Modeling Customer Lifetime Value in the Telecom Industry

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Preface

This Master's thesis is written at the department of Production Management at Lund University, Faculty of Engineering (LTH), in cooperation with Ericsson. It has been a very interesting and challenging project that has required experience from previous course work at LTH as well as new knowledge in the fields of probability, statistics and telecom.

First, we want to thank our supervisors Peter Berling at the department of Production Management and Martin Englund at Ericsson for supervising us on the project. Without their guidance and expertise this thesis would not have been what it is. Furthermore, we want to acknowledge fellow employees Ericsson for helping us with contacts, interviews and data – most significantly Ola Saltvedt, Kajsa Arvidsson and Anders Kälvemark. This thesis is the final step of our program in Industrial Engineering and Management.

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Abstract

Title Modeling Customer Lifetime Value in the Telecom Industry

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Background The fierce competition in the telecom industry makes operators heavily invest in acquiring new customers. This is most often done with marketing campaigns and subsidies of handsets. But to be truly profitable, it is crucial not only to attract new customers, but also to make sure they retain with the company for as long time as possible. This turns the mobile operators' attention to customer lifetime value (CLV). Knowing what drives CLV give ideas of what is best to invest in, and this information can be very valuable for Ericsson in their sales and relationship to the operators.

Purpose The purpose is to develop a model to analyze what drives customer lifetime value of smartphone users. Furthermore, it will also be investigated how changing these parameters affects the total CLV, in order to show how different investments increases or decreases the customer lifetime value.

Theoretical Framework The theoretical framework builds on present CLV theory. Markov chain modeling is used to model the CLV, and ordered probit regression is applied to analyze the survey data.

Methodology This thesis takes a quantitative approach to model the customer lifetime value. The data used to derive the drivers of CLV is compiled from smartphone user survey questionnaires completed by Ericsson's Consumer Lab. The calculations are performed by simulating a large number of fictitious company-customer relationship processes in MATLAB.

Results The main result is a model that describes the dynamic relationship between a customer's preferences and the profit it generates during its lifetime. The model is then applied on six different markets across a number of segments to produce valuable information on how the CLV changes when customer satisfaction in different areas increase.

Keywords Customer Lifetime Value, CLV, Telecom, Churn, Retention, Ordered Probit Regression, Simulation

Sammanfattning

Titel	Modellering av kunders livstidsvärden inom telecomindustrin
Författare	Petter Flordal och Joakim Friberg, Lunds Tekniska Högskola
Handledare	Peter Berling, Lunds Tekniska Högskola Martin Englund, Ericsson
Bakgrund	Den hårda konkurrensen som råder inom telecomindustrin har gjort att operatörer investerar stora mängder pengar för att attrahera nya kunder. Ofta sker detta genom marknadsföringskampanjer och subventionerade mobiltelefoner. För att verkligen vara lönsamma är det viktigt att inte bara attrahera ny kunder, utan också behålla kunder så länge som möjligt. Det gör att intresset för kundernas hela livstidvärde ökar. Att förstå vad som driver en kunds livstidsvärde gör det enklare att utvärdera vilka investeringar som ger störst verkan. Denna information är mycket värdefull för Ericsson i deras försäljning- och markandsföringsarbete mot operatörerna.
Syfte	Syftet med detta examensarbete är att utveckla en model för att analysera vilka parametrar som driver kunders livstidsvärde inom telecomsektorn. Uppsatsen ämnar också att analysera hur förändringar i de drivande parametrarna påverkar det totala livtidsvärdet för en kund, för att på så sätt kunna ställa investeringar mot varandra.
Teori	Denna rapport bygger på de senaste teorierna inom området för kunders livstidsvärde. För att modellera livstidsvärdet används Markovkedjemodellering och för att analysera enkätdatan används en regressionsmetod kallad ordered probit regression.
Metod	Det här examensarbetet har ett kvantitativt förhållningssätt till kunders livstidsvärde. Datan som används för att härleda de drivande parametrarna

av livstidsvärden är hämtad från enkätundersökningar gjorda av Ericsson Consumer Lab. Uträkningar sker genom att simulera ett stort antal kundrelationer i MATLAB.

Resultat Huvudresultatet i denna rapport är en modell som beskriver det dynamiska förhållandet mellan kunders preferenser och den vinst som genereras under dess livstid. Modellen är därefter applicerad på sex olika marknader för att ge information om hur en kunds livtidsvärde förändras när olika nöjdhetsparametrar ökar.

Nyckelord Livstidsvärde, telecom, kundavhopp, Ordered Probit Regression, simulering

List of Abbreviations

CLV	Customer Lifetime Value
MNO	Mobile Network Operator
ARPU	Average Revenue Per User
WACC	Weighted Average Cost of Capital

Reading Instructions

This master thesis begins with a short introduction, including the background to and definition of the problem. The next chapter walks through the theory of customer lifetime value modeling and explains the fundamentals. The reader is expected to have basic knowledge in statistical and probability theory; hence the most basic concepts are not revised.

After the theory section, a methodology overview is given. Please note that this section only briefly introduces the method, in order to simplify reading. More details about and motivations to chosen methods and models can be found in *A.3 Key Methods and Models* in the appendix.

The fourth chapter contains hypotheses, followed by step-by-step analysis and results from the quantitative study.

The fifth chapter comprises a discussion section on the results and methodology. This is followed by the appendix, containing extended explanations and motivations to chosen methods and models, and paragraphs about the company overview and background.

Contents

1. Introduction

1.1 Background

Ericsson is one of the world's leading providers of communications technology and services. Their offering includes services, software and infrastructure within information and communications technology for telecom operators and other industries. In order to provide best in class products and services and achieve trust and reputation among its clients, Ericsson puts great effort in understanding the end user. Insights about the end users are an important sales tool to generate business and improve customer relations.

In today's fast changing society, staying connected is crucial. New customer behavior and products drive demand for higher performance in networks, creating intense competition over customers. Operators spend big money to acquire new customers, and to recoup the investment it is important to understand what drives customer retention and churn. Understanding these parameters makes it possible for operators to assess the customer lifetime value (CLV) of smartphone users, which is defined as *the measure of how much profit can be generated over the lifetime of a customer*.

1.2 Problem Definition

When Ericsson is approaching a customer, it is most often channeled through the IT or technical division of that company. The experience is that an investment in network performance is mostly considered in a separate budget compared to investments towards the end user. As a result, a company tends to prioritize marketing investments over improvements in the network, even though this is something customers value to a high extent. From understanding what drives customers' satisfaction, and ultimately what increases the customer life time value, Ericsson can put more effort on convincing the operators about investing in technology. The main problem can hence be summarized to*: what are the most important factors to increase CLV, and how can it be modeled in order to capture the impact of marketing and product investments?*

1.3 Purpose

The purpose is primarily to use existing statistical frameworks in order to model the customer lifetime value of mobile smartphone users. Furthermore, it aims to understand the drivers behind CLV and how they impact the profit of a firm. The insights will be used to assess, for a number of key markets, how different investment decisions affect the overall profit of a mobile network operator. Building on probability and statistical theory and applied in a practical marketing setting, this thesis aims to provide a framework for how quantitative methods can increase marketing knowledge in the telecom sector.

2. Theory

In the following section, a brief discussion of the main theories on Customer Lifetime Value is given. First, background of a number of models for customer lifetime value is presented. Then, theories are given about its main stochastic components – the probability of customers retaining and the profits over time.

2.1 Background to Customer Lifetime Value (CLV)

In the present marketing context, firms are increasingly focused on relationship marketing – developing and maintaining long-term relationships with profitable customers – rather than focusing on individual transactions.[1] This has proven to be more profitable over time. Not only is it important to build relationships with customers - it has to be with the *right customers*. The right customers are those that in the long term will generate the most profit to the firm, with which the firm will want to establish a loyal relationship through customer satisfaction.[2]

In order to ascertain that sufficient marketing efforts are focused on the most profitable customers, it is crucial for marketing divisions to evaluate the *customer lifetime value*. Kotler and Armstrong define CLV as the returns over time from a person, household or company, that exceed the cost of acquiring the customer and delivering the product.[3] In other words, CLV is a measure of how much profit can be generated over the lifetime of the customer. The vast amounts of data that marketing functions collect about customers give insights about the consumer behavior, and not only facilitate for calculating expected lifetime value of a customer but also enable ways to optimize it. This way, it can be ensured that the right marketing investments are made towards the right clients.

In estimations, CLV is mostly discounted to represent present monetary value, and incorporates the probability of a customer leaving the company for a competitor or another product. To understand the CLV models, we first define a few main components:

[1] Berger, P. and Nasr, N., *Customer Lifetime Value: Marketing Models and Applications,* Journal of Interactive Marketing, 1998

[2] ibid

[3] Kotler, P. and Armstrong, G., *Principles of Marketing,* Prentice Hall, New Jersey, 1996

Retention Rate – p	The probability that a customer stays with a company over a given period. The retention rate can be estimated with historical data
Churn Rate - *γ*	The probability that a customer ends the relationship with a company during a given period, for any reason. *The churn rate is (1-p), meaning it is the counterpart of retention rate*
Discount Factor - *d*	The factor with which the future cash flows are discounted in order to represent value for the firm today
Net Return – r	The sum of all returns generated from a customer during a period
Net Costs – c	The sum of all costs from serving a customer during a period, including production costs, delivery cost, service, etc.
Net Profit - *P*	The difference between returns and all costs involved in delivering product and connected services to a given customer during a given period, (r – c)
Time Horizon - *T*	The upper bound on which the CLV analysis is conducted. The time horizon is set to simplify calculations, or to compensate for the fact that the future business climate will imply different conditions for the relationship between company and customer

To achieve a high CLV, a company should develop a marketing strategy that *maximizes* retention rate and net profit, and *minimizes* acquisition costs, remarketing costs and obviously churn rate. However, there is a close relationship between the positive and negative factors. For example, a company might achieve a higher retention rate by increasing spending on customer service, which will on the other hand lower net profits. CLV is an efficient way to evaluate this kind of actions.

2.3 CLV models

In the following sub-sections, different models for calculating the customer lifetime value are presented.

2.3.1 Simple models

The simplest way to model CLV is to sum up all excess cash flows during the time horizon, discounted to a certain factor d. For customer j, this can be expressed with the following formula[4]:

$$CLV_j = \sum_{t=0}^{T} \frac{(r_{tj} - c_{tj})}{(1+d)^t} \tag{2.1}$$

This formula assumes that the cash flows are known for each period during the time horizon. For example, if customer j churns at $t = 5$, it means that $r_{tj} = 0$ for $t > 4$. This deterministic model gives an easily calculated estimate of CLV when cash flows are known, which is rarely the case. To give a more realistic estimate, one must use a model that accounts for stochastic nature of the CLV.

2.3.2 Retention Models

A retention-based model describes a situation where, for each time period, there is a probability that the customer stops purchasing from the company. Once a customer has left the company, it is considered gone forever. This is realistic when there is a high cost barrier for a customer to switch supplier, and it is therefore unlikely that the customer will come back once it has left. First, the probability that a customer remains a customer over one period is denoted as:

$$Pr(customer\ retains\ over\ period\ t) = retention\ rate = p_t \tag{2.2}$$

It can be assumed that this probability is constant over all periods, meaning the likelihood of the customer leaving the company is unconditional on how long the relationship has lasted. In a general case, the probability that a customer stays with a company from time $t = 0$ through time $t = n$ is given by:

[4] Tirenni, G., *Allocation of Marketing Resources to Optimize Customer Equity*, University of St. Gallen, Gutenberg AG, FL, 2005

$$Pr(customer\ retains\ through\ period\ n) = p^n \tag{2.3}$$

Furthermore, it is assumed that the net profit is constant over time. These assumptions give the following model[5]:

$$E[CLV_j] = (\overline{r_j} - \overline{c_j}) \sum_{t=0}^{T} \left(\frac{p}{(1+d)}\right)^t \tag{2.4}$$

The time unit for a discount factor and time horizon is commonly given in years. However, both retention rate of the customer and cash flows might preferably be described in terms of shorter time periods. In the following formula, every time period is divided into n sub-periods[6]:

$$E[CLV_j] = \left(\overline{r_j}' - \overline{c_j}'\right) \sum_{t=0}^{nT} \frac{p'^i}{(1+d)^{\frac{i}{n}}} \tag{2.5}$$

$$where \begin{cases} i_j' = average\ return\ in\ a\ \dfrac{1}{n} period \\ c_j' = average\ cost\ in\ a\ \dfrac{1}{n}\ period \\ p' = \ retention\ rate\ in\ a\ \dfrac{1}{n}\ period \end{cases}$$

The assumption that cash flows are constant is obviously weak in most cases. The function $\pi(t)$ is introduced, which represent the net profit as a function of time. Now, CLV can be expressed in continuous representation, since returns and costs can occur at any given time. In the continuous case, a continuously compounded discount rate is used, which is given by $\grave{d} = \ln(1+d)$. This gives the following formula[7]:

$$E[CLV_j] = \ \pi(0) + \int_0^n \pi(t)\, p^t e^{-t\grave{d}} dt \tag{2.6}$$

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[5] Berger, P. and Nasr, N., *Customer Lifetime Value: Marketing Models and Applications,* Journal of Interactive Marketing, 1998
[6] ibid
[7] ibid

For this model to be efficient, it is necessary to estimate a function for profits over time. This can be challenging in many cases, but might be derived from historical customer data (section A.3.10).

2.3.3 Migration Models

In migration-based models, one rejects the assumption that a customer that doesn't buy in one period is lost forever. Instead, the recency of the last purchase of a customer is used to determine the probability of a purchase in the present period. Usually, the longer a customer has been absent, the less likely it is that he will purchase again. There are a number of ways to use the migration-based idea, of which Dwyer developed the most popular[8]. His methodology is divided into two steps. In the first step, the number of customers who purchase at time t is given by the following expression, where p_j is the probability of purchase if the customer's last purchase was j periods ago:

$$N_t = \sum_{j=1}^{t} \left[N_{t-j} p_j \prod_{k=1}^{j} (1 - p_{j-k}) \right] \tag{2.7}$$

In the expression, the summation is conducted over all previous periods. This can be simplified by deciding a recency for which the customer is considered gone forever. The intuition behind this expression is that it sums up the number of customers for each recency since last purchase, multiplied by the probability that they buy at time t. Now, given the number of customers in each period, an expression for average CLV is derived[9]:

$$E[CLV_j] = \frac{\overline{r_j} - \overline{c_j}}{N_0} \sum_{t=0}^{T} \frac{N_t}{(1+d)^t} \tag{2.8}$$

[8] Dwyer, R., *Customer Lifetime Valuation to Support Marketing Decision Making,* Journal of Direct Marketing, 1997

[9] ibid

2.3.4 Markov Models

Markov chain models are based on the idea of the migration model, but are generalized to a case that is more adjustable to a real marketing situation. In order to explain the nature of Markov models, the concept of states is introduced. The state vector $\{S_0, S_1, S_2, \dots, S_k\}$ contains k states, of which each describes a number of attributes of the relationship between the company and the firm. The most commonly used description for each state is recency, i.e. number of periods since last purchase. However, in many situations it is more relevant with other – or more – attributes, i.e. amount of money spent, type of customer, type of purchased product, etc. Below is a figure that visualizes an example Markov chain with four states S_0, S_1, S_2 and S_3:

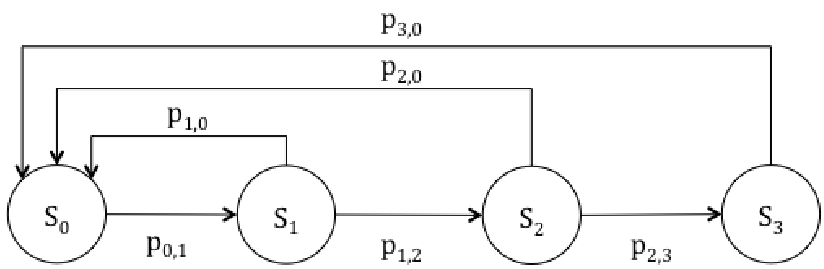

Figure 2.1Markov Chain

A condition for a Markov chain to be valid is that the probability for a customer to move from one state to another is only dependent on the present state, and unconditional on all previous states[10]:

$$Pr(S_{t+1} | S_t,\ S_{t-1}, S_{t-2}, \dots) =\ Pr(S_{t+1} | S_t) \tag{2.9}$$

The probability that a customer moves from one state to another is described by the transition probability matrix P, where $p_{i,j}$ denotes the probability of moving from state i to state j:

$$P = \begin{bmatrix} p_{0,0} & p_{0,1} & \cdots & p_{0,k-1} & p_{0,k} \\ p_{1,0} & p_{1,1} & & p_{1,k-1} & p_{1,k} \\ \vdots & & \ddots & \vdots & \\ p_{1,k-1} & p_{k-1,1} & \cdots & p_{k-1,k-1} & p_{k-1,k} \\ p_{1,k} & p_{k,1} & & p_{k,k-1} & p_{k,k} \end{bmatrix} \tag{2.10}$$

[10] Dwyer, R., *Customer Lifetime Valuation to Support Marketing Decision Making,* Journal of Direct Marketing, 1997

Associated with the state vector $\{S_k\}$, a profit vector $\{R_0, R_1, R_2, \ldots, R_k\}$ is declared, where R_i denotes the expected return for a customer in state i during one period. Using these expressions, we can now express the customer lifetime over the time horizon T[11]:

$$E[CLV^T] = \sum_{t=0}^{T} \left(\frac{P}{1+d}\right)^t R \tag{2.11}$$

This expression can be generalized to infinite time horizon[12]:

$$\lim_{T\to\infty} E[CLV^T] = \left\{I - \frac{P}{1+d}\right\}^{-1} R \tag{2.12}$$

The actual calculation of the expression above is fairly easy, however it might be difficult the estimate the transition probability matrix and the profit vector.

2.3.5 Markov Decision Processes

Markov models allow for including decision variables in the model, besides the stochastic variables. Such models are known as *Markov Decision Processes* (MDP)[13]. In each state in an MDP, there is a choice to make for the company. This choice is likely to affect the transition probabilities for next period. For example, if a customer of mobile services has reached the end of her contract period, the service provider may choose to offer the customer a new phone to no additional cost to convince her to retain, or do nothing. In this case, offering a new phone is an action with the ambition to improve the probability of keeping the customer. Below is a graphic example of what a Markov Decision Process might look like. The white and black nodes represent states and actions respectively. The dashed lines represent probabilities conditional that a specific action has taken place.

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[11] Pfiefer, P. and Carraway, R., *Modeling Customer Relationships as Markov Chains*, Journal of Interactive Marketing, Charlottesville, VA, 2000
[12] Tirenni, G., *Allocation of Marketing Resources to Optimize Customer Equity*, University of St. Gallen, Gutenberg AG, FL, 2005
[13] ibid

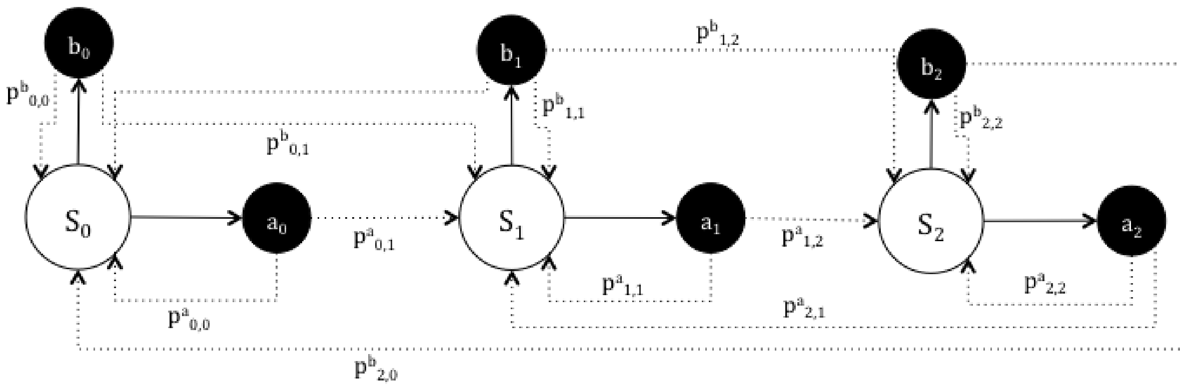

Figure 2.2 Markov Decision Process

Drawing conclusions from the MDP is not quite as straight forward as the previous models, since it involves alternatives of action. Rather than extracting an absolute value of the customer lifetime value, the Markov Decision Process has a purpose of finding a *strategy* that optimizes the lifetime value[14].

