ON THE PROFITABILITY OF LONG LIFETIME CUSTOMERS: AN EMPIRICAL INVESTIGATION AND IMPLICATIONS FOR MARKETING

by

W. J. REINARTZ*
and
V. KUMAR

2000/04/MKT

* Assistant Professor of Marketing, INSEAD, Boulevard de Constance, 77305 Fontainebleau Cedex, France.

** Marvin Hurley Professor of Business Administration, University of Houston, College of Business Administration, Houston, TX 77204-6283, Texas, USA.

ON THE PROFITABILITY OF LONG LIFETIME CUSTOMERS: AN EMPIRICAL INVESTIGATION AND IMPLICATIONS FOR MARKETING

Werner J. Reinartz

and

V. Kumar

February 1, 2000

Werner J. Reinartz is Assistant Professor of Marketing at INSEAD, Boulevard de Constance, 77305 Fontainebleau Cedex, France, Phone (33)-1-6072-4244, E-mail Werner.reinartz@insead.fr

V. Kumar (VK), Marvin Hurley Professor of Business Administration, Director of Marketing Research Studies and Director, Center for International Business at the University of Houston, College of Business Administration, Department of Marketing, Houston, TX 77204-6283, Phone 713-743-4569, E-mail Vkumar@uh.edu.

The authors thank Ed Blair, Pierre Chandon, Rajesh Chandy, Jagdish Sheth, and David Schmittlein for their helpful comments on an earlier version of the paper. Special thanks are also owed to the catalog retailer for providing the data for this study. Thanks are also due to the participants of the 1999 Marketing Science Conference, Syracuse, NY, for providing valuable feedback on the content of this paper, and the participants of the 1999 John A. Howard Doctoral Dissertation Award Presentation, San Francisco, CA.

ABSTRACT

On the Profitability of Long-lifetime Customers: An Empirical Investigation and Implications for Marketing

The analysis of customer lifetime value is seeing a strongly increasing interest in the marketing community. This interest has been sparked for three reasons. First, firms are interested in customer management processes for which an understanding of the lifetime value concept is a prerequisite. Second, the Marketing Science Institute (1998) has elevated the topic to a capital research priority – which reflects the interest of both, academics and managers. Third, given this high interest of multiple constituencies, empirical evidence is particularly scarce in this domain.

The paper focuses on the managerial aspects of lifetime dynamics with the purpose of contributing to a better understanding of the customer management process. Our study presents a structured framework for identifying the customer lifetime profitability pattern in a non-contractual context. The explicit research objective is to empirically investigate the nature of the association of customer lifetime duration and customer profitability. For this purpose, four commonly stated propositions are tested: 1) customer lifetime duration and customer profitability are strongly related, 2) profits of long life customers increase over time, 3) the cost of serving long-life customers are lower, and 4) long-life customers pay higher prices.

The propositions are tested in the context of the general merchandise direct marketing industry with customer cohort data covering three years. Our results represent evidence that it is a gross oversimplification to simply equate long-life customers with higher profits. In fact, we find a very differentiated picture in that both long- and short life customers can be highly profitable.

The contribution of this research lies in the structured framework for analyzing the customer lifetime profitability pattern. It enables the manager to understand the specific driving forces of customer lifetime profitability. Based on this framework, the firm can identify at any given time the general nature of its customer's lifetime patterns and the individual-specific status along the lifetime continuum. Knowing these two dynamic characteristics is a necessary prerequisite for the manager to engage in true customer management.

Key Words: customer lifetime, loyalty, profit, customer management, relationship marketing, cohort analysis, NBD/Pareto, direct marketing

Are Longer Lifetime Customers Necessarily Profitable Customers? An Empirical Investigation and Implications for Marketing

Introduction

A basic tenet of relationship marketing is that firms benefit more from maintaining long-term customer[1] relationships as compared to short-term customer relationships. Convincing conceptual evidence for this argument has been advanced by a number of authors (Sheth and Parvatiyar 1995; Morgan and Hunt 1994). Likewise, Bendapudi and Berry (1997) argue that the [relationship marketing] payoff to the firm comes only when relationships endure. In a widely quoted HBR article, Reichheld and Sasser (1990) state that,

> *"Customer defections have a surprisingly powerful impact on the bottom line. As a customer's relationship with the company lengthens, profits rise".*

While anecdotal evidence on the lifetime-profitability relationship seems to be plentiful, Reichheld and Teal's (1996) study seems to be the only well-documented empirical evidence to substantiate the hypothesized positive lifetime-profitability relationship. Contrary to the anecdotal evidence that long-life customers are most profitable to the firm, Dowling and Uncles (1997) caution that,

> *"The contention that loyal customers are always more profitable is a gross oversimplification".*

In particular, Dowling and Uncles question the existing contentions that the costs of serving loyal customers are presumably lower, that loyal customers presumably pay higher prices, and that loyal customers presumably spend more with the firm. Obviously, Dowling and Uncles are concerned with the widespread assumption of a clear-cut positive lifetime-profitability relationship and underline the importance of a differentiated analysis. Consequently, there seems to be a need for more rigorous empirical evidence on the lifetime-profitability relationship. In fact, longer lifetime consumers expect value-added relationships in order to buy more products (Mohs 1999). Otherwise, their expenditures can be lower. In other words, short term consumers, may not form any expectations of value-added relationships and therefore, may have no inhibitions in buying products from the vendor.

Lifetime analyses have typically been conducted in contractual settings (Bolton 1998; Li 1995). Examples for this type of relationships are magazine subscriptions and cellular phone

[1] The terms customer, household, and subject will be used interchangeably in this paper.

‘

services. In contractual settings, expected revenues can be forecasted fairly accurately and, given a constant usage of the service, one would expect increasing cumulative profits over the customer’s lifetime. However, in non-contractual settings, the firm has to ensure that the relationship stays alive since the customer typically splits his/her category expenses with several firms (Dwyer, 1997). Examples for non-contractual settings are department store purchases or mail order purchases in the catalog and direct marketing industry.

Catalog marketing involves selling through catalogs mailed to a select list of customers. Consumers can buy just about anything from a catalog. Over 14 billion copies of more than 8,500 different consumer catalogs are mailed out annually, and the average household receives some 50 catalogs a year. In 1995, catalog sales accounted for more than $86 billion in sales, almost 4 percent of total retail sales (Hodges, 1996). For example, each year Lillian Vernon sends out 33 editions of its catalogs with total circulation of 178 million copies to its 20-million person database, selling everything from shoes to decorative lawn birds and monogrammed oven mitts (Direct marketing, 1998). Direct marketing industry is important because in 1998 U.S. sales revenue attributable to direct marketing was estimated to reach close to $1.4 trillion. Approximately 13.2 million workers were employed throughout the US economy as a result of direct marketing activity (DMA, 1999). A differentiated analysis of the lifetime-profitability relationship of customers in the catalog marketing industry can lead to reductions in the huge costs of operation in this industry.

In a non-contractual setting such as the catalog industry, specifically, a customer who starts to purchase in a given time period may then buy repeatedly at some irregular time intervals. If the time intervals are relatively longer, then is it wise for the firm to assume that this customer is likely to purchase again in the near future and if so, to expect him/her to spend a certain amount of dollars? The firm dealing with limited/finite resources, has to decide when it is appropriate to make contact (through mailing of catalogs or other means) with the customer or stop contacting the customers. Given the cost implications, is it worthwhile to chase the dollars from some customers with longer lifetime duration?

Currently, firms use the recency, frequency and monetary value (RFM) framework to determine the allocation of spending to customers in their database. Specifically, firms assign maximum importance to recency then to monetary value and the lowest importance to frequency and subsequently determine the selection of their mailing targets based on the customer’s RFM

‘

score. For an illustration of how this model is actually employed in the industry please refer to Aaker, Kumar, and Day (1998).

Since the firm has to constantly invest in each individual customer, and revenues from customers are much more unstable in a non-contractual setting, the link between firm profits and customer lifetime duration might be weaker. Higher profits from customers with longer lifetime duration can typically come from many sources, such as lower costs of serving them, willingness to pay higher prices, and periodic buying. To what extent each of these sources contributes to profits has not been explored in the literature so far. This study makes an attempt to address these specific issues.

Our research takes place in the context of the catalog and direct marketing industry. Given the contradictory statements and sparse empirical evidence available in the literature, the main objective of this study is a rigorous and differentiated empirical analysis of the lifetime-profitability relationship in a non-contractual context. In order to achieve this objective, we test,

- for the strength of the lifetime duration – profitability relationship,
- whether profits increase over time (lifetime profitability pattern),
- whether the costs of serving long-life customers are actually less, and
- whether long-life customers pay higher prices.

Once we understand what happens in the marketplace then we can address the issue of why it happens that way. As data becomes available across different situations, empirical generalizations can be advanced. This is important especially in the non-contractual setting as the uncertainty for a firm is maximum here. An additional objective is to derive marketing implications from the findings. That is, if distinct lifetime and profitability segments can be delineated, what implications can be derived for a customer management strategy (i.e. tailored communication, early warning indicators, etc.).

The rest of the paper is organized as follows: The next section provides details on the conceptual model used in this study and offers four propositions. Then, in the Research Methodology section, the data used to test the proposed relationships are discussed along with the model for measuring customer lifetime duration which focuses on obtaining estimates of the lifetime duration for each customer. Also, the method used to test the propositions offered in this study are discussed. Next, the empirical findings section assesses the relationship between lifetime duration and profitability and verifies the veracity of all the propositions. The section on Further

‘

Analysis develops the early warning indicators for efficient customer management strategy. Finally, implications for marketing managers are drawn and limitations of the study are presented.

Conceptual Model

Individual customer lifetime profits are modeled as a function of a customer’s lifetime duration, revenue flows over the course of a customer’s lifetime, and firm cost’s associated with the marketing exchange. We want to investigate the consequences of customer retention, namely profitability. While a number of authors (Sheth and Parvatiyar 1995; Morgan and Hunt 1994) and much anecdotal evidence point towards a strong positive association between lifetime duration and profits accruing to the firm over time, very little empirical evidence actually exists in that regard. The study by Reichheld and Teal (1996) is the only published empirical evidence that underscores this claim. Given the scarce empirical evidence and the cautionary notes by Dowling and Uncles (1997), we want to explore the direction and the strength of the lifetime-profitability relationship in a non-contractual scenario.

Customer Lifetime and Firm Profitability

We offer four propositions in this study and subsequently test each one of the propositions in a non contractual scenario.

Proposition 1: The Nature of the Lifetime-Profitability Relationship is Positive

Ongoing relationships in consumer markets have received substantial attention in recent years (Berry 1995). The building of strong customer relationships has been suggested as a means for gaining competitive advantage (McKenna 1993). The underlying assumption of much of the existing research is that long-term relationships are desirable because they are more profitable for the firm as compared to short-term relationships. The reason for this assumption has been attributed to greater exchange efficiencies, which are created by customer retention economics (Sheth and Parvatiyar 1995; Sheth and Sisodia 1995). Following this line of reasoning, we clearly would expect a substantial positive association between the duration of a customer-firm relationship and the firm profits derived thereof[2]. Figure 1 summarizes this situation. In line with the argument, one would expect the majority of relationship outcomes to fall along the diagonal, as shown in Figure 1. In other words, one would expect a substantial positive correlation between the two variables. Thus, an

‘

assessment of the numbers of customers falling into each quadrant along with a simple measure of association between lifetime profits and lifetime duration would readily yield some insight into the nature of the lifetime-profitability relationship.

