among those that we used to predict guest counts in week t.
2. To allow for nonlinearity in the possible effects, we specified a multiplicative model (also called log-log). In this model, the effects of log(lag_comeback_1) and log(lag_comeback_2) on log(guest counts) are linear. (Details of this model are provided in Appendix B.)
3. Because of the client's organization structure, we developed separate models for the company's three restaurant divisions (concepts A, B, and C). Within each of these groups, data are pooled across restaurants to estimate the model, since there is insufficient data at the restaurant level for reliable estimation of model effects. Restaurant characteristics, such as number of seats and lot square footage, are included in the model to control for differences in guest counts arising from these differences.

   Since we expect local prosperity to be related to the decision to eat out in a restaurant, the model included the effects of monthly unemployment rates for the ZIP code in which a restaurant appears. While the estimated effect was as we expected (that is, higher local unemployment is correlated with lower restaurant guest counts), data for April 2006 were unavailable. As a consequence, we omitted unemployment rates in the final model.

4. Differences in guest counts over time may also arise due to marketing activities. Therefore, we include in the models TV and radio advertising as well as free-standing insert (FSI) and direct marketing (DM) activities.

Marketing activities. Data on the following four types of marketing activities were available to us for each restaurant-week: TV total rating points (TRPs), radio TRPs, drop of an FSI, and drop of a DM piece. The marketing data are merged with the guest-count data. For each of the marketing activities, we also know the effective weeks. For instance, an FSI may have carried a coupon that was valid for four weeks. Each marketing initiative is defined as being "active" in each week it was effective. Although in certain weeks there may be more than one FSI or more than one DM piece, we define these two promotional activities to be binary—each activity is either present or it is absent. We had no way to measure the quality or effectiveness of any given FSI or DM piece.

Effects of radio and TV advertising on guest counts are assumed to persist for up to four weeks from the time of the campaign. In the model, this is accommodated by allowing guest counts in week t to be influenced by values of TV TRPs and radio TRPs in weeks t, t-1, t-2, and t-3. To that end, we created the following two variables for TV: TV1, which is the sum of TV TRPs for weeks t and t-1, and TV2, which is the sum of TV TRPs for weeks t-2 and t-3. We did the same thing for radio.

In future modeling efforts, it may be useful to include the characteristics or attributes of different marketing instruments, such as campaign details for TV and radio and the face value of coupons for FSI or DM pieces. However, currently these more detailed marketing attributes were not available to us.

Not all marketing activities were employed for all three restaurant groups. Concept A restaurants did not have DM activity, concept B did not purchase radio advertising, and concept C did not use TV advertising or DM. The model specifications for the three groups of restaurants are accordingly different. (Again, see Appendix B for the technical details of the model and its estimation procedures.)

The variables in the model are as follows:

Guest_count: The average daily number of entrées sold (note that the model is based on weekly data, but this variable is defined as daily guest counts);

Lag_comeback_1: The average comeback score in weeks t, t-1, t-2, and t-3;

Lag_comeback_2: The average comeback score in weeks t-4, t-5, t-6, and t-7;

TV1: The sum of TV TRPs in weeks t and t-1;

TV2: The sum of TV TRPs in weeks t-2 and t-3.;

Radio1: The sum of radio TRPs in weeks t and t-1;

Radio2: The sum of radio TRPs in weeks t-2 and t-3;

