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Chao Wang
Ilaria Dalla Pozza

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IPAG Business School
184, Boulevard Saint-Germain
75006 Paris
France

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THE ANTECEDENTS OF CUSTOMER LIFETIME DURATION AND DISCOUNTED EXPECTED TRANSACTIONS: DISCRETE-TIME BASED TRANSACTION DATA ANALYSIS

CHAO WANG

Head of Business Architecture
Direct Line Group
London, UK

ILARIA DALLA POZZA

IPAG Business School, Paris

ABSTRACT

Maintaining long-term customer relationships and increasing customer value are always the two crucial objectives in service management and relationship marketing. Both researchers and market practitioners are ardent on exploring and comprehending the drivers of customer lifetime duration and number of future transactions (discounted expected transactions). This study implements a probability model to estimate the lifetime duration and discounted expected transactions with relatively simple and standard discrete-time based transaction data which are easily approachable for managers, and identifies the relational and demographic factors that have significant contribution in the explanation of the variance in customer lifetime duration and discounted expected transactions. Several important managerial implications are discussed to offer some insights to marketing managers and decision makers.

Introduction

With the increasing awareness of the importance of relationship marketing in both academia and business practice (Berry 1995; Dwyer et al. 1987; Morgan and Hunt 1994; Sheth and Parvatiyar 1995), more and more firms started to put massive investments in customer relationship management (CRM) to prevent customer defections and maintain long-term relationships (Kerstetter 2001; Reinartz et al. 2004; Reinartz and Kumar 2000; Winer 2001). Based on his consulting experience, Reichheld (1996) supported the tangible advantages of retaining customers and claimed that a 5 percent increase in retention rate led to an increase in the net present value of customers from 25 to 85 percent in a wide range of industries, from credit card and insurance brokerage to motor services and office building management.

Various definitions of retention have appeared in previous studies. Reichheld (1996) suggested that customer retention can be described in terms of the absolute number of those staying as a percentage of the original number over a specific period, for example one year. Ngobo (1999) presented his definition of retention, making a distinction with loyalty in that "loyalty refers to a customer's psychological predisposition to repurchase from the same firm, while retention represents the actual product/service repurchase over time". Accordingly, Lewis (2004) identifies retention with repeat buying. In some studies customer retention is also identified with the duration of the customer-company relationship (Bolton 1998; Reinartz and Kumar 2003; Verhoef 2003). This paper is aligned with such definition and focuses on the customer lifetime duration in relationship marketing.

Although previous studies have investigated a number of factors affecting the duration of the relationship (Crie' 2004), such as satisfaction (Bolton 1998; Dick and Basu 1994; Fornell 1992; Rust and Zahorik 1993); switching barriers as (a) interpersonal relationship (Berry and Parasuraman 1991; Turnball and Wilson 1989), (b) switching costs (Guiltinan 1989; Jackson 1985), and (c) attractiveness of alternatives (Berry and Parasuraman 1991); and relationship marketing instruments (such as loyalty programs or direct mail) (Bolton et al. 2000; Hart et al. 1999; Roberts and Berger 1999), they are mainly constrained in the contractual context in which customer lifetime duration is relatively easy to measure. Related empirical research in non-contractual settings, however, is scarce (Reinartz and Kumar 2003).

Non-contractual setting (such as retailers, automotive) are characterised by an absence of a contract between buyer-seller, low switching costs (Bowman and Narayandas 2001) for customers and high promotional expenditure for companies to maintain the relationships. In such kind of contexts, companies face a much higher uncertainty since profitability cannot be forecasted accurately. In particular, customers can seek variety across firms, and be easily acquired by competitive offers. Retention, therefore, becomes a major issue in non-contractual settings.

In this study, we explored the non-contractual relationship issues in the telecommunication industry. Specifically, we investigated a leading mobile service company in Italy. In Italy, the majority of the customers (92%) in the telecommunication industry do not hold a contract with the provider, but they have a prepaid ("pay as you go") service. As a consequence, it is a very interesting non-contractual setting to investigate.

Apart from the research context, a crucial aspect distinguishing our study from previous studies is that our data track repeat-transactions on a discrete-time basis. Although such transaction track is constrained in providing accurate and deep information, it has been widely used for its convenience and efficiency. How to capture the customer lifetime durations and extract buyer-seller relationship antecedents based on such relatively simple information stand great academic and managerial value. Moreover, the data used in this study are left-truncated, different from most of the datasets used by previous researchers, such as Reinartz and Kumar (2003), which captured customers' purchase history from the very beginning. Such extension greatly expands the application scope of the model.

Although the data we use do not contain the customer profit information so that we cannot calculate customer lifetime value (CLV) directly, we are able to get the present value of future transaction flow by assuming a constant cash flow per transaction per customer over time and factoring out the value of each transaction (Fader et al. 2004b; Libai et al. 2002). The impacts of relational and demographic characteristics on expected customer value are investigated based on this discounted expected transaction (DET).

The final goal here is to better understand the structure of customer-company relationship by providing valid antecedents analysis. Although customers' perceptions of service contact (such as satisfaction or loyalty) and market competition (such as competitors' price strategies and switching barriers) play their roles in determining the customer lifetime duration (Bolton 1998; Dick and Basu 1994; Guiltinan 1989; Jackson 1985), the focus of our inquiry is on the basis of customer-company exchange nature and customer characteristics. Such approach may be limited in finding the environmental influence, it does capture the most powerful predictors

of future customer behaviour such as purchase scope and time (Neslin et al. 1985), and signal customers' intentions (through previous relationship length). Moreover, observed customer heterogeneities are taken into account in this paper to strengthen my findings (Schmittlein and Peterson 1994).

