RESEARCH SUPPORT
UNIVERSITY OF MICHIGAN BUSINESS SCHOOL

MAY 1997

DRIVERS OF CUSTOMER SATISFACTION FOR FINANCIAL SERVICES: IMPLICATIONS FOR PRODUCT OFFERINGS AND SERVICE DEIVERY

WORKING PAPER #9705-15

BY

MAYURAM S. KIRSHNAN
UNIVERSITY OF MICHIGAN BUSINESS SCHOOL
MARY C. MEYER, DEPARTMENT OF STATISTICS,
UNIVERSITY OF MICHIGAN
VENKATRAM RAMASWAMY
UNIVERSITY OF MICHIGAN BUSINESS SCHOOL
PAUL DAMIEN
UNIVERSITY OF MICHIGAN BUSINESS SCHOOL

Drivers of Customer Satisfaction for Financial Services: Implications for Product Offerings and Service Delivery

Mayuram S. Krishnan
University of Michigan Business School, Ann Arbor MI 48109

Mary C. Meyer
Department of Statistics, University of Michigan, Ann Arbor, MI 48109

Venkatram Ramaswamy
University of Michigan Business School, Ann Arbor, MI 48109
Phone: 313 763 5932; E-mail: VenkatR@umich.edu

Paul Damien
University of Michigan Business School, Ann Arbor, MI 48109

May 1997

We would like to thank Steve Cohen, President, Stratford Associates and a large financial services firm (that wishes to remain anonymous) for their cooperation and support in collecting the data used in this paper. Financial support for this study was partly provided by the University of Michigan Business School.

Abstract

In this paper, we study the drivers of overall customer satisfaction for financial services. We discuss a full Bayesian analysis based on 1280 responses from customers of a large financial services company. Our methodology allows us to explicitly accommodate missing data and enables quantitative assessment of the impact of the drivers of satisfaction across the customer population. Unlike traditional customer satisfaction analyses that focus only on average effects, we also consider the variability in these effects across customers.

We find that satisfaction with product offerings is a primary driver of overall customer satisfaction. The quality of financial statements and services provided through different channels of delivery such as automated call centers and traditional branch offices are also important in determining overall satisfaction. However, our analysis indicates that the impact of service delivery factors may differ substantially across customer segments. Further, to facilitate managerial action, we identify specific operational quality attributes in designing and delivering financial services that enhance satisfaction with product offerings. Our methodology and results have significant implications for managing customer satisfaction in the financial services industry.

1. Introduction

Deregulation and increased competition due to the entrance of banks, mutual fund companies, brokerage services, and insurance firms have revolutionized the financial services industry over the last decade. In the recent past, the industry has witnessed an average overall annual growth that exceeds 25%, with the traditional bank deposits at the lower end and investment products like mutual funds, annuities and trust services at the higher end. Advent of information technology and rapid changes in customer needs have also contributed to the growth in the industry through new product offerings that were not possible a few years back (Kalakota and Frei, 1996). The number of both national and foreign firms that offer financial services has also increased over the last decade. With increased competition from new products and delivery channels, service delivery has emerged as an important attribute in satisfying customers. It has been reported that more than 70% of the defection of customers in the financial services sector is due to dissatisfaction with the quality of services delivered (Bowen and Hedges, 1993).

Managers in financial services firms are placing increased emphasis on customer satisfaction (Reichheld and Teal 1996) to enhance customer loyalty for long-term profitability and success (Fornell, Ryan and Westbrook, 1990). The basic argument is that satisfied customers of a firm decide to stay with the firm for future business. More importantly, the cost of retaining existing customers by improving the products and services that are perceived as being important is significantly lower than the cost of winning new customers. Consequently managers in the financial services industry are placing increasing emphasis on listening to the "voice" of the customer and identifying the drivers of overall satisfaction (Zeithaml, Parasuraman and Berry, 1990). Feedback from customers enables firms to identify their specific needs and efficiently allocate resources to design products and services that maximize satisfaction (Kekre , Krishnan, and Srinivasan 1995).

In order to meet the needs of various segments of customers, firms in the financial services industry offer multiple products and services through different channels of delivery. For example, services on a brokerage account may be provided directly to a customer at a branch office and the same service may also be provided through an automated telephone call center, or more recently through computerized trading services via home PC or over the Internet. In this industry, the notion that the value of the products offered is shaped by the channel of delivery, suggests that firms should change their traditional view of cost control in managing their products and distribution channels. A key issue among managers in this industry concerns the impact of automated and electronic delivery of services versus traditional delivery through branches, on overall customer satisfaction.

Quantitatively assessing the impact of various drivers of overall customer satisfaction for any firm in the financial services industry through survey research leads to two major operational challenges. First, incomplete or missing data is inevitable in surveys of customer satisfaction (Naumann and Giel, 1995). In the financial services sector, although firms offer many products and services through different channels of delivery, a single customer often responds to only a subset of items that they use in customer satisfaction surveys.

The second operational challenge is related to the heterogeneity in the customer population of the perceived importance of various products and services. For example, busy business professionals may not view services provided at the firm's branch offices as important as the services provided over the automated telephone system. On the other hand, customers who visit branch offices frequently may perceive services provided at the branch offices as very important. Thus it may not be appropriate to assume the perceived importance of these services to be the same across all customers.

In this paper, we provide a framework and methodology to cope with these challenges and effectively manage customer satisfaction for financial services. Our framework entails two levels of analysis, based on responses from 1280 customers. In the first level, we identify and assess the relative importance of various strategic drivers of overall customer satisfaction for a financial services firm. These drivers entail customer satisfaction for product design factors and channels of delivery offered by the firm. Our methodology estimates the variation in the effect of the drivers of overall satisfaction across customers. Once the key strategic drivers of overall satisfaction are identified, we estimate a model at the second level for specific managerial action. In particular, we assess the impact of various quality attributes of the firm that might influence customer satisfaction with the firm's product offerings and channels of delivery. Together, both these levels of analysis enable the firm to understand what drives overall customer satisfaction, how their effects vary across customers, and what the firm could do to specifically influence these drivers of overall satisfaction.

The contributions of this paper are both managerial and methodological. On the methodological front, this paper introduces a new Bayesian approach for estimating customer satisfaction models, using recent advances in statistical computation. A major advantage of the proposed approach is that we can handle the problem of missing data that is endemic to assessing customer satisfaction for firms in the financial services sector. Moreover, our methodology allows us to estimate the heterogeneity across customers for all the parameters in our model. This enables us to understand the inherent variability in the perceived importance of customer satisfaction factors across the population. Thus our analysis provides a richer inference base for managerial decisions as compared to traditional models of customer satisfaction that estimate only average effects.

On the managerial front, our analysis of overall customer satisfaction indicates that satisfaction with product offerings is the most critical, followed by satisfaction with the quality of financial reports and account statements, and satisfaction with the services provided in branch offices. We find that the quality of automated telephone service is also important, although its relative impact is less than the other factors in our study. However, we note that the impact of satisfaction with automated telephone service may be substantially higher for a specific customer segment.

In the second level of analysis, we focus on customer satisfaction with the firm's product offerings, the primary driver of overall satisfaction. We identify the specific operational quality attributes that influence satisfaction with product offerings and assess their relative impacts. For instance, we find that ease of opening and closing accounts, and customer education are major determinants of satisfaction with product offerings. In this analysis, we again illustrate the importance of capturing the variability in perceived importance of these attributes. Thus, the results of our models provide insights for managers to design and deliver products that are appropriate for various customer segments. Our results can be used to facilitate resource allocation decisions that maximize overall customer satisfaction with the firm.

