Incorporating Satisfaction into Customer Value Analysis: Optimal Investment in Lifetime Value

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March 2005

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Abstract

We extend Schmittlein, Morrison, and Colombo’s model (1987) of customer lifetime value to include satisfaction. Customer purchases are modeled as Poisson events and their rates of occurrence depend on the satisfaction of the most recent purchase encounter. Customers purchase at a higher rate when they are satisfied than when they are dissatisfied. A closed-form formula is derived for predicting total expected dollar spending from a customer base over a time period \((0, T]\). This formula reveals that approximating the mixture arrival processes by a single aggregate Poisson process can systematically under-estimate the total number of purchases and revenue.

Interestingly, lifetime value is increasing and convex in satisfaction. If the cost is sufficiently convex, our model reveals that the aggregate model leads to an over-investment in customer satisfaction. The model is further extended to include three other benefits of customer satisfaction: (1) Satisfied customers are likely to spend more per trip on average than dissatisfied customers; (2) Satisfied customers are less likely to leave the customer base than dissatisfied customers; and (3) Previously satisfied customers are more likely to be happy in the current visit than previously dissatisfied customers. We show that all the main results carry through to these general settings.

Keywords: Customer Satisfaction, Customer Value Analysis, Probability Model
1 Introduction

Customers are assets and their values grow and decline. Segmenting customers based on their lifetime value is a powerful way to target them because marketing mix activities can then aim at enhancing customer value. In fact, predicting and managing customer lifetime value has become central to marketing because the health of a firm is intimately linked to the health of its customer base. This paper develops an analytical framework for forecasting customer lifetime value based on her satisfaction with the firm.

The relevance of this research is evident in the burgeoning practitioner literature on customer relationship management. Industry observers have emphasized the importance of incorporating satisfaction metrics into customer valuation and exhorted firms to balance customer satisfaction and cost control (e.g., Forrester Research 2003, Jupiter Research 2000). This paper provides a formal methodology to assess investment in customer satisfaction by linking it to likely future shopping and purchase patterns and hence revenue flow.

Our analytical modeling framework rests on two premises. First, we posit that customer satisfaction is a key controllable determinant of customer lifetime value. That is, \textit{ceteris paribus}, a satisfied customer has a higher lifetime value than a dissatisfied customer. This occurs through three behavioral mechanisms discussed below. This premise is both intuitively appealing and empirically sound. Several studies have shown that customer satisfaction is a good predictor for likelihood of repeat purchases and revenue growth (e.g., Anderson and Sullivan 1993, Jones and Sasser 1995). In addition, prior research has shown that customers react negatively to poor service (e.g., stockouts) by switching to another firm on subsequent shopping trips (Fitzsimons 2000).

Second, customer satisfaction can be increased by investing in costly technology or productive processes. For instance, a call center that increases its number of customer representatives will reduce queueing time. Similarly, a catalog firm can improve its logistics processes to shorten delivery time and reduce the incidence of wrong shipments. The investment in these costly productive processes, however, requires a formal quantification of their revenue implication. A goal of this research is to derive a precise relationship between revenue and customer satisfaction by developing a micro-level stochastic purchase model.

We build on the seminal work of Schmittlein, Morrison, and Colombo (hereafter, abbreviated as...
SMC) (1987) and Schmittlein and Peterson (1994). Their model assumes that customer purchase arrivals are Poisson events. Customers are allowed to die (i.e., switch to another firm or leave the product category entirely) in a Poisson manner so that the number of active customers can decline over time. Customers are heterogeneous in their purchase intensity and death propensity. The amount spent on each purchase is normally distributed and is assumed to be independent of the arrival and death processes. They derive an elegant formula to predict the total expected dollar spending from a customer base over a time period.

There are three behavioral mechanisms customer satisfaction can affect this classical stochastic purchase model. First, a satisfied customer is likely to have a higher purchase arrival rate and make more trips to the firm. In other words, the firm can increase its market share of the product category by making the customer satisfied. Second, a satisfied customer is less likely to switch to another seller or leave the product category entirely. That is, a satisfied customer has a lower death rate. Third, a satisfied customer may increase her average spending in the product category on each purchase visit.

The basic model in Section 2 extends SMC to capture situations where arrival rate depends on satisfaction. We derive a closed-form formula for determining the total expected dollar spending and characterize the optimal level of customer satisfaction. Section 3 extends the basic model to capture the effects of satisfaction on death rate and average expenditure. Furthermore, we extend the basic model to allow satisfaction in the current visit to depend on satisfaction in the previous visit. We show analytically that most qualitative insights remain unchanged with these extensions. Section 4 conducts a comprehensive numerical analysis to illustrate the main theoretical results for the general case. Section 5 concludes and suggests future research directions.

This paper makes three contributions. First, we extend the SMC framework to include satisfaction in predicting customer lifetime value. We derive a closed-form formula to predict the total expected dollar spending from a customer base. This formula allows the firm to predict lifetime value based on customer satisfaction, a key indicator of customer health. Second, we show that the total number of purchases is convex and increasing in customer satisfaction. In addition, we find that one will systematically under-estimate the total expected dollar spending if one ignores the nonstationarity in customer arrivals and departures due to the variation in customer satisfaction. Third, the analytical framework allows the firm to actively manage its productive processes to in-
crease customer lifetime value. We prove that if the cost is sufficiently convex, a firm will over-invest in productive processes when it fails to account for the variation in customer satisfaction.

2 The Basic Model

We consider a firm that offers a homogeneous product or service to a group of $N$ customers. The production process is inherently stochastic so that a customer is satisfied with probability $p$, and dissatisfied with probability $(1 - p)$ at each purchase encounter.\(^2\) We assume that the production process does not discriminate customers and that it is independent of previous purchase encounters so that customer satisfaction can be modeled as independent and identically distributed binomial trials.

