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Customer Satisfaction, Customer Retention, and Market Share

ROLAND T. RUST
Director, Center for Services Marketing
Owen Graduate School of Management
Vanderbilt University
Nashville, Tennessee

ANTHONY J. ZAHORIK
Assistant Professor of Marketing
Owen Graduate School of Management
Vanderbilt University
Nashville, Tennessee

We provide a mathematical framework for assessing the value of customer satisfaction. The framework enables managers to determine which customer satisfaction elements have the greatest impact, and how much money should be spent to improve particular customer satisfaction elements. This makes it possible to hold customer satisfaction programs accountable, in the way that other business programs are held accountable, by forcing them to demonstrate their benefits with respect to bottom-line profitability. We use an individual-level model of loyalty and retention, and then build up to market share by aggregation. We demonstrate the application of our approach in a pilot study of a city's retail banking market.

INTRODUCTION[1]

> "Service Quality as an issue is seriously overrated; service certainly is not as important as the mythic proportions it has taken on in industry trade publications and conferences." (Council on Financial Competition 1989)

The above quote, from a leading banking trade organization, reflects the growing need for those in the customer satisfaction/service quality field to demonstrate the financial impact of improvements in serving the customer The euphoria over the total quality movement inspired by the work of W.

[1] "Total quality" includes both product quality and service quality. "Service quality" following current usage among progressive companies such as AT&T and Xerox, is assumed to be that which satisfies the customer Thus, we tend to use the terms "service quality" and "customer satisfaction" almost interchangeably, although a more traditional view of service quality would restrict it to "objective" performance, such as response time

Edwards Deming (1986), which was spawned during the booming 1980s, met the hard realities of recession in the 90s The mood of business has changed to cost cutting (e.g., Carroll 1991), with a hard-line attitude toward service improvement programs, typified by the quote at the beginning of this article This attitude discounts the potential of these programs to increase profits, largely because their benefits generally cannot be measured In this view service quality is to be improved only as a side benefit from efforts to improve measurable operating efficiency!

This skepticism about the value of service quality makes it imperative that research be undertaken to address the quantification of the impact of customer satisfaction on observable financial measures, to place programs to improve customer satisfaction and service quality on an even footing with most other business programs that must justify themselves financially. Unfortunately, until now managers have had only aggregate-level correlational studies (Buzzell and Gale 1987; Anderson and Sullivan 1992) and numerous anecdotes of profitable customer-oriented companies (e.g., Zemke and Schaaf 1989) to back up their requests for funds. (See Zahorik and Rust 1992 for a thorough review of the previous work in this area.) Such evidence is supportive at a general level, but offers little guidance as to whether, and how much, a specific program will improve profits or build share.

This paper addresses the issue of how to quantify the dollar impact of customer satisfaction at the program attribute level. We provide a framework that allows a marketing manager to determine which elements of customer satisfaction have the greatest impact on corporate performance, and to determine the financial value of various managerial actions that focus on improving aspects of service We also provide an example of how the framework can be used.

Measures and Models of the Process

The first work began with measurements of customer satisfaction (Oliver 1980; Churchill and Surprenant 1982, Bearden and Teel 1983) and service quality (Parasuraman, Zeithaml, and Berry 1985, 1988) Each is generally defined to depend on a comparative judgment against some standard which depends upon disconfirmation of expectations Thus dissatisfaction may be due to inherently poor service, or perhaps to the continuation of a once-acceptable level of service that no longer meets customer expectations, due to competitive marketing of improved standards or changing customer tastes.

Quantitative modellers have sought to link customer satisfaction and service quality to other managerially meaningful measures. For example, Bolton and Drew (1991b) and Boulding, et al (1993) showed how overall service quality and behavioral intentions could be predicted by customer satisfaction and service attributes. Bolton and Drew (1991a) showed that service changes could affect customer attitudes, and provided a methodology for measuring the effect.

The relationship of satisfaction to profits was examined by Fornell and Wernerfelt (1987, 1988) in studies of the effect of compliant handling programs on customer retention, and therefore profitability. Other researchers have investigated the profitability of service quality using aggregate, cross-sectional data, most notably Buzzell and Gale's (1987) analysis of the PIMS data. Reichheld and Sasser (1990) have also described the profit impact of reducing a company's "defection rate."

Nevertheless, there exist no published studies that have discussed the entire chain of effects from resource allocation to customer satisfaction to profitability. But, understanding of the complete chain is necessary to tie service quality improvement efforts to the bottom line.

The next section presents a conceptual framework for linking customer satisfaction to market share. The third section presents a methodology for determining the extent to which customer satisfaction impacts customer retention, and discusses the feasibility of obtaining optimal levels of resource allocation for customer satisfaction programs. Section four discusses issues in modelling the impacts of managerial programs on customer satisfaction Concepts introduced in the third and fourth sections are illustrated using an example from the retail banking industry. The fifth section presents limitations, conclusions, and directions for future research.