The rest of the paper is organized as follows. In section two, we discuss our research design and data collection. In the third section, we elucidate the methodological issues and discuss our full Bayesian analysis approach. We report our results and discuss the managerial implications in the next section. Section five concludes the paper and offers some directions for future research.

2. Research Design and Data Collection

Financial services companies produce products such as checking and savings accounts, mutual funds and brokerage accounts, cash and margin accounts, and in some cases may also offer insurance policies. One of the unique features of the financial services industry is that many customers seldom use some of the products produced by the firms on a daily basis. Often, once a product is sold, it is never used again until it expires or matures. Since customers do not view the actual product as a full product, the service accompanying the product is very important in determining the overall satisfaction with the firm. As a consequence, in modeling overall customer satisfaction for financial services companies, it is important to include both product and service attributes.

Our research effort is linked to the growing literature on identifying specific quality attributes and leveraging product design to enhance customer satisfaction in various industries. Mapping the needs of customers to product design is often the central theme in new product development efforts (Hauser and Clausing, 1988; Wind and Mahajan, 1997). Prior research has identified specific attributes of quality that are linked to customer satisfaction in both manufacturing and service industries (Garvin, 1988; Zeithaml, Parasuraman, and Berry, 1990). However, the notion of quality in financial services firms is quite different from that in manufacturing companies. As noted earlier, the nature of the financial services industry is such that its products are mostly intangible. For example, in an investment company, the product delivered is not the stock certificate but the investment it represents, as well as the peripheral services such as online account services and accurate periodic reports.

Another interesting aspect of financial services companies is that they do not fully fit into the mold of full service industries such as hotel and travel agencies. Thus financial services companies fall some where in between manufacturing industries, which offer tangible products, and full service industries. While research on service quality has generally investigated the quality attributes of certain service encounters, there is a paucity of research and guidance in understanding the drivers of overall customer satisfaction at the firm level. This is true especially for multi-channel firms that are increasingly becoming the norm in the financial services sector (Frei et. al, 1995).

2.1 Research Design

Our research site is one of the leading firms in the nation providing retail financial services (that wishes to remain anonymous). The firm offers a number of products to its customers and provides services over automated telephone systems and other electronic channels, and a multitude of branch offices located throughout the nation. The product offerings include various types of savings, checking, credit card, and investment products and accounts. The firm has also started providing account services over the Internet through the World Wide Web. However, during our data collection, the service offered over the Internet was not fully operational. In the recent past, the management has focused on quality initiatives to improve customer satisfaction and profitability. Our research effort was aimed to provide an analytical framework to carefully identify the critical needs of its customers and support this quality initiative.

With the help of this leading multi-channel financial services firm, we first sought to identify the characteristics of products and services offered by the firm that are perceived as important by customers in determining overall satisfaction with the firm. Our exploratory research involving focus groups with several customers identified the factors that are salient to customers in evaluating the firm's product offerings and delivery of services. It was evident that customers in the financial services sector derive value from the quality of products, accounts, and services offered by the firm. The various types of products and accounts offered by the firm allow customers to select offerings based on their changing needs. It was apparent that since the actual products delivered is not fully viewed as a product by the customers, the service accompanying the product becomes an important factor that determines the overall satisfaction with the firm. It has been observed that financial services firms often lose customers due to poor service than poor products (Bowen and Hedges, 1993). The quality of customer service delivered through multiple channels, as well as accurate and timely statements of various accounts appear to be critical in the financial services sector.

Over the last decade, information technology has revolutionized the concept of delivering financial services. Firms find automated telephone service as a cost-effective tool for account inquiries and other transactions. Over 50% of the financial transactions are currently conducted over automated telephone systems and other electronic means (Kalakota and Frei, 1996). Information technology has also enabled firms to provide customized reporting of accounts in the financial services sector.

Financial services firms in general also provide direct services to their customers through a large number of branch offices. Though routine transactions may be provided over the telephone or other electronic means, important services such as opening an account, changing account information and investment advice are provided through direct contact with customers in the branch offices. In addition, an industry survey finds that not all customers prefer online delivery of services (Morrall, 1996).

After careful review of the findings from the exploratory research, four key factors were identified to be included in a comprehensive survey. These include the quality of the types of products and accounts offered by the firm, quality of financial reports and account statements, quality of service rendered through automated telephone systems, and the quality of service offered through direct contact with customers at their branch offices. For the subsequent phase of survey research, a questionnaire was designed and pre-tested with a pool of customers. The questionnaire was revised and mailed to a representative sample of customers from the firm's customer database. Besides questions pertaining to customer satisfaction, the firm also sought to obtain information on customers' usage patterns and behaviors, as well as some descriptive background characteristics of its customers. The response rate was 44% of the total surveys mailed. Our analysis is based on responses from 1280 current customers.

2.2. Variable Definitions

Details of the measure of overall satisfaction and other factors used in our analysis are given below.

Overall Satisfaction (OVSAT): In the survey, customers were asked to provide an overall satisfaction measure of their experience with the firm on a seven point ordinal scale ranging from very satisfied (7) to very dissatisfied (1). A mid-level score of four indicated neutral evaluation by the customers. Other anchor points on the scale were satisfied (6), somewhat satisfied (5), somewhat dissatisfied (3), and dissatisfied (2). The same scale was also used for the four key factors discussed below.

Automated Telephone Service Satisfaction (AUSAT): Financial services firms view automated telephone systems and other electronic channels of service delivery as an effective solution to improve customer service at a much lower capital cost. The automated telephone systems may be improved through easy to use menu design and a variety of transaction options. The reliability of this system is also critical in determining customer's perception of service quality. Firms invest significantly in information technology to ensure highly reliable and accurate service over these automated systems. Hence, this factor captures customers' perception of the quality of service provided over automated telephone systems.

Branch Service Satisfaction (BRSAT): Companies in the financial services industry operate through a large number of branch offices and this is one of the major capital investments for these firms. A certain segment of customers still visit branch offices for normal service, though the number of such customers is decreasing due to the advent of other channels of service. In addition, a large number of customers often visit branch offices for more complex services such as financial advice, information about products to meet their needs, and resolution of problems. Although the financial services industry has been consolidating, the number of branches has been increasing (Morrall, 1996). In order to provide an important contact point and retain profitable customers, firms try to provide the best service at their branch offices through right people and processes. Hence this factor measures customers' perception of overall quality of service provided at the branch office.

Product Line Satisfaction (PLSAT): This variable measures customer's satisfaction with the types of products and accounts offered by the firm. The products offered by the firm include different kinds of accounts offered to meet investment needs of customers. Firms provide a variety of products and services to provide a one stop option to satisfy the investment needs of their customers. In our analysis, this factor is also influenced by customers' perception of interest rates and fees for the firm's products. Hence, customers' evaluation of this factor is influenced by multiple operational quality attributes of the firm's product offerings.

Financial Report Satisfaction (FRSAT): Periodic statements and reports on account transactions and summaries are valuable to customers. For financial products such as retirement accounts, quarterly reports are the only source of information that customers in certain segments review. Firms have begun to make their account statements and reports accurate and timely in order to better serve their customers. This factor in our model gauges the satisfaction of the firm's customers with the account statements and reports provided by the firm.

3. Methodology and Analysis

In order to effectively deploy resources to improve overall customer satisfaction, it is important to assess the relative impact of the four factors mentioned above on the overall satisfaction with the firm. However, as indicated earlier, a major methodological challenge for analyzing customer satisfaction data in the financial services sector concerns the preponderance of missing data. In the present context, less than 25% of the respondents provided complete responses to the variables defined above. While almost all of the respondents gave their overall satisfaction rating, a majority of the respondents had some form of missing data pattern in their responses to the remaining four factors. For instance, on the factors pertaining to satisfaction with service delivery through automated telephone and branch services, there is as much as 36% and 39% of missing responses respectively. Yet, none of the respondents had missing values on all the four key factors, and there is no evidence of a systematic pattern of the missing responses.