The arrival of customers is assumed to follow a Poisson process whose rate changes with the outcome of each purchase encounter and depends on who the customer is.\(^3\) For customer $i$, her next purchase comes with arrival rate $\lambda_i D$ if she is dissatisfied, and $\lambda_i S$ if she is satisfied.\(^4\) Customers buy more when they are satisfied than when dissatisfied so we assume $\lambda_i S > \lambda_i D$ for all $i$. Our model can accommodate any parameter values.

We assume a Markovian property that the arrival rate depends only on the most recent purchase encounter. This assumption is reasonable if the customer exhibits a kind of “recency effect” and reacts strongly to the most recent purchase encounter. In Section 3.3, we will allow a customer’s current satisfaction to also depend on the previous purchase encounter.\(^5\) When a customer defects, she is “dead”; otherwise, the customer is “alive”. Clearly, a customer’s satisfaction may affect her propensity to defect. For ease of exposition, in this section we assume that all customers have a

\(^2\)Our model may be extended to investigate more than two levels of satisfaction (e.g., three levels such as below expectation, met expectation, above expectation). For ease of exposition, we restrict ourselves to dichotomous levels such as happy versus unhappy, above expectation versus below expectation, satisfied versus dissatisfied, and so on.

\(^3\)Like Schmittlein, Morrison, and Colombo (1987), we assume exponential inter-purchase times for its analytical tractability. The exponential assumption (i.e., purchase events are Poisson arrivals) has been applied extensively in the marketing literature because of its parsimony and empirical performance (see for example Fader, Hardie, and Huang 2004, Fader, Hardie, and Zeithammer 2003, Morrison and Schmittlein 1981). The exponential assumption appears to work well for some product categories (e.g., frequently purchased consumer goods) (Schmittlein, Morrison, and Colombo 1987). It should be noted that we do not have a stationary Poisson process. We allow purchase and death rates to be dependent on customer satisfaction. Thus, they are nonstationary. In fact, our model shows customer satisfaction can be an important source of nonstationarity in customer value analysis.

\(^4\)Anderson, Fitzsimons, and Simester (2004) empirically show that this difference in arrival rates can be significant in catalog purchases.

\(^5\)We do not consider the related questions of sizing of customer segment (i.e., which customers to serve) and optimal contact frequency (e.g., number of catalogs to send). See Elsner et al. (2004) for a nice model and application.
common defection rate of $\mu$. In Section 3.2, we relax this assumption and let the defection rate vary by customer as well as satisfaction level.

On each purchase encounter, a customer spends a random dollar amount that is independent of purchase outcome (i.e., whether she is satisfied or dissatisfied). The dollar spending follows a general random distribution with expectation $\bar{Q}$. This assumption is reasonable for necessity product markets (e.g., hospital visits) where spending is mainly driven by needs. In Section 3.1, we relax this assumption to allow it to be contingent on purchase outcome in order to capture some discretionary product markets (e.g., restaurants) where customers may modify spending based on service outcome.

We are interested in addressing the following three managerial questions: (1) What is the probability of each customer being “alive” at time $T$?; (2) What is the total dollar spending from the customer base during $(0, T]$?; (3) Given a cost of providing customer satisfaction, what is the optimal customer satisfaction probability $p^*$ that maximizes total profit or lifetime value of the customer base?

We will address these questions one by one.\(^6\) We first derive the probability of a customer being alive at time $T$. The death rate is a fixed $\mu$, so the “departure time” for each customer has an exponential distribution with rate $\mu$. Therefore,

$$\Pr[\text{A customer is alive at time } T] = e^{-\mu T}. \tag{1}$$

Since all customers have the same death rate $\mu$, we can expect $e^{-\mu T}$ proportion of the customer base to remain alive by time $T$.

### 2.1 Total Expected Dollar Spending During $(0, T]$

Because the customers purchase more frequently when they are satisfied, a customer’s total expected dollar spending during $(0, T]$ depends on whether she is satisfied or dissatisfied at time $t = 0$.

Define $\gamma_i = p\lambda_i D + (1-p)\lambda_i S, \forall i$. If customer $i$ is dissatisfied at time 0, her total expected dollar spending during $(0, T]$ is:

$$r_{iD} = Q \left[ \frac{\lambda_i D \lambda_i S \gamma_i \mu}{\gamma_i \mu} \left(1 - e^{-\mu T}\right) - \frac{p\lambda_i D (\lambda_i S - \lambda_i D)}{\gamma_i (\gamma_i + \mu)} \left(1 - e^{-(\gamma_i + \mu) T}\right) \right]. \tag{2}$$

\(^6\)Proofs of all the results in this paper are available from the authors upon request.
If customer $i$ is satisfied at time 0, her total expected dollar spending during $(0, T]$ is:

$$r_{iS} = Q \left[ \frac{\lambda_i D \lambda_i S}{\gamma_i \mu} (1 - e^{-\mu T}) + \frac{(1-p)\lambda_i S (\lambda_i S - \lambda_i D)}{\gamma_i (\gamma_i + \mu)} (1 - e^{-(\gamma_i + \mu) T}) \right]. \quad (3)$$

Note $r_{iS} > r_{iD}$ so that customer spends more when she is initially happy. Let $\Delta r_i = r_{iS} - r_{iD}$. It can be easily shown that $\Delta r_i$ increases with the differences in arrival rates ($\lambda_i S - \lambda_i D$), $\forall i$: This difference is higher for more sensitive customers. The difference $\Delta r_i$ decreases with the death rate $\mu$: Satisfaction is more important in markets where customers have a long expected life.

