Relationship characteristics and cash flow variability: implications for satisfaction, loyalty, and customer portfolio management

Crina O. Tarasi
Central Michigan University

Ruth N. Bolton
Arizona State University

Anders Gustafsson
BI Norwegian Business School
Karlstad University

Beth A. Walker
Arizona State University

RELATIONSHIP CHARACTERISTICS AND CASH FLOW VARIABILITY: IMPLICATIONS FOR SATISFACTION, LOYALTY AND CUSTOMER PORTFOLIO MANAGEMENT

Abstract

Service firms seek customers with high revenues, profits or lifetime value. However, they frequently ignore variations in consumption that lead to cash flow variability and adversely influence service operations and financial performance. This study shows that variation in individual customers' consumption or spending on services can be decreased in ways that are actionable by most managers, without decreasing revenues or profits. Empirical findings are robust across two settings: telecommunications and financial services. Customer satisfaction has a "double-whammy" effect: lower cash flow variability and higher cash flow levels. This finding is important because firms can increase satisfaction in many ways. Second, customers who participate in loyalty programs have more variable cash flows, but not higher average cash flows. Hence, firms should design loyalty programs to improve customer satisfaction or intangible benefits (e.g., membership recognition), rather than offering economic incentives. Third, customers who purchase many different offerings, or allocate a large share of their purchases to the firm, have higher cash flow variability and higher average cash flows. Firms can optimize the customer portfolio by combining customers with high variability with customers who have different, offsetting cash flow patterns. Fourth, personal characteristics, such as age and income, also influence cash flow variability. The study describes sensitivity analyses of how different service and relationship marketing strategies influence a firm's business outcomes. The article concludes with insights on how to integrate service management principles, which emphasize consistency or low variability in processes, with customer relationship management principles that emphasize growing relationships and cash flows.

Key Words: *Customer Portfolio Management, Customer Satisfaction, Loyalty Programs, Cash Flow Variability, Service Management Customer Lifetime Value, Relationship Marketing, Segmentation.*

Service management theory and practice explicitly recognize that services entail process-based consumption over time rather than simply outcome-based consumption. Grönroos (1998, p. 322) goes as far as stating that "A central part of service marketing is based on the fact that the consumption of a service is process consumption rather than outcome consumption." A firm must understand and manage a customer's consumption process across multiple transactions and touch points over time, where variation in consumption levels may be due to changes in customers' needs, their life situations and brand loyalty (Van de Ven 1992). The relationship marketing (RM) literature provides an important contribution to the process perspective of service management by emphasizing that creating, maintaining, and enhancing relationships with customers yields favorable business outcomes for service firms (Reinartz, Krafft, and Hoyer 2004), as well as for customers (Berry 1995). Hence, both service management and RM theory emphasize that variation in customers' consumption patterns is important to understand and manage (Grönroos 1998; Rust et al. 2004). Consequently, customer relationships cannot be managed by simply managing service consumption or cash flow levels. Variability in service consumption patterns and cash flows throughout the customer-firm relationship is important to both firms and customers.

Recently, marketers have explicitly recognized that variation in consumption processes (ultimately) influences a firm's financial outcomes. Managers typically focus on aggregate cash flow variability because the economic value of a business depends on the cash flows it is expected to generate (Srinivasan and Hanssens 2009). Lower variability in aggregate customer cash flow can reduce the level of risk associated with the firm (Srivastava, Shervani, and Fahey 1998). A firm can

maximize returns by acquiring or retaining customers or market segments on the basis of how their spending patterns contribute to the cash flow variability of the overall customer portfolio (Dhar and Glazer 2003, Tarasi et al., 2011). The intuition behind customer portfolio methods is that, by combining customers or market segments with different (i.e., offsetting) cash flow patterns, firms reduce aggregate cash flow variability – moving closer to an optimal customer portfolio on an efficient frontier (characterized in terms of risk and return). A service firm can build value over time by managing an entire portfolio of customer relationships so that relationships in different stages balance each other (Johnson and Selnes 2004). The number and types of ties a firm builds with its best customers reduce the variability of their purchases over time, and also increase revenue levels (Tuli, Bharadwaj, and Kohli 2010).

Research has shown that service firms can use customer portfolio management techniques to manage the variability or risk in aggregate cash flows, thereby improving business performance (Buhl and Heinrich 2008; Tarasi et al. 2011). Higher variability in cash flows is only acceptable when there are commensurate returns in the form of higher cash flow levels. In general, if variability in cash flows can be reduced without decreasing cash flow levels, it is desirable to do so. In many service businesses, considerable variability in cash flows arises from variability in underlying service consumption processes. Average service levels, variability in service levels and timing of service delivery influence customers' re-purchase decisions for support services (Bolton, Lemon, and Bramlett 2006). Hence, it may be possible for the firm to reduce cash flow variability without adversely affecting cash flow levels by better managing service consumption processes.

An alternative approach to managing cash flow variability is appealing because, even if service firms use sophisticated customer portfolio management methods, they are constrained by their (potential or existing) customers' cash flow patterns. Tarasi et al. (2011) show how the efficient frontier of customer portfolios for a service firm is derived from clusters of business

customers with distinctive cash flow patterns derived from ten industry sectors. (See their Figures 1, 2 and 3 on pages 7-9). Most service firms use classic segmentation and target marketing methods; consequently they face a similar scenario: cash flow patterns ultimately influence the shape of the efficient frontier of customer portfolios. Hence, it is useful for managers to ask whether cash flow patterns, the building blocks of the customer portfolio, can be changed by managing underlying service consumption processes. Specifically, is there a way for service firms to reduce aggregate variability in cash flows without adversely affecting cash flow levels? This managerial question leads to the following research question: Is it possible to modify the cash flow variability of individual customers or groups of customers while maintaining their average cash flow levels? To answer this question, it is necessary to understand the predictors of variability in individual customers' cash flows.

In contrast to recent research, this paper investigates the predictors of variability in individual customers' cash flows − rather than studying the consequences of cash flow variability for customer portfolio management. Despite extensive research on the importance of consistency or reliability in the customer's service consumption experience (e.g., Parasuraman, Zeithaml, and Berry 1998; Bolton, Lemon, and Bramlett 2006), we have not discovered any research that links actionable variables to individual cash flow variability.

A better understanding of the predictors of individual customers' cash flow variability allows service firms to manage aggregate cash flow variability, which is important to them for four reasons. First, high variability in demand can strain service firms' resources. Efforts to satisfy customers will incur high costs during peak demand periods, whereas low-demand periods are often associated with wasted (idle) resources (Weatherford and Bodily 1992). This challenge is critical for service firms that are characterized by simultaneity in production and consumption. Second, high variability can be a symptom of defection, switching or customer share erosion, indicating

customers who purchase from multiple suppliers or are vulnerable to competitors and other economic conditions. For example, Lemon and Wangenheim (2009) show that lower levels of cross-buying lead to lower core-service usage and shorter customer-firm relationships; these behavior changes will increase variability in cash flows. Third, lower variability in a service firm's aggregate cash flows reduces the firm's cost of capital (Srivastava, Shervani, and Fahey 1998) and increases levels of confidence in a firm's future (Campbell 2001). Fourth, service management and RM theory emphasize that a firm must manage customers' consumption process across multiple transactions and touch points over time as customers' needs, situations and brand preferences change (Berry 1995; Grönroos 2000). Consequently, it is important for long-term business success that service managers know how different variables influence variability in individual and aggregate customer cash flows.