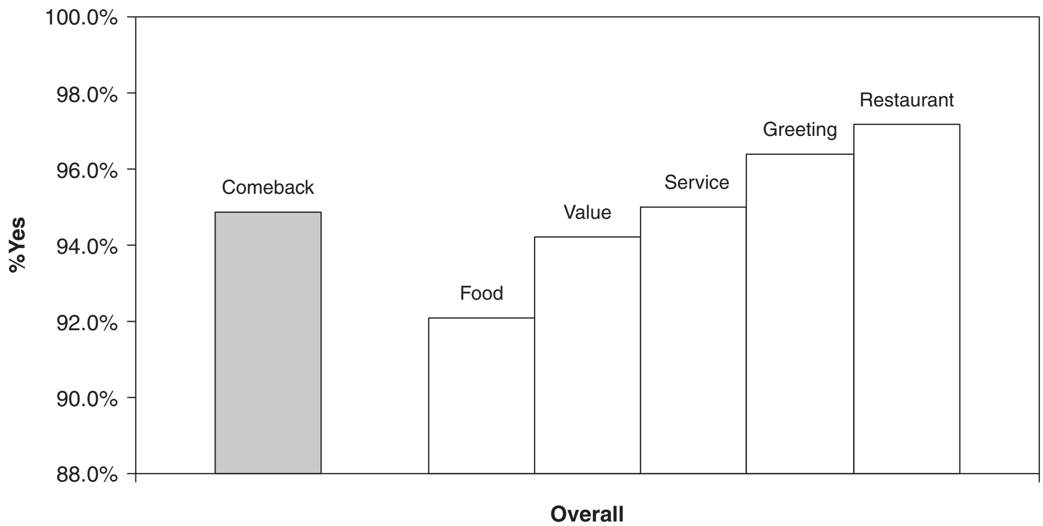
FSI: 1 if there was at least one active FSI in week t, 0 otherwise; and

DM: 1 if there was at least one active DM piece in week t, 0 otherwise.

Model validity. We assessed the validity of each model via the overall fit of the model (R^2 and F-statistic), face validity of estimated parameters, and statistical significance of the estimated parameters. In terms of face validity, we expect all estimated effects to be positive.

Interpretation of effects. In the multiplicative model, the estimated effects of lag_comeback_1 and lag_comeback_2 are interpretable as elasticities. Thus, δ_1 is an estimate of the percentage change in daily guest_ count in week t when lag_comeback_1 changes by 1 percent. (Note that this definition of an elasticity is slightly

Exhibit 2:
Mean Overall Attributes



Note: The interpretation of the remaining attributes is the same. For the overall attributes, "overall food quality" has the lowest satisfaction level (92 percent), while a "clean, comfortable and inviting restaurant" has the highest satisfaction ratings (97 percent).

different from the elasticity in the logit model.) Similarly, γ_1 through γ_4 are elasticities of the various TV and radio TRPs. Since FSI and DM are binary (or, indicator) variables that only take values 0 or 1, their effects are interpreted differently. In particular, $\exp(\gamma_5)$ is a multiplier that measures the multiplicative factor by which guest_count is predicted to increase when FSI is 1 compared with when FSI is 0. Similarly, $\exp(\gamma_6)$ is the multiplier for DM. For ease of interpretation, we translate all elasticities into incremental guest counts, relative to the current average guest count.