A factor that complicates the firm’s objective of establishing long-term relationships with its customers is that of intrinsic retainability of customers (Blattberg and Deighton 1991). The relationship between customer satisfaction and customer retention is intuitively easy to discern. However, different competitive conditions modify this relationship. For example, in less competitive markets, customers are more easily retained even with poor levels of customer satisfaction because there are few substitutes or switching costs are high. However, in highly competitive markets with many choices and low customer switching costs, even relatively high levels of customer satisfaction may not insure against customer defection (Oliver 1999). Clearly, not all customers want to engage in a long-term relationship with the firm for many possible reasons. For example, in the long distance telephone service market, many 10-10-xxx companies have emerged. There is no need to sign any contract with the service providers. Here, customers use a particular 10-10-xxx company depending on the quality of service, unit price and the speed of connection. As discussed before, in order to retain customers, it is important to satisfy the customers. The satisfaction of customers may come at a significant cost to the company. Thus, whenever the costs of satisfying customers exceed the profit margin offered by the customer, the expected positive lifetime profitability relationship need not hold good.

Blattberg and Deighton (1991) suggest that firms should partition their customer base into behaviorally and attitudinally homogenous groups that spend at different levels (see Figure 2) and then estimate the retention characteristics for each group. Irrespective of the segmentation scheme, conventional wisdom argues for a positive relationship between profitability and time. While the available evidence suggests a positive lifetime-profitability relationship it need not true if the cost of serving the customer is greater than the profit margin generated by the customer. In fact there could be many customers who may be receiving catalogs on a regular basis because they bought at least one item in the recent past even though it may be of lower dollar value.

- Figures 1 and 2 approximately here -

---

[2] At this point, we are concerned with the sign and strength of the relationship – a one-shot, ex-post assessment. In addition, in proposition 2 we will look at the *dynamics of the relationship over time*.

‘

Proposition 2: Profits Increase Over Time

While a correlational measure is important and insightful, it presents only a *static* picture of the lifetime-profitability relationship. While related to proposition 1, the analysis of the *dynamic aspects* of the lifetime-profitability relationship yields further important insights. The important difference is that we analyze profits dynamically across time, whereas in proposition 1 we analyze profits in a single lifetime measure across subjects. Fournier, Dobscha and Mick (1998) advocate this longitudinal approach to make the correct inferences about customer behavior over the course of a relationship. Clearly, an investigation of the profitability *evolution* is of immense interest to managers. Best (2000) argues that retained (longer life) customers produce higher revenues and margin per customer than do lost or newer customers and therefore, the total profits should increase over time. Recall that Reichheld and Teal (1996) find evidence for *increasing* profits per time unit over the length of the customer’s tenure. By analyzing longitudinal data, it can be assessed whether this study’s results add to the findings of Reichheld and Teal.

Using the same long distance telephone service example as discussed under the previous proposition, it is necessary for the firm offering the 10-10-xxx service to send monthly bills to all the customers, who have started to use their service. Even if a customer does not use their service in a given month, that customer receives a bill. Here, the cost of serving the customer clearly exceeds the profit margin from the customer and this loss becomes significant for the firm over a period of time and across many such customers. This type of phenomenon occurs in the credit card industry also. Thus, it is not obvious that profit for the firm increases over time. Therefore, it is worthwhile to test this relationship.

Proposition 3: The Costs of Serving Longer-life Customers are Lower

Another commonly held contention is that long-life customers are less costly to serve than short-life customers are. Reichheld and Teal (1996) quote several instances where this situation holds, for example in financial planning. Likewise, Blattberg and Deighton (1996) assert that customers who are converted and retained in committed relationships are relatively low-maintenance. In the same line of reasoning, Wang and Spiegel (1994) argue that loyal customer segments generate higher contribution margins due to lower marketing costs. On the other hand, Dowling and Uncles (1997) caution to not over-generalize these statements. They argue that there is little reason to believe that short-life customers are more expensive to serve. In fact, there may be

‘

costs associated with keeping customers for longer lifetime and that is through the reward program. Since loyalty programs offer benefits to customers over a period of time, it can be a significant cost to the firm offering the reward program (Mohs 1999). Thus, it may not be true that the costs of serving longer life customers are lower. However, if experience factors do play a role in transactions, we would expect lower costs with increased transaction frequency. Yet, for the broad retail sector, we would hardly expect lower transaction costs for longer-life versus shorter-life customers. For example there is little reason to believe that transaction costs for a piece of garment in the second purchase encounter with a firm is different from say the tenth purchase encounter.

Other costs that are incurred over the course of a relationship are the costs of the promotional mix directed at each customer. In a direct marketing context, promotional costs are typically the largest non-product cost factor in a customer firm relationship. Following the commonly held contention, we would expect that the cost of promotional expenditures per dollar sales revenue is lower for longer-life customers. The reason would be that the promotional mix has a greater efficiency in relation to the longer-life customer. This is possibly due to cumulative effects or due to a more favorable attitude towards the firm’s communication. Thus, we propose that the cost of promoting to a customer, in relation to her revenues, is lower for long-life customers. Yet, to our knowledge, there is no empirical evidence in the literature to substantiate this claim. Therefore, it will be interesting to test whether the costs associated with promotional expenditures directed at longer- and shorter-life customers actually differ.

Proposition 4: Longer-life Customers Pay Higher Prices

Reichheld and Teal (1996) have argued that in most industries, existing customers pay effectively higher prices than new ones, even after accounting for possible introductory offers. This would imply that the average price paid by customers and the customer lifetime duration could be positively related. They argue that customers who have been around long enough to learn a company’s procedures and acquaint themselves with its full product line will almost invariably get greater value from a business relationship and, hence, it is not surprising that they are less price sensitive on individual items. In the context of Internet shopping, Smith, Bailey, and Brynjolfsson (1999) highlight that retailers with strong customer awareness, such as Amazon or CDNow, are able to charge prices that are 7-12% higher then lesser known retailers. In our case, customers who have been dealing with the firm over a longer time have naturally a higher awareness of the firm. In the

‘

same vein, this would suggest that these long-term high awareness customers are more likely to pay higher prices than new or frequently switching customers. Mohs (1999) argues that having a reward program tied in with an excellent customer service will help take the consumer’s eye off the price. For example, if somebody is a member of the frequent flier program with an airline then even if that airline’s fares are slightly higher the customer would be indifferent to the higher price. However, there is a threshold effect.

For every firm, there are some customers who always spend the least. For example, AT&T has over 20 million customers who do not spend anything on long distance. However, the customers get their monthly bill. These type of customers spend the least irrespective of whether they exist as long or short life customers for a firm. Therefore, one may not find any difference in spending between long life (segment 2) and short life (segment 4) customers among low revenue customers.

On the other hand, company managers told us that their informal experience suggests a higher value consciousness (i.e. lower average prices paid) for long-term customers. That is, if a customer buys more product units for a given dollar amount, she exhibits a higher degree of value consciousness, i.e. she gets more “bang for the buck”. If this observation were true it would contradict the existing evidence from Reichheld and Teal (1996). A possible reason for higher value consciousness of long-term customers might be that customers learn over time to trust lower priced items or brands rather than established name brand products.

Thus, there seems to exist some reasonable evidence for both possibilities. Therefore, instead of proposing a directional effect, we suggest to test this proposition empirically.

Research Methodology

Data

Data from an established U.S. catalog retailer are being used for the empirical estimation in this study. The items sold by the firm cover a broad spectrum of general merchandise. The firm’s products are offered and can be purchased all year round. We do not disclose the name of the company for reasons of maintaining confidentiality. The data for this study cover a three-year window and are recorded on a daily basis. The total number of observations in this data set is a sample of 9,167 households. An observation is the entire purchase history in this time window for each household in combination with a set of covariates. A key characteristic of this data set is that the customers are tracked from their very first purchase with the firm and these households have not

‘

been customers of the company before. Consequently, the observations are not left-censored. Out of the entire sample, 4,202 households started buying from the firm in January of 1995 and are observed through December 97. This group is termed Cohort 1. Likewise, Cohort 2, consisting of 4,965 customers, started buying during February of 1995 and is also observed through December 97. Thus, the behavior of Cohort 1 is tracked through a 36-month time period and the behavior of Cohort 2 through a 35-month time period. Cohort 2 serves as a validation sample for the results observed with Cohort 1. The number of purchases ranges from 1 to 46 across the sample with a median number of 5 purchases. Likewise, the median interpurchase time is 117 days and the median transaction amount is $91 for each purchase.

A Model for Measuring Customer Lifetime for Non-Contractual Relationships

A critical component in our model is customer lifetime duration. The modeling process of a customer’s lifetime is contingent upon a valid measurement framework that adequately describes the process of *birth, purchase activity and defection*. Once such a measurement framework is established, an investigation into the factors that impact lifetime duration can be performed. If lifetime analysis is to be conducted in a contractual context, the actual lifetime is finite and typically known. In this case, the analysis of lifetime is relatively straightforward with appropriate statistical methodology. The study by Bolton (1998) represents a good example for this case. The situation is far more difficult in the case where a customer purchases completely at his/her discretion, i.e. the non-contractual scenario. This situation is by far the most common across different product categories. Towards that end we empirically implement and extend a procedure previously suggested by Schmittlein and Peterson (1994). Once the lifetime duration is computed for each customer, we can develop testable propositions dealing with lifetime duration based on conventional wisdom and past literature.

Schmittlein, Morrison and Colombo (1987) and subsequently Schmittlein and Peterson (1994) have proposed and validated the Negative Binomial Distribution (NBD)/Pareto model that is applicable in this context. The underlying assumptions of the NBD/Pareto model have received substantial support in the marketing literature (Schmittlein, Morrison and Colombo 1987). Schmittlein, Morrison and Colombo (1987) develop a model based on the negative binomial distribution that can be used to determine how many of a firm’s current customers are “active”, based on a customer’s transaction activity in the past. The key result of the NBD/Pareto model is an

‘

answer to the question: “Which individual customers are most likely to represent active or inactive customers?” This is a non-trivial question since the purchase activity is a random process and the defection is not directly observed. Based on the customer-specific probability of being alive, the model can be used to determine which customers should be deleted from active status. The outcome of the NBD/Pareto model, the probability that a customer with a particular observed transaction history is still alive at time T since trial, is of key interest to our modeling effort (see Schmittlein and Peterson, p. 65, Appendix 1). Schmittlein, Morrison and Colombo (1987) show that this probability depends on the customer’s past purchase history only through the number of purchases x and the time t (since trial) at which the most recent transaction occurred. The desired probability for $\alpha > \beta$ is given in Schmittlein and Peterson as: $P\ [Alive \mid r, \alpha, s, \beta, x, t, T] =$

$$\left\{1+\frac{s}{r+x+s}\left[\left(\frac{\alpha+T}{\alpha+t}\right)^{r+x}\left(\frac{\beta+T}{\alpha+t}\right)^{s}F(a_1,b_1;c_1;z_1(t))-\left(\frac{\beta+T}{\alpha+T}\right)^{s}F(a_1,b_1;c_1;z_1(T))\right]\right\}^{-1} \qquad (1)$$

Where $a_1 = r+x+s$, $b_1 = s+1$, $c_1 = r+x+s+1$, $z_1(y) = (\alpha-\beta) / (\alpha+y)$, $F(a_1, b_1; c_1; z)$ is the Gauss hypergeometric function, r, α, s, β = model parameters, x = number of purchases, t = time since trial at which the most recent transaction occurred, and T = time since trial. The corresponding probabilities for $\beta > \alpha$ and $\alpha = \beta$ are given in Schmittlein and Peterson (1994) - see page 65.

