Mat-2.177 Project Seminar in Operational Research

Report, Group Nokia 1

Mobile Phones Replacement Forecasting: Theories and Drivers

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Executive Summary

Replacement market is getting more and more important as the new customer market saturates. So far the market forecasting methods have emphasized the new customer business and the replacement market forecasting has been insufficiently sophisticated. This paper approaches replacement demand forecasting from two directions: *Firstly*, it explains some models of replacement demand found from the literature. *Secondly*, it explores drivers for replacement behavior.

Unfortunately the literature overview reveals no directly applicable models, but the models examined are all helpful. Duration model would have required accurate data on the age and life cycles of the mobile phones in use, from which the former poses a problem: the age could only be estimated or acquired through a survey, because there is no data on which devices are replaced and which ones still are in use. A generation-based approach was not directly applicable to mobile phones. The bottom-up-approach using aspiration levels of phone users seemed interesting but it was not easily convertible to the case at hand. The idea to start from the motivation vs. cost of replacing that was used in the search for drivers was, however, inspired by this approach. Finally, the approach of using probability functions to describe life cycles seemed feasible, but would require analysis on how the life cycles could be estimated.

The four groups of drivers identified for replacement of a functional phone were technological change, subsidy policy of the operators, change in the consumption ability and the price of the mobile phones. The applicability of some consumption ability indicators was analyzed against recent development of replacement demand. The data, however, was somewhat insufficient for the purpose of verifying the drivers, and although the analysis showed that there exist correlations between replacement sales and different parameters, such as GDP, these relations were not consistent across different markets. Due to the fast increase in the amount of cellular phones also the amount of replacement sales has increased independent of many economic drivers.

The next step would be to include drivers of other categories and examine their applicability in estimating the life cycles in mature markets.

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1 Introduction

1.1 Background

As the first-time buyer market for mobile phones is saturating, the interest of the handset manufacturers is drawn to the old customers replacing their current device. The replacement market differs from the new customer market, and so the replacement demand needs to be forecasted separately from the demand of the new customer market. The client (Nokia Mobile Phones) does have methods for forecasting replacement demand, but the market forecasting methods have emphasized the new customer business. Figure 1 illustrates the standpoint of this study for evaluating replacement demand. Our primary focus is on "The share of consumers replacing".

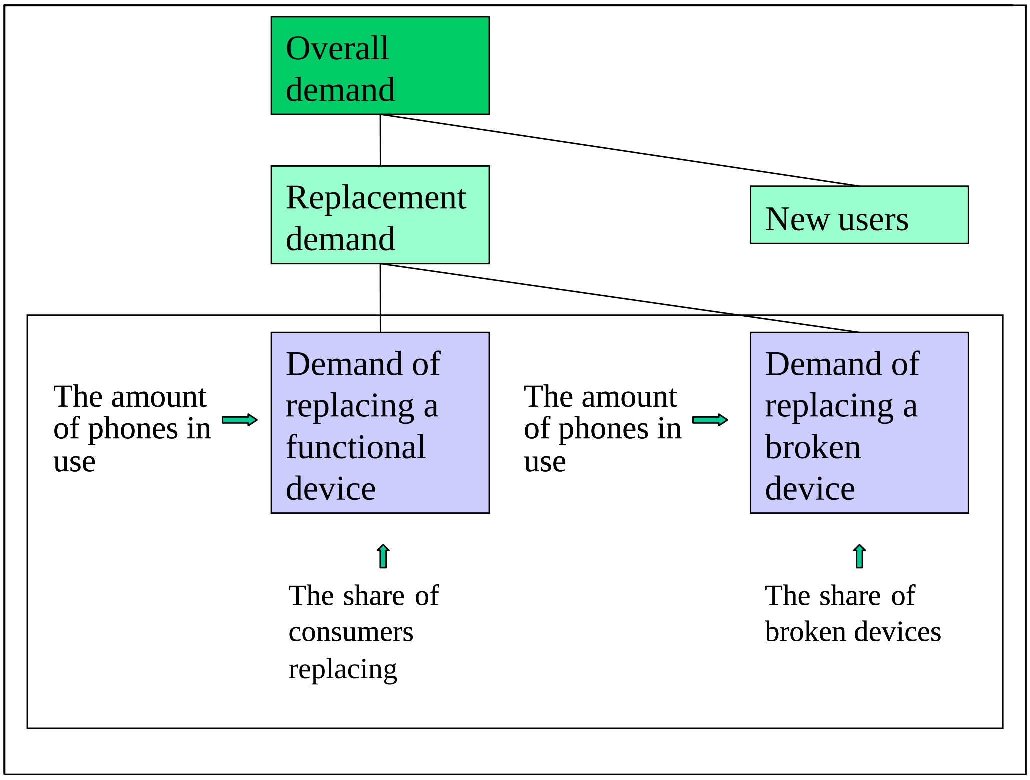

Figure 1 The overall picture of replacement demand. The amount of replacements of mobile phones is a function of the amount of phones in use and the share of the owners replacing their device.

1.2 Research Problem and Objectives

The research problem is the following: *How should replacement demand of mobile phones be forecasted?*

The research problem is divided into the following questions:

- *What are the models for replacement demand forecasting described in the academic literature?*
    - *Can these models be used in the Nokia case?*
- *Are there external drivers, based on which the replacement demand could be forecasted?*

The objectives of the study are the following:

- *To find ideas for replacement modeling from the literature*
- *To find drivers for changes in replacement demand and test how well they explain changes in replacement demand*

1.3 Focus of the Study

The literature review will take a more general perspective on replacement modeling, whereas the practical part will be more focused. In the following, the focus of the practical study is described and justified.

Replacement demand consists of replacements of broken devices and devices that do not meet with the aspiration level of the consumer anymore. The share of broken devices is probably quite constant, whereas substitution of functional devices is more variable. This is why our analysis on indicators focuses on the situation where the current devise is still working. The data we have on replacement sales includes both kinds of replacement, but the changes in the level of replacement demand are mostly due to consumers replacing an operable phone.

The study on indicators focuses on the factors *indicating change in the share of mobile phone users* replacing their handsets. The actual number of replacement demand requires information on the past sales so that the number of mobile phones currently in use can be calculated. This is taken into account in the analysis on data.

Forming a complete model of replacement demand forecasting is not in the scope of this paper. The search for drivers ultimately serves the purpose of forming such models, so the requirements a good model poses on the drivers have to be taken into account.

1.4 Structure of the Report

The report is organized in four parts: introduction, theoretical approach, practical approach and conclusions. The theoretical approach includes a review of the literature concerning replacement demand modeling and discusses the findings with regard to the client. Practical approach deals with the drivers for replacement demand- first explaining which factors could indicate changes in replacement demand of mobile phones and then testing the reliability of the drivers. The last section of the part will conclude the findings. Finally, the results are summarized and discussed in the last part of the report.

2 Theoretical Study

The purpose of this section is to explore academic literature on the field of replacement demand modeling. The approach we use is to summarize theories brought up by four relevant articles and discuss their applicability and usefulness in the case of Nokia.

2.1 Literature Overview on Replacement Demand Modeling

2.1.1 Observable and unobservable determinants of replacement of home appliances (Fernandez 2001)

Duration models have lately become popular in modeling replacement purchase behavior (Fernandez 2001). This is because they are better in analyzing complex dynamic processes, such as choice behavior, than conventional discrete choice models. The duration models are constructed to estimate the duration, i.e. the length of some event. In stead of a regular probability distribution the duration models are usually based on a hazard function (see e.g. Kiefer 1988). A hazard function is a conditional probability function that is denoted here $\lambda(t)$. The hazard function λ describes the probability at which events will be ending at time *t* given that it had lasted until time *t*. A hazard function is constructed as follows. Let the cumulative distribution function be

$$F(t) = P(T < t) \tag{1}$$

which specifies the probability that the random variable T is less than some given value t. The corresponding density function is then

$$f(t) = dF(t)/dt \tag{2}$$

The survivor function is defined as

$$S(T) = 1 - F(T) = P(T \geq t)$$

which is the complement of the cumulative function F(t) giving the probability that the random variable is greater than some given value t. The hazard function is then defined as

$$\lambda(t) = f(t)/S(t) \tag{3}$$

The most commonly used distributions are the exponential distribution and the Weibull distribution due to the fact that their hazard functions are rather simple and thus convenient to use. The hazard functions of the normal and lognormal distributions are much more complex.

When modeling economic behavior it is useful to add other components than time in to the model as well. Lancaster (1979) and Kiefer (1988) add explanatory variables to the model. Using a proportional hazard specification the function becomes

$$\lambda(t, x, \beta, \lambda_0) = \Phi(x, \beta)\, \lambda_0(t) \tag{4}$$

where λ_0 is a "baseline" hazard function, x is a vector containing the explanatory variables and β is a vector containing the coefficients of the variables. This means that the distribution is identical for all events if considered only with respect to time. The addition of the explanatory variables shifts the distributions up and down and along the time axis. This brings differences between events in varying conditions defined by the explanatory variables. The parameters of the model are estimated with the maximum likelihood method.

Both Lancaster (1979) and Kiefer (1988) apply the duration model to analyzing unemployment and re-employment. However, newer studies (e.g. Raymond et al. 1993 and Fernandez 2001) apply the duration model approach to the replacement of home appliances. Raymond et al. state that hazard models allow for much richer relationships between the ages of the goods and the probabilities of their replacement than typical dependent variable models. Fernandez uses the duration model to analyze observable and unobservable determinants of replacement of heating equipment and central air conditioning systems. She recognizes the importance of demographic and lifestyle variables, perceived obsolescence, styling and fashion and environmental awareness among other variables, on the likelihood of replacement and tries to take them into consideration in the duration model. Using the hazard function approach presented by Lancaster (1979) and Kiefer (1988) she adds explanatory variables – regressors – into the model. She uses variables describing the wealth and conservatism of the customers, the operating costs of the appliances and the usage of the appliances (deprecation).

The duration model is very versatile; it is useful in studying both macro and microeconomic phenomena. The general formulation of the hazard function allows for many different variations simply through changing the explanatory variables. However, the application of the hazard function approach requires that there is data on the distribution of the ages of current appliances and the lengths of the life cycles of the appliances. So, as such the duration model is not applicable to the case of Nokia Mobile Phones (we don't have the required data so that we could apply this model).

2.1.2 A Choice-Based Diffusion Model for Multiple Generations of Products (Jun and Park 1999)

Jun and Park (1999) develop a model that incorporates both diffusion and choice effects to capture simultaneously the diffusion and replacement processes for each successive generation of durable technology. The model differs from previous diffusion models in that effects of exogenous variables such as price are incorporated into the diffusion process by modeling choice behavior of the consumer. The model also set low requirements on sales data, since replacement and first-purchase sales mustn't necessarily be distinguishable.