There are two major ways to analyze a MDP. The first is to mathematically find an optimal strategy. This analysis can be performed by *dynamic programming*, either analytically with *backward induction*, or using computer programming. A second way is to simulate the process for a specified strategy. Simulations allow evaluating a strategy rather than finding the optimal. The actual simulations can be performed by running a large number of fictitious customers through the stochastic process, using MATLAB or other programs that has functions for generation of random variables with a given distribution. A distribution of the aggregate CLV is then generated by the array of results – the CLVs for all fictive customers. This procedure is often referred to as *Monte Carlo simulations*.

2.4 Retention Rate

As all models for customer lifetime value incorporate some kind of stochastic variable for a customer to retain (or churn), it is crucial to find a good way to determine the characteristics of this variable. First, retention is defined based on current literature. Second, what influences the retention rate in the mobile telecommunications industry is examined. Third, theories are assessed on how the retention rate might be estimated.

[14] Tirenni, G., *Allocation of Marketing Resources to Optimize Customer Equity*, University of St. Gallen, Gutenberg AG, FL, 2005

The study of retention (and churn) focuses on measuring the degree to which a company satisfies its customers, and on identifying the customers with a high probability to churn[15]. The retention rate is defined as the probability that a customer continues its relationship with the company through a given time period. Modeling retention involves explaining the retention level based on customer behavior and characteristics[16].

The factors that are considered to have most influence on the customers' likelihood to churn greatly vary between markets and customer segments. In telecom, the most commonly mentioned in recent literature include network quality, handset, cost structure, customer service and brand image.

When it comes to modeling retention predictions, the procedures depend on what kind of data is available. Most recent theory apply to cases when the dataset constitutes of usage data and consumer characteristics, i.e. call history, contact with customer service, amounts spent, age, gender, etc. There are a number of advanced techniques that originate from data of this nature:

- Keramati and Ardabili (2011) models churn prediction from a binomial logistic regression using a series of factors, with churn history as the dependent variable[17], applied to the Iranian market. The method uses classical econometrics in order to test the significance of the factors[18]
- De Bock and Van den Poel (2011) introduces a rotation-based ensemble classification algorithm, using Rotation Forest for classification and Principal Components Analysis, Independent Component Analysis and Sparse Random Projections for extractions[19].
- Kim, Lee, Jung and Kim (2012) uses a similar technique, but with an SVM classifier and Principal Components Analysis[20]
- Song, Yang, Wu, Wang and Tang (2006) present a mixed process neural network approach, based on Fourier orthogonal base functions, and apply the method on China Mobile[21]

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[15] De Bock, K. and Van den Poel, D., *An Empirical Evaluation of Rotation-Based Ensemble Classifiers for Customer Churn Prediction*, Expert Systems with Applications, Lille, France, and Ghent, Belgium, 2011
[16] ibid
[17] Keramati, A. and Ardabili, S., *Churn Analysis for an Iranian Mobile Operator,* Telecommunications Policy, ed. 35, Tehran, 2011
[18] ibid
[19] De Bock, K. and Van den Poel, D., *An Empirical Evaluation of Rotation-Based Ensemble Classifiers for Customer Churn Prediction*, Expert Systems with Applications, Lille, France, and Ghent, Belgium, 2011
[20] Kim, N., Lee, J., Jung, K. and Kim, Y., *A New Ensemble Model for Efficient Churn Prediction in Mobile Telecom,* 45th Hawaii International Conference on System Sciences, 2012

- Hung, Yen and Wang (2006) uses advanced data-mining techniques, incorporating some of the techniques mentioned above[22]

Although these techniques are very sophisticated and show a high degree of accuracy compared to actual outcomes, they demand vast amounts of customer data directly extracted from operator CRM systems. Also, the techniques demand a very high level of data programming abilities and data-mining programs. In cases when the dataset and time frame is limited, other prediction models have to be studied.

Some researchers approach the problem by applying Discrete Choice Theory which originates from McFadden (1981), for which he was awarded the Nobel Prize in 2000. In Discrete Choice Theory, the probability that a person makes a certain choice is modeled based on the performance of the alternatives and individual attributes. In the mobile market, the performance of the alternatives can be represented by the customer satisfaction on a number of areas, and the individual attributes are customer demographics and usage habits. The theories also express the asymmetry between the consumer's utility and the researcher's ability to observe it, in order to capture unobservable factors or irrational behavior of the consumer.[23]

An example of a model based on discrete choice theory applied to mobile telecommunication is Kim and Joon (2004)[24], who apply an econometric binomial logit model to predict retention in the Korean mobile market. The binomial choice is whether to retain or to churn, and they use discrete variables based on customers' responses in satisfaction surveys, and perform a regression in order to determine the probability. The basic idea is that the probability of churning can be determined by comparing utility between staying with current mobile carrier k and leaving the carrier for an alternative provider[25]:

$$Pr(churn|k) = Pr(U_{churn} > U_{not\ churn}) \tag{2.13}$$

[21] Song, G., Yang, D., Wu, L., Wang, T. and Tang, S., *A Mixed Process Neural Network and its Application to Churn Prediction in Mobile Communications*, Data Mining Workshops, 2006
[22] Hung, S., Yen, D. and Wang, H., *Applying Data Mining to Telecom Churn Management,* Expert Systems with Applications, ed. 31, 2006
[23] McFadden, D., *Economic Choices,* University of California, Berkeley, CA, 2001
[24] Kim, H. and Yoon, C., *Determinants of Subscriber Churn and Customer Loyalty in the Korean Mobile Telephony Market*, Telecommunications Policy, ed. 28, Hanyang University, Republic of Korea, 2004
[25] ibid

The utility of each choice is the sum of the *observed* utility and an unobservable error term. The error term represents the part of the individual's behavior that a researcher cannot explain. Let the observed utility be denoted by V_k for alternative *k*, and ε_k denote the error term for alternative *k*:

$$U_k = V_k + \varepsilon_k \tag{2.14}$$

The expression for the churn probability above can then be rewritten as[26]:

$$\begin{aligned} Pr(churn|k) = Pr(U_{churn} > U_{not\ churn}) &= Pr(V_{churn} + \varepsilon_{churn} > V_{not\ churn} + \varepsilon_{not\ churn}) \\ &= Pr(\varepsilon_{churn} - \varepsilon_{not\ churn} > V_{not\ churn} - V_{churn}) \end{aligned} \tag{2.15}$$

This probability can be reformulated to a function where the observed part is dependent on a number of variables describing customer characteristics and satisfaction about the performance of the carrier. If k represent the current carrier, *j* represents the customer, x_{jk} is a vector of factors and β is a vector of coefficients, this function can be written as[27]:

$$P_{j\ churns} = Pr\left(\max_{alternatives\ i=1,2\ldots} U_i > U_k\right) = F(x_{jk}\beta) \tag{2.16}$$

The unobserved part can be added by an error term, which gives:

$$P_{j\ churns} = Pr\left(\max_{alternatives\ i=1,2\ldots} U_i > U_k\right) = F\left(x_{jk}\beta\right) + \varepsilon_j \tag{2.17}$$

2.5 Ordered Logit and Probit Models

In some situations, dependent and/or independent variables are observed from discrete sets (binomial or multinomial), rather than continuous sets. Originating from discrete choice theory, *ordered logit* and *probit models* are tools developed to perform regressions in these cases. Their application to retention rate analysis is exemplified in Kim and Joon (2004)[28] and in Donkers,

[26] McFadden, D., *Economic Choices*, University of California, Berkeley, CA, 2001
[27] Kim, H. and Yoon, C., *Determinants of Subscriber Churn and Customer Loyalty in the Korean Mobile Telephony Market*, Telecommunications Policy, ed. 28, Hanyang University, Republic of Korea, 2004
[28] ibid

Verhoef and de Jong (2007)[29].These models come from the idea of a latent regression model or an underlying random utility model[30]:

$$y_i^* = \beta' x_i + \varepsilon_i, \qquad i = 1, \ldots, N \tag{2.18}$$

where y_i^* is a utility that is measured in discrete form through a censoring function:

$$y_i = \begin{cases} 0 \text{ } if \text{ } \mu_{-1} < y_i^* \leq \mu_0 \\ 1 \text{ } if \text{ } \mu_0 < y_i^* \leq \mu_1 \\ 2 \text{ } if \text{ } \mu_1 < y_i^* \leq \mu_2 \\ \qquad \ldots \\ J \text{ } if \text{ } \mu_{J-1} < y_i^* \leq \mu_J \end{cases}$$

The model contains unknown coefficients β and threshold values μ_k. These need to be estimated using N observations.[31] The last specification of the model concerns the error term. The logit model assumes standard logistic distribution, and the probit model assumes that it is standard normally distributed.[32] With respect to the model above, the probability for each outcome is defined by[33]:

$$Pr(y_i|x_i) = Pr(\varepsilon_i \leq \mu_j - \beta' x_i) - Pr(\varepsilon_i \leq \mu_{j-1} - \beta' x_i) \tag{2.19}$$

Often the data is normalized such that σ_ε is constant. In the probit case, it set to $Var(\varepsilon_i|x_i) = 1$, and in the logit case $Var(\varepsilon_i|x_i) = \frac{\pi^2}{3}$. Then, the likelihood function is given by[34]:

$$Pr(y_i = j|x_i) = \left[F(\mu_j - \beta' x_i) - F(\mu_{j-1} - \beta' x_i)\right] > 0, \qquad j = 0, 1, \ldots, J \tag{2.20}$$

[29] Donkers, B., Verhoef, P. and de Jong, M., *Modeling CLV: A test of competing models in the insurance industry* ,Quantitative Marketing and Economics, 2007
[30] Greene, W. and Hensher, D., *Modeling Ordered Choices: A Primer and Recent Developments*, New York University, New York, NY, 2008
[31] ibid
[32] ibid
[33] ibid
Note: the original formula in the reference contains an error, which is corrected upon discussion with the author of the article, Professor Greene of New York University
[34] Greene, W. and Hensher, D., *Modeling Ordered Choices: A Primer and Recent Developments*, New York University, New York, NY, 2008

Estimation is most efficiently performed with Maximum Likelihood, with the log likelihood function[35]:

$$logL = \sum_{i=1}^{n} \sum_{j=0}^{J} m_{ij} \log\left[F(\mu_j - \beta' x_i) - F(\mu_{j-1} - \beta' x_i)\right] \tag{2.21}$$

where $m_{ij} = 1$ if $y_i = j$ and *0* otherwise.

Note the similarities with the churn probability regression models in the section above. For this model to be appropriate, one needs to ensure that the measured outcomes indeed have an ordered nature, meaning that the ranking is monotonic on a (or something corresponding to) a preference scale[36]. If a higher number doesn't necessarily imply a more positive outcome, a different model should be considered.

2.6 Discount Rate

An important part of the CLV models described is the rate to which the net contributions are discounted, known as the discount rate. There are different theories on how to choose an appropriate discount rate, but according to capital budgeting theory investing in customers should be viewed as project investments. Therefore, it should be discounted with the project opportunity cost of capital - the rate of return investors could achieve by investing in a project with similar risk.[37] To calculate the opportunity cost of capital one can turn to the capital asset pricing formula (CAPM) which is a well-established way of determining an appropriate discount rate.[38] The CAPM states the relationship between the opportunity cost of capital for the project as followed[39]:

$$r_{project} = r_f + \beta_{project} * (r_m - r_f) \tag{2.22}$$

where

$$r_{project} = project\ opportunity\ cost\ of\ capital$$

[35] Greene, W. and Hensher, D., *Modeling Ordered Choices: A Primer and Recent Developments,* New York University, New York, NY, 2008
[36] ibid
[37] R. Blattberg, E. C. Malthouse, S. A. Neslin, *Customer Lifetime Value: Empirical Generalizations and Some Conceptual Question*, Journal of Interactive Marketing, 2009
[38] ibid
[39] Brealy, R., Myers, S. and Allen, F., *Principles of Corporate Finance,* McGraw-Hill/Irwin, Northwestern University, 2008

$r_f = risk\ free\ rate$

$\beta_{project}$ = correlated volatility of the project to the market

$r_m = market\ return$

The beta of the project is in general hard to observe or estimate and consequently it becomes difficult to calculate a fair discount rate. If, however, one assumes that the risk of the project investment is similar to the risk of projects that the firm normally pursues, the opportunity cost of capital for the whole firm can be used.[40] The opportunity cost of capital for the firm can be approximated with the company's weighted average cost of capital (WACC)[41]. The WACC takes the debt policy of the company as well as the tax shield into account and is given by the following formula:

$$WACC = g * (1 - T) * \left(R_f + DRP\right) + (1 - g) * (R_f + \beta_j * ERP) \tag{2.23}$$

where

$$g = \frac{D}{D + E}$$

The parameters are defined as follows:

- D is the sum of the debt
- E is the sum of the equity
- T is the corporate tax rate
- DRP is the debt risk premium (the difference between the risk free rate of return and the interest of company's debt)
- R_f is the risk free interest rate
- ERP is the equity risk premium (the required return on the market portfolio above the risk free rate)
- β_j is the asset beta (the sensitivity of the return on asset j relative to the market portfolio)

[40] Brealy, R., Myers, S. and Allen, F., *Principles of Corporate Finance,* McGraw-Hill/Irwin, Northwestern University, 2008

[41] ibid

2.7 Customer Equity

The Customer Equity (CE) is the lifetime value of all customers in the company's customer base, and is obviously closely related to CLV[42]. The Customer Equity is simply given by the formula:

$$CE = \sum_{j=1}^{N} CLV_j \tag{2.24}$$

Customer Equity is a popular measure of a company's value.

3. Methodology Overview

This section will present an overview of the methodology. More detailed descriptions and motivations for chosen methods and models are available in section A.3.

3.1 The Model

To model Customer Lifetime Value, a *Markov Chain Model* will be used. The Markov model allows for more flexibility than most other potential models, and can incorporate variables such as non-constant retention rate, which is not possible in the simpler models.[43] The model allows looking at individual customer relationships as well as averages, and its probabilistic nature makes the uncertainty of the profits apprehensible[44]. The Markov Decision Process is also appealing, but since dynamic decisions along the lifetime of the customer will not be evaluated the Markov Chain is the simplest model that still meets the requirements. Each state in the Markov Chain will represent a person being a customer for one month, with an infinite number of states (section A.3.1). The transition probability to move from one state to the next is equivalent to a customer retaining with the operator to the next month. A customer that has churned will be considered lost forever. For each state, there will be a corresponding net profit (section A.3.10). The cash flows will be discounted to present value using an industry and market specific discount rate (section A.3.11). The figure below visualizes the Markov Chain. S_0 represents not being a

[42] Tirenni, G., *Allocation of Marketing Resources to Optimize Customer Equity*, University of St. Gallen, Gutenberg AG, FL, 2005

[43] Pfiefer, P. and Carraway, R., *Modeling Customer Relationships as Markov Chains*, Journal of Interactive Marketing, Charlottesville, VA, 2000

[44] ibid

customer, and p_1 is the probability that a customer is acquired. Since it is the CLV of a present customer that is to be estimated, the relevant states are $S_1, \ldots, S_k, k \to \infty$, each representing one month as a customer.

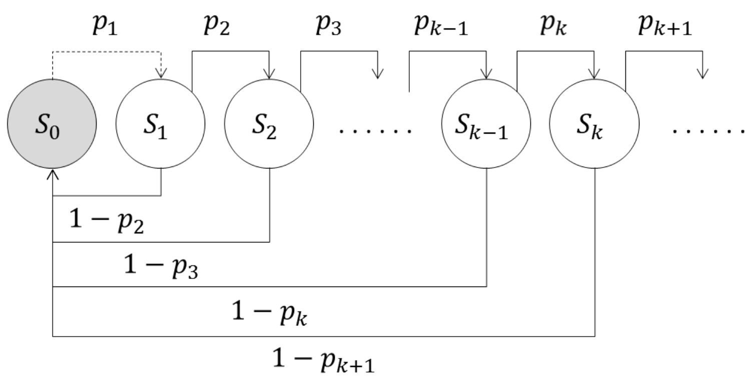

Figure 3.1Markov Chain Model

In the chart below, the general steps of the analysis process are illustrated. There are three major inputs needed in the Markov model: the *retention rate* (i.e. the transition probabilities), the *discount rate* and *net profit* for any given state. The retention rate is given from survey data[45] and the discount rate and net profit are estimated using industry averages.

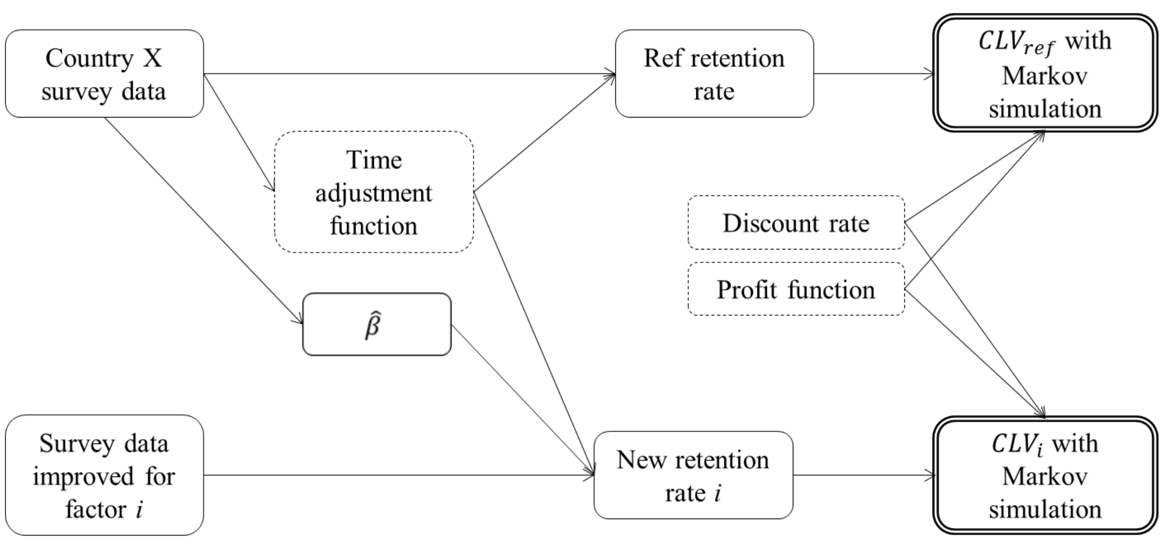

Figure 3.2 Analysis Process, Overview

45 Ericsson Consumer Lab, *INFOCOM – Smartphone Quality, New Markets*, 2012

3.2 Deciding the Retention Rate

In order to determine the retention rate, an *ordered probit regression* will be performed on a set of survey data. Customer satisfaction levels in a number of areas will be the independent variables, and stated likelihood of switching operators will be the dependent variable (section A.3.2). The probit regression is adapted to ordered, discrete data, which makes it appropriate to use on the survey dataset. It has also been used in previous research on churn in the telecom business, most notably in Kim and Joon[46] and in Donkers, Verhoef and de Jong[47]. The derived β's will be used on the dataset to compute an average *retention score* – meaning the average likelihood of switching operators on a scale 0-10. This value will be put in relation to true retention rates given by customer statistics. A certain retention score is then assumed to correspond to a certain true retention rate through a linear relationship.

By looking at how the retention score differs depending on how long an individual has been a customer, it will be investigated if the retention rate is dependent on time. A *time adjustment function* for the time dependency will be derived and included in the model. The effect is that the transition probability between states in the Markov chain is not constant – rather the probability will be adjusted over time to match the true nature of the retention rate.

3.3 Discount Rate and Profit Function

The discount rate that will be used in the CLV calculations is the *weighted average cost of capital*, or WACC. The WACC is calculated using factors described in the section A.3.11. Some factors in the WACC formula are country specific and some are company specific, which will be estimated with industry averages in order to generate a WACC that represents a standard MNO in the specific country. The profit function will be calculated by deducting an industry average percentage from the ARPU to end up with the net profit. The change in ARPU due to competition in the industry and the time being a customer will also be analyzed in order to capture the behavior of profits over time.

