



# Applications of CRM in B2B and B2C Scenarios

## Part I

### 16.1 Measuring Customer Profitability – 331

16.1.1 Computing CLV – 331

16.1.2 Drivers of CLV – 332

### 16.2 The Lifetime-Profitability Relationship in a Noncontractual Setting – 334

16.2.1 Background and Objective – 334

16.2.2 Conceptual Model – 335

16.2.3 Research Methodology – 338

16.2.4 Empirical Findings – 341

16.2.5 Implications – 346

### 16.3 Model for Incorporating Customers' Projected Profitability into Lifetime Duration Computation – 346

16.3.1 Background and Objectives – 346

16.3.2 A Dynamic Model of the Antecedents of Profitable Lifetime Duration – 346

16.3.3 Research Methodology – 348

16.3.4 Determining Profitable Customer Lifetime Duration – 349

16.3.5 Analysis – 350

16.3.6 Results – 352

16.3.7 Technical Appendix: Estimation of  $P(\text{Alive})$  – 356

### 16.4 Model for Identifying the True Value of a Lost Customer – 358

16.4.1 Conceptual Background – 358

16.4.2 Modeling the Effects of Disadoption on the Value of a Lost Customer – 359

16.4.3 The Key Determinants of the Value of a Customer – 359

### References – 361

### Overview

Delta Airlines had long been operating a customer loyalty program that computed the accumulated frequent-flier reward points solely on the basis of the total number of miles flown by a customer (Kumar & Ramani, 2003). The loyalty program did not differentiate between those customers who pay economy class fares and those who pay business class fares, to fly the same distance. From a profitability viewpoint, this program was misaligned. Delta Airlines' loyalty program was clearly not based on the customer's value to the firm. No wonder, then, this program was recently replaced with one that differentiated between customers paying for different fare classes. Now, a customer flying business class gets 50% more points than does a customer traveling economy class. This new approach recognizes customers who are more profitable to the firm need to be rewarded more.

General Motors revised the redemption scheme on its 10-year-old GM card in 2002. The maximum amount of earnings a customer can redeem toward the purchase or lease of a new GM car, truck, or SUV now depends on the year, make, and model chosen. This move is similar to the one adopted by Delta, in that a customer who spends on a premium product is rewarded more than a customer who purchases a low-end product.

There seems to be two complementary reasons why firms are becoming unabashedly profit-oriented in their approach toward customer rewards programs. First, firms are in a better position, thanks to technology, to record customer actions and ascertain their individual profitability levels. Thus, firms no longer use surrogate measures like unit volume of business, share of wallet, and duration of association to reward their customers. Let us examine the share of wallet measure some firms use to decide on customer-level investments. Share of wallet (SOW) is defined as the ratio of the total customer spending with the firm to the total category spending (the firm plus its competitors) for that customer. It is clear that achieving a large SOW a low-spending client may not be as good as achieving a low SW of a high-spending client. Thus, firms do not need to continue using surrogate measures because the drawbacks inherent in these measures can now be over-

come by concentrating directly on individual customer profitability. Second, customers realize they can no longer expect a firm to believe they are special if they are not genuine high-value buyers. Differential treatment of customers is therefore being accepted as a way of life by both firms and customers. However, differential treatment can work for a firm in the long run, only if it has an eye on the future. The challenge for a firm today is to develop an optimal blend of differential levels of treatments such that over every customer's lifetime, the profits earned by the firm are maximized. Not every firm understands how to develop a strategy which balances customer relations and profitability.

The level of sophistication of the adoption of the customer value metric approach into a firm's marketing program could vary. A firm operating a loyalty program can start using the customer value metric to examine whether the customers being rewarded are indeed the profitable ones. It should take corrective action if it finds that such is not the case. At the next level, a firm can begin to observe when its customers are beginning to turn unprofitable. The firm can decide to let go of these customers without wasting further efforts on them. Moving up another level, a firm could determine the factors likely to affect how long a customer is likely to stay profitable. This enables the firm to control and manage the variables necessary to increase a customer's profitability. At the next level, a firm can plan investments in marketing initiatives on the basis of an analysis of expected profits from its customers during a given planning period. A firm can achieve the next level of sophistication by understanding the impact of changing the frequency of its marketing communication elements on the profitability of each customer. In this manner it can allocate its resources optimally across marketing initiatives, by cutting down on wasteful efforts and increasing the frequency of effective efforts, one customer at a time. At the next level, a firm can predict the timing of purchase of each of the products in its portfolio and tailor the communication message around the product likely to be next purchased by a customer. Mathematical models necessary to carry these levels of analyses and predictions have been developed in the CRM literature (Venkatesan & Kumar, 2004).

## 16.1 Measuring Customer Profitability

Successful marketing initiatives are contingent upon the firm having a good understanding of how their actions affect customers. This becomes difficult for firms since their customer base is dynamic and involves interplay of several marketing variables such as tenure of the customers with the firm, profitability of the customers, purchase behavior over time, adoption of multiple channels to purchase, and demographic factors governing purchase behavior, among others. With so many inputs making up individual customer profiles how can firms expect to offer effective marketing initiatives to attract the largest number of desirable customers?

Management has access to a tool, which takes into account all of these inputs and allows segmentation based on future profitability. The metric is known as Customer Lifetime Value (CLV). By using CLV as the primary planning tool for marketing initiatives, firms can ensure that they only target those customers who have the most future value to the company. From this they can optimize scarce marketing resources and ensure the future profitability of the firm.

Customer Lifetime Value is defined as follows:

- The sum of cumulated future cash flows – discounted using the weighted average cost of capital (WACC) – of a customer over their entire lifetime with the company (Kumar, 2007, 2008).

In other words, CLV is a multi-period evaluation of a customer's value to the firm, and it assists managers to allocate resources optimally and develop customer-level marketing strategies.

### 16.1.1 Computing CLV

To compute CLV, it is essential to consider the setting in which the customer's purchases are being made i.e., contractual and non-contractual. A contractual setting is one where the customers are bounded by a contract such as a cable TV subscription. On the contrary, in a non-contractual setting such as grocery store purchases the customers are not bounded by a contract. The business implication of these two

situations is that in a contractual setting, the firm gets *stream revenue* or fixed monthly revenue through the subscription. But, in a non-contractual setting, the stream revenue would be absent. Therefore, these differences will have to be included while computing CLV. To cover both the situations, CLV can be expressed in the following form:

$$CLV_i = \underbrace{\sum_{t=1}^T \frac{\text{Base GC}}{(1+d)^t}}_{\text{Baseline}} + \underbrace{\sum_{t=1}^T \frac{\hat{p}(\text{Buy}_{it}=1) * \hat{G} C_{it}}{(1+d)^t}}_{\text{Augmented CLV}} - \frac{\hat{M} C_{it}}{(1+d)^t} \quad (16.1)$$

where,

- $CLV_i$  = lifetime value for customer  $i$
- $\hat{p}(\text{Buy})_{it}$  = predicted probability that customer  $i$  will purchase additional product(s)/service(s) in time period  $t$
- $GC_{it}$  = predicted gross contribution margin provided by customer  $i$  in time period  $t$
- $MC_{it}$  = predicted marketing costs directed toward customer  $i$  in time period  $t$
- $t$  = index for time periods; such as months, quarters, years, etc.
- $T$  = marks the end of the calibration or observation time framed = monthly discount factor
- Base GC = predicted base monthly gross contribution margin

As is evident from (Eq. 16.1), this formula can be applied in both the contractual and non-contractual settings. The baseline CLV represents the net present value of the future stream revenue from the customer. The augmented CLV represents the net present value of future cash flows from a customer based on the products/services purchased. In the case of a contractual business setting, the CLV would be the sum of the baseline CLV and the augmented CLV, since the customers will be contributing revenue to the firm by way of their monthly subscription. In the case of a non-contractual setting, the CLV would only be the augmented CLV, since the customer

**Table 16.1** Transaction details of Amy

	June	July	August	September
$\hat{p}(\text{Buy})$	0.55	0.50	0.40	0.20
Monthly purchase (\$)	20	10	10	15
Profit margin (%)	20	20	20	20
Marketing cost (\$)	5	7	7	10

is not contractually obligated to contribute any monthly revenue to the firm. Now, let us look an example that can help us compute CLV in each setting.

Consider the case of Amy, a customer of a mobile phone company. The monthly subscription or the base GC provided by Amy is \$40. At the end of May, the company wants to know the value Amy is likely to provide to the company in the next 4 months (June, July, August, and September). **Table 16.1** provides Amy's probability of buying additional services or  $p(\text{Buy})$  (such as downloads, ringtones, text messaging, etc.) for the next 4 months, her monthly purchase amount, the percentage of margin for each purchase, and the marketing cost incurred by the company in contacting Amy.

Assuming an annual discount rate ( $r$ ) of 12% (or 1% monthly rate), we can now compute the CLV of Amy for the next 4 months. First, let us compute the CLV of Amy at the end of July using (Eq. 16.1).

$$\begin{aligned} &\text{Amy's lifetime value at the end of June} \\ &= \frac{40}{(1.01)^1} + \frac{(0.55)^* (20*20\%)}{(1.01)^1} - \frac{5}{(1.01)^1} \end{aligned}$$

Therefore,  $CLV_{\text{Amy, June}} = \$36.9$ .

Similarly, we can compute the value Amy would give to the company at the end of each subsequent month as follows—July: \$33.2, August: \$32.8, and September: \$29.6. A summation of all the 4 months' CLV would yield a value of \$132.5. In other words, over the next 4 months

Amy would provide \$132.5 in value to the company through her subscription and additional purchases.

**Table 16.1** can also be used to explain the case of non-contractual purchases. Assume that **Table 16.1** indicates Amy's monthly cappuccino purchases from her nearby café. However, this case will not have the monthly subscription or baseline CLV. Now, let us compute Amy's CLV at the end of July using (Eq. 16.1).

$$\begin{aligned} &\text{Amy's lifetime value at the end of July} \\ &= \frac{(0.55)^* (20*20\%)}{(1.01)^1} - \frac{5}{(1.01)^1} \end{aligned}$$

Therefore,  $CLV_{\text{Amy, June}} = -\$2.7$ .

In other words, Amy will be costing the café \$2.7 in June by receiving marketing communication from the café and by being a part of their customer base. Similarly, we can compute the value Amy would give to the café at the end of each subsequent month as follows—July: -\$6.0, August: -\$6.0, and September: -\$9.0. A summation of all the 4 months' CLV would yield a value of -\$23.7. That is, over the next 4 months Amy would cost the café \$23.7 in value by being its customer. In other words, the amount spent by the café on marketing to Amy will be more than the revenue contributed by her to the café.

Now that we have learnt the concept of CLV and how to calculate it, we need to clearly understand the factors that drive a profitable relationship with the customer and how they affect CLV. The identification of drivers benefit the firm in (a) providing a better understanding of a profitable customer relationship, and (b) helping managers take proactive measures to maximize a customer's lifetime value.

## 16.1.2 Drivers of CLV

In order to successfully implement a marketing initiative based on CLV, management must understand the drivers of CLV and know how to measure those drivers. The drivers can be broadly classified into the following categories:

- **Exchange characteristics:** Broadly, exchange characteristics are those variables which affect the customer firm-relationship.