The present study makes four contributions. First, it encourages service managers to look beyond the level of customer cash flows to consider their variability over an extended period. We identify a new segmentation variable – the variability in an individual customer's cash flow – that can complement existing measures of the attractiveness of a market segment (Wangenheim and Lentz 2005). Second, the findings from two study contexts shed light on the relationship between traditional market segmentation variables and individual customers' cash flow patterns. Customers personal and relationship characteristics influence their relational and service preferences (Danaher, Conroy, and McColl-Kennedy 2008). Service firms that understand how these variables are linked to cash flow variability are better able to manage service consumption processes, as well as target segments and optimize overall cash flows (Tarasi et al. 2011). Third, the study shows that firms can integrate the management of cash flow variability within their service strategies. Specifically, service firms can use segmentation, service and RM strategies, such as loyalty programs, to match their activities with customers' relational orientations (Berry 1995; Grönroos 2000). The present

study shows that, in the contexts studied, loyalty programs are associated with higher variability in customer cash flows whereas high customer satisfaction is associated with lower variability. These insights are critical for understanding how market segmentation, service and RM strategies are linked to cash flow variability, as well as cash flow levels. Hence, the study helps firms allocate resources more effectively thereby better managing service processes and cash flow outcomes. Fourth, it provides actionable tools for managing the variability of customer cash flows, enabling service managers to accurately evaluate the implications of allocating resources to programs and to customers with specific characteristics.

The remainder of this paper discusses prior research regarding variables that influence service consumption and cash flow, emphasizing the role of customer satisfaction. Since this paper is the first to study individual customers' cash flow variability, it focuses on identifying and estimating the effects of predictor variables rather than investigating the underlying theoretical mechanisms that may be operating. Using data from financial and telecommunications service firms we then estimate a model of how satisfaction, relationship and personal variables influence the cash flow variability of individual customers, as well as their cash flow levels. The paper also analyzes how these variables influence the cash flow patterns of market segments (e.g., large customers versus small) and all customers in aggregate. We conclude by discussing the implications of our findings for services management theory and practice.

MODEL DEVELOPMENT

This section begins by describing the definition and measurement of our focal dependent variable, cash flow variability for an individual customer. We then identify predictor variables based on prior research. The latter part of this section describes how individual cash flow variability can be explained by satisfaction, relationship characteristics (e.g., depth and breadth of a relationship and participation in loyalty programs) and personal or household characteristics (e.g., age or income).

Definition and Measurement of Cash Flow Variability

The attractiveness of different segments can be substantially different in the long run compared to the short run. Our study focuses on long run variability in the cash flows of individual customers – i.e., looking beyond seasonal variability, which most service firms are able to manage (e.g., Eliashberg and Steinberg 1987). The volatility or variability associated with cash flow is traditionally estimated by the standard deviation or variance. The present study follows the finance literature by defining cash flow as the difference between cash receipts and cash payments (Wiesel, Skiera, and Villanueva 2008). In situations where cost allocation by customer is cumbersome, revenues can be used as a proxy for cash flow (ibid). To obtain a standardized measure of variance that corrects for differences in the average levels of cash flows across customers, we computed the coefficient of variation, $CoV_A = \sigma_A / x_A$, where σ_A and x_A represent the standard deviation and the average, respectively, that characterize the cash flow from customer A for the length of the relationship. Using the coefficient of variation (rather than a raw measure of variability) controls for average cash flow levels. This dependent variable made it possible to pool customers with substantially different cash flow levels in the analysis.[1] However, the coefficient of variation fails to make the distinction between customers who have large revenues or profits and customers who have small revenues and profits, hereafter referred to as "whales" and "minnows" respectively. Since whales or large revenue customers may be more valuable, we will investigate differences between the cash flows of whales and minnows in the empirical portion of the paper.[2]

Linking Satisfaction and Customer Characteristics to a Customer's Cash Flow Variability.

Prior research has suggested that *Satisfaction* is an important antecedent of customer repeated purchasing behavior (e.g., Seiders et al. 2005). Increases in customer satisfaction are associated with increases in customer purchases and firms' revenues (Fornell, Rust, and Dekimpe 2009). A cross-firm study by Gruca and Rego (2005) showed that higher levels of satisfaction are

associated with growth and reduced variability in cash flow, and that the influence of satisfaction is greater for low-involvement product categories. Anderson, Fornell, and Mazvancheryl (2004) developed a theoretical framework that links satisfaction with the level, timing, and variability of future cash flows, as a measure of shareholder value. These studies used a sample of firms with aggregated cash flow; none looked at segment data or individual customer data. At the individual level, previous research has shown that satisfaction has a significant positive effect on relationship duration and loyalty (Bolton 1998), cross-buying and share of wallet (Cooil et al. 2007, Lemon and Wangenheim 2009), and customer retention (Gustafsson, Johnson, and Roos 2005; Verhoef 2003). Since satisfaction influences customer consumption and purchase behavior, it is also likely to affect the variability of individual customers' cash flows.

Relationship Characteristics

Existing customers can be segmented using relationship characteristics, defined as the "formal and informal bonds between the firm and its customers" (Seiders et al. 2005, p. 30). Relationship characteristics influence how customers react to firm actions (Dagger and Sweeney 2007; Dawes 2009). Prior research has studied relationship length, breadth and depth (Anderson, Fornell, and Mazvancheryl 2004; Anderson, Fornell, and Rust 1997; Anderson and Mittal 2000; Bolton 1998). The effects of relationship characteristics on consumption and purchase behavior over time have received less attention. The present study looks at three relationship characteristics: the depth of relationship (participation in loyalty programs), relationship breadth (number of product categories a customer buys and customer share) and relationship length.

Loyalty. Enrollment in a loyalty program is a behavioral manifestation of a customer's willingness to engage in a formal relationship with a service firm. Loyalty programs can be defined as "long-term oriented programs that allow customers to accumulate some form of program currency, which can be redeemed later for free rewards" (Liu and Yang 2009, p.94). Loyalty

programs that offer economic incentives, such as airline miles, increase customer retention and share and make it difficult for customers to evaluate competitive offerings (Verhoef 2003).

Enrollment in a loyalty program (*Loyalty*) affects the consumption process and characteristics of the customer-firm relationship. Specifically, the preferential pricing policies of such programs are likely to increase short-term purchases and cross-buying (Bolton, Lemon, and Verhoef 2004), especially for related products. In addition, cross-buying leads to higher core-service usage and increases the length of the relationship (Lemon and Wangenheim 2009). Enrollment in a loyalty program can be a powerful motivator (Latham and Locke 1991). As points accumulate, people often act to obtain faster future rewards (Kivetz, Urminsky, and Zheng 2006). The effects of the loyalty program on individual customer behavior are moderated by program specifics and market factors, such as, competitive intensity and availability of substitutes (Bolton, Kannan, and Bramlett 2000). Several research papers have shown that some loyalty programs fail to change customer behavior (Dowling and Uncles 1997; Meyer-Waarden and Benavent 2009) or provide the desired returns for the firm (Liu and Yung 2009).

Relationship Breadth. The number of different services a customer purchases from a firm can measure the *Breadth* of a relationship. Greater relationship breadth allows for (and requires) greater knowledge of customer's needs and desires and more communication between buyer and seller, which justify greater relationship-specific investments.