3.4 Calculating the CLVs

Once the retention rate, profits and discount rate are determined, the *reference CLV* for each market will be computed. The *reference CLV* refers to the average lifetime value, given the

[46] Kim, H. and Yoon, C., *Determinants of Subscriber Churn and Customer Loyalty in the Korean Mobile Telephony Market*, Telecommunications Policy, ed. 28, Hanyang University, Republic of Korea, 2004
[47] Donkers, B., Verhoef, P. and de Jong, M., *Modeling CLV: A Test of Competing Models in the Insurance Industry* ,Quantitative Marketing and Economics, 2007

current levels of satisfaction among the customers. The CLV will be calculated using MATLAB Monte Carlo simulations, running a large number of fictitious customer-company relationship processes, and extracting the results of the average customer. Simulation is more efficient than analytical methods, since an indefinite number of states make matrix algebra complicated. It also allows visualizing the distribution of the results more easily than with algebraic calculations.

When the reference CLV is determined, the influence of improvement in factors will be examined – representing the CLV sensitivity of the factors. First, the significance of the factors will be analyzed for each individual market. Then, one at a time, each factor (satisfaction level) will be given an increased average score of 10 % in the dataset series. The intuition behind this is to examine the return on an investment that on average is expected to increase a specific satisfaction level with 10 %[48] [49]. The improvement in satisfaction will give a new average retention score, which is translated to a new retention rate. Using the same calculation method as for the reference CLV, a new CLV will be derived. Comparing the improved CLVs with the reference CLV and each other will be the base for analysis of which factors are the strongest drivers of improved CLV.

4. Quantitative Analysis and Results

This chapter will, after a presentation of the main hypotheses, walk through the calculations step by step. The correlation of the survey factors will be assessed in order to determine which factors to incorporate. Then the main parameters of the CLV will be analyzed, followed by a presentation of the results from the calculations.

4.1 Hypotheses

The quantitative analysis will focus on investigating, and in some cases proving, the following hypotheses:

- Satisfaction levels from survey datasets give a fair explanation of what drives the retention rate among smartphone users

[48] Two examples:

1. An investment in a bigger customer service apparatus can lead to improved satisfaction level on the customer service factor
2. Investing in a more sophisticated network can give improved satisfaction level on the network performance factor

[49] Note: the *size* of these investments is difficult to determine. For example, and investment to improve network performance satisfaction with on average 10 % might be significantly bigger than an investment leading to an equally high average increase in customer service satisfaction.

- Retention rate is expected to be non-constant over time
- Profits are expected to be non-constant over time
- *Network Performance, Value for Money* and *Offered Handset* are believed to be the most significant drivers behind CLV
- *Network Performance* is expected to be more significant in countries where the overall network quality is lower
- Post-paid customers are believed to have a higher retention rate than pre-paid customers

4.2 Correlation

A reference series of data from US, UK and Sweden is used to determine which factors to include. The correlation matrix of the factors from the aggregated series can be found below:

	Purchase Process	*Billing/ Payment*	*Account Mngmt*	*Customer Support*	*Network Perf.*	*Value for Money*	*Handset Offered*	*Price Plan Options*	*Commun ication*	*Loyalty Rewards*
Purchase Process	1,000	0,727	0,716	0,667	0,578	0,637	0,691	0,637	0,640	0,466
Billing/Payment	0,727	1,000	0,826	0,696	0,590	0,653	0,638	0,661	0,652	0,459
Account Mngmt	0,716	0,826	1,000	0,743	0,616	0,657	0,664	0,661	0,700	0,484
Customer Support	0,667	0,696	0,743	1,000	0,651	0,684	0,636	0,652	0,736	0,579
Network Performance	0,578	0,590	0,616	0,651	1,000	0,711	0,609	0,606	0,661	0,492
Value for Money	0,637	0,653	0,657	0,684	0,711	1,000	0,662	0,792	0,745	0,649
Handset Offered	0,691	0,638	0,664	0,636	0,609	0,662	1,000	0,710	0,703	0,464
Price Plan Options	0,637	0,661	0,661	0,652	0,606	0,792	0,710	1,000	0,769	0,625
Communication	0,640	0,652	0,700	0,736	0,661	0,745	0,703	0,769	1,000	0,678
Loyalty Rewards	0,466	0,459	0,484	0,579	0,492	0,649	0,464	0,625	0,678	1,000

Figure 4.1 Correlation Matrix

The correlations between the factors for the aggregated series correspond to the individual series to a large extent (all correlation matrices can be found in A.4). Therefore, the matrix above can be considered representable. A few main points can be extracted from the matrix:

- First, there is a high correlation between Billing/Payment and Account Management, which is intuitive. Due to the high correlation, these factors will be combined
- Value for Money, Price Plan Options and Communication all have a high correlation to each other, and might therefore be considered to be combined. However, Value for Money is believed to have a high influence on the retention score, and will therefore be kept individual. Price Plan Options and Communication will be combined.

4.3 Retention Score over Time

Many CLV models assume that the retention probability is constant over time. This assumption greatly simplifies calculations. However, the Markov Chain model allows the retention probability to be time dependent, and therefore more realistic. In the survey, the recipients have stated how long they have been a customer, given in buckets (less than 3 months 3-6 months, 6-12 months, etc.). Putting the duration in relation to their declared likelihood of switching operators can explain how the retention varies over time, which is visualized in the graph below:

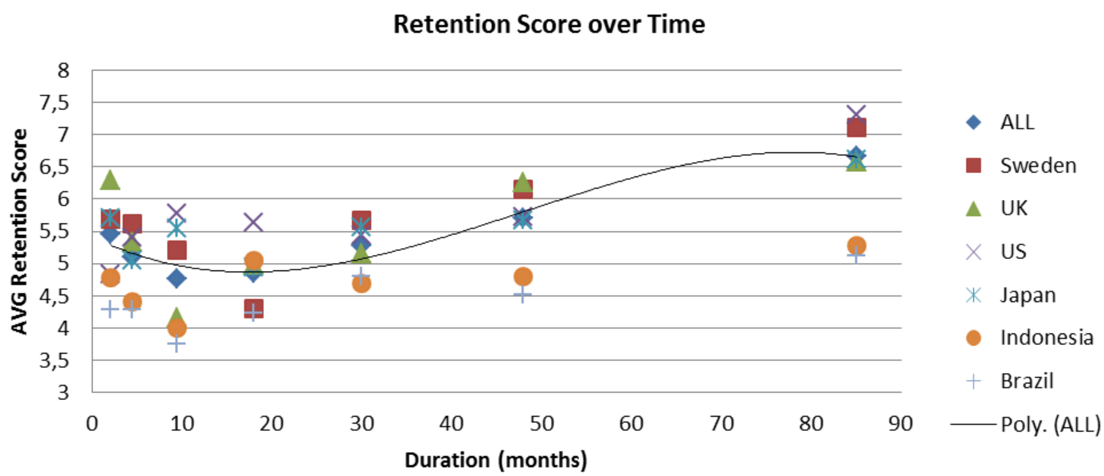

Figure 4.2 Graph: Retention Score over Time

Note that each bucket is approximated to its mean, e.g. 3-6 months is stated as 4.5 months. The highest bucket, more than 5 years, is approximated to 85 months. The figures can be normalized to each individual market's average, in order to more clearly show the trend:

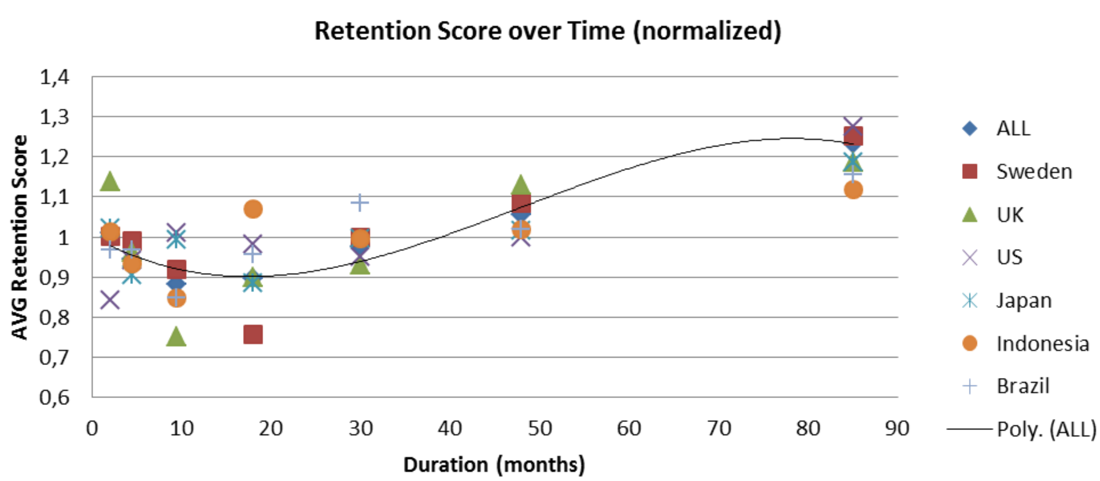

Figure 4.3 Graph: Retention Score over Time, Normalized

Looking at the graph, one can conclude that the average retention score is in fact not constant over time. Instead, it tends to be quite high initially, and then drop around 12-24 months. This drop can be explained by binding periods, which are commonly 12-24 months long. When the binding period ends or is about to end, it is intuitive that customers are more likely to switch operators. Beyond the end of the binding period, customers have an increasing average probability of retaining.

This observation means that, given that retention scores in fact explain true retention rates, the probability to retain in each period must be dependent on time, in accordance to the trend above. Therefore, an adjustment function should be introduced, to recalculate the retention score from a constant value to values that matches the behavior. It is unlikely that this adjustment will be perfect, since it all comes down to average figures. But to capture the overall trends, an interpolation curve normalized to correspond to the average retention score for each individual market (given in figure 4.3) is assumed to be appropriate.

The fact that the customer relationship duration is given in buckets is clearly a restriction in the interpolation. Also, there is an upper bound (more than 5 years) over which all customers are put in the same bucket. To cope with this limitation, it was assumed that the retention rate curve is constant from the point where the interpolation curve derivative equals zero, which happens around 68 months. This is intuitive, since it is unlikely that the retention rate would actually decline at higher durations, as a third order interpolation curve suggests. Given these assumptions, the *time adjustment function* is given by:

$$f(t) = \begin{cases} -3 * 10^{-6}t^3 + 0.0005t^2 - 0.0126t + 1.0028 & if\ 0 \leq t < 68 \\ 1.0523 & if\ t \geq 68 \end{cases} \tag{4.1}$$

4.4 Transforming Retention Score into Retention Rate

In order to translate retention scores from the survey analysis into retention rates to be used in the CLV calculations, their relationship needs to be investigated. The basic assumption, as discussed above, is that a certain retention score from the surveys correspond to a certain probability of remaining as a customer, i.e. retention rate. Looking at the average retention scores for each market in the sample and their corresponding retention rate derived directly from user data[50], the relationship can be evaluated:

[50] Strategy Analytics, *Wireless Operator Strategies, Worldwide Cellular User Forecasts, 2012-2017*, 2013

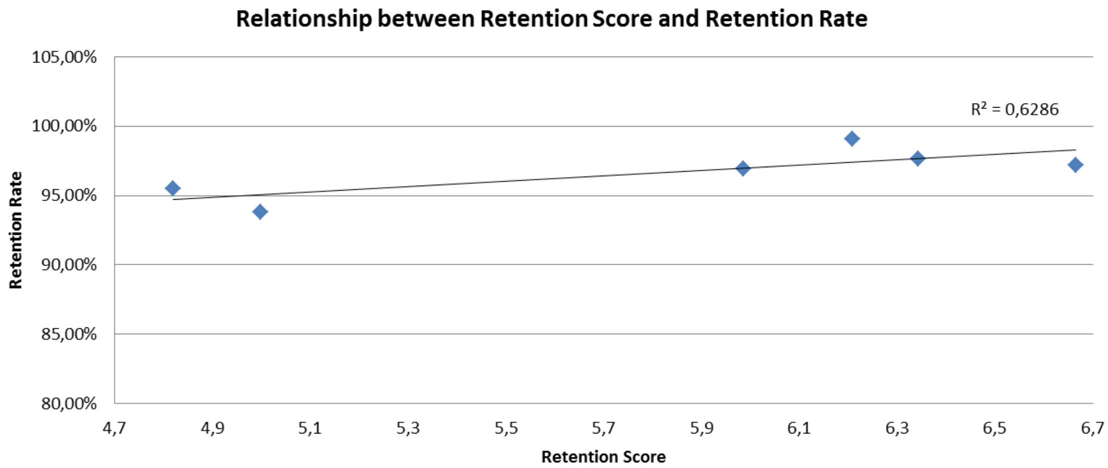

Figure 4.3 Graph: Retention Score and Retention Rate

R^2-value of 0.6286 is not perfect, but is considered sufficiently high to state that a higher retention score indeed corresponds to a higher retention rate. However, with the interpolation above, the retention rate would be over 100 % as the retention score grows. An upper bounds needs to be introduced. A realistic assumption is that the ultimate retention score, 10.0, will correspond to the highest retention rate recorded for any operator under any circumstances, which is 99.6% (even with the perfect offer, 100 % retention can obviously never be attained). A transformation formula is used to translate retention scores into retention rates used as transition probabilities in the Markov model. From interpolation, the following *retention transformation formula* is given by:

$$p_i = 0.009 * RET\_SCORE_i + 0.9134 \tag{4.2}$$

where

$$p_i = retention\ rate\ for\ market\ or\ segment\ i$$
$$RET\_SCORE_i = retention\ score\ for\ market\ or\ segment\ i$$

The retention score is time dependent, as discussed in earlier section, which in turn affects the retention rate:

$$p_i = 0.009 * (\,f(t) * RET\_SCORE_i\,) + 0.9134 \tag{4.3}$$

where

$$p_i = retention\ rate\ for\ market\ or\ segment\ i$$
$$RET = retention\ score\ for\ market\ or\ segment\ i$$
$$f(t) = duration\ adjustment\ function$$

4.5 Profits over Time

The profit over time is a variable that is indeed hard to determine. As described in section A.3.10, the most convenient way derive the net profits for each time period is to start with the average revenue per user (ARPU), and deduct the variable costs according to industry estimates. What one ends up with then is a rough estimate of the net profit, but in order to understand the time dimension of the variable two additional aspects needs to be considered. The first is the industry change in ARPU due to competition in pricing, and the second is how the customers' purchasing patterns develop along their lifetime.

Looking at the industry average for the ARPU in different countries over the recent ten years it is hard to distinguish a clear trend. However, since 2009 the ARPU seems to have been quite stable for all of the countries analyzed, which indicates that the ARPU more or less has reached equilibrium. With this in mind it is concluded that the change in ARPU due to competition is insignificant and thus won't be considered in the calculations for profit over time.

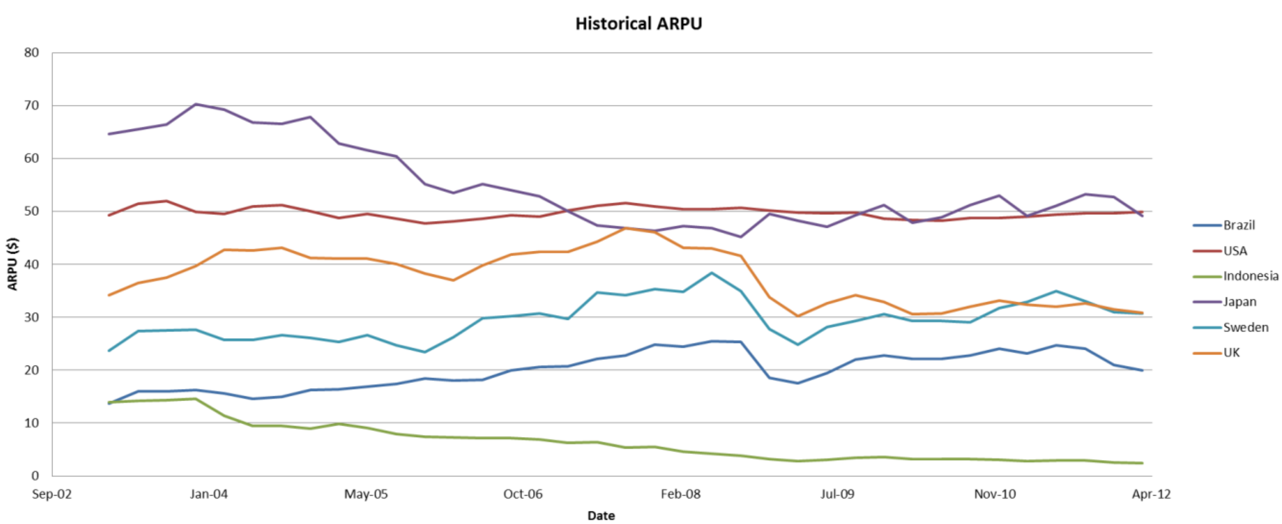

Figure 4.4Graph: Historical ARPU

The purchasing pattern trend is analyzed by plotting the survey data on spending against time as a customer (displayed in local currencies):