## 16.1 · Measuring Customer Profitability

— **Customer characteristics:** These characteristics refer to the demographic variables such as location of the customer, age, income levels, among others. In a B2B setting, these characteristics include variables such as industry, annual revenue and location of the business. In a B2C setting, these characteristics include variables such as age, gender, spatial income and physical location of the customers.

■ Table 16.2 provides an explanation of the exchange characteristics and its impact on B2B and B2C companies by recent studies.

A clear understanding of the drivers listed above is essential for building and managing

profitable customer loyalty. Even as CLV is widely gaining acceptance as a metric to acquire, grow, and retain the right customers, managers often face the challenge of achieving convergence between marketing actions (e.g., contacts across various channels) and CRM. Once the computation of CLV is completed, firms can look forward to maximizing it so as to reap the full benefits of the metric. The rest of this chapter discusses the various strategies that firms can use to maximize customer lifetime value.

The following sections in this chapter discuss several strategies based on empirical studies that demonstrate the importance of the Customer Value Metric in evaluating and monitoring a firm's profitability.

■ **Table 16.2** Exchange characteristics and its impact on B2B and B2C firms

Exchange characteristics	What do they mean?	Impact on CLV in a B2B setting (Kumar, Venkatesan, Bohling, & Beckmann, 2008; Venkatesan & Kumar, 2004)	Impact on CLV in a B2C setting (Kumar, Shah, & Venkatesan, 2006; Reinartz & Kumar, 2003)
Spending level	Monthly spending level in a given period of time	A high spending level of a customer resulted in a high CLV	When average spending level increased by \$10, the likelihood of customer churn decreased by 33%
Cross-buying behavior	Degree to which customers buy products/services from a large number of available categories	A high level of cross-buying behavior resulted in a high CLV	A 15% increase in cross-buying resulted in a 20% increase in CLV
Multi-channel shopping	Degree to which customer shop across multiple channels	NA	A 15% increase in shopping across multiple channels resulted in a 18% increase in CLV
Focused buying	Level of purchases made by a customer within a single category	A heavy instance of customer purchases from within a single category resulted in a lower CLV	A 15% increase in spending in a specific product category resulted in a 14% increase in CLV
Average inter-purchase time	Average number of days between two purchases	Too short or too long inter-purchase time resulted in a lower CLV	CLV tends to be smaller when the inter-purchase time is either too short or too long
Product returns	Number of products the customer returns between two purchase periods	Too few or too many product returns resulted in a lower CLV	Too many or too few returns indicate a low CLV. Moderate amount of returns indicate a high CLV

(continued)

**Table 16.2** (continued)

Exchange characteristics	What do they mean?	Impact on CLV in a B2B setting (Kumar, Venkatesan, Bohling, & Beckmann, 2008; Venkatesan & Kumar, 2004)	Impact on CLV in a B2C setting (Kumar, Shah, & Venkatesan, 2006; Reinartz & Kumar, 2003)
Relationship benefits	Indicates whether a B2B customer is a premium service member (based on revenue contribution in the previous year)	A premium service member status resulted in a higher CLV	NA
Loyalty instrument	Indicates the status of the B2C customer with the firm	NA	Usage of a loyalty instrument increases the CLV
Frequency of marketing contacts	Number of times a customer is contacted through the various communication channels between two purchase periods	Too few or too many marketing contacts resulted in a lower CLV	Too few or too many marketing contacts have a negative impact on CLV. Moderate level of contacts increases CLV
Bi-directional communication	Ratio of the number of customer-initiated contacts to the total number of customer- and firm-initiated contacts made	Greater the bi-directional communication, greater is the CLV	NA

## 16.2 The Lifetime-Profitability Relationship in a Noncontractual Setting

### 16.2.1 Background and Objective

A basic tenet of relationship marketing is that firms benefit more from maintaining long-term customer relationships as compared to short-term customer relationships (Reinartz & Kumar, 2000). Convincing conceptual evidence for this argument has been advanced by a number of authors (Sheth & Parvatiyar, 1995). Also, it has been shown that the relationship-marketing pay-off to the firm comes only when relationships endure (Bendapudi & Berry, 1997). In a widely quoted HBR article, Reichheld and Sasser state, «Customer defections have a surprisingly powerful impact on the bottom line. As a customer's relationship with the company lengthens, profits rise (Reichheld & Sasser, 1990).»

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 (Reichheld & Teal, 1996). Contrary to the anecdotal evidence that long-life customers are most profitable to the firm, Dowling and Uncles caution, «In short, the contention that loyal customers are always more profitable is a gross oversimplification (Dowling & Uncles, 1997).»

In particular, this study questions 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 than nonloyal customers. Obviously, the study shows concern with the widespread assumption of a clear-cut positive lifetime-profitability relationship and underlines the importance of a differentiated analysis. Consequently, there seems to be a need for more rigorous empirical evidence on the lifetime-profitability relationship.

Lifetime analyses have typically been conducted in contractual settings (Bolton, 1998; Li, 1995). Examples for this type of relationships are magazine subscriptions, cable service subscriptions, and cellular phone 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 *noncontractual* settings, the firm must ensure the relationship stays alive because the customer typically splits his category expenses with several firms (Dwyer, 1997). Examples of *noncontractual* 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 almost anything from a catalog. More than 20 billion consumer catalogs are mailed out annually, and the average household receives nearly 200 catalogs a year (Valentino-Devries, 2011). In 2008, U.S. sales revenue attributable to direct marketing was estimated to surpass \$2.158 trillion (Direct Marketing Association, 2007). In 2009, direct marketing accounted for 8.3% of total US gross domestic product. Also in 2009, there were 1.4 million direct marketing employees in the US. Their collective sales efforts directly supported 8.4 million other jobs, accounting for a total of 9.9 million US jobs (Direct Marketing Association, 2009).

In a noncontractual 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, is it wise for the firm to assume this customer is likely to purchase again in the near future, and, if so, to expect him to spend a certain amount of dollars? 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 small number of active customers—people who have regular and frequent interactions with the provider—and a large number of inactive customers. Drawing the line is not easy, as inactive customers can become active customers in the future.

In many cases, the actual duration of the relationship is not especially revealing due to 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 in the database. What appears on the surface to be dormancy actually may be a naturally occurring pat-

tern which 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 (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?

The 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. In order to achieve this objective, we test for the following:

- 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.
- Whether long-life customers pay higher prices.

Once we understand what happens in the marketplace, then we can address *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 level of uncertainty for a firm is very high. 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, and so on)?

## 16.2.2 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 is associated with the marketing exchange. We want to investigate the consequences of customer retention namely, profitability.

## Customer Lifetime and Firm Profitability

We offer the following four propositions and subsequently test each one of the propositions in an non-contractual scenario.

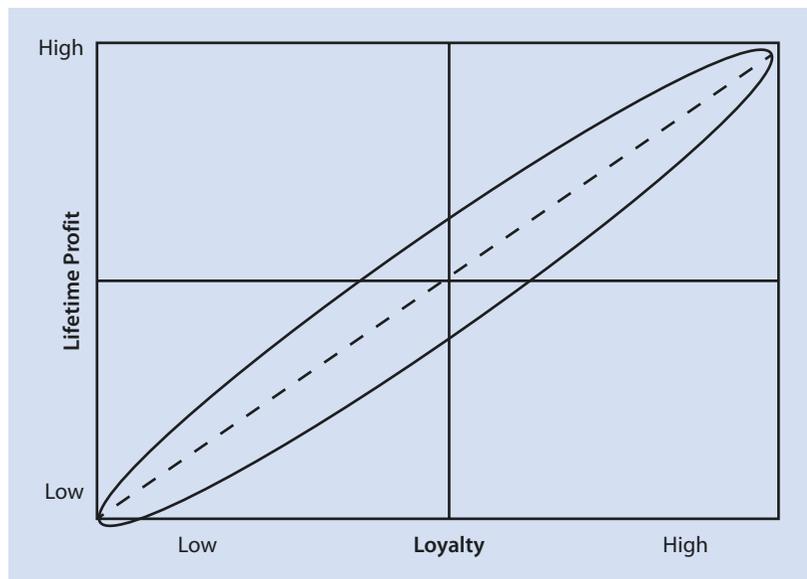
### Proposition 1: The Nature of the Lifetime-Profitability Relationship Is Positive

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 (Reinartz & Kumar, 2002). 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. Following this line of reasoning, we would expect a substantial positive association between the duration of a customer-firm relationship and the firm profits derived thereof. (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) This is true for a contractual case; where there is no repeated cost to entice customers into buying. ■ Figure 16.1 summarizes this situation. In line with the argument, one would expect the majority of relationship outcomes to fall along the diagonal, as shown in ■ Fig. 16.1. In other words, one

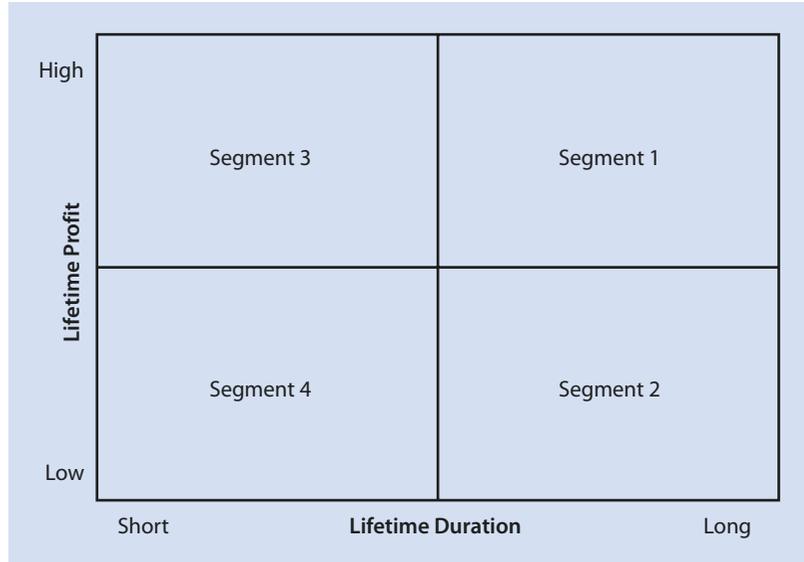
would expect a substantial positive correlation between the two variables. Thus, an assessment of the numbers of customers falling into each quadrant, along with a simple measure of association between lifetime profits and lifetime duration, would readily yield some insight into the nature of the lifetime-profitability relationship.

A factor that complicates the firm's objective of establishing long-term relationships with its customers is that of intrinsic ability to retain customers. 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, to retain customers, it is important to satisfy the customers. The satisfaction of customers may come at a significant cost to the company. In a noncontractual case like catalog shopping, a household might have to be sent many catalogs over a period of time before they decide to buy again. Thus, when 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 be buying less from a catalog company due to competitive offerings, need for limited spending, or other reasons over a period

■ Fig. 16.1 Lifetime-profitability association



■ Fig. 16.2 Segmentation scheme



of time. This forces companies in a noncontractual scenario to look at the spending levels of each of their customers.

Firms should partition their customer base into behaviorally and attitudinally homogeneous groups that spend at different levels (see ■ Fig. 16.2) and then estimate the profitability 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—may help managers to make better decisions. Irrespective of the segmentation scheme, conventional wisdom argues for a positive relationship between profitability and time. Although the available evidence suggests a positive lifetime-profitability relationship, it need not be 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.

