IMPLEMENTING A CREDIT RISK MANAGEMENT SYSTEM BASED ON INNOVATIVE SCORING TECHNIQUES

by

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Abstract

In recent years, most developed countries have suffered a severe recession due to a financial crisis starting in the US with mortgages loans. The lack of credit risk management has been pointed out as one of the causes of this bank panics. To avoid a similar situation, the credit card companies need to have proper risk management tools. This thesis presents a credit scoring system which aims at setting credit lines and thus, controlling credit risk. It includes three types of models: application scorecards, early detection scorecards and behavioral scorecards. They have been built on real and recent data coming from a German credit card company. The models have been built with a training sample and validated accordingly, using logistic regression. Information value and validation charts have been used for comparing the models. In the scoring process described, the scorecards are used in a sequential order. The author shows that minimizing losses might not be optimal in order to maximize profit. Finally, the author presents possible extensions to the research. The author hopes that the microeconomic analysis of the mechanics of a particular lender's credit allocation process described in this thesis can play some part in preventing future financial crisis.

Dedication

To Hanène for her friendship
&
To my mother for her support

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AIC: Akaike's Information criterion
Amex: American Express
ANN: Artificial Neural Network
ANOVA: Analysis of variance
APR: Annual Percentage Rate
AS: Application scorecard
ATM: Automatic Transfer Machine
BaFin: Bundesanstalt für Finanzdienstleistungsaufsicht
BC: Before Christ
BLUP: Best Linear Unbiased Predictor
BPN: Backpropagation neural networks
BS: Behavioral scorecard
B2B: Business to business
Cat.: Category
CS: Combined scorecard
CV=CVEF: Coefficient of variation
DA: Discriminant Analysis
DDL: Degree of freedom
DTC: Decision Tree Classifiers
EAD: Exposure at default
ECOA: Equal Credit Opportunities Act
EDS: Early detection scorecard
EUR: Euro
FSA: Financial Services Authority
GA: Genetic algorithms
GP: Genetic programming
GSE: Government Sponsored enterprises
I: Interval
IAS: International Accounting Standards
IASB: International Accounting Standards Board
ID: Identification document
i.e.: Id est
IV: Information Value
k-NN: k-Nearest Neighbor
KS: Kolmogorov-Smirnov
LAUS: Local Area Unemployment Statistics
LDA: Linear discriminant analysis
LDM: Linear discriminant model
LGD: Loss given default
LR: Logistic regression
LRA: Linear regression analysis
Max: Maximum
MARS: Multivariate adaptive regression splines
MDA: Multiple discriminant analysis

Min: Minimum
Miss: Misclassified
MLFNs: Multi layer feed forward nets
MS: Mean Square
n: Number of observations
NN: Neural Network
NPV: Net Present Value
OTC: Over the counter
PCA: Principal Component Analysis
PCRs: Public Credit Registers
PD: probability of default
PhD: Philosophy Doctorate
PNNs: Probabilistic neural networks
P60: 60 days in delay
P30: 30 days in delay
P0: 5 days in delay
P&L: Profit & Loss
Q: Quotient
R^2 = RSQ: coefficient of determination
RR: Recovery rate
SAIPE: Small Area Income & Poverty Estimates
SBC: Schwarz’s Bayesian Criterion
SD: Standard deviation
SE: Small Enterprises
SME: Small medium Enterprises
SVM : Support Vector Machine
t-test: Student test
UK: United-Kingdom
US: United States
VaR: Value-at-Risk
VIP: Very Important Person
WOE: Weight of Evidence
x: explanatory variables
y: single-response variable
°: Degree
<: Inferior
%: Percent
>: Superior
$\sigma^2 = s^2$: Variance
$-\infty$: Negative infinite horizon
$+\infty$: Positive infinite horizon
$: Dollar

Introduction

The world has recently been facing a very serious financial crisis. It is widely agreed that the inadequacies of systems of credit risk management were largely to blame. The 2008 financial crisis arose largely because credit had been too lax and has resulted in its suddenly becoming too restrictive. This widely accepted view stresses how urgent and important it is to look closely at the provision and pricing of credit. The financial crisis began in 2007 with sub-prime loans to US borrowers whose ability to repay proved deeply suspect. These loans were provided by Fannie Mae and Freddie Mac and other institutions. The mortgage back securities related to them were wrongly accorded an AAA status. This infected financial systems across the world. Among the underlying reasons for this mortgage loans debt rising, the credit underwriting criteria[1] used by the GSEs to grant the mortgage loans have been pointed out.

Credit risk is a dominant concern for lenders. The credit card market which is the focus of this PhD thesis is clearly exposed to credit risk. In order to control their credit risk, the credit card companies need to have proper risk management tools, and especially an appropriate credit risk control. Indeed, risk management aims at preventing or at least minimizing the banks 'exposure. Risk management covers many types of risk but credit risk is the one this thesis focuses on that commands most interest.

[1] Poor credit applicants, with a fico score below 620, were being allowed to get mortgage loans. "Created by the Fair Isaac Corporation, FICO is the best-known credit scoring system in the United States. Based on the information in your credit report, your FICO score is calculated using complex, proprietary formulas that weigh the amount of debt you carry relative to your available credit, the timeliness of your payments, the type of debt you carry, and a great many other factors to assign you a credit score between 300 and 850. The top 20% of credit profiles receive a score over 780 and the lowest 20% receive scores under 620." (Dictionary of Financial Terms, 2008)

The first chapter of this thesis gives the reader an introduction to the banking industry and the credit card business. The main activities of a bank are described as well as the type of risk it has to deal with and also the regulations that they are subject to.

The second chapter provides insights into risk management and especially credit risk in relation to credit cards. Credit scoring is one of the tools used to control credit risk in the credit card business and can be used in various ways depending on its purpose.

In the third chapter, all statistical techniques used for segmenting the portfolio are described. This literature review covers major published papers related to credit scoring. The different reports / indicators / analysis used for monitoring and maintaining scoring models are described.

The fourth chapter discusses the issues with credit scoring, such as the ability to understand statistics and the technical aspects that have been raised by researchers when applying credit scoring. The chapter also mentions various ways of improving credit scores.

The fifth chapter introduces the credit card market in Germany and to the product's specific features. The main data for the German economy are included as well as indicators related to the credit card business. The major players and products in the credit card industry are presented. This chapter also includes an application on real data provided by a credit card company. The portfolio is German and the data cover the 2006-2009 period. After reviewing the data used by different authors for implementing credit scorecard, the data available and their quality are described. The process of implementation / development of a scorecard is detailed and illustrated with seven models implemented for the company. Those models aim at tracking the performance of each customer across time. The sequential usage of those scorecards is scrutinized and discussed.

The sixth chapter explains what profit means and the different financial components that affect the overall results of the bank. By reviewing those financial components, the author presents the parameters that a lender's credit policy should set. Indeed, the target is to find the optimal method of using the scorecards to minimize losses, and maximize profit. In order to find this optimum, one of the methods suggested by the author is to perform tests on real data which consists of testing the champion strategy of the bank versus challenger strategies.

The last chapter summarizes the original contributions of the dissertation, and considers possible extensions to this research. The main original feature of this PhD thesis consists of the application to real data and the level of details covered. Indeed, some of those models are innovative and the presentation of a scoring process with this level of detail is really rare, if not unique. Even though for confidentiality and competition reasons, the equations cannot be detailed, it gives enough insight for the reader to appreciate all the concepts involved. The equations as well as the strategies are not the key elements of this thesis as it depends on the company and the products. The underlying concepts behind them are the main assets of this paper.

Chapter 1: The Credit Card market

The aim of this chapter is to introduce the area of focus of this PhD thesis which is the credit card industry. The first step is to introduce the reader to the banking sector, then by explaining what a credit card is compared to other methods of payment and the different ways customers might use it.

The main questions that will be answered in this chapter are:

- What is a bank? What are its functions?
- What is a credit card and how has it been established?
- How does it differ from other method of payments?
- How do people use credit cards?

Once those questions answered, the reader will be able to situate this thesis in its context.

1.1 Banking industry

The purpose of this section is to remind the reader what a bank is as well as her functions. It also introduced the reader to the different types of risk a bank is facing as well as the regulations they are subject to.

1.1.1 What is a bank?

Freixas & Rochet (2008) suggest in their book Microeconomics of Banking, a simple operational definition of a bank which is:

“A bank is an institution whose current operations consist in granting loans and receiving deposits from the public”.

As outlined in their book and stressed in many others influential treatments, such as Diamond & Dybvig (1986), Edgeworth (1988), Klein (1971) and Heffernan (2005); this definition has the advantage of focusing on the key activities of a bank which are deposits and loans. Each word emphasizes a precise fact about banks. For instance, “current” refers to the fact that firms will rarely borrow money from their suppliers and lend money to their customers. These activities are usually delegated to banks. “Granting loans and receiving deposits” refers to the two core activities of commercial banks which are lending and borrowing. The last term “public” refers to the general public to whom banks will offer deposits. As Freixas & Rochet explain, the general public which supplies deposit usually lax a sufficient financial background to assess the risk associated with investment. This is why “the protection of depositors and the safety and efficiency of the payment system have traditionally justified public intervention in banking activities” (Freixas & Rochet, 2008).

Various definitions of a bank are available. The simple definition of Freixas and Rochet has the benefit of focusing on the essentials.

1.1.2 Bank functions

In recent banking theory, different activities can be distinguished within banking. Diamond & Dybvig (1986) described those activities following the balance sheet items: (i) Asset services, (ii) Liability services and (iii) transformation services.

Not all banks perform all three activities. Universal banks will, but specialized banks focus on some subset of those activities.

1.1.2.1 Asset services

Asset services are services offered to the borrowers and include three different activities: evaluating, granting, and monitoring loans (Diamond & Dybvig, 1986).

The next chapters of this dissertation cover in depth those three activities in relation with credit card, the topic of this Ph.D thesis.

1.1.2.2 Liability services

Liability services are services offered to the depositors. Therefore, the first service offered by bank is deposits. Historically, a bank has also offered currency exchange facilities and payments services to its depositors. Those include: exchanging money in different currencies from distinct institutions and offering payment services.

Payment services refers to the different systems / networks to transfer money from one bank account to another, for example, the buyer account to the seller account. It includes customer relationship management and the guarantee by the bank that the debt of the purchaser has been settled to the merchant via a money transfer.

To summarize, liability services include four different activities: holding deposits, clearing transactions, maintaining an inventory of currency and service flows related to payment services (Diamond & Dybvig, 1986).

1.1.2.3 Transformation services

Transforming assets include three different activities (Freixas & Rochet, 2008):

- Convenience of denomination: it refers to the fact that banks are solely responsible for the set up of their products which includes the amount and exposure associated with it. Considering a simple business case, where the bank will mainly concentrate on two activities:

deposits and loans, the bank would be able to define the maximum amount that could be deposited and also the maximum amount that could be borrowed. For instance, it is common that large loans are financed by many small deposits; the bank is then playing the role of intermediaries by receiving the deposits and granting the loans.

- Quality transformation: it refers to the fact that under specific conditions a bank deposit can be more financially advantageous than investing directly into the project. Those conditions can be:

  - Indivisibilities in the investments: For example an individual can only invest a small amount and therefore, he is not able to diversify his portfolio, making a deposit to a bank is the most appropriate solution.

  - Asymmetric information situation: in the case where a bank would benefit from information that would not be available to the depositors.

- Maturity transformation: this last activity concerns the fact that banks will transform short term products such as deposits into long term products, such as loans. Changing securities with short maturity to long term maturity securities implies a risk of liquidity for the bank. Even though those solutions might be costly, the bank can ultimately relies on interbank loans and derivative financial instruments such as swaps and futures to limit her exposure.

1.1.3 Managing risk in the banking industry

Banking risks can be split in three main categories: credit risk, interest rate risk, and liquidity risk. Each type of risk is reported in the bank's balance sheet such as:

- Credit risk: Credit risk occurs when a borrower is unable to full his contractual obligations, i.e. paying back the loan he has been granted.

- Liquidity risk: Liquidity risk occurs when a bank is facing unexpected cash withdrawals on deposit accounts. A deposit is a liquid financial product where the customer is allowed to demand his money at any time. A massive number of withdrawals would lead to a liquidity shortage for the bank.

- Interest rate risk: Interest rate risk occurs when maturity transformation happens. For instance, deposit is a short term interest product whereas loans are long term interest products.

There is a fourth risk, systemic risk, which is not included in the balance sheet. Group of Ten - Consolidation in the Financial Sector (2011) defines systematic risk as follows:

"Systemic financial risk is the risk that an event will trigger a loss of economic value or confidence in, and attendant increases in uncertainly [sic] about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy."

1.1.3.1 Credit risk

In order to minimize credit risk, financial institutions must establish a sound risk management of retail and corporate lending. However, managing credit risk within retail lending is significantly different than managing credit risk within corporate lending as corporate lending reviews a multiple set of ratios that often are not suitable for small firm or single individual lending (Heffernan, 2005). In retail lending, access to data is rather constrained. Nevertheless, historically, corporate lending has proven to be highly exposed to credit risk due to the size of the loans involved. Heffernan (2005) listed the following examples: Maxwell and a number of London-based banks; Schroder and deutsche Bank; and the collapse of Enron and WorldCom. On the contrary, retail lending has been little subject to such phenomenon. This dissertation focuses solely on retail banking and lending to single individuals.

Financial institutions can minimize credit risk in five different ways: through accurate loans pricing, credit rationing, use of collateral, loan diversification and moiré recently through asset securitization and/or the use of credit derivatives (Heffernan, 2005). This research concentrates on credit rationing in the credit card industry and particularly, on assigning the right lines of credit to the borrowers based on the credit risk profiles assessed by the bank.

In retail banking, credit risk can be assessed in two different ways, by using qualitative or quantitative methods. Ideally, the bank relies on qualitative methods to decide whether to grant a loan or not. The most well-know and also recognized quantitative method is credit scoring, which is the main focus of this thesis.

However, under specific circumstances, information might not be available. For instance, the credit bureau is unable to find a credit report for a particular applicant. The bank is then likely to switch to a qualitative approach and evaluating the borrower's application manually. This implies checking a list of elements helping defining the risk profile of the borrower. It includes elements such as time with the bank, employment history and wealth of the borrower.

In order to monitor credit risk exposures, financial institutions rely on a number of credit risk related performance indicators such a probability of default, exposure at default and loss given default.

Banking institutions will be facing different regulations from one country to another and therefore, in some countries, those regulations will act as entry barriers whereas in other countries, those will facilitate the establishment of banking activities.

1.1.3.2 Market risks

The second activity of a bank, transforming asset, is also subject to risks.

In the case of maturity transformation, the banks will transform short term products such as deposits into long term products, such as loans. The bank is taking a risk. Indeed, the bank needs to ensure that the cost associated with the liquid product, i.e. the interest rate of the deposit accounts, is not higher than the interest rate charged on the loans considering that interest rates on loans are long term rates whereas deposits interest rates are short term rates (Freixas & Rochet, 2008). Therefore, a bank facing a liquidity shortage would be able to increase the interest rate on the deposit accounts but only to a certain extent.

For example, in the case of a bank runs, the bank is then facing both an excess of unexpected withdrawals. In this situation, the bank has to find other funding sources that will potentially be costly. The bank is then facing both interest rate risk due to maturity difference; and Liquidity risk due to products' marketability difference

1.1.3.3 Systemic risk

1) Definition of systemic risk

Many authors attempted to give a definition of systemic risk (Bullard et al., 2009; Borio, 2003; Danielsson et al., 2009; de Bandt & Hartmann, 2000; Freixas & Rochet, 2008; Perotti and Suarez, 2009) but no consensus has been found yet.

According to Freixas & Rochet (2008), a bank runs usually refers to a phenomenon where customers decide at an instant t to withdraw all their money from their deposit account.

Customers will take such actions based on information available on the market that can be false or true but that will suggest a bad performance of the bank or a form of risk for the bank.

Two different types of bank runs are possible: (i) "fundamental bank run": due to negative information on the value of the bank's asset and (ii) "speculative bank run": due to negative information such as a large withdrawal. Bank runs is a phenomenon that will affect only the bank concerned whereas a bank panics will affect the whole banking industry. A massive number of withdrawals would negatively affect the bank that would face a liquidity shortage and thus, a risk of bankruptcy. The phenomena could expand to the whole banking industry if customers started to fear the same risk of bankruptcy in other institutions. A bank runs would then be contagious and would become a bank panics.

However, the author wants to illustrate the lack of consensus by adding Borio's definition (2003). The definition from Borio (2003) differs from the definitions of Freixas & Rochet (2008) in what the starting point of the crisis is and how the phenomenon gets amplified.

> "Generally, there is first of all a build-up phase. This is normally characterized by booming economic conditions, benign risk assessments, a weakening of external financing constraints, notably access to credit, and buoyant asset prices. (…) The economy may be perceived as being on a permanently higher expansion path. This configuration promotes and masks the accumulation of real and financial imbalances; the system becomes overstretched. At some point, the process goes into reverse. The unpredictable trigger can reside either in the financial sphere (eg an asset price correction) or in the real economy (eg a spontaneous unwinding of an investment boom). If the system has failed to build up enough buffers and the contraction goes far

enough, a financial crisis can erupt. Ex post, a financial cycle, closely intertwined with the business cycle, is evident."

Defining systemic risk is raising high debates. However, this thesis does not aim at answering this question but at least, mentioning it.

2) Examples of bank runs / panics

An example of countries that faced many bank runs is the United States. In 1910, Kemmerer listed 21 banks panics in the country in the period 1890-1908. However, the five biggest banks panics experienced in the United States took place between 1929-1933 (Friedman & Schwartz, 1963). Until 1934, bank runs were frequent in the United States. As described in several papers, the phenomenon was not specific to the United States. Several other countries also faced bank runs like Northern Rock in England in the 1990s. Recently, the world has started facing a global economic crisis raising the issue of properly controlling risk. Indeed, in 2008 and 2009, most developed countries have suffered a severe recession due to a financial crisis that began in the US with mortgages loans. The financial crisis started in 2007 with sub-prime loans that borrowers could not pay back infecting other loans and assets. Among the reasons for this mortgage loans debt rising, the interbank loans failure and the decline of the asset prices, one is a weak regulation to access credit. The consequences of this recession are worldwide and involve a large rise in unemployment and a decline of international trade but the most important lesson to retain was that the initial reason of this crisis was financial deregulation.

Historically, bank runs and bank panics have happened recurrently. Various devices for minimizing bank runs include: bank inspections and regulations, deposit insurance systems and mandatory minimum reserve ratios.

1.1.4 Banking regulations

All over the world, wherever a banking system has been implemented, banks have been subject to regulation. Regulations affect not only the management of the bank but also the industry as a whole.

1.1.4.1 General framework

Historically, banks have always been subject to some form of regulations. Back to the middle age, the population was already subject to some form of taxation. Nowadays, banks are subject to more and more requirements set by regulators.

Usually, regulations imposed on banks apply to structure and to conduct. As noted by Freixas & Rochet (2008), major regulatory requirements fall into six categories: deposit interest rate ceilings, entry, branching, network, and merger restrictions, portfolio restrictions, including reserve requirements, deposit insurance, capital requirements and regulatory monitoring and supervision (including closure policy).

The regulatory and supervisory function relating to banks is carried out by the National regulators. In Europe, the supervision of banks will follow the internationally accepted standards for bank supervision set out by the Basel Committee for Banking Supervision. The national regulators are empowered to undertake the following responsibilities:

- Supervision of the financial sector which includes off-site and on-site examination as well as enforcement of regulatory actions.
- Granting / revoking banking licences.
- Oversees / Define prudential regulatory framework.

Just below examples of national regulators:

Table 1 – Examples of National Regulators

Country	Regulator
Belgium	Banque Nationale de Belgique
France	Banque de France
Germany	Deutsche Bundesbank
Luxembourg	Commission de Surveillance du Secteur Financier
Netherlands	Nederlandsche Bank
United Kingdom	Financial Services Authority
United States of America	Federal Deposit Insurance Corporation

The next section emphasized on one of the latest regulations from the Bank of International Settlement, Basel III.

1.1.4.2 Basel 3

"Basel III" is an international regulatory framework published the 16th of December 2010 which encompasses a set of reform measures agreed upon by the Basel Committee on Banking Supervision. Those reforms aim at strengthening: (i) the regulation, to avoid or at least reduce systemic risks, (ii) the supervision of the banking sector by requiring more transparency and disclosures and (iii) the risk management and governance of the banking sector.

Those two main objectives of those measures are to establish: first, a microprudential regulation, which consists in enforcing individual banks' ability to face period of financial stress; and second, a macroprudential regulation which consists in reducing system wide risks and their procyclical amplification over time.

The target of those two reforms is clearly to reduce bank's exposure to systemic risk.

The Basel III framework is summarized in a table which provides an overview of the various measures taken by the Committee.

“Basel III represents a fundamental strengthening - in some cases, a radical overhaul - of global capital standards. (…) The implementation of Basel III will considerably increase the quality of banks' capital and significantly raise the required level of their capital. In addition, it will provide a "macroprudential overlay" to better deal with systemic risk. Lastly, the new package will allow sufficient time for a smooth transition to the new regime.” (Caruana, 2010).

As described above, banks are heavily regulated and even more with the recent emergence of new payment services. All those payments systems have raised concerns among governments in spite of the clear advantages of those new methods of payments such as safety. The next section aims at describing those different payment services and in particular, credit cards.

1.2 What is a Credit Card?

The purpose of this section is to remind the reader what a credit card is and where / when / why it has appeared on the market.

1.2.1 Definition of a credit card

Credit is a method of selling goods or services without the buyer having cash in hand. A credit card is only an automatic way of offering credit to a consumer. Today, every credit card carries an identifying number that speeds shopping transactions.

To distinguish the two products debit card and credit card, credit card banks have offered their customers possibilities to borrow a limited amount with their card. This service or credit is also a way to attract them. However, even if customers have the possibility to revolve, not all of them use this service.

1.2.2 The History of the Credit card

According to Encyclopedia Britannica, "the use of credit cards originated in the United States during the 1920s, when individual firms, such as oil companies and hotel chains, began issuing them to customers." However, references to credit cards have been made as far back as 1890 in Europe. Early credit cards involved sales directly between the merchant offering the credit and credit card, and the merchant's customer. Around 1938, companies started to accept each other's cards. Nowadays, credit cards allow making purchases with countless third parties (Bellis, no date).

Through the years, credit cards have changed shape. At first, credit cards were credit tokens made from metal coins. They became credit tokens made of metal plates, and celluloid, metal, fiber, paper. Nowadays, they are made of plastic (Bellis, no date).

According to Bellis, the inventor of the first bank issued credit card was John Biggins of the Flatbush National Bank of Brooklyn in New York. In 1946, Biggins invented the "Charge-It" program between bank customers and local merchants. Merchants could deposit sales slips into the bank and the bank billed the customer who used the card.

One of the first credit cards was the Diners Club credit card. It appeared in 1950 in the United States and was invented by Diners' Club founder, Frank McNamara. The aim of the card was to pay restaurant bills. A customer could eat without cash at any restaurant that would accept Diners' Club credit cards. Diners' Club would pay the restaurant and the credit card holder would repay Diners' Club. The Diners Club card was, at first, technically a charge card rather than a credit card since the customer had to repay the entire amount when billed by Diners Club (Bellis, no date).

In 1958, American Express issued their first credit card, and the Bank of America issued the Bank Americard (now Visa) bank credit card (Bellis, no date). The main target was traveling salesmen for use on the road (Bellis, no date).

In the 1960s, credit cards were promoted as a time saving device rather than a form of credit. American Express and MasterCard became huge successes very quickly (Bellis, no date).

However, as success is also linked with abuses, in the mid-70's, the US Congress began regulating the credit card industry. An example is that the mass mailing of active credit cards to those who had not requested them was forbidden. However, not all regulations have been as consumer friendly. Deregulation has also allowed very high interest rates to be charged (Bellis, no date).

After defining the credit card, the next section will aim at describing the different possible usage of the product.

1.2.3 A credit card as a transaction medium

According to Zywicki, "over half and probably as much as 68% of credit card users should be considered "convenience users", who use credit cards primarily as a transactional medium and who pay off their balances in full each month". In addition, "60% of total bankcard volume generates no interest, up from roughly 50 percent six years ago" based on a study made by Visa in 2000 (Zywicki, 2000).

The two main reasons usually cited[2] for using credit card as a transaction medium are:

- To minimize their cash balances: credit cards facilitate the possibility to shift their financial assets into investments more profitable.
- Convenience: credit card is a simple transaction medium, easy to use and widely distributed / accepted.

Depending on the costs and advantages of using one payment method toward another, customers will decide to use different forms of payments (Zywicki, 2000). The next sub

[2] (Zywicki, 2000)

sections will describe the most common forms of transactional media: cash, cheques, debit cards and credit cards.

1.2.3.1 Cash

One of the oldest payment methods is cash. However, nowadays, there are few advantages in relying on cash.

Advantages of cash include convenience for low value purchases and anonymity. When making purchases for small amounts like for example newspaper, cash is the most preferred way of paying for consumers. Cash has also the advantage of being an anonymous payment media compared to cheques, debit cards and credit cards.

Against these, cash has drawbacks: costs of matrix transactions, absence of return and inconvenient for specific transactions. Compared to other medium of payments, cash is more costly and therefore less attractive payment method. When using cash, the customer is losing the interest he could get by keeping this money on savings account. In addition, electricity bills, phone bills but also purchase orders via internet or mail do not accept cash as a payment medium. Moreover, for large purchases, cash has not proved to be an adequate or safe method of payment. Indeed, travelling with a large amount of money is risky and costly.

1.2.3.2 Cheques

Cash has always been preferred for low value purchases whereas cheques were the preferred media of payment for large value purchases.

Advantages of cheques include: convenience for high value purchases and for specific transactions. Rather than carrying large amount of cash, customers prefer to pay via cheques.

Electricity bills, phone bills but also purchase orders via mail accept cheques as a payment medium but standing order usually preferred. However, payment order via the internet does not accept cheques.

Cheques have a specific drawback which is the lack of transparency. In nature, cheques are not fundamentally different than any other revolving facility. The main difference with debit cards and credit cards is that cheques do not allow verifying that customers have sufficient funds on their accounts to cover for the purchase they are making. System wise, the merchant cannot verify at the time the check is drawn that he will get paid back.

However, it is important to note that in many countries, drawing a cheque without having sufficient funds is punished by law. For example, in France, drawing cheques without sufficient funds will lead to a criminal penalty and to an “Interdit Bancaire”. The customer will be banned from all banks for several years. Financial cards have recently appeared as an alternative to cheques while making high value purchases. Indeed, in the United Kingdom, for example, plans to eliminate cheques completely are under discussion.

1.2.3.3 Debit Cards

In recent years, debit cards have often been used as substitutes for cash for low value purchases at grocery stores and gas stations. Debit cards have appeared as a substitute for cash rather than cheques. Debit cards have also proved to be much more reliable than cheques. Indeed, the merchant is able to get an instant electronic confirmation that the buyer has sufficient funds on his account to make the purchase. Nowadays, as Zimman notes (2009), debit cards are dominating the market due to one main reason: its cost.

The five key metrics for customers' payment preference, as first described by Jevons (Jevons, 1918), have been reviewed by Zimman (2009) for both credit card and debit cards:

- Acceptance: Both products have a similar high acceptance rate.
- Security: Both products have a similar level of protection and incurred the same fraud risk.
- Time costs: Both products do not require going to a bank.
- Portability: Both products have similar advantages.
- Pecuniary costs: the different consequences/costs for a customer that would exceed his line of credit are: Overlimit fee, decrease of the credit score, "Penalty pricing".

Zimman suggested that considering solely the non-pecuniary drivers, a customer would rather use a debit card than a credit card due mostly to time cost saving (using debit for cash back or to eliminate the nuisance of paying a credit card bill).

His research confirmed that the minimization of pecuniary cost and time cost were key criteria when selecting debit card as a payment method.

1.2.3.4 Credit Cards

The second medium of payment that has seen a massive spread in the recent years is credit cards:

"The greatest growth (in terms of dollar value) has come in credit cards, which doubled from ten to twenty percent of the total between 1975 and 1995, reducing the share of cheques accordingly. Cash held its own, and debit cards have made hardly dent...Consistent with the predictions of economic theory, it appears that rational consumers have consciously decreased their use of cheques and increased their use of credit cards as the latter medium has become more attractive as a means of financing current purchases (Zywicki, 2000)".

Advantages of credit cards include:

- Convenient for specific transactions: Electricity bills, phone bills but also purchase orders via internet or mail accept financial cards as a payment medium. Nowadays, financial cards appear as the only existing viable payment method in the coming years.

- Flexibility: Credit cards offer the flexibility for customers to manage themselves their incomes and expenditures. For instance, credit card statements are generated at month end and the balance is usually due 2-3 weeks later at max. Therefore, customers can make purchases before receiving their salary and do not need to worry about the amount that is left on their account. This convenience in credit card usage is definitely one of the key advantages of this type of product.

- Interest free incentives: Credit cards companies usually offer marketing incentives including free interests periods to attract new customers. Those free interests periods can start from one month to as far as 6 months and there is usually a period of several weeks after the transaction before the payment is due and any interest is payable. The opportunity to revolve a significant amount of money without incurring any interests / charges is a major advantage for many consumers.

- Safe mean of payment: Credit cards are also subject to fraud attacks like account take over, identity theft... However, compared to cash, credit cards are much more secured when one's victim of a theft.

- Benefits: credit cards offer several benefits and functionalities that are not available with other payments medium and that accentuate the convenience of using credit cards versus cash, cheques and other types of financial cards. An example is cash rebates on the amount charged.

- Advantageous for merchant: Credit cards do not benefit to customers only but also to merchants. Indeed, the risk of non-payment is transferred to the card issuer, which makes credit card relatively attractive for merchants. Large merchants can bear the risk of non-payment but for small and medium businesses, this advantage is crucial.

The last advantage which is also the most controversial one is often considered as a disadvantage by economists. It is the revolving facility; credit cards offer one last advantage compared to cash, cheques and debit cards: the possibility to revolve wherever and whenever, customers can decide to revolve their full balance or part of it. The principle is simple: buying now something that will be paid for later.

This last facility is what distinct credit cards from the other products and what has made this product so popular but also controversial. Nevertheless, as Zywicki (2000) explained: "It is difficult to understand why the bankruptcy and legal community treat credit card obligations differently from cheques. Both credit cards and cheques represent a promise to pay".

Disadvantages of credit cards include: fraud (identity theft, account take over and skimming), high rate of interest for customers that miss deadlines or do not pay the full balance, and growth of private debt which impatient individuals may later bitterly regret.

1.2.4 Credit card as a source of credit

Most economists have ignored the transactional advantages of credit cards, transactors / convenience users being the majority of the credit card users and have focused on the borrowing aspect of it.

1.2.4.1 Borrowing mediums

In the current society, there are two types of liquidity needs. Long term needs are usually related to real estate's purchases, car loans or private business initiatives. Short term loans usually reflect a punctual need.

Someone facing an urgent need of cash at a certain point in time and having a lack of liquidity at the exact same time will tend to look for the different borrowing opportunities available.

The following options are usually available (Zywicki, 2000):

- Home equity loan: This option is only available to the portion of the population that are home-owners. Depending on the amount to borrow and the amount of equity available, some will be able to draw money through home equity loan or home equity line of credit. However, home property is not accessible to everyone, i.e. young people as well as poor people.
- Selling assets: One solution is to sell his belongings in order to cover for the coming expenditure.
- Pawn assets: Another solution is to pawn belongings in order to cover for the coming expenditure.
- Bank loans: The most commonly used option will be to go to the bank and asked for a loan. However, it is important to note that banks are rather selective and do not grant loans to everyone. Moreover, small short terms bank loans are usually rather expensive due to transactions costs.
- “Loan sharks” loans: another lending option is to deal with a “loan shark”. In spite of all the new financial facilities that are available, not everybody can get access to those and “loan sharks” still appear then as the lender of the last resort. Nevertheless, this type of loan is usually illegal and outrageously expensive.
- Retailers’ loans: In specific situations, it might be possible to get a loan directly from the retailer. However, most merchants do not provide this facility.
- Credit cards: In addition to be a transaction medium, credit cards also offer revolving facilities. In the situation of an urgent short term liquidity need, credit card should be

considered as one of the option. Indeed, the other options investigated above are comparatively not more attractive. Even cost wise, it is not obvious that interest rates charged by credit card companies will be that outrageous compared to the costs associated with the other options.

1.2.4.2 Credit Cards

Credit card is mostly used as a transactions device. Nevertheless, it also allows users to borrow money from one month to another. The borrower can pay back the borrowing balance in full or by doing partial payments equal or above the minimum payment required by the borrowing institution.

Zywicki (2000) claims that empirical evidence strongly supports the view that the growth in credit card use by low-income credit-constrained cardholders has been primarily a rational substitution towards credit cards and away from less-attractive forms of consumer credit. Indeed, comparing to the other options for small short term loans, credit cards are clearly an attractive medium of borrowing available to even low-income credit-constrained people. “The Economics of Credit card” by Zywicki (2000) concludes that:”it is difficult to see how the plight of low-income earners can be improved by denying them the option of using credit cards by making it more difficult to gain access to credit cards, their reliance on pawn shops and loan sharks increases”. This argument is cogent. However, the next section will explore why people get over indebted when using credit cards and if credit card, as a product is solely responsible for it.

1.3 Credit card usage

Credit card is a payment system competing with other products. This section aims at describing how consumers perceived credit card as payment device.

"Credit cards have become the primary source of unsecured open-end revolving credit" (Durkin, 2000). For Durkin (2000), there are two main concerns related with credit card usage: if customers do understand all the product specificities such as costs and contractual terms and if credit cards are one of the causes of over indebtedness.

1.3.1 Type of users

The industry distinguishes two types of customers: transactors, also named convenience users and revolvers.

1.3.1.1 Convenience users

Most credit card users are convenience users. Credit card is a simple transaction medium, easy to use and widely distributed / accepted. Most users carry small balances and paid in due time, therefore, it is doubtful that their main decision criteria will be interest rates or other related fees (Zywicki, 2000).

Convenience users will not only look at interest rate as a decision factor but also at all the other benefits that will be offered with it such as (Zywicki, 2000):

- "Pay-at-the-pump" facility at gas stations
- Travelling facility, especially in countries with different currencies
- Reward programs in the form of flyer miles, "bonus point", purchase insurance...

- Yearly-end statements, itemizing purchases by category for budget-planning purposes and identifying potentially tax-deductible charges.
- Additional services such as car rental insurance, travel agent services...
- Cash rebates on the amount charged.
- Customer service, access to a 24 hour customer service.

Convenience users will then be encouraged to take advantages of such benefits rather than a low interest rate.

1.3.1.2 Revolvers

The other type of credit card users is revolvers. In contrast to convenience users, revolvers will review all financial charges associated with the card such as interest rate, late payment fee, overlimit fee... The higher the amount they will plan to borrow, the more attention they will give to financial charges and especially interest rate.

The last couple of years have seen the emergence of a new phenomena “card surfing”. It consists in switching from on card to another one then another one and benefiting from the initial interest free promotion of the first card and then of the following ones. The main advantage of such technique is that revolvers will benefit from the “teaser rates” used by banks to attract new customers.

1.3.2 Overindebtedness

In the recent years, the world has experienced the results of mistaken credit decisions. How is it possible that so many people have ended up being overindebted? Few authors have been interested in the relationship between financial literacy and indebtedness. Lusardi is one of the authors that suggested that the reason why so many individuals take out mortgages and credit card debts they could not afford was primarily the lack of financial knowledge.

The next sections are largely inspired from her work and the results that came out of her survey.

1.3.2.1 Financial Literacy

It is in the 90's that Bernheim (1995, 1998) raised the concern that in the United States, many individuals were missing financial competencies. He was one of the first to point out this important fact.

The lack of financial knowledge or understanding might have severe consequences on the financial situation of one individual. More and more researchers are starting to investigate the impact of financial literacy on debt burdens. First, the author reviewed the literature about mortgages loans, where repayments are often onerous. Moore (2003) indicated that households engaged in mortgages loans tend to be financially unknowledgeable. Bucks and Pence (2007) report that for mortgages loans, households with flexible interest rate loans misunderstand or even do not understand the terms of their contract. Campbell (2006) documented that households failed to renegotiate their mortgages when interest rates were dropping. In particular, households particularly concerned were characterized by low education and low income. Those results are worrying as this type of loans is usually expensive and involved a high borrowing amount.

Regarding loans, in general, Stango and Zinman (2007) concluded that households with a lack of financial knowledge, for instance, being unable to calculate interest rates, would tend to carry more debt than usual and have less savings. Moore (2003) reviewed a survey of U.S residents and confirmed that households frequently partially understand or do not understand their loans / mortgages contract. Miles (2004) reached the same conclusion while analysing UK borrowers finding that they were often unable to understand contractual and interest rates concepts.

Similar conclusion applies to other financial products. Indeed, Hilgerth, Hogarth, and Beverly (2003) have pointed out the fact that financial literacy was positively correlated with a favourable financial situation. Analyzing the US population, they concluded that most residents failed to understand basic financial principals of products such as bonds, stocks, and mutual funds.

Regardless of the financial product concerned, all those financial experiences are clearly mistakes that could have been avoided if those persons would have been financially literate.

From a demographic stand point, Agarwal, Driscoll, Gabaix and Laibson (2007) identified the young and the old as less financially knowledgeable and to be prone to end up in financial difficulties. Lusardi and Mitchell (2007) and Campbell (2006) described those having a lack of financial knowledge or cognitive ability as having the following characteristics: low education, low income and part of minorities. Another research from Lusardi and Mitchell (2007b) identified a lack of financial literacy among the elderly, African-American and Hispanics, women, and those with low education (Lusardi and Mitchell, 2007b).

As mentioned by Lusardi & Tufano (2009), the concern about financial literacy is not specific to the United States. It is a much broader issue as shown in the 2005 O.E.C.D. report and Smith and Stewart (2008).

Financial illiteracy leads on to erroneous decisions. This conclusion would not be so worrying if individuals were relying on professional advice and financial experts in order to take financial decisions (Lusardi, 2003). Indeed, in many areas, researchers identified that individuals were having difficulties in getting access to information and taking decisions. Few obtain advice from financial experts such financial advisers, bankers, certified public accountants, and other professionals in their financial decisions (Lusardi, 2003). Lusardi reviewed the Survey of Consumer Finances and reported that the majority of people rely on advices from family and friends while taking financial decisions. This fact is especially true for those with low education. However, individuals with low education are more likely to have the same demographics characteristics that their relatives and friends. Raising the concern that individuals will most likely rely on inappropriate advices when making financial decisions.

Lusardi & Tufano (2009) conclude that "Financial literacy cannot be taken for granted among the population, particularly among specific groups (including those with low education, women, and minorities). This raises concerns about how to communicate information effectively, particularly to those who need it most. Given low numeracy and low literacy, it may be useful to consider more effective ways of communication... Given the increased complexity of financial instruments, the evidence of illiteracy raises the question of whether consumers will appreciate and take advantage of the opportunities offered by financial markets or more easily fall prey to scams or unscrupulous brokers".

1.3.2.2 Debt literacy

This thesis focuses on credit cards, so we turn now to one particular aspect of financial literacy: debt literacy. "Debt literacy refers to the ability to make simple decisions regarding debt contracts, applying basic knowledge about interest compounding to everyday financial choices "(Lusardi & Tufano, 2009).

Many studies have shown that a large portion of the population has not only a lack of financial knowledge but simply of numeracy and cognitive abilities in all areas of life (Peters et al., 2007; Chen and Rao, 2007; Volk, 2007; Lusardi & Tufano, 2009).

In order to assess debt literacy, Lusardi & Tufano (2009) proceeded to a three questions survey: (a) Are individuals able to calculate interest compounding?, (b) Are individuals able to calculate the number of years needed to pay off their balance assuming that they only pay the minimum amount which equals to the sum of the interests charged on the outstanding balance? and (c) Are people able to compare different payment options?. Even though a large population of the population is familiar with credit cards and credit card debt, only a few understand the full mechanism of interest compounding. In their survey, Lusardi & Tufano (2009) found that one-third of respondents were able to correctly answer a question about interest compounding in relation with credit cards. The results confirmed that individuals tend to underestimate the interests that are charged on their credit card when using the revolving facility. Reading the second question, it is obvious that if the individual will only repay the interest portion, the loan balance would never decline. However, the authors came to the same conclusion as for the first question: Even though a large population of the population is familiar with credit cards and credit card debt, only a few understand the full mechanism of credit debt. Finally, less than a third of the respondents were able to pick the most favourable method of payment when comparing two different options involving somewhat difficult calculations. The authors raised some concerns about this result and the fact that nowadays, borrowing is something rather common.

The conclusion that comes out of this paper is that debt illiteracy is widespread and especially in specific demographic groups. The results suggest that young and elderly, women, those with lower income and minorities are lacking financial knowledge and do not understand the basic fundamentals of borrowing money. Referring to Salop & Stiglitz's model (Salop & Stiglitz, 1977) and considering that financial literacy is only achievable at a certain cost, imperfectly informed consumers (young and elderly, women, those with lower income and minorities) will pick less advantageous financial decisions.

Another noticeable result is that elderly considered that they are financially aware whereas based on the debt literacy evaluation; they present a lack of financial knowledge. This brings to the next point of this section - self awareness.

1.3.2.3 Financial awareness

Financial literacy including debt literacy is correlated with the debt situation of households but are households aware of their financial situation? Credit card users who make only minimum payments on their credit card bills and incur late payment fees and overlimit fees have a low level of debt literacy, even after checking for other demographics variables. A similar result was found for regular credit card users: those with a low level of debt literacy are the ones paying fees and financial charges (Lusardi & Tufano, 2009). In the literature, few authors have considered that indebtedness would be caused by mistaken decisions resulting from a lack of knowledge / awareness.

Lusardi & Tufano (2009) investigated whether the respondents to their survey were self-aware of their financial situation. They found a strong correlation between debt literacy and self awareness. Individuals showing a high level of debt literacy where usually the ones also assuming they were self aware of their financial situation. The authors also identified a correlation between debt literacy (and therefore self-awareness) and overindebtedness. Respondents with a low level of debt literacy tend to overestimate their debt position or to be unsure about the “appropriateness” of their debt position (Lusardi & Tufano, 2009). Lusardi & Tufano (2009) asked how many years would be needed for a loan to double considering a certain interest and no payment. By linking questions, they concluded that:

- Those who recognized that they would / might have issues to pay back all their debts were most likely those who overestimated the time needed for the amount to double.
- Those who were not able to estimate their amount of debt were most likely those who did not answer correctly or did not answer at all.

From their study, it appears clearly that financial literacy is correlated with the amount of debt: a lack of financial literacy is causing a large amount of debt.

From a demographic standpoint, women were evaluating themselves as having a lower level of financial self awareness than men. The same conclusion is valid for African-Americans and Hispanics as well as for low income earners. This analysis shows that the groups of individuals identified as lacking debt literacy are also less self aware about it. This result is worrying as it means that those lacking financial knowledge and not aware about it are the ones subject to onerous loans / contracts and presenting risky behaviours. Indeed, they won’t be able to understand all aspects of a contract / loan like for instance interest calculation and therefore, won’t be able to pick the most advantageous offer.

Nowadays individuals are exposed to a large number of financial products. However, one concern that came out of those readings is that:

"While it may be reassuring to know that the people who always pay credit cards in full are more financially skilled, it is troubling that the people whose financial transaction patterns are characterized by high-cost borrowing are those who come from vulnerable demographic groups and –even after controlling for these factors – are less debt literate. People who make financial choices that incur avoidable fees and charges (e.g., only paying the minimum balance on credit cards, incurring late or over-the-limit fees, using alternative financial service credit such as payday loans, tax refund loans, or pawnshops) are those with a weaker understanding of the implications of debt" (Lusardi & Tufano, 2009).

1.3.2.4 Costs of ignorance

As described previously, the lack of financial knowledge and numeracy are the main reasons why households get involved on onerous loans and get in financial distress. Lusardi & Tufano (2009) gave some indications to estimate the cost of lacking financial knowledge that they called "the cost of ignorance".

Based on their definition, Lusardi & Tufano find that the "cost of ignorance" appears related to the likelihood of for example, paying bills late, going over the credit limit, using cash advances, and paying the minimum amount only, that will lead to explicit fees or finance charges.