In response to the issues mentioned above, the key research objectives are to:

1. Empirically measure lifetime duration for non-contractual customer-firm relationships based on discrete-time based data;
2. Understand the impacts of key relationship characteristics and customer heterogeneities on the customer lifetime duration in the telecommunication industry;
3. Explore influences of those antecedents on customer expected future transactions;
4. Develop managerial implications for building and managing customer-firm relationships in the telecom industry.

Model Establishment

The main purpose of our model is to explain the systematic differences in customer lifetime duration by analyzing the antecedents of lifetime duration in a non-contractual context. A dynamic model is applied at individual customer level to achieve this objective.

In line with the discrete-time based repeat transaction data, instead of exploring the profitable lifetime duration by taking into account of revenues and cost (Reinartz and Kumar 2003), this study focuses on the impacts of exchange characteristics and observed heterogeneities on "pure" customer lifetime duration in non-contractual settings. Besides, we are also interested in such influences on present value of the expected future transaction

stream. Figure 1 displays the research framework of this study. The dynamic model could be conceptually formulated as:

Customer Lifetime Duration$_i$ = f(exchange characteristics$_{it}$, customer heterogeneity$_i$);

Discounted Expected Transaction$_i$ = f(exchange characteristics$_{it}$, customer heterogeneity$_i$).

/* Insert Figure 1 about Here */

Exchange Characteristics

The relationship between two parties is shaped by the frequency, depth, and scope of interaction (Kelly and Thibaut 1978). With the same logic, purchase amount, purchase frequency, and purchase variety will determine the relationship duration between buyers and sellers (Oliver and Winer 1987; Reinartz and Kumar 2003). In this study, we mainly look at the cross-buying, customer type, and customer previous relationship with focal company.

Cross-buying. Cross-buying refers to the customers' practice of buying additional products and services from the existing service provider in addition to the ones they currently have (Ngobo 2004). It denotes that customers purchase across different product categories from the company. For example, a cellphone network company could provide a wide range of services from traditional voice or sms service to advanced wap (Internet on phone) or sms with content (information order) service. Customer may choose to receive all kinds of services corresponding to a very high cross-buying, or only stick to one service without cross-buying. In fact, the cross-buying behaviour represents the scope of interaction between customers and service providing company. In the context of non-contractual relations, wide range of purchase could help customers get to know the service company and its products

more comprehensively, so that the willingness to keep a high cross-buying behaviour could be regarded to be a sign of customer's confidence in future relationship. Cross-buying, therefore, has been considered as an indication of customers' repurchase intentions since cross-buying behaviours are usually on the basis of high service quality perception and high level of satisfaction, and customers perceive it as a way to raise the quality of the relationship (Bendapudi and Berry 1997; Gwinner et al. 1998). Furthermore, the benefits of switching cost avoidance and price advantage associated with cross-buying also stimulate customers to stay with the service companies (Guiltinan 1987; Reichheld and Sasser 1990). Highly positive impacts of satisfaction and payment equity on cross-buying also have been found in Verhoef and his colleagues' (2001) study. Reinartz and Kumar (2003) also suggested that cross-buying behaviour is positively related to profitable customer lifetime duration. Apart from duration, customer future purchase frequency might be more concerned by the company since it provides the information of each customer's profitability if customer consumption level in the future is consistent. Therefore, the loyal tendency of a customer that is embodied by cross-buying behaviour reinforces the repurchase intention and eventually turns into the large number of transactions. So we propose that:

H_1: Customer lifetime duration is positively related to the degree of customers' cross-buying behaviour.

H_2: Customers' discounted expected transaction number positively links to the degree of customers' cross-buying behaviour.

Pioneering Consumption. With the development of telecommunication technology, cellphone network companies have started to provide more and more high-tech related

services. Through continuous provisions of new services, companies might be able to resist to competitors' invasions by product differentiation, innovation, and shifting customers' tastes (Carpenter and Nakamoto 1989). It has been shown that "market pioneers" or "first movers" perform significant better in terms of market share (Robinson 1988; Urban et al. 1986). Furthermore, once reaching certain penetration level, the new services create a significant knowledge barrier to a later entrant and increase the costs of defection for customers. However, despite of these advantages associated with new services, customers who actively adopt them have been demonstrated to be somehow unstable. The innovators or early adopters are described as those who "give the new concept initial physical visibility and functional application" (Baumgarten 1975). And previous studies have shown that early adopters from various industries, such as medical, farm, fashion, and etc, shared a very similar profile—younger, low dogmatic, cosmopolite, and more gregarious (Baumgarten 1975; Coleman et al. 1966; Jacoby 1971; Wilkening 1952). As a consequence, they are more adaptive on the acceptance of change in a variety of situations, more likely to take the risk without getting ample information, and more willing to be susceptible to competitive offers. The high volatility of cellphone services may further exaggerate such behaviours of early adopters.

H_3: Customer lifetime duration is negatively related to the degree of technological interest of the customer.

H_4: Customers' discounted expected transaction number is negatively related to the degree of technological interest of the customer.

Previous Relationship Length. Since the data used in this paper are left-truncated, the majority of the customers had already stayed with the focal company before the observation commencement. Unlike the new customers, the longer the relationships between customers and the cellphone service company, more comprehensive customers' knowledge on the products will be, and more intensive and intimate the customers' emotions associated with the company will be. Consequently the previous relationship length in large degree reflects the essence of information richness (Daft and Lengel 1984; Kellogg and Chase 1995), which increases the switching costs for defected customers. Furthermore, customers have to count on the related knowledge which is mainly gained from their past contact experience with the corresponding company to determine organizations' credibility and benevolence. Previous studies have been demonstrated that the increase of relationship time could improve the trust between customers and service companies since on one hand the long term investments are perceived by cusotmers as the indication of companies' commitment, and on the other hand long relationships make it easier for customers to predict service companies' future behaviors so as to increase their perceptions on service companies' reliability (Doney and Cannon 1997). And such cumulative experience not only enables customers to have clear ideas on the consistency of the focal company's actions and decision making so as to prevent their anxiety caused by the unexpected, but also provides customers strong clues and gestures on company's long-term relational interests so as to establish the benevolent images which eventually lead to trust. A huge body of studies have demonstrated that trust is a crucial determinant of relational commitment, a key element of customer relationship establishment,

and the foundation of long-term relationship by enhancing the cohesion of the two parties (Sirdeshmukh et al. 2002; Spekman 1988; Tax et al. 1998; Urban et al. 2000). We expect that:

H_5: Customer lifetime duration is positively associated with customer's previous relationship length with the focal company.