Given that the outcome of the NBD/Pareto model is a continuous probability estimate, Schmittlein and Peterson’s model is extended by transforming the continuous *P(Alive)* estimate into a dichotomous “alive/dead” measure. Knowing a person’s “time of birth” and given a specified probability level (threshold), we can approximate when a customer is deemed to have left the relationship. The time from birth, t_0, until the date associated with the cut-off threshold, $t_{cut\text{-}off}$, then constitutes the lifetime of the customer. Figure 3 illustrates the procedure. This procedure allows us to calculate a finite lifetime for each customer, which then will be use for the profitability analysis.

- Figure 3 approximately here -

The above discussion has been based on the assumptions that the time t_0 when the customer came on file or when she executed the first purchase is known. Given the widespread existence of customers’ databases in organizations, this assumption is not difficult to meet (Petrison et al. 1997). Furthermore, any attempt to empirically measure lifetime should be reflected in the available data. This means that the observation window should be long enough to be able to capture the true lifetime phenomenon. Finally, since the horizon of the analysis is finite, the analysis should be able to accommodate right-censored observations. These assumptions outline the conditions for

‘

modeling lifetime in a non-contractual context. Given that these assumptions are met, we show that the calculation of the lifetime of an individual consumer becomes feasible and empirically meaningful.

Parameter Estimation

The four parameters of the NBD/Pareto model were derived from bootstrap method-of-moments estimates for the entire sample of 9,167 households. While bootstrapping is not a requirement for parameter estimation, it gives us the additional benefit of understanding the parameter sampling properties. For each parameter 20 bootstrap samples were drawn. All households were observed for at least 35 months. The estimated parameters are $r = 4.24$, $\alpha = 14.95$, $s = 0.93$ and $\beta = 13.85$. The gamma distribution shape parameter value of $r = 4.24$ represents a low level of heterogeneity in transaction rates across customers. That is, consumers behave somewhat uniformly in their purchasing behavior while being alive. The moderate value of 0.93 for *s* says that the death rate varies considerably from customer to customer, i.e. a considerable level of "between household" heterogeneity exists in the sample. Overall, the model estimates seem very reasonable and show a high degree of face validity and internal consistency. Based on the above parameter estimates, we proceed to calculate the statistic of main interest: $P[Alive \mid r, \alpha, s, \beta, X, t, T]$.

The estimated parameter *s* which impacts the defection behavior exhibited a substantial degree of heterogeneity which means that we expect substantially different shapes of the *P(Alive)* patterns on a disaggregate level. Therefore, we are likely to see segments that exhibit different lifetime behavior. The implications of this issue become very important from a managerial standpoint of managing customers. Segmenting the customer base is beneficial for aligning the marketing mix with the lifetime activity pattern and possibly altering the lifetime activity.

Establishment of Cut-off Threshold

The choice of cut-off threshold *c* determines the length of the lifetime estimate for each customer. A natural choice for the classification threshold would be $c = 0.5$. If a customer's *P(Alive)* is above 0.5 he/she would be assigned the status "alive", else she would be assigned the status "not alive". The threshold of choice in the classification literature is 0.5 (Sharma, 1996). In survival analysis, Helsen and Schmittlein (1993) have used 0.5 in the prediction of purchase events. Because one could argue that a threshold of $c = 0.5$ might be sub-optimal, we conducted a sensitivity analysis to assess whether a cut-off threshold other than 0.5 is possibly better suited to produce a valid lifetime estimate. For this purpose, the 36 month time horizon was split into two

‘

periods: estimation period (18, 24, and 30 months) and corresponding prediction period (18, 12 and 6 months, respectively). Based on the estimate of *P(Alive)* at month 18, 24, and 30 and the assumed cut-off threshold (0.1, … 0.9), the household is classified as being either alive or dead, where: classification = “Alive” if $P(Alive)_{18, 24, 30} \geq c$, and classification = “Not Alive” if $P(Alive)_{18, 24, 30} < c$ for c = 0.1, …, 0.9. Given this classification, the predicted classification for each c is compared to the actual purchase behavior in the holdout period. If the subject exhibits any purchase activity in the holdout period, he/she is assigned as being active, if not, he/she is assigned inactive. The cut-off threshold that produces the highest percentage of correct classifications is obviously the choice that is most consistent with the data.

The threshold of 0.5 clearly produces the highest percentage of correct classifications for the three samples. As a result, for the purpose of the lifetime analysis, we will be using 0.5 as the cut-off threshold.

Lifetime Estimation

Based on the proposed model and the implementation of the validation process, the final step in the analysis is the calculation of a finite lifetime estimate for each customer. The average lifetime across Cohort 1 is 28.7 months, and the average lifetime across Cohort 2 is 27.9 months (Table 1). The consistency between the two Cohorts is very high. In both Cohorts, about 60% of the sample have a lifetime that is less than the observation window. Thus, the available observation window is obviously adequate for describing lifetime purchases of the given sample.

- Table 1 approximately here -

Profit Calculation

Net-present value of profit is calculated on an individual customer basis for the period of 36 months using equation 2 (Berger and Nasr, 1998).

$$LT\pi_i = \sum_{t=1}^{36} (GC_{ti} - C_{ti}) \left(\frac{1}{1+.0125} \right)^t \qquad (2)$$

where $LT\pi_i$ = individual net-present lifetime profit for 36 months, GC_{ti} = gross contribution in month t for customer i, C_{ti} = mailing cost in month t for customer i, and 0.0125 = monthly discount rate (based on 0.15% rate per year). The discount rate is set to 15%, which equals US prime rate in 1999 plus 7%. This estimate is in line with other marketing studies, which have used discount rates in the range of 12% to 20% (Kim, Mahajan and Srivastava 1995; Berger and Nasr 1998). Gross contribution GC_{ti} is calculated from the monthly revenue, which is the total household

‘

purchase amount for every month of the observation period. The monthly gross contribution is calculated, on average as 30% profit margin of the monthly revenues. This is a rather conservative figure and reflects the firm’s managerial judgement. Due to the wide assortment the firm offers, the calculation of an average profit seems reasonable. Furthermore, estimates of individual item direct cost are not available within the firm. The cost component C_{ti} constitutes the total cost of mailing catalogs and solicitations per month and per customer. These costs include catalog production cost, lettershop, and mailing costs. Individual customer mailing cost in the observation window vary between \$2.5 and \$111.1 for Cohort 1 (mean = \$53.3) and \$3.3 and \$108.5 for Cohort 2 (mean = \$57.6). Acquisition costs are not included since the company does not track them on a per-customer basis. Now that lifetime duration and profitability have been computed, we can proceed to test the propositions offered in this study.

Test of Propositions

Proposition 1: The nature of the Lifetime-Profitability Relationship is positive

In line with Blattberg and Deighton’s (1991) suggestion we propose a segmentation scheme based on behaviorally different sub-groups (Figure 3). Using *Profit* as the dependent variable, one can segment the customer base with a median split of the independent variables *Lifetime Duration* and *Lifetime Revenues*. A median split has been widely used in the marketing literature (for example Schmittlein, Cooper, and Morrison 1993; Bearden, Rose, and Teel 1994). Likewise, for the lifetime variable, research has demonstrated that the *median* lifetime duration is a better descriptor of the lifetime distribution than the *mean* lifetime (Collett 1994). This is particularly true if the survival time comes from a distribution that is skewed or if the data are censored; both of which may be true for most cases. In fact, if the highest lifetime duration is right censored, the mean lifetime estimate will be biased (Collett 1994). Therefore, in line with existing research and due to methodological requirements, we will employ a median split and create a shorter and a longer “lifetime-half” and a higher and a lower “revenue-half”.

Obviously, we would expect that the longer a customer’s tenure with the firm and the higher the revenues of a customer, *ceteris paribus*, the more profitable that customer would be. In line with the relationship marketing literature, we would expect the customers falling into segment 1 to generate the highest profits. Likewise, customers in Segment 4 would be expected to yield the lowest profits. However, in addition to providing empirical evidence for the above expectations, this

‘

segmentation scheme lets us test the importance of the off-diagonal segments to the firm. An analysis of the off-diagonal quadrants could provide an answer to an important question. Could we possibly encounter a situation where customers with shorter tenure might actually be more profitable than long-term customers? A claim that runs counter to the theoretical expectations of a relationship perspective. Furthermore, which group of customers is of more interest to the firm, the one that buys heavily for a short period (Segment 3) or the one with small spending but with long-term commitment (Segment 2)? This is a particularly important question in combination with the size of the segments. That is, for example, if the total number of customers in Segment 1 were comparably small, it is imperative for the firm to pay very close attention to the characteristics of their second-most profitable segment. As pointed out previously, Garbarino and Johnson (1999) and Ganesan (1994) have shown that there is a need to treat long-term and short-term customers differently. Answers to the above questions provide important information to managers regarding the optimal design of the communication strategies that efficiently reach each of their most profitable segments.

Proposition 2: Profits increase over Time

To test the proposition of increasing profits over time we will (a) examine the profitability evolution visually and (b) analyze the sign of the slope coefficient. If profits were to increase over a customer’s tenure, we would expect a positive slope parameter for the same variable. In addition to the linear effect, a dummy variable is included for the first purchase period in order to reflect the large first month purchase amount. The exact specification of the regression is:

$Profit_{ts} = a_s + b_{1s}*Dummy + b_{2s}*t_s + error$

where t = month,

b_{is} = regression coefficient

s =segment,

Dummy = 1 if first purchase month, else 0.

The profit figures are derived for those customers who either have purchase activity in a given month <u>and/or</u> for those who incur cost due to mailings in a given month. The dummy variable was included to achieve a better fit of the estimation because purchases in month 1 were considerably higher for all groups. As a result, the estimation better reflects the actual profit pattern beyond month 1.

‘

Proposition 3: The Costs of Serving Long-life Customers are Lower

In order to test this proposition, we will compute the ratio of promotional costs in a given period over the revenues in the same period. Promotional costs are the total cost of producing and mailing promotions and catalogs, starting with the birth of the customer. This varies for each customer depending on the purchase transaction history. Within each segment, the mean promotional costs are computed across all households and then the costs are compared across segments to see if the costs of serving longer-life customers are actually lower.

Proposition 4: Longer-life Customers Pay Higher Prices

We test in our study whether longer-life customers do pay higher prices as compared to shorter-life customers. Therefore, we will compare the average price paid across products and purchase occasions for each of the four segments. Next, we discuss the findings from the test of propositions.

