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On the Profitability of Long-Life Customers in a Noncontractual Setting: An Empirical Investigation and Implications for Marketing

Relationship marketing emphasizes the need for maintaining long-term customer relationships. It is beneficial, in general, to serve customers over a longer time, especially in a contractual relationship. However, it is not clear whether some of the findings observed in a contractual setting hold good in noncontractual scenarios: relationships between a seller and a buyer that are not governed by a contract or membership. The authors offer four different propositions in this study and subsequently test each one in a noncontractual context. The four propositions relate to whether (1) there exists a strong positive customer lifetime–profitability relationship, (2) profits increase over time, (3) the costs of serving long-life customers are less, and (4) long-life customers pay higher prices. The authors develop arguments both for and against each of the propositions. The data for this study, obtained from a large catalog retailer, cover a three-year window and are recorded on a daily basis. The empirical findings observed in this study challenge all the expectations derived from the literature. Long-life customers are not necessarily profitable customers. The authors develop plausible explanations for findings that go against the available evidence in the literature and identify three indicators through discriminant analysis that can help managers focus their efforts on more profitable customers. The authors draw several marketing implications and acknowledge the limitations of the study.

A basic tenet of relationship marketing is that firms benefit more from maintaining long-term customer relationships than short-term customer relationships.[1] Convincing conceptual evidence for this argument has been advanced by several authors (Morgan and Hunt 1994; Sheth and Parvatiyar 1995). Likewise, Bendapudi and Berry (1997) argue that the relationship marketing payoff to the firm comes only when relationships endure. In a widely quoted *Harvard Business Review* article, Reichheld and Sasser (1990, p. 105) state that "Customer defections have a surprisingly powerful impact on the bottom line. As a customer's relationship with the company lengthens, profits rise."

Although anecdotal evidence on the lifetime–profitability relationship is 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, p. 78) caution that "In short, 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 money with the firm than nonloyal customers. Dowling and Uncles doubt the widespread assumption of a clear-cut positive lifetime–profitability relationship and underline the importance of a differentiated analysis. Consequently, there is a need for more rigorous empirical evidence on the lifetime–profitability relationship. For example, long-life consumers expect value-added relationships in order to buy more products (Mohs 1999). Otherwise, their expenditures can be lower. In contrast, short-term consumers might not form any expectations of value-added relationships and therefore will have no inhibitions about buying products from the vendor.

Lifetime analyses typically have been conducted in contractual settings (Bolton 1998; Li 1995). Examples of this type of relationship are magazine subscriptions and cellular telephone services. In contractual settings, expected revenues can be forecast fairly accurately, and given a constant usage of the service, increasing cumulative profits over the customer's lifetime would be expected. However, in noncontractual settings, the firm must ensure that the relationship stays alive, because the customers typically split their

[1]The terms "customer," "household," and "subject" are used interchangeably in this article.

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category expenses among several firms (Dwyer 1997). Examples for noncontractual settings are department store purchases or mail-order purchases in the catalog and direct marketing industry.

Catalog marketing involves selling through catalogs that are mailed to a select list of customers. Consumers can buy just about anything from a catalog. Approximately 14 billion copies of more than 8500 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, almost 4% of total retail sales (Hodges 1996). For example, each year Lillian Vernon sends out 33 editions of its catalogs, with a total circulation of 178 million copies to the 20 million people in its database, selling everything from shoes to decorative lawn birds and monogrammed oven mitts (*Direct Marketing* 1998). Direct marketing is an important industry: In 1998, for example, 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 U.S. economy as a result of direct marketing activity (Direct Marketing Association 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 noncontractual setting such as the catalog industry, specifically, customers who start to purchase in a given time period may then buy repeatedly at some irregular time intervals. If the time intervals are relatively longer, is it wise for the firm to assume that these customers are likely to purchase again in the near future and, if so, to expect them to spend a certain amount of money? This is a necessary element for estimating customer lifetime value. Although duration seems like a simple concept, it can be complicated. The customer portfolios of many companies are composed of a few active customers—people who have regular and frequent interactions with the provider—and many inactives. Knowing where to draw the line is not easy, as inactives can be future actives.

In many cases, the duration of the relationship is not especially revealing because of normal fluctuations in customer activity over time. For example, direct mail publishers may learn more from the seasonal and life stage variations in customer buying patterns than from the specific number of years the customer has been on the database. What appears on the surface to be dormancy may actually be a naturally occurring pattern that will trigger purchasing when the next cycle comes around. Different customer segments may exhibit different patterns of attrition, switching, and reactivation (Wyner 1999). The firm dealing with limited/finite resources must decide when it is appropriate to make contact with (through mailing catalogs or other means) 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, less to monetary value, and the least to frequency. Subsequently, firms determine the selection of their mailing targets on the basis of the customer's RFM score (for an illustration of how this model is employed in the industry, see Aaker, Kumar, and Day 1998). In this study, we show how the use of the RFM model can result in suboptimal allocation of limited resources, and we therefore develop a better, alternative methodology. Because the firm must constantly invest in each customer and revenues from customers are much more unstable, the link between firm profits and customer lifetime duration might be weaker. Higher profits from customers with longer lifetime duration typically can 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. In this study, we 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 noncontractual context. To achieve this objective, we test

- How strong the lifetime duration–profitability relationship is,
- Whether profits increase over time (lifetime–profitability pattern),
- Whether the costs of serving long-life customers are less, and
- Whether long-life customers pay higher prices.

When we understand what happens in the marketplace, we can address the issue of why it happens that way. As data become available across different situations, empirical generalizations can be advanced. This is important especially in the noncontractual 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 (e.g., tailored communication, early warning indicators)?

The rest of the article is organized as follows: In the next section, we provide details on the conceptual model used in this study and offer four propositions. In the Research Methodology section, we discuss the data used to test the proposed relationships along with the model for measuring customer lifetime duration, which focuses on obtaining estimates of the lifetime duration for each customer. We also discuss the method used to test the propositions offered in this study. Next, in the Empirical Findings section, we assess the relationship between lifetime duration and profitability and the veracity of all the propositions. We develop the early warning indicators for efficient customer management strategy in the Further Analysis section. Finally, we draw implications for marketing managers and present limitations of the study.

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 costs associated with the marketing exchange. We investigate the consequences of customer retention, namely, profitability. Although several authors (Morgan and Hunt 1994; Sheth and Parvatiyar 1995) and much anecdotal evidence point toward a strong positive association between lifetime duration and profits accruing to the firm over time, little empirical evidence exists in that regard. Reichheld and Teal's (1996) study is the only published empirical evidence that underscores this claim. Because of the scarce empirical evidence and the cautionary notes by Dowling and Uncles (1997), we explore the direction and the strength of the lifetime–profitability relationship in a noncontractual scenario. Because of the nonexistence of empirical evidence in the noncontractual setting and weak theoretical justification, we provide arguments both for and against the proposed relationship. The directional effects of the propositions, however, are observed empirically.