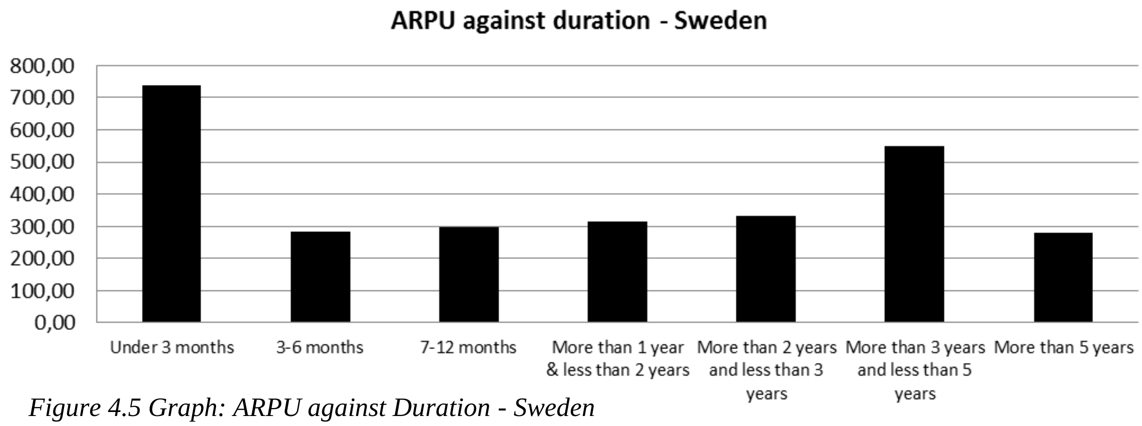

Figure 4.5 Graph: ARPU against Duration - Sweden

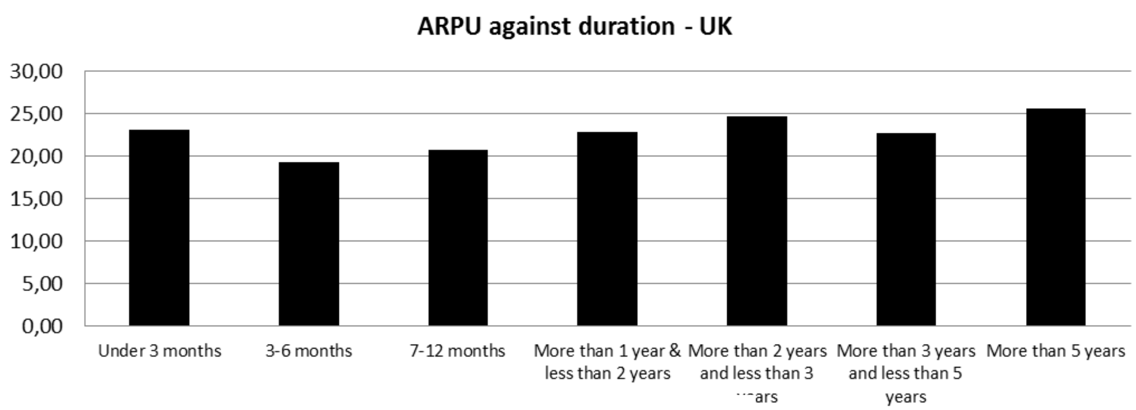

Figure 4.6 Graph: ARPU against Duration - UK

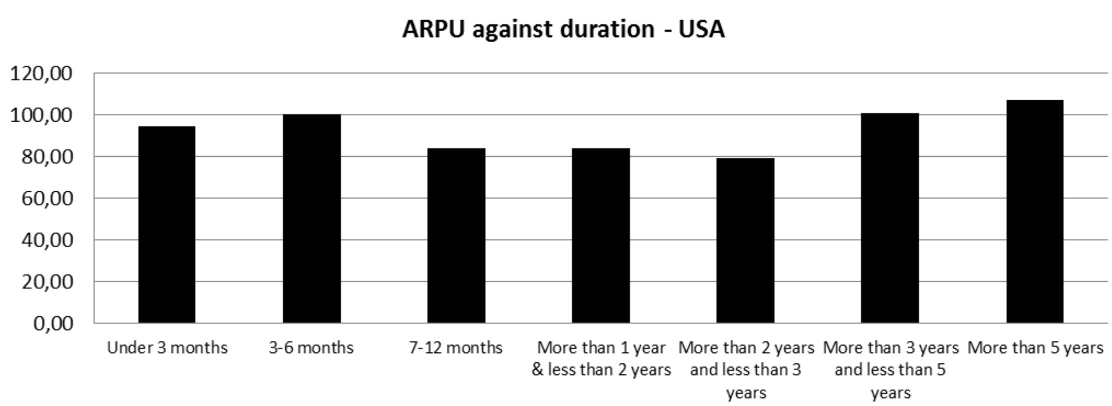

Figure 4.7 Graph: ARPU against Duration - USA

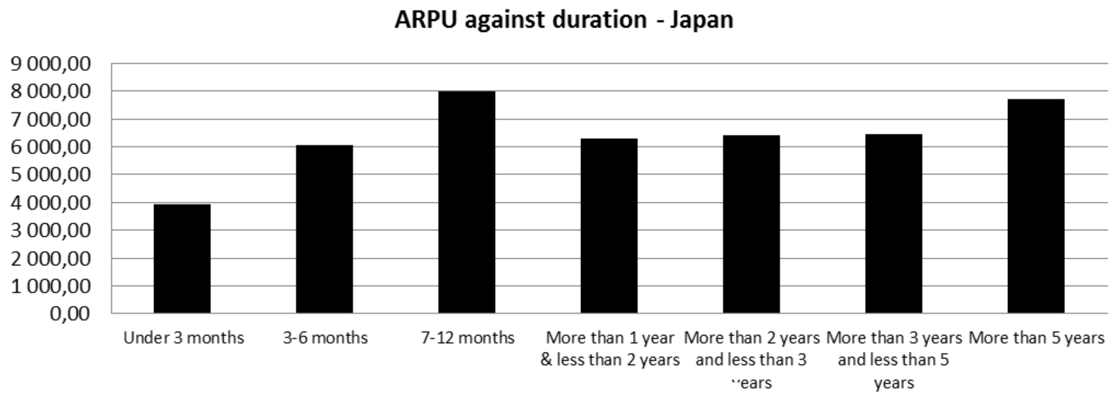

Figure 4.8 Graph: ARPU against Duration - Japan

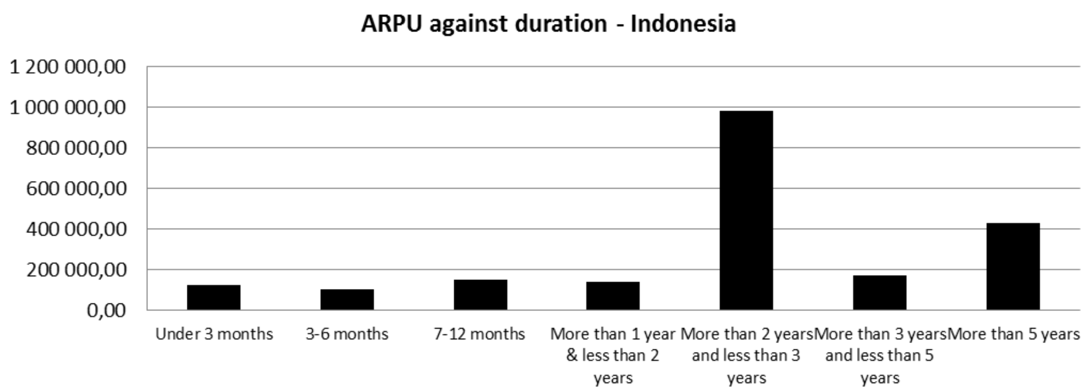

Figure 4.9 Graph: ARPU against Duration - Indonesia

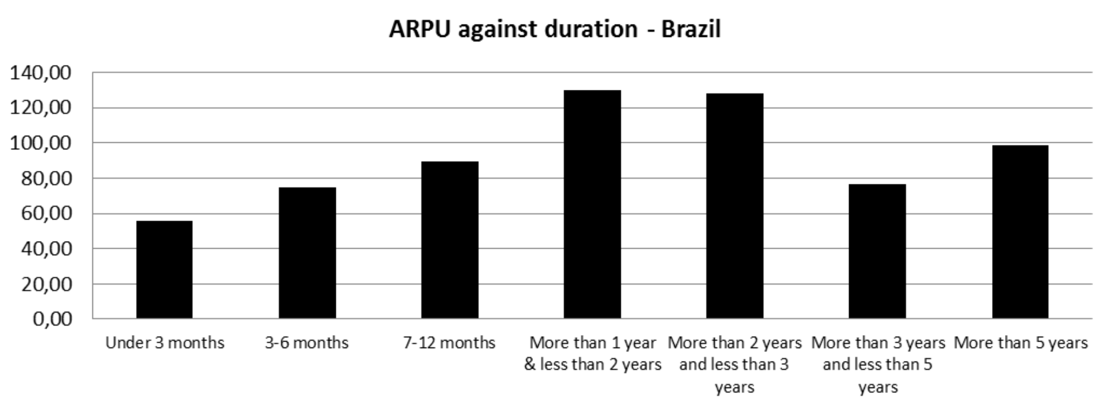

Figure 4.10 Graph: ARPU against Duration - Brazil

As can be concluded from the graphs, there is no clear trend in how the ARPU varies over the lifetime of a customer. This can be a result of too few data points and outliers making the averages inept, or there simply is no trend to observe. Either way, with respect to the lack of a trend, one will have to use one average for all durations.

The conclusion of the analysis is that the ARPU must be considered to be constant over time and since it has leveled out during the last three years, an average ARPU from the 2009-2012 will be used. To calculate the profit over time, the corresponding average OPEX for the same time period will be used. From that value 47 % will be considered to be fixed costs in accordance with the following calculations:

	Min	Max
Support Process OPEX	15%	20%
Operational Process OPEX (fixed)	23%	37%
Total	38%	57%
Average		47%

Figure 4.11 Table: OPEX

Thus only 53 % of the OPEX will be considered variable costs and the following calculations are done to end up with the net profit.

Q1 09-Q1 12	Average ARPU	Average OPEX	OPEX*53%	***Net Profit***
Brazil	22	17,9	9,4	***12,6***
USA	49,3	42,6	22,4	***26,8***
Indonesia	3	1,9	1	***2***
Japan	50,2	50	26,3	***23,9***
Sweden	30,4	25,2	13,3	***17,1***
UK	32	26,5	14	***18***

Figure 4.12 Table: Net Profit

4.6 Discount Rate

To calculate a fair discount rate for the CLV calculations, the WACC formula presented in section A.3.11 is used. Since it is the country specific WACC rates for a representative mobile network operator that should be calculated, some of the components in the WACC formula will be real financial figures and some approximates to represent a typical telecom operator.

Looking at the formula, the cost of debt is calculated with both real figures and approximates. The risk free rates are country specific and represented by 10 years government bond yields.[51][52]

[51] Damodran, A., *What Is the Risk-free Rate? A Search for the Basic Building Block*, Stern School of Business, New York University, New York, 2008
[52] Bloomberg Markets - Rates and Bonds, http://www.bloomberg.com/markets/rates-bonds/, 2013-04-05

As debt risk premium, an industry average of 200 basis points yield spread is used to represent a typical telecom operator.[53] The corporate tax levels are also country specific and the gearing of 35% is constant across the countries as an industry average.[54][55]

Just as the cost of debt, the cost of equity is calculated with a combination of approximates and real figures. In addition to the risk free rate and the gearing the beta is estimated to be 0.95 according to industry average.[56] Market risk premiums are country specific and estimated in an extensive rapport made by Pablo Fernandez, Javier Aguirreamalloa and Luis Corres at the IESE Business School.[57]

Together, these numbers are used to calculate a country specific WACC for a standard mobile network operator. The result is presented in the table below:

Country	*Riskfree rate*	*Corporate Tax rate*	*Market risk premium*	*Gearing*	*Debt risk premium*	*WACC*
USA	0,80%	40,00%	5,50%	35,00%	2,00%	5,40%
Sweden	1,27%	22,00%	5,90%	35,00%	2,00%	6,32%
United Kingdom	0,68%	24,00%	5,30%	35,00%	2,00%	5,28%
Brazil	9,81%	34,00%	7,70%	35,00%	2,00%	15,11%
Indonesia	5,47%	25,00%	7,30%	35,00%	2,00%	11,21%
Japan	0,12%	38,01%	5,00%	35,00%	2,00%	4,44%

Figure 4.13 Table: WACC/Discount Rate

The WACC will be used as discount rate for each specific market.

4.7 Coefficient Derivation

For every individual market in focus, $\beta's$ was estimated using the ordered probit regression in Stata. In cases there was sufficient data, the markets were segmented on the most relevant customer features, which was type of contract (prepaid or postpaid) and level of ARPU (high or low)[58].

[53] The Swedish Post and Telecom Authority, *Cost of Capital for Swedish Mobile Telecom Networks*, Copenhagen Economics, 2008
[54] KPMG, *Corporate and Indirect Tax Survey 2012*, KPMG Tax, 2013
[55] The Swedish Post and Telecom Authority, *Cost of Capital for Swedish Mobile Telecom Networks*, Copenhagen Economics, 2008
[56] Ernst & Young, *Valuation Drivers in the Telecommunications Industry*, Ernst & Young Global Telecommunications Center, 2011
[57] Fernandez, P., Aguirreamalloa, J. and Corres, L., *Market Risk Premium used in 56 Countries in 2011*, IESE Business School, 2011
[58] Decided upon recommendations from supervisor at Ericsson, Martin Englund of Marketing and Communications

The results are presented in the table below. A green β indicates significance, and a red β indicates insignificance. Segments that didn't have a sufficient number of data points are excluded from the table. Please note that these $\beta's$ shouldn't be interpreted as if they were estimated from an ordinary least squares or maximum likelihood regression – meaning the value doesn't quite represent the sensitivity compared to each other. One needs to consider the cuts between the different outcomes to get a grasp of the actual relative sensitivity. However, a higher β *within one market or segment* does imply a stronger influence on the retention score.

	Sweden			US			UK		
	All Postpaid	*Postpaid, high ARPU*	*Postpaid, low ARPU*	*All Postpaid*	*Postpaid, high*	*Postpaid, low ARPU*	*All Postpaid*	*Postpaid, high*	*Postpaid, low ARPU*
purchase	-.0263622	-.0293271	.0027674	.0435276	.0306465	.0544046	-.0278962	-.0463567	-.0144975
billAcc	.008932	-.0072002	.0116578	-.0265325	-.0332432	-.0157326	-.0038776	-.0058478	-.0030598
support	.010023	.0004281	.0213121	.0478045	.0146993	.0924372	.0568142	.0707437	.0429101
network	.1083836	.0117814	.1408526	.1650116	.1806891	.1345849	.1368751	.1137268	.1455142
value	.172207	.2353447	.1195755	.0232805	.047375	.0055237	.144412	.1435057	.1699753
handset	.0264992	.0217022	.0207483	.0172817	-.0114585	.0499197	.0003884	.0288583	-.026171
planCom	-.0205039	6.94e-06	-.0069019	.0044467	.0026537	.0030559	-.0017658	.01704	-.0147017
rewards	.0160928	.0348334	.0105227	-.002942	.0234359	-.0333506	.0179417	.0089416	.0255435

	Japan			Indonesia			
	All Postpaid	*Postpaid, high ARPU*	*Postpaid, low ARPU*	*All Postpaid*	*All Prepaid*	*Prepaid, high ARPU*	*Prepaid, low ARPU*
purchase	.0507693	.0552154	.0499749	-.0094571	.0040753	-.0083638	-.0074385
billAcc	-.0165011	-.0115739	-.0244966	.0088109	.0023354	-.0290109	.0349309
support	.054864	.0412121	.0790376	.0022495	-.0067833	-.0981942	.0052462
network	.0514569	.0678469	.0416956	.140586	.1512794	.2148588	.1287722
value	.0135522	-.0369939	.0428782	.0675496	.0758809	-.0021835	.1252349
handset	.0569927	.0404195	.093233	-.0082787	-.0932155	-.0692639	-.0914865
planCom	-.0005796	.0179057	-.017971	-.0000581	.0110529	.0467832	.0002022
rewards	.0678344	.0661235	.0825074	-.001298	-.0126356	.0380414	-.0531579

	Brazil					
	All Postpaid	*Postpaid, high ARPU*	*Postpaid, low ARPU*	*All Prepaid*	*high ARPU*	*Prepaid, low ARPU*
purchase	-.0195137	-.0273793	.0151591	.0212542	.0091048	.050911
billAcc	-.0054292	-.01543	.0057806	-.0012914	-.006113	-.0031672
support	-.0041481	.060336	-.0722791	-.0085626	-.0221781	-.0395249
network	.1031572	.0905691	.0909575	.1007199	.1252668	.0748172
value	.0145095	-.0102176	.0706819	.03611	.1058464	.0340607
handset	.0366748	.0470059	.0058811	.0512235	-.0331536	.0697573
planCom	.0254483	.0201253	.0350776	-.0001821	.0108093	.0023309
rewards	-.000982	-.0347272	.0840745	-.0213275	-.0084528	-.0046679

Figure 4.14 Table: Coefficients

4.8 CLV Calculations

For each market/segment, each factor is given an increased average satisfaction score of 10 %. With the upper and lower boundaries and mean of the concerned coefficient, a high, low and mean retention score is generated. Given the retention translation formula and the time adjustment function, the Markov chains for calculating the CLVs can now be simulated. Each simulation performs 100 000 fictitious customer-company relationships, each generating a realization of one lifetime value. Since the focus is on looking at the typical customer, the average is the most interesting. However, it might still be interesting to look at the distribution of CLVs. In the graph below, an example is given. It shows the CLV distribution for post-paid customers in United Kingdom, visualized with histograms. The graph to the left is with current satisfaction levels, and in the graph to the right the network performance satisfaction was increased with 10 %.

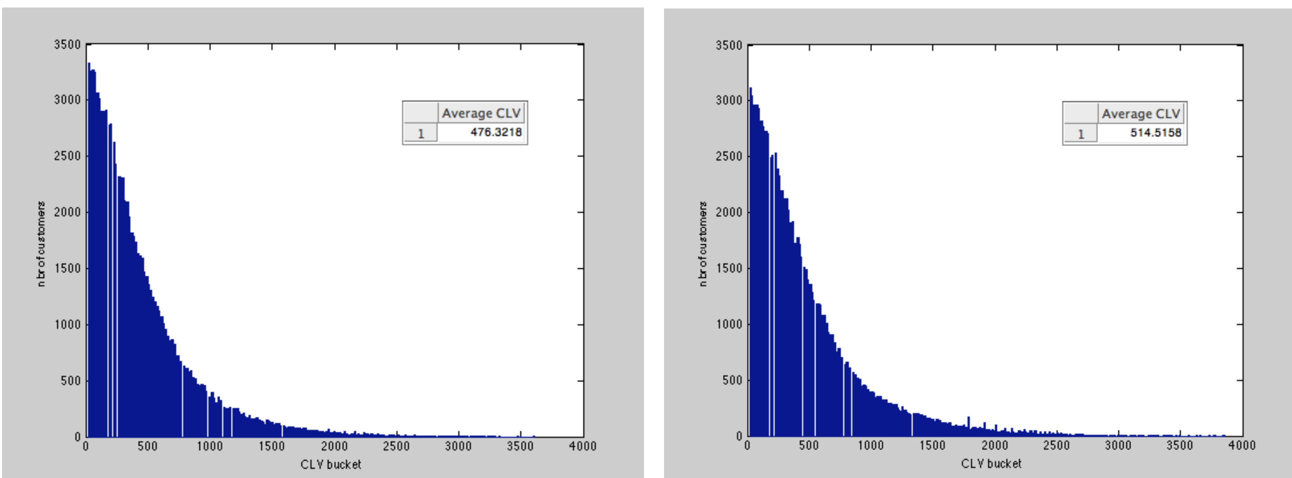

Figure 4.15 Graph: Distribution Example

The CLV simulations generate plenty of interesting information for each segment; however for overview purposes the amount presented here will be limited. In the graphs below, average CLVs *without increased satisfaction levels* are given. These are presented in order to give purpose to the relative improvements, graphed later. For Sweden, United Kingdom, USA and Japan, the number of recipients with pre-paid pay plan were considered too few to include, and the overall average therefore equals the post-paid average.

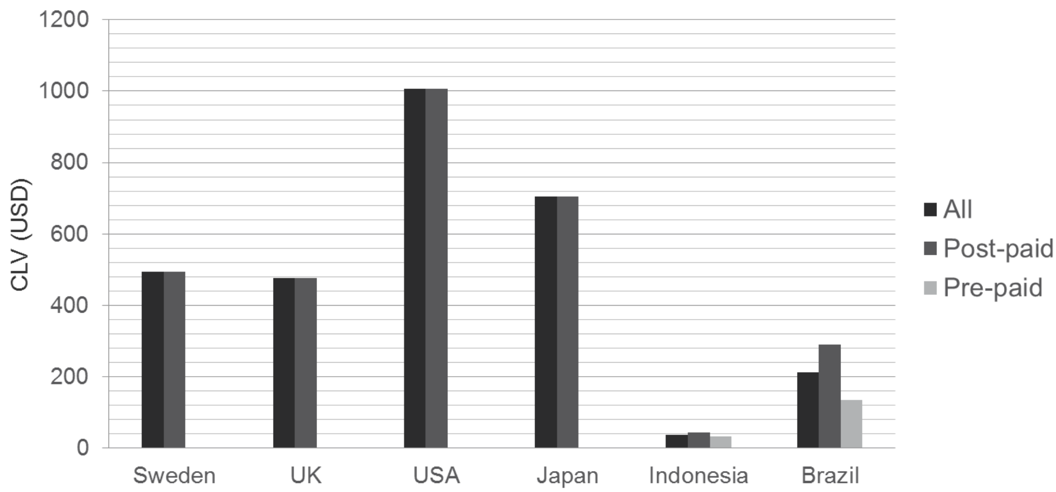

Figure 4.16 Graph: Average CLV per Payment Type

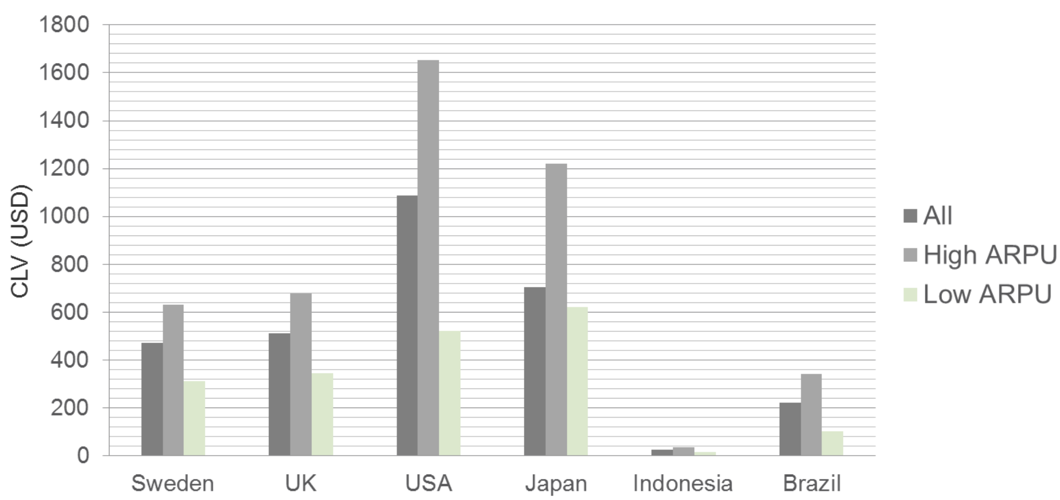

Figure 4.17 Graph: Average CLV per ARPU segment

Henceforth, focus will be on the relative increase in CLV if a satisfaction level for one factor is increased.

Overall, *the most significant drivers behind CLV are Network Performance and Value for Money*. The *least* significant factors are *Billing/Account Management* and *Price plans & Communications.*

In the graphs below, the CLV increase for each market is given for the estimate of the corresponding coefficient, as well as for the high and low boundaries of that coefficient. These are accompanied by the current satisfaction for each factor, which is the top line. This gives an idea of what to expect if one decides to invest in a factor, as well as the uncertainty in the payoff. The graphs will be accompanied by some brief main takeaways for each country.