Empirical Findings

What is The Nature of the Lifetime-Profitability Relationship?

In order to test the strength of the lifetime-profitability relationship, the bivariate Pearson correlation between lifetime duration (in months) and lifetime profit ($) is calculated. The correlation coefficient r is 0.175 for Cohort 1 and 0.219 for Cohort 2, which means that only a moderate linear association between lifetime duration and lifetime profits exists. Although a positive association significant (at $\alpha = 0.05$) and in line with theoretical expectations, clearly exists – overall, it seems weak. Clearly, lifetime duration alone does not explain very well overall lifetime profitability. Furthermore, when segmenting the customers in Cohort 1 using a median split we find that 2,530 out of 4,202 households fall in the diagonal of Figure 2 (1,322 in the upper right quadrant; 1,208 in the lower left quadrant). That means, a very substantive 39.9 % of the customers fall into the off-diagonal quadrants. Thus, the large percentage in the off-diagonal quadrants signals that there is a sizable segment (18.7%) that generates high profits even though the customer tenure is short and another segment (21.2%) that generates low profits even though they exhibit long lifetime. While our findings moderately support the theoretical predictions from the relationship marketing perspective, additional analyses seem warranted to explain the apparently

‘

counterintuitive results. Specifically, we are interested in how much *each segment* contributes to overall profits. The goal is to optimally uncover the underlying relationship of lifetime with profitability. Table 2 summarizes these results

- Table 2 approximately here -

Several results in Table 2 are remarkable. The first finding is that the average net present lifetime profit per customer is highest for Segment 1 ($289.83). That is, customers who have long lifetimes and who generate high revenues represent the most valuable customers to the firm. Of key interest however is the comparison of Segments 2 and 3. Clearly, it can be found for this setting that customers in Segment 3 are on average *far* more profitable ($257.96) than customers in Segment 2 ($50.85). The mean profit for segment 3 is significantly ($\alpha = 0.01$) different from the mean profit of segment 2. In terms of total segment profitability, the short-lived Segment 2 generates 29.2% of the total Cohort profits. Thus, while long-term customers in Segment 1 are obviously important to the firm, short-term customers in Segment 3 are also important as well because they generate more than a quarter of the total Cohort profits.

Thus, this is a case where both long-term customers (Segment 1) *and* short-term customers (Segment 3) constitute the core of the firm’s business. Likewise, we find empirical support for Dowling and Uncles’ (1997) speculation that the relationship between lifetime and profits can be far from being positive and monotonic. Consequently, an implication for managers is that a firm strategy focussing on relational buyers only as opposed to transactional buyers would clearly be disadvantageous. Thus, the firm has to develop and maintain operational and communication tools that effectively cater to each of the two groups.

Another very interesting outcome of the analysis is, that in terms of relative profits, i.e. profit per month, customers in Segment 3 are the *most* attractive of *all* (Figure 5). Segment 3 customers purchase with high-intensity, thus generating higher profits in a relatively shorter period of time. Thus, in terms of sustaining cash flow, they play a vital role for the firm. The mean relative profit for each segment is significantly different from the other segment at least at $\alpha = 0.05$ (using the multiple comparison test). The results for Cohort 2, which are also shown in Figure 5, reinforce the previous implications since they do not differ in direction and magnitude of the effects.

One needs to speculate on the reasons for this interesting pattern of results. Obviously the Segment 1 customers are the most desirable set for the firm – representing the loyalty effect at its best. These customers’ desires are likely to be matched well by the firm’s offerings over time and

‘

they are more likely to be habitual mail-order buyers. For Segment 3 customers (high revenue but short lifetime), we still suspect a good match between offerings and desires but we assume that their relationship duration is complicated by moderating factors. Several factors can be responsible for that. For example consumer factors such as an intrinsic transactional buying behavior, the execution of a limited set of planned purchases, being less of a typical mail-order buyer, or a higher susceptibility to competitor’s offers. We suspect that it has less to do with product or service dissatisfaction since they spend at a high level. Dissatisfaction might rather occur for Segment 4 whose customers spend the lowest amount. While we highlight the speculative nature of these inferences it seems worthwhile to search for the underlying consumer motivations[3].

Do Profits Increase Over Time?

Recall that we wanted to test the proposition of increasing profits over time. For that purpose, we first examine the profitability evolution visually. Figures 4 and 5 show the lifetime profitability plots for the four segments. A visual inspection of the charts reveals that three of the four segments actually exhibit *decreasing profits* over time. Only for Segment 2 (long life, low revenue) we find a slightly positive trend in the profitability evolution.

- Figures 4 and 5 approximately here -

For a more formal test, we compare sign and significance of the time coefficient from the regression analysis of profits as a function of time. The results are presented in Table 3. With exception of Segment 2, we generally find that the coefficient for the linear effect has a negative sign, thus highlighting the negative profit trend over time for the three segments. All the coefficients for time are significant at $\alpha = 0.01$.

- Table 3 approximately here -

It is not uncommon that proponents of relationship marketing mention that profits due to loyal customer are higher in each subsequent period. This is typically the case for contractual settings where a firm derives most or all of the business of a customer, for example for life insurances or health club memberships. However, for non-contractual settings this might be different. For some products and services this would clearly not be the case (e.g. there is no reason to believe that people bring more and more clothes to their dry cleaner over time). Yet, the few

[3] We are indebted to a reviewer for suggesting more discussion, even though speculative, as to the underlying circumstances which could lead to our results.

‘

empirical evidence by Reichheld and Teal (1996) advances that this assumption would mostly hold Even if this claim would not hold for all customer segments, one would it expect to hold at the very least for the most loyal group (Segment 1).

However, our results do not support this claim. This is obviously an important empirical finding that adds to the scarce empirical knowledge in the relationship marketing literature.

The theoretical claim is that loyal customers enter a virtuous cycle where satisfaction with transactions in previous periods feeds not only into loyalty in future periods but also a reinforcement and growth in firm profits. The counter-forces to this virtuous cycle are for example variety-seeking across firms, customers getting tired of interacting with the same firm, firm’s competitive actions, and the fact that no contracts exist. This negative relationship is also possible if the customer contact costs through mailing catalogs is high compared to the potential revenue from the sales realized from each customer. If costs exceed revenue, then over time, this gap can increase to a point where the negative relationship is prevalent. Obviously, these counter-forces are strong enough to block the theoretically existing virtuous cycle, thereby leading to decreasing profits over time. Even for Segment 1, the long life high revenue group, the theoretical expectation does not hold. Thus, our finding questions the general claim that loyalty is always desirable to achieve because we do not find support for the underlying argument, i.e. that profits of long life customers increase over time.

Are the Costs of Serving Long-Life Customers Lower?

The objective was to test whether the cost associated with promotional expenditures directed at longer- and shorter-life customers differ. In order to test this argument, we compute the ratio of promotional costs in a given period over the revenues in the same period for each segment. The segment mean represents the $ amount that is necessary to sustain a $1 amount of revenue. Results are shown in Table 2 for Cohort 1 and Cohort 2.

The notion that customers with long tenure are associated with lower promotional costs is clearly rejected. The ratio of mailing cost per dollar sales in the longer-life segment (Segment 1) is statistically not different from the mailing cost per dollar sales in the shorter-life segment (Segment 3). This means, in terms of cost efficiency, Segments 1 and 3 are the most attractive to the firm, although they have very different lifetime properties. Sheth and Parvatiyar (1995) speculate that long-relationships are desirable because they are associated with higher marketing efficiency. Our

‘

findings show that the ratio of mailing cost and revenues – which is one measure of efficiency – need not necessarily be lower for long-life-customers. However, what we can observe is that the efficiency of serving customers increases with increasing customer revenues. The resulting effect is very beneficial for the firm – regardless of lifetime duration. This can be traced back to the promotional tool, which is utilized by most direct marketing firms: Recency, Frequency and monetary value (RFM) framework. Promotions are mainly allocated based on people’s amount of purchases and only to a lesser degree based on their lifetime duration. Thus, even though the absolute level of promotions to high revenue customers is higher, this is more than offset through their high expenses, resulting in the better efficiency to serve.

Do Long-Life Customers Pay Higher Prices?

We wanted to empirically test whether longer-life customers pay, on average, higher or lower prices for their chosen products as compared to customers in the short-life segments. We compute for each transaction the ratio of dollar spending over number of items purchased and average this figure across purchase occasions and customers within segments. Results are shown in Table 2 for Cohort 1 and Cohort 2. The average price per item for segment 3 is significantly ($\alpha = 0.05$) different from (and greater than) that of segment 1.

The highest average price paid for a single product item is encountered in Segment 3, the short-life segment. Segment 3 spends on average 8.04% (Cohort 1) and 10.6% (Cohort 2) more on a single product as compared to Segment 1. One could argue though that this effect might possibly be due to different types of products purchased by the different segments (e.g. higher priced categories such as furniture or electronic items versus lower priced categories such as apparel). To verify this, we performed the same analysis while controlling for the general product category (hardgoods and softgoods). The effects were identical to the one reported above. Short-life (Segment 3) customers pay higher prices than long life (Segment 1) customers even when controlling for the general product category. As a result, our observation of the higher value consciousness of Segment 1 customers goes counter to the argument that long-life customers are less price-sensitive. It is in fact the highly profitable short-term customer who seems to be less sensitive to the product’s price.

This finding is possible given that longer-life customers may have tried different products and have found ways to identify a lower priced but better quality product. Thus, the average price paid per item is relatively smaller compared to shorter-life customers.

‘

So far, four objectives have been accomplished in the analysis. First, we showed that a strong linear positive association between lifetime and profits does not necessarily exist. Second, we demonstrated how a static and a dynamic lifetime-profit analysis can exhibit a very differentiated picture: profitability can occur for the firm from high *and* low lifetime customers. We discovered that, for our case at least, profits do not increase with increasing customer tenure, thereby adding new empirical evidence to the domain. Third, we found that the cost of serving long life customers is not lower and fourth, we discovered that long life customers do not pay higher prices. Clearly, the transaction characteristics in different industries vary considerably and consequently, we expect these factors to have differential impact in different industries. However, for the case of the general merchandise catalog industry, we do not find support for *any* of the propositions. On the other hand, Reichheld and Teal (1996) mention general merchandise retailing and direct mail specifically as examples of industries where evidence for the factors should be found. Due to these inconsistencies, further empirical research into the nature of the lifetime-profitability relationship is advocated. Given that managers are always interested in chasing customers, is it possible to develop some early warning indicators to distinguish longer-life and shorter-life consumers?

Further Analysis

Let the Butterflies Fly

The idea of maintaining relationships with the *right* customers has gained much momentum recently (Blattberg and Deighton 1996; Dowling and Uncles, 1997). Reichheld (1993), for example, advises companies to separate customers into groups of “barnacles”; those who are fiercely loyal and tend to be big spenders over time, and “butterflies”, those who flit from vendor to vendor at the slightest whim. Our segmentation scheme exhibits the existence of two groups that are distinctly characterized by their lifetime activity pattern. We demonstrated ex-post that we are able to separate the two groups and describe them in terms of their differential behavior. For example, one disturbing fact is that the short-lived but high value Segment 3 does not generate any profit starting from month 25 until the end of the observation window, month 36 (see Figure 6).

