

Customer Metrics and Their Impact on Financial Performance

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Abstract

The need to understand the relationships among marketing metrics and profitability has never been more critical. Firms experience ever-increasing pressure to justify their marketing expenditures. The objective of this paper is to integrate existing knowledge about the impact of customer metrics on firms' financial performance. We investigate both unobserved or perceptual customer metrics (e.g., customer satisfaction) and observed or behavioral metrics (e.g., customer retention and lifetime value). We begin with an overview of unobservable and observable metrics, showing how they have been measured and modeled in research. We next offer nine empirical generalizations about the linkages between perceptual and behavioral metrics and their impact on financial performance. We conclude the paper with future research challenges.

Customer Metrics and Their Impact on Financial Performance

1. Introduction

Customers are the lifeblood of any organization. Without customers, a firm has no revenues, no profits and therefore no market value. This simple fact is not lost on most senior executives. In a worldwide survey of 681 senior executives conducted by *The Economist* during October-December 2002, 65% of the respondents reported customers as their main focus over the next three years compared to only 18% who reported shareholders as their main focus (The Economist 2003). Oddly enough, while senior executives recognize the importance of customers, they still rely heavily on financial measures because customer metrics are not clearly defined (Ittner and Larcker 1996).

In this paper we review and integrate existing knowledge on customer metrics (e.g., customer satisfaction, retention) and provide several generalizations about their impact on the financial performance of firms. As marketing strives for greater accountability, it is critical that we understand how customer metrics link to profitability and firm value. This paper has three objectives: (a) provide a review of key customer metrics and the measurement and modeling issues related to them, (b) highlight generalizable findings about the links between customer metrics and financial performance of a firm, and (c) suggest areas for future research.

Customer metrics include a variety of constructs. We categorize them into observable/behavioral and unobservable/perceptual measures. Observable measures involve behaviors of customers that typically relate to purchase or consumption of a product or service. From a customer's perspective, these include decisions of when, what, how much, and where to buy a product. From a firm's perspective, this translates into decisions about customer acquisition, retention, and lifetime value. Unobservable constructs include customer perceptions (e.g., service quality), attitudes (e.g., customer satisfaction) or behavioral intentions (e.g., intention to purchase). In economists' terminology, unobserved constructs are stated preferences while observed constructs are revealed preferences.

Intuitively, unobserved constructs are related to observed behavior which leads to financial gains. Satisfaction, for example, is expected to lead to repurchase behavior which translates into increased sales and profits. In Figure 1, we suggest a simple

framework to link what companies do (i.e. their marketing actions), what customers think (i.e., unobservable constructs), what customers do (i.e., behavioral outcomes) and how customers' behavior affects firm's financial performance (i.e., profits and firm value).² Most research studies on these topics either investigate relationships in one of the boxes, or at best link relationships among constructs in two of the boxes. For example, some studies have established a link between unobservable constructs (e.g., satisfaction) and firm value but do not consider intervening behavioral outcomes. Several researchers have also established a direct link between marketing actions and firm's financial performance (e.g., Joshi and Hanssens 2005) without examining antecedents in the "black box," the term used by many researchers for the unobserved constructs. Given the vast literature in this field, we will focus on three links: (1) impact of unobservable constructs on financial performance (e.g., link between satisfaction and profitability), (2) impact of unobservable constructs on observable constructs (e.g., link between satisfaction and retention), and (3) impact of observable constructs on financial performance (e.g., link between retention and profitability).

The paper is organized to reflect relationships indicated in Figure 1. In section 2, we begin by describing key unobservable customer metrics. For each construct we briefly discuss how it has been defined and measured. In section 3, we describe key observed customer metrics and the modeling issues surrounding them. Section 4 describes main findings from research that links unobservable metrics to financial performance. Research results about the link between unobserved and observed metrics are discussed in section 5. Section 6 discusses findings that focus on linking observed metrics to financial performance. In section 7, we identify unresolved issues and suggest directions for future research. We conclude in section 8.

2. Unobserved/Perceptual Customer Metrics

Research on the concepts in the "black box" is more extensive and has a longer tradition than research on the metrics outside the black box. These unobservable concepts have been studied extensively for many reasons. First, because they are collected almost exclusively through surveys, they have been relatively easy to obtain

² Market and competitor factors are implicit in Figure 1.

and share. Methodologies and best practices were developed both in companies and in marketing research organizations. During the 1990s, for example, all of the major marketing research suppliers had units or practices in customer satisfaction and the American Marketing Association sponsored an annual Customer Satisfaction Congress that often drew close to a thousand registrants from companies. Second, using these metrics as dependent variables allowed companies to diagnose key attribute drivers that could then be addressed by specific marketing and operational strategies within a company. Third, the measures helped companies track performance over time, benchmark against competitors' offerings, and compare performance across different parts of an organization (e.g., branches, units, territories, countries).

Of all the unobservable metrics, customer satisfaction has been the most widely studied by researchers and used by firms because the construct is generic and can be universally gauged for all products and services (including nonprofit and public services). Even without a precise definition of the term, customer satisfaction is clearly understood by respondents and its meaning is easy to communicate to managers. Other unobservable measures, such as service quality, loyalty, and intentions to purchase have also had widespread use in companies and been examined extensively in academic research. Service quality has been widely measured since the mid-80s but is not as prevalent as customer satisfaction because it is limited to examining the intangible aspects of an offering. To a far lesser extent, constructs like commitment, perceived value, and trust have made their way into company measurement systems and academic research. Other possible measures, such as product quality, have not been measured consistently enough to be linked to behaviors or financial performance in studies. We focus on the metrics of customer satisfaction, service quality, loyalty, and intentions to purchase in this paper because of their prevalence in use and maturity in measurement. For variety of reasons, we chose to eliminate perceived value, trust, and commitment from this discussion.

Perceived value was excluded because it is the most ambiguous and idiosyncratic customer metric. While it can be defined in a general sense, operationalizing and measuring the construct has proven difficult. Most definitions state that perceived value is the consumer's objective assessment of the utility of a brand based on perceptions of what is given up for what is received (e.g., Zeithaml 1988). However, this definition itself

is so broad and vague that the construct is virtually impossible to measure with validity, reliability and consistency. In many academic and company studies, perceived value has been measured with a single item or a small number of items (Bolton and Drew 1991) but these measures leave to the customer the precise meaning of the term. Researchers have developed complex conceptualizations and measures (Sirdeshmukh, Singh and Sabol 2002) but these measures are not used in any consistent manner across studies and in companies.

We also eliminated commitment as a metric in this paper. Commitment is a construct that has been proposed as an alternative to customer satisfaction because it signifies a stronger attachment to a product or company. Moorman, Zaltman and Deshpande (1992, p. 316) define commitment as “an enduring desire to maintain a valued relationship.” A small number of studies have measured commitment in business-to-business contexts (Gruen, Summers and Acito 2000, Morgan and Hunt 1994), consumer contexts (Verhoef, Franses, and Hoekstra 2002), and in the context of relational ties among channel members (Kim and Frazier 1997, Kumar, Sheer and Steenkamp 1995). Many researchers in marketing have viewed commitment as a unidimensional concept and measured it simply, but others have elaborated dimensions and attributes (Garbarino and Johnson 1999, MacKenzie, Podsakoff and Ahearne 1998; Morgan and Hunt 1994). The inconsistent conceptualizations, particularly among components of commitment, have led to myriad ways to measure the concept. Because the research on commitment has rarely been linked to the behavioral or financial variables we emphasize in this paper, we eliminated commitment from our study.

2.1. Customer Satisfaction

Customer satisfaction has been defined in many different words but essentially as the consumer’s judgment that a product or service meets or falls short of expectations. Research has typically portrayed the evaluation of customer satisfaction as disconfirmation of expectations (see Oliver 1997 or Yi 1990 for a full review). This view holds that a consumer compares what is received with a pre-consumption standard or expectation.

One of the pivotal definitional issues in the literature is whether satisfaction is best conceived as a transaction-based evaluation or as an overall, cumulative evaluation similar to attitude. Traditionally, satisfaction was viewed as transaction specific, an immediate post-purchase evaluative judgment or affective reaction (Oliver 1993). Reflecting the more global perspective, studies such as Anderson, Fornell and Lehmann (1994) consider satisfaction to be an “overall evaluation based on the total purchase and consumption experience with a good or service over time,” (page 54).

Both in practice and in academic research, customer satisfaction has been measured at the transaction level (as in trailer or event-triggered surveys) and at the overall level (as in the American Customer Satisfaction Index). In early studies, academics often focused on measuring confirmation/disconfirmation and expectations, and the nature and type of expectations varied considerably from predictive expectations (Oliver 1997, Tse and Wilton 1988), to desires and experience-based norms (Cadotte, Woodruff and Jenkins 1987). Applied marketing research tends to measure satisfaction at the transaction level but more recently as an overall evaluation, a cumulative construct that is developed over all the experiences a customer has with a firm.

2.2 Service Quality

Perceived service quality is the degree and direction of discrepancy between customers’ service perceptions and expectations (Sasser, Olsen, and Wyckoff 1978, Zeithaml and Parasuraman 2004). While multiple interpretations of expectations have emerged in service quality research as they have in customer satisfaction research, the notion that service quality is a comparative process is one of the most basic building blocks in the field.

