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The Impact of Customer Relationship Characteristics on Profitable Lifetime Duration

by

W. J. Reinartz*
and
V. Kumar**

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

** ING Aetna Chair Professor, and Director, ING Aetna Center for Financial Services at the University of Connecticut, School of Business Administration, Department of Marketing, Storrs, CT 06269-1041, USA.

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Please correspond to:

V. Kumar (VK), ING Aetna Chair Professor, and Director, ING Aetna Center for Financial Services at the University of Connecticut, School of Business Administration, Department of Marketing, Storrs, CT 06269-1041, Phone 860-486-1086, Fax 860-486-5246, E-mail Vk@sba.uconn.edu.

Werner J. Reinartz is Assistant Professor of Marketing at INSEAD, Boulevard de Constance, 77305 Fontainebleau Cedex, France, Phone +33-1-6071-2648, Fax +33-1-6074-5500, E-mail Werner.reinartz@insead.edu

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ABSTRACT

Customer management oriented organizations recognize the dynamic evolving nature of the customer-firm relationship over time. The basis of this recognition is an understanding of the customer lifetime duration construct, the customer lifetime profit construct, and the drivers of these two constructs. The applicability of these concepts, however, depends on the context. An area in need for further research is that of non-contractual relationships – relationships between buyer and seller that are not governed by a contract. This study focuses on three key objectives that are important and that have remained unresolved so far. These are to (1) empirically measure profitable lifetime duration for *non-contractual* customer-firm relationships, (2) propose and test factors that potentially affect a customer's *profitable* lifetime duration and, (3) develop managerial implications for building and managing a profitable longer lifetime.

The hypothesized antecedent factors include exchange and customer heterogeneity characteristics. If managers can understand the temporal dynamics involved in a customer's relationship with the firm, they can for example predict the vulnerability of a customer to leave the relationship. Consequently, they can spend marketing dollars more effectively by either not chasing customers "whose time has come" or by employing judicious marketing actions to save customers who are at risk. Factors such as quantity of merchandise returned, across department purchases, company specific charge card ownership in addition to the traditional factors – frequency and monetary value – (recency has already been incorporated in the computation of lifetime duration) are found to be important predictors of a customer's lifetime duration. The results are validated with a split sample using three cohorts in the B-to-C industry and with data from a high technology firm in the B-to-B industry. The dynamic nature of the customer purchase process is captured in our framework by variables, which vary over time. Several managerial implications are drawn regarding the customer relationship management process.

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Introduction

Relationship marketing – the establishment and maintenance of long-term buyer-seller relationships has profoundly influenced marketing theory and practice. While the concept of relationship marketing is not new, the fact that organizations have started to focus on identifying and retaining long-term customers is more of a recent occurrence. Managers profess to do it in new and better ways every day (Fournier, Dobscha, and Mick 1998). Consider the following example:

> Before the 1990's, AT&T spent hundreds of millions of dollars per year trying to attract prospects to use its long-distance phone service. Most prospects received similar offerings regardless of their specific needs. As a result, AT&T sent out millions of pieces of largely undifferentiated direct mail solicitations several times a year, yet less than 5% of the cases resulted in conversions and even worse, many of these conversions were lost again due to a high rate of churn (Grant and Schlesinger 1995). Today, AT&T carefully analyzes its relationships with its customers and tracks in particular retention and termination characteristics. Through conscientious modeling efforts, AT&T attracted in 1994 seven times as many customers as it did in 1990. Even more important, these customers have a very different quality in their retention behavior. By analyzing the factors that drive retention, AT&T is much more efficient in (a) keeping customers who are at risk of defection and (b) AT&T can better pinpoint in its acquisition campaigns those customers who are likely to be long-life customers (Li 1995). Thus, AT&T has embraced the core of relationship marketing: it is considerably more profitable to keep and satisfy existing customers rather than to constantly renew a strongly churning customer base.

To make relationship marketing really work, marketers have started to adopt a customer management orientation. A customer management orientation emphasizes the importance of customer lifetime analysis, retention, and the dynamic nature of an individual's customer-firm relationship over time (Kotler 1994). Given the discrepancies between concept and reality in relationship marketing, it is important to study the concept of customer management and customer lifetime for two reasons.

First, we need to better understand the facets of a customer management orientation. For example, firms that adopt a customer management orientation have to consider *how* their activities impact their relationship with different customers. Anderson and Narus (1991) highlight that every industry is characterized by its own bandwidth of transactional and relational exchanges. Garbarino and Johnson (1999) show that short and long-term oriented customers differ in the factors that determine their future exchanges. Their results imply that a focus on customer satisfaction is likely to be effective for weak relational customers whereas marketing focused on building trust and commitment will be more effective for the long-term relational group. Likewise, given the need to cater to specific customers rather than all possible customers (Dowling and Uncles 1997), an analysis of the relationship dynamics over time, such as lifetime activity patterns, becomes of paramount importance (Reichheld and Teal 1996). The results of Jap and Ganesan's (2000) study highlight the need to incorporate dynamic effects over the duration of the customer-

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firm relationship. Specifically, they find that the differential efficacy of various relationship management mechanisms changes over the course of a relationship.

The need for research in this domain finds its expression also in the Marketing Science Institute's research priorities. It has elevated the topic of customer management and the analysis of surrounding issues (e.g. value of loyalty, measuring lifetime value) to one of its capital research priorities.

Secondly, while the importance of an analysis of the dynamic customer-firm relationship is hardly disputed, empirical evidence is certainly scarce. In particular, areas in need of research are non-contractual relationships – relationships between buyers and sellers that are not governed by a contract or by membership. Specifically, how can the length of a customer's relationship with a firm be measured, given that the customer "never signs off"? How can the relationship be managed? Given that switching costs are low and that customers choose to interact with firms at their own volition, this is a non-trivial question for non-contractual relationships. What is the strength and directional impact of the antecedent factors on the duration of a customer's relationship with a firm? If managers can understand the temporal dynamics involved in a customer's relationship with the firm, they can, for example, predict the vulnerability of a customer to leave the relationship. Consequently, they can spend marketing dollars more effectively by either not chasing customers "whose time has come" or by employing judicious marketing actions to save customers who are at risk. This issue gains added importance given the findings of Reinartz and Kumar (2000) that both long-term and short-term customers can be profitable. Thus, it is imperative to develop a framework that incorporates projected profitability of customers in the computation of lifetime duration. Further, this framework should also identify factors under managers' control that could increase the value of each customer for the firm. In other words, in the case of a non-contractual setting, it is a two-step process. *First, one has to measure lifetime duration that incorporates projected profits, and in the next step identify factors that can explain the variation in duration.*

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 framework, 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/antecedents that drive the profitable lifetime duration. In response to this phenomenon, this study presents an integrated framework for measuring profitable customer lifetime duration and assessing antecedent factors. The key research objectives are to:

1. Empirically measure lifetime duration for *non-contractual* customer-firm relationships, incorporating projected profits,
2. Demonstrate the superiority of our proposed framework by comparing it to the widely used Recency, Frequency and Monetary value (RFM) framework using the criterion of generated profits,

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3. Understand the structure of profitable relationships and to test the factors that impact a customer's profitable lifetime duration, and
4. Develop managerial implications for building and managing profitable relationship exchanges.

Our research takes place in the context of the direct marketing industry. This industry is important because in 1999 U.S. sales revenue attributable to direct marketing was estimated to reach close to $1.6 trillion. Approximately 15 million workers were employed throughout the US economy as a result of direct marketing activity (DMA, 1999). Specifically, our research will be conducted for one of the leading general merchandise direct marketers (B-to-C setting) in the U.S. We obtained the data for this study from Reinartz and Kumar (2000, hereafter R&K (2000)). Furthermore, the results are validated with a customer sample from a high-technology firm (B-to-B setting) selling computer hardware and software.

Review of Lifetime Duration Research

The number of studies (Allenby, Leone and Jen 1999; Bolton 1998; Dwyer 1997; Schmittlein and Peterson 1994) that are concerned with the empirical aspects of customer lifetime duration is somewhat limited due to the general lack of customer purchase history data. Given this historical lack of longitudinal customer information, researchers have predominantly focused on the retention construct (Crosby and Stephens 1987). Nevertheless, researchers have increasingly started to take a longitudinal perspective in their empirical work. Given the exploding managerial interest in how to manage the customer–firm relationship and the increasing availability of longitudinal customer databases, researchers focused increasingly on empirically measuring and modeling a customer's relationship with a firm (Schmittlein and Peterson 1994; Bolton 1998; R&K 2000). While some authors have analyzed lifetime behavior in contractual contexts (Bolton 1998; Allenby et al. 1999), findings from non-contractual settings (Schmittlein, Morrison, and Colombo 1987; R&K 2000) are interesting and require further investigation. Table 1 gives a brief review of the academic literature concerned with Customer Lifetime Duration as the focal construct. As can be seen from Table 1, research on Customer Lifetime Duration, and in particular Profitable Lifetime Duration, is scarce.

- Table 1 approximately here -

Specifically, the characteristics of a non-contractual setting, as explained earlier, results in both long and short lifetime customers being profitable to the firm. Thus, we believe there exists a need for conceptual and empirical exploration of the antecedent variables that could characterize profitable customers and not just the longer lifetime customers – thereby advancing our relationship management understanding.

A Dynamic Model of the Antecedents of Profitable Lifetime Duration

Reinartz and Kumar (2000) provide a descriptive model of the lifetime duration - profitability relationship. This study attempts to build on their results and to furnish new understanding in two key areas.

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First, the primary objective of our study is to show how an analysis of the antecedents of lifetime duration can help to explain systematic differences in profitable customer lifetime duration. The goal is twofold: to better *understand the structure* of profitable relationships and to derive implications for managers to *better manage* a customer's profitable tenure with the firm.

The second key goal of our study builds on R&K (2000) key finding that "it is better (i.e. more profitable) to stop contacting some customers at a certain point in time" even though they may be contributing to the sales currently. Their study doesn't tell the manager at *what point* the customers should not be pursued and *which customers* to let go. In this study we attempt to provide managers with the framework to determine "which customers to let go" and "when to let go of these customers" (based on their expected contribution margin). Even though a customer may be buying from the firm, but if his or her transactions are causing the firm to lose money, it is better for the firm to stop contacting those customers. In other words, the present study offers a framework to identify, for each customer, the time periods beyond which they may not be profitable. Niraj et al. (2001) also argue that estimating profitability at the individual level is important to distinguish the more profitable customers from the less profitable ones.