Let $R_D = \sum_{i=1}^{N} r_{iD}$ and $R_S = \sum_{i=1}^{N} r_{iS}$. Then the total expected dollar spending from the entire customer base is $R = pR_S + (1 - p)R_D$. Proposition 1 provides a closed-form expression for predicting the total expected spending:

**Proposition 1** The total expected dollar spending during $(0,T]$ from the customer base is predicted to be:

$$R = Q \sum_{i=1}^{N} \left[ \frac{\lambda_i D \lambda_i S}{\gamma_i \mu} (1 - e^{-\mu T}) + \frac{p(1-p)(\lambda_i S - \lambda_i D)^2}{\gamma_i (\gamma_i + \mu)} (1 - e^{-(\gamma_i + \mu) T}) \right]. \quad (4)$$

Note that the above closed-form expression reduces to the SMC formula when $p = 1$ or $\lambda_i S = \lambda_i D, \forall i$. Hence, we contribute to this stream of literature by generalizing the SMC model to incorporate customer satisfaction. To the best of our knowledge, it is also the first to incorporate customer satisfaction in a stochastic customer purchase model. The formula allows the benefits of customer satisfaction to be quantified in terms of total dollar spending so that a firm can weigh the benefits of customer satisfaction against the costs of providing it.

Since the purchase arrival rate of each customer depends on the outcome of the previous purchase encounter, a generic inter-arrival time for customer $i$ is a hyper-exponential random variable: with probability $(1-p)$ it is exponential with rate $\lambda_i D$; and with probability $p$ it is exponential with rate $\lambda_i S$. In the rest of the paper, we will use the term SMC-$p$ model to refer to the model which ignores the probability of adequate service $p$, and estimates the dollar spending for each customer by using the SMC formula with the average (aggregate) customer arrival rate. The aggregate arrival rate of customer $i$ in the SMC-$p$ model, $\lambda_i^c$, should give an average inter-purchase time equivalent to that of the hyper-exponential random variable:

$$\frac{1}{\lambda_i^c} = \frac{1-p}{\lambda_i D} + \frac{p}{\lambda_i S} \quad \Rightarrow \quad \lambda_i^c = \frac{\lambda_i D \lambda_i S}{p \lambda_i D + (1-p) \lambda_i S} = \frac{\lambda_i D \lambda_i S}{\gamma_i}, \quad \forall i. \quad (5)$$
Note that even though the SMC-p model does not directly model customer satisfaction, it does account for it indirectly through its parameter $\lambda_i^e$. The SMC formula suggests that the total dollar spending for customer $i$ is:

$$R^e = \bar{Q} \sum_{i=1}^{N} \frac{\lambda_i^e}{\mu} \left( 1 - e^{-\mu T} \right). \quad (6)$$

The importance of our model’s revenue prediction, equations (2)–(4), can be assessed by a comparison with that of the SMC-p model, equation (6). Equations (2)–(4) and (6) imply the following important revenue equalities:

$$R_D = R^e - \eta_D, \quad R_S = R^e + \eta_S, \quad and \quad R = R^e + \eta,$$

where $\eta_D$, $\eta_S$ and $\eta$ are strictly positive, or equivalently, $R_D < R^e$, $R_S > R^e$ and $R > R^e$.\(^7\)

The equations regarding $R_D$ and $R_S$ are quite intuitive. The first suggests that when the customer base is dissatisfied, their dollar spending is less than that given by the SMC-p model. The second implies that when the customer base is satisfied, their dollar spending is more than that given by the SMC-p model. Both results simply capture the fact that customers buy more when they are satisfied.

The revenue equation regarding $R$ states a surprising result: The total expected dollar spending from the customer base is higher than that given by the SMC-p model, and the difference is represented by $\eta$. We state this important result formally below.

**Proposition 2** If the firm ignores the probability of adequate service, $p$, and uses the SMC-p model to predict the total expected dollar spending, it under-estimates it (i.e., $R > R^e$). This systematic bias $\eta$ is given by:

$$\eta = \bar{Q} \sum_{i=1}^{N} \left[ \frac{p(1-p)(\lambda_i S - \lambda_i D)^2}{\gamma_i (\gamma_i + \mu)} \right] \left( 1 - e^{-(\gamma_i + \mu) T} \right). \quad (7)$$

Several points are worth noting. First, when $p = 0$ (i.e., the customer is always dissatisfied), $p = 1$, (i.e., the customer is always satisfied) or $\lambda_i S = \lambda_i D, \forall i$ (i.e., customer arrival rates are not affected by satisfaction), the bias vanishes. That is, our model and the SMC-p model give the same prediction. Second, the bias increases in the total number of customers ($N$) and increases linearly in the average dollar spent ($\bar{Q}$) per trip. Third, the bias increases in a quadratic manner in the

\(^7\)The expression of $\eta$ is given in Proposition 2, and $\eta_D$ and $\eta_S$ are given by:

$$\eta_D = \bar{Q} \sum_{i=1}^{N} \frac{p\lambda_i D (\lambda_i S - \lambda_i D)}{\gamma_i (\gamma_i + \mu)} \left( 1 - e^{-(\gamma_i + \mu) T} \right), \quad \eta_S = \bar{Q} \sum_{i=1}^{N} \frac{(1-p)\lambda_i S (\lambda_i S - \lambda_i D)}{\gamma_i (\gamma_i + \mu)} \left( 1 - e^{-(\gamma_i + \mu) T} \right).$$
incremental purchase rate from satisfaction, i.e., $\lambda_{iS} - \lambda_{iD}, \forall i$. This result implies that the bias is more dramatic in product or service markets where customers are more sensitive to service quality. Fourth, the bias is larger when customers have a longer expected life (i.e., a low death rate, $\mu$).

From Proposition 1, one can verify that the total expected dollar spending as a function of the probability of adequate service $p$ is increasing. The proposition below establishes that it has an increasing return in $p$.

**Proposition 3** *The total expected dollar spending during $(0,T]$ from the customer base is convex in the probability of adequate service. That is, $\frac{d^2R}{dp^2} > 0$.*

This is an important and surprising result. One would have expected customer satisfaction to have a diminishing return. The result provides a formal justification of why many firms invest relentlessly in customer satisfaction. Our result suggests that this is optimal as long as the costs are not “too convex” in $p$. We shall show below (see Proposition 4) that it can be seriously flawed if the costs are sufficiently convex (which is likely in practice).