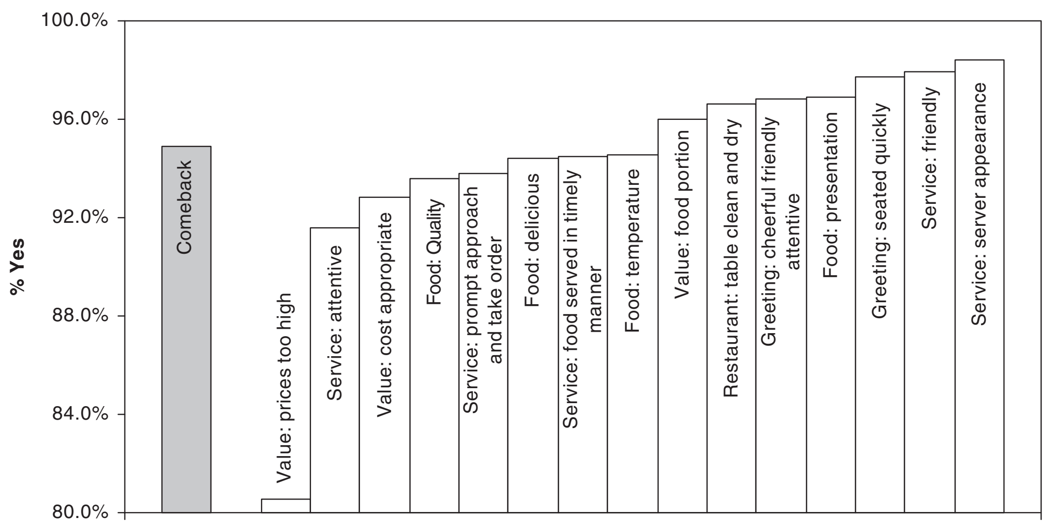
Results

We have 80,845 surveys available in the sample. In Exhibit 2 we show the average response to the five overall attribute questions, while in Exhibit 3 we show the results of the fifteen detailed attribute questions, along with the question on intention to come back. As shown in Exhibit 2, approximately 95 percent of guests responded that their visit made them "want to come back in the next 30 days."

For the overall attributes, "overall food quality" has the lowest satisfaction level (92 percent), while "a clean, comfortable and inviting restaurant" has the highest satisfaction ratings (97 percent). For the detailed attributes, the value-attribute measuring the perceived value in the level of menu prices scored lowest in respondent satisfaction (80.5 percent), while the attribute describing server appearance as being "neat and clean" recorded the highest satisfaction rating (greater than 98 percent).[1]

1. For the attribute "prices: too high," the proportion of "no" responses is shown in Exhibit 3, in contrast with all other attributes for which the proportion of "yes" responses is shown.

Exhibit 3:
Mean Specific Attributes



In Exhibit 4 we show descriptive statistics of the three restaurant groups. Concept A is the leader in several of these key measurements. It has the largest number of restaurants of the three groups (145), the largest average guest count per day (496), the largest average sales per day per restaurant, and the greatest seating capacity measured in average number of seats per restaurant (165). However, despite having a smaller daily guest count and smaller average daily restaurant sales, concept B has both a larger average lot size (49,027 sq. ft.) and a larger average building size (4,307 sq. ft.). Except for average building size and weeks with active FSIs, concept C has the lowest numbers of all three groups. It has fewer restaurants (48), fewer customers per day (323), lower average daily sales ($3,113), fewer seats per restaurant (4,218), and smaller lot size (27,637 sq. ft.).

Marketing activity is allocated quite differently across the three restaurant divisions. Concept B displays more advertising intensity relative to the other two concepts. Concept B uses about three-quarters more (76 percent) TV TRPs in an average week than does Concept concept A (264 vs. 150), while concept C uses no TV at all. Moreover, concept B exhibits over twice the FSI frequency of concept A (80.0 percent of weeks with active FSIs versus 37.7 percent), while concept C is higher still at 83.5 percent of weeks with active FSIs. Additionally, concept B relies on various direct mail promotions (20.9 percent of weeks record an active DM activity), while the other two regions do not employ DM marketing. The one exception where concept B is not the most advertising intensive is in radio advertising. Concept B employs no radio advertising while concept A and concept C use modest amounts (15 TRPs for concept A and 10 TRPs for concept C).

Overall Comeback Score

All five overall attributes have positive and significant effects on the comeback score. The

Exhibit 4:
Descriptive Statistics of the Restaurant Data

	Concept A	Concept B	Concept C
Number of restaurants	145	104	48
Average guest count per day per restaurant	496	360	323
Average sales ($) per day per restaurant	3,984	3,220	3,113
Average number of seats (range)	165 (96-220)	152 (106-208)	144 (94-230)
Average lot size (square feet)	33,462	49,027	27,637
Average building size (square feet)	3,833	4,307	4,218
Average weekly TV TRPs	150	264	0
Average weekly radio TRPs	15	0	10
Percentage of weeks with active FSIs	37.7	80.0	83.5
Percentage of weeks with active DM pieces	0	20.9	0

Note: TRPs = total rating points; FSI = free-standing inserts; DM = direct marketing.

significance of effects is particularly impressive because of the limited range of variation of attribute perceptions, as indicated in Exhibits 2 and 3 (e.g., the maximum proportion of negative responses in Exhibit 2 is 8 percent). In Exhibit 5 we show the elasticities of the five attributes. Effectively, these elasticities measure the responsiveness of overall comeback scores to changes in the overall attributes. Thus, when the elasticity of value overall is .26, for instance, the overall comeback score is predicted to increase from the current 95 percent to 95.26 percent. By the same token, when the elasticity is –.12, we expect the overall comeback score to decrease from 95 percent to 94.88 percent). It is worthwhile noting that the order of magnitude for "up and down" elasticities is the same. Whether the attribute score is increased or decreased by 1 percentage point, the magnitude of change in the overall comeback score is greatest for overall value, followed by services overall, food overall, restaurant overall, and greeting overall.