Customer Lifetime and Firm Profitability

We offer four propositions in this study and subsequently test each one in a noncontractual scenario.

> P_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 than short-term relationships. 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 expect a substantial positive association between the duration of a customer–firm relationship and the firm profits derived thereof.[2] This is true for a contractual case, in which there is no repeated cost to entice customers into buying. In Figure 1, we summarize this situation. In line with this argument, the majority of relationship outcomes would be expected to fall along the diagonal, as shown in Figure 1. In other words, a substantial positive correlation would be expected 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 (Jones and Sasser 1995). For example, in less competitive markets, customers are more easily retained even at 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 ensure against customer defection. For many possible reasons, not all customers want to engage in a long-term relationship with the firm. For example, in the long-distance telephone service market, many "10-10" companies have emerged. There is no need to sign any contract with the service providers. Customers use a particular 10-10 company depending on the quality of service, unit price, and speed of connection. As discussed previously, to retain customers, it is important to satisfy them. The satisfaction of customers may come at a significant cost to the company. In a noncontractual case such as catalog shopping, members of a household might have to be sent many catalogs over a period of time before they decide to buy again. 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. Also, some customers may buy less from a catalog company because of competitive offerings, need for limited spending, or other factors over a period of time. This forces companies in a noncontractual scenario to examine the spending levels of each of their customers.

Blattberg and Deighton (1991) suggest that firms should partition their customer bases into behaviorally and attitudinally homogeneous groups that spend at different levels (see Figure 2) and then estimate the retention characteristics for each group. This grouping is considered appropriate by many managers in the direct marketing industry as they focus on the revenue generated by each customer over a period of time. Thus, the two dimensions—lifetime duration and revenues—appear to help managers make better decisions. Irrespective of the segmentation scheme, conventional wisdom argues for a positive relationship between profitability and time. Although the available evidence suggests that the lifetime–profitability relationship is positive, it might not be if the cost of serving the customer is greater than the profit margin generated by the customer. There could be many customers who receive catalogs on a regular basis because they bought at least one item in the recent past, even though it was of low dollar value.

[2]At this point, we are concerned with the sign and strength of the relationship—a one-shot, ex post assessment. In addition, in P_2 we examine the dynamics of the relationship over time.

FIGURE 1
Lifetime–Profitability Association

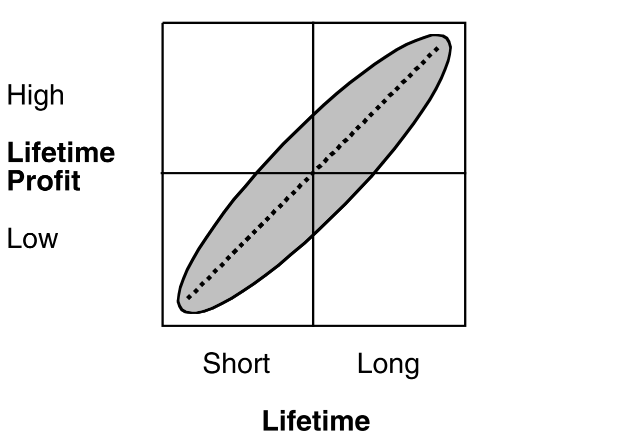
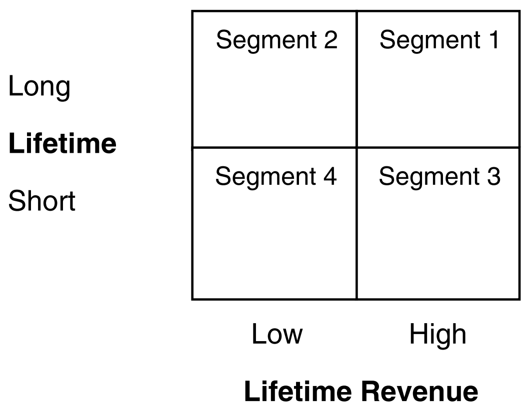


FIGURE 2
Segmentation Scheme



P_2: Profits increase over time.

Although a correlational measure is important and insightful, it presents only a static picture of the lifetime–profitability relationship. Although P_2 is related to P_1, analysis of the dynamic aspects of the lifetime–profitability relationship yields further important insights. The difference is that in P_2 we analyze profits dynamically across time, whereas in P_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. An investigation of the profitability evolution is of immense interest to managers. Best (2000) argues that retained (long-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. Analyzing longitudinal data can help assess whether our study's results add to the findings of Reichheld and Teal. The previous arguments can be true for a contractual setting but might not hold good for a noncontractual scenario. In the case of catalog shopping or direct mail offerings, the customer may end up buying once a year and spending a smaller amount. If this pattern prevails, the cost of serving this customer can easily exceed the profit margin brought in by the customer. Therefore, profits may not increase over time.

Using the same long-distance telephone service example discussed under P_1, in several cases the overhead costs of serving long-life customers are higher than the percentage of profit margin offered by the customer. It is necessary for a firm offering the 10-10 service to send monthly bills to all the customers who have started to use its service. Even if a customer does not use the service in a given month, that customer receives a bill. In this situation, the cost of serving the customer 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 also occurs in the credit card industry. Thus, it is not obvious that profit for the firm increases over time. Therefore, it is worthwhile to test this relationship.

P_3: The costs of serving long-life customers are lower.

Another commonly held contention is that long-life customers are less costly to serve than short-life customers. Reichheld and Teal (1996) quote several cases in which 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 because of lower marketing costs. Again, the research findings quoted previously are possibly true for contractual setting. In contrast, Dowling and Uncles (1997) caution not to overgeneralize these statements. They argue that there is little reason to believe that short-life customers are more expensive to serve. There may be costs associated with keeping customers for a longer lifetime through the reward program. Because loyalty programs offer benefits to customers over a period of time, they 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 long-life customers are lower. However, if experience factors play a role in transactions, we expect lower costs with increased transaction frequency. Yet for the broad retail sector, we do not expect lower transaction costs for long-life versus short-life customers. For example, there is little reason to believe that transaction costs for a 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 noncontractual scenario such as the direct marketing context, promotional costs are typically the largest nonproduct cost factor in a customer–firm relationship. Following the commonly held contention, we expect that the cost of promotional expenditures per dollar of sales revenue is lower for long-life customers, because the promotional mix has a greater efficiency in relation to the long-life customers. This is possibly due to cumulative effects or a more favorable attitude toward the firm's communication. Thus, we propose that the cost of promoting to customers, in relation to their revenues, is lower for long-life customers. Yet, to our knowledge, no empirical evidence in the literature substantiates this claim. Therefore, it will be interesting to test whether the costs associated with promotional expenditures directed at long- and short-life customers differ.