### 2.2 Optimal Investment in Customer Satisfaction

Proposition 3 suggests that the total expected dollar spending as a function of the probability of adequate service $p$ is convex. To determine the optimal service, one must know the shape of the cost function. In general, we expect the total cost to be increasing in the probability of adequate service ($p$) and the total expected number of customer encounters ($\Lambda$). A survey of several call center outsourcing firms suggests the following two-part tariff pricing structure:

$$TC(p) = F(p) + c(p) \cdot \Lambda.$$  

For analytical tractability, we assume a constant marginal cost per purchase encounter and set $c(p) = c$. From Proposition 1, we have $R = \bar{Q} \Lambda$. Thus, the profit function is as follows:

$$\pi = R - TC = (\bar{Q} - c) \cdot \Lambda - F(p) \overset{\text{def}}{=} R_m - F(p). \quad (8)$$

It is clear that the modified revenue function, $R_m$, is convex in $p$ (just as $R$ is). We consider two separate cases of $F(p)$. First, $F(p)$ is concave (possibly linear) in $p$. As the company invests more in customer satisfaction, it receives an increasing marginal revenue but incurs a constant or decreasing marginal cost. Therefore, the better the service, the higher the profit. It makes sense for companies
to seek to achieve a perfect customer satisfaction of 100%. Second, $F(p)$ is strictly convex in $p$. Here, it costs more to improve each additional incremental level of customer satisfaction. More often than not, this is the case we face in reality. It is not immediately clear what the shape of the profit function looks like as a function of $p$. Intuitively, when the cost function is “less convex” than the revenue function (i.e., both marginal revenue and marginal cost are increasing in $p$, but the former outpaces the latter), it again makes sense to pursue a perfect customer satisfaction. If the cost function is “more convex” than the revenue function, however, the profit function will eventually decrease as $p$ becomes higher and higher. This means that an interior optimal point exists for $p$. That is, it is best to invest in customer satisfaction up to a level less than 100%.

We now analyze the third case (convex cost function) in detail. Examples of convex cost function in $p$ abound in service systems:

- In an $M/M/c$ queueing service system (to conform to conventional queueing notation, we reuse the notation $\mu$ to denote the service rate), if the cost is directly proportional to either individual $\mu$ or the number of servers $c$, and service quality is measured as the probability of not having to wait in queue at all, $p_0$, or the average waiting time in the system, $W_q$, then the cost function is convex (for details, see Kleinrock 1975).

- In a $M/M/c/K$ finite-waiting-space queueing service system, if the service quality is measured by loss rate and the cost function is directly proportional to either individual $\mu$ or the number of servers $c$, then the cost function is convex in service quality.

- In the well-known single-period newsboy inventory model, demand is uncertain with a given CDF $F(\cdot)$. The service level is usually defined as the probability that the customer demand is satisfied. Therefore, if the firm carries $x$ units of inventory, the service level it provides is $F(x)$. To achieve such service level, the firm incurs an inventory holding cost of $hx$ where $h$ is the inventory holding cost per unit inventory per unit time. Clearly, if the service level is equivalent to service quality $p$, and the inventory holding cost is the investment necessary to achieve such service quality, then the cost function is $hF^{-1}(p)$. As long as $F^{-1}$ is convex in $p$ (or, $F$ is concave in $x$), the cost function is convex. Any distribution that has a monotonically non-increasing PDF satisfies such a condition. For example, exponential distribution, certain
Weibull and Gamma distributions, and uniform distribution all have monotonically non-increasing PDF.

To obtain insights, we assume a straightforward convex function that is quadratic: \( F(p) = a + bp^2 \). Here, parameter \( a \) represents the cost necessary to achieve the lowest service level, and \( b \) represents how fast the cost increases in \( p \). As we stated before, when \( b \) is small such that the cost function is less convex than the revenue function, then the profit is convex, and the optimal service level is achieved at either \( p = 0 \) or \( p = 1 \). The interesting case is when the cost function is more convex than the revenue function. We analyze this case below. The following proposition states that in most practical cases, companies over-invest in service when they do not explicitly account for the nonstationarity in customer arrivals and departures due to variation in customer satisfaction. Similar to equation (8), we define the SMC-\( p \) model profit to be \( \pi^e = R^e - TC(p) = R^e_m - F(p) \), where

\[
\pi^e = (\bar{Q} - c) \sum_{i=1}^N \left[ \frac{\lambda^e_i}{\mu} (1 - e^{-\mu T}) \right].
\]

Just as \( R = R^e + \eta \), we also have \( R_m = R^e_m + \eta_m \) and \( \pi = \pi^e + \eta_m \), where

\[
\eta_m = (\bar{Q} - c) \sum_{i=1}^N \left[ \frac{p(1 - p)(\lambda_iS - \lambda_iD)^2}{\gamma_i(\gamma_i + \mu)} (1 - e^{-(\gamma_i + \mu)T}) \right].
\]

**Proposition 4**

(i) There exists a \( \bar{p} \in (0,1) \) such that to the right of \( \bar{p} \), \( \eta_m \) is decreasing in \( p \).

(ii) Assume

\[
b > (\bar{Q} - c) \left( \frac{1 - e^{-\mu T}}{\mu} \right) \max \left\{ \sum_{i=1}^N \frac{\lambda_iS(\lambda_iS - \lambda_iD)^2}{\lambda_i^2D}, \sum_{i=1}^N \frac{\lambda_iS(\lambda_iS - \lambda_iD)^2}{2\lambda_iD} \right\}.
\]

Let \( p^* \) be the maximizer of \( \pi \), and \( p^e* \) the maximizer of \( \pi^e \). Then \( p^e* \geq \bar{p} \Rightarrow p^e* \geq p^* \).