Requirements for data

Jun and Park (1999) categorize sales data for multigenerational products according to data availability. Type I data distinguish between replacement and first-purchase demand, whereas in Type II data these two different types of demands are not distinguishable. When Type I data is available, installed base of the product for each generation can be observed. Installed base is the number of products in use for that generation in the time period. With Type II data, only the number of sales for each generation can be observed in the time period. Two slightly different models are developed to manage the tasks with both kinds of sales data. Exogenous variables can be included in the utility functions of consumers, thus the diffusion model can include control variables.

The model

By studying the choice behavior of consumers, the sales patterns of new products can be understood and sales forecasting models for those products can be developed. The model introduced by Jun and Park (1999) makes some assumptions of choice behavior and diffusion effects:

1. Newer generation products completely replace older ones
2. Consumer buys one unit if she/he chooses to by a product
3. Consumer's choice in each time period is independent of her/his choice in previous periods and depends on the choice utility for generations available at the time

The model also assumes that the error term of utility function follows the extreme value distribution. This simplifies the model and the justification of this assumption is given by Moshe and Lerman (1985). The complete description of the model details are omitted here. In principle the model basis on the fact that consumer chooses a specific product that maximizes her/his utility (or is happy doing nothing). Utility functions with or without exogenous variables for both first- and replace-purchasers are generated. With help of utility functions the following probabilities can be estimated for Type I model

- The probability that the k^{th} generation will be chosen from set of alternatives by first-purchaser at specific time.
- The probability that an i^{th} generation user upgrades to the k^{th} generation at specific time.

and for Type II model:

- The probability that a consumer (either first- or replacement demand) purchases k^{th} generation product at specific time.

These probabilities are used in estimating the installed base for Type I data and the number of sales of each product generation for Type II data.

Applications

Jun and Park (1999) introduce two applications of the model. The data used to validate the Type I model consists of 24 yearly observations of sales data for four successive generations of IBM computers from 1955 to 1978. The generations of computers were launched: 1) vacuum tubes 1955, 2) transistors 1959, 3) integrated circuits 1965, and 4) silicon chips 1971. The installed bases of each generation can be observed and no exogenous variables, such as price, are available. The model is applied to estimate the number of IBM computers representing the four possible generations in use as a function of time.

The Type II model is tested with data consisting 46 quarterly observations of worldwide shipments for four generations of DRAM memory from the 1st quarter of 1974 to the 2nd quarter of 1985. The generations of DRAM were launched: 1) 4k 1st quarter of 1974, 2) 16k 3rd quarter of 1976, 3) 64k 1st quarter of 1979, and 4) 256k 4th quarter of 1982. Only the number of quarterly shipments (not the number of products in use) is available for each generation. The price per bit is available for this application as an exogenous variable. The model is applied to estimate the shipments of different DRAM generations as a function of time.

Usability in case Nokia

Information of the sales of different mobile phone models should be available, in order to apply the methods suggested by Jun and Park (1999). Still, Nokia’s data would be of Type II assuming that it is impossible to keep track of the number of different phone models in use in time periods. This assumption is based on the fact that although we could observe operators’ sales to new customers and we knew the total number of sold phones in time periods, we would not know which generations the customers old and new phones represent. As a consequence of only Type II data available, the forecasts using the model suggested by Jun and Park (1999) would measure the total sales of different mobile phone models in future. These forecasts would surely be interesting, but they wouldn’t meet our demand for replacement sales.

It can also be argued that the generations of mobile phones does not necessarily fulfill the assumptions of the model suggested by Jun and Park (1999) because the differences between the phone generations aren’t as clear as with the applications tested by the authors. There are simultaneous many different phone models fitted to different kinds of consumer profiles in the market and these models don’t exclude each other. Still it can be supposed that the launching of a new model decreases the sales of older models. The importance of the paper by Jun and Park (1999) related to the Nokia’s existing forecasting model is the completely different starting point to the study: analyze the successive generation of durable technology. It may be assumed that the launching of a new mobile phone model and also exogenous variables (e.g. price, advertising) have something to do with the replacement behavior of customers. The problems are encountered with the need of information of the number of different phone models used in the market at each time period. With this information available, the future replacement sales forecasts could be distinguished out of the Type I model.

2.1.3 Modelling diffusion and replacement (Islam and Meade 2000)

Islam and Meade (2000) survey and evaluate different forecasting models for total sales of consumer durables, which include both a diffusion component and a replacement component. When estimating replacement demand, Islam and Meade (2000) conclude that it is critical to estimate the lifetime of the consumer durable accurately.

Replacement sales depend on the number and ages of consumer durables already sold. The first modeling approach tries to decompose historical time series of total sales into first time and replacement sales. Replacement sales are further divided into one year old durables, two year old, and so on, which makes it possible to estimate crucial replacement parameters for different probability functions. The second approach taken is to use a model-free replacement process, where the shape of the distribution of product lifetime is estimated from time series data.

The time series data sets available for calculations contained data from approximately 10-30 years.

Modeling Approach

Islam and Meade (200) model replacement sales using a density function $f(T)$, which is a function of the lifetime T of the product. Using this function the proportion of durables that have survived i time periods can be calculated using a function called survival function:

$$M(i) = \int_i^{\infty} f(T)dT \ .$$

Using the survival function the value of replacement sales at time can be calculated to be

$R_t = \sum_{t=1}^{t} [M(i-1) - M(i)] s_{t-i}$, where s_{t-i} is the total sales in a period t-i.

As one can already see the crucial part is to estimate a correct density function $f(T)$ for the products lifecycle. Islam and Meade (2000) divide different alternatives into one parameter density functions (Triangular, Poisson, and Rayleigh) and two parameter models (Gamma, Weibull, Truncated Normal, and Super-position).

For the chosen models parameters are calculated using two different variables that can be estimated from the time series data. These parameters are the average service life of a product E(t) and the maximum service life T^M. Islam and Meade (2000) continue to conclude that maximum likelihood methods were used to calculate the parameters, but fail to show the actual functions used. Parameters for different distribution functions were later derived from the average service life and maximum service life using specific transformation functions. (Islam and Meade, 2000)

Estimation

Islam and Meade (2000) used 42 data sets for the estimation of the replacement models. Parameters were estimated using maximum likelihood methods. The actual estimation process was conducted with two different philosophies. In the first one, average life cycle data was taken from existing sources and only the other shape parameters were calculated from time series data. In the second approach all the parameters were calculated from time series data.

The first approach using average life cycle data from outside sources showed that the two parameter models were clearly better than one parameter models. Out of these the Gamma distribution was the best one, as it provided the most accurate estimates. The actual difficulty with two parameter models was the calculation of needed parameters, which succeeded only in 40% of the cases. In one parameter models the calculation of parameters always succeeded.

The second approach using only time series information was even more complicated. Here the demands on the data sets are far greater because more parameters have to be estimated. It was found, that the parameter estimation rarely converged to allowable values. For example in the case of Gamma distribution only 14% of the tests succeeded.

Overall the success rate of valid parameter estimation was only in the range of 20-40% for all models.

Summary

The different life cycle density functions were shown to provide a good approximation for the life cycle of a durable good. The major difficulty was in the parameter estimation and over half of the cases failed because of this.

In the end Islam and Meade (2000) concluded that just as good estimations can be done using a distribution free approach, where does not use any specific distribution. The needed “shape parameters” are roughly estimated from the data or be based on expert opinion.

Case Nokia

For Nokia the article provides clear signals. First of all it should be understood that the estimation of the parameters may not be possible from the existing data, especially in a young and dynamic industry as telecommunications.

If the parameters are estimated using an expert opinion one should not necessarily use any specific distribution function, but could do fine with a rough estimation of the product life cycle from previous data.

2.1.4 Environmentally friendly replacement of automobiles (Marell, Davidson and Gärling 1995)

Context of the study

Majority of purchases are replacements for products such as automobiles, refrigerators, TVs, VCRs and CD players. According to previous studies product failure is seldom an important reason for replacement. Instead market price, advertising, styling and new features are found to have a greater impact. However the timing of durable-replacement purchases has not been an important target for theories. Not much literature on the topic exists.

Conceptual framework and study hypotheses

Marell, Davidson and Gärling (1995) hypothesize that an owned durable becomes a candidate for replacement when assessed as being worse than consumer's aspiration level (i.e. the replacement purchase intention will increase). The aspiration level is defined as a minimally acceptable quality (Simon 1955, 1956). The aspiration level has a key role, because it is supposed to mediate influences of many factors, such as expected changes in economy, changes in sociodemographic factors, changes in taste, and marketing of technological innovations. The mediating affect of aspiration level may be understood as an effect of directing attention towards different attributes. For example, if styling is an important feature of a product then the quality of the currently owned product will be more influenced by styling. Aspiration level both changes and causes changes in the assessment of the current durable.

Marell et al. (1995) assume several mediating steps to take place before a replacement is made. Conceptualization of these steps is presented in Figure 2.

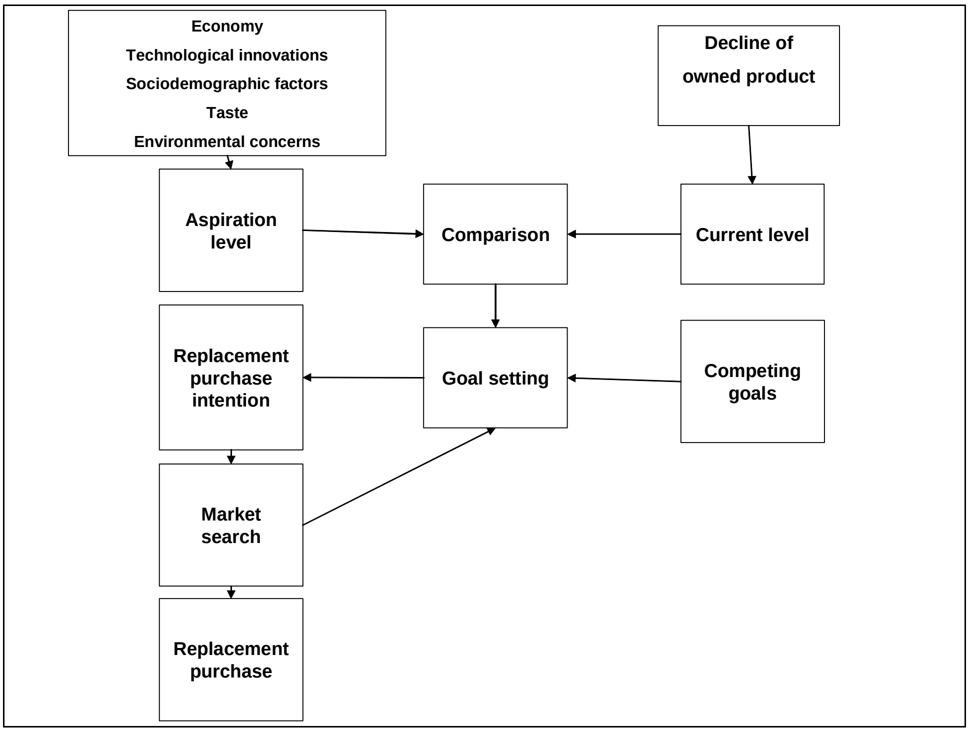

Figure 2 A conceptualization of factors affecting replacement purchase

Applied in the case of Nokia

The idea of the difference between aspiration level and perceived quality level as a factor affecting in replacement purchases is very tempting. However, applying this kind of approach into Nokia's forecasting models would require totally new procedures. The biggest question is how to define and measure aspiration levels and perceived quality levels. If duplicating this article's approach, Nokia should conduct consumer surveys and measure aspiration level and perceived quality level by questions. This method would be bottom-up instead of top-down, and would require significant resources. For curiosity it is described next how the difference between aspiration level and perceived quality level was studied in this particular case of automobiles.