In the paper "Debt Literacy, Financial Experiences, and Overindebtedness", the authors estimate the costs of ignorance and conclude that: the average fees paid by those lacking financial knowledge are 50% higher than the average fees paid by an average cardholder, a third of the fees paid are due to lack of knowledge, after controlling for several variables such as income, wealth, family status and the cost of ignorance is sizable.

Referring to credit cards, the authors came to the conclusion that individuals lacking financial knowledge are more subject to fees and financial charges compared to the literate ones.

1.3.2.5 Other consequences - Savings

The lack of financial knowledge, numeracy and cognitive abilities also prevent many from saving moneys and ensure a sound financial situation. Financial literacy does not only affect the household's debt but also its retirement planning. By ignoring basic financial principals, households tend to forget planning for their pensions and by not savings, their overall wealth is impaired.

Gustman and Steinmeier (2005) described those lacking knowledge about Social Security and retirement planning as having low education, low income, African-Americans and Hispanics and mostly women. This profile matches with the profile of those lacking financial knowledge in borrowing activities. Indeed, saving and borrowing activities are highly correlated, it is logical that it affect the same population.

For pension planning, the ability to understand a contract is crucial and lacking financial competencies is preventing part of the population to engage in such programs.

Lusardi (2008) concluded her paper "Household Saving Behavior: The role of Financial Literacy, information, and Financial Education Programs" by the following comments:
"Saving decisions are derived from maximizing utility not only under a lifetime budget constraint but also under the limitations imposed by low financial literacy, lack of information, and crude sources of financial advice...

It is also important to recognize that, while the private industry is spending millions of dollars every year advertising products to entice consumers to spend more, relatively little is spent in encouraging people to save and provide for their future. However, if consumption is excessive and saving too scarce, taxpayers may be asked to support those who have not provided enough for retirement. Thus, the government may have to think of ways to engage in marketing campaigns. It's up against tough competition: One recent ad from American Express, advertising cash back to card holders on the amount spent with their card, argues that by spending more, people... save!"

Indeed, the credit card industry, being a highly competitive market, advertising in favour of a saving behaviour is rather difficult in the current economic context. However, as described previously, credit cards users are mostly convenience users. Data from the Surveys of Consumer Finances indicated that even if consumers raised concerns about the costs as well as the understanding of credit card, they appreciate the convenience associated with card-based open-end credit lines (Durkin, 2000). Carrow & Staten (1999) confirmed that the convenience of credit card was mentioned as the main advantage for using credit cards even before the capacity of credit granted.

In addition to the lack of financial literacy and awareness, it is also important to note that humans' behaviours and preferences can also be sometimes inconsistent. This concept has lead to the hyperbolic discounting function (Ainslie, 1992; Frederick, 2002; Laibson, 1997): today's preference might not be tomorrow's preference depending on the angle the person is looking at. Someone who is today a convenient user might become tomorrow a revolver under new circumstances like uncertainty, changing tastes or utility changes.

Chapter 2: Credit Risk management in the Credit Card industry

Chapter 1 and 2 are purely theoretical chapters, the first one being on introduction to the banking / credit card business and the second to the field of concerned.

At this point, this thesis could have taken two different directions: lender oriented and/or consumer centric. Indeed, one can decide to focus on a credit risk system for financial institutions aiming to maximize their profit but one could also focus on a credit risk system that would be in favour of consumer's welfare. The author has decided to orient the thesis toward the lender's interest.

Therefore, after introducing the reader to the credit card market, next step is to introduce the reader to the risk area as defined by financial institutions, i.e. the different components and especially credit risk, which is the main focus of this thesis. The main indicators used in the credit risk area / financial sector are described as well as what a credit risk management structure should be.

This chapter also describes what credit scoring is and where it comes from. Credit scoring can have different targets and various types of scorecards can be implemented. The author gives some examples of possible scorecards and especially application scorecard and behavioral scorecard which are the ones that will be applied in this thesis.

This chapter aims at answering the following questions:

- What is credit risk? How is it managed?
- What is a scorecard and how can it be used to minimize credit risk?

- What are the different scorecards that can be used to minimize credit risk?

The objective of this chapter is to show how scorecards have proved to be relevant in the credit risk management process, in order to minimize credit losses.

2.1 Risk management and credit risk

Risk management aims at controlling all risks that the bank may take. In this section, the reader is given an introduction about financial risks. As this research focuses on credit risk, some concepts of credit risk are detailed. The objectives of the credit risk function are also described.

2.1.1 Introduction to financial risks

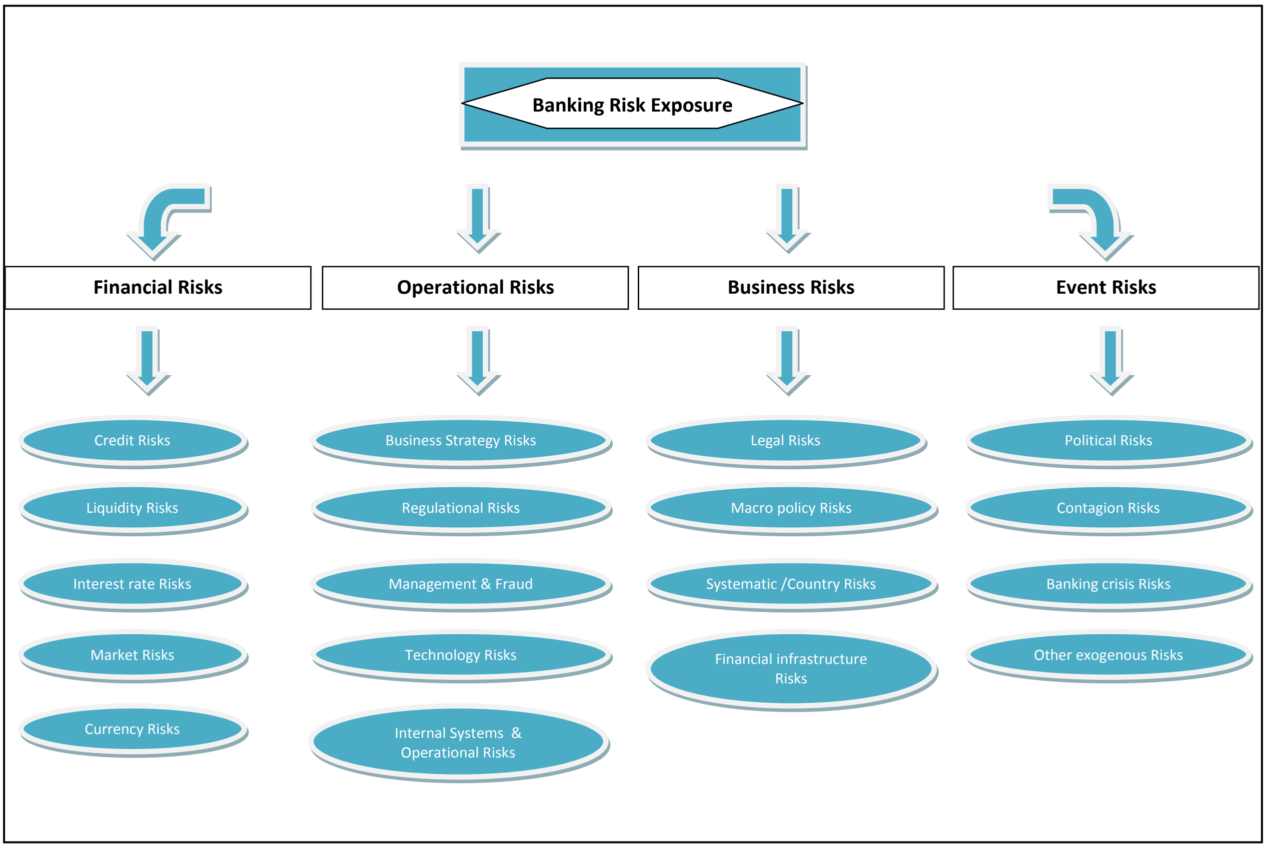
Risk is defined as an element or factor indicating a certain danger that will affect the ability to reach one objective.

Risk is defined in ISO 31000 as the effect of uncertainty on objectives, whether positive or negative.

In financial terms, risk is an unknown component of the future value of a financial asset. A bank will estimate the expected return for one asset and the risk associated reflected in the anticipated volatility of the expected return. Risk is the variation around the expected return: it can denote the volatility of one asset but also the volatility of the default rate for a credit portfolio. The forecast level of default is one feature of risk, and possible variation around the forecast, particularly upwards, another.

In the banking industry, risk is usually divided in 4 pillars which cover related risks.

Figure 1 – Organization chart of banking risks



The bank sponsoring this thesis was subject to the following risks: credit risk, counterparty credit risk, liquidity risk, market risks, concentration risks, fraud risks and operational risks. Credit risk is the single largest risk encountered by the bank. The next section focuses on credit risk.

2.1.2 Principles of credit risk

The first written document mentioning credit risk was issued in 1790 BC. The Hummurabi's law code, as it was titled, is the first written law in recorded human history that stated that a failure to pay a debt is a crime (King, 2005).

Since then, the evolution of credit risk has been substantial, especially in the last century with the banking Act and the National bank Surveillance in 1975 in 1933 in the United States, and the various Basel regulations, culminating in Basel III.

This thesis examines credit cards and how to build a system to assign appropriately credit lines. Therefore, understanding what default and credit risk mean is an indispensable foundation for this.

2.1.2.1 Definition of default

A default occurs when one party is not compliant with its financial commitments. Commonly, a defaulter is defined as such once the first payment on any financial obligations is missed. In most financial institutions, a default is a failure to make required debt payments by or at the stipulate time. The rating agency, Standard & Poor's (2003), defines a debtor as a defaulter when he can't fulfil his contractual obligations and pay in due time.

In the credit card business, a credit card holder receive a bill every month, the bill will state the amount to be paid and the due date. Depending of the institutions, either the full amount, or partial amount, can be required. If the card holder does not fulfil his contractual obligations, paying the required amount for the due date, he will receive a reminder including late payment fees and the interests he is accountable for. To get his account back to good standing, the card holder should pay his billing statement as soon as possible.

In the credit industry, a default is commonly defined as being more than 60 days past due. An example of partial payment could be 3% of the balance due with a minimum of EUR30.

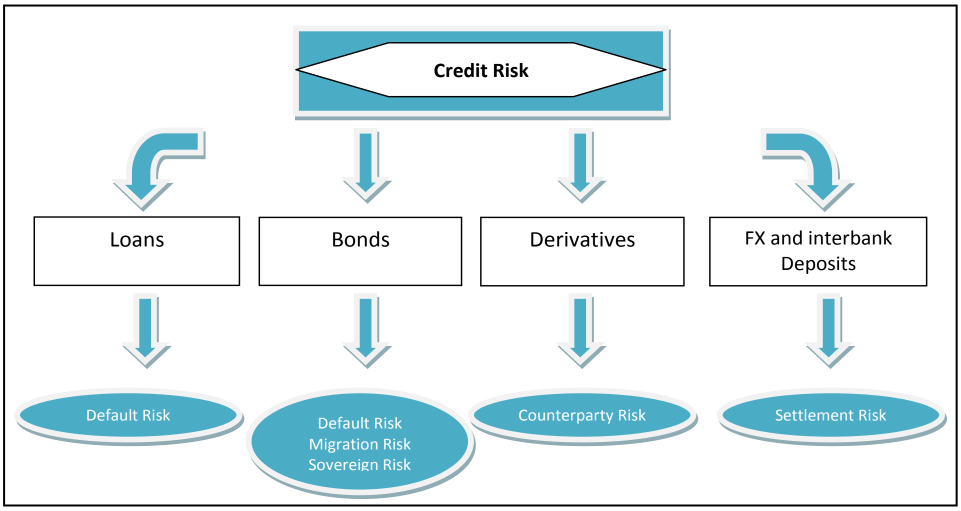
Usually, an account is sent to collections after 180-210 days past due; collectors are in charge of reminding a debtor that an account is overdue and to seek payment.

The definition of default used in this thesis is the one described above.

2.1.2.2 Definition of credit risk

Credit risk is inherent to banking activity. The financial asset the most concerned with credit risk is loan followed by bonds but in a smaller extent. However, other products such as OTC derivatives, Asset Backed Securities and Structures bonds, inter-bank transactions, commitments and guarantees are also more and more affected by credit risk.

Figure 2 - Credit risk categorization



Credit risk is the risk that one party bounded by a financial contract is unable or unwilling to fulfil his obligations in due time, causing a financial loss for the other party. When the borrower defaults, the next exposure for the lender is the amount owed by the borrower. However, the final loss incurred equals the net exposure (including protection that the creditor holds such as third party guarantees, collateral…) minus the amount that can be recovered by the collection agencies (or internally through bankruptcy negotiations).

2.1.3 Credit risk components

The 3 major components of Credit risk are the probability of default, the exposure at default and the loss given default. Credit risk can be expressed as a function of those parameters:

Credit risk = f(PD, EaD, LGD) where

PD: probability of default

EaD: exposure at default

LGD: loss given default

The credit VaR is another key element of credit risk.

2.1.3.1 Probability of default

The probability of default, also known as delinquency rate, bad rate or expected default frequency is the probability that a borrower will default over a certain time horizon.

Usually banks will use several notions of default rate. When the time horizon is one year, it expresses the probability that a borrower will default in the subsequent twelve months. For most financial institutions, a one year probability of default is a logical and a reasonable period to estimate the overall risk exposure. Considering this fact, a one year probability of default satisfies the requirements of the Basel Committee for the calculation of the regulatory capital requirements. By contrast, it is recommendable that for a bank where the probability of default needs two years to stabilize to use a two year probability of default. When the time horizon is cumulative for t years, it expresses the probability that a borrower will default in the subsequent t years. A “transition matrix” is usually used to take into account the probability that the score of the borrower will fluctuate over the t years. The cumulative probability of default is used for the internal credit approval and for loan pricing purposes. For a certain point in time, the probability that the borrower will default exactly within year T is the forward probability of default.

Below, two examples of calculation of default rates commonly used in the credit card industry are presented:

- Default risks based on the number of customers defaulting, the so-called *default unit rate or incidence rate*.

The general formula (based on the whole portfolio) is as follows:

$$r_i = \frac{n_i}{N_i}$$

Where

r_i : Default rate for month i

n_i: Number of customers P60 and + for month i

N_i: Number of active customers at month i

The formula for the default rate based on only eligible customers (i.e. customers that got the possibility to be P60 and +) is as follows:

$$r_i = \frac{n_i}{(N_i - N_{i-1,i} - N_{i-2,i} - N_{i-3,i})}$$

Where

$N_{i-1,i}$: Number of customers who started using their card in month i-1 that used their cards in month i

$N_{i-2,i}$: Number of customers who started using their card in month i-2 that used their cards in month i

$N_{i-3,i}$: Number of customers who started using their card in month i-3 that used their cards in month i

- Second, default risk based on the amount spent by the defaulting customers, the so-called *default amount rate* or *loan loss rate or dollar delinquency rate*.

The general formula is as follows:

$$r_i = \frac{a_i}{A_i}$$

Where

r_i : Default rate for month i

a: Amount spent by customers P60 and + for month i

A_i: Amount spent by active customers at month i

The formula for the default rate based on only amount spent by eligible customers (i.e. customers that got the possibility to be P60 and +) is as follows:

$$r_i = \frac{a_i}{(A_i - A_{i-1,i} - A_{i-2,i} - A_{i-3,i})}$$

Where

$A_{i-1,i}$: Amount spent by customers who started using their card in month i-1 that used their cards in month i

$A_{i-2,i}$: Amount spent by customers who started using their card in month i-2 that used their cards in month i

$A_{i-3,i}$: Amount spent by customers who started using their card in month i-3 that used their cards in month i

2.1.3.2 Exposure at Default

The exposure at default is the amount that the borrower owes to the lender at the point where he is going in default, i.e. he is not fulfilling his obligations. This is this outstanding amount or claim at the date of the borrower's default that will be sent to the collection agencies. It is the stock of outstanding debt, and not just the inherent payment unpaid.

The recovery rate is the proportion of the claim due by the defaulting borrower that will be recovered by the lender. The loss given default is commonly associated with the recovery rate: LGD=1-RR

2.1.3.3 Loss Given Default

The loss given default is the expected effective loss of a defaulting borrower that will not be recovered. The difference between the exposure at default and the loss given default indicates how much of what the borrower owes to the lender, the bank has recovered.

Note that as opposed to the default rate, the loss given default is expressing a facility, as the loss given default is dependent from factors specific to the defaulted security such as seniority, collateral or contractual clauses.

2.1.3.4 Credit VaR (Value-at-Risk)

Value-at-Risk (VaR) is the worst case losses at a certain confidence level over a given time horizon (Jorion 2001). This dissertation deals with a credit card company issuing small loans. Therefore, the author concentrates on the credit VaR when applied to a retail credit portfolio.

Each loan has a probability of turning bad. In other words, for each good loan, the possible loss will be 0% but by contrast, the probable loss for bad accounts is 100%.

To calculate the VaR, there are two different approaches: (i) the first approach relies on the distribution of the value of the portfolio, or (ii) the second approach relies on the distribution of the losses in the portfolio. Both methods are different but lead to the same outcomes.

To estimate the credit VaR, Mukul (2010) recommends the following steps:

- Estimate the portfolio value (P.V.) and portfolio losses: For a portfolio value of $X, the maximum future value of the portfolio will be $X and the portfolio losses of $0. The minimum value of the portfolio will be $0 and the portfolio losses of $X. In reality, the future value of the portfolio will be somewhere between the minimum and maximum values as over a certain future horizon, losses will arise and the value of the portfolio will lower.

Assume that the default rate after collections efforts remains at t%, the expected value of the portfolio will be 100-t%*X of the loans and the expected loss will be t%*X.

- Calculate the expected losses (E.L.): Expected losses are the losses expected on the credit portfolio. These losses are integrated in the P&L and influenced the pricing strategy of the bank. These losses are expected happen and expected to materialize over an indefinite time horizon. Assume that the default rate after collections efforts remains at t%, the expected loss will be t%*X.

- Calculate the unexpected losses (U.L.): Unexpected losses are calculated at a given confidence interval, and are equal to the losses minus expected losses at the given confidence interval. Assume the value of the portfolio at 95% confidence level is $x, the total losses are $X- x, and unexpected losses are equal to:

U.L.=P.V. – P.V._95% - E.L.= X- x- t%*X.

- Calculate Credit VaR: The two ways to calculate according to two approaches as follows:

(1) Credit VaR is the distance from the mean to the percentile of the forward distribution, at the desired confidence level. It is then the unexpected credit loss at the given confidence level.

VaR= U.L.=P.V. – P.V._95% - E.L.= X- x- t%*X.

(2) Credit VaR are the total losses at that level of confidence, i.e. including both expected losses and unexpected losses.

VaR= E.L.+U.L.=t%*X+X- x- t%*X.=X-x=P.V.-P.V._95%

The first approach is usually the preferred approach as this is the most reasonable and consistent method (Mukul, 2010).

In this PhD thesis, the main focus is to establish a credit scoring solution for the underwriting process. The three main purposes of establishing such solution are: loan approval, determination of the minimum capital needed to fulfill requirements and the implementation of loan pricing and capital management policies that allow covering the expected and unexpected credit losses. The solution presented in this thesis is mainly focusing on the optimal credit policy which includes loan pricing and especially credit lines.

2.1.4 Credit risk in the organization

The thesis focuses on credit risk. Credit risk is managed by the risk management department.

2.1.4.1 Risk management

Banks and financial institutions are exposed to financial risks. In the banking business, managing those risks is crucial. The objective of the risk function is not so much to minimize risk but to accept them and to optimize the risks and their relation to profitability, within the bank.

Risk management relies on five principles:

- Identification: the risk function is responsible for identifying the different risks the bank is exposed to and quantifying the financial exposure related to it.
- Acceptance: The risk function is responsible for communicating the different risks to the hierarchy and ensuring that all the members of the decision bodies understand the implications of taking the different risks.
- Measurement: The risk function quantifies the different risks and the financial exposures related to it. The risk function can also be responsible for quantifying the expected return from taking the risk.
- Monitoring: The risk function follows up all decisions made by the bank management related to risk and ensure they follow strictly the bank's strategy set by the board of directors.
- Reporting: The risk function is responsible to inform the senior management as well as the board of directors of the different risks incurred. They are responsible to report any material risk within the bank but also toward the regulatory body.

- Control: The bank must have enough assets to support the risks that they are taking. The risk function is responsible to ensure that the bank exposure is within the limit set by the bank and is following all regulatory requirements.

In financial institutions, roles and responsibilities need to be clearly defined in order to build a sound and solid risk management infrastructure. The overall risk management is usually supervised by a dedicated unit / department as well as a dedicated committee (Risk Management Committee: RMC). This committee would include the managers of all the key departments such as the chief finance officer, the chief marketing officer and the chief executive officer. A sound organisational structure would separate the risk taking functions, the risk management department and the deciding body responsible for accepting risks on behalf of the bank and make final decisions.

The purpose of risk management is to ensure the measurement, monitoring and evaluation of risks incurred by the bank. However, it is crucial that risk management functions are not influenced by risk taking unit and report directly to the RMC or even to the Board of directors if such committee is not in place.

The organization of the risk management unit and the risk management processes should ensure that the bank is able to capture all potential risks the institution is exposed to by fulfilling the following recommendations:

- Independent and centralized Risk Management Unit by defining roles and responsibilities within the organisation.

The risk management department is responsible for controlling and monitoring the risks taken by the bank. Thus, this department has to be independent and autonomous from the rest of the bank. They should not be connected to the front offices. Indeed, to be impartial, neutral and respected by management, the risk managers must include analysts with the required expertise to perform the analysis, review and report the identified risks, directly to the management team or the board. The risk management unit usually includes internal audit, compliance, information risk management and enterprise risk management. The risk management unit also centralizes all types of risks (Market, Credit, etc.) in order to achieve an integrated view and control of risk. Those functions are solely dedicated to the risk management department.

- Written policies and procedures that will describe how the bank is respecting the five principles mentioned earlier: identification, acceptance, measurement, monitoring, reporting and control.
- Risk authorities should implement and review risk management policy and procedures as well as risk controls to monitor processes and systems and to detect any additional risk exposure as well as a procedure describing the process to follow in case of violation of the policy and the measures to implement.
- Approval and review of risk policies by top management / board of directors as well as by regulators and auditors. The internal Capital Adequacy Assessment Process (ICAAP) lists / reviews all risks applicable to the bank and assesses their status on a yearly basis.

2.1.4.2 Credit risk management

The definition of credit risk management will vary from one bank to the other depending of the type of business they are into. While defining the credit risk management process, the bank has to consider seriously the specific features of its target market to develop an appropriate credit strategy.

The bank’s strategy requires an in-depth knowledge of the business:

- the type of products that will be offered: credit cards are the products emphasized in this thesis.

- the target market: in this research, the market targeted could be defined as a subprime consumer market.

- the country / geographical area and the legal requirements associated: if Germany is the country of interest, German law is applicable.

- the currency : the euro is the currency used.

- the maturity of the market within the country / area: Germany is well-known for being a cash payer country. There is still ample room for credit card companies to develop businesses.

One additional element that might interfere in the set up of credit risk management process as well as the credit policy is the pricing strategy. In this thesis, the credit card is free and the maximum interest rate is given at 16.90%. The late payment fee is around EUR10. Those features have been set according to German law.

The credit policy formalizes and articulates the credit risk management process of the bank and states the tolerance of the bank's Board and management for credit exposure. Once the risk appetite of the bank clearly defined, the credit policy will articulate how the bank plans to control credit risks within the predefined limits. The policy details techniques and processes for avoiding, mitigating, and effectively managing credit exposure to an acceptable level for the bank. The credit policy is usually revised once a year.

A credit policy should spell out:

- The credit risk management framework: it would formalize what credit risk management includes for the banks, the credit risk management structure (list of the employees involved in the acquisition and portfolio management process with their roles and responsibilities), the credit committee's role, and the escalation process.

- The application process: It would detail the data provided by the customers, the identification checks (ex: IP Address verification), the compliance checks (ex: Scanning with the E.U. Sanctions list), the fraud checks...

- The acquisition process: It would describe the initial credit line assignment process, how credits are originated as well as the different scores cutoffs.

- The portfolio management process: It would describe the credit line assignment process for all subsequent months or transactions, how the credits are administrated.

- Portfolio monitoring: It would include a list of all necessary reports to identify, to measure, to monitor and to control credit risks.

- Forecasting-Impairment: It would describe the loan loss reserve calculation and monitoring.

- Overrides guidelines: It would formalize all exceptional circumstances where a customer might not fulfil one of the conditions described in the previous chapter. It would also mention the approval authority to allow the exceptions.

- Fraud prevention and detection: It would detail what the fraud detection process is, how suspicious accounts are treated, what the process is in case of a fraud ring...

- Collections: The Collections policy usually describes the overall collections process. However, a sound credit policy should describe how delinquent accounts will be managed and what the collections process will be. From a credit risk side, it is not the operational side of collections that is of interest but the different treatment strategies of the bank and the collections agencies.

The bank's board is the main authority to approve the bank's credit strategy and policy. In the context of this research, the board was reviewing the policy on a quarterly basis.

Documentation procedures are completing the credit policy. Those are reviewed and approved by the Credit committee as well as any request for change that would affect the credit risk management process.

The Credit Committee, also named the Firm Wide Risk Committee, takes decisions regarding measures that affect the credit policy of the bank but the credit risk function / department is responsible for reporting on the status of the credit risk inside the bank and proposed relevant measures in order to improve the results of the bank. The final decision is taken by the Credit Committee which includes members / managers from the different bodies involved in the credit life cycle and in specific cases, might require board approval.

The Credit committee is responsible for: defining the risk appetite of the bank, maintaining the credit risk within the established limits for credit exposure by avoiding a material credit failure that exceeds the Bank’s risk appetite, reviewing and validating policies and procedures, and supervising the credit risk department by ensuring a high level of expertise and awareness of credit risk and sound processes to identify measure, monitor and control credit risks.

The credit risk department is responsible for identifying, measuring, monitoring and controlling credit risks but also reporting to the Credit committee. As an example, the credit department, in this research, is responsible for:

- Managing credit Risk / portfolio within the Bank's risk appetite
- Implementing, maintaining & monitoring the bank's Credit Policy
- Recommending policy changes to Credit Risk Committee
- Reporting / presenting performance updates to the Credit Risk Committee

- Building and managing relationships with key stakeholders

- Reviewing performances of all credit risk management processes on a regular basis

2.1.5 Focus of this thesis

The main objective of this thesis is to predict when a customer will default or start to be in financial distress and the cost associated with this default if it happens (George et al., 2008).

To control / predict credit risk in a credit card company, this thesis has focussed on the two following pillars.

2.1.5.1 1st Pillar - Reporting

It consists of tracking the evolution of different indicators considered to be key predictors of the risk of the bank. The monitoring of those indicators is followed up in the credit report and separate reports. Those reports are produced on a monthly basis. According to Lafferty, most credit strategy units produce a regular management report containing, for example, information on acceptance and override rates, default trends, and experimentation results. For a new portfolio, these types of reports should be produced monthly as a minimum (Cavell, 2004).

For more details on credit reporting, please refer to Chapter 3.

2.1.5.2 2nd Pillar - Modelling

For credit card companies, credit granting is one of the most important decisions. The profit of the bank depends on whether a credit line is allocated correctly or not. This implies that credit risk is one of the main risks for credit institutions as granting incorrectly credits could in extreme cases lead to the bankruptcy of the company (Mileris, 2010). Therefore, the main concern is to find out who will pay and who will default. In order to solve this problem, researchers have worked on finding statistical methods / classification techniques / prediction models to automate and support credit granting decisions (Zakrzewska, 2007).

The second pillar consists of developing models in order to better control the credit risk of the bank. Those models belong to the whole credit risk management system of the bank. Each model is a project itself that required development and modelling on the skills side and time capacity on the practical side.

Three types of models are usually used in credit risk measurement (Georgakopoulos, 2004):

- Traditional models that predict default rate.
- Modern credit risk measurement approaches like the option-theoretic structural approach, the reduced form approach and others.
- Proprietary credit risk measurement approaches that are in-house credit risk models built by financial institutions to predict firms' defaults.

Credit card companies focus mostly on traditional models. Those models focus on predicting the probability of default of a customer and do not consider the loss given default. Compared to market models, those models do not consider "the downgrades and upgrades in credit quality that are studied by market models, but they analyze the "failure" like the bankruptcy, the default or liquidation" (Falavigna, 2006).

Traditional models include (Falavigna, 2006):

- Expert systems (neural networks, genetic algorithms, decision trees, fuzzy logic)

- Ratings systems (rating system forecasting PD and/or LGD and following current regulations)
- Credit scoring models (discriminant analysis, logit analysis, probit analysis)

As this research is based on data provided by a credit card company, the author has focused on building a credit scoring system aiming at setting credit lines with the objective of controlling the credit exposure for the bank.

2.2 Credit risk scorecards

The reader is introduced to the topic of credit scoring which is the assignment of a value usually going from 1 to 20 to an applicant or customer representing his probability of default.

The historical background of credit scoring is described in three steps. The first one describes the emergence of credit scoring and how statisticians and mathematicians have worked on improving the accuracy of the divers techniques whereas the second part is more focussing on the economists and econometrician perception of credit and default. The third part is dealing with a more recent issue which is the ethical aspect linked with credit scoring.

The next step is to introduce the reader to the type of data that is used for building those models.

Finally, the author describes the different types of credit scoring models that can be implemented and the ones this thesis is focusing on.

2.2.1 Credit scoring: a review

This sub-section defines credit scoring and the historical background behind it.

2.2.1.1 Definition

A credit is defined as an amount of money borrowed by an individual to a lender that has to be repaid in full with interest, usually over a specified intent. The repayment is usually by instalments, occurring on a regular basis.

If credit granting is not controlled properly, it might lead to a financial crisis. For example bad credit decisions will lead to an inadequate credit control or an over liberal credit policy that will often contribute to an excessive amount of accounts receivables (Chong & Escarraz, 1998). The 2007-2009 financial crisis was partly triggered by lax lending in the US

In the credit card industry, different elements can be modified such as the interest rate, the credit limit, the annual fee, the conditions and duration of any initial discount, and whether special marketing incentives are offered. The internet or telephone application process means that the offer can be calculated in real time as a function of the customers' characteristics, given as part of the credit scoring check on risk and the information the organization currently has on the acceptance rates (Seow & Thomas, 2006).

But what is credit scoring? Credit scoring is the process of assigning a single quantitative measure, or score, to a potential borrower representing an estimate of the borrower's future loan performance (Feldman, 1997).

In fact, credit scoring is the process used to predict which customers are going to default, i.e. customers missing to make their payments for a certain number of consecutive months. The result is a model that is also called a score, a scorecard or a classifier.

Scores are just statistically derived tools summarizing many predictive characteristics into a single model facilitating strategy implementation, policy changes, monitoring / tracking … In the literature, these predictive characteristics are also called predictor variables and their modalities or values are called attributes. Those characteristics are rated with points. The sum of the points will allow the quantification of the exante probability of expected default of each customer.

Common methods used to develop a scorecard are discriminant analysis, logistic regression and decision trees. A scorecard usually belongs to one of this category: application scorecard, behavioral scorecard (or the so-called performance scorecard), profit scorecard or fraud scorecard (or suspicious scorecard). Boggess (1967) defined a credit scoring system as a system that provides management with a basis for measuring and controlling profits from credit sales because it balances the probabilities of both good and bad credit risks and enhance the user's ability to vary credit policy with changing market conditions.

Traditionally, loan officers have been responsible for granting credit and their decision was based on a judgmental approach. Over time, automated processes have appeared. Mehta (1968) presented a sequential decision process for granting credits to firms where each piece of information obtained on the firms applying for credit would be considered as a cost.

Credit screening has been discussed for many years. Authors have compared advantages and drawbacks of manual decisions and automated decisions.

The processing time is one of the key advantages of credit scoring. Several authors confirmed this fact as will be seen below. In 1985, Chalos compared the results of loan officers as against credit scoring model and / or credit review committees, and concluded that credit scoring was outperforming individual loan officers but the credit review committee was the best method for granting credit. However, he raised the issue of the processing time (Chalos, 1985). Indeed, such method would not be applicable for mass-market banks like a credit card company where manual interventions should be reduced as much as possible. Alexander (1989) pointed out the key advantage of credit scoring which is the time needed to screen on application, he estimated that a credit scoring model would need 5 to 6 minutes to review an application. Based on a 1995-empirical study of a Canadian Bank, Leonard (1995) compared the number of days needed for screening loan applications before and after implementing credit scoring. Without credit scoring, it was taking 9 days. With credit scoring, it was taking 3 days. Bilgin and Yavas (1995) also advised the use of computerized credit scoring system. In 2000, Banaslak and Kiely (2000) recommended the use of credit scoring to financial institutions for its high performance in classifying loans and for its short application processing time.

Another advantage of credit scoring versus manual underwriting processes is cost reduction. Barefoot (1995) is one of the authors that insisted on the fact that automating credit evaluation would reduce the cost of issuing credit.

Accuracy of decisions is also one of the advantages. Overstreet and Kemp (1986) confirmed that credit scoring models should be used to check the decisions made by loans officers. Witkowska (2006) pointed out weaknesses of relying on credit officers such as training costs, long processing time and lack of accuracy. He recommended the automation of credit risk management decisions (Witkowska, 2006). Nevertheless, Chalos found that the credit review committee was the best method in granting credit (Chalos, 1985). Indeed, some authors found out that combining manual and automated decisions could lead to even more accurate decisions. Edmister (1988) raised the possibility of combining both methods based on his findings, i.e. loans officers and credit scoring models combined were highly accurate in granting credits in his research.

The last key advantages of credit scoring are its various possible applications. Indeed, Avery et al. (2000) mentioned that credit scoring could also be used for pricing loans and setting interest rates. Sandler et al. (2000) also indicated that credit scoring could be used for setting credit lines. Punch (2000) listed several ways to use scorecards for credit risk purposes: acceptance/rejection, setting credit lines, managing existing account and forecasting accounts' profitability.

The next section intends to go deeper in what credit scoring is. Before going into details, the author reviews the history of credit scoring.

2.2.1.2 Historical background of Credit scoring

In 1936, Fisher treated the possibility of discriminating sub population within a population of individuals. It is in the 1930's that the first numerical scoring systems were developed for the mail order industry (Capon, 1982). In 1941, Durand pushed this idea further by suggesting that good and bad loans might be distinguished using the same approach of discriminant analysis. In 1949, Wolbers presented a study in one branch of a nationwide department store chain. In 1957, Myers and Cordner did a similar study reviewing credit accounts in one branch of a nationwide department store chain (Myers, 1963). Historically, discriminant analysis is the oldest technique presented in the literature used for credit granting. Lachenbruch (1979) listed 579 references in his classic book on discriminant analysis. However, it is after the 1960's that findings in the area of credit scoring exploded. Linear regression followed discriminant analysis and opened the path for other techniques such as logistic regression, probit analysis, nonparametric smoothing methods, mathematical programming, Markov chain models, recursive partitioning, expert systems, genetic algorithms, neural networks and conditional independence models. Since the 1960's, credit scoring has been extensively studied due to the limited use of discriminant analysis (Rosenberg, 1994). It is in the 1960's and 1970's, that some of the most famous models, especially time varying models, were presented in research papers. Examples are the Cyert Davidson Thompson model for doubtful account in 1962 (Cyert et al., 1962) and the Bierman Hausman credit granting model in 1970 (Bierman & Hausman, 1970). The 1970's was a period of experimentation of credit scoring techniques as well as a period of study of the different issues related to the field. The multiperiod methods were improved. In the 1980's, discriminant analysis and multiperiod models were put aside whereas all interests turned towards expert systems, credit policy adjustments, multiple scorecards … (Rosenberg, 1994). However, little attention in the literature has been put on credit limit adjustment, reissue period and promotions strategy. As the number of research papers, in the field, was increasing, authors started to review it and point out issues that needed further research. In 1977, Eisenbeis reviewed all the different techniques discussed in this paper and listed more 820 references. In 1978, he added some more references, 63 in total. The 1977 book deals with statistical concepts linked to discriminant analysis whereas the 1978 book is more a valuable guide for further non technical or moderately technical reading on discriminant analysis (Rosenberg, 1994). In 1982, Capon reviewed different problems faced along the process while implementing scoring systems. In 1994, Rosenberg, in its literature review, concluded that "Only the Bierman-Hausman model (and its refinements) considers the credit limit, and no theory exists for the reissue period and promotional strategies". In 1995, Prakash (1995) mentioned that GE Capital Mortgage Corporation was using credit scoring to review applications for mortgage insurances. In the 1980s, William Fair estimated that between 20% and 30% of all consumer credit decisions were made by credit scoring (Capon, 1982). In the 1990's, a survey reported that 82% of banks using expert systems were using credit scoring as a decision tool for commercial, consumer, and mortgage loans. In this survey, the cost of building and implementing a scorecard was estimated to be $50000-$100000 (Rosenberg, 1994).

It is important to note that not only scientists, mathematicians and statisticians have put interest in credit scoring but also economists and econometricians. Some of the most famous researchers in the economic literature such as Bierman and Hausman (1970), Stiglitz and Weiss (1981 and 1983), Bester (1985), have shown interest in credit scoring and its effects. In the 1970s, Bierman and Hausman presented a credit policy including a section describing the granting process. The more conservative a credit policy will be, the more the bank is taking the risk of limiting its sales and profit. While implementing a credit scoring model, it needs to have the following attributes: allowance for prior probabilities of collection, appropriate inclusion of potential future profit, systematic revision of probabilities based on collection experience (Bierman & Hausman, 1970). Bierman and Hausman focused mostly on the credit granting process whereas Stiglitz and Weiss focused more on the effects related to the interest rates. In the 1980's, Stiglitz and Weiss (1981 and 1983) and Riley (1987) argued that credit markets are typified by both adverse selection and moral hazard: consumers are unlikely to engage in riskier purchase in response to higher interest rates and higher interest rates above a certain level may induce the 'good risks', who are relatively prudent with low default probabilities, to exit the pool of potential borrowers (Drake et al., 1995).

In 1989, Crook presented some estimates of demand functions for installment credit financed by retailers in Great Britain. The conclusion of his study was that "the demand for such retailer financed installment credit was not significantly related to interest rates and that the main determinants of such demand were personal disposable income, expectations and terms control". Bernanke is also one famous economist that published papers dealing with the credit industry. In 1988, Bernanke and Blinder presented a model of aggregate demand that they qualified as simple, which allows roles for both money and credit. This model is a variant of the textbook IS/LM model. In 1992, they tested this model and they concluded that "monetary policy works in part by affecting the composition of bank assets. Tighter monetary policy results in a short run sell off banks' security holdings, with little effect on loans. Over time, however, the brunt of tight money is felt on loans, as banks terminate old loans and refuse to make new ones". In 1995, Bernanke and Gertler investigated why the central bank actions should have any effect on the external finance premium in credit markets. They found that "the impact of monetary policy on housing (and, perhaps on the overall economy) has weakened since the phasing out of interest rate ceilings and the introduction of innovations such as liquid secondary market for mortgages". More precisely, one famous economist in the field of econometrics, Professor William Green (1998), discusses several important problems relating to credit cards. His paper aims to estimate the probability of default on credit card loans as well as to extend his analysis to predict consumer expenditure. He also focuses on predicting major derogatory reports (Greene, 1998). Yasuhiro Sakai (1998) that reviewed Greene's paper added that the problem of default is not only a personal one, but also a social phenomenon. If the economy performs well and the society is stable, fewer people make defaults. One other interesting comment in this review was the question of the importance of default per se. Indeed a company is much more concerned with profit than with default. The author suggests that future research put more interest on the profit side and especially on how a credit company's profits are related to default (Yasuhiro Sakai, 1998). Therefore, credit scoring is not only a statistical technique but also depends on credit policy, the impact of interest rates, economic factors, etc. and should not only focus on predicting default but in combining it with the profit.

2.2.1.3 Moral / Ethical aspect of Credit scoring

The emergence of credit scoring has raised the issue that the use of certain characteristics in the credit granting model may involve discriminating between applicants, especially on gender, ethnic or religious criteria.

In the United States, the government adopted the Equal Credit Opportunities Act (ECOA) which prohibits discrimination against an applicant for credit on the grounds of race, colour, religion, natural origins, sex, marital status, age or receipt of public benefit (Banasik, 1996). Historically, it is in 1974 that the first version of the ECOA was adopted. The ECOA was only prohibiting discrimination based on sex and marital status (ECOA 1975). In 1976, the ECOA was amended to include the rest of the criteria mentioned in the definition above. In 1977, the Federal Trade commission decided to devote a significant percentage of its then increased resources to the handling of all forms of credit abuse problems (Advertising Age, 1977) (Capon, 1982). However, almost everything about the interaction of credit scoring and ECOA remains unsettled. Credit scoring users usually ignore if their system is fulfilling those requirements, as well as lawyers who are not able to decide whether scoring systems respects this law (Hsia, 1978). Regarding the ECOA and the dispute about discriminating variables, the position of Fair Isaac and Company is that "no issue other than statistical predictability is of any consequence" (Capon, 1982). Moreover, Wasseman (2000) explained that the fact that minorities have lower credit scores than white applicants is due to the fact that scorecard used information such as income, property, education and employment and those factors are distributed differently depending on the race / origin of the applicant in the United States. In the recent years, those laws have been extended to more characteristics such as the income.

In Europe, there is no law forbidding the usage of certain variables in credit scoring models. Therefore, modelers are able to use all the information available. In this thesis, sex, marital status, age and income were information available. Variables such as gender were not significant to predict the probability of default of an individual whereas age and income were some of the most predictive variables. One can wonder if using those variables was causing financial exclusions.

For this specific research, all applicants without legal issues (court cases, under collections...) were approved for a loan. In other words, no one was rejected based on age and income. The only impact was on the line assignment. Credit card holders fulfilling their obligations could after a couple of months obtained a line's increase. The inclusion of those variables, in this specific context, was therefore, not causing exclusions. However, if the scores were used for acceptance and rejection purposes (as it is commonly done in the credit card industry), it would be relevant to point out this possible issue.

After summarizing the historical background of credit scoring and discussing possible moral and ethical issues, the different type of credit information will be reviewed.

2.2.2 Credit information

Scores are just statistically derived tools summarizing many predictive characteristics into a single model facilitating strategy implementation, policy changes, monitoring and tracking.

The quality and relevance of the characteristics used to build the score are crucial. In order to get information about their customers, banks used usually different sources of information.

The two major ones are: (a) internal data: data collected inside the bank, it includes application data, payment data and collections data and (b) external data: in the credit card business, one key element is information sharing and this depends from country to country. The exposure for the bank is significantly reduced if the bank is informed and informed the authorities about customers financially constraints. The two types of organizations that store consumers' data are Credit bureaux and PCRs.

2.2.2.1 Internal data

In the practical application – Chapter 5, the author presents a detailed description of the data provided by the bank that has sponsored this thesis. Chapter 5 – 5.2.1.2 describes the application data. Data were available on 28 socio-demographic and economic variables. Chapter 5 – 5.2.1.3 describes the behavioral data. The behavioral data covers two types of information: transaction information and billing information.

2.2.2.2 External data: Information sharing

According to Jappelli & Pagano, most of the literature neglected exchange of information with other lenders as an alternative way to learn about one's own customers. Depending on the country, this exchange will be voluntary or imposed by regulation.

It exists two different approach regarding credit information sharing:

- The credit bureaux approach: Credit bureaux are information brokers which operate on the principle of reciprocity, collecting, filing and distributing the information supplied voluntarily by their members (Jappelli & Pagano, 2000).
- The public credit register approach: Public registers are generally managed by central banks, with compulsory reporting of data on borrowers which are then processed and returned to the lenders (Jappelli & Pagano, 2000). Public registers are still present in many countries.

Credit bureaux

The credit bureau distributes its information to its partners in credit reports. As soon as the credit institution sends a request for one customer to the credit bureau, the request will be processed either in batch mode or via an online system. The result of this request will be a credit report which will include the credit bureau's score plus details about the banking history of the customer. Customers who will have a credit report are the ones who were reported as already having a credit or asking for a credit or having public records. The report will follow up the different items; for instance if there are changes in the public record, if the customer is paying his credit, if he is seeking for credit, etc.