Share of Customer. Customers consider many services when making purchases, although a firm may find it difficult to observe and measure its competitors' effects (Boulding et al. 2005). The "share of customer" measure (*Share*) explicitly recognizes that customers give a share of their business to the focal service firm and the rest to competitors within the category (e.g., Glady and Croux 2009; Verhoef 2003). Customers engage in "serially monogamous or polygamous relationships" (Cooil et al. 2007, p. 68); share of customer represents a measure of customer's

judgment of how the firm's offer compares with that of the competition (Reinartz, Thomas, and Kumar 2005). Researchers have argued that customer share is an important segmentation variable (Du, Kamakura, and Mela 2007). When a customer allocates more purchases to a focal vendor, competitors have less access to that customer (Glady and Croux 2009).

Personal Characteristics. Beyond relationship characteristics, it is well established that personal or household characteristics influence consumption and purchases. Therefore, marketers typically incorporate demographics in models of customer, household, or market demand levels. The present study focuses on age and income, which are generally considered highly influential across diverse contexts (Anderson, Pearo, and Widener 2008; Seiders et al. 2005). Hence, we believe they will influence the cash flow variability of individual customers. *Age* is linked to the level and variation of consumption and purchases through life events (Zeithaml 1985). People have different buying intentions and behavior at different ages, depending on the product category (Namias 1960). *Income* typically has a positive relation to customer lifetime value or CLV (Reinartz and Kumar 2000) and to customers' routine expenditures for many services (Nichols and Fox 1983). Income is a major factor that influences household decisions (Myers, Stanton, and Haug 1971). Higher income allows customers greater flexibility in mental budgeting and strongly determines specific allocations (Heath and Soll 1996).

MODEL SPECIFICATION AND ESTIMATION

Prior research suggests that the relationship between individual customer's cash flow variability and its predictors will be non-linear. The link between satisfaction and profitability is non-linear and possibly asymmetric (Anderson and Mittal 2000). The relationship between satisfaction and other outcome variables (such as purchase intentions, sales, and cash flow) is complex and potentially non-linear as well, and there are several pieces of evidence that support this view. First, there is a trade-off between satisfaction and productivity (Anderson, Fornell, and Rust

1997), and the combined effect on profitability depends on the balance between standardization and customization. Second, Ho, Park, and Zhou (2006) demonstrated that customer revenue is convex in satisfaction. Third, Ittner and Larcker (1998) showed that the influence of satisfaction on customer retention and revenue is positive, albeit with diminishing returns past a certain threshold. Since the equation for variability in cash flow is potentially non-linear and there are diminishing returns to reducing variability, we specified a semi-log model; we will compare this functional form with alternative functional forms. A semi-log model captures non-linear relationships with diminishing returns (Lilien, Kotler, and Moorthy 2005). Semi-log functions have been used in marketing to capture decreasing returns and thresholds for sales models (ibid). The model specification is as follows, where it is assumed that ε is normally distributed:

$$CoV = a + b\ Ln(Satisfaction) + c\ Ln(Relationship\ Characteristics)$$
$$+ d\ Ln(Personal\ Characteristics) + e\ Ln(Control\ Variables) + \varepsilon$$

The remainder of this paper describes the model estimation and tests of the predictions in two different study contexts: financial and telecommunications services. In addition to a model of cash flow variability, we also present results for a model of cash flow levels. We do not explicitly discuss the predictors for cash flow <u>levels</u> (i.e., sales) because they have already been studied in depth (see Seiders et al. 2005). The results from estimating a linear model of average cash flow levels are included in the results tables to provide a context for interpreting variability.

STUDY CONTEXTS

We investigate the effect of satisfaction, relationship and personal characteristics on cash flow variability in two service contexts, financial and telecommunication services. Both studies provided access to similar variables. We describe each context individually. However, given the similarity in findings, we will discuss the results together. In both studies, individuals make purchases on behalf of their household, but household size is not statistically related to purchases. Our unit of analysis can be considered to be the household or the individual.

Study 1: Financial Services Industry

The first study is based on data from a European financial services company, as described by Verhoef (2003). The dataset contains individual customers' sales over time, augmented by customer satisfaction survey data,[3] and includes a probability sample of 2306 customers active in 1999, and all their previous and subsequent purchases until 2001. Customer satisfaction measures were available for 1986 customers in the sample. The records with missing observations and customers with just one year of activity (for which we could not compute variance) were removed from consideration, which yielded 1754 usable records for the analysis. The financial company offers 28 products in five categories; the insurance services division is considered the core business. The sales records provide the items purchased by the customer each year.[4] The profit level for each product was provided by the collaborating company.

Satisfaction was measured as in Verhoef (2003); customers are assessing their satisfaction with the quality of all financial services, as well as interactions with the firm. The loyalty program offers points for each purchase, so loyalty points are potentially highly correlated with the overall cash flow. Hence, we chose the length of time the customer was enrolled in the loyalty program (*Loyalty Duration*) as the predictor variable. Relationship breadth (*Breadth*) is measured by the number of business divisions from which a customer has purchased products. There are five different business divisions, where the largest division (in terms of the firm's revenues and expenditures) is the insurance division. Customers often purchase insurance services from multiple providers. To capture the depth of the relationship with the company we computed the share of the customer by dividing the number of products purchased from the company by the total number of insurance products a customer buys (*Share*). *Length of relationship* has been measured in years given that customers sign annual contracts. The length of relationship coincides with the length for which the variability and average cash flow were measured.

Covariates. Income was self-reported on the survey using an interval scale with five

categories, the ranges described in local currency. Income data were not available for 16% of

customers, so we imputed the variable using other personal characteristics available in the model.[5]

Share of Income accounts for substitute and complement effects of purchases of other goods or

services, given that customer face a budget constraint (after controlling for a main effect of income).

It measures the percentage of income that customers allocate to purchases from the service from –

which is not available to purchase other goods or services. For example, when *Share of Income* for a

particular service is higher, customers may be substituting consumption of this service for other

goods or services – or they may be consuming more of this service because it is a complement for

other goods and services. Hence, *Share of Income* is intended to account for how customer demand

may be influenced by consumption of other goods or services. The variable *Mailings a*ccounts for

promotional communications that reached specific customers. Sources and specific measures used

for the other variables in the model are provided in Table 1. Table 2 provides descriptive statistics

and correlations for each of the variables in the model.

<<TABLES 1 AND 2 ABOUT HERE>>

One important limitation for Study 1 is that satisfaction was measured in 1999, towards the

end of the study period. In other words, we have implicitly assumed that this recent measure of

satisfaction was an enduring characteristic over the customer's entire lifetime. Since satisfaction is

typically conceptualized as an antecedent (not a consequence) of purchase behavior, it is preferable

to measure satisfaction prior to observing cash flows so that the causal flow is unambiguous.

Consequently, Study 2 measures satisfaction at the beginning of the period over which customer

cash flows were observed. The telecommunications service context also overcomes two minor

shortcomings of Study 1. Namely, in Study 2, variability in cash flows primarily depends on the

level of usage (rather than cross-buying), and income data were available for all customers. It is

also useful to test the findings in a different industry. For ease of comparison and conciseness, we will present the results for both studies concurrently.

Study 2: Telecommunication Services Industry

Study 2 analyzes data containing customers' monthly purchasing records from a company that offers fixed telephone, cellular phone, and internet services.[6] This telecommunications service firm is the market leader in its country. The data describe a random sample of 2246 customers surveyed in July 2003 and their subsequent monthly transactions until December 2006. All customers have been with the firm for more than two periods and none exhibited zero variance in cash flow. The firm provided individual customer revenues for each service. The cost to serve each customer is relatively constant within a service and revenue per customer is highly correlated with profit. Revenue per customer is a good proxy for consumption and demand. Variability in revenue is primarily due to usage, but can arise from dropping or adding services.