Study objectives

- Whether the timing of replacement purchases is related to the difference between owner's assessment of the current quality of their automobile and their aspiration level.
- Whether information indicating that either early or late replacement is better for the environment affects the timing of replacement.
- Whether or not such an effect of information is mediated by changes in aspiration level.

Method and sample

The researchers interviewed one hundred automobile owners in Sweden through a telephone. Interviewees were randomly divided in two groups. For the first group it was communicated that an early replacement of an automobile is better and for the second group a late replacement was communicated to better in terms of environment. The following information was gathered from each respondent.

- Sosiodemographic factors (household size, age of household members, education, occupation, income)
- Factors related to the car and its usage (type and frequency of use, cost, year of purchase, recent repair costs, number of other automobiles available to the household.)
- Aspiration level (measured with a set of three questions, such as "Please indicate on this scale (0=legal to drive to 100= brand new) what is the worst level (lowest quality/lowest standard) of automobile you find acceptable to own?" The aspiration level was then determined by average.)
- Environmental concern (measured with a set of seven questions on a scale 0=very little, 100=very much)
- Perceived level of quality (on the scale from 0 to 100 of their own car)
- Replacement purchase intention (timing)

- Actual replacement purchases (from the national register of automobiles)

Results

Marell et al. (1995) used path analyses to examine whether replacement purchase intention is related to the difference between aspiration level and current level. Maximum-likelihood estimates were used to form two models. With the first model it was found that all path coefficients reached significance except that associated with the path from aspiration level to replacement purchase intention, which was only marginally significant (see Figure 3). In the second model, which contained additional factors, the age of the automobile was found to be insignificant and environmental concern and income close to be significant. Other factors were found to affect as predicted (see Figure 4).

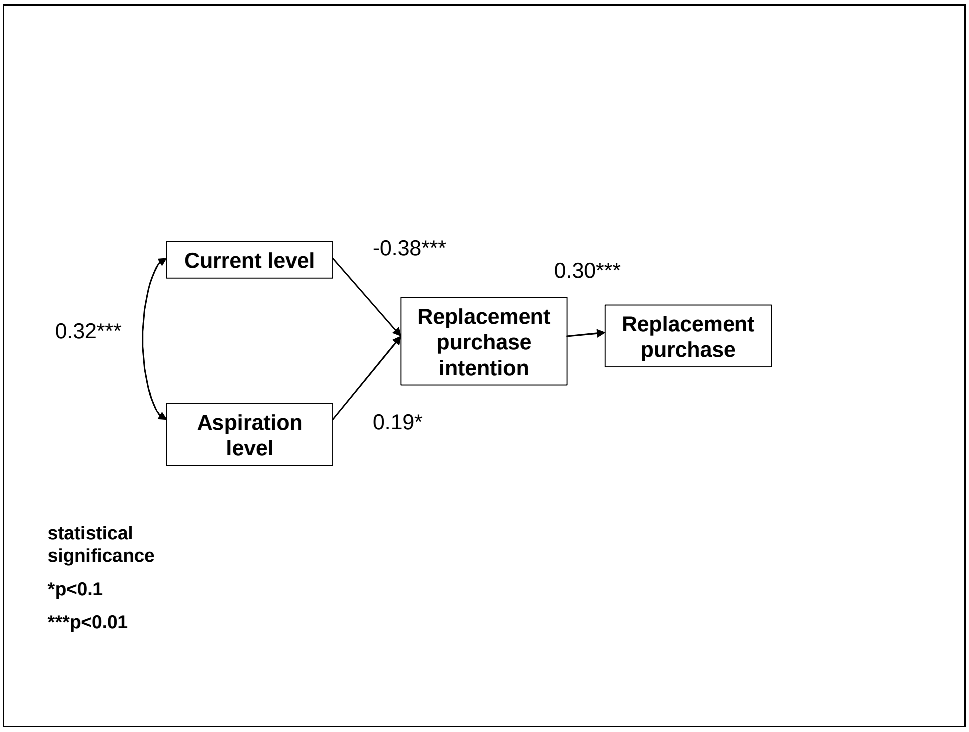

Figure 3 Model 1

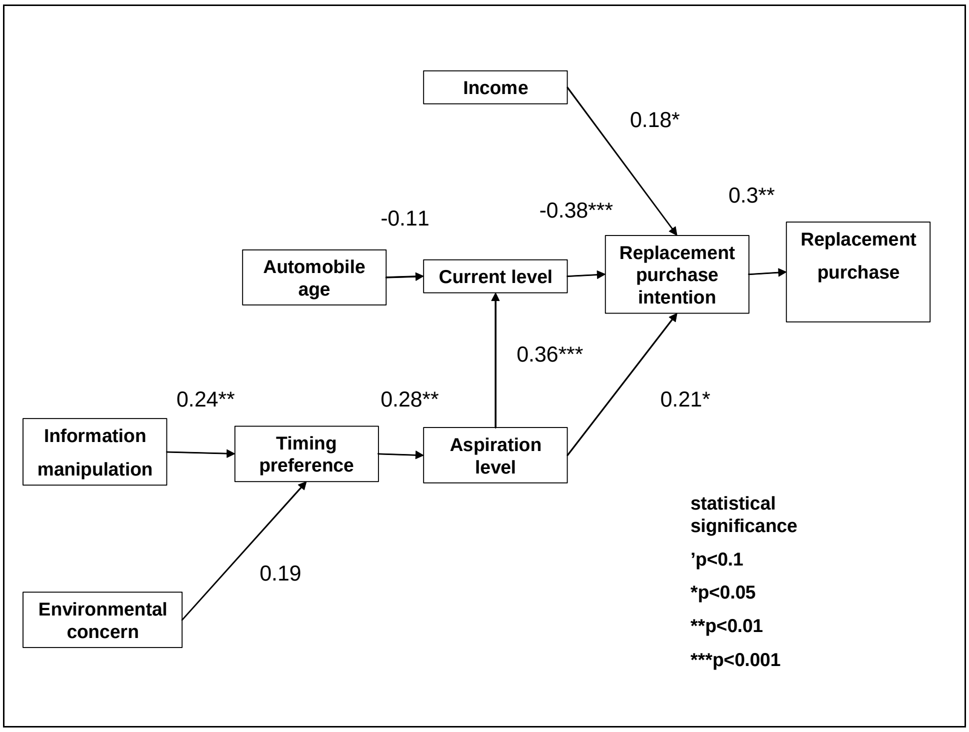

Figure 4 Model 2

As drawing a conclusion from Marell at al.'s study, it can be said that replacement purchase intention was causally related to the current level and the aspiration level in both models. Further the information (early replacement better/late replacement better) given was found to affect the aspiration level.

2.2 Discussion on Findings of Literature Overview

Four different replacement forecasting approaches were just examined. There were fundamental differences between each one of them as, for example, the approach taken by Jun and Park (1999) meant that a totally new, generation based approach would be needed. Marell, Davidson and Gärling (1995) in turn argued that by defining aspiration levels one could adopt a bottom-up approach to replacement forecasting. As good as these methods might be, they are out of our project's scope.

We also studied the dynamics of the duration model. The model was certainly feasible, but the real problem was that one would need precise data on the ages of current mobile phones and the lengths of the life cycles of these phones. If feasible data is available the method provides a promising approach for Nokia to base their estimations on. Islam and Meade (2000) suggested an easier way to forecast replacement demand: we would just need to specify a probability function that would describe life cycles of mobile phones. Just as with the duration model, the real problem is to estimate the life cycle lengths correctly, as well as the maximum life time of a phone.

With current data the estimates for the life cycle lengths and average life cycles are hard to conduct, as not long enough time series are available. Mobile phones are a relatively young market, where the constantly changing dynamics of the industry make forecasting based on historical data almost impossible.

This brings us to our next question of what should be done to correct the situation. The following chapter tries to give ideas to the problem and implicitly focus on the question of what factors should be considered when estimating, for example, the average life cycle of mobile phones.

3 Practical Study

In this section, a more practically oriented point of view is taken compared to the previous section with a theoretical emphasis. Now our goal is to give ideas that are applicable with regard to the data and methods available. However, it should be emphasized that the goal is not to give a direct answer to the problem of how to forecast replacement demand, because forming a complete model would be beyond the scope of this project. Instead, we aim at explaining what factors should be taken into the model and proving this by using actual market data.

Before going into the details of the drivers, we shall explain what the requirements of the model are, and hence, what is required from the drivers as well.

3.1 Practical Requirements of Replacement Forecasting Models

Replacement forecasting methods should fulfill several requirements regarding practicality. The model should be easy to explain, understand and challenge: both the assumptions and the output of the model should be discussable also among people that have no expertise on the field. This is highly important for two main reasons: the model should be verifiable and open for further development if the assumptions of the model are no longer valid.

The model should be parameterized in such a manner that most changes in the replacement environment do not demand a change in the core of the model, but rather in the parameters of the model.

The usability of the model is a significant characteristic. The model should be quick and easy to use and the costs of the usage should not be excessive.

Table 1Characteristics of a good replacement demand model

Understandability
Usability
Moderate costs of usage

Ideal drivers have the following characteristics: their values are known or at least possible to forecast very accurately, the information should be inexpensive to gather, and finally they should be both reliable and powerful predictors.

