A Dynamic Model of the Duration of the Customer's Relationship with a Continuous Service Provider: The Role of Satisfaction

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A DYNAMIC MODEL OF THE DURATION OF THE CUSTOMER'S RELATIONSHIP WITH A CONTINUOUS SERVICE PROVIDER: THE ROLE OF SATISFACTION

Abstract

Many service organizations have embraced relationship marketing with its focus on maximizing customer lifetime value. Recently, there has been considerable controversy about whether there is a link between customer satisfaction and retention. This research question is important to researchers who are attempting to understand how customers' assessments of services influence their subsequent behavior. However, it is equally vital to managers who require a better understanding of the relationship between satisfaction and the duration of the provider-customer relationship to identify specific actions that can increase retention and profitability in the long run. Since there is very little empirical evidence regarding this research question, this study develops and estimates a dynamic model of the duration of provider-customer relationship that focuses on the role of customer satisfaction.

This article models the duration of the customer's relationship with an organization that delivers a continuously provided service, such as utilities, financial services, and telecommunications. In the model, the duration of the provider-customer relationship is postulated to depend on the customer's subjective expected value of the relationship, which he/she updates according to an anchoring and adjustment process. It is hypothesized that cumulative satisfaction serves as an anchor that is updated with new information obtained during service experiences. The model is estimated as a left-truncated, proportional hazards regression with cross-sectional and time series data describing cellular customers perceptions and behavior over a 22 month period.

The results indicate that customer satisfaction ratings elicited prior to any decision to cancel

or stay loyal to the provider are positively related to the duration of the relationship. The strength of the relationship between duration times and satisfaction levels depends on the length of customers' prior experience with the organization. Customers who have many months experience with the organization weigh prior cumulative satisfaction more heavily and new information (relatively) less heavily. The duration of the service provider-customer relationship also depends on whether customers experienced service transactions or failures. The effects of perceived losses arising from transactions or service failures on duration times are directly weighed by prior satisfaction, creating contrast and assimilation effects.

How can service organizations develop longer relationships with customers? Since customers weigh prior cumulative satisfaction heavily, organizations should focus on customers in the early stages of the relationship -- if customers' experiences are not satisfactory, the relationship is likely to be very short. There is considerable heterogeneity across customers because some customers have a higher utility for the service than others. However, certain types of service encounters are potential relationship "landmines" because customers are highly sensitive to the costs/losses arising from interactions with service organizations and insensitive to the benefits/gains. Thus, incidence and quality of service encounters can be early indicators of whether an organization's relationship with a customer is flourishing or in jeopardy. Unfortunately, organizations with good prior service levels will suffer more when customers perceive that they have suffered a loss arising from a service encounter -- due to the existence of contrast effects. However, experienced customers are less sensitive to such losses because they tend to weigh prior satisfaction levels heavily.

By modeling the duration of the provider-customer relationship, it is possible to predict the revenue impact of service improvements in the same manner as other resource allocation decisions.

The calculations in this article show that changes in customer satisfaction can have important financial implications for the organization because lifetime revenues from an individual customer depend on the duration of his/her relationship, as well as the dollar amount of his/her purchases across billing cycles.

Satisfaction levels explain a substantial portion of explained variance in the durations of service provider-customer relationships across customers, comparable to the effect of price. Consequently, it is a popular misconception that organizations that focus on customer satisfaction are failing to manage customer retention. Rather, this article suggests that service organizations should be proactive and learn from customers *before* they defect by understanding their current satisfaction levels. Managers and researchers may have under-estimated the importance of the link between customer satisfaction and retention because the relationship between satisfaction and duration times is very complex and difficult to detect without advanced statistical techniques.

Key words: Customer Satisfaction, Durations, Retention, Defensive Strategy, Proportional Hazards Model

<u>One Sentence Abstract</u>: *Customer satisfaction ratings elicited prior to any decision to cancel or stay loyal to the provider explain a substantial portion of explained variance in the durations of service provider-customer relationships across customers.*

Introduction

Throughout the 1980's, service organizations relied on customer satisfaction and quality ratings obtained from surveys to monitor performance, compensate employees, and allocate resources. Initial customer satisfaction and quality improvement efforts tended to focus on tracking customer survey ratings over time, benchmarking them against competitors' ratings or linking them to service operations. Higher survey ratings became -- in effect -- a goal in their own right. However, in the 1990's, organizations have become increasingly concerned about the financial implications of their customer satisfaction and quality improvement. The financial justification for customer satisfaction and quality improvement programs primarily rests on management's belief that higher levels of satisfaction or quality increase retention rates, stimulate consumption levels, allow firms to charge a premium for their products/services and/or decrease costs. These beliefs have become critical as service organizations have embraced relationship marketing with its focus "attracting, maintaining and . . . enhancing customer relationships" (Berry 1983, p. 25). Thus, understanding the link between a customer's satisfaction and the duration and strength of his/her relationship with a service provider has become increasingly important for organizations that are attempting to predict future customer preferences and behavior on the basis of past preferences, and use these predictions to develop competitive marketing strategies.

Relationship marketing efforts have typically emphasized customization of products to individual customers, augmentation of core services, pricing and other so-called defensive marketing strategies that are purported to encourage satisfaction, loyalty and the duration of the provider-customer relationship. In their article in the Harvard Business Review, Grant and Schlesinger (1995) argue that the gap between companies current and full-potential profitability is enormous, and suggest that managers ask themselves three questions including: "How long on average do your customers remain with the company? [and] What if they remained customers for life?" Their emphasis on extending the duration of relationships with end users is driven by the economics of retention (Reichheld 1996a; Payne and Rickard 1997) and insulation from competition (Anderson and Sullivan 1993). Specifically, small increases in retention rates can have a dramatic effect on the profits of a company because the cost of retaining an existing customer is less than the cost of acquiring a new customer, existing customers tend to purchase more than new customers and there are efficiencies in dealing with existing customers rather than new customers (e.g., Fornell and Wernerfelt 1987, 1988; Reichheld and Sasser 1990).

Recently, the question of whether there is a link between customer satisfaction and retention has become highly controversial. For example, Gale (1997) claims that "satisfaction is not enough" and Reicheld (1996b, p. 58) argues that many organizations have fallen into a "satisfaction trap" in which managers focus on satisfaction survey scores at the expense of understanding customer retention and lifetime purchases. Surprisingly, given recent managerial and academic interest in maintaining and enhancing provider-customer relationships, there is very little empirical evidence concerning the link between a customer's satisfaction and the duration of his/her relationship with the organization. This omission is particularly striking for continuously provided services -- such as health, insurance, utilities, telecommunications, health and financial services -- in which the duration of the provider-customer relationship is closely tied to revenue streams. In these industries, lifetime revenues from an individual customer depend on: (a) the duration of the provider-customer relationship and (b) the average dollar amount of the customer's purchases of services across billing cycles (which reflects both price structure and usage characteristics).

This study develops and estimates a dynamic model of the duration of provider-customer relationship for continuously provided services, focusing on the role of customer satisfaction. This research issue is important to researchers who are attempting to understand how customer's experiences with services and their assessments of these services influence their subsequent behavior. However, it is equally vital to managers who require a better understanding of the relationship between satisfaction and the duration of the provider-customer relationship to identify *specific actions* that can increase retention and profitability in the long run.

This paper begins by reviewing prior research on customer satisfaction and retention. Then, it develops a model of the duration of the provider-customer relationship for a continuously provided service as a function of customer satisfaction and other antecedent variables. The model is estimated with cross-sectional and time series data describing cellular customers over a 22 month period. This industry is characterized by considerable variability in customer behavior; over 30% of the typical cellular providers' customers exit -- either switching providers or discontinuing cellular usage -- each year. Specific hypotheses about customer behavior are tested, and the results and managerial impliations are discussed.

Perspective

This section reviews prior research relevant to understanding the factors influencing the duration of the provider-customer relationship for a continuously provided service. Since there is virtually no research that directly addresses this topic, it describes *longitudinal* studies of customers' satisfaction, repeat purchase intentions and behavior regarding services. It focuses on the role of customer satisfaction, but also considers relevant prior research on the role of perceived service quality because the two constructs are related (albeit different) constructs (Dabholkar 1993).

Customer Satisfaction and Retention.

At the individual level, there is very little theoretical or empirical research concerning the relationship between a customer's prior cumulative satisfaction and the duration of his/her relationship with a service organization (Zahorik and Rust 1992). A notable exception is a study by Crosby and Stephens (1987) which found that whether or not customers had replaced their insurance policies or allowed them to lapse depended on their prior overall satisfaction with their whole life coverage. At the aggregate level, two notable studies are Kordupleski, Rust and Zahorik's (1993) brief mention that market share for one division of AT&T lags aggregate quality ratings by about four months, and Danaher and Rust's (1996) finding that overall service quality is positively associated with cellular service usage rates.