The dominant measurement approach for quantitative assessment of service quality is SERVQUAL, a multiple-item measure first developed in the 1980s, then tested and refined throughout the 1990s (see a review in Zeithaml and Parasuraman 2004). Researchers first operationalized the service quality gap as the difference between two scores – customer expectations and perceptions of actual service performance for the perceptual attributes that respondents indicated were pivotal. Through this early research five dimensions of service quality were derived as factors: reliability, responsiveness,

assurance, empathy and tangibles (Zeithaml and Parasuraman 2004). Refinement and assessment of SERVQUAL over two decades indicate that it is a robust measure of perceived service quality. However, concerns about SERVQUAL have been raised and debated, including the interpretation of and need to measure expectations, the appropriateness of measuring service quality using difference scores, and the generalizability of the five dimensions across all service contexts.

2.3 Loyalty/Intentions to Purchase

Behaviorally, consumers can be defined as loyal if they continue to buy the same product over some period of time. Jacoby and Chestnut (1978), however, took exception to this simple definition and were the first researchers to view loyalty psychologically rather than behaviorally. They recognized that behavioral loyalty could be spurious because it could be based on convenience and switching costs, or misleading if consumers were multi-brand loyal. In a representative definition that combines both the behavioral and attitudinal perspectives, Oliver (1997, p. 392) defines loyalty comprehensively as:

“A deeply held commitment to rebuy or repatronize a preferred product/service consistently in the future, thereby causing repetitive same-brand or same brand-set purchasing, despite situational influences and marketing efforts having the potential to cause switching behavior.”

Consumer loyalty is indicated by an intention to perform a diverse set of behaviors that signal a motivation to maintain a relationship with the focal firm, including allocating a higher share of the category wallet to the specific service provider, engaging in positive word of mouth, and repeat purchasing (Zeithaml, Berry and Parasuraman 1996).

Loyalty has been measured both behaviorally as repeat purchase frequency or relative volume of purchasing (Tellis 1988) and attitudinally as repurchase intentions (e.g., Reynolds and Arnold 2000), intention to recommend to others (e.g., Mattila 2001) likelihood of switching and likelihood of buying more (e.g., Selnes and Gonhaug 2000). Zeithaml, Berry and Parasuraman (1996) combined these different aspects of loyalty and developed a behavioral-intentions battery with four factors—loyalty, propensity to

switch, willingness to pay more, and external response to service problems—comprised of fourteen specific behavioral intentions likely to result from perceived service quality.

In a departure from the rigor of academic research, some scholars and practitioners claim that complex measurements are unnecessary to capture loyalty. Notably, Reichheld (2003) recently claimed that the only number a company needs is customers' intention to recommend the firm to others. Reichheld suggests using a "net promoter score," defined as the percentage of respondents answering 9 and 10 on a 10-point willingness-to-recommend scale minus the percentage of respondents answering 0 through 6. Reichheld argues that companies commonly get net promoter scores that range from 10% to 16%, and that the best companies get scores between 75% and 80%. Because of its simplicity and ease of measurement, the index has gained popularity with many companies. General Electric CEO Jeffrey Immelt encourages his executives to use net promoter scores in all of GE's divisions. The Wall Street Journal, Symantec and Intuit are other proponents of the net promoter score.

3. Observed/Behavioral Customer Metrics

The implicit assumption in using unobserved customer metrics is that they anticipate or predict observable behavior such as retention or increased consumption. In the 1990s, companies began to question whether the relationship between unobservable measures such as customer satisfaction and observable behavior such as purchasing was sufficiently strong to justify its use as the primary unobservable predictor. Additionally, as database management and customer relationship management have evolved, researchers and companies find that they can bypass unobserved metrics and directly link firm's actions to customers' observed behavior and firm's financial performance.

In this section we discuss behavioral/observed outcome metrics. These metrics include customer decisions of what, when, how much, and where to purchase products or service. A vast literature on choice models attempts to elucidate the impact of marketing variables on such consumer decisions (e.g., Guadagni and Little 1983, Gupta 1988). The equivalent decisions from a firm's perspective are which customers to acquire, how to retain them, and how to cross-sell different products and services to them. Research in customer relationship management or CRM uses this terminology (e.g., Kamakura et al

2005). Even though the terminology used by these two streams is different, they are effectively capturing similar aspects of consumer purchase behavior. For example, models of cross-category purchase (e.g., Manchanda, Ansari and Gupta 1999, Iyengar, Ansari and Gupta 2003) can also be used for the purpose of cross-selling. We will adopt the terminology and the metrics used in CRM in this paper because they have direct implications for firms' financial performance. Specifically we will focus on customer acquisition, retention and cross-selling, which in turn determine customer lifetime value (CLV) and customer equity (CE).

3.1 Customer Acquisition

Customer acquisition refers to the first-time purchase by new or lapsed customers. The basic model for customer acquisition is a logit or a probit. Specifically, customer j buys at time t (i.e., $Z_{jt} = 1$) as follows,

$$\begin{aligned} Z^*_{jt} &= \alpha_j X_{jt} + \varepsilon_{jt} \\ Z_{jt} &= 1 \quad \text{if } Z^*_{jt} > 0 \\ Z_{jt} &= 0 \quad \text{if } Z^*_{jt} \leq 0 \end{aligned} \tag{1}$$

where X_{jt} are the covariates and α_j are consumer-specific response parameters.

Depending on the assumption of the error term, one can obtain a logit or a probit model (Thomas 2001, Lewis 2005b). Some researchers (e.g., Kim, Mahajan and Srivastava 1995, Gupta, Lehmann and Stuart 2004) have followed the diffusion modeling tradition to forecast the number of new customers. For example, Gupta et al. (2004) suggest the following model for forecasting the number of new customers at time t :

$$n_t = \frac{\alpha \gamma \exp(-\beta - \gamma t)}{[1 + \exp(-\beta - \gamma t)]^2} \tag{2}$$

where α , β , and γ are the parameters of the customer growth curve. As in the diffusion literature, marketing mix covariates can also be included in this model.

Most studies on customer acquisition examine the short- and long-run impact of marketing variables on the construct. As an example, Thomas, Blattberg and Fox (2004) found that while low price increased probability of acquisition, it reduced relationship duration. Therefore, customers who may be inclined to restart a relationship may not be the best customers to retain. Similarly, Lewis (2003) showed how promotions that

enhance customer acquisition may be detrimental in the long run. In contrast, Anderson and Simester (2004) found that deep price discounts have a positive impact on the long-run profitability of first-time buyers but negative long-term impact on established customers.

3.2 Customer Retention

Customer retention is the probability of a customer being “alive” or repeat buying from a firm. In contractual settings (e.g., cellular phones), firms clearly know when customers terminate relationships. However, in non-contractual settings (e.g., buying books from Amazon) firms must infer whether a customer is still active.

Two broad classes of retention models exist – “lost for good” and “always a share” (Dwyer 1997, Jain and Singh 2002). The “lost for good” class considers customer defection as permanent while the “always a share” class considers customer switching to competitors as transient. The former class typically predicts the probability of customer defection using hazard models, which fall into two broad groups – accelerated failure time (AFT) or proportional hazard (PH) models. The AFT models have the following form for customer j (Kalbfleisch and Prentice 1980):

$$\ln(y_j) = \beta_j W_j + \sigma \mu_j \quad (3)$$

where y is the purchase duration and W are the covariates. Different specifications of σ and μ lead to different models such as Weibull or generalized gamma (Allenby, Leone and Jen 1999, Venkatesan and Kumar 2004). For example, if $\sigma=1$ and μ has an extreme value distribution, then we get an exponential duration model with constant hazard rate.

Proportional hazard models are another group of commonly-used duration models. These models specify the hazard rate (λ) as a function of baseline hazard rate (λ_0) and covariates (W),

$$\lambda(t; W) = \lambda_0(t) \exp(\beta W) \quad (4)$$

Different specifications for the baseline hazard rate provide different duration models such as exponential, Weibull or Gompertz. This approach has been used by Bolton (1998) and Gonul, Kim and Shi (2000). Other researchers have used semi parametric models where the baseline hazard is discretized for each time interval (Manchanda et al. 2005).

Schmittlein, Morrison and Colombo (1987) and Schmittlein and Peterson (1994) proposed a NBD/Pareto model for assessing the probability that a customer is still alive. This model has been used by Reinartz and Kumar (2000) and modified recently by Fader, Hardie and Lee (2005).

Instead of modeling duration of relationship, one can model whether or not a customer is likely to defect in a pre-specified time period using a form of discrete-time hazard model. Examples of these are logistic or probit models. Neslin et al. (2005) describe such models which were submitted by several academics and practitioners as part of a “churn tournament”. Models emanating from machine learning, such as bagging and boosting, have also been recently used for modeling customer churn (Lemmens and Croux 2005).

The “always a share” retention models view customer switching to competitors as transient. This category typically uses migration or Markov models to estimate transition probabilities of customers being in a certain state. Bitran and Mondschein (1996), Gonul and Shi (1998) and Pfeifer and Carraway (2000) defined these states based on RFM measures while Rust, Lemon and Zeithaml (2004) used brands as states and estimated transition probabilities using a logit model. Iyengar (2004) defined wireless phone plans and customer defection as states, thereby using a structural model to obtain transition probabilities. Simester, Sun and Tsitsiklis (2005) used a binary tree approach to define the state space and estimated the transition probabilities using a non parametric approach. Most of these studies use dynamic programming to arrive at the optimal marketing programs that maximize firm profits. While the idea of using dynamic programming to determine marketing policy is not new, the availability of large scale data and the computing power has generated a renewed interest in this area. It is interesting to note that the dynamic programming approach allows the managerial flexibility by considering the value of options to base marketing policy on customer states.