H_6: Customers' discounted expected transaction number is positively associated with customer's previous relationship length with the focal company.

Customer Heterogeneity

Both in academia and business practice, demographic variables are used in customer segmentation so as to come up with appropriate marketing strategies for each segment. It has been demonstrated that demographic variables can be significantly related to certain response variables despite of relatively low portion of explained variation. Here we mainly examine the impacts of location and age of customers.

Region. The relationship length is shown to be the consequence of the cost and the benefits generated from the relation at certain degree (Reinartz and Kumar 2003). Customers are always searching for the products or services that bring them maximized utilities. Utility is a multi-dimension concept, and the importance of each component of utility varies from one customer to another. Although in general customers are all relatively price-sensitive indicating that lower cost is associated with higher utility for the same product or service, however, those customers who have lower income budget will put more weight on cost issue. As a consequence, we expected that in the non-contractual context where penalty related switching cost is low, highly price-sensitive customers are driven by the cost and easy to defect in the price wars. In this study, customers are divided into two regions according to

where they live, South and North. Since north Italy is more developed than the south and there are more job opportunities in the north, the average income per se in the north is higher than that in the south Italy. Thus we expect that customers in south Italy are more price-sensitive. Given the fact that market strategies of the company and its competitors do not vary greatly across the whole country, customers in both regions face the similar choice options, southern customers should be easier to defect. Here we have:

H_7: Customer lifetime duration is higher for customers living in north Italy than those in south Italy.

H_8: Customers' discounted expected transaction number is higher for customers living in north Italy than those in south Italy.

Age. The impact of age in customer purchase behaviour in general is unexpected because different types of products or services create different switching motivations or barriers for customers. However, the use of cellphone services investigated in this study requires certain degree of specific knowledge so that learning about novel services provided by other network companies may bring problems for customers (Carpenter and Nakamoto 1989). Such learning problems are usually more serious for elder customers than for relatively young customers. Thus, elder customers are more likely to stick to their existing service provider instead of exploring new services and new companies.

H_9: Customer lifetime duration is positively related to customer age.

H_{10}: Customers' discounted expected transaction number is positively related to customer age.

Research Methodology

Data

The study context is the telecommunication industry, which is characterized by both high customer turnover and high customer acquisition costs. We used data from an Italian cellphone network firm for the estimation. The firm offers a broad assortment of services including voice, voice mail, sms, sms with content (when the customer asks for information on a particular topic sent by sms), mms, wap (Cellphone Internet service), and 412 (the city information providing service, such as restaurant, taxi, and etc.) services. The data for this study cover a 21 months window and are recorded on a season basis from September 2003 to June 2005. All of the customers have been already with the firm (left-truncated) at the beginning of observation, and their previous relationship lengths range from 6 months to 111 months. Every three months, it has been indicated as 1 if in that period of time customer has used each service at least once (otherwise, 0). The dataset contains 1956 observations (customers who use "pay as you go" services). Each observation has the entire service usage history in this time window for each customer in combination with a set of covariates.

Customer Lifetime Duration Estimation

In order to investigate the impacts of customer relationship and demographic characteristics on customer duration, the accurate information on each customer's lifetime is usually required. Since in non-contracted context the time of customers' defection is usually unknown, the valid measurement for lifetime duration is the first critical part of this study.

Different models have been proposed in the literature to deal with the non-contracted customer lifetime duration. Negative binomial distribution (NBD)/Pareto model has been

suggested and validated by Schmittlein, Morrison, and Colombo (1987) and Schmittlein and Peterson (1994) to capture the repeating-buying behaviour in settings where customer's dropout is unobserved. More specifically, time to dropout is modelled using the Pareto (exponential-gamma mixture) timing model, and repeat-buying behaviour while active is modelled by the NBD (Poisson-gamma mixture). NBD/Pareto model has also been applied in Reinartz and Kumar's studies. Despite its power for customer-based analysis, the empirical application of this model is somehow challenging, especially in terms of parameter estimation. Fader, Hardie, and Lee (2005b) proposed an easier way to be the alternative to the NBD/Pareto model—NBD/BG model. The only difference between these two models lies in how/when customers become inactive. The Pareto timing model assumes that customers can drop out at any point in time, independent of the occurrence of actual purchases, while the dropout occurs immediately after a purchase in the case of using beta-geometric model. Fader et al. (2005b) have showed that the two models yielded similar estimation results in a wide variety of purchasing environments.