Since purchase intentions are easier to measure than behavior, there are numerous studies of the relationship between satisfaction and intentions. These studies must be interpreted with caution because satisfaction and intentions measures will usually be correlated due to survey measurement procedures and the predictive validity of intentions measures varies depending on the product, the measurement scale, the time frame, and the nature of the respondents (e.g., Morwitz and Schmittlein 1992; Morwitz 1997). With these caveats, the customer satisfaction/dissatisfaction literature includes several studies utilizing a panel design in which satisfaction is an antecedent of purchase intentions. For example, in a two-stage field study, consumers' intention to participate in a flu inoculation campaign depended on their satisfaction and attitudes towards an earlier federal flu program (Oliver 1980). Also, customers' intentions regarding automobile repair and service outlets depended on their attitudes, which in turn depended on their satisfaction (Bearden and Teel 1983). The statistical relationship between satisfaction and intentions is typically small but significant.

Process Models of Repeat Purchase Intentions

There are no longitudinal studies of how *cumulative satisfaction* influences the subsequent purchase behavior of individual customers. However, two studies have described process models of how a customer's *perceived service quality* influences his/her subsequent attitudes, intentions or preferences. Rust, Inman and Jia (1997) assume that the customer has a known prior distribution of the average quality of a brand and that he/she updates the prior distribution based on the perceived quality of the transaction. They also assume the utility function is continuous, twice differentiable and concave -- implying that the customer suffers more from unfavorable disconfirmation (performance is less than expectations) than from a favorable disconfirmation (performance is greater than expectations) of equivalent magnitude. Under these assumptions, they find support for three predictions: (1) favorable disconfirmation increases preference for the chosen brand and unfavorable disconfirmation decreases preference (2) when the customer chooses a brand that *meets* (but doesn't exceed) his/her expectations, he/she is more likely to choose the same brand again *whether or not it is most preferred* and (3) the customer will not necessarily choose the brand with the highest expected performance.

Boulding, Kalra, Staelin and Zeithaml (1993) propose and estimate a dynamic model of service quality that traces the way customers form and update their perceptions of service quality and behavioral intentions. Perceived service quality is modeled as a function of current perceptions of the service, where current perceptions depend on prior expectations and the most recent service transaction. Their model distinguishes between predictive ("will") and normative ("should") expectations, and postulates that these expectations are subject to a Bayesian-like updating over successive service experiences. In an extension to this model, Boulding, Kalra and Staelin (1997) model (1) predictive expectations as a function of past expectations and perceptions of current service experiences, and (2) normative expectations as increasing when perceptions of delivered service exceed prior normative expectations (but not decreasing in the reverse situation). They predict that, as a customer gains more confidence or experience over time in evaluating service quality, he/she weighs his/her prior assessment of service quality more heavily and places less weight on new information. These predictions are supported by a laboratory study concerning hotel visits by executives.

These two studies suggest that (1) a customer's prior satisfaction is positively associated with his/her purchase intentions and subsequent behavior (2) service that meets or exceeds a customer's expectations increases his/her preference and (3) a customer's assessments of a service vary over time as he/she gains experience with it. It seems likely that these processes may influence customers' decisions about the duration of their relationship with a service provider.

A Model of the Duration of the Customer's Relationship With a Continuous Service Provider

The goal of this paper is to develop and estimate a dynamic model of the duration of the provider-customer relationship, focusing on the role of satisfaction. The model describes how duration times differ across customers. It also exploits information obtained within customers at different points in time, so we refer to it as a dynamic model. This section develops the model and presents specific hypotheses.

A Model of Subjective Expected Value and Duration Times

The customer's decision to maintain an existing relationship with a service provider is modeled as a tradeoff between his/her assessments of the future costs and utility (i.e., benefits). Consistent with subjective utility theory (Oliver and Winer 1987), it is postulated that the customer assesses the future value of the relationship, where the benefits provided by the service organization are weighed against the costs of discontinuing the relationship. The customer's perception of the future value of a relationship is considered to be similar to a belief or expectation. Thus, the duration of the relationship between a service provider and customer i ($Duration_{it}$) is postulated to depend on his/her subjective expected value of the relationship at time t ($Value_{it}$). Algebraically,

$$Duration_{it} = h_{0t} \ (Value_{it} , \boldsymbol{X}_i) \qquad (1)$$

where X_i represents a vector of variables that captures differences across customers (e.g., demographics). Prior support for equation (1) is provided by Lemon and Winer (1995) who find that customers perceiving higher value in the service relationship are significantly less likely to discontinue a new service than those with lower perceptions of value.

Updating of Subjective Expected Value

The customer's subjective expected value for the relationship should depend primarily on his/her anticipation of experience utility or the hedonic quality of the experience. This prediction should be relatively straightforward for continuously provided services when the customer currently uses the service. Since people tend to predict future preferences based on current preferences and do not incorporate future taste changes (Kahneman and Snell 1992; Luce 1992; Simonson 1990), the customer's subjective expected value for a service should primarily depend on his/her current cumulative satisfaction with the service (Sat_{it-1}).

Following Hogarth and Einhorn's (1992) theory of belief updating, we believe that customers update their beliefs about the future value of a relationship though a sequential anchoring and adjustment process in which the individual's prior cumulative satisfaction (i.e., the anchor) is adjusted by the impact of succeeding pieces of new information (Slovic and Lichenstein 1971). This notion is consistent with models of intertemporal planning in economics, in which customers re-estimate future consumption levels each period by combining prior estimates and new information (c.f., Deaton and Muellbauer 1980), as well as many "extrapolative expectations" models (c.f., Oliver and Winer 1987). The availability heuristic (Tversky and Kahneman 1973) suggests that the customer will rely on new information about the service provider that can be readily brought to mind.

The customer has an opportunity to acquire new information regarding a continuously provided service during service encounters that take place during the relationship -- that is, when an facilitating *transaction* takes place or when there is a *failure* in the organization's continuous delivery of the service.[1] Facilitating transactions occur when the customer *seeks out an encounter with the organization*, typically to obtain information about existing service, purchase additional products, ask about his/her bill and so forth. Service failures include disruptions in the *core* service (e.g., a "blackout" of electrical service or unscheduled "downtime" in computing services) and failures in service *processes* (e.g., static on a telephone line or a burnt out street lamp). Sometimes, they are observed by service organizations that monitor their service delivery system (e.g., computerized tests of telephone lines). Sometimes, they trigger a complaint to the service provider, who may or may not make a recovery effort. Service encounters (customer initiated or failure initiated) provide the customer with opportunities to acquire new information about the service, compare current service with his/her prior cumulative assessment and to form a new assessment of the value of future service. We postulate that the customer forms an assessment of his/her subjective expected value by *encoding new information (denoted* $\boldsymbol{Info_{it}}$*) as a deviation relative to his/her prior cumulative satisfaction* (Sat_{it-1}). We refer to this deviation as $\boldsymbol{New_{it}}$. This specification is consistent with prior research concerning customers' assessments of subjective expected value. For example, Thaler (1985) defines a consumer value function over differences relative to a reference point -- i.e., over perceived gains and losses -- rather than absolute levels in a purchase situation. Algebraically,

$$Value_{it} = \alpha_{it}\, Sat_{it-1} + \omega_{it}\, \boldsymbol{New_{it}} \qquad (2)$$

where α_{it} is a weight reflecting the contribution of prior satisfaction for customer i at time t, ω_{it} is a weight reflecting the contribution of new information for customer i at time t, and $0 < Sat_{it-1} < 1$.[2]

Differential Effects of Satisfaction and New Information Due to Experience

The magnitudes of the effects of prior cumulative satisfaction and new information should differ across customers depending on their prior experience with the provider. The weight representing the contribution of prior cumulative satisfaction is expressed algebraically as:

$$\alpha_{it} = (1 + a\ Experience_{it\text{-}1})\ \alpha\ ; \tag{3}$$

and the weight representing the contribution of new information is expressed algebraically as:

$$\omega_{it} = (1 + b\ Experience_{it\text{-}1})\ w_{it}; \tag{4}$$

where $Experience_{it-1}$ represents the length of time (e.g., in months) over which customer i has had prior experience with the provider. If the coefficients of a and b are unconstrained, the effects of prior satisfaction and new information can be larger or smaller due to prior experience. In other words, the amount of time/experience that the customer had to form his/her assessment of subjective expected value is important -- thereby explaining variability in duration times across customers.