The modeling process of a customer's lifetime is contingent upon a valid measurement framework that adequately describes the process of birth, purchase activity and defection. The situation is far more difficult for non-contractual settings where a customer purchases completely at his/her discretion. To our knowledge, *no study* has devised and tested a framework for measuring a customer's lifetime duration that considers projected profitability in a non-contractual context. Towards that end we want to suggest a procedure for estimating the lifetime of customers and implement this procedure empirically.

The goal of this section is to conceptualize a model of profitable duration of the customer-firm relationship that is theoretically and empirically defendable. This model describes and analyzes how and why duration times differ systematically across customers. It is thus a customer-level analysis. An important aspect to keep in mind is that the customer's tendency to maintain a relationship is reflected in the evolutionary characteristics of his exchange with the firm over time (Ganesan 1994). Since our approach exploits longitudinal information obtained *within* customers, we refer to it as a dynamic model (see also Bolton 1998).

Figure 1 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. In the hypothesis section we will discuss the exact nature of these influences. Figure 1 not only illustrates how the current study differs from R&K (2000) but also shows how the present study incorporates the findings of R&K (2000) in the proposed framework, through the incorporation of revenues and cost in measuring lifetime duration. In a nutshell, R&K (2000) focus on the consequences of lifetime duration while the present study focuses on the antecedents of profitable lifetime duration. Managers understand the important consequences of both longer and shorter lifetime duration from the R&K (2000)

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study. Only this study tells them how to incorporate those findings in deciding when to stop chasing a customer.

- Figure 1 approximately here -

The focus of our inquiry is on variables that determine the nature of the customer-firm exchange. Exchange characteristics encompass the set of variables that define and describe relationship activities in the broadest sense. To start with, the basic building blocks of any exchange can probably be characterized as the timing, scope, and depth of buying (Neslin, Henderson and Quelch 1985; Blattberg, Getz, and Thomas 2001). For example, there is ample evidence in the marketing literature that behavioral exchange characteristics, such as past purchases, are strong predictors of future customer behavior (Rossi, McCulloch, and Allenby 1996; Dwyer 1997). In managerial practice, the key exchange characteristics reflect themselves in traditional customer scoring models that primarily take into account information on purchase frequency and purchase amount (Hughes 1996). In addition to these basic behavioral exchange variables, we consider other characteristics that are relevant to the growth or decline of a relationship. This would, for example, include not only the communication between the firm and the customer in the form of marketing efforts but also in the form of signaling dissatisfaction (possibly through product returns) or signaling commitment (possibly through participation in loyalty programs).

Secondly, accounting for observed customer heterogeneity seems clearly warranted. Observed customer heterogeneity is the degree to which customers differ on observed characteristics such as for example demographic or psychographic descriptives. It is important to consider these differences because demographic and psychographic indicators are most commonly used for segmentation purposes. For example, demographic information has been traditionally used in modeling customer response (Rossi, McCulloch, and Allenby 1996). Schmittlein and Peterson (1994) advocate the use of demographic information even though they point out that past purchase behavior (i.e. core exchange) generally outpredicts geodemographic information.

In general, the antecedents that are included in our model have received broad support in the relationship marketing literature (Sheth and Parvatiyar 1995). Since our effort deals with a single firm, competitive information is not included. Specifically, it is postulated that the profitable duration of a customer-firm relationship depends, differentially, on the exchange characteristics at time *t*, and customer heterogeneity. Conceptually,

$$\textit{Profitable Lifetime Duration}_i \quad = \quad f\,(\textit{Exchange characteristics}_{it},\ \textit{Customer heterogeneity}_i)$$

The dynamic nature of the customer-firm relationship is captured through the time-varying nature of the independent variables. While the impact of these variables has been studied in a response-modeling context (e.g. brand choice, interpurchase time), we are not aware of any study that assesses their impact on

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profitable lifetime duration (or for that matter on just lifetime duration itself) in a non-contractual lifetime context.

Development of Hypotheses

In this section, we advance expectations about the effects of exchange characteristics on profitable lifetime duration. These expectations are derived from theoretical and empirical knowledge from the relationship marketing paradigm, the social exchange paradigm, and loyalty and satisfaction related research. Given the lack of research in the Lifetime Duration area in general and more so with respect to Profitable Lifetime Duration, we also draw upon the evidence available in related contexts (e.g. contractual settings, business to business settings) for developing the hypotheses.

When customers enter into commercial relationships they seek to maximize their expected utility from the entirety of the exchange (Oliver and Winer 1987). The overall derived utility is a function of a multitude of factors, which of course varies across customers. In most cases, however, the substance of the expected utility is derived from the goods or services themselves.

Exchange characteristics

Any given spending of a customer with the focal firm over time can be decomposed into three components: purchase frequency, purchase amount per incidence, and purchase composition (single or cross-category). This notion is also reflected in the generalized context of personal relationships as brought forward by Kelley and Thibaut (1978). They suggest that the interaction between two parties manifests itself in frequency of interaction, depth of interaction, and scope of interaction. Relationships intensify as exchange parties communicate more often, more deeply, and across a larger scope of issues. Thus, the argument brought forth from the Social Exchange domain would suggest that as customers buy more, buy more frequently, and buy more across different categories, the relationship between them and the vendor becomes more durable. The same logic is supported by Oliver and Winer's (1987) utility framework that would suggest that buyers who buy more, buy more frequently, and buy more across different categories have a better fit with the vendor's product and positioning, derive greater utility from it, and thus, the relationship between the two parties is prolonged.

Purchase Amount: Specifically, with respect to purchase amount, Bendapudi and Berry (1997) argue that customers who have a higher commitment are also likely to seek greater relationship expansion and enhancement. There is empirical evidence in a contractual context that more satisfied customers have longer relationships with their service providers (Bolton 1998) and higher usage levels of services (Bolton and Lemon 1999). Storbacka and Luukinen (1996) find in a financial services context that satisfaction is a function of relationship volume. Thus, one would expect a positive correlation between relationship duration

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and purchase volume as well. Stated differently, if a consumer devotes a larger share-of-wallet to a firm, the bond should be stronger. Consequently, we would expect that long duration customers would, on average, have higher spending levels than those with shorter duration.

H_1: *Profitable Customer Lifetime Duration is positively related to the customer's spending level*

Cross Buying: Assuming the firm offers products or services in different categories, consumers can purchase products in a very focused manner or they can purchase across a variety of very different categories. Cross buying refers to the degree to which customers purchase products or services from a set of related or unrelated categories of the company. For example, in a general merchandise context, one customer might buy only women's shoes and formal wear whereas another customer might purchase shoes, high-fashion, formal wear, sports wear, accessories, and textiles. In the latter case, the scope of interaction with the firm is rather broad, whereas in the former case it is focused. With respect to scope of purchases (operationalized as cross-buying), there is little empirical evidence that links cross-buying with a customer's tenure. The few existing studies in the marketing domain have focused on the related, yet different construct of cross-selling (Drèze and Hoch 1998; Chen, Hess, Wilcox, and Zhang 1999) - in particular on the direct effect of cross-selling on aggregate level outcomes, such as store sales or store choice. As compared to the cross-selling construct, far fewer studies deal with the cross-buying construct. According to Coughlan (1987), the benefits of one-stop shopping are the key drivers of customers engaging in cross-buying. What remains rather open in the literature is the effect of cross-buying on individual level outcomes such as customer retention or lifetime duration.

With respect to the impact of cross-buying on retention, the reasoning is as follows. In the context of contractual relations, customer retention is enhanced with cross selling of multiple accounts or services as customer switching costs increase with multiple relationships (Srivastava and Shocker 1987). Although these switching costs do not exist in a non-contractual setting, customers benefit from getting to know the retailers' product range, the quality levels and interaction processes (Reichheld and Teal 1996). Evidence for this contention comes also from the business-to-business context where O'Neal and Bertrand (1991) find that customers who are in long-term relationships with their suppliers are characterized by a greater scope of the relationship (measured in terms of products supplied). Likewise, Hoch, Bradlow, and Wansink (1999) state that variety in offerings is viewed as the entry fee for maintaining future customer loyalty. Thus, it is believed that those consumers who consume from a variety of product lines are less prone to leave the relationship.

H_{2a}: *Profitable Customer Lifetime Duration is positively related to the degree of cross-buying behavior exhibited by the customers.*

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Focus of Buying: In addition to the reasoning that lifetime duration increases as the degree of cross-buying increases, one could make a qualifying argument, which is specific to a very focused buyer.[1] For example, a customer may buy on a regular basis a very specific item; say jeans, from the retailer. Even if the person would not buy any other product from the retailer, it would suggest something about that customer's desire to be a long lifetime customer. On the other hand one could argue that the wear-off of involvement with the firm and decrease in excitement about the product is greater when there is only limited interaction. This would, unlike the cross-buying hypothesis, suggest a negative effect on lifetime duration. Due to the conflicting argument, we want to test the specific effect of very focused buying (i.e. one single department/category) versus non-focused buying (anything more than a single department/category). Due to the reasoning above, we do not posit a directional hypothesis but instead we will test empirically for the effect.

H_{2b}: *Profitable Customer Lifetime Duration is related to focused buying behavior exhibited by its customers*

Average Interpurchase Time: The variable average interpurchase time (*AIT*) has been used in the context of modeling purchase events – representing the frequency of interaction. The impact of a customer's *AIT* on lifetime duration can be argued from two perspectives. Lower *AIT* (i.e. more frequent purchasing given that the customer is alive) could be associated with higher lifetime since this would be an indicator of a strong relationship. Morgan and Hunt (1994) argue that to the extent that interactions are satisfactory, frequency of interactions might lead to greater trust which should in turn lead to a longer relationship duration. This argument is in line with the Kelley and Thibaut's (1978) Social-exchange perspective as well as the Person-perception literature (Neuberg and Fiske 1987) that suggest a stronger link between persons once their interaction frequency increases. These arguments would favor a *negative* relationship between *AIT* and lifetime, i.e. the longer an individual's interpurchase time, the shorter his lifetime.

The above argument purports that an extremely frequent buyer (very low AIT) should have the longest lifetime. However, sustaining a very high purchase frequency over a long life seems unreasonable, in particular for the general merchandise category. One might reasonably argue that there seems to be a lower limit for interpurchase time because purchases might occur on a regular basis. For example, it is unlikely that an individual purchases many different clothes in one instance and then pauses to buy for several years. Rather, apparel is bought on a continuous yet intermittent way. This argument would suggest that a long customer life is associated with an intermediate length of interpurchase time. Furthermore, if a customer buys with a short burst of very high intensity (very low *AIT* given the customer is alive), it would seem that this individual would have a rather low lifetime since the customer has stocked up on items that should last him

[1] We thank a reviewer for suggesting this possible effect.