However, in this paper, as mentioned earlier, customers' repeat service usages were tracked on a discrete-time basis, and only information in terms of whether or not each customer used certain service in each period is available. In this case, a customer's purchase history is not represented as the number of transactions, but a binary string where 1 denotes a purchase and 0 means no purchase on any given transaction opportunity. Therefore, while active, on any given transaction opportunity a customer could choose either buy (with probability p) or not (with probability 1-p), following a binomial distribution. Customer's dropout behaviour is still following the beta-geometric distribution. The new stochastic model

capturing the discrete-time transaction data is, therefore, beta-binomial/beta-geometric (BB/BG) model (Fader et al. 2004b). So BB/BG model is based on the following five assumptions:

1. On any given transaction opportunity, the probability of customer purchase is *p* when they are active, which implies customer's buying behaviour is distributed across transaction opportunities according to a binomial distribution.
2. The heterogeneity in *p* follows a beta distribution with pdf $f(p|\alpha,\beta) = p^{\alpha-1}(1-p)^{\beta-1}/B(\alpha,\beta)$, $0<p<1$.
3. Customer becomes inactive at the beginning of the next transaction opportunity with probability *q*, which implies that customer's lifetime is distributed across transaction opportunities according to a shifted geometric distribution.
4. The heterogeneity in *q* follows a beta distribution with pdf $f(q|\gamma,\delta) = q^{\gamma-1}(1-p)^{\delta-1}/B(\gamma,\delta)$, $0<q<1$.
5. *p* and *q* vary independently across customers.

The key interest of this model is to calculate the probability that the customer is still active. Fader, Hardie, and Berger (2004b) show that if a customer purchases x times in n transaction opportunities with the last purchase occurring on transaction opportunity m (m<=n), the probability he/she is still active is:

$$P(\text{active}|x,n,m,\alpha,\beta,\gamma,\delta) = B(\alpha+x,\beta+n-x)B(\gamma,\delta+n+1)/\{B(\alpha,\beta)B(\gamma,\delta)L(\alpha,\beta,\gamma,\delta|x,n,m)\} \quad (1)$$

Where, $L(\alpha,\beta,\gamma,\delta|x,n,m) = B(\alpha+x,\beta+n-x)B(\gamma,\delta+n+1)/\{B(\alpha,\beta)B(\gamma,\delta)\} + \sum_{i=0}^{n-m-1} B(\alpha+x,\beta+m-x+i)B(\gamma+1,\delta+m+i)/\{B(\alpha,\beta)B(\gamma,\delta)\}$

α , β , γ , δ are model parameters.

In order to estimate the customer lifetime duration, we need to transform the continuous P(active) into a dichotomous active/inactive measure. Certain probability level should be decided as the cutoff threshold under which the corresponding customer is allocated to be inactive. Reinartz and Kumar (2000) suggested three assumptions in lifetime calculation: (1) customer first purchase time is known; (2) observation window should be long enough to reflect the true lifetime phenomenon; (3) right-censoring should be allowed in the analysis. Although all of the estimation models do not require that customers' observation data are available from their first purchase, most of the related empirical applications choose to make use of the customer trial data to ensure that customers are alive at the observation starting point (Fader et al. 2004b; Fader et al. 2005b; Reinartz and Kumar 2003; Reinartz and Kumar 2000). In this study, we will justify the validity of BB/BG model in estimated the left-truncated data.

Parameter Estimation. The data we have cover 7 periods/seasons, however, in order to ensure that all of the customers are alive at the first analysis period, we only keep those customers who used cellphone services during the first observation period (from September/2003 to November/2003), and take the remaining 6 seasons to do the analysis. Thus all of the customers are at least active at the beginning of December/2003, which is the first period for analysis. Eventually 1668 customers remained in the dataset.

We obtained the distribution parameters of the BB/BG model for the entire sample through the maximum likelihood estimation (MLE), they are α =2.01, β =0.13, γ =0.27, δ =5.15. Then we further examine how heterogeneous/homogeneous customers'

purchase/dropout behaviours are. The heterogeneity/homogeneity captured by beta distribution is reflected via polarization index $\phi = 1/(1+\alpha+\beta)$. If both α and β are close to 0，the probabilities are concentrated near both 0 and 1, then the purchase/dropout behaviours are highly polarized, and $\phi \to 1$. On the contrary, if both α and β are very huge, the distribution becomes a spike at $\alpha/(\alpha+\beta)$. In such a case, the purchase/dropout behaviours are very homogeneous, and $\phi \to 0$. The polarization index for service usage behaviours and dropout behaviours are 0.318 and 0.156 respectively. In this case, customers are not very different in their purchase and dropout behaviours, and customers' dropout behaviours tend to be more similar than their purchase behaviours.

How good is this model? We illustrate the fit of our model through comparing the expected number of customers using cellphone services in 0, 1, …, 6 of the following six periods to the actual frequency distribution. Figure 2 demonstrates that our model fits the data reasonably well.

/* Insert Figure 2 about Here */

As mentioned before, the data we used in this study are left-truncated, how well our model could perform on such dataset? We divide the data into calibration part (first four periods/seasons) and prediction part (last two periods), and examine the model performance in terms of the quality of the predictions of individual-level transactions in the forecast period conditional on the number of observed transactions in the model calibration period. The expected number of purchases over the next n* periods by a customer with purchase history (x, n, m) is given by Fader et al. (2004b) :

$$E(X^* \mid n^*, x, n, m, \alpha, \beta, \delta, \gamma) = \{B(\alpha + x + 1, \beta + n - x)/B(\alpha, \beta)\} * \{B(\gamma - 1, \delta + n + 1) - B(\gamma - 1, \delta + n + n^* + 1)\}/\{B(\gamma, \delta) * L(\alpha, \beta, \delta, \gamma | x, n, m)\} \quad (2)$$

Since here the γ is less than 1, the formula (2) could be transformed into:

$$E(X^* \mid n^*, x, n, m, \alpha, \beta, \delta, \gamma) = \{B(\alpha + x + 1, \beta + n - x)/B(\alpha, \beta)\} * \{(\gamma - 1) * \tau(\delta)/\tau(\delta + \gamma)\} * \{\tau(\delta + \gamma + n)/\tau(\delta + n + 1) - \tau(\delta + \gamma + n + n^*)/\tau(\delta + n + n^* + 1)\} * \{1/L(\alpha, \beta, \delta, \gamma | x, n, m)\} \quad (3)$$

Figure 3 illustrates the conditional expectations along with the average of the actual number of transactions that took place in the forecast period.