Table 2 Characteristics of good replacement drivers

Availability of forecasts/data
Inexpensiveness
Reliability of forecasts/data
Powerfulness as a predictor

3.2 Drivers for Replacement Demand

There are two fundamental factors affecting replacement demand for functional mobile phones: the relative costs of replacement and the desirability of new phones. If we are able to identify the most significant factors affecting replacement demand, analyzing the change in these factors (variables) should reveal the change in replacement demand. We shall thus call these factors drivers.

This chapter introduces and explores the usability of four groups of drivers for replacement demand: 1) change in consumption ability, 2) price of mobile phones, 3) subsidy policy of the telecom operators and 4) technological changes. The first three capture the relative costs of replacement and the technological changes affect the desirability of the new phones. The following Figure 5 demonstrates the identified factors affecting replacement demand.

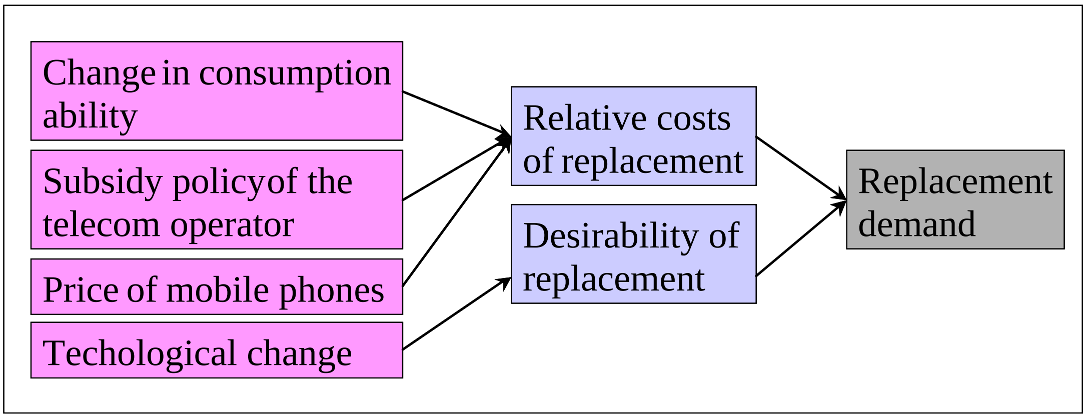

Figure 6 Factors affecting replacement demand

3.2.1 Indicators of Change in Consumption Ability

The change in people's ability to consume will have an effect on the sales of mobile phones. One could conclude that the more money people have to spend the more they will consume, which will directly affect the level of replacement sales.

To measure these changes we need to have indicators that fill the criteria introduced in the beginning of chapter 3.1. Possible measures are for example gross domestic products (GDP), consumer price indexes (CPI), wage indices, and different interest rates. What makes the estimation difficult, are the fundamental differences between different markets. Let us introduce a small example to clarify the dilemma. In market 1 the GDP has been growing steadily over the past 5 years and so has the replacement sales. However, market 2 went into a recession when 3 years had passed and the GDP actually fell, while the replacement rate grew.

The mobile phone market in general is in its infancy. General economic indicators have existed for decades, while mobile phones have become common only in the recent years. Due to this effect, the mobile phone penetration rate, as well as the amount of replacement sales, has increased almost independently of many indicators. In the long run we can expect this relation to strengthen, which makes a factor to consider.

3.2.2 Price of Mobile Phones

It is obvious that the price of mobile phones affects the willingness to buy a new one. As prices drop and more attractive models are offered at lower prices, people are more willing to replace their old ones.

One could say that it is enough just to measure the overall price across all mobile phone categories. Our argument is, however, that the average price is likely to stay the same over time, as new, more expensive models are constantly introduced. This forces us to divide the market into different categories. We could for example classify phones into three generic classes and calculate the average price for each one.

In reality the different prices are relatively hard to gather and the forecasting of price development is almost impossible in a dynamic industry.

3.2.3 Subsidy Policy of the Operators

In most markets the operators subsidize mobile phones in order to tempt new customers: the phone is bought as a package deal with the subscription, where the price of the phone is not transparent. In such package deals the customer commits himself or herself with the telecom operator for a given period of time. The level of subsidy is an indicator of how small a share of the retail price of the phone is left to the consumer to pay and how big a part is covered by the operator.

It is probable that the subsidies affect the replacement behavior: the customer is likely to change the phone between the deals with the operator. Replacement is thus also affected by the length of the contracts.

One could think that the level of subsidies is similar to the price as an indicator. On one hand it is, as subsidized phones seem cheaper to consumers, but on the other the level of subsidies affects the extent to which the replacement behavior is dictated by the telecom operators and their contract policy. If the level of subsidies is high and the contracts short, replacement cycle is shorter than in situations where the level of subsidies is low or the contracts are long. The following figure demonstrates the relationships between level of subsidy, length of contract between the operator and the customer, and the length of replacement cycle.

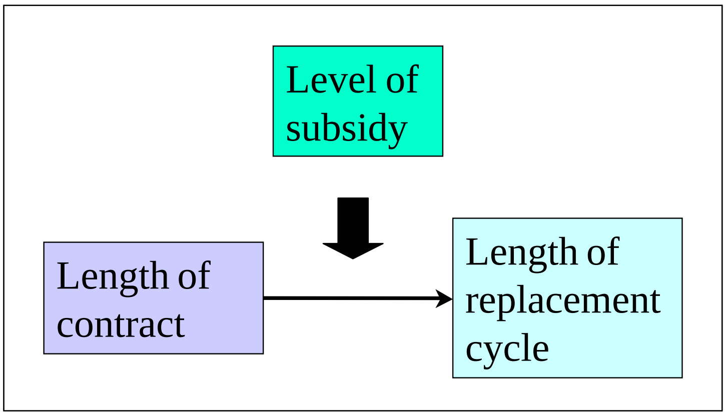

Figure 7 Subsidy policy affects length of replacement cycle

3.2.4 Technological Change

It is quite obvious that development of the products make replacement more tempting. If there are only similar products in the market as the current device, there is only little desire to replace it with the available models. The change in technology can be gradual and incremental or totally disruptive. The transition from analogical mobile phones to digital phones is an example of a technological discontinuity. Such fundamental changes are still relatively rare. Minor technological changes include the launch of SMS messages and color screens.

Technological change is undoubtedly a very difficult indicator to measure. Firstly, how could a discontinuity be distributed across time? The affects of discontinuities often are distributed over a long time period. How should this be taken into account in the model? Secondly, evaluating the significance of technological change is very difficult beforehand. Comparing color screens against the ability to take pictures with the phone sounds easier than it is. Who would have thought that SMS messages would become such a success?

One way to overcome the problem could be to use expert opinion. Analysts could be asked to assign a value between zero and one to describe the relevance of the technological improvement: zero for a barely significant improvement and one for a discontinuity. Also, the variable should be measured from the consumers' point of view. It should measure the *perceived* technological change rather than the actual difference.

A less challenging indicator would be, for example, the number of phone models in the market, which is fairly easily estimated.

3.3 Evaluation of the Drivers

In this chapter the drivers are evaluated against the criteria for a good indicator: availability of data, the cost of collecting the data/making forecasts, reliability of the data/forecasts and powerfulness in explaining change in replacement behavior. Table 3 below presents the evaluation on a scale of low, medium and high.

Availability of data (and forecasts) is good if the data is available inside of Nokia or there are public sources of information easily accessible. There are, for example, a plenty of estimates on the development of GDPs. The number of upcoming Nokia's models is probably relatively easily available inside of Nokia.

What makes data and forecasts expensive is the use of expert opinion. If the data is easily quantifiable, collecting the data and forecasts should be significantly cheaper.

Forming a technological index out of experts' opinions is time consuming and therefore costly. The more effort is needed, more costly the indicator is to form.

Reliability is at the highest with data that is received from Nokia itself. Data given by another party may be corrupted and therefore untrustworthy, whereas forecasts have problems of accuracy.

Powerfulness of the drivers is a pure guesstimate. It seems logical, that GDP or consumer price index is more distantly related to replacement behavior than technological change. However, these drivers should be considered as especially in the mature markets the replacement rate may largely depend on them.

When forming a model out of these drivers, there should be drivers of all the categories included. The drivers within the same category may replace each other.

The previous discussion shows, that especially the number of new models of Nokia should be included in the model. Also the prices of mobile phones could be a good indicator. GDP could be used as well, but not with a high emphasis, because it is cheap, yet only distantly related to replacement demand.

In the end, none of the factors itself is enough. But by combining the effects of these factors one could, for example, forecast the development of the average life cycle of mobile phones, which could then be fed into the forecasting models examined earlier.

Table 3, Evaluation of the drivers

		Usefulness			Powerfulness
		Availability of data	Cost of data	Reliability	
Consumption	GDP, CPI, Wages, Interest rates, etc.	high	low	high	medium
Subsidies	Subsidy level	medium	medium	low	medium
	Contract length	medium	medium	medium	medium
	Switching costs	low	high	Low	medium
Phone prices	The whole market				
	category prices	low	high	medium	not tested
	average prices	low	high	medium	not tested
	Nokia alone				
	category prices	high	low	high	not tested
	Average prices	high	Low	high	not tested
Technology	Number of models				
	the whole market	low	medium	medium	not tested
	Nokia alone	high	Low	high	not tested
	Discontinuity index	Low	medium	low	not tested
	Change index	Low	medium	low	not tested

3.4 Description of the Data

Unfortunately only some of the drivers presented previously were available for testing. The data received from the client was incomplete – probably partly due to confidentiality concerns, and probably partly because it would have been rather difficult to acquire just for testing purposes. The most interesting variables, such as the price and number of new models, were not available. In addition, the data we actually received contained holes that could not be repaired without knowing what the market in question was and what the real figures were – the data being indexed. The period of time that was presented in the data was also too short to give any reliable results. More data points would have been helpful. The data was testable, but one should be cautious with interpreting the results, which are presented in the next chapter.

The data we used in the analysis consists of 13 variables. All variables have quarterly data from 1996 to 2002. The data is collected from 11 markets (countries), which are anonymous. The variables and the type of data are presented in Table 4.