4.8.1 Sweden

In Sweden, the only two factors that are significant are *network performance* and *value for money*. Value for money is much more valued by high ARPU customers, while low ARPU customers' CLV increase more with improved network performance. *Handset offered* and *customer support* have a higher impact on low ARPU customers, however they remain insignificant. Out of the focus markets, Swedish customers' CLV are the ones that would be most increased from satisfaction improvements in value for money.

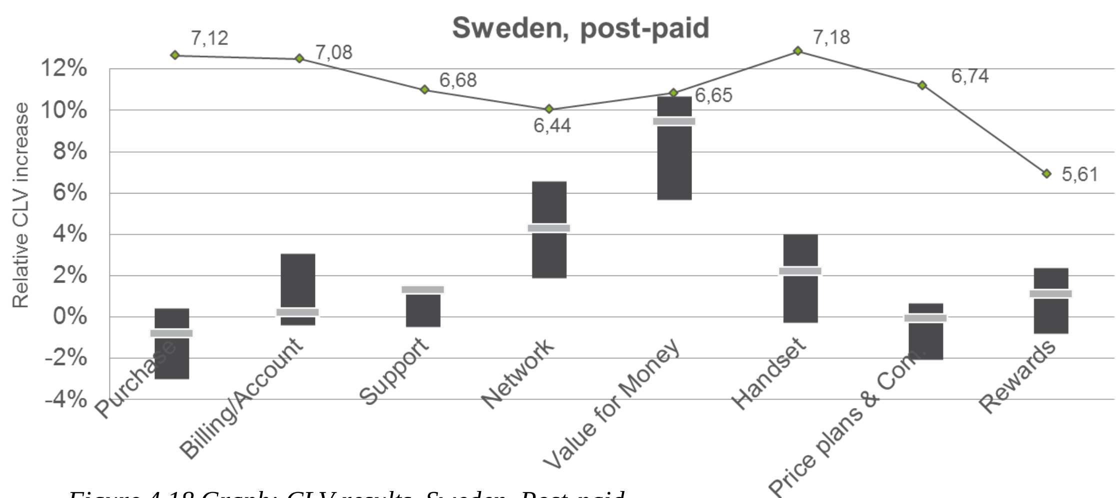

Figure 4.18 Graph: CLV results, Sweden, Post-paid

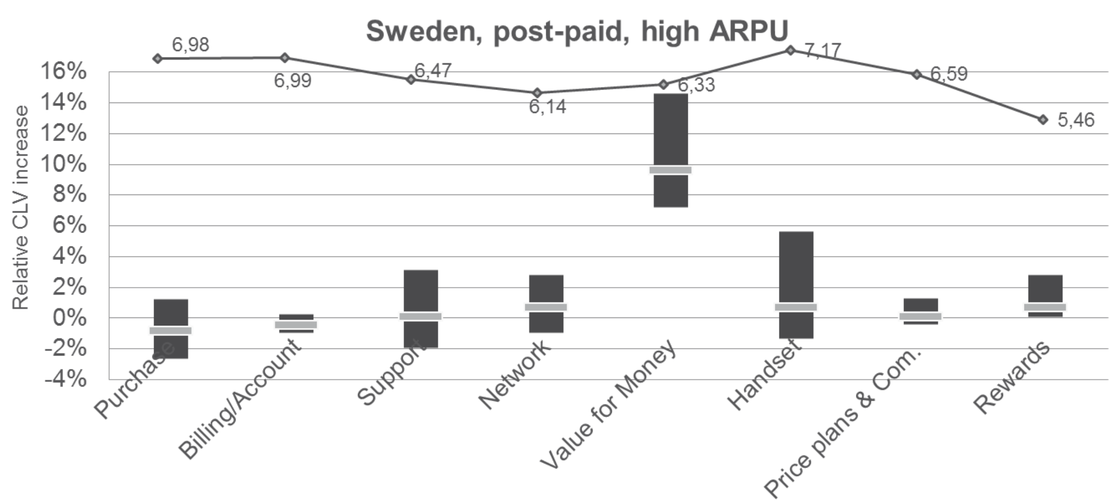

Figure 4.19 Graph: CLV results, Sweden, Post-paid, high ARPU

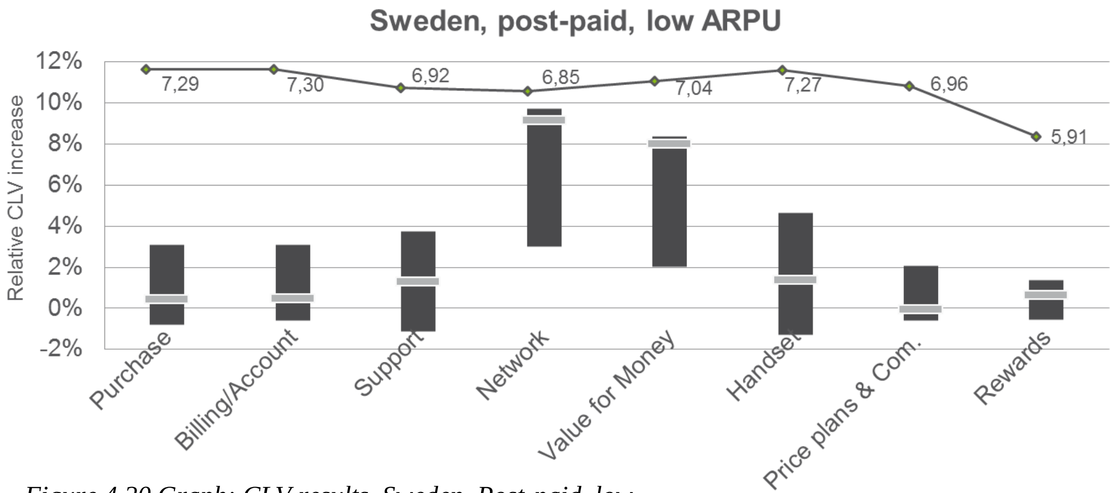

Figure 4.20 Graph: CLV results, Sweden, Post-paid, low ARPU

4.8.2 United Kingdom

Also in the United Kingdom, the average and potential impacts of *network performance* and *value for money* are very high. Also *customer support* has an overall high significant impact, which is especially distinguished for high ARPU customers. The potential impact of network and value for money is equally high for high and low ARPU customers, however the mean is higher for low ARPU.

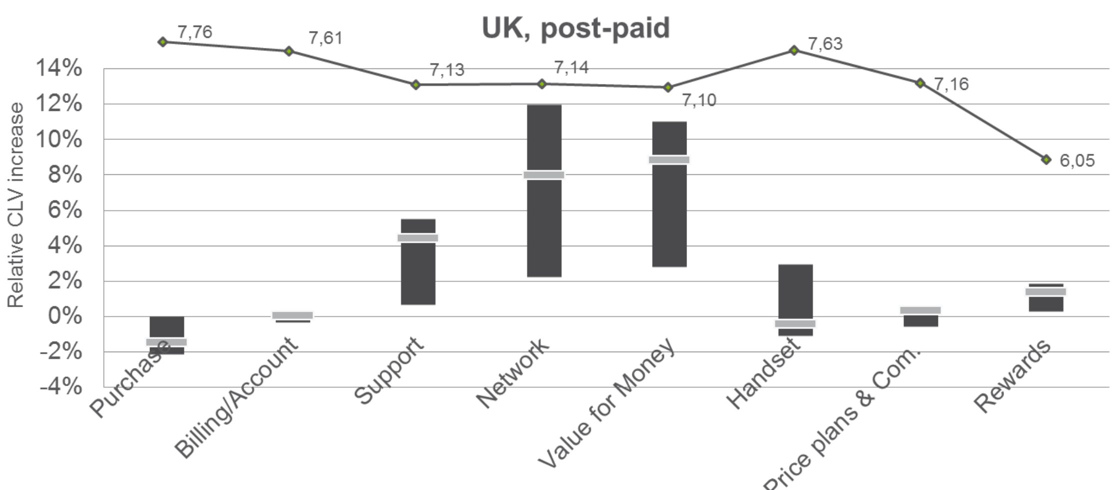

Figure 4.21Graph: CLV results, UK, Post-paid

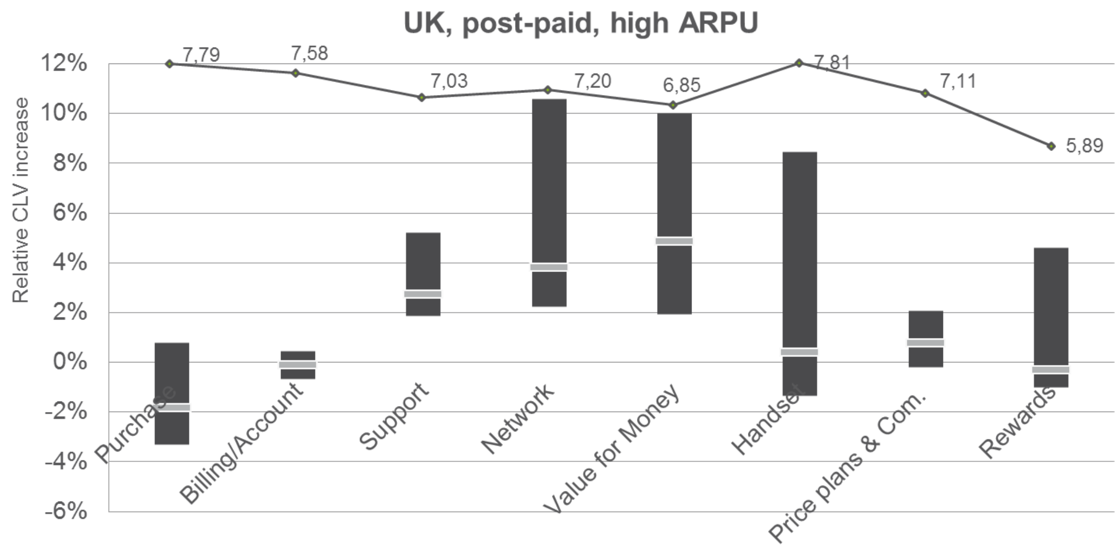

Figure 4.22 Graph: CLV results, UK, Post-paid, high ARPU

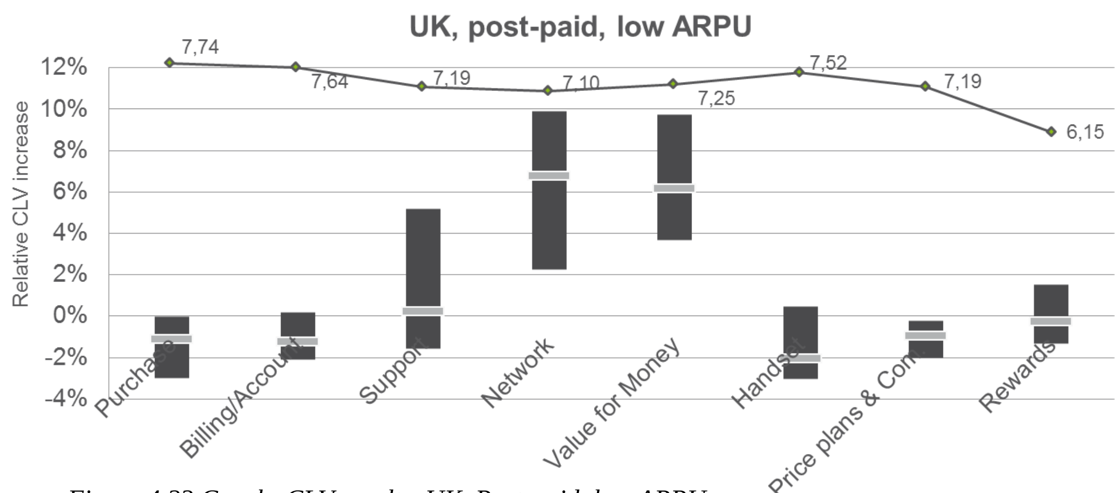

Figure 4.23 Graph: CLV results, UK, Post-paid, low ARPU

4.8.3 USA

In the US, the by far highest CLV increase would come from increasing satisfaction in *network performance*. The mean increase of all post-paid customers would be around 12 %, which is the highest noted increase of any factor in any market. This is even more significant for high ARPU customers. Also the *purchasing process* is important, and *customer support* is highly valued by low ARPU customers. *Billing/account management* has a significantly negative impact for post-paid low ARPU customers.

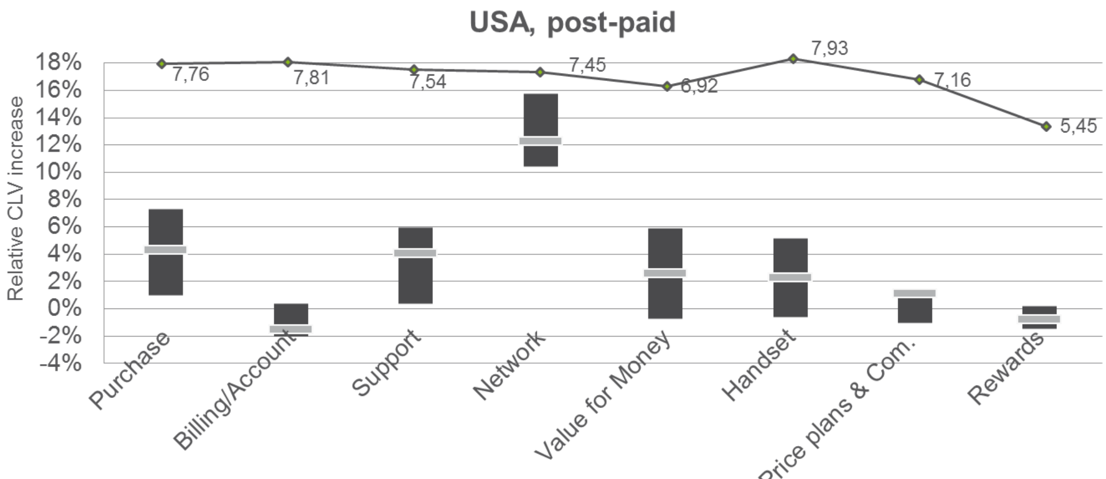

Figure 4.24 Graph: CLV results, US, Post-paid

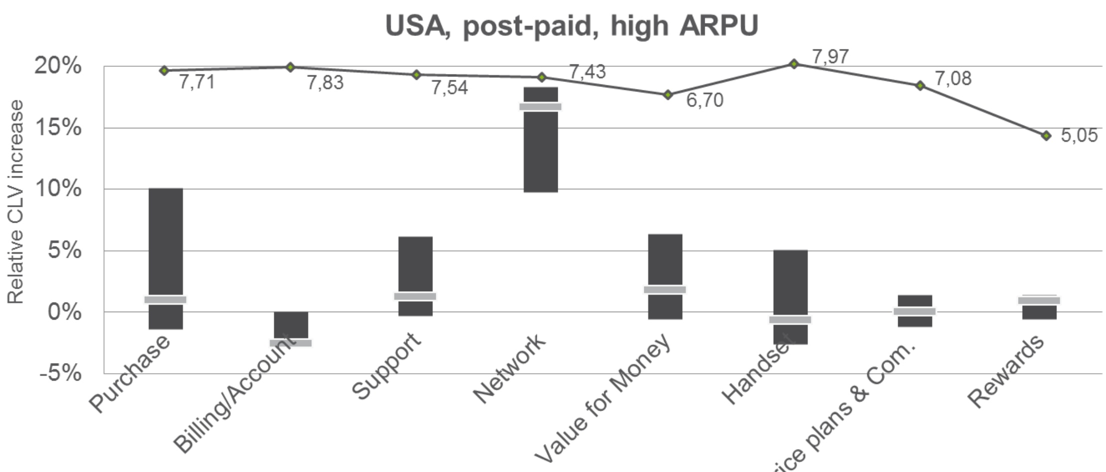

Figure 4.25 Graph: CLV results, US, Post-paid, high ARPU

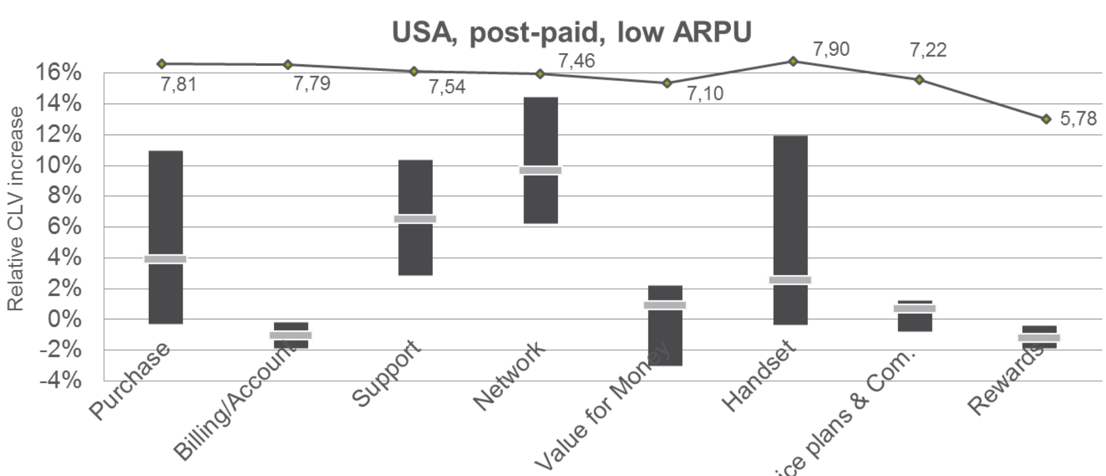

Figure 4.26 Graph: CLV results, US, Post-paid, low ARPU

4.8.4 Japan

Out of the focus markets, Japan is the only one where *loyalty rewards* has a significant and high impact on increased CLV. *Handset* and *customer support* have a potentially high influences, however it is it relatively risky to invest in this factors, as the wide confidence ranges suggest. Japan is the market where *value for money* is least important.