In practice, "best-fit" imputation methods such as correlational imputation are often used for statistical analysis of missing data (Little and Rubin 1987). While such methods are useful for obtaining descriptive statistics, they are of limited value in the present context for two reasons. First, such methods are not "model-based" – for example, as discussed below, our model of customer satisfaction relies on the ordinal properties of the dependent variable. Second, since we are also interested in capturing the variability in the drivers of satisfaction across customers, multiple imputations of the missing data are necessary rather than a single best-fit imputation (Rubin 1987). Until recently, it was computationally burdensome to implement the idea of multiple imputation (Tanner and Wong 1987). With recent computational advances in numerical

Bayesian methods as discussed shortly, a full Bayesian analysis of the missing data structure can now be carried out in conjunction with the estimation of any parametric model specified for the entire data. This allows the firm to utilize all the data that have been collected in a comprehensive model-based framework. Another major advantage of this method is the ability to place constraints on the model parameters. For example, when there is considerable correlation among the explanatory variables, prior knowledge of the model parameters can help alleviate the effects of multicollinearity. Although multicollinearity is not a concern in our analysis (the maximum correlation among the factors is less than 0.40), we constrain the parameters associated with the explanatory variables to be positive, consistent with our model of overall satisfaction.

We next discuss our customer satisfaction model and then describe how a full Bayesian inference of this model can be carried out.

3.1 The Model

The dependent variable in the first level of our analysis is overall satisfaction with the firm. As discussed earlier, the ratings by customers are on a seven-point ordered scale. It may be noted that in such a scale, though level seven is higher than level six and the latter is higher than level five, the difference in satisfaction between levels five and six is not necessarily the same as that between levels six and seven. Since the dependent variable is discrete (a rank-ordered ordinal variable) and not continuous, the classical regression model is not appropriate (Greene, 1995). A more appropriate model specification is one which recognizes that the dependent variable is not merely categorical but is inherently ordered, such as an ordered probit model (Zavoina and McElvey 1975; Kekre, Krishnan, and Srinivasan, 1995).

In an ordered probit model, we define a latent (unobserved) continuous variable that measures the continuous (cardinal) value of overall satisfaction. For the i-th customer, the latent variable Z_i is specified as a linear function of the explanatory variables:

$$Z_i = \tilde{X}_i'\tilde{\beta} + \varepsilon_i \quad (1)$$

where $\tilde{X}_i$ is a vector of explanatory variables (**AUSAT, BRSAT, PLSAT, FRSAT**) for the i-th customer, $\tilde{\beta} = (\beta_1, \beta_2, \beta_3, \beta_4)$ is the respective vector of parameters associated with these drivers of overall satisfaction, and ε_i is a randomly distributed error term that follows a standard normal distribution across observations. For each customer, this unobserved cardinal value Z_i is mapped to the observed overall satisfaction rating Y_i as follows:

$$\Pr(Y_i = j) = \Pr(\delta_{j-1} < Z_i \le \delta_j) \quad (2)$$

where $\Pr(Y_i = j)$ is the (ordered) probability that the observed rating, **OVSAT**, for the i-th customer is the j-th level of the overall satisfaction scale (j = 1,...,J), and δ_j is the threshold value (j = 0 ,..., J+1) such that $\delta_0 < \delta_1 ... < \delta_J < \delta_{J+1}$.

As discussed earlier, several methodological complexities arise in the present context:

(i) foremost, we are interested in capturing the variability in the parameters over the population;

(ii) we need to allow for the incorporation of prior knowledge of the parameters such as positivity constraints for the impact of the drivers of satisfaction; and,

(iii) given the presence of missing values for the explanatory variables, we need to incorporate a model-based imputation method to take advantage of all the collected data. A full Bayesian approach is introduced next that addresses these challenges, and yet is computationally efficient.

3.2 A Full Bayesian Analysis

Bayesian estimators combine information contained in the data with prior knowledge about model parameters $\tilde{\theta} = \{\tilde{\beta}, \tilde{\delta}\}$ to arrive at the posterior distribution $\pi(\tilde{\theta} \mid \tilde{Y})$, given the observed data $\tilde{Y}$:

$$\pi(\tilde{\theta} \mid \tilde{Y}) \propto \ell(\tilde{Y} \mid \tilde{\theta})\, \pi(\tilde{\theta}), \tag{3}$$

where π denotes a probability density function, $\pi(\tilde{\theta})$ is a prior distribution of the parameters $\tilde{\theta}$, and $\ell(\tilde{Y} \mid \tilde{\theta})$ denotes the likelihood of the observed data given the model parameters. A major advantage of this framework is that the missing data can, in principle, be treated as random variables to be estimated along with the model parameters. Hence, we can simply specify $\tilde{\theta} = \{\tilde{\beta}, \tilde{\delta}, \tilde{X}_{(m)}\}$ where $\tilde{X}_{(m)}$ denotes the missing values of the explanatory variables. Until recently, the application of Bayesian methods has been limited to cases where the posterior distribution has a closed form and/or is computationally tractable (Gelman et al., 1996). This occurs for instance in classical regression models. In this paper, our goal is to conduct statistical inference in the context of an ordered categorical response model subject to the challenges indicated above. In this case, the posterior distributions of the parameters do not have a tractable closed form.

Recent advances in Markov Chain Monte Carlo methods of estimation using the Gibbs Sampler (Smith and Roberts, 1993) allow draws to be simulated from non-standard posterior distributions, given the knowledge of the full conditional distributions. In what follows, we use the following type of notation: when the dimension is clear within a context, a vector is simply denoted by a symbol such as, $Z = (Z_1, \cdots, Z_K)$; likewise, a matrix is denoted simply by a symbol such as X. The notation "$A|B$" implies the conditional distribution of A given B, which, at times, will be simplified to $A|.$, where the conditioning is with respect to all the remaining unknown and uncertain random quantities.

Following the ordered probit model, suppose that $Y_1,\cdots,Y_N$ are the observed overall satisfaction ratings provided by customers where Y_i belongs to one of J ordered categories, $1,\cdots,J$. Further, as before, suppose there exists a latent continuous variable Z_i distributed $N(X'\beta,1)$, where X is a matrix of covariates, β is the corresponding parameter vector, and where we observe Y_i such that $Y_i = j$ if $\delta_{j-1} < Z_i \leq \delta_j, i = 1,\cdots,N$, and $j = 1,\cdots,J-1$. (Note that in an ordered probit model, δ_0 and δ_N, are set equal to $-\infty$ and ∞, respectively, and $\delta_1 = 0$ for identification purposes.)

Now, with a diffuse prior for (δ,β), the posterior distribution is given by (Albert and Chib 1993):

$$\pi(\beta,\delta,Z,X_{(m)}|Y) \propto \prod_{i=1}^{N} [exp(-(Z_i - X'_i\beta)^2/2)\times\{\sum_{j=1}^{J} I_{(j)}(Y_i)\,I_{(\delta_{j-1},\delta_j)}(Z_i)\}], \qquad (4)$$

where I(·) is the indicator function. Although a Bayesian solution to a posterior distribution like the one appearing above can, *in principle*, be accomplished via the Gibbs sampler (e.g., Smith and Roberts, 1993), implementing it requires knowledge of the full conditionals, up to proportionality. Typically, these conditional distributions are standard densities from which random variate generation is possible; alternatively, in certain cases, stylized sampling schemes based on rejection based algorithms and/or the Metropolis-Hastings algorithm can be constructed (see Gilks, Richardson and Spiegelhalter, 1996). The problems with these latter approaches include, among others, identifying dominating densities, calculating supremums, and acceptance rates; these may be difficult to obtain in many contexts (Chib and Greenberg, 1995).