CONCEPTUAL FRAMEWORK

Customer Satisfaction and Market Share

The value of customer satisfaction rests on its relationship to choice and market share. The consideration of this relationship belongs to the domain of *defensive marketing,* which augments the *offensive marketing* paradigm that has traditionally been predominant.

The traditional view of market share considers sales and market share to arise primarily from offensive marketing actions, such as the econometric literature (Aaker 1982; Bass 1969; Bass and Clarke 1972, Bass and Leone 1983; Blattberg and Jeuland 1981), which views sales to be a result of levels of advertising and other offensive marketing variables, and in the sales promotion literature (Guadagni and Little 1983; Lattin and Bucklin 1989; Neslin 1990; Fader and McAlister 1990), which views sales to be a result of promotional activity and other variables.

This view of marketing is not "wrong." However the effects of customer satisfaction and customer retention on market share and profitability are generally not emphasized in these models, except for adjustment terms for "loyalty" or "inertia" (Guadagni and Little 1983) On the other hand, *defensive marketing* (Fornell and Wernerfelt 1987, 1988) recognizes these effects by emphasizing that marketing resources may be better spent keeping existing customers than by attracting new ones. Conclusions of research conducted for the U.S Office of Consumer Affairs that it may be five times as costly to attract a new customer as to keep an old one (Peters 1988) provide some support for the new position.

Figure 1 shows how customer satisfaction might impact market share, and thus profitability, over time in a simplified two-firm ("us" and "them") universe. For example, active customers in period t are either new entrants to the market or are continuing customers from earlier periods. Let a_t be the fraction of the market which remains active from one period to the next, so that $(1 - a_t)$ leaves the market each period Customer satisfaction has no direct impact on new entrants, because the potential customers at this point have no experience with the competitors.

The probability, c_{jt}, of a new entrant choosing "us" in period t may be considered a rough measure of the relative effectiveness of our offensive marketing effort, advertising, promotion, location, price, etc. (The j subscript here refers to firm j, "us ") Customer satisfaction has no direct impact on brand choice because the entrants have no experience. A customer may either remain loyal or leave. Let r_{jt} be the proportion of our customers who remain loyal during period t, a function of satisfaction. The rest of our customers who remain in the market $1 - r_{j,t}$, will switch to competitors due to dissatisfaction with some aspect of our service.

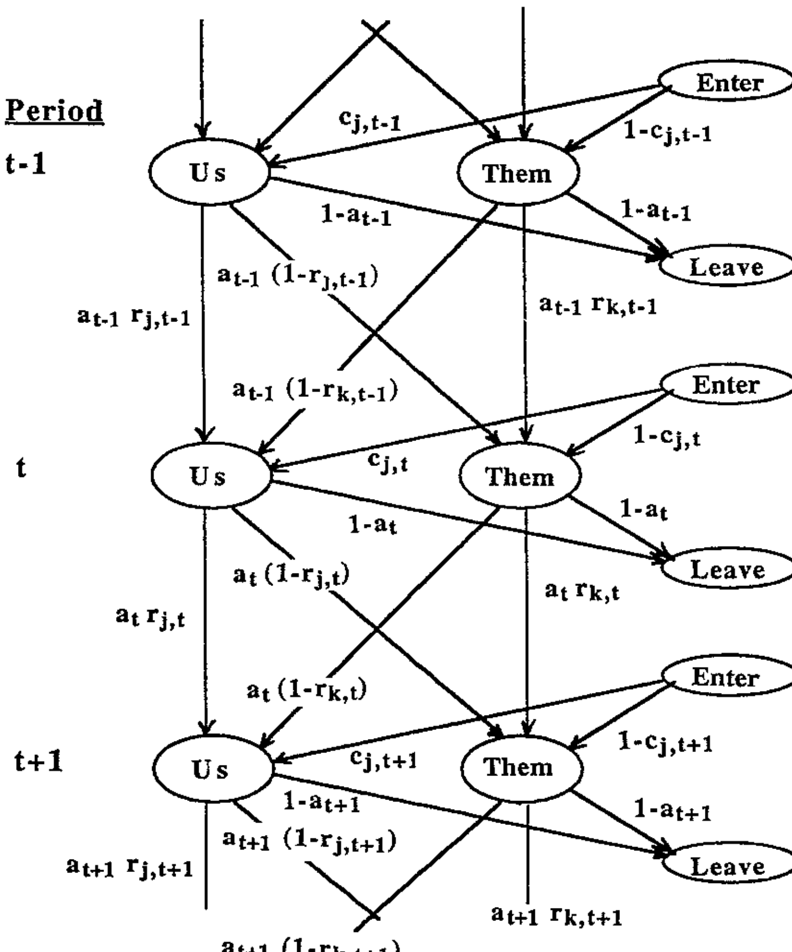
According to this model, if we assume that customers switch at most once during a period, then the market share for firm j at the start of period $t + 1$ comes from three sources:

1. Of the firm's market share in the previous period, $MS_{j,t}$, a fraction, a_t, dependent on the category and market but independent of the particular firm, will remain in the market, and, of those, r_{jt} will remain loyal to firm j. The retained market share is thus $a_t r_{jt} MS_{j,t}$.