P_4: Long-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 possible introductory offers are accounted for. 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 therefore it is not surprising that they are less price sensitive on individual items. In the context of Internet shopping, Smith, Bailey, and Brynjolfsson (2000) highlight that retailers with strong customer awareness, such as Amazon.com or CDNow, are able to charge prices that are 7%–12% higher than those of lesser-known retailers. In our case, customers who have been dealing with the firm over a longer time naturally have 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 a consumer is a member of an airline's frequent flier program, 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 more than 20 million customers who do not spend anything on long distance. However, the customers get their monthly bill. These customers spend the least, irrespective of whether they are long- or short-life customers for a firm. Therefore, there may not be any difference in spending between long-life and short-life customers (Segments 2 and 4, respectively, in Figure 2) among low-revenue customers.

However, 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 customers buy more product units for a given dollar amount, they exhibit a higher degree of value consciousness; that is, they get 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 is that customers learn over time to trust lower-priced items or brands rather than established name brand products. Thus, there exists some reasonable evidence for both possibilities. Therefore, instead of proposing a directional effect, we test this proposition empirically.

Research Methodology

Data

Data from an established U.S. catalog retailer are 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 9167 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 first purchase with the firm, and these households have not been customers of the company before. Consequently, the observations are not left-censored. Of the entire sample, 4202 households started buying from the firm in January 1995 and are observed through December 1997. This group is termed Cohort 1. Cohort 2, consisting of 4965 customers, started buying during February 1995 and is also observed through December 1997. 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, and the median number is 5 purchases. The median interpurchase time is 117 days, and the median transaction amount is $91 for each purchase.

A Model for Measuring Customer Lifetime for Noncontractual Relationships

A critical component in our model is customer lifetime duration. The modeling process of a customer's lifetime is contingent on a valid measurement framework that adequately describes the process of birth, purchase activity, and defection. After such a measurement framework is established, an investigation into the factors that affect 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. Bolton's (1998) study represents a good example for this case. The situation is far more difficult when customers purchase completely at their discretion, that is, the noncontractual scenario. This situation is by far the most common across different product categories. Toward that end, we empirically implement and extend a procedure previously suggested by Schmittlein and Peterson (1994). When the lifetime duration is computed for each customer, we can develop testable propositions that deal with lifetime duration on the basis of conventional wisdom and prior 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 NBD that can be used to determine how many of a firm's current customers are active, on the basis of 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 nontrivial question, because the purchase activity is a random process and the defection is not directly observed. On the basis of 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 1994, 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. Schmittlein and Peterson give the desired probability for $\alpha > \beta$ as

$$(1) \quad P[\text{Alive}|r, \alpha, s, \beta, x, t, T] = \left(1 + \frac{s}{r+x+s}\left\{\left(\frac{\alpha+T}{\alpha+t}\right)^{r+x}\right.\right.$$

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

where $a_1 = r + x + s$; $b_1 = s + 1$; $c_1 = r + x + s + 1$; $z_1(y) = (\alpha - \beta)/(\alpha + y)$; $F(a_1, b_1; c_1; z_1)$ is the Gauss hypergeometric function; r, α, s, and 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 by Schmittlein and Peterson (1994, p. 65).

Given that the outcome of the NBD/Pareto model is a continuous probability estimate, Schmittlein and Peterson's (1994) 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 cutoff threshold, t_{cutoff}, then constitutes the lifetime of the customer. Figure 3 illustrates the procedure. This procedure enables us to calculate a finite lifetime for each customer, which we then use for the profitability analysis.

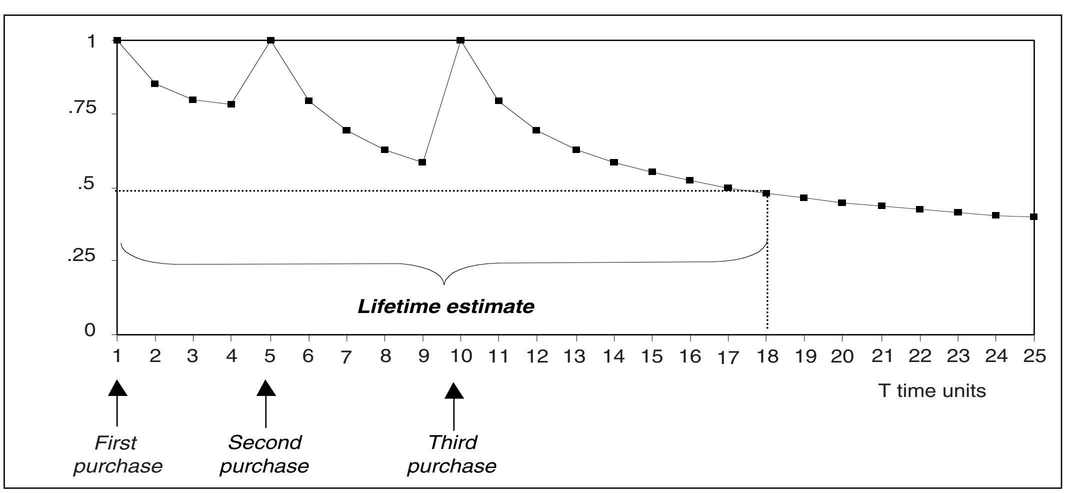
The previous discussion has been based on the assumptions that the time t_0 when the customer came on file or executed the first purchase is known. Given the widespread existence of customers' databases in organizations, this assumption is not difficult to meet (Petrison, Blattberg, and Wang 1997). Furthermore, any attempt to measure lifetime empirically should be reflected in the available data. This means that the observation window should be long enough to capture the true lifetime phenomenon. Finally, because the horizon of the analysis is finite, the analysis should accommodate right-censored observations. These assumptions outline the conditions for modeling lifetime in a noncontractual context. If these assumptions are met, we show that the calculation of the lifetime of an individual consumer becomes feasible and empirically meaningful.

Parameter estimation. We derived the four parameters of the NBD/Pareto model from the bootstrap method-of-moments estimates for the entire sample of 9167 households. Although bootstrapping is not a requirement for parameter estimation, it gives us the additional benefit of understanding the parameter sampling properties. For each parameter, we drew 20 bootstrap samples. We observed all households for at least 35 months. The estimated parameters are r = 4.24, α = 14.95, s = .93, and β = 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 alive. The moderate value of .93 for s indicates that the death rate varies considerably from customer to customer; that is, a considerable level of between-household heterogeneity exists in the sample. Overall, the model estimates seem reasonable and show a high degree of face validity and internal consistency. On the basis of the parameter estimates, we proceed to calculate the statistic of main interest: $P[\text{Alive}|r, \alpha, s, \beta, X, t, T]$.

The estimated parameter s, which affects 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, segments are likely to exhibit different lifetime behavior. The implications of this issue become important from the 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 cutoff threshold. The choice of cutoff threshold c determines the length of the lifetime estimate for each customer. A natural choice for the classification threshold would be c = .5. If customers' P(Alive) is above .5, they are assigned the status alive; otherwise, they are assigned the

FIGURE 3
Illustrative Lifetime Determination of Individual Household



status not alive. The threshold of choice in the classification literature is .5 (Sharma 1996). In survival analysis, Helsen and Schmittlein (1993) have used .5 in the prediction of purchase events. Because it could be argued that a threshold of c = .5 is suboptimal, we conducted a sensitivity analysis to assess whether a cutoff threshold other than .5 is 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). On the basis of the estimate of P(Alive) at Months 18, 24, and 30 and the assumed cutoff threshold (.1, …, .9), the household is classified as either alive or dead, where classification = alive if $P(\text{Alive})_{18,\,24,\,30} \geq c$ and classification = not alive if $P(\text{Alive})_{18,\,24,\,30} < c$ for c = .1, …, .9. Given this classification, the predicted classification for each c is compared with the actual purchase behavior in the holdout period. If subjects exhibit any purchase activity in the holdout period, they are designated active; if not, they are designated inactive. The cutoff threshold that produces the highest percentage of correct classifications is the choice that is most consistent with the data.