However, based on their current selection tool, RFM framework, the firm keeps mailing to this segment. Thus, the firm incurs cost on this segment without a chance of recovering their investment. Of course, given their use of RFM, the firm is not able to distinguish between the short-life and long-life group. Therefore, based on the hypothesis that there is a substantial group of

‘

intrinsically short-lived customers, it is necessary to identify these customers as early as possible and then to stop chasing this highly profitable yet short-lived group after they stopped buying. Thus, the logical next step is to explore the potential for cost savings using the previously generated knowledge. For that purpose we conduct an ex-ante analysis to explore the profit benefits of our framework. The difficulty obviously is to predict customer behavior at the *individual level*.

The firm needs to identify the customers on whom the expended effort of mailing is wasted. For that purpose the manager has to classify each customers *a priori* into either the long-life or the short-life segment. Given that a customer is classified *a priori* into the short-life group, the firm can stop mailing to this customer early, i.e. avoid chasing this customer for too long. Given the empirical nature of this task, misclassification will be inherent. Thus, we need to address the issue of when the loss of wasted mailings to the short-life segment is larger than the foregone profits of the mis-classified long-life customers *if we were to stop mailing them*. This is a very important question, because the absolute size of Segment 3 is comparatively large and therefore even small profit differences matter. If the loss through wasted mailings becomes large, then it becomes increasingly beneficial to forego a certain amount of profits from the mis-classified long-life customers. Of course, this tradeoff depends largely on the quality of the classification. In the following section we will discuss how to separate the two segments of interest (Segments 1 and 3) at different points in time and how to derive profit implications thereof.

Indicators of Shorter- and Longer-Life Customer Segments

We use discriminant analysis to separate the two segments of interest, Segment 1 and Segment 3. In order to predict segment membership, we will use information on exchange variables and demographic characteristics. For sensitivity purposes, a prediction is performed for each of the months 25 through 36 using the information up to the previous month. For example, when we predict for the remaining 12 months at the end of month 24 we use information from month 1 to month 24. Thus, a total of 12 different discriminant analyses are performed. This approach simulates a managerial forecasting problem.

For the specification of the discriminant function we use the individual level exchange variables such as *P(Alive),* and *Recency of last purchase incidence,* and demographic characteristics such as *Age,* and *Income*. Monetary value is not included as it is part of the dependent variable classification. The frequency of purchase or the average inter-purchase time variable is not included

‘

as P(Alive) contains that information. Thus, the key variable of interest is obviously the probability of being alive. *P(Alive)* summarizes their past purchase activity and it is expected that this variable discriminates strongly between the two segments. Figure 6 shows the distinct *P(Alive)* characteristic of the four segments. Due to their high purchase intensity, the short-life high revenue group has the highest average *P(Alive)* in the beginning. This average *P(Alive)* drops until it coincides at some point with *P(Alive)* for Segment 1 (approximately month 17). After that time, the difference in the *P(Alive)* characteristic increases continuously. Using this information, we should be better able to distinguish between these two groups as we move through time.

The variable *Recency* was included because it is obvious that a relatively long inactivity of a customer signals to the firm that the customer may have ceased the relationship. In fact, in a non-contractual setting, this is the major indicator for an active or inactive relationship (Dwyer 1997) and thus, this variable is part of the widely used RFM model in direct marketing. Finally, we include the customer specific constant covariates of age and income.

- Figure 6 approximately here -

The discriminant analysis was based on customers that belonged to Segment 1 or Segment 3. Thus, the total sample size for Cohort 1 was 1818 and the total sample size for Cohort 2 was 2146. The null-hypothesis that the group means are equal is rejected for every month at 0.001 for both Cohorts. The null hypothesis of homogeneity of within-group covariance matrices is also rejected for every month at 0.05 for both Cohorts. Therefore, we use the within-group covariance matrices for estimation of the discriminant function (Morrison 1976). Originally proposed by Lachenbruch (1967), it holds out one observation at a time, estimates the discriminant function based on n_1+n_2-1 observations (where n_1 the size of group 1 and n_2 is the size of group 2), and classifies the held out observations.

Results

All discriminant functions for both Cohorts are significant at $p < 0.001$. The canonical correlations of the 12 analyses range between .437 for month 25 to .868 for month 36 (Cohort 1) and .369 for month 25 to .876 for month 36 (Cohort 2). Thus, the discriminatory power of the independent variables is substantial. Regarding the relative importance of the predictor variables, *P(Alive)* and *Recency* are the most important predictors followed by *Income*. *Age* was not significant in any of the discriminant analysis. While the standardized weights for the three significant variables varied somewhat across the 12 discriminant analyses, *P(Alive)* and *Recency*

‘

remained as the most important of all the predictors. For example, the standardized weights for *P(Alive)*, *Recency* and *Income*, were 0.495, -0.583 and 0.101 respectively in one of the discriminant analyses for Cohort 1. The coefficients of *P(Alive)* and recency clearly exhibit face validity – the larger the probability of being alive and the fewer days elapsed since last purchase, the longer the lifetime. When discriminant analysis was performed with Cohort 2 data, the standardized weights were quite similar to that of Cohort 1. In terms of the classification results, the proportional chance criterion for Cohort 1 is 52.3% and for Cohort 2 is 52.9%. The maximum chance criterion for Cohort 1 is 62.76% and for Cohort 2 is 62.16 %. The hit ratio of total correct classification exceeds both these thresholds in every month (see Table 4). Also, the hit ratio improves substantially from month 25 to month 36. For example, whereas in Cohort 1 in month 25, 21.03 % of the long-life customers are mis-classified as short-life customers, this figure shrinks to 2.2% in month 36. Likewise, the percentage of correctly classified Segment 3 customers (short-life) increases from 71.05 to 96.75%. Obviously, moving through time, the manager can constantly improve her prediction about segment membership. Cohort 2 results are very similar to the Cohort 1 results thus adding validity to the findings.

- Table 4 approximately here -

Based on the classification results in Table 4 and the expected profits and losses generated by the two segments, we can show the profit implications of making marketing decisions for the firm. Table 5 shows the process of predicting profits or losses that are likely to be incurred by the firm if the mailings were stopped at a given month *t*. The numbers in the table are calculated for a profit margin of 0.25 on cost of goods sold. While we focus on Cohort 1, results for Cohort 2 are very similar.

- Table 5 approximately here -

The objective of the analysis is to find out if and when the losses due to foregone revenues (profits) from long-life customers who are erroneously mis-classified as short-life customers are smaller than the cost savings due to not sending excess mailings to actual short-life customers. Thus, we provide a profitability framework to the manager that helps her to base the decision of pursuing a customer further strictly on profitability grounds.

For the example in Table 5, if the firm were to stop mailing to the customers who are predicted to be short-life customers (Segment 3), using the information up to month 30 and calculating with a profit margin of 0.25, then the firm would encounter losses of $611. This is a result of $6,170 of foregone profits from mis-classified long-life (Segment 1) customers for the

‘

remaining 6 months (assuming they stop buying) and $5,558 in saved mailing costs to the correctly classified short-life customers for the remaining 6 months. Since forgone profits are larger than savings in mailings, it would not be optimal to stop mailing at month 30. On the other hand, the savings by stopping the mailing after month 32 ($2,960) are larger than the foregone profits ($1,279). This is a function of better classification results which in turn depends on the discriminatory power of the variables *P(Alive), Recency,* and *Income*.

We conducted the analysis in the same manner for four different profit margins for cost of goods sold (0.15 to 0.30). According to one of the firm's managers, the profit margins reflect those encountered by the firm in their business transactions. The curves in Figure 7 depict the result of this analysis.

- Figure 7 approximately here -

One can readily see that, if a lower profit margin is assumed, the time to stop the mailings to shorter-life customers shifts further to the left. The currently implemented RFM framework treats all customers as a single population and assigns them a score based on the same decision rule, regardless of their belonging to two behaviorally very different segments. As a result, considerable resources are wasted in mailings that will never lead to purchase activity simply because the lifetime activity pattern of a certain segment is not accounted for.

Clearly, in the case where customer segments exhibit different lifetime activity patterns, it becomes an important managerial decision *when* to stop mailing to the "butterflies", the highly active, yet short-lived Segment 3. The currently implemented RFM framework obviously overspends on this substantial group of customers. Besides putting forth an empirical procedure that uncovers lifetime profitability patterns, we apply this framework such that substantial cost savings are realized. Remember that the above example is calculated for a relatively small sample of 1818 customers. If the savings were calculated for 200,000 cases (which is still low given that the firm maintains a much higher number of accounts) at a decision date of month 33, the suggested procedure would save the firm $184,928 if the average profit margin were 0.25, and $222,880 if the average profit margin were 0.2. Small savings do make a difference, and when extended to their entire customer base, the firm's savings will become very large.

Managerial Implications

The positive association between customer lifetime and profitability has found considerable conceptual support in marketing. Yet, Dowling and Uncles (1997) caution that there does not exist

‘

much well documented empirical evidence to substantiate this association. Most of Reichheld and Teal’s (1996) empirical examples were drawn from contractual contexts where a firm usually receives all of the customer’s business, once the customer signs up for the service. Even in a contractual context, there can be instances where long life customers do not yield higher profits. For example, AT&T has at least 20 million residential customers who do not make a single long distance telephone call in one year and the annual average cost of customer care and billing is at least $72.00. To avoid such losses, many long distance telephone companies have instituted a monthly fee if the value of calls does not exceed a certain amount. While anecdotal evidence may exist, it is worthwhile to study empirically the nature of the lifetime-profitability relationship. We want to add to the findings of Reichheld and Teal (1996) and present an empirical study that demonstrates the existence of high profitability for both, short- *and* long-life customers, a situation that has not been addressed sufficiently.

Attempting to Generalize

We showed that managers cannot simply equate a long-life customer with increased lifetime spendings, with decreasing costs of serving, and with lower price sensitivity. In our case it is clearly the revenues that drive the lifetime value of a customer and not the duration of a customer’s tenure. In this case, it seems that a customer with high revenue is always preferable, regardless of lifetime. Thus the significance of the lifetime construct seems limited. As a consequence, our situation is an example of a case where managers should mainly be concerned with revenue and transaction management and only then with lifetime duration management. Our results represent evidence for Dowling and Uncles’ (1997) claim that it is a gross oversimplification to equate loyal customers with higher profits. A structured framework for analyzing the customer lifetime profitability pattern is presented here that enables the manager to understand the specific driving forces of customer lifetime profitability.

Why do we observe this interesting pattern? We believe that a combination of several factors might be at play here. First, we suspect that the non-contractual nature of the customer-firm relationship drives to a large extent the result. Customers incur virtually no switching cost in case they want to weaken or terminate the relationship. Since this non-contractual setting is very common in business-to- consumer settings, the results become all the more important. What keeps the customer interested in maintaining a relationship in a non-contractual setting? Obviously it is

‘

the match between a firm’s offerings and the customer’s desires – as compared to competition. However, since switching cost play such a small role, competitive and other forces impact on the existing relationship with full vigor. Thus, at any given point, the firm cannot neglect the transaction orientation of its business and has to manage accordingly the short-term aspect. This position stands in stark contrast with, for example, contractual relationships such as insurances or health clubs. What can a firm do in such a situation? As pointed out – while managing the short term aspect, they should try to raise switching cost as much as possible, for example through the introduction of an affinity program, charge cards, bonus point system and the like. However, the question remains whether these measures will be successful after all in binding the transactional customer. Of course, another managerial strategy might be to try to predict the lifetime characteristics of a customer as early as possible and then to act accordingly.