### Proposition 2: Profits Increase Over Time

Although a measure of correlation 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. Recall that we mentioned finding evidence for *increasing* profits per time unit over the length of the customer's tenure. These arguments may be true for a contractual setting but need 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 small amount. If this pattern prevails, then 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 Proposition 1, there are several instances where the overhead costs of serving long-life customers are higher as compared to the percentage of profit margin offered by the customer. It is necessary for a 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 the 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 overtime. 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. This is possibly true for contractual setting. But, 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 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 non-product cost factor in a customer-firm relationship. Following the commonly held contention, we would expect 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 a more favorable attitude toward 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

Previous research (Reichheld & Teal, 1996) has 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.

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 a customer buys more product units for a given dollar amount, the customer exhibits a higher degree of value consciousness (i.e., wants more «bang for the buck»).

If this observation were true, it would contradict the existing evidence. 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.

## 16.2.3 Research Methodology

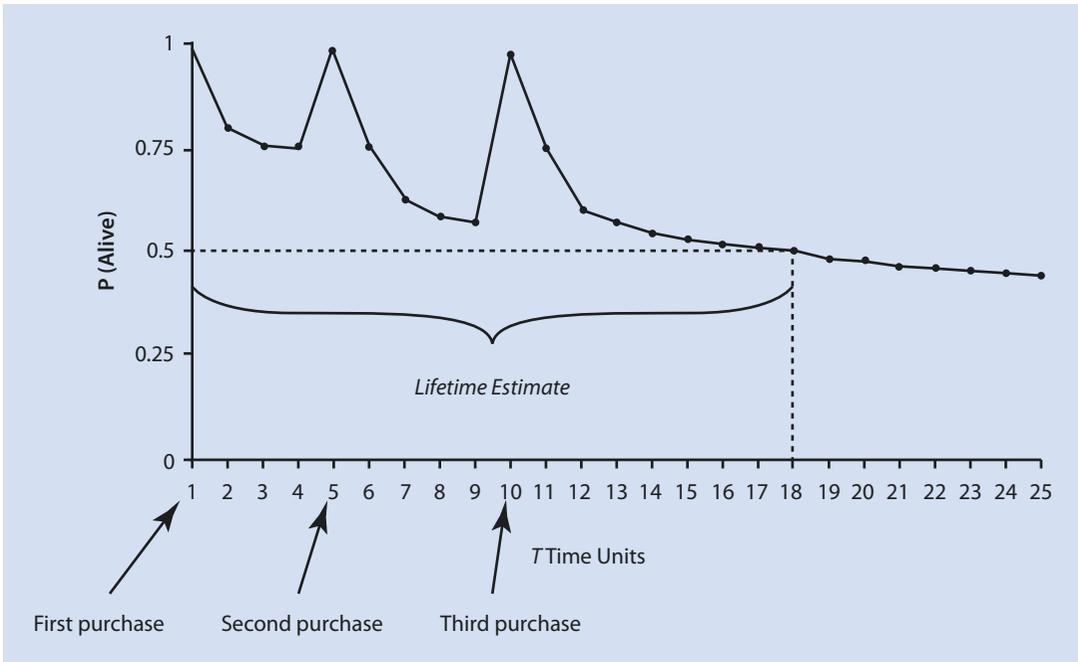
### Data

Data from an established U.S. catalog retailer were 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. The data for this study cover a 3-year window and are recorded on a daily basis. Two key characteristics of this data set are that the customers are tracked from their very first purchase with the firm, and these households have not previously been customers of the company. Consequently, the observations are not left-censored.

### 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*. Toward that end, we empirically implement and extend a procedure previously suggested (Schmittlein & 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.

We are using the *negative binomial distribution* (NBD)/Pareto model, which has been proposed and validated in a previous study. 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



■ Fig. 16.3 Illustrative lifetime determination of individual household (Source: Reinartz & Kumar, 2000)

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.

Given that the outcome of the NBD/Pareto model is a continuous probability estimate, the continuous  $P(\text{Alive})$  estimate is transformed into a dichotomous alive/dead measure. Knowing a person's time of birth (when the person became a customer) 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,  $t_{\text{cut-off}}$ , constitutes the lifetime of the customer. ■ Figure 16.3 illustrates the procedure. This procedure allows us to calculate a finite lifetime for each customer, which then can be used for the profitability analysis.

This 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.

### Establishment of Cut-off Threshold

The choice of cut-off of the  $P(\text{Alive})$  threshold  $c$  determines the length of the lifetime estimate for each customer. The cut-off threshold that produces the highest percentage of correct classifications is obviously the choice most consistent with the data. In this study, the threshold of 0.5 produces the highest percentage of correct classifications. As a result, for the purpose of the lifetime analysis, we use 0.5 as the cut-off threshold.

### Lifetime Estimation

Based on the 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 16.3). A cohort is a group of customers who started their relationship at the same point in time (e.g., a particular month or quarter). Cohort 2 consists of customers who started the relationship with the firm 1 month after Cohort 1. The consistency between the two cohorts is very high. In both cohorts, about 60% of the sample has a lifetime less than the observation window. Thus, the available observation window is obviously adequate for describing lifetime purchases of the given sample.

Table 16.3 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

## Profit Calculation

Net-present value of profit is calculated on an individual customer basis for the period of 36 months using the following equation:

$$LT\pi_i \sum_{t=1}^{36} (CG_{ti} - C_{ti}) \left( \frac{1}{1 + 0.125} \right)^t \quad (16.2)$$

where

- $LT_i$  = 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 U.S. prime rate in 1999 plus 7%. 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 judgment. 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, letter shop, 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 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 the Propositions

The analysis of the test of propositions does not include the acquisition costs for each customer, as the data are not available. If acquisitions costs were available they can be easily integrated into the proposed framework. If acquisition costs are somewhat 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 are \$11, compared to \$82 for Internet-only retailers. If acquisition costs are so low for catalog companies, then the variation in acquisition costs across customers should not affect the results of this study (see: Quick, 2000).

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

As Fig. 16.2 shows, 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*. Thus, we will employ a median split and create a shorter and a longer *lifetime half* and higher and lower *revenue half*.

Obviously, we would expect 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 these 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 right actually be more profitable than long-term customers, a claim which 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. Naturally, the answer to this question is driven by whether revenues and contribution margin are similar or dissimilar.

### 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 to reflect the large first month purchase amount. The exact specification of the regression is as follows:

$$\text{Profit}_{ts} = a_s + b_{1s} \times \text{Dummy} + b_{2s} \times t_s + \text{error}$$

where  $t$  = month

- $b_{1s}$  = 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 and/or 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. 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.

### Proposition 3: The Costs of Serving Long-Life Customers Are Lower

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.

## 16.2.4 Empirical Findings

### What Is the Nature of the Lifetime-Profitability Relationship?

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 significant positive association (at  $\alpha = 0.05$ ) 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 2530 out of 4202 households fall in the diagonal of  Fig. 16.2 (1322 in the upper right quadrant; 1208 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 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. Although 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 16.4 summarizes these results.

Table 16.4 Tests of propositions—results (Cohort 2 results in parentheses)

		Segment 1					Segment 2				
Long lifetime	1	2	3	4	5	1	2	3	4	5	
	Number of customers	Lifetime profit per customer (\$)	Relative profit (\$/month)	Mailing cost/sale ratio	Average item price	Number of customers	Lifetime profit per customer (\$)	Relative profit (\$/month)	Mailing cost/sale ratio	Average item price	
	889	50.85	1.43	0.128	47.74	1332	289.83	8.18	0.063 <sup>a</sup>	58.43 <sup>b</sup>	
	(973)	(55.26)	(1.56)	(0.124)	(48.72)	(1546)	(322.03)	(9.31)	(0.062) <sup>a</sup>	(58.25) <sup>b</sup>	
		Segment 4					Segment 3				
Short lifetime	1	2	3	4	5	1	2	3	4	5	
	Number of customers	Lifetime profit per customer (\$)	Relative profit (\$/month)	Mailing cost/sale ratio	Average item price	Number of customers	Lifetime profit per customer (\$)	Relative profit (\$/month)	Mailing cost/sale ratio	Average item price	
	1208	50.49	2.41	0.141	47.97	783	257.96	11.67	0.065	63.54	
	(1504)	(53.67)	(2.67)	(0.143)	(46.80)	(942)	(284.20)	(12.57)	(0.064)	(64.47)	
	Low lifetime revenue					High lifetime revenue					

<sup>a</sup>Difference between Segment 1 and Segment 3 is not significant

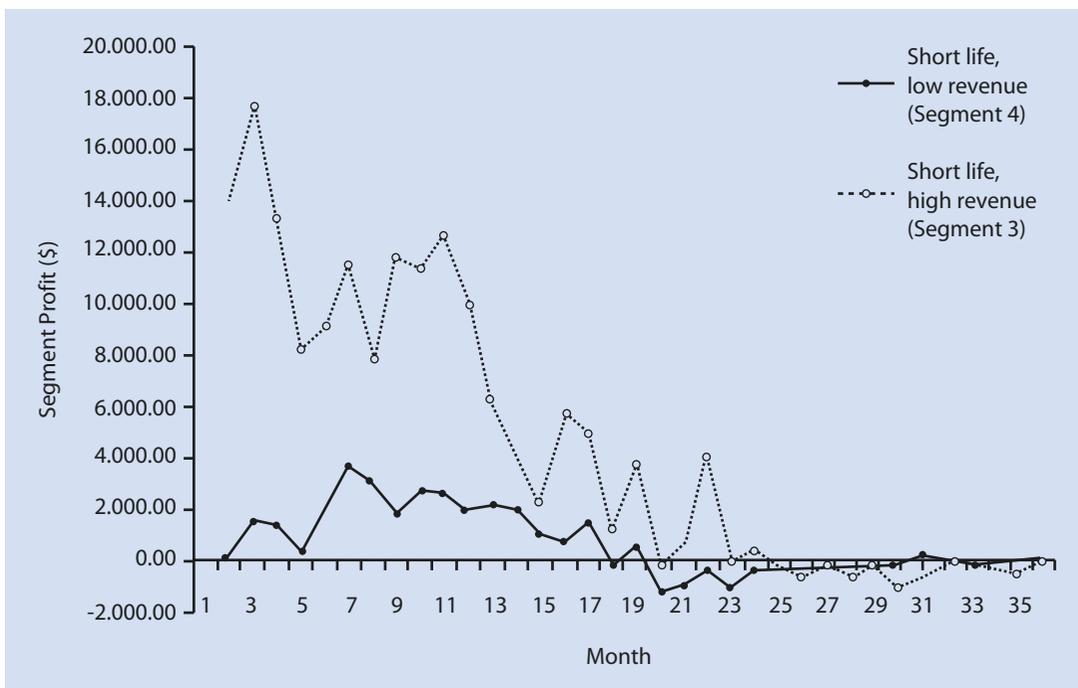
<sup>b</sup>Difference between Segment 1 and Segment 3 is significant at  $\alpha = 0.05$

Several results in [Table 16.4](#) 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 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 3 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 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 the relationship 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 clearly be disadvantageous.