A credit report usually contains sections untitled Court, Collection and Account. Those three sections are the so-called public records which includes all bad marks referring to the customer on those three items. Examples of bad marks are bankruptcy, court cases, garnishment, foreclosure and collection accounts. If a bad mark is listed, the following details are included in the report: date of event, borrowed amount, amount paid and date of release. A code also tells if the case was satisfied or paid off or accepted or denied. Depending on the credit bureau, the bad marks are kept in credit report for a certain length of time; this will depend on the bad mark and the credit bureau. In this research, one of the credit bureaux is keeping data for three years and the other for 10 years.

Most information included in the credit report comes from its creditors or partners as banks, consumer finance companies, credit unions, collection agencies, and depending on the country, state, federal courts, liens, and bankruptcy filings may also provide information. The information provided is updated monthly or daily depending on the institution concerned. In case of court or collection information, the updates are more subject to be daily. From the credit report, it will be possible to have the debt list of the customer, the inquiries (information from other banks or financial institutions), the account warnings, the payment behavior, the type of financing, the reason of financing, the delays on payments and the closing date if the cases are solved. It will also be possible to know if the customer is involved at a high level in a company or if he has relocated. Of course, this list is non exhaustive, other credit bureau may give more information or different types of information.

Three advantages that would result of the use of the credit bureau approach are effects linked with pure information sharing:

o Credit bureaux improve banks' knowledge of applicants' characteristics.

o Credit bureaux reduce the informational rents that banks could otherwise extract from their customers.

o Credit bureaux reduce moral hazard and adverse selection.

Moreover, in a previous paper, Pagano & Japelli (1993) presented a pure adverse selection model where, information sharing improved the pool of borrowers, decreased defaults and reduced the average interest rate. They also presented two other effects of pure information sharing, those arising in the presence of moral hazard, that are that information sharing can reinforce borrowers' incentives to perform, either via a reduction of banks' rents or through a disciplinary effect (Pagano & Jappelli, 1993). Padilla and Pagano (1999) showed that pure information sharing was creating a disciplinary effect. When banks share default information, default becomes a signal of bad quality for outside banks and carries the penalty of higher interest rates (Padilla and Pagano, 1999).

Jappelli & Pagano (2000) presented the result of a survey in 2000. They proceeded to a cross country comparison. The summary table in their paper is presented below:

- Starting date: 1990s.

- Type of information shared: B=Black, refers to default and arrears; W=White, refers to other information like debt exposure.

- Credit reports: level / Percent of population (year): level is the number of credit reports issued by all credit bureaux in the country (if available); otherwise by the credit bureaux responding in that country. Percent is the number of reports divided by the population multiplied by 100 for the year given in parentheses.

Table 2 – Summary of a cross country survey about credit bureaux

Country	Starting Date	Type of Information Shared	Credit reports: Level / Percent of Population (year)
Argentina	1950	B-W	1.2 / 3.4 (1997)
Australia	1930	B	5.8 / 34.0 (1990)
Austria	1860	B-W	N/A.
Belgium	1987	B	10.6 / 104.8 (1998)
Brazil	1996	B	200.0 / 128.3 (1997)
Canada	1919	B-W	24.0 / 82.7 (1998)
Chile	1990	B-W	7.0 / 49.3 (1997)
Denmark	1971	B	2.6 / 50.3 (1996)
Finland	1900	B	3.5 / 70.2 (1990)
France	none		
Germany	1927	B-W	48.0 / 59.1 (1996)
Greece	none		
Egypt	none		
Hong-Kong	1982	B	N/A.
India	N/A.	N/A.	N/A.
Ireland	1963	B-W	0.8 / 22.5 (1996)
Israel	none		
Italy	1990	B-W	2.6 / 4.6 (1996)
Japan	1965	B-W	149 / 121.5 (1990)
Jordan	none		
Kenya	none		
Mexico	1997	N/A.	N/A.
Netherlands	1965	B-W	9.8 / 64.1 (1996)
New Zealand	N/A.	B	N/A.
Nigeria	none		
Norway	1987	B	0.5 / 12 (1990)
Pakistan	none		
Peru	1995	B-W	N/A.
Philipines	1982	B	N/A.
Portugal	N/A.	B-W	N/A.
Singapore	1978	B	N/A.
South Africa	1901	B-W	N/A.
South Korea	1985	B-W	N/A.
Spain	1994	B	N/A.
Sri Lanka	none		
Sweden	1890	B-W	2.2 / 26.0 (1990)
Switzerland	1968	B-W	1.7 / 24.1 (1997)
Taiwan	1975	B-W	N/A.
Thailand	none		
Turkey	none		
United-Kingdom	1960	B-W	60.0 / 104.8 (1989)
Uruguay	1950	B	N/A.
United-States	1890	B-W	600.0 / 228.1 (1997)
Venezuela	N/A.	N/A.	N/A.
Zimbabwe	none		

Source: Jappelli & Pagano (Jappelli & Pagano, 2000)

In Germany, the market is dominated by one large credit bureau. Only a few other countries such as Australia, Argentina, Brazil, Finland, and Ireland are in this category. In the US, UK and Japan, competition is limited to 2 or 3 large vendors.

Canada, the US, the UK, Japan, Germany, South Africa, Sweden and Switzerland have the highest number of credit reports per person. In Argentina, Brazil, Finland, the Netherlands, and Australia, credit bureaux operate but on a smaller scale. In Italy, the credit bureau is a new phenomenon. Latin America and Asian countries, credit bureaux are still in their infancy. Pagano and Japelli (1993) document that the number of credit reports per capita are largest where household mobility is highest.

Another element coming from this survey (Jappelli & Pagano, 2000) is that in the US, Brazil and Argentina, the major credit bureaux are for-profit operations owned by private entrepreneurs, although there are also several local non-profit bureaux owned by chambers of commerce or merchants' associations. In Japan and in most of Europe, credit bureaux are typically incorporated as private companies owned by a consortium of lenders (Jappelli & Pagano, 2000). This is the case for the major credit bureau in Germany. In Finland and Belgium, they are operated or licensed by government agencies. With the process of cross-border acquisitions of local credit bureaux, especially by the large US vendors, the industry is becoming increasingly profit-oriented (Jappelli & Pagano, 2000).

Public Credit Registers (PCRs)

Public credit registers are present in all countries. All of them cover real estate collateral (mortgages) in order to protect the rights of collateralized creditors. In addition, they give the creditors access to bankruptcy information that is publicly disseminated to alert present creditors and potential new lenders (Jappelli & Pagano, 2000).

Germany is an exception concerning public credit registers. The German public credit registers was created in 1934 whereas for most other countries, public credit registers have been established in the last two decades. Other exceptions are Italy (1964) and Mexico (1964) as well as Latin America countries (Jappelli & Pagano, 2000).

The PCRs are usually managed by central banks. However, there are some exceptions. Chile, Costa Rica and Peru PCRs are managed by the banking supervisory authorities. Finland is managed by a private company (Jappelli & Pagano, 2000).

PCRs do not have the same requirements. Those vary according to the country considered. In Germany, loan exposure and guarantees will be reported. Some countries will require more information such as Argentina who covers data on defaults, arrears, loan exposure, interest rates and guarantee and some other less such as Belgium where only defaults and arrears are reported (Jappelli & Pagano, 2000). One other interesting element is that most of European countries PCRs only cover information on relatively large loans to businesses except for Belgium and France that also cover consumer loans (Jappelli & Pagano, 2000).

To evaluate the data quality of PCRs, a reporting threshold is specified. However, the implementation of this threshold varies considerably depending on the country. The way to interpret it will depend on its value. For instance, the higher the threshold set by regulators, the fewer the borrowers covered and credit reports issued. Another consequence is that the threshold is also a separator to determine where credit bureaux do not face competition from the PCRs. If a PCR reporting results reach or is higher than the threshold, there will be a risk for credit bureaux that lenders asked the credit reports from the public registers (Jappelli & Pagano, 2000).

An example is that in 1998, the reporting threshold is the highest in Germany and the lowest in Belgium. In other words, lenders will prefer asking credit reports to Credit bureaux in Germany whereas in Belgium, they will ask the PCRs.

Jappelli & Pagano (2000) presented the result of a survey in 2000. They proceeded to a cross country comparison. Just below the summary table presented in their paper:

Table 3 – Summary of a cross country survey about public credit registers

Country	Starting Date	Number of Subjects covered	Credit Reports Issued	Minimum Reporting Threshold (USS)	Data Reported by Participating Institutions
Argentina	1991	4000000	N/A.	50	D, A, L, G
Australia	none				
Austria	1986	55585 (1997)	10267 (1997)	430700	L, G
Belgium	1985	360000 households (1997), 400000 firms (1990)	3550000 households (1997)	223 for households, 27950 for firms	D, A (consumer and mortgage credit only)
Bolivia	1989	N/A.	1300000	0	D, A, L, R, G, repayments
Brazil	1997	N/A.	4000000 households 6000000 firms	0	D, A, L
Canada	none				
Chile	1975	2200000 households 600000 firms (1998)	Information transferred to a private credit bureau	0	D, A, L, G, risk class, sector, type of debt, etc.
Colombia	1994	N/A.	N/A.	N/A.	N/A.
Denmark	none				
Finland	none				
France	1989 for households, 1984 for firms	370000 (1990)	5400000 (1990)	118293 (1990)	D, A for households, L, G, undrawn credit facilities for firms
Germany	1934	1200000	1800000	1699800	L, G
Greece	none				
Egypt	none				
Hong-Kong	none				
India	none				
Ireland	none				
Israel	1975	15000	N/A.	169500	D, L
Italy	1964	2200000 (1994), 6536914 (1998)	1400000 (1994)	0 for bad loans 86010 for other loans	D, A, L, G
Japan	none				
Jordan	1966	N/A.	14300	42065	A, L
Kenya	none				
Malaysia					
Mexico	1964	260000 (1997)	129870 (1997)	20111	D, A, L, economic activity of debtor, type of credit
Netherlands	none				
New Zealand	none				
Nigeria	none				
Norway	none				
Peru	1968	1920000 (1998)	N/A.	0	D, A, L, G
Philippines	none				
Portugal	1977	2469120 (1998)	N/A.	286860	D, A, L, G, undrawn credit facilities
Singapore	none				
South Africa	none				
South Korea	none				
Spain	1983	4600000 (1991)	758000 (1997)	6720 for residents, 336000 for non-residents	D, A, L, G, regional, sectoral and currency risk
Sri Lanka	1990	N/A.	102175 (1997)	1493 for bad loans, 7465 for other loans	D, A, G
Sweden	none				
Switzerland	none				
Taiwan	none				
Thailand	none				
Turkey	none				
United-Kingdom	none				
Uruguay	1984	N/A.	8000 (1997)	N/A.	D, A, L
United-States	none				
Venezuela	1980s	N/A.	N/A.	0	D, A, L
Zimbabwe	none				

Source: Jappelli & Pagano (Jappelli & Pagano, 2000)

The data reported to the register are defaulted loans (D), arrears (A), total loan exposure (L), interest rates (R), and guarantees (G). The exchange rates used to convert the minimum reporting threshold into US dollars are those of September 1, 1998.

As mentioned earlier, the credit information will be shared differently depending if the lender has to report to the PCR or not. The PCR is compulsory and so lenders are constrained by regulations to report to them all elements that they require. However, even if for credit bureaux, the information are shared on a voluntary basis and thus, that credit bureaux are less complete in coverage, they have the advantages to offer details on individual loans and that they are able to merge credit data with other data to be more predictive in terms of default. For this reason, countries such as the ones following the French civil code for example are amongst those which afford the weakest legal protection to creditors (Jappelli & Pagano, 2000).

Another problem faced by PCRs is the growing integration of national credit markets, particularly within the European Union. The European Commission has made some attempts to set up an international credit reporting system but with little success. They only could show differences between systems which are already in place in the individual countries and the fact that countries without PCR were not willing to set up a credit reporting system at the national level (Jappelli & Pagano, 2000). According to Jappelli & Pagano, there is a certain probability that in the longer run, PCRs gets progressively replaced by credit bureaux due to the difficulty they had in agreeing on a common set of rules (Jappelli & Pagano, 2000).

The key information of this section to remember for the rest of this research is that in Germany, the main sources for credit information are credit bureaux. In the next chapters, the author will investigate how internal and external information can be used for predicting credit risk within a bank and will detail information provided by the German credit bureaux.

The author wants to highlight that external and internal information are not comparable as external data come from related and unrelated businesses whereas internal data will take into consideration the specificities of the business. For the following reason, the objective of this research has been to capture information provided by both internal and external sources to be as accurate as possible in predicting credit risk, i.e. building the different scorecards.

2.2.3 Types of scorecard

This section aims to describe credit scoring and the different types of scorecard. Those reviewed in this section are the application scorecard, the behavioral scorecard, the collection scorecard and the fraud scorecard. Other scorecards could have been presented such as the churn scorecard. However, to implement those, the process is similar to the application scorecard; only the variables are different.

2.2.3.1 Introduction to Credit Scoring

A complete risk management system would include the following components: scoring systems, policy and exception rules, and judgmental analysis. This risk evaluation system must be designed and implemented to fit within the overall evaluation system of the bank. The different components need to be coordinated.

The key point is that the overall evaluation system and its components should be closely monitored on regular basis in order to manage the system properly.

The credit scoring system is a set of models developed in order to improve the allocation of credit by the bank. Depending on the model applied, the bank will be able to focus on a specific target and to minimize its risk. For instance, combining the use of three types of models (e.g. application scoring, behavioral scoring for short term, behavior scoring for long term), the bank will be able to define the profile of customers that should be approved, what credit limit they should be assigned initially and along the process in order to optimize the credit policy of the bank. More precisely, an application scorecard will include information concerning the applicant included in the application form. In some cases, past credit records may be accessible through credit bureaux and could be included while modelling for application scoring. Behavioral credit scoring is also using application data and credit bureaux information. The plus of behavioral scoring is that it is also building the scorecard with behavioral data linked to customers' payment behavior. The advantage is that it is based on the actual performance of the customers.

In this PhD thesis, three behavioral scorecards will be implemented with the objective of predicting the probability of default of the customers along their full banking history.

While modelling in the scorecard process, the dependent variable or outcome or Y-variable is the probability to predict that a customer will be a "good" one. This outcome is binary. The "good" customers are opposed to the "bad" ones who are customers defaulting. A complete definition of a "bad" customer would be: customers who received three consecutive reminders for missed payments during the observation period. In other words, a "bad" customer is a customer who is 90 days or more overdue at the end date of the observation period. In some cases, those between 30 and 90 days overdue may be included in an intermediate category called "ugly" customers. The "good" customers are those paying regularly and that didn't receive during the period more than two reminders for a payment. Depending on the profile and his score, a credit limit will be given to this customer. The possible elements that could significantly define a "bad" customer will be investigated such as identification data, payment patterns, purchase behavior… while establishing the different scorecards.

References that used the "good" and "bad' terminology are for example Banasik et al., 2001; Banasik et al., 2003; Boyes et al., 1989; Chen & Huang, 2003; Desai et al., 2003; Guillen & Artis, 1992; Hand & Henley, 1997; Hand & Kelley, 2000; Kim and Sohn, 2004; Lee et al., 2002; Lee & Chen, 2005; McGrath, 1960; Orgler, 1971; Thomas et al, 1999; Yang, Wang, Bai & Zhang, 2004. This list is not exhaustive as most authors used this terminology. What is less common is to differentiate the loans into more categories. Steenackers & Goovaerts (1989) distinguished "Good" and "bad" and "Refused". Sarlija et al. (2004) differentiate "Good" and "Poor" and "Bad". A particular case has been presented by Kim & Sohn (2004). They divided the commonly used "good credit and bad credit" into two subgroups according to their classification results. The authors used neural networks to build the model. The subgroups were established based on misclassification patterns of the credit scoring model. The existing customers were divided into four groups according to their current credit status and classification results. The result is four new categories where can fall the loans:

Group 1: Customers who have not delayed and are not likely to delay future payments;

Group 2: Customers who have not delayed but are likely to delay future payments;

Group 3: Customers who are currently delinquent but would pay back eventually; and

Group 4: Customers who are currently delinquent and would not pay back.

The authors inferred the characteristics of customers in each group and proposed management strategies appropriate to the characteristics of the groups (Kim & Sohn, 2004).

Lee et al. (1997) considered that logistic regression was one of the most appropriate techniques for credit scoring while predicting dichotomous outcome. Logistic regression is used by credit bureaux and banks and has a certain number of advantages listed in the next chapter. For more detailed on statistical techniques, please refer to the chapter 3.

Those scores have several possible applications. Frame et al. (2001) summarized researchers' interest for scorecard and listed those:

- Credit limit assignment: The classification of loan / credit limit sizes scored.
- Rejection factor: An applicant will be denied automatically based on his score.
- Loan terms: The loan terms (that, is risk based pricing) will vary depending on the applicant's profile.
- Comparison of in-house and credit bureaux / vendors' score
- Credit scoring usage: For how long, a bank has been using credit scoring for accepting loans.

Those areas of interests could also be considered as possible areas of applications. However, in most literature, credit scoring is used as a factor of rejection and much less used to assign the credit limit (or increases of credit limit) to the right customers, i.e. the main interest of this PhD thesis.

Regarding the credit limit assignment, the question is how to settle those limits. One possibility is to develop a profit model, including the behavioral score as a risk evaluator and the profit of the customer and then find the optimal credit limit. However, the notion of profit is usually difficult to define due to the complexity of the different financial elements to take into account. That is why most banks do not use such models. For most institutions, setting credit limits is based on hunches and experience. The author will suggest on alternative method.

2.2.3.2 Application scorecards

Application scoring, in consumer credit risk assessment, will connect the characteristics on the application and the creditworthiness of a customer. Payments patterns could be identified statistically after a 6 month period. This score will give the default risk associated with each customer depending on his application data and his past credit record.

Application scoring may also have another use. The scorecard model includes the most significant variables or characteristics. When application forms are reviewed or updated, the questions where the less significant characteristics are coming, may be dropped. This can also be reviewed while implementing data warehouse.

While a new scorecard has been developed, before implementing it, Hopper and Lewis (1992) recommended using the champion-versus-challenger approach. Instead of replacing straight away the old scorecard by the new one, the new scorecard should be tested on a sample of customers and compared with the results of the initial group where the old scorecard that is still in place. Changes in policy shall be based on the results of this test. The results of the two scorecards should be compared; depending on the result, the bank will decide if the new policy shall be adopted or not.

The main issue of such an approach is that effects of a scorecard on the default rate of a portfolio are long term effects. Therefore, this process requires a long time in order to be conclusive and to lead to a revision of the credit policy. Indeed, by changing a scorecard, one would see the transactions and closing balances increasing steadily without seeing effects on the loss side. The point is that profit is increasing continuously whereas bad debt takes time to be visible. Three months are needed normally to see the first defaulters. So, to get a clear evaluation of the debt involved, one would advise at least a six months testing period. Thomas et al. advised that such competitions should be kept going for at least 12 months (Thomas et al. 2002).

2.2.3.3 Behavioral scorecards

Behavioral scoring uses characteristics of customers' recent behavior to predict their potential risk of being defaulters. The difference between application scoring and behavioral scoring is that behavioral scoring includes more characteristics than application scoring and especially dynamic elements. For instance, application scoring includes only the application data and the credit bureau data whereas in addition to those two, the behavioral approach includes variables related to the history of the customer. Those variables are the result of the repayment and usage behavior of the customer. However, a pure behavioral scorecard would normally not include any other variables that the performances ones and would use the most recent credit bureaux information.

Behavior is one element that explains the customer's default probability. The behavior of a customer is conditioned by the customer perception of the situation (issue of rational vs. less than rational behavior). Personal circumstances have also to be considered such as credit bureau information.

In the literature, a twelve to twenty four month period is recommended. It is possible to use a shorter period of observation, for example, six months. However, in this case, the outcome will be defined slightly differently. “Bad” customers will not only be customers that default but also those who present some characteristics of potential defaulters.

Behavioral data are extracted from the bank database that stored the history of all customers within the bank. The observation period has to be delimited. An end date has to be defined. The status of the customer at this date will define the outcome variable, i.e. if he is “good” or “bad”. The start date is usually fixed twelve to twenty four months prior to the end-date. This observation period is also called performance period as all information stored about customers within this length of time will be used while modelling. Those performance characteristics will be added to the application data and the credit bureau information.

The performance characteristics will include the current balance owed by the account and various averages of this balance. For instance, typical variables, recommended in the literature, would be average, maximum and minimum levels of balance, credit turnover, and debit turnover. It will also include the amount repaid in the last month, six month, etc., as well as the amount of new credit extended and the usage made of the account over similar periods. In order to estimate the payments trend, those variables could even be combined into weighted averages or ratios of performances at the start date of the observation period with performances at the end date of the observation period. The status of the account, such as the number of times it had exceeded its limits, how many warnings letters had been sent, and how long since any repayment had been made are also information that will be used. Characteristics may indicate difficulties in money management and thus, lead to a delinquent behavior such as ATM transactions (Thomas et al. 2002). Many patterns could be investigated, such as gambling patterns or traveling patterns.

Once the scorecard is finalized, the question is how to use the score in order to maximize the net expected profit. The application scorecard is essentially used to decide if a customer will be accepted or rejected. If the applicant is accepted, the score is also used to define his initial credit limit. The behavioral score, as the application score, will indicate the risk that a customer will default within the next coming months. In this context, using the behavioral scorecard as a rejection factor is not to envisage. Those customers were accepted and cannot be rejected only based on their potential risk. A possible use of the score which is also the most common use is to cut the score into a certain number of bands (usually twenty). The bands will allow the bank identifying precise segments of customers which is an asset in the bank strategy. It can especially identify expected delinquent customers. The credit limits will be decreased while the risk is increasing and the initial limit affected low. Another option is to combine the behavioral score with another factor like the credit turnover, of the return involved. The aim of doing this is that the risk side and profit side are both taken into account.

The results will be a matrix with a column for the different bands of score and a row for the initial credit limits. The credit limits increases would vary depending on the cells the customer is. The better the score is, the higher the increase of the limit will be. The higher the initial credit limit is, the higher the increase of the limit will be.

Behavioral scoring may have other uses than credit limits increases. It can also be used as a quality indicator. For instance, one customer with a good behavioral score may be allowed to be over limit temporarily. On the marketing side, target for campaigns such as direct mailing offers may be easier to identify. Another possible use is to consider the score as a decision tool regarding the ones in delay.

Thomas et al. advocate experimentation using a champion challenger approach. In this, one splits the customers randomly and applies different collection policies to each to find out which work best on which band of behavioral score. One uses the existing policy (champion) for the majority of the customers and tries the new policy (the challenger) on a much smaller subset until it is clear which one is the most successful (Thomas et al. 2001). Of course, the subset must be large enough to apply conventional statistical significance tests.

Lim & Sohn (2007) presented an innovative behavioral scoring model. This model takes into account the time aspect that could affect someone‘s payment behavior, which means that characteristics incorporated in the model will vary upon time. The model is based on a k-means algorithm that allows clustering similar data and therefore, to be more accurate. The observation period is fractionized in order to build a specific model for each sub performance period, and reaching more accurate classifiers over time. Basically, their model takes into account the time factor; i.e. it predicts a certain type of borrower at a desired point of time; and clusters customers based on their behavior; i.e. it considers the segmented individual behavior patterns (Lim & Sohn, 2007). Based on the misclassification rate, the model was giving improvements compared to a classical single rule model both by clustering the customers and by fractionizing the performance period. The authors concluded that the dynamical model presented in their paper was improving the performance of the currently used static model in predicting bad losses. The main advantage of their model is that creditors will be more accurate for predicting customers with a high probability of default over time (Lim & Sohn, 2007).

2.2.3.4 Collection scorecards

A collection scorecard aims at predicting the collections activity a bank should carry out. The data used for implementing a collection scorecard are similar to the data used for behavioral scoring. According to Thomas et al., to build the model, the approach should follow a champion versus challenger approach where different possible strategies are tested in order to find the most effective and efficient one (Thomas et al. 2002).

While the tests have been performed, a scorecard can be developed that will predict the best action to take depending on the case.
Possible actions include: to carry on, to send it to a collection agency, to start the legal process, to sell it or to write off the account.

The collection scorecard will give the probability of recovery of a claim. Some actions might lead to the same results and therefore, some other elements should play a role in the final decision such as man power or related costs (Thomas et al. 2002).

2.2.3.5 Fraud scorecards

Behavioral fraud is when details of legitimate cards have been obtained fraudulently and sales are made on a “Cardholder present” basis. These sales include telephone sales and e-commerce transactions where only the card details are required (Bolton and Hand, 2002). Behavioral fraud can be detected by implementing a fraud scorecard predicting which customers are likely to default.

Traditional credit scorecards are used to detect customers who are likely to default, and the reasons for this may include fraud (Bolton and Hand, 2002). As to the process, using scoring for fraud prevention is similar to any other use. A scorecard is always built on the same process that it is a scorecard for fraud, profit, default, collection. The score is a model built on experience of past cases based on the hypothesis that it will follow the same trend. The result is a binary outcome: genuine customer or fraudster.

The key difference is that talented fraudsters will make their application look very genuine. Therefore, some scoring developments for fraud prevention have not proved worthwhile because they are unable to differentiate between genuine applications and fraudulent applications. On the other hand, if one uses scoring as a fraud check in addition to using a different scoring model as a credit risk check, any improvement will add value. However, the value of this additional check relies on it not presenting too many false-positive cases (Thomas et al. 2002).

To detect fraudulent applications is possible once they have been through the system and they have behaved for a certain time within the bank (after a certain time, certain suspicious transaction patterns might be visible). To build a scorecard, it is important to define what the profile of a fraudulent customer is, and especially the cardholder level profiles encapsulating normal transaction pattern as frequency of use, typical value range, types of goods purchased, transaction types, retailer profiles, cash usage, balance and payment histories, overseas spending patterns and daily, weekly, monthly and seasonal patterns (Thomas et al. 2002).

As for traditional scorecards, the process is starting with defining the business goals. The next steps are to understand the data and then to prepare them. Those steps are the most time consuming. Once it is obtained, the data can be modeled in order to get the expected outcome.

Further on the model will be evaluated and tested. The end of the process includes plan deployment, monitoring and maintenance, producing a final report, and reviewing the project.

With application fraud, fraudsters will only be detected while accounts are sent out or repayment dates begin to pass. Time delays are the main issues with suspicion scorecards. Generally a bank would need a twelve-month period to collect enough relevant data to build this model and to have such a model fully implemented.

As the number of fraudulent transactions is much less than the total number of transactions, the system will have to handle skewed distributions of the data. Otherwise, the data need to be split into training samples where the distribution is less skewed (Chan et al. 1997). The system has to be accurate in performing the classifier and to be capable of handling noise in the data. A solution is to clean the data (Fawcett et al. 1997). The system should be able to handle overlaps. Fraudulent transactions may be similar to normal transactions and vice versa. As fraudsters reinvent new techniques constantly, the system needs to be adaptive and evaluated regularly. A cost profit analysis is also a must in fraud detection to avoid spending time on cases that are not worth it.

For new issuing banks, a proposal would be to rely on credit bureau’s score in order to control fraud and possible losses. Even though those scorecards are primarily used to predict defaulting customers, one could allow using those for fraud as fraud and default are strongly correlated.

2.2.3.6 Profit scorecards

In the banking industry, there are two types of account: those that bring profit to the bank or at least not causing trouble, and those generating net losses. The major issue is to be able to detect the low risk customers and to assign them a higher limit.

According to Thomas et al., parameters that have to be taken into account in the profit calculation are administrative and funding costs, timing of early payment, cross-selling opportunities, acquisition costs, overhead-type costs (recover our system development costs), NPV (Net Present Value) calculation and the risk of allocation of costs if no measurement is possible (Thomas et al. 2002).

When the profit scorecard is finalized, the lender will have to decide how to use the score. In fact, in some cases, some customers with their application or behavioral score will be classified as "good" customers whereas with their profit score they will be classified as "bad". The opposite is also true some "bad" customers with their credit scores might be classified as "good" by the profit scorecard. Both type 1 and type 2 errors are possible.

According to Thomas et al., the lender will have three options:

- The easiest one is simply to reject those customers. In fact, they are always paying on time and they don't represent a high portion of the total profit of the bank.
- Another option is to propose to those customers products that could satisfy them and this time, bring profit.
- The lender may also accept them knowing that they are not (very) profitable but considering them as business costs accepted by the bank or he may decide to assign specific

fees or rates to those customers. Part of those customers will turned into profitable ones while the rest will possibly stopped their contract.

Note that customers that always pay on time will even though generate revenue as the merchants will have to pay the interchanges[3] to the bank.

In the case studied, the second option was not appropriate. The third one would probably be the one chosen. Often companies will use a mixture of the second and the third options. Depending on the type of business of the bank, the solution will be different.

Technically, implementing a profit scoring is similar to implementing any other type of scorecards.

After presenting the whole concept of credit scoring and the various types of scorecards, the next step is to apply it on real data and to suggest possible enhancement in order to achieve an optimal credit risk management system.

[3] Interchanges are the fees typically paid by the retailer to the credit card company every time a credit card is used.

Chapter 3: Developing and implementing application / behavioral scorecards

The chapter 3 is a theoretical chapter focusing the theoretical aspects of scorecards implementation. In this chapter, the author has reviewed all statistical techniques that are relevant for segmenting customers, giving their advantages / drawbacks and areas of application. However, as pointed out in Chapter 4, some drawbacks of credit scoring are relevant for whatever techniques, as well as areas of improvements on this field.

In this chapter, the author gives: a definition of the technique and the formula if applicable, papers' references and a description of the main findings for the different statistical techniques.

The techniques reviewed are the following: Discriminant analysis, Logistic regression, Probit regression, Neural Networks, Time varying model, K-nearest neighbour, Recursive partitioning, Mathematical programming, expert systems, Genetic algorithms, Rough sets, Multi-variate adaptative splines, Support Vector Machine.

From this review, it appears that the techniques the most relevant for credit scoring but also the most popular are discriminant analysis, logistic regression and neural network. However, some new techniques such as genetic algorithms have also a promising potential.

The author also presents the different methods / reports used to evaluate and monitor credit scoring models.

In this chapter, the main questions that will be answered are:

- What are the different methods available for building credit scoring models?

- Why has the author decided to focus on logistic regression?
- What are the different methods to evaluate and monitor the scoring models?

3.1 Scorecard Modelling

This sections aims at describing the different statistical techniques that can be used to build credit scoring models and presenting the one the author has decided to use to build the different scorecards that will be integrated in the credit scoring solution.

3.1.1 Review of techniques used in Credit Scoring

For measuring credit risk, Lai et al. (2006) listed the following techniques: discriminant analysis, logit analysis, probit analysis, linear programming, integer programming, k-nearest neighbour (k-NN), classification tree, artificial neural networks, genetic algorithm, support vector machine and some hybrid models

The PhD thesis covers the following statistical methods:

Parametric statistical methods (discriminant analysis, logistic regression, probit regression),

Non-parametric statistical methods (k-NN, recursive partitioning),

Soft computing approaches (artificial neural network, rough sets, fuzzy logic)

Time varying models

Genetic algorithm

Mathematical programming (Linear programming, Integer programming)

Techniques that are not covered are:

- Survival analysis:

Survival analysis has been tested by Hand and Kelley (2000) to solve credit scoring problems. Their model is not only able to predict when a new customer will go bad over a certain period but also evolves as new information becomes available. This type of techniques might fit for behavioral scoring. Other authors that tested survival analysis on credit scoring issues are Thomas et al. (1999). On the short term, their model is competitive with traditional techniques but on the long term, the model became less accurate.

- Markov chains:

The following papers might be of interest: Hoel (1954); Liebman (1972); Marks & Dunn (1974); Scherer & Glagola (1994); Weiss et al. (1982). However, it has been rarely applied to credit scoring issues.

- Composite Rule Induction System (CRIS): Refer to Liang (1992) but it has not been applied to credit scoring.

- Data Envelopment Analysis (DEA): This technique has been applied for forecasting firm's distress (Simak, 1992; Troutt et al., 1996; Yeh, 1996; Cielen & Vanhoof, 1999; Emel et al., 2003; Min & Lee, 2008).

This dissertation reviewed techniques investigated / tested for predicting customer's default and that have proved to be relevant. For each techniques covered in the literature review, the author gives the technical details in a box. The author has done an extended literature review and has added key authors' findings in the related fields. In addition, the author has proceeded to an evaluation of each technique.

3.1.1.1 Discriminant analysis

Table 4 – Definition of Discriminant analysis

Definition

A discriminant function is a measure that combines a set of variables in such a manner as to maximize the difference between two populations' means per unit of dispersion about those means and that minimizes the likelihood of misclassification (Lane, 1972).

Lee et al (2002) encapsulate DA in the following formula:

$$Z = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k$$

Where Z = Discriminant score
$x_1, \ldots x_k$ = Independent variables
β_0 = Constant
$\beta_1, \ldots, \beta_k$ = Coefficients

Desai et al. (1996) presented the assumptions behind DA:

- The independent variables are multivariate normal.
- Their covariance matrices have to be equal.
- They are measured on an interval scale.

Major contributions to the history of DA are as follows. Durand (1941) first introduced discriminant analysis for classifying financial data. Beaver (1966) applied univariate discriminant analysis on a set of financial ratios and found that the cash flow to debt ratio was the best predictor for forecasting firms' distress. Boggess (1967) advised and applied discriminant analysis considering that this method was the most efficient in order to determine "weights" or "scores" for the different characteristics. Altman (1968) used a multiple discriminant analysis to predict repayment ability based on the 134 firms of his sample, this model is called the Z-score model. He also used discriminant analysis as a classification tool in subsequent papers (Altman, 1993; Altman et al., 2007). Bates (1973) decided to estimate a discriminant function based on multiple discriminant analysis in order to identify the successful loan applications from urban black entrepreneurs. Apilado et al. (1974) compared the use of multivariate discriminant analysis with univariate discriminant analysis and concluded that multivariate discriminant analysis has greater predictive powers than those constructed via univariate procedure. Eisenbeis (1977) reviews all problems encountered while applying discriminant analysis technique which are the distribution of the variables, the group dispersions, the interpretation of the significance of individual variables, the reduction of dimensionality, the definition of the groups and the choice of the appropriate a priori probabilities and / or costs of misclassification. Reichert et al. (1983) discuss the application of the multiple discriminant analysis (MDA). The authors' objectives were to clearly signify the requirements to implement such techniques properly and to evaluate the consequence of not fulfilling those requirements. The conclusion of the authors was that one could develop a model fulfilling most of the assumptions behind multiple discriminant analysis.

Romer et al. (1990) also present problems encountered while applying discriminant analysis. Crook et al. (1992) investigated how discriminant analysis may be of use for credit card companies. Trevino and Daniels (1995) adopted dicscriminant analysis in judging the resultant performance from investments and of whether direct investments in American market do have substantial impacts on cooperate investors. Lee et al. (1999) used discriminant analysis to conduct bankruptcy prediction and indicated that discriminant analysis is the most commonly used technique applied for bankruptcy prediction. Kim, Kim, Kim, Ye and Lee (2000) endeavoured to implement a classification analysis on the real estate markets in Korea and to forecast the consumer behaviors using discriminant analysis. Recently, Mileris (2010) reviewed LDA. His research has shown that banks using discriminant analysis and simple Bayesian classifier can measure default probability of their clients.

After reviewing the literature, arguments in favour of linear discriminant analysis (LDA) were the following: most efficient technique for credit scoring purposes, easy to implement and to interpret and most efficient technique when apply to large sample. Indeed, Boggess (1967) advised and applied discriminant analysis considering that this method was the most efficient in order to determine "weights" or "scores" for the different characteristics. Mileris (2010) listed two advantages of LDA which are that this is easy to implement and easy to interpret. Moreover, Altman et al. (1994) reported that LDA was outperforming neural networks while applied to a large sample size. Yobas et al. came to the same conclusion in their research (Yobas et al., 2000).

Arguments raised against LDA include the following: need for statistical assumptions, need for ordered categorical variables and outliers sensitivity. Eisenbeis (1977) reviews all problems encountered while applying discriminant analysis technique which are the distribution of the variables, the group dispersions, the interpretation of the significance of individual variables, the reduction of dimensionality, the definition of the groups and the choice of the appropriate a priori probabilities and / or costs of misclassification. Reichert et al. (1983) discuss the application of the multiple discriminant analysis (MDA). The authors' objectives were to clearly signify the requirements to implement such techniques properly and to evaluate the consequence of not fulfilling those requirements. The conclusion of the authors was that one could develop a model fulfilling most of the assumptions behind multiple discriminant analysis. Romer et al. (1990) also described those problems encountered while applying discriminant analysis. Additional drawbacks raised by Mileris are that LDA needs strong statistical assumptions (as mentioned by the authors above), ordered categorical variables and is very sensitive to outliers compared to logistic regression (Karwowski, 2006).

3.1.1.2 Logistic Regression

Table 5 – Definition of Logistic regression

Definition

This type of modelling approach is based on the concept that each single attribute should be tested before inclusion in the model. Logistic regression (LR) can be spitted in several categories: binomial logistic regression, multinomial logistic regression, ordinal logistic regression…

The general formula is as follows:

$$Logit\ (p_i) = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k$$

Where p= probability of default based on the characteristics given
$x_1, \ldots x_k$ = Independent variables
β_0 = Constant
$\beta_1, \ldots, \beta_k$ = Coefficients
Logit= log (p (default) / p (non-default))

Orgler (1970) first used multivariate regression analysis to predict whether a customer will default or not. Turning to the theoretical aspects, assuming that if the observations for fitting a polytomous logistic regression model satisfy certain normality assumptions, the maximum likelihood estimates of the regression coefficients are the discriminant function estimates, Haggstrom (1983) shows that these estimates, their unbiased counterparts, and associated test statistics for variables' selection can be calculated using ordinary least squares regression techniques, thereby providing a convenient method for fitting logistic regression models in the normal case. Steenackers & Goovaerts used a stepwise logistic to implement a credit scoring model to predict whether a loan will be good or turn bad (Steenackers & Goovaerts, 1989). Using logistic regression, Banasik (1996) compared a scorecard built on the full population with scorecards built on subpopulation. He concluded that scorecards for subpopulations tend to reject fewer applicants than full population scorecard and that splitting on subpopulations is not worthwhile for all variable's splits. The author advised to ensure that the subpopulations are sufficiently different that the extra variance in the coefficients and that the difficulty in setting compatible cut-offs between the populations is more than compensated. Berkowitz and Hynes (1999) used logit regression in order to predict personal bankruptcy on mortgages. West also found in his research that logistic regression is a good alternative to the neural models to build a scorecard (West, 2000). In Cramer's paper, a bank applied logistic regression with state-dependent sample selection to predict loans that may default (Cramer, 2004). After investigations, he came to the conclusion that the state dependent technique did not work because the data do not satisfy the standard logit model. He then tried several variants on this model and found that a bounded logit with a ceiling of less than 1 fit the data better. However, regarding their performance in an independent data-set, the differences between the various methods of analysis were negligible (Cramer, 2004).

3.1.1.3 Probit Regression

Table 6 – Definition of Probit regression

Definition

Probit is a technique that finds coefficient values, i.e. the probability of a binary coefficient (Abdou et al., 2008). The word probit refers to the probability unit.

The general formula is as follows:

$$Prob(y = 1) = \Phi(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k)$$

Where y = Dichotomous outcome

Φ = Value from the cumulative normal distribution

$x_1, \ldots x_k$ = Independent variables

β_0 = Constant

$\beta_1, \ldots, \beta_k$ = Coefficients

Using an ordered probit technique, Badu and Daniels (1997) examined the relative significance internal factors used in grading municipal general obligation bond ratings in the Commonwealth of Virginia. In another paper, Badu et al. (2002) measured the probability of default, the credit risk premium and their impact on net interest cost for the Commonwealth of Virginia using 1995 data. The results of their paper indicated the probability of default as measured by ordinal probit is determined by population size, population change, ratio of long term debt to total debt, real estate taxes, per capita income, and the organization form of government. In Boyes et al. paper, the authors present a model for credit assessment focusing on expected earnings. They show how maximum likelihood estimates of default probabilities can be obtained from a bivariate 'censored probit' framework using a 'choice-based' sample originally intended for discriminant analysis. The authors conclude their paper with recommendations for combining these default probability estimates with other parameters of the loan earnings process to obtain a more meaningful model of credit assessment (Boyes et al., 1989). Regarding probit models, Crook (2001) used an univariate probit model with standard errors corrected for sampling weights to answer the question: What factors determine whether a credit applicant is likely to be rejected and/or discouraged from further applications?

Tsaih et al (2004) use the probit regression to develop a credit scoring model. The specific feature of their credit scoring model was that they suggested a N-tier architecture integrated with the idea of Model View Controller that would allow the scoring model to be easily altered in accord with the change of business environment. The advantage of that design is that it is less time consuming for the system engineers as the time and effort in communicating with the model managers for finalizing the scoring models would be reduced. Moreover, the model managers can easily alter the scoring models later at any time (Tsaih, et al, 2004). Another application of the probit model is Wallace (1978; 1981) who applied regression and multivariate probit models to predict bond ratings for 106 new general obligation and revenue bond issues in the state of Florida.

A review of the literature reveals some arguments in favour of probit regression: less time consuming to implement and easy to alter the models at any time. Tsaih et al (2004) use the probit regression to develop a credit scoring model. The specific feature of their credit scoring model was that they suggested a N-tier architecture integrated with the idea of Model View Controller that would allow the scoring model to be easily altered in accord with the change of business environment. The advantage of that design is that it is less time consuming for the system engineers as the time and effort in communicating with the model managers for finalizing the scoring models would be reduced. Moreover, the model managers can easily alter the scoring models later at any time (Tsaih, et al, 2004).

3.1.1.4 Neural Networks

Table 7 – Definition of Neural Networks

Definition
Technically, a neural network is a computer with an internal structure that imitates the working of the human brain and the nervous system. This parallel distributed processing system is made of processing entities called neurons, the connection strengths between which are weights which are adjusted to store experiential knowledge and make it available for later use in prediction, clustering and classification (Haykin, 1994). Neural networks provide a new alternative to classical statistical techniques, particularly in situations where the dependent and independent variables exhibit complex non-linear relationships (Lee et al., 2002). Types of Neural Networks: Multilayer Perceptron Networks , Probabilistic Neural Networks, General Regression Neural Networks, Radial Basis Function Networks, Cascade Correlation, Functional Link Networks, Kohonen networks, Gram-Charlier networks, Learning Vector Quantization, Hebb networks, Hopfield network, Adaline networks, Heteroassociative networks, Recurrent Networks and Hybrid Networks. Neural networks can be classified into two different categories (Lee et al., 2002): - The feedback networks contain nodes that can be connected to each other, enabling a node to influence other nodes as well as itself. Ex: Kohonen self organizing network, Hopfield network... -The feed forward networks contain nodes that can take inputs only from the previous layer and send outputs to the next layer. Ex: ADALINE, backpropagation neural networks (BPN), probabilistic network, Radial Basis Function, Perceptron (single- layer / multilayer), Heteroassociative networks...

It is in the 1990's that neural networks (NNs) started to appear as an 'avangardiste' tool. Neural networks have emerged as a practical technology, with successful applications in many fields in financial institutions in general and banks in particular (Abdou et al, 2008).

To confirm the potential improvement in prediction by using NNs, researchers have compared traditional and advanced statistical techniques (Lee & Chen, 2005; Lee et al., 2002; Zekic-Suzac et al., 2004; Malhotra & Malhotra, 2003; Ong, Huang, & Tzeng, 2005) and extended their research to include feed forward nets and back propagation nets (Abdou et al., 2008; Arminger, Enache & Bonne, 1997; Malhotra & Malhotra, 2003).

In the literature, the focus has been on two of the most well-known neural networks:

- Probabilistic networks (PNN): are used to predict binary outcomes. The concept of probabilistic network is closely related to the k-NN method. Only a few authors focused on this type of neural network (Masters, 1995; Zekic-Susac, Sarlija, & Bensic, 2004; Ganchev et al., 2007).
- Multilayer Perceptron Networks (also known as multilayer feed-forward network) (MLFN): Many authors have developed scorecard using multi-layer feed-forward network (Bishop, 1995; Desai et al., 1996; Dimla & Lister, 2000; Reed & Marks, 1999; Trippi & Turban, 1993; West, 2000; Erbas & Stefanou, 2008).

Extensive literature reviews on neural networks are provided by Wong et al. (1997) and Vellido et al. (1999). Wong et al. reviewed 213 articles published between 1988 and 1995 on neural networks regardless of the domain. Vellido et al. (1999) reviewed articles published between 1992 and 1998 dealing with neural networks related to business.