Effects of Detailed Attributes on Intent to Return

All fifteen detailed attributes have statistically, significant effects on the comeback score. As shown in Exhibit 6, elasticities of the detailed attributes are interpreted in the same manner as with the overall attributes. When the elasticity of "food delicious" is .26, for instance, the overall comeback score is predicted to increase from the current 95 percent to 95.26 percent. A down elasticity works in the same way. If the elasticity is –.09 for "food delicious," we expect the likelihood of returning to decline from 95 percent to 94.91 percent. We note that "food delicious" has the greatest elasticity values at .26 and –.09, and the "value: cost appropriate" is not far behind with elasticity values of .16 and –.06. In contrast, the attribute with the smallest elasticity in either direction is "value: prices" at .02 and –.01.

Our results allow us to combine two of our key findings—satisfaction levels and

Exhibit 5:
Up (Shaded Light) and Down (Shaded Dark) Elasticities of Comeback: Overall Attributes

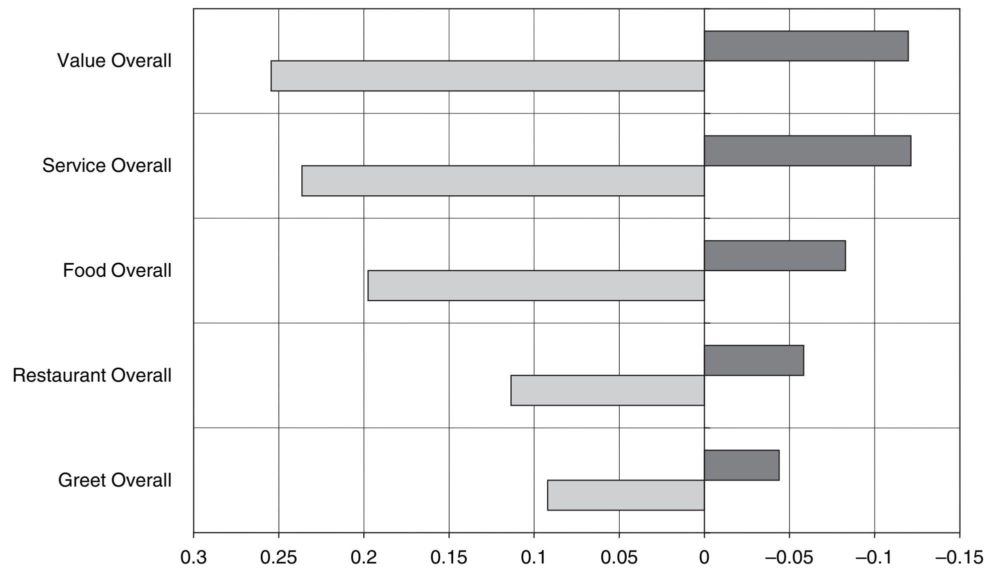


Exhibit 6:
Up (Shaded Light) and Down (Shaded Dark) Elasticities of Comeback: Detailed Attributes