/* Insert Figure 3 about Here */

The BB/BG model provides excellent predictions of the expected number of transactions except for those customers used their cellphone services twice during the first four periods. However, we should be aware that here the usages are recorded as a binary form, so the overall prediction is fairly good.

Customer Lifetime Duration Estimation. On the basis of the parameter estimates, we could calculate the probability a customer is still active: P(active| x, n, m, α, β, δ, γ). Since the data are discrete-time based and do not contain the profit information for each customer, the choice of active threshold entirely depends on the performance of correct classifications test based on all possible estimation/prediction combination samples.

First of all, we split the 6 periods into estimation period and prediction period, and got five different combinations (1/5, 2/4, 3/3, 4/2, and 5/1). Then we calculated the P(active) at the end of each period. Based on any possible cutoff threshold (.1, .2, … , .9), we assigned each customer into the status of active if P(active) was no less than assumed cutoff threshold, or inactive if it was on the contrary. We compared the assigned status of each customer with

the actual purchase behaviour in the prediction period (active if using any services, inactive otherwise). Finally we chose the cutoff threshold that produced the highest percentage of correct classifications in five situations. Figure 4 illustrates the comparison results.

/* Insert Figure 4 about Here */

Although a natural choice for the classification threshold might be .5 which has been used in some studies (Helsen and Schmittlein 1993b; Reinartz and Kumar 2000; Sharma 1996), the appropriate threshold decision should be based on such sensitivity analysis as we did above. Figure 4 tells us that the threshold .9 always produces the highest percentage of correct classification in five situations, it should be the criterion in customer status decision.

Now we could calculate a finite lifetime estimate for each customer. The average lifetime across all of the customers is 15.4 months. Approximately 24% of the sample has a lifetime that is shorter than the observation window, which indicates that this study might be constrained in that the observation period may be not long enough to entirely capture the true lifetime phenomenon.

Discounted Expected Transactions Estimation

Although we do not have the profit information for each customer, however, if we assume a constant cash flow per transaction per customer over time, we can get the flow of expected future transactions and discount to yield a present value. Fader, Hardie, and Berger (2004b) derived the formula of discounted expected transactions (DET):

$$DET(d|x,n,m,\alpha,\beta,\delta,\gamma) = B(\alpha+x+1, \beta+n-x)B(\gamma, \delta+n+1)\,{}_2F_1(1, \delta+n+1; \gamma+\delta+n+1; 1/(1+d)) / \{B(\alpha,\beta)B(\gamma,\delta)L(\alpha,\beta,\gamma,\delta|x,n,m)\} \quad (4)$$

F is the Gaussian hypergeometric function and d is the discount rate.

We set d at normal level (.1) and calculate the DET for each customer. The average number of discounted expected transactions is 6.5 and the values of DET range from .1 to 8.4 across all customers. Table 1 lists the DET for different customer groups.

/* Insert Table 1 about Here */

From table 1, we notice that DETs increase with the increase of frequency and decrease as the recency increases. we will examine the impact of customer relationship characteristics on expected future transactions on the basis of the estimated DETs.

Analysis

On the basis of the customer lifetime duration and discounted expected transaction estimation, we now turn to the main interest of this paper—the impact of customer relationship characteristics on them.

In the analysis of CLD, as hypothesized, customer relationship characteristics or dependent variables include cross-buying, previous relationship length, and consumption mode. These variables include time-dependent variables, changing during the customer lifetime spell, and constant variables. Specifically, cross-buying variable is operationalized as the number of different types of services in a three-month period. There are seven services in total provided by the cellphone network company, and in every period each customer may need to use one or multiple services. Allowing the cross-buying values to change with time, instead of using a constant statistical mean, could better illustrate the dynamic trend of customers' interactions with the focal company. The pioneering consumption is captured by time-dependent variable—"advanced service usage" which denotes whether a customer used

any advanced services (sms with content, mms, wap, and 412) during a three-month period. It is coded as a dummy variable.

The previous relationship length variable keeps constant during customer lifetime duration. It reflects the number of months customers have stayed with the focal company before the observation starting point.

Besides relationship characteristics, we also include demographic variables—customer living area and customer age, into the analysis.

For the analysis of the impacts of these dependent variables on customer lifetime durations, conventional regression will be biased because of right-censoring lifetime duration data, so we use proportional hazard function to deal with the model (Bolton 1998, Reinartz and Kumar 2003). The duration time for a customer is taken as a random variable with certain p.d.f. $f(t)$ and c.d.f. $F(t)$. Let $h(t|x)$ be the hazard rate for a customer i with certain relationship and demographic characteristics captured by the vector x, and it is assumed to take the form:

$$h(t|x) = h_0(t)\exp(\beta' x_{it}) \quad (5)$$

where $h_0(t)$ is the baseline hazard function that captures the longitudinal effects and β' indicates the effects of dependent variable on the hazard rate.

Usually there are two ways to handle the baseline hazard. One approach sets a particular distribution for baseline hazard, such as a constant λ if we assume that duration times are exponentially distributed, or $c\,\lambda\,t^{c-1}$ if duration time follows Weibull distribution. However, the challenge of this method is that we have to make reasonable assumption on the duration time distribution. The second approach allows $h_0(t)$ to take on any shape, called semi-parametric approach (Helsen and Schmittlein 1993a; Kalbfleisch and Prentice 1980).