Another very interesting outcome of the analysis is that in terms of relative profit (i.e., profit per month), customers in Segment 3 are the *most* attractive of *all* ([Table 16.4](#), [Fig. 16.4](#)). 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 profits per month for longer-life segments are shown in [Fig. 16.5](#), which capture the implications discussed so far.

One needs to speculate on the reasons for this interesting pattern of results. Obviously, 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 overtime, 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 several moderating factors. For example, consumer factors such as an intrinsic transactional buying behavior, the execution of a limited set of planned purchases, are less of a typical mail-order buyer,



**Fig. 16.4** Aggregate profits (\$) for short-life segments (Note: Month 1 profits omitted from chart)

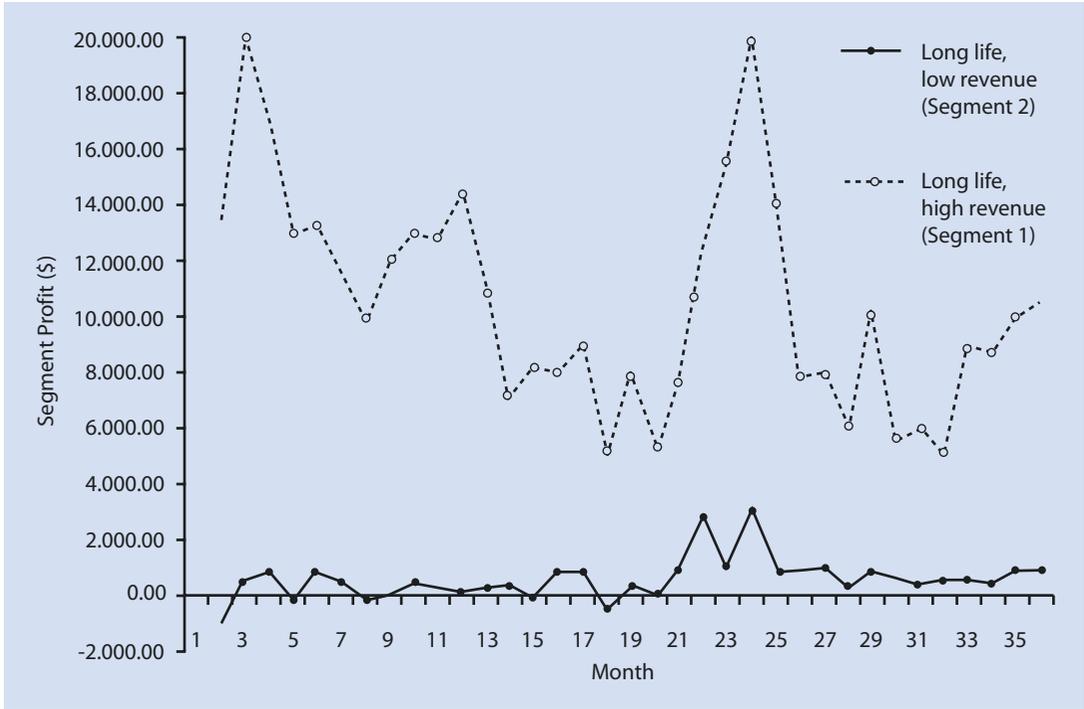


Fig. 16.5 Aggregate profits (\$) for long-life segments (Note: Month 1 profits omitted from chart)

Table 16.5 Regressions results for T = 1–36 months (Cohort 1), validation results in parentheses (Cohort 2)

Segment	Intercept (a)	Dummy coefficient for t = 1 (b1)	Coefficient for t (b2)	R <sup>2</sup>
1	12.11 (12.73)	45.77 (46.38)	-0.13 (-0.14)	0.85 (0.85)
2	n.s. (n.s.)	30.24 (30.91)	0.07 (0.071)	0.92 (0.91)
3	19.40 (20.9)	57.85 (58.29)	-0.70 (-9.75)	0.95 (0.94)
4	3.25 (3.69)	29.53 (31.45)	-0.14 (-0.15)	0.94 (0.95)

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

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. Although we highlight the speculative nature of these inferences, it seems worthwhile to search for the underlying consumer motivations.

**Do Profits Increase Over Time?**

To test the proposition of increasing profits over time, we first examine the profitability evolution visually. Figures 16.4 and 16.5 show the lifetime

profitability plots for the four segments. A visual inspection of the charts reveals 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.

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. The results are presented in Table 16.5. With the 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  $\alpha = 0.01$ .

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 noncontractual settings this might be different. For some products and services this is clearly not the case (e.g., there is no reason to believe people bring more and more clothes to their dry cleaner over time).

The theoretical claim is that loyal customers enter a virtual cycle where satisfaction with transactions in previous periods feed not only into loyalty in future periods but also a reinforcement and growth in firm profits. The counter forces to this virtual cycle are, for example, variety seeking across firms, customers getting tired of interacting with the same firm, firms' competitive actions, and the fact that no contracts exist. This negative relationship is also possible if the customer contact costs through mailing catalogs are 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 overtime. Even for Segment I, 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). However, loyalty might lead to increased profit over time if there is a forced ongoing relationship, an inertia-driven relationship, or if cost of maintenance decreases over time at a faster rate than revenue falls off.

### 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. 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 promotional cost necessary to sustain a dollar amount of revenue. Results are shown in ■ Table 16.4 for Cohort I 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, that Segments 1 and 3 are the most attractive to the firm, although they have very different lifetime properties. 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.

### 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 16.4 for Cohort I and Cohort 2. The average price per item for segment 3 is significantly ( $\alpha = 0.05$ ) different from (and greater than) that of segment I.

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 I) and 10.6% (Cohort 2) more on a single product as compared to Segment I. As a result, our observation of the higher value consciousness of Segment I 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. One possible explanation for the behavior of Segment 3 customers could be that these are heavy users of the catalog but not all that brand focused. Thus, they might shop heavily from more retailers and switch more easily for smaller benefits, since 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. Thus, our empirical evidence showed four things:

- A strong linear positive association between lifetime and profits does not necessarily exist.
- A static and a dynamic lifetime-profit analysis can exhibit a much-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.
- The cost of serving long-life customers is not lower.
- Long-life customers do not pay higher prices.

### 16.2.5 Implications

In this study, we showed a context where managers cannot simply equate a long-life customer with increased lifetime spending, with decreasing costs of serving, and with lower price sensitivity. When a firm examines its customer database, it should not be too surprised to find a significant set of customers who transact with the firm for a short while, but in that duration contribute handsomely to the firm's profits. A firm focused purely on rewarding and retaining customers on the basis of how long they have been with the firm may thus miss out on the opportunity to maximize returns from the higher-value, but shorter-lifetime customers. Similarly, rewarding customers simply because they keep coming to your firm for most of their needs and do not conduct much business with your competitors might also not be the shrewdest strategy to adopt in terms of profits.

## 16.3 Model for Incorporating Customers' Projected Profitability into Lifetime Duration Computation

### 16.3.1 Background and Objectives

No firm would want to waste its resources by chasing customers who are not likely to be transacting profitably in the future (Reinartz & Kumar, 2003). Deciding when to let go of an unprofitable customer is critical. From a managerial standpoint, it would be extremely desirable to know, at any given time, whether it will be profitable to mail a catalog or send a salesperson to a given customer. If it is profitable, then the manager decides to mail the

catalog or initiate a personal contract, otherwise not. Based on this decision metric, it is possible to compute lifetime durations for each customer. Once profitable lifetime duration is obtained for each customer, managers are interested in knowing the factors that drive the profitable lifetime duration. In response to this phenomenon, we conducted a study which presents an integrated metric for measuring profitable customer lifetime duration and assessing antecedent factors. The key research tasks were as follows:

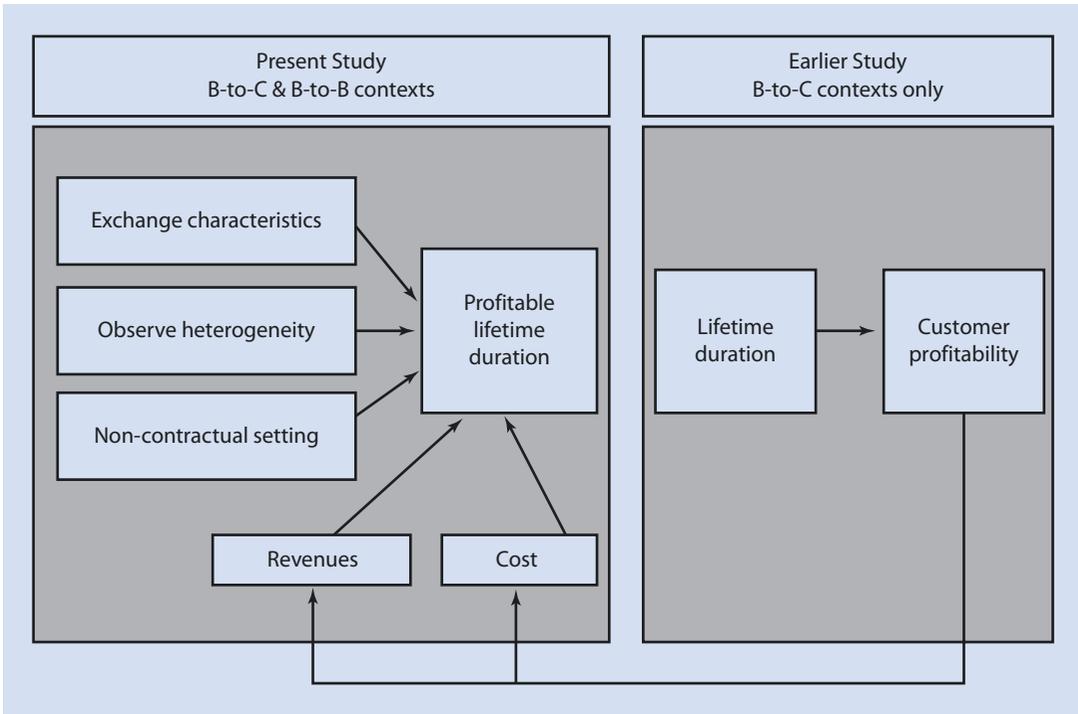
- Empirically measure lifetime duration for *noncontractual* customer-firm relationships, incorporating projected profits.
- Understand the structure of profitable relationships and test the factors which impact a customer's profitable lifetime duration.
- Develop managerial implications for building and managing profitable relationship exchanges.

The research took place in the context of the direct marketing industry. Specifically, our research was conducted for one of the leading general merchandise direct marketers (business-to-consumer, or B-to-C, setting) in the United States. Furthermore, we validated the results with a customer sample from a high-technology firm (business-to-business, B-to-B, setting) selling computer hardware and software.

### 16.3.2 A Dynamic Model of the Antecedents of Profitable Lifetime Duration

In this section, we offer a metric to identify, for each customer, the time periods beyond which they may not be profitable. Toward that end we want to suggest a procedure for estimating the lifetime of customers and implementing this procedure empirically.

Since the model describes and analyzes how and why duration times differ systematically across customers, it is a customer-level analysis. Since our approach exploits longitudinal information obtained *within* customers, we refer to it as a *dynamic* model. ■ Figure 16.6 details the conceptual framework that centers on the, focal construct of profitable lifetime duration of customers. *Profitable lifetime duration* is conceptualized to be a function of the characteristics of the relationship.