The threshold of .5 produces the highest percentage of correct classifications for the three samples. As a result, for the purpose of the lifetime analysis, we use .5 as the cutoff threshold.

Lifetime estimation. On the basis of 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 high. In both cohorts, approximately 60% of the sample has a lifetime that is shorter than the observation window. Thus, the available observation window is adequate for describing lifetime purchases of the given sample.

Profit calculation. We calculate net-present value of profit on an individual customer basis for the period of 36 months using Equation 2 (Berger and Nasr 1998):

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

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 .0125 = monthly discount rate (based on a .15% rate per year). The discount rate is set to 15%, which equals the U.S. 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% (Berger and Nasr 1998; Kim, Mahajan, and Srivastava 1995). 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 a 30% profit margin of the monthly revenues. This is a rather conservative figure and reflects the firm's managerial judgment. Because of 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, lettershop, and mailing costs. Individual customer mailing costs 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 because the company does not track them on a per-customer basis. Now that lifetime duration and profitability have been computed, we proceed to test the propositions offered in this study.

Test of Propositions[3]

P_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 subgroups (Figure 2). Using profit as the dependent variable, we 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 (e.g., Bearden, Rose, and Teel 1994; Schmittlein, Cooper, and Morrison 1993). Likewise, 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 in most cases. If the highest lifetime duration is right-censored, the mean lifetime estimate will be biased (Collett 1994). Therefore, in line with existing research and because of methodological requirements, we employ a median split and create a shorter and a longer "lifetime-half" and a higher and a lower "revenue-half."

[3]The analysis of the test of propositions does not include the acquisition costs for each customer, because the data are not available. If acquisition costs are available, they can easily be integrated into the proposed framework. If acquisition costs are similar across all customers, the findings of the study hold good. For example, the acquisition costs for catalog companies to acquire a customer on the Web is \$11 compared with \$82 for Internet-only retailers (Quick 2000). If acquisition costs are so low for catalog companies, the variation in acquisition costs across customers should not affect the results of this study.

TABLE 1
Finite Lifetime Estimates

	Mean Lifetime (Months)	Standard Deviation	Percentage Right-Censored	Minimum	Maximum
Cohort 1	28.7	7.8	41.1	11	36
Cohort 2	27.9	7.9	41.7	12	35

We 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 will be. In line with the relationship marketing literature, we expect the customers who fall into Segment 1 to generate the highest profits. Likewise, we expect customers in Segment 4 to yield the lowest profits. However, in addition to providing empirical evidence for these expectations, this segmentation scheme enables us to 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 encounter a situation in which customers with shorter tenure are more profitable than long-term customers? This finding would run 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 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 is comparably small, it is imperative for the firm to pay close attention to the characteristics of its second most profitable segment. As pointed out previously, Garbarino and Johnson (1999) and Ganesan (1994) have shown that long-term and short-term customers must be treated differently. Answers to these questions provide important information to managers regarding the optimal design of the communication strategies that efficiently reach each of their most profitable segments.

P_2*: Profits increase over time*. To test the proposition of increasing profits over time, we (1) examine the profitability evolution visually and (2) 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, we include a dummy variable for the first purchase period to reflect the large first month purchase amount. The exact specification of the regression is

$$\text{(3)} \qquad \text{Profit}_{ts} = a_s + b_{1s} \times \text{dummy} + b_{2s} \times t_s + \text{error},$$

where

t = month,
b_{is} = regression coefficient,
s = segment, and
dummy = 1 if first purchase month, otherwise 0.

The profit figures are derived for customers who either have purchase activity in a given month or incur cost because of 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. This higher purchase could be the reflection of the novelty of the situation such as the new vendor, new goods, or new deals. As a result, the estimation better reflects the actual profit pattern beyond Month 1.

P_3*: The costs of serving long-life customers are lower*. To test this proposition, we 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, we compute the mean promotional costs across all households and then compare the costs across segments to determine if the costs of serving long-life customers are lower.

P_4*: Long-life customers pay higher prices*. We test in our study whether long-life customers pay higher prices than short-life customers do. Therefore, we 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?

To test the strength of the lifetime–profitability relationship, we calculate the bivariate Pearson correlation between lifetime duration (in months) and lifetime profit ($). The correlation coefficient r is .175 for Cohort 1 and .219 for Cohort 2, which means that only a moderate linear association between lifetime duration and lifetime profits exists. Although a significant positive association (at α = .05) exists, in line with theoretical expectations, overall it seems weak. Lifetime duration alone does not explain overall lifetime profitability well. Furthermore, when segmenting the customers in Cohort 1 using a median split, we find that 2530 of 4202 households fall in the diagonal of Figure 2 (1322 in the upper right-hand quadrant, 1208 in the lower left-hand quadrant). This means that a 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 a long lifetime. Although our findings moderately support the theoretical predictions from the relationship marketing perspective, additional analyses are warranted to explain the apparently counterintuitive results. Specifically, we are interested in how much each segment contributes to overall profits. The goal is to uncover optimally the underlying relationship of lifetime with profitability. In Table 2, we summarize these results.

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. In noncontractual settings, 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 (α = .01) different from the mean profit of Segment 2. In terms of total segment profitability, the short-lived Segment 3 generates 29.2% of the total cohort profits. Thus, although long-term customers in Segment 1 are important to the firm, short-term customers in Segment 3 are important as well, because they generate more than a quarter of the total cohort profits.