Instead of maximizing the likelihood function associated with formula (5) simultaneously over β and $h_0(t)$, this semi-parametric approach is based on a partial likelihood which estimates β by considering a particular observable event in the process whose likelihood does not depend on $h_0(t)$. If subject i has a non-censored duration $T_i=t$, the partial likelihood is the likelihood that customer i is the one, of those customers who had not yet experienced the duration event (the "risk set"), who has duration of t, given that someone is known to have a duration of t:

$$L(i|t, j_1,\ldots,j_{n(t)})=h_i(t)/ \sum_{m=0}^{n(t)} h_{jm}(t) \quad (6)$$

Where n(t) is the number of customers at risk at t, and these customers are denoted by $j_1,\ldots,j_{n(t)}$. Substituting (5) into (6) yields:

$$L(i|t, j_1,\ldots,j_{n(t)})= \exp(\beta' x_i)/ \sum_{m=0}^{n(t)} \exp(\beta' x_{jm}) \quad (7)$$

β is obtained by maximizing the product (7) over all observed duration times. Here we should note that actually right-censored observations are also taken into account in the partial likelihood since the denominator of (7) captures all of the customers who were at risk at t but did not experience the event by that time.

Another issue needed to note is that the duration time data in the study are left truncated (Schmittlein and Helsen 1993). Recall that all customers in the dataset were observed from March, 2003 (T_L), and they are not left-censored since we are able to fill in the duration's starting time (T_{si}) for all the customers still in the process. However, those customers starting at T_{si} but leaving at $T_{oi} < T_L$ were not included in the dataset. Left truncation is caused by such occasional purgation of completed duration time. The problem arises since those customers whose duration events occurred early enough would not have been included in the

dataset at all so that left truncated customers were not really at risk for their entire duration time. Consequently, the denominator in (5) (risk sets) will be incorrect and the estimate of β may be seriously biased, and such bias will be more serious for the coefficients of time-dependent covariates.

Schmittlein and Helsen (1993) proposed a very convenient way to make the standard PHR program in SAS valid to deal with such left-truncated data by constructing a specific set of pseudo-observations in which different stratums are created and each stratum consists of all members of risk set for duration time t ($t=1,\ldots,t_{max}$). The overall partial likelihood across strata is computed as the product of the within-stratum likelihoods, again as desired.

Thus, the model is formulated as a proportional hazards regression and estimated by PHREG procedure in SAS, with ties handled with exact likelihood method (Reinartz and Kumar 2003). The complete model specification is given as following:

$$h_i(t) = h_0(t)\ \mathrm{Exp}(\beta_1 \text{cross-buying}_{it} + \beta_2 \text{basic service usage}_{it} + \beta_3 \text{advanced service usage}_{it} + \beta_4 \text{previous relationship length}_i + \beta_5 \text{previous value}_i + \gamma_1 \text{age}_i + \gamma_2 \text{region}_i) \quad (8)$$

In this paper, we also conducted the analysis on how customers' future transaction flows were affected by relationship and demographic characteristics. We used regression to examine the impacts of relationship and demographic characteristics on DET. In order to do that, we created average values for the variables. (Helsen and Schmittlein 1993a). For instance, we calculated the average value of cross-buying number for each customer and created a new column—"average cross-buying" to replace the previous time-dependent variable. The advanced service usage was captured by a dummy variable which is coded as 1 if the customer had not used any advanced services, and 0 otherwise.

All variables are summarized in Table 2.

/* Insert Table 2 about Here */

We estimated the models in three steps to check the incremental variance explained. The first model only included the traditional relational variables (cross-buying and previous relationship length). The consumption mode variable (advanced service usage) was added into the second model. And we entered the demographic variables into the third model.

Results

Customer Lifetime Duration

Table 3 reports the results of the customer lifetime duration model. In order to handle the left truncation issue, we create a cohort (a stratum) for each possible duration time as described earlier. We get 8949 pseudo-observations in this manner and 8753 (97.8%) customers with complete information are eventually analyzed. The hypothesis that the independent variable vector is equal to 0 is rejected by a chi-square likelihood ratio test ($p<.0001$).

/* Insert Table 3 about Here */

Since the customer lifetime duration model is estimated by hazard function, a natural valid choice to compare the goodness-of-fit of different models is partial deviance test. Akaike's information criterion[1] (AIC) (Gheissari and Bab-Hasiashar 2003) is used to compare different models. A pseudo-R^2 (R^2 =1-exp(-G^2/n, where G^2 is the likelihood ratio chi-square and n is the sample size) is also used to provide more direct and traditional comparisons (Magee 1990;

[1] AIC is suitable in this case since the number of data points (N) is much larger than the number of parameters (P) in our analysis. Also, other criteria could be used here, such as BIC, CAIC, but they make no significant difference in model comparison with large number of samples. (Gheissari & Bab-Hadiashar, 2003)

Reinartz and Kumar 2003). The pseudo-R^2 increases with the complexity of the models and the partial deviation tests reject the hypotheses that the inclusions of new variables from model 1 to model 2 and from model 2 to model 3 do not significantly improve the proportion of variance explained. Thus, not only most of the independent variables has a significant impact on customer lifetime durations, but also they are all eligible to stay in the model.

Cross-buying. Cross-buying behaviour has been argued to demonstrate the broad scope of interactions between customers and the company so as to positively link to customer lifetime duration. This hypothesis is supported for all the models ($p < .001$, Table 3), indicating that the usages of more kinds of mobile services do imply a longer relationship between the customers and the focal company.

We make use of the hazard ratio (risk ratio) to help us better understand the relative impact of the independent variables in the hazard function. The hazard ratio is calculated by e^{β}, which is the ratio of the estimated hazard for those with a value of 1 to the estimated hazard for those with a value of 0 (controlling for other covariates). For quantitative covariates, a more helpful statistic is obtained with the formula: $100*(e^{\beta}-1)$. This gives the estimated percent change in the hazard for each one-unit increase in the covariate. When applied to the cross-buying, customers add one more service to their product portfolio, the hazard of termination (defection) goes down between 38.0 and 47.2 percent. This is a very important finding since it is in line with many mobile service companies' strong desire to create new services not only to attract new customers but, more importantly, to keep existing ones.