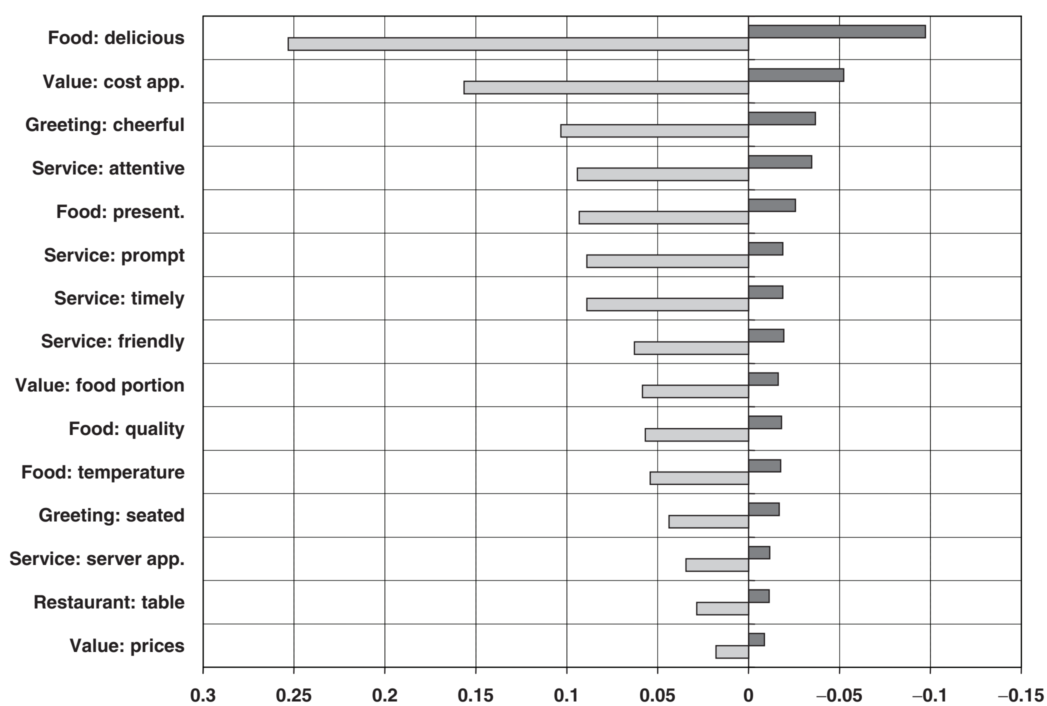
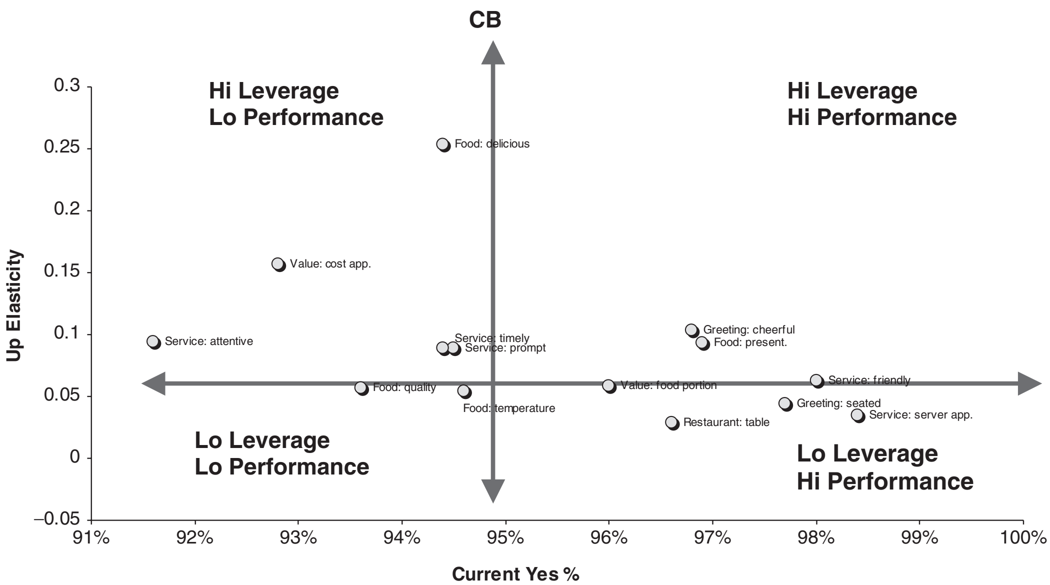


Exhibit 7:
Opportunity Matrix



Note: CB = comeback.