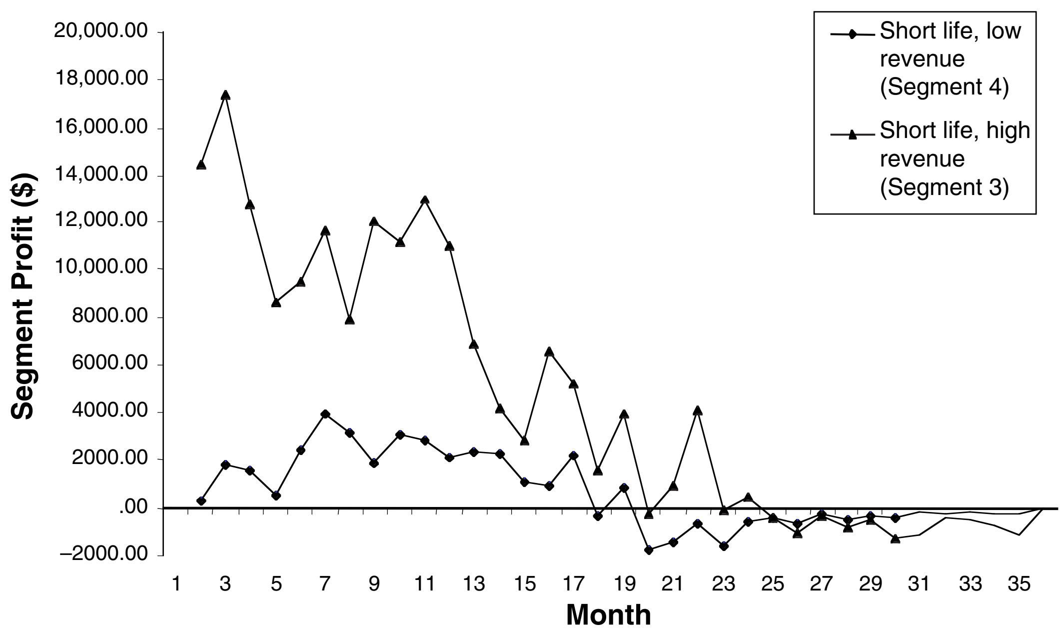
Thus, this is a case in which both long-term (Segment 1) and short-term (Segment 3) customers constitute the core of the firm's business. Likewise, we find empirical support for Dowling and Uncles's (1997) speculation that the relation-

TABLE 2
Tests of Propositions: Results

	Segment 2					Segment 1				
Long Lifetime	**Number of Customers**	**Lifetime Profit per Customer (Dollars)**	**Relative Profit (Dollars/ Month)**	**Mailing Cost/Sales Ratio**	**Average Item Price**	**Number of Customers**	**Lifetime Profit per Customer (Dollars)**	**Relative Profit (Dollars/ Month)**	**Mailing Cost/Sales Ratio**	**Average Item Price**
	889 (973)	50.85 (55.26)	1.43 (1.56)	.128 (.124)	47.74 (48.72)	1322 (1546)	289.83 (322.03)	8.18 (9.31)	.063* (.062)*	58.43** (58.25)**
	Segment 4					**Segment 3**				
Short Lifetime	1208 (1504)	50.49 (53.67)	2.41 (2.67)	.141 (.143)	47.97 (46.80)	783 (942)	257.96 (284.20)	11.67 (12.57)	.065 (.064)	63.54 (64.47)
	Low Lifetime Revenue					**High Lifetime Revenue**				

*The difference between Segment 1 and Segment 3 is not significant.
**The difference between Segment 1 and Segment 3 is significant at least at $\alpha = .05$.
Notes: Cohort 2 results are in parentheses.

FIGURE 4
Aggregate Profits (Dollars) for Short-Life Segments



ship between lifetime and profits can be far from positive and monotonic. Consequently, an implication for managers is that a firm strategy focusing on relational buyers only, as opposed to transactional buyers, would be disadvantageous. Thus, the firm must develop and maintain operational and communication tools that effectively cater to each of the two groups.

Another interesting outcome of the analysis is that in terms of relative profits—that is, profit per month—customers in Segment 3 are the most attractive of all (Table 2, Figure 4). Segment 3 customers purchase with high intensity and thus generate 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 $\alpha = .05$ (using the multiple comparison test). The profits per month for long-life segments are shown in Figure 5, which captures the implications discussed so far.

There are several possible reasons for this interesting pattern of results. Segment 1 customers are the most desirable 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, because Segment 3 customers spend at a high level. Dissatisfaction might occur rather for Segment 4, whose customers spend the lowest amount. Although we highlight the speculative nature of these inferences, it seems worthwhile to search for the underlying consumer motivations.

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 exhibit decreasing profits over time. Only for Segment 2 (long life, low revenue) do we find a slightly positive trend in the profitability evolution.

For a more formal test, we compare the sign and significance of the time coefficient from the regression analysis of profits as a function of time and present the results in Table 3. With the exception of Segment 2, we generally find that the coefficient for the linear effect has a negative sign, which thus highlights the negative profit trend over time for the three segments. All the coefficients for time are significant at $\alpha = .01$.

It is not uncommon for proponents of relationship marketing to mention that profits due to customer loyalty are higher in each subsequent period. This is typically the case for contractual settings, in which a firm derives most or all of the business of a customer—for example, for life insurance or health club memberships. However, for noncontractual settings, this might be different. For some products and services, this would 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 little empirical evidence available from Reichheld and Teal (1996) argues that this assumption would hold for the most part. Even if this claim would not hold for all customer segments, it can be expected

FIGURE 5
Aggregate Profits (Dollars) for Long-Life Segments

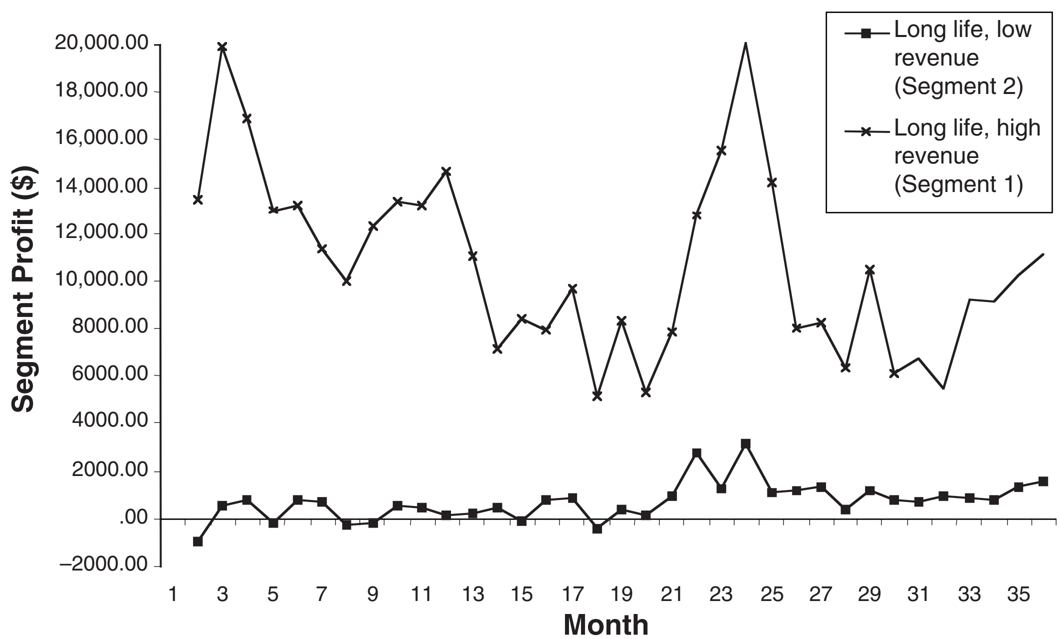


TABLE 3
Regression Results for t = 1 to 36 Months (Cohort 1)