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for an extended time. In addition, sustaining very low *AIT* over the long term seems rather improbable given finite income resources.

Both arguments that have been advanced above seem to have merit and the only way to reconcile them is by way of accommodating an *inverse U-shaped* relationship between *AIT* and lifetime duration. Consequently, we propose that *AIT* and lifetime duration are related in an inverse U-shaped fashion whereby intermediate *AIT* is associated with the longest lifetime. It must be noted that the construct AIT is not tantamount to modeling frequency of purchases. While these two constructs are related, frequency is an absolute measure and AIT is a relative measure. Thus,

H_3: *Profitable Customer Lifetime Duration is related to Average Interpurchase Time in an inverse U-shaped manner, whereby intermediate AIT is associated with the longest profitable lifetime.*

From a managerial standpoint, it is interesting to note that the variables of purchase frequency, and purchase amount are key input to traditional scoring models for customer evaluation. Furthermore, these variables are also reflected in customer valuation models such as the customer equity model by Blattberg, Getz and Thomas (2001) – thus adding face validity to the conceptualization of our exchange variables.

Returns: Merchandise returns pose a significant problem for direct marketers (Hess and Mayhew 1997). It is suggested that increasing returns are associated with increasing dissatisfaction. Customers return merchandise because they are dissatisfied with one or more attributes of the product such as for example quality, fit, or performance. This is particularly true in the direct marketing context, where the evaluation of the product attributes cannot be performed directly but only through reading the catalogs or the product descriptions via the Internet. If we accept an inverse relationship of proportion of returns and overall satisfaction then we would deduce that high returns should also be associated with shorter lifetimes. There is conceptual and empirical evidence that cumulative satisfaction/dissatisfaction leads to higher/lower repurchase intentions (Anderson and Sullivan 1993) and that cumulative satisfaction is associated with longer lifetimes for a long distance phone service (Bolton 1998). However, Gruen (1995) notes that although research generally supports the link between dissatisfaction with a relationship and the propensity to leave that relationship, the link is weak at best. Nevertheless, if return behavior were evidence of dissatisfaction with the firm's merchandise we would consequently argue for *lower* lifetime duration expectations for those individuals that return proportionally more.

H_4: *Profitable Customer Lifetime Duration is inversely related to the proportion of merchandise returned by the customers.*

Loyalty Instrument: Another variable that should have an impact on characteristics of the exchange is whether a customer subscribes to the loyalty instrument of the focal firm. The firm's loyalty instrument takes

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the form of a charge card that customers can sign up for. The charge card itself is a free service although customers have to go through a credit rating process. Furthermore, the charge card is vendor specific, thus it cannot be used at other stores. While the charge card performs a function in itself (i.e. the payment function), from a theoretical perspective, ownership of a charge card can also be explained through the process of identification with the firm. This is because customers have to spend additional efforts (application process, danger of rejection due to credit rating, etc) to obtain the card. Given that purchase payment can be managed in multiple ways (e.g. credit card, check), the identification with the focal firm seems to be a substantive driver behind the ownership. Customers typically using the firm's loyalty instrument get some discount or accumulate points for redeeming in the future. Given that card programs come at a significant cost, it seems imperative to assess their impact on relevant outcomes, one of which is customer tenure. The empirical evidence so far is quite mixed. Hartnett (1997) quotes evidence that store card programs are associated with increased sales in the form of higher average purchases and more frequent store visits. However, Sharp and Sharp (1997) and Crié, Meyer-Waarden and Benavent (2000) find that loyalty programs in the grocery context have only a marginal effect on customer loyalty. Clearly, in this study we are not looking at a classical loyalty program where customers can redeem loyalty incentives. Consequently, there is no question whether the loyalty program creates loyalty towards the firm or towards the program itself. We believe, that it is the identification with the firm aspect that would drive adoption of the card. As such, this suggests a positive association between company specific credit card ownership and lifetime duration. Besides the directional impact, it will also be very useful to assess the size of the impact of card ownership on lifetime duration.

H_5: *Profitable Customer Lifetime Duration is positively related to the customer's ownership of the company's loyalty instrument.*

Mailings: In general merchandise direct marketing the prime communication channel from firm to customer is the product catalog. In our case, the company engages in virtually no broadcast advertising but relies nearly exclusively on list rental and mail solicitation (promotions, catalogs). Therefore, the inclusion of mailing efforts into the model seems to represent the major marketing component of the firm. An impediment to the straightforward inclusion of mailing efforts into the model is the inherent complexity of the simultaneous nature of marketing effort and customer response probability. This simultaneity in modeling response is caused through the application of customer scoring models and the problem is widely known in the direct marketing field (Dwyer 1997). Nevertheless, we suggest that the effect of mailings should be taken into account. We do this by including the company's marketing effort as a lagged variable in the model. Thereby, we avoid causal misinterpretation of the effect of marketing efforts by removing the associated variance from the model. Similar to Bult and Wansbeek (1995), we will operationalize mailings

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by the number of efforts/mail pieces sent to the customer. Overall, we would expect a positive impact of mailings on a customer's lifetime duration.

H_6: *Profitable Customer Lifetime Duration is positively related to the number of mailing efforts of the company.*

Product category: General merchandise products are classified customarily into two broad categories – softgoods and hardgoods. Softgoods include all types of apparel, clothes, and fashion. Hardgoods comprise all non-fashion items, such as small electronics, houseware, kitchenware, gifts and the like. In order to control for potential systematic lifetime differences associated with one or the other category, we introduce a dummy variable that characterizes a buyer as being either a softgood or a hardgood purchaser depending on his majority of purchases. Since the variable is introduced for control purposes only, no directional hypothesis is advanced.

Customer Heterogeneity

Demographic variables that capture observed customer heterogeneity have been used consistently in response modeling. The main motivation to include these variables is for statistical control purposes as well as for potential segmentation purposes. According to Zeithaml (2000), firms need to characterize attractive segments into identifiable and measurable groups of customers. There exists ample empirical evidence that demographic variables can be related significantly to the response variable (sales, choice, interpurchase time), yet the portion of explained variation is somewhat low (Rossi, McCulloch, and Allenby 1996). In this context, we look specifically at heterogeneity in terms of the customer's spatial location, age, and income.

Spatial location of consumer: The maintenance of relationships can be argued from a (customer's) economic perspective. It has been shown that the continuance of a relationship is a function of the cost and the benefits that accrue from the relation. Thus, this view emphasizes switching cost and dependence as key drivers of relationship maintenance (Williamson 1975; Dwyer, Schurr and Oh 1987). For example, it has been consistently shown that for grocery purchases, store location is a key driver of store choice (Craig, Gosh, and Lafferty 1984). Thus, from an economic perspective, if a more expensive store is more conveniently located relative to the buyer's location, ceteris paribus the customer might still establish a relationship with that store because the customer minimizes overall cost (purchasing plus travel cost). Similarly, in our case, we would expect that customers in rural areas, which are characterized by a lower population density, have fewer options in choosing their most preferred store. Less store options in the customer's local environment would translate, ceteris paribus, into a higher level of mail order shopping. Consequently, due to the cost minimization argument, we would expect a higher proportion of long lifetime customers to live in low-density areas as opposed to high-density areas (e.g. cities).

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H_7: *Profitable Customer Lifetime Duration is higher for customers living in areas with lower population density.*

Age and Income: Furthermore, age and income are used as individual level control factors. We do not propose directional hypotheses for the age variable due to lack of an appropriate theory. However, we posit a directional hypothesis for income. High-income households have high opportunity costs of time. They tend to substitute time by buying goods that will save time and are willing to pay for the added convenience. Therefore, high-income households tend to spend more money for the same bundle of products than low income households do. In general, customers with higher incomes are less susceptible to higher price sensitivity (Kumar and Karande 2000) and are expected to keep buying from the firm for the added convenience. Thus,

H_8: *Profitable Customer Lifetime Duration is positively related to the Income of the customer.*

Research Methodology

The data (B -to -C setting) for the present study were kindly obtained from Reinartz and Kumar (2000). The use of the same data set is critical because we are trying to evaluate if the findings of Reinartz and Kumar can be implemented successfully to determine which customers to let go and when to let go. In addition to the two cohorts used in R&K (2000), an additional cohort of data was also used from the dataset provided to us. Thus, we can validate the results across three different sets of customers. While the data are partially the same for both studies, the studies have entirely different objectives. Furthermore, it is worthwhile to highlight that it is imperative, for this type of research, to use cohort data (Reichheld and Teal 1996; Parasuraman 1997).

Database

Data from a U.S. general merchandise catalog retailer are used for the empirical estimation in our paper. The firm offers a broad assortment of products all year round (apparel, gift items, decoratives, small electronics, kitchenware). We do not disclose the name of the company for reasons of maintaining confidentiality as per the agreement. We describe the data here for the purpose of clarity and continuity. The data for this study cover a three-year window and are recorded on a daily basis. The database for the three cohorts consists of a total number of observations of 11,992 households. The customers are tracked from their very first purchase with the firm and these households have not been customers of the company before (i.e. no left-censoring). The sample of households belongs to three different cohorts, the structure of which is depicted in Figure 2.

- Figure 2 approximately here -

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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 5 purchases, the median interpurchase time is 117 days, and the median transaction amount is $91 for each purchase.

Estimation of P(Alive)

We replicate the estimation of NBD/Pareto model used by R&K (2000) to obtain the necessary parameter estimates for this study. In contrast to R&K (2000), we derived the distribution parameters of the NBD/Pareto model for the entire sample through the maximum likelihood estimation (details are given in the technical appendix). An added benefit of using maximum likelihood estimation (MLE) in this study is that we can compare the results with the method-of-moment estimates that are available from R&K (2000).

A key finding from the parameter estimation is that the method-of-moments and the maximum likelihood estimation yield very similar results (see Table 2). We also calculated the Pearson product moment correlation between the *P(Alive)* estimate from the MLE estimates and the *P(Alive)* estimates resulting from Reinartz and Kumar (2000). The correlation is above 0.99 for all three cohorts (Table 2), which also shows the convergent validity between the MLE and method-of-moment estimates. Given the convergent validity of the estimation method, we use the result of the NBD/Pareto model estimated by MLE. Specifically, the probability of being alive is calculated from month 4 to month 36 of the observation window. The resulting average probability for Cohorts 1 to 3 is plotted in Figure 3. Next, we use *P(Alive)*, and propose in the next section a rule for obtaining a finite lifetime estimate – based on the expected future contributions of a customer. The procedure suggested below is different from the one suggested by R&K (2000). However, it integrates the knowledge gained from their study.