As mentioned earlier, retention models are typically categorized into two groups – lost for good or always a share. Recently, some researchers have argued that customers should be treated as renewable resource (Dreze and Bonfrer 2005). Thomas, Blattberg and Fox (2004) explicitly build a model for recapturing lost customers.

Studies have suggested models that link customer acquisition and retention. For example, Hansotia and Wang (1997) indirectly linked acquisition and retention using a logit model for acquisition and a right-censored Tobit model for customer lifetime value. More recently, researchers have explicitly linked acquisition and retention. Thomas (2001) and Thomas, Blattberg and Fox (2004) used equation (1) for customer acquisition and a variant of equation (3) for customer retention. Retention was linked to acquisition through the error correlation between the two models.

3.3 Cross-Selling

As cost of customer acquisition increases, firms attempt to maximize returns from existing customers. Cross-selling, attempting to sell related products to current customers, involves decisions such as assessing which products to cross-sell, to whom, and at what time. Cross-selling research also includes the choice of appropriate marketing instruments (e.g. contact strategy or pricing).

In many product categories customers acquire products in some natural sequence. For example, in financial services customers may start with a checking or savings account and over time buy more complex products such as loans and stocks. Kamakura, Ramaswami and Srivastava (1991) argued that customer are likely to buy products when they reach a “financial maturity” commensurate with the complexity of the product. They modeled this by positioning both products and consumers along a common latent difficulty/ability dimension. Specifically, the probability that consumer j would buy product k was given by,

$$P_{jk} = [1 + \exp\{\alpha_k(\beta_k - O_j)\}]^{-1} \quad (5)$$

where O_j is the position of consumer j and β_k is the position of product k along the latent dimension.

Recently, Li, Sun and Wilcox (2005) used a similar conceptualization for cross-selling sequentially ordered financial products. Instead of a logistic model, they used a multivariate probit model. This model was earlier posited by Manchanda, Ansari and Gupta (1999) to model consumer purchases of multiple product categories. Here,

$$\begin{aligned} \mathbf{u}_{jt} &= \mathbf{X}_{jt}\beta_j + \varepsilon_{jt} \\ \varepsilon_{jt} &\sim MVN(\mathbf{0}, \Sigma) \end{aligned} \quad (6)$$

where \mathbf{u}_{jt} is the vector of utilities for consumer j at time t for multiple products, \mathbf{X} are covariates, and $\boldsymbol{\varepsilon}$ are the errors that are correlated across products. Li et al. (2005) used latent dimension of Kamakura et al. (1991) and ownership of previous products as two of the covariates in equation (6). Verhoef, Franses and Hoekstra (2001) used an ordered probit to model consumers' cross-buying. Knott, Hayes and Neslin (2002) used logit, discriminant analysis and neural network models to predict the next product to buy.

The models discussed to this point focus only on which product a customer is most likely to buy next. Knott et al. (2002) augmented their choice model with a hazard model to predict the timing of this purchase. Kamakura, Kossar and Wedel (2004) used a multivariate split hazard model to find physicians' propensity to *ever* prescribe a drug as well as the timing of their adoption. The likelihood for physician j to prescribe drug k is,

$$L_j = \prod_{k \in C_j} \theta_{jk} f(t_{jk}) \prod_{k \notin C_j} [\theta_{jk} S(t_{jk}) + (1 - \theta_{jk})] \quad (7)$$

where θ_{jk} is the probability that physician j will ever prescribe drug k (this allows for the possibility that some physicians would never adopt a drug, and hence the name split hazard), C_j is the set of drugs adopted by physician j , f is the density function and S is the survival function for adoption time.

In principle, many of these models are similar to the choice and incidence models used by researchers many years ago to model consumer purchases in scanner panel data (e.g. Gupta 1988). Current researchers have simply augmented these models by including current ownership of product A as a covariate to predict purchase behavior of product B.

3.4 Customer Lifetime Value (CLV)

Customer acquisition, retention and cross-selling determine the long-run profitability or lifetime value of a customer. Customer lifetime value (CLV) is defined as the present value of all future profits obtained from a customer over his/her life of a relationship with a firm. CLV is similar to the discounted cash flow approach used in finance except for two key differences. First, CLV is defined at an individual customer or segment level, recognizing that some customers are more important and profitable than others. Second, CLV explicitly incorporates the possibility of a customer defecting to competitors in the future.

CLV for a customer (for simplicity we are omitting consumer subscript) has been modeled in two ways. The first approach estimates a customer's expected life T^* (based on a retention model) and evaluates the NPV over this time horizon (Reinartz and Kumar 2000, Thomas 2001). Specifically,

$$CLV = \sum_{t=0}^{T^*} \frac{(p_t - c_t)}{(1+i)^t} - AC \quad (8)$$

where, p_t = price paid by a consumer at time t ,

c_t = direct cost of servicing the customer at time t ,

i = discount rate or cost of capital for the firm,

T^* = expected lifetime of a customer

AC = acquisition cost

Two other modifications are possible in this approach. First, rather than a discrete time frame, the model can be constructed for continuous time. Second, instead of estimating CLV up to time T^* , an infinite time horizon can be used (Dreze and Bonfrer 2005). Note, cross-selling and up-selling are implicitly built in this model since these will change the profit ($p-c$) generated by a customer at any point in time.

Alternatively, the probability of retention is directly included in the CLV equation as follows (Gupta, Lehmann and Stuart 2004, Reinartz and Kumar 2003),

$$CLV = \sum_{t=0}^T \frac{(p_t - c_t)r_t}{(1+i)^t} - AC \quad (9)$$

where, r_t = probability of customer repeat buying or being "alive" at time t ,

T = time horizon for estimating CLV.

Gupta and Lehmann (2005) show that using equation (8) generally overestimates CLV, sometimes quite substantially. This results from the implicit assumption in equation (8) that even if a customer's retention probability is, say, 0.8, s/he is providing profits for the next five years with certainty.

Researchers commonly build separate models for future contribution margin ($p_t - c_t$) and probability of repeat buying or being alive in the future (r_t), then combine them to estimate CLV. Most studies either use average contribution margin based on past purchase data (Reinartz and Kumar 2000, Gupta, Lehmann and Stuart 2004) or a Tobit model to predict it (Lewis 2003). Gupta and Lehmann (2003, 2005) argue that under a

variety of conditions it may be appropriate to consider a constant margin ($m=p-c$) and constant retention rate (r) per time period so that retention probability in period t is simply r^t . Using an infinite time horizon, CLV greatly simplifies to the following expression,

$$CLV = \sum_{t=0}^{\infty} \frac{(p-c)r^t}{(1+i)^t} = m \frac{r}{(1+i-r)} \quad (10)$$

In other words, CLV simply becomes margin (m) times a *margin multiple* ($r/1+i-r$). When retention rate is 90% and discount rate is 12%, the margin multiple is about four. Gupta and Lehmann (2005) show how equation (10) can be modified when margin and retention rates are not constant.

3.5 Customer Equity

Customer lifetime value is the long-run profitability of an *individual* customer. It is useful in identifying which customers to acquire, how much to spend on them, and how to customize marketing and product offerings to them. While this micro-marketing is useful from operational perspective, it must be aggregated at a higher level to be a useful metric for senior managers. For this purpose, many researchers focus on customer equity which is defined as the lifetime value of current and future customers (Blattberg, Getz and Thomas 2001, Rust, Lemon and Zeithaml 2004, Gupta and Lehmann 2005).

Recently, some researchers have demonstrated a link between customer equity and firm's market value (discussed later). Others have shown that decisions based on customer equity can be qualitatively different from the decisions that focus on share and sales (Yoo and Hanssens 2004).

4. Link between Unobserved Metrics and Financial Performance

Do customer satisfaction and other perceptual metrics lead to improved financial performance? Most recent research has focused on exploring or establishing a link between satisfaction and financial impact. Researchers have used different metrics for financial performance: profit, stock price, Tobin's q (ratio of market value of a firm to the replacement cost of its tangible assets), return on assets (ROA), return on investment

(ROI), abnormal earnings, and cash flows (Rust et al. 2004). Based on a review of more than two decades of research, we offer the following empirical generalizations.³

G1: Improvement in customer satisfaction has a significant and positive impact on firms' financial performance.

Many studies have shown a strong link between customer satisfaction and firm profitability (Table 1). Using 200 of the Fortune 500 firms across 40 industries, Anderson, Fornell and Mazvancheryl (2004) showed that while market share has no impact on shareholder value, a 1% change in ACSI (as measured by the American Customer Satisfaction Index on a 0-100 scale) is associated with 1.016% change in shareholder value as measured by tobin's q. This implies that 1% improvement in satisfaction for these firms will lead to an increase in firm's value of approximately \$275 million. Ittner and Larcker (1998) also used ACSI and financial data on 140 firms and find remarkably similar results. Specifically, they demonstrate that a 1-point increase in ACSI leads to \$240 million increase in market value of a firm. Using similar data, Gruca and Rego (2005) found that a 1-point increase in ACSI results in an increase of \$55 million in a firm's net operational cash flow next year and a decrease of 4% in cash flow variability.