Some of the first papers dealing with neural networks are by Dutta and Shekhar, and Surkan and Singleton. In their studies, the authors applied NNs to generate improved risk ratings of bonds (Dutta & Shekhar, 1988; Surkan & Singleton, 1991). Trippi and DeSieno presented a specific NN-based intra-day trading system for S&P 500 future contracts (Trippi & Desieno, 1992). Hutchinson et al. priced options via learning networks and reported that in many cases the network pricing formula outperforms the Black-Scholes model (Hutchinson et al., 1994). Franses and Van found that artificial neural network (ANN) should not be used in forecasting the daily exchange rate return relative to Dutch guilder (Franses & Van, 1998). Plasmans et al. applied feedforward ANN to investigate the prediction performance of structural and random walk exchange rate models. They did not find any non-linearity in the monthly data of US dollar rates in Deutsche marks, Dutch guilders, British pounds and Japanese yen (Plasmans et al., 1998).

Based on statistical inferences techniques, Anders et al. established NN models in order to explain the prices of call options on the German stock index DAX. The result of their study was that neural networks performed better than the Black-Scholes model (Anders et al., 1998).

After reviewing the literature, arguments in favour of NN were: memory, ability to generalize, robustness, absence of any explicit problem description, ability to handle large amount of data, need for less statistical assumptions, non parametric and non linear method. Stern (1996) first mentioned its memory characteristics and generalization capability, especially while modelling non-stationary processes (Stern, 1996). Dimla & Lister presented in their paper a neural networks based modular tool condition monitoring system for cutting tool-state classification. They described neural networks as robust mathematical processing devices capable of non-linear modelling and function approximation. They particularly outlined advantages of neural networks which are that they don’t require explicit problem description and they are capable of handling large amounts of data (Dimla. & Lister, 2000). Erbas & Stefanou reviewed major research on neural networks and mentioned three advantages of ANN (2008): it needs less assumptions (Santin et al., 2004), it’s a non parametric method and a non linear method (Santin et al., 2004, Hill et al., 1994).

NNs were not free of drawbacks, however. These include: issue when apply to small samples, may incorporate irrelevant attribute, long training time, selection time, overfitting when apply to large dataset, hard to interpret and issue of trial and error process

In some studies, the performance of neural networks when applied to small samples or when incorporating irrelevant attributes has been pointed out (Castillo, Marshall, Green &Kordon, 2003; Feraud & Cleror, 2002; Nath, Rajagopalan & Ryker, 1997). Neural networks have also been criticized for its long training and therefore, for its limited applicability to credit scoring problems (Chung & Gray, 1999; Graven & Shavlik, 1997). Indeed, artificial neural networks present two main drawbacks when dealing with large datasets (Yim & Mitchell, 2005): selection time and overfitting. Hills et al. (1994) also mentioned one drawback of NN which is that NN is hard to interpret. Santin et al. (2004) also raised the issue of trial and error process.

We turn now to examine two ways of overcoming some of these difficulties: pruning and hybrids. Altman et al. (1994) reported that LDA was outperforming neural networks while applied to a large sample size. Yobas et al. came to the same conclusion in their research (Yobas et al., 2000). Indeed, artificial neural networks present two main drawbacks when dealing with large datasets (Yim & Mitchell, 2005): selection time and overfitting. There are two known ways to improve ANN: pruning (Weigend & Neueier, 1995) and hybrids (Han et al., 1996).

Pruning aims at reducing the size of the NN and maintains its generalization ability (Yim & Mitchell, 2005), it includes the following methods: simple weight elimination Weigend et al., 1991; Bebis et al., 1997; Cunha, 2000), genetic algorithm (Miller et al., 1989, Bebis et al., 1997; Yao, 1997). Back et al. (1996) mentioned that pruning methods have been applied to predict firm bankruptcy in several papers (Yim & Mitchell, 2005).

The other option is hybrids. Combining ANN with statistical method, the new model /hybrid will benefit from the other technique. By using the other technique for doing the selection, the risk of overfitting will be less and the ANN will benefit from using the outcome of another model as it will reduce the amount of data to pull into the ANN (Yim & Mitchell, 2005).

Some of the first authors that suggested combining ANN with other techniques to optimize the performances of the ANN were Altman et al. (1994), Markham and Ragsdale (1995) and Han et al. (1996). Markham and Ragsdale (1995) found that the hybrid neural network outperformed DA and ANN. Han et al. (1996) also introduced the idea of hybrid neural networks. The result of their study was that hybrid neural network models were seen to be highly accurate for bankruptcy prediction. Back et al. (1996) combined PNN with MDA for the preprocessing phase and achieved impressive results. Sexton et al. (1998) came to the same conclusion combining NN with genetic algorithm. Lee et al. (1996) investigated three hybrids neural networks. Based on the z test, the most accurate model was the SOFM. (Self Organizing feature map) (MDA)-Assisted NN. It benefited from the discriminatory power of MDA Yim and Mitchell (2002) experimented multilayer perceptron nets and three hybrid models and compared their results versus classical statistical techniques. He concluded that the hybrid models were the best models to forecast bankruptcies, one to two years prior to the event. Lee et al. tested the performance of a two-stage hybrid modelling procedure with artificial and multivariate adaptative regression splines (M.A.R.S.) in predicting loans failure. The result from this test was that the two-stage hybrid model was outperforming traditional modelling techniques such as discriminant analysis, logistic regression, and NN models and was an efficient alternatives for predicting if a loan would default or not (Lee & Chen, 2005). Chen & Huang presented a computation that they qualified as evolutionary combining two techniques: neural networks (N.N) and genetic algorithms (GA) (Chen & Huang, 2003). The

NN is used to classify the applications as either accepted or rejected to minimize the lenders' risk. The GA is used to reassign the rejected instances to the preferable accepted class, which balances between adjustment cost and customer preference. After applying the computation on real credit dataset, they found that the proposed evolutionary computation based approach has shown enough attractive features for the computer-aided credit analysis system (Chen & Huang, 2003). Hsieh (2005) suggested a hybrid system based on clustering and neural network techniques. Yim & Mitchell (2005) tested a relatively new hybrid technique to predict corporate distress in Brazil and concluded that hybrid neural networks outperformed all other models while predicting one year prior to the event. Abdou et al. examined two different types of neural networks: probabilistic neural networks (PNNs) and multi layer feed forward nets (M.L.F.N.s) (Abdou et al., 2008). They compared the accuracy of neural networks to the accuracy of conventional techniques, such as discriminant analysis, probit analysis and logistic regression in predicting defaults. They applied the different techniques to data from the Egyptian banks (Abdou et al., 2008). They concluded that considering the highest average correct classification rate, the PNNs have the best performance, whereas comparing the lowest estimated misclassification cost, MLFNs were the best. Recently, he confirmed this outcome investigating the efficiency and effectiveness of alternative credit-scoring models for consumer loans in the banking sector (Abdou, 2009). His conclusion was based on the classification efficiency rate of consumer loans and the cost effectiveness associated with classification errors. For both indicators, neural networks gave the best results.

3.1.1.5 Time varying model

Table 8 – Definition of Time varying model

Definition

A time varying model is built on time series which is a chronological sequence of observations for a specific predictor variable. First, the model is built such as it represents the time series and secondly, the aim of the model is to predict the future probable value of the outcome (DTREG, no date). The observations are selected and collected on regular intervals, i.e. days, months, quarters or years which do not mean that the sample selection needs to be regular.

If the following assumption is fulfilled, a model predicting the future values of the outcome would be:

$$Y_t = f(Y_{t-1}, Y_{t-2}, \dots, Y_{t-k}) + e_t$$

Where Y = Outcome

Y_t = Value of Y at time t.

$Y_{t-1}, \dots Y_{t-k}$ = Lag values, values of Y at time t-1, …, t-k.

e_t= Noise

$\beta_1, \dots, \beta_k$ = Coefficients

Anderson and Goodman (1957) mentioned that a Markov chain is sometimes a suitable probability model for certain time series in which the observation at a given time is the category into which an individual falls. Cyert, Davidson and Thompson (1962) used techniques of Markov chains to study the long-term, expected uncollectible amount in each age category. Cyert and Thompson (1968) developed another Markov chain model to predict the behavior of charge accounts in retail establishments. According to Dirickx and Wakeman (1976), the first rigorous model of the credit granting process was that of Bierman and Hausman (1970) who utilized multi-period analysis (Dynamic programming) combined with Bayesian analysis (to allow for information up-dating). Seow and Thomas (2006) model the lenders decision problem in the credit granting process. The aim of this paper was to develop a model of adaptive dynamic programming where Bayesian updating methods are employed to better estimate a take-up probability distribution. The significance of Bayesian updating in this model is that it allows previous responses to be included in the decision process. (Seow & Thomas, 2006).

The types of time varying model are numerous. This type of modelling techniques is usually used for behavioural scoring.

After reviewing the literature, the main argument in favour of time varying model was the integration of the factor of time, and the improvement this gave when applied to data. Indeed, even though, the aim of time varying model is the same as other models, i.e. predicting the future value of the outcome as close to possible to the value it will get, the advantage of time varying models compared to classical one is its ability to include the time factor into the model, lag values are used to predict the future value.

3.1.1.6 K-Nearest Neighbour

Table 9 – Definition of K-Nearest Neighbour

1-Nearest Neighbour (1-NN)

"In each iteration of the feature selection algorithm, a number of features are activated. For each sample of the test set, its Euclidian Distance from each sample of the training set is calculated as follows:

$$D_{ij} = \sqrt{\sum_{l=1}^{d} \left|x_{il} - x_{jl}\right|^2}$$

Where D_{ij} is the distance between the test sample i and the training j, and l=1,..., d is the number of activated features in each iteration.
With this procedure the nearest sample from the training set is calculated. Thus, each test sample is classified in the same class that its nearest sample from the training set belongs" (Marinakis et al., 2008).

k-Nearest Neighbour (k-NN)

The k-Nearest Neighbour (k-NN) method is an extension of the one above. It examines the k-nearest samples from the training set and classifies the test sample by using a voting scheme. Each member of the k nearest has the same weight in the vote (Marinakis et al., 2008). The Weighted k Nearest Neighbour (wk-NN) is similar to the k-nn except that a weight is proportionally assigned to each member based on their distance from the test sample (Marinakis et al., 2008):

$$W_i = \frac{i}{\sum_{i=1}^{k} i}$$

$$w_k \geq w_{k-1} \geq \cdots \geq w_1 > 0$$

$$w_k + w_{k-1} + \cdots + w_1 = 1$$

(i=1 refers to the most distant neighbours; i=k refers to the closest neighbours)
The k-nearest neighbour algorithm is one of the easiest machine learning algorithms. The algorithm could be described as a technique for classifying objects. The class the most often selected by the k nearest neighbours (k > 0 and small) will be the one assigned to the object.

The idea of k-NN was originally introduced by Fix and Hodges (1952) and Cover and Hart (1967). In 1970, Chatterjee and Barcun presented a nonparametric approach to the problem of credit scoring. The concept aims at classifying an observation in that population with which it has most similarity or most in common, after discounting the losses for possible misclassification. This method is the so-called “closest neighbour” rules given by Hills (1966). Henley and Hand (1996) also applied the k nearest neighbours’ method that they defined as a standard technique in pattern recognition and nonparametric statistics, to the credit scoring problem. It is a standard nonparametric technique used for probability density function estimation and classification.

A review of the literature established three arguments in favour of k-NN: (i) it enables modelling irregularities in the risk function over the feature space, (ii) the k-NN method performs better than other nonparametric techniques such as kernel methods when the data are multidimensional (Henley and Hand, 1996) and (iii) it is a fairly intuitive procedure and as such could be easily understood by business managers who would need to approve its implementation and it can be used dynamically.

3.1.1.7 Recursive Partitioning

Table 10 – Definition of Recursive Partitioning

Definition

A classification or regression tree is the collection of many rules displayed in the form of a binary tree. The rules are determined by a procedure known as recursive partitioning. Tree-based models provide an alternative to linear and additive models for regression problems, and to linear and additive logistic models for classification problems (S-Plus 6, 2001).

In describing tree-based models, the terminology mimics real trees:

- Root: the top node of the tree
- Leaf: a terminal node of the tree
- Split: a rule for creating new branches

There is a set of explanatory variables (x), and a single-response variable (y).

In growing a tree, the binary partitioning algorithm recursively splits the data in each node until either the node is homogeneous or the node contains too few observations (5, by default).

Tree-based modelling is an exploratory technique for uncovering structure in data, increasingly used for 4 functions. These are: (i) devising prediction rules that can be rapidly and repeatedly evaluated, (ii) screening variables, (iii) assessing the adequacy of linear models and (iv) summarizing large multivariate.

Decision trees first appeared in the early 1960s. Raiffa and Schlaifer (1961) were the first authors to present a decision tree. In 1968, Metha proposed to handle individual credit requests using a sequential decision process based on the following assumptions: First, since not all relevant information can be secured in time or without cost, only some of the relevant information is needed for or worth including in making a decision. Second, past experience can be effectively employed in dealing with uncertainty as to the future. In 1972, David Sparks used a decision tree to build a credit scoring model. A detailed mathematical discussion of decision trees is given in Breiman et al. (1984).

A review of the literature shows the arguments in favour of Recursive Partitioning to be: (i) logical relationship, (ii) easy to interpret, (iii) efficiency, (iv) flexibility and (v) high dimensionality issue can be avoided. Indeed, in 1968, Metha mentioned that the advantage of such approach lies in the logical relationship between the operating decision rules that meaningfully take into account past experience, and the control indices, i.e. frame an optimal credit policy. Safavian and Landgrebe (1991) focus on the hierarchical approaches where historical classifiers are a special type of multistage classifiers that allow rejection of class labels at intermediate stages. According to the authors, the main feature of Decision Tree Classifiers (DTC) is their capability to break down a complex decision-making process into a collection of simpler decisions, thus providing a solution that is often easier to interpret.

In a review of the advantages of DTC by Safavian and Landgrebe (1991), the following stood out: first, global complex decision regions can be approximated by the union of simpler local decision regions at various levels of the tree; second, a sample is tested against certain subsets of classes, eliminating unnecessary computations; and third, flexibility of choosing different subsets of features at different internal nodes of the tree such that the feature subset chosen optimally discriminates among the classes in that node. The problem of high dimensionality may be avoided in a DTC by using a smaller number of features at each internal node without excessive degradation in the performance.

By contrast, in Safavian and Landgrebe, the arguments against DTC were seen to be: overlap, errors in a large tree and difficulties in designing an optimal DTC.

3.1.1.8 Mathematical Programming

Table 11 – Mathematical Programming

Example of linear programming to the credit scoring problematic (Hardy & Adrian, 1985)

Their linear programming formulation was as follows:

$$Maximize \sum_{j=1}^{m} a_i D_j^+ - \sum_{j=1}^{m} b_j D_j^-$$

Subject to: $W_1 V_{1j} + W_2 V_{2j} - D_j^+ + D_j^- \geq C_j$ For each acceptable borrower j.

$W_1 V_{1j} + W_2 V_{2j} + D_j^+ - D_j^- \leq C_j$ For each unacceptable borrower j, and

$$\sum_{j=1}^{m} D_j^+ \leq \sum_{j=1}^{m} C_j$$

V_1, V_2unrestricted in sign; $D_j^+, D_j^- \geq 0$.

Where D_j^+: Appplicant above the cut-off

D_j^-; Applicants below the cut-off

$a_j$and b_j: Weights assigned to deviational variables with $a_j < b_j$.

$W_1$and W_2: Weights of measurement variables

V_{1j} and V_{2j}: measurement variables

C_j = C: cut-off score, arbitrary value.

Example of integer programming to the credit scoring problem (Gehrlein & Wagner, 1997)

Assumptions:
- an applicant i,
- a set of n observations / applicants
- one knows who the defaulters are,
- data include a list of the numerical values for each of the k attributes recorded on the initial application.

Their single-stage integer programming formulation is as follows:

$$Minimize\ C_{dp} \sum_{i \epsilon D} I_i + C_{pd} \sum_{i \epsilon P} I_i$$

Subject to $F(i) = \sum_{j=1}^{k} w_j A_{ij}$,

$F(i) + MI_i \geq X_c + e, \forall i \, \epsilon P,$

$F(i) - MI_i \leq X_c - e, \forall i \, \epsilon \, D,$

Where

$F(i)$: credit score

X_c: Cut-off value; the applicant is accepted if $F(i) > X_c$and rejected if $F(i) < X_c$.

D: Set of applicants who will default

P: Set of applicants who will pay

C_{dp}: Cost associated with classifying a defaulter as a payer

C_{pd} : Cost of classifying a payer as a defaulter, M is a large number and e is a small number

w_j: Weight of attribute j

I_i: if the classification is made correctly, I_i =0 and if the classification is made incorrectly, I_i =1

The mathematical programming method is less commonly used. Examples of mathematical programming are linear programming (Hesteness & Stiefel, 1952; Hardy and Adrian, 1985; Glover, 1990) and integer programming (Koehler & Erenguc, 1990; Gerlheim and Gempesaw, 1991; Gehrlein and Wagner, 1997; Rubin, 1997; Glen, 1999).

Charnes, Cooper and Ferguson (1955), Karst (1958), and Kiountouzis (1973) were the first authors to use linear programming for regression purposes (Hardy & Adrian, 1985). Hardy & Adrian (1985) applied linear programming to the credit scoring problematic and concluded that the model was satisfactory. Freed (1978) investigated the use of linear programming for solving discriminant analysis problems and concluded after performing tests that linear programming was giving satisfactory results. Later on, he extended his research with Freed & Glover (1981) to goal programming (Hardy & Glover, 1985). Showers and Chakrin (1981) applied mathematical programming to telecommunication data. Due to a dramatic growth in Bell System uncollectible revenues, a set of credit granting practices have been developed. Kolesar and Showers (1985) using a simple decision theoretic view of the credit screening problem focused on those situations where the data are binary variables. They used mathematical programming to solve the problem and concluded that their method produces flexible credit screens that are robust and very easy to implement. Gerlheim and Gempesaw (1991) applied integer programming for credit scoring purposes. Their objective was to use a simple modelling technique in order to reduce costs. For credit scoring purposes, Gehrlein & Wagner (1997) also tested tow different models using integer programming. They concluded that the two-stage least cost credit scoring model was clearly outperforming the single-stage one in minimizing the total cost of granting credit to potential defaulters.

A review of the literature revealed the arguments in favour of mathematical programming to be: the ability to treat complex problems and various objectives (Erenguc & Koelher, 1990), no need for high statistical background (Hardy & Adrian, 1985), no restrictive assumptions required (Hardy & Adrian, 1985) and flexibility and ability to change the weights (Hardy & Adrian, 1985).

Meanwhile, arguments against mathematical programming include: the computational time, unbounded solutions (Erenguc & Koelher, 1990), the discriminating power (Erenguc & Koelher, 1990), judgmental approach (Hardy & Adrian, 1985) and no intercept term (1985). Coefficients must consider all variations while classifying (Hardy & Adrian, 1985).

3.1.1.9 Genetic Algorithms

Table 12 – Genetic Algorithms

Definition
GAs are considered as a part of evolutionary computing, which is a rapidly growing area of optimization (Chen & Huang, 2003). It is also called Genetic programming (GP) while applied to build credit scoring related fields. GP is automatically and heuristically determining the adequate discriminant functions and the valid attributes simultaneously (Ong et al, 2005). Ong et al. qualified the GP display as a tree-based structure composed of the function set and terminal set.

Genetic algorithms (GAs) were inspired by Darwin’s theory of evolution in order to simulate the biological evolution process. The first experiment applying GAs on computer was in 1954. However, it was in the 1980’s that the use of GAs really took off.

Koza (1992) was the first researcher publishing a paper dealing with genetic programming. He used GP to automatically extract intelligible relationships in a system. Since that, researchers have used GP in many applications. For example, authors have used it for symbolic regression (Davidson, Savic & Walters, 2003) and classification (Stefano, Cioppa & Marcelli, 2002; Zhang & Bhattacharyya, 2004).

Ong et al. reported that GP is the modelling technique that deserves to be considered for credit scoring for several reasons. First, it is a non-parametric tool and therefore suitable for any situations and data sets. Second, it suits small and large datasets when compared to ANNs.

Third, it determines the adequate discriminant function automatically rather than assigned the transfer function by decision makers. Furthermore, tests served that it outperforms induction algorithms. The discriminant function which is derived by GP can provide the better performance than the induction based algorithms (Ong et al, 2005).

3.1.1.10 Rough sets / Fuzzy Logic method

Table 13 – Rough sets / Fuzzy Logic method

Definition
Rough sets are a mathematical tool used to deal with vagueness or uncertainty (Ong et al, 2005) and were introduced by Pawlak in 1982 (Pawlak, 1982). Ong et al. suggested for a more detailed discussion about the process of rough set theory to refer to Walczak and Massart (1999). The fuzzy logic method is a technique that allows one to take into account applicants' characteristics, building systems and managing accounts (Falavigna, 2006). Falavigna (2006) qualified fuzzy logic as "a very good technique for representing the complex reality but the rules are created for a specific problem and these are not objective". For details on the six steps to implement fuzzy logic, refer to Flavigna's paper (Falavigna, 2006).

Fuzzy logic has been applied to credit scoring problem by Hoffmann et al. (2007, 2002). They tested a genetic fuzzy classifier and a neuro fuzzy classifier.

Recently, rough set theory and fuzzy set theory have been used to complement or incorporate (Chakrabarty, Biwas & Nanda, 2000; Mordeson, 2001; Radzikowska & Kerre, 2002) each other rather than to compete (Dubois & Prade, 1991).

A reviewing of the literature shows that the main argument in favour of rough sets is the fact that there is no need for pre-assumption. Rough sets do not need any pre-assumptions or preliminary information about the data, such as the grade of membership function in fuzzy sets (Grzymala-Busse, 1988).

3.1.1.11 Multi-Variate Adaptative Splines

Table 14 – Multi-Variate Adaptative Splines

Definition
Multivariate adaptive regression splines (MARS) can be defined as a non-linear and non-parametric regression which models relationships that are nearly additive or involve interactions with fewer variables (Lee & Chen, 2005).

As rough sets, neural networks and other recent techniques, multi-variate adaptive splines, the so-called MARS techniques, are examples of the new classification techniques that interest researchers (Friedman, 1991).

Lee & Chen gave the following advantages: (a) no need for pre-assumptions, so that it can model complex non-linear relationships among variables without strong modelling assumptions; (b) it selects important variables automatically, thus, capturing the relative importance of independent variables for the dependent variable when many potential independent variables are considered; (c) there is no long training process and (d) easy to interpret.

3.1.1.12 Support Vector Machine (SVM)

Table 15 – Support Vector Machine

Definition

The technique starts by constructing an N-dimensional hyperplane that optimally separates the data into two categories (DTREG, no date).

Just below a description of least square support vector machines given by Zhou et al. (2009). The assumptions are as follows:

- Training dataset: $\{x_k, y_k\}_{k=1}^{N}$
- Input data: $x_k \in R^n$
- Output data: $y_k \in N$ and $y_k \in \{1, -1\}$.

Given that the set can be separated linearly, the classifier would be the following:

$$w^T x_k + b \geq 1 \; if \; y_k = 1$$
$$w^T x_k + b \leq -1 \; if \; y_k = -1$$

Where the separating hyperplane is $H(x) = w^T x + b = 0$

the linear classic is: $y(x) = sign(w^T x + b)$

The optimal separating hyperplane can be obtained by solving the following optimization problem:

$$\min_{w,b} \frac{1}{2} w^T w$$

Subject to: $y_k(w^T x_k + b) \geq 1, k = 1, \dots, N$

However in real life, the optimal separating hyperplane does not exist. Therefore, an error term needs to be introduced in the model.
The optimization problem is then:

$$\min_{w,b,\varepsilon} L(w, b, \varepsilon) = \frac{1}{2} w^T w + C \sum_{k=1}^{N} \varepsilon_k^2$$

Subject to: $y_k(w^T x + b) = 1 - \varepsilon_k, k = 1, \dots, N$

Where C: penalty parameters on the training error.

ε_k: error variable

The Lagrangian function for this problem is:

$$L(w, b, \varepsilon) = \frac{1}{2} w^T w + C \sum_{k=1}^{N} \varepsilon_k^2 - \sum_{k=1}^{N} \alpha_k [y_k(w^T x + b) - 1 + \varepsilon_k]$$

Where α_k is the Lagrange multiplier.

By differentiating with respect to $w, b, \varepsilon, \alpha_k$, it results the following conditions:

$$\frac{\delta L(w, b, \varepsilon, \alpha)}{\delta w} = 0 \rightarrow w = \sum_{k=1}^{N} \alpha_k y_k x_k$$

$$\frac{\delta L(w, b, \varepsilon, \alpha)}{\delta b} = 0 \rightarrow w = \sum_{k=1}^{N} \alpha_k y_k = 0$$

$$\frac{\delta L(w, b, \varepsilon, \alpha)}{\delta \varepsilon_k} = 0 \rightarrow \alpha_k = 2C\varepsilon_k$$

$$\frac{\delta L(w, b, \varepsilon, \alpha)}{\delta \alpha_k} = 0 \rightarrow y_k(w^T x + b) - 1 + \varepsilon_k = 0, k = 1, \dots, N$$

The classifier that results from those conditions is as follows:

$$y(x) = sign(w^T x + b) = sign\left[\sum_{k=1}^{N} \propto_k y_k (x_k^T . x) + b\right]$$

Further on, Vapnik (2000) suggested a non linear approach to SVM. The main concept was to "input data into a high dimensional feature space which can be infinite dimensional and then to construct the linear separating hyperplane in this high dimensional feature space" (Zhou et al., 2009).
The classifier is constructed as follows:

$$y(x) = sign[\sum_{k=1}^{N} \propto_k y_k K(x, x_k) + b]$$

Where $K(x, x_k)$ is called kernel function
$K(x, x_k) = \varphi(x)^T . \varphi(x_k)$; $\varphi(x)$= the mapping function.

Examples of kernel functions are:
Linear: $K(x, x_k) = x^T x_k$
Polynomial: $K(x, x_k) = (x^T x_k + 1)^d$
Radial-basis function network: $K(x, x_k) = \exp(-\frac{\|x-x_k\|^2}{\sigma^2})$

Support Vector Machine (SVM) is also a new classification technique applied for credit screening purposes.

Vapnik (1995) was the first researcher to be interested in Support Vector Machine (SVM). Schölkopf, Smola, and Müller (1996, 1998) have investigated the concept of SVM in order to extend principal component analysis (PCA) to nonlinear kernel PCA for extracting structure from high-dimensional data sets (Baudat & Anouar, 2000). Vapnik (2000) applied SVM to financial data; the outcome of his research was that the performance of SVM was promising.

A review of the literature indicates that arguments in favour of SVM include the accuracy and the robustness of the method. According to Zhou et al. (2009), SVM is an efficient modelling technique to build credit scoring models. For testing their models, they used two real datasets and found that the model built using the direct search-SVM was the most accurate and robust and was also the one keeping the least dependencies on the initial search space or point setting (Zhou et al., 2009).

However, arguments against SVM concerned the choice of the optimal input feature subset and of the best kernel parameter (Frohlich & Chapelle, 2003), the training time and the Black box property.

Huang et al. (2007) mentioned the issue of the training time while testing SVM-GA and SVM-GP-Based as well as the black box property of SVM. They suggested creating an SVM hybrid that would combine SVM with a more understandable modelling technique. Burges & Scholkopf (1997) tested SVM to solve patterns recognition problems and compared their results with the results of LeCun et al. (1995) and concluded that SVM classification speeds were much lower than those of the neural networks tested by LeCun et al.. Nevertheless, they mentioned possible enhancements like invariances and virtual support vectors. Zhou et al. (2009) pointed out that it would be difficult to explain the decisions taken by the model as the SVM technique works as a black box (Zhou et al., 2009).

For more references on each of those techniques, please refer to the Appendix - appendix 1 List of references.

3.1.2 Comparison of the different techniques

To decide which method to use, the author has reviewed several papers comparing the different techniques but also taken into accounts the pros and cons mentioned previously.

Table 16 – Comparison of the different techniques

		Statistical techniques											
		L.D.A.	Logit	Probit	N.N.	Time varying model	k-N.N.	D.T.C.	M.P.	G.A.	Rough sets / Fuzzy Logic	M.A.R.S.	S.V.M.
Pros	- Efficiency / Accuracy / Robustness	x	x	x	x		x	x					x
	- Easy to implement	x	x	x									
	- Easy to interpret	x	x	x			x	x				x	
	- Easy to alter the models at any time		x	x									
Cons	- Long training				x				x				x
	- Black box property				x								x
	- Lack of applications to Credit Scoring			x		x				x	x	x	

3.1.2.1 Step 1: Exclude methods rarely applied to credit scoring

The author decided quickly to exclude several methods such as probit model, on the basis of the drawbacks discussed above.

One of the very few papers that compares a probit model with the different statistical methods was conducted by Loviscek and Crowley (1990). While analyzing municipal bond ratings, they concluded that the probit model may be superior to the use of discriminant analysis based on debt and income variables.

Nonetheless, this method is so rarely used for credit scoring purposes that the author decided to adopt neither it, nor the Rough sets / Fuzzy Logic method, multi-variate adaptive splines, time varying model and genetic programming methods. Ong et al. reported that ANN and logistic regression could be perfectly satisfactory substitutes to GP.

The author decided to focus on those two techniques as well as others well-known for their classification power.

3.1.2.2 Step 2: Exclude methods with a black box property

- NN

The credit scoring accuracies of NN is reported as better than other statistical techniques such as DA and LR techniques (Lee & Chen, 2005). Yun et al. (2007) tested different techniques such as multivariate discriminant analysis, logistic regression, decision tree and neural network on real data coming from national commercial banks. They recommended using decision tree and neural networks to predict default of credit customers.

Other references supporting NN are: Odom & Sharda, 1990; Roy and Cosset, 1990; Sharda & Patil, 1990; Tang et al., 1991; Duliba, 1991; Kang, 1991; Jensen, 1992; Fletcher and Goss; 1993; Coats & Fant, 1993; Wilson & Sharda, 1994; Lacher et al., 1995; Desai, Crook & Overstreet, 1996; Sharda & Wilson, 1996; Desai, Conway & Overstreet, 1997; Piramuthu, 1999; Zhang et al., 1999; West, 2000; Malhotra & Malhotra, 2003; Desai, Crook & Overstreet, 1996; Desai, Conway & Overstreet, 1997; Jensen, 1992; Lacher, Coats, Sharma, & Fant, 1995; Malhotra & Malhotra, 2003; Piramuthu, 1999; Sharda & Wilson, 1996; West, 2000; and Zhang, Hu, Patuwo, & Indro, 1999.

Bell et al. (1989) reported that neural network was the most accurate model compared with logit regression in predicting bankruptcy in commercial banks. Kimoto et al. used a neural network model to determine the optimum by time and sell time for an equity index (Kimoto et al., 1990). Odom & Sharda (1990) applied ANN and DA to predict firms' default and found that NN was outperforming DA.

Salchenberger, Cinar and Lash (1992) reported that NN performs as well as or better than the LRA when predicting the financial health of savings and loans. Tam and Kiang (1992) concluded that NN is most accurate, adaptative and robust in bank failure prediction, followed by LDA, LRA, K.NN and decision trees. Other papers from those authors (Tam, 1991, 1994; Tam & Kiang, 1990) supported the conclusions that A.N.N was preferable. Swales and Yoon apply neural networks for predicting stock performances and reported that NN model performs significantly better than LDA models (Swales & Young, 1992). Coats and Fants concluded that NN is more accurate than LDA for predicting the distressed companies (Coats & Fants, 1993). Neural networks also generated better results than DA in Kerling & Podding (1994)'s research.

Comparing the performance of neural networks with MDA while applied to predict corporation distress, Altman et al. found that ANN was not performing as well as MDA (Altman et al., 1994). Lacher et al. (1995) also use neural network model to predict the financial health of thrift institutions and concludes that NN models require fewer assumptions, achieve a higher degree of prediction accuracy, and are more robust. In 1996, Desai et al. concluded that neural networks, and more precisely backpropagation networks, performed as well as linear discriminant analysis for predicting the bad loans while applied to the data from three credit unions.

Ntungo and Boyd compared a time series model, ARIMA, to a NN model for trading returns for corn, silver, and Deutsche mark futures contracts. The NN's results were positive and at about the levels as the returns with ARIMA models (Ntungo & Boyd, 1998). Desai and Bharati compared the accuracy of NN to linear regression in forecasting returns on stock and bond indices. They found that NN's forecasts are significantly consistent for large stocks and corporate bounds, whereas for small stocks and intermediate-term government bonds it was not (Desai & Bharati, 1998). In forecasting UK pound / US dollar exchange rate, Zhang and Hu found that NN outperformed linear models, particularly for short-term forecast horizon (Zhang & Hu, 1999). Zang et al. concluded that NN was significantly performing better than logistic regression in bankruptcy prediction (Zang et al., 1999). In their study, Indro et al. reported that comparing neural networks with linear models, NN was the best technique for forecasting the performance of mutual funds that follow value, blend and growth investment styles (Indro et al., 1999).

Malhotra & Malhotra compared the performance of multiple discriminant analysis (MDA) and neural networks for credit screening purposes and reported that the neural network models was significantly performing better than the MDA models in predicting poor loans (Malhotra & Malhotra, 2003). Witkowska (2006) applied different classical classification techniques and two types of neural networks to model corporate credit ratings. He found that radial basis function network was giving the smallest classification errors, costs of misclassification, share of noncredible clients but also the smallest share of properly recognized firms and that multilayer perception was giving the biggest share of properly recognized firms. Kumar & Bhattacharya (2006) reported that artificial neural network was outperforming linear discriminant analysis in forecasting corporate credit ratings. They concluded that ANN was more appropriate while predicting large datasets and that it was not requiring conditions such as normality and linearity. Therefore, they recommended using ANN for credit scoring purposes.

However, NN has several drawbacks. Neural networks have especially been criticized for their long training and therefore, for their limited applicability to credit scoring problems (Chung & Gray, 1999; Graven & Shavlik, 1997). In addition the black box property of this method is a major drawback in the business industry.

- SVM

Burges & Scholkopf (1997) tested SVM to solve patterns recognition problems and compared their results with the results of LeCun et al. (1995) and concluded that SVM classification speeds were much lower than those of the neural networks tested by LeCun et al.. Nevertheless, they mentioned possible enhancements like invariances and virtual support vectors.

Baudat & Anouar (2000) developed a model based on linear discriminant analysis. Their objective was to develop a generalized discriminant analysis (GDA) by mapping the input space into a high-dimensional feature space with linear properties (Baudat & Anouar, 2000). The outcome of this research was that, based on the classification rate, the GDA was competing with support vector machines and probabilistic neural network classifier. Using credit rating of banks, Gestel et al. (2003) experimented Ordinary Least Square (OLS) regression, Ordinal Logistic Regression (OLR), Multilayer Perceptrons (MLPs) and least squares support vector machines (LS-SVMs). The best results were obtained while using LS-SVMs. (Gestel et al., 2003).

Baesens et al. (2003) found that both least squares support vector machines and neural network classifiers yield a very good performance for credit scoring. SVM models are often compared and associated to neural networks. In fact, the two techniques are closely related, i.e. a SVM model using a sigmoid kernel function is equivalent to a two-layer, perceptron neural network. Huang et al. (2004) applied backpropagation neural networks and SVM methods on data from United States and Taiwan markets. Both methods leaded to an 80% accuracy rate. Schebesch & Stecking (2005) applied SVM to predict if an applicant should be approved or rejected. The authors concluded that “Using non-linear SVM, more ‘surprising’ critical regions may be detected, but owing to the relative sparseness of the data, this potential seems to be limited in credit scoring practice” (Schebesch & Stecking, 2005). Huang et al. (2007) confirmed that SVM was at least as good as back-propagation neural network (BPN), genetic programming (GP) and decision tree in respect of classification accuracy. Nevertheless, the authors noted that while using the SVM technique, the parameters included in the model should be selected carefully as those would have a significant effect on the classification performance of the model. Moreover, they tested as well three types of strategies for building SVM classifier: Grid search, Grid search and selecting input features using F-score, GA-Based approach. The outcome of their research was that the GA- SVM strategy could to perform feature selection task and model parameters optimization confirming outcomes from previous research (Goldberg, 1989; Holland, 1975).

According to Zhou et al. (2009), SVM is an efficient modelling technique to build credit scoring models. In order to optimize SVM performances, they tested different optimization parameter such as direct search-SVM, grid-search-SVM and method based on design of experiment- SVM as well as other techniques such as linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), logistic regression (LogR), Decision tree (DT) and k-nearest neighbour classifier (k-NN) with k=10. For testing their models, they used two real datasets and found that the model built using the direct search- SVM was the most accurate and robust and was also the one keeping the least dependencies on the initial search space or point setting (Zhou et al., 2009).

However, as for NN, its black box property is a major drawback in the business industry, even though, both techniques are the most accurate techniques for predicting loan failures. The fact that those are hard or even impossible to interpret makes them not suitable for this research.

3.1.2.3 Step 3: Final Choice

Concerning discriminant analysis, a couple of authors found DA to be the best method for credit scoring purposes.

Myers and Forgy (1963) tested different scoring techniques on a same sample of data. The techniques tested were the following: discriminant analysis, stepwise regression, equal weights for all predictive variables used and discriminant analysis weights based upon selected subsamples of cases. The best results were those coming from discriminant analysis weights based upon selected subsamples of cases.

Ohlson (1980) tested a logit model in predicting firms' failure. He compared the classification rate of the logit model versus the classification rate of MDA from previous research made by Altman (1968) and Altman et al. (1977). However, Lo (1985) reviewed several papers and based on empirical results, he concluded that there was no significant difference between the classification accuracies of MDA and logit analysis. Srinivasan and Kim (1987b) examined four statistical models: multiple discriminant analysis (MDA), logistic regression (logit), goal programming (GP), recursive partitioning algorithm (RPA), a judgmental model based on the Analytic Hierarchy Process (AHP). Wiginton (1980) suggested to use the maximum likelihood estimation of the logit model as an alternative to the linear discriminant function and to compare the two models. The results were that the linear discriminant function was not better than the logit function in classifying the individuals but the logit function does not appear to make a significantly high proportion of correct classifications to warrant use for unaided decision-making. However, the author mentioned that better data might have given better results.

Liang (2003) carried out a statistical analysis and found that compared to other techniques, discriminant analysis had the best classification power but not the best prediction power.

Recently, a new topic of interest for researchers is modelling credit risk for SMEs (Frame et al., 2004; Berger & Scott, 2007; Altman & Sabato, 2007). Indeed, governments raised concerns on the fact that SMEs, which contributes substantially to the global economic growth, could be penalized by generic corporate models. Many authors have used discriminant analysis for classifying enterprises. Bandyopadhyay (2006) modified the z-Score model of Altman (1968) in order to predict the default probability of Indian firms. Altman et al (2007) built a specific Z-Score model for predicting Chinese firms in financial distress. Kim (2007) reviewed Altman's Z-score and considered that the loss of prediction of the model was due to the fact that the model should rely on more recent information. He believed that "the reduction of prediction time span of the Z-score and the better performance of the option-based measure implies that bankruptcy prediction should be based on immediately and continuously changing information about the event because the more efficient market shortens the information transition time in the market and discrete or sporadic variables mislay the interpretation of information concerning bankruptcy" (Kim, 2007). Berger & Scott (2007) focused on credit scoring applied to SEs. Based on their empirical study, they concluded that credit scoring specifically built for SEs could increase credit availability for SEs. Altman & Sabato (2007) supported Berger & Scott's view. Their model for SMEs was 30% more accurate than the generic model used by the bank and logistic regression outperformed MDA while using the same input variables. They recommended managing SMEs separately with their own scoring and rating models. Ciampi & Gordini reported that discriminant analysis was giving a 75.5% prediction accuracy and logistic regression 80% while applied to SEs from the manufacturing sector in Italy (2008).

Most of the recent papers show that other new techniques are more relevant for credit screening purposes.

Henley and Hand (1996) compared the k-NN method to other classification techniques, they found that the k-NN method performed well, achieving the lowest expected bad risk rate. The authors confirmed the validity of their results for populations with lower proportions of bad risks in the full population.

More recently, Marinakis et al. (2008) investigated the optimization of nearest neighbour classifiers via metaheuristic algorithms. They tested three different metaheuristic algorithms: tabu search (TS), genetic algorithm (GA) and ant colony optimization (ACO) and the different nearest neighbors methods: the 1-nearest neighbour, the k-nearest neighbor and the wk-nearest neighbour. They also compared those models with more traditional techniques such as support vector machines (SVM), logistic regression (LR), nearest-neighbor algorithms, probabilistic neural networks (PNN), classification and regression trees (CART) and discriminant analysis. The models were tested on real credit rating to predict firms' failures. The authors found that the model providing the best accuracy rate was ACO-1nn. In addition, the model was only using almost half of the available features (Marinakis et al., 2008).

Chwee (2004) tested different techniques for building a credit scoring model using credit card data and concluded that the decision tree was the most accurate technique followed by neural networks and logistic regression.

Zakrzewska (2007) presented a hybrid solution combining unsupervised and supervised classification methods. First, the author used a clustering algorithm to cluster customers into groups presenting the same features. Second, he built decision trees and classification rules for each group defined above. The aim was to test if the hybrid solution would predict credit defaults more precisely than using only one of each technique. The author found that the hybrid solution was more precise and the rules for the different clusters were simpler than the global rules for the whole data set (Zakrzewska, 2007).

Yun et al. (2007) tested different techniques such as multivariate discriminant analysis, logistic regression, decision tree and neural network on real data coming from national commercial banks. They recommended using decision tree and neural networks to predict default of credit customers. In comparing the different type of DTC with neural networks, Safavian and Landgrebe (1991) concluded that there is not enough evidence yet(theoretical or empirical) to provide a strong support for either one of the approaches alone.

Baesens et al. studied the performance of various ‘avangardiste’ modelling techniques and applied those to eight real life credit scoring data sets (Baesens et al., 2003). The results from their study was that both least squares support vector machines and neural network classifiers yield a very good performance as well as simple classifiers such as logistic regression and linear discriminant analysis (Baesens et al., 2003).

West tested five neural networks models to compare their potential predictability; these five neural networks tested were: multilayer perceptron, mixture-of-experts, radial basis function, learning vector quantization, and fuzzy adaptive resonance. He also tested neural networks versus other traditional techniques: linear discriminant analysis, logistic regression, k nearest neighbor, kernel density estimation and decision trees. He found out that the multilayer perceptron was not the most accurate neural network model whereas both the mixture-of-experts and radial basis function NN models gave positive results. Amongst the other techniques, logistic regression appeared to be the most predictive (West, 2000). West (2000) found that NN can improve the credit scoring accuracy but also suggested that LRA is a good alternative to NN.

Ong et al. reported that ANN and logistic regression could be satisfactory substitutes to GP.

After proceeding to this wide literature review and talked with professional of the credit industry, a clear statement is that nowadays, the two techniques the most well known for credit screening are neural networks for its high predictability and logistic regression for practical reasons (easily understood and implemented). Both have their own advantages and disadvantages as mentioned earlier.

However, the concept of neural network being too complex, the technique is not widely used by credit bureaux or even private companies. Logistic regression, on the opposite, is commonly used in the credit industry.

Therefore, after proceeding to this extensive review and reviewed the pros and cons for each of the techniques, the author had three options left: k-NN, decision three and logistic regression and decided to use logistic regression as this technique is slightly easier to technically implement and also most recognised in the credit card business.

3.1.3 Logistic Regression

The modelling technique that will be used in this PhD thesis is logistic regression. This section presents this technique giving its definition, presenting binomial logistic regression, the selection process and the overfitting issue that has been mentioned previously.

3.1.3.1 Definition

Regression techniques such as linear regression and logistic regression are some of the most sophisticated and potentially informative statistical method. This type of modelling approach is based on the concept that each single attribute should be tested before inclusion in the model. The test will tell if the characteristic is significantly explaining the outcome or if it does not bring significant information to the model. Depending on the result of the test, the decision will be to include or not the variable in the model.

Generally, characteristics are included step by step or simultaneously. Tests will be produced. If all variables are included at once, the test will tell which variable should be removed first, i.e. the least significant variable is first removed. The test is run each time that one variable is removed. If the variables are included by step, the most significant is the one entering first. The test is run each time that one variable is included. Those different selection processes will be reviewed in details later on. The aim of the test is to identify the most discriminant characteristics and to avoid including characteristics bringing the same information. If the test is successfully set up, the scorecard should be intuitive, predictive and robust.