- Table 2 approximately here -

- Figure 3 approximately here -

Measuring Profitable Customer Lifetime Duration

Lifetime Duration Calculation

We suggest a 4-step process for obtaining individual lifetime duration estimates that integrates projected profitability:

1) Calculate net present value (NPV) of expected contribution margin (ECM_{it})
2) Decision of relationship termination by comparing NPV of ECM_{it} with cost of mailing (i.e. if NPV of ECM_{it} < Cost of next mailing$_{i,}$ then terminate)
3) Calculation of finite lifetime estimate

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4) Back-end performance analysis of the suggested procedure.

In the non-contractual setting, measuring lifetime duration becomes a non-trivial case. Here, customers are subject to *silent* attrition and firms can only *infer* when a person has left the relationship. For example, even though a person makes no purchase for a much longer period than the average interpurchase time, the person might still have some non-zero probability of purchasing again. This spirit is captured by the NBD/Pareto model that reflects the probability of the customer being alive given her particular purchase history. However, even though a customer might have a small probability of being alive (and thus to potentially purchase) this might not justify investing in this customer - *for all practical purposes*. For example, in the direct mail context, customers are being sent mail regularly so firms have to optimize their resource allocation across customers. Therefore, given that customers reach a low activity level at some point, *the firm has to make a decision* whether to let this customer go or not. This managerial viewpoint reflects exactly the spirit of our suggested procedure. If we want to determine the factors that impact on the length of a customer's tenure with the firm we have to establish a finite lifetime estimate which in turn critically depends on our capability to determine the "death event". We therefore argue that our suggested procedure of converting the continuous customer-specific *P(Alive)* estimate into a customer-specific finite lifetime estimate is fully compatible with the managerial decision-making process of retaining customers in the database, and at the same time, is a necessary intermediate step for our key modeling effort (i.e. hazard model).

Having established the raison d'être for our process, the next question is how to determine the lifetime estimate. In this section we will show how the expected future income stream can be utilized to determine the cut-off for the computation of profitable lifetime duration.

1) Calculate net present value (NPV) of expected contribution margin (ECM_{it})

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(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 as:

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

where ECM_{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

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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 $P(Alive)_{in}$ 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 that 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 profit. 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 month 1-18 by summing up all the 18 contribution margins and dividing it 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 it by 36. Thus, the AMCM estimate is updated monthly –in other words, dynamically modelled 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(Alive)* estimate. It thus contains endogenously the information about the mailing process as well. The future time horizon is limited to 18 months because the associated *P(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/her probability of being alive is small. Since the predicted *P(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.

2) Decision of relationship termination

Formally, if $NPV\ of\ Expected\ CM_{it} < Cost\ of\ Mailing$ 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 average flat contribution margin before mailings of 25 percent. The discount rate is assumed to be 15%, which is in the range of what has been used by other authors (e.g. Berger and Nasr 1998).

3) Calculation of finite lifetime estimate

Based on the decision of relationship termination, the average lifetime across Cohort 1 is 29.3 months, across Cohort 2 is 28.6 months, and across Cohort 3 is 27.8 months (Table 2). The consistency between the three cohorts is very high. In all the cohorts, little more than 60% of the samples have a lifetime that is 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.

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Thus, we expect considerable scope for exploring the factors that impact on lifetime duration. Note that the lifetime duration estimates that incorporates projected profits are different from the one that doesn't incorporate profits (as in the Reinartz and Kumar (2000) study)

4) Back-end performance analysis of the suggested procedure

The performance of the proposed method is assessed by performing three different tests. First, we assess the quality of classification. For that purpose we compute the proportion of customers who were misclassified, i.e. whose relationship was declared as terminated, however, they purchased at least once after the lifetime event. The result is given in column 7 of Table 2. Slightly more than 90% of the subjects are being classified correctly within the 3-year observation window. This result underlines the strength of the expected future contribution margin method.

Then, we compare the proposed method to the widely used *RFM* framework. Most direct marketing firms use the *R*ecency-, *F*requency-, *M*onetary-value method (RFM) as a scoring method for customers and as a method for determining the mailing status of customers. While classical RFM analysis is based on the customer's past purchase behavior along the three dimensions (Hughes 1996), we employ an advanced form of RFM scoring in this research. Specifically, we use a regression analysis that contains the RFM variables as well as measures on cross-buying, depth of buying, and observed heterogeneity.[2] R&K (2000) do not provide any explicit comparison of their method with the RFM framework. We compare for two different time periods (18 and 30 months) the prediction of the NBD/Pareto model with the prediction resulting from the advanced RFM model. To make the results as comparable as possible, we assume that the firm spends a fixed mailing budget at each of the two dates. The sample is sorted according to the score and, given the fixed budget, the top 30%, 50%, and 70% respectively of the customers are selected for targeting. We then compare the total actual revenues generated for those customers from months 18 and 30 respectively onwards until the end of the observation window for the two methods.[3] Table 3 shows that the proposed framework seems clearly superior to the RFM decision rule.

-Table 3 approximately here-

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[2] We thank a reviewer for suggesting the benchmark comparisons with the state-of-the-art RFM scoring and past customer value scoring.

[3] The dependent variable for the RFM regression is the purchase amount in season 3 (i.e. month 13-18) and season 5 (i.e. month 25-30) to reflect two different time periods. The eight independent variables are measures for R (whether customer bought in previous season), F (number of times bought in previous season), M ($ purchases in previous season), cross-buying (in previous season), depth of buying (up to focal period), spatial location (population density), income, and age. After estimating the coefficients, customers are scored on their purchase behavior in the current season, i.e. season 3 and 5. The score is used to determine the selection.

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For example, the proposed framework selection method yields revenues of \$590,452 (Column 3, for Cohort 1) whereas the corresponding result using the RFM method yields \$442,534. In every case, the proposed framework selection approach yields higher revenues as compared to the RFM selection approach. Similarly, the proposed framework selection method yields a profit of \$123,076 whereas the RFM selection method yields only \$78,555. While this result is obtained for 30% of customers selected from the top, the findings hold good across the percentages of customers selected as well as across the different points in time. This finding is a remarkable support for the performance of the suggested framework, which uses the estimates of *P(Alive)* from the NBD/Pareto model in combination with the NPV of the expected contribution margin.

Finally, we compare our method with another classification benchmark. We use cumulative *past customer value* as the variable to determine mailing status of the customer. The reason for choosing lifetime value is that managers expend significant efforts to retain high lifetime value customers. Similar to the RFM model, we compare for the same two time periods (18 and 30 months) the prediction of the NBD/Pareto model with the prediction resulting from the past customer value benchmark. The results are also reported in Table 3. The results show that our model, which is based on the dynamic NBD/Pareto model, performs better than the traditional methods. Thus, including the dynamics of the customer lifetime value evolution seems to hold considerable potential in terms of customer scoring and customer selection.

The realized profits across the entire customer database could be of the order of millions of dollars, thereby enhancing the utility of our framework. Thus, while our suggested procedure is a theoretically sound procedure for the profitable lifetime calculation, it is also extremely well aligned with the actual managerial decision making process. In and of itself, the result is already useful to managers for optimizing mailing decisions.

In summary, we suggest a procedure for transforming the continuous NBD/Pareto outcome into a dichotomous “alive/dead” variable, which integrates projected profitability into a finite lifetime calculation. Recall that Reinartz and Kumar (2000) classify consumers with greater than a probability value of 0.5 for *P(alive)* as being “Alive” and “Dead” otherwise without any consideration for profits. Our procedure improves upon their heuristic. Secondly, one could also compare the NBD/Pareto framework to a customer migration model (for an example see Dwyer 1997). While a migration is based on *average* transition probabilities, our suggested framework allows for heterogeneity across customers. Even though the NBD/Pareto model might still be limited in capturing heterogeneity across the customer base it appears to be an improvement over static approaches such as migration models.

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Analysis

Survival analysis will be used for the analysis of profitable customer lifetime durations. It is the method of choice in dealing with duration data, in particular because it is well suited for the handling of censoring. We use the proportional hazard model, which assumes a parametric form for the effects of the explanatory variables, but allows for an unspecified form for the underlying survivor function (Cox 1972). In the proportional hazard model, the hazard rate $h_i(t)$ for individual i is assumed to take the form:

$$h_i(t) = h_0(t)\, e^{x_{it}\beta} \qquad (2)$$

where $h_0(t)$ is the baseline hazard rate and $(x_{it}\beta)$ is the impact of the independent variables. We estimate the hazard model with the semi-parametric partial likelihood method (Helsen and Schmittlein 1993). The partial likelihood considers the probability that a customer experiences the lifetime event, out of all customers that are still being considered alive. We use the PHREG procedure in SAS for the estimation, with ties being handled using the exact likelihood instead of the more commonly used, yet less precise Breslow approximation.

Variable Operationalization

The criterion variable is the household specific estimate of profitable lifetime duration. Thus, there is only a single event associated with each household. The length of the duration is measured in months. The predictor variables in the model comprise both constant and time-varying variables. Time-varying variables may change during the course of an individual's lifetime spell and they are measured and updated for each month. This procedure is exemplified with the *Returns* variable. For example, a customer makes purchases worth \$100 in month 1 and returns \$20 worth of goods, then he does not purchase in month 2, subsequently he buys products for \$60 in month 3 and returns nothing, and finally he buys in month 4 for \$40 and returns 50%. Thus, the proportion of goods returned would be dynamically updated for every month such that his returned proportion would be 0.2 for month 1 (since he returns 20%), 0.2 for month 2 (since nothing is bought), 0.125 for month 3 (\$20 total returns/\$160 total purchases), and 0.2 for month 4 (\$40 total returns/\$200 total purchases). This updating is performed for all time varying variables and lies at the very heart of the proportional hazard model. We do not provide means for the time varying variables because a simple mean statistic has limited value due to its averaging across time periods and across individuals. The detailed means report for every time period is available from the authors.