Anderson and Mittal (2000) examined the data from 125 Swedish firms using the Swedish Customer Satisfaction Barometer (SCSB) and found that a 1% increase in satisfaction leads to a 2.37% increase in ROI. With the SCSB data for 1989-1992, Anderson, Fornell and Rust (1997) found that satisfaction elasticity for ROI ranges from 0.14 to 0.27. The Swedish data led Anderson, Fornell and Lehmann (1994) to conclude that a 1-point annual increase in SCSB for five years is worth about \$94 million or 11.4% of current ROI. Using data from 12,000 retail banking customers from 59 divisions of a retail bank, Hallowell (1996) supported results from SCSB data by showing that a 1-point improvement in satisfaction (on a 1-7 scale) increased ROA by 0.59%.

With data from 106 firms in 68 industries during the period 1981-1991, Nayyar (1995) found that news reports about increases in customer service led to average

³ There is a vast literature on each topic. Given the space constraints, we would be able to highlight only a few main studies in each area.

cumulative abnormal earnings (CAR) of about 0.46% or \$17 million in market value. Ittner and Larcker (1998) also found that announcement of ACSI improvement led to increase in abnormal returns approximating 1% in a 10-day period.

Rucci, Kirn and Quinn (1998), describing the transformation at Sears during the period 1994-1995, developed a model to relate changes in employee attitude, customer satisfaction, and revenue growth. Results indicated that a 5-point improvement in employee attitude led to a 1.3 point improvement in customer satisfaction, which in turn led to a 0.5% improvement in revenue growth. They further estimated that 4% improvement in customer satisfaction translates to more than \$200 million in additional 12-month revenues. These extra revenues would increase Sears' market capitalization by nearly \$250 million.

Some studies explicitly consider the impact of service quality on financial performance while others subsume service quality as a driver of customer satisfaction and therefore focus on the impact of satisfaction on financial performance. With PIMS data, Buzzell and Gale (1987) found that the short-run elasticity of ROI of quality was 0.25. Anderson, Fornell and Lehmann (1994) reported this elasticity at about 0.2 from the Swedish data. Nelson et al. (1992), with data from 51 hospitals, found that selected dimensions of service quality explain 17%-27% of the variation in financial measures such as hospital earnings, net revenue, and ROA. Using data from almost 8,000 customers of a national hotel chain, Rust, Zahorik and Keiningham (1995) found that return on investment in service quality (e.g., cleanliness) was almost 45%. Aaker and Jacobson (1994), using data from 34 firms and over 1,000 customer surveys, concluded that quality perceptions positively influence stock returns even after controlling for accounting measures.

Collectively, these studies show a strong and positive impact of customer satisfaction on firm performance. They further provide a rough benchmark about the effect size. For example, Anderson, Fornell and Mazvanherly (2004) and Ittner and Larcker (1998) show that 1% change in ACSI can lead to a \$240-275 million improvement in firm value. In sum, these results provide a strong guideline to firms about how much they should spend on improving customer satisfaction.

G2: The link between satisfaction and profitability is asymmetric and nonlinear.

While there are fewer studies in this area than discussed in G1, their collective conclusion provides strong support for generalization G2. Anderson and Mittal (2000) found that a 1% increase in satisfaction led to 2.37% increase in ROI, while a 1% drop in satisfaction reduced ROI by 5.08%. Nayyar (1995) found that positive news about customer service led to increase in CAR of about 0.46%, while reports of reductions in customer service were met with declines in CAR of about half or 0.22%. Anderson and Mittal (2000) document several studies that found both asymmetric and nonlinear effects across the service profit chain (similar to Figure1). Roy (1999) showed that using a linear approach underestimated the impact of “completely satisfying” physicians by 31%, which would represent an underestimation of revenue by \$150 million.

Although several studies have established the asymmetric and nonlinear nature of the link between satisfaction and profitability, the exact form of this nonlinearity needs further examination. For example, Anderson and Mittal (2000) found that a drop in satisfaction produced twice the impact on ROI than an increase in satisfaction. In contrast, Nayyar (1995) found negative news of customer service had only half the impact on CAR than the positive news. Future research should examine the nature of this asymmetry both theoretically and empirically.

G3: The strength of the satisfaction-profitability link varies across industries as well as across firms within an industry.

In G1, we showed the impact of satisfaction on firm profitability on *average*, but the strength of this relationship is not consistent across industries. Ittner and Larcker (1998) confirmed this by showing that the “value relevance” of customer satisfaction varies across industries. Using ACSI on 140 firms from five different industries, they found that ACSI had positive but insignificant impact on market value of durable and nondurable manufacturing firms but a positive and significant impact on the market value of transportation, utility and communication firms. The effect was strongly negative for retailers. Anderson, Fornell and Rust (1997) found that tradeoffs between customer satisfaction and productivity (e.g., labor productivity) were more likely for services than

for goods. Specifically, a simultaneous 1% increase in both customer satisfaction and productivity is likely to increase ROI by 0.365% for goods, but only 0.22% for services.

Anderson, Fornell and Mazvancheryl (2004) also found significant differences in the satisfaction-profitability link across industries. While a 1% change in satisfaction had an *average* impact of 1.016% on shareholder value (Tobin's q), the impact ranged from 2.8% for department stores to -0.3% for discount stores. They further demonstrated that only 14.5% of the variance in association between ACSI and Tobin's q was due to industry differences with 85.5% due to differences across firms within the same industry. Gruca and Rego (2005) found that industry characteristics explain 35% of the variance in cash flow growth and 54% of the variance in cash flow variability. They also found that the influence of customer satisfaction on cash flow growth is greatest for low-involvement, routinized, and frequently purchased products (e.g., beer and fast food).

Although these studies found significant differences across industries, two questions remain. First, do some industries systematically show a stronger link between satisfaction and profitability? Ittner and Larcker (1998) found a negative link in the retail industry, while Anderson, Fornell and Mazvancheryl (2004) showed the strongest positive link in the same industry. Second, why is this link stronger for some industries than others? Although we have some initial results, we need more studies that relate industry characteristics to strengthen this relationship.

5. Link between Unobserved and Observed Metrics

In a recent paper, Kamakura et al. (2002) show that superior satisfaction alone is not an unconditional guarantee of profitability. Based on their analysis of 500 branches of a national bank in Brazil, they further argued that managers should not only be efficient in achieving superior customer satisfaction, but also efficient in translating these attitudes and intentions into relevant behaviors.

Reichheld (1996) cautions against the exclusive use of the satisfaction metric without establishing its link with retention and profits. He argues that in the automobile industry, dealers are "gaming" satisfaction measures without necessarily improving customer value. Based on research conducted by Bain & Company, he found that in many businesses 60-80% of defected customers said on a survey just prior to defecting

that they were satisfied or very satisfied. This concern argues even more in favor of establishing a link between satisfaction and retention.

Most marketing studies that examine the association between customer satisfaction and purchase behavior use surveys to obtain measures of purchase *intent* rather than *actual* behavior (e.g., Anderson and Sullivan 1993, Rust, Zahorik and Keiningham 1995). Although these studies show a strong link between satisfaction and purchase intent, they do not establish the relationship with actual behavior. Using a survey to measure both satisfaction and purchase intent creates strong method bias. For example, Mazursky and Geva (1989) found that satisfaction and intentions were highly correlated when measured in the same survey (time t_1) but that the same subjects' satisfaction at t_1 had no correlation with their intentions after a two-week interval (t_2). We will focus mostly on studies that show a relationship between unobserved metrics (e.g., satisfaction) and observed actual behavior (e.g., retention or repurchase rather than repurchase intentions).

G4: There is a strong positive relationship between customer satisfaction and customer retention. However, the relationship between other unobserved and observed metrics is not well-established.

Table 2 provides a summary of studies that support this result. Using logistic regression on 100 retail bank customers, of which 21 switched, Rust and Zahorik (1993) found that increasing customer satisfaction (1-5 scale) from 4.2 to 4.7 is likely to increase retention from 95.9% to 96.5%. Using almost 2,500 telecommunication customers, Ittner and Larcker (1998) inferred that a 10-point increase in satisfaction (0-100 scale) increased retention by 2% and revenues by \$195. Using business unit data from 73 retail bank branches, they also demonstrated that satisfaction was positively related to revenues and number of customers.

Bolton (1998) examined duration of relationship of 650 cellular phone customers by tracking their actual behavior over a 22 month period. Using two waves of surveys to get information on satisfaction, she found that satisfaction was positively related to the duration of relationship but explained only 8% of the variance. Hallowell (1996) studied 12,000 customers from 59 divisions of a retail bank and also found that satisfaction was

positively related to retention and length of tenure. Unlike Bolton, however, he found that satisfaction explains as much as 37% of the variance of customer retention and duration.

Loveman (1998), with data from 45,000 customers across 450 bank branches, showed that satisfaction was positively related to customer retention, number of services used by a customer (cross-sell), and customer share of wallet. He further found that customer satisfaction had the biggest impact on cross-selling. In contrast, Verhoef, Franses and Hoekstra (2001) used data from over 2,000 insurance customers over two time periods and concluded that there was no main effect of satisfaction on cross-buying. Consistent with Bolton (1998), however, they found that as relationship length increases, the effect of satisfaction on cross-buying increases.