Table 5 Variables and their explanations

Variable	Type
Replacement sales	Replacement sales volume, unit unknown
New sales	New sales volume, unit unknown
Mobile Subscribers	Number of subscribers, unit unknown
Population	Indexed; base 2000 Q4 = 1
Retail sales	Indexed; base 2000 Q4 = 1
GDP	Indexed; base 2000 Q4 = 1
CPI	Indexed; base 2000 Q4 = 1
Exchange rate (with the dollar)	Indexed; base 2000 Q4 = 1
Long term interest rate	Long term interest rate (exact duration unknown)
Short term interest rate	Short term interest rate (exact duration unknown)
Subsidy level	Classification into 6 categories (0, 1, …, 5) with 5 being the highest subsidy level
Wage compensation	Indexed; base 2000 Q4 = 1, one observation per year only so each quarter was given the same value
Consumer confidence	Percentage change in CC-index from one quarter to the next.

The data is obtained from the client, but the details of the data were left out due to security reasons. Thus, for example we do not know the countries the markets represent. Also, to hide the size of the market, variables like population and GDP were indexed so that we can only see the proportional changes within each market. The consumer confidence indices had to be manipulated because they were not measured on the same scale in every market. To take care of this problem we calculated the percentage change in the index from one quarter to the next.

The dependent variable we were interested in was the percentage of subscribers replacing their cellular phones each quarter. This new variable, "Replacements per subscribers" (i.e."renewal rate"), was calculated from the variables "Replacement sales" and "Mobile subscribers". The replacement sales volume during a quarter was divided by the number of mobile subscribers at the end of the previous quarter.

Similarly, we calculated the portion of the population buying their first phone ("New sales" divided by "Population") and used this combined variable in the analysis.

3.5 Results

3.5.1 Correlations

We calculated the pair-wise Pearson correlation coefficients between the independent variables and the dependent variable. We used "Replacements per subscribers" as the dependent variable in the analysis. We used the risk level of 0.05 as the criteria for statistically significant results. The correlations were estimated for each market individually and then for the combination of all the markets. Market 3 was left out from the analysis because there were no observations available for the independent variables from this market.

The correlation coefficients between the dependent variable and the independent variables in each market are presented in Tables 6 and 7. If there were no data available for some independent variable in a particular market or if the variable was constant, the correlation coefficient could not be calculated. This is denoted by "N/A" (Not Available) in the following tables. For each market there were 27 cases or less available. The statistically significant correlations are bolded and underlined. The results of the correlation analyses are presented in more detail (including the p-values) in Appendix 1.

Table 6 Pair-wise Pearson correlation coefficients for "Replacements per subscribers" and the independent variables for individual markets (1/2)

Variable / Market	Consumer confidence	Consumer price index	Exchange rate	GDP	Long term interest rate	New sales
Market 1	***-0,510***	***0,901***	N/A	***0,893***	***-0,569***	***0,774***
Market 2	0,013	***-0,441***	-0,252	***0,677***	N/A	***0,513***
Market 4	-0,029	***0,885***	***0,712***	***0,790***	-0,266	-0,088
Market 5	-0,206	***0,619***	***0,568***	***0,645***	***-0,705***	0,378
Market 6	-0,084	***0,405***	0,313	0,286	0,026	***0,524***
Market 7	0,061	0,095	0,009	***0,472***	***-0,754***	-0,268
Market 8	0,109	0,287	***0,644***	***-0,536***	***0,683***	***-0,584***
Market 9	N/A	***-0,473***	***-0,477***	0,242	N/A	0,304
Market 10	N/A	-0,346	***-0,455***	-0,353	N/A	-0,222
Market 11	N/A	***-0,619***	***0,788***	***0,599***	N/A	-0,337

Table 7 Pair-wise Pearson correlation coefficients for "Replacements per subscribers" and the independent variables for individual markets (2/2)

Variable / Market	New sales/population	Retail sales	Short term interest rate	Subsidy level	Wage compensation
Market 1	***0,756***	***0,931***	***-0,682***	N/A	***0,892***
Market 2	***0,510***	***0,612***	N/A	***0,358***	***0,419***
Market 4	-0,095	***0,864***	0,001	N/A	***0,887***
Market 5	0,374	***0,737***	***-0,821***	N/A	***0,536***
Market 6	***0,524***	N/A	***-0,450***	***0,426***	0,351
Market 7	-0,279	***-0,692***	***-0,488***	-0,094	-0,148
Market 8	***-0,619***	0,052	0,013	N/A	N/A
Market 9	0,295	N/A	-0,135	N/A	N/A
Market 10	-0,230	N/A	-0,200	N/A	N/A
Market 11	-0,357	***-0,796***	N/A	-0,084	N/A

Based on these results it would seem that "Consumer confidence" is not a good predictor of replacement behavior. The correlations between the two variables and the dependent variable are not significant in any of the markets (except "Consumer confidence" in market 1). "Consumer price index" was significantly correlated with the dependent variable in seven markets. However, the sign of the coefficient was not consistent throughout the markets. "Exchange rate", "GDP", "Population" and "Retail sales" were significant in six markets, but again the signs were not consistent. The rest of the variables were significant in a couple markets. Also, one should note the fact that data were not available for all the variables in all the markets. For instance, the correlation between "Subsidy level" and "Replacements per subscribers" could only be calculated from four markets due to the lack of data or the fact that subsidy level was constant in many of the markets. The changes in the sign of "Exchange rate" can be explained through the fact that some countries export whereas others import cellular phones. Thus the exchange rate has the opposite effect on imposters and exporters. Also, the calculation of the consumer confidence index varies a lot from country to country, so it might not be a reliable measure.

After this we combined together the data from all the markets (still excluding market 3) and calculated the same pair-wise correlations. The results are presented in the following table.

Table 8 Pair-wise Pearson correlation coefficients for "Replacements per subscribers" and the independent variables for the combined data

Variable	Correlation	p-value	Cases included	Missing cases
Consumer confidence	0,028	0,713	175	105
Consumer price index	***0,171***	***0,005***	270	10
Exchange rate	0,067	0,272	270	10
GDP	***0,212***	***0,001***	270	10
Long term interest rate	***-0,695***	***0,000***	140	140
New sales	***0,241***	***0,000***	270	10
Population	***0,229***	***0,000***	270	10
Retail sales	***0,275***	***0,000***	189	91
Short term interest rate	***-0,388***	***0,000***	216	64
Subsidy level	***0,319***	***0,000***	198	82
Wage compensation	***0,317***	***0,000***	158	122
New sales/population	***0,237***	***0,000***	270	10

From the above table it can be seen that only "Consumer confidence" and "Exchange rate" were not significantly correlated with "Replacement sales per subscribers" when all markets were taken into account. It is worth noticing that the p-values of the significant correlations are extremely small. The number of cases included in the analyses is quite large for each independent variable. It is interesting to note that

“New sales per population” is now significantly correlated with the dependent variable even though it was not significant for each market alone. Also, the signs of the correlation coefficients are what one could expect based on economic theory. Only the appropriate sign of the consumer price index is debatable. On one hand, increasing prices should diminish purchases but on the other, increasing inflation is an indicator of an economic upswing.

3.5.2 Linear Regression

We started out with the combined data. Our attempt was to build a regression model with as many statistically significant independent variables as possible and with a high coefficient of multiple determination (R^2) for the overall model. In addition, the plotted residuals should not show any significant errors in the construction of the model. First we formulated a model that included all variables. This resulted in a model where there was multicolinearity present. The VIF-values over 10 was a clear indicator of this. We studied the pair-wise correlations between the variables that had high VIF-values. It turned out that “Wage compensation” was highly correlated with “Consumer price index” and “GDP” and “Short term interest rates” were correlated (naturally) with “Long term interest rates”. Thus we excluded these two variables. After this there was no multicolinearity present, but all the individual variables were not statistically significant (the p-value of the t-test was greater than 0.05). We excluded the insignificant variables one by one until there were only statistically significant variables in the model. The results of this last regression model are presented Table 9.

Table 9 The final model for the combined data

UNWEIGHTED LEAST SQUARES LINEAR REGRESSION OF REPPERSUB					
PREDICTOR					
VARIABLES	COEFFICIENT	STD ERROR	STUDENT'S T	P	VIF
---------	-----------	---------	-----------	------	---
CONSTANT	-0.07732	0.07375	-1.05	0.2976	
LTINTERES	-0.65194	0.14851	-4.39	0.0000	3.3
RETAILS	-0.20989	0.03049	-6.88	0.0000	3.4
SUBSIDY	0.01449	0.00156	9.27	0.0000	3.9
EXCHANGE	-0.05409	0.02350	-2.30	0.0240	2.5
GDP	0.40825	0.09240	4.42	0.0000	2.2
R-SQUARED	0.8104	RESID. MEAN SQUARE (MSE)	2.782E-04		
ADJUSTED R-SQUARED	0.7986	STANDARD DEVIATION	0.01668		
SOURCE	DF	SS	MS	F	P
----------	---	----------	----------	-----	------
REGRESSION	5	0.09514	0.01903	68.39	0.0000
RESIDUAL	80	0.02226	2.782E-04		
TOTAL	85	0.11740			
CASES INCLUDED 86	MISSING CASES 194				

The variables that were significant in the model were: “Long term interest rate”, “Retail sales”, “Subsidy level”, “exchange rate” and “GDP”. The model explains about 81 % of the variation of the dependent variable and the F-test value is quite large. This means that the model has explanatory power in the statistical sense. Also, the plot of the residuals (Figure 8) indicates, that there are no coarse errors in the structure of the model. However, only 86 cases were included in the model because the observations for some variables are missing from many markets and all the cases with one missing value are omitted from the entire model. So actually, markets 2, 6, 9, 10 and 11 are not included in this regression model. Surprisingly, the sign of "Retail sales" was negative even though the sign of the pair-wise correlation with the dependent variable was positive. One reason for this is undoubtedly the fact that only few markets are included in this model.