Proposition 4 states that when the SMC-\( p \) model optimally invests in high service level (\( p^e* \geq \bar{p} \)), it results in over-investment (\( p^e* \geq p^* \)). In practice, when firms pursue a high customer satisfaction strategy, they tend to over-invest if they use the SMC-\( p \) model.

This result is not obvious. Since the SMC-\( p \) model under-estimates total dollar spending (see Proposition 2), one would expect the same model to prescribe a lower optimal service level. The

\[8\text{Similarly we can show that there exists a } \bar{p} \text{ such that } p^e* \leq \bar{p} \Rightarrow p^e* \leq p^*. \text{ But this is of less importance (because customer satisfaction is often high in practice) so we choose to leave it out.} \]
under-estimation is measured by \( \eta_m \). However, it is not the value of \( \eta_m \), but its first derivative \( \eta'_m \), that matters in determining the optimal customer satisfaction. To see this, we note that at the optimal investment level, marginal cost equals marginal revenue. For both models, marginal cost is identical; the difference is in the marginal revenue. Since \( \eta_m = \pi - \pi^e \), the derivative of \( \eta_m \) plays an important role. From Proposition 4 we know that to the right of \( \bar{p} \), \( \eta'_m \) is negative. Therefore, when \( p^e^* \) is to the right of \( \bar{p} \), the additional negative marginal revenue \( \eta'_m \) makes the total marginal revenue smaller than the marginal cost at \( p^e^* \). Therefore, the firm should choose a lower customer satisfaction when using our model (accounting explicitly for nonstationarity in customer arrivals and departures caused by variation in customer satisfaction).

In the proof of the proposition, we show that as \( \mu \) gets smaller, the threshold \( \bar{p} \) also gets smaller. This yields an interesting implication: If the customers are more loyal in general, it is more likely for the firm to over-invest in customer satisfaction if they use the SMC-\( p \) model, leading to suboptimal profits. Therefore, the importance of capturing variation in customer satisfaction cannot be over-emphasized when a firm has a high customer loyalty.

3 Model Extensions

In the previous section, we present a basic model that explicitly accounts for the impact of customer satisfaction on purchase arrival. We have kept the model simple, and consequently we are able to derive some clear insights. In this section, we show how the main results are robust to three important model extensions. As we discussed above, the probability of adequate service impacts customer behavior in two other ways: (1) Higher probability of adequate service increases average expenditure on each visit; (2) Higher probability of adequate service decreases defection rate. We extend our basic model to capture these behavioral mechanisms in Sections 3.1 and 3.2. In Section 3.3, we further extend the model to allow a customer’s satisfaction probability to also depend on her previous purchase outcome.

3.1 Contingent Spending Amount

We consider the case where the amount spent on each purchase visit depends on whether the customer receives adequate service. Specifically, when a customer is satisfied, she spends a random amount with an average of \( Q_S \); and when a customer is dissatisfied, she spends a random amount
with an average of $Q_D$. It is natural to have $Q_S \geq Q_D$.

Since the death rate remains at $\mu$, the probability of a customer being alive at time $T$ is $\Pr\{\text{A customer alive at time } T\} = e^{-\mu T}$. That is, the total expected number of customers at time $T$ remains unchanged at $N \cdot e^{-\mu T}$.

Since customer satisfaction at each visit is independent and identically distributed, the number of satisfactory visits is $p$ fraction of the total visits and the number of dissatisfactory visits is $(1 - p)$ fraction of the total visits. Therefore, the total amount a customer is expected to spend is simply $Q_S$ times the number of satisfactory visits, plus $Q_D$ times the number of dissatisfactory visits. Consequently the total expected dollar spending during $(0,T]$ from the customer base is given by this:

**Proposition 5** The total expected dollar spending during $(0,T]$ from the customer base is predicted to be:

$$R = [pQ_S + (1 - p)Q_D] \sum_{i=1}^{N} \left[ \frac{\lambda_i D \lambda_i S}{\gamma_i \mu} \left(1 - e^{-\mu T}\right) + \frac{p(1 - p)(\lambda_i S - \lambda_i D)^2}{\gamma_i (\gamma_i + \mu)} \left(1 - e^{-(\gamma_i + \mu) T}\right) \right]. \quad (12)$$

We show that the SMC-$p$ model under-estimates the above expression by an amount given by:

$$\eta = [pQ_S + (1 - p)Q_D] \sum_{i=1}^{N} \left[ \frac{p(1 - p)(\lambda_i S - \lambda_i D)^2}{\gamma_i (\gamma_i + \mu)} \left(1 - e^{-(\gamma_i + \mu) T}\right) \right]. \quad (13)$$

The revised revenue function is convex in $p$. Also, the SMC-$p$ model still leads to an over-investment in customer satisfaction with this model extension. Hence, we conclude that all the main results in Section 2 generalize to this more realistic setting. It shows that our main results are robust to some of the key assumptions made.

### 3.2 Contingent Death Rate

We now allow the death rate $\mu$ to vary according to whether the customer receives adequate service. For customer $i$, her defection occurs with a rate of $\mu_i D$ if she is dissatisfied, and with a rate of $\mu_i S$ if she is satisfied. As we shall see below, this extension has significantly increased the complexity of the analysis.

Let $PA_i$ represent the probability that customer $i$ is alive at time $T$. Because the following proposition applies to all the customers, we suppress the subscript $i$ to simplify exposition.