Using insurance data, Verhoef, Franses and Hoekstra (2002) tested the impact of trust, commitment, and satisfaction on customer referrals and number of services purchased (or cross-selling). While trust, affective commitment, and satisfaction were positively related to customer referrals, only affective commitment had a positive impact on the number of services purchased.

G5: While customer satisfaction and service quality are strongly correlated with behavioral intentions, behavioral intentions imperfectly predict actual behavior.

Published research offers strong evidence that customer satisfaction and service-quality perceptions affect customer intentions in positive ways—praising the firm, preferring the company over others, increasing the volume of purchases, or agreeing to pay a price premium. Woodside, Frey and Daly (1989), for example, found a significant association between overall patient satisfaction and intent to choose a hospital again. Cronin and Taylor (1992), using a single-item purchase-intention scale, found a positive correlation with service quality and customer satisfaction. In a series of studies Parasuraman, Zeithaml and Berry (1988, 1994) found a positive and significant relationship between customers' perceptions of service quality and their willingness to recommend the company. Boulding et al. (1993) found positive correlations between service quality, repurchase intentions and willingness to recommend. Anderson and Sullivan (1993) found that satisfaction has a strong positive impact on repurchase

intention. Zeithaml, Berry and Parasuraman (1996) empirically validated the relationship between service quality and behavioral intentions.

Individual companies have also monitored the impact of service quality on selected behavioral intentions. Toyota found that intent to repurchase a Toyota automobile increased from a base of 37% to 45% with a positive sales experience, from 37% to 79% with a positive service experience, and from 37% to 91% with both positive sales and service experiences (McLaughlin 1993). A similar study by Gale (1992) quantitatively assessed the relationship between level of service quality and willingness to purchase at AT&T. Of AT&T's customers who rated the company's overall quality as excellent, over 90% expressed willingness to purchase from AT&T again. For customers rating the service as good, fair, or poor, the percentages decreased to 60%, 17% and 0% respectively. According to these data, willingness to repurchase increased at a steeper rate, i.e., by 43% as the service-quality rating improved from fair to good than when it went from poor to fair (17%) or from good to excellent (30%). These results suggest that the impact of service quality on willingness to repurchase is most pronounced in some intermediate level of service quality.

When it comes to predicting actual behavior from intentions, however, researchers have found that statements of intentions are not always fulfilled in reality. A large body of theoretical and empirical literature examining the relationship between statements of intent and subsequent behavior (Ajzen 1985, Fishbein and Ajzen 1975) indicates that situational influences and monetary constraints are but two of the many factors that lead intentions to imperfectly predict behavior.

Although many studies have shown a positive correlation between intention and actual purchase behavior, their predictive power has been somewhat limited (Juster 1966, Kalwani and Silk 1982). Jamieson and Bass (1989) surveyed 900 consumers over three waves to find their purchase intentions and actual trial of five nondurable and five durable products. They divided consumers into three groups based on their purchase intention – definitely/probably won't buy, might/might not buy, and definitely/probably will buy. Actual trial rates for these groups were 12.6%, 24.3% and 36.0% for nondurables, and 4.1%, 5.5% and 10.0% for durables. These results show that while the relationship between intention and actual behavior is positive, significant "adjustment" is

needed to convert intention scores into purchase. Not surprisingly, market research companies routinely use rules of thumb (e.g., top-box or top-box and a half) to convert intention data into purchase probabilities.

In the context of service profit chain, Loveman (1998) used data from 450 branches of a bank and found that while employee satisfaction is significantly related to their stated loyalty, it is not associated with longer job tenure. In contrast, the same study found that customer satisfaction was positively related to actual customer behavior (retention, share of wallet etc.). Kamakura et al. (2002) also examined bank data using a set of structural equations and found a positive path coefficient of 0.27 between customer intentions (willingness to recommend) and customer behavior (bank share, number of transactions).

Another series of studies demonstrates a mere measurement effect: measuring intent increases the tendency for consumers to increase subsequent purchase behavior (Morwitz, Johnson and Schmittlein 1993; Dholakia and Morwitz 2002a, 2002b). Individual studies in this stream indicate that the frequency of asking intent influences purchases (Morwitz, Johnson and Schmittlein 1993); that measuring satisfaction changes one-time purchase behavior as well as more stable relationship behaviors such as likelihood of defection and increased product use (Dholakia and Morwitz 2002b). For this reason, customers who were asked their satisfaction were shown to be more profitable than those who were not (Dholakia and Morwitz 2002a).

G6: The relationship between unobserved and observed metrics is typically nonlinear.

Why do satisfied customers defect? Jones and Sasser (1995) argued that defection occurs because of a major difference between satisfied and very satisfied customers. While the latter are loyal, the former may defect. Using data from over 100,000 automotive customers, Mittal and Kamakura (2001) confirmed that the relationship between satisfaction and actual behavior exhibited increasing returns (i.e., a convex function). They found that a linear model would underestimate the impact of a change in satisfaction score from 4 to 5 by 64%, causing managers to incorrectly pull back resources from “completely” satisfying customers. In contrast, the difference between “somewhat” and “very dissatisfied” customers is not as large as a linear model suggests.

Ittner and Larcker (1998) also found that the relationship between satisfaction and retention was characterized by several satisfaction thresholds that must be reached before retention increases. In contrast to Jones and Sasser (1995) and Mittal and Kamakura (2001), they found that at very high level of satisfaction, retention shows diminishing, rather than increasing returns.

Many studies have argued that the relationship between satisfaction and repurchase intention is also nonlinear. Anderson and Sullivan (1993) used a large dataset of Swedish customers to show that quality that falls below expectations has a greater impact on satisfaction and repurchase intention than quality that exceeds expectation. Further, the elasticity of repurchase intention with respect to satisfaction is lower for firms that provide high satisfaction. In other words, long-run reputation effect insulates firms that consistently provide high satisfaction. Anderson and Mittal (2000) use the Swedish Customer Satisfaction Barometer to confirm nonlinear relation between satisfaction and repurchase intention. Ngobo (1999) examined this relationship in four industries and found decreasing returns in insurance industry, two thresholds in camera and bank markets, but linear relationship in retail sample.

Several studies have also shown that the relationship between intentions (repurchase, willingness to recommend) and actual behavior is nonlinear. Using data from over 5,000 bank customers, Kamakura et al. (2002) show that the customers' likelihood to recommend has a nonlinear association with their transactions per month, number of years they stay with the bank and overall firm profits. However, the relationship with share of wallet was linear.

While several researchers have confirmed the nonlinear relationship between satisfaction and retention (as well as repurchase intention), it is far from clear if this relationship is convex (Jones and Sasser 1995) or concave (Ittner and Larcker 1998). Mittal and Kamakura (2001) show that while the satisfaction-intention link shows decreasing returns, the satisfaction-behavior link shows increasing returns. Further, this relationship seems to vary by the metrics (Kamakura et al. 2002) as well as industry (Ngobo 1999). Significant work is needed in the future before we can arrive at empirical generalizations about the exact nature of this nonlinearity.

6. Link between Observed Metrics and Financial Performance

In this section, we discuss three generalizations about the link between observed customer metrics and financial performance of a firm. The first generalization demonstrates that a focus on observed metrics leads to improved financial performance; the second suggests which metric is the most critical in driving performance; and the third bridges marketing and finance by linking these customer metrics to the market value of a firm.

G7: Marketing decisions based on observed customer metrics, such as customer lifetime value, improve a firm's financial performance.

At a conceptual level, a link between observed customer metrics, such as customer lifetime value (CLV), and financial performance of a firm is guaranteed almost by definition. CLV focuses on the long-term profit rather than the short-term profit or market share. Therefore maximizing CLV is effectively maximizing the long-run profitability and financial health of a company. There are two additional reasons for this strong link. First, decisions based on CLV help in better customer selection. Second, CLV leads to better/optimal allocation of marketing budget (Berger et al. 2002).

Customers vary dramatically in their overall profitability to a company. This variability is even more than the usual 80-20 rule (where it is commonly believed that 80% of a firm's profits come from top 20% of the customers). Several companies have found that this variability is better described as 220-20 rule, where 20% of the customers provide 220% of the profits.⁴ In other words, a large number of customers destroy value. This makes customer selection critical. Models of CLV help in the selection of profitable customers (Table 3).

Niraj, Gupta and Narasimhan (2001) studied 650 customers of a distributor and found that based on their CLV model, 32% customers were unprofitable. Kamakura et al. (2003) examined 5,550 customers of a Brazilian bank and found that the top 30% cross-selling prospects of phone banking cards have predicted usage probability of greater than 80%. Li, Sun and Wilcox (2005) built a cross-selling model for 1,201 bank customers.

⁴ See, for example, Harvard Business School case studies on Kanthal (case # 9-190-002) and Pilgrim Bank (case # 9-602-104).

They showed that while a randomly drawn group that constitutes 10% of the sample will, on average, contain 10% of the overall purchases, the top 10% of customers as selected by their model contain almost 50% of the purchases. Reinartz and Kumar (2003) used a catalog retailer's data of almost 12,000 customers over 3 years and compared several models. They found that the revenue from the top 30% customers based on their CLV model was 33% higher than the top 30% customers selected based on RFM model. Venkatesan and Kumar (2004) also compared several competing models for customer selection. Using data on almost 2,000 customers for a computer hardware and software manufacturer, they found that the models varied significantly in their customer selection. Specifically, the profit generated by the top 5% customers as selected by the CLV model was 10-50% higher than the profit from the top 5% customers of other models (such as RFM, customer lifetime duration, past value).