Substituting equations (3) and (4) into equation (2), the customer's subjective expected value can be expressed algebraically as follows.

$$Value_{it} = (1 + a\ Experience_{it-1})\ \alpha\ Sat_{it-1} + (1 + b\ Experience_{it-1})\ w_{it}\ \boldsymbol{New}_{it} \tag{5}$$

When $a > 0$ and $b < 0$, the effect of Sat_{it-1} is larger and the effect of $\boldsymbol{New}_{it}$ is smaller for customers with more experience — similar to the the pattern in customers' assessments of service quality found by Boulding, Kalra and Staelin (1997). Other patterns of effects due to differences in experience levels across customers can be captured with different values of a and b. Thus, the model is flexible in allowing for differential effect sizes across customers with different experience levels. Equation (5) has similarities to the service value equations described by Bolton and Drew (1991) and Bolton and Lemon (1997).

Differential Effects of Losses versus Gains

Recall that we have postulated that customers' assessments of subjective expected value are generated by an averaging model, in which new information is encoded as a deviation relative to the preceding anchor. It is a well-known psychological principle that losses relative to a reference value loom larger than gains (Kahneman and Tversky 1979; Tversky and Kahneman 1992), suggesting that customers will weigh negative service experiences more heavily than positive experiences in assessing subjective expected value. Re-writing equation (5) in terms of gains and losses,

$$Value_{it} = (1 + a\ Experience_{it-1})\ \alpha\ Sat_{it-1} + (1 + b\ Experience_{it-1})\ w_{Lit}\ \boldsymbol{NewLoss}_{it}$$
$$+ (1 + b\ Experience_{it-1})\ w_{Git}\ \boldsymbol{NewGain}_{it} \qquad (6)$$

where $\boldsymbol{NewLoss}_{it}$ is defined as the absolute value of the customer's assessment of an *unfavorable or negative* deviation relative to his/her prior cumulative satisfaction at time t, and zero otherwise. Similarly, $\boldsymbol{NewGain}_{it}$ is defined as the absolute value of the customer's assessment of a *favorable or positive* deviation of new information relative to his/her prior cumulative satisfaction at time t, and zero otherwise.

Customers who subscribe to continuously provided services incur losses during service transactions and failures. They also receive gains from the organization's reponse or handling of the service transaction or failure. Thus, for continuously provided services, gains (i.e., a service response) are conditional on the occurence of the loss (i.e., the transaction or failure). Consistent with Rust, Inman and Jia's (1997) preference model, we expect that that losses will have a negative effect ($w_{Lit} < 0$) and gains will have a positive effect ($w_{Git} > 0$) on the customer's subjective expected value.

Contrast and Assimilation Effects.

We believe that perceived losses and gains are differentially weighed, depending on customers' anchors. Following Hogarth and Einhorn's (1992) belief updating model, the adjustment weights (w_{Lit}, w_{Git},) are considered to depend on the customer's prior satisfaction level (i.e., Sat_{it-1}), as well as the sign of the deviation of the new information from the customer's reference value. Specifically, we postulate that the customer weighs perceived losses more heavily when his/her prior satisfaction level is high ($Sat_{it-1} > 1/2$) and perceived gains more heavily when his/her prior satisfaction level is low ($Sat_{it-1} < 1/2$) -- that is, a contrast effect. Conversely, the customer weighs perceived losses less heavily when his/her prior satisfaction level is low and perceived gains less heavily when his/her prior satisfaction level is high (i.e., an assimilation effect).

In other words, if the new service experience is less favorable than prior cumulative satisfaction (i.e., a perceived loss), the weight is postulated to be directly proportional to satisfaction. Algebraically,

$$w_{Lit} = w_L \, Sat_{it-1} \tag{7}$$

If the new service experience is more favorable than prior satisfaction (i.e., a perceived gain), the weight is postulated to be inversely proportional to satisfaction. Algebraically,

$$w_{Git} = w_G \, (1 - Sat_{it-1}) \tag{8}$$

The role of gains and losses can be made more apparent by substituting equations (7) and (8) into equation (6) and re-writing it as follows.

$$\begin{aligned} Value_{it} &= (1 + a\, Experience_{it-1})\, \alpha\, Sat_{it-1} + (1 + b\, Experience_{it-1})\;\; w_L\, Sat_{it-1}\; \boldsymbol{NewLoss}_{it} \\ &\quad + (1 + \mathrm{b\ Experience}_{\mathrm{it-1}})\, (w_G\, (1 - Sat_{it-1})\, \boldsymbol{NewGain}_{it} \end{aligned} \tag{9}$$

The Model

A model of the duration of an existing customer's relationship with a continuous service provider can be obtained by substituting equation (9) into equation (1) and grouping terms, as follows.

$$\begin{aligned} Duration_{it} &= \alpha\, Sat_{it-1} + a\, \alpha\, \mathrm{Sat}_{\mathrm{it-1}}\, Experience_{it-1} + \\ &\quad w_L\, Sat_{it-1}\, \boldsymbol{NewLoss}_{it} + w_L\, b\, Sat_{it-1}\, \boldsymbol{NewLoss}_{it}\;\; Experience_{it-1} + \end{aligned} \tag{10}$$

$$w_G\,(1 - Sat_{it-1})\,\boldsymbol{NewGain}_{it} + w_G\, b\,(1 - Sat_{it-1})\,\boldsymbol{NewGain}_{it}\, Experience_{i\text{-}1t} + \mathbf{c}\,\boldsymbol{X_i}$$

For notational convenience, the re-scaling of the parameters has been ignored. Equation (10) describe how duration times vary across customers due to the differential effects of prior satisfaction and experience. The first two terms describe the effects of prior satisfaction mediated by experience, the second two terms describe the effects of perceived losses mediated by prior satisfaction and experience, and the last two terms describe the effects of perceived gains mediated by the inverse of prior satisfaction and experience.

Hypotheses

We can now develop formal hypotheses concerning the duration of the provider-customer relationship, stated in terms of restrictions imposed on the model parameters. Consistent with intuition and prior research, we predict that a customer with a higher level of prior cumulative satisfaction will have a higher subjective expected value for the service and, consequently, a longer relationship with the organization. (All hypotheses are stated under ceteris paribus conditions.)

H_1: The duration of the provider-customer relationship is longer for customers who have high levels of cumulative satisfaction with their service ($\alpha > 0$).

We have postulated that customers update their beliefs about the future value of a relationship though an anchoring and adjustment process in which the individual's prior cumulative satisfaction is adjusted by the impact of succeeding pieces of new information encoded relative to prior cumulative satisfaction. The notion of a reference value yields two predictions. We predict that the customer's subjective expected value will be lower when he/she acquires new information encoded as a loss -- leading to a shorter relationship. It will be higher when he/she acquires new information encoded as a gain -- leading to a longer relationship.

H_{2a}: The effect of perceived losses on the duration of the provider-customer relationship is negative ($w_L < 0$).

H_{2b}: The effect of perceived gains on the duration of the provider-customer relationship is positive ($w_G > 0$).

Furthermore, as described by equations (7) and (8), we predict the existence of contrast and assimilation effects. Perceived losses will be weighed heavily by customers with high prior cumulative satisfaction and perceived gains will be weighed heavily by customers with low prior cumulative satisfaction (a contrast effect), as well as the converse (an assimilation effect).

H_{2c}: The effect of perceived losses is weighed by prior cumulative satisfaction (Sat_{it-1}) and the effect of perceived gains is weighed by the inverse of prior cumulative satisfaction ($1\text{-}Sat_{it-1}$).

Since we believe that perceived losses have a greater effect on subjective expected value than perceived gains (e.g., Thaler 1985), we predict that this feature will be reflected in duration times.

H_3: The absolute magnitude of the effect of a perceived loss on the duration of the provider-customer relationship is greater than the absolute magnitude of an (equivalent) perceived gain ($|w_L \, Sat_{it-1}| > |w_G \, (1 - Sat_{it-1})|$).

Consistent with Boulding, Kalra and Staelin (1997), we believe that, as customers gain more experience over time, they form evaluations of services by weighing their prior assessments more heavily and placing less weight on new information. If so, the effect of cumulative satisfaction on customers' subjective expected value becomes larger in absolute magnitude -- and the effect of new information (i.e., perceived losses or gains) on customers' subjective expected value becomes smaller in absolute magnitude -- as the duration of the relationship increases. Consequently, prior cumulative satisfaction will have a greater effect on duration times, and new information will have a smaller effect, as customers gain more experience over time.

H_{4a}: The effect of prior cumulative satisfaction on the duration of the provider-customer relationship is larger in absolute magnitude for customers who have more experience with the organization ($a > 0$).

H_{4b}: The effect of new information on the duration of the provider-customer relationship is larger for customers who have more experience with the organization ($b < 0$).

These four hypotheses have been grounded in prior research concerning how customers form assessments of services. However, it is an empirical question whether these notions will explain the durations of provider-customer relationships. The empirical portion of this paper estimates the model (i.e., equation (9)) to test these hypotheses.