Previous relationship length. Based on the left-truncated data, we analysed customers with different relationship lengths with the focal company and we expected that those customers who had stayed with the company longer should be more loyal and have longer lifetime durations as well. This hypothesis is supported (Table 3) for all the models described ($p<.001$). As a consequence, customers with a longer previous relationship with the company are more likely to remain loyal. The hazard ratio test for this variable demonstrates that one more season (just three months) increase in length in the relationship with the company causes an enormous decrease in the hazard (around 52%).

Pioneering consumption. Customers who choose to experience new and innovative services are labelled as innovators with certain types of psychological and behavioural characteristics, such as risk-taking and curiosity. So we expect that the usage of advanced technological services will have negative effects on customer lifetime duration. According to Table 3, the impact of "advanced service usage" on CLD is highly significant in both models ($p < .001$). And since it has been coded as dummy variable, we directly check the hazard ratio to understand the magnitude of this impact. As the results show, the hazard of termination of those pioneering customers is about 2.1 times of those basic users who use only traditional products. To sum up, companies should also be aware of the fact that customers who adopt new technological services are also more unstable (Chau and Hui 1998; Roger 1983).

Region. As it is shown in Table 3, the region is significantly related to customer lifetime duration ($p < .05$) and the hazard ratio indicates that the risk ratio of termination of the relationship for Northern customers is only about 88.3% of the hazard of customers living in South Italy.

Age. Generally speaking, young customers are more high-tech sensitive than elder customers, and more willing to look for new and innovative services. So customer lifetime duration is expected to increase with the increase of customers' age. We find that age is significantly related to customer lifetime duration ($p < .001$), and that the increase of a year in age makes the hazard go down by an estimated 1.2 percent. Thus, elder customers tend to be more loyal and have longer lifetime duration. Dissimilarly from previous studies, in this analysis the square of age variable did not have significant ($p<.1$) effect on customer lifetime duration.

Discounted Expected Transactions

In table 4, we report the results of the discounted expected transactions model in Table 4. In order to rule out the influence of multicollinearity, we checked all of the main effects of the variables on DET and performed collinearity diagnostic analysis. All of the variance inflation factors (VIF) were less than 2 and no evidence of collinearity problems could be found in the diagnostics result. Thus, multicollinearity is not an issue in this analysis.

/* Insert Table 4 about Here */

All the three models are significant at .001 level and the majority of the explanatory variables is significant as well. Adjusted R^2s of the three models indicate that the proportion of variance explained increases with the addition of independent variables.

Cross-buying. Results show that cross-buying has a significant impact on DET ($p < .001$). Thus, hypothesis 2 is supported. The strong association demonstrates that the wide range of services customers use will not only prolong the customers' survival duration but also increase the usage frequency during their active period. In other words, a customer with a

long lifetime duration may purchase not very frequently (with long purchase intervals), however, cross-buying behaviours could ensure that customers not only will stay longer with the company, but also they will be more active in the future.

Previous relationship length. The hypothesis that the length of the customer previous relationship with the focal company is positively related to the DET is supported across all the three models ($p < .001$). Just as cross-buying behaviour, the length of the previous relationship encourages customers not only to stay with the company longer but also to buy more often. The improvement in the knowledge of the company's products or services accumulated during the duration of the relationship push customers to purchase more often once they have the opportunity.

Pioneering consumption. A dummy variable is used in this analysis to classify customers into either advanced users (coded as 0), who used at least one of the advanced services during the observation span, or basic/non-pioneering users who did not (coded as 1). We argued that those customers associated with advanced services are more unstable and have less future transactions than basic customers. The hypothesis is supported according to the results presented in Table 4, indicating that customers without advanced services usage experience have a bigger number of discounted expected transactions. Consistent with the analysis of customer lifetime duration, although high technological/advanced customers are crucial target for many companies when they provide new products or services, companies should also consider the fact they are less willing to become loyal.

Region. In contrast with hypothesis 8 that northern customers will purchase more frequently than southern customers, the results show that there is no significant difference

between northern and southern customers in terms of DET. According to the customer lifetime duration analysis, northern customers are more likely to stay with the company for relatively longer time; however, there is no evidence to indicate that a longer relationship of northern customers will lead to more transactions with the company. A possible explanation will be the cultural difference between south Italy and north Italy. Although the north region drives the Italian economy, perhaps just because of the relatively less industrialization in the south Italy, people living in the south cultivate more personal relationships with family and friends. The close attachment to relatives makes southern customers use the mobile phone to keep in touch with their family and friends more often than northern customers. Therefore, despite of the shorter lifetime, southern customers may have the same contributions of northern customers in terms of number of transactions, and therefore are a very important target for mobile services companies.

Age. As we hypothesized, the results demonstrate that age is highly related to discounted expected transactions. Customers tend to use the services more with the increase of their age.

Conclusions and Managerial Implications

In this study, we investigated the impact of relationship (cross buying behaviour, previous relationship length) and demographic characteristics (region and age) on customer lifetime duration and customers' expected number of future transactions with the company.

According to the analysis performed in this paper, customers' cross-buying behaviour does affect the lifetime duration and the number of discounted expected transactions. Since customers are more likely to use more services when they face more possible choices, the broader product line is able to motivate customers to stay with the company longer, purchase

more frequently in the future, thus bringing more profitability to the company. As a consequence, managers should be willing to develop strategies that encourage the cross buying behaviour.