Let $\beta_1$ and $\beta_2$ be the two roots of the quadratic equation:

$$0 = \beta^2 + [p\lambda_D + (1 - p)\lambda_S + \mu_D + \mu_S] \beta + [\mu_S \mu_D + (1 - p)\lambda_S \mu_D + p\lambda_D \mu_S].$$
The probability that a customer is alive at time $t$ is given the following lemma:

**Lemma 1**

$$PA = A e^{\beta_1 T} + B e^{\beta_2 T},$$

(14)

where

$$A = \frac{p(\beta_1 + \lambda_D + \mu_D) \left[ (1-p)\lambda_S(\mu_S - \mu_D) + \beta_2 \mu_S + \mu_S^2 \right]}{p(1-p)\lambda_D\lambda_S \beta_1 - \beta_1 [\beta_1 + \mu_D + p\lambda_D][\beta_2 + \mu_S + (1-p)\lambda_S]},$$

$$B = \frac{(1-p) \left[ \beta_1 \mu_D + \mu_D^2 + p\lambda_D (\mu_D - \mu_S) \right] (\beta_2 + \lambda_S + \mu_S)}{p(1-p)\lambda_D\lambda_S \beta_2 - \beta_2 [\beta_1 + \mu_D + p\lambda_D][\beta_2 + \mu_S + (1-p)\lambda_S]}.$$

Note that the above expression is more complex than the one given in equation (1) where the death rate is independent of customer satisfaction. Note also that the probability of being alive for each customer is a superposition of two exponential terms. It can be shown easily that when $\lambda_S = \lambda_D$ or $\mu_S = \mu_D$, equation (14) reduces to equation (1). The expected number of customers remaining at the end of $T$ is $\sum_{i=1}^{N} PA_i$.

**Proposition 6** The expected revenue from a customer during $[0,T]$ is

$$r = C \left( 1 - e^{\beta_1 T} \right) + D \left( 1 - e^{\beta_2 T} \right),$$

(15)

where

$$C = \bar{Q} \frac{p\lambda_S (\beta_1 + \lambda_D + \mu_D) \left[ \beta_2 + \mu_S + (1-p)(\lambda_S - \lambda_D) \right]}{p(1-p)\lambda_D\lambda_S \beta_1 - \beta_1 [\beta_1 + \mu_D + p\lambda_D][\beta_2 + \mu_S + (1-p)\lambda_S]},$$

$$D = \bar{Q} \frac{(1-p)\lambda_D (\beta_2 + \lambda_S + \mu_S) [\beta_1 + \mu_D + p(\lambda_D - \lambda_S)]}{p(1-p)\lambda_D\lambda_S \beta_2 - \beta_2 [\beta_1 + \mu_D + p\lambda_D][\beta_2 + \mu_S + (1-p)\lambda_S]}.$$

The total expected dollar spending from the customer base during $[0,T]$ is $R = \sum_{i=1}^{N} r_i$. Even though the expression is much more complex, we can again show that it is convex in $p$.

The new revenue function is too complex for us to prove that the corresponding SMC-$p$ model still leads to a systematic downward bias in terms of revenue estimation and an over-investment in customer satisfaction in this new setting. However, an extensive numerical analysis in Section 4 suggests that both results do carry through to this new setting as well.

### 3.3 Hidden Markov Model of Customer Satisfaction

In our basic model, we assume that for any customer, the outcomes of her purchase encounters are independent of each other. This makes sense if customer satisfaction is primarily driven by factors determined by the service provider, such as the stocking level in the store and the staffing level on
that day. There exist scenarios in which the customer’s satisfaction on a particular visit depends on the result of the previous visit. This dependence could either be negative or positive. For example, if a customer was dissatisfied last time, her service expectation for the forthcoming visit may be lower as a consequence and hence she is more likely to feel satisfied. On the other hand, one can also argue that if the customer was satisfied last time, she is likely to be more positive in assessing the current service encounter.

In this section, we use a Hidden Markov model (HMM) to model this dependency of customer satisfaction over time. Our extension is similar to that in Netzer, Lattin, and Srinivasan (2005). Specifically, we use a two-state Markov chain to model the transition of the probability of satisfaction. Let $p_1$ be the probability of satisfaction if the customer was dissatisfied last time, and let $p_2$ be the probability of satisfaction if the customer was satisfied last time. Then the transition probability of satisfaction is

$$
\begin{pmatrix}
1 - p_1 & p_1 \\
1 - p_2 & p_2
\end{pmatrix}.
$$

Given this transition probability matrix, the steady-state probabilities (or long-run average) of a customer being dissatisfied and satisfied are $\frac{1 - p_2}{1 - p_2 + p_1}$ and $\frac{p_1}{1 - p_2 + p_1}$ respectively. If one focuses on the “steady-state” behavior, one can use $p = \frac{p_1}{1 - p_2 + p_1}$ in our basic model to provide a forecast for the expected revenue.

**Proposition 7** Let $p = \frac{p_1}{1 - p_2 + p_1}$. Then the total expected dollar spending during $(0, T]$ from the customer base is predicted to be:

$$R = (1 - p_2 + p_1)Q \sum_{i=1}^{N} \left[ \frac{\lambda_i D \lambda_i S}{\gamma_i \mu} (1 - e^{-\mu T}) + \frac{p(1 - p)(\lambda_i S - \lambda_i D)^2}{\gamma_i (\gamma_i + \mu)} (1 - e^{-(\gamma_i + \mu)T}) \right]. \quad (16)$$

It is interesting to compare this revenue function with (4) in Proposition 1: They are different only by a multiplicative factor of $(1 - p_2 + p_1)$. When a company does not explicitly model the HMM dynamics of satisfaction, but instead uses the steady-state customer satisfaction as $p$ in our basic model, the revenue prediction will be off by a factor of $(1 - p_2 + p_1)$. In the case of positive correlation, $p_1 < p_2$, the basic model, using the steady-state $p$, over-predicts revenue. In the case of negative correlation, $p_1 > p_2$, the basic model, using the steady-state $p$, over-predicts revenue. Clearly, when there is no dependence, we have $p_1 = p_2$ and the predictions by both models agree.
4 Numerical Study

The general model consists of two different arrival and death rates for a consumer, one when the customer is satisfied and one when she is not. As discussed in Sections 2 and 3, a failure to account for the nonstationarity in customer arrivals and/or departures due to variation in customer satisfaction (i.e., using the SMC-\(p\) model) can lead to a systematic downward bias in estimating the total expected number of purchases and hence customer lifetime value. In addition, the SMC-\(p\) model can lead to an over-investment in customer satisfaction and suboptimal profits.