Study Design

The study context is the cellular telephone industry, which is characterized by both high customer turnover and high customer acquisition costs. The national average cost of acquisition for a new subscriber is about $600 and, since the cellular industry's "churn" rate is currently 2.7% each month (i.e., roughly 30% per year), the typical firm experiences the equivalent of complete customer turnover every three years. Historically, cellular telephone companies have directed little marketing effort at existing customers. However, customer retention strategies have (potentially) substantial revenue implications. For example, a customer retention strategy that reduces the churn rate by 30% increases customer turnover to about every five years, representing an estimated 15% increase in long term revenues (*Cellular Business* 1991).

Data Collection Procedure

The data base for this study is a probability sample of customers subscribing to service from a single cellular communications firm. The sample was drawn from the company's billing records in December 1991. In this cross-section of customers, the average length of service varies widely. To be eligible for the study, a customer must have subscribed to the service for at least three months. However, some customers had subscribed since the early days of cellular service -- as long as 74 months prior to the commencement of the study. Our study tracked these customers over a 22 month period, from December 1991 through September 1993. (See Figure 1.) Customers' billing records were captured throughout this period, plus customers were administered telephone surveys that elicited satisfaction measures at two points in time. The survey response rate at each wave was about 44%. This rate is reasonably good for such a highly mobile group -- particularly since the surveys were conducted over the wireline telephone (so that the customer would not incur a charge for receiving the interviewer's call over his/her cellular phone).

Figure 1 here

Billing Data. Customers' billing records were accumulated for the period December 1991 through September 1993. These records provide information about access charges, airtime charges, minutes of use, activation date, termination date and so forth. Access charges are the fixed dollar amount that a cellular customer pays each month. Airtime charges are the variable charges incurred per minute of cellular telephone use. Total airtime charges depend on peak/off-peak usage, roaming and so forth. Activation date is the date that the company began providing service to the customer. Termination date is the date (if applicable) when the cellular phone number is no longer assigned to that particular customer.

Wave One Survey Data. Customers were first surveyed in January through March 1992. Each customer was interviewed by telephone using the company's standard customer satisfaction survey (which is administered quarterly to a new probability sample). The survey elicited a global, cumulative judgment of satisfaction with the service offering based on prior experience with the company, ratings of specific service attributes, and judgments of customer service transactions.

Wave Two Survey Data. A randomly chosen subset of customers were re-interviewed approximately six months after the first survey -- that is, in July through September 1992. *In addition*, customers exiting anytime between January 1992 and September 1993 were re-interviewed by telephone within 4-6 weeks of their termination date. Both groups were administered virtually identical surveys -- hereafter referred to as the "wave two" customer satisfaction survey. The reason for interviewing exiting customers as soon as possible after their termination date was to ensure adequate recall of recent service experiences.[3]

The presence of a termination date in a billing record does not necessarily imply that the customer discontinued his/her relationship with the company. The cellular company may terminate service if a customer does not pay his/her bill. Equally importantly, the customer may terminate use of one telephone number *and replace it with another provided by the same company* when his/her employer reassigns cellular handsets, he/she moves to a new geographic location or he/she is a victim of cellular fraud. In other words, the cellular telephone number may have changed, but the relationship has continued. Therefore, it was necessary to verify whether or not the respondent continued to subscribe to the company's cellular service at the beginning of each interview.

Table 1 here

<u>The Data Base</u>. The data base ultimately consisted of 650 records. Each customer record contained two waves of survey data, plus billing records, matched by cellular telephone number. (Customers who could not be contacted at wave two are eliminated from the analyses.) Table 1 shows summary statistics that describe the customer data base. 51% of customers are "very satisfied" with their cellular service. The average length of service is about 35 months, and ranges from four months to 96 months (i.e., eight years). This average is calculated across customers who have terminated their service, and those who had yet to do so at the end of the study period (i.e., by treating the end of the study period as the termination date and ignoring right censoring).

Table 2 here

Operationalization of Model Constructs

The study measures the dependent variable, $Duration_{it}$, in the following way. If a customer has canceled his/her service prior to September 1, 1993, it is relatively straightforward to calculate *total* months of service: simply subtract the activation date from the termination date. However, if the customer is still a subscriber, his/her total months of service are unknown (i.e., right censored) because he/she will continue to subscribe for additional months after the end of the study period. The only information available is that total months of service is *at least* equal to the difference between September 1, 1993 and the activation date.

Measures of the predictor variables are described in Table 2. Cumulative satisfaction (Sat_{it-1}) was measured by the customer's self-reported satisfaction level *at wave one*. This feature is important because it ensures that overall satisfaction is measured *prior* to any decision to exit or stay loyal to the cellular provider. The length of the customer's experience with the company ($Experience_{it-1}$) is measured as the scaled logarithm of the number of months that the customer has subscribed to the service at the *beginning* of the study period (i.e., at wave one in January 1992). The scaling procedure avoids numerical instability in the computations. Note that the measure of experience is *not* the same as the measure of customer's duration time -- the latter is determined at the *end* of the study period.

Coding of Perceived Losses and Gains

In this study, customers formed assessments of cumulative satisfaction at wave one and acquired new information through service transactions and failures that took place thereafter. Facilitating service transactions include customer initiated telephone requests for changes in service, billing inquiries, requests for help with cellular service features (e.g., roaming) and so forth. Service failures include problems such as dropped calls, which the customer may or may not have reported to the company. We measured perceived losses and gains by customers' retrospective self-reports concerning transactions and failures that took place during the three months *prior to wave two*. We chose not to use a longer reference period so that respondents would be unlikely to telescope events from prior to wave one.

Perceived Losses. Customers' perceived losses were represented by three dichotomous variables representing different types of losses. Perceived losses *associated with service transactions* were represented by a single variable.[4] (Note that, although transactions are likely to be perceived as inconvenient/costly, they are not necessarily coincident with failures or disruptions in service — in fact, about 60% of calls were by customers who had not experienced any service failure during that time period.) Perceived losses *associated with service failures* were represented by two variables representing failures not reported to the service provider and failures reported to it (i.e., complaints). If there was a failure or disruption, the customer reported it to the cellular telephone company on over 90% of occasions. However, we represent reported and unreported failures by separate variables because we believe that reported failures are likely to be more severe.[5] For each of these three variables, a positive value indicates an encounter took place -- so that a loss/cost potentially was incurred. The estimated coefficients should approximate the (relative) magnitudes of the perceived losses associated with each type of encounter.

Perceived Gains. There were perceived gains, as well as losses, associated with these service transactions and failures. The perceived gains arise from the company's *response* or handling of the service transaction or failure. As noted earlier, perceived gains are conditional on the occurence of the loss (i.e., the transaction or failure). Customers' perceived gains were represented by two ratings variables. Perceived gains associated with all types of service transactions were represented by a single retrospective self-report measure of how the employee handled the transaction. The survey question was: [If transaction occurred] “How satisfied were you with the representative you spoke with?” Perceived gains due to service recovery efforts after a failure was reported to the cellular company were represented by a retrospective self-report measure of how the problem was handled.. The survey question was: “Now I’d like you to think about how [the company] handled your problem. Would you say you were very satisfied . . . very dissatisfied?" For both ratings variables, a higher value indicates a more satisfactory transaction -- that is, a larger gain. (A zero indicates no encounter took place.)

Covariates.

Cellular price structures are rather complicated and vary across markets *and* customers within a market, so they are represented by four measures. Demographics are captured by five indicator variables. (These variables are not described in detail at the request of the cooperating cellular communications company).

Estimation Procedure

The dependent variable in equation (10) is the length of the provider-subscriber relationship in months or the "duration time." Customers' duration times are right censored -- that is, it isn't possible to observe when customers subscribing at the end of the study period will terminate their relationships with the company. Consequently, conventional regression (i.e., OLS) estimates will be biased, so the model is formulated as a proportional hazards regression (Cox 1972; 1975), with ties handled using the approximate likelihood method of Breslow (1974).

The duration time for a customer is considered to be a random variable with some p.d.f. $f(t)$ and c.d.f. $F(t)$. In modeling duration times, it is convenient to consider the hazard rate $h(t)=f(t)/(1-F(t))$, which is the conditional likelihood that service termination occurs at duration time t, given that it has not occurred in the duration interval (0,t).[6] Let $h(t|x)$ denote the hazard rate for a customer i with specific characteristics captured by the vector x (such as different levels of overall satisfaction). The hazard rate is assumed to take the form:

$$h(t|x) = h_0(t) \exp(\beta' x_{it}) \tag{11}$$

where $h_0(t)$ is the baseline hazard function which captures longitudinal effects and β indicates the effect of a variable (x_{it}) on the hazard rate. The assumption of proportional hazards is that $h(t|x_1)/h(t|x_2)$ does not depend on t, so that the effects of the variables are constant over time. In our formulation, this assumption is relaxed by introducing the interaction terms involving $Experience_{it-1}$.