The derivation of the full conditionals for the specification in (4), is given in Appendix A. These full conditional densities take the form of truncated multivariate normals (for $\beta, X_{(m)}$, and Z), and a uniform distribution restricted to an easily identifiable set (for δ_j). Until recently there have been few well-known efficient algorithms to simulate from a truncated multivariate normal density (see Devroye, 1986, Robert, 1995). If one were to impose, based on prior information, that either all, or certain, elements of the parameter vector β should be constrained to be, say, positive, then the resulting posterior conditional distribution of $\beta|$. will be a truncated multivariate normal (Gelfand et al. 1990). What this means is that the efficiency of the resulting Gibbs sampler would be reduced considerably. This reduction, of course, would increase if the dimension of the parameter vector and the number of constraints were increased. Hence, it would be useful to have a *general* Gibbs sampler which bypasses such computational special cases.

In this paper, we utilize such a sampler called the *Slice sampler* (Damien, Walker, and Wakefield, 1997) which can be set up so that the full conditional distributions, following the introduction of auxiliary variables, will *all* be uniform densities. This greatly simplifies computation and also has superior convergence properties compared to other methods (Damien and Walker 1996; Roberts, 1997). Details of our implementation of the Slice sampler are provided in Appendix B. For the illustrations described in this paper the Gibbs sampler was run for 10,000 iterations: the first 8000 iterates were the "burn in" samples. Inferences are based on the last 2000 iterates.

4. Results and Discussion

Using the full Bayesian procedure discussed above, we estimated the posterior distributions of all the parameters in our study. For the firm in our study, the customers were distributed on the overall satisfaction scale as follows: 25% very satisfied, 55% satisfied, 15% somewhat satisfied, 3% neutral, and 2% dissatisfied. The relatively small number of dissatisfied customers is not surprising for a high-performance firm in the financial services sector (Peterson and Wilson 1992). Consequently, for our analysis, we combined the bottom four categories. In fact, the firm in our study had stated goals of total satisfaction, and is focusing its quality initiatives on shifting customers to the very satisfied category to ensure long-term loyalty.

Figure 1 depicts the posterior distribution of the effects of the drivers of overall satisfaction (i.e. $\tilde{\beta}$ in equation 1). As noted earlier, our methodology enables us to capture the variability in these effects across all customers. The mean of these distributions indicates the average effect of the respective factors whereas the variance captures the inherent differences in these effects across customers. As illustrated in Figure 1, our analysis suggests that product offerings *(β_3)* exhibits the highest average impact. Among the remaining drivers of overall satisfaction, the quality of services provided at the branch offices *(β_2)* and satisfaction with financial reports and account statements *(β_4)* appear to have a somewhat larger impact than automated telephone systems *(β_1)*. To fully understand the relative impacts of these factors on overall customer satisfaction, we need to conduct a marginal effect analysis to assess the relative payback for the firm in terms of *gains* in very satisfied customers from improving each of these factors. This is especially important since the inherent relationship between the factors and overall satisfaction is non-linear.

4.1 Marginal Effect Analysis

In order to conduct a marginal effect analysis, we first tabulated the initial frequency of the customers across the various levels of satisfaction. Since the firm was primarily interested in enhancing the number of very satisfied customers, for ease of presentation of the marginal effects, we combine all the levels of satisfaction below "Very satisfied" to one group called "Not Very Satisfied Customers". Keeping all the other factors at their current levels, we increased the score of a specific factor by one level across all customers who are not fully satisfied with that factor. Subsequently with the enhanced level of satisfaction in that specific factor and the parameter estimates from the model, we computed the new frequency of customers across various levels of satisfaction. The difference in the new number of very satisfied customers and the initial number of very satisfied customers is the *net* increase in the number of very satisfied customers from enhancing the specific factor by one level across all customers. We conducted this marginal effect analysis for all the four factors in our model.

One of the limitations of earlier customer satisfaction models is that the impact of the drivers is typically estimated to be linear and is interpreted based only on mean effects. However, for effective managerial actions to improve overall satisfaction, it is important to assess not only the mean, but also to incorporate the variability in $\tilde{\beta}$ observed in Figure 1, so as to target the specific factors that provide maximum improvements in overall satisfaction. Specifically, firms need to target factors that exhibit a higher average effect and *lower variability* in their impact on overall satisfaction.

An advantage of the full Bayesian analysis procedure employed is that since the parameters in our model are random variables, the marginal effect is also a random variable. Hence, unlike traditional methods of assessing marginal effects only at the mean level (cf. Greene 1995), our approach allows us to compute the *distribution* of the marginal effects for each of the factors across the population. The distributions of the marginal effects (defined in terms of increase in number of very satisfied customers) for all the four factors in our model are depicted in the top row of Figure 2. In the bottom row of Figure 2, we provide the mean percentage of increase in very satisfied customers.

In order to compare the pertinent impacts of the four factors in our models, we define a relative impact index ρ for the marginal effects of these factors. This index incorporates both the average effects of the factors and variability in these effects across the population. The relative impact index ρ for a particular factor is defined as the ratio of its mean value of marginal effect over its standard deviation across the population. Thus for effective managerial actions, firms need to target factors that exhibit a higher value of ρ. The relative index for the marginal effect distributions depicted in Figure 2 are 4.31, 6.97, 10.25 and 7.26 for **AUSAT**, **BRSAT**, **PLSAT**, and **FRSAT** respectively. Note that in this case the factor with highest average effect, i.e. **PLSAT**, also has the highest relative index. Hence it is clear that the firm needs to focus on satisfaction with its product offerings in order to reap the maximum gains in overall satisfaction. However this may not always be the case and it is important to assess both the average value of marginal effects and the variability in these effects through the relative index. We further illustrate this point in our quality attribute analysis discussed later.

Although the marginal effect on overall satisfaction due to the improvements in quality of automated telephone service (**AUSAT**) and branch service satisfaction (**BRSAT**) is relatively low in the full sample, the impact of these factors on specific customer segments can be substantial. For instance, managers at our research site postulated that busy professionals who are employed full time and are experienced users of computers may find quality of automated telephone service (**AUSAT**) to be more important. Hence, we defined a customer segment based on customer's experience in using personal computers and employment status of the customers.

We then conducted a similar marginal effect analysis as discussed earlier on this customer segment. The size of this segment was 25% of the entire sample. However, we found that 33% of gains in very satisfied customers from improving the quality of automated telephone service emerged from this specific segment. Additional analyses identified specific segments for the other factors. Subsequently, the firm was able to compare these results with customer segment analyses based on in-house definitions that had been utilized for database marketing purposes. Unfortunately, we are unable to share these analyses and findings for confidential reasons.

Nevertheless, the general managerial implications based on these findings are twofold. First, the financial services firm in our study needs to channel its resources to improve product offerings. Second, the firm can target specific customer segments to reap the full benefits of improving customer satisfaction on quality of automated telephone delivery and services provided through its branches.

4.2 Quality Attribute Analysis

Based on the estimation of our model thus far, it is clear that in order to improve overall customer satisfaction, the firm needs to allocate resources to increase customer ratings of their product offerings. This raises the need for specific direction for improving the firm's product offerings. It should be noted that the four factors defined in our model are directly affected by multiple operational quality attributes. Firms need to identify and understand the relative effects of these quality attributes on the customer ratings of the four factors (Armstrong and Harker, 1995). We illustrate this next for the most important factor in our model, i.e. customer ratings of the firm's product offerings.