Logistic regression is one of the techniques the most frequently used in credit scoring. Thomas et al. define it as follows:

“The regression approach to linear discrimination has one obvious flaw. The right-hand side could take any value from -∞ and +∞, but the left-hand side is a probability and so should take only values between 0 and 1. It would be better if the left-hand side were a function of pi, which could take a wider range of values. Then one would not have the difficulty that all the data points have very similar values of the dependent variable or that the regression equation predicts probabilities that are less than 0 or greater than 1. One such function is the log of the probability odds. This leads to the logistic regression approach” (Thomas et al. 2002).

3.1.3.2 Binomial Logistic Regression

Logistic regression can be divided into several categories: binomial logistic regression, multinomial logistic regression, ordinal logistic regression… Binomial logistic regression is a type of regression where the outcome is dichotomous or binary whereas multinomial logistic regression is used to predict outcomes with more than two categories, i.e. defaulters, non defaulters and ugly. However for both forms of logistic regression, the dependent variables can be either categorical or numerical. Note that ordinal logistic regression will be preferred to multinomial regression when the different categories can be ranked. Logistic regression is also used to predict a continuous dependent variable. As the dependent variable is usually binary, i.e. defaulters or not defaulters, binomial logistic regression is the method that will be used to implement the scorecards.

The independent variables have usually various forms. In the case where the outcome is binary, the usual way to treat them is to transform categorical variables into flag variable or dummy variable and to keep the numeric variables in their format. In order to avoid effects of input variable units, standardized estimates are used.

Another option is to transform numerical into categorical variable (average of each group, weighted average, dummy variables). According to Thomas et al., using dummy variables for categorical variables has a serious drawback, as it assumes that the difference from one categorical variable group to the next is the same (Thomas et al. 2002). They recommend using the weight of evidence of each grouping as the input for several reasons. First, it solves the problem of differing input unit. Second, it takes into account the exact trend and scale of the relationship from one group to the next. Third, it also helps in the development of scorecards by keeping each characteristic intact. And finally, if the grouping is done right, this will also ensure that the allocation of points to each group during scorecard scaling is logical and represents the difference in the relationships between groups. The chapter 3 – 3.2.2.1 explains in details the weight of evidence calculation and how it is employed.

3.1.3.3 The selection process

Basically, a scorecard includes the most significant characteristics to predict the expected outcome. Using logistic regression, the result of the scorecard, the score, gives in fact the probability that the outcome will come true. In the case of this study, this is the probability that a customer will default. An example of equation would be:

$$Logit\ (p_i) = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k$$

Where p= probability of default based on the characteristics given

$x_1, \ldots x_k$ =independent variables, characteristics, attributes…

β_0 = constant

$\beta_1, \ldots, \beta_k$ = coefficients

Logit= Logit transformation, log of the odds, log (p (default) / p (non-default))

Thanks to the Logit transformation, the probability of default will be linear and limited between 0 and 1. The coefficients are estimated by the maximum likelihood and measure the rate of change of logit for one unit change in the input variable.

To select the variables to be included in the model, three different options have to be considered:

- Forward selection: The variable entering first is the most significant for predicting the outcome. The test is run at each step. Each step, a new variable is added to the model based on its result at the updated test. The process stops while no new variable has a p-value of less than 0.5%, standard level. This level may be modified. The advantage of this method is its efficiency. The disadvantages are that too many variables might enter in the model and especially inter-correlated ones.

- Backward Elimination: It consists in starting with all variables and deleting them one at a time using as a criterion the results from the selection test. The least significant is the first dropped. The test is run at each step. The process stops when no variable has a p-value of more than a 0.5% level. This level may be modified. The advantage is that variables not highly predictive may enter in the model. The disadvantage is that the first variables to enter may be over fitted.

- Stepwise: The stepwise logistic regression is the one to focus on; it combines both forward and backward selections. The selection is based on the likelihood ratio test, statistical test calculated from the chi-square difference. Depending on the results of this test, a variable will be automatically added or dropped from the model. The process stops when the best combination is reached.

The method of selection that will be applied to the data is the stepwise selection. This is the usual option. It consists of starting with the constant-only model and adding and dropping variables one at a time. The variables will enter in the order they are best based on the statistic chosen until they reached the cut-off level, i.e. until the step at which all variables not in the model have a significance higher than .05. By contrast, some variables may be dropped along the process if for instance their coefficients are not rational or variables are too strongly correlated.

The statistics commonly used to select the variable to enter at each step are Rao's efficient score statistic and the likelihood ratio method. Rao's efficient score statistic is similar but not identical to a likelihood ratio test of the coefficient for an individual explanatory variable (Scholarpedia, no date).

The theory behind the Rao's efficient score statistic is the following:

Let $X = (x_1, \dots, x_n)$ be an i.i.d. sample from a probability density function $p(x, \theta)$, where θ, is an r- vector parameter. Let $P\,(X, \theta) = p(x_1, \theta) \dots p(x_n, \theta)$, the score vector of Fisher is

$$S(\theta) = [s_1(\theta), \dots, s_r(\theta)]' \qquad s_j(\theta) = \frac{1}{P}\frac{\partial P}{\partial \theta_j} \qquad j = 1, \dots, r$$

The Fisher information matrix of order r*r is defined by

$$I(\theta) = \left(i_{jk}(\theta)\right), \;\; i_{jk}(\theta) = E(s_j(\theta)s_k(\theta))$$

The Rao's score (RS) test for a simple hypothesis H_o: $\theta = \theta_o$, introduced in Rao (1948), is

$$RSS = S(\theta_o)'[I(\theta_o)]^{-1}S(\theta_o)$$

which has an asymptotic chi-square distribution on r degrees of freedom.

The likelihood ratio test and the Rao's efficient score are tests used in the variable inclusion process in logistic regression and also to generate an “overall statistics” significance test for the model. It aims at testing whether the logistic regression coefficient of an explanatory variable is zero or not. An explanatory variable with a $p>0.05$ on the likelihood ratio test or the Rao’s efficient score test is considered as non significant and leads to the conclusion that the null hypothesis can be treated as true, so that the coefficient of the explanatory variable is zero and should not be kept in the model. In the forward logistic regression, the process will run until all variables not included in the model have a significance greater than 0.05. The advantage of the Rao’s efficient score compared to the likelihood test is that it is non-iterative and that it is fast computed compared to the likelihood ratio test. Indeed, the likelihood ratio test usually used four-five iterations before estimating the parameters whereas the Rao’s efficient score statistic used one iteration.

By contrast, while dropping variables, other statistics may be chosen to eliminate the variables such as the likelihood ratio test, the Wald statistic, or the conditional statistic. Comparing those statistics, the likelihood ratio test is the most accurate followed respectively by the c-statistic and the Wald test. However, the likelihood ratio test is also the most time consuming method to compute. That is why the conditional statistic is usually the preferred option of the three.

The c-test is a non parametric two-sample test which measures the classifier performance for all score bands. Graphically, it is represented by the area under the Sensitivity vs. (1-Specificity) curve for all score band (Hosmer & Lemeshow, 2000).

The Wald test is a parametric statistical test. The null hypothesis being $H_0: \beta = \beta_o$, the test statistic is as follows:

$z = (\hat{\beta} - \beta)/SE$ where $SE \neq 0$

Where Z follows a normal distribution when $\beta = \beta_o($ (Agresti, 2002).

In Agresti's book (2002), the test statistic for the multivariate extension is as follows:

$W = (\hat{\beta} - \beta_o)'[cov(\hat{\beta})]^{-1}(\hat{\beta} - \beta_o)$

Where:

the non-null covariance is based on the curvature of the log likelihood at $\hat{\beta}$.

the asymptotic multivariate normal distribution for $\hat{\beta}$ implies an asymptotic chi-squared distribution for W.

df= the rank of $cov(\hat{\beta})$= the number of non-redundant parameters in β.

Robert Engle demonstrated that the Wald test, the likelihood-ratio test and the Lagrange multiplier test are asymptotically equivalent (Engle,1983).

3.2 Scorecard Evaluation / Monitoring

This sections aims at describing the different tools that can be used to evaluate / monitor credit scoring models and presenting the ones the author has decided to use in order to determine the scoring models that would be integrated in the credit scoring solution.

3.2.1 Commonly used validation tools

In order to evaluate / monitor a scorecard, a set of indicators / reports needs to be implemented.

Their main purposes are to be able to detect when the scorecards need to be maintained, how to optimize the usage of the scorecards and first of all picking the best model.

3.2.1.1 Validation indicators

To find the best model, validation indicators are common performance indicators for scorecard and are often used by modelers and in the credit card industry. When validating a model, the technique consists in calculating statistical indicators for the development sample and the validation samples.

However, most of those indicators can be used for validating models but also characteristics / variables. It is calculated for each score band / variable's characteristics to describe how different scores / characteristics of the goods and the bads are different (Thomas et al. 2002).

The conclusion resulting from those indicators will vary; a variable / model might be predictive enough for some and not for others.

Table 17 – List of statistical indicators for validating scoring models

Validation indicators	
Report's title	**Purpose**
Information value (I.V.)	IV=∑_i(g_i/g-b_i/b) WoE_i Where g_i = the number of goods with attribute i b_i = the number of bads with attribute i g = the total number of goods b = the total number of bads Results (Siddiqi, 2006): - Less than 0,002: unpredictive - 0,02 to 0,1:weak - 0,1 to 0,3: medium - 0,3 +: strong
Weight Of Evidence (W.O.E.)	WoE_i=log[(g_i b)/(b_i g)] Where g_i = the number of goods with attribute i b_i = the number of bads with attribute i g = the total number of goods b = the total number of bads Should follow a logical order and the associated sign should correspond to the logical sign (Siddiqi, 2006).
R-square statistic	R2=1-(Σ_i(y_i-y^_i)2/ Σ_i(y_i-y-)2) Where Y_i: original value Y^_i: Modeled value y-: Average Results (Siddiqi, 2006): - 0: no predictive ability - 1: perfect discrimination
Akaike's Information criterion (A.I.C.)	AIC=-2lnL_max+2k where k is the number of parameters in the statistical model, L_max is the maximum likelihood achievable by the model (Akaike, 1974). The model that will be selected is the one with the lowest A.I.C. value (Liddle, 2008).
Bayesian Information criterion (B.I.C.)	BIC=-2lnL_max+klnN where k is the number of parameters in the statistical model, L_max is the maximum likelihood achievable by the model N is the number of data points used in the fit (Schwarz, 1978). The model that will be selected is the one with the lowest A.I.C. value (Liddle, 2008).
Schwarz's Bayesian Criterion (S.B.C.)	BIC=-2lnL_max+klnN where k is the number of parameters in the statistical model, L_max is the maximum likelihood achievable by the model N is the number of data points used in the fit (Schwarz, 1978).

Validation indicators	
Report's title	**Purpose**
Kolmogorov-Smirnov (K.S.)	KS=max|P_G (s)-P_B (s)| Where P_G (s)=∑(x≤x)p_G (x) P_B (s)=∑(x≤x)p_B (x) . The larger the K.S. statistic is, the stronger the model is (Thomas et al. 2002).
Divergence statistic	D2=(MeanG-MeanB)2/((σG2+ σB2)/2) The larger the divergence statistic, the greater the predictive power of the model (Anderson, 2007).
Gini coefficient	D= 1- sum ((cp Yi-cp Yi-1) (cp Xi+cp Xi-1)) where CpY is the cumulative percentage of goods and CpX is the cumulative percentage of bads. For application scoring: - More than 50: Good quality - 50-30: Average - Less than 35: Poor quality For behavioural scoring: - More than 80: Good quality - 80-60: Average - Less than 60: Poor quality (Anderson, 2007).
C-statistic	C-statistic=(C+0.5*(P-C-D))/PA where C = the number of concordant pairs D = the number of discordant pairs P = the total number of pairs Area under the curve (AUC) is also known as the c-statistic or c index: - 0.5: no predictive ability - 1: perfect discrimination
Somers'D, Gamma, Tau-a	Similar to the c-statistic.
Wilcoxon-Mann-Whitney test	A non parametric two-sample test. H0: two populations have identical distribution functions. n1 and n2= sample sizes, mean: n1(n1+n2+1)/2, variance: n1*n2(n1+n2+1)/12, z= T-mean/square root of variance N(0,1)

The author has not found in the literature any proof that one statistic is unambiguously superior to another. In this thesis, the author has decided to use the Weight of Evidence combined with the information value.

3.2.1.2 Validation charts

Validation statistics, such as the information value and goodness of fit, are one way to validate a model but another option is validation charts.

The graphical display is an easy way of comparing the performance of one scorecard on different samples or also the performance of different scorecards.

Table 18 – List of statistical charts for validating scoring models

Validation charts	
Report's title	**Purpose**
Validation chart	To plot the distribution of the non delinquent versus the distribution of the delinquent across the score for the development and the validation sample (Siddiqi, 2006).
Lorenz Curve	To plot the distribution of the delinquent customers versus the total number of customers by deciles across all score ranges (Siddiqi, 2006).
Gains Chart	To plot the cumulative positive predicted value versus the distribution of predicted positives (Siddiqi, 2006).
Lift / Concentration Curve	To plot the distribution of the predicted positives versus the sensitivity which is as explained above, sensitivity= (true positives) / (total actual positives) (Siddiqi, 2006).
ROC Curve	To plot the sensitivity versus (1-Specificity) where the Specificity= (true negatives) / (total actual negatives) (Siddiqi, 2006).

In this thesis, the author uses the validation chart. It plots the distribution of the non delinquent versus the distribution of the delinquent across the score for the development and the validation sample. It can also plot the cumulative distribution of the non delinquent versus the cumulative distribution of the delinquent. This is the type of graphical display that is presented in this thesis.

3.2.1.3 Validation charts

Additional tools that can be used for validating models are validation reports. Those reports are frequently displaying validation indicators such as Information value and R-Square.

Table 19 – List of statistical reports for validating scoring models

Validation reports	
Report's title	**Purpose**
Analysis of grouped variables	The Information value can be calculated for each chracteristic. Characteristics will be defined as follow (Siddiqi, 2006): - Less than 0,002: unpredictive - 0,02 to 0,1:weak - 0,1 to 0,3: medium - 0,3 +: strong This report can be used for characteristics and models.
Logical W.O.E trend	Graphical display of W.O.E., the graph should show that: - the W.O.E. follow a logical order - the associated sign should correspond to the logical sign. This report can be used for characteristics and models.
Coarse display / Gains table	To display the weight of evidence and information value (Siddiqi, 2006).
Model characteristics	The R-squared can be calculated at each iteration of the logistic regression starting by calculating with the first variable entering and continuing until all the variables of the models are in. The R-square values should be increasing at each iteration.
Confusion matrix	To create a misclassification matrix (Anderson, 2007): - choose a score cut-off - Mark all accounts below the cut-offs as expected bads, and all those above as expected good; - cross-tabulatng the expected goods and bads against the actual, using the development definition, or any other definition of interest; - Determine the percentage of accounts that fall into each cell; - calculate the various ratios that can be derived from the model. Four different statistical measures can be derived (Siddiqi, 2006): Accuracy= (true positives and negatives) / (total cases) Error rate= (false positives and negatives) / (total cases) Sensitivity= (true positives) / (total actual positives) Specificity= (true negatives) / (total actual negatives)

To display the weight of evidence and information value, one device is coarse display or gains table. This output provides a summary of the characteristic's strength and pattern of behavior in predicting the value of the performance variable. In our case, the outcome is binary, Goods vs. Bads. The Gains tables can be produced over time for the different vintages to monitor the accuracy of the scorecards.

In this thesis, the author uses coarse display.

3.2.2 Tools used for this research

In order to evaluate a scorecard, a set of indicators and reports needs to be implemented.

The main purposes are to be able to optimize the usage of the scorecards and first of all picking the best model.

3.2.2.1 Weight of Evidence

1) Definition

Information that will be gained from others as well as personal judgement will affect probabilities' calculation (Anderson, 2007). This topic has been addressed in 1950 in Irving John (Jack) Good's book. The concept is described as follows:

"For any decision, one assesses the circumstances and determines a weight of evidence. Basically, this converts the risk associated with a particular choice onto linear scale that is easier for the human mind to assess." (Anderson, 2007)

In credit scoring, the standard formula for expressing weight of evidence is the following:

$$\mathrm{WoE_i} = \log\left[\frac{\mathrm{g_i b}}{\mathrm{b_i g}}\right]$$

Where $\mathrm{g_i}$= the number of goods with attribute i

$\mathrm{b_i}$= the number of bads with attribute i

g = the total number of goods

b = the total number of bads

2) When / How to use it

There are different reasons for using weight of evidence (Anderson, 2007):

- To assess the relative risk of each attribute of a characteristic

- To indicate the ones that are most likely to feature within a scorecard

- To transform characteristics into variables.

The main issue with Weights of Evidence is that it only takes into account the risk associated with the attribute and not the proportion of accounts associated to this attribute (Anderson, 2007). This is why, in this thesis, the information value is also used as an evaluation criterion as it takes into account the contribution of each attribute.

A positive value means that the cell is more likely to be GOOD than the average of the population in question; a negative value means that the cell is less likely to be GOOD than the average of the population. It is called "weight pattern", because if this numeric variable was the only variable in a logistic regression model, this would be the weight assigned to each cell.

Just below, three examples of weight of evidence calculation are presented:

- Example for a qualitative variable:

Table 20 – Weight of Evidence for a qualitative variable

Living Status						
Obs	Stats	BADS	GOODS	PROB. BADS	PROB. GOODS	WEIGHT PATTERN
1		5110	17228	0.365	0.203	-0.589
2	Other	273	1752	0.02	0.021	0.55
3	Owner	1470	24970	0.105	0.294	1.03
4	Parent	1340	5692	0.096	0.067	-0.358
5	Renter	5801	35391	0.415	0.416	0.004
	Total	13994	85033			

For first observation, the probabilities are the following:

$\frac{b_i}{b}$=5110/13994=0.365 and $\frac{g_i}{g}$=17228/85033=0.203

The weight of evidence for this observation is:

$\mathrm{WoE_i} = \log\left[\frac{g_i b}{b_i g}\right]$=log(0.203/0.365)=-0.589

- Example for a quantitative variable:

Quantitative variables are usually not monotonic and can therefore not be integrated in the model without being transformed. Monotonic means that the weight of evidence increase or decrease but never changed direction (Anderson, 2007).

Let us take the example of Age. In credit scoring, it is well-known pattern that Age is increasing with risk. Nevertheless, minor variations occur. A common approach is to sort the variable and to class it into 20 bands. By using weight of evidence and coarse classing, each band will be built such as the average point allocation increases with the Age. The new variable will be monotonic.

Table 21 – Weight of Evidence for a quantitative variable

Age						
Obs	Stats	BADS	GOODS	PROB. BADS	PROB. GOODS	WEIGHT PATTERN
1	19.917	1213	1223	0.087	0.014	-1.796
2	21.833	1084	2096	0.077	0.025	-1.145
3	23.667	959	2716	0.069	0.032	-0.763
4	25.25	903	3063	0.065	0.036	-0.583
5	26.833	848	3417	0.061	0.04	-0.411
6	28.417	808	3608	0.058	0.042	-0.308
7	30	790	3691	0.056	0.043	-0.263
8	31.75	743	3936	0.053	0.046	-0.137
9	33.667	693	4126	0.05	0.049	-0.02
10	35.583	696	4238	0.05	0.05	0.002
11	37.5	666	4570	0.048	0.054	0.122
12	39.25	651	4369	0.047	0.051	0.099
13	41.167	581	4920	0.042	0.058	0.332
14	43.25	594	5071	0.042	0.06	0.34
15	45.5	545	5021	0.039	0.059	0.416
16	48.083	558	5184	0.04	0.061	0.424
17	51.333	492	5392	0.035	0.063	0.59
18	55.417	444	5823	0.032	0.068	0.769
19	61.25	405	6078	0.029	0.071	0.904
20	116.583	321	6491	0.023	0.076	1.2
	Total	13994	85033			

It is also important to note that the weights of evidence have a linear relationship with the logistic function. Anderson recommended using this technique while using logistic regression (Anderson, 2007).

- Example for a score:

Table 22 – Weight of Evidence for a score

Score						
Obs	Stats	BADS	GOODS	PROB. BADS	PROB. GOODS	WEIGHT PATTERN
1	-2.92267462	416	49	0.084	0.010	-2.158
2	-2.23562752	430	99	0.086	0.019	-1.488
3	-1.77244948	411	103	0.082	0.020	-1.403
4	-1.43045707	420	84	0.084	0.017	-1.629
5	-1.14229046	360	139	0.072	0.027	-0.971
6	-0.87607794	369	136	0.074	0.027	-1.018
7	-0.61516804	336	169	0.067	0.033	-0.707
8	-0.36097294	308	195	0.062	0.038	-0.477
9	-0.14038662	284	220	0.057	0.043	-0.275
10	0.03236706	287	216	0.058	0.043	-0.304
11	0.24274706	225	279	0.045	0.055	0.196
12	0.484980414	241	261	0.048	0.051	0.060
13	0.72094706	247	256	0.050	0.050	0.016
14	0.92354706	181	323	0.036	0.064	0.560
15	1.157528946	121	381	0.024	0.075	1.128
16	1.37134706	104	399	0.021	0.079	1.325
17	1.706540061	86	418	0.017	0.082	1.562
18	2.00244706	74	428	0.015	0.084	1.736
19	2.39013932	44	458	0.009	0.090	2.323
20	6.872009867	38	467	0.008	0.092	2.489
	Total	4,982	5,080			

A model without monotonic weights of evidence will be unstable. To set credit limits, a scoring model must have monotonic weight of evidence when score bands are ranked in an ascending or descending order. The reason is that credit limits need to be assigned appropriately based on the risk profile of the customer. The riskier customers should get the lowest limit and the less risky ones should get the highest credit limit. As for weight of evidence, credit limits must increase or decrease but never change direction.

3.2.2.2 Information value

1) Definition

In 1958, Salomon Kullback was one of the first who published about information value. However, little credit was given to his research. At that time, he was referring to information value as the Kullback divergence measure; this measured the distance between two distributions. Fair Isaac used this measure to quantify the predictive power of characteristics, naming it "information value". The information statistic is related to measures of entropy that appear in information theory (Thomas et al. 2001). The information value is also called divergence.

The log of the ratio of the number of goods to the number of bads (the log odds ratio), is calculated for each band/observation and for the overall sample. From the log odds of each band, subtract the log odds of the population overall. Each of these values is the weight of evidence for each band. The more the log odds of a group differ from the log odds for all bands, the greater the absolute value of its weight of evidence is.

To obtain the information value, calculate the percentages of good loans and bad loans in each band/observation and multiply the weights of evidence for each by the difference between the good percentage and the bad percentage. This yields the attribute information value, which is always positive. To get the total information value for the variable, sum these values.

The standard formula used to calculate the information value where the i subscript to the ith band of values within a variable is as follows:

$$\mathrm{F} = \sum_{\mathrm{i}} \left(\frac{\mathrm{g_i}}{\mathrm{g}} - \frac{\mathrm{b_i}}{\mathrm{b}}\right) \mathrm{WoE_i}$$

Where g_i = the number of goods with attribute i

b_i = the number of bads with attribute i

g = the total number of goods

b = the total number of bads

$\mathrm{WoE_i} = \log\left[\frac{g_i b}{b_i g}\right]$

The information formula can be explained as follows:

- The aim is to find out in which extent $p(x/G)=\frac{g_i}{g}$ and $p(x/B)=\frac{b_i}{b}$ are different when x takes attribute value I.

- The core piece of the information statistic is $\sum_i(\frac{g_i}{g}) \log\left[\frac{g_i}{g}\right]$.

- Assume $N_g = \frac{g!}{g_1!g_2!\dots g_n!}$ if there are n types in total, information is the log of the number of ways the distribution occurs, so $I_g = \log N_g = \log g! - \sum_i \log(g_i !) \approx g\log(g) - \sum_i g_i \log(g_i)$.

- The average information is $\frac{I_g}{g} \approx -\sum_i\left(\frac{g_i}{g}\right)(\log(g_i) - \log(g)) = -\sum_i\left(\frac{g_i}{g}\right)\log\left(\frac{g_i}{g}\right)$.

- The information value is the difference between the information in the goods and the information in the bads, i.e. $-\sum_i(\frac{g_i}{g} - \frac{b_i}{b})\left(\log\left(\frac{g_i}{g}\right) - \log\left(\frac{b_i}{b}\right)\right)$ (Thomas et al. 2001).

2) When / How to use it

Generally, information value ranges from 0 to about 3. The larger the value is, the stronger the relationship between the dependent and the independent variable.

When a characteristic has an information value greater than 0.3, this variable can be considered as strongly informative in predicting the expected outcome. By contrast, variables with information value of 0.1 or lower, need to be investigated as it brings small information to the model. Further testing will be recommended. In most cases, an information value below 0.1 indicates that the predictability of a variable is so low that it should be excluded from the model unless there is a compelling business reason not to do so.

The Information value can be used not only to evaluate the variables discriminating power, but also to evaluate the quality of the model as a whole. The higher the information value is, the better the model is. In this thesis, information value has been used for both purposes.

Just below, three examples of information value calculation are presented.

- Example for a qualitative variable:

Table 23 – Information Value for a qualitative variable

Living Status							
Obs	Stats	BADS	GOODS	PROB. BADS	PROB. GOODS	WEIGHT PATTERN	INFORMATION VALUE
1		5110	17228	0.365	0.203	-0.589	0.096
2	Other	273	1752	0.02	0.021	0.55	0
3	Owner	1470	24970	0.105	0.294	1.03	0.194
4	Parent	1340	5692	0.096	0.067	-0.358	0.01
5	Renter	5801	35391	0.415	0.416	0.004	0
	Total	13994	85033				**0.3**

The information value for the first observation is $F_i = (\frac{g_i}{g} - \frac{b_i}{b})\ WoE_i$=(0.203-0.365)*-0.589=0.096

The information value for the overall variable is $F = \sum_i F_i$= 0.096+0+0.194+0.01+0=0.3

- Example for a quantitative variable:

Typically, to calculate the information value, the observations must be ranked by the value of the predictive variable to be analyzed. The observations are divided into equal sized bands. Twenty bands are typical.

Table 24 – Information Value for a quantitative variable

Age							
Obs	Stats	BADS	GOODS	PROB. BADS	PROB. GOODS	WEIGHT PATTERN	INFORMATION VALUE
1	19.917	1213	1223	0.087	0.014	-1.796	0.13
2	21.833	1084	2096	0.077	0.025	-1.145	0.06
3	23.667	959	2716	0.069	0.032	-0.763	0.028
4	25.25	903	3063	0.065	0.036	-0.583	0.017
5	26.833	848	3417	0.061	0.04	-0.411	0.008
6	28.417	808	3608	0.058	0.042	-0.308	0.005
7	30	790	3691	0.056	0.043	-0.263	0.003
8	31.75	743	3936	0.053	0.046	-0.137	0.001
9	33.667	693	4126	0.05	0.049	-0.02	0
10	35.583	696	4238	0.05	0.05	0.002	0
11	37.5	666	4570	0.048	0.054	0.122	0.001
12	39.25	651	4369	0.047	0.051	0.099	0
13	41.167	581	4920	0.042	0.058	0.332	0.005
14	43.25	594	5071	0.042	0.06	0.34	0.006
15	45.5	545	5021	0.039	0.059	0.416	0.008
16	48.083	558	5184	0.04	0.061	0.424	0.009
17	51.333	492	5392	0.035	0.063	0.59	0.017
18	55.417	444	5823	0.032	0.068	0.769	0.028
19	61.25	405	6078	0.029	0.071	0.904	0.038
20	116.583	321	6491	0.023	0.076	1.2	0.064
	Total	13994	85033				**0.428**

- Example for a score: the approach is the same as for numerical variable.

Table 25 – Information Value for a score variable

Score							
Obs	Stats	BADS	GOODS	PROB. BADS	PROB. GOODS	WEIGHT PATTERN	INFORMATION VALUE
1	-2.92267462	416	49	0.084	0.010	-2.158	0.159
2	-2.23562752	430	99	0.086	0.019	-1.488	0.099
3	-1.77244948	411	103	0.082	0.020	-1.403	0.087
4	-1.43045707	420	84	0.084	0.017	-1.629	0.110
5	-1.14229046	360	139	0.072	0.027	-0.971	0.044
6	-0.87607794	369	136	0.074	0.027	-1.018	0.048
7	-0.61516804	336	169	0.067	0.033	-0.707	0.024
8	-0.36097294	308	195	0.062	0.038	-0.477	0.011
9	-0.14038662	284	220	0.057	0.043	-0.275	0.004
10	0.03236706	287	216	0.058	0.043	-0.304	0.005
11	0.24274706	225	279	0.045	0.055	0.196	0.002
12	0.484980414	241	261	0.048	0.051	0.060	0.000
13	0.72094706	247	256	0.050	0.050	0.016	0.000
14	0.92354706	181	323	0.036	0.064	0.560	0.015
15	1.157528946	121	381	0.024	0.075	1.128	0.057
16	1.37134706	104	399	0.021	0.079	1.325	0.076
17	1.706540061	86	418	0.017	0.082	1.562	0.102
18	2.00244706	74	428	0.015	0.084	1.736	0.120
19	2.39013932	44	458	0.009	0.090	2.323	0.189
20	6.872009867	38	467	0.008	0.092	2.489	0.210
	Total	4,982	5,080				**1.364**

3.2.2.3 Validation Chart

1) Definition

In the scoring process, the validation chart is a common method of evaluating the scorecard model. The validation chart belongs to the summary chart family like lift chart and is commonly used in data mining.

A validation chart is a graphical display allowing the evaluation of the quality of a model and the usefulness of the information that it is providing. It can be used for both a binary dependent variable and a multinomial dependent variable (more than two categories). For multinomial outcome, the validation chart can be produced for each category.

In our case, the outcome variable, Y, is categorical, and more precisely binary. The two responses are Y=1 or Y=0, when Y=0, it means that the customer never reached the P60 status and therefore, has not been sent to collection, so the so-called good customers, when Y=1, it means that the customer is delinquent and is not paying in due time, i.e. the so-called bad customers.

2) How to build a validation graph

For building a validation chart, one needs the distribution of good and bad customers through the different score bands of the scoring model.

Table 26 – Example of validation table

				Example				Random		Perfect	
Points	#acct	#good	#bad	#cumgood	#cumbad	%cumgood	%cumbad	%cumgood	%cumbad	%cumgood	%cumbad
						0%	0%	0%	0%	0%	100%
1	112	9	103	9	103	1%	8%	5%	5%	5%	100%
2	110	11	99	20	202	2%	16%	10%	10%	10%	100%
3	134	19	115	39	317	3%	25%	15%	15%	15%	100%
4	117	16	101	55	418	5%	33%	20%	20%	20%	100%
5	113	33	80	88	498	7%	39%	25%	25%	25%	100%
6	161	44	117	132	615	11%	48%	30%	30%	30%	100%
7	125	48	77	180	692	15%	54%	35%	35%	35%	100%
8	131	46	85	226	777	19%	61%	40%	40%	40%	100%
9	108	52	56	278	833	23%	66%	45%	45%	45%	100%
10	138	65	73	343	906	29%	71%	50%	50%	50%	100%
11	161	76	85	419	991	35%	78%	55%	55%	55%	100%
12	124	63	61	482	1,052	40%	83%	60%	60%	60%	100%
13	163	104	59	586	1,111	49%	87%	65%	65%	65%	100%
14	109	72	37	658	1,148	55%	90%	70%	70%	70%	100%
15	116	79	37	737	1,185	62%	93%	75%	75%	75%	100%
16	117	83	34	820	1,219	69%	96%	80%	80%	80%	100%
17	118	98	20	918	1,239	77%	98%	85%	85%	85%	100%
18	113	98	15	1,016	1,254	85%	99%	90%	90%	90%	100%
19	108	98	10	1,114	1,264	93%	100%	95%	95%	95%	100%
20	87	81	6	1,195	1,270	100%	100%	100%	100%	100%	100%
Total	2,465	1,195	1,270								

#acct the total number of observations, with totals at the bottom.

#good the number of observations with Y = 0 (not delinquent), with totals at the bottom.

#bad the number of observations with Y = 1 (delinquent), with totals at the bottom.

#cumgood the cumulated number of observations with Y = 0 (not delinquent).

#cumbad the cumulated number of observations with Y = 1 (delinquent).

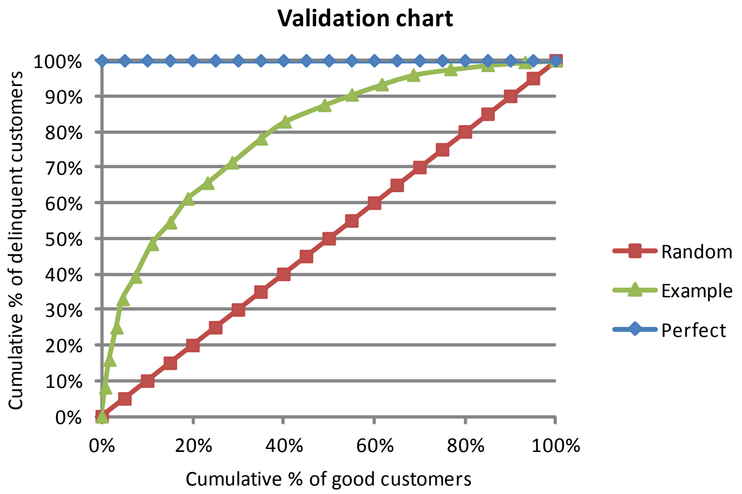
%cumgood the cumulative probabilities obtained by summing the corresponding probability columns from the first through the 20th cell.

%cumbad the cumulative probabilities obtained by summing the corresponding probability columns from the first through the 20th cell.

The model curve will be obtained by plotting the cumulative probabilities of good customers versus the cumulative probabilities of bad customers.

3) How to read a validation chart

Table 27 – Example of validation chart



x-coordinate	The percentage of the cumulated number of sorted data records of the current model. The data records are sorted in descending order by the confidence that the model assigns to a prediction of the selected value of the target field.
y-coordinate	The percentage of the number of records that actually contain the selected target field value for the appropriate amount of records on the x-coordinate.
Random curve	The random curve is a linear curve. It assumes that the ordering is done at random. Therefore the percentage of records that actually have the selected target field value is expected to be the same for all subsets of the data.
Perfect curve	The optimum curve is a stepwise linear curve. It assumes that the data records are sorted perfectly, so that all the records that actually contain the selected target field value occur before the records that do not contain the selected target field value.
Model curve	The data records are sorted by the confidence values that are provided by the model.
Target Field	It will depend on the purpose of the model, the outcome is usually binary and takes the value 0 or 1.

In the context of credit scoring, a validation chart is structured as follows:

- The x-axis shows the percentage of good customers. This is a percentage of customers that did not default.
- The y-axis shows the percentage of bad customers, which is a percentage of the total portfolio or a percentage of the training sample.
- Model curve (overall response rate): By selecting X% of bad customers, the bank will get X% of good customers.

Out of a set of customers applying for a credit card, the objective is to predict those customers who will default and not pay in due time. During a previous similar period, the bank has collected useful information about those customers (e.g., demographic information, previous purchasing patterns) that could be related to the default rate, describing whether the respective customers defaulted or not.

Given the baseline response rate and the cost of assigning high credit limit to risky customers, giving the same credit limit to all customers would result in a net loss. The bank wants to use statistical analyses to identify the customers who are most likely to default.

Suppose the bank build such a model based on the data collected in the previous time period, they can now select only the 10 percent of the portfolio who, according to prediction from the model, are most likely to default. They can also compute the number of accurately predicted good customers, relative to the total number of good customers in the sample; this percentage is the gain from using the model. Put another way, of those customers likely to default in the current sample, one can accurately identify ("capture") y percent by selecting from the customer list the top 10% who were predicted by the model with the greatest certainty to turn bad (where y is the gains value).

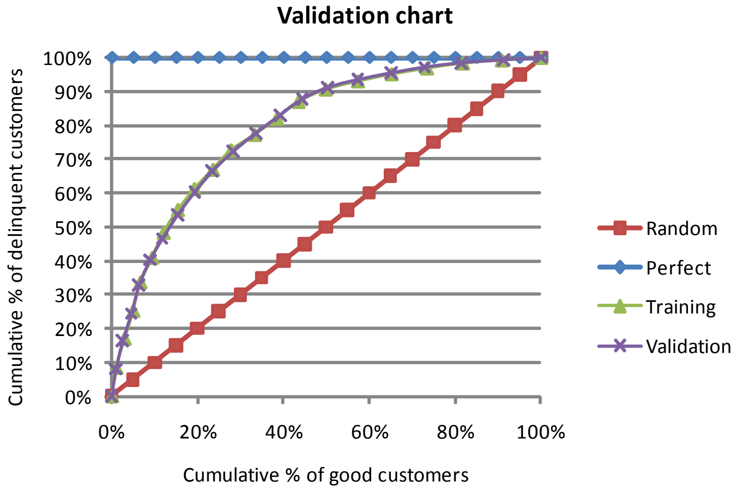
Analogous values can be computed for each percentile of the population (portfolio). The bank could compute separate gains values for selecting the top 20% of customers who are predicted to be among likely defaulters, the top 30%, etc. Hence, the gains values for different percentiles can be connected by a line that will typically ascend slowly and merge with the baseline if all customers (100%) were selected.

4) How to interpret the results of a validation chart

A validation chart can be used for two purposes:

- Validating a model: comparing the results of a model on the training and validation sample.

Table 28 – Example of validation chart

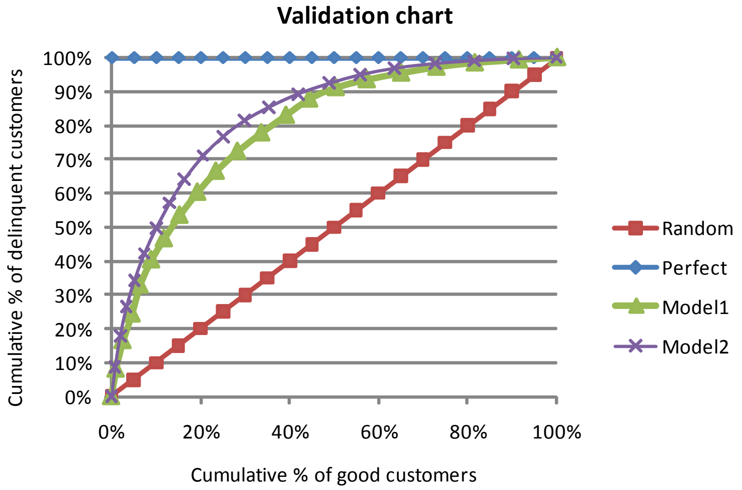


Training	Model fitted with the training sample.
Validation	Model tested on a validation sample.
Interpretation	The closer the training and validations curves the lower the risk of overfitting. The 2 curves should be the closer as possible to the perfect curve, i.e. the highest predictive power.

A validation chart can be used to compare curves resulting from computations based on different data sets: one curve built with the dataset to build the model, and the other one resulting from the dataset to test the model.

- Selecting models: comparing the results of different models

Table 29 – Example of validation chart



Interpretation	Comparing different curves in the same diagram is a powerful way to see the quality of different models at first glance. The model curve the closest from the perfect curve indicates the model with the highest predictive power (Model 2). The model curve the closest from the random curve indicates the model with the lowest predictive power (Model 1).

If more than one predictive model is used, multiple validation charts can be overlaid (as shown in the illustration above) to provide a graphical comparison of the utility of different models.

The final scorecard models will be evaluated with the validation chart and compared with credit bureaux validation chart, even though, there are other techniques.

3.2.2.4 Coarse Display

To display the weight of evidence and information value, one device is coarse display. This output provides a summary of the characteristic's strength and pattern of behaviour in predicting the value of the performance variable. In this thesis, the outcome is binary, i.e. Goods vs. Bads.

According to Thomas et al., the objective is to maximize the predictive power of a variable by defining classes. The two reasons for coarse classifying the variables depend on the type of the variable:

- If the variable is categorical with a lot of attributes, the number of observation within each attribute may be too low to build a robust model. Using Weights of Evidence and Information value allow transforming categorical variables into more predictive categorical variables.
- For numerical variables, the aim is to obtain the best model possible. The weights of evidence and the information value calculation allow transforming numerical variables into categorical variables; it consists in grouping neighbouring ranges of values of the variable into a family of non-overlapping intervals. However, a model with a non linear risk in the continuous variable might be preferred if its predictive power is higher (Thomas et al. 2001).

Table 30 – Example of Coarse Display

Score									
Obs	Stats	BADS	GOODS	PROB. BADS	PROB. GOODS	WEIGHT PATTERN	%CUM. BADS	%CUM. GOODS	INFORMATION VALUE
1	-2.92267462	416	49	8%	1%	-2.158	1%	8%	0.159
2	-2.23562752	430	99	9%	2%	-1.488	3%	17%	0.099
3	-1.77244948	411	103	8%	2%	-1.403	5%	25%	0.087
4	-1.43045707	420	84	8%	2%	-1.629	7%	34%	0.110
5	-1.14229046	360	139	7%	3%	-0.971	9%	41%	0.044
6	-0.87607794	369	136	7%	3%	-1.018	12%	48%	0.048
7	-0.61516804	336	169	7%	3%	-0.707	15%	55%	0.024
8	-0.36097294	308	195	6%	4%	-0.477	19%	61%	0.011
9	-0.14038662	284	220	6%	4%	-0.275	24%	67%	0.004
10	0.03236706	287	216	6%	4%	-0.304	28%	73%	0.005
11	0.24274706	225	279	5%	5%	0.196	33%	77%	0.002
12	0.484980414	241	261	5%	5%	0.060	38%	82%	0.000
13	0.72094706	247	256	5%	5%	0.016	43%	87%	0.000
14	0.92354706	181	323	4%	6%	0.560	50%	91%	0.015
15	1.157528946	121	381	2%	8%	1.128	57%	93%	0.057
16	1.37134706	104	399	2%	8%	1.325	65%	95%	0.076
17	1.706540061	86	418	2%	8%	1.562	73%	97%	0.102
18	2.00244706	74	428	1%	8%	1.736	82%	98%	0.120
19	2.39013932	44	458	1%	9%	2.323	91%	99%	0.189
20	6.872009867	38	467	1%	9%	2.489	100%	100%	0.210
	Total	4,982	5,080						**1.364**

Score: Name of the characteristic.

Obs: Number of bands, usually 20.

Stats: High end value of the band.

BADS: number of observations with Y = 1 (delinquent), with totals at the bottom.

GOODS: number of observations with Y = 0 (not delinquent), with totals at the bottom.

PROB. BADS: an estimate of P[i|1] = probability of the variable being in the i-th cell, given that Y=1.

PROB. GOODS: an estimate of P[i|0] = probability of the variable being in the i-th cell, given that Y=0.

WEIGHT PATTERN: weight of evidence for each attribute. For a numerical variable, the weight pattern should be monotone.

CUM. BADS: the cumulative probabilities obtained by summing the corresponding probability columns from the first to the last cell.

CUM. GOODS: the cumulative probabilities obtained by summing the corresponding probability columns from the first to the last cell.

INFORMATION VALUE: information value for each attribute. The information value is always nonnegative and it is also a measure of each characteristic's strength. The characteristic's information value is the total of the last column.

3.2.3 Monitoring Reports

In order to monitor a scorecard, a set of indicators / reports needs to be implemented.

The main purposes are to be able to detect when the scorecards need to be maintained and how to optimize the usage of the scorecards.

3.2.3.1 Portfolio Performance Report

Below four examples of portfolio performance reports are listed:

Table 31 – Example of Portfolio performance reports

Portfolio Performance reports	
Report's title	**Purpose**
Vintage analysis	To track default, churn, profit, bankruptcy, recovery. Also named Cohort analysis/ Dynamic delinquency report/ Delinquency trend report (Siddiqi, 2006).
Default rate development	Graphical display of the table above (Siddiqi, 2006).
Default rates by attributes	To calculate the default risk associated with each attribute of each characteristic. When the risk is significantly different for the different attributes, the attributes can be used as possible segments (Siddiqi, 2006).
Default rates by predefined segments	To select one specific characteristic that potentially seems discriminating with defined segments . If, for certain segments of the characteristic, the distribution of the probability of default are different, segmentation might be needed (Siddiqi, 2006).