The semi-parametric estimation procedure for estimating hazard model parameters is based on a partial likelihood. The partial likelihood is the likelihood that customer i has a particular duration of all the customers who were "at risk" -- that is, customers who had not terminated their cellular service prior to reaching that particular duration (including right censored customers). In other words, it is the likelihood that a customer i has a duration t, given that some customer in the risk set is known to have a duration of t. At a time t when a customer i experiences a duration (T_i = t), the partial likelihood that this duration happened to customer i (and not to another customer in the same risk set) is:

$$L(i|t, j_1, \ldots j_{n(t)}) = h_i(t) \,/\, \sum_k h_{j(k)}(t) \tag{12}$$

where n(t) is the total number of customers in the risk set at time t (i.e., those who are eligible to terminate service) and these customers are denoted by j_k (j_1 through $j_{n(t)}$). The partial likelihood estimate of β is obtained by substituting equation (11) into equation (12), simplifying and then maximizing the product of the resultant equation over all observed duration times.

It is important to note that the duration times in this study are left truncated. In other words, although the study observes the activation dates of all customers in the sample drawn in December

1991, the customer data base had already been purged of customers who had terminated service prior to that date. Customers in the sample couldn't have terminated service prior to the start of the study or they would have been purged from the customer data base. Thus, they were not really at risk for their entire duration time and they are not “eligible” to be included in some risk sets. For example, a customer that has subscribed to cellular service for 96 months, wasn't really at risk for the first (96 - 22) 74 months prior to the commencement of the study. If he/she had terminated prior to the commencement of the study, he/she would have been purged from the data base. Therefore, he/she is not eligible to be included in risk sets for completed durations of 74 months or less.

Left truncated durations data will not be handled correctly by standard proportional hazards regression software. The resultant parameter estimates will be biased because (stated intuitively) “loyal” customers are over-represented in the risk sets. This study uses a new method described by Schmittlein and Helsen (1993) to obtain the correct parameter estimates by re-weighing the data using existing SAS (1990) proportional hazards regression procedures. Their method entails the construction of "pseudo observations" which are stratified into the correct risk sets corresponding to each completed duration time. Customers in a stratum for a given risk set share the same baseline hazard $h_0(t)$. Details are described in Schmittlein and Helsen (1993). Statistical tests require appropriate adjustments to account for the correct degrees of freedom.

Proportional hazards regression (PHR) provides the necessary information for our duration time model (equation (10)). Since PHR considers the likelihood that a customer terminates the provider-customer relationship at duration t given that some customer terminates, the signs of the hazards model coefficients will be the *opposite* of the signs of the duration time model coefficients. We can use the model results to estimate the numeric effect of covariate x on duration times. Furthermore, PHR is superior to common methods (e.g., regression, logit, probit) in terms of stability, face validity and predictive accuracy for typical marketing durations data (Helsen and Schmittlein 1993).

Results

This section describes nested and non-nested model comparisons, and the resultant model coefficient estimates. The next section discusses the hypothesis tests and how they contribute to our understanding of the role of customer satisfaction in our model of the duration of the customer's relationship with a service organization.

A Nested Model Comparison

After omitting customers with incomplete billing records, the proportional hazards regression model was estimated with observations for 599 (92%) of the 650 customers. A likelihood ratio test of the hypothesis that the vector of model coefficients are jointly equal to zero is rejected ($p < 0.0001$). However, it was immediately apparent that none of the individual coefficients of the *experience dependent effects of new information* (i.e., Sat_{it-1} $\boldsymbol{NewLoss_{it}}$ $Experience_{it-1}$ and (1- Sat_{it-1}) $\boldsymbol{NewGain_{it}}$ $Experience_{it-1}$) were statistically different from zero. Also, a chi-square test could not reject the null hypothesis that these coefficients were jointly equal to zero ($p > 0.15$), so there was no empirical support for H_{4b}, implying $b = 0$. This finding indicates that the magnitude of the effect of new information on the duration of the provider-customer relationship does not vary depending on the amount of experience customers have with the organization. Note that, although the magnitude of the effect of new information does not vary depending on experience *in absolute terms*, it does become smaller *relative* to the magnitude of the effect of prior cumulative satisfaction.

The Restricted Model

Based on the above result, a restricted model was estimated, omitting the experience dependent effects of new information. A likelihood ratio test of the hypothesis that the vector of restricted model coefficients are jointly equal to zero is rejected ($p < 0.0001$). The proportional hazards coefficients of the restricted model are displayed in Table 3. It is important to note that, since the signs of the hazards model coefficients are the *opposite* of the desired estimates of the effects of the predictor variables on duration times, they have been *reversed* in Table 3 so that the middle column shows *the direction of the effect* on duration time. The relative importance of each category of variables in explaining variation in customer's durations was approximated as follows. Importance weights were calculated for each independent variable as $|\beta|S$, where S is the standard deviation of the predictor variable. The weights were re-scaled to sum to 100. Thus, the numbers in the right column of Table 3 can be interpreted as estimates of the proportion of explained variance in duration times accounted for by the predictor variables.

Table 3 here

Comparison with an Alternative Non-nested Model

It is useful to compare the restricted model described in Table 3 with an alternative model that describes a different opinion updating mechanism. For example, suppose that customers weigh new information more heavily when it is consistent with their prior cumulative satisfaction. Algebraically, this notion is equivalent to replacing the "original" weights described by equations (7) and (8) with "alternative" weights described by $w_{Lit} = w_L\,(1 - Sat_{it-1})$ and $w_{Git} = w_G\, Sat_{it-1}$. We substituted these alternative weights into the restricted model and re-estimated it. Since the original and alternative models are not nested, they cannot be compared on the basis of statistical tests. Instead, we can identify the more desirable model on the basis of the Akaike Information Criterion (AIC), a popular statistical fit criterion (Akaike 1973). Since both models have the same number of variables, using the AIC is equivalent to selecting the model which maximizes the value of the log-likelihood function. We find that the value of the log-likelihood function is higher for the original model than for the new model. Thus, we conclude that the original model provides a better fit than the alternative model.

Cumulative Satisfaction

Customers who rate their prior cumulative satisfaction with cellular service higher tend to have longer duration times ($p < 0.001$). This variable accounts for about eight percent of the explained variance in duration times. Note that the model has detected a statistically significant relationship between duration times and satisfaction ratings elicited *many months prior* to any decision by the customer to discontinue the relationship. (Recall that wave one satisfaction ratings were elicited in early 1992, and any cancellations of cellular service took place during the following 22 months).

Customers who have many months of experience with the cellular communications company weigh their prior cumulative satisfaction more heavily than those with few months of experience, so that they tend to have longer duration times. The interaction term of $Sat_{t-1}Experience_{it-1}$ is large in magnitude and statistically significant ($p < 0.001$), accounting for 18% of the explained variance in duration times. This result is consistent with the aforementioned Bayesian models which predict that customers with more experience are more certain in their opinions, and consequently more predictable in their behavior. The combined main and interaction effects explain a substantial portion (25%) of the explained variance in duration times.

New Information

Perceived Losses. Consider the coefficients of the three variables that capture the effects of perceived losses associated with recent service transactions or failures (Sat_{it-1} $\boldsymbol{NewLoss_{it}}$). Consistent with our model, customers who have perceived losses associated with billing, service, equipment or other transactions have shorter durations, where the magnitude of this effect is larger for customers with higher satisfaction levels ($p < 0.01$). Customers who reported a service failure subsequent to the wave one interview have shorter duration times, but the effect is statistically insignificant ($p > 0.15$). Customers who experienced a failure and did not report it have longer duration times ($p < 0.15$). This finding does not mean that failures are perceived as "good." Rather, this variable has captured heterogeneity across customers and the positive coefficient indicates that customers who do not report failures are a more tolerant group -- probably because they have a higher utility for the service. In this study, the estimated model coefficients indicate that perceived losses associated with transactions have a greater effect on duration times than perceived losses associated with failures. This result is probably industry-specific. It seems likely that customers will perceive the losses associated with transactions (e.g., a delay in responding to a request for a detailed billing statement or a new service) as larger in magnitude than the losses associated with typical failures (e.g., a dropped call, poor reception). Altogether, perceived losses explain 16% of the explained variance in duration times, comparable in size to the effects of satisfaction.