2. For each of the other brands k, with initial market shares $MS_{k,t}$, a fraction $a_t(1 - r_{kt})$ will switch to other brands in the market. We assume for now that switchers also choose brands in proportion to the offensive

FIGURE 1

The offensive and defensive sources of market share



attractiveness or "pull," $c_{j,t}$, used earlier to describe the choices of new customers to the market. In particular, the fraction of those leaving brand k for firm j is $c_{j,t}/(1 - c_{k,t})$. (Division by $1 - c_{k,t}$ scales the probabilities to add to one across the brands other than k.) This model does not assign separate attraction probabilities to customers who previously left the brand but consider returning. If brand switching is truly infrequent, one could assume that previous experience with a firm is greatly discounted in making choices. Thus the market share gained from competitors is

$$a_t c_{j,t} \sum_{k \neq j} MK_{k,t}(1 - r_{kt})/(1 - c_{k,t}).$$

3. We assume the market is of stable size, so that the fraction $1 - a_t$ of the market which departed is replaced by new entrants[2]. Of them firm j will attract a fraction $c_{j,t}$ on the basis of its offensive pull. Thus the market share obtained from new customers is $(1 - a_t)c_{j,t}$.

Combining the three sources of market share, we arrive at the market share for the next period:

$$MS_{j,t+1} = a_t r_{jt} MS_{j,t} + \left[a_t c_{j,t} \sum_{k \neq j} MS_{k,t}(1 - r_{kt})/(1 - c_{k,t}) \right] + (1 - a_t)c_{j,t} \tag{1}$$

Comparison with Markov Brand Choice Models. Note that this model is far different in concept from Markov brand choice models (Ehrenberg 1965, Urban 1975; Lilien and Kotler 1983). In particular, "transitions" do not represent choice points, but rather regularly spaced observations of ongoing customer-vendor relationships.

The types of services being modelled in this process, such as banking, telephone service, and other contractual relationships are not characterized by brand choices being made at each service encounter. The likelihood of a single bad service encounter causing brand switching is low, and "satisfaction" and the probability of a customer remaining with a firm are assumed to be fairly stable, summary attitudes, but affected by reactions to specific service experiences. This is similar to Bolton and Drew's model (1991a) in which short-run satisfaction with individual service encounters are used to update more enduring attitudes about quality in Bayesian fashion.

The Model Parameters. In general, the attractiveness and retention parameters $c_{j,t}$, r_{jt}, r_{kt} and a_t may vary over time with changing market activity. However, if their future values can be predicted, then estimates of future market share are straightforward using equation (1). For example, if parameters are assumed to be constant over time, it may be possible to estimate them from past data. These estimates are readily obtained if one has panel data tracking customers' behaviors and levels of satisfaction over

[2] Extension of the model to the situation in which a market is growing or shrinking is straightforward

time. However, panels of service customers are rare. Alternatively, we may use a cross-sectional market survey, described below.[3]

Equation (1) also provides a framework for studying the approximate market share impact of a change in retention rates, r_{jt}, which are themselves the results of changed satisfaction with service levels. These estimates may somewhat underestimate the full effect on market share, because the model addresses only retention rates and not the offensive effects of service improvements, i.e., increases in new business due to positive word-of-mouth. Offensive effects are much harder to model in general, given the time lags involved. (See Kordupleski, Rust, and Zahorik 1993.) Nevertheless, predictions of market share improvements due solely to increased retention may provide conservative estimates of the impact of customer satisfaction.

Modelling Customer Satisfaction and its Effect on Retention

Individual process. We develop an individual model of customer satisfaction and loyalty, which can be aggregated to predict market level effects of improvements in service quality. The underlying assumptions are.

1. Satisfaction toward specific "service elements" produces satisfaction on a smaller number of broader "loyalty factors."
2. Propensity to be loyal to the firm results from satisfaction on the loyalty factors.
3. Loyalty is a probabilistic process, based on propensity to be loyal.

The motivation behind assumption 1 is to permit the linking of *specific* areas that management can directly affect (service elements) to *general* impressions that drive loyalty (loyalty factors). Empirical research has long shown that satisfaction can affect loyalty (Newman and Werbel 1973; LaBarbera and Mazursky 1983).

Assumptions 2 and 3 have as their rationale the general approach often employed in logit choice models (Gensch and Recker 1979; Guadagni and Little 1983; Luce 1959, McFadden 1980). The idea is that staying loyal or not involves a choice, and that importance weights may be estimated for the loyalty factors, just as is done routinely in choice models. The loyalty process, like the typical choice process, is assumed not to be deterministic, but rather probabilistic.