3.2.3.2 Segmentation Performance Report

The following reports can be acquired:

Table 32 – Example of Segmentation performance reports

Segmentation performance reports	
Report's title	**Purpose**
Comparing improvements through segmentation	Based on the c-statistic or the Kolmogorov-Smirnov (K.S.)statistic (Siddiqi, 2006).
Gauging business benefit of segmentation	Based on performance indicators such as the approval rate and the expected bad rate (Siddiqi, 2006).

3.2.3.3 Performance Indicators

In order to evaluate the performance of a scorecard, the following statistics are calculated and analyzed on a regular basis (Leonard, 1995):

Table 33 – Example of Performance indicators

Performance indicators	
Report's title	**Purpose**
Acceptance rate	Approvals of the application volume (Leonard, 1995).
Adherence to expected score distributions	Adherence to expected score distributions (Leonard, 1995).
Frequency of reversing score decisions	Frequency of reversing score decisions (Leonard, 1995).
Frequency of overrides	Frequency of overrides (Leonard, 1995).
Bad rate	Number of accounts as a percentage of total number of accounts (Leonard, 1995).
Loan losses versus profitability	Loan losses versus profitability (Leonard, 1995).
Approval time	Time for approved application for credit (Leonard, 1995).
Approval accuracy	Approval accuracy (Leonard, 1995).
Authorization time	Time for authorizing a transaction (Leonard, 1995).
Override level	Override level (Leonard, 1995).
Average dollars	Average dollars spent per account (Leonard, 1995).
Interest revenue	Interest revenue per account (Leonard, 1995).
Utilisation rate	Current balance as a percentage of outstanding dollars (Leonard, 1995).
B2 delinquent to outstanding	Dollars 30 day delinquent balance as a percentage of outstanding dollars (Leonard, 1995).
Write-off dollars	Write-off dollars per account (Leonard, 1995).
Collection time	Time spent on collection per account (Leonard, 1995).

3.2.3.4 Financial Performance Indicators

There are other indicators, not purely statistics, which take also into account the cost of taking decisions:

Table 34 – Example of Financial Performance Report

Financial Performance indicators	
Report's title	**Purpose**
Misclassification Cost	Estimated cost = C(B/G) * P(B/G) * π1 + C(G/B) * P(G/B) * π0 Where C(B/G) = C(predicted bad / actually good) = Type 1 errors C(G/B) = C(predicted good / actually bad) = Type 2 errors P(B/G) = probabilities of type 1 errors P(G/B) = probabilities of type 2 errors. π1 are the prior probabilities of good π0 are the prior probabilities of bad (West, 2000).
Bayes Rule	To minimize the minimum expected misclassification cost.
Cost Ratio	Cost ratio = C(G/B) / C(B/G)= Type 2 error/ Type 1 error

3.2.3.5 Characteristic Reports

The following reports can be implemented:

Table 35 – Example of Characteristic Reports

Characteristic reports	
Report's title	**Purpose**
Characteristic analysis report	To track any change in the characteristic's distribution (Characteristics included and not included in the model) and the impact of it on the scorecard. An index sum(Actual%-Expected%)*Points calculated for each attribute: - "Expected%": the distribution on the development / training sample in % for each attribute. - "Actual%": the distribution on a current sample in % for each attribute (Siddiqi, 2006).
Scorecard Characteristic analysis report	To track any change in the characteristic's distribution and the impact of it on the scorecard (Siddiqi, 2006).
Characteristic report	Two elements: one table that tracks each characteristic included in the scorecard / monitoring report, a second one to evaluate the effects of a cut-off on the distribution of the portfolio over the different attributes or segments of each characteristic (Siddiqi, 2006).

3.2.3.6 Stability Reports

The following reports can be acquired:

Table 36 – Example of Stability Reports

Stability Reports	
Report's title	**Purpose**
Account quality	To display the distribution of the training sample across the score bands and is compared to the distribution of customers' samples coming after the development phase (Siddiqi, 2006).
System stability trend	Graphical display of the table above (Siddiqi, 2006).
System stability Report	Index= sum(Actual%-Expected%)*ln(Actual%/Expected%) calculated for each attribute. - "Expected%": the distribution on the development / training sample in % for each attribute. - "Actual%": the distribution on a current sample in % for each attribute. Results: - Less than 0.10: no significant change, the current sample is similar to the training sample. - 0.10 to 0.25: a change that needs to be clarified, one needs to investigate its source by analyzing the characteristic analysis report for instance to identify any shift in one of the variables that could explain the index's value. - 0.25 +: a significant change, it indicates a clear change between the current distribution and the training one in the score distribution. Also named Population stability report / Scorecard stability report (Siddiqi, 2006).

3.2.3.7 Delinquency Monitoring Reports

The following reports can be implemented:

Table 37 – Example of Monitoring Reports

Delinquency Monitoring Reports	
Report's title	**Purpose**
Scorecard accuracy	To assess if the risk is properly ordered amongst the different score bands, i.e. if the bad rate on the current sample is similar to the expected bad rate (Siddiqi, 2006).
Delinquency Migration report	To present the migration number and rate for each previous delinquency status to its new status (Siddiqi, 2006).
Delinquency report / Performance report	To present the delinquency rate and the loan loss rate for the different bands of the score and by various definition of delinquency: - Current - P60 and +: the customer has currently more than 45 days' delay - Current - P90 and +: the customer has currently more than 75 days' delay - Current - P120 and +: the customer has currently more than 105 days' delay - Worst - P60 and +: the customer has had more than 45 days' delay - Worst - P90 and +: the customer has had more than 75 days' delay - Worst - P120 and +: the customer has had more than 105 days' delay (Siddiqi, 2006).
Roll Rate Analysis	To follow the development of the portfolio taking a specific point in time a vintage or cohort, and reporting at a second point in time its development (Siddiqi, 2006).
Current versus worst delinquency comparison	To compare the worst delinquency status of the customers with their most current delinquency status (Siddiqi, 2006).
Roll rate across time	To present the number of accounts and the associated amount for each delinquency status for the different vintages (Siddiqi, 2006).
Approval rate by score-worst delinquency at bureau	To present for each score band how many customers have never been delinquent and the worst delinquency status that have reached the others, such as bankruptcy (Siddiqi, 2006).

3.2.3.8 Acceptance and Override Reports

Below two examples of acceptance and overrides reports are listed:

Table 38 – Example of Acceptance and Override Reports

Acceptance & override reports	
Report's title	**Purpose**
Override Report	To display the number of overrides, the number of low side (those that are accepted whereas they should have been rejected), and the number of high side (those that are rejected but should have been accepted). This has also to be documented by types of overrides (manually / automatically) and categories (Siddiqi, 2006).
Final score report	To display the number of applicants, the number accepted, the associated percentage (i.e. approval rate), the number of low side and high side overrides (Siddiqi, 2006).

3.2.3.9 Other Reports

The following reports can be acquired:

Table 39 – Example of other reports

Other reports	
Report's title	**Purpose**
Portfolio chronology log	Document where changes affecting the scorecard are stored and documented: changes of characteristics in the scorecard, changes in the credit lines / credit policy, changes in the cut-offs, changes in the marketing campaigns, changes of the product (e.g. the interest rate), … (Siddiqi, 2006).
Credit Line Strategy	Ex. of strategy based on two independent elements: the application score and the debt service ratio: - The application score gives the probability of default of the customer. - The debt service ratio gives indication of the ability of the customer to pay back based on his current debt situation; the ratio is the portion of his income already dedicated to debts (Siddiqi, 2006).
Tradeoff chart	To plot the following (Siddiqi, 2006): - Default rate and approval rate for each score band. - Default rate and profit rate for each score band. - Default rate and churn rate for each score band.

Chapter 4: Discussion on recent issues / improvements of credit scoring

The chapter 1, 2 and 3 are theoretical chapters introducing the reader to the topic of this thesis, the chapter 5 and 6 are more practical chapters based on results from real data. This chapter is a transitional chapter. It describes the different directions that this research could follow.

First, the author lists the major issues that one can encounter while using credit scoring. The author had to deal with most of those challenges for this research. In addition, from the literature review, practical difficulties with using scoring systems have been pointed out. Example of these include the definition of default, sample size especially when small samples, the treatment of missing values, outliers, inclusion of macroeconomic variables and the use of dynamic models for behavioral scoring,. One of the biggest concerns was reject inference. This refers to the fact that the population to whom credit was denied are invisible to the researcher. However, the bank that provided the data had an acceptance policy relatively tolerant and therefore, was barely subject, if at all, to problems of that kind.

Possible improvements to scorecards have been also notified by various researchers. This PhD thesis comes the following items: credit limit vs. score value, combination of in-house scores and credit bureau scores, developing behavioral scorecards, describe a complete credit scoring system, optimal credit policy. The reader is introduced to these different ideas.

In this chapter, the main questions that will be answered are:

- What are the commonly faced issues when implementing credit scoring both on the practical and technical side?
- What measures can be taken to improve scorecards?

4.1 Practical issues face with scoring systems

The author included this section to highlight that technical challenges are not the only issues that credit risk analysts have to deal with.

This section aims to raise some difficulties faced by credit risk analyst while presenting their figures to the management and trying to explain why credit scoring and extensively data mining as a whole have to face barriers between analysts and managers.

4.1.1 Issues with Statistics

For fulfilling a credit position, one needs a strong quantitative background which often leads to problem of communication with the management. According to Raeside and Walker (2001), the main causes of miscommunication between analyst and managers are the following:

- The term statistic is not understood. According to Rutgagi and Wolfe, statistics should be known as an application of the scientific method and as a problem solving method (Rutgagi and Wolfe, 1982).
- Techniques are not always known (at least in full) (Weil and Vardeman, 1992).
- Scientific approaches are not recognized in all cultures – countries and might be considered as suspicious.

- Senior managers do not use statistics and avoid using statistical information, preferring to rely more on their own “expert” judgment or bias.
- Statistics have been badly taught in business schools or degree courses.
- Statisticians have often over complicated the problem, the solution, or both.
- Statisticians are famous for being too negative and too inflexible.
- Many managers do not understand the statistical techniques and more training is needed (Dale et al., 1987).

4.1.2 Issues with Credit Scoring

According to Raeside and Walker (2001), the main challenges related to data mining and credit scoring are the following:

- Issues such as the direction of causality are often not well handled and false patterns and relationships can be generated (Chung and Grey, 2000). In credit scoring, the variables and the coefficients of the model might be contradictory. The analyst has to be careful while building the model.
- There is also a tendency to over react to non representative groups. In credit scoring, a model cannot be built without enough data. For example, a fraud attack will not give enough data to build a model and a sufficient lengthy observation period is needed.
- Data cleaning is one of the most time consuming tasks and if not correctly done, rises questions about subjective decision making. In credit scoring, data cleaning requires time.
- It is rather difficult to determine the efficacy and reliability of certain models while implementing them. To be considered as accurate, a scorecard should be compared with another score. Credit bureaux’ scores might be an alternative.
- The behaviour of the customers might change over time and therefore, modelling may be questionable, especially when needed in order to build a long term model. Behavioraul

scorecards must face this issue and thus, the model's validity and logic has to be above reproach.

- Neural networks are one of the techniques with the highest accuracy. However, neural networks are treated as a black box which makes this technique difficult to understand and to accept. This is one of the reasons why the analyst often prefers using logistic regression when modelling.
- Most statistical techniques are considered model-free and can only identify large effects (Jorgensen and Gentleman, 1998). Possible ways of avoiding this issue in credit scoring are segmenting the portfolio and building a specific scorecard for each.

This list of difficulties gives a reasonable indication of the challenges faced by modellers. However, for researchers, the main interest will be directed to technical issues faced, while implementing credit scoring.

4.2 Technical challenges with scoring systems

While dealing with credit scoring, the problems of interest for researchers include the following:

4.2.1 Definition of default

A default occurs when one party is not compliant with its financial commitments. Commonly, a defaulter is defined as such once the first missing payment occurs on any financial obligations, rated or un-rated. In most financial institutions, a default is a failure to make required debt payments by or at the stipulated time. According to the rating agency Standard & Poor's (2003), a debtor is considered as a defaulter when he cannot fulfil his contractual obligations and pay in due time.

The Basel Committee on Banking Supervision (2006) has defined a default as follows:
"A default is considered to have occurred with regard to a particular obligor when either or both of the two following events have taken place. The bank considers that the obligor is unlikely to pay its credit obligations to the banking group in full, without recourse by the bank to actions such as realising security (if held)..The obligor is past due more than 90 days on any material credit obligation to the banking group. Overdrafts will be considered as being past due once the customer has breached an advised limit or been advised of a limit smaller than current outstanding."

However, in the credit card industry a default is frequently defined as being more than 60 days past due, so the debtor has not fulfilled the terms of his contract and paid the minimum payment required after receiving three reminders (i.e. three consecutive months). In this thesis, this is the definition used.

4.2.2 Sample size

Another issue is the sample size: Credit scoring systems are frequently developed with an insufficiently large sample to achieve reliability in the assignment of point values.

Different samples were used to build the different models presented in this PhD thesis.

While selecting the training and testing samples, there were different possibilities. The main focus was placed on two of them in particular. The “50% vs. 50%” and the “80% vs. 20%” selections are some of the most used in the literature. Myers and Forgy (1963), Altman (1968), Meyer and Pifer (1970), Chatterjee & Barcun (1970), Orgler (1970), Apilado & al. (1974) and Eisenbeis (1977) use the “50% vs. 50%” whereas Fawcett & Provost (1997), Henley & Hand (1996) and Abdou et al. (2008) use the “80% vs. 20%”. Banasik et al. (2001) used in their paper a training sample including 70% of cases and a holdout sample including the 30% remaining.

Chan & al. (1997) and Chan & al. (1999) compare the effects of both selections. Chan & al. (1997) completed a full study dealing with distribution and partitions. They tested the 50:50, 33.3:66.6, 15:75 and 20:80 distributions. According to Chan et al. (1997), “50%:50% improves the accuracy for the all the learners under study”. A 50:50 distribution was found to give good results in the presence of skewed data. In another article, Chan & al. (1999) compared the following distributions: 50:50, 20:80, 30:70, 10:90, 1:99 and 1:999. In this paper, the authors concluded that the desired distribution depended on the given distribution.

For instance, if the given distribution is 20:80, the desired distribution is 50:50. If the given distribution is 10:90, the desired distribution is 30:70.

In this PhD thesis, the sampling selection used is the 50:50 distribution. The total number of observations, the total sample available to build the application scorecard, contains 4853 individuals. The training sample includes 2388 observations and the testing sample includes 2465 observations. The sample size is rather small compared to the number of records usually used in scorecard development which is about 10 000 records. The restrictions on data need to be considered in order to determine the best approach while working with restricted data.

According to Henley and Hand (1996), in practice, the proportion of bad risks in the full population will vary according to the credit product and will commonly be less than 20%. For that reasons, the authors restricted attention to the results obtained when the full population bad risk rate is assumed to be 20%. In the total sample for this thesis, 2449 individuals are considered “good” customers which means not delinquent. 2404 individuals are considered “bad” customers which means delinquent. A customer is considered delinquent if the customer does not pay the minimum payment required by the bank within 60 days.

For the behavioral scoring, there was no restriction on data as the models were built later on. The sampling was more complex and it is discussed in detail in 3.1.3.

4.2.3 Missing values

In this practical application on data, modelling an application scorecard was not an easy task as the data available for the applicants varied depending on the marketing campaigns they were coming from and also on the credit bureau data available.

In some marketing campaigns, the applicant would only give his name, date of birth, e-mail address and postal address. For others, the full questionnaire was filled. It means that when calculating the frequencies, several of the variables coming from the application had a high number of missing values.

For the credit bureaux' scores, three categories can be distinguished:

- Those that have a score.
- The filtered customers who received complaints in the past but which are solved now, the so-called Filtered Cat.1.
- The filtered customers who have received complaints and are still dealing with thm: they are rejected automatically, the so-called Filtered Cat.2.
- The ones without a score.

The two credit bureaux' scores are requested in the credit review process. Of course, not all individuals are found in the Credit Bureaux' registers. So, missing values posed difficulties.

For the following reason, using credit bureaux' data and the application data was rather complex. Ideally, all applicants should be asked to fill the questionnaire and the bank would only accept those identified by the credit bureaux.

Nevertheless, this PhD thesis will present a solution for dealing with such difficulties: segmentation.

For the behavioural scorecards, there was no specific problem.

4.2.4 Outliers

An outlier is a value that is separated or far from the majority of the data points. Those values are usually defined as 'extreme' or 'unlikely'.

Outliers can be detected automatically but also manually. Usually, a common approach is to look at the data using a simple histogram of the variable distribution or “box and whiskers” plot. Usually to identify an outlier, the easiest technique is to display the distribution of the variable. For example, if a variable follows a normal distribution, an outlier will be a highly deviant value at the right end tail or left end tail.

4.2.5 Credit Scoring techniques

After proceeding to a wide literature review and talked with professional of the credit industry, a clear statement is that nowadays, the two techniques the most recognized are neural networks for its high predictability and logistic regression for practical reasons (they easily understood and implemented). Both have their own advantages and disadvantages as was seen (Refer to Chapter 3 – 3.1.2 Comparison of the different techniques).

As West mentioned in his paper, both the mixture-of-experts and radial basis function NN models gave positive results. Amongst the other techniques, logistic regression appeared to be the most predictive (West, 2000). Ong et al. reported that ANN and logistic regression could be satisfactory substitutes to GP. The credit scoring accuracies of NN is reported as better than other statistical techniques such as DA and LR techniques (Lee & Chen, 2005). Yun et al. (2007) tested different techniques such as multivariate discriminant analysis, logistic regression, decision tree and neural network on real data provided by national commercial banks. They recommended using decision tree and neural networks to predict default on the past of credit customers.

Other references supporting NN are: Desai, Crook & Overstreet, 1996; Desai, Conway & Overstreet, 1997; Jensen, 1992; Lacher, Coats, Sharma, & Fant, 1995; Malhotra & Malhotra, 2003; Piramuthu, 1999; Sharda & Wilson, 1996; West, 2000; and Zhang, Hu, Patuwo, & Indro, 1999.

However, the concept of neural network is complex and opaque. So this technique is not widely used by credit bureaux or even private companies. Logistic regression, on the contrary, is commonly used in the credit industry.

4.2.6 Validation indicators

K.S. is commonly used in the United States to validate models whereas European countries tend to use the Gini coefficient. Fair Isaac uses the Information value criterion.

In simple words:

- The Kolmogorov-Smirnov statistic is the deviation between the cumulative distribution of goods and the cumulative distribution of bads.
- The Gini coefficient is also based on the cumulative distribution of goods and bads.
- The information value is obtained by multiplying the weights of evidence for each band/observation by the difference between the good percentage and the bad percentage.

There is no clear indication from the literature that one indicator is superior to the others. The decision to use one or another indicator is clearly influenced by cultural / statistical background / education.

4.2.7 Reject inference

'Reject inference' is the process of attempting to infer the true creditworthiness status of the rejected applicants (Hand. and Henley, 1993).

References concerning reject inference include the following authors: Hsia (1978), Reichert et al. (1983), Joanes (1993), Hand and Henley (1993, 1994, and 1997), Rosenberg and Gleit (1994), Thomas (2000), Banasik et al. (2003). "Reject inferences" is a topic that has been discussed for a long time and by many researchers.

Hsia (1978) describes the augmentation method while other approaches are suggested in Reichert, Cho and Wagner (1983) and Joanes (1993). In 1982, Capon listed different issues. While implementing scoring, the sample used to develop the scorecard has to be selected randomly from an historic applicant population. He explained that since a considerable percentage of applicants were historically denied credit, systems based only on a population of accepted applicants where there is a corresponding population of denied applicants must be biased. This is the so called reject inference effects. Hand and Henley (1993) provided a detailed study of the problem. They concluded that it cannot be overcome unless one can assume particular relationships between the distributions of the goods and the bads which hold for both the accepted and the rejected population. One way around it, suggested by Thomas (2000), is to accept everyone for a short period of time and to use that group as a sample.

Reject inference cannot work unless additional assumptions were made, such as assuming particular forms for the distributions of the good and bad risks. The only way to get a perfect classification and thus information about the good and the bad would be to study the reject region, in other words, it means accepting applicants who would normally be rejected. Nevertheless, it is only interesting to implement such a measure if the loss due to the increased number of delinquent customers is adequately compensated by the increased accuracy in classification.

According to Siddiqi (2006), if the approval rate is rather high, the reject inference will not be significant as the total portfolio will be similar to the total applicant portfolio.

Banasik et al. (2003) considered the scope for improving credit scoring models on the basis of deploying information about rejected applicants. This line of research, and in particular the data source, is rarely observed. In their study, applicants who would normally be rejected have been accepted in order to observe their repayment performance. They reported that there is a little improvement for the model accuracy in incorporating rejected applicants; they even qualified it as “modest”. They made the hypothesis that maybe sufficiently risky applicants have been accepted in the current process as almost no additional information could be gathered by including even the worst applicants (Banasik et al., 2003).

As the acceptance rate of the credit card company the data were coming from was extremely high and as explained above, the author has decided not to consider reject inferences within this PhD thesis.

4.2.8 Overfitting

Using stepwise logistic regression, the model is fitted to the training sample. At this point, major issues are that a model can suffer from either underfitting or overfitting. A model which is too simple can fail to detect the elements present in the training sample, causing the model to be underfitted. On the contrary, a model that is too complex could integer elements specifically applicable to the training sample causing noise and the model to be overfitted. It raised the risk of getting a model that is overfitting the data due to a noise in the training sample. Overfitting may happen while the training sample is not representing correctly the population, while some statistical irregularities might be found in the training sample or while the model built is too complex. In logistic regression as well as neural network and other methods, overfitting problems are frequent.

Applying the logistic regression, overfitting may result by the inclusion of variables statistically significant but in reality, that are actually just noise. This can happen while the model is too complex for the amount of data available. The model includes too many parameters. The model even if it is a false one will predict perfectly on the training sample if the model is complex enough compared to the amount of data available.

One clear indicator of the presence of “overfitting” is when the model is applied to the overall data or to the future data. Indeed, the model will not predict well future responses.

Before the modelling phase, the easiest solution to avoid overfitting is to divide the data into two samples: a training sample and a validation sample. The model is developed using the training sample. The bigger the training sample is, the more accurate the results are and the less the issue of “overfitting” will apply. In the case of this thesis, for the application scorecard, small samples are available. The issue will be to avoid adjusting to some specific random features present in the training sample, that in reality have no real significant values in predicting the outcome.

To avoid the “overfitting issue” while using logistic regression, different solutions are possible. One can stop the stepwise procedure while adding new variables is not improving the model significantly, i.e. “last step” method. One can use the Akaike Information Criterion (AIC) at each step and stop the stepwise procedure when the AIC is the lowest. One can also use the Bayesian Information Criterion (B.I.C.) instead of the Akaike Information Criterion. Applications of these two criteria have usually shown broad agreement in the conclusions reached, but occasional differences in the detailed ranking of models (Liddle, 2008).

Using the weights of evidence, numerical variables and attributes of categorical variables will be collapsed in order to improve their predictiveness. By grouping, overfitting will be reduced as a discrepancy in one attribute will be less present.

In this study, the method used will be the stepwise logistic regression combined with an evaluation based on the Weights of Evidence, Information Value and validation charts.

4.2.9 Judgemental interactions

In 1982, Capon listed a number of problems related to credit scoring. He mentioned that judgmental interactions will affect the accuracy of the scoring model. He listed three types of human interventions:

- Judgmental aggregation: the empirical requirement for credit scoring systems is violated when credit scorers attempt to overcome the reliability problem.
- Judgmental system constraints: to overcome the consequent problems of credit scoring personnel ignoring the system, developers impose constraints on point assignments a priori.

- Overriding: Overriding happens when a declined applicant calls to complain and, either on the basis of no information other than the protest or on the basis of some extra information, the decision is reversed and credit is awarded.

Ideally, manual interventions would not be allowed. However, in reality, it is difficult to exclude them.

4.2.10 Multicollinearity

Multicollinearity is another issue (Capon, 1982). This arises when the final point values assigned are far from being a true reflection of the discriminatory power of the single variable and are contaminated by a host of possible intercorrelations between the independent variables.

Usually, logistic regression will avoid facing this problem. Variables bringing the same information will be excluded automatically from the model. In addition, the fact that the model is built on a training sample and tested on a validation sample will also reduce the risk of undetected multicollinearity.

Another important element is data knowledge; familiarity with the business and the data generated is also one way to detect multicollinearity.

4.2.11 Histogram Error

One more issue listed by Capon (Capon, 1982) is the so-called Histogram Error. When continuous characteristics such as time are used, serious errors may be introduced to the scoring table by using a series of discrete categories rather than the underlying continuous characteristics.

In this thesis, which employs weights of evidence and information value, the author has tested every single continuous variable versus different discrete ones (resulting from transformation of the continuous one).

Age, for instance, was less predictive when transformed into a discrete variable. Nevertheless, the variable was not monotonic. In order to avoid any modelling issues further on, when confronted by the lack of stability, the author has used a log transformation to improve on the distribution curve of the variable. This solution has worked effectively and the variable has not lost any predictability power.

4.3 Possible improvements to scorecard

Some authors have suggested ways of improving traditional credit scoring models while dealing with loan failure.

4.3.1 Segmentation

To put in place a profitable system of credit risk management, the banking institution needs to identify the characteristics of segments of its portfolio in order to put in place the best approach for each segment. This segmentation will be based on the segment's quality, the cost and revenue[4] they will generate, and the future net earnings that they could bring.

Banasik et al. presented a two-stage scoring model in order to find out if the predictive accuracy of an application scorecard can be improved by estimating separate scoring models for applicants who are predicted to have high or low usage of the card (Banasik et al., 2001). The first model has for objective to predict the desired usage of a card. The second component includes in fact two scorecards, one for the applicants predicted to be high usage customers and one for the applicants predicted to be low usage customers; depending on the scorecards the credit limit will be different. They described their model as a two stage Heckman model considering that the usage factor is constrained by their credit limit.

After testing it, they concluded that their two-stage model was giving only marginal improvements over a traditional scoring model. Nevertheless, they could predict a greater percentage of bad payers for low users that for high users and a greater percentage of good payers for high users than for low users (Banasik et al., 2001).

[4] But the matrix of correlations between net earnings in each segment is also important from the standpoint of overall risk management.

Using logistic regression, Banasik (1996) compared a scorecard built on the full population with scorecards built on each subpopulation. He concluded that scorecards for subpopulations tend to reject fewer applicants than full population scorecard and that splitting on subpopulations is not worthwhile for all variable's splits. The author advised risk managers to ensure that the subpopulations are sufficiently different that the extra variance in the coefficients and that the difficulty in setting compatible cut-offs between the populations is more than compensated.

In this PhD thesis, the author had to deal with data constraints. Depending on the marketing campaigns the applicant was responding to, he did not have to provide the same data. One possible solution would have been imputation. However, this would have caused a loss of accuracy. Therefore, the author has decided to use segmentation even though this will add complexity to the underwriting process.

4.3.2 Combination of the two scores

Regarding the application scorecard, Zhu et al. (2001) presented a combination of two credit scores constructed using logistic regression. Their analysis shows that a combined score based on two consumer credit scores dominates the individual scores in terms of both sufficiency and Bayes profit. Even though the improvements made by this method are not outstanding, the authors concluded that in the actual context, credit companies would benefit even from such small improvements and that it could even represent a substantial competitive advantage (Zhu et al., 2001).

A combination of two scorecards (in-house and credit bureau) is tested in chapter 5. The conclusions resulting from the comparison of the combined model with the in-house application scorecard and the credit bureaux scorecard will be presented.

4.3.3 Profit modelling

Until now, most of the published papers focused on predicting if a loan would turn bad or not regardless of the profit losses generated while rejecting those applicants. Yasuhiro Sakai suggested that future research put more emphasis on the profit side and especially on how a credit company's profits are related to default (Sakai, 1998).

Another aspect that has not been discussed in depth is acceptance scoring related to profit modelling. The reasons are that it is complex to measure profit/loss, to get some clear decision rules regarding doubtful cases and fulfil the assumptions that are required for the profitability assessment. Nevertheless, no application on real data could be found. A concrete application would be informative and valuable.

In this thesis, the author used a profit ratio to identify the most profitable credit policy. However, profit modelling is clearly another area of research that the author could concentrate on in future research.

4.3.4 Confidence intervals in the prediction of credit risk models

Scores are used for taking business decisions and rarely, one considers the error associated with the score itself. Taking into consideration the error level is especially relevant knowing that across a score, the error level might vary.

Stirling and Robinson (2007) described a technique to derive optimal score bands to minimize the experimental and theoretical variation in predictions. They present a method to estimate confidence intervals for the different score points. From their application, they found that:

- Some errors may be large and can be carried over whenever a function of score is used in a calculation.

- Bootstrapping[5] is one method to generate hypothetical errors in score.

- The mechanism presented provides an optimised set of score bands for producing confidence error limits and using those bands is strongly recommended.

One interesting line of research would be to test two different credit policies, one without confidence intervals and one taking into consideration confidence intervals and measuring the improvements gained in predicting default. Confidence intervals width depends, among other things, on the confidence level. The author recommends testing confidence intervals with a 95% and a 99% confidence level.

4.3.5 Inclusion of macroeconomic variables

Stine and Lang (2007) studied space-time models for retail credit. They tested if including macroeconomic variables would improve the overall predictability of the model. The macroeconomic variables that they tested were:

- Monthly unemployment: data were provided by the Bureau of Labor Statistics, Local Area Unemployment Statistics (LAUS) and the department of Labor.

[5] "Bootstrapping is a well-known resampling method that may be used to assess properties (such as the standard error) of an inferred quantity or statistical estimator (Efron, 1979; Efron and Tibshirani, 1993). The process that generated the data is estimated by an approximating distribution from which samples may be drawn. Bootstrap datasets are then obtained from this distribution, and the statistical estimator is calculated for each. This induces a sampling distribution over the estimator, from which we may assess, for example, its variance amongst all of the bootstrap datasets."(Kirk & Stumpf, 2009)

- Annual median income, percentage in poverty: data were provided by Small Area Income & Poverty Estimates (SAIPE), US Census Bureau.

The question they wanted to answer was "Do local macroeconomic variables add value beyond usual bank information?". They concluded that the gain was small but significant and that these variables were stabilizing the model structure.

In the current economic environment, the inclusion of macroeconomic variables is becoming something crucial. It can help preventing over indebtedness and detecting early signals of financial distress. In future research, this extension will be considered.

4.3.6 Use of dynamic models for behavioral scoring

Please refer to Chapter 3 -3.1.1.5 Time varying Model for more details.

Thomas and So (2007) presented a comprehensive application of Markov decision process to optimize credit limit policies. The method presented would be worth testing with the data and scorecards of this thesis.

4.3.7 Credit Limit, Reissue period and promotions strategy

One topic that is also worth discussing is credit decisions, such as adjustment of the credit limit, reissue period, and promotions strategy. On this topic, there is no published evidence of quantitative methods in use and little theory: Only the Bierman-Hausman model (and its refinements) considers the credit limit, and no theory exists for the reissue period and promotional strategies (Bierman & Hausman, 1970).

The main topic of this thesis is credit underwriting and how to assign the appropriate line of credit to the appropriate customer.

4.3.8 Information Sharing

A model with poor performance will accept more bad applicants; the consequences on the financial side will be larger losses and thus, less profit. Blochlinger & Leippold suggested another way of improving the accuracy of credit scorecards. The more accurate a scorecard is, the lower the risk of adverse selection is and the higher the revenues for the bank are. The two researchers advised banks to share their information about customers and their in-house scores such as the increase of profit will compensate the cost of sharing their information with a competitor. However, they conceded that banks should be cautious about sharing their scoring details (Blochlinger & Leippold, 2006).

All the subjects described above are interesting subjects for future research. However, those covered various topics inferring at different stage of the scoring process. For the following reason, this PhD thesis will only cover some of those issues.

The purpose of a PhD thesis is to bring new material or to confirm a statement already presented by another author or on the opposite, to contradict a statement already published.

Chapter 5: Practical applications on real data from a credit card company in Germany

The chapter 5 and 6 are more practical chapters based on results coming from real data; chapter 5 is focusing on scorecards implementation and the chapter 6 on the practical applications of scorecards to optimize the bank performances. This chapter will be a key chapter in this PhD thesis as it focuses on applying scorecards techniques to a data set provided by a German bank.

As this PhD application focuses on the German credit card market, a brief introduction to the German economy is given as well as of the credit card market. The main economic indicators related to the credit card business are presented such as employment ratios and insolvency figures which are one of the major concerns for credit card companies. Within Germany, the credit card market is filled of competitors. The different credit card products and their particularities are listed. The author also gives some indications about the product where the data used for the practical application came from. The objective is that the reader understands the specificity of the product this thesis is focusing on compared to the rest of the market and that the reader gets a feeling of the consumers market that is targeted.

The data available, coming from an e-bank selling credit cards, are then detailed. The data available are shortly described and compared with the ones used in published papers. On the data quality side, the main issue with the data available is that different data were available depending on the channel the customer was coming from.

The reader is then introduced to the development process of scorecards. The following steps are described: the sampling, the variables optimization with the WOE and IV, the modelling through the logistic regression, the evaluation through the IV and gains chart. The results of the process for the application scorecards and behavioral scorecards are presented. The detailed equations are not shown but the main essence which is sufficient to understand the models. The three behavioral models which is something that has not been covered previously is something rather innovative. Additional research has been made to achieve an optimal application scoring process by combining application data with C.B. data. The idea was coming from a published paper but the authors did not apply the idea (Zhu et al., 2001). The ending process is a complete credit scoring solution.

In this chapter, the main questions that will be answered are:

- What are the main characteristics of the credit card market in Germany?
- What are the specific features of the product used for the application?
- What are the data available?
- Which sampling, selection and modelling techniques have been used?
- What are the results of the implementation for the application scorecard and the behavioral scorecard?

Once those questions answered, the following issues stated above will be answered:

- A combination of two scorecards (in-house and credit bureau):

The conclusions resulting from the comparison of the combined model with the in-house application scorecard and the credit bureaux scorecard will be presented.

- Developing behavioral scorecards:

Techniques for implementing behavioral scorecard have been described in the literature. This thesis presents several types of behavioral scorecards and compares those with the previous models mentioned above.

All those elements are key elements in the credit risk management process. Those tools will help the banking institution to minimize its losses in the credit granting process but also in the credit increases process.

5.1 The Credit Card market in Germany

In this section, the reader is introduced to the German economy as well as of the credit card market.

5.1.1 Key figures

“More card payments push market value” declares Euromonitor (Euromonitor International, 2006). Impressively, 120 million cards (Debit cards, Credit cards, Charge cards…) were taken into use in 2004 in Germany. The total transaction value generated by cards reached some EUR375 billion in 2004, up nearly 4% from 2003, including cash withdrawals (Euromonitor 2006).

Because of the increasing usage of cards for payments, the amount spent on sales and internet purchases between 2003 and 2004 with any kind of cards has jumped by 5% reaching EUR170 billion. By contrast, cash withdrawals faced a lower growth. Those new patterns in customer payment behavior are probably correlated assuming that customers substitute cash payments by cards payments (Euromonitor International, 2006).

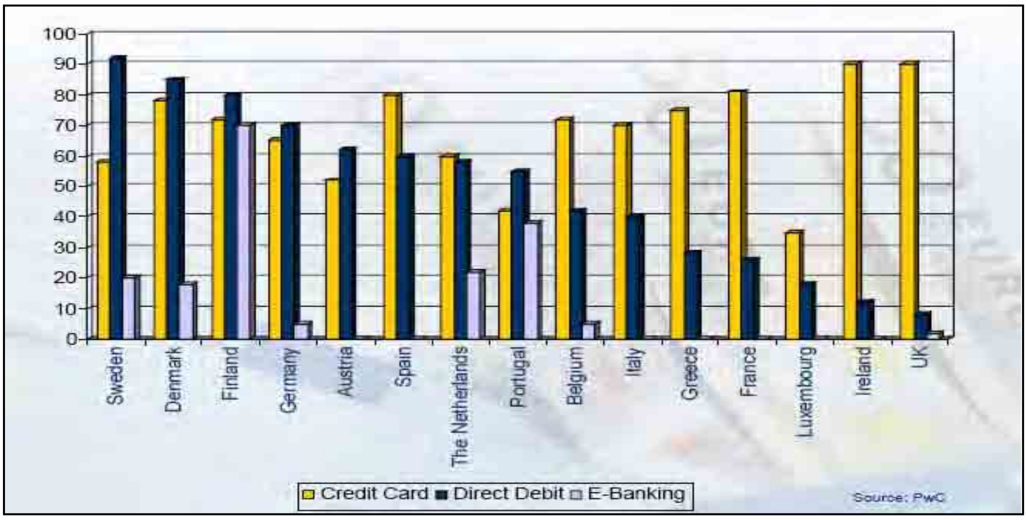
Payment by cards has been increasing in German market over the past few years. The market for Credit and Charge cards is forecasted to grow by 23.3% from 2004 to 2009, to reach a value of EUR 56,477 million (US$ 69,724 million) (Euromonitor International, 2006).

Because of the increasing usage of cards for payments, the amount spent on sales and internet purchases with any kind of card has jumped by 5% between 2003-2004 reaching EUR 170 billion. By contrast, cash withdrawals displayed lower growth. Those new patterns in customer payment behavior are probably correlated assuming that customers substitute cash payments by cards payments (Euromonitor International, 2006).

Focusing on the credit card business, a special feature of the German market is that the word “Kreditkarte” refers to both charge cards and credit cards. There is no clear distinction between the two whereas in English the different products have their own terms.

To distinguish the two products debit cards and credit cards, credit card banks have offered the opportunity to their customers to borrow a limited amount with their card. This service or credit is also a way to attract them. However, even if customers have the possibility to revolve, not all of them use this service. Nevertheless, in 2004, credit cards enjoyed a faster growth than charge cards (Euromonitor International, 2006).

Figure 3 – Transaction products in Europe

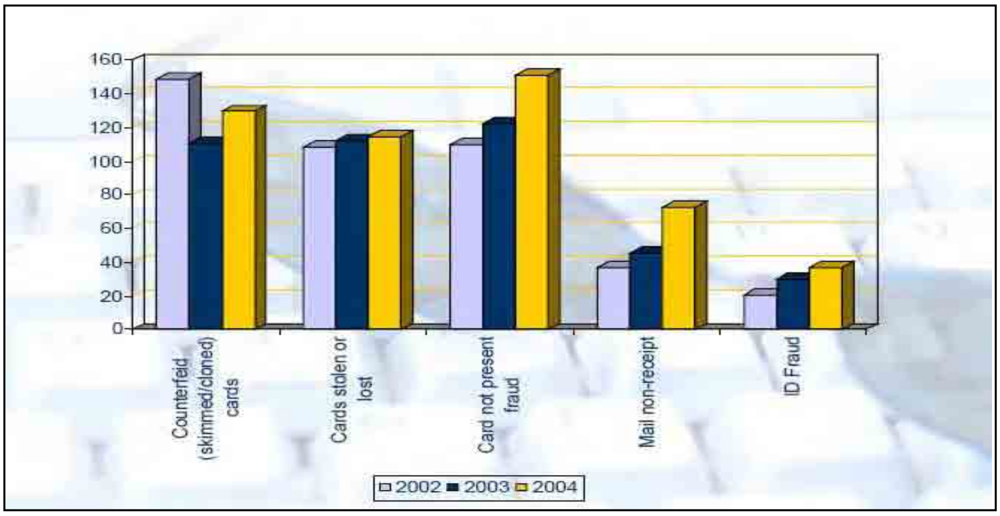


Source: PwC.[6]

In 2005, as shown in the graph above[7], the market for transaction products in Europe is split into two groups. In one group, credit card is leading the market. This group includes some of the following countries: Spain, Belgium, Italy, Greece etc. In two countries, credit cards have no competitors in terms of transaction product. Those two countries are the United Kingdom and Ireland. By contrast, another group of countries is using mostly debit cards; this is especially the case for Sweden. However for this group, the standard deviation between the two types of transaction product is less visible than for the other group. Focusing on Germany, the German market appears to be underserved on credit cards.

Figure 4 – Fraud distribution in Europe

[6] Cited in DRF EU Speech, Amsterdam, April 19, 2005 (Pago e-Transaction Services GmbH, 2005)
[7] All the graphs in this paper are used with permission of Pago eTransaction Services GmbH, October 30, 2007.



Source: DRF EU Speech, Amsterdam, April 19, 2005 (Pago e-Transaction Services GmbH, 2005)

Indeed, payment by cards has been increasing in German market over the past few years. The market for Credit and Charge cards is forecast to grow by 23.3% from 2004 to 2009, to reach a value of EUR 56,477 million (US$ 69,724 million) (Euromonitor International, 2006). With this extensive use of credit card, credit scoring appeared as a key element for controlling the credit risk of the financial institutions as well as information sharing between institutions.

The next section aims at presenting the credit information sharing context in Germany compared to other countries and how the customer credit data are obtained.

As this thesis focused on the credit card market, one key economic indicator is the insolvency trend. Indeed, Sullivan (1987) highlighted that debt burden as well as the unemployment rate were the two main factors that would affect default rates trend for a credit institution offering revolving products (Sullivan, 1987).

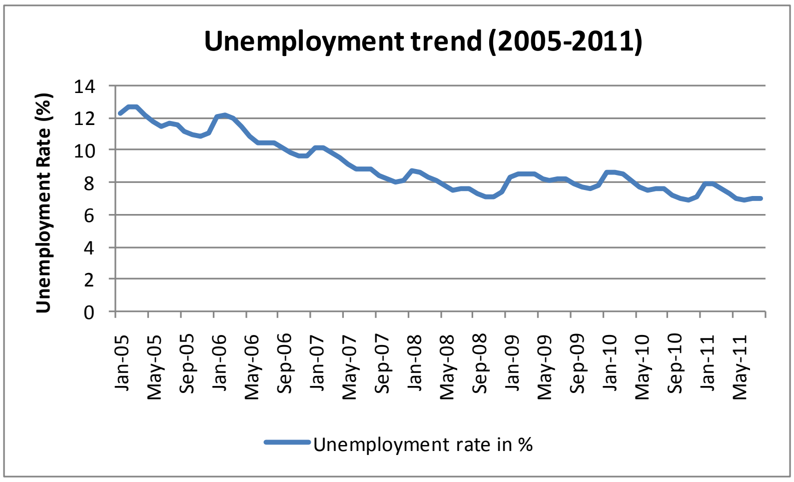
5.1.2 Economic Indicators

5.1.2.1 Unemployment

According to the Federal Statistical Office, the number of persons in employment whose place of employment was in Germany increased from 40.53 million end of 2008 to 41.02 in July 2011.

Unemployment has been on a declining trend since 2005, with occasional reveres, for example in the 2008 financial crisis. Since late 2010, the unemployment rate has stabilized at around 7.00%.

Figure 5 – Unemployment rate, original value, percent

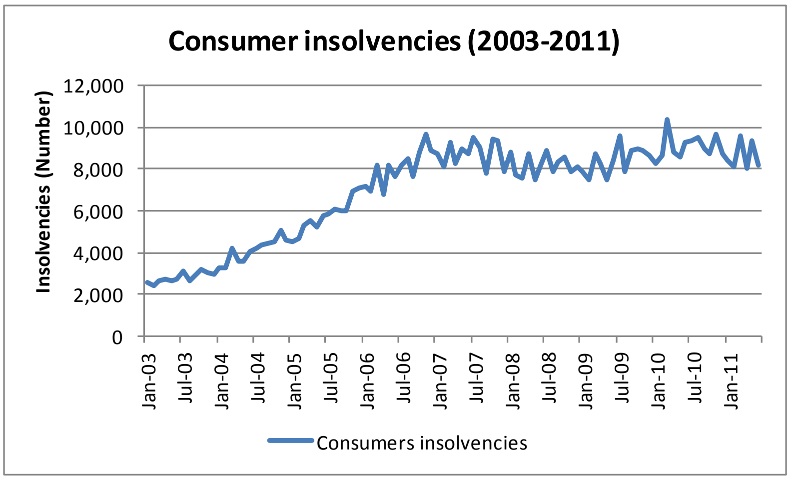


Source: Federal Statistical Office Germany (Federal Statistical Office Germany, 2011)

5.1.2.2 Overindebtedness

According to provisional results of the Federal Statistical Office, it is difficult to find proper data covering overindebtedness. From one source to the other, the number of households varies between three millions and much more. The problem is that the definitions of overindebtedness vary with the source. The most exact data come from the court as they have access to the official figures. One person is considered as insolvent when he has not been able to fulfill his contractual obligations, usually a payment, for a period long enough that his last resort is to be declared as insolvent. According to the Federal Office of Germany (2009), after the insolvency law of 1999, total of about 400 000 persons have decided to use the possibility to overcome their insolvency by means of a consumer insolvency procedure. The annual average figure for newly insolvent individuals is about 9000.