Another very important exchange variable in this study is pioneering usage, which is expressed as the customer willingness to try high and new technological products. In the telecommunication industry, as well as other competitive industries, companies usually invest a lot on new product or service development and market promotion to attract more customers. However, the findings of this analysis show that those "advanced users" are more likely to defect and have a lower expected number of future purchases. Given the negative effects of pioneering usage behaviours, there are several issues managers may need to keep in mind in their new product or service development. Although early adopters are relatively volatile and value-low, they are the dissemination motivators to spread the information of novelty and affect other people's adoption decision. To achieve this goal, companies need to ensure superb experience for early adopters and offer comprehensive instructions and information in order to encourage pioneering customers to spread positive WOM and share their knowledge with other people. Apart from that, managers should not ignore the risk associated with new products or services. Since many novel designs cannot stay in the market long enough to be adopted by the majority of customers, the market test and prediction are fairly crucial to make sure that the new products or services will be accepted and welcomed by the majority or non-pioneering customers. Otherwise, according to the results obtained, it seems unlikely to have decent returns for the investment by serving only the early adopters.

Regarding demographic variables, this study suggests that customer age and location do affect CDL and DET at a certain degree. Aged customers usually choose to stay in the same company longer and purchase more frequently in future transaction opportunities. However, there may be no significant difference on the value or profitability created by aged customers and young customers. In fact young customers tend to spend heavily but do not last long, while aged customers like to distribute the similar expenditure in a longer period. Companies, therefore, should have different tactics to extract as much value from customers with different age as possible. For an instance, companies could provide new services or promotion activities to intrigue their targeting young customers to spend more when they are still active. For aged customers, companies might need to focus on the improvement of service quality so as to satisfy them and prolong their lifetime.

Because of the different economic and cultural situations of North and South Italy, location is included in the analysis. Surprisingly, despite of all the difference between north Italy and south Italy, northern customers and southern customers exhibit the same purchase frequency and profitability level. They only difference is on lifetime duration, since southern customers are more likely to be attracted by competitors.

In general, this study demonstrates that customers are heterogeneous in their customer lifetime duration and number of discounted expected transactions, and shows the antecedents of the heterogeneity. Based on relatively simple discrete-time transaction and standard exchange and demographic data, this study provides great insights for managers on how to generate useful knowledge with their purchase history records.

Limitations and Future Directions

Although this study provides ways to empirically examine the customer lifetime duration and expected transaction issues, it is important to notice that there are some limitations which need to be explored in the future research.

More importantly, the BB/BG allows us to estimate customer lifetime duration based on discrete-time transaction data, however, such data set constrains the understanding on the difference of purchase intensities varying among customers. For each purchase opportunity, this data only distinguish whether customers buy or not, but there is no information on the purchase amount. Although it is the advantage of BB/BG model to make simple data analyzable and useful, we have to somehow be discreet on the application of the results.
Future research might be needed to investigate the companies in the same industry with detailed profitability information to test and validate the results.

Moreover, according to the analysis, customers with different service preferences, age, and even locations will demonstrate different in terms of their lifetime and purchase behaviours. A very interesting future direction could be done by classifying customers into different groups based on certain relational and demographic variables, and then investigating the customer lifetime duration and the antecedents for each segment so as to gain more elaborate knowledge.

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Table 1: DET as a function of recency and frequency (d = 0.1)

# Periods customer used services	Period of last service usage						
	Jun/05	Mar/05	Dec/04	Sep/04	Jun/04	Mar/04	Dec/03
6	8.4						
5	7.4	3.0					
4	6.3	5.4	0.6				
3	5.3	4.8	3.2	0.2			
2	4.2	4.0	3.3	1.8	0.1		
1			2.8	2.2	1.2	0.1	
0							0.1

Table 2: Variables for CLD and DET models

Dependent Variables	**Measured as**	
Customer Lifetime Duration	Months	
Discounted Expected Transactions	Times	
Explanatory Variables	**Measured as**	
	CLD	**DET**
Cross-buying	Number of services used in each period (three months)	Average number of services used
Advanced service usage	Dummy: 1=use advanced service in that period, 0=otherwise	Dummy: 0=use advanced service in that period, 1=otherwise
Previous relationship length	Months with the focal company before observation	Months with the focal company before observation
Age	Age of customer in years	Age of customer in years
Location	Dummy: 1=living in north Italy 0=otherwise	Dummy: 1=living in north Italy 0=otherwise

Table 3: Customer Lifetime Duration Model Estimation[+]

Independent Variables	Model 1		Model 2		Model 3	
	Para-estimates	Stand-errors	Para-estimates	Stand-errors	Para-estimates	Stand-errors
Cross-buying$_{it}$	0.479*	0.031	0.624*	0.036	0.639*	0.036
Previous relationship length$_{i}$	0.740*	0.021	0.738*	0.021	0.736*	0.021
Advanced service usage$_{it}$			- 0.750*	0.102	- 0.757*	0.102
Age$_{i}$					0.012*	0.002
Region$_{i}$					0.124^	0.058
2Log-Likelihood	12023.090		11972.919		11935.559	
AIC	12027.090		11978.919		11945.559	
Pseudo-R^2	.353		.357		.360	

[+] Signs of coefficients have been reversed to reflect effect on lifetime

* Significant at $p < .001$

^ Significant at $p < .05$

Table 4: Discounted Expected Transaction Model Estimation

Independent Variables	Model 1		Model 2		Model 3	
	Para-estimates	Stand-errors	Para-estimates	Stand-errors	Para-estimates	Stand-errors
Intercept	1.861*	0.187	0.213	0.229	-1.052*	0.289
Average Cross-buying	2.135*	0.059	2.559*	0.067	2.602*	0.067
Previous relationship length	0.043*	0.008	0.036*	0.007	0.035*	0.007
Advanced service usage			1.608*	0.139	1.600*	0.137
Age					0.030*	0.004
Region					-0.148	0.11
Adjusted R^2	0.459		0.500		0.516	

* Significant at $p < .001$