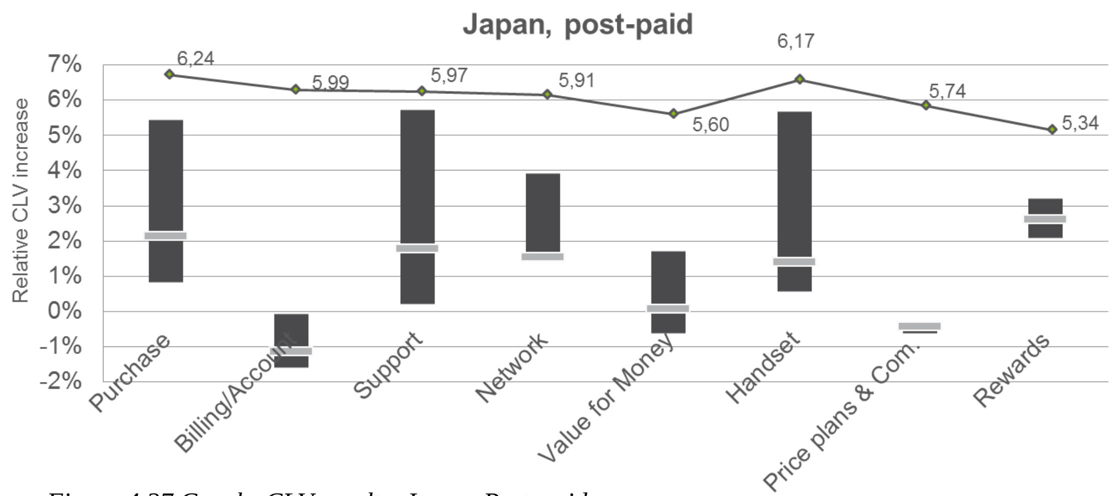

Figure 4.27 Graph: CLV results, Japan, Post-paid

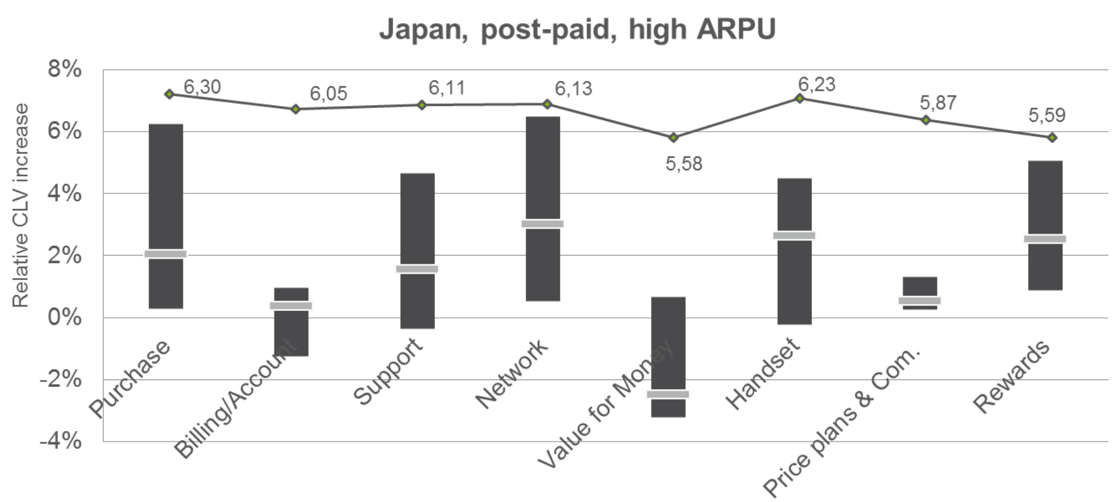

Figure 4.28 Graph: CLV results, Japan, Post-paid, high ARPU

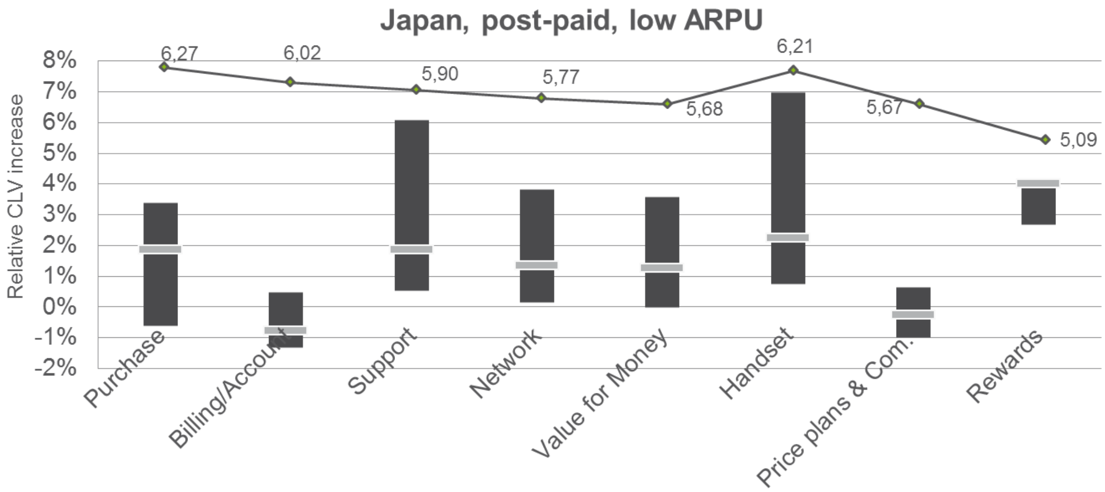

Figure 4.29 Graph: CLV results, Japan, Post-paid, low ARPU

4.8.5 Indonesia

Network performance consistently has the highest impact in Indonesia. It is closely followed by *value for money* for pre-paid customers, most significantly low ARPU customers.

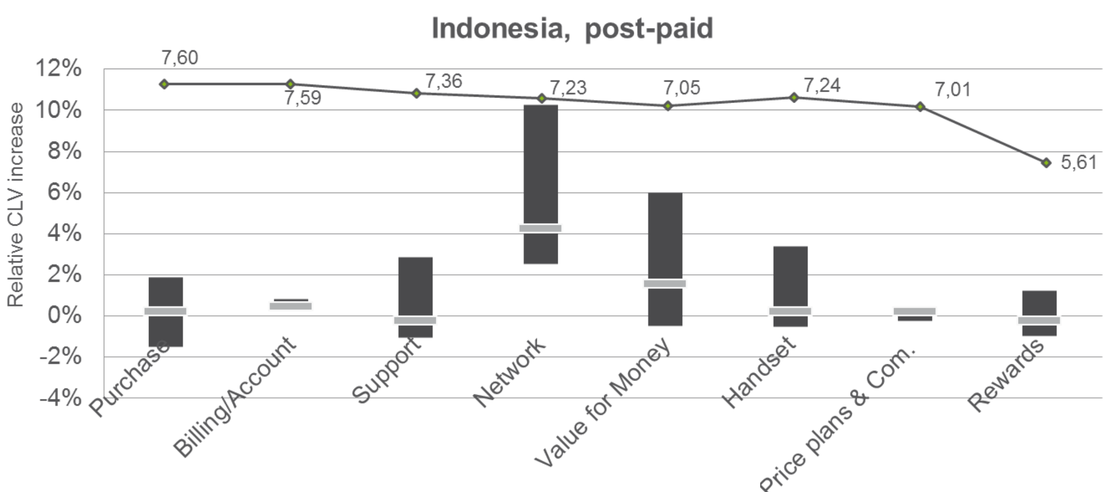

Figure 4.30 Graph: CLV results, Indonesia, Post-paid

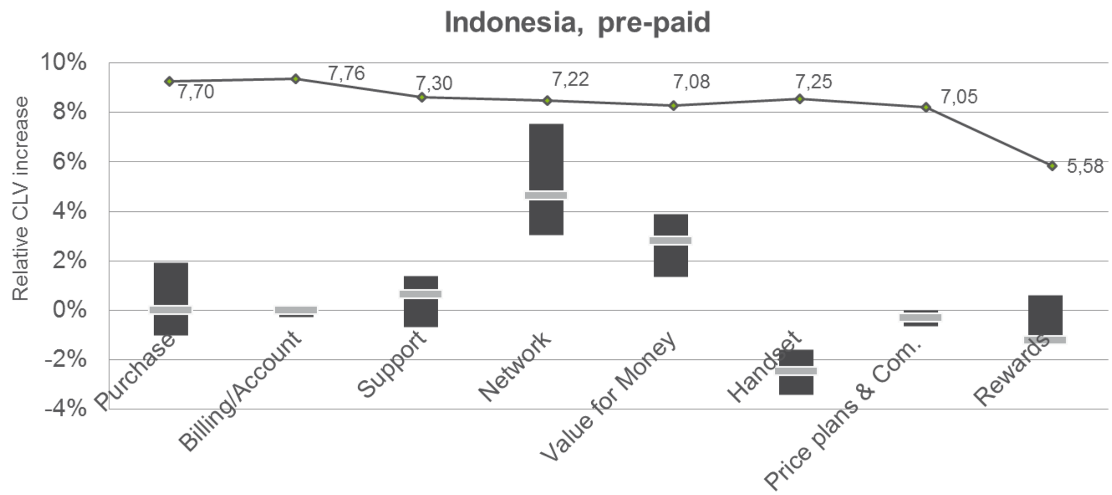

Figure 4.31 Graph: CLV results, Indonesia, Pre-paid

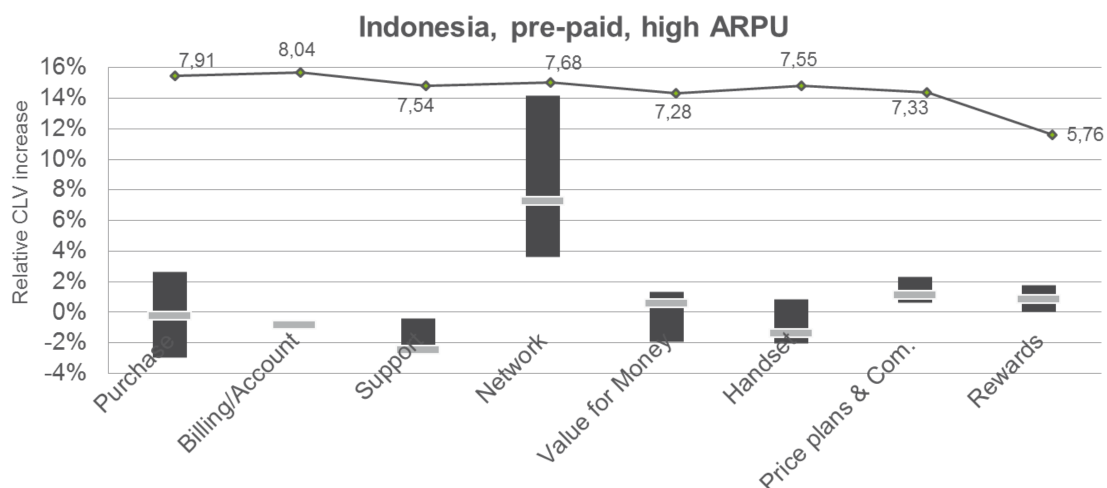

Figure 4.32 Graph: CLV results, Indonesia, Pre-paid, high ARPU

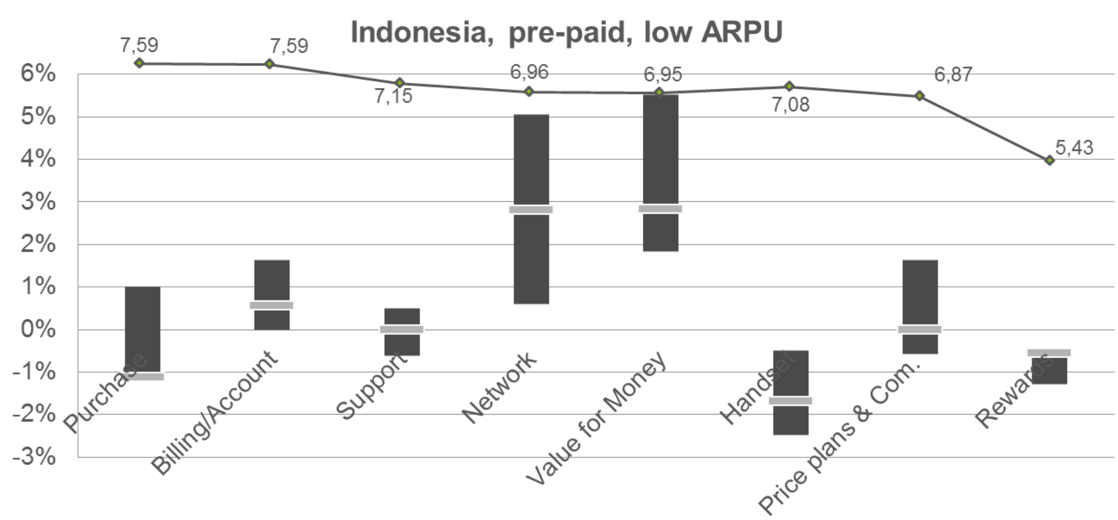

Figure 4.33 Graph: CLV results, Indonesia, Pre-paid, low ARPU

4.8.6 Brazil

Also in Brazil, investments in *network performance* consistently offers the highest potential and mean increase in CLV, with the exception of pre-paid high ARPU customers, where *loyalty rewards* is the highest.

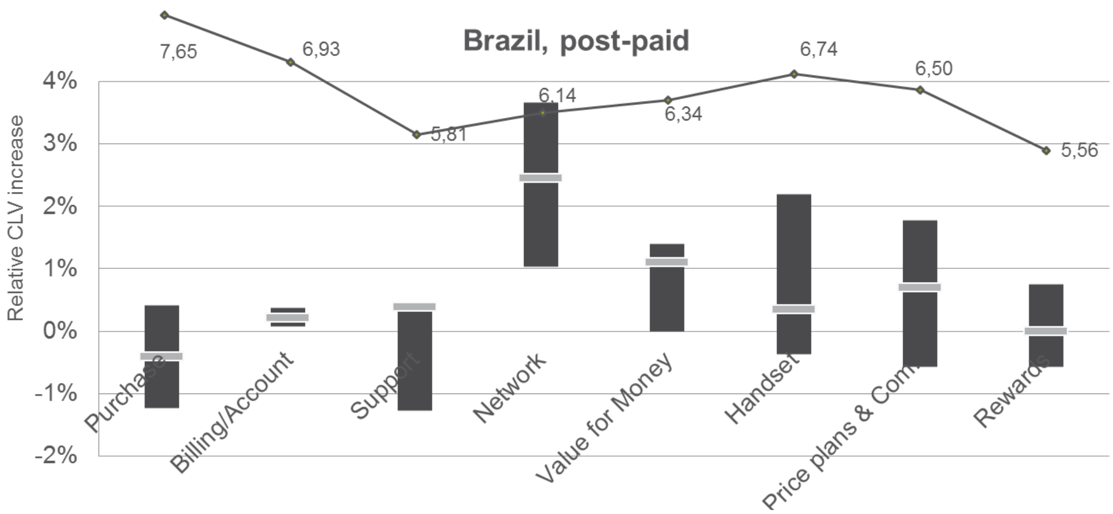

Figure 4.34 Graph: CLV results, Brazil, Post-paid

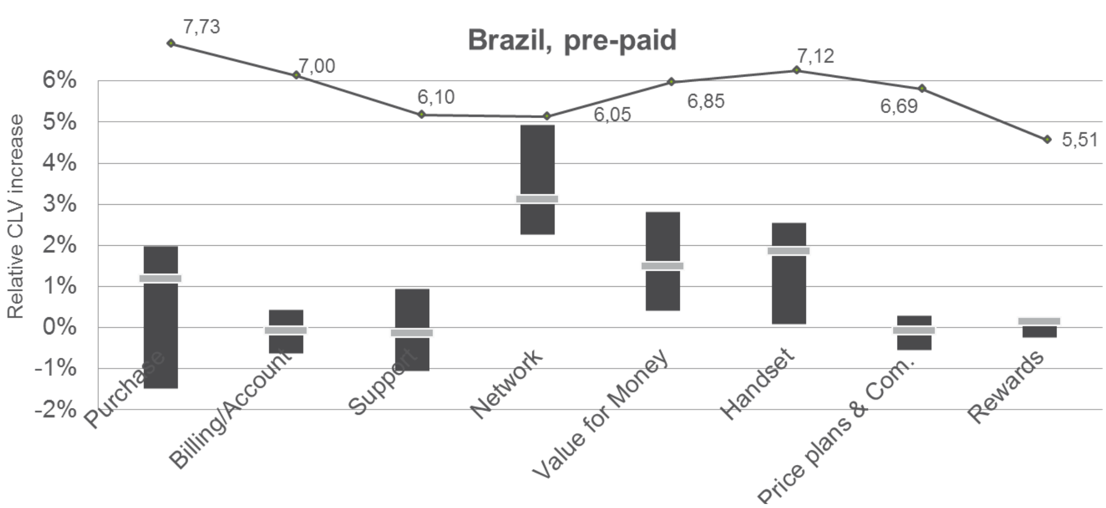

Figure 4.35 Graph: CLV results, Brazil, Pre-paid

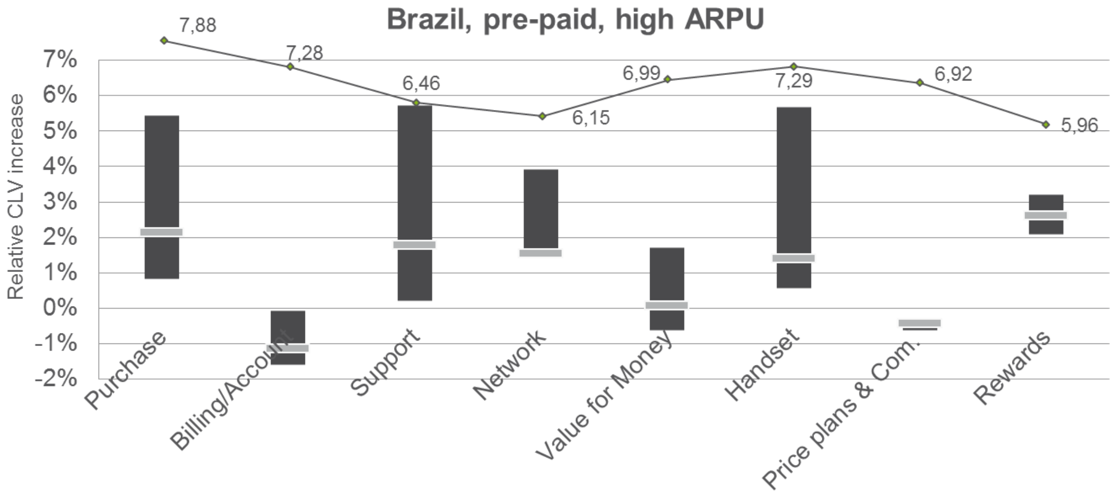

Figure 4.36 Graph: CLV results, Brazil, Pre-paid, high ARPU

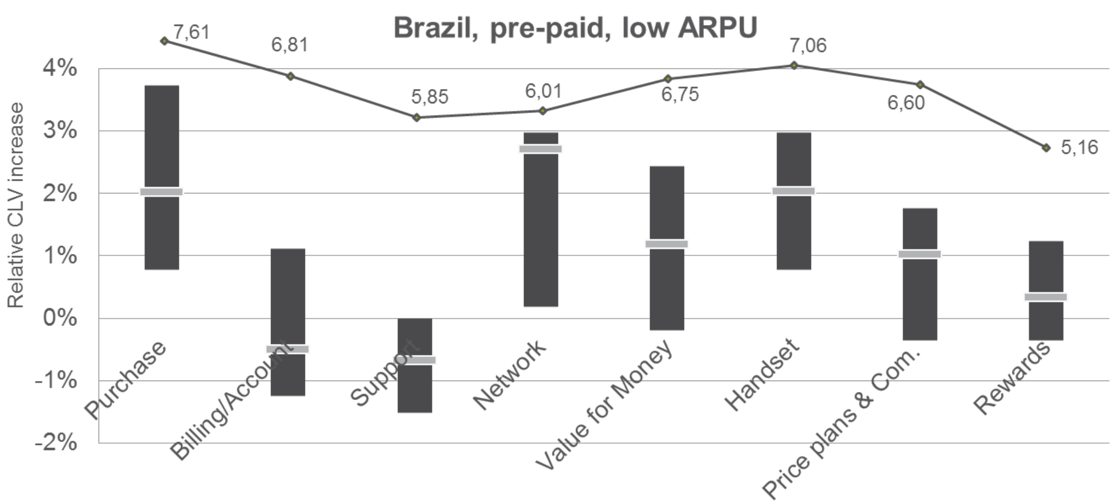

Figure 4.37 Graph: CLV results, Brazil, Pre-paid, low ARPU

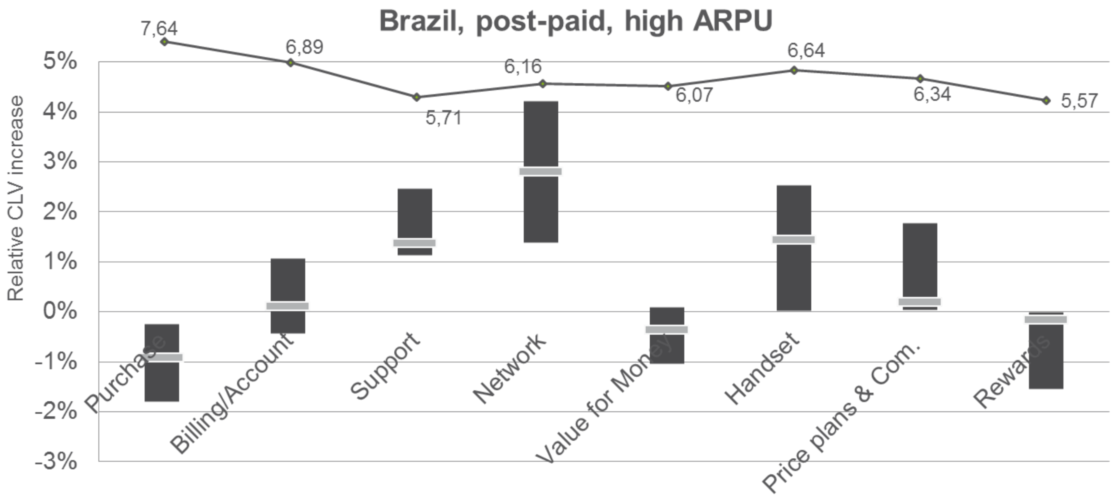

Figure 4.37 Graph: CLV results, Brazil, Post-paid, high ARPU

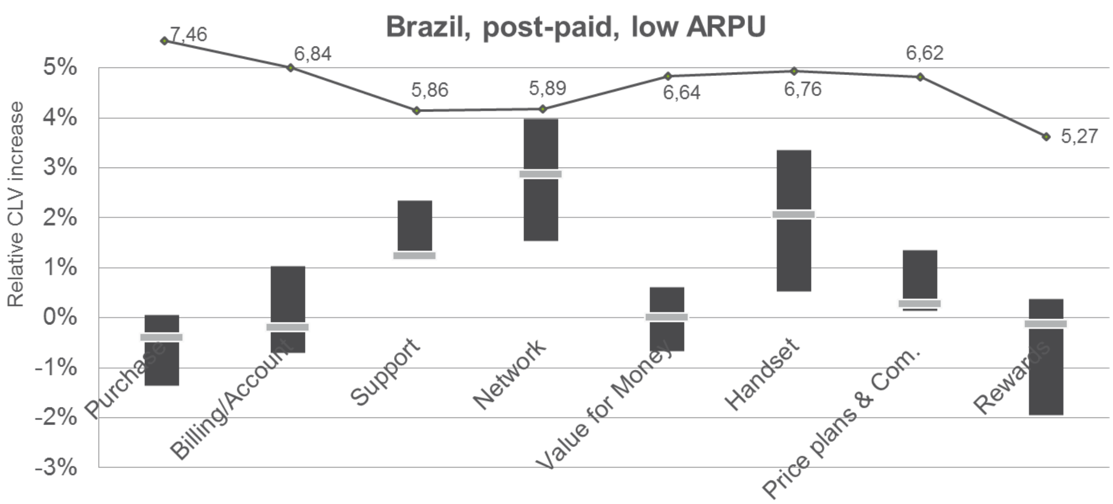

Figure 4.38 Graph: CLV results, Brazil, Post-paid, low ARPU

5. Discussion

5.1 Results

With respect to the hypotheses, there are numerous areas in which the results can be discussed. The first hypothesis stated that *satisfaction levels from survey data give a fair explanation of what drives retention rate.* This was investigated by comparing retention scores, given by satisfaction in survey data, and retention rate across markets. If a higher retention score corresponded to a linearly higher retention rate, the hypothesis would be fulfilled. For this to be completely valid, one could have hoped that the deviations in figure 4.3 would have been smaller. The average retention scores and retention rates for Sweden, UK, USA and Brazil shows a clear linear relationship, so if these were the only markets included in the analysis it would have been assumed that the hypothesis was almost perfectly true. But Japan and Indonesia is clearly out of bounds. There are two possible explanations, either the data is not good enough, or the relation between perception and action differs across markets. It is possible that although customers aren't very satisfied with the services, there is a high degree of loyalty in the Japanese society, making the customers reluctant to churn. Also, there are only five major mobile operators in Japan, which must be considered few with respect to the population. In Indonesia, on the other hand, a higher number of major operators (ten) might push down the switching barriers. Indonesia also has an overwhelming majority of pre-paid customers.