Figure 6 – Consumer Insolvencies, number



Source: Federal Statistical Office Germany (Federal Statistical Office Germany, 2011)

The current trend for insolvencies is stabilizing and with the current economic context, the probability of further declines is rather low. Depending on the cause of the insolvency and the time needed before the only solution is to be declared as insolvent, it might take several years before the case is sent to court. Therefore, the probability of a considerable increase is non negligible.

Table 40 – Bankruptcy in Germany

How to fill for bankruptcy in Germany:

"Private bankruptcy in Germany can be procedurally divided into four stages, which the honest debtor (§1 InsO[8]) has to go through one after another if he wants to be debt-free after approximately six years.
- Phase 1 describes the so-called attempt to reach an out-of-court agreement during which the debtor tries to come to an arrangement with his creditors about a debt clearing plan.
- If this attempt fails, i.e. if there is no agreement with the creditors, the debtor enters into phase 2: After a formal filing of an application by the debtor and an examination by the relevant insolvency court, the opening of the juridical debt clearing procedure is constituted. In this procedural stage again the parties try to agree on a debt clearing plan.
- If this attempt to reach an agreement fails, phase 3, the simplified insolvency procedure follows. A custodian appointed by court now distributes – if available – the debtor's personal estate equally on all creditors (equal treatment principle in accordance with §294 InsO). Thus the debtor loses all rights of disposal over his admitted assets.
- In the last phase 4, the procedure of discharge from remaining debts, the so-called period of good conduct ("Wohlverhaltensperiode") with six years of duration begins.

Among others the debtor is obligated, in the context of the obligation to pursue a gainful employment, to perform a reasonable job ("angemessene Arbeit") or, in case of unemployment, to try really hard to get a job; in addition, half of the legacies are to be transferred to custodians. With the end of the period of good conduct ("Wohlverhaltensperiode"), the discharge of remaining debts is announced by court and with it, the debtor is released from all of his debt."(Backert et al., 2007)

The court provides a list of all insolvency cases but does not detail the cause or does not analyze if there is a particular explanation for these instances of overindebtedness that could help in segmenting and / or explaining the event. Moreover, the court does not know all overindebted people, but only the ones already at the stage where judicial process has started.

According to the Statistiches Bundesamt (2009), the main cause of bankruptcy is a change in personal circumstances. Unemployment, a personal social event such as divorce and the failure of a self employed business are the main reasons explaining bankruptcy. In 2009, 28.5% of the persons that called debt advice centres indicated unemployment as the main cause for falling into bankruptcy.

Table 41 – Survey results on the main cause of overindebtedness

[8] Insolvenzordnung - German Insolvency Regulations

Main reason for overindebtedness in %		
Specification	**2008**	**2009**
Unemployment	28.2	28.5
Separation, divorce, death of partner	13.8	14
Sickness, addiction, accident	10.7	11.1
Inefficient housekeeping	9.4	10.2
Failed self-employment	9.3	8.6
Payment obligations due to guarantee, assumption of debt or joint liability	2.2	2.3
Failure of real-estate financing	4.1	4
Insufficient loan or guarantee advice	3.5	3
Others	18.8	18.4
Total	**100**	**100**

Source: Federal Statistical Office Germany (Federal Statistical Office Germany, 2009)

Backert, Brock, Lechner and Maischatz (2007) analysed the results of a survey conducted in 2007. Interestingly, when asked about the nature of their debts, 53.5% of the respondents answered first an overdrawn bank account. The second answer was debt combined with banks and credits in connection with car loans (21.9%) and thirdly, credit cards (12.4%). Backert et al. (2007) also identified the "lack of knowledge", "no experience in dealing with banks" and "loss of financial overview" as the main factors of over indebtedness. They also found that the lack of information on how to prevent bankruptcy is also one key factor explaining the problem of over indebtedness in Germany.

The German market appears as a typical example that illustrates how financial literacy / debt literacy and cost of ignorance are responsible of financial distress rather than credit card itself.

The next section aims at detailing the competition landscape and credit card products available in the German market.

5.1.3 Competitors and Products

In 2009, CreditCards.com has published a ranking of the top 10 credit card providers in the world.

Table 42 – List of the top 10 credit card issuers in the world

Credit Issued	Fast Facts	Figures	Comments
1	Bank of America	$194.70 billion (includes outstandings from US, UK, Ireland, Canada, Spain)	Bank of America was ranked No. 10 in the J.D. Power and Associates 2009 Credit Card Satisfaction Study Rankings.
2	Chase	$184.09 billion (US, Canada, France, Germany, Ireland, UK, Mexico and 22 other countries)	Chase is the largest issuer of general purpose credit cards in the US at 119.4 million cards in circulation.
3	Citi	$148.90 billion (US, Canada, Mexico, Brazil, Australia, Korea, Taiwan, Hong Kong and 34 other countries)	Citi is the second largest distributor of general purpose credit cards in the US at 92 million in circulation.
4	American Express	$105.00 billion (US, Canada, Australia, New Zealand, UK, Mexico, Italy, Japan, France, Germany, Hong Kong, Singapore and 34 other countries)	American Express was ranked No. 1 in credit card customer satisfaction by J.D. Power and Associates in September 2009.
5	Capital One	$68.78 billion (US, Canada, UK)	Capital One holds just 6.95 percent of the general purpose credit card market share in the US.
6	HSBC	$58.50 billion (US, UK, Mexico, Hong Kong, Turkey, Canada and 45 other countries)	Though HSBC is the sixth largest issuer of credit cards worldwide, the bank has just 2.05 percent of the general purpose credit card market in the US.
7	Discover	$49.60 billion (US)	Discover had 54.4 million cards in circulation at the end of 2009, down 6 percent from the year prior.
8	Wells Fargo	$36.40 billion (US, Canada)	Wells Fargo has 17.3 million credit cards in circulation in the United States.
9	Barclays	$32.60 billion (US, UK, Germany, South Africa and more than 30 other countries)	
10	Lloyds TSB/HBOS	$19.29 billion (UK)	Figures released by the Bank of England suggest that Britons owed a combined £61.5 billion ($94.51 billion) to credit card companies as of January 2010.

Sources: Parten (Parten, 2010) (through year-end 2009 and ranked by total worldwide outstandings)

Barclays, the 9th biggest credit card issuer states that Germany was the first country where they set up an office in outside the UK. Since the establishment in 1991, Barclays became one of the leading credit card issuers in Germany, issuing more than 1.4 million cards (Barclaycard, 2010).

Datamonitor (Datamonitor, 2010) stated that:

- the largest credit card issuer in Germany is Barclaycard Deutschland.
- the most popular credit card issuer in Germany in terms of frequency of use in 2008 is Deutsche Bank.
- the top players in terms of total value of transactions and average transaction value, respectively, in 2008 were Sparkassen and Advanzia Bank.

According to Datamonitor, the credit card market in Germany has been recently changing from a market controlled by major big players to a market dominated by many small players (Datamonitor, 2010). Datamonitor (2010) listed Barclaycard, the Sparkassen and Landesbank Berlin as the largest credit card issuers in the German credit market.

In 2011, Germany Trade and Invest mentioned that “With a balance sheet total of EUR 130 billion, the Landesbank Berlin AG is one of the leading savings banks and the largest credit card issuer in Germany”(Dutschmann, 2011). Nevertheless, “the leading German banks are generally reticent when it comes to credit cards. Deutscher Sparkassen- & Giroverband (DSGV), Bundesverband der Deutschen Volksbanken & Raiffeisenbanken (BVR), Commerzbank, Deutsche Bank and Postbank have tight lending criteria for credit cards, with this tightening further towards the end of the review period in response to the economic downturn. They are not generally interested in pushing for growth in credit card volume. Credit cards are mainly offered in order to complete their financial card portfolios. Consequently, while these banks accounted for a combined 81% share of debit card issuer volume in 2009 and 71% share of charge card issuer volume, they accounted for less than a 20% share of total credit card issuer volume. Domestic banks further lost share in card volume in 2009 over the previous year, due to imposing tighter lending criteria for credit cards" (Datamonitor, 2010).

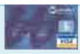
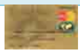
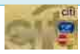
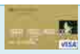
According to economywatch, the most prominent credit card providers competing in Germany are (economywatch, 2009): Deutsche Bank AG , Commerzbank AG, Dresdner Bank AG, DZ Bank AG, Landesbank Baden-Wurttemberg, KfW Bankengruppe, HVB Group, BayernLB, WestLB AG, Eurohypo AG, Citibank, Santander, Barclays.

Many credit card issuers do not release statistics, particularly about the number of credit cards they have in circulation. This is the true, for example, of Citibank. Lafferty Publications estimated that end of 2011, Citibank had about 1.34 million cards in circulation in Germany, Belgium, Spain, and Greece, becoming the eighth-largest card issuer for Europe (Wallace, 1998).

Nevertheless, labelled market share for volume is considered sensitive information, due to the competition climate and remains confidential for most banks.

Below, a list of the most well-known credit cards in Germany is presented. In the table, Interest rate, card fees and exchange rate fee are included. Of course, those credit cards do not have the exact same terms and conditions but it gives an idea of the values of those three parameters within the German market.

Table 43 – List of the major credit card competitors and products in Germany

Issuer, Product	Column1	Type	Yearly fee for the card	Fee on exchange rate	If partial payments accepted
1 KarstadtQuelle Bank AG, Karstadt MasterCard		Credit Card	-	1,50%	Yes, current interest rate of 16,90%
2 Bayerische Hypo- und Vereinsbank AG, HVB FlexibleCard (MasterCard)		Credit Card	-	1,75%	Yes, current interest rate of 13,16%
3 Barclaycard, Barclaycard for Students (MasterCard and VISA)		Credit Card	EUR 12,00 except 1st year	1,75%	Yes, current interest rate of 18,99% (ATM: 19,99%)
4 Santander Consumer Bank AG, Santander VISA Card		Credit Card	EUR 15,00 (except if the customer's bank account is within the bank)	1,50%	Yes, current interest rate of 13,98%
5 ING-DiBa AG, ING-DiBa Kreditkarte (MasterCard oder VISA)		Credit Card	EUR 21,00	1,25%	Yes, current interest rate of 10,90%
6 Barclaycard, Barclaycard New Visa		Credit Card	EUR 19,00, except 1st year and if the yearly turnover exceeds EUR 1.200	1,75%	Yes, current interest rate of 17,49% (ATM: 19,49%)
7 webmiles GmbH, webmiles VISA Card premium		Credit Card	EUR 14,00	1,00%	Yes, current interest rate of 16,77%
8 Santander Consumer Bank AG, Santander 1plus Card (VISA)		Credit Card	EUR 19,90 (except if during the 1st year, the bank account is opened within the bank)	1,50%	Yes, current interest rate of 13,98%
9 Volkswagen Bank direct, Volkswagen VISA Card		Credit Card	EUR 20,00 (Reimbursed depending on the yearly turnover)	1,50%	Yes, current interest rate of 14,71%
10 Barclaycard, Barclaycard Green		Credit Card	EUR 19,00, except 1st year	1,75%	Yes, current interest rate of 17,49% (ATM: 19,49%)
11 Citibank Privatkunden AG & Co. KGaA, Citibank MasterCard Student (oder als VISA Card)		Credit Card	EUR 15,00, except 1st year and card ordered on-line	1,65% in addition of 2,00%	Yes, current interest rate of 15,63%
12 Deutsche Postbank AG, Postbank Kreditkarte (MC or VISA)		Credit Card	EUR 22,00, except 1st year and card ordered on-line: EUR 15,00 (Reimboursed if the bank account is opened within the bank)	1,85%	Yes, current interest rate of 15,90%(Interests start to be calculated when the statement is received)
13 PAYBACK Rabattverein e.V., PAYBACK Premium (VISA)		Credit Card	EUR 25,00	1,50%	Yes, current interest rate of 13,13%
14 Citibank Privatkunden AG & Co. KGaA, Citi Cash Back Card		Credit Card	EUR 25,00	1,65% in addition of 2,00%	Yes, current interest rate of 12,45%
15 Citibank Privatkunden AG & Co. KGaA, Citibank MasterCard Plus (oder als VISA Card)		Credit Card	EUR 20,00	1,65% in addition of 2,00%	Yes, current interest rate of 15,63%
16 Deutsche Bank Privat- und Geschäftskunden AG, Deutsche Bank Kreditkarte (MC or VISA)		Charge Card	EUR 30,00	1,75%	-
17 Bank 1 Saar Direkt, Bank1Saar Card Direkt (MasterCard oder VISA)		Credit Card	yearly turnover < EUR 1.999: EUR 30,00, EUR 2.000 - 3.999: EUR 20,00, EUR 4.000 - 5.999: EUR 10,00, free if turnover> EUR 6.000 and the bank account is opened in the 1st year	1,50%	Yes, current interest rate of 13,75%
18 Barclaycard, Barclaycard New Double (MasterCard und VISA)		Credit Card	EUR 35,00, except 1st year	1,75%	Yes, current interest rate of 14,49% (9,99% if balance>EUR 500,00 and 16,49% for ATM)
19 American Express International Inc., American Express Blue Card		Charge Card	EUR 35,00, except 1st year and if the yearly turnover exceeds EUR 3.500	2,00%	-
20 Santander Consumer Bank AG, VISA Classic Karte		Credit Card	EUR 38,00, in the 1st year: EUR 28,50	1,50%	Yes, current interest rate of 13,77%
21 Landesbank Berlin AG, LBB-Kreditkarten-Doppel (MasterCard und VISA)		Credit Card	EUR 44,00	1,00%	Yes, current interest rate of 16,77%
22 Barclaycard, Barclaycard Gold Visa		Credit Card	EUR 49,00, except 1st year and if the yearly turnover exceeds EUR 3.000	1,75%	Yes, current interest rate of 16,49%
23 Santander Consumer Bank AG, Santander TravelCard (MasterCard)		Credit Card	EUR 48,00	1,50%	Yes, current interest rate of 10,91%
24 Santander Consumer Bank AG, Santander Classic Doppel (MasterCard und VISA)		Credit Card	yearly turnover < EUR 7.499: EUR 90,00, EUR 7.500 - 12.499: EUR 45,00, Free if > EUR 12.499	1,50%	Yes, current interest rate of 13,77%
25 Deutsche Postbank AG, Postbank VISA Card Gold		Credit Card	EUR 49,00, in the 1st year: EUR 29,00 if the bank account is opened within the bank	1,85%	Yes, current interest rate of 15,90% (Interests start to be calculated when the statement is received)
26 Bank 1 Saar Direkt, Bank1Saar MasterCard Gold		Credit Card	EUR 65,00	1,50%	Yes, current interest rate of 13,75%
27 comdirect bank AG, comdirect American Express Gold Card		Charge Card	EUR 75,00, except 1st year	2,00%	-
28 Citibank Privatkunden AG & Co. KGaA, Citibank MasterCard Gold (oder als VISA Card)		Credit Card	EUR 66,00	1,65% in addition of 2,00%	Yes, current interest rate of 15,63%
29 Bank 1 Saar Direkt, Bank1Saar VISA Gold		Credit Card	EUR 65,00	1,50%	Yes, current interest rate of 13,75%
30 American Express International Inc., American Express Card		Charge Card	EUR 55,00	2,00%	-
31 Santander Consumer Bank AG, VISA Gold Karte		Credit Card	yearly turnover < EUR 7.499: EUR 90,00, EUR 7.500 - 12.499: EUR 45,00, Free if > EUR 12.499	1,50%	Yes, current interest rate of 10,81%
32 American Express International Inc., American Express Aurum Card		Credit Card	EUR 75,00, except if the annual loan balance exceeds EUR 5.000	2,00%	-
33 Santander Consumer Bank AG, Santander Gold Doppel (MasterCard und VISA)		Credit Card	yearly turnover < EUR 7.499: EUR 90,00, EUR 7.500 - 12.499: EUR 45,00, Free if > EUR 12.499	1,50%	Yes, current interest rate of 10,81%

Source: Modern-banking (Modern-banking, 2009)

All credit cards companies try to offer what they claims to be a most competitive product, in order to attract new customers. Depending on the product offered, the services associated with the card may be different. Interest rate, card fees, exchange rate fee, late payment fee, credit limit, terms and conditions etc., are elements that can vary from one bank to another, from one product to another, and from one customer to another. Based on the 2009 figures presented, the interest rate fluctuates between 10.81% and 18.99%. The annual fee for a card can be zero or reach as high as EUR75. The Karstadt Mastercard is the product the closest to the one that illustrates this PhD thesis. This card is free and the interest rate is 16.90%.

5.1.4 The German market vs. European / Worldwide markets

According to Datamonitor (2010), “the payment card market in Germany is well-developed, but cards are not the preferred electronic method for consumers due to the popularity of credit transfers for high-value purchases. German consumers are uncomfortable with using revolving credit cards, and as a result these products are not especially popular”.

The author sought to verify this fact, by investigating the number of cards, both debit and credit cards, in circulation in the major powers of the world and to compare it with the German market. Based on the table below, it appears that regarding financial cards (credit cards and debit cards), the world is split in two: the countries mainly using credit cards and those mainly using debit cards.

North American countries are not surprisingly showing a strong preference for credit cards versus debit cards. Some of the most powerful Asian countries like Japan and South Korea show the same pattern. What is surprising is that Israel is exclusively relying on credit cards with 97% of their cards in circulation being credit card. Mexico is the 2nd country which relies strongly on credit cards.

Regarding debit cards, China and Germany are the two countries that relies the most on debit cards followed by Russia, Vietnam and India. The majority of the countries show a preference for debit cards. In Europe, the four main powers show slightly different degree of preferences for debit cards. While Germany shows a strong preference, the United Kingdom is the closest to the North American model with a moderated preference. Spain and France show a growing share of credit cards.

Another interesting element is the number of credit and debit cards per inhabitant. Some countries appeared to be clearly saturated like Japan, the United States, Canada and South Korea whereas others like India and Vietnam present business opportunities. In Europe, Germany and Spain have the lowest number of cards per inhabitant.

In addition, it is worthwhile noting that Germany is well–known for being a “Cash payer” country. Germans have a strong preference for cash versus other payment devices as shown in the survey published by the Deutsche Bundesbank (Hoffman et al., 2009).

Table 44 – Credit and Debit cards statistics in the world

Country	Debit Card (in Million)	Share of DC (%)	Credit Card (in Million)	Share of CC (%)	Population	Nber of cards/Hab
Australia	36	69%	16	31%	20.1	2.6
Brazil	233	55%	191	45%	186.1	2.3
Canada	37	34%	72	66%	32.8	3.3
China	1800	96%	72	4%	1306	1.4
France	78	70%	34	30%	61.4	1.8
Germany	91	96%	4	4%	82.4	1.2
India	130	84%	24	16%	1080.3	0.1
Indonesia	39	80%	10	20%	242	0.2
Israel	0.16	3%	6	97%	6.3	1.0
Japan	427	55%	346	45%	127.4	6.1
Mexico	12	32%	26	68%	106.2	0.4
The Philippines	33	80%	8	20%	93.9	0.4
Russia	119	92%	10	8%	143.4	0.9
Saudi Arabia	22	88%	3	12%	26.4	0.9
South Korea	66	41%	96	59%	48.4	3.3
Spain	31	63%	18	37%	43.2	1.1
Thailand	29	67%	14	33%	65.4	0.7
Turkey	63	58%	45	42%	69.7	1.5
United Kingdom	80	57%	60.7	43%	60.4	2.3
United States	488	42%	686	58%	295.7	4.0
Venezuela	12	67%	6	33%	25.4	0.7
Vietnam	15	88%	2	12%	83.5	0.2

Source: CreditCards.com (CreditCards.com, 2010), CIA World Factbook millesime 2005 (CIA World Factbook millesime 2005, 2005)

Based on this review, it appears that there are still opportunities for new credit card companies with competitive advantages in Germany.

5.1.5 Specific features of this thesis

After reviewing the different major players in Germany and located the German credit card business compared to other countries, this section aims at describing the context of this application.

In the credit card business, the portfolio that will attract a bank will depend on the product sold and its specifics. The bank that provided the data for this thesis follows the traditional definition of a bank as presented in Chapter 1. The bank is lending by offering revolving credit card and borrowing by offering deposits to their customers.

The credit card product offered is a revolving credit card with the following features:

- No annual fees:
- Revolving facilities: The client has to repay any amount between the minimum amount and the full balance. If the client is not paying back the full balance at once, interests will start to be calculated on the remaining balance.

Interest rate: 16.9%

Late payment fees: >EUR 10

- Speed: The bank is connected to one of the two largest payment networks.
- Application process: The application is made online and no specific documents are requested.
- Customer service: The bank offers a 24 hour customer service. In addition, the customer can access his or her account information such as invoices, transactions, payment activities as well as marketing campaigns online via an online portal.
- Travel insurance: All travels purchased with the credit card will benefit from an option for travel insurance.
- Safety: The credit card includes EMV (chip on the card) and MasterCard SecureCode.
- Reputation: The bank is regulated by the local authorities as well as subject to regular internal and external audits.

The second main product offered by the bank is deposit. Deposits allow the bank to fund the credit card business as well as having liquidity reserves.

Product specificities include: (a) monthly interest calculation and (b) variable interest rate.

Clients might have both products. However, as a whole, the customer basis of the two segments is significantly different.

Other specific characteristic worth mentioning are related to the credit underwriting process. The credit risk management solution presented in this research aimed at maximizing the profit of the bank that provided the data.

The credit granting process has the following features:

1- The bank has an acceptance rate which is extremely high (type 2 errors, customer rejected but that were genuine, and true negative do not exist; type 1 errors, customer approved but that defaulted, and true positive are the only categories this bank is dealing with),

2- The bank does not use credit scoring, but only legal requirements for rejection purposes.

3- The credit lines are granted based on the credit risk profile of the applicants and thus, their ability to pay back. Initial credit lines' range is far lower than in traditional banks.

This type of lending could be assimilated to subprime lending if the third feature above was not in force. Indeed, without the third characteristic and considering the fact that the interest rate applied by the bank is the maximum level of interest authorized in the country, the bank would be lending credit to clients with high risk profile with low credit bureaus scores.

As explained previously, transactors / convenience users are not relying on interest rate. Therefore, those customers would apply anyway for the product. However, revolvers are concerned by the level of interest. The bank was granting credit to customers that would normally not be eligible for credit in any traditional banks. Even if those customers were aware of the level of interest, the bank would be for them the bank of the last resort.

However, the fact that the bank assigned the lines based on the credit risk profiles and that the range of the lines was starting from a credit limit of x EUR (x being on insignificant amount of money for the bank, and even a normal individual and far below any credit line offered in traditional banks), the bank was making sure most clients would be able to pay back. The credit lines' increase process that will be described in the next section is also ensuring the bank that loans would not be increased to clients showing weak payment behaviour.

The next section will aim at describing the data that was available at the bank and the models implemented to control the credit risk exposure of the bank.

5.2 Presentation of the data

This section presents the data, i.e. which elements were available and the data quality of those elements.

Typical question in the literature to be answered in the development of a scorecard are:

- o Which characteristics are to be used in the scoring model as variables that can discriminate between a ‘good’ loan and a ‘bad’ loan?
- o How to obtain the score for each characteristic? (Steenackers & Goovaerts, 1989)

Those two answers will be answered in the following sub-sections.

5.2.1 Data available

In this sub-section, the author has reviewed which elements other researchers were using in their credit scoring application. Comparing the researchers’ selection, the data available for this research includes similar information. The detailed description of those elements is presented in the next sub-section.

5.2.1.1 Literature review

The first part of this section reviews the application data used in articles that were dealing with loans, credit cards and accounts.

Table 45 - Reference table for the list of variables resulting from the literature review

Nber	Authors
1	Abdou et al. 2008
2	Apilado et al. 1974
3	Banasik, 1996
4	Banasik et al. 2001
5	Banasik et al. 2003
6	Berkowitz& Hynes, 1999
7	Boggess, 1967
8	Boyes et al. 1989
9	Capon, 1982
10	Carrow & Staten, 1999

Nber	Authors
11	Chatterjee & Barcun, 1970
12	Crook, 1996
13	Crook et al. 1992
14	Crook, 2001
15	Desai et al. 1996
16	Hand & Henley, 1997
17	Hsia, 1978
18	Japelli, 1990
19	Lee & Chen, 2005
20	Lovie, 1986

Nber	Authors
21	Malhotra & Malhotra, 2003
22	Myers & Forgy, 1963
23	Ong et al. 2005
24	Reichert et al. 1983
25	Rosenberg, 1994
26	Showers & Chakrin, 1981
27	Smith, 1964
28	Srinivasan & Kim, 1987
29	Steenackers & Goovaerts, 1989
30	Stepanova & Thomas, 2002

Nber	Authors
31	Stepanova & Thomas, 2001
32	Thomas et al. 2001
33	Volker, 1983
34	West, 2000
35	Wiginton, 1980

Table 46 - The list of variables resulting from the literature review

Literature Review: Application fields																																				
1: filed in the application 0: not included	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	Total
Age	1	1	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	1	1	1	0	0	1	0	1	1	1	1	1	1	0	26
Sex	1	1	0	0	0	1	0	0	0	1	0	1	0	1	0	0	0	1	1	0	0	0	1	0	0	0	1	0	1	0	1	0	1	1	0	13
Marital Status	1	1	1	1	0	1	1	1	0	1	1	1	0	1	0	1	0	0	1	1	0	1	1	0	0	0	1	0	1	1	1	1	1	1	0	22
Living Status	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	0	1	0	1	1	1	0	0	1	1	24
Income	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	0	0	1	0	27
Spouse-family income	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	5
Dependents-Children nber	0	1	1	1	1	0	1	1	1	0	0	1	1	1	1	0	0	1	0	0	0	1	0	0	1	0	1	0	1	1	1	0	1	0	1	20
Time at present address	0	0	1	1	1	0	1	1	1	0	0	0	1	1	1	1	1	1	1	0	1	1	0	0	1	1	1	0	1	1	1	0	0	1	1	23
Time with employer - previous	0	1	0	1	0	0	0	1	1	0	1	1	1	0	1	1	0	1	0	0	0	1	0	0	1	0	1	0	1	1	1	0	0	1	1	18
Telephone	1	0	0	1	1	0	1	0	1	0	1	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	1	0	1	1	0	1	0	13
Auto information	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	1	0	0	1	7
Debt	0	0	0	0	0	1	0	0	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	11
Race	0	0	0	0	0	1	0	1	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5
CC and Other cards	0	0	1	0	0	0	0	1	1	1	0	1	1	0	1	1	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	11
Employment (title, class, place…)	1	0	1	1	0	0	0	1	1	0	1	1	1	1	0	1	0	1	1	1	0	1	1	1	1	1	1	0	1	1	0	1	1	1	1	24
Location	0	0	0	0	1	0	0	0	1	0	1	1	1	0	0	1	0	1	0	1	0	1	0	1	0	0	1	0	1	0	0	0	1	0	0	13
Education	1	0	0	0	0	0	0	1	0	1	0	1	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6
Age difference between man/wife	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2
Location of relatives	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2
Bank accounts	0	1	1	1	1	0	0	1	1	0	0	1	1	0	1	1	1	0	0	0	0	1	1	0	0	1	1	0	0	0	0	0	0	1	0	16
Credit reference	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	4
Other reference	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3
CB information	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	0	1	0	0	1	1	1	1	1	0	0	0	1	0	0	0	0	1	0	11
Inquiries	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	4
Payments - outgoings	1	1	1	0	0	0	0	1	1	0	0	0	1	0	1	0	0	0	0	1	1	1	0	1	0	0	1	0	1	1	1	0	0	0	0	14
Purpose of loan	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	1	0	0	0	1	0	0	1	1	1	0	1	0	9
Years at bank	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	4
Other loans	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	1	0	0	0	0	1	0	6
Financial company reference	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
Electoral role	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	2
Wealth	0	0	0	0	0	1	0	0	0	0	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	7
Insurance	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	3
Term of loan	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	1	1	0	0	0	5
Trade Union	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2
Down payment	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	2
Amount of loan	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	1	0	0	1	0	7
Account opening	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	3
Account closing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	2
Loan type	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	2
Nationality	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	2
Bank reference	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3

From this review, fields used by credit scoring researchers differ depending on the credit institution providing the data. Nevertheless, socio-demographic fields such as income, age, marital status, living status, employment status, number of dependants (children) or time at present address are often mentioned. Detailed bank information, electoral information, trade unions information, nationality and certain references are fields not commonly used in application forms.

This review suggests that fields such as age for instance are highly predictive. Date of birth has the advantage of being a fixed element and is usually a highly predictive field. It is possible to assume that the reason why certain fields are coming recurrently in the application forms is that it has a high explanatory power while not fulfilling contractual obligations. Indeed, the top 12 variables are often used in scorecard development whereas some other fields mentioned in this review will be predictive or not depending on the product the application is for.

5.2.1.2 The application data

In this thesis, the data were supplied by a bank which must remain anonymous. Data were available on 28 socio-demographic and economic variables.

When an applicant fills in the information, he has to answer the following:

- Gender: the applicant has to select between male or female.
- Date of birth: he has to fill his date of birth. From this variable, the age when he applied will be calculated.
- Name and Last name: this information is not used for the scorecard.
- Address, city and postal code: he has to give his complete address. From those elements, two variables will be extracted one for the city and one for the area.

- E-mail address: The e-mail domain and e-mail provider will be used as information in the modelling process. Binary variables will be extracted for e-mail domain such as .de, .com, .info... and for e-mail providers such as hotmail, yahoo, webmail...

At this stage, some additional information can be gathered such as:

- Creation date: The date when the customer applied will be stored and will be used for calculating the age of the applicant. The time when the customer applied will also be extracted.
- Marketing campaigns: via which channels the applicant as applied to the bank web pages.
- B2B: The applicant can also belong to a specific business channel such as business to business.
- Number of applications: The bank can also find how many times an applicant has applied to get a card.

Other information will be asked to the customer. However, it is not mandatory to fill this in. The questions are related to the following information:

- Mobile phone and phone: the question is opened.
- Labour market status: some options are given to the applicants such as employed, unemployed, self-employed, retired, student, public agent…
- The estimated income: it is the yearly gross income of the applicant.
- The employer: it is an optional question so only a few applicants answer this question.
- The number of credit cards and which ones: the applicant will provide the number of credit cards he owns. From this question, some binary variables will be created for the different credit cards brands such as Visa, MasterCard, Amex...

- Debts: the applicant can choose between 0, 0-10000, 10000-100000 and 100000+.
- Living status: the options are owner, renter, living with parents...
- Family status: The applicant will inform the bank if he is married, divorced, single...
- Change of civil status: the applicant will inform the bank if he changed of civil status within the 12 last months.

The applicant will also sign a clause allowing the bank to get access to credit bureaux data. The bank is using two credit bureaux.

The first one provides the following information: a score value, number of court files, number of collection files, amount on the collection files, number of directory files, number of researched files, number of application files, number of accounts, total amount on accounts, number of removals. The bank has no information on how the score values are calculated as the credit bureaux keep their scorecard secret. All the information provided by the credit bureau was used to build the models.

The second credit bureau also provides the same information. The main advantage of the second credit bureau is that their portfolio is the biggest of Germany; therefore more applicants are found and identified via this credit bureau. The quality of their scorecard is also higher as their scorecard is built on large data.

For all scorecards presented in this thesis, the selection procedure was random and based on account number. The samples were selected from those who applied for and were granted the bank’s credit card during the period 2006 to 2008 and who were recruited by the bank.

The reason why binary variables have been extracted from some variables is to make them more predictive. Banasik, in 1996, presented two methods when only a small number of characteristics are available. First, the attributes of the categorical variables are given the values of their weight of evidence. This approach can also be applied to continuous variables since the default risk is not monotonic with most continuous variables. He concluded that splitting such variables into a number of ranges and using this transformation is more likely to give good predictive scorecards (Banasik, 1996).
A similar approach to weights of evidence or simpler transformations is to use binary dummy variables for each range.

In the chapters to follow, both techniques will be used.

5.2.1.3 The behavioral data

Data available at the application stage is rather limited. However, once the customer starts to use the card, the analyst gets access to much more information, i.e. behavioral information. The behavioral data can be split in two groups: transaction information and billing information.

Transaction information will tell where the customer is spending his money, the country, the shop, the frequency, the amount spent. Based on a payment network classifying codes, the transactions belonging to the same sub category or category were collapsed together in order to get the number of time and the amount spent on that specific type of transactions.

The different categories are: Airlines, automobile / vehicle rentals, amusement and entertainment, automobiles and vehicles, business services, clothing stores, contracted service, government services, hotels and motels, mail order / telephone order providers, miscellaneous stores, personal service providers, professional services and membership organizations, repair services, retail stores, service providers, transportation, United-Kingdom, Utilities, Wholesale Distributors and Manufacturers...

The bank can also identify in which geographical area the transactions took place.
Please refer to the appendix for more details.

Additional variables will be extracted from the transaction file such as: Number of ATM, Number of Purchases, Amount spent on ATM, Amount spent on Purchases, Cash usage vs. ATM usage.

Billing information will tell how much the customer is spending, how much he is paying back, how many times he has been in delay, if he is paying interest...

From the data available, the following variables will be created:
Average utilization, Closing Balance per invoice, Max utilization, Min utilization, Max last payment, Number of months with less 10% usage, Number of months with more 10% usage, Number of months with more 20% usage, Number of months with more 30% usage, Number of months with more 40% usage, Number of months with more 50% usage, Number of months with more 60% usage, Number of months with more 70% usage, Number of months with more 80% usage, Number of months with more 90% usage, Number of months with more 100% usage, Number of months with interest, Number of months with overlimit cat1 (Highly overlimit), Number of months with overlimit cat.2 (Lowly overlimit), Number of months with overlimit cat1 or cat2, Number of months with positive Balance, Number of months with P60, Number of months with P30, Number of months with P0, Number of

months with payment indicator 1 (Paying full), Number of months with payment indicator 2 (Paying partially), Number of months with payment indicator 3 (Paying less than minimum or not paying), Average Min Payment, Indicator for payment behavior, Average utilization vs. Lowest utilization, Average utilization vs. Highest utilization, First credit limit, Min number of customers using the same account, Max number of customers using the same account, Number of accounts used, Number of credit limits, Number of late fees.

Those variables will be created both for the three first months of the observation period and the six months of the observation period.

All the variables listed above are examples; it doesn't pretend to be exhaustive. However, having access to such information will allow building scorecards with the condition that the data quality is satisfying.

5.2.2 The quality of the data

In this section, the focus is placed on in reviewing the data quality before initiating the development and implementation of the scorecards.

In this practical application on data, modelling an application scorecard was not an easy task as the data available for the applicants were varying depending on the marketing campaigns they were coming from and also on the credit bureau data available.

In some marketing campaigns, the applicant would only give his name, date of birth, e-mail address and postal address. For others, the full questionnaire was filled. It means that when calculating the frequencies, a lot of variables coming from the application had a high number of missing values.

For the credit bureaux scores, three categories can be distinguished:

- The ones that have a score.
- The filtered customers who received complaints in the past but which are solved now, the so-called Filtered Cat.1.
- The filtered customers who have received complaints and are still dealing with those: they are rejected automatically, the so-called Filtered Cat.2.
- The ones without a score.

The two credit bureaux scores are requested in the credit review process. Of course, not all individuals are found in the Credit Bureaux registers. So, missing values were also an issue.

For the following reason, using credit bureaux data and the application data was rather complex. Ideally, all applicants should be asked to fill the questionnaire and the bank would only accept the ones found by the credit bureaux. Nevertheless, this PhD thesis will present a solution for dealing with such difficulties.

For the behavioral scorecards, there was no specific problem.

Another issue dealing with data quality is the conception of the website. The problem is that all applicants can fill whatever they want. Date cleaning is possible but it is not ideal and one should think about fixing some lengths for the field and not allowing letters or special characters when the applicant is supposed to provide a numeric value and vice versa. There should be also some checks; for example, if the date of birth is less or equal to the creation date, a message should appear saying that the date of birth is not valid. Those recommendations can seem straight forward. However, in a working environment, it is much more difficult to get it done due to general conflict with marketing department.

The data quality is essential in building credit scoring models and it should not be ignored. It is also the most time consuming task but also the most crucial one.

5.2.3 Data sampling

Different samples were used to build the different models presented in this PhD thesis.

While selecting the training and testing samples, there were different possibilities. The main focus was placed on especially two of those. The "50% vs. 50%" and the "80% vs. 20%" selections are some of the most used in the literature. Myers and Forgy (1963), Altman (1968), Meyer and Pifer (1970), Chatterjee & Barcun (1970), Orgler (1970), Apilado & al. (1974) and Eisenbeis (1977) are using the "50% vs. 50%" whereas Fawcett & Provost (1997), Henley & Hand (1996) and Abdou et al. (2008) are using the "80% vs. 20%". Banasik et al. (2001) used in their paper a training sample including 70% of cases and a holdout sample including the 30% left.

Chan & al. (1997) and Chan & al. (1999) are comparing the effects of both selection. Chan & al. (1997) completed a full study dealing with distributions and partitions. They tested the 50:50, 33.3:66.6, 15:75 and 20:80 distributions. According to Chan et al. (1997), "50%:50% improves the accuracy". A 50:50 distribution gives good results in presence of skewed data. In another article, Chan & al. (1999) compared the following distributions: 50:50, 20:80, 30:70, 10:90, 1:99 and 1:999. In this research paper, the authors concluded that the desired distribution was depending on the given distribution. For instance, if the given distribution is 20:80, the desired distribution is 50:50. If the given distribution is 10:90, the desired distribution is 30:70.

In this PhD thesis, the sampling selection used is the 50:50 distribution. The total number of observations, i.e. total sample available to build the application scorecard contains 4853 individuals, i.e. the training sample includes 2388 observations and the testing sample includes 2465 observations. The sample size is rather small compared to the number of records usually used in scorecard development which is about 10 000 records. The restrictions in data need to be considered in order to determine the best approach while working with restricted data.

According to Henley and Hand (1996), in practice, the proportion of bad risks in the full population will vary according to the credit product and will commonly be less than 20%. For that reasons, the authors restricted attention to the results obtained when the full population bad risk rate is assumed to be 20%. In the total sample, 2449 individuals are considered "good" customers which means not delinquent. 2404 individuals are considered "bad" customers which means delinquent. A customer is considered delinquent if the customer does not pay the minimum payment required by the bank within 60 days.

For the behavioral scoring, the sampling will be more complex and presented in detail in Chapter 5 – 5.3.1.3.

5.3 Evaluation of the application / behavioural scorecards

The aim of this section is first to evaluate the results of the application and behavioral scorecards with the credit bureaux scores and second, to find out an optimal application scorecard and set up an optimal scoring process using all those scorecards.

5.3.1 Presentation of the different scorecards

This sub-section examines the credit bureaux scores, the application scorecard and the behavioral scorecard.

5.3.1.1 Credit bureaux scores

A credit bureau score is a scorecard based on findings from already completed projects as well as expectations regarding a future portfolio. Credit bureau scorecards are also called generic scoring systems.

The objective of developing such a scorecard is to create a module for forecasting the payment behavior using the characteristic data available for that applicant. Characteristic data are typically gathered from experiences of several credit institutions / lenders. The function of a credit bureau is to provide a score and details of the banking history with contractual credit institutions. Credit institutions in return will have to report on the behavior of his portfolio to the credit bureau. Typically, credit institutions update their information to the credit bureau every month. However, generic systems have a cost and are sold to creditors who are interested in this service. For credit institutions with high volumes of applicants, credit bureaux are an expensive alternative.

The reputation of a credit bureau will have a huge impact on the data quality provided to credit institutions. A credit bureau playing a major role in the credit card industry will dominate most generic models and will have an impact on every decision taken by credit institutions. The competition amongst credit bureaux is intense. The credit bureau scorecard models are confidential and the credit institutions are not informed about its exact content in order to protect their model and avoid duplication. Therefore, a credit bureau provides generic scores to creditors. The score of an individual is included in a credit report.

Credit bureau scorecards are developed by scoring experts and credit bureau development staffs. Even by using only one credit bureau scorecard, the sample sizes could range from the hundreds of thousands to over a million files. Comparing a customized model with a generic credit bureau model, the generic credit bureau model is usually found as the most predictive.

In this thesis, scores from two well-known credit bureaux were accessible. By combining the information coming from those two credit bureaux, the risk of non identification of a customer is highly reduced as well as the risk of accepting applicants with banking problems.

One of the scorecards is based on data from the mobile phone sector which have been calibrated in such a way that, with regard to age and sex, they reflect to the overall distribution of the country concerned. With multi-variant regression analysis, the credit bureau compiled the characteristics Age and Sex and variables such as Risk, Social Status, Family Status, House Type, Street Type.

The other scorecard is based on logistic regression and includes similar information.

Those two scores will be compared with customized scorecards. Commonly, creditors will have to decide whether to use both or one of the two methods.

In the literature, advantages of a credit bureau scorecard include the fact that those scores are available immediately to all creditors, that development feasibility is not an issue, that it is easy to implement and supported by a network of advice, that it is not limited by the creditor's historical experience, that it is less reliant on the user's knowledge, that they are detailed in their treatment of credit bureau information, that it is very economical in their use of credit bureau information, that it is better able to predict certain outcomes, and that it is secure.

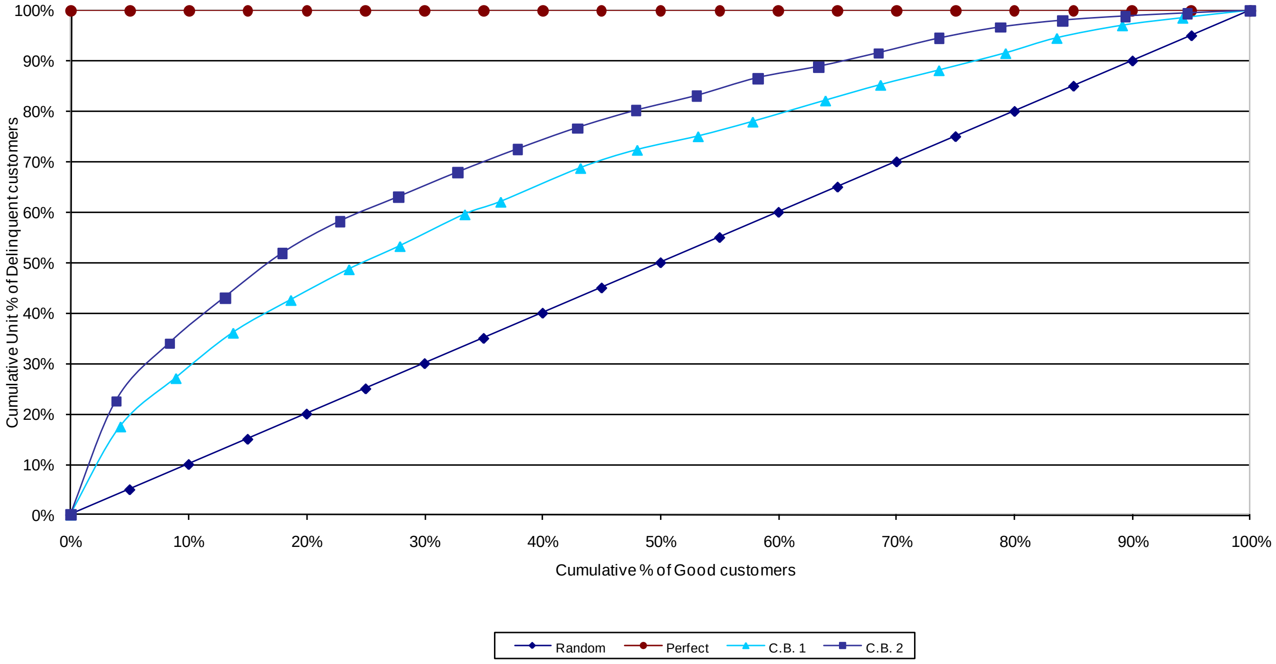
However, credit bureau scorecards have also disadvantages such as being too conservative and strict in the assignment of the score and bad marks, expensive for large credit institutions, available to competitors, confidential and harder to use in forecasting. The major one is that it is not based on the creditor's own experience, product, and customers and so it may omit information specific to the credit institution.