A second factor that might drive our results and which compounds the non-contractual issue is the fact that impulse buying and the potential thereof is tremendously large. The underlying issue is that consumers are offered a tremendous array of choices. While a certain group of people actively restrict their choices and thereby become relationship oriented (Sheth and Paravatiyar 1995; Oliver 1999), others readily take advantage of their choice potential (Peterson 1995). Consequently, only a certain segment of the customer base has an a-priori high potential of being a long-life customer, for example, committed mail-order buyers and highly relational customers. This goes hand in hand with a realistic and firm-specific estimate of an average customer lifetime duration and the associated customer replacement rate. As a result, we think managing for the long-term must be a carefully designed proposition and should be well aligned with the firm and industry’s general buying characteristics. Examples for failing to do so are abound

A very different possible reason for the observed pattern can possibly be attributed to unobservable affective factors. For example, while most buyers would assess the value of a transaction by rather objective measures such as price in comparison to competition or level of service, others might rely to a higher degree on their affective state towards the firm. According to Peterson (1995), this dimension has remained unexplored in the relationship marketing stream. One could argue that consumers have a very positive attitude towards the firm based on positive initial affects. However, it has been shown that affects are more transient than cognitions at least in a frequently marketed consumer goods (FMCG) environment (Hoyer 1984). This view is seconded by Carlston and Smith (1996) who point to the more transient nature of affects versus the more

‘

enduring cognitive representations. It is imaginable that certain customers build up a very positive attitude towards a firm, which subsequently subsides rather quickly. The positive attitude could explain a high initial intensity of purchasing which could be a potential explanation for the Segment 3 (short life, high revenue) behavior, which was one of the surprising findings in this study.

A fourth aspect of our attempt to generalize our findings might be that high value customers have stronger motives to engage in their intensive purchase behavior. As explained before, these motives may be driven mostly by an affective momentum for the short-life high revenue customers or by a cognitive element for the long-life high revenue customers. However, regardless of the particular nature, we would expect their level of motives to be stronger as compared to the two low revenue segments[4].

Having attempted to develop the generalities of our findings, we have to focus our attention on the managerial consequences. We therefore highlight the need for managers to be very aware that both types of relationships – short and long-term - can be highly profitable. Since they can coexist at the same time, the firm must learn to (a) identify the type of relationship with *each* of its customers, and (b) customize its marketing strategy differentially.

Identifying Long- and Short-Life Customers

Our study presents a structured framework for identifying the customer lifetime profitability pattern in a non-contractual context. We have employed Cohort analysis, a methodology that has been advocated by Parasuraman (1997) as a powerful tool in the context of lifetime applications. The key variables *P(Alive)* and time elapsed since last purchase can easily be estimated and updated for every customer in the database. Based on this information, the firm can identify at any given time the general nature of its customer's lifetime patterns and the individual-specific status along the lifetime continuum. Knowing these two dynamic characteristics is a necessary prerequisite for the manager to engage in true customer management – which has been called for by several authors (Blattberg and Deighton 1996; Wang and Spiegel, 1994; Kotler 1994).

Customization of Marketing Strategy

[4] As it turns out, the percentage of customers who actively requested an initial catalog rather than being solicited is significantly higher for the two high revenue segments (Segment 1 and 3). While this is clearly an ex-post test, the result could hint towards the stronger underlying motive for the two segments in question.

‘

We agree with the contention that some customers don’t ever stay loyal to the company. However, we do not agree with the statement that the firm has to avoid these people altogether. Rather, we argue that the challenge is to know *when* to let them go. Some customers behave like butterflies – it is wonderful when they are around, yet unfortunately they leave easily. On the contrary, long-life customers are like barnacles, they are strongly attached to the firm, but may cost the firm more in the long run. We showed how by using the above framework, short-life customers can be recognized earlier than with the currently utilized RFM model which in turn leads to substantial cost savings.

The timing of marketing actions assumes greater importance in reference to this context. There is tremendous opportunity for improving the quality of the interaction as well. Our framework allows managers to truly *manage customers*. While the importance to treat long-term and short-term exchange partners differently has long been understood in business-to-business environments (Anderson and Narus 1991), this idea is relatively new to consumer markets (Garbarino and Johnson 1998). Marketing managers must know the time orientation of a customer to select and use marketing tools that correspond to the time horizon of the customer (Ganesan 1994). Garbarino and Johnson (1999) show that short and long-term customers differ in the factors that determine their future exchanges. Their results imply that a different marketing focus is needed for the different types of customers; the traditional focus on customer satisfaction is likely to be effective for weakly relational customers but not so for strongly relational ones. Communication that stresses promotions and highlights store variety is likely to be more profitable. According to Garbarino and Johnson (1999), marketing focused on building trust and commitment will be more effective for the long-term relational group. Since we showed that both, long and short-life customers can be highly profitable, the company’s differential communication strategy towards the two groups becomes all the more important.

One strategy to get customers to spend more with the firm is to offer a variety of products and newer products. Catalog retailers have to become more innovative in reducing the costs and using other effective media such as Internet and Trade Shows or Event Sponsorship.

Conversion of Short-life to Long-life Customer

Another managerial option might be to attempt conversions of customers. That is, both short life/high revenue customers and short life/low revenue customers might be converted to a more

‘

attractive segment. While we clearly acknowledge that such a strategy might have its limits given the transactional buying habits of the short life group, the firm could include this strategy in its portfolio.

Limitations and Future Research

This research represents one of the very few empirical inquiries into a phenomenon of great managerial and academic interest. Clearly though, a number of limitations are warranted to qualify our findings and to encourage future research efforts.

First and foremost, additional research should extend the proposed empirical analysis to other product categories and industries. While our data come from a large and established company in an important consumer goods industry, further empirical analyses in other non-contractual contexts seem necessary. We provide a framework for analysis and an application of this framework to other Cohort databases should yield fruitful insights.

Second, it would be very interesting to integrate consumer’s opinions and attitudes into the behavioral database (Bolton 1998). For example, in our study we could not control for the impact of customer satisfaction on lifetime duration. Likewise, it would be interesting whether customer attitudes can be used as discriminators between intrinsic disposition towards short and long lifetime duration. We believe that the integration of behavioral and attitudinal data opens up a large potential for explaining customer behavior and customizing marketing actions.

The third issue that deserves attention is customer acquisition. The relationship of acquisition cost and lifetime profitability remained unexplored in this analysis due to unavailability of data. Thomas (1998) has shown that the type of customer a firm acquires impacts the long-term relationship that the customer will have with the firm. At this point, we do not know whether long and short-life customers have differential acquisition costs or whether they differ in acquisition mode. Future research can address this issue with the availability of relevant data.

Fourth, the data used in this study spans only three years. While three years yield multiple purchase opportunities, larger duration of data may offer additional insights. For example, Keane and Wang (1995) compare segments of 3 (low) and 6 (high) year average durability in the context of newspaper publishing.

Finally, an area of fascinating inquiry would be to test how a qualitatively differential treatment of customers impacts on their lifetime behavior. Clearly, while this type of experimental research is complex, it would put the concept of customer management to the test.

‘

Table 1: **Finite Lifetime Estimates**

	Mean Lifetime (months)	Standard deviation	% Right-Censored	Minimum	Maximum
Cohort 1	28.7	7.8	41.1	11	36
Cohort 2	27.9	7.9	41.7	12	35

Table 2: Tests of Propositions - Results (Cohort 2 results in parentheses)

	Segment 2					Segment 1				
Long Lifetime	1) # of custo-mers	2) Lifetime Profit per Customer ($)	3) Relative Profit ($/month)	4) Mailing Cost/ Sales Ratio	5) Average Item Price	6) # of custo-mers	7) Lifetime Profit per Customer ($)	8) Relative Profit ($/month)	9) Mailing Cost/ Sales Ratio	10) Average Item Price
	889 (973)	50.85 (55.26)	1.43 (1.56)	0.128 (0.124)	47.74 (48.72)	1322 (1546)	289.83 (322.03)	8.18 (9.31)	0.063* (0.062)*	58.43** (58.25)**

	Segment 4					Segment 3				
Short Lifetime	# of custo-mers	Lifetime Profit per Customer ($)	Relative Profit ($/month)	Mailing Cost/ Sales Ratio	Average Item Price	# of custo-mers	Lifetime Profit per Customer ($)	Relative Profit ($/month)	Mailing Cost/ Sales Ratio	Average Item Price
	1208 (1504)	50.49 (53.67)	2.41 (2.67)	0.141 (0.143)	47.97 (46.80)	783 (942)	257.96 (284.20)	11.67 (12.57)	0.065 (0.064)	63.54 (64.47)
	Low Lifetime Revenue					**High Lifetime Revenue**				

* Difference between Segment 1 and Segment 3 is not significant
** Difference between Segment 1 and Segment 3 is significant at least at $\alpha = 0.05$

Table 3: **Regression Results for t = 1 to 36 Months (Cohort 1)**
Validation Results in Parentheses (Cohort 2)

Segment	Intercept *(a)*	Dummy Coefficient for t =1 (b_1)	Coefficient for t (b_2)	R^2
1	12.11 (12.73)	45.77 (46.38)	-0.13 (-0.14)	.85 (.85)
2	n.s. (n.s.)	30.24 (30.91)	0.07 (0.071)	.92 (.91)
3	19.40 (20.9)	57.85 (58.29)	-0.70 (-0.75)	.95 (.94)
4	3.25 (3.69)	29.53 (31.45)	-0.14 (-0.15)	.94 (.95)

All coefficients are significant at $p < 0.01$ except n.s.
n.s. not significant

‘

Table 4: Classification Results from Discriminant Analysis using Cross-Validation for Cohort 1 Validation in Parentheses (Cohort 2)

	Month											
	25	26	27	28	29	30	31	32	33	34	35	36
1) % of long-life customers mis-classified as short-life customers. (false positive)	21.0 (20.7)	19.1 (18.8)	17.9 (16.8)	17.7 (19.2)	18.2 (15.6)	17.4 (15.8)	14.4 (14.1)	12.1 (12.1)	9.3 (10.5)	6.0 (7.7)	3.1 (4.2)	2.2 (3.0)
2) % of short-life customers correctly classified as short-life customers	71.0 (61.1)	73.1 (64.2)	75.6 (67.1)	78.7 (69.0)	82.4 (74.5)	85.5 (78.9)	88.6 (82.5)	91.0 (86.5)	93.2 (90.5)	94.4 (91.8)	96.2 (94.8)	96.7 (96.9)
3) Hit ratio (% total correct classification)	76.0 (72.5)	78.0 (74.8)	79.6 (77.2)	80.9 (76.4)	82.0 (80.7)	83.6 (82.2)	86.7 (84.6)	89.0 (87.4)	91.6 (89.8)	94.1 (92.1)	96.6 (95.4)	97.4 (96.9)

Table 5: Process of Profit Calculation (Cohort 1)