Satisfaction is measured as overall satisfaction with the company services, on a 10 point scale as in Gustafsson, Johnson, and Roos (2005). Loyalty points accumulated and length of enrollment in the loyalty program was not available, therefore *Loyalty* is measured using an indicator variable that captures whether the customer enrolled in the loyalty program. *Breadth* is measured as the number of products purchased from the company (e.g., if a customer purchases mobile and internet services the score is 2, but if he/she purchases just mobile phone services, the score is 1). The range of this variable is 1 to 3. The *Share* variable could not be computed for this group since it is rare that customers would purchase any one of the services concurrently from multiple providers. Hence, it is omitted from the model for this study context. However, the *Breadth* variable also captures the share of customer's business given that any customer who does not buy any of the three services from the collaborating company, it is likely that that customer purchases them from competitors. This conclusion was inferred given the high penetration of the services (92

to 98%) in the country. *Length of relationship* is measured as the number of months that have passed between the first purchase and the last purchase over the duration of the study and coincides with the duration for which the variability and the average cash flow was computed. *Age* and *Income* (measured in the country's currency) are recorded when the customer opens an account with the firm; they are not reported on the survey. This information is stored in the customer records.

RESULTS

Model Estimation. The dependent variable is the coefficient of variation for individual customers' profits over time (Study 1) or revenues over time (Study 2). The coefficients for the predictor variables are listed in Table 3. For both study contexts the error term ε was normally distributed. The Shapiro-Wilk W test was 0.94 for the financial services and 0.88 for telecommunications ($p < 0.05$) (Shapiro and Wilk 1965). In Study 1 (financial services), customers who purchased only one insurance product were characterized by identical cash flows over many years, such that one-third of customers were characterized by zero variance in cash flow. To account for numerous observations where the dependent variable takes on the value zero we estimated a Tobit model (Amemiya 1973). In Study 2 (telecommunication services), all customers exhibited some variability, so Ordinary Least Squares estimation is appropriate.

Model Fit. We tested six alternative functional forms (including linear models and log-transformed models). The semi-log model fit the data best for both study contexts based on three criteria: the true R-square, Akaike Information Criterion (AIC) and Schwartz Criterion (BIC).[7] The semi-log functional form indicates that variability in individual customers' cash flows is subject to diminishing returns as customer variables take on higher values (e.g., higher satisfaction). For Study 1, the correlation between observed and predicted values of the dependent variable (i.e., true R-Square) is 0.25, providing evidence that the influence of satisfaction and of relational characteristics on the cash flow variability of individual customers is subject to diminishing returns. This level of

explanatory power is very good, given that we are explaining the coefficient of variation for profits of individual customers with simple descriptor variables. *Satisfaction* is significant at $p < 0.05$ and all other variables in the variance model are significant at $p < 0.001$ (Table 3). The right-hand column of Table 3 shows the results for a model of average cash flow levels as a linear function of the same predictor variables (based on prior research). For Study 2, the correlation between observed and predicted values (i.e., true R-Square) equals 0.14. (This value is lower than Study 1, possibly because the dependent variable, the coefficient of variation, is calculated using revenues not profits.) *Satisfaction* and *Share of Income* are significant at $p < 0.01$), *Loyalty* at $p < 0.05$ and all other variables are significant at $p < 0.001$ (Table 3).

<<TABLE 3 ABOUT HERE>>

DISCUSSION AND INTERPRETATION OF RESULTS

Satisfaction: Improvements in customer satisfaction levels decrease cash flow variability and are subject to diminishing marginal returns. Both studies showed that higher satisfaction is associated with lower individual customer cash flow variability, as well as higher average cash flow. Satisfied customers have significantly more stable cash flows over time. This research shows that variability in cash flow over the customer's active lifetime is smaller when there are higher levels of satisfaction, while the level of cash flows is higher (Table 3).

Relationship Characteristics: Participation in loyalty programs is associated with larger variability in customers' cash flows, without higher levels of cash flows; higher Share of Customer is associated with higher variability in cash flows and higher levels of cash flow. The results show that loyal customers who have deeper relationships actually have <u>less</u> consistent (or more variable) cash flows. This finding may be explained by Kivetz, Urminsky, and Zheng (2006), who showed that customers accelerate their pace when they are closer to getting a desired reward. However, loyalty program membership was not associated with higher cash flow levels. This finding supports

research suggesting that the design of many loyalty programs does not have a favorable effect on business performance (Dowling and Uncles 1997). Both loyalty programs offered economic (rather than social) rewards. They may have attracted price-sensitive customers who are likely to exhibit more variable behavior. Other programs or incentive systems might have different effects. Meyer-Waarden and Benavent (2009) suggested that the effect of loyalty program enrollment should wear off after six to nine months. Both our study periods exceeded nine months, yet participation in loyalty programs was significantly associated with higher cash flow variability.

People who purchase many different offerings (*Breadth*) of the financial service company or allocate a larger share of their purchases to the firm (*Share*) or both have higher cash flow variability, and higher levels of average cash flows. These findings complement previous research that shows that initial cross-selling of related products leads to further increase in sales of core product (Lemon and Wangenheim 2009), but that it can also backfire (Günes et al. 2010). Customers are more desirable, and their cross-buying can be encouraged, if they have disproportionately low variability relative to their *Breadth* or *Share*.

Length of Relationship is measured as the period of time for which the variability measure was computed. The coefficient for *Length* was positive and significant, indicating that longer relationships are more likely to include events that affect variability. Note that *Length* measures the number of periods (years or months, respectively, for each context) for which the variability was measured, not the influence of length of relationship over subsequent variability. The latter measure would have been appropriate to investigate whether customers who have been with the company longer are more likely to have found a better fit and reached equilibrium, implying more stable and predictable relationships. However, it is interesting to note that longer relationships are not associated with higher average cash flow. They are associated with lower average cash flow for Study 1 and the relationship is not statistically significant in Study 2.

Covariates: Personal Characteristics. Older (age) customers generate less variable cash flow and the effect of income depends on the nature of the service. Both models include two covariates: age and income. *Age* is associated with lower variability in cash flows over time, but not with higher cash flow levels. Lower variability in individual cash flows has two potential explanations: older consumers are less likely to experience life-changing events than younger consumers because they have identified solutions that meet their needs, or older consumers are more loyal (or more inert) when considering competitors' offers. These findings suggest that by serving older customers (often regarded as less desirable), some service firms may generate less variable cash flows without lowering cash flow levels.

The findings regarding *Income* are different across the two studies. Customers who have high income have high variability in cash flow (profits) over time in the <u>financial</u> service context. For the <u>telecommunication</u> services context, higher income was associated with lower variability in individual customers' cash flows (revenues) over time, indicating that high income customers do not vary their consumption or purchases based on available income. Higher income was not associated with higher cash flows in either context. We believe that the nature of the service influences the effect of income on customer cash flows. The demand for financial services (and especially insurance coverage) may not be easily satiated; customers' demand varies with their income level. For example, insurance coverage is often purchased for products with low satiety (e.g., boats, motorcycles), so individuals' insurance purchases are likely to fluctuate with variability in their purchases of other products. In contrast, telecommunication services are a necessity for customers in developed economies; customers become accustomed to them (habituate), so demand does not fluctuate as income levels change. This notion is consistent with Voss, Godfrey, and Seiders' (2010) finding that satiation and habituation operate differently depending on the re-purchase context.