The overall credit environment will often determine whether to use customized or generic scoring systems or both. Since generic scoring systems have generic definitions of outcomes, creditors should seek performance forecasts based on outcome definitions that match their own objectives.

As the data used for this thesis come from a large scale credit institution selling a specific product, the implementation of customized scorecards was a must to control the credit risk in an efficient way. That's why in this thesis, the customized application scorecard, will be developed and compared with credit bureau models.

But before proceeding to the comparison of the scores, the Validation chart of the two credit bureaux were plotted in order to evaluate the quality and predictability of those and to get a better picture of what quality is expected for the customized scorecard. From their Validation chart, Credit Bureau 2 is outperforming Credit Bureau 1. To confirm this fact, the information value has been calculated and Credit Bureau 2 has clearly a higher information value.

Figure 7 - Credit Bureaux Validation chart



Just below, the information value and weights of evidence are presented.

Table 47 - Credit Bureau 1 statistics

Bands	CB1 IV	CB1 wt. pattern	CB1 Default rate
1	0,1881	-1,4193	18,96%
2	0,0349	-0,7136	10,36%
3	0,0255	-0,6171	9,49%
4	0,0045	-0,2835	6,99%
5	0,0025	-0,2120	6,54%
6	0,0002	-0,0633	5,69%
7	0,0011	-0,1346	6,08%
8	0,0011	0,1971	4,44%
9	0,0000	0,0102	5,30%
10	0,0035	0,2898	4,06%
11	0,0160	0,6490	2,87%
12	0,0081	0,4689	3,42%
13	0,0076	0,3844	3,71%
14	0,0065	0,4107	3,62%
15	0,0110	0,5362	3,20%
16	0,0114	0,5085	3,29%
17	0,0050	0,3707	3,76%
18	0,0244	0,7988	2,48%
19	0,0444	1,2280	1,63%
20	0,0570	1,3437	1,45%
Total	0,4529	3,7526	5,36%

Table 48 - Credit Bureau 2 statistics

Bands	CB2 IV	CB2 wt. pattern	CB2 Default rate
1	0,3296	-1,7647	27,32%
2	0,0640	-0,9275	13,99%
3	0,0292	-0,6621	11,09%
4	0,0227	-0,5854	10,36%
5	0,0038	-0,2607	7,71%
6	0,0000	0,0236	5,91%
7	0,0000	0,0253	5,90%
8	0,0005	0,1006	5,50%
9	0,0015	0,1823	5,09%
10	0,0056	0,3654	4,27%
11	0,0123	0,5586	3,55%
12	0,0063	0,3824	4,21%
13	0,0241	0,8304	2,73%
14	0,0152	0,6323	3,31%
15	0,0129	0,5731	3,50%
16	0,0253	0,8540	2,67%
17	0,0535	1,3591	1,63%
18	0,0825	1,8481	1,00%
19	0,1001	2,1487	0,75%
20	0,1111	2,3135	0,63%
Total	0,9002	7,9970	6,05%

5.3.1.2 The application scorecard

To develop the application scorecard, the sample was selected from those who applied for and were granted the bank's credit card during the period 2006 to 2007 and who were recruited through the bank marketing channels (for more details, please refer to Chapter 5 – 5.2.3 Data sampling).

To remind the reader, scores are statistically derived tools summarizing many predictive characteristics into a single model facilitating strategy implementation, policy changes, monitoring / tracking, etc… These techniques help in deciding who will get credit, how much credit they should get, and what operational strategies will enhance the profitability of the borrowers to the lenders. Since a score is really just a tool, it is really the policies, strategies, offerings, etc… that determine who gets credit. The purpose of this scorecard is to assign the right credit limit to the right customer initially in order to minimize losses/ increase profit.

The characteristics available in the application are the following: Gender, Postal Code, Phone, Mobile Phone, Country, Employment Status, Yearly Income, Employer Category, Cards, Family Status Change, Debts, Living Status, Family Status, Age, Email address and financial information (for more details, please refer to Chapter 5 – 5.2 Presentation of the data).

At the end of the modelling process, the model contains 9 variables which is a standard number of variables in scorecards (8-12 variables).
The dependent variable of the model is binary, i.e. defaulters (Y(1)) or not defaulters (Y(0)).

Binomial logistic regression is the method used to implement the scorecard. The forward selection has been applied. The variable entering first is the most significant one to predict the outcome. Each step, a new variable is added to the model based on its result at the updated test.

As the final scoring model should remain confidential, the detailed equation of the scorecard will not be reproduced here.

The model is the following:

$$Logit\ (p(Y=1)) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9$$

Where

Logit= Logit transformation, log of the odds, log (p (default) / p (non-default))

p= probability of default based on the characteristics given

β_0= constant

$x_1, \dots x_9$ = independent variables, characteristics, attributes…

x_1= independent variable 1, E-mail provider(s)

x_2= independent variable 2, E-mail domain(s)

x_3= independent variable 3, Employment status

x_4= independent variable 4, Living status

x_5= independent variable 5, Financial information

x_6= independent variable 6, Age

x_7= independent variable 7, Income

x_8= independent variable 8, Credit Card(s)

x_9= independent variable 9, Other Credit Card(s)

$\beta_1, \dots, \beta_9$ = coefficients

β_1 = coefficient < 0

β_2 = coefficient > 0

β_3 = coefficient > 0

β_4 = coefficient > 0

β_5 = coefficient < 0

β_6 = coefficient < 0

β_7 = coefficient < 0

β_8 = coefficient > 0

β_9 = coefficient > 0

From the results of this data application, the signs of all the weights correspond to the theoretical considerations.

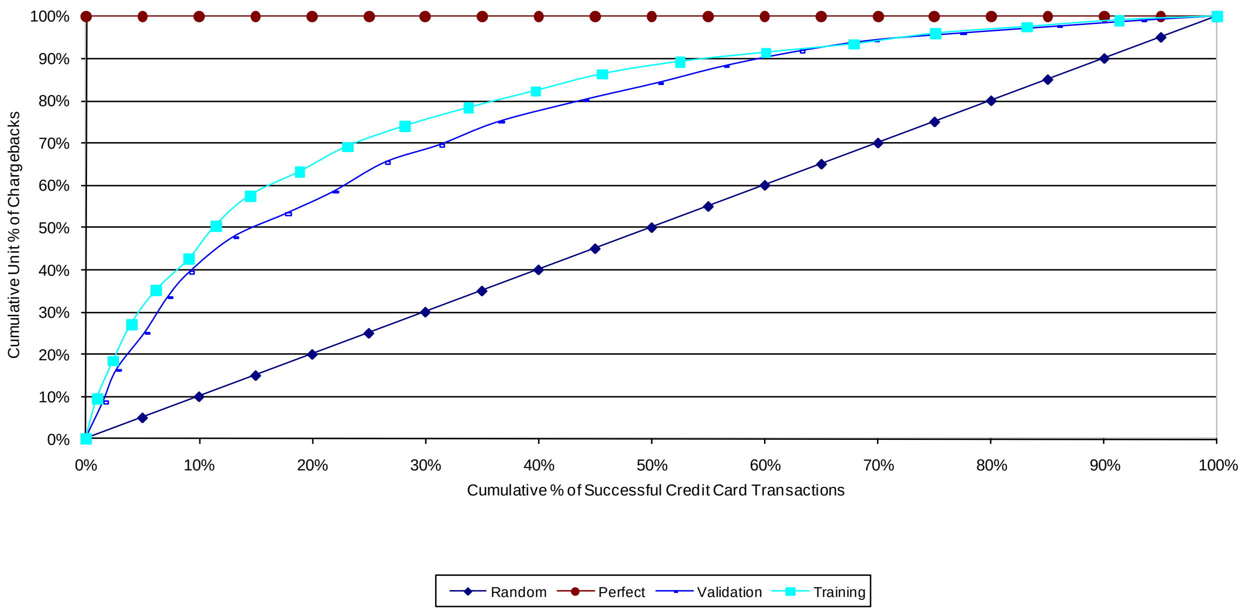
Among these characteristics, Age is the best predictor. People who are younger will get a higher weight (and a resulting higher probability of default and a lower probability to pay back their loan) than people whose age is older. One could think that the younger a customer is, the longer the period over which he may gain from future borrowing opportunities that would be sacrificed by defaulting now. However, based on the result presented above, presumably, the young can't figure this out or are too impatient or have less self respect.

An applicant, who does not own a credit card, will get a higher weight for this characteristic (and a resulting higher probability of default) whereas a customer who has a certain credit card(s) will get a zero weight. The credit limit will be based on the profile of the customer: a customer with a low risk profile will be eligible for a high credit limit.

Finally, one point that needs to be reminded is that as a scorecard relies on past experience for information on the applicants' characteristics and behavior, the model needs to be periodically reviewed and adjusted for shifts in the underlying factors, i.e. income levels (Steenackers & Goovaerts, 1989).

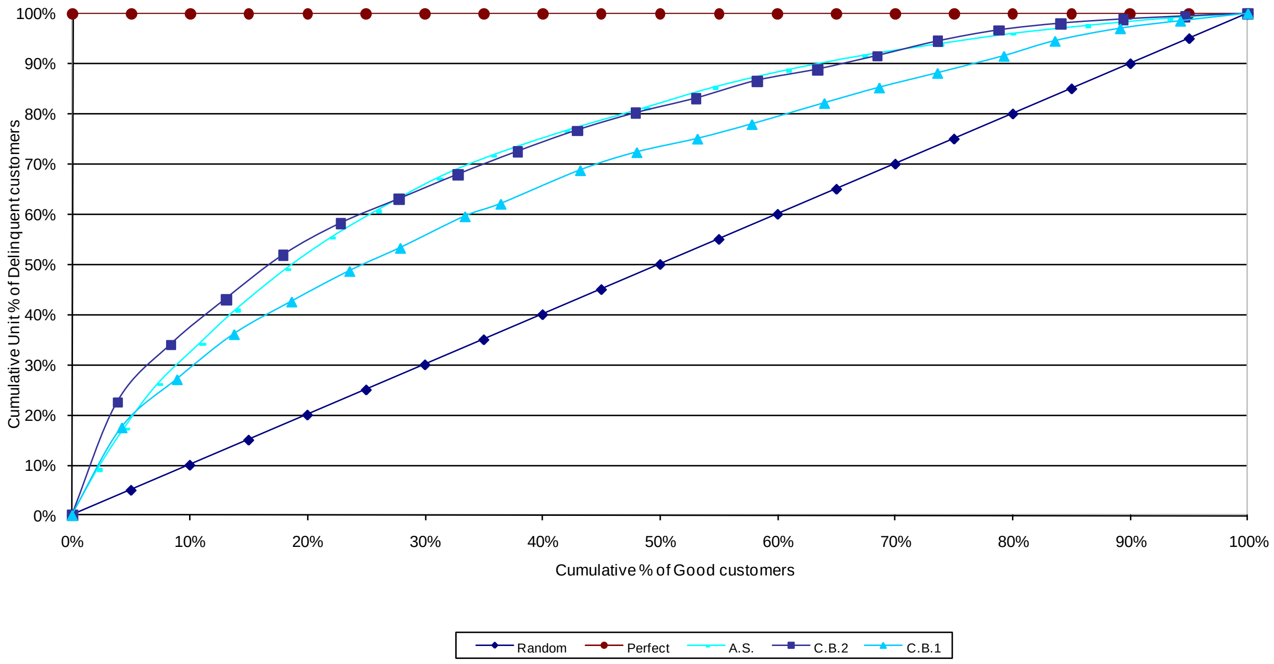
Technically, this model has been built on the training sample and validated on the testing sample. Just below, the validation chart is presented.

Figure 8 - Validation chart of the AS



Later on, when more data have become available, the application scorecard has been tested versus the credit bureaux scores.

Figure 9 - Validation chart of the AS vs. C.B.1 vs. C.B.2



With this new test, the application scorecard has confirmed to be competitive with credit bureaux scores even though one would have expected the application scorecard to outperform the bureaux ones. Indeed, the Credit bureau 2 score is giving really close result to the application scorecard.

As mentioned earlier, the validation chart is one element used to evaluate the application scorecard but additional criteria used are the information value and weights of evidence.

Table 49 - AS statistics

Bands	A.S. IV	A.S. wt. pattern	A.S. Default rate
1	0,0980	-1,4326	22,04%
2	0,0769	-1,2839	19,59%
3	0,0673	-1,1333	17,33%
4	0,0372	-0,8160	13,24%
5	0,0283	-0,7844	12,88%
6	0,0250	-0,6465	11,41%
7	0,0120	-0,4918	9,94%
8	0,0048	-0,3243	8,54%
9	0,0031	-0,2303	7,83%
10	0,0000	0,0284	6,16%
11	0,0032	0,2393	5,04%
12	0,0082	0,3807	4,41%
13	0,0064	0,3624	4,49%
14	0,0164	0,5897	3,61%
15	0,0286	0,8010	2,94%
16	0,0425	1,0255	2,36%
17	0,0455	1,1047	2,19%
18	0,0656	1,3766	1,67%
19	0,0850	1,5450	1,42%
20	0,1126	1,9357	0,96%
Total	0,7664	2,2457	6,32%

Comparing the information value, Credit Bureau 2 has a higher one (IV=0.8957) than the internal model (IV=0.7664) which can also be seen in the validation chart. In practice, this means that Credit Bureau 2 is able to predict better than the application scorecard in the low-end and the high-end of the score.

However, Credit Bureau 2 is much less stable than the application scorecard model. As the purpose of this scorecard is for credit limit allocation, the monotonicity of the model is a must and is the primary criteria of comparison between the two. Moreover, with an in-house scorecard, the entire portfolio can be scored whereas Credit Bureau 2 cannot identify everybody.

Please note that in the section 5.3.2.1 of this chapter, the objective will be to find an optimal model that combines both the Credit Bureau 2 score and the application score.

Statistically, the application model has proved to be relevant but the author also investigated if the content, i.e. the variables included in the model, were pertinent and logical.

Backert et al. (2007) reviewed the main characteristics of overindebted persons through a survey and isolated the following criteria as being correlated with overindebtedness: (a) personal circumstances (Unemployment, Lack of financial overview and Divorce), (b) age, (c) number of children, (d) income, (e) amount of debt, (f) number of creditors (54.2% of the respondents had more than 6 creditors) and (g) education.

Interestingly, one can connect those results with the model presented above:

- Indeed, not surprisingly, Age and Income were the two most powerful predictive variables of this model and appear to be strongly correlated with bankruptcy filing.
- Personal circumstances correspond to the employment status variable in the model.

-The financial information variable, the credit card variables and living status can be assimilated with the amount of debt and number of creditors.

Based on those results, credit card defaulting customers and overindebted persons present similar traits. Linking this survey evidence to the key variables which emerge from the application scorecard has proved to provide a definite additional robustness check of the model.

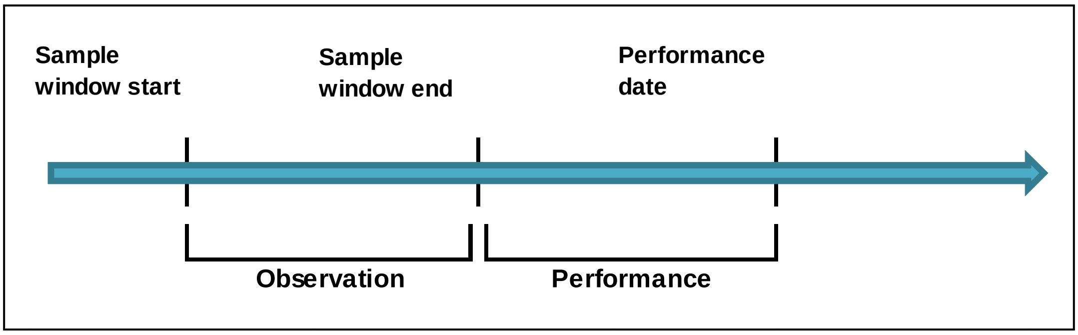
5.3.1.3 The behavioral scorecard

The behavior of the customers will be tracked via two types of scorecards:

- A short term scorecard – a transaction based scorecard
- Long term scorecard – behavioral scorecards

The two scorecards will predict the same outcome, which is the performance of a customer. Defining performance typically includes two aspects, the severity of the “performance definition” and the duration of the “performance window”.

Figure 10 - Sampling chart



Binary performance definitions consisting of two performance categories, often called “goods” and “bads”, are typically recommended. “Indeterminates” are those accounts or transactions that are not quite “Good” yet not bad enough to be considered as “Bad”. In our case, “Indeterminates” will be accounts that have been less than 60 past due but more than 0 while “Goods” are accounts that have never been delinquent and “Bads” are accounts that have been 60 days past due or plus at least once.

The short term scorecard will aim to predict the probability of default of a customer based on his first day of transactions. This scorecard will be used prior to the long term one, which needs payments data.

The first step is to prepare the data. The database has been constructed so that only the data of the day of the first transactions were stored. It also includes the date when the slip was signed and when the application was created. For all types of transactions, three variables have been created: One with number of transactions, one binary which equal to 1 if this type of transaction has been made, one with the amount spent on this type of transaction. Sample sizes must be large enough to provide a statistically significance and stability. Approximately 1,000 or more each of “goods”, “bads”, and “rejects” for a model development with validation are recommended.

For the goods, the data available are sufficient. For the “bads”, it is much lower but enough to build a solid model. However, as a predictive discretized model can be developed with as few as 600 “bads” and continuous variable models such as non-discretized, logistic Regression requires fewer observations. The sample size will be more than acceptable. In general, the larger the sample sizes of “Goods” and “Bads”, the more sophisticated the development.

Table 50 - E.D.S. Sampling figures

Early Detection Score Sample

	First Day's Trxns 02/01/2008	1st Statement 01/02/2008	5 Days Past due 01/03/2008	30 Days Past due 01/04/2008	60 Days Past due 01/05/2008
Sample 1	NORM Observation		P0	P30 Performance	P60

* Samples dependent upon first transaction date
* All first day's transactions must be aggregated to generate characteristics
* Data availability for score calculation is key and determines strategies.

	Goods	Bads	Total
Sample Training	5080	4982	10062
Sample Validation	66791	7085	73876
Sample All	71871	12067	83938

Only customers with at least 3 months history has been selected that they had time to become delinquent. However, the period of observation is only the first day of usage. The indeterminates have been excluded.

Early Detection scores support Fraud Detection and Account Management by combining bureau, application, and transaction data to identify fraud, mitigate losses, and support marketing. For the list of characteristics available, please refer to Chapter 5 – 5.2.Presentation of the data.

At the end of the modelling process, the model contains 12 variables which is a standard number of variables in scorecards (8-12 variables).
The dependent variable of the model is binary, i.e. defaulters (Y(1)) or not defaulters (Y(0)).

Binomial logistic regression is the method used to implement the scorecard. The forward selection has been applied. The variable entering first is the most significant one to predict the outcome. Each step, a new variable is added to the model based on its result at the updated test.

As the final scoring model must by law remain confidential, the detailed equation of the scorecard cannot be reproduced here.

The model is the following:

$$Logit\ (p(Y=1)) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \beta_{10} x_{10} + \beta_{11} x_{11} + \beta_{12} x_{12}$$

Where

Logit= Logit transformation, log of the odds, log (p (default) / p (non-default))

p= probability of default based on the characteristics given

β_0= constant

$x_1, \dots x_{12}$ = independent variables, characteristics, attributes…

x_1= independent variable 1, Marketing flag for 2 specific high risk campaigns

x_2= independent variable 2, Marketing flag for 2 specific low risk campaigns

x_3= independent variable 3, Country where the largest amount was spent.

x_4= independent variable 4, Transaction flag related to travel expenses

x_5= independent variable 5, Transaction flag related to risky usage

x_6= independent variable 6, Transaction flag related to purchase places

x_7= independent variable 7, Transaction flag related to purchase places

x_8= independent variable 8, Amount spent on risky usage

x_9= independent variable 9, Credit Bureau 2 Score

x_{10}= independent variable 10, Application Score

x_{11}= independent variable 11, Time before 1st usage

x_{12}= independent variable 12, Number of transactions done within the first day

$\beta_1, \dots, \beta_{12}$ = coefficients

β_1 = coefficient >0

β_2 = coefficient < 0

β_3 = coefficient > 0

β_4 = coefficient < 0

β_5 = coefficient > 0

β_6 = coefficient > 0

β_7 = coefficient < 0

β_8 = coefficient > 0

β_9 = coefficient < 0

β_{10} = coefficient > 0

β_{11} = coefficient < 0

β_{12} = coefficient > 0

From the results of this data application, the signs of all the weights correspond to the theoretical considerations.

Among these characteristics, the credit bureau 2 score is the most predictive variable followed closely by the application score. People who get a bad credit bureau 2 score (and a resulting higher probability of default and a lower probability to pay back their loan) will get a worse early detection score than people whose credit bureau 2 score is good.

An applicant, who does not travel, will get a higher weight for this characteristic (and a resulting higher probability of default) whereas a customer who spent money travelling will get a zero weight.

Finally, as mentioned earlier, one point that needs to be reminded is that as a scorecard relies on past experience for information on the applicants' characteristics and behavior, the model needs to be periodically reviewed and adjusted for shifts in the underlying factors (Steenackers & Goovaerts, 1989).

Technically, this model has been built on the training sample and validated on the test sample. Just below, the validation chart is presented.

Figure 11 - E.D.S. validation chart

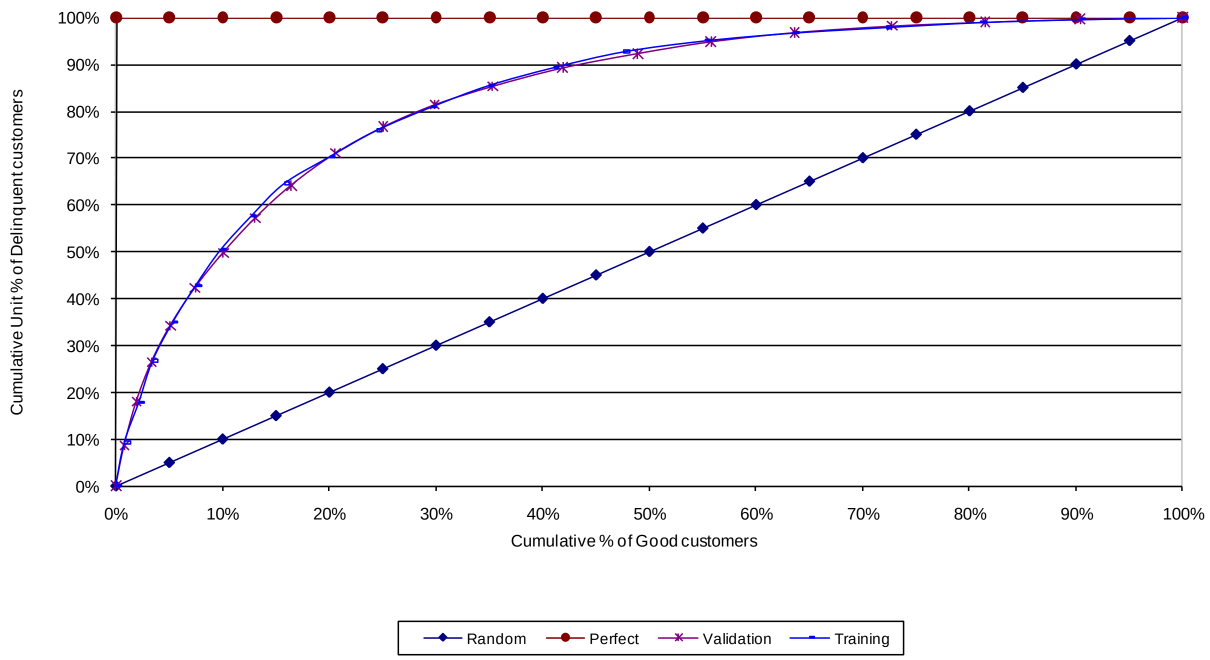


Table 51 - E.D.S. statistics

Bands	E.D.S. IV	E.D.S. wt. pattern	E.D.S. Default rate
1	0,1989	-2,4634	57,85%
2	0,1566	-2,0621	47,88%
3	0,1309	-1,7532	40,29%
4	0,0784	-1,4175	32,53%
5	0,0743	-1,2690	29,36%
6	0,0554	-1,1058	26,09%
7	0,0392	-0,8832	22,04%
8	0,0264	-0,7091	19,19%
9	0,0103	-0,4498	15,49%
10	0,0029	-0,2408	12,94%
11	0,0002	0,0714	9,81%
12	0,0037	0,2715	8,18%
13	0,0111	0,4754	6,77%
14	0,0337	0,8546	4,74%
15	0,0570	1,1509	3,57%
16	0,0747	1,3350	2,98%
17	0,1109	1,6360	2,23%
18	0,1899	2,2981	1,16%
19	0,2282	2,7079	0,77%
20	0,3057	3,3188	0,42%
Total	1,7887	1,7658	10,46%

As mentioned earlier, the validation chart is one element used to evaluate the scorecard but additional criteria used are the information value and the weights of evidence. As the purpose of this scorecard is for credit limit allocation, the monotonicity of the model is a must and is the primary criteria of model selection and in the example presented, the model is perfectly monotonic. The weights pattern is developing properly confirming the good quality of the model.

The long term scorecard will aim to predict the probability of default of a customer based on a one year period of observation. The first step is to prepare the data. All information related to the behavior of the customer has been stored in a database. Behavioral scores support ongoing risk and marketing programs using data coming from credit bureaux, application, transactions and payment behavior sources. For the list of characteristics available, please refer again to Chapter 5 – 5.2.Presentation of the data.

A first model, called behavioral scorecard 1, will be based on the six first months of usage. A second model, called behavioral scorecard 2, will be based on a six rolling months period excluding the six first months. Therefore, the observation window is a 6 month window. The performance window is 6 months.

The reason for selecting a 6 month period rather than a 12 months period is dearth of data. Ideally, 12-24 months would have been preferable especially in the context where the default unit rate is constantly increasing over time even for the oldest vintages. However, a 6 months observation period and a 6 month performance period will be used.

Sample sizes must be large enough to provide a statistically significance and stability. Approximately 1,000 or more each of “goods”, “bads”, and “rejects” for a model development with validation are recommended. The indeterminates have been excluded.

Table 52 - BS Sampling figures

Behavioral Score 1 Sample

	Application	First Day's Trxns	1st Statement	2nd Statement	3rd Statement	4th Statement	5th Statement	6th Statement	7th Statement	8th Statement	9th Statement	10th Statement	11th Statement	12th Statement
Sample 1	Observation								Performance					

	Application	First Day's Trxns	1st Statement	2nd Statement	3rd Statement	4th Statement	5th Statement	6th Statement	7th Statement	8th Statement	9th Statement	10th Statement	11th Statement	12th Statement
Type 1	NORM				P0	P30	P60	P90	P120	P150	P180	P210	P240	P270
Type 2	NORM					P0	P30	P60	P90	P120	P150	P180	P210	P240
Type 3	NORM						P0	P30	P60	P90	P120	P150	P180	P210
Type 4	NORM							P0	P30	P60	P90	P120	P150	P180
Type 5	NORM								P0	P30	P60	P90	P120	P150
Type 6	NORM									P0	P30	P60	P90	P120
Type 7	NORM										P0	P30	P60	P90
Type 8	NORM											P0	P30	P60

* Samples include 8 types of delinquent customers
* Samples dependent upon first statement received
* All 6 first months variables must be aggregated to generate characteristics
* Data availability for score calculation is key and determines strategies.

	Goods	Bads	Total
Sample Training	5524	4573	10097
Sample Validation	80013	8917	88930
Sample All	85537	13490	99027

Behavioral Score 2 Sample

	2nd Statement	3rd Statement	4th Statement	5th Statement	6th Statement	7th Statement	8th Statement	9th Statement	10th Statement	11th Statement	12th Statement	13th Statement	14th Statement	15th Statement	16th Statement	nth Statement
Sample 1a	Observation						Performance									
Sample 1b		Observation						Performance								
Sample 1c			Observation						Performance							
Sample 1d				Observation						Performance						
Sample 1e					Observation						Performance					

* nth-12 tells the number of sub samples of 12 months that will be extracted from one sample.
* Samples dependent upon first statement received
* All 6 first months variables must be aggregated to generate characteristics
* Data availability for score calculation is key and determines strategies.

	Goods	Bads	Total
Sample Training	5084	4952	10036
Sample Validation	512432	50846	563278
Sample All	517516	55798	573314

For the behavioral scorecard 1, at the end of the modelling process, the model contains 11 variables and for the behavioral scorecard 2, the model contains 12 variables which is a standard number of variables in scorecards (8-12 variables). The dependent variable of the model is binary, i.e. defaulters (Y(1)) or not defaulters (Y(0)).

Binomial logistic regression is the method used to instruct the scorecard. The forward selection has been applied. The variable entering first is the most significant one to predict the outcome. Each step, a new variable is added to the model based on its result at the updated test.

The first model is the following:

$$Logit\ (p(Y=1)) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \beta_{10} x_{10} + \beta_{11} x_{11}$$

Where

Logit= Logit transformation, log of the odds, log (p (default) / p (non-default))

p= probability of default based on the characteristics given

β_0= constant

$x_1, \dots x_{11}$ = independent variables, characteristics, attributes…

x_1= independent variable 1, Utilization ratio

x_2= independent variable 2, Utilization ratio

x_3= independent variable 3, Ratio combining interests and delay for the 3 first months

x_4= independent variable 4, Ratio combining interests and delay for the 6 first months

x_5= independent variable 5, Utilization flag for over limit accounts

x_6= independent variable 6, Payment pattern indicator for the 3 first month

x_7= independent variable 7, Payment pattern indicator for the 6 first month

x_8= independent variable 8, Application Score

x_9= independent variable 9, Credit Bureau 2 Score

x_{10}= independent variable 10, Number of transactions within the 3 first months

x_{11}= independent variable 11, Amount spent on a special type of risky transaction

$\beta_1, \dots, \beta_{11}$ = coefficients

β_1 = coefficient > 0

β_2 = coefficient > 0

β_3 = coefficient > 0

β_4 = coefficient > 0

β_5 = coefficient > 0

β_6 = coefficient > 0

β_7 = coefficient <0

β_8 = coefficient >0

β_9 = coefficient < 0

β_{10} = coefficient > 0

β_{11} = coefficient > 0

From the results of this data application, the signs of all the weights correspond to theoretical priors.

The second model is as follows:

$$Logit\ (p(Y = 1)) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \beta_{10} x_{10}$$

Where

Logit= Logit transformation, log of the odds, log (p (default) / p (non-default))

p= probability of default based on the characteristics given

β_0= constant

$x_1, \dots x_{10}$ = independent variables, characteristics and attributes

x_1= independent variable 1, Utilization ratio

x_2= independent variable 2, Ratio combining interests and delay for the 3 first months

x_3= independent variable 3, Ratio combining interests and delay for the 6 first months

x_4= independent variable 4, Utilization flag for accounts using 60% of their credit line

x_5= independent variable 5, Payment pattern indicator for the 3 first month

x_6= independent variable 6, Payment pattern indicator for the 6 first month

x_7= independent variable 7, Payment pattern indicator for the 6 first month

x_8= independent variable 8, Application Score

x_9= independent variable 9, Credit Bureau 2 Score

x_{10}= independent variable 10, Utilization pattern indicator

$\beta_1, \dots, \beta_{10}$ = coefficients

β_1 = coefficient > 0

β_2 = coefficient > 0

β_3 = coefficient > 0

β_4 = coefficient > 0

β_5 = coefficient > 0

β_6 = coefficient >0

β_7 = coefficient < 0

β_8 = coefficient <0

β_9 = coefficient < 0

β_{10} = coefficient >0

From the results of this data application, the signs of all the weights correspond to the theoretical priors.

Among the characteristics in both models, the ratio combining interests and delay for the 3 first months is the most predictive variable. It can be interpreted as the maximum number of the defaulters will reveal themselves quickly, i.e. most customers that get a reminder during the three first months have a high probability of default.

An applicant, who does exhibit a risky behavior (ex: not paying in due time, spending money on gambling, exceeding his credit line), will have a higher probability of default whereas a customer exhibiting a low risk behavior will get a zero weight. The credit limit will be based on the profile of the customer: a customer with a low risk profile will be eligible for a high credit limit.

The next characteristics coming in model 1 and 2 are different. However, at the end of the process, the two models have 6 identical variables. Three variables of model 2 are derived from two variables in model 1. It means that over time only some parts of the variables are necessary for predicting risk.

The changes of variables within the model can be explained by the fact that usage information is related to credit limit and in the six first months, not many customers get a high credit limit whereas after that period, the credit lines are significantly modified, affecting the usage indicators.

The same explanation can be made regarding the payments. It is when the credit limit is getting higher that customers will start to miss payments as they will not be able to repay their debts.

Just below the validation chart of the two behavioral scorecard models as well as their statistics.

The weights of evidence of both scorecards are perfectly monotonic. The information value of behavioral scorecard 1 is a little bit higher than the information value for behavioral scorecard 2. However, both models are highly predictive and accurate.

Figure 12 - BS validation chart

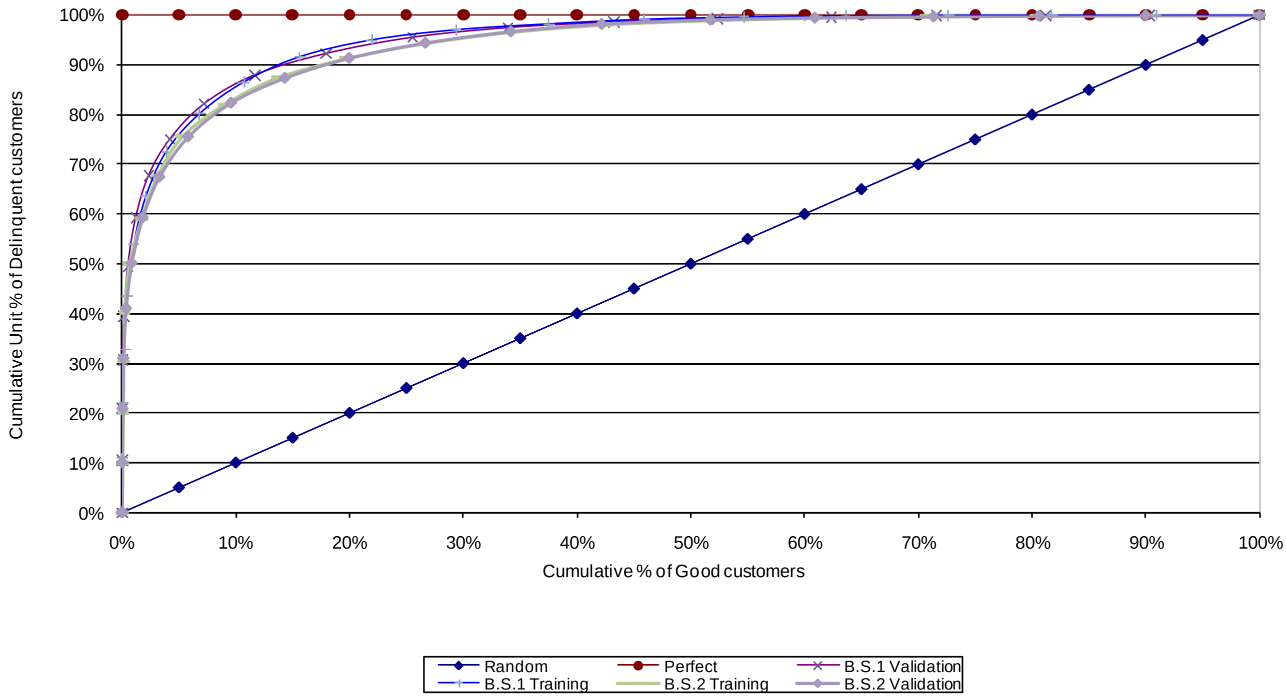


Table 53 - BS statistics

Bands	B.S.1 IV	B.S.1 wt. pattern	B.S.1 Default rate
1	0,7004	-6,8181	99,03%
2	0,6412	-6,0518	97,93%
3	0,5029	-5,2181	95,36%
4	0,3812	-4,2964	89,11%
5	0,3269	-3,4306	77,49%
6	0,2369	-2,6652	61,56%
7	0,1516	-1,9940	45,01%
8	0,0779	-1,4051	31,24%
9	0,0332	-0,8359	20,45%
10	0,0039	-0,2783	12,83%
11	0,0070	0,3640	7,19%
12	0,0397	0,8942	4,36%
13	0,0889	1,3880	2,71%
14	0,1709	2,1015	1,34%
15	0,2280	2,7162	0,73%
16	0,3383	3,4413	0,36%
17	0,3320	3,7109	0,27%
18	0,4264	4,4577	0,13%
19	0,4113	4,5139	0,12%
20	0,5402	5,6526	0,04%
Total	5,6386	-3,7534	10,03%

Bands	B.S.2 IV	B.S.2 wt. pattern	B.S.2 Default rate
1	0,6109	-6,3134	98,21%
2	0,6622	-6,0094	97,59%
3	0,5072	-4,9646	93,43%
4	0,3684	-3,8939	82,97%
5	0,2541	-2,8810	63,89%
6	0,1895	-2,2894	49,48%
7	0,1172	-1,6996	35,19%
8	0,0644	-1,1715	24,25%
9	0,0178	-0,5936	15,23%
10	0,0001	-0,0550	9,49%
11	0,0055	0,3390	6,60%
12	0,0285	0,7849	4,33%
13	0,0599	1,1956	2,91%
14	0,1122	1,6751	1,82%
15	0,2089	2,3992	0,89%
16	0,2919	3,1819	0,41%
17	0,3421	3,6213	0,26%
18	0,3881	4,1838	0,15%
19	0,4822	4,9347	0,07%
20	0,5564	5,6830	0,03%
Total	5,2678	-1,8731	9,03%

5.3.2 Post implementation

From the results of the scorecards vs. credit bureau score, a combined model has been tested. The scoring process described in this sub-section includes the combined scorecard (application scorecard + credit bureau score) and the behavioral scorecard.

5.3.2.1 Combining the application scorecard and the credit bureaux scorecard

According to Blochlinger & Leippold (2006), credit scoring models can lead to two types of errors:

- First, the model predict a low risk when in fact the risk is high, this will lead to a loss of credit amount or/and interest.
- Second, the model does not predict a low risk when in fact the risk is low, this will lead to a loss of return and fees, drop in market share when loans are either turned down or lost through non-competitive pricing.

To avoid such errors, the author tried to improve the accuracy and to secure the application scorecard presented. A deeper analysis of the application scorecard and the Credit Bureau 2 is presented in the next paragraphs.

In the next table, the weights of evidence and information value of the application scorecard and the Credit Bureau 2 scores are presented.

The weights of evidence of the application scorecard are more monotonic between bands 5 and 16 than the ones for the Credit Bureau 2 score for all three indicators: weight of evidence, information value and default risk.

However, the Credit Bureau 2 score discriminates better than the application scorec for all three indicators, weight of evidence, information value and default risk, between bands 1 and 4 and between bands 17 to 20. The possible explanation is that Credit Bureau 2 has access to information not available to the bank.

As the Credit Bureau 2 score has proved to predict better than the application scorecard in the low-end and the high-end of the score, using this information seems valuable.

Table 54 - Comparison of AS and BS2 statistics

Bands	A.S. wt. pattern	C.B.2 wt. pattern	A.S. IV	C.B.2 IV	A.S. Default rate	C.B.2 Default rate
1	-1,4326	-1,7647	0,0980	0,3296	22,04%	27,32%
2	-1,2839	-0,9275	0,0769	0,0640	19,59%	13,99%
3	-1,1333	-0,6621	0,0673	0,0292	17,33%	11,09%
4	-0,8160	-0,5854	0,0372	0,0227	13,24%	10,36%
5	-0,7844	-0,2607	0,0283	0,0038	12,88%	7,71%
6	-0,6465	0,0236	0,0250	0,0000	11,41%	5,91%
7	-0,4918	0,0253	0,0120	0,0000	9,94%	5,90%
8	-0,3243	0,1006	0,0048	0,0005	8,54%	5,50%
9	-0,2303	0,1823	0,0031	0,0015	7,83%	5,09%
10	0,0284	0,3654	0,0000	0,0056	6,16%	4,27%
11	0,2393	0,5586	0,0032	0,0123	5,04%	3,55%
12	0,3807	0,3824	0,0082	0,0063	4,41%	4,21%
13	0,3624	0,8304	0,0064	0,0241	4,49%	2,73%
14	0,5897	0,6323	0,0164	0,0152	3,61%	3,31%
15	0,8010	0,5731	0,0286	0,0129	2,94%	3,50%
16	1,0255	0,8540	0,0425	0,0253	2,36%	2,67%
17	1,1047	1,3591	0,0455	0,0535	2,19%	1,63%
18	1,3766	1,8481	0,0656	0,0825	1,67%	1,00%
19	1,5450	2,1487	0,0850	0,1001	1,42%	0,75%
20	1,9357	2,3135	0,1126	0,1111	0,96%	0,63%
Total	2,2457	7,9970	0,7664	0,9002	6,32%	6,05%

Based on this comparison, two possible ways of improving the application scorecard have been investigated:

a- A matrix approach

As for scorecards, the score of the credit bureau is split into 20 bands. The Credit Bureau 2 score is in vertical, the application scorecard is in horizontal. The better the scores are, the higher the credit limit is.

The matrix is constructed so that it takes into account the performance advantages of each scores mentioned previously, i.e. the application score is more accurate for the middle bands whereas the Credit Bureau 2 is more accurate on the high and low bands.

Table 55 - Matrix approach

											Credit Bureau 2												
	Bands	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Bands	
	1					3	3	4	4	5	5	6	6	7	7	8	8					1	
	2					3	4	4	5	5	6	6	7	7	8	8	9					2	
	3					4	4	5	5	6	6	7	7	8	8	9	9					3	
	4		Credit Bureau 2			4	5	5	6	6	7	7	8	8	9	9	10		Credit Bureau 2			4	
	5	3	3	4	4													11	11	12	12	5	
	6	3	4	4	5													11	12	12	13	6	
	7	4	4	5	5													12	12	13	13	7	
	8	4	5	5	6													12	13	13	14	8	
	9	5	5	6	6													13	13	14	14	9	
Application scorecard	10	5	6	6	7													13	14	14	15	10	Application scorecard
	11	6	6	7	7													14	14	15	15	11	
	12	6	7	7	8													14	15	15	16	12	
	13	7	7	8	8													15	15	16	16	13	
	14	7	8	8	9													15	16	16	17	14	
	15	8	8	9	9													16	16	17	17	15	
	16	8	9	9	10						Application scorecard							16	17	17	18	16	
	17					11	11	12	12	13	13	14	14	15	15	16	16					17	
	18					11	12	12	13	13	14	14	15	15	16	16	17					18	
	19					12	12	13	13	14	14	15	15	16	16	17	17					19	
	20		Credit Bureau 2			12	13	13	14	14	15	15	16	16	17	17	18		Credit Bureau 2			20	
	Bands	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Bands	
											Credit Bureau 2												

b- A combined model

As mentioned earlier, Zhu et al. (2001) presented a combination of two credit scores constructed, using logistic regression, that leads to small improvement but that might represent a significant competitive advantage (Zhu et al., 2001). The author has applied the same methodology in combining the application scorecard with the Credit Bureau 2 score.

As mentioned previously, the final scoring model must remain confidential; the detailed equation of the scorecard cannot be reproduced here.

However, the model is theoretically as follows:

$$Logit\ (p(Y = 1)) = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

Where

Logit= Logit transformation, log of the odds, log (p (default) / p (non-default))

p= probability of default based on the characteristics given

β_0= constant

x_1, x_2 = independent variables, characteristics, attributes…

x_1= independent variable 1, the application score

x_2= independent variable 2, the Credit Bureau 2 score

β_1, β_2 = coefficients

β_1 = coefficient < 0

β_2 = coefficient > 0

From the results of this data application, the signs of all the weights correspond to the theoretical considerations.

The model has been developed using a training sample and applied on a testing sample.

The combined model has been tested versus the application model and the two credit bureaux scores. With the Validation chart, it is clear that the combined model outperforms all models. The information value, the weights of evidence and the default rate confirmed the last statement.

Figure 13 - Validation chart of AS vs. C.B.1 vs. C.B.2 vs. CS