■ Fig. 16.6 Conceptual model of profitable customer lifetime

■ Figure 16.6 not only illustrates how the current study differs from the previous one, but also shows how the current study incorporates the findings of the previous study in the proposed framework—through the incorporation of revenues and cost in measuring lifetime duration. In a nutshell, our research in the last section focuses on the consequences of lifetime duration, while the study in this section focuses on the antecedents of profitable lifetime duration. Once managers understand the important consequences of both longer and shorter lifetime duration (described in the first study), this study tells them how to incorporate those findings when deciding to stop chasing a customer.

The first step involves determining the contribution margin expected from each customer in future periods based on the average of the contribution margins in the past. The second step is to determine for each future period, the probability that the customer will be alive and will transact with the firm. The third step is to combine these two components. The fourth step is to discount the expected contribution margin in each future period to its *net present value* (NPV) using the cost of capital applica-

ble to the firm. If, in a given month, the cost of additional marketing efforts turns out to be greater than the NPV, we determine that the profitable lifetime duration of the customer has ended.

Although it is useful to know the profitable lifetime duration of each customer to determine when to withdraw marketing efforts directed at that customer, it is also important to understand the antecedents of profitable lifetime duration. This provides a manager with knowledge about the controllable and environmental variables that explain systematic differences in profitable customer lifetime durations. With this information, a manager is able to focus on appropriate marketing initiatives likely to improve profitability during the tenure of every customer. By analyzing and modeling variables for which data are readily available, a firm can determine which factors are significant in affecting customers' profitable lifetime durations.

The focus of our inquiry is on variables which determine the nature of the customer—firm exchange. Typically, we would need to choose predictor variables of two types to incorporate into the model:

1. **Exchange variables:** Amount purchased, degree of cross-buying, degree of focused buying, interpurchase time, number of product returns, ownership of loyalty instruments, and mailing efforts undertaken by the firm are some variables that can be expected to contribute significantly.
2. **Customer heterogeneity variables:** Location and income of the customer can be expected to add explanatory power to the lifetime duration model

Conceptually,

$$\begin{aligned} &\text{Profitable lifetime duration} \\ &= f\left(\begin{array}{l} \text{Exchange characteristics,} \\ \text{Customer heterogeneity} \end{array}\right) \end{aligned}$$

### Exchange Characteristics

The model provides intuitive explanations for the expected effects of some of these variables. For instance, it is likely that the profitable lifetime duration of a customer is higher for a customer who has spent more than the others and thus has a higher value for the variable *Amount purchased*. Similarly; we can expect a customer who has a tendency to buy across the product line of a firm and therefore exhibits a high *Degree of cross-buying*, should exhibit sustained profitability compared to other customers. Customers who demonstrate a moderate but stable time interval between successive purchases (*Interpurchase time*) are likely to be profitable for a longer duration than customers who have long interpurchase intervals or those who burn out after a rapid series of purchases. Surprisingly, *Number of product returns* can relate positively to profitable lifetime duration, because heavier buyers are also likely to return more merchandise, and a positive experience during the return procedure is likely to boost the buyer-seller relationship.

### Customer Heterogeneity

Demographic variables that capture observed customer heterogeneity have been used consistently high response modeling. The main motivation to include these variables is for statistical control purposes, as well as for potential segmentation purposes.

### Spatial Location of Consumer

We would expect a higher proportion of long lifetime customers to live in low-density areas as opposed to high-density areas (i.e., cities).

### Income

In general, customers with higher incomes are less susceptible to higher price sensitivity (Kumar & Karande, 2000) and are expected to continue buying from the firm for the added convenience.

## 16.3.3 Research Methodology

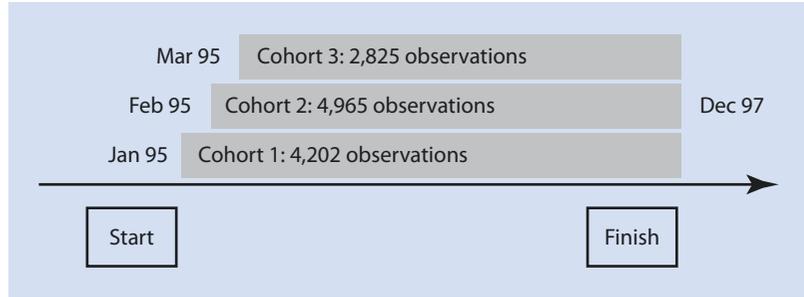
The data we use for this research are the same data we used for the study in the last section. The use of the same data set is critical because we are trying to evaluate if our previous findings can be implemented successfully to determine which customers to let go and when to let go. In addition to the data from the two cohorts used in the last study, data from an additional cohort were also used. Thus, we can validate the results across three different sets of customers. Although the data are partiality the same for both studies, the studies have entirely different objectives.

### Database

The data are provided by the same U.S. general merchandise catalog retailer, of which the characteristics have been described in the last section. The data for this study also cover a 3-year window and are recorded on a daily basis, the database for the three cohorts consist of a total number of observations of 11,992 households. The sample of households belongs to three different cohorts, the structure of which is depicted in ■ Fig. 16.7.

The customer-firm interaction of Cohort 1 households is tracked for a 36-month time period, the behavior of Cohort 2 households for a 35-month time period, and the behavior of Cohort 3 households for a 34-month time period. The households are sampled randomly from all households that started in January, February, and March 1995, respectively. The number of purchases ranges from 1 to 46 across the sample with a median number of five purchases, the median interpurchase time is 117 days, and the median transaction amount is \$91 for each purchase.

■ Fig. 16.7 Database structure for B-to-C setting



### 16.3.4 Determining Profitable Customer Lifetime Duration

#### Calculate Net Present Value (NPV) of Expected Contribution Margin (ECM<sub>it</sub>)

Given the nature of our data (and the data structure in the direct marketing industry in general), managers can easily determine past purchase and spending activity for each customer. Likewise, an estimate of the  $P(\text{Alive})$  status, using the NBD/Pareto model, can be obtained for both past and future periods. This allows us to establish the following decision rule: If the sum of the expected discounted future contribution margin were smaller than a currently planned marketing intervention, we would establish the death event for the customer (A managerial consequence would be to stop mailing to that customer, even though this is not our primary concern.) More formally, we compute the estimated future contribution margin:

$$\text{NPV of } ECM_{it} = \sum_{n=t+1}^{t+18} P(\text{Alive})_{in} \times AMCM_{it} \left( \frac{1}{1+r} \right)^n \quad (16.3)$$

where  $EC_{it}$  is the estimated expected contribution margin for a given month  $t$ ,  $AMCM_{it}$  is the average contribution margin in month  $t$  based on all prior purchases since birth (updated dynamically),  $r$  is the discount rate (15% on a yearly basis),  $i$  is the customer,  $t$  is the month for which NPV is estimated,  $n$  is the number of months beyond  $t$ , and  $P(\text{Alive})_{in}$  is the probability that customer  $i$  is alive in month  $n$ .

For example, the NPV of *expected contribution margin* for customer  $i$  in month 18 is calculated as follows: For each month and for each customer, we observe the total purchases in dollars. Then, we multiply the purchase amount by 0.3 to reflect the

gross margin. In other words, the *Cost of goods sold* is accounted for, and what we have is gross margin. Next, we subtract the *Cost of actual marketing* efforts (in this case, the cost of catalogs plus the mailing costs) to obtain the monthly contribution margin. If a decision is made at the end of month 18, then we take the average ( $AMCM_i$ ) of months 1–18 by summing up all the 18 contribution margins and dividing the sum by 18. If we are at the end of time period 36, then we take the average ( $AMCM$ ) of the previous 36 months' contribution margins by summing up all the 36 contribution margins and dividing the sum by 36. Thus, the  $AMCM$  estimate is updated monthly—in other words, dynamically modeled and used as a baseline for future purchases (i.e., purchases between  $t$  and  $N$ ). The past purchase level at time  $t$  is projected into the future and multiplied monthly with the predicted  $P(\text{Alive})$  estimate. It thus endogenously contains the information about the mailing process as well. The future time horizon is limited to 18 months because the associated  $P(\text{Alive})$  estimate becomes only marginally different from zero after 18 months. For example, according to the NBD/Pareto model, if a customer hasn't bought in a long time, his probability of being alive is small. Since the predicted  $P(\text{Alive})$  for the next 18 months will be even smaller, the net present value of the expected future contribution margin stream will be very low. Thus, having to decide whether to invest in this person (i.e., marketing intervention), chances are that this person would not be deemed as a lucrative future customer—given the cost of mailing.

#### Decision of Relationship Termination

Formally, if  $\text{NPV of } ECM_{it} < \text{Cost of mailing}$ , then the firm would decide to terminate the relationship. Using this decision rule, we establish for every customer at what point he is subjected to the proposed termination policy. The decision rule incorporates the cost of mailings and an

**Table 16.6** NBD/PARETO model characteristics and finite lifetime estimates

	Sample size	Pearson correlation of P(Alive) <sup>a</sup>	Mean average percentage error <sup>b</sup>	Mean lifetime (months)	Lifetime standard deviation	Percentage right – censored
Cohort 1	4202	0.9981	5.83%	29.3	7.5	42.9
Cohort 2	4965	0.9988	5.22%	28.6	7.7	45.6
Cohort 3	2825	0.9987	4.75%	27.8	7.2	47.2

<sup>a</sup>Generated from the NBD/pareto estimates of Reinartz and Kumar (2000) and those of the current study, respectively

<sup>b</sup>The P(Alive) of Reinartz and Kumar (2000) and P(Alive) of the current study

average flat contribution margin before mailings of 25% the discount rate is assumed to be 15%.

### Calculation of Finite Lifetime Estimate

Based on the decision of relationship termination, the average lifetime across Cohort is 29.3 months, across Cohort 2 is 28.6 months, and across Cohort 3 is 27.8 months (Table 16.6). The consistency between the three cohorts is very high. In all the cohorts, little more than 60% of the samples have a lifetime less than the observation window. Households clearly show variability in lifetime duration. This is evidenced through several factors, such as the wide range between lowest and highest lifetime estimate, the standard deviation of the lifetime estimate, and the relatively small value of  $s$  in the NBD/Pareto model.

Thus, we expect considerable scope for exploring the factors that affect lifetime duration. Note that the lifetime duration estimates that incorporate projected profits are different from the one that doesn't incorporate profits.

### 16.3.5 Analysis

In the proportional hazard model, the hazard rate  $h_i(t)$  for individual  $i$  is assumed to take this form:

$$h_i(t) = h_0(t)e^{x_i\beta} \quad (16.4)$$

where  $h_0(t)$  is the baseline hazard rate and  $(X_i\beta)$  is the impact of the independent variables. We can estimate the hazard model with the semi-parametric partial likelihood method (Helsen & Schmittlein, 1993).