1) Use information up to month	**2) Forecast horizon (months)**	**3) Number of long-life customers mis-classified as short life**	**4) Foregone monthly profits ($)**	**5) Foregone total profits ($)**	**6) Number of correctly classified short-life customers**	**7) Monthly savings due to not mailing ($)**	**8) Total savings due to not mailing ($)**	**9) Net profit/ (loss) ($)**
24	12	240[a]	(1505)[b]	(18058)[c]	481[d]	743[e]	8912[f]	**(9146)**[g]
25	11	218	(1367)	(15035)	495	764	8407	**(6628)**
26	10	204	(1279)	(12791)	512	791	7905	**(4886)**
27	9	202	(1267)	(11399)	533	823	7407	**(3992)**
28	8	208	(1304)	(10433)	558	862	6892	**(3541)**
29	7	199	(1248)	(8734)	579	894	6258	**(2476)**
30	6	164	(1028)	(6170)	600	926	5558	**(611)**
31	5	138	(865)	(4326)	616	951	4756	**429**
32	4	106	(665)	(2658)	631	974	3897	**1239**
33	3	68	(426)	(1279)	639	987	2960	**1681**
34	2	35	(219)	(439)	651	1005	2010	**1571**
35	1	25	(157)	(157)	655	1011	1011	**855**

a: e.g. 21.0% were misclassified (Table 3, row 1), total number of long-life customers 1141, thus 0.21*1141=240
b: Average monthly profit for long life customers in month 25-36 with 0.25% gross margin: $6.27, thus 240*6.27=1505
c: Accumulation of forgone monthly profits for duration of forecast horizon, thus 1505*12=18058
d: e.g. 71.0% were correctly classified (Table 3, row 2), total number of short life customers 677, thus 0.21*677=481
e: Average monthly loss for short life customers in month 25-36: $1.54, thus 481*1.54=743
f: Accumulation of losses for duration of forecast horizon, thus 743*12=8912
g: Net of column 4) and column 7)

Figures are rounded to integers.

‘

Figure 1: Lifetime-Profitability Association

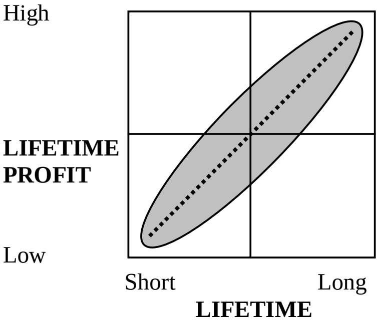


Figure 2: Segmentation Scheme

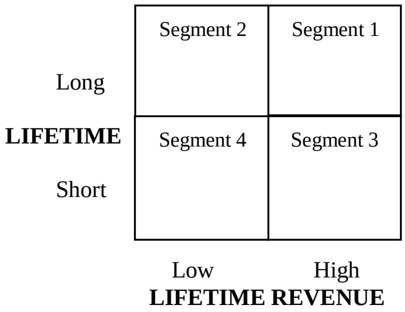


Figure 3: Illustrative Lifetime Determination of Individual Household

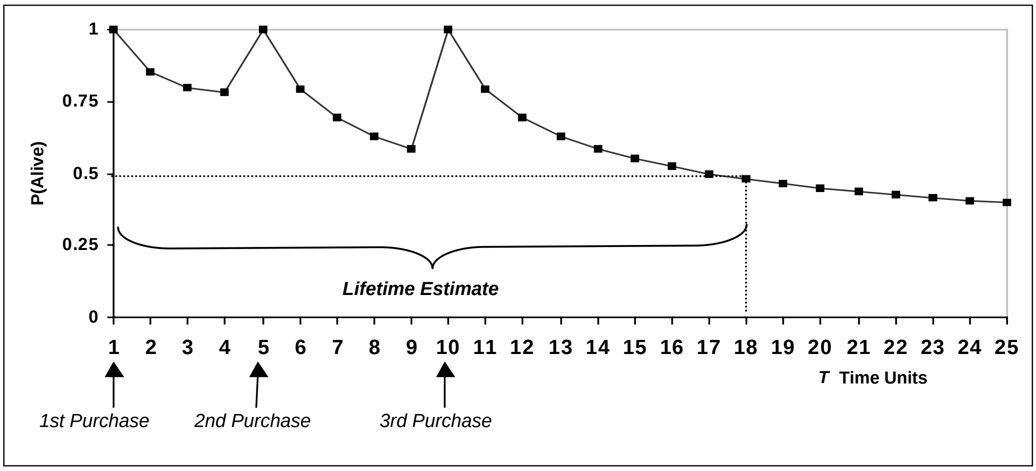
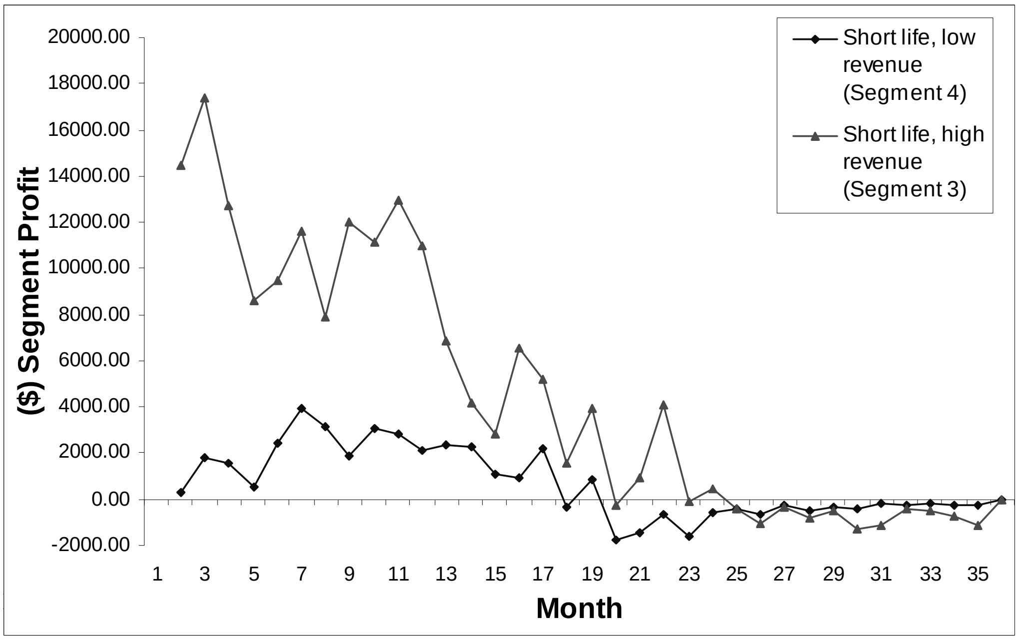
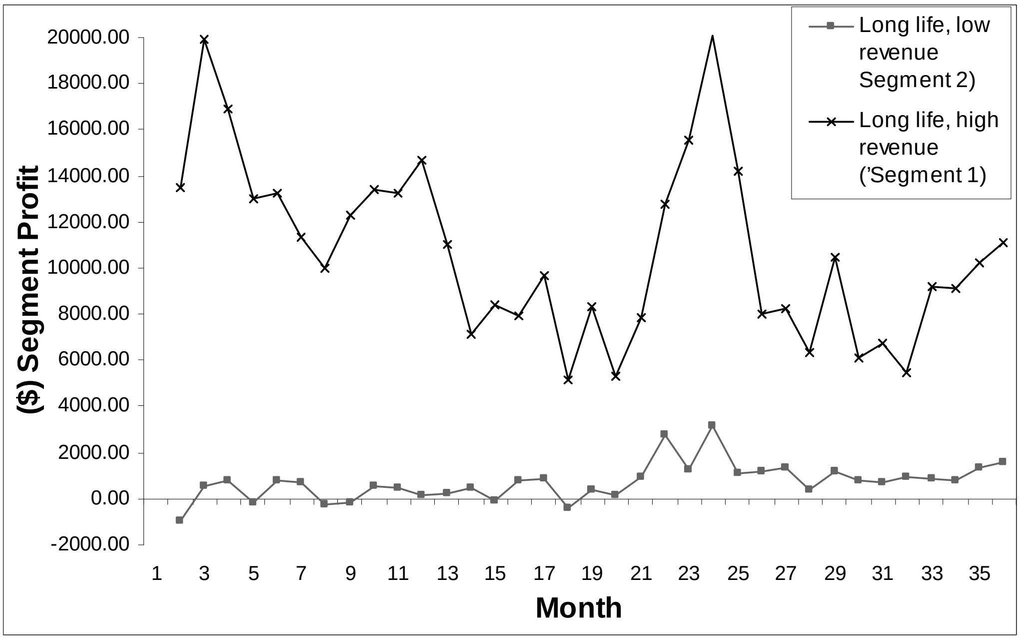