Share of Income accounts for substitute or complement effects due to purchases of other goods or services, given budget constraints (and after controlling for a main effect of income). As purchases of a particular service increase as a percentage of budget (and purchases of other goods and services decrease as a percentage of budget), there is a substitution effect. For example, when *Share of Income* for telecommunications services is higher, customers are (apparently) substituting telecommunications for other goods or services over the long run. Table 3 shows a negative and statistically significant coefficient for telecommunications. However, we do not observe a substitution effect for financial services because when consumers buy more of other goods, they need more financial services (e.g., insurance). In other words, financial services are a complement, not a substitute, for other goods and services. Consequently, variability in cash flows is heightened. For this reason, Table 3 shows that the coefficient for *Share of Income* is positive for financial services. (Note that *Share of Income* was not included in either average cash flow model because this variable is mathematically derived by dividing average cash flow – the dependent variable – by *Income*, a predictor variable; inclusion of *Share of Income*, given that *Income* is already included, would create severe multicollinearity.) The coefficient for *Mailing*, included in Study 1 only, was positive and significant for both variability and average cash flow, indicating that customers respond to direct communication.

Findings are robust across two different service settings. Since the market conditions and time periods are very different across the two studies, we believe that our findings are likely to generalize to non-contractual service settings. Financial services customers hold annual contracts; the unit for analysis is the year and cash flow was not studied within the contract period. Telecommunications customers hold a diverse range of contracts, including no contract, annual contract, or even multiple-year contracts.[8] The telecommunications market was expanding and was characterized by intense competition. The cooperating service firm (and their competitors) offered

loyalty programs with highly attractive promotions to encourage customers to switch from competitors. Customers could easily cash in loyalty points, which removed another roadblock to changing providers. Switching costs were effectively zero, which meant customers were <u>not</u> bound by the contract. Customer behavior within the telecommunications market has considerable monthly variability, which is similar to non-contractual services.

ROBUSTNESS ANALYSES WITH MANAGERIAL IMPLICATIONS

This section shows how managers can use information about the predictors of variability in individual customers' cash flows to allocate resources that improve service and RM strategies, as well as associated business outcomes. To understand the model results, it is useful to start by decomposing the customer base to recognize sources of variability in cash flows. We consider two splits in the data: whales versus minnows (i.e., large versus small revenue/profit customers) and high versus low-growth (or no-growth) customers. These analyses allow us to consider customer heterogeneity, beyond the variables incorporated in the equation. Specifically, we can investigate whether our predictor variables influence some customer groups in different ways than other customer groups. Then, we provide some sensitivity analyses that simulate how a change in resources allocated to specific programs (e.g., improvements in service) influence aggregate cash flow levels and variability. These analyses show how managers might use our findings to better manage service processes and business outcomes.

Whales versus Minnows

For both study contexts, we used a median split to separate customers into two groups: *whales* (customers with high profits or revenues) and *minnows* (customers with low profits or revenues). It was not necessary to estimate separate models of the variability in cash flows for each group because the null hypothesis that the error variances of the two equations were the same was not rejected (Toyoda and Ohtani 1986, *p > 0.05*). Hence, we created interaction terms to allow each

group to have a separate vector of coefficients in a single model estimated with the pooled data. In this model, there is a separate vector of variables for *Whales* and for *Minnows*. For example, we included in the model *Satisfaction* x *Whale*, where *Whale*=1 for customers with *high* profits or revenues, and 0 otherwise; and *Satisfaction* x *Minnow*, and *Minnow*= 1 for customers with *lower* profitability or revenue and 0 otherwise. *Minnow*=1-*Whale*, so that *Satisfaction* x *Whale* + *Satisfaction* x *Minnow* = *Satisfaction*. By coding interactions with all variables in this way, when *Whale* = 1, we are estimating model coefficients for high revenue or profit customers only, and when *Whale* = 0 (and *Minnow*=1), we are estimating the coefficients for low revenue or profit customers only. We estimated this expanded equation with pooled data and separately tested the null hypothesis that each pair of coefficients of a given predictor variable is the same for the two groups. When the null hypothesis was rejected at $p < .05$, we retained separate terms for each group for a given predictor variable. The results are presented in columns 3 and 4 in Table 3. Many results remain the same, so we briefly note the differences between the two data subsets below.

      Study 1. For the whales or high profit customer group, *Length of relationship* and *Share of income* do not affect variability ($p > 0.1$), and the effect of *Income* is smaller than for *minnows*. We examined the means for these three predictor variables and discovered that *whales* tend to have longer relationships (*Length of Relationship*), higher *Share of Income* and *Income* ($p < 0.01$, t-test). The financial services firm may deliberately allocate more resources to this group, consistent with industry practice. The results for minnows or low profit customers are identical in significance and direction of coefficients with the pooled model.

      Study 2. In the telecommunications study, the coefficient of variation is based on individual customers' revenues, not profits. In the model for whales or large revenue customers, there are three major differences. *Satisfaction* and cross-buying (*Breadth*) are not statistically significant, and customers who have longer relationships (*Length*) have lower variability in cash flows (i.e., the sign

of the coefficient is the opposite of the pooled model). To further investigate, we calculated the means of these three predictor variables for both groups. Whales have lower satisfaction levels ($p <$ 0.05), higher cross-buying and longer relationships ($p < 0.001$) than minnows. Since this market is highly competitive, the company seems to have made extensive efforts to acquire and please new customers. Since we do not observe profits, we cannot know whether this decision is appropriate. The model for minnows or low revenue customers resembles the full model in terms of the sign and statistical significance of coefficient estimates.

Growth versus No-Growth (or Declining) Customers

Variability in individual customers' cash flows can arise from underlying variability in the service consumption process, but it can also be associated with a positive or negative trend in individual cash flows over time. The following analysis disentangles these effects. We analyzed the individual level data so that we could identify growth customers (who exhibit a statistically significant positive cash flow trend over time), zero growth customers and customers with declining cash flows (who exhibit a statistically significant negative cash flow trend over time). In Study 1, *growth* customers – i.e., customers with a significant positive trend in cash flow levels over time – represent 6% of customers. There were only six customers (0.3%) with a negative trend in cash flows over time, so we pooled them with the no-trend customers. Thus, the vast majority of Study 1 customers (94%) exhibited no statistically significant trend in cash flows over time. In Study 2, 24% of the customers have a statistically significant positive trend in cash flow levels over time; 15% of customers exhibited no trend; the remainder, (60%) of customers exhibited statistically significant declines (i.e., negative trends).[9] Thus, 75% of Study 2 customers exhibited a statistically significant negative or no trend over time. Similar to the previous analysis, the null hypothesis that the error variances of the two equations were the same was not rejected (Toyoda and Ohtani 1986, *p > 0.05*) and we estimated the equations for both groups simultaneously. As before, we created interaction

terms to allow each group to have a separate vector of coefficients, estimated this expanded

equation with pooled data and tested the null hypothesis that each pair of coefficients (of a given

predictor variable) is the same for the two groups. For each group, we retained separate coefficients

for about half the predictor variables. The results are presented in Table 4.

<< TABLE 4 HERE >>

Study 1. The cash flow variability model for *no-growth* customers is identical in terms of

sign and significance of coefficients with the full model. *Growth* customers, differ from the overall

sample on *Share, Length of Relationship, Income* and *Share of Income.* Except *Income,* which is not

significant though is in similar direction, increases for all these variables are associated with lower

variability ($p < 0.1$ for *Share*, $p < 0.001$ for *Length of Relationship* and $p < 0.01$ for *Share of

Income*). This suggests that the growth customers, although not numerous, may have more

consistent relationships with the firm than other customers.