### Variable Operationalization

The criterion variable is the house hold specific estimate of profitable lifetime duration. The time varying variable *Purchase amounts<sub>it</sub>* enters the model as the monthly spending level (\$). The time varying variable *Cross buying<sub>it</sub>* is operationalized as the number of different departments shopped in, in a given 6-month period. There are a total of 90 different merchandise departments. The *Focus-of-buying* variable is operationalized as a dummy variable. The percentages of customers coded as 1 (buying consistently in one department) are 0.04, 0.05, and 0.04 across the three cohorts. The time varying variable *Average interpurchase time<sub>it</sub>* is measured in number of days between purchases.  $AIT_{it}^2$  is the square of the  $AIT_{it}$  variable. The *Return<sub>it</sub>* variable is the ratio of returned goods (\$ value) to purchased goods (\$ value). The *Loyalty instrument* variable is operationalized as a dummy variable, indicating ownership of the corporate charge card. The proportion of customers holding a charge card is 0.39, 0.52, and 0.59 across the three cohorts. The effect of *Mailings<sub>it</sub>* will be operationalized as a lagged finite exponential decay of past marketing efforts, similar to procedures in advertising-sales relationship literature.

Since the merchandise changes on a continuous basis, the use of a finite decay period seems more realistic than an infinite period. The variable is measured in terms of the number of efforts/mall pieces sent to the customer. The dummy variable *Product category<sub>i</sub>* describes whether a buyer predominantly shops in hard goods or in soft goods. The proportion of customers buying predominantly hard goods is 0.50,

## 16.3 · Model for Incorporating Customers' Projected Profitability

0.49, and 0.45 across the three cohorts. The variable *Population density* enters the model as the absolute population number in a given two-digit ZIP code into the model. These numbers were derived from the 2000 U.S. census. The variable *Income* comes from the firm's database and is coded on a scale from 1 to 7, where 1 is a yearly income of lesser than \$10,000 and 7 is a yearly income of more than \$150,000. The mean rating is 5.19, 4.88, and 5.01 across the three cohorts. Finally, the *Age* variable is measured as the age of the individual in years, calculated from the date of birth information from the database. The mean rating is 34.4, 34.8, and 35.2 years across the three cohorts. A summary of all variables is given in ■ Table 16.7.

The complete model specification is given in (Eq. 16.5). The hazard of a lifetime event of a household  $i$  at time  $t$  is given as follows:

$$\begin{aligned}
 h_i(t) = h_0(t) \text{EXP}(\beta 1 \text{Purchase amount}_{it} & \\
 + \beta 2 \text{Cross buying}_{it} & \\
 + \beta 3 \text{Focus of buying}_i & \\
 + \beta 4 \text{Average Interpurchase Time}_{it} & \\
 + \beta 5 (\text{Average Interpurchase Time}_{it})^2 & \\
 + \gamma 1 \text{Returns}_{it} + \gamma^2 \text{Loyalty instrument}_i & \\
 + \gamma 3 \text{Mailings}_{it} + \gamma 4 \text{Product category}_i & \\
 + \delta 1 \text{Population density}_i + \delta 2 \text{Income}_i & \\
 + \delta 3 \text{Age}_i) & \quad (16.5)
 \end{aligned}$$

■ Table 16.7 Variables for profitable lifetime model

Dependent variable	Measured as	
Profitability lifetime <sup>a</sup>	Months	
Independent variables	Measured as	Hypothesized directional impact on profitable lifetime
Purchase amount <sub>it</sub> <sup>b</sup>	Monthly spending level (\$), moving average over a 6-month period	+
Cross buying <sub>it</sub>	Number of departments shopped in	(+)
Focus of buying <sub>i</sub>	Dummy: 1 = buys consistently in single dept. only; 0—all other	Nondirectional hypothesis
Average interpurchase time <sub>it</sub>	Number of days	(=) Inverse U-shaped relationship for AIT and AIT2
(Average interpurchase time <sub>it</sub> ) <sup>2</sup>	(Number of days) 2	(−) Inverse U-shaped relationship for AIT and AIT2
Returns <sub>it</sub>	Proportion of returns (of sales)	(−)
Loyalty instrument <sub>i</sub>	Ownership of charge card. Dummy variable, 1 = owns card, 0 = no card	(+)
Mailings <sub>it</sub>	Number of mailings sent in last 6 months (=1 season_ since current t, exponential decay, 1 month lag	(+)
Product category <sub>i</sub>	1 = More than 50% of purchases in softgoods, 0 = more than 50% in purchase of hard goods	No directional hypothesis
Population density	Number of people in the two-digit ZIP code	(−)
Income <sub>i</sub>	Scale from 1 to 9 where 1 is < \$10,000 and 9 is > \$150,000	(+)
Age <sub>i</sub>	Age of individual in years	No directional hypothesis

<sup>a</sup>Subscript<sub>i</sub> = variable value does not change over time; subscript<sub>it</sub> = time—varying variable

<sup>b</sup>Time—varying variables are updated each month

### 16.3.6 Results

The results of the profitable lifetime duration model for the three cohorts are reported in [Table 16.8](#). The table contains the final model parameters, including an interaction term (Returns X Purchase amount).

#### Effects of Exchange Variables

##### Purchase Amount

We hypothesized the level of spending for merchandise ( $\beta_1$ ) is positively related to profitable lifetime-duration. We find support for this hypothesis across all three cohorts and across all three models ( $p < 0.01$ ). Thus,  $H_1$  is supported. Due to the strong association between these two measures, it is important to take information on amount of purchases into account when managing profitable lifetime duration.

To better understand the relative impact of this variable on the hazard of relationship termination we analyze the risk ratio. From a managerial standpoint, the risk ratio helps in gauging the impact of the drivers of profitable lifetime duration. The risk ratio can be interpreted as the percent change in the hazard for each one-unit increase in the independent variable—controlling for all other independent variables. The risk ratio is calculated as  $((\exp(-\beta) - 1) \times 100)$ . When the above insight is applied to the purchase amount variable, we observe that a change of only \$10 in the monthly spending results in a decrease in the hazard of termination of between 31% and 35%, depending on cohort.

##### Cross Buying

The degree of buying across departments ( $\beta_2$ ) was argued to be positively related to profitable lifetime duration because a broader scope of interaction constitutes a stronger relationship. This contention is supported for all models and for all cohorts in our model ( $p < 0.01$ ). Apparently, a long customer life is sustained by a higher degree of purchasing *across* departments. Given a certain income, people heed longer time to fill their needs if they purchase across the board rather than in a focused manner. When calculating the risk ratio for this variable, we find that purchases in an additional department are associated with a decreasing hazard of between 59.6% and 72.8%, depending on cohort. Thus, it seems to be extremely desir-

able for the firm to induce customers to engage in cross-departmental shopping. Hence,  $H_2$  is supported. This is an important finding because the effect of cross-buying on lifetime duration has not yet been documented.

##### Focus of Buying

We did not advance a directional hypothesis with respect to focus of buying ( $\beta_3$ ) because of conflicting arguments. The empirical test resulted in a negative relationship between focused buying behavior and lifetime duration. Thus, the result is in line with the results of the cross-buying construct—broader buying is generally associated positively with an increase in lifetime duration.

##### Average Interpurchase Time

$AIT$  ( $\beta_4$ ) was hypothesized to be related to profitable customer lifetime duration in an inverse U-shaped fashion. That is, the longest profitable lifetime should be associated with intermediate interpurchase times. We tested for this relationship by introducing a nonlinear term  $AIT^2$  ( $\beta_5$ ). We do find support for our hypothesis with both terms being significant at ( $p < 0.01$ ) and having the hypothesized sign ( $\beta_4$  positive and  $\beta_5$  negative). That is, lifetime tends to be shorter when interpurchase times are either very short or very long and lifetime is longest with an intermediate value of  $AIT$ . Hence,  $H_3$  is supported. Together, the impact of the core exchange variables on profitable lifetime duration is substantial. Between 65.2% and 69.7% of the variance is explained by this group of variables. This once again demonstrates that the exchange variables dominate even in a non-contractual situation.

##### Returns

Regarding the proportion of returned goods ( $\gamma_1$ ), our reasoning assumed a negative association of returns and profitable lifetime. That is, the higher the proportion of returned goods, the lower the associated profitable lifetime duration. Our original results (not shown in [Table 16.7](#)) showed the effect was significant at ( $p < 0.01$ ), but had a positive sign for all three cohorts. Thus, the hypothesis that higher returns were a sign of greater dissatisfaction and therefore would lead to shorter lifetimes was not supported ( $H_4$ ). A possible explanation for this outcome could be that customers who returned merchandise had

**Table 16.8** Coefficients (Std. errors) for profitable lifetime duration model

Independent variable	Parameter	Cohort 1			Cohort 2			Cohort 3		
		Model 1 <sup>a</sup>	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Purchase amount <sub>it</sub> <sup>b</sup>	$\beta_1$	.0497 <sup>c</sup> (0.00209)	.0360 <sup>c</sup> (0.00212)	.0354 <sup>c</sup> (0.00213)	.0486 <sup>c</sup> (0.00186)	.0373 <sup>c</sup> (0.00192)	.0364 <sup>c</sup> (0.00192)	.0433 <sup>c</sup> (0.00228)	.0341 <sup>c</sup> (0.00240)	.0324 <sup>c</sup> (0.00239)
Gross buying <sub>it</sub>	$\beta_2$	1.389 <sup>c</sup> (0.0407)	1.293 <sup>c</sup> (0.0417)	1.276 <sup>c</sup> (0.0419)	1.226 <sup>c</sup> (0.0327)	1.172 <sup>c</sup> (0.0338)	1.154 <sup>c</sup> (0.0340)	.970 <sup>c</sup> (0.0346)	.908 <sup>c</sup> (0.0356)	.912 <sup>c</sup> (0.0360)
Focus of buying <sub>i</sub>	$\beta_3$	-.315 <sup>c</sup> (0.0647)	-.257 <sup>c</sup> (0.0660)	-.270 <sup>c</sup> (0.0662)	-.297 <sup>c</sup> (0.0624)	-.306 <sup>c</sup> (0.0630)	-.269 <sup>c</sup> (0.0632)	-.289 <sup>c</sup> (0.0841)	-.213 <sup>c</sup> (0.0862)	-.0177 (0.0865)
Average interpurchase time <sub>it</sub>	$\beta_4$	.0121 <sup>c</sup> (0.000521)	.0133 <sup>c</sup> (0.000521)	.0127 <sup>c</sup> (0.000521)	.0146 <sup>c</sup> (0.000515)	.0153 <sup>c</sup> (0.000517)	.0147 <sup>c</sup> (0.00519)	.0171 <sup>c</sup> (0.000718)	.0178 <sup>c</sup> (0.000724)	.0171 <sup>c</sup> (0.000726)
(Average interpurchase time <sub>it</sub> ) <sup>2</sup>	$\beta_5$	-8.994 E-6 <sup>c</sup> (6.276 E-7)	-9.880 E-6 <sup>c</sup> (5.892 E-7)	-9.487 E-6 <sup>c</sup> (5.892 E-7)	-.0000121 <sup>c</sup> (6.243 E-7)	-.0000123 <sup>c</sup> (6.013 E-7)	-.000019 <sup>c</sup> (6.046 E-7)	-.0000151 <sup>c</sup> (8.912 E-7)	-.0000154 <sup>c</sup> (8.660 E-7)	-.0000147 <sup>c</sup> (8.747 E-7)
Returns <sub>it</sub>	$\gamma_1$		-2.214 <sup>c</sup> (0.222)	-2.050 <sup>c</sup> (0.226)		-1.690 <sup>c</sup> (0.214)	-1.557 <sup>c</sup> (0.215)		-1.323 <sup>c</sup> (0.320)	-1.323 <sup>c</sup> (0.320)
Loyalty instrument <sub>i</sub>	$\gamma_2$		.666 <sup>c</sup> (0.0577)	.685 <sup>c</sup> (0.0577)		.745 <sup>c</sup> (0.0482)	.753 <sup>c</sup> (0.0484)		.598 <sup>c</sup> (0.0618)	.614 <sup>c</sup> (0.0622)
Mailing <sub>it</sub> <sup>5</sup>	$\gamma_3$		.00552 <sup>c</sup> (0.00153)	.00686 <sup>c</sup> (0.00154)		.00628 <sup>c</sup> (0.00148)	.00712 <sup>c</sup> (0.00148)		.00610 <sup>c</sup> (0.00224)	0.00898- (0.00229)
Product category <sub>i</sub>	$\gamma_4$		-0.0278 (0.0437)	-0.0554 (0.0438)		-0.0360 (0.0414)	-0.0476 (0.0414)		-0.0422 (0.0556)	-0.0740 (0.0558)
Returns <sub>it</sub> × purchase Amount <sub>it</sub>	$\gamma_5$		.221 <sup>c</sup> (0.0188)	.208 <sup>c</sup> (0.0189)		.148 <sup>c</sup> (0.0155)	.134 <sup>c</sup> (0.0155)		.105 <sup>c</sup> (0.0186)	.0985 <sup>c</sup> (0.0183)