Perceived Gains. Next, consider the coefficients of the two variables that capture the effects of perceived gains associated with service transactions or failures ($(1 - Sat_{it-1})$ $\boldsymbol{NewGain_{it}}$). Recall that these perceived gains arise from the company's *response* or handling of the service transaction or failure, so they are conditional on the occurence of the loss (i.e., the transaction or failure). We find that customers' satisfaction with the organization's response or handling of transactions or failures does not have a statistically significant effect on duration times ($p > 0.15$). This weak effect cannot be explained by lack of variability in customers' perceptions of service encounters; their responses ranged from very satisfied to very dissatisfied. Perceived gains account for three percent of the explained variance in duration times, substantially less than perceived losses.

Covariates

The effect of access charges is small and statistically insignificant ($p > 0.15$), but customers are responsive to the airtime charges ($p < 0.01$). An increase in price -- measured by the percentage change in the airtime rate -- was associated with shorter duration times ($p < 0.01$). Customers who have lower average airtime rates or who have experienced price decreases tend to have longer duration times, altogether explaining (19%) of the explained variation in duration times. Duration times are also different for different customer groups ($p < 0.01$) and these effects are large in magnitude, accounting for 36% of the variance in duration times.

Discussion

The model of the duration of the provider-customer relationship for cellular service is well-supported by the data. Customers who have higher prior cumulative satisfaction havelonger relationships with the organization. Customers who have many months experience with the cellular provider weigh their prior cumulative satisfaction more heavily than those with few months experience. In other words, the relationship between duration times and satisfaction is stronger for customers who have more experience with the service organization. Customers who have longer relationships with the organization also have fewer/lower perceived losses associated with service transactions or failures, weighing them in direct proportion to their prior cumulative satisfaction levels. Organizations' response to service transactions and failures do not offset the negative impact of these perceived losses. Prior cumulative satisfaction and perceived losses associated with recent transactions or failures account for about 42% of explained variance in the model. The specific features of the model can be explored by examining the results of a series of nested model tests of the hypotheses, displayed in Table 4.

Table 4 here

Duration Times are Explained By an Anchoring and Adjustment Process

We postulated that customers update their beliefs about the future value of a relationship though a sequential anchoring and adjustment process in which the individual's prior cumulative satisfaction (i.e., the anchor) is adjusted by the impact of succeeding pieces of new information -- and that this process is reflected in customers' duration times. The duration of the provider-customer relationship is longer for customers who have higher levels of cumulative satisfaction with their service ($\alpha > 0$), confirming H_1 ($p < 0.001$). Furthermore, a nested model test of the (joint) hypothesis that the coefficients of the vector of variables representing new information encoded as perceived losses and gains -- i.e., variables representing recent transactions and failures -- are jointly equal to zero is rejected ($p < 0.001$). These results provide overall support for an anchoring and adjustment model.

Encoding of New Information as Losses as Gains. Supporting H_{2a}, customers who experience perceived losses during service encounters (i.e., recent transactions or *reported* service failures) tend to have shorter relationships with the organization ($w_L < 0$). Contrary to H_{2b}, customers who experience perceived gains during service encounters do not have longer duration times ($w_G = 0$) -- *despite the fact that customers may have perceived the encounter to have been handled in a "very satisfactory" manner*. It is not entirely surprising to disover that customers who experience perceived losses have shorter duration times. Prior research has shown that that service encounters have a strong effect on customers' perceived service value (Bolton and Drew 1991; 1992), and there is some empirical evidence linking customer complaints and exit behavior or switching behavior (e.g., Solnick and Hemenway 1992; Keaveney 1995). However, our study extends prior research by showing that "very satisfactory" responses by service organizations do not increase the duration of the relationship.

Contrast and Assimilation Effects. We hypothesized that the customer weighs perceived losses more heavily when his/her prior satisfaction level is high and perceived gains more heavily when his/her prior satisfaction level is low (i.e., a contrast effect) and (conversely) that he/she weighs perceived losses less heavily when his/her prior satisfaction level is low and perceived gains less heavily when his/her prior satisfaction level is high (i.e., an assimilation effect). The non-nested model comparison described earlier provides support for the notion of assimilation/contrast effects. However, to directly test for the presence/absence of assimilation and contrast effects (H_{2c}), an "expanded" model was estimated which contained main effects of new information (i.e., $\boldsymbol{NewLoss_{it}}$ and $\boldsymbol{NewGain_{it}}$ variables), as well as mediated effects of new information (i.e., $Sat_{it}\,\boldsymbol{NewLoss_{it}}$ and $(1 - Sat_{it})\,\boldsymbol{NewGain_{it}}$ variables). Based on this expanded model, chi-square tests rejected the hypothesis that the mediated effects were equal to zero ($p < 0.10$), but did not reject the hypothesis that the main effects were equal to zero ($p > 0.50$). Thus, tests indicate that perceived losses are weighed by prior cumulative satisfaction and perceived gains are weighed by its inverse ($p < 0.10$), so H_{2c} is supported.

Losses Loom Larger Than Gains. Since the effect of perceived losses is negative and statistically significant and the effect of perceived gains is not statistically different from zero, H_3 is supported. Thus, our study extends prior research showing that "losses loom larger than gains" by showing that this well-established psychological principle is reflected in the duration of provider-customer relationships. This finding contradicts anecdotal evidence concerning service encounters in the services marketing literature.

Service recovery -- i.e., the effective handling of a failure -- is typically considered an opportunity to delight a customer and create a stronger relationship. For example, in a rare study of actual purchase behavior, Gilly and Gelb (1982) find that customers who are more satisfied with a gas and oil company's response to their complaints are more likely to repurchase, and tend to have slightly higher re-purchase levels. However, there is no empirical evidence that this phenomenon is widespread. In fact, Smith and Bolton (1997) have recently shown that cumulative satisfaction and repatronage intentions decrease after a service failure and recovery encounter for a majority of customers in restaurant and hotel settings. Organizations are likely to differ in their ability to recover from disruptions/complaints depending on the industry and failure context. For example, in the cellular communications industry, the effects of service recovery may be weak because certain issues (e.g., industry-wide cellular fraud, poor geographic coverage due to location of transmitters) are difficult to address in the short run. In summary, even when customers are "very satisfied" with the organization's handling of transactions or failures (as they frequently were in this study), their assessments of the organization's response do not influence the duration of the provider-customer relationship.

<u>Differential Effects of Satisfaction and New Information Due to Experience</u>

The effect of prior cumulative satisfaction on the duration of the provider-customer relationship is larger for customers who have more experience with the organization ($a > 0$), supporting H_{4a} ($p < 0.01$). However, the magnitude of the effect of recent transactions on the duration of the provider-customer relationship does not vary depending on the amount of experience customers have with the organization ($b = 0$), contrary to H_{4b} ($p > 0.15$). In other words, customers who have many months of experience with a service organization weigh their prior cumulative satisfaction more heavily than those with only a few months of experience, so that they have longer duration times. Thus, customers with many months of experience are characterized by stable assessments of the subjective expected value of the service -- and consequently stable behavior -- whereas newer customers seem relatively "less certain" in their opinions or "more vulnerable" to opinion changes that could lead them to terminate their relationship with the service organization.

<u>Summary</u>

Our study finds that prior cumulative satisfaction influences duration times indirectly, as well as directly. First, the strength of the relationship between duration times and satisfaction levels depends on the length of customers' prior experience with the organization. Specifically, customers who have many months experience with the organization weigh prior cumulative satisfaction more heavily and new information (relatively) less heavily. Second, the duration of the service provider-customer relationship depends on whether customers experienced service transactions or failures, where the effects of perceived losses are directly weighed by prior satisfaction, creating contrast and assimilation effects. Third, there is considerable heterogeneity across customers because some customers have a higher utility for the service than others. These findings concerning the differential effects of prior cumulative satisfaction on duration times are new to the services marketing literature.

Although new, our study's findings are consistent with prior research showing that, as a an individual customer gains more confidence or experience, he/she weighs his/her prior assessment of *service quality* more heavily and places less weight on new information in *evaluating service quality* (Boulding, Kalra and Staelin 1997). Furthermore, the differential effects captured by our model help explain cross-sectional models of firm-level satisfaction and retention data. For example, our model describes a mechanism that can explain Anderson's (1994) finding that the correlation between satisfaction and purchase intentions is stronger *across firms* when involvement or experience is high. Also, examining Swedish Customer Satisfaction Barometer data for 114 companies, Anderson and Sullivan (1993) report that the elasticity of purchase intentions with respect to satisfaction is lower for firms that provide high satisfaction. One explanation is that there is a long run reputation effect "insulating" firms that consistently provide high satisfaction. Our model suggests that a possible underlying mechanism for the insulation effect is that prior cumulative satisfaction operates as a main effect and a differential effect in influencing individual customers' duration times, outweighing any contrast effects associated with perceived losses.