Study 2. Again, the model for *no-growth* customers mirrors the overall model. For *growth*

customers, *Breadth* is not significant, though in the same direction with the overall sample, and all

other variables differ in the magnitude of coefficients, but have similar levels of significance and

direction of the relationship. In general, these findings indicate that growth and no-growth

customers who share the same characteristics (as measured by our predictor variables) display

similar variability in cash flows. This result might be because newer customers, who are more

volatile, are the focus of company's campaigns and exhibit most growth, while the older

relationships receive fewer resources in this highly competitive market. We should interpret the

results for growth customers with caution given the small size of the data subset.

Sensitivity Analyses

Managers cannot fully understand the cash flow implications of a change in an actionable

firm variable – such as an investment that increases satisfaction levels or participation in loyalty

programs – simply by examining the coefficients for the models of variability in cash flows and cash flow levels. Predictions of customers' cash flow levels and variability must take into account how customer characteristics are distributed across the entire customer base. This analysis must consider the distribution of whales versus minnows and growth versus no growth customer groups, as well as the distribution of values for predictor variables. We can show aggregate cash flow implications by conducting sensitivity analyses using the individual cash flow level and variability models that we have estimated. We consider the following situation. Suppose the same investment (in dollars) could stimulate each customer to purchase 10% additional services from the firm (increasing *Breadth* or *Share of Customer*) or increase each customer's *Satisfaction* by 10%. Which investment would yield a better financial outcome when considering both variability and levels of cash flow? We simulated the financial outcomes for these two different scenarios and the results are displayed in Table 5. For the financial services context we simulated three different scenarios: 10% increase in *Satisfaction*, 10% increase in *Share of Customer* and 10% increase in *Breadth*. Recall that the Telecommunications services context does not include a *Share of Customer* variable. Hence, for the Telecommunication services context we simulated two different scenarios: 10% increase in *Satisfaction* and 10% increase in *Breadth*.

<< TABLE 5 HERE >>

Study 1: Financial Services. Investments that increase customer satisfaction reduce cash flow variability by 10%, while increasing the level of cash flows (i.e., profits) by four percent. In this study, a 10% increase in customer purchases from the service firm is operationalized once as an increase in cross-buying across product categories (*Breadth*), and then as an increase in *Share of Customer*. An increasing in *Breadth* of 10% yields an increase in variability by 46% and an increase in cash flow by only 1%, while an increasing in *Share of Customer* of 10% yields a 31% increase in variability, and cash flow levels increase by two percent. These results provide a

compelling argument that the company obtains the best return by focusing on satisfaction.

Study 2: Telecommunications Services. The simulations show that higher levels of both satisfaction and purchases of multiple services (*Breadth*) have beneficial financial outcomes for the service firm – both in terms of variability in cash flows and cash flow levels. Recall that cash flows are measured using revenues, not profits in this study. A 10% higher satisfaction level is associated with one percent smaller variability in revenues and four percent higher revenue levels. In the telecommunications study, an increase in customers' purchases is operationalized as a 10% increase in *Breadth*. The simulation shows that a 10% increase in *Breadth* is associated with four percent higher variability in revenues and also eight percent higher revenue levels. These outcomes provide critical information that managers can use to make trade-offs in decision making.

CONCLUDING REMARKS

This paper has shown that variability in the cash flows of individual customers can be statistically linked to managerially actionable variables. Moreover, it has shown that most (but not all) of these effects are consistent across customer groups characterized by different revenue/profit levels (i.e., whales/minnows, growth/no-growth), as well as across two study contexts. Our sensitivity analyses simulate how an increase in satisfaction levels – i.e., that might be achieved through service improvements – influences aggregate cash flow levels and variability. Both study contexts show that some changes in service firm's decision variables may be associated with lower individual and aggregate cash flow variability without adversely affecting cash flow levels. Since these findings are robust across different customer sub-groups, study contexts and scenarios, it seems likely they will generalize to other service industries and firms.

Implications for Service Management and Relationship Marketing

Service Management. Grönroos (1994) views marketing as an interactive process in a social context where relationship building and management are vital cornerstones. Researchers have also

noted the importance of accounting for and managing customer heterogeneity, as opposed to controlling for it (Rust et al. 2004). Rather than using models with parameters that vary across or within individual customers, managers should build models that are actionable by service managers. Our approach addresses these challenges by showing that variability in customers' cash flows can be linked to classic market segmentation and relationship variables. By doing so, we have linked variability in individual and aggregate cash flows to the underlying variability in service consumption processes. Hence, firms can manage variation in service consumption processes, by improving service reliability (or service quality efforts), to lower the variability in cash flows without adversely affecting cash flow levels. This finding is rather surprising because firms seldom think about how service operations decisions (e.g. total quality management initiatives) might influence cash flow patterns. Consequently, a key contribution of this research is that service managers <u>can</u> (and should) take variation in customers' cash flows into account when allocating resources to service or marketing programs targeted at specific customer groups. It is time for measures of cash flow variability to be included in the toolbox of service firms.

Second, the present study extends the research on the association between customer satisfaction and business performance. The results indicate that satisfaction has a "double-whammy" effect, in that it is associated with smaller cash flow variability for individual customers and higher cash flow levels (revenues and profits). In this way, customer satisfaction provides two important routes to increase the value of the customer portfolio and the service firm's shareholder value. This finding is especially important for service managers because research has shown that customer satisfaction levels can be increased in a myriad of ways. This study traces these effects over extensive time periods, demonstrating the importance of considering how service strategies, especially strategies targeting specific customer groups, (e.g., service improvements for whales only) can influence shareholder value in the long run. This supports Johnson and Selnes' (2004) call

for a dynamic approach to managing the service firm's portfolio of customer relationships.

Relationship Marketing. Third, our research provides practical ways to anticipate customer service consumption patterns and manage cash flows based on relationship and personal characteristics. We have shown that an objective measure of cash flow variability is a relevant way of describing individual customers. Our analyses provide managers with insight into the advantages (higher cash flow levels) and disadvantages (higher cash flow variability) of allocating service resources to specific customers or market segments. Thus, a measure of individual customer cash flow variability can be used to augment the ways that traditional segmentation variables (including CLV) are used. Thus, it can complement existing measures of the attractiveness of a market segment. It can also augment current approaches to customer portfolio management.

Fourth, this study has implications for service programs that aim to increase customer satisfaction and loyalty, as well as match firm activities with customers' relational orientations. Our findings suggest that loyalty programs can increase the variability associated with customers' cash flows. This observation is consistent with prior research indicating that the characteristics of the particular loyalty program (e.g., economic versus non-economic rewards) may influence the effectiveness of the program. We have shown that the underlying influence of satisfaction, not a loyalty program per se, is critical to reducing cash flow variability. Hence, a challenge for many service firms is to design loyalty programs that influence customer satisfaction, rather than offering incentives for short-run increases in purchases. Since services build strong favorable relationships with customers, there are many strategies that could be explored. For example, Drèze and Nunes (2009) show that consumers seek the intangible benefits associated with loyalty club membership status, such as services associated with specific loyalty membership tiers.