The consequence of the deviations from the linear relationship between retention score and retention rate is that the *absolute figures* in CLV from the markets deviating should be treated carefully. However, it is believed that the *relative figures* will still make sense, due to the clear general trend that a higher retention score implies a higher retention rate. The deviations can then be interpreted as differences in intercept of the curve.

The hypothesis that *retention rate is expected to be non-constant over time* was satisfactory proved. Although, referring to figure 4.3 (retention score over time), the trend wasn't quite as clear at short durations, the overall conclusion is that treating the retention rate as constant is too great of a simplification. As it all comes down to predicting the behavior of the average customer, the derived time adjustment function is an adequate way of making the model more realistic.

Profits were expected to be non-constant over time, which couldn't be proved. General ARPU figures from quarter to quarter showed a stabilizing trend, and the stated amount spent showed no trend with respect to time of being a customer. Although the hypothesis couldn't be proved, it is still believed that it is true. The revenue side might lack trends, but it is still highly possible that the variable costs of a user varies (decreases) with time, making the profits non-constant. Due to lack of information about the operators' cost structure, this couldn't be investigated; generalized industry estimates had to be used.

When it comes to the CLV results, *Network Performance* and *Value for Money* indeed proved to be the overall most significant drivers behind CLV. However, the importance of *Offered Handset* was lower than expected, only showing significant impact in a few markets. This might be explained by the fact that most operators at this time offers almost all attractive handset available, compared to a few years ago when one operator could have exclusivity on offering a certain handset (for example, AT&T were the only American operator offering iPhones for a few years).

The potential CLV increase given by improvements in *Network Performance* proved to be highest in United Kingdom and USA, which rejects the hypothesis that it would be higher in markets where the overall network penetration is lower. A potential explanation to this is that it doesn't matter what the current level of quality is, since satisfaction levels stem from what *expectations* you have.

The last hypothesis, that *post-paid customers are believed to have a higher CLV than pre-paid customers,* was proven to be correct.

As the figures in the results suggest, some increases in satisfaction levels would have *negative* effect on customer lifetime value. Mostly, this is the case when the coefficient is insignificant, but some results are in fact significantly negative. This is concerning, since it is not intuitive that *improved* satisfaction could give *decreased* CLV. There are two possible explanations to this. Either, there is a weakness in the model that causes misleading results. Or, it is in fact true, and can have other behavioral explanations.

5.2 Methodology

The greatest weakness with the analysis process is that it is built on three levels of estimations. The coefficients of the factors are estimated with ordered probit regression, and the retention translation formula and the time adjustment function are estimated with OLS. The consecutive estimations make the final results very sensitive to deviations in the input data. The risk of misleading coefficients is somewhat accounted for by not only using the actual estimate, but also looking at results using the upper and lower boundaries for its confidence range. However, there is a weakness also in performing that analysis; the possible dependency between the coefficients might give skewed results. If one uses a lower β for a certain factor, when for example looking at the lower boundary of its range, the other coefficients are in reality also likely to change. It is therefore important to be aware that the confidence ranges shouldn't be interpreted literally, but more to give indications about the risk.

To mitigate the sensitivity to deviations in input data, it would be necessary to use estimations or generalizations in fewer of the steps. However, it is a tradeoff between comprehensiveness and detail. If the focus was on finding the exact CLV, advanced analysis could have been performed using manually collected data. But with available time and resources, the number of markets/segments that could have been covered this way would have been *very* limited. It is not realistic that analysis on more than one small segment could have been performed, based on a less than respectable dataset. With the data Ericsson has provided, and bearing in mind that general trends and comparisons between markets are more valuable than exact CLVs in absolute figures, a more generalizes and simplified analysis was considered more rewarding.

When measuring the increased CLVs, it is assumed that there is an investment that gives a 10 % improved satisfaction level for a specific factor. An obvious question is then what such an investment would be, and more importantly, how much would it cost. A more appealing analysis would be to investigate how much the *actual* return on investment would be for each factor. In order to do so, one would need to know how much satisfaction would increase for each factor, given an investment of a certain amount. This would indeed be even more valuable for Ericsson and the operators. However, measuring the satisfaction payoff for investments is comprehensive enough to be a thesis itself. Still, the results in this thesis give a hint on what budget could be allocated to a certain investment. If an investment in network would give a CLV increase of $1.000.000, this constitutes an upper boundary for the size of the investment to be profitable, given that it is expected to increase the network satisfaction of 10 %.

If the dataset on which the analysis is based, there is a high representation of customers with a high duration, i.e. they have been customers with the operator for a long time. There are suspicions that this proportion is too high, although the dataset is claimed to be representative of the customer base.

Although the survey satisfaction parameters cover a significant part of the customer experience, it might not be considered entirely exhaustive. One thing that is missing is the customers' perception of the brand of the operator. Operators spend vast amounts of money on brand image, and it would have been worth investigating what impact these investments have on CLV, compared to the others.

When looking at the relationship between retention score and retention rate, six data points are very few to draw reliable conclusions. In retrospect, although only six markets were analyzed, more markets should have been included to verify this relationship, or divide the focus markets into segments to increase the number of data points. An alternative approach, that could have been equally efficient, would have been to analyze each market separately. The survey responses would then have been calibrated, so that each score corresponds to a retention rate which aggregated sums up to the markets' recorded overall retention rate. This is a technique that has been used by Ericsson's statistical research function.

5.3 Further Research

To further develop the analysis, there are numerous areas in which deeper research could be performed. Most interesting would be to try to measure what amount of investment gives what satisfaction improvement for the factors. Basically, one would be interested in what is the price for increasing the satisfaction level with 10 % (or any arbitrary improvement). This would allow the results to be put in a more absolute monetary context. In fact, there are ambitions within Ericsson to actually measure this. The results from that study would give more purpose to this thesis.

Furthermore, it would be interesting to analyze more countries to find general trends in different regions and maybe link these trends to cultural differences and demographic statistics.

To complement the analysis, one could also look at raw data from mobile phone user. This thesis is built on survey data, but adding raw data from operators on i.e. phone usage, customer service time and exact revenue per user, further segmentation and precision could be accomplished.

A. Appendix

A.1 Company Background

Ericsson was founded in 1876 when Lars Magnus Ericsson opened a mechanical engineering repair shop in Stockholm together with his companion Carl Johan Andersson. The same year Alexander Graham Bell filed the first patent for a telephone in the United States and it didn't last long until the invention was introduced in Sweden[59]. While repairing and customizing telephones, Ericsson had found flaws in the design and tried to improve the product. Two years later, in 1878, Ericsson began to produce and sell his own telephone equipment. The following years were characterized by high growth and many new customers, and in 1900 the company had grown to 1000 employees globally and generated SEK 4 million in revenue.[60] During the first two decades of the 20th century, continuous improvements were made to the products. As before, production was mainly focused on telephones and switching equipment and the technical knowledge was most often assimilated in the United States. In 1918 Stockholms Allmänna Telefonaktiebolag (SAT), the largest telephone operator in Stockholm, and L M Ericsson merged to form Allmänna Telefonaktiebolaget L M Ericsson.[61] The two companies had been closely tied for a long time and the merger was natural to form a full service business. As the company continued its geographical expansion the technological development improved rapidly. Governments started to organize the local town-by-town systems into a single integrated system and leased out the contract to operators. Ericsson managed to get some of these contracts, which boosted the sales of its products. However, they were later forced to move out of the operator industry due to financial problems and went back to produce telephones and switchboards again. In the late 1970's Ericsson developed one of the first computer controlled telephone exchanges called the AXE-system. The system's speed and flexibility made the AXE very popular, doubling the company's market share and facilitated Eriksson's entry into the American market.[62] Orders from around the world started drop in as deregulations of markets became a reality. Even though the technology existed earlier it was not until the beginning of the 1990's mobile telephony started to catch up to speed and reach the majority. Ericsson helped to build networks in numerous of countries as well as providing the physical cell phones. In 2001, Ericsson the cell phone division merged with the Japanese home electronics firm Sony to form Sony Ericsson. The joint venture was however sold

[59] The History of Ericsson, http://www.ericssonhistory.com/company, Centre for Business History, Stockholm and Telefonaktiebolaget LM Ericsson, 2013-04-15
[60] ibid
[61] ibid
[62] ibid

entirely to Sony in 2012, moving Ericsson's focus back to providing networks and the services surrounding these products. [63]

A.2 Company Overview

Ericsson is organized into three major business divisions with a shared go to market model. The research department is shared over all business units and the supporting activities under group functions stretches over the whole value chain.

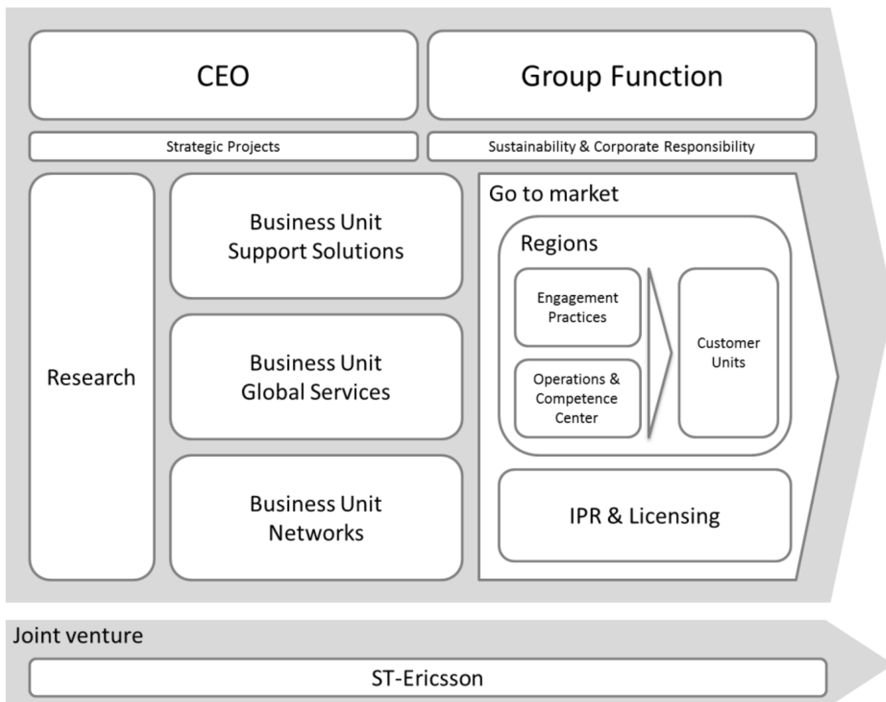

Figure A.1 Ericsson Organization

Business Unit Networks (BNET) is the division within Ericsson that provides mobile systems solutions to network operators around the world. They offer complete end-to-end solutions including base stations, mobile switching centers, network controllers and more. In addition to the described portfolio, they also offer solutions supporting core and fixed access networks, Internet Protocol (IP) networks and microwave transport. The business unit is accounts for 55 per cent of Ericsson's net sales.

In addition to the products of BNET, Business Unit Global Services (BUGS) offers consulting service, system integration, network deployment and education and support services. The third

[63] The History of Ericsson, http://www.ericssonhistory.com/company, Centre for Business History, Stockholm and Telefonaktiebolaget LM Ericsson, 2013-04-15

leg, Business Unit Support Solutions (BUSS) develops and delivers operations- and business support systems.

A.3 Key Methods and Models

In this section, the methods to analyze the Customer Lifetime Value are presented. Also, motivations to what models to use are given. First, the choice of CLV model is discussed. Second, the method to estimate the most crucial components is given. Third, required data is specified and the process to collect and aggregate data is stated. Last, methods are presented to conduct quantitative analysis on the model and data.

A.3.1 CLV Model Formulation

In section 2.3, a number of models for estimation of CLV are given. The model that will be used is the *Markov Chain Model*. A strength with the Markov Chain is that it allows for unique conditions in different situations. For example, it is easily adjusted if profits and retention probability prove to be varying over time. Although the possibility to include marketing decisions along the process makes the Markov Decision Process appealing, it has been rejected since the focus is not to find an optimal dynamic strategy. Rather, the objective is to study the influence of initial decisions or investments, and with a static offering the Markov Chain an efficient and simple way to fulfill the purpose.

In the Markov Chain, each state will represent a person being a customer for one month, with infinite number of states. The transition probability to move from one state to the next is equivalent to a customer retaining with the operator to the next month. The figure below visualizes the Markov Chain. S_0 represents not being a customer, and $p_1$is the probability that a customer is acquired. Since it is the CLV of a present customer that is estimated, the relevant states are $S_1, \ldots, S_k, k \to \infty$.

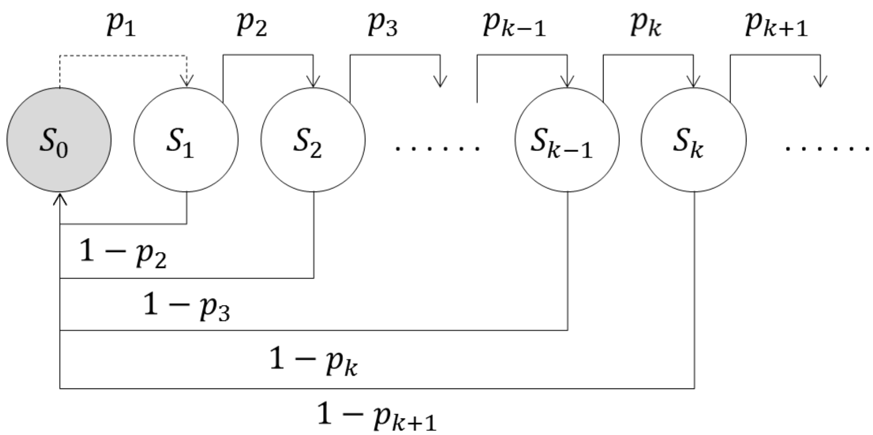

Figure A.2 Markov Chain Model

A.3.2 Retention Analysis

The method that will be used for estimation of retention probabilities is ordered probit regression of customer survey data. There are methods – as mentioned in the theory section – that are more accurate predictors, however they require vast databases and very advanced data-mining techniques. In the context of this thesis, it is not realistic to pursue these techniques. Instead, a comprehensive set of survey data about customer satisfaction will be used, and for this kind of data the probit (and logit) model is in fact appropriate.[64] The survey data has an ordered nature, where a higher outcome monotonically implies a higher degree of satisfaction. This is a prerequisite for the probit model. Although one shouldn't expect to get exact retention probabilities, it will give good indications on what drives the churn and how it would change in relative terms if satisfaction levels are improved.

In Kim and Joon's article, the customer satisfaction levels are represented by ordered discrete variables based on scores in customer surveys.[65] The motivation is that it is hard to determine the satisfaction based on quantitative data. The customer satisfaction is something subjective that is based on the individual's emotions and preferences, which is problematic to estimate from any other sources than directly from the customer[66]. A customer's perception of the relationship to the carrier can therefore be considered to be an accurate estimation of the utility. However, although a survey of customers' satisfaction will give an idea about the utility with the current carrier, it does not say anything about what the utility would have been with competitors. Therefore, a

[64] Kim, H. and Yoon, C., *Determinants of Subscriber Churn and Customer Loyalty in the Korean Mobile Telephony Market*, Telecommunications Policy, ed. 28, Hanyang University, Republic of Korea, 2004
[65] ibid
[66] ibid

direct comparison cannot be made. But the conclusion of the individual's comparison can be glimpsed in whether he decides to churn or not. If there is information about how likely the customer is to change operator, expressed by himself,[67] it can give a hint of whether or not he values the utility of the current operator higher than an alternative.

With appropriate survey data, a similar analysis as Kim and Joon can be performed. As opposed to Kim and Joon, the probit model will be used using satisfaction levels – representing utility – as independent variables and the likelihood of switching operator as dependent variable. The probit model is chosen over the logit model because the error terms are assumed to be normally distributed. The regression will be performed in Stata, and a covariance analysis will establish that the factors are sufficiently independent.

An alternative would have been to use externally estimated churn rates for input in the model. This is an appealing idea, since more effort could have been put on the statistical analyses of CLV. However, there is a limitation in using existing churns. There will be no way of analyzing the sensitivity in the model to changes in the product (for example improved network performance), which is one of the main objectives with the thesis.

A.3.3 Ordered Probit Regression

As motivated above, an ordered probit regression will be performed across markets, once the final factors are determined. This can be performed in statistical software such as Stata. The result from the regression will be $\beta's$ - coefficients – for each factor. The $\beta's$ explain the relationship between the satisfaction levels and the likelihood of switching operators. The survey generated likelihood of switching will henceforth be called the *retention score*, given on a scale 0-10. The average retention scores will be compared to true retention rates assessed by research agencies, given from customer data. If the results are reliable, the relative difference between the derived retention scores from the regression and the true retention rates should correspond across markets, most preferably with a linear relationship. If this in fact is true, a certain retention score can be translated into a retention rate.

Alongside the estimated coefficients for each factor, the regression will provide standard errors and confidence intervals. These will be used to determine if a certain factor in fact has a significant influence on the retention score and in what range an investment would influence the

[67] This likelihood can be given from for example the question ”How likely are you to switch operator in the coming year?”. Although this doesn't say anything about whether the customer actually will switch, it can give an idea about the probability. If transaction data is available, it can be verified with what he eventually decided.

CLV, giving an idea of the risk of the investment. The $\beta's$ are estimated values – paying attention to uncertainty in the coefficient is crucial to capture the uncertainty in the outcome of an investment.

A.3.4 Retention Score over Time

Using the stated duration of being a customer with a given operator, which is one of the questions in the survey, the behavior of the retention score over time can be investigated. In case the retention score is not constant over time (of course forgiving some deviation), this needs to be compensated for in the model. The relationship between duration and average retention score will be plotted and analyzed. If so needed, a *time adjustment function* will be determined, to make the retention score and retention rate in the model follow the observed behavior.