The time varying variable Purchase Amount_{it} enters the model as the monthly spending level (\$).The time varying variable Cross-Buying_{it} is operationalized as the number of different departments shopped in, in a given 6-month period. There is a total of 90 different merchandise departments. The Focus-of-Buying variable is operationalized as a dummy variable. The percentage of customers who are coded as "1" (buying consistently in one department) are 0.04, 0.05, and 0.04 across the 3 cohorts. The time varying variable Average Interpurchase Time_{it} is measured in number of days between purchase. AIT_{it}^2 is the square of the

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AIT_{it} variable. The $Return_{it}$ variable is the ratio of returned goods ($ value) to purchased goods ($value). The Loyalty $Instrument_i$ variable is oprationalized 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 $Mailings_{it}$ 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 by the number of efforts/mail pieces sent to the customer. The dummy variable Product $Category_i$ describes whether a buyer predominantly shops in hardgoods or in softgoods. The proportion of customers buying predominantly hardgoods is 0.50, 0.49, and 0.45 across the three cohorts. The variable Population Density enters the model as the absolute population number in a given 2-digit Zip code into the model. These numbers were derived from 2000 US Census. The variable $Income_i$ 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_i variable is measured as the age of the individual in years, calculated from birthdate 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 4.

- Table 4 approximately here -

The complete model specification is given in equation 3. The hazard of a lifetime event of a household *i* at time *t* is given as follows:

$$\begin{aligned} h_i(t) = h_0(t)\ EXP\ (&\beta_1 \text{Purchase Amount}_{it} + \beta_2 \text{Cross Buying}_{it} + \beta_3 \text{Focus of Buying}_{i} \\ &\beta_4 \text{Average Interpurchase Time}_{it} + \beta_5 (\text{Average Interpurchase Time}_{it})^2 + \\ &\gamma_1 \text{Returns}_{it} + \gamma_2 \text{Loyalty Instrument}_{i} + \gamma_3 \text{Mailings}_{it} + \gamma_4 \text{Product Category}_{i} + \\ &\delta_1 \text{Population Density}_{i} + \delta_2 \text{Income}_{i} + \delta_3 \text{Age}_{i}) \end{aligned} \tag{3}$$

We estimate the model for each cohort in three steps in order to judge the incremental variance explained by the three models. First, we model the traditional key exchange variables (*β's*), then we add the additional exchange variables (*γ's*), and finally we enter the observed heterogeneity variables (*δ's*).

Results

The results of the profitable lifetime duration model for the three cohorts are reported in Table 5. The table contains the final model parameters, including an interaction term (Returns x Purchase Amount), which was added post-hoc.

- Table 5 approximately here -

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The effective sample size for Cohort 1 is 3692 households, for Cohort 2 is 4323 households and for Cohort 3 is 2491 households. We had to exclude 510 observations (12.1%), 642 observations (12.9%), and 334 observations (11.8%) respectively due to missing values for the demographic variables. A chi-square likelihood ratio test of the hypothesis that the vector of independent variables is jointly equal to zero is rejected for all models ($p < .0001$).

As in all regression analysis, a measure analogous to R^2 is certainly of interest as a measure of model performance. As shown in a detailed study by Schemper and Stare (1996), there is not a single, easy to estimate and useful measure for the proportional hazard model. The statistic utilized in this context was proposed by Cox and Snell (1989) and was also one of the three statistics endorsed by Magee (1990): $R^2 = 1-\exp(-G^2 / n)$ where G^2 is the likelihood ratio chi-square statistic and n is the sample size. The R^2 estimates are given in Table 5 for all models. The increment in the proportion of variance explained in the more complex models is significant for all models and for all cohorts ($p < .01$)

Effects of Exchange Variables

Purchase Amount: We hypothesized that the level of spending for merchandise (β_1) is positively related to profitable lifetime duration. We find support for this hypothesis across all three cohorts and across all three models ($p < .01$). 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.

In order 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 $((\exp(-\beta)-1)*100)$. Applied to the purchase amount variable, 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 (β_2) was argued to be positively related to profitable lifetime duration since a broader scope of interaction constitutes a stronger relationship. This contention is supported for all models and for all cohorts in our model ($p < .01$). Apparently, a long customer life is sustained by a higher degree of purchasing *across* departments. Given a certain income, people need 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 desirable for the firm to induce customers to engage in cross-departmental shopping. Hence, H_2 is supported.

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This is an important finding since the effect of cross-buying on lifetime duration has not been documented so far.

Focus of Buying: We did not advance a directional hypothesis with respect to focus of buying (β_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* (β_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 non-linear term AIT^2 (β_5). We do find support for our hypothesis with both terms being significant at ($p < .01$) and having the hypothesized sign (β_4 positive and β_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.

Altogether, 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 (γ_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 5) showed that the effect was significant at ($p < .01$), 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 a positive encounter with the firm's service reps, which then might impact 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 that they 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 be become stronger.[4] In order to pursue this line of thought we added, post-hoc, an interaction between amount of purchases and the

[4] We thank a reviewer for suggesting this interaction effect.

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proportion of returns to the model. The final results including the interaction are included in Table 5. The interaction turns out to be significant for all three cohorts ($p < .01$). 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 $ purchases and the level of returns are high. Figure 4 depicts this situation graphically. Clark, Kaminski and Rink (1992) show evidence 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 Kesler (1985) who states that Omaha Steaks, a mail order supplier of high-quality meat, found higher profitability for those customers for which it had quickly resolved complaints.

- Figure 4 approximately here -

Loyalty Instrument: Interestingly, the loyalty instrument (γ_2) is significantly related to profitable lifetime duration ($p < .01$). 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, H_5 is supported. Remember, the findings in the literature so far were 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. This is in line with Day (2001) who suggests that while investments in relationship building programs might result in relationship advantages, the effect on profits is far from clear. While we are finding support for Day's first contention, Day's second proposition will be much more difficult to test.

In terms of magnitude of effect, the risk ratio analysis indicates that adopting the loyalty instrument is associated with a 45%-52% decrease in hazard of relationship termination – a substantive amount.

Mailings: The mailing variable (γ_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 ($p < .01$) 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 (γ_4) could have a systematic effect on a customer's lifetime. For example, it could be that durable goods (i.e.

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hardgoods) 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 γ_4 for the dummy variable is not significant ($p > .1$) 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 (δ_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 ($p < .05$), thus underlining the need (a) to account for observed heterogeneity in duration modeling and (b) to demonstrate support for the transaction cost minimization argument.

Income and Age: In terms of the two demographic variables income (δ_2) and age (δ_3), we find that while age does not seem to be related to profitable lifetime duration ($p > .05$), income does ($p < .01$). Our model indicates that 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.

Model Validation

The data for validating the proposed framework is obtained from a high technology firm located in the U.S. The organization sells computer related products to both small and large businesses. The products range include PCs, printers, software, networking equipment, servers, storage, e-business applications, etc. The data cover an eight-year period starting from 1993 to 2000. Given the product category, the eight-year period gives multiple opportunities for the businesses to purchase from this firm repeatedly. From this database, a cohort of customers is chosen such that their first purchase occurred in the first quarter of 1993. These customers are tracked from their first purchases for a period of 8 years and have not purchased from this firm prior to this date. This resulted in a sample size of 4128 businesses. The number of purchases ranges from 4 to 39 across the sample with a median number of 11 purchases, the median interpurchase time is 179 days, and the median transaction amount is $18,481 for each purchase. Unlike the catalog industry, where customers are contacted through mailing the catalog, in this firm businesses are contacted through tele-sales people (sales people contact the businesses over the telephone). The details on the cost of each contact and the frequency of contact are also available at the firm level.

The NBD/Pareto model parameters are estimated, as before, using the MLE procedure and estimates for *P(Alive)* are computed. The profitable lifetime duration estimates are obtained using the first three of the four steps described earlier. The lifetime estimates are then used in the calibration of the hazard model (see equation (5)). The majority of the variables in equation (5) are common to both the B-to-C and B-to-B

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settings. A few points of differences between these two settings are worth noting. The Loyalty Instrument variable is replaced with a dummy variable as to whether a Line of Credit is available or not. Similarly, the mailings variable is replaced with the number of contacts, and the product category variable is operationalized as hardware versus software. In terms of heterogeneity variables, the age and the income variables are replaced with the age of the firm and the average annual revenue of the firm.

The results for the B-to-B case are similar to that of the B-to-C catalog industry. Most notable observations are that the variance explained by the key exchange, other exchange, and customer heterogeneity variables are 59%, 11% and 4% respectively. The businesses buying only in one department such as PC or networking equipment have shorter lifetime duration; firms with larger revenues have longer lifetime duration; and age of the firm was not significant. The average interpurchase time (AIT) variable is significant but not the square of the AIT. However, the coefficient for AIT is negative which indicates that shorter AIT is associated with longer profitable lifetime duration. It is possible that the range of the data is such that only a linear relationship is observed. Overall, there are more similarities than differences between the two settings. The findings clearly indicate that the proposed theoretical framework holds good across settings providing evidence for generalizability of the results.

Managerial Implications

The research objectives of this study are fourfold. First, we wanted to empirically measure customer lifetime duration that integrates projected profitability in a non-contractual setting. Next, we demonstrated the superiority of the proposed framework over the commonly used RFM framework and Customer Value framework. Third, we attempted to show how an analysis of certain factors (the antecedents) could help to explain systematic differences in profitable customer lifetime duration, both in a B-to-C and a B-to-B setting. Now, we want to discuss how managers can use this knowledge in their decision-making.

The use of proportional hazard framework with finite lifetime estimates derived from the combination of NBD/Pareto framework and expected NPV allows for a comprehensive and accurate analysis. We show that the model has a substantive explanatory power. Specifically, our analysis leads to the following implications:

- The proportion of variance explained in the dependent variable rests to a large degree in the exchange variables. Thus, we find that the information that is quite easily available in the form of purchase history data is also strongly associated with the profitable lifetime duration of a customer. In terms of actionable results, this is good news for the manager who can draw on an existing set of well-known variables to start managing profitable customer lifetime.
- The B-to-C data seem to support our assertion that the average interpurchase time is related in an inverse U-shaped fashion to profitable customer lifetime. Both, very long and very short interpurchase times are seemingly associated with lower overall lifetime durations, however, for very

different reasons. Interestingly, the common view is that the higher the buying frequency, the 'better' the customer. This might be true if one takes a short-term cash-flow perspective. Traditional promotion-oriented marketing has clearly focused on this short term response. However, what becomes clear here is that the evaluation of what success is depends very much on the short and long-term stance. In this context, the real impact of buying frequency is only revealed by looking at the impact on lifetime duration. For many reasons (e.g. data availability, methodological issues), managers could not make a valid judgment about the long-term impact of relationship characteristics simply because it couldn't be measured. Given the knowledge that was available (i.e. about the short-term behavior and response), short-term actions were implemented. Our approach shows clearly that, with respect to lifetime duration, it might mislead managers to regard high frequency purchasers as the most attractive. The results show that if one takes a long-term (lifetime) perspective, it is the buyers with intermediate frequency that are most likely to be long duration customers.