Finally, the present study shows that customers with higher cash flow levels (e.g., younger, purchasing more products in more categories) have higher variability in their cash flow. Managers

can make better decisions regarding the allocation of RM effort to customer segments using variables that are typically recorded in service firms' databases. Customers who might typically be considered less desirable because of their lower level of cash flows (e.g., older customers or customers with a relatively lower share of purchases) may represent a balancing force in the customer portfolio due to their relatively low variability. For example, though younger customers are easier to acquire and lose, and therefore more unpredictable, older customers could be more reliable and predictable, and therefore easier to serve and plan for. By combining information on cash flow levels and variability, service firms can make tradeoffs and proactively manage some of the variability associated with the incoming cash flows (c.f., Ryals 2002; 2003). Our approach helps service firms move from CRM strategies (i.e., "one-to-one" strategies that encourage service firms to consider customers in isolation) to customer portfolio management strategies that consider how market segmentation influences the firm's aggregate cash flow characteristics. We worked with a service firm to apply our approach; managers layered measures of individual cash flow variability over their existing segmentation scheme to assess the attractiveness of different market segments. This helped managers decide how to allocate sales and service efforts to segments.

Limitations and future research

Future research is needed into customer cash flow patterns over time for different products or services and market conditions. Business-to-business service firms tend to know more about their customers and rely on different customer and relationship characteristics than business-to-consumer firms, so our approach may be especially useful for them. Second, the present study looked at high-satiety, utilitarian products, where cash flow levels are unlikely to increase dramatically with high levels of satisfaction. Our findings may generalize to grocery shopping, cable television, and other household services. However, they may not apply to low-satiety/hedonic services (such as entertainment services), for which satisfied customers are likely to increase their average

consumption levels. Hence, studies of hedonic services might not replicate our findings.

Third, this study primarily focused on variability in individual cash flows as measured by the coefficient of variation, which does not distinguish between customers with different cash flow levels. It described additional analyses that made these distinctions (whales versus minnows, growth versus no-growth), and considered the effect that that our predictor variables had on aggregate cash flow levels in our sensitivity analyses. Hence, the present study finds evidence to support the notion that cash flow variability can be managed without adversely affecting cash flow levels. However we studied two services in relatively mature markets. The composition of the customer base changed slowly and neither service firm was experiencing significant and substantial growth (although there was growth in some small customer segments). Hence, future research could investigate whether these findings generalize to service firms experiencing rapid growth.

Fourth, this observation leads to an interesting alternative approach to studying cash flow variability. Future research could measure and study an individual customer's *beta* (i.e., the association between the customer's cash flows and aggregate cash flows) and relate it to actionable market segmentation variables. The use of a customer *beta* would be especially useful if the composition of the customer base changes relatively quickly over time. It is also attractive because it is a metric that is used in customer portfolio management methods.

Last, future research could investigate how cash flow patterns in different groups evolve over time, and potentially complement each other. Hence, studies could develop time series models of cash flow levels and variability and study whether these variables are stationary over time (depend on the underlying processes that drive consumption). Yet another approach would be to remove any growth trends from the cash flow data before calculating the coefficient of variation.

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FOOTNOTES

[1] Without this adjustment, the mean and variance would be mathematically related. Specifically, the correlation between variability and average cash flow is .56 in Study 1 and .71 in Study 2. By using the coefficient of variation as a measure of variability the correlation is reduced to .11 in Study 1 and -.17 in Study 2.

[2] We thank an anonymous reviewer for this terminology and for suggesting the robustness analyses.

[3] Verhoef (2003) studied a smaller sample of this dataset. We are grateful to the researcher for sharing the data with us. Our analysis differs in that Verhoef investigated the effects of CRM efforts on customer retention and customer share, whereas the present study focused on the effects of relationship and personal characteristics on cash flow variability.

[4] As a general rule, the data interval (that is, monthly versus quarterly versus annual measures of cash flows) was selected bearing in mind the purchase frequency of the product category. If the customer terminated the relationship, the coefficient of variation is calculated for the length of the *active* relationship. If the customer left and then returned, the coefficient is calculated for the entire length of the relationship, including periods of no purchase (coded zero).

[5] We imputed missing values for income using a regression equation in which income was modeled as a function of five socio-economic variables: age, household size, gender, car ownership (yes/no) and home ownership (yes/no). Then, we estimated our model using predicted values from the income equation for the missing income observations. These results are reported in Table 3. To assess whether the reported results were sensitive to the method of imputation, we compared them with three alternative models. The second model was identical to the reported model, except that it also included a dummy variable to indicate when a value was imputed. The third and fourth models imputed missing values for income based on the average income across respondents; we ran this model with and without a dummy variable to indicate when a value was imputed. All four models were highly similar in terms of the significance and signs of all estimated coefficients, including the coefficient of the income variable. The dummy variable that indicated a missing income value had been imputed was not significant in any model ($p > 0.50$). We also re-estimated the model after deleting the observations with missing values of income, and the signs and significance of the coefficients were unchanged. The coefficient estimates are robust across methods of imputation, as well as using case-wise deletion.

[6] Gustafsson et al. (2005) used a different sample of data from the telecommunications company to explain customer churn using customer satisfaction, affective and calculative commitment, triggers, and previous behavior. For the purposes of the present study, additional observations regarding subsequent behavior have been added (specifically, covering a longer time period). We are grateful to the researchers for agreeing to share their data.

[7] These results are available from the authors.

[8] Contracts can be none, 12, 18, or 24 months for all service

[9] We cannot infer that aggregate cash flow levels over time exhibit positive or negative trends from this information because it will depend on the relative proportion of whales versus minnows, as discussed earlier. Hence, when we trade-off cash flow levels and variability in our sensitivity analyses, we relied on the models we built for each dependent variable.

Table 1: Measurement of Model Constructs

Construct	Measure		Source
	Financial Services (1)	**Telecommunication Services (2)**	
Customer Satisfaction (*Satisfaction)*	Five-point scale* (level of satisfaction with different aspects, 1 = very dissatisfied, 5 = very satisfied)	Ten-point scale** (Overall satisfaction, 1 = very dissatisfied, 10 = very satisfied)	Customer survey
Relationship characteristics			
Loyalty	Years since enrolling in the loyalty program *(Loyalty Duration)*	Enrollment in the loyalty program (yes/no) *(Loyalty)*	Company database
Relationship Breadth (*Breadth*)	Number of categories from which a customer purchases products. Range 1 to 5.	Number of categories from which a customer purchases products. Range 1 to 3.	Company database
Share of Customer (*Share*)	The number of insurance products bought at the firm divided by the total number of insurance products bought (*Share*)	NA	Company database for numerator and customer survey for denominator (1)
Length of Relationship (*Length*)	Duration of relationship (years)	Duration of relationship (months)	Company database
Covariates			
Age	Age at the time of the study (Years)	Age at the time of the study (Years)	Company database
Income	Interval measure, coded on a scale from 1-5, based on self-reported information collected in the survey	Income in local currency, from the firm's customer records	Customer survey (1) / company database (2)
Share of Income	Average spending divided by the the income category (%)	Proportion of income spent on company's products, calculated by dividing expenditures on products by income (both obtained from the firm's customer records).	Company database (2)

Note: * *Satisfaction measured according to Verhoef (2003)*
       ** *Satisfaction measured according to Gustafsson, Johnson, and Roos (2005)*