Figure 4: Aggregate Profits ($) for Short Life Segments



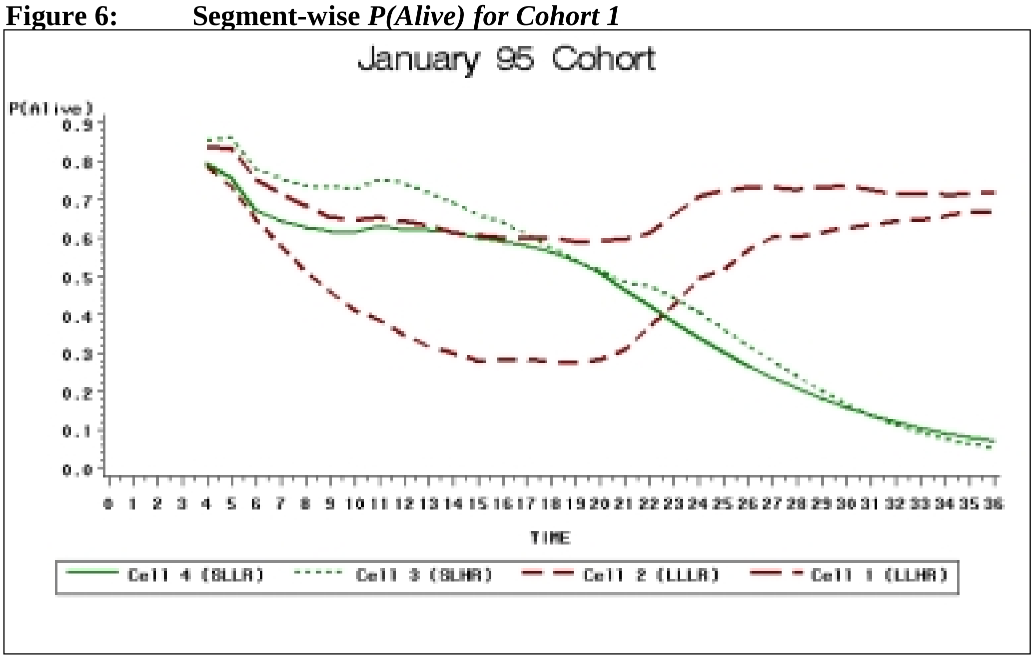
‘

Figure 5: Aggregate Profits ($) for Long Life Segments



Month 1 profits omitted from chart

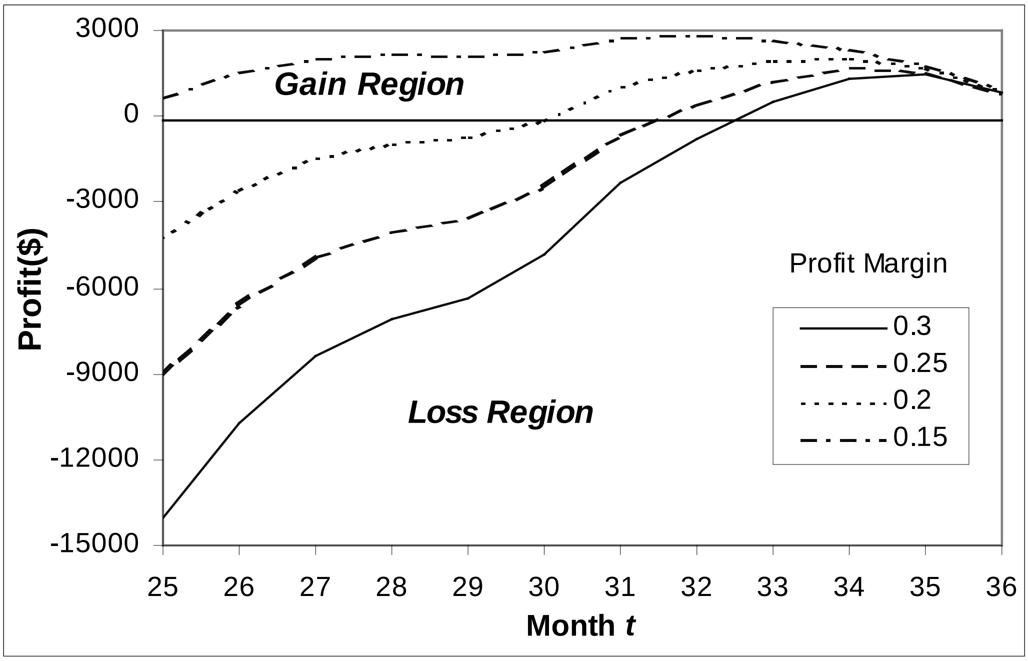
Figure 6: Segment-wise *P(Alive) for Cohort 1*



SLLR = short life, low revenue, SLHR = short life, high revenue,
LLLR = long life, low revenue, LLHR = long life high revenue

‘

Figure 7: **Profit Loss/Gain if Mailings were Stopped at Month *t* (Cohort 1)**



n = 1818

‘

References

Aaker, David A., V. Kumar and George S. Day (1998), *Marketing Research*, New York, NY: John Wiley.

Anderson James and James A. Narus (1991), “Partnering as a Focused Market Strategy,” *California Management Review*, (Spring), 95-113.

Bearden, William, Randall L. Rose, and Jesse E. Teel (1994), “Correlates of Conformity in the Consumption of Illicit Drugs and Alcohol,” *Journal of Business Research*, 30(1), 25-31.

Bendapudi, Neeli and Leonard L. Berry (1997), “Customers’ Motivations for Maintaining Relationships With Service Providers,” *Journal of Retailing*, 73, 15-37.

Berger, Paul D. and Nada I. Nasr (1998), “Customer Lifetime Value: Marketing Models and Applications,” *Journal of Interactive Marketing*, 12 (Winter), 17-30.

Berry, Leonard (1995), “Relationship Marketing of Services – Growing Interest, Emerging Perspectives,” *Journal of the Academy of Marketing Sciences*, 23 (Fall) 236-45.

Best, Roger J. (2000), *Market Based Management*. Upper Saddle River, NJ: Prentice Hall.

Blattberg, Robert C. and John Deighton (1991), “Interactive Marketing: Exploiting the Age of Addressability,” *Sloan Management Review*, (Fall), 5-14.

Blattberg, Robert C. and John Deighton (1996), “Manage Marketing by the Customer Equity Test,” *Harvard Business Review*, (July-August), 136-44.

Bolton, Ruth N. (1998), “A Dynamic Model of the Duration of the Customer’s Relationship with a Continuous Service Provider: the Role of Satisfaction,” *Marketing Science*, 17 (1), 45-65.

Bult, Jan Roelf and Tom Wansbeek (1995), “Optimal Selection for Direct Mail,” *Marketing Science*, 14 (4), 378-94.

Bulte, Christophe, van den (1998), “Changes in the Speed of New Product Diffusion: Mere Acceleration versus Economic and Demographic Conditions,” *Working Paper*, The Wharton School, University of Pennsylvania.

Carlston Donal and Eliot R. Smith (1996), “Principles of Mental Representation,” in *Social Psychology*, Tory Higgins and Arie W. Kruglanski, eds. New York: The Guilford Press.

Collett, D. (1994), *Modeling Survival Data in Medical Research.* London: Chapman and Hall.

Direct Marketing (1998), “Lillian Vernon announces New Catalog Title,” April 15-16.

DMA (1999), *Economic Impact: U.S. Direct Marketing Today/1998 Update*. The WEFA Group, Chicago.

Dowling, Grahame R. and Mark Uncles (1997), “Do Customer Loyalty Programs Really Work?,” *Sloan Management Review*, Summer, 71-82.

Dwyer, Robert F. (1997), “Customer Lifetime Valuation to Support Marketing Decision Making,” *Journal of Direct Marketing*, 11 (Fall), 6-13.

‘

Fournier, Susan, Susan Dobscha and David G. Mick (1998): “Preventing the Premature Death of Relationship Marketing,” *Harvard Business Review,* (January-February), 42-51.

Ganesan, Shankar (1994), “Determinants of Long-Term Orientation in Buyer-Seller Relationships,” *Journal of Marketing*, 58 (April), 1-19.

Garbarino, Ellen and Mark S. Johnson (1999), “The Different Roles of Satisfaction, Trust, and Commitment in Customer Relationships,” *Journal of Marketing,* 63 (April),

Hartnett, Michael (1997), “Private Label Credit Programs Enjoy Discount Store Boom,” *Stores,* 79 (7), 44-46.

Helsen, Kristiaan and David C. Schmittlein (1993), “Analyzing Duration Times in Marketing: Evidence for the Effectiveness of Hazard Rate Models,” *Marketing Science,* 11 (Fall), 395-414.

Hodges, Jane (1996), “Direct Marketing Tackles Benefits of New Media,” *Advertising Age,* November 4, 22.

Hoyer, Wayne (1984), “An Examination of Consumer Decision Making for a Common Repeat Purchase Product,” *Journal of Consumer Research.* 11, 822-829.

Huberty, C. J. (1984), “Issues in the Use and Interpretation of Discriminant Analysis,” *Psychological Bulletin*, 95, 156-71.

Keane, Timothy J. and Paul Wang (1995), “Applications for the Life Time Value Model in Modern Newspaper Publishing,” *Journal of Direct marketing*, 9(2), 59-66.

Kelley, Harold H. and John Thibaut (1978), *Interpersonal Relations: A Theory of Independence*, New York: John Wiley and Sons.

Kim, Namwoon, Vijay Mahajan, and Rajendra Srivastava (1995), “Determining the Going Market Value of a Business in an Emerging Information Technology Industry: The Case of the Cellular Communications Industry,” *Technological Forecasting and Social Change*, 49, 257-79.

Kotler, Philip (1994), *Marketing Management*. New Jersey: Prentice Hall, Inc.

Jones, Thomas and W. Earl Sasser Jr.(1995),“ Why Satisfied Customers Defect,” *Harvard Business Review*, Nov/Dec, 88-89.

Lachenbruch, P. A. (1967), “An Almost Unbiased Method of Obtaining Confidence Intervals for the Probability of Misclassification in Discriminant Analysis,” *Biometrics*, 23, 639-45.

Li, Shaomin (1995), “Survival Analysis,” *Marketing Research,* 7 (Fall), 17-23.

Marketing Science Institute (1998), *Research Priorities. A Guide to MSI Research Programs and Procedures*. Cambridge, MA.

McKenna, Regis (1993), *Relationship Marketing: Successful Strategies for the Age of the Consumer*. Boston, MA: Harvard Business School Press.

Mohs, Julia (1999), “Frequency Marketing,” *Retail Report*, University of Florida, 12(4), 3.

‘

Morgan, Robert M. and Shelby D. Hunt (1994), “The Commitment-Trust Theory of Relationship Marketing,” *Journal of Marketing,* 58 (July), 20-38.

Morrison, Donald (1976), *Multivariate Statistical Methods*. 2nd edition, New York: McGraw Hill, Inc.

Nash, Edward L. (1994), *Direct Marketing*, Third edition, New York: McGraw Hill, Inc.

Oliver, Richard L. (1999), “Whence Consumer Loyalty?,” *Journal of Marketing*, Special Issue, 63 (4),

Parasuraman, A. (1997), “Reflections on Gaining Competitive Advantage Through Customer Value,” *Journal of the Academy of Marketing Science,* 25, 154-61.

Petrison, Lisa, Robert C. Blattberg, and Paul Wang (1997), “Database Marketing. Past, Present and Future,” *Journal of Direct Marketing,* 11 (4), 109-23

Reichheld, Frederick F. and Earl W. Sasser (1990), “Zero Defections: Quality Comes to Services,” *Harvard Business Review,* (September-October), 105-11.

Reichheld, Frederick F. (1993), “Loyalty-Based Management,” *Harvard Business Review,* (March-April), 64-73.

Reichheld, Frederick and Thomas Teal (1996), *The Loyalty Effect.* Boston, MA: Harvard Business School Press.

Schmittlein, David, Lee G. Cooper and Donald Morrison (1993), “Truth in the Concentration in the Land of (80/20) Laws,” *Marketing Science*, 12 (Spring), 167-83.

Schmittlein, David C., Donald G. Morrison, and Richard Colombo (1987), “Counting Your Customers: Who Are They and What Will They do Next?,” *Management Science,* 33 (January), 1-24.

Schmittlein, David C. and Robert A. Peterson (1994), “Customer Base Analysis: An Industrial Purchase Process Application,” *Marketing Science,* 13, 41-67.

Sharma, Subhash (1996), *Applied Multivariate Techniques.* New York: John Wiley & Sons, Inc.

Sheth, Jagdish N. and Atul Parvatiyar (1995), “Relationship in Consumer Markets: Antecedents and Consequences,” *Journal of the Academy of Marketing Science,* 23 (4), 255-71.

Sheth, Jagdish N. and Rajendra Sisodia (1995): Improving the Marketing Productivity. In Encyclopedia of Marketing for the Year 2000. Chicago: American Marketing Association – NTC Publishing.

Smith, Michael D., Joseph Bailey, and Erik Brynjolfsson (2000), “Understanding Digital Markets: Review and Assessment,” In Understanding the Digital Economy. MIT Press (forthcoming)

Thomas, Jacquelyn (1998), *Avoiding Data Truncation Bias in Customer Lifetime Analysis*. Unpublished Manuscript, Stanford, CA: Stanford University.

Wang, Paul and Ted Spiegel (1994), “Database Marketing and Its Measurement of Success: Designing a Managerial Instrument to Calculate the Value of a Repeat Customer Base,” *Journal of Direct Marketing*, 8 (2), 73-81.