Managerial Implications

This study shows that satisfaction levels explain a substantial portion (26%) of explained variance in the durations of service provider-customer relationships across customers. Consequently, it is a popular misconception that service organizations that focus on customer satisfaction are failing to manage customer retention. Managers and researchers may have under-estimated the importance of the link between customer satisfaction and retention because the relationship between satisfaction and duration times is very complex and difficult to detect without using advanced statistical techniques. Consequently, instead of "learning from defections" (Reicheld 1996b, p. 57-8), we suggest that service organizations should be proactive and learn from customers *before* they defect by understanding their current satisfaction levels.

The strength of the relationship between duration times and satisfaction levels depends on the length of customers' prior experience with the organization. Customers with more experience weigh their prior cumulative satisfaction more heavily and new information (relatively) less heavily. The duration of the service provider-customer relationship also depends on whether customers experienced service transactions or failures and their satisfaction with how the organization responded. Service encounters are potential relationship "landmines" because customers seem to be highly sensitive to the costs/losses arising from interactions with service organizations. Thus, service encounters are early indicators of whether an organization's relationship with a customer is flourishing or in jeopardy.

How can service organizations develop longer relationships with customers? Since customers weigh prior cumulative satisfaction heavily, new customers are particularly vulnerable. Organizations should focus on customers in the early stages of the relationship -- if their experiences are not satisfactory, the relationship is likely to be very short. In the long term, service organizations with good prior service levels benefit from experienced customers' reliance on prior satisfaction levels whereas firms with poor prior service levels are hurt. However, organizations with good prior service levels will suffer more when customers perceive that they have suffered a loss arising from a service encounter -- due to the existence of contrast effects. Furthermore, it seems to be very difficult to create service encounters in which customers perceive gains relative to their current satisfaction levels -- thereby inducing them to stay longer with their service provider. Instead, service encounters seem to act as "triggers" that can lead to the termination of a provider-customer relationship. These findings seem likely to generalize to other continuously provided services, such as public utilities and health services.

Customer satisfaction with continuously provided services is likely to be relatively dependent on customization and it will be costly for the organization to customize and standardize simultaneously. Under these conditions, there is a negative association between changes in customer satisfaction and changes in productivity for services (Anderson, Fornell and Rust 1997). Therefore, it is important to carefully assess the effects of investments in productivity on customer satisfaction. Our study highlights the importance of accurately assessing how investments in productivity will influence the duration of provider-customer relationships. Productivity changes that engender perceived losses -- due to more costly transactions or disruptions in service -- will lead to shorter duration times and (potentially) smaller revenues from the existing customer base. However, our study shows some evidence that customers are heterogeneous with respect to the tolerance for costly transactions or failures. Customers who value a service more highly are less likely to react to a perceived loss by exiting from the relationship.

In their article on the "customer equity test," Blattberg and Deighton (1996) emphasize the importance of attracting and keeping the highest value customers, recommending that organizations manage customers rather than products, and describing a method for calculating the optimal level of retention spending. Our study shows that any method of assessing investments designed to increase retention should forecast the effect of these changes on duration times and lifetime revenues. Fortunately, our model of the duration of the provider-customer relationship can be used to generate such forecasts. The predicted change in duration time due to a given service improvement for customers in a given risk set is multiplied by the average bill size of customers in that risk set.[7] (In this study, average bill sizes were slightly lower for customers with smaller duration times, so it was assumed that bill sizes remain unchanged for customers with a given duration time.) Then, the predicted impact of the service improvement on revenues *for all customers* can be calculated as the average of the predicted impact for customers within each risk set weighed by the relative size of the risk sets.

For example, the cellular communications company conducted a root-cause analysis of the reasons for calls to customer service and determined that the number of calls about service-related issues could be reduced by about three per cent if representatives spent an additional one-third hour with new customers when activating the service. The annual (net) cost to the company of changing activation procedures was estimated to be about $887,638. By modeling the duration of the provider-customer relationship, it was projected that the increase in annual revenues due to longer duration times would be about $4,482,000. Hence, profitability was projected to increase by $3,594,362 (that is, roughly two percent of the company's current annual profits).

Prior research provides well-established methods for identifying potential satisfaction/quality improvement efforts that will increase customer satisfaction/quality ratings in different industries. For example, Bolton and Drew (1991; 1994) have described how field experiments and correlational studies can be used to quantify the linkage between actual service operations (e.g., changes in physical plant that affect service levels) and satisfaction/quality survey ratings. Rust Zahorik and Keiningham (1995) have shown how judgmental calibration methods can also be used to quantify this linkage (e.g., changes in hotel services).[8] These or other methods can be used to quantify the effect of service improvements on costs and on satisfaction ratings. The durations model described in this paper complements these methods by providing a method to quantify the effect of service improvements on revenues, thereby making it possible to assess their profitability.

Conclusions

This study developed a model of the duration of the provider-customer relationship for a continuously provided service. In the model, customers form expectations about the value of the service, anchored by their prior cumulative satisfaction and updated by new experiences. Customers who have longer relationships with the firm have higher prior cumulative satisfaction ratings and fewer/smaller subsequent perceived losses associated with subsequent service encounters. Satisfaction affects duration times in several ways . (1) Prior cumulative satisfaction directly affects duration times. (2) Customers who have many months experience with the organization weigh their prior cumulative satisfaction heavily. (3) The effect of perceived losses arising from transactions or service failures on duration times is directly weighed by prior satisfaction, creating contrast and assimilation effects. (4) There is considerable heterogeneity across customers because some customers have a higher utility for the service than others, so that they are more tolerant of dissatisfactory experiences (i.e., losses). Consequently, the explanatory power of the effect of cumulative satisfaction on duration times is comparable to the effect of price, a conventional marketing variable. Furthermore, our calculations show that changes in customer satisfaction can have important financial implications for the organization because lifetime revenues from an individual customer depend on the duration of his/her relationship, as well as the dollar amount of his/her purchases across billing cycles.

These findings should generalize to other continuously provided services. However, from a managerial perspective, cross-sectional studies are necessary to investigate how customer satisfaction affects duration times across industries. The relative size of the impact of customer satisfaction on duration times is likely to vary depending on product differentiation, switching costs and so forth. Secondly, the scope of this investigation should be expanded to include the potential impact of customer satisfaction on other behaviors, such as existing customers' consumption levels and the company's ability to attract new customers. Lastly, from a technical perspective, more complex models of the duration of provider-customer relationships could be developed (e.g., Wedel, Kamakura, DeSarbo and Hofstede 1994). Dynamic covariates, such as marketing decision variables that change over time, could be incorporated. It is also possible to allow for different forms of heterogeneity across customer segments.

Table 1

Descriptive Statistics*

Variable	Statistics
Customers' Mean Satisfaction Rating	4.3
Customers with Unreported Failures	8%
Customers Who Made Reports/Complaints about Failures	20%
Customers' Mean Rating of Recovery Efforts (after Complaints)	2.7
Customers With One or More Transactions**	40%
Customers' Mean Rating of Transactions	4.3
Average access charge	$28.35/month
Average airtime rate	$0.26/minute
Average length of service	35 months

*Number of observations = 599. Ratings are on the (raw) scale of very satisfied (5) to very dissatisfied (1). However, in the model, ratings are re-scaled to lie between zero and one so that contrast and assimilation effects are correctly represented.
**Transactions were of four types: bills (17%), service (20%), equipment (6%) and other (4%).

Table 2
Operationalization of Duration Time Equation Constructs

Predictor Variable	Measure(s)
Prior cumulative satisfaction (Sat_{it-1})	Customers' rating elicited at wave 1: "Overall, how satisfied are you with the services you receive from [the company]? Are you very satisfied, somewhat satisfied, neither satisfied or dissatisfied, somewhat dissatisfied or very dissatisfied?" 5 = very satisfied . . . 1 = very dissatisfied. Re-scaled to lie between zero and one.*
NewLoss$_{it}$	*Transactions:* Four self-report measures elicited at wave 2, representing calls about billing, service, equipment and other transactions, where 1 = transaction occurred and 0 = none.
	Failures: Two self report measures elicited at wave 2 representing unreported and reported failures, where 1 = failure occurred and 0 = none.
NewGain$_{it}$	*Handling of Transactions:* Customer's rating of the service representative on a five point scale where 5 = very satisfied, 1 = very dissatisfied and 0 = no transaction, elicited at wave 2. Re-scaled to lie between zero and one.**
	Handling of Failures: Customer's rating of problem handling on a five point scale where 5 = very satisfied, 1 = very dissatisfied and 0 = no problem, elicited at wave 2. Re-scaled to lie between zero and one.**
Length of Experience ($Experience_{it-1}$)	Scaled logarithm of the number of months that the customer has subscribed as of January 1992 (at wave 1). Note: this is not the same as the dependent variable.
Covariates ($\boldsymbol{X}_{it}$)	
ACCESS	Average access charge over the study period ($x.xx/month)
AIRTIME	Average of airtime rates (airtime charges/minute of use) over the study period ($x.xx/minute)
AIRTIME^2	Average airtime rate squared (quadratic term)
CHANGE	Percentage change in the average airtime rate between time t-1 and t, where t is two months prior to the wave 2 interview date. (A positive value implies an increase in the rate.)
DEMO1 - DEMO5	Five indicator variables capturing demographics

* Re-scaled so that Sat_{it-1} and $(1\text{-}Sat_{it-1})$ lie between zero and one.
**Re-scaled so that effect sizes are comparable.