Focus groups were conducted to identify the different quality attributes that are perceived important by customers in determining their rating on firm's product offerings. After a careful review we identified the following four quality attributes of product offerings: ease of opening and closing of accounts (**QATR1**); competitive interest rates and fees (**QATR2**); lucid information on all products and services (**QATR3**); and product variety which enables customers to consolidate services one place (**QATR4**). While our focus here is on satisfaction with the firm's product offerings, our methodology may be used to investigate similar quality attributes for the other three factors in the model.

In the second level of our analysis, we measured customer satisfaction with the four quality attributes identified above. Thus, similar to our model of overall satisfaction, in this level we specify a model for satisfaction with product offerings as a function of these four quality attributes:

$$\mathbf{PLSAT} = f(\mathbf{QATR1, QATR2, QATR3, QATR4}). \tag{5}$$

The parameter estimates of this model enable managers to assess the relative impacts of these quality attributes. We utilized the methodology discussed earlier to estimate this model, enabling assessment of variability in these impacts across the sample. We also computed the marginal effects of each of these attributes as discussed earlier. The distributions of these marginal effects are depicted in Figure 3.

Note that in Figure 3, the average value of the marginal effect from improvements in customer education of product offerings (**QATR4**) is substantially higher than the average value of marginal effects from the rest of the three attributes. On the surface, this may appear as the most important attribute for improving satisfaction with firm's product offerings. However, an interesting finding is that the variability in the marginal effect from **QATR4** is also the highest among all four attributes. We conclude that the firm's customer base is heterogeneous with respect to familiarity and expertise with financial services. Some customers may be very sophisticated, while others may be naïve and need to be educated about financial goals and product options (Ramaswamy, Chatterjee, and Cohen 1996). This underscores the importance of computing a relative index ρ for the marginal effect as defined earlier.

The computed values of ρ based on the distributions of marginal effects of the four attributes **QATR1**, **QATR2**, **QATR3** and **QATR4**, are 8.32, 7.58, 5.90 and 5.53 respectively. Note that ease of opening and closing of accounts exhibits the highest relative index. Hence in order to improve satisfaction with product offerings across the customer population, firms need to focus on improving the process of opening and closing accounts. Interestingly, this attribute has also been identified as being important in bank process efficiency studies (Frei and Harker, 1996). Thus in general, it may be appropriate for managers to assign priority to the attributes based on the relative impact index ρ. In addition, it should be noted that the cost incurred in improving each of the four quality attributes might differ substantially.

In summary, the results of our analysis in this paper allows managers to identify the specific factors that significantly impact overall customer satisfaction with the firm and quantitatively assess the relative impacts of these factors. Our approach also helps managers to target the right customer segments to obtain the maximum benefits from each of these factors. In addition, our analysis at the second level enables managers in financial services firms to recognize the explicit operational quality attributes that need to be improved.

4.3 Limitations

From Figure 2, although we find that **BRSAT** and **FRSAT** exhibit similar marginal effects in increasing the number of very satisfied customers, the cost incurred by the firm to improve satisfaction with branch services and financial reports may differ substantially. Armstrong (1995) has provided a framework for identifying cost drivers of quality attributes in service satisfaction. In this paper, we do not address the cost issues in these attributes. However, managers must recognize the relative tradeoffs in costs and benefits in improving customer ratings in each of these quality attributes so as to effectively deploy resources towards improving customer satisfaction with the firm.

A key limitation with the data used in our analysis is that the respondent pool was limited to a single firm, though this firm is a market leader in the financial services industry. While the analysis focused on satisfied customers, dissatisfied customers are unlikely to remain as customers of the same firm. Their lack of representation in the data may lead to a positive bias in the evaluation. Further, in any survey, errors in measurement of the factors is a potential problem. Though we attempted to minimize such errors by using a pilot study to design the survey instrument, this problem can never be fully eliminated.

The cross sectional nature of data used in our analysis also exhibits certain limitations. As noted earlier, missing data is endemic to customer satisfaction surveys in financial services and other service industries. Given the difficulty of obtaining complete customer satisfaction data, our approach attempts to fully exploit the available information. However by obtaining longitudinal data from each customer, individual specific-effects and dynamic changes in the impacts of various factors can be better investigated. Finally, customer satisfaction may also be affected by firm-specific factors such as advertising and corporate reputation. We have partially controlled for these factors since our analysis is conducted for a given firm.

5. Conclusion

In this paper, we provide a framework and methodology for translating customer feedback into managerial actions for improving overall customer satisfaction with financial services. Based on customer feedback on various products and services offered, we identify four factors that affect customer satisfaction. Our full Bayesian analysis allows us to explicitly accommodate missing data and enables a quantitative assessment of the average effects and variability in the impact of these factors across customers.

Our analysis indicates that satisfaction with product offerings is the primary driver of overall customer satisfaction. Quality of services offered at the branch and satisfaction with financial reports and account statements also have significant impact on overall satisfaction. Though the impact of satisfaction with the automated telephone system on overall satisfaction appears more modest, the impact is substantially higher for a specific customer segment.

To facilitate managerial action, we identify specific quality attributes and assess their relative impacts on customer satisfaction with the firm's product offerings, which is the primary driver of overall satisfaction. We speculate that the cost to improve the specific quality attributes identified in our study may be substantially different (Krishnan et. al, 1996). In order to quantitatively assess the costs to improve customer satisfaction, a detailed framework as proposed in Armstrong and Harker (1995) is needed.

In the recent past, advances in information technology have enabled financial services firms to innovate their product offerings and service delivery. The number of customers who engage in electronic commerce for financial transactions has increased considerably in the past year. Due to the dynamic changes in the financial services industry, achieving high levels of customer satisfaction may be more like a moving target. Hence it is important for firms to continually assess and identify the drivers of satisfaction so as to retain their profitable customers.

Appendix A

To motivate the Gibbs sampler (see Gelfand and Smith, 1990 for a detailed discussion), consider a simple case involving two random variables A and B whose observed values are denoted by a and b. Let [A, B] denote the joint density of A and B, [A | B] the conditional density of A given B, and [B] the marginal density of B. Assuming that the conditional distributions [A | B] and [B | A] are known, and it is feasible to draw random variates from these distributions, the Gibbs sampling procedure follows an iterative process such that:

$$A^s \sim [A \mid B = b^s], \quad B^{s+1} \sim [B \mid A = a^s], \tag{A1}$$

thereby generating a sequence $b^0, a^0, b^1, a^1, \ldots, b^s, a^s$. It has been shown that under reasonably general conditions, the distribution of $\{b^s, a^s\}$ converges to the joint distribution [A,B] as $s \rightarrow \infty$. Computing appropriate sample statistics from the posterior distribution is straightforward, given the draws that have been generated (after ignoring the initial "burn-in" iterations).

However, as discussed, several modeling complexities arise for the model formulation in our paper. We now show how a Gibbs sampler can be set up so that the full conditional distributions, following the introduction of auxilliary variables, will *all* be uniform densities. The major advantage with the resulting sampler, known as the *Slice sampler* (Damien, Walker, and Wakefield, 1997), is two-fold: (i) it is computationally very easy to code; and (ii) has superior convergence properties compared to other methods (Damien and Walker 1996; Polson 1996; Roberts 1997). The goals here are to develop a *general* Gibbs sampler which can be readily adapted to encapsulate special cases; for example, the case of an informative prior, as well as bypass rejection sampling while simulating from, in our context, truncated multivariate normals.