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)	–.13 (–.14)	.85 (.85)
2	n.s. (n.s.)	30.24 (30.91)	.07 (.071)	.92 (.91)
3	19.40 (20.9)	57.85 (58.29)	–.70 (–.75)	.95 (.94)
4	3.25 (3.69)	29.53 (31.45)	–.14 (–.15)	.94 (.95)

Notes: Validation results are in parentheses (Cohort 2). All coefficients are significant at $p < .01$ except those marked n.s. (not significant).

to hold at the very least for the most loyal group (Segment 1). However, our results do not support this claim. This is 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 virtual cycle in which satisfaction with transactions in previous periods feeds into not only loyalty in future periods but also a reinforcement and growth in firm profits. The counterforces to this virtual cycle are, for example, variety seeking across firms, customers' boredom from interacting with the same firm, firms' competitive actions, and the lack of contracts. This negative relationship is also possible if the customer contact costs through mailing catalogs are high compared with the potential revenue from the sales realized from each customer. If costs exceed revenue, this gap can increase over time to a point at which the negative relationship is prevalent. These counterforces are strong enough to block the theoretically existing virtuous cycle, which thereby leads 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, because we do not find support for the underlying argument—that is, that profits from long-life customers increase over time. However, loyalty might lead to increased profit over time if there is a forced ongoing relationship or an inertia-driven relationship, if costs of maintenance decrease over time at a faster rate than revenues fall off, and so forth.

Are the Costs of Serving Long-Life Customers Lower?

Our objective was to test whether the costs associated with promotional expenditures directed at long- and short-life customers differ. 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 dollar amount that is necessary to sustain a $1 amount of revenue. Results are shown in Table 2 for Cohorts 1 and 2.

The notion that customers with long tenure are associated with lower promotional costs is rejected. The ratio of mailing cost per dollar sales in the long-life segment (Segment 1) is statistically not different from the mailing cost per dollar sales in the short-life segment (Segment 3). This means that, in terms of cost efficiency, Segments 1 and 3 are the most attractive to the firm, though they have different lifetime properties. Sheth and Parvatiyar (1995) speculate that long-life relationships are desirable because they are associated with higher marketing efficiency. Our findings show that the ratio of mailing cost to revenues, which is one measure of efficiency, might 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 beneficial for the firm, regardless of lifetime duration. This can be traced back to the promotional tool that is used by most direct marketing firms: the RFM framework. Promotions are allocated mainly on the basis of people's amount of purchases and only to a lesser degree on the basis of their lifetime duration. Thus, the absolute level of promotions to high-revenue customers is higher. However, higher revenues more than offset this level of promotions, resulting in greater efficiency of serving the customers.

Do Long-Life Customers Pay Higher Prices?

We empirically tested whether long-life customers pay, on average, higher or lower prices for their chosen products than customers in the short-life segments. We compute for each transaction the ratio of dollar spending to the number of items purchased and average this figure across purchase occasions and customers within segments. Results are shown in Table 2 for Cohorts 1 and 2. The average price per item for Segment 3 is significantly ($\alpha = .05$) greater than that for 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 than does Segment 1. It could be argued, though, that this effect might be due to different types of products being 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 (hard goods and soft goods). The effects were identical to the analysis reported previously. Short-life (Segment 3) customers pay higher prices than long-life (Segment 1) customers, even when we control 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 the highly profitable short-term customer who seems to be less sensitive to the product's price. One possible explanation for the behavior of Segment 3 customers is that these people are heavy users of the catalog but are not very brand focused. These people are likely to be well informed about the alternative brands and their benefits as well as more concerned about getting what they want given their high category involvement. Thus, they might shop heavily from more retailers and switch more easily for smaller benefits, because for these customers even a small benefit may have a large value. Therefore, the higher spending (average prices paid) by Segment 3 customers may be due to some other benefit sought by them.

This finding is possible given that long-life customers may have tried different products and found ways to identify a lower-priced but better-quality product. Thus, their average price paid per item is lower than that of short-life customers. However, the average price paid for an item by customers in Segments 2 (long life, low revenue) and 4 (short life, low revenue) is not significantly different, because some customers always spend less, irrespective of short or long life.

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–profitability analysis can exhibit a differentiated picture: Profitability can occur for the firm from long- and short-life customers. We discovered that, in this case at least, profits do not increase with increasing customer tenure, which thereby adds new empirical evidence to the domain. Third, we found that the cost of serving long-life customers is not lower. Fourth, we discovered that long-life customers do not pay higher prices. The transaction characteristics in different industries vary considerably, and consequently we expect these factors to have differential impacts in different industries. However, for the case of the general merchandise catalog industry, we do not find support for any of the propositions. In contrast, Reichheld and Teal (1996) mention general merchandise retailing and direct mail specifically as examples of industries in which evidence for the factors should be found. Because of 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 long-life and short-life consumers?

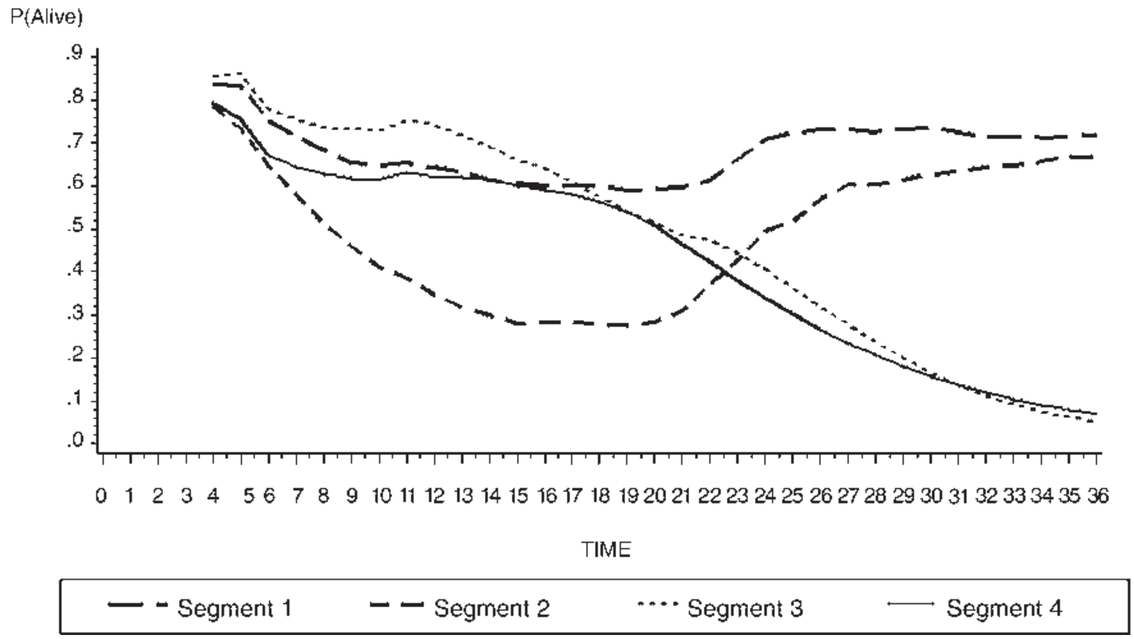
Further Analysis

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 patterns. We demonstrated ex post that we can 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, on the basis of their current selection tool, the RFM framework, the firm keeps mailing to this segment. Thus, the firm incurs cost on this segment without a chance of recovering its investment. Given its use of RFM, the firm is not able to distinguish between the short-life and long-life groups. Therefore, on the basis of the hypothesis that there is a substantial group of intrinsically short-lived customers, it is necessary to identify this highly profitable yet short-lived group as early as possible and then stop chasing these customers after they stop 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