To formalize, let $\underline{S}_i$ be a row vector of satisfaction scores for individual i on the relevant service elements. Then we assume the existence of a linear

[3] We recognize that these data must be collected carefully, to ensure that the measures obtained are valid and reliable Calibration of these measures on a population of known recent behavior is desirable, when feasible, to detect any systematic response biases

transformation which converts the satisfaction scores on the service elements to loyalty factor satisfaction scores.

$$\underline{F}_i = \underline{S}_i\underline{\delta} \tag{2}$$

where $\underline{F}_i$ is a row vector of loyalty factor scores and $\underline{\delta}$ is a matrix of factor coefficients

Then we assume that the propensity to be loyal is an exponential function of a linear combination of the factor scores:

$$L_i = exp(\underline{F}_i\underline{\beta} + \epsilon_i) \tag{3}$$

where L_i is the propensity to be loyal, $\underline{\beta}$ is a column vector of coefficients, and ϵ_i is an error term distributed extreme value The probability of remaining loyal to Brand j, r_{ij} is then assumed to be logistic:

$$r_{ij} = (1 + exp(-\underline{F}_i\underline{\beta}))^{-1} \tag{4}$$

where $exp(-\underline{F}_i\underline{\beta})$ is the reciprocal of the deterministic part of L_i.

Aggregate Retention Rate. The aggregate retention rate for option j over a population of triers, as used in equation (1), is then r_j = mean (r_{ij}). Because the value of r_{ij} depends upon the individual's satisfaction ratings, and because the formula for r_{ij} is not linear in those ratings, mean (r_{ij}) must be calculated as the mean of individually computed r_{ij} values.

IDENTIFYING THE FACTORS WHICH DETERMINE RETENTION

Exploratory Analysis

Determining which service attributes most determine customer satisfaction commonly involves focus groups and one-on-one interviews (Griffin and Hauser 1992), although the general SERVQUAL dimensions (Parasuraman, Zeithaml, and Berry 1985, 1988), tangibles, reliability, responsiveness, assurance, and empathy, should probably be put on any first pass at a list of attributes for a service Research methods specifically designed to handle the interactive and time-dependent nature of services are also advised, including "service script" interviews (Abelson 1976; Smith and Houston 1983; Solomon, et al. 1985), and the critical incident technique (Bitner, Booms, and Tetreault 1990; Bitner, Nyquist, and Booms 1985).

This checklist, after including other dimensions management feels necessary, and perhaps after reducing the number of dimensions by a method such as factor analysis, forms the basis of a questionnaire that is used to have customers rate firms in the industry.

Example. In a pilot study of retail banking customers, which will be used to illustrate our procedure, focus groups and industry literature produced a list of nine key attributes which seem to define customers' ongoing relationship with their "primary" banks, i.e. the banks they consider to be their major banking service suppliers. (For details of this study, see Rust and Zahorik 1992.) The elements of the list were.

1. The friendliness of the bank
2. How well the managers know me
3. How well the bank listens to my needs
4. How many money machines the bank has around town
5. How many tellers are available at busy times
6. The cost of checking
7. How close the bank is to my home
8. How close the bank is to my place of employment
9. How convenient the bank is to my route to work

Data Collection Options

The model may be estimated and applied on either longitudinal or cross-sectional data. Within the longitudinal approach there are two distinct options. Ideally, one would have individual-level data across many time periods, which would show customer satisfaction measures at specific points in time, as well as switching behavior This would make possible dynamic choice models of the sort which have been used often in analysis of scanner data for product choices, including the parameterizing of attraction and retention variables, $c_{j,t}$ and r_{jt}, as functions of offensive and defensive marketing efforts. Unfortunately, service companies rarely track panel data on service satisfaction and brand switching, so fully dynamic analyses are generally not feasible at this time.

In lieu of extensive panel data a more modest longitudinal approach could be used to determine the relationship between satisfaction and switching. At a point in time customer satisfaction and current choice of service provider are determined for a sample of customers. At a second, perhaps six months later, the respondents from the first wave are asked whether or not they have switched. This approach may not work well in services that have high retention rates, because the number of switchers may be too small to permit accurate model estimation. Moreover, there are not sufficient data to determine the relationship between marketing efforts and customer behavior. Thus forecasts must assume that r_{jt} and $c_{j,t}$ are constant over time

Another alternative, given a limited ability to collect data, is a cross-sectional data collection approach using a single survey. Respondents are asked whether they switched to their current service providers due to dissatisfaction, and customer satisfaction ratings are obtained from both the previous and current providers This approach is clearly the cheapest and fastest, although, since the satisfaction ratings are collected after the fact, this approach may risk bias based on response inaccuracy due to memory limitations. Moreover, dissonance may cause subjects to exaggerate certain differences in service levels between current and former providers, causing the fitted model to overstate the effect on retention of certain service improvement programs. However, the reduction in cost may often justify the somewhat reduced validity, and can provide an organization with initial parameter estimates until a suitable longitudinal data base has been collected. We have found that customers appear to be relatively objective in such recollections—they claim to know precisely what made them switch firms, and, as will be seen below in the bank study, they did not downgrade the rejected firms on all attributes. In fact, some respondents occasionally even gave their former bank a higher mark on one of the (presumably less important) attributes

Example Due to time and budget constraints, we used this crosssectional approach in the retail banking study, and illustrate its use here. A random sample of 100 retail banking customers in a metropolitan area was interviewed by telephone. Of the 100 respondents, 21 had switched banks for reasons of dissatisfaction, a percentage that is similar to values quoted by the Council on Financial Competition (1989).