(continued)

Table 16.8 (continued)

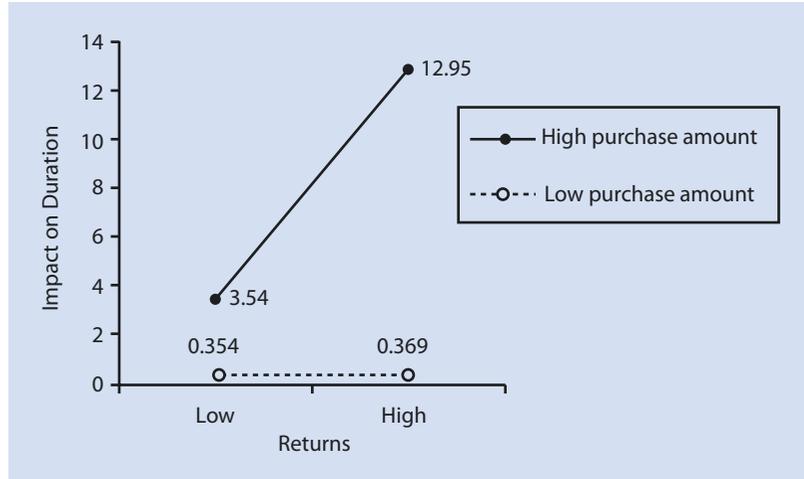
Independent variable	Parameter	Cohort 1			Cohort 2			Cohort 3		
		Model 1 <sup>a</sup>	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Population density <sub>j</sub>	δ1			-3.475 E-8 <sup>c</sup> (1.252 E-2)			2.23 E-8 <sup>b</sup> (1.196 E-8)			5.305 E-9 (1.584 E-8)
Income <sub>i</sub>	δ2			.124 <sup>c</sup> (0.00863)			.111 <sup>c</sup> (0.00805)			.133 <sup>c</sup> (0.0104)
Age <sub>i</sub>	δ3			4.032 E-7 (4.668 E-6)			3.628 E-6 (4.123 E-6)			4.684 E-6 (5.446 E-6)
-2 Log Likelihood		13,728.6	1337.7	13,126.8	15,678.0	15,200.7	15,004.6	9089.4	8807.7	8639.2
R <sup>2</sup>		0.697	0.727	0.743	0.684	0.719	0.730	0.652	0.672	0.693

<sup>a</sup>Signs of coefficients have been reversed to reflect effect on lifetime

<sup>b</sup>Significant at 0.05

<sup>c</sup>Significant at 0.01

■ **Fig. 16.8** Interaction between proportion of returns and purchase amount



a positive encounter with the firm's service representatives, which then might affect their future purchase behavior (Hirschman, 1970). It is interesting to mention that managers told us (upon further inquiry) of their experience, that heavy buyers tend to return proportionately more. A possible reason for this might be that these buyers are accustomed to the procedures of returning merchandise and are able to do it efficiently. Thus, it might be that these customers see the return process as part of the mail-order buying process. If this effect dominates, then one would expect a positive relationship. Likewise, this would probably mean that as customers spent more with the firm, the effect should become stronger.

To pursue this line of thought, we added post-hoc, an interaction between amount of purchases and the proportion of returns to the model. The final results including the interaction are included in ■ Table 16.7. The interaction turns out to be significant for all three cohorts ( $p < 0.01$ ). Thus, we find evidence for the conjecture that the degree of returns depends on the degree of spending. Thus, the positive impact on lifetime duration is greatest when the level of dollar purchases and the level of returns are high. ■ Figure 16.8 depicts this situation graphically. Evidence (Clark, Kaminski, & Rink, 1992) has been shown of the impact of positively disconfirming complainants' expectations to achieve (restore) satisfaction. Moreover, the impact of this response seems to be maintained over time. Therefore, we believe, proportionally higher returns might be an indication of this positive

disconfirmation. If, for example, the firm has a no-hassle return policy and the customers have come to accept the technical return procedures, greater satisfaction with the exchange can result and therefore greater profitable lifetime duration. Clearly, it would be desirable to have stated satisfaction measures at hand to add additional validity to our results. Similar empirical support for our finding comes from another study (Kesler, 1985) in which Omaha Steaks, a mail-order supplier of high-quality meat, found higher profitability for those customers for which it had quickly resolved complaints.

### Loyalty Instrument

Interestingly, the loyalty instrument ( $\gamma_2$ ) is significantly related to profitable lifetime duration ( $p < 0.01$ ). According to our hypothesis, the use of the charge card as a loyalty instrument should lead to a higher lifetime. Thus, in our sample, issuing a charge card appears to be successful as a loyalty instrument because it does seem to be associated with longer customer lifetime. Thus, this is supported. Remember, the findings in literature thus far are not very favorable in terms of loyalty instrument efficiency. However, in this case, it seems at least successful with respect to profitable lifetime duration. Nevertheless, we cannot make a statement about the cost effectiveness of the program. In terms of magnitude of effect, the risk ratio analysis indicates adopting the loyalty instrument is associated with a 45–52% decrease in hazard of relationship termination—substantive amount.

## Mailings

The mailing variable ( $\gamma_3$ ) was introduced as an important control variable specified as a lagged effect. Recall that mailings and sales are typically not independent in a direct marketing context. The hypothesized effect on lifetime duration was positive. We find a positive significant effect ( $p < 0.01$ ) for all three cohorts—thus, our decision to control for the variable is correct. Hence,  $H_6$  is supported in that the mailing effort is significantly related to profitable customer lifetime duration.

## Product Category

A concern in our modeling effort was that the choice of product category ( $\gamma_4$ ) could have a systematic effect on a customer's lifetime. For example, it could be that durable goods (i.e., hard goods) have a potentially long lifetime and thus there is little need for replacement, leading to a potentially shorter customer lifetime. This concern, however, is not substantiated since the parameter  $\gamma_4$  for the dummy variable is not significant ( $p > 0.1$ ) for any cohort.

## Effects of Observed Heterogeneity

### Spatial Location of Customer

It was argued that the spatial location is linked to a customer's tenure with a direct marketer ( $\delta_1$ ) such that the population density is inversely associated with customer lifetime duration. Our results confirm this hypothesis ( $H_7$ ) for two out of the three cohorts ( $p < 0.05$ ), thus underlining the need (1) to account for observed heterogeneity in duration modeling, and (2) to demonstrate support for the transaction cost minimization argument.

### Income and Age

In terms of the two demographic variables representing income ( $\delta_2$ ) and age ( $\delta_3$ ), we find that while age does not seem to be related to profitable lifetime duration ( $p > 0.05$ ), income does ( $p < 0.01$ ). Our model indicates higher income is associated with longer lifetime. Thus  $H_8$  is supported.

Overall, the information on observed customer heterogeneity adds explanatory power to the duration model, above and beyond the exchange variables. The results are validated in a

B-to-B setting. The summary of results is available in [Table 16.9](#).

## 16.3.7 Technical Appendix: Estimation of P(Alive)

The likelihood of a customer being alive can be computed either through the *method-of-moments* or through *maximum-likelihood* approaches. Due to the computational constraints imposed by the maximum likelihood estimation (MLE), method-of-moment estimates have been the method of choice. It has also been shown for the NBD model that the method-of-moments approach and MLE yield approximately the same results (Schmittlein, Morrison, & Colombo, 1987). Thus, there seems to be support in favor of the more manageable method-of-moments routine.

Using the likelihood as given in AI, we estimate the four parameters of the NBD/Pareto model ( $r, \alpha, s, \beta$ ) with a Fortran routine. The likelihood is:

$$LL(r, \alpha, s, \beta) = \prod_{i=1}^M P[X_{i=1} = x_i, t_i, T_i | r, \alpha, s, \beta] \quad (16.6)$$

with  $M$  being a random sample of customers, and customer  $i$  made  $X_i = x_i$  purchases in  $(0, T_i)$  with the last transaction time at  $t_i$ . The resulting MLE parameters are  $r = 3.01$ ,  $\alpha = 9.65$ ,  $s = 0.82$  and  $\beta = 11.91$  (estimation horizon 30 months). The parameters are quite consistent with the estimates derived by Reinartz and Kumar, who used estimates of  $r = 4.24$ ,  $\alpha = 14.95$ ,  $s = 0.93$  and  $\beta = 13.85$  (Reinartz & Kumar, 2000). In particular, the critical parameters  $r/\alpha = 0.312$  and  $s/\beta = 0.069$  are similar to Reinartz and Kumar ( $r/\alpha = 0.481$  and  $s/\beta = 0.069$ ), resulting in little bias in the  $P(\text{Alive})$  estimates (see [Table 16.10](#)). Since the results are robust and the computational resources required for MLE are substantially larger, the method-of-moment estimation is preferred.

The model parameters can be explained as follows. The variation across customers in their long-run purchase rate is reflected in the estimate of  $r$  only and is independent of  $\alpha$ . In other words, the larger the value of the shape parameter  $r$ , the more homogeneous is the population of customers in terms of purchase rate. Thus,  $r$  can be viewed as an overall inverse measure of

**Table 16.9** Summary of results

Hypothesis	Description	B-to-C setting	B-to-B setting
H1	Profitable customer lifetime duration is positively related to the customer's spending level	Supported	Supported
H2a	Profitable customer lifetime duration is positively related to the degree of cross-buying behavior exhibited by the customers	Supported	Supported
H2b	Profitable customer lifetime duration is related to the focused buying behavior exhibited by customers	Supported. However, the relationship is negative, indicating that buying only a single department results in shorter lifetime duration	Supported. However, the relationship is negative, indicating that buying in only a single department results in shorter lifetime duration
H3	Profitable customer lifetime duration is inverse U-shaped manner, whereby intermediate AIT is associated with the longest profitable lifetime value	Supported	Partial support. Only the linear term is significant
H4	Profitable customer lifetime duration is inversely related to the proportion of merchandise returned by the customers	Not supported. However, the interaction of returns with purchase amount variable is significant	Not supported. However, the interaction of returns with purchase amount variable is significant
H5	Profitable customer lifetime duration is positively related to the ownership of the company's loyalty instrument (B-to-C) or the availability of line of credit (B-to-B)	Supported	Supported
H6	Profitable customer lifetime duration is positively related to the number of mailing efforts of the company (B-to-C) or the number of contacts (B-to-B)	Supported	Supported
H7	Profitable customer lifetime duration is higher for customers living in areas with lower population density (B-to-C) or business existing in lower population density (B-to-B)	Supported	Not supported
H8	Profitable customer lifetime duration is positively related to the income of the customer (B-to-C) or income of the firm (B-to-B)	Supported	Supported

the concentration in purchase rates across households. In other words, the larger the value of the shape parameter  $s$ , the more homogeneous is the population of customers in terms of dropout rate. The concentration in dropout rates,  $\beta$ , depends on the parameter  $s$  only. Overall, the model esti-

mates seem reasonable and show a high degree of face validity and internal consistency. Having calculated the distribution parameters, the characteristic of interest is the probability that a customer with a particular observed transaction history is still alive at time  $T$  since trial.