Table 3

Duration Equation Coefficients

Variable	Coefficient	Explanatory Power
Sat_{it-1}	1.698****	7.9%
Sat_{it-1} $Experience_{it-1}$	0.953****	17.8%
Sat_{it-1} $\boldsymbol{NewLoss_{it}}$		
Transaction	-1.112****	16.2%
Unreported Failure	1.051**	
Reported Failure (i.e., Complaint)	-0.210	
(1- Sat_{it-1}) $\boldsymbol{NewGain_{it}}$		
Rating of Handling of Transaction	-0.571	3.0%
Rating of Handling of Reported Failure	-0.459	
Sat_{it-1} $\boldsymbol{NewLoss_{it}}$ $Experience_{it-1}$	H_{4b} not supported.	
(1- Sat_{it-1}) $\boldsymbol{NewGain_{it}}$ $Experience_{it-1}$	H_{4b} not supported.	
$Access_{it}$	0.008	55.2%
$Airtime_{it}$	+0.997	
$Airtime_{it}^2$	-1.143****	
$Change_{it}$	-0.257****	
$Demo1_i$	0.743***	
$Demo2_i$	0.941****	
$Demo3_i$	1.283****	
$Demo4_i$	1.126****	
$Demo5_i$	0.701****	

**** $p \leq 0.01$*** $p \leq 0.05$ ** $p \leq 0.10$ * $p < 0.15$

Note: (1) Recall that the signs of the hazards model coefficients are the *opposite* of the desired estimates of the effects of the predictor variables on duration times. In this table, the signs of the coefficients have been *reversed*, so that they represent the effect of the predictor variable on duration times. Thus, the positive coefficient on Sat_{it-1} should be interpreted as an indicator of a positive relationship between satisfaction and the duration of the relationship. (2) Percentages do not sum to 100 due to rounding. Among covariates, price variables account for 19% and demographics for 36.2% of explained variance.

Table 4

Summary of Results Regarding Hypotheses

	Hypothesis	Result*
H_1	The duration of the provider-customer relationship is longer for customers who have high levels of cumulative satisfaction with their service ($\alpha > 0$).	Supported ($p < 0.001$)
H_{2a}	The effect of perceived losses on the duration of the provider-customer relationship is negative ($w_L < 0$).	Supported ($p < 0.001$) for transactions.
H_{2b}	The effect of perceived gains on the duration of the provider-customer relationship is positive ($w_G > 0$).	Not Supported ($p > 0.15$).
H_{2c}	The effect of perceived losses is weighed by prior cumulative satisfaction (Sat_{it-1}) and the effect of perceived gains is weighed by the inverse of prior cumulative satisfaction ($(1\text{-}Sat_{it-1})$) .	Supported ($p < 0.10$).
H_3	The absolute magnitude of the effect of a recent service failure on perceived service value is greater than the absolute magnitude of a recent service transaction ($\lvert w_L \, Sat_{it-1}\rvert > \lvert w_G \, (1 - Sat_{it-1})\rvert$).	Supported.
H_{4a}	The effect of prior cumulative satisfaction on the duration of the provider-customer relationship is larger for customers who have more experience with the organization ($a > 0$).	Supported ($p < 0.001$)
H_{4b}	The effect of new information on the duration of the provider-customer relationship is smaller for customers who have more experience with the organization ($b < 0$).	No positive or negative time dependent effects ($p > 0.50$).

* All results are from chi-square tests that compare nested models, except H_3 (as discussed in the text).

Figure 1

<table>
<tr><th rowspan="2">Dates</th><th rowspan="2">Wave 1</th><th colspan="2">Wave Two</th><th rowspan="2">Billing Data</th></tr>
<tr><th>Random Subset</th><th>All Exiting Customers</th></tr>
<tr><td>12/91</td><td>Sample Drawn</td><td colspan="2"></td><td rowspan="8">Monthly billing data collected</td></tr>
<tr><td>1Q92</td><td>Interviews</td><td rowspan="2"></td><td rowspan="7">Interviews within 4-6 weeks of termination date</td></tr>
<tr><td>2Q92</td><td></td></tr>
<tr><td>3Q92</td><td></td><td>Interviews</td></tr>
<tr><td>4Q92</td><td></td><td rowspan="4"></td></tr>
<tr><td>1Q93</td><td></td></tr>
<tr><td>2Q93</td><td></td></tr>
<tr><td>3Q93</td><td></td></tr>
</table>

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Footnotes

1. The distinction between service encounters that are customer initiated (herein referred to as transactions) and service encounters triggered by service failures is partially supported by Keaveney's (1995) exploratory study of service switching behavior. It is particularly useful for continuously provided services, rather than services characterized by discrete transactions (e.g., hotels, hospitals), because it recognizes that disruptions in the continuous provision of service can provide new information to the customer (e.g., about the reliability of the service).

2. Satisfaction is scaled (i.e., $0 < Sat_{it-1} < 1$) for convenience in specifying the contrast and assimilation effects (discussed later). Note that we do not constrain $\alpha_{it} = 1 - \omega_{it}$ because Sat_{it-1} and $\boldsymbol{New_{it}}$ are measured on different scales.

3. The effect of this procedure is to "oversample" customers who terminated service. Oversampling does not affect the model results. However, the attentive reader may have noted three other issues. (1) A customer could be interviewed in 3Q92, and then subsequently interviewed when he/she terminated. In the few instances where this occurred, the more recent interview data were used. This decision rule does not affect the results. (2) Customers who terminated are typically interviewed more recently (relative to the end of the study) than customers who didn't. Analyses (not reported in this paper) suggest that this feature of the study did not influence the results. (3) Customers who terminated could do so prior to the wave 2 survey. In fact, 29 customers who canceled in the first six months of the study were interviewed shortly after they canceled, so they were not re-interviewed at the six month mark

4. This measure was obtained from customers' answers to the following two survey questions: "Have you personally called [the company's] customer service in the last three months?" [If yes] "Generally, what was the purpose of this call?" [coded by interviewer into pre-specified categories]. A chi-square test of the null hypothesis that the coefficients of dichotomous variables representing the four major types of facilitating service transactions (billing, service, equipment and other) are equal could not be rejected ($p > 0.15$). Similarly, a chi-square test of the null hypothesis that the coefficients of the *ratings* of each type of facilitating service transaction are equal could not be rejected ($p > 0.15$). Consequently, the final form of the estimated equation represents transactions by a single dichotomous variable and employees handling of transactions by a single ratings variable.

5. These measures were obtained from customers' answers to the following survey questions: "Have you had any problems with the cellular service, equipment or bills provided by the company?" [If yes] "Did you report this problem / these problems to customer service?"

6. The hazard rate is the conditional likelihood that service termination occurs at duration time t, *given that it has not occurred in the duration interval (0,t).* In contrast, a multinomial logit model

considers the likelihood that the service termination occurs during the study period (ignoring the duration interval). In other words, it considers *whether* the customer will terminate the relationship during the study period, rather than *when* the customer will terminate. The logit model does not incorporate all the information about the relationship that is typically available to the analyst, i.e., the duration times. Also, if only a small percentage of customers terminate service, it will have difficulty discriminating between customers who leave and those who do not.

7. The proportional hazards model can be used to make predictions about any point on the distribution of duration times for customers *within a given risk set*. In this example, the 75th percentile was chosen was chosen as the "base" duration time because it can be interpreted as the duration time at which 75% customers have not yet terminated their relationship with the firm. As such, it is more meaningful to managers than (say) the median -- which can be interpreted as the duration time at which 50% of customers have terminated their relationship with the firm.

8. This linkage can also be considered a two stage process in which physical/operational features are related to subjective attribute perceptions, and attribute perceptions to overall evaluations or affect (e.g., Holbrook 1981). A few studies focus on the link between features and perceptions, such as research relating service features to customers' perceptions of outpatient health services (Neslin 1983). Numerous studies have used compositional techniques -- particularly multi-attribute attitude models to investigate how perceptions influence affect (e.g., Crosby & Stephens, 1987).