Table 1 shows the switching matrix which we used to obtain the choice and retention constants that are used in the analysis. The retention rates in

TABLE 1

Switching Data and Estimated Switching Constants

Bank	Original Users	Switched From	Switched To	Current	c_{j1}	r_j
A	33	9	4	28	33	94
B	25	6	6	25	25	95
C	21	4	4	21	21	96*
OTHER	21	2	7	26	21	98
TOTAL	100	21	21	100		

* Computed as follows, for example, for Bank C: The bank retained 17 of 21 original users, or 81%. Assuming that customers stay with a bank for an average of five years, the annual retention rate is estimated as $(\ 81)^{1/5} =\ 9587$ or 96 (rounded)

the table are estimates of annualized rates obtained from the responses of test subjects, which were not time-restricted. (Converting this switching matrix to a period-by-period transition matrix is described in Appendix A of Rust and Zahorik 1992.)

Sampling

The sample of customers surveyed must include enough who switch service providers (in the cross-sectional case, who *have* switched) for reasons of dissatisfaction that the model can statistically differentiate between the average customer perceptions of firms not switched from, from those of firms switched from. If one wishes to avoid firm-specific bias the sample should be drawn from the market at large, rather than just individuals who have switched into and/or out of a particular firm.

Data required of each subject includes a measure of his/her satisfaction with each of the salient service attributes. The form of the model is not dependent on a particular satisfaction measure, and a discussion of the merits of each is beyond the scope of this paper. The growing literature on satisfaction indicates that the concept is quite complex and mediated by many factors. Although many industrial researchers use a simple (say, five-point) scale to measure satisfaction, Oliver (1980) argues that satisfaction may not be a unidimensional concept and is better measured by using a battery of questions to tap different forms of satisfaction. Suffice it to say that practical constraints such as time, money, and customer willingness to respond will require that the modeler be judicious in keeping the data instrument to a tractable size.

Switchers must be asked why they switched. Those who have switched for reasons other than necessity (e.g., because of dissatisfaction, rather than because they moved out of the provider's service area) provide the information which is critical to determining significant differences between retained and rejected firms.

Example. In the retail banking pilot study used for illustration, simple measures of satisfaction with the nine attributes of the bank were obtained by asking subjects to rate each on a simple, 1 to 5 scale, with 1 labeled as "very dissatisfied" and 5 labeled as "very satisfied." Each of the subjects who had switched banks due to reasons of dissatisfaction was asked to also rate his/her previous bank on the nine attributes.

To eliminate redundancies among attributes and to provide orthogonal dimensions the ratings were factor analyzed. Three factors emerged, based on the criterion of having an eigenvalue greater than one. Table 2 shows the rotated factor loadings. (The rightmost column of Table 2 shows the

TABLE 2

Factor Analysis of Satisfaction Measures

Satisfaction Measure	Factor 1 Convenience	Factor 2 Warmth	Factor 3 Checking Ease	Equity Estimator Coefficients for Factor 2
	Factor Loadings			
ATM machine availability	496	− 242	120	− 167
Convenience to work	932	203	−.038	221
Convenience to commute	921	181	− 035	206
Friendliness	303	627	340	686
Manager knows me	− 026	705	304	631
Listens to my needs	− 131	570	576	546
Convenience to home	120	748	− 220	648
Number of tellers	.041	− 010	797	120
Cost of checking	− 039	167	671	244

estimate of factor loadings using the equity estimator of Krishnamurthy and Rangaswamy (1987) and Rangaswamy and Krishnamurthy (1992). The similarity of these values with the rotated factor loadings suggests that multicollinearity is not a problem for the stability of the factor coefficients) The first two factors are easy to label as "Convenience" and "Warmth," respectively. The third factor is harder to characterize, but we have elected to call it "Cost of Checking "

Logit Analysis

The link between satisfaction with attributes and retention can now be made using logistic regression analysis to fit equation (4) to the data. Using the attribute satisfaction scores as independent variables and a dependent variable which has value 1 for current firms and 0 for rejected firms, a logistic model can be fit to the data using maximum likelihood methods. The resulting logistic function can be interpreted as providing an individual i's retention probability r_{ij} of a firm j, given his/her perceptions of its quality as given by attribute ratings F_{ij1} through F_{ijk} with the coefficients

β indicating the relative importance of each of the service factors to customer retention

Example. The results of the logit regression of retention on the banking factors are shown in Table 3. Only the Warmth factor is significant. We infer from this that Warmth and its constituent elements, "friendliness," "how well the manager knows me," "listens to my needs," and "convenience to home," are the keys to customer loyalty in this market, a result supported by sentiments expressed in many customer focus groups. In fact, the friendliness and warmth of bank personnel is of great concern to bank managers and an area of continuous training.