These studies confirm the value of CLV-based models in better selection of profitable customers which in turn improve the overall financial performance of a firm. Since none of these studies used real field test to compare the model *predicted* profit with the *actual* profit realized in the market place, they are based on the implicit assumption that it is indeed possible to accurately predict future profitability of the customers. Recently, Malthouse and Blattberg (2005) challenged this assumption. Using a wide range of large datasets they build regression-based models of CLV using approximately 2 years of data. They then used about 3 years of future data for assessing the accuracy of predictions. Their results show that 55% of the top 20% customers and 15% of the bottom 80% customers were misclassified. Given the focus of most CLV-based models to predict the "best" customers, they questioned the ability of these models to actually predict future profitability of customers. In contrast, Donkers, Verhoef and Jong (2003) used insurance data of 1.3 million customers for 3 years to conclude that most CLV models predict quite well (mean error is about 17%). It is possible that the difference in the accuracy of predictions is related to the nature of the model. This issue needs further investigation.

The second reason for CLV-based decisions to improve financial performance is their ability to better allocate marketing resources. Using data of about 12,000 prospects of a B2B manufacturer, Reinartz, Thomas and Kumar (2005) show that when budgets are

allocated as per the CLV model, marketing spending goes down by 68.3% and profits go up by 41.5%. Thomas, Reinartz and Kumar (2004) confirm these results for two other applications. They show that as per the CLV-model, a pharmaceutical company should spend 31.4% more on marketing which will improve its profits by 35.8%, while a catalog retailer should cut its marketing budget by 30.7% to boost its profits by 28.9%. Lewis (2005a) used data of 1,326 active and prospective customers of a major newspaper to suggest optimal pricing path that maximize customer value. His results show that compared to a simple 2-pricing structure (where a low introductory price is followed by a higher regular price), an optimal pricing policy improves customer value by almost 14%.

The studies mentioned above *predict* an improvement in profits but don't actually show it in the field. Several studies have taken this next step. In the context of cross-selling loan products for customers of a retail bank, Knott, Hayes and Neslin (2002) developed a cross-selling model. In addition to performing the usual validation tests, they also conducted a field test. In this test they created 3 main groups of 24,000 to 50,000 customers. The first group was selected based on the cross-selling model developed by the authors. The second group included customers who were selected using the bank's heuristic. The third group consisted of non-customers of the bank based on the names purchased from a list broker. The field test results showed that the ROI of the model based group was 530%, while that for the other two groups was -17% and -30% respectively. Simester, Sun and Tsitsiklis (2005) used 1.73 million customers of a catalog retailer to develop an optimal catalog mailing policy. They then tested their model in the field with 60,000 customers. These customers were divided into low, medium and high value customers (as per the model-based value). Customers in each group were randomly assigned to the treatment (optimal) or control (company policy) group. Differences in the profit of the treatment and control groups for each of the three customer value groups were recorded after six months. Results showed that compared to the control groups, the treatment groups did significantly better for low (+7% profit difference) and medium (+10%) value groups, but not for the high (-16%) value group. These results may resonate with Malthouse and Blattberg (2005) who also found it hard to correctly classify the "best" customers.

In addition to the academic studies, there are a handful of practical case studies that also demonstrate the rewards of focusing on customer metrics. A good example of this is Harrah's Entertainment Inc. that drove its entire business based on observed customer metrics such as "theoretical win" (similar to CLV) and share of wallet. While it is difficult to isolate the impact of this focus on its stellar financial performance, its CEO Gary Loveman argues that this focus played a major role (Loveman 2003).

G8: Customer retention is one of the key drivers of customer lifetime value and firm profitability.

Customer lifetime value is affected by acquisition cost, customer retention and margin (hence cross-selling). Several studies show that customer retention is the most critical of these variables. Reichheld and Sasser (1990) show that a 5% improvement in customer retention for a variety of service companies could improve their overall profitability by anywhere from 25% to 85%. Gupta, Lehmann and Stuart (2004) examined five companies and also found that retention is more important than margin or acquisition cost. Specifically, they found that a 1% improvement in retention can improve customer profitability by about 5% while a similar improvement in margin and acquisition cost improves profits by 1.1% and 0.1% respectively.

Reinartz, Thomas and Kumar (2005) found that suboptimal allocation of retention expenditure has a greater detrimental effect on CLV than a suboptimal allocation of acquisition budget. In their application for a B2B manufacturer, they found that 25% under spending on retention reduces ROI by about 55%, while a similar under spending on acquisition reduces ROI by only about 3%. Consequently, their optimal budget allocation was 79% retention and 21% acquisition. Thomas, Reinartz and Kumar (2004) found a similar result for a pharmaceutical company where the optimal budget allocation turned out to be 86% retention and 14% acquisition.

Some researchers have argued that retention may not be so critical in all situations. Coyles and Gokey (2002) studied 1,600 households across 16 industries and found that margins and cross-selling may be more critical than retention in many industries. For example, they report that in retail banking only 5% of customers with checking accounts defect annually, leading to a 3% reduction in the deposit balances for

the bank. In contrast, 35% customers reduce their balances, adversely affecting bank balances by 24%. Keiningham et al. (2005) also question Reichheld and Sasser's (1990) results by showing that their findings will hold only if the profit margins for a firm are very low (e.g., 5%) or the firm has a fairly high retention rate to begin with (when cost of improving retention will be larger). Finally, we believe that the allocation of retention and acquisition budget depends on the life cycle of a product and industry. For example, in high growth markets such as India and China it may make more sense to focus on customer acquisition instead of retention.

G9: Customer metrics, especially customer lifetime value and customer equity, provide a good basis to assess the market value of a firm.

This is a relatively new topic and therefore only a limited number of studies exist in this area. Nonetheless, they all point in the same direction. Kim, Mahajan and Srivastava (1995) used subscriber data in the cellular phone industry to estimate the value per "pop" (i.e., the number of people living in a service area). They found that their model is able to capture and predict this value quite well. While Kim et al. (1995) used the basic elements of customer metrics (e.g., number of subscribers) to assess value at the industry level, they did not incorporate customer retention which is critical in the valuation of a firm. Gupta, Lehmann and Stuart (2004) used publicly available customer data for five firms to estimate their customer equity (i.e., value of their current and future customers). They found that their customer value estimates are close to the market value for three of the five firms (exceptions were Amazon and eBay).

Libai, Muller and Peres (2005) use a Bass diffusion model with customer defection and replicate the customer valuation for the same five firms examined by Gupta et al. (2004). Their results confirm the findings of Gupta et al. (2004). Rust, Lemon and Zeithaml (2004) used a survey of 100 customers for airlines to estimate CLV for American Airlines. Using this estimate and the total number of airline passengers, they estimated the overall customer value of American Airlines in 1999 as \$7.3 billion. Considering that this estimate does not include international traffic and other non flight sources of revenue, it was reasonably close to the \$9.7 billion market value of American Airlines at that time.

Linking customer value to firm value is important for at least two reasons. First, it helps to make marketing more accountable. Second, it also provides a tool for firm valuation when traditional financial models may not work. For example, many of the companies examined by Gupta et al. (2004) had no cash flow (to do a discounted cash flow model) and no earnings (to assess the P/E ratio). Not surprisingly, a customer-based valuation approach is also catching up on the Wall Street. For example, CIBC recently used this approach to value XM Satellite radio.⁵

7. Future Challenges

We indicated several controversies and potential areas of research during our discussion in sections 4-6. For example, many studies indicate that the link between satisfaction and retention is nonlinear, but there is conflicting evidence concerning whether this relationship is convex or concave. Similarly, some studies show that customer lifetime is difficult to predict while others demonstrate that it is indeed possible. These conflicting results provide avenues for future research. In this section, we highlight additional areas of research.

7.1 Research on Unobserved/Perceptual Metrics

Do we need all the perceptual constructs?

Conducting this survey of customer metrics has made one thing very clear: considerable overlap exists in definition and measurement of the constructs on which customer metrics are based. For this reason, strong correlations are present among the constructs. Research studies have focused on different pairs or combinations of variables, and the pattern of relationships among the variables is not clear. For example, more than thirty empirical studies measure both service quality and customer satisfaction, many of them in an effort to differentiate the constructs from each other and determine the directionality of the relationship between them. While some academic researchers have acknowledged the interchangeability of the constructs (Rust, Zahorik and Keiningham 1995), most have attempted to be very precise about the differences between service quality and customer satisfaction, resulting in considerable

⁵ Details are available in their equity research report dated November 11, 2004.

debate (Parasuraman, Zeithaml and Berry 1994, Cronin, Brady and Hult 2000). Future research should identify situations where some constructs are more appropriate than others. For example, there seems to be an emerging recognition that customer satisfaction is most appropriate for business-to-consumer situations whereas trust or commitment are more appropriate for business-to-business situations. Garbarino and Johnson (1999) showed that for low relational customers (transactional customers, typically business-to-consumer customers), satisfaction is the primary mediating construct between attitudes and future intentions. For high relational customers (e.g., business-to-business customers), trust and commitment rather than satisfaction are the mediators.

Online service quality measurement.