The implication is that managers are most likely to be successful in maximizing the customer's value to the firm, if they fully understand the impact of specific relationship characteristics on short *and* long-term success measures. Our empirical finding is thus an important contribution to the managerial toolkit of actively managing customer equity. In terms of actionable results, this means that managers can now optimize their marketing efforts with respect to traditional short-term as well as new long-term objectives. There is no doubt that some traditional marketing practices will be questioned in the future. Concretely, the results allow managers to compare a customer's current interpurchase times with lifetime duration maximizing interpurchase times and adjust their solicitation plans accordingly. This should result in longer lifetime customers as well as higher customer satisfaction since the benefit to the customer is a communication policy, which is more consistent with his/her real needs. The insight in lifetime maximizing inter-purchase times can and should be combined with other key long-term measures such as customer profitability.

- The results allow managers to re-assess their perceptions about the reasons for product returns. It was shown that longer lifetime customer had proportionally higher returns than shorter lifetime customers. The implications are twofold. First it establishes that higher returns can be a symptom of a durable relationship and thus, that the firm can use the information about return behavior to infer lifetime affinity. Clearly the argument is only one way. If a customer does not return it maybe so for many reasons, e.g. she is not dissatisfied, she is not accustomed to the return process, or she is very dissatisfied and doesn't want to deal anymore with the firm. All the managers know in this case is that the likelihood of being a long-term customer is lower. This knowledge might lead a manager to conduct more in-depth investigations such as customer feedback surveys to assess their state-of-the-relationship. If the customer returns merchandise, it shows that the customer does not shy away from the procedural hassle. Also, it gives the firm a further opportunity to interact and to bond with the customer. This also empirically

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supported by the findings from Bowman and Narayandas (2001) who find that loyal customers value how they have been treated (in a customer-initiated-contact) more highly than whether they walked away from the contact having not received something valuable from the company. To be clear, we are not suggesting that the firm should promote returns (as if it would make customers to stay longer). However, managers should not necessarily be concerned about the relationship quality if returns from long duration customers are higher.

The second implication is that managing the cost component of the firm's return policy becomes highly critical. For example, a customer might order two different sizes of the same shirt with the purpose of trying them on and returning the one that fits worse. This behavior is more compatible with that of a regular, long lifetime client than that of a new client. If the client knows that the return process is hassle-free, he might as well use it. Thus, the managerial challenge is to satisfy the important client while at the same time to contain operational cost.

- The implication on the loyalty instrument policy is somewhat similar to the returns variable. From a response perspective, the loyalty instrument seems to be associated with longer lifetime customers, whichever way the causality works. By signing up to the card program, customers 'flash a card', indicating that they are in it for the long haul. This is an important early signal for the manager, given that predictions on future lifetime duration are not easy to make. Thus, a manager can take this information and start treating this individual as a likely long-term customer with all the relevant marketing-mix offers he deems appropriate. Besides the loyalty instrument's impact on exchange characteristics, cost management seems to be a major factor. While an overall consensus on the effectiveness of loyalty programs is still not very clear, the cost implications remain large (Day 2001).
- Demographics do matter, not only with respect to purchase response and choice but also with respect to long-term objective such as lifetime duration. In particular, we find that the higher the income and lower the population density the greater the likelihood of being long-term customers. The overall incremental variance explained is relatively low which is in line with other published research (Gupta (1991) and Rossi, McCulloch, and Allenby (1996)). However, the notion that an increasingly diversified and individualized population will render the value of demographics less and less useful (Sheth, Mittal and Newman 1999) does not appear to hold. Thus, segmentation exercises based on demographic characteristics of the target customer groups still seem warranted. A significant advantage of the findings related to spatial location and demographics is regarding the *acquisition* of customers. If managers in the catalog industry are interested in recruiting new customers then a potential fertile group is to look for higher income people in lower population density areas.

Besides these substantive conclusions, our model provides the manager with a comprehensive general framework to analyze the role of antecedent factors in profitable customer lifetime duration. The

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time-varying nature of our model captures dynamic purchase behavior and is an advancement over many static approaches. Specifically, the model allows managers to *dynamically* update and quantify the direction and degree of impact on lifetime in a non-contractual context – something that has not been established so far. Thus, the model can be used as tool for making *profitability-based* retention decision. For example, as new data become available, managers can re-estimate the model and identify customers who are likely to be profitable in the future but who stopped purchasing from the firm. Consequently, appropriate retention actions can then be taken to induce repeat purchases from these customers. On the other hand, the model allows to identify the point when a relationship turns unprofitable – even though these relationships might generate revenues. This is certainly an advancement over other methodologies that focus on revenue as the key dependent variable. Thus, the model allows for selecting customers where lower levels of investments or no investment at all are more appropriate marketing decisions.

The firm that provided the B-to-B database actually collects data on share of wallet from the buying firms' universe. This information can be combined with the profitable lifetime duration measure that is obtained in this study to create a 2x2 matrix as shown in Figure 5. The information in the figure should help managers to deal with the existing customer. As indicated in the figure, if a customer belongs to the high share of wallet and high profitable lifetime duration, then, marketing strategies should aim at nurturing, defending and retaining existing customers along with rewarding them for being such loyal customers. On the contrary, if a customer belongs to a low-low segment in Figure 5, then, the focus could be on reducing marketing expense, considering divesting or even outsourcing those customers for servicing by an outside agency who can operate on a percentage basis. If a customer has high share of wallet but low profitable lifetime duration, then the firm can use selective or optimal mailing/contract strategy to reduce cost, and ensuring up-selling and cross-selling to increase the profit potential. Finally, if a customer's share of wallet is low but has high profitable lifetime duration, then, marketing strategies that focus on luring customer dollars from competition should be developed along with developing strategies for up-selling/cross-selling to encourage higher spending, and lucrative loyalty programs. In summary, the findings in the study derive the strategies suggested here.

- Figure 5 approximately here -

On a more general note, our analysis shows clearly the relevance and importance of establishing customer relationship management capabilities. Our study shows that customers are heterogeneous on an important relationship characteristic – lifetime duration. Having documented how this heterogeneity can be measured and what the drivers of this heterogeneity are, managers have to take this knowledge and initiate systematic and appropriate supply-side responses. An appropriate firm response would be to develop customer management capabilities in situations where customer behavior heterogeneity is present. Besides establishing the appropriate data recording, duration measurement, and profitability analysis capabilities,

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managers have to develop systematic response procedures towards short and long-life customers. For example, long-life customers can have access to more expensive but also more effective customer support. Alternatively, this can mean that short-life customers are subject to relationship enhancing activities. Regardless, of the specific marketing tactics, what is common to this kind of response is that firms must build their capabilities of handling an increasingly diverse customer base. In line with Day (2001), we believe that these are first and foremost strategic capabilities. Also, we believe that building these new customer management capabilities, which allow firms to establish competitive advantage, is one of the next frontiers of modern management. Given the importance of actively managing the customer base, our suggested framework provides an important tool towards this end.

Limitations and Suggestions for Future Research

It is important to point out limitations of this study, some of which could be worthwhile topics for future research. Our empirical setting provides ways of testing previously unexplored issues in lifetime duration modeling, but it also limits the generalizability of the study. While our data come from established companies in important industries, further empirical analyses in other non-contractual settings seem necessary. Thus, while we implement a framework for analysis, other applications of this framework to cohort databases should yield fruitful insights.

We were not able to include competitive effects/environmental conditions or capture behavior based on buying only on promotion that might impact on our dependent variable – profitable lifetime duration. Including these effects in the general domain of customer management research seems an excellent extension of the present study.

Another possible shortcoming could be the operationalization of the exchange construct. We use exclusively behavioral measures for operationalizing the duration antecedents. While they provide for a strong and rich explanation, one could argue that attitudes such as satisfaction or attitudinal loyalty might interact with these behavioral constructs. We agree with this argument but we have to leave this test to future inquiries due to unavailability of appropriate data.

In our calculation of a customer's net present value we incorporate implicitly marketing mix spendings in the observation period. This approach of course does not incorporate the quality of the marketing mix. For example, while our model might recommend "letting a customer go", a different, better marketing mix for that customer would actually enable him/her to be profitable. We do not consider these effects and thus, this might be an avenue for future endeavors.

From a technical perspective, one could consider the use of a two-step procedure of our model as a limitation. The two-step modeling process, however, is not particularly new to our problem but has been used and applied to many other marketing situations (e.g. Takada and Jain 1991). A well-known example is the new product diffusion context where the first step consists of estimating the diffusion parameters and the

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second step regresses these parameters on a set of certain independent variables. Furthermore, while it has been shown that the benefit of integrating the two estimation procedures yields a gain in efficiency, this gain is typically small (Krishnamurthi and Raj 1988). The two-step approach also has an interesting precedent in a Grangerian sense in the econometrics literature. Our approach calculates and removes the effect of the recency of the last purchase in the NBD/Pareto model. Since the outcome variable *P(Alive)* has been pre-whitened of the former variable's effect, the second step examines only the effect of "what's left".

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Technical Appendix

Estimation of P(Alive)

Due to the computational constraints imposed by the maximum likelihood estimation (MLE), method-of moment estimates have been the method of choice hitherto (Schmittlein and Peterson 1994; R&K 2000). Nevertheless, there seems nothing wrong with using method-of-moment estimates. First, method-of-moment estimation is advocated as a method of choice by the authors of the NBD/Pareto model (Schmittlein, Morrison, and Colombo 1987) and has been used by Schmittlein and Peterson (1994) in their empirical application. Second, Morrison and Schmittlein (1981) have shown for the NBD model that method-of-moments and MLE yield approximately the same results. Similarly, Gupta and Morrison (1991) have shown in a simulation study that method-of-moment estimation and MLE yield similar results when using Number-of-Purchases data (similar to our study). Thus, there seems to be support in favor of the more manageable method-of-moment routine.