Consider the satisfaction element "listens to my needs," the element of Warmth with the smallest estimated impact. Based on the logit coefficients and equations (1) and (5) we may investigate the impact on a bank's retention rate and market share of a shift in customer satisfaction on this attribute. Consider Bank C, which has a share of 21 percent, an annual retention rate of 95.9 percent and a mean satisfaction score of 4.2 on "listens to my needs." With such a high rating on this attribute, and a very strong retention rate, there is not much prospect for major improvement. An improvement in average satisfaction from 4.2 to 4.7 is expected to increase the annual retention rate from 95.9 to 96.5 percent and market share from 21.0 percent to 21.4 percent.

This shift may seem small, but depending on the size of the market the result can be a substantial shift in revenues. Also it must be remembered that this shift arises from a mere half point shift on only one satisfaction element: "listens to my needs " It is possible that such a shift may be

TABLE 3

Impact of Satisfaction Factors on Retention Rate—Logit Regression Results

Model	Variable*	Parameter Estimate	Standard Error	Chi-Square	*p*-value
All factors	Intercept	4 962	2 107	5 54	019
	Convenience	− 191	162	1 39	238
	Warmth	650	228	8 15	004
	Checking Ease	068	.206	11	742
Warmth only	Intercept	7.540	2 120	12 65	000
	Warmth	.672	162	17 23	000

* Satisfaction factors are reverse coded to give positive coefficients for positive effects

TABLE 4

Impact of Satisfaction Shift on Retention Rate, Market Share, and Contribution

Magnitude of Satisfaction Shift Variable Shifted	△ Retention Rate	△ Market Share	△ Contribution
.1 Friendliness	0069	00145	$ 48,651
Manager knows me	.0078	.00164	$ 55,026
Listens to my needs	.0060	.00126	$ 42,276
5 Friendliness*	—	—	—
Manager knows me	0289	00607	$203,664
Listens to my needs	0240	.00504	$169,105

* Average satisfaction is already 4 81 A 5 shift is not possible

possible to produce with little cost, just by making the proper personnel aware of which things to emphasize.

Table 4 shows the projected impact on annual retention rate, the change in market share after five years and the net present value (NPV) of net contribution margin (over 5 years) of a .1 or 5 shift in customer satisfaction on each of the satisfaction elements[4], which load heavily on the factor Warmth (except for "convenience to home," which cannot be manipulated easily by management without building new branches). The model does not include competitive response, which one might anticipate within a five-year horizon. However, these activities are directed primarily at increasing retention of the bank's current customers and would not necessarily incur strong competitive reactions.

RELATING MANAGEMENT EFFORT TO CUSTOMER SATISFACTION

Identifying the Most Sensitive Service Dimensions

The logit analysis provides information on which satisfaction elements have the greatest impact on retention and where efforts should be made to

[4] In each case, it is assumed that the other satisfaction elements were held constant

improve service levels However, it is not necessarily clear what specific steps must be taken, or how much money should be spent, if any.

Guidance in relating these "voice of the customer" attributes to technical service design elements can be found in Griffin and Hauser (1992) and in the literature on quality function deployment (Akao 1990; Hauser and Clausing 1988). Other techniques to understand the customer's view of the dynamics of the service experience, such as that of Bitner, Booms, and Tetreault (1990) or blueprinting (Shostack 1985, 1987), can also be helpful. The problem of effective allocation of resources is a complex one, and a thorough discussion of the topic is beyond the scope of this paper.

Example. In the retail banking example a wide number of commercial training programs are available specifically for training front-line personnel in listening and interpersonal skills to improve customers' assessments of a bank's friendliness, willingness to listen, etc.

Calibrating the Effort Function

If the above analysis determines that the best way to improve customer satisfaction requires spending money on improving particular attributes, the question arises of how much to spend. Optimal effort allocation requires the calibration of a function relating dollar effort to satisfaction. S-curves or concave functions seem most appropriate for this application, because intuition suggests diminishing returns as expenditure levels became large.

We suggest three main approaches to calibrating the effort function. The first two are empirical, and the third is judgmental.

Cross-sectional effort analysis. If a firm has many stores or other business units, each of which has a different allocation of effort and a different average satisfaction score, a function relating average satisfaction level to effort can be fit across these cross-sectional data, provided that level of effort has been scaled for size. Although relatively fast and data-driven, this method may suffer from spurious correlations due to third-variable causality. Data fitting could be done by linear regression, nonlinear regression (Rust 1988), splines (Wegman and Wright 1983), or some other curve-fitting technique.