FIGURE 6
Segmentwise P(Alive) for Cohort 1



ex ante analysis to explore the profit benefits of our framework. The difficulty 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 must classify each customer a priori into either the long-life or the short-life segment. If a customer is classified a priori into the short-life group, the firm can stop mailing to this customer early—that is, avoid chasing this customer for too long. Given the empirical nature of this task, misclassification will be inherent. Thus, we must address the issue of when the loss of wasted mailings to the short-life segment is larger than the forgone profits of the misclassified long-life customers if the firm were to stop mailing them. This is an 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 is large, it becomes increasingly beneficial to forgo a certain amount of profits from the misclassified long-life customers. This trade-off depends largely on the quality of the classification. In the following section, we 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 Short- and Long-Life Customer Segments

We use discriminant analysis to separate the two segments of interest, Segment 1 and Segment 3. To predict segment membership, we use information on exchange variables and demographic characteristics. For sensitivity purposes, we perform individual predictions for 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, we perform a total of 12 different discriminant analyses. 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 interpurchase time variable is not included, as P(Alive) contains that information. Thus, the key variable of interest is the probability of being alive. P(Alive) summarizes consumers' past purchase activity, and we expect that this variable discriminates strongly between the two segments. Figure 6 shows the distinct P(Alive) characteristic of the four segments. Because of its 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.

We included the variable recency because a relatively long inactivity of a customer signals to the firm that the customer may have ceased the relationship. Indeed, in a noncontractual 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.

The discriminant analysis was based on customers who belonged to Segment 1 or Segment 3. Therefore, 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 .001 for both cohorts. The null hypothesis of homogeneity of within-group covariance matrices is also rejected for every month at .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 is 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 $p < .001$. 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. Although the standardized weights for the three significant variables varied somewhat across the 12 discriminant analyses, P(Alive) and recency remained the most important of all the predictors. For example, the standardized weights for P(Alive), recency, and income were .495, –.583, and .101, respectively, in one of the discriminant analyses for Cohort 1. The coefficients of P(Alive) and recency exhibit face validity—the larger the probability of being alive and the fewer days elapsed since last purchase, the longer is the lifetime. When discriminant analysis was performed with Cohort 2 data, the standardized weights were quite similar to those of Cohort 1. For 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, in Cohort 1, whereas 21.03% of the long-life customers are misclassified as short-life customers in Month 25, 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%. Over time, managers can constantly improve their predictions about segment membership. Cohort 2 results are similar to the Cohort 1 results and thus add validity to the findings.

On the basis of 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. In Table 5, we show 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 .25 on the cost of goods sold. Although we focus on Cohort 1, the results for Cohort 2 are similar.

The objective of the analysis is to find out if and when the losses due to forgone revenues (profits) from long-life customers who are erroneously misclassified as short-life customers are smaller than the cost savings due to not sending excess mailings to short-life customers. Thus, we provide a profitability framework for managers that helps them base the decision of further pursuing a customer 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 .25, the firm would encounter losses of $611. This is a result of $6,170 of forgone profits from misclassified long-life (Segment 1) customers for the remaining six months (assuming they stop buying) and $5,558 in saved mailing costs to the correctly classified short-life customers for the remaining six months. Because forgone profits are larger than savings in mailings, it would not be optimal to stop mailing at Month 30. In contrast, the savings from stopping the mailing after Month 32 ($2,960) are larger than the forgone profits ($1,279). This is a function of better classification results, which in turn depend 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 (.15 to .30). According to one of the firm's managers, the profit margins reflect those encountered by the firm in its business trans-

TABLE 4
Classification Results from Discriminant Analysis Using Cross-Validation for Cohort 1

	Month											
	25	26	27	28	29	30	31	32	33	34	35	36
Percentage of long-life customers misclassified 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)
Percentage 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)
Hit ratio (percentage 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)

Notes: Validation results are in parentheses (Cohort 2).

actions. The curves in Figure 7 depict the result of this analysis.

If a lower profit margin is assumed, the time to stop the mailings to short-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, even though they belong to two behaviorally different segments. As a result, considerable resources are wasted on mailings that will never lead to purchase activity, simply because the lifetime activity pattern of a certain segment is not accounted for.

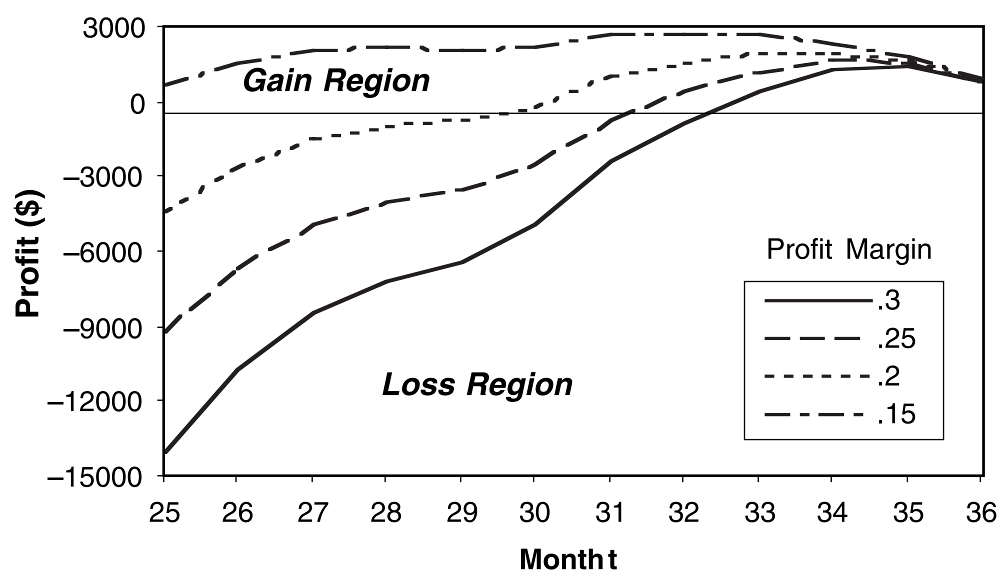
When customer segments exhibit different lifetime activity patterns, it becomes an important managerial decision when to stop mailing to the butterflies, the highly active yet short-lived Segment 3. The currently implemented RFM framework overspends on this substantial group of cus-

TABLE 5
Process of Profit Calculation (Cohort 1)

Use Information up to Month	Forecast Horizon (Months)	Number of Long-Life Customers Misclassified as Short-Life	Forgone Monthly Profits (Dollars)	Forgone Total Profits (Dollars)	Number of Correctly Classified Short-Life Customers	Monthly Savings Due to Not Mailing (Dollars)	Total Savings Due to Not Mailing (Dollars)	Net Profit/ (Loss) (Dollars)
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]21.0% were misclassified (Table 3, row 1), and the total number of long-life customers = 1141; thus, .21 × 1141 = 240.
[b]Average monthly profit for long-life customers in Months 25–36 with .25% gross margin = $6.27; thus, 240 × 6.27 = 1505.
[c]Accumulation of forgone monthly profits for duration of forecast horizon; thus, 1505 × 12 = 18,058.
[d]71.0% were correctly classified (Table 3, row 2), and the total number of short-life customers = 677; thus, .71 × 677 = 481.
[e]Average monthly loss for short-life customers in Months 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 forgone total profits and total savings due to not mailing.
Notes: Figures are rounded to integers.