elasticities—into an opportunity matrix, as shown in Exhibit 7. This 2 × 2 matrix locates the detailed attributes according to how satisfied guests are with each particular attribute—we call this performance—and the elasticity associated with each, which is a measure of how guest count responds to an attribute. Placement of each attribute in one of the quadrants of this matrix shows at a glance areas in need of improvement, or opportunity. For example, the satisfaction rating of "food: delicious" is a little less than average (below 95 percent shown by the vertical arrow) but the elasticity is quite high (.26), placing the attribute in the quadrant of low performance–high responsiveness. Thus, efforts to improve the performance of "food: delicious" may represent an area of opportunity for restaurants since guest-count responsiveness is strong. Conversely, server appearance is associated with quite a high level of satisfaction as reported by guests (98.5 percent) but the guest-count responsiveness is quite low (.04). Further improvements in server appearance are not likely to generate much response in overall guest counts.

Results of Model 2

In Exhibit 8 we show parameter estimates of model 2 for each of the three restaurant groups. These are the estimated effects of changes in each variable on restaurant performance (measured as average daily number of entrées sold, which we call guest counts). The confidence that we can have in these estimates is in part indicated by the extent to which each of these independent variables is a significant predictor of guest counts. We can be reasonably certain that the most significant of these predictors, indicated in bold (significant at a 5 percent level), really make a difference in guest counts. For example, in the concept B model, six of the

Exhibit 8:
Untransformed Parameter Estimates (and Standard Errors) of Model 2

	Concept A	*Concept B*	*Concept C*
Log(lag_comeback_1)	**.307 (.080)**	**.411 (.208)**	–.100 (.104)
Log(lag_comeback_2)	**.301 (.082)**	**.327 (.117)**	.010 (.100)
Log(TV1+1)	*.010 (.005)*	**.011 (.004)**	—
Log(TV2+1)	–.002 (.003)	**.010 (.003)**	—
Log(Radio1+1)	.008 (.011)	—	.001 (.007)
Log(Radio2+1)	–.014 (.009)	—	–.004 (.007)
FSI	–.025 (.027)	–.001 (.027)	**.087 (.032)**
DM	—	.026 (.022)	—
Log(Seats)	*.077 (.042)*	**.213 (.040)**	*.123 (.057)*
Log(Lot_sqft)	.001 (.001)	**.021 (.002)**	.003 (.004)
Number of observations	3,082	2,377	953

Note: Bold = most reliable (significant at 5 percent). Italics = less reliable (significant at 10 percent). Neither italics nor bold = least reliable (not significant at 10 percent). FSI = free-standing insert; DM = direct marketing.

eight variables are highly significant predictors of restaurant guest counts. Because our sample was quite large—at least for concept A and concept B—small differences in the reported numbers can be detected as influencing guest counts.

Considering only statistically significant effects, we can now predict the effects of a 1-percentage-point increase in the comeback score on guest counts as follows. In the average concept A restaurant, the guest count is predicted to increase by 1,100 per year, which is computed as the average guest count per day (see Exhibit 4) times the elasticity of comeback (496 × 0.608% = 0.307 + 0.301; see Exhibit 8) times 365 days in a year. Analogously, in the average concept B restaurant, the guest count is predicted to increase by 970 per year, which is computed as the average guest count per day (see Exhibit 4) times the elasticity of comeback (360 × 0.738% = 0.411 + 0.327; see Exhibit 8) times 365 days in a year. The estimated effects of the comeback score on guest counts in concept C restaurants are not statistically reliable.

The effects of TV advertising on guest counts can be quantified in a similar fashion. We consider the impact of a 10 percent increase in TV TRPs on guest counts. For concept A restaurants, only TV1 has a significant effect. Taking the effect of TV2 to be zero, we predict that the increase in guest counts for the average restaurants will be 181 per year, which is given by the average guest count per day (see Exhibit 4) times the elasticity of TV1 times the 10 percent increase in TV TRPs (496 × 0.010% × 10%; see Exhibit 8) times 365 days in a year. Similarly, for the average concept B restaurant, the predicted increase in guest count per year is 276, which is computed as the average guest count per day (see Exhibit 4) times the elasticity of TV (360 × 0.021% = 0.011 + 0.010; see Exhibit 8) times 365 days in a year.