Longitudinal effort analysis. Data from cross-sectional analyses may suffer from reverse causality. That is, high satisfaction (and thus high market share and high profits) may increase the effort expended, or vice-versa. The only way to partial out the effect and establish causality is by experiment, in which dollar effort is manipulated for some stores (business units) and the ensuing satisfaction scores monitored. This method is the most accurate, but also the most time-consuming and costly

Decision calculus. If empirical data are not available or historical data do not reflect future conditions, the effort function can still be callibrated using decision calculus (Little and Lodish 1969; Little 1970), by eliciting judgments from managers, which are then fit to a response curve. This approach has the important advantages of being fast and easy to employ, but may suffer from poor managerial input (Stewart and Zahorik 1990). Nevertheless a body of research indicates that decision calculus can be surprisingly effective (Fudge and Lodish 1977; McIntyre 1982; McIntyre and Currim 1982). The combination of managerial judgments and statistical models used in our approach has been shown to be superior to either managerial judgments or statistical models alone (Blattberg and Hoch 1990)

We employ the response curve used in the ADBUDG model (Little 1970):

$$\text{Avg Sat} = (HI - LO)(A^{\gamma}/(a^{\gamma} + A^{\gamma})) + LO \qquad (6)$$

where HI is the upper asymptote (corresponding to infinite expenditure), LO is the minimum (corresponding to zero expenditure), a and γ are model parameters, and A is the current level of expenditure. Because the model has four parameters, four data points are needed to calibrate the function. Those obtained are usually the current level, 0, ∞, and another easily esitimatable level, such as twice the current level This curve may be concave or it may be S-shaped, depending on the values of the parameters.

Example. In the retail banking study a decision calculus technique was used. A consultant who had implemented satisfaction improvement programs at Bank C estimated the current annual dollar expenditures devoted to "listens to my needs" to be $50,000, which was currently producing a 4.2 average attribute satisfaction rating. He also estimated that if these expenditures were totally halted, the satisfaction rating would drop to 3.0, while unlimited funds might generate at most a 4.5. If expenditures were doubled to $100,000 satisfaction was estimated to rise to 4.35. The resulting effort curve is concave over all spending levels.

Satisfaction shifts. The link between average satisfaction shifts and retention is not straightforward to compute. The concept of raising average satisfaction scores is used because managers are comfortable with it, but in fact there is usually a diversity of ratings among a firm's customers, so that the effect of a service improvement would necessarily have different impacts on different customers. In addition, because the relationship between satisfaction and retention, r_{ij}, is a non-linear, individual-level function the effect of an increase in satisfaction on average retention, r_j, cannot be computed directly from the logit function, because the average of r_{ij}'s is not necessarily equal to the logit function evaluated at the average levels of satisfaction. Therefore, the manager's estimate of a shift in average satisfaction must somehow be translated into an estimate of its effect at the individual level and means computed. A method for estimating the effect of shifts of average satisfaction on average retention using beta distributions is described in Rust and Zahorik (1992).

Optimal Spending Levels

The link between dollars spent on service improvement programs and profitability is now complete. The previous section described how to estimate a functional relationship between marketing effort and satisfaction. By linking satisfaction to the firm's probability of retaining its customers through the logistic function for r_{ij}, which is in turn related to market share and revenue, it becomes possible to predict the profit impact of managerial actions which increase customer satisfaction. If this increase in customer satisfaction must be accomplished by expenditures on specific programs, it is possible to determine the optimal level of spending for the model and, insofar as the model's assumptions are realistic, for the manager's problem. As always when determining "optimal" actions from simplified models, one must keep in mind that the solutions suggest directions for improvement rather than precise estimates of optimal behavior.

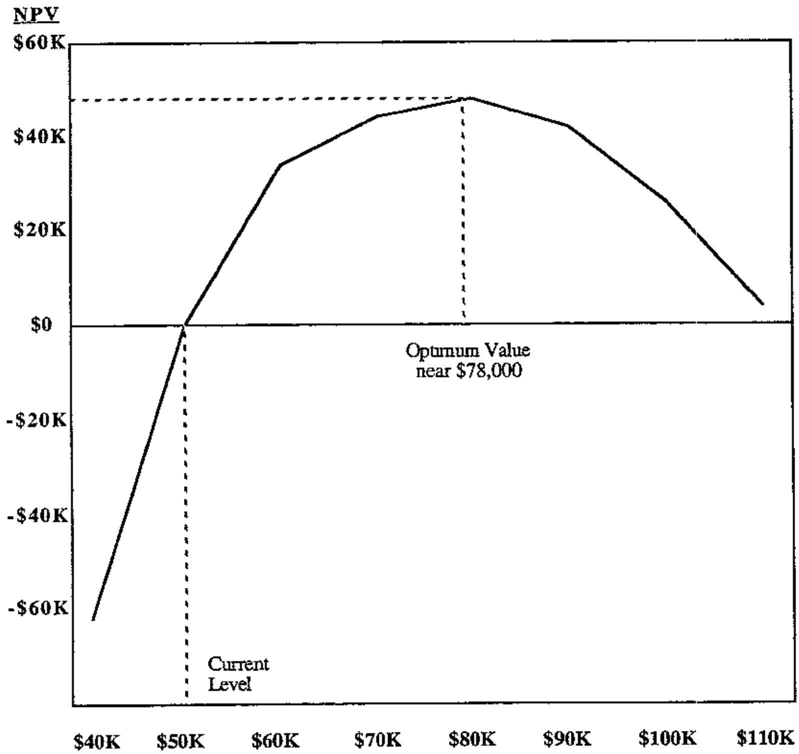
Example. The relationship between dollar effort to improve "listens to my needs" and retention was determined by relating average satisfaction shift to retention combined with the decision calculus curve obtained above. Equation (1) then provides the means to calculate the effect on market share of a new retention rate on market share over time for various levels of effort.