To illustrate these points more clearly, we present a systematic numerical analysis based on a two-segment market (heavy versus light user segment) in which we compare the SMC-\(p\) model with the general model. For “equivalent” arrival rates in the SMC-\(p\) model, we follow equation (5). In order to properly compare the two models, we need to derive the “equivalent” death rates as well. We do this by equating (1) and (14) for each segment. This numerical study allows us to quantify the nature and magnitude of potential biases.

We choose the model parameters such that satisfied customers are twice as quickly to return and half as quickly to defect. The light user segment has \(\lambda_{LS} = 1.2\), \(\lambda_{LD} = 0.6\), \(\mu_{LS} = 0.3\), and \(\mu_{LD} = 0.6\) and the heavy user segment has \(\lambda_{HS} = 2.0\), \(\lambda_{HD} = 1.0\), \(\mu_{HS} = 0.5\), and \(\mu_{HD} = 1.0\). These values are consistent with previous empirical estimates (e.g., Morrison and Schmittlein 1981, Schmittlein, Morrison and Colombo 1987). Without loss of generality, we normalize \(T\) to 1.0. The customer base size (\(N\)) is set to 1000.

Based on the above parameters (and the probability of adequate service \(p\) and the heavy user segment size \(\delta\)), we simulate the purchases for each of the 1000 customers. We compare the performance of our model and that of the SMC-\(p\) model (superscript \(e\)) in predicting expected revenue based on Proposition 6 and (6) respectively. We use the relative difference in the mean absolute deviations (MAD) between the two models, i.e., \(\frac{\text{MAD}^\ast - \text{MAD}}{\text{MAD}}\). Table 1 shows the model prediction errors across a wide range of \(p\) (0.2, 0.5, 0.8) and \(\delta\) (0.2, 0.5, 0.8). It shows that our model dominates the SMC-\(p\) model based on the relative error measure. It also shows that the relative error measure can be as high as 31% and appears to be highest when \(p = 0.5\).

We also consider the relative magnitude in the total expected dollar spending between the SMC-\(p\) model and our model, i.e., \(\frac{R - R^e}{R} = \frac{\eta}{R}\). If this difference tends to be small, we have evidence
that the SMC-p model is robust to misspecifications involving customer satisfaction. For this exercise, we normalize \( \bar{Q} \) to 1.0. The bar chart in Figure 1 shows the importance of accounting for nonstationarity due to variation in customer satisfaction. It shows the positive revenue bias at three levels of probability of adequate service \( p = 0.2, 0.5, 0.8 \). In this example, similar to the relative difference in the mean absolute deviations, the revenue bias appears to be highest when \( p = 0.5 \). This result reinforces the analytical results that if the firm uses the SMC-p model to predict the total expected dollar spending, there will be a significant downward bias.

**Insert Figure 1 about here**

We observe a relatively small variation in the revenue bias across different values of \( \delta \) under the same service quality \( p \). When \( p \) is 0.8, for instance, the bias \( \frac{\eta}{R} \) is 5.54\% (\( \delta = 0.2 \)), 5.09\% (\( \delta = 0.5 \)), and 5.59\% (\( \delta = 0.8 \)). Hence, we conclude that the revenue bias is more sensitive to the service quality \( p \) than the segment size \( \delta \).

We now investigate the degree of over-investment in customer satisfaction and its corresponding suboptimal profits. To this end, we set a constant marginal cost per purchase encounter (\( c \)) equal to 0.3 and the cost necessary to achieve the lowest customer satisfaction (\( a \)) equal to 100. In order to choose the cost parameter \( b \) which represents how fast the cost increases in \( p \), we check whether the cost is sufficiently convex in order to obtain realistic scenarios. We choose three levels of \( b \): 400, 425, 450.

Figure 2 shows the difference in the optimal levels of customer satisfaction between the SMC-p model and our model, i.e., \( (p^e - p^*) \). We observe, as expected, that the optimal customer satisfaction under the SMC-p model (\( p^e \)) is always greater than that under our model (\( p^* \)). In particular, when \( \delta \) is equal to 0.5, the difference in the optimal levels of customer satisfaction between the two models is 22\%, 30\%, 37\% for the three different levels of cost parameter \( b \) (400, 425, 450), respectively. As shown in Figure 2, the cost parameter \( b \) plays an important role in deciding the optimal customer satisfaction.

Figure 3 translates the investment bias associated with the SMC-p model in Figure 2 into implications on profit. The figure shows that when \( \delta \) is 0.5, the firm can increase its profit by 2.12\%, 4.88\%, 8.40\% if it optimally provides a lower level of customer satisfaction based on our model under three different levels of \( b \) (400, 425, 450). When \( \delta \) is close to 1.0, similar to Figure 2,
the bias vanishes and the two models give the same prediction.

**Insert Figures 2 and 3 about here**

We also investigate the impact of changes in the relative magnitudes of arrival and death rates on the three measures of our interest: \( \frac{a}{b} \), \((p^e^* - p^s^*)\), and \( \frac{\pi(p^e^*) - \pi(p^s^*)}{\pi(p^s^*)} \). In the numerical analysis described below, \( \delta \) and \( b \) are set at 0.5 and 400, respectively.