The effects of radio advertising are found to be statistically insignificant in both concept A and concept B restaurants. The multiplier effect of an additional effective FSI week is computed for the average concept C restaurant as 1.091 (= exp[0.087]; see

Exhibit 8). This implies that daily guest count in a restaurant is predicted to increase on a one-time basis by 9.1 percent with the insertion of an additional FSI week in the media plan. The effects of direct marketing are uniformly not significant.

Managerial Implications and Further Work

The chief implication for this chain's three restaurant concepts is that its managers need to stick to the knitting. The factors that had the greatest influence on whether a guest would return are those at the core of restaurant operation, namely, delicious food, an appropriate cost, a cheerful greeting, and attentive service. Doing well on these factors, particularly serving delicious food at an appropriate cost, has the almost certain effect of encouraging your guests to return. Failure on these attributes does not seem fatal but will certainly diminish the likelihood that a guest will return.

More to the point, our study has quantified the connection between intent to return and actual traffic counts. Even considering the caveat that our data cover a relatively brief time span, our models show that this relationship is distinct for each restaurant concept, and we can offer no blanket rule. One restaurant concept alone (concept A) could count on gaining another 1,100 customer visits per year just by boosting its customers' comeback score by 1 percentage point. While this is a seemingly modest 0.6 percent increase in traffic, or an average of about $25.00 per day, this still means an increase of approximately $1.3 million ($25 × 145 restaurants × 365 days) just from ensuring an excellent performance that will boost intent to return.

Looking at the opportunity matrix, it is clear that this restaurant company has the possibility of taking advantage of our findings, because its performance was low for appropriate cost and attentive service, and it could pay more attention to its food quality.

Further study. The data provided for this study were rich and allowed for the analysis reported here. However, the complexities of the models, particularly the sales-performance model (model 2), require data over a longer period of time than were available to us. With longer series of data, we could produce more robust models and gain greater insight into a restaurant's strategic options. Moreover, in the future, opportunities exist to improve the data quality by modifications to the guest-satisfaction survey design.

Appendix A

Model Specification and Estimation

The mathematical form of Model 1: Overall is as follows:

$$\text{Prob(comeback} = 1) = \frac{\exp(\alpha + \beta_1 F0 + \beta_2 S0 + \beta_3 R0 + \beta_4 V0 + \beta_5 G0)}{1 + \exp(\alpha + \beta_1 F0 + \beta_2 S0 + \beta_3 R0 + \beta_4 V0 + \beta_5 G0)}$$

and

$$\text{Prob(comeback} = 0) = 1 - \text{Prob(comeback} = 1).$$

The mathematical form of Model 1: Detailed is analogous, with the fifteen detailed attributes taking the place of the overall attributes as explanatory variables.

The parameters of these models are estimated by pooling data across surveys. Thus, if there are N complete surveys available, there are N observations in the data set used to estimate each of the two models. The estimation method we employed is maximum likelihood.

Appendix B

Model Specification

The general form of the multiplicative model for guest counts is as follows:

$$Guest\_count_{rt} = \alpha(lag\_comeback\_1_{rt})^{\delta_1}(lag\_comeback\_2_{rt})^{\delta_2}(TV1_{rt}+1)^{\gamma_1}(TV2_{rt}+1)^{\gamma_2}(Radio1_{rt}+1)^{\gamma_3}(Radio2_{rt}+1)^{\gamma_4}(\gamma_5)^{FSI_{rt}}(\gamma_6)^{DM_{rt}}(Seats_r)^{\tau_1}(Lot\_sqft_r)^{\tau_2}$$

where the subscript *r* indicates restaurant *r*, and subscript *t* indicates week *t*. As noted previously, specific marketing activities are omitted in the models for each of the three restaurant groups.

We transform, or log-linearize, the model by taking natural logarithm of both sides of the model. Data are pooled across restaurants and weeks, within each restaurant group. The parameters of the model are estimated using ordinary least squares.

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