While the measurement of traditional service quality is in a mature stage, online service quality measurement is relatively new. Scales to measure online service quality are now being developed (Parasuraman, Zeithaml and Malhotra 2005) but need refinement and testing. All scales currently under development – including WebQual, .eTailQ, and E-S-QUAL – should be examined for their psychometric properties and diagnostic value and improved where needed. When concepts and measures of electronic service quality have been validated it will be possible to investigate questions about the importance of different dimensions and perceptual attributes to overall electronic service quality and its consequences. One issue that needs to be studied is the relative impact of traditional and electronic service quality on customers touched by both. A key managerial research need is a measurement scale that can be used to capture service quality both in online and offline channels for the same company. Given the differences between SQ and e-SQ, this may be difficult, yet it would be valuable for managers to be able to compare their online and offline service quality.

7.2 Research on Observed/Behavioral Metrics

Accounting for network effects.

Most of the research on CLV has implicitly assumed that the value of a customer is independent of other customers. In many situations customer network effects can be strong and ignoring them may lead to underestimating CLV. Hogan, Lemon and Libai

(2003) show that word of mouth or direct network effects can be quite substantial for online banking. In many situations there are also strong indirect network effects. For example, firms such as Ebay and Monster.com have two related populations (buyers and seller, or job seekers and employers). The growth in one population affects the growth of the other populations and vice versa. Hogan et al. (2002) also suggest more research in this direction.

Modeling retention using different approaches.

The empirical literature in marketing has traditionally favored structured parametric models (such as logistic or probit regression or parametric hazard specifications) that are easy to interpret. In contrast, the vast literature in data mining, machine learning and non-parametric statistics has generated a plethora of approaches that emphasize predictive ability. These include projection-pursuit models, neural network models, tree structured models, spline-based models such as Generalized Additive Models (GAM), and Multivariate Adaptive Regression Splines (MARS), and more recently approaches such as support vector machines and boosting. These machine learning approaches remain alien to the marketing literature, not surprisingly because of the tremendous emphasis that marketing academics place on substantive insights and interpretability. Predictions can also be improved by combining models. The machine learning literature on bagging, the econometric literature on the combination of forecasts, and the statistical literature on model averaging suggest that weighting the predictions from many different models can yield improvements in predictive ability (Lemmens and Croux 2005, Neslin et al. 2005). Further work is needed to understand the relative merits and disadvantages of these different approaches.

Impact of cross-selling on retention.

Many firms believe that cross-selling improves customer retention. In other words, customers who buy multiple products from a firm are likely to be more loyal. This may indeed be true. However, the evidence to date is generally correlational. Causality may, in fact, go in the opposite direction, i.e. customers who are more loyal to a firm may tend to buy multiple products instead of the other way around. If cross-selling does

indeed enhance customer loyalty, then it also has strong implications for pricing of subsequent products sold to a customer. Almost no research has been done in this area.

Accounting for endogeneity.

Customer metrics help a firm identify high and low value customers as well as design appropriate customer offers. For example, catalog companies group customers into deciles based on their past purchase behavior, and the most responsive or high-value group receives more catalogs than the low-value group. Similarly, in the airline industry, frequent fliers receive better treatment than infrequent fliers--low value customers get lower service levels, lower status in the loyalty programs and lower overall benefits.

This could be a self-fulfilling prophecy where low levels of investments in customers lead to lower customer profitability, which in turn leads to an even lower level of investment from the firm. In other words, customers are not only responding to firms' actions, but firms are also responding to the behavior of customers. Most customer metrics and models ignore this endogeneity issue and instead assume that an individual customer's value over his/her lifetime is given. Our task as researchers is to estimate the endogeneity and use this estimate to provide service that is commensurate with the value of a customer.

Accounting for competition.

It is ironic that even as company databases are growing larger and models are becoming more sophisticated, they ignore competition and thus provide an incomplete and sometimes misleading picture. For example, service quality of a firm may be improving over time but may have no impact on customer satisfaction if the service quality of competitors is improving even faster. Similarly, two customers with the same CLV may have different shares of wallet and therefore different future potential. While customer defection clearly depends on competitive offerings, most models of customer defection do not include such information.

A few studies have found innovative ways to avoid these problems. For example, Kamakura et al. (2003) supplemented a bank's internal customer database with a survey of a few thousand customers. Since it is impossible to survey millions of bank customers,

they used the data from the survey sample to impute the missing information (e.g., wallet share) for the remaining customers in the database. We need more studies that either use such innovative methods to account for competition or that show the potential bias from ignoring this information.

7.3 Research on the Links

Incorporate perceptual constructs in behavioral outcome models.

In spite of the popularity of perceptual measures (e.g., customer satisfaction) among both academics and practitioners, it is surprising to find that very few studies have directly incorporated them in the behavioral outcome (e.g., CLV) models. There are at least three reasons for this lack of connection. First, in academia there are two parallel groups of researchers, those who primarily work with perceptual measures and those that focus mainly on behavioral outcomes, with very little interaction among the two groups. This is often also true in companies, where groups of researchers “silo” their customer data (e.g., a marketing research group deals with complex modeling techniques and a customer satisfaction group deals with survey feedback). Second, perceptual data are usually collected for a sample of customers through surveys whereas behavioral data are available for all customers based on transaction data. Merging the databases requires handling of missing observations for the majority of customers. Third, survey data are often collected anonymously, making researcher ability to connect it with behavioral data difficult if not impossible.

Satisfaction as a leading indicator of future behavior and financial performance.

As indicated in sections 4 and 5, satisfaction is strongly correlated with behavioral outcome and financial performance. However, almost all these studies use cross-sectional data. Mazursky and Geva (1989) find that satisfaction and intentions are highly correlated when measured in the same survey (time t_1). However, for the same subjects, satisfaction at t_1 has no correlation with intentions after a two-week interval (t_2). In a large scale study, Bernhardt, Donthu and Kennett (2000) studied over 342,000 consumer responses from 472 restaurants over a 12 month period. They found that customer satisfaction at time t_1 had no impact on financial performance of a restaurant at t_1 .

However, they found a significant impact of change in customer satisfaction during time t and $t+1$ on change in a restaurant's profits during time $t+1$ and $t+2$. Specifically, restaurants with change in satisfaction of more than 0.1 above an average restaurant had more than 30% improvement in profit over an average performer. Unfortunately, Bernhardt et al. (2000) is one of the few studies that provides this time-series perspective. Cross-sectional studies, while useful, may suffer from endogeneity bias. Longitudinal studies will not only help alleviate this problem, but may also be able to establish satisfaction as a leading indicator of a firm's financial performance. While there are a handful of studies that take this perspective, we need more research in this area to enable us to make generalizations.

Build comprehensive models of service-profit chain.

Kamakura et al. (2002) is one of the few studies to take a comprehensive view of customer metrics that includes unobservable, observable and financial measures. They empirically investigate the service profit chain that links operational inputs (e.g., investment in personnel or ATMs in a bank), customers' perceptions, their behavior and firm profit. We need more studies that view customer metrics comprehensively rather than examining only a few constructs at a time. These studies can help us understand how the constructs in Figure 1 are related, which constructs mediate others, which constructs lag or lead other constructs, and how these relationships change by contexts and industries. This should eventually lead to robust empirical generalizations.

Linking customer and brand metrics.

For more than a decade, marketing has focused quite heavily on brand equity. This literature developed its own set of perceptual (e.g., awareness, association and attachment), behavioral (e.g., price sensitivity) and financial (e.g., brand value) metrics. Many academic studies show that brand equity forms a large part of a firm value. Companies such as Interbrand routinely estimate the financial value of brands. Even accountants have taken notice of the intangible value of brands and there is currently a debate about putting these intangible assets on the balance sheet. At the same time

research on customer metrics has developed its own set of perceptual, behavioral and financial metrics.

However, the two streams have grown almost independently. Each stream uses its own set of metrics and is rarely linked to the other. Many researchers are confused about the difference between brand and customer equity. Is one a subset of the other? Does brand equity affect customer equity or is it the other way around? Is it possible for a firm to have low brand equity but high customer equity and vice versa? Rust, Lemon and Zeithaml (2004) suggest that brand value is one of the components of customer equity. However, more work is needed to clarify the distinction and relation between these two important areas.

8. Conclusion

In this paper we set out to review and integrate existing knowledge on customer metrics. We provided a simple yet comprehensive framework for customer metrics, examined both unobservable and observable metrics, and made nine empirical generalizations about the relationship between these metrics and firm profitability. We also highlighted future research challenges to address as firms feel an ever-increasing need to justify their investment in customers. Firms must demonstrate the link between their actions, customer behavior, and their financial performance. Our review and research agenda provide a foundation for these relationships. Our hope is that researchers will continue to move the field forward by further clarifying these relationships.