Consider the posterior distribution of interest in the present context. From expression (4):

$$\beta,\delta,Z,X_{(m)}|Y \propto \prod_{i=1}^{N}[exp(-(Z_i - X'_i\,\beta)^2/2)\times\{\sum_{j=1}^{J}1(Y_i = j)\,1(\delta_{j-1} < Z_i < \delta_j)\}]. \quad \text{(A2)}$$

We state first, the full conditionals as follows:

$$\delta_j\,|\,. \sim U(a,b),\; j = 1,\cdots,J, \quad \text{(A3}$$

$$Z_i\,|\,. \sim N(X'_i\,\beta,1)\,I_{(\delta_{j-1},\delta_j)}(Z_i), i = 1,\cdots,N; \quad \text{(A4)}$$

$$\beta\,|\,. \sim MVN((X'X)^{-1}(X'Z),(X'X)^{-1})\,I_{(0,\infty)}(\beta); \quad \text{(A5)}$$

$$X_{i(m)}\,|\,. \sim N(((Z_i - X_i{}'\beta_{(k_0)})/|\beta_{(k_0)}|),|\beta_{(k_0)}|^{-1})\,I_{(1,7)}\,(X_{i(m)}); \quad \text{(A6)}$$

where the m-th missing data point is indexed by i and k_0, I denotes the indicator function, "MVN" denotes the multivariate normal distribution, "U" denotes the uniform distribution, $a = max\{max\{Z_i\!:\!Y_i = j\},\delta_{j-1}\}$, and $b = min\{min\{Z_i : Y_i = j+1\},\delta_{j+1}\}$.

Following Damien and Walker (1996), simulation from the above conditional densities is easily accomplished via uniform random variables. Let f be a continuous density function defined on the real line. Damien and Walker (1996) address the problem of generating a random variate A from f. The basic idea is to introduce an auxilliary variable Q, construct the joint density of Q and A with marginal density for A given by f, and to use the Gibbs sampler to generate random variates from f. This is done by simulating a Markov chain $\{A_n\}$ where given $A_n = a, Q$ is taken from $f(q\,|\,a)$ and then A_{n+1} is taken from $f(a\,|\,Q = q)$. Under mild regularity conditions $A_n \rightarrow_d A \sim f$. Additionally, we are interested in conditional distributions which can be sampled directly. (For an overview of Markov chain methods and the use of auxilliary variables, the reader is referred to Besag and Green, 1993 and Higdon, 1996). In particular, the approach described here is a consequence of the original idea introduced by Edwards and Sokal (1988) and highlighted by Besag and Green (1993). Damien and Walker (1996) prove that if:

$$f(a) \propto h(a) \prod_{l=1}^{L} g_l(a), \qquad \text{(A7)}$$

where the g_l are nonnegative invertible functions (not necessarily densities), that is, if $g_l(a) > u$ so that the set $T_l(u) = \{a : g_l(a) > u\}$, and $h(.)$ is a density of known type, then it is possible to implement a Gibbs sampler for generating random variates from f in which all the full conditionals are of known types. Additionally, all but one of these full conditionals will be uniform densities.

Damien and Walker's (1996) approach provides an elegant means of sampling from the full conditionals in our model (A3 to A6) within the context of a Gibbs sampler — via the introduction of auxilliary variables which has the effect of extending the Gibbs loop by the number of auxiliary variables introduced. The Gibbs sampler that can be constructed wherein all the full conditionals are uniform densities is called the *Slice sampler* (Neal and Roberts, 1997). The reason for this description is that the density from which a sample is desired has been "sliced" into sections by uniform partitions of each of the coordinate axes. Details on our implementation of this Slice sampler are discussed in Appendix B.

Appendix B

We provide details on implementing the Slice sampler discussed in Appendix A. Expression A5 requires sampling from a truncated multivariate normal distribution, while expressions A4 and A6 involve univariate normals. We first discuss the general problem of sampling from a truncated multivariate normal distribution. Consider the Gibbs sampler proposed by Robert (1995) for this purpose. We can greatly simplify this algorithm using the idea of auxilliary variables. Therefore, consider:

$$f_{x_1,\ldots,x_p}(x_1,\ldots,x_p) \propto \exp\left(-0.5\,(x-\mu)'\Sigma^{-1}(x-\mu)\right)I(x \in A), \tag{B1}$$

where $f(.)$ is a multivariate normal density. We assume, as does Robert (1995), that the bounds for x_i given x_{-i} are available and given by, say, (a_i, b_i). Therefore

$$f_{x_i|x_{-i}}(x_i \mid x_{-i}) \propto \exp\left(-0.5\,(x_i - v_i)^2/\sigma_i^2\right)I(x_i \in (a_i, b_i)), \tag{B2}$$

for $i = 1,\ldots,p$, are the full conditionals, and $v_i = \mu_i - \sum_{j\neq l}(x_j - \mu_i)e_{ij}/e_{ii}$ and $\sigma_i^2 = 1/e_{ii}$, where e_{ij} is the ij th element of Σ^{-1}. Robert uses his rejection algorithm for sampling these truncated univariate normal densities. However, since we are already in a Gibbs sampler it seems appropriate to implement the auxilliary variable idea.

We do not need to introduce p auxilliary variables — only one is sufficient. Therefore, we define the joint density of $(X_1,\ldots,X_p,Y)$ by

$$f_{X_1,\ldots,X_p,Y}(x_1,\ldots,x_p,y) \propto \exp(-y/2)\,I\left(y > (x-\mu)'\Sigma^{-1}(x-\mu)\right)I(x \in A). \tag{B3}$$

The full conditional distributions are given by

$$f_{X_i|X_{-i},Y}(x_i \mid x_{-i}, y)\;\alpha\; I(x_i \in A_i), \tag{B4}$$

where $A_i = (a_i, b_i) \cap B_i$, and B_i is the set $\{x_i \mid x_{-i} : (x-\mu)'\Sigma^{-1}(x-\mu) < y\}$ and so the bounds for B_i are obtained by solving a quadratic equation. The full conditional for (Y | X) is a truncated exponential distribution which can be sampled using the cdf inversion technique (see Devroye, 1986). Therefore, we have a Gibbs sampler which runs on $p+1$ full conditionals which can all be sampled directly using uniform variates, rather than p full conditionals sampled via rejection algorithms.

To illustrate sampling from truncated univariate normals, consider the specific case of sampling from the full conditional in expression A4:

$$Z_i \mid . \sim N(X'_i \beta, 1)\, I_{(\delta_{j-1}, \delta_j)}(Z_i), i = 1, \cdots, N. \tag{B5}$$

We sample from a standard normal truncated on $(a,b) = (\delta_{j-1} - X_i{}'\beta,\ \delta_j - X_i{}'\beta)$ as follows. Define Y such that:

$$f(x,y) \propto e^{-y/2}\, \mathrm{I}\{ y > x^2, a < x < b)\}. \tag{B6}$$

Then, the marginal density for x is the desired density, and the conditionals are:

$$f(x \mid y) = U(x_1, x_2), \tag{B6}$$

where $x_1 = \max(a, -\sqrt{y}), x_2 = \min(b, \sqrt{y})$, and

$$f(y \mid x) = e^{-0.5y} I_{(x^2, \infty)}(y),$$

so that if $V \sim U(0,1)$,

$$y = x^2 - 2\, log(1\text{-}V).$$

In summary, the Slice Sampler we have discussed above is computationally very efficient and should be of immense benefit to researchers in solving business problems, especially when faced with sampling from nonstandard or truncated functions and additional complexities imposed by real-world constraints.

<u>**References**</u>

Albert, J. H. and S. Chib, "Bayesian Analysis of Binary and Polychotomous Response Data," *Journal of the American Statistical Society,*. 88 (1993), 669-679.

Armstrong, P. K., "A Systems Approach for Analyzing Quality in High Contact Services," *Unpublished Ph.D dissertation*, Operations and Information Management Department, The Wharton School, University of Pennsylvania, Philadelphia, PA, 1994.