We first vary the rate of \( \frac{\lambda yD}{\lambda yS} \) for \( y = H, L \) from 0.4 to 0.6 (note that the base case shown in Figures 1–3 is set at 0.5 for each segment). Table 2 shows the sensitivity analysis results. We find that as consumer purchases are less influenced by satisfaction (i.e., the arrival rates between satisfied and dissatisfied customers are closer in magnitude), the bias \( \frac{a}{b} \) gets smaller, which is as expected. However, the difference in the optimal levels of customer satisfaction \((p^e^* - p^s^*)\) increases which results in a significant profit loss using the SMC-\( p \) model. Note that when \( \frac{\lambda yH}{\lambda yS} = \frac{\lambda yD}{\lambda yS} = 0.6 \), for instance, the bias in profit, i.e., \( \frac{\pi(p^e^*) - \pi(p^s^*)}{\pi(p^s^*)} \), is 9.37%.

We next vary the rate of \( \frac{\mu xS}{\mu xD} \) where \( x = S, D \) from 0.5 to 0.7 (note that the base case shown in Figures 1–3 is set at 0.6 for satisfied and dissatisfied customers). Table 3 shows the sensitivity analysis results. The highest bias in profit is 11.00% and occurs when \( \frac{\mu xS}{\mu xS} = \frac{\mu xD}{\mu xS} = 0.6 \).

**Insert Tables 2 and 3 about here**

Similarly, we vary the rate of \( \frac{\mu yS}{\mu yD} \) for \( y = H, L \) from 0.4 to 0.6 in Table 4 and the rate of \( \frac{\mu xS}{\mu xD} \) for \( x = S, D \) from 0.4 to 0.6 in Table 5. Tables 4 and 5 show the sensitivity analysis results. The bias in profits is smaller when compared with the above results with the arrival rates. The highest bias in profit is 5.24% in Table 4 and is 3.26% in Table 5.

**Insert Tables 4 and 5 about here**

The difference in the magnitude of the profit bias estimates suggests that, in the range of the model parameters we study in this section accounting for the dependence on satisfaction is more critical for the arrival rates than for the death rates.

Taken together, we find the magnitudes of a variety of bias estimates are significant enough to warrant attention from marketing managers to their customers’ satisfaction level in order to compete successfully. The analysis also hints at some tradeoffs that managers must make between
the desired customer spending (by influencing arrival and death rates) and the costly investment in customer satisfaction.

5 Discussion

In this paper, we present a model that incorporates satisfaction into customer value analysis. By doing so, we integrate the behavioral customer satisfaction and quantitative customer value analysis research streams. This is significant because customer satisfaction is an important, if not the most important, contributor of customer lifetime value. Also, customer lifetime value is inherently tied to repeat purchases and it seems odd to ignore customer satisfaction in estimating lifetime value.

We develop our model by building on the seminal work of Schmittlein et al. (1987) and Schmittlein and Peterson (1994). This generalized model allows the purchase rate to vary with purchase outcome so that better service leads to a higher purchase rate. Like the previous work, we explicitly capture heterogeneity by allowing customers to have different purchase and departure rates. Consequently, the purchase rate changes both across customer population and over time in our model.

We derive a formula for determining the total dollar spending from a customer base over a time period. This formula reveals a surprising and powerful result: Customer lifetime value has an increasing return to scale in the probability of a customer receiving adequate service. This may explain why there is a relentless pursuit for customer satisfaction by many firms. Our formula also suggests a downward bias in revenue prediction if one approximates the mixture Poisson processes by a single aggregate Poisson process (the SMC-\( p \) model). Finally, we examine how the firm should optimally invest in customer satisfaction when the latter can only be achieved via costly productive processes. We show that the SMC-\( p \) model leads to over-investment in customer satisfaction.

To improve the applicability of our results, we extend our model to have satisfaction-dependent expenditure and death rate, and to allow customer satisfaction to be temporally correlated. While these extensions make the formula for the total expected number of purchases more complex, they do not change the qualitative predictions of the formula.

Our model has several managerial implications. First, our model implies that it is crucial to include customer satisfaction into the prediction of total expected purchases from a customer
base. This finding suggests a natural extension of the classical RFM (Recency, Frequency and Monetary value) model to the RFMS (Recency, Frequency, Monetary value, and Satisfaction) model of predicting total purchases. Second, our model yields a formula for quantifying the benefits of customer satisfaction. Firms can now use our formula to weigh the potential benefits against the costs of increasing customer satisfaction. Third, we believe our model can serve as a useful backend engine for customer relationship management since every purchase encounter outcome can be captured and used to modify the expected lifetime value of a customer. In this way, customer lifetime value can be updated dynamically and continuously to provide an accurate estimate of the value of a customer base.

Our model opens up several new research opportunities. First, it will be useful to estimate our model on a field data set. Such estimation will allow us to study how purchase arrival rates differ across the satisfaction categories and provide a direct way to assess the usefulness of our model in field settings. Second, the firm can offer distinct service classes (e.g., premium versus regular) based on lifetime value so that a premium customer receives a better service than a regular customer. It will be fruitful to examine how this kind of discriminating production process will affect optimal investment in customer value. Third, it will be worthwhile to investigate how referrals by happy customers might affect the level of service to offer and the design of referral reward (e.g., Bialogorsky et al. 2001). Finally, our model ignores active competition. It will be interesting to explore how optimal investment in lifetime value changes with active rivalry (e.g., Villas-Boas 2004).

References


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Table 1: Relative Difference in the Mean Absolute Deviations

Table 2: The Impact of Changes in \( \frac{\lambda_{HD}}{\lambda_{LS}} \) on the Bias Estimates

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Table 3: The Impact of Changes in \( \frac{\mu_{HD}}{\mu_{LS}} \) on the Bias Estimates

Table 4: The Impact of Changes in \( \frac{\mu_{LD}}{\mu_{LS}} \) on the Bias Estimates

Table 5: The Impact of Changes in \( \frac{\mu_{LD}}{\mu_{LS}} \) on the Bias Estimates
Figure 1: Revenue Bias

Figure 2: Over-investment in Service Quality

Figure 3: Profit Difference