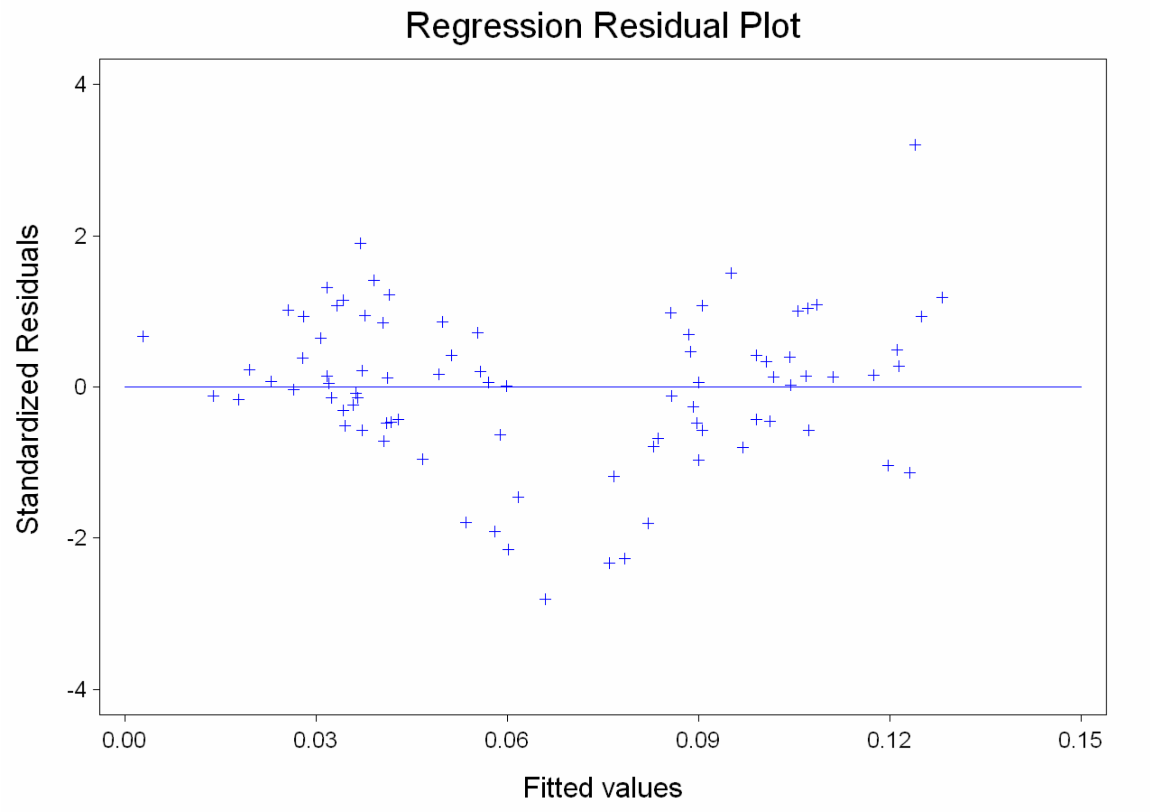

Figure 8 The plot of regression residuals

If we omit "Long term interest rate" from the model we get 61 additional cases. However, after this the model only explains 62.5 % of the variation in the dependent variable, so the model is significantly worse. Also, the sign of "Retail sales" remains negative.

We built regression models also for the individual markets. However, it is worth noticing that each model is based only on about 27 cases. This means that it will be difficult to construct models with more than two significant independent variables.

The following table lists all statistically significant variables for each market. If the sign of the coefficient of some variable was negative, this is indicated by a minus sign in front of the variable name. In addition, the coefficient of multiple determination (R^2) and the F-test value are presented for each. For some of the markets it was possible to build alternative models by replacing few variables. These replacements possibilities are shown in the last column. However, any of the alternative models result in lower R^2 values.

Table 10 A summary of the results of the regression analysis for each market

Market	Variables	R^2	F	Alternatives
Market 1	Consumer confidence, wage compensation	0,847	66,45	wage -> retail sales
Market 2	GDP	0,458	21,16	GDP -> (CPI)/retail sales/(wage)
Market 4	CPI	0,783	90,18	GDP, wage, ratail sales
Market 5	Long term interest rate, retail sales	0,615	19,16	single variable: GDP, wage or CPI
Market 6	CPI	0,164	4,90	
Market 7	GDP, subsidy, exchange rate, long term interest rate	0,784	20,00	
Market 8	Exchange rate, -retail sales	0,636	20,99	-retail sales -> -CPI
Market 9	CPI	0,224	7,21	
Market 10	-CPI, short term interest rate	0,349	6,48	-CPI -> -GDP
Market 11	GDP, -retail sales	0,780	42,45	

The most common significant variable in the models was CPI. It was a significant explanatory variable in four markets and could have been used in three others.

The second most common variable was GDP, which was found in three models. All other variables were encountered in one or two cases.

The best models in terms of the coefficients of multiple determination were found for the markets 1, 4, 7 and 11. The weakest models were found for the markets 6, 9 and 10.

3.5.3 Discussion of the Results of the Correlation and Regression Analyses

Correlations

The correlation and regression analysis did not produce clear results. We will first analyze the results of the correlation analyses and compare the results from different markets with each other. Finally, we will discuss the findings of the regression analyses.

When all the data was grouped together, all the drivers except "Consumer confidence" and "Exchange rate" were significantly correlated with the dependent variable, "Replacements per subscriber". Also, the signs of the coefficients were consistent with economic theory. The only variables with negative coefficients were the long and short term interest rates. The expected sign of effect of "Consumer price index" is debatable. An increase in the index indicates an increase in the general price level. The effect of an increased price level can have either a positive or a negative effect on consumption, depending on the development of wages. If wages increase less than prices, consumers' purchasing power will decline, but if wages increase more, the purchasing power will improve. It is therefore impossible to know the effect of inflation without having additional information on the economy.

The problem with the coefficients is that they are quite small, ranging mainly from 0.2 to 0.4 indicating that there is no clear linear relationship between the drivers and the dependent variable. The best linear correlation, -0.7, was found between "Long term interest rate" and the dependent variable.

Most of the drivers we tested turned out to be significantly correlated with the dependent variable in many of the individual markets as well. Also, the correlation coefficients (for the significant correlations) were in principle much larger than for all the markets put together. Interestingly, some variables behaved differently from market to market. The signs of the correlations varied pretty randomly between markets. Both interest rates were mainly negatively correlated (if the correlations were significant), but “Long term interest rate” was positively correlated with the dependent variable in market 8. “GDP” was positively (and significantly) correlated with the dependent variable in the majority of the markets, but it was negatively correlated in market 8 with a coefficient of -0.5835. The signs of the coefficients of “Exchange rate” and “Consumer price index” varied a lot. A summary of the behavior of all the variables is presented in Table 11.

Table 11 A summary of the behavior of the independent variables in the correlation analysis

Variable	Significant in n markets	Sign of the coefficient
Consumer confidence	1	minus:1
Consumer price index	8	minus:3 plus:5
Exchange rate	6	minus:2 plus:4
GDP	8	minus:1 plus:7
Long term interest rate	5	minus:4 plus:1
New sales	5	minus:1 plus:4
Retail sales	7	minus:2 plus:5
Short term interest rate	5	minus:5
Subsidy level	3	plus:3
Wage compensation	5	plus:5

This implies that models could be built better for each market individually rather than constructing one general model to fit all markets. It would seem that there are no universal drivers, at least not among the ones we have tested. It is possible, that markets behave differently in the analysis because they are in different phases of the product life cycle. It is very plausible that saturated markets behave differently than emerging markets. However, we cannot speculate on that here, since we do not know the identities of the markets.

Regression Analysis

Regression shows that many independent variables are correlated (multicolinearity in the model), i.e. many drivers describe or are the result of the same economic phenomena. In most models “Wage compensation”, “GDP”, “Consumer price index”, and “Retail sales” were highly correlated with each other. Thus they were interchangeable in the regression models. Naturally, also “Short term interest rate” and “Long term interest rate” were correlated with each other, so only one of them could be included in the model.

When constructing models for the individual markets we were not able to construct models including on average more than two variables. This is because each market included only 27 cases and values for some variables were missing from many markets.

Based on the regression analyses, the best drivers would be “GDP”, one of the interest rates and “Consumer price index”. These were most commonly the explanatory variables in the regression models. However, the behavior of these variables was not consistent at all times. For example, the coefficient of “GDP” in market 8 was negative. Also, half of the models did not explain the variation of the dependent variable (“Replacements per subscribers”) too well and there were only one or two independent variables in the models. The values of R^2 in these models ranged between 0.2 and 0.6 for six markets. For four markets (markets 1, 4, 7, 11) the models were somewhat better; at least the explanatory power was higher. This is because more statistically significant variables could be included in the models.

The results from the analyses are somewhat vague and at times even conflicting. This could be due to the fact that countries in different phases behave differently. One should also consider the results with caution: perhaps the drivers are too general and the purchase of a cellular phone too minor. A cellular phone is relatively inexpensive, so the purchasing decision of a cellular phone is not as important as that of a larger appliance or a car. One could expect that general trends in the economy, which our drivers monitor, would affect the demand for cars more clearly.

The results of the regression analyses as well as the correlation analyses indicate that there are some economic indicators that could explain changes in the replacement pattern. The best drivers seemed to be the GDP and the consumer price index. The results also indicate that there are other factors affecting replacement behavior than the ones we have tested. One reason for these results is that we have included only drivers from only one category (change in consumption abilities).

Also, cellular phones are a relatively new product and the markets – especially for replacement purchases – are newly developed. At this point in time the replacement demand is increasing no matter what. In most markets there has been a huge growth in new phone purchases in the past few years. It is only natural that the replacement sales are increasing now (due to phones breaking or becoming old-fashioned); there were no replacements in the past because nobody had a phone. Therefore the development of macro phenomena, such as GDP growth may not seem to have any effect on the replacement behavior. We should wait for a few more years to be able to examine relationships between the drivers and the replacement demand. Then the growth would have leveled off and the markets would have become more stable.

3.6 Neural Network- approach

3.6.1 Visualizing variables with Self-Organizing Map

Self-Organizing Map, or more briefly SOM, is a tool commonly used in explorative data mining. SOM is an example of more general class of neural network algorithms. The power of SOM is its capability to visualize multidimensional data in a convenient way to human being. It is extremely hard to get idea of the dependencies of different variables, cluster structure or possibly irrelevant variables in the data if we have measurements consisting of, let’s say, a couple of dozen variables. SOM offers one way to face this challenge of high dimensionality. The advantages of SOM with respect to many other methods are its capability to capture nonlinear properties and its lack of assumptions (e.g. Gaussian features) of the data in hand. The SOM method doesn’t build any model, but it can be treated as descriptive tool. The purpose of introducing SOM algorithm in this context is deepen the analysis made in previous sections. We re-analyze the situation where data from all markets are grouped together and find possible explanations to small linear correlations reported in Table 8. The SOM method suits best in situations where the amount of observations in data is high, so analysis of the individual markets is excluded.

Overview of the SOM method

A brief overview of the SOM algorithm will be given next. For a more detail description, we encourage to familiarize oneself with the book by Kohonen (1997). SOM consists of a certain number of neurons. The number of neurons can be freely chosen, but in practice the dimensionality of the data and the wanted abstraction level fix this amount. Each neuron has got a position in the data space spanned by the variables of the data. We call this space input data space. At the very beginning, the positions of the neurons are randomized. The SOM algorithm tries to organize the positions of the neurons to match the probability density of the data. This means that there are more neurons in those parts of input space where the number of observations is also high. The neuron map will be loose in the parts of the input space where the existence of observations is rare. The trained SOM map can thus be interpreted as an abstraction of the primary data. It is a collection of points in the input data space, the number of these points is lower than the number of observations in the primary data and these points try to represent the whole collection of primary data observations.