Armstrong P.A. and P. T. Harker, "Design of Incentive Systems for Service Quality Improvement," *Working paper*, School of Business, Georgetown University, Washington D. C., 1995.

Besag, J. and P. J. Green, "Spatial Statistics and Bayesian Computation," *Journal of the Royal Statistical Society* Series B 55 (1993), 25-37.

Bowen, J. W., and R. B. Hedges, "Increasing Service Quality in Retail Banking," *Journal of Retail Banking*, 15, 3 (1993), 21-28.

Chakravarty, S., R. A. Fienberg, and R. Widdows, "What do Consumers want from Banks?," *Journal of Retail Banking*, 17, 2 (1995), 15-20.

Chakravarty, S., R. Widdows, and R. A. Feinberg, "How Moments of Truth Define Bank Customer Relationships," *Journal of Retail Banking*, 18, 1 (1996), 29-34.

Chib, S. and E. Greenberg, "Understanding the Metropolis-Hastings Algorithm," *American Statistician*, 49 (1995), 327-335.

Cumbus, C. K., P. Damien, and S. G. Walker, "Sampling truncated Poisson distributions, and multivariate normal distributions via the Gibbs sampler," Submitted for publication, *Michigan Business School Working Paper #* 9316-34, 1996.

Damien, P. and S. G. Walker, "Sampling Probability Densities via Uniform Random Variables and a Gibbs Sampler,", *Michigan Business School Working Paper* #9316-21, 1996.

Damien, P. S. G. Walker, and J. Wakefield, "Gibbs Sampling For Bayesian Nonconjugate Models Using Auxilliary Variables," Michigan Business School Working Paper (under revision for the *Journal of Royal Statistical Society*, Series B), 1996.

Devroye, L., *Non-Uniform Random Variate Generation*, Springer, New York, 1986.

Edwards, R.G. and A. D. Sokal, "Generalization of the Fortuin-Kasteleyn-Swendsen-Wang representation and Monte Carlo algorithms," *Probability Letters*, 38 (1988), 2009-2012.

Fornell, C., M. J. Ryan, and R. A. Westbrook, "Customer Satisfaction: The Key to Customer Retention," *MOBIUS*, 9 (1990), 3, 14-18.

Frei, F. X., P. T. Harker, and L. W. Hunter, "Performance in Consumer Financial Services Organizations: Framework and Results from the Pilot Study," *Working Draft*, Wharton School, University of Pennsylvania, Philadelphia, PA 19104, 1995.

Frei, F. X., and P. T. Harker, "Measuring the Efficiency of Service Delivery Process: With Applications to Retail Banking," *Working Paper*, University of Rochester, Rochester, NY 14627, 1996.

Garvin, David A., *Managing Quality: the Strategic and Competitive Edge*, The Free Press, New York, 1988.

Gelfand, A. E., and A. F. M. Smith, "Sampling-based Approaches to Calculating Marginal Densities," *Journal of the American Statistical Association*, 85 (1990), 398-409.

Gelfand, A. E., Hills, S. E., Racine-Poon, A., and A. F. M. Smith, "Illustration of Bayesian Inference in Normal Data Models Using Gibbs Sampling, " *Journal of the American Statistical Association*, 85 (1990), 972-985.

Gelman, A., J. B. Carlin, H. S. Stern, and D. B. Rubin, *Bayesian Data Analysis*, Chapman and Hall, London, 1996.

Gilks, W. R., S. Richardson, and D. Spiegelhalter, *Markov Chain Monte Carlo in Practice*, Chapman and Hall, London, 1990.

Greene, W.H., *Econometric Analysis*, Macmillan Publishing Company, New York, NY, 1995.

Hauser, J.R. and D.P. Clausing, "The House of Quality," *Harvard Business Review*, 66, 3 (1998), 63-73.

Higdon, D., "Auxilliary Variable Methods for Markov Chain Monte Carlo with Applications," *Technical Report*, Duke University, 1996.

Kalakota, R., and F. X. Frei, "Frontiers of Online Financial Services," *Working paper*, University of Rochester, Rochester, NY 14627, 1996.

Kekre, S., M. S. Krishnan, and K. Srinivasan, "Drivers of Customer Satisfaction for Software Products: Implications for Design and Service Support," *Management Science*, 41, 9 (1995), 1456-1470.

Krishnan, M. S., "Cost and Quality Considerations in Software Product Management," *Unpublished Doctoral Dissertation*, Graduate School of Industrial Administration, Carnegie Mellon University, Pittsburgh, PA 15213, 1996.

Klinkerman, S., "Online Banking: Profits or Peril?," *Banking Strategy*, March-April (1997), 36-43.

Little, R. J. A. and D. B. Rubin, *Statistical Analysis With Missing Data*, John Wiley, New York, 1987.

McFadden, D., "A Method of Simulated Moments for the Estimation of Discrete Response Models without Numerical Integration,' *Econometrica*, 57, 5 (1991), 995-1026.

Morrall, K., "Stand and Deliver: Branch Site Selection and Alternative Delivery," *BANK Marketing*, 9 (1996), 17-25.

Naumann, E. and K. Giel, *Customer Satisfaction Measurement and Management*, Thomson Executive Press, Cincinnati, Ohio, 1995.

Neal, R. and G. O. Roberts, *Personal Communication, 1997.*

O'Connor, D. A., "The Delivery System is the Message," *United States Banker*, National Edition, March 1989.

Peterson, R. A. and W. R. Wilson, "Measuring Customer Satisfaction: Fact and Artifact," *Journal of the Academy of Marketing Science*, 20, 1 (1992), 61-71.

Ramaswamy, V., R. Chatterjee and S. H. Cohen, "Joint Segmentation on Distinct Interdependent Bases with Categorical Data," *Journal of Marketing Research*, 33, 8 (1996), 337-350.

Reichheld, F. F. and T. Teal, *The Loyalty Effect: The Hidden Force behind Growth, Profits and Lasting Value*, HBS Press, Cambridge, MA, 1993.

Rose, S., "Retail is Coming of Age," *Journal of Retail Banking*, 14, 4 (1993), 4-11.

Robert, C.P., "Simulation of truncated normal variables," *Statistics and Computing*, 5 (1995), 121-125.

Rubin, R. J. A., *Multiple Imputations for Nonresponse in Surveys*, John Wiley, New York, 1987.

Smith, A. F. M., and G. O. Roberts, "Bayesian Computations via the Gibbs Sampler and Related Markov Chain Monte Carlo Methods," *Journal of the Royal Statistical Society Series* B 55 (1993), 3-23.

Tanner, M. A. and W. H. Wong, "The Calculation of Posterior Distribution by Data Augmentation," *Journal of the American Statistical Association*, 82 (1987), 805-811.

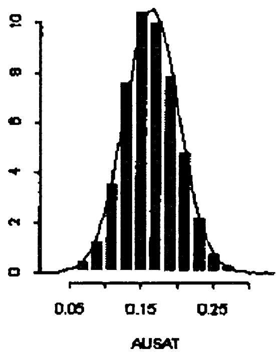
Tierney, L. "Markov Chains for Exploring Posterior Distributions," *The Annals of Statistics* 22 (1994), 1701-1762.

Wind, J. and V. Mahajan, Issues and Opportunities in New Product Development: An Introduction to the Special Issue, *Journal of Marketing Research*, 34 (1997), 1-12.

Zavonia T. and W. McElvey, "A Statistical Model for the Analysis of Ordinal Level Dependent Variables," *Journal of Mathematical Sociology*, Summer (1975), 103-120.