Using the likelihood as given in (Schmittlein, Morrison, and Colombo 1987), we estimate the four parameters of the NBD/Pareto model (r, α, s, β) with a Fortran routine. The likelihood is

$$L(r,\alpha,s,\beta) = \prod_{i=1}^{M} P[X_i = x_i, t_i, T_i | r, \alpha, s, \beta] \qquad \text{(A1)}$$

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 probability on the right of (1) is given in (Schmittlein, Morrison, and Colombo 1987, appendix, equation A15 and A16). The resulting MLE parameters are $r = 3.01$, $\alpha = 9.65$, $s = 0.82$ and $\beta = 11.91$ (estimation horizon 30 month). The parameters are quite consistent with the estimates derived by R&K (2000) who used estimates of $r = 4.24$, $\alpha = 14.95$, $s = 0.93$ and $\beta = 13.85$. In particular, the critical parameters $r/\alpha = 0.312$ and $s/\beta = 0.069$ are similar to Reinartz and Kumar (r/α =0.281 and $s/\beta = 0.069$), resulting in little bias in the *P(Alive)* estimates (see Table 3, column, 2 and 3.). Since the results are very robust and the computational resources required for MLE are substantially larger, we can recommend for future endeavors, the method-of-moment estimation.

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 α. The larger the value of the shape parameter r the more homogeneous the population of customers in terms of purchase rate. Thus r can be viewed as an overall inverse measure of the concentration in purchase rates across households. The larger the value of the shape parameter s the more homogeneous the population of customers in terms of dropout rate. The concentration in dropout rates, β, depends on the parameter s only. Overall, the model estimates seem very reasonable and show a high degree of face validity and internal consistency. Having calculated the

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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. Schmittlein, Morrison and Colombo (1987) show that 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. The desired probability for $\alpha > \beta$ is given in Schmittlein and Peterson (1994) as: $P\,[Alive \mid r,\ \alpha,\ s,\ \beta,\ x,\ t,\ T] =$

$$\left\{1+\frac{s}{r+x+s}\left[\left(\frac{\alpha+T}{\alpha+t}\right)^{r+x}\left(\frac{\beta+T}{\alpha+t}\right)^{s}F(a_1,b_1;c_1;z_1(t))-\left(\frac{\beta+T}{\alpha+T}\right)^{s}F(a_1,b_1;c_1;z_1(T))\right]\right\}^{-1} \quad \text{(A2)}$$

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. The corresponding probabilities for $\beta > \alpha$ and $\alpha = \beta$ are given in Schmittlein and Peterson (1994, p. 65).

The importance of analyzing cohort data is well exemplified in the following discussion. In the aggregate form, the curve in Figure 3 sheds light on a hidden, yet extremely important phenomenon: what are the characteristics of the customer defection process? While a cross-sectional time-series analysis of customers would yield an average *P(Alive)* for each period, it would yield no insight into the dynamic pattern of customer defection. In other words, the average *P(Alive)* would contain people who are early in the relationship and who are late in the relationship. This would yield a constant *P(Alive)* over time whereas in our case *P(Alive)* is declining over time. Thus, a time series-cross-section analysis allows one to answer how many active customers the firm has and whether that number is growing or declining, and which individual customer is most likely to be active. Yet, an analysis of the *lifetime activity pattern* is only possible by combining the NBD/Pareto model with Cohort data analysis (i.e. customers having the same starting period). Thus, in order to reveal the lifetime activity pattern at the aggregate level, we use only the cohort data.

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Table 1: Major Findings of Studies Concerned with Customer Lifetime Duration Modeling

Study	Nature of Study	Data	Highlights of Key Results / Remarks
Dwyer, (1997)	▪ Description of the nature of customer lifetime and the procedures for lifetime estimation	n.a.	▪ Differentiation of always-a-share and lost-for-good customers ▪ Author proposes taxonomy for lifetime value estimation
Crosby and Stephens, (1987)	▪ Modeling satisfaction with service provider ▪ DV: satisfaction, retention	Life Insurance	▪ Non-lapsing customers report higher satisfaction than lapsed customers (customers followed for 13 months only)
Schmittlein and Peterson, (1994)	▪ Individual level analysis of purchase history ▪ DV: probability of being alive	Office products in business-to-business context	▪ Model can be used to infer the likelihood of a customer of being still active in a non-contractual context ▪ Model allows inferences about purchase and dropout process
Li, (1995)	▪ Proportional hazard model of customer tenure	Long-distance telephone service	▪ Model identifies variables (usage, marketing and demographic variables) that impact on length of customer subscription ▪ Build profile of customers with high and low lifetime
Bolton, (1998)	▪ Model of the duration of customer's relationship with firm (proportional hazard approach) ▪ DV: customer tenure	Cellular phone service	▪ Customer satisfaction is related positively to subscription duration ▪ Prior cumulative satisfaction is weighted more heavily than recent satisfaction in decision to continue or not ▪ Since satisfaction plays a large role in explaining subscription duration, understanding and managing satisfaction becomes very important
Allenby, Leone and Jen, (1999)	▪ Bayes model of Customer Interpurchase Time	Financial brokerage services	▪ The model allows to recognize when a customer is changing his purchase patterns (i.e. showing signs of defection). This prediction can be used managerially as a signal for the firm to employ some kind of intervention. ▪ Individual customer level prediction
Reinartz and Kumar, (2000)	▪ Customer Lifetime Duration in a non-contractual setting	U.S. Catalog retailer	▪ Both, long and short lifetime duration customers can be profitable to the firm. ▪ "It is better to let go of some customers."
Present Study	▪ Measuring Profitable Lifetime Duration ▪ Explaining the variation in Profitable Lifetime Duration	-U.S. Catalog retailer -High tech B-to-B	▪ Model uses time varying variables for explaining the impact of relationship characteristics on Profitable Lifetime Duration. ▪ Tells "which" customers to let go and "when" to let go of those customers.

Legend: DV= Dependent Variable; n.a.= not applicable

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Table 2: NBD/Pareto Model Characteristics and Finite Lifetime Estimates

	1) Sample size	2) Pearson Correlation of P(Alive)*	3) Mean Average Percentage Error (MAPE)**	4) Mean Lifetime (months)	5) Lifetime Standard deviation	6) % Right-Censored	7) Correct classification
Cohort 1	4202	.9981	5.83%	29.3	7.5	42.9	92.7%
Cohort 2	4965	.9988	5.22%	28.6	7.7	45.6	91.1%
Cohort 3	2825	.9987	4.75%	27.8	7.2	47.2	92.5%

* generated from the NBD/Pareto estimates of Reinartz and Kumar (2000) and those of the current study respectively
** of *P(Alive)* of Reinartz and Kumar (2000) and *P(Alive)* of the current study

Table 3: Actual Revenues ($) and Profits ($) for the Selected Group of Customers Based on NBD/Pareto, RFM, and Past Customer Value Selection (Cohort 1 only)

1) Customer selection based on:	2) % of cohort (selected from top)	3) Evaluation at 18 months	4) Evaluation at 30months
NBD/Pareto with expected contribution margin	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)

* Profits ($) in parentheses
Results are similar for Cohort's 2 and 3.

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Table 4: Variables for Profitable Lifetime Model

Dependent Variable	Measured as	
Profitable Lifetime$_i^*$	Months	

Independent Variables	Measured as	Hypothesized Directional Impact on Profitable Lifetime
Purchase amount $_{it}$**	Monthly spending level ($), moving average over 6 month period.	+
Cross Buying$_{it}$	Number of departments shopped in	(+)
Focus of Buying$_i$	Dummy: 1 = buys consistently in single dept. only 0 = all other	Non-directional hypothesis
Average Interpurchase Time$_{it}$	Number of Days	(+) Inverse U-shaped relationship for AIT and AIT^2
(Average Interpurchase Time$_{it}$)^2	(Number of Days)^2	(-) Inverse U-shaped relationship for AIT and AIT^2
Returns$_{it}$	Proportion of returns (of sales)	(-)
Loyalty Instrument$_i$	Ownership of Charge card. Dummy variable, 1 = owns card, 0 = no card	(+)
Mailings$_{it}$	Number of mailings sent in last 6 months (= 1 season) since current *t*, exponential decay, one month lag	(+)
Product Category$_i$	1 = more then 50 % of purchases in softgoods, 0 = more then 50 % of purchases in hardgoods	No directional hypothesis
Population Density	Number of people in 2 digit zip code	(-)
Income$_i$	Scale from 1 to 9 where 1 is < $10,000 and 9 is > 150,000	(+)
Age$_i$	Age of individual in years	No directional hypothesis

* Subscript "$_i$" = variable value does not change over time, subscript "$_{it}$" = time-varying variable; ** Time-varying variables are updated each month

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Table 5: Coefficients (Standard errors) for Profitable Lifetime Duration Model

Independent Variables	Para-meter	Cohort 1			Cohort 2			Cohort 3		
		Model 1†	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
1) Purchase amount$_{it}$	B_1	.0497* (.00209)	.0360* (.00212)	.0354* (.00213)	.0486* (.00186)	.0373* (.00192)	.0364* (.00192)	.0433* (.00228)	.0341* (.00240)	.0324* (.00239)
2) Cross Buying$_{it}$	B_2	1.389* (.0407)	1.293* (.0417)	1.276* (.0419)	1.226* (.0327)	1.172* (.0338)	1.154* (.0340)	.970* (.0346)	.908* (.0356)	.912* (.0360)
3) Focus of Buying$_i$	B_3	-.315* (.0647)	-.257* (.0660)	-.270* (.0662)	-.297* (.0624)	-.306* (.0630)	-.269* (.0632)	-.289* (.0841)	-.213** (.0862)	-.177** (.0865)
4) Average Interpurchase Time$_{it}$	B_4	.0121* (.000521)	.0133* (.000521)	.0127* (.000521)	.0146* (.000515)	.0153* (.000517)	.0147* (.000519)	.0171* (.000718)	.0178* (.000724)	.0171* (.000726)
5) (Avg. Inter-purchase Time$_{it}$)^2	B_5	-8.994 E-6* (6.276 E-7)	-9.880 E-6* (5.900 E-7)	-9.487 E-6* (5.892 E-7)	-.0000121* (6.243 E-7)	-.0000123* (6.013 E-7)	-.0000119* (6.046 E-7)	-.0000151* (8.912 E-7)	-.0000154* (8.660 E-7)	-.0000147* (8.747 E-7)
6) Returns$_{it}$	γ_1		-2.214* (.222)	-2.050* (.226)		-1.690* (.214)	-1.557* (.215)		-1.323* (.320)	-1.323* (.320)
7) Loyalty Instrument$_i$	γ_2		.666* (.0577)	.685* (.0577)		.745* (.0482)	.753* (.0484)		.598* (.0618)	.614* (.0622)
8) Mailings$_{it}$	γ_3		.00552* (.00153)	.00686* (.00154)		.00628* (.00148)	.00712* (.00148)		.00610* (.00224)	.00898* (.00229)
9) Product Category$_i$	γ_4		-.0278 (.0437)	-.0554 (.0438)		-.0360 (.0414)	-.0476 (.0414)		-.0422 (.0556)	-.0740 (.0558)
10) Returns x Purchase Amount$_{it}$	γ_5		.221* (.0188)	.208* (.0189)		.148* (.0155)	.134* (.0155)		.105* (.0186)	.0985* (.0183)
11) Population Density$_i$	δ_1			-3.475 E-8* (1.252 E-8)			2.23 E-8** (1.196 E-8)			5.305 E-9 (1.584 E-8)
12) Income$_i$	δ_2			.124* (.00863)			.111* (.00805)			.133* (.0104)
13) Age$_i$	δ_3			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 L		13728.6	13337.7	13126.8	15.678.0	15200.7	15004.6	9089.4	8807.7	8639.2
R^2		0.697	0.727	0.743	0.684	0.719	0.730	0.652	.672	.693