A.3.5 Transforming Retention Score into Retention Rate

The format of the probability of retaining with the current operator will be represented by the retention score, a scale 0-10, in the survey data. In the Markov model, it needs to be represented by an actual transition probability, i.e. a retention rate. From industry research[68], retention rates for a number of markets are given. These are derived from user information gathered from operators in each market. Due to the nature of this source they are expected to be very accurate, and are therefore called *true* retention rates.

The average retention scores from the survey data will be compared to the true retention rates, across the markets included in the analysis. If there is sufficiently clear relationship, a certain retention score can be said to correspond to a certain retention rate (i.e. transition probability in the Markov model), and a *retention transformation formula* will be derived based on OLS. Of course, it is hard to determine what is a *sufficiently clear relationship.* For simplification, it will be considered to be sufficiently clear if higher retention score in most cases correspond to a higher retention rate.

A.3.6 Data Specification

For analyzing the retention probabilities, survey data from Sweden, United Kingdom, USA, Japan, Indonesia and Brazil will be collected. For each person, information that explains what the

[68] Strategy Analytics, *Wireless Operator Strategies, Worldwide Cellular User Forecasts, 2012-2017*, 2013

likelihood of switching operator is needed. A number of questions from Ericsson surveys in the past were chosen to explain this. The chosen questions concerned:

Area	Subject
Characteristics	Gender
	Age
	Income
Subscription	Current Carrier
	Type of pay plan
	Smartphone or not
	Who pays the bill
	Duration of being a customer
	Likelihood of switching during the coming 12 months
	Average amount spent per month
Satisfaction	Purchasing process
	Billing and payment
	Account management
	Customer Support
	Network Performance
	Value for money
	Handset offered
	Value for money
	Price plan options
	Communication
	Loyalty rewards
	Overall experience of the carrier
	Promotion score

Figure A.3 Table: Data Specification

The demographic attributes of each recipient will be collected in order to enable segmentation of the sample. There is a point in distinguishing between segments because each segment represents a different customer behavior, and should therefore maybe be analyzed separately. There are many advanced techniques to segment telecom customers after usage behavior (K-mean, self-organizing maps, support vector clustering, etc.), but this is not the focus of the thesis and therefore simple demographic attributes will be used to conduct a sufficiently efficient segmentation. In choosing segmentation parameters, the ones considered in the Ericsson surveys and the amount of data were drawing the limitations.

A.3.7 Data Collection

The primary source of data will be Ericsson's internal database, more specifically their surveys that have targeted 1000-2000 mobile customers in a number of markets. This source is expected to cover the data requirements to perform the analysis on drivers of retention probabilities. To compare the results to true retention rates, retention statistics will be collected from industry analysis performed by research agencies and the operators' statistics. Also profits over time will be acquired from industry research, and hopefully be validated by interviews with representatives from operators.

A.3.7 Structuring Data

When data is collected, the first step is to structure the survey data to fit the chosen regression method. As far as possible, the demographic variables will be transformed to ordered representation, in order to facilitate for regression. For example, gender will be represented by a binary variable (male = 0, female = 1), and likelihood of switching will be represented by a scale from 0-10 (will definitely switch = 0, will definitely not switch = 10). In cases when a variable has a continuous nature, it will initially be put into buckets to maintain the robustness of the model. For example, household income will be represented by a scale 1-3 (low income = 1, medium income = 2, high income = 3).

An issue is how to handle missing data. One alternative is to simply count out the recipients that contain missing data points. Although easy to carry out, it has two flaws: the result might be misleading because the cut out recipients represent a certain group, and the amount of data is almost halved.

A.3.8 Covariance of Independent Variables

Looking at the satisfaction levels from the survey data, there are a few parameters that expected to be closely related. In order to make the model as simple as possible, a correlation matrix will be set up and analyzed. If some factors have a very high correlation, they will be considered to be combined. This way, the total number of factors can be reduced without losing important information. Conducting this analysis on all individual markets is comprehensive; therefore a reference series will be used under the assumption that it represents the covariance of the factors across all markets. The reference series consist of data from USA, United Kingdom and Sweden. This choice of markets is not ideal since it isn't quite representative for the world, but due to time limitation and chronological access to survey data for different markets, it was decided adequate. To ensure that the aggregation of this data is in fact illustrative, the correlation matrix was set up for each individual market. Comparing them among each other and with the aggregated series shows very clear similarities, and the reference series is therefore considered valid.

In case two or more independent variables are highly correlated, they will be combined. The average score of the two factors will then be used in the regression.

A.3.9 Significance of Variables

By performing a regression with satisfaction levels as well as characteristics parameters, one can determine which factors are significant. A significance test of the influence on the dependent variable is appropriate. For each factor, the corresponding β is tested under the hypothesis:

$$H_0: \beta_i \neq 0$$
$$H_1: \beta_i = 0$$

Insignificant factors can simply be excluded from proceeding analysis. In case characteristics parameters prove to have big influence on the dependent variable, they will set the terms for segmentation of the data.

In the table below, an example of a probit regression result is presented. The example aims to point out how the significance of factors is determined. The confidence interval for each specific factor is given in the rightmost columns:

```
Ordered probit regression                         Number of obs   =       1775
                                                  LR chi2(8)      =     580.22
                                                  Prob > chi2     =     0.0000
Log likelihood = -3769.0858                       Pseudo R2       =     0.0715
```

ret_score	Coef.	Std. Err.	z	P>|z|	[75% Conf.	Interval]
purchase	-.0079202	.0181321	-0.44	0.662	-.0287785	.012938
bill_acc	-.0132523	.00575	-2.30	0.021	-.0198668	-.0066379
customer_sup	.0503062	.0161003	3.12	0.002	.0317852	.0688271
network	.1469281	.015552	9.45	0.000	.1290378	.1648183
value	.0222119	.0186863	1.19	0.235	.0007161	.0437077
handset	.0883025	.0188988	4.67	0.000	.0665622	.1100427
plan_com	-.0021573	.0063425	-0.34	0.734	-.0094533	.0051388
loy_rew	-.000848	.0110445	-0.08	0.939	-.013553	.0118571

Figure A.4 Stata Regression Results, Example

For each of the factors, the null hypothesis $H_0: \beta_i \neq 0$ is to be tested against $H_1: \beta_i = 0$. The null hypothesis can be rejected if the confidence interval spans over zero, which is the case for Purchase Process, Price Plan Options and Communication, and Loyalty Rewards. In this example, these factors can therefore be neglected in proceeding analysis. Note that this significance analysis will be performed on each market individually, since different factors will be more significant depending on market characteristics.

A.3.10 Profits over Time

To calculate the net profits for a customer over time one has to find the revenue for each period and deduct the variable costs associated with that specific customer. Since focus is on the average customer, one can estimate the revenue per user with ARPU - the Average Revenue per User. This is given by dividing the total revenue with the number of subscriptions. To come up with a decent approximation of the costs associated with a customer one can turn to the income statement and more precisely the variable costs. It is, however, very hard to obtain and dissect the income statement of the mobile operators in some markets due to the lack of public information, and thus an approximation needs to be done. By looking at historical data, the industry average for operating expenditures (OPEX) per subscriber can be found. From this value, industry estimates of fixed costs can be deducted, leaving only the variable cost for an average user. According to a report made by Deloitte the OPEX can be divided into three categories[69]:

- *Non-process OPEX* – is usually around 35 to 40 percent for mobile operators and include interconnection fees, taxes, telephones and uncollectible items
- *Support process OPEX* – this figure includes marketing, HR, IT, finance and other administrative costs and normally accounts for 15 to 20 percent of the total OPEX
- *Operational process OPEX* – normally accounts for 40 to 50 percent for mobile carriers and is divide into the following sub components (% of Operational process OPEX):
    - *Billing* (7 – 12%)
    - *Customer service* (10 – 15%)
    - *Sales* (20 – 25%)
    - *Network installation and repair* (40 – 50%)
    - *Network Operations and Design* (18 – 23%)

By using these industry estimates, the variable cost and net profit of an average customer can be roughly estimated. From the ARPU, the non-process OPEX together with sales, customer service and billing should be deducted to end up with an approximation of net profit for an average customer.[70]

To see how the profit changes over time as a result to price competition an analysis of the ARPU time series will be conducted. Furthermore, a similar analysis will also be conducted on the customer level to see how the revenues are related to the time being a customer.

A.3.11 Discount rate

The method used to calculate the discount rate is known as the weighted average cost of capital (WACC) and presented in section 2.6. The following formula for calculating the WACC is used:

[69] Deloitte, *Rethinking Operational Processes Can Offer Telcos Competitive Savings*, Deloitte Consulting LLP, 2009

[70] Brealy, R., Myers, S. and Allen, F., *Principles of Corporate Finance*, McGraw-Hill/Irwin, Northwestern University, 2008

$$WACC = g * (1 - T) * \left(R_f + DRP\right) + (1 - g) * (R_f + \beta_j * ERP)$$

where

$$g = \frac{D}{D + E} \tag{A.1}$$

The parameters are defined as follows:

- D is the sum of the debt
- E is the sum of the equity
- T is the corporate tax rate
- DRP is the debt risk premium (the difference between the risk free rate of return and the interest of company's debt)
- R_f is the risk free interest rate
- ERP is the equity risk premium (the required return on the market portfolio above the risk free rate)
- β_j is the asset beta (the sensitivity of the return on asset j relative to the market portfolio)

This formula is very straight forward and easy to use. Some of the parameters are company specific and most often found in the annual reports and some are given by market information. In this paper however, there is no interest in a specific firm but rather a typical mobile network operator in one of the countries analyzed. To approximate the discount rate one needs to find good estimates for the company specific parameters in the formula above. These parameters include the sum of debt, the sum of equity, the debt risk premium and the asset beta.

The gearing, also referred to as the sum of debt divided by the sum of the debt plus the sum of equity, is quite hard to approximate. This is a very individual ratio because different firms tend to have different gearing ratios due to regulations and ownership policies. Since it is very hard to find financial figures for private companies an industry estimate of the gearing ratio will be used. The same problem arises when the asset beta is to be calculated. Finding betas for publically traded firms poses no problem but a lot of the mobile network operators are private firms. Because of this, an approximate asset beta will be used to represent a standard MNO. The debt risk premium is also estimated with the help of a market estimate. This is because the debt risk premium is only observable for the companies that issues public bonds.

Regarding the non-company specific parameters, these are collected from market data. The corporate tax levels are easily found for each country and as the risk free rate the interest rate of country's government bond is used.[71] It is important to choose a government bond with around the same maturity as the investment; hence a 10 year government bond is a good approximation of the risk free rate.[72] The equity risk premium is also based on market estimates and all together the WACC formula will produced a fair benchmark value to be used as the discount rate.

A.3.12 CLV Calculations

Reference CLV

From the ordered probit regression, estimates of the coefficients for each factor are given. This includes standard error and confidence intervals. The coefficients will be used to calculate customer lifetime value for all markets and segments. In order to assess what is the return on investment for the investigated factors, a *reference CLV* will first be derived. The reference CLV is based on the *current* satisfaction levels, which give an average retention score. This score is input in the simulation, which runs a large number of fictitious customer-company relationship processes, in order to extract an average lifetime value. A more detailed description of the simulations is given below.

Improved CLVs

The next step is to measure the influence on CLV if the satisfaction level was improved for a given factor. One at a time, each factor will be given an increased average satisfaction score of 10 %[73]. Using the estimated coefficients, new retention scores will be calculated and used in the simulation to extract improved CLVs. However, only using the estimated coefficients might indicate a false reliability in the factor's influence in CLV. In order to capture the uncertainty in investing in a certain factor, the upper and lower boundaries of the confidence interval for the coefficient will be used to generate an interval in which the improved CLV is likely to end up. Note that this interval should not be interpreted strictly, estimating the coefficients at a 75 % confidence level does not necessarily imply that the CLV will end up within the derived interval with 75 % confidence. There might be a correlation between the coefficients that is not accounted for in such analysis. However, it gives insightful indications about the risk in investing in each factor.

[71] Damodran, A., *What Is the Riskfree Rate? A Search for the Basic Building Block,* Stern School of Business, New York University, New York, 2008
[72] ibid
[73] The choice of 10 % is arbitrary. Any number could have been chosen - since the point is to measure and compare sensitivity to the factors it is more important that the score increases are equivalent.

The improved CLVs will be put in relation to the reference CLVs, to give percentage changes. This way, the results can be compared across markets.

Simulations

Calculating the expected lifetime value of a customer can either be done analytically or with simulations. When more simple models are used – for example when profits and retention rate is constant over time – an analytical solution is quick and simple to compute. When profits and retention (i.e. the transition probability) is dependent on time and there is an indefinite number of states, the calculations become too comprehensive. In these cases, *Monte Carlo simulation* is an efficient method to solve the problem. When performing the simulations, a large number of fictitious customer-company relationship processes are simulated. Each month, a random variable is generated, deciding whether the customer retains or churns, based on the retention rate. If the customer retains, a discounted profit for that specific month is added to the CLV. After thousands of simulations, an average CLV can be calculated, representing the typical customer.

The simulations can easily be performed in MATLAB. The simulation code can be found in A.5.

A.4 Correlation of Independent Variables

ALL	Purchase Process	Billing/Payment	Account Mngmt	Customer Support	Network Perf.	Value for Money	Handset Offered	Price Plan Options	Communication	Loyalty Rewards
Purchase Process	1	0,727134	0,71612	0,6674724	0,578019	0,636562	0,69068	0,6374642	0,639959	0,46576
Billing/Payment	0,727134	1	0,82553	0,6963279	0,589512	0,653152	0,63765	0,6612942	0,651716	0,4592
Account Mngmt	0,716118	0,82553	1	0,7426478	0,615762	0,657108	0,66418	0,661192	0,699765	0,48404
Customer Support	0,667472	0,696328	0,74265	1	0,651133	0,68385	0,63552	0,6516439	0,73573	0,5792
Network Perf.	0,578019	0,589512	0,61576	0,6511327	1	0,710845	0,60867	0,6061174	0,661139	0,49233
Value for Money	0,636562	0,653152	0,65711	0,68385	0,710845	1	0,66228	0,7917887	0,745094	0,64885
Handset Offered	0,69068	0,637653	0,66418	0,6355179	0,608674	0,662284	1	0,7103755	0,70261	0,46427
Price Plan Options	0,637464	0,661294	0,66119	0,6516439	0,606117	0,791789	0,71038	1	0,769417	0,62477
Communication	0,639959	0,651716	0,69976	0,7357299	0,661139	0,745094	0,70261	0,7694168	1	0,6785
Loyalty Rewards	0,465756	0,459203	0,48404	0,5792046	0,492329	0,64885	0,46427	0,6247674	0,6785	1

SWE	Purchase Process	Billing/Payment	Account Mngmt	Customer Support	Network Perf.	Value for Money	Handset Offered	Price Plan Options	Communication	Loyalty Rewards
Purchase Process	1	0,744835	0,72832	0,6723961	0,528974	0,644252	0,71243	0,6799523	0,679869	0,50929
Billing/Payment	0,744835	1	0,84534	0,6621277	0,562477	0,624106	0,6276	0,6824278	0,65184	0,48121
Account Mngmt	0,728318	0,845345	1	0,7416203	0,580459	0,659391	0,62687	0,6861424	0,715126	0,52887
Customer Support	0,672396	0,662128	0,74162	1	0,631637	0,681253	0,61278	0,6439968	0,767071	0,62733
Network Perf.	0,528974	0,562477	0,58046	0,6316367	1	0,793653	0,56367	0,6751132	0,662354	0,53738
Value for Money	0,644252	0,624106	0,65939	0,6812534	0,793653	1	0,71609	0,8041799	0,772988	0,59677
Handset Offered	0,712428	0,627603	0,62687	0,6127812	0,563666	0,716094	1	0,7579745	0,727296	0,50962
Price Plan Options	0,679952	0,682428	0,68614	0,6439968	0,675113	0,80418	0,75797	1	0,801015	0,57663
Communication	0,679869	0,65184	0,71513	0,7670705	0,662354	0,772988	0,7273	0,8010151	1	0,72552
Loyalty Rewards	0,509286	0,481212	0,52887	0,627331	0,537377	0,596772	0,50962	0,576631	0,725524	1

US	Purchase Process	Billing/Payment	Account Mngmt	Customer Support	Network Perf.	Value for Money	Handset Offered	Price Plan Options	Communication	Loyalty Rewards
Purchase Process	1	0,661293	0,65741	0,6670743	0,573732	0,619276	0,65138	0,5812954	0,654421	0,45877
Billing/Payment	0,661293	1	0,80189	0,731397	0,556344	0,634654	0,61163	0,6107763	0,657376	0,43476
Account Mngmt	0,657407	0,801888	1	0,7652831	0,615375	0,619696	0,68964	0,6157469	0,700292	0,45355
Customer Support	0,667074	0,731397	0,76528	1	0,628316	0,639014	0,61042	0,622824	0,686189	0,52827
Network Perf.	0,573732	0,556344	0,61538	0,6283164	1	0,638848	0,59065	0,5183895	0,619948	0,44693
Value for Money	0,619276	0,634654	0,6197	0,6390136	0,638848	1	0,58662	0,758774	0,726277	0,65308
Handset Offered	0,651381	0,611629	0,68964	0,6104213	0,590652	0,586618	1	0,6460589	0,696224	0,41661
Price Plan Options	0,581295	0,610776	0,61575	0,622824	0,51839	0,758774	0,64606	1	0,779229	0,64537
Communication	0,654421	0,657376	0,70029	0,6861892	0,619948	0,726277	0,69622	0,7792291	1	0,63962
Loyalty Rewards	0,458766	0,434758	0,45355	0,5282701	0,446927	0,653076	0,41661	0,6453724	0,639621	1

UK	Purchase Process	Billing/Payment	Account Mngmt	Customer Support	Network Perf.	Value for Money	Handset Offered	Price Plan Options	Communication	Loyalty Rewards
Purchase Process	1	0,755917	0,73666	0,634476	0,583741	0,623168	0,68218	0,6429298	0,554833	0,43455
Billing/Payment	0,755917	1	0,80967	0,656104	0,600366	0,674791	0,62548	0,6827785	0,608158	0,46966
Account Mngmt	0,736658	0,809668	1	0,6864619	0,592	0,677008	0,61776	0,6845098	0,647446	0,50195
Customer Support	0,634476	0,656104	0,68646	1	0,650872	0,724226	0,6356	0,6931696	0,730779	0,62668
Network Perf.	0,583741	0,600366	0,592	0,6508721	1	0,703074	0,6167	0,6378774	0,667944	0,5294
Value for Money	0,623168	0,674791	0,67701	0,7242257	0,703074	1	0,67773	0,8061212	0,731644	0,68123
Handset Offered	0,682179	0,625481	0,61776	0,6355982	0,616695	0,67773	1	0,7446989	0,650138	0,50215
Price Plan Options	0,64293	0,682779	0,68451	0,6931696	0,637877	0,806121	0,7447	1	0,736641	0,6219
Communication	0,554833	0,608158	0,64745	0,7307789	0,667944	0,731644	0,65014	0,7366412	1	0,71603
Loyalty Rewards	0,434547	0,469659	0,50195	0,6266809	0,529397	0,681233	0,50215	0,6218975	0,716034	1

Figure A.5 Correlation Matrices

A.5 MATLAB Code for Monte Carlo Simulations

```
function [AVG, AVGmonths] = CLV(ret_score,profit,n,d)
%   Simulating CLV n times.

% INPUT
% p = AVG retention rate derived from regression
% ft = time function
% fp = profit function
% n = number of simulations
% arpu = initial ARPU

% FUNCTION

clv = zeros(n,1);                % vector containing CLVs for each individual simulation
months = zeros(n,1);

for i = 1:n
    prob = rand;                 % randomized value to determine churn or not

    t = 0;                       % state

    clv(i,1) = profit;           % profit in state 0
    t = 1;
    prob = rand;

    while prob < ft(ret_score,t)
        clv(i,1) = clv(i,1) + profit/(1+d)^(t/12); % add profit in state i
        t = t+1;
        prob = rand;
    end
    months(i,1) = t;

end

AVG = mean(clv);
AVGmonths = mean(months);

hist(clv,300);
xlabel('CLV bucket');
ylabel('nbr of customers');
uitable('Data',AVG,'ColumnName','Average CLV','Position',[350 300 110 40]);


end


function [ret] = ft(ret_score,t)

adj = 0;
if t<=68
    adj = -3e-6*t^3+0.0004*t^2-0.0126*t+1.0028;
else
    adj = 1.053;
end

ret = 0.009*ret_score*adj + 0.9134;


end
```

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