FIGURE 7
Profit Loss/Gain if Mailings Were Stopped at Month t (Cohort 1, Segments 1 and 3)



Notes: n = 1818.

tomers. In addition to putting forth an empirical procedure that uncovers lifetime profitability patterns, we apply this framework such that substantial cost savings are realized. Remember that the previous 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 several million accounts) at a decision date of Month 33, the suggested procedure would save the firm $184,928 if the average profit margin were .25, and $222,880 if the average profit margin were .2. Small savings make a difference, and when extended to the entire customer base, the firm's savings will be 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 in which a firm usually receives all the customer's business after the customer signs up for the service. Even in a contractual context, there can be cases in which 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. Although anecdotal evidence may exist, it is worthwhile to study empirically the nature of the lifetime–profitability relationship. We 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.

An Attempt to Generalize

We show that managers cannot simply equate a long-life customer with increased lifetime spendings, decreased costs of serving, and lower price sensitivity. In the noncontractual setting, it is 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 study is a case in which 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's (1997) claim that it is a gross oversimplification to equate loyal customers with higher profits. We present a structured framework for analyzing the customer lifetime–profitability pattern 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. First, we suspect that the noncontractual nature of the customer–firm relationship drives the result to a large extent. Customers incur virtually no switching costs in case they want to weaken or terminate the relationship. Because this noncontractual setting is common in business-to-consumer settings, the results become all the more important. What keeps the customer interested in maintaining a relationship in a noncontractual setting is a match between a firm's offerings, compared with those of competition, and the customer's desires. However, because switching costs play such a small role, the impact of competition and other forces on existing relationships is large. Thus, at any given point, the firm cannot neglect the transaction orientation of its business and must manage the short-term aspect accordingly. This position stands in stark contrast with, for example, contractual relationships such as insurance or health clubs. What can a firm do in such a situation? As we point out, while managing the short-term aspect, it should try to raise switching costs as much as possible—for example, through the introduction of affinity programs, charge cards, bonus point systems, and the like. However, the question remains whether these measures will be successful after all in binding the transactional customer. Another managerial strategy might be to try to predict the lifetime characteristics of a customer as early as possible and then act accordingly.

A second factor that might drive our results and that compounds the noncontractual issue is that impulse buying and the potential thereof is very large. The underlying issue is that consumers are offered a tremendous array of choices. Although certain people actively restrict their choices and thereby become relationship oriented (Sheth and Paravatiyar 1995), 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 long-life customers—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 believe that managing for the long run must be a carefully designed proposition and should be well aligned with the firm's and industry's general buying characteristics. Examples for failing to do so are abundant.

A third and different possible reason for the observed pattern is unobservable affective factors. For example, although most buyers would assess the value of a transaction by objective measures, such as level of service or price in comparison with competition, others might rely to a higher degree on their affective state toward the firm. According to Peterson (1995), this dimension has remained unexplored in the relationship marketing stream. It could be argued that consumers have a positive attitude toward the firm that is 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 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 positive attitude toward a firm, which subsequently subsides rather quickly. The positive attitude could explain a high initial intensity of purchasing, which could be an explanation for Segment 3's (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 previously, 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 expect their level of motives to be stronger than that of the two low-revenue segments.[4]

Having attempted to develop the generalities of our findings, we focus our attention on the managerial consequences. We therefore highlight the need for managers to be aware that both types of relationships—short- and long-term—can be highly profitable. Because they can coexist, the firm must learn to (1) identify the type of relationship with each of its customers and (2) 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 noncontractual context. We have employed cohort analysis, a methodology that Parasuraman (1997) has advocated 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. On the basis of this information, the firm can identify at any given time the general nature of its customers' lifetime patterns and the individual-specific status along the lifetime continuum. Knowing these two dynamic characteristics is a prerequisite for managers to engage in true customer management, which has been called for by several authors (Blattberg and Deighton 1996; Kotler 1994; Wang and Spiegel 1994).

Customization of Marketing Strategy

We agree with the contention that some customers do not ever stay loyal to the company. However, we do not agree with the statement that the firm must avoid these people altogether. Rather, we argue that the challenge is to know when to stop targeting them with individual and expensive communications. 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 show how short-life customers can be recognized earlier through the previous framework than through the currently used 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 enables managers to truly manage customers. Although the importance of treating 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 1999). 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. Garbarino and Johnson's 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 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. Because we show that both long- and short-life customers can be highly profitable, the company's differential communication strategy toward the two groups becomes all the more important.

One strategy to encourage customers to spend more with the firm is to offer a variety of products and newer products. Catalog retailers must become more innovative in reducing the costs and using other effective media, such as the Internet, trade shows, and event sponsorship.

Conversion of Short-Life to Long-Life Customers

Another managerial option is 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. This is possible through enrolling every customer in a frequent shoppers program that gives reward points on the basis of the frequency as well as the dollar value of purchases. Because a short life can also be due to customer dissatisfaction, efforts should be made to satisfy customers during presales, sales, and postsales processes. Although we 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 Further Research

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

First and foremost, additional research should extend the proposed empirical analysis to other product categories and industries. Although our data come from a large and established company in an important consumer goods industry, further empirical analyses in other noncontractual 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 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 to examine whether customer attitudes can be used as discriminators between intrinsic disposition toward short and long lifetime duration. We believe that the integration of behavioral and attitudinal data

[4]As it turns out, the percentage of customers that actively requested an initial catalog instead of being solicited is significantly higher for the two high-revenue segments (Segments 1 and 3 in Figure 2). Although this is an ex post test, the result could hint toward the stronger underlying motive for the two segments in question.

opens up a 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 because of unavailability of data. Thomas (1998) has shown that the type of customer a firm acquires affects the long-term relationship the customer has 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. Further research can address this issue with the availability of relevant data.

Fourth, the data used in this study span only three years. Although three years yield multiple purchase opportunities, a longer duration of data may offer additional insights. For example, Keane and Wang (1995) compare segments of three-year (low) and six-year (high) average durability in the context of newspaper publishing.

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

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