An important property of SOM map is the fact that for each of the neurons, the neighboring neighbors are specified. Although the positions of the neurons are randomized at the beginning of the training procedure, the neighboring neurons are close to each other after the training has been completed. This is the explanation for the name self-organizing. The neighborhood preserving property of SOM makes it possibly to arrange the neurons on a discrete grid revealing the neighboring connections between the neurons. Here we restrict to the situation, where each neuron has six neighbors and the resulting SOM grid becomes hexagonal. We call the discrete grid as output data space. As earlier stated, each neuron has got a position in the continuous input data space. Now the neurons can also be placed on the discrete output space too. The capability to visualize high dimensional data comes from the fact that we can observe properties of the high dimensional input space from two-dimensional discrete grid in output space.

In Figure 9 is presented a simple example of SOM trained from two-dimensional data consisting 270 observations. A hexagonal SOM map with 120 neurons arranged in [12×10] output space grid is trained with the data. Since the input space is only two-dimensional, we can plot the observations and also the neurons on a plane. From Figure 9 can be seen, that the positions of the neurons after the training are distributed along the density of the observations on the input data space. There are many possibilities to visualize the output space, see e.g. Vesanto (1999). Here we have drawn two component planes visualizing the two variables of the data. The topology of the component planes is similar. It means that a hexagonal cell that is in same location in every component plane refers to the same neuron. Interpretation of colors of the cells is following. Select one hexagon from output space, for simplicity we take upper left corner. We can find out the position of this neuron in input data space by reading the colors of upper left corner hexagon in the two component planes and then verifying the colors to the color bars beside the component planes. In this neuron's case Variable 1 is about 3 and Variable 2 is about 2.5.

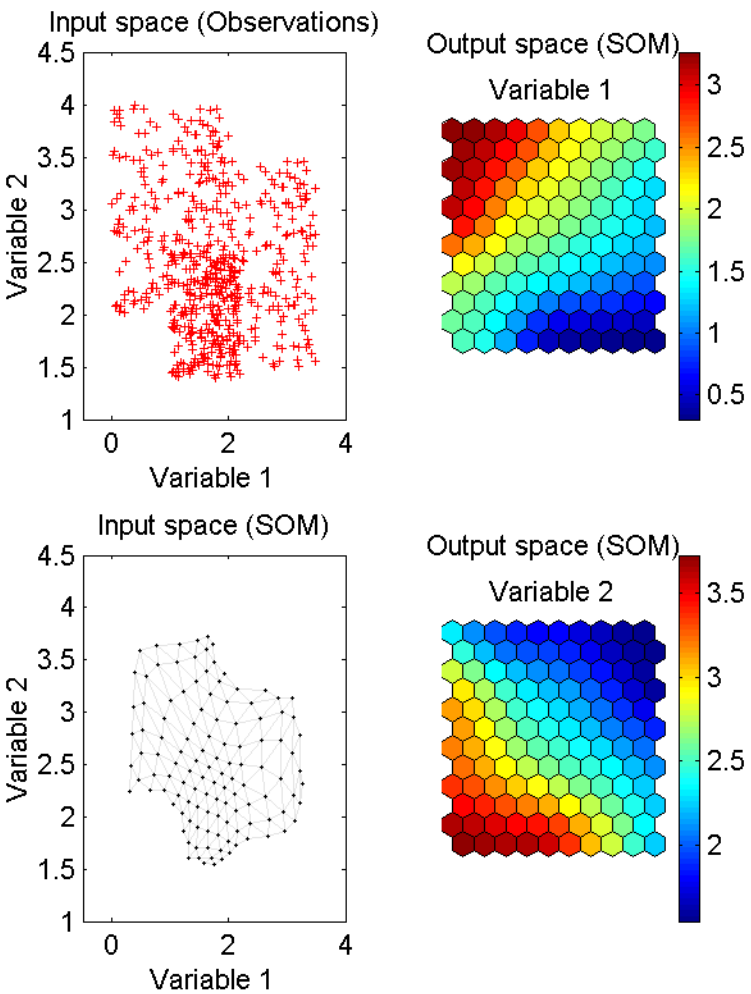

Figure 9 Example of SOM trained from two-dimensional data. On the upper left subfigure are plotted the observations from the data. The lower left figure shows the organized SOM neurons and connections between them in the primary data space. The subfigures on the right hand side are SOM component planes in the discrete output grid.

Applying SOM method to the data

In the previous sections we calculated linear correlations (Table 8) and built linear regression models (Table 9). Pair-wise linear correlations are very small and linear regression model is extremely sensitive to missing values as stated earlier. These facts encouraged us to make some reanalysis with different type of method. SOM suits well in this purpose, since it truly differs from the methods applied earlier. Nonlinear dependencies between the dependent and explanatory variables weren't earlier taken into account and the found correlation results with t-values may be doubtful because normality of the data cannot be assumed.

The training data for SOM consists of quarterly observations from 10 market areas over the total available time period. The markets were aggregated into one matrix containing total 270 observations. Market 3 was again excluded because the lack of most values. One observation was lost from each market since the presence of a variable derived from one year lagged values. The resulting SOM is presented in Figure 10 and the variables included in the training can be found on the top of the component planes. Interpretation of the map is harder than usually, because the values of most variables in the observations are proportions or differences from the reference quarter defined by the supplier of the data. The reference value is from same year in every market, but each market has its own value. Thus the results from the SOM map must be interpreted as market's deviation from its own reference value. The lack of knowledge about the absolute values and the preceding manipulations done to the data makes again the found results doubtful.

The analysis of nonlinear dependencies means seeking such areas from different component planes that looks someway similar. In Figure 10, there is a strong correlation between "GDP" and "Wage compensation". An example of more local nature of correlation is between "Consumer price index" and "Exchange rate". The important thing in our problem context is that there is not preset any single variable or combination of several variables, which could explain the shape of the component plane representing the dependent variable, "Replacement per subscribers". Only the lowest values of "Long term interest rate" indicate high "Replacement per subscribers" value. This negative correlation was found earlier during linear correlation analysis. The SOM training procedure was repeated with some variables left out, but the situation remained quite same. The SOM based analysis doesn't thus reveal any latent properties of regression that the linear analysis might earlier have unobserved.

Still, the use of SOM method can give valuable information of other properties from the problem in hand. One way to increase the value of SOM is incorporate the time behavior of markets in the analysis. SOM is static itself, but if we assume that the neurons represent the possible “states of the world”, we can analyze changes of markets’ states in time on the component planes. In Figure 10 is represented the trajectory of Market 1 starting from the Q2 of 1996 and ending at Q4 of 2002. The trajectory reveals that the Market 1 has increased the total sales. The increase is at first sales to new customers and at the latter part of time interval the market is heading to the high replacement sales area of the map. This example shows how SOM can be used in monitoring a market’s change in time versus several variables.

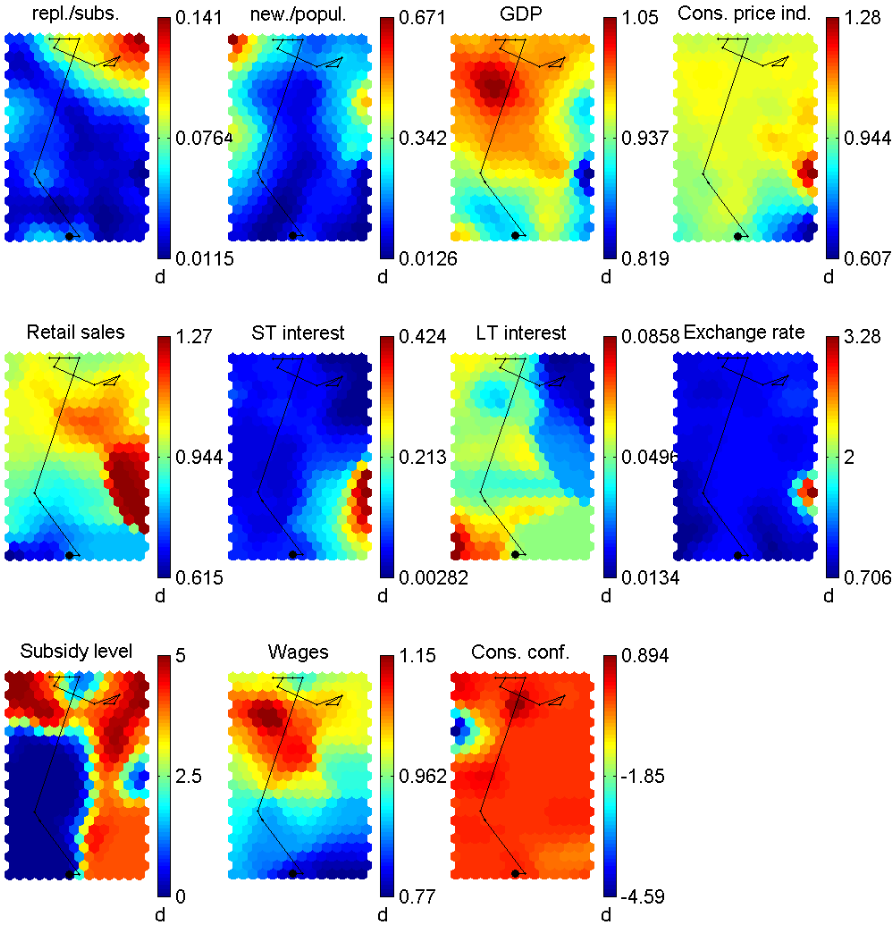

Figure 10, SOM component planes representing eleven measured variables. The trajectory indicating the quarterly movement of Market 1 (from Q2 of 1996 to Q4 of 2002) is shown on top of each component plane. The starting point of the trajectory is marked with dot.

4 Conclusions

Replacement demand forecasting provides a formidable challenge in the telecommunications industry due to its dynamic nature. Many traditional methods are rendered useless as there does not exists sufficient amounts of time series data and even if feasible data is found it contains so many discontinuity points that estimation relying on it will require significant effort.

The contribution and focus of this paper was in introducing different factors that might be used in estimating replacement parameters. Our analysis showed that Nokia should clearly focus on parameters from four categories, which were parameters influencing consumption abilities, price of mobile phones, subsidy levels, and the overall technological change in the industry. We believe that through these parameters Nokia could accurately estimate, for example, the average life cycle of mobile phones and so use some of the models found in the literature search.