Table 2: Descriptive Statistics and Correlations

	Mean	STD	CoV	Average Expenditure	Satisfaction	Loyalty Duration	Breadth	Share	Length	Age	Income	Share of income
					Financial Services							
Coefficient of Variation (CoV)	0.25	0.28	1.00									
Cash Flow Level ($)[1]	185.82	161.42	0.11	1.00								
Satisfaction	3.76	0.45	0.02	0.06	1.00							
Loyalty Duration (years)	1.99	0.74	0.37	0.10	0.09	1.00						
Breadth (# of Categories)	1.35	0.62	0.12	0.27	0.09	0.20	1.00					
Share (%)	0.24	0.19	0.41	0.14	0.05	0.51	0.08	1.00				
Length (yrs.)	10.40	6.91	0.24	-0.01	0.08	0.36	0.10	0.28	1.00			
Age (Years)	43.22	9.13	0.00	0.03	0.10	0.11	0.14	-0.01	0.36	1.00		
Income (Interval)	2.76	0.90	0.09	0.00	-0.03	0.12	0.00	0.06	0.03	0.09	1.00	
Share of Income	79.87	86.03	0.06	0.82	0.06	0.03	0.21	0.08	-0.00	-0.01	-0.35	1.00
					Telecommunication Services							
	Mean	STD	CoV	Average Expenditure	Satisfaction	Loyalty	Breadth	Length	Age	Income	Share of income	
Coefficient of Variation (CoV)	0.45	0.27	1.00									
Cash Flow Level	352.96	249.04	-0.17	1.00								
Satisfaction	7.15	1.63	-0.04	-0.01	1.00							
Loyalty (yes/no)	0.31	0.46	-0.01	0.25	0.01	1.00						
Breadth (# of Categories)	2.15	0.72	0.07	0.49	0.00	0.23	1.00					
Length (months)	32.3	6.90	-0.23	0.22	0.01	0.09	0.41	1.00				
Age (Years)	44.41	11.84	-0.07	0.03	0.05	0.11	0.06	0.08	1.00			
Income (Thousands $)	298.95	122.66	-0.03	0.06	-0.01	0.06	0.05	-0.02	-0.04	1.00		
Share of Income	.02	.02	-0.09	0.78	0.00	0.15	0.36	0.23	0.07	-0.32	1.00	

[1] Cash flow level is measured as average expenditure over time per customer (in local currency).

Table 3: Estimation Results for Semi-log Models

Variables	Full Variability Model	Full Average Cash Flow Model
	Financial Services Coefficients (*t*-Values)	
Satisfaction[a]	-.126**	20.138**
	(-1.79)	(1.92)
Loyalty Duration	.082****	3.672
	(7.19)	(.33)
Breadth	.022****	144.986**
	(4.78)	(2.49)
Share	.127****	109.367****
	(10.59)	(4.74)
Length of Relationship	.086****	-.008****
	(4.63)	(-4.12)
Age	-.173****	.643
	(-3.81)	(1.45)
Income	.127****	3.902
	(4.64)	(.95)
Share of Income	.073****	
	(5.25)	-
Mailings	.023****	5.423***
	(3.79)	(2.67)
Constant	.072	33.769
	(.34)	(.77)
	N=1754	N=1754
	R^2=.25[b]	R^2Adj=.10
	LL=-821	LL=-11328
	Telecommunications Services Coefficients (*t*-Values)	
Satisfaction[a]	-.050***	21.487*
	(-2.71)	(1.29)
Loyalty	.025**	27.937
	(2.03)	(.64)
Breadth	.244****	151.730****
	(13.36)	(21.80)
Length of Relationship	.167****	4.473
	(7.32)	(1.48)
Age	-.072****	.328
	(-3.78)	(.20)
Income	-.195****	.000***
	(-11.90)	(2.87)
Share of Income	-.175***	
	(-17.70)	-
Constant	1.725****	-163.555
	(8.69)	(-1.37)
	N=2246	N=2246
	R^2Adj=.14	R^2Adj=.31
	LL=-106	LL=-15147

Note: [a]*One-tailed tests*
[b]*True R^2 computed for Tobit model (regression of the dependent on the predicted variable)*
* p < .1; ** p < .05; *** p < .01; ****p < .001

Table 4: Estimation Results for Semi-log Models – Robustness Tests

Variables	Whales Variability		Minnows Variability	Growth Customers' Variability		No Growth (or Declining) Customers' Variability
Financial Services Coefficients (*t*-Values)						
Satisfaction[a]	-.128**		-.128**	-.107*		-.107*
	(-1.85)	=	(-1.85)	(-1.62)	=	(-1.62)
Loyalty Duration	.085****		.085****	.085****		.085****
	(7.60)	=	(7.60)	(7.90)	=	(7.90)
Breadth	.024****		.024****	.015****		.015****
	(5.24)	=	(5.24)	(4.43)	=	(4.43)
Share	.126****		.126****	-.096*		.115****
	(10.58)	=	(10.58)	(-1.75)	<	(10.02)
Length of Relationship	-.032		.265****	-.720****		.050***
	(-1.10)	<	(8.86)	(-4.64)	<	(2.78)
Age	-.160****		-.160****	-.154****		-.154****
	(-3.53)	=	(-3.53)	(-3.61)	=	(-3.61)
Income	.079*		.225****	-.175		.128****
	(1.95)	<	(5.38)	(1.51)	<	(4.90)
Share of Income	.024		.169****	-.165***		.085****
	(.91)	<	(7.38)	(-3.06)	<	(6.69)
Mailings	.013**		.013**	.026****		026****
	(2.09)	=	(2.09)	(4.54)	=	(4.54)
Minnows / No-growth			-3.047****			-8.306****
			(-7.37)			(-5.69)
Constant	1.299****		1.299****	8.467****		8.467****
	(3.71)	=	(3.71)	(6.10)	=	(6.10)
	N=888		N=866	N=104		N=1650
	R²=.25[b]			R²=.33[b]		
	LL=-814			LL=-754		
Telecommunications Services Coefficients (*t*-Values)						
Satisfaction[a]	-.016		-.087***	-.048**		-.048**
	(-.67)	>	(-3.26)	(-2.60)	=	(-2.60)
Loyalty	.033***		.033***	.021*		.021*
	(2.77)	=	(2.77)	(1.76)	=	(1.76)
Breadth	.045		.348****	.057		.299****
	(1.47)	<	(16.31)	(1.43)	<	(14.57)
Length of Relationship	-.592****		.180****	-.217		.166****
	(-5.64)	<	(7.26)	(-1.13)	<	(7.07)
Age	-.075****		-.075****	-.075****		-.075****
	(-4.06)	=	(-4.06)	(-4.06)	=	(-4.06)
Income	-.160****		-.160****	-.160****		-.208****
	(-8.18)	=	(-8.18)	(-8.18)	>	(-11.40)
Share of Income	-.104****		-.104****	-.142****		-.186****
	(-6.12)	=	(-6.12)	(-5.98)	>	(-17.29)
Minnows / No-growth			-3.143****			-.793
			(-7.26)			(-.97)
Constant	4.361****		4.361****	1.167****		1.167****
	(10.20)	=	(10.20)	(5.24)	=	(5.24)
	N=1209		N=1037	N=539		N=1707
	R²Adj=.19			R²Adj=.19		
	LL=-278			LL=-86		

Note: [a]One-tailed tests

[b]True R² computed for Tobit model (regression of the dependent on the predicted variable)

* $p < .1$; ** $p < .05$; *** $p < .01$; ****$p < .001$

Table 5: Simulation Results

	Original Variance (CoV)	Simulated Variance (CoV)	Change in variance (CoV), %	Original Average Cash Flow	Simulated Average Cash Flow	Change in Average Cash Flow,%
Financial Services						
10% increase in Satisfaction	0.1236	0.1116	**-10%**	185.6020	193.3305	**4%**
10% increase in Breadth	0.1236	0.1800	**46%**	185.6020	188.1158	**1%**
10% increase in Share	0.1236	0.1616	**31%**	185.6020	188.4395	**2%**
Telecommunication Services						
10% increase in SAT	0.4535	0.4487	**-1%**	352.9610	368.3225	**4%**
10% increase in Breadth	0.4535	0.4722	**4%**	352.9610	382.6870	**8%**