**Table 16.10** Actual revenues & profits for the selected group of customers based on NBD/PARETO, RFM, and past customer value selection (Cohort 1)

Customer selection based on	Percentage of cohort (selection from top)	Evaluation at 18 months (\$)	Evaluation at 30 months (\$)
NBD/Pareto with ECM	30 (n = 1260)	590,452 (123,076)	318,831 (62,991)
	50 (n = 2101)	756,321 (148,922)	361,125 (61,636)
	70 (n = 2941)	864,114 (165,735)	380,855 (60,305)
Advanced RFM	30 (n = 1260)	442,534 (78,555)	140,781 (27,582)
	50 (n = 2101)	599,100 (99,831)	186,267 (36,380)
	70 (n = 2941)	687,163 (110,244)	216,798 (42,839)
Past customer value	30 (n = 1260)	508,997 (86,820)	179,665 (35,916)
	50 (n = 2101)	648,772 (112,723)	210,860 (41,729)
	70 (n = 2941)	789,526 (138,124)	225,910 (44,738)

Schmittlein, Morrison, and Colombo show this probability depends on the customer’s past purchase history (through the number of purchases  $x$ ) and the time  $t$  (since trial) at which the most recent transaction occurred (Schmittlein et al. 1987). The desired probability for  $\alpha > \beta$  is given in (Eq. 16.7) as follows:

$$\begin{aligned}
 &P[\text{Alive}|r, \alpha, s, \beta, x, t, T] \\
 &= \left\{ 1 + \frac{s}{r+x+s} \left[ \left( \frac{\alpha+T}{\alpha+t} \right)^{r+x} \left( \frac{\beta+T}{\alpha+t} \right)^s \right. \right. \\
 &\quad \times F(a_1 + b_1 + c_1 + (t)) - \left. \left. \left( \frac{\beta+T}{\alpha-t} \right)^s \right] \right\}^{-1} \\
 &\quad \times F(a_1 + b_1 + c_1 + (T)) \tag{16.7}
 \end{aligned}$$

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,  $r, \alpha, s, \beta =$  model parameters,  $x =$  number of purchases,  $t =$  time since trial at which the most recent transaction occurred, and  $T =$  time since trial.

It is important to mention that this methodology requires cohorts of customers. Only the cohort analysis yields insight into the dynamic pattern of defection over time, whereas a simple cross-section of customers would not give such insight (because customers are at different stages in their lifecycle).

## 16.4 Model for Identifying the True Value of a Lost Customer

### 16.4.1 Conceptual Background

The authors of this study, John B. Hogan, Katherine N. Lemon, and Barak Libai, argue the traditional customer profitability models evaluate customers in isolation from one another and that the effects of social interactions are not accounted for (Hogan, Lemon, & Libai, 2003). Customers are involved in social interactions and they may advocate positive or negative word of mouth about the products and the firm. This, in turn, could influence future prospects to become customers and existing customers to cease transactions. The exclusion of these indirect social effects could lead to misallocation of scarce marketing resources during the critical early stages of a new product market.

The value of a lost customer depends on whether the customer defects to a competing firm or disadopts the product category. Customer defection refers to a situation where a customer leaves one firm and starts transacting with a competing firm. As a consequence, the firm loses direct sales from that customer. In contrast, disadoption occurs when a customer stops purchasing from that product category altogether. This affects the long-term profitability in two ways one is the loss of direct sales and the other is in terms of indirect effects of word of mouth, imitation, and other social effects.

### 16.4.2 Modeling the Effects of Disadoption on the Value of a Lost Customer

If  $\alpha$  is the proportion of disadopters in a firm's lost customers, then the value of an average lost customer (VLC) is calculated in (Eq. 16.8):

$$VLC = VLC_{disadopters} + (1 - \alpha)VLC_{defectors} \quad (16.8)$$

The value of  $\alpha$  may vary across firms and markets. The sales effect of slower customer acquisitions caused by the social effects and reduced level of word of mouth is then estimated using the Bass new product growth model. The profit impact of a lost customer is estimated by calculating the difference in the expected profitability of the firm before and after the customer has disadopted. In other words, profit impact of a lost customer = sales estimate from new product growth model without disadoption—the sales estimate when the customer disadopts after certain time. This takes into account both the direct and indirect effects of disadoption.

### 16.4.3 The Key Determinants of the Value of a Customer

To study the phenomenon of the lost customer, a Monte Carlo simulation was used in which the key parameters such as external influence ( $p$ ), internal influence ( $q$ ), discount rate ( $r$ ), and disadoption time ( $t_1$ ) were variable based. The results indicated: (1) the time when customer disadopts has the largest impact on the value of the lost customer, (2) the external influence,  $p$

Table 16.11 Effect of firm and market variables on the value of a lost customer

Parameter		Standardized coefficient	P-Value
$p$	External influence	-0.432	<0.0001
$q$	Internal influence	0.147	0.0103
$r$	Discount rate	0.213	0.0003
$t_1$	Disadoption time	-0.594	<0.0001

Source: Hogan et al. (2003)

has a negative impact, (3) the internal influence,  $q$  has a positive impact on penetration because higher  $q$  signifies stronger word of mouth, and (4) discount rate has positive impact on the value of lost customer. The study shows that the earlier a customer disadopts the more money the company loses. This is because at the early stages of a product life cycle, there are only a few adopters to influence the future adoption through word of mouth. Hence, a single disadoption can have larger impact. The effects of various variables on the value of a lost customer are given in Table 16.11.

It is also important to note the value of a lost customer is affected by stages in the product life cycle, the firm's market share, and the rate at which competitors' customers disadopt. This has important managerial implications in terms of spending on customer retention, allocation of retention, and acquisition spending over time, extended return on investment analysis, and managing competitive environment.

#### Summary

A study of the lifetime-profitability relationship in a noncontractual setting highlights a concern with the widespread assumption of a clear-cut positive lifetime-profitability relationship and underlines the importance of a differentiated analysis. In the 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 is associated with the marketing exchange. In a noncontractual scenario such as the direct marketing context, promotional costs are typically the largest nonproduct cost factor in a customer firm relationship. 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 as much as established-name brand products.

The empirical evidence showed that (1) a strong linear positive association between lifetime and profits does not necessarily exist, (2) profits do not necessarily increase with increasing customer tenure, (3), the cost of serving long-life customers is not lower, and (4) long-life customers do not pay higher prices. However, these factors may have differential impacts in different industries.

The objectives of the second study were (1) to empirically measure lifetime duration for *noncontractual* customer-firm relationships, (2) to incorporate projected profits to the structure of profitable relationships and to identify the antecedents of customer's profitable lifetime duration, and (3) to develop managerial implications for building and managing profitable relationship exchanges. The model first estimated the probability of a customer being alive and then integrated this with the individual lifetime duration. The main drivers of customer's profitable lifetime duration are classified as exchange characteristics and customer heterogeneity. The customer's spending level, cross-buying, focus of buying, average interpurchase time, amount of returns, customer's ownership of loyalty instrument, and the mailing efforts of the company are identified as important exchange characteristics. Spatial location of consumer and his age and income are the important customer heterogeneity factors influencing the profitable lifetime duration.

In the third study, a model is developed for determining the effects of disadoption on the value of a lost customer. This takes into account not only the direct effects of lost sales but also the indirect effects of social effects such as word of mouth. The key determinants of the value of a lost customer are identified as disadoption time, external and internal influence, and the discount rate. The disadoption time is found to have the maximum negative impact on the value—that is, the earlier a customer disadopts, the higher the value of the lost customer.

Customer equity is the aggregation of the expected lifetime values of a firm's entire base of existing customers and the expected future value of newly acquired customers. The NPV objective function required to maximize the customer equity of a firm is related to the cash flow from

each customer, the expected interpurchase time, and the cost and frequency of the marketing/communication strategies employed. The objective function is based on a probability model which predicts the interpurchase time of each customer, a panel data model which predicts the cash flows from each customer, and an optimization algorithm which maximizes the profits. By applying an optimization model, a manager can know the extent to which he should use various contact channels. Cross analysis of duration of relationship and customer value obtained on the basis of the NPV maximization objective function indicates not all short-duration customers deliver lower profits, and not all long-duration customers deliver higher profits. Identifying and targeting responsive and profitable customers and deemphasizing efforts on some customers who were not profitable—irrespective of whether they are classified as long-duration or short-duration customers—would be a better approach. Customer value-based approach demonstrated its superiority to the duration of association approach in terms of profitable segmentation of customers.

Purchase sequence model captures the differences in the durations between purchases for different product categories. An individual customer-level profit function is developed to predict customer value. The success of the experiment based on the model demonstrated.

By higher revenue, lower cost of communication, lower number of attempts before a purchase is made, higher profits, and higher ROI for the test group, when compared to the control group, indicates the scope to which the customer value approach offers in improving the quality of marketing decisions.

The acquisition-process is an integral component of the research model. By linking acquisition and the retention process, it is possible to see a complete and unbiased picture of the drivers behind customers election/acquisition, relationship duration, and customer profitability. Also, making the necessary trade-off between offensive processes and defensive processes requires a full specification of the key dimensions of the customer-firm relationship. A more complete model specification addresses the key managerial question of whether the

maximization of the respective objective functions as acquisition likelihood, lifetime duration, and customer value would lead to convergent or divergent resource allocation recommendations. This model applies mainly to situations where managers rely mostly on direct customer communication. Acquisition expenditures will have diminishing marginal associations with customer profitability. Retention expenditures will have diminishing marginal associations with relationship duration and with customer profitability. Highly

interpersonal contact channels have a greater association with the likelihood of customer acquisition and relationship duration than less interpersonal contact channels. Though the results are specific to the empirical context, the model can be applied to any environment where acquisition and retention efforts can be separated. Managers can use the proposed integrated framework not only to better understand the drivers of profitability, but also to know how to maximize profitability through optimal allocation of resources.

### ? Exercise Questions

1. How can we measure a customer's worth? What factors typically influence a customer's worth?
2. Discuss the differences in the analysis of customer loyalty between contractual and non contractual settings.
3. In the credit card industry, what drivers of profitable lifetime duration would you expect?
4. Discuss the effect of a lost customer on a firm. How would you capture and quantify this effect?

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