We also conducted an example analysis with data from Nokia’s sources. The idea was to test how we could estimate replacement sales parameters in the consumption abilities category. The analysis shows that there exists a correlation between replacement sales and different parameters like GDP, consumer price index and retail sales. However, these relations are individual for each market and differ a lot between markets. This could be due to the fact that the markets are in different phases of economic development. One can expect industrialized countries to behave differently from developing countries. Also, an economic crisis in a country can affect the behavior of the drivers in the market.

From the correlation and regression analyses, as well as the SOM approach we can conclude that models would be better built for each individual market rather than trying to group all the markets together. There are some drivers among those that we tested that would seem to explain changes in the replacement pattern. However, we have tested drivers from only one category (changes in consumption abilities) out of four. The next step would be to add drivers from the other three categories as well. This would be a good topic for future research into the replacement pattern of cellular phones. The data for the three other categories is more difficult to obtain. Especially the measurement of technological change is difficult. One point of interest in the future would be to construct a technology index as a proxy for technological change.

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Appendices

5.1 Appendix 1 – Correlations

Correlations with *replacements per subscribers,* **all markets**				
Variable	**Correlation**	**p-value**	**Cases included**	**Missing cases**
Consumer confidence	0,028	0,713	175	105
Consumer price index	***0,171***	***0,005***	270	10
Exchange rate	0,067	0,272	270	10
GDP	***0,212***	***0,001***	270	10
Long term interest rate	***-0,695***	***0,000***	140	140
Retail sales	***0,275***	***0,000***	189	91
Short term interest rate	***-0,388***	***0,000***	216	64
Subsidy level	***0,319***	***0,000***	198	82
Wage compensation	***0,317***	***0,000***	158	122

Correlations with *replacements per subscribers,* **Market 1**				
Variable	**Correlation**	**p-value**	**Cases included**	**Missing cases**
Consumer confidence	***-0,510***	***0,007***	27	1
Consumer price index	***0,901***	***0,000***	27	1
Exchange rate	N/A			
GDP	***0,893***	***0,000***	27	1
Long term interest rate	***-0,569***	***0,002***	27	1
Retail sales	***0,931***	***0,000***	27	1
Short term interest rate	***-0,682***	***0,000***	27	1
Subsidy level	N/A			
Wage compensation	***0,892***	***0,000***	27	1

Correlations with *replacements per subscribers,* **Market 2**				
Variable	**Correlation**	**p-value**	**Cases included**	**Missing cases**
Consumer confidence	0,0126	0,9643	15	13
Consumer price index	***-0,4407***	***0,0214***	27	1
Exchange rate	-0,2523	0,2042	27	1
GDP	**0,6771**	**0,0001**	27	1
Long term interest rate	N/A			
Retail sales	***0,6124***	***0,0007***	27	1
Short term interest rate	N/A			
Subsidy level	***0,3581***	***0,0038***	27	1
Wage compensation	***0,4193***	***0,0464***	23	5

Correlations with *replacements per subscribers,* **Market 4**				
Variable	**Correlation**	**p-value**	**Cases included**	**Missing cases**
Consumer confidence	-0,029	0,888	27	1
Consumer price index	***0,885***	***0,000***	27	1
Exchange rate	***0,712***	***0,000***	27	1
GDP	***0,790***	***0,000***	27	1
Long term interest rate	-0,266	0,179	27	1
Retail sales	***0,864***	***0,000***	27	1
Short term interest rate	0,001	0,996	27	1
Subsidy level	N/A			28
Wage compensation	***0,887***	***0,000***	27	1

Correlations with *replacements per subscribers,* **Market 5**				
Variable	**Correlation**	**p-value**	**Cases included**	**Missing cases**
Consumer confidence	-0,206	0,300	27	1
Consumer price index	***0,619***	***0,001***	27	1
Exchange rate	***0,568***	***0,002***	27	1
GDP	***0,645***	***0,000***	27	1
Long term interest rate	***-0,705***	***0,000***	27	1
Retail sales	***0,737***	***0,000***	27	1
Short term interest rate	***-0,821***	***0,000***	27	1
Subsidy level	N/A			
Wage compensation	***0,536***	***0,004***	27	1

Correlations with *replacements per subscribers,* **Market 6**				
Variable	**Correlation**	**p-value**	**Cases included**	**Missing cases**
Consumer confidence	-0,084	0,676	27	1
Consumer price index	***0,405***	***0,036***	27	1
Exchange rate	0,313	0,112	27	1
GDP	0,286	0,149	27	1
Long term interest rate	0,026	0,937	12	16
Retail sales	N/A			
Short term interest rate	***-0,450***	***0,019***	27	1
Subsidy level	***0,426***	***0,027***	27	1
Wage compensation	0,351	0,073	27	1

Correlations with *replacements per subscribers,* **Market 7**				
Variable	**Correlation**	**p-value**	**Cases included**	**Missing cases**
Consumer confidence	0,061	0,764	27	1
Consumer price index	0,095	0,638	27	1
Exchange rate	0,009	0,966	27	1
GDP	***0,472***	***0,013***	27	1
Long term interest rate	***-0,754***	***0,000***	27	1
Retail sales	***-0,692***	***0,000***	27	1
Short term interest rate	***-0,488***	***0,010***	27	1
Subsidy level	-0,094	0,640	27	1
Wage compensation	-0,148	0,460	27	1

Correlations with *replacements per subscribers,* **Market 8**				
Variable	**Correlation**	**p-value**	**Cases included**	**Missing cases**
Consumer confidence	0,109	0,604	25	3
Consumer price index	0,287	0,147	27	1
Exchange rate	***0,644***	***0,000***	27	1
GDP	***-0,536***	***0,004***	27	1
Long term interest rate	***0,683***	***0,001***	27	1
Retail sales	0,052	0,795	27	1
Short term interest rate	0,013	0,947	27	1
Subsidy level	N/A		27	1
Wage compensation	N/A		27	1

Correlations with *replacements per subscribers,* **Market 9**				
Variable	**Correlation**	**p-value**	**Cases included**	**Missing cases**
Consumer confidence	N/A			
Consumer price index	***-0,473***	***0,013***	27	1
Exchange rate	***-0,477***	***0,012***	27	1
GDP	0,242	0,223	27	1
Long term interest rate	N/A		27	1
Retail sales	N/A		27	1
Short term interest rate	-0,135	0,502	27	1
Subsidy level	N/A		27	1
Wage compensation	N/A		27	1

Correlations with *replacements per subscribers,* **Market 10**				
Variable	**Correlation**	**p-value**	**Cases included**	**Missing cases**
Consumer confidence	N/A			
Consumer price index	-0,346	0,077	27	1
Exchange rate	***-0,455***	***0,017***	27	1
GDP	-0,353	0,071	27	1
Long term interest rate	N/A			28
Retail sales	N/A			28
Short term interest rate	-0,200	0,920	27	1
Subsidy level	N/A			28
Wage compensation	N/A			28

Correlations with *replacements per subscribers,* **Market 11**				
Variable	**Correlation**	**p-value**	**Cases included**	**Missing cases**
Consumer confidence	N/A			280
Consumer price index	***-0,62***	***0,00***	27	1
Exchange rate	***0,79***	***0,00***	27	1
GDP	***0,60***	***0,00***	27	1
Long term interest rate	N/A			28
Retail sales	***-0,80***	***0,00***	27	1
Short term interest rate	N/A			28
Subsidy level	-0,08	0,68	27	1
Wage compensation	N/A			28

5.2 Appendix 2 - Project

This chapter will introduce how the actual project was conducted, what were the different phases and what went well and what could have been done better.

5.2.1 Phases

The project was divided into three major phases, which were the theory phase, the application phase, and the recommendations and writing phase.

5.2.1.1 Phase 1 – Theory

In the theory phase we conducted a literature research. This was done by searching different articles from databases and company websites and finally building a portfolio of feasible papers. It was found that articles on replacement demand forecasting were few and only four relevant studies were found.

The findings were discussed within the group and presented to the client. Based on these discussions the plans were refined and the project was ready to move into phase two.

5.2.1.2 Phase 2 - Application

Phase 2 consisted of multiple different subproblems. First we had to familiarize ourselves with Nokia's current model used in replacement forecasting. This was done with the help of manuals and the actual model.

After spending some time with the current model it was decided that it should not be emphasized, as new ways of doing things should be introduced. Also the articles proved to be pretty much useless to our purposes, as they provided only few feasible ideas and the data available to us did not fill the required criteria.

The emphasis was then shifted to introducing new drivers, which Nokia could use in estimating parameters for their current model. To do this we analyzed other market data received from Nokia against historical replacement numbers. We also tried to apply some new analyzing methods like self-organizing maps so that the data could be looked at more thoroughly.

5.2.1.3 Phase 3 – Recommendations and writing

In the final phase recommendations for the client were done and the final report was written. The findings were also discussed with the client in detail.

5.2.2 Workload

The workload experienced during the course is introduced in detail in Table 12. As one can see, the hours exceeded the hours projected for the course.

The first phase went according to our initial schedule and a theory base of four different approaches was identified. The second phase, however, exceeded our initial time projections. Here getting to know the data and analyzing it took far beyond time that we had estimated and proved to be a real problem with ever changing data. In the end, phase 3 went according to our plans, as it mostly consisted of writing our results on paper and discussing them with the client. The project took a little bit longer than expected. Especially, the analysis of the data and the discussion of the results exceeded the time allocated for them. However, the actual writing of the report was faster than we anticipated.

Table 12, The course workload (per person)

	Hours
Phase 1	
Meeting client	3
Article search	5
Reading the articles	10
Compiling results	10
Writing the plan and presenting it	4
Total	32
Phase 2	
Getting to know the model	5
Data	
Getting familiar with data	15
Analyzing	20
Meeting with clients	4
Writing the report	5
Excursions	5
Total	54
Phase 3	
Further analysis	15
Developing recommendations	10
Writing the paper	15
Communicating results to client	4
Attending seminar sessions	2
Total	46
Total duration of project	132

5.2.3 Lessons learned

In many ways, one could say that the project was successful and did not contain any major failures.

First of all, the project was conducted on time and according to client wishes, secondly we were able to fulfill our research problem at least in some form. During the project our team functioned well.

On the other hand, some things could have been done better. In the beginning the goals were too ambitious as we desired to test new models with Nokia's data and thereby introduce new ways of conducting forecasts. However, this proved not to be the case as it was not possible to apply the models directly to the available data. Also, when defining the project scope we could have identified a clear, realizable goal. The scope of the project changed during the course of the semester, so we had to spend additional time refiguring the specifications. However, things like these are hard to foresee and from our perspective we managed the project fine