† Signs of coefficients have been reversed to reflect effect on lifetime. * Significant at 0.01, ** Significant at 0.05

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Table 6: Summary of Results

Hypothesis	Description	B-to-C Setting Result	B-to-B Setting Result
1	Profitable Customer Lifetime Duration is positively related to the customer's spending level	Supported	Supported
2_a	Profitable Customer Lifetime Duration is positively related to the degree of cross-buying behavior exhibited by the customers.	Supported	Supported
2_b	Profitable Customer Lifetime Duration is related to the Focused Buying behavior exhibited by customers.	Supported However, the relationship is negative, indicating that buying in 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
3	Profitable Customer Lifetime Duration is related to Average Interpurchase Time in an inverse U-shaped manner, whereby intermediate AIT is associated with the longest profitable lifetime.	Supported	Partial Support Only the linear term is significant
4	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
5	Profitable Customer Lifetime Duration is positively related to the customer's ownership of the company's loyalty instrument (B-to-C) or the availability of line of credit (B-to-B).	Supported	Supported
6	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
7	Profitable Customer Lifetime Duration is higher for customers living in areas with lower population density (B-to-C) or businesses existing in lower population density (B-to-B).	Supported	Not Supported
8	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

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Figure 1: Conceptual Model of Profitable Customer Lifetime

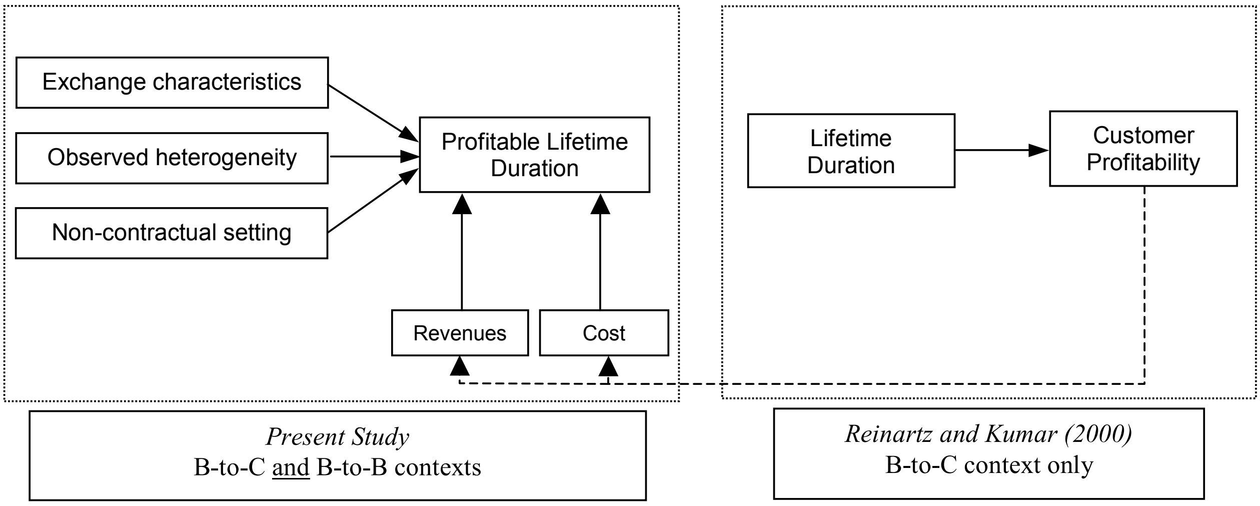

Figure 2: Database Structure for B-to-C Setting

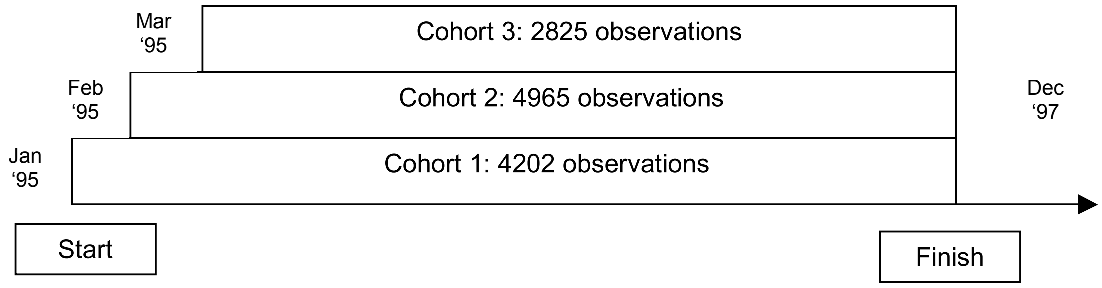

Figure 3: Average *P(Alive)* for Cohort 1-3

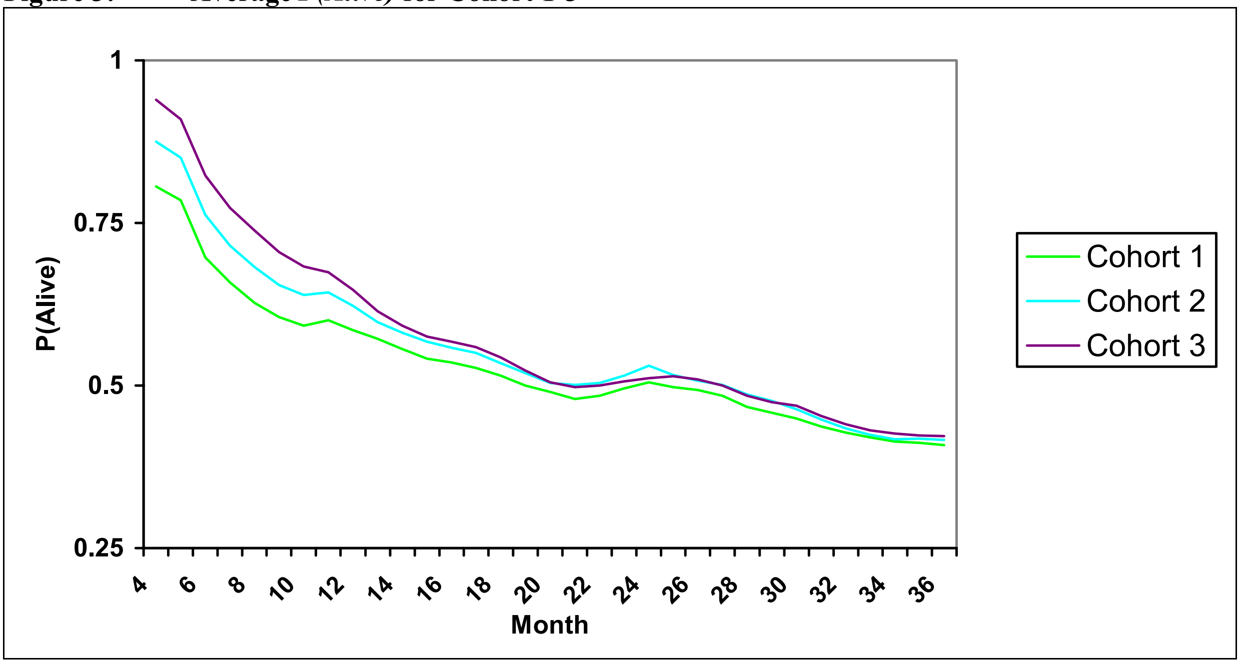

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Figure 4: Interaction between Proportion of Returns and Purchase Amount

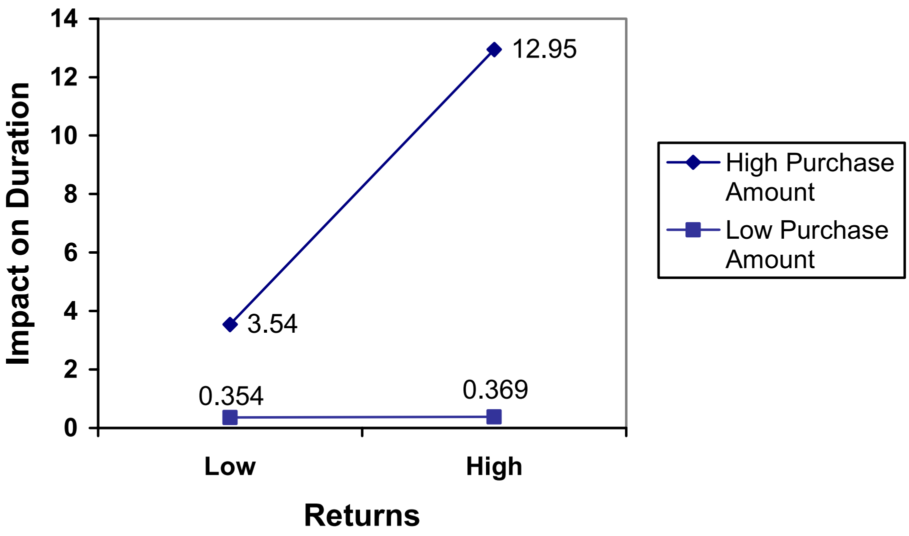

Figure 5: Firm's Strategy Based on Share of Wallet vs. Profitable Lifetime Duration

Share of Wallet \ Profitable Lifetime Duration	Low	High
High	• Use selective or optimal mailings/strategy to reduce cost • Attempt to cross-sell and up-sell	• Invest to nurture/defend/retain • Reward with loyalty program
Low	• Lower marketing expenses • Consider divestment strategy • Possibly customer outsourcing	• Use conversion strategy to lure from competition • Encourage cross-buying and up-buying • Offer lucrative loyalty programs

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