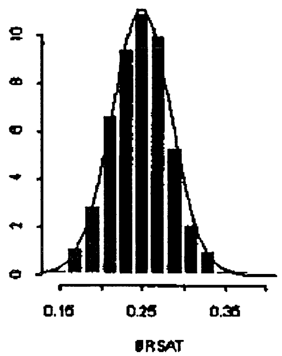
Zeithaml, V. A., A. Parasuraman and L. L. Berry, *Delivering Quality Service*, The Free Press, New York, NY, 1990.

FIGURE 1: DISTRIBUTION OF FACTOR IMPACTS ON OVERALL SATISFACTION



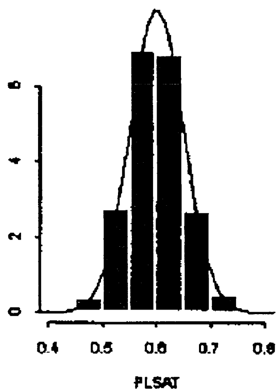
AUTOMATED TELEPHONE SERVICE

Mean = 0.16
Std. Dev. = 0.04



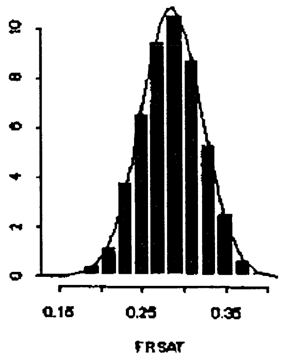
BRANCH SERVICE

Mean = 0.25
Std. Dev. = 0.04



PRODUCT LINE

Mean = 0.60
Std. Dev. = 0.05



FINANCIAL REPORT

Mean = 0.29
Std. Dev. = 0.04

FIGURE 2: MARGINAL EFFECT OF FACTOR IMPACTS ON OVERALL SATISFACTION

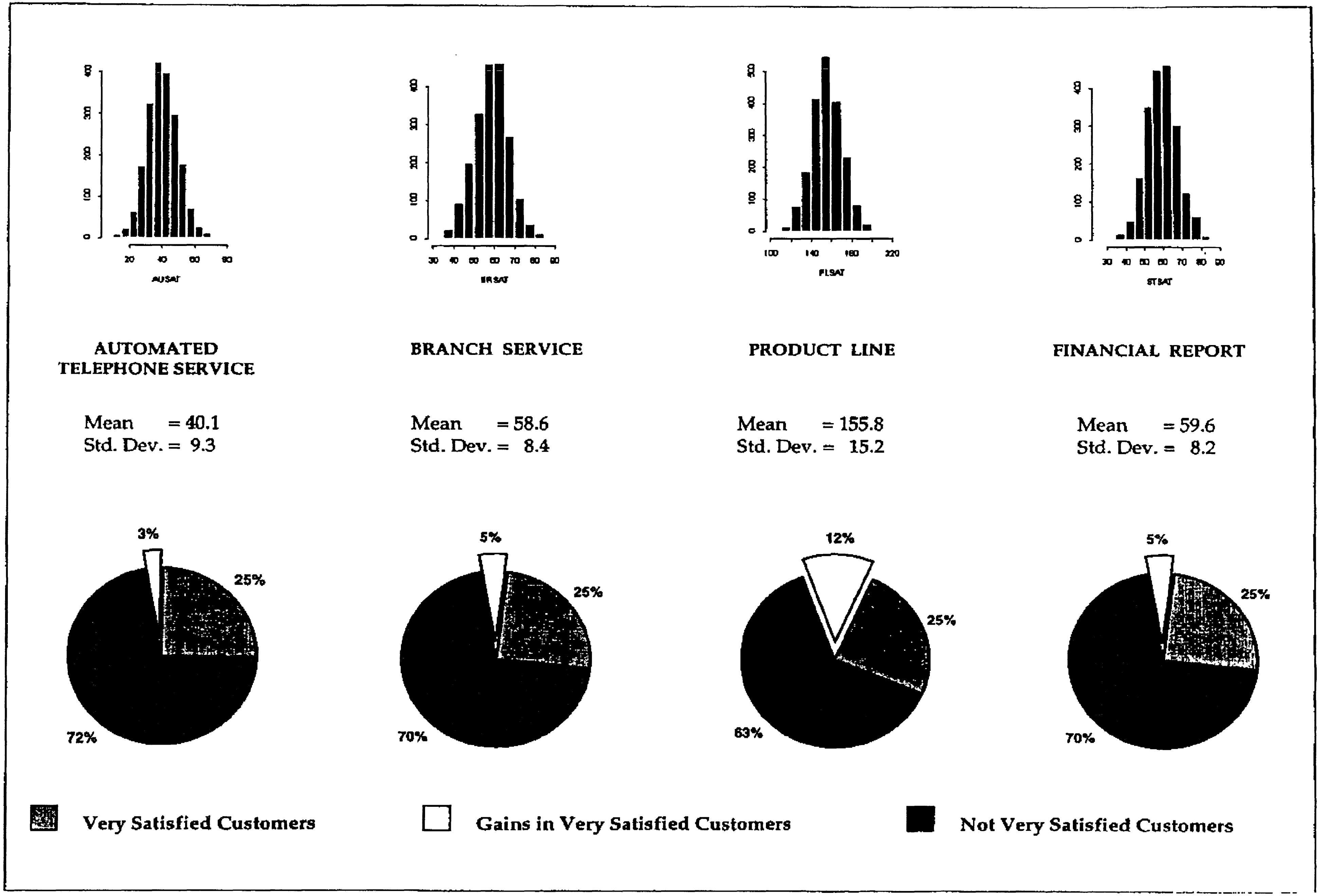
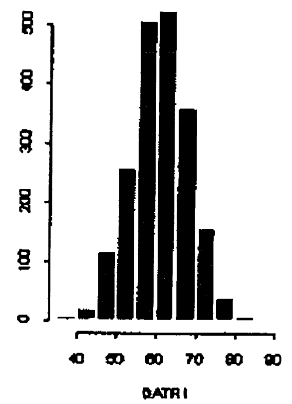
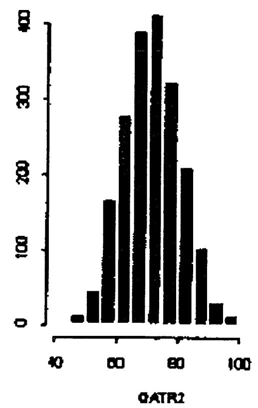


FIGURE 3: MARGINAL EFFECT OF QUALITY ATTRIBUTES ON SATISFACTION WITH PRODUCT OFFERINGS



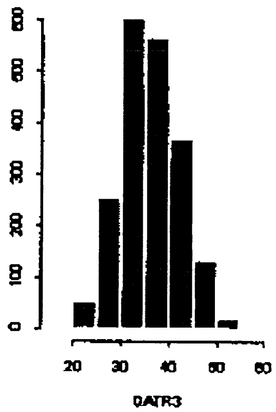
EASE OF OPENING & CLOSING OF ACCOUNTS

Mean = 60.9
Std. Dev. = 7.3



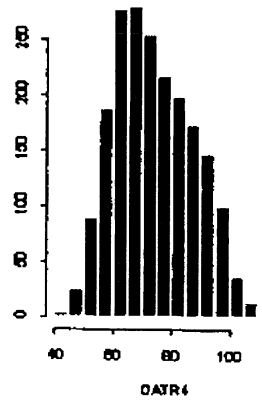
COMPETITIVE RATES & FEES

Mean = 71.3
Std. Dev. = 9.4



ONE-STOP SERVICES

Mean = 36.1
Std. Dev. = 6.1



CUSTOMER EDUCATION OF PRODUCT OFFERINGS

Mean = 74.1
Std. Dev. = 13.4