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Table 1**Impact of Unobserved Metrics on Firms' Financial Performance**

Study	Data	Results
Anderson, Fornell and Mazranchevyl (2004)	200 Fortune 500 firms in 40 industries during 1994-97 with American Customer Satisfaction Index (ACSI), 1-100 scale	1% change in ACSI → 1.016% change in Tobin's q or \$275m in firm value
Ittner and Larcker (1998)	140 firms and ACSI index	1 unit increase in ACSI → \$240 m increase in market value
Gruca and Rego (2005)	ACSI and Compustat data from 1994 – 2002 for 105 firms in 23 industries	1 point increase in ACSI → \$55 m increase in cash flow in the next year and 4% reduction in variability
Anderson and Mittal (2000)	125 firms and Swedish customer satisfaction barometer (SCSB)	1% increase in satisfaction → 2.37% increase in ROI 1% drop in satisfaction → 5.08% drop in ROI
Anderson, Fornell and Rust (1997)	Swedish data for 1989-92	Satisfaction elasticity for ROI = 0.14 – 0.27
Anderson, Fornell and Lehmann (1994)	Swedish data on 77 firms	1 point increase in SCSB → 11% of current ROI or \$94 million Short run elasticity of ROI with respect to quality = 0.196
Hallowell (1996)	1 retail bank, 59 divisions 12,000 retail banking customers satisfaction measured on 1-7 scale	1 point change in satisfaction → 0.59% point change in ROA
Nayyar (1995)	106 firms from 68 industries for 1981-91	Increase in customer service → 0.46% average cumulative abnormal return (CAR) Decrease in customer service → -0.22% CAR
Rucci, Kirn and Quinn (1998)	Sears 1994-95	4% increase in satisfaction → \$200 million

		in additional revenue or \$250 m in market cap.
Nelson et al. (1992)	51 general hospitals, each with a sample of 300 patients	Service quality explains 17% - 27% of variation in financial performance of hospitals
Rust, Zahorik and Keiningham (1995)	7,882 responses over one year from a national hotel chain customers	44.6% projected return on quality
Aaker and Jacobson (1994)	34 firms and 1,000 – 2,000 customer surveys over four years	quality perceptions → stock returns

Table 2**Relationship between Unobserved and Observed Customer Metrics**

Study	Data	Results
Rust and Zahorik (1993)	100 retail bank customers, of which 21 had switched banks	Increase in satisfaction from 4.2 to 4.7 → increase in annual retention rate from 95.9% to 96.5%
Ittner and Larcker (1998)	2,491 telecommunication customers	10 point increase in satisfaction (0-100 scale) → 2% increase in retention and \$195 increase in revenue
	73 retail bank branches	Satisfaction positively associated with revenues and number of customer
Bolton (1998)	650 cellular phone customer tracked over 22 months (1991-93)	Satisfaction positively related to duration of relationship
Hallowell (1996)	59 division, 12,000 customers of a retail bank	Satisfaction positively related to retention and length of tenure
Loveman (1998)	450 bank branches and 45,000 customers	Satisfaction positively related to retention, number of services used and share of wallet. Biggest impact on cross-sell.
Verhoef, Franses, Hoekstra (2001)	2,018 insurance customers surveyed twice over 1 year period	No main effect of satisfaction on cross-buying
Verhoef, Franses, Hoekstra (2002)	1,986 insurance customers	Trust, affective commitment and satisfaction → referrals; Affective commitment → no. of services purchased
Jamieson and Ban (1989)	900 consumers surveyed over three waves for five durables and five nondurable products	Only 10% (durables) and 36% (nondurable) of consumers who indicated that they'll definitely or probably will buy, actually bought the product

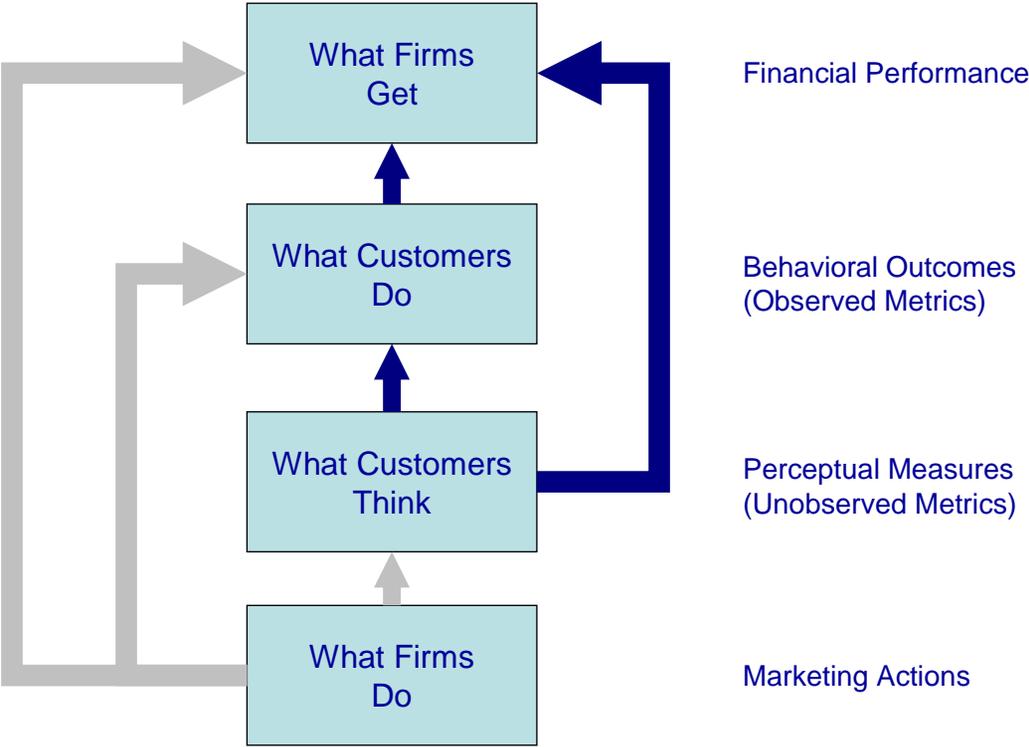
Kamakura, Mittal, de Rosa and Mazzon (2002)	5,055 customers from 500 branches of a national bank in Brazil	Intent to recommend → share of wallet, duration of relationship and transaction per month
Mittal and Kamakura (2001)	100,040 automotive customers	Satisfaction – intention link shows decreasing returns Satisfaction – behavior link shows increasing return
Anderson and Sullivan (1993)	22,300 Swedish customers from 114 companies in 16 industries	Asymmetric impact of quality on repurchase intention Elasticity of repurchase intention with respect to satisfaction is lower for high satisfaction firms

Table 3**Link between observed customer metric and firms' financial performance**

Study	Data	Result
Niraj, Gupta and Navajimhan (2001)	650 customer of a distributor	32% customers were unprofitable
Kamakura et al (2003)	5,550 customer of a Brazilian bank	Top 30% customers have over 80% usage probability
Li, Sun and Wilcox (2005)	1,201 customer of a bank	Top 10% customers account for almost 50% of all purchases
Reinartz and Kumar (2003)	11,992 households, 3 years from a catalog retailer	33% higher revenue from top 30% customers based on CLV vs. RFM model
Venkatesan and Kumar (2004)	2 cohorts (1,316 and 873 customer) from computer hardware, software manufacturer	10-50% higher profit from top 5% customer based on CLV vs. RFM model
Malthouse and Blaltinger (2005)	71,381 customer from a service company 68,026 customer from nonprofit, 24,047 customer from B2B 41,669 customer from catalog 3,000 to 95,000 customer from 131 companies	Of the top 20% customers, 55% misclassified Of the bottom 80% customer, 15% misclassified
Donkers, Verhoef and Jong (2003)	1.3 million insurance customer for 1998 – 2001	Mean prediction error in CLV models = 17%
Reinartz, Thomas and Kumar (2005)	12,024 prospects of a B2B company	CLV model-based allocation: 68.3% reduction in marketing expense → 41.5% increase in profit 25% under spending on retention → 55% drop in ROI 25% under spending on acquisition → 3% drop in ROI

Thomas, Reinartz and Kumar (2004)	Pharma and catalog retailers	Catalog: 30.7% ↓ spend → 28.9% ↑ profit Budget: retention = 86%, Acquisition = 16% Pharma: 31.4% ↑ spend → 35.8% ↑ profit
Lewis (2005a)	1,326 current and prospective customer of a newspaper	Optimal pricing policy improves CLV by 13.9%
Knott, Mayes and Neslin (2002)	24,000 – 50,000 retail bank customer in three groups for field test	ROI from cross-selling model = 530% ROI from heuristic = -17% ROI from purchased list = -30%
Simester, Sun and Tsitsiklis (2005)	Catalog retailer, 1.73m customers during 1996 – 2002. Field test on 60,000 customer	Difference in profit for treatment and control group Low value customer = 7% Moderate value customer = 10% High value customer = -16%
Reichheld and Sasser (1990)	Several service industries	5% improvement in customer retention → 25 – 85% improvement in profit
Coyles and Gokey (2002)	1,600 householders in 16 industries	5% defection → 3% ↓ balance of a bank 35% customers reduce balance → 24% ↓ balance for the bank
Kim, Mahajan and Srivastava (1995)	Cellular phone industry	Links market penetration (subscribers) to market value for the industry
Gupta, Lehmann and Stuart (2004)	Publicly available data for Amazon, Ameritrade, Etrade, Capital one and Ebay	Value of customers for the industry provides a good proxy for firm value 1% improvement in retention, increases firm value by 5%
Libai, Miller and Peres (2005)	Same as Gupta et al.	Customer value provide a good proxy fro firm value
Rust, Lemon and Zeithaml (2004)	100 – 137 customer surveys in five industries	Firm actions → customer equity → ROI

Figure 1: Framework for Customer Metrics and their Impact on Firm's Financial Performance



Note: The links/arrows in black are the focus of this study