The average annual contribution per retail bank customer in the study market is $158. Combining this with market share, and market size, we computed the marginal change in contribution each year after the change for each level of effort, deducted the cost of the effort to achieve it, and computed the net present value of this net contribution for a five year horizon (the average duration of a banking relationship.) The relationship between effort and the NPV of incremental profits is shown in Figure 2.

The curve indicates that more should be spent on training programs to improve customers' perceptions of the bank's ability to "listen to their needs," (assuming the consultant's estimates of response are correct.) In particular, the optimal expenditure level is $78,000, an increase of 56 percent over the current level. However, the NPV of profits would be projected to increase by almost $47,000, an excellent return on the in-

FIGURE 2

Net Present Value of Change in Market Share due to Change in Customer Retention for Various Levels of Spending on Service Improvement Programs



creased investment. The absolute numbers are quite small in this case, but then the bank was already doing very well on all measures, and there was little room for improvement. Had the average score for the bank been in the area of 3, several hundreds of thousands of dollars could have been earned in retained customers for rather modest expenditures on personnel training programs.

The value obtained above is subject to the usual qualifications for optimization models, but it does suggest that a manager who feels the consultant's estimates are correct would be advised to increase spending on personnel training. In fact, the model may understate the true benefits of this training, because, as mentioned earlier, it does not incorporate the offensive marketing effects of positive word-of-mouth that could result from increased customer satisfaction.

In practice, the location of the maximum value of the profit function must be established by heuristic search procedures, because of the complicated nature of the profit function. If a single satisfaction improvement program is under consideration, a simple enumeration of profits expected at various spending levels will quickly reveal the shape of the profit function and the location of the optimal level of spending as in Figure 2. If multiple satisfaction improvement programs are to be undertaken simultaneously, the heuristic search is not as fast, but is still feasible, unless the number of satisfaction elements for which expenditures are to be optimized is large. Even in that event, the framework above makes possible a "what if" analysis in which various expenditure combinations can be explored

DISCUSSION

Managerial Implications

How does a firm improve customer satisfaction with its service? How can the firm serve its customers better? For companies that already have a strong customer service orientation, further improvements in customer ratings may come only through the addition of new programs aimed at specific remaining weaknesses. Training programs to help personnel to be more responsive to customers, upgraded facilities, better data-handling systems, customer surveys and newsletters, etc., have costs that are generally measurable—although their impact on customer satisfaction levels may be difficult to predict. In such situations, where management is convinced that customer satisfaction can be improved only by spending money, the above models, coupled with a response function linking spending to customer satisfaction, can be used to determine the optimal amount to spend.

On the other hand, it may not require additional spending to improve customer satisfaction. For companies with weak customer service cultures, and even for some weak programs within service-oriented companies, the answer to improving customer satisfaction is not necessarily an expenditure of funds, but a change in the ways the firm does business. In some cases, a simple change of procedures can greatly improve the customer's experience with the service at little or no cost to the company. Our model can demonstrate the value of making such changes in terms of increased customer retention, market share and profits.

Of course, in non-service-oriented firms, such changes may require a veritable revolution in the culture of the organization. There are certainly costs incurred in creating such revolutions, but they are more difficult to assess in monetary terms. Nevertheless, our model can still be used to demonstrate the value of pursuing this cultural revolution by showing the magnitude of the expected improvement in market share, while pinpointing the areas of customer satisfaction which require the most immediate attention

Conclusions

This work provides a mathematical framework for making accountable resource allocation to improve customer satisfaction. In an era of cutbacks, only programs that demonstrably improve bottom-line profitability stand to survive. This paper makes the value of customer satisfaction accessible to accountants and financial managers by translating it into the language of revenues and costs

This framework is based on the relatively new, defensive marketing view of market share, discussed earlier by Fornell and Wernerfelt. Retention rate is seen to be the most important component of market share, and it is driven by customer satisfaction Thus, in the new view of market share, customer satisfaction is a central issue.

We show how customer satisfaction may be linked sequentially to individual loyalty, aggregate retention rate, market share, and profits and how the dollar value of a shift in customer satisfaction can be measured

Based on this approach, we are able to identify the satisfaction elements which strongly affect the bottom line, and those which don't. This indicates where increased expenditure might be necessary, and where expenditures might be cut with no adverse impact. Specifically, we are able to determine the spending levels on each satisfaction element which will maximize profitability, subject to the assumptions of the model and accuracy of parameter estimation. We reemphasize that we have isolated only the effect of service improvement efforts on retention, and not its likely effect on the attraction of new customers through positive word-of-mouth.

This paper describes only a mathematical framework and a pilot study. Considerable additional work is needed to operationalize this approach on a large scale. We hope that this work will stimulate extensions and practical applications which quantify and objectify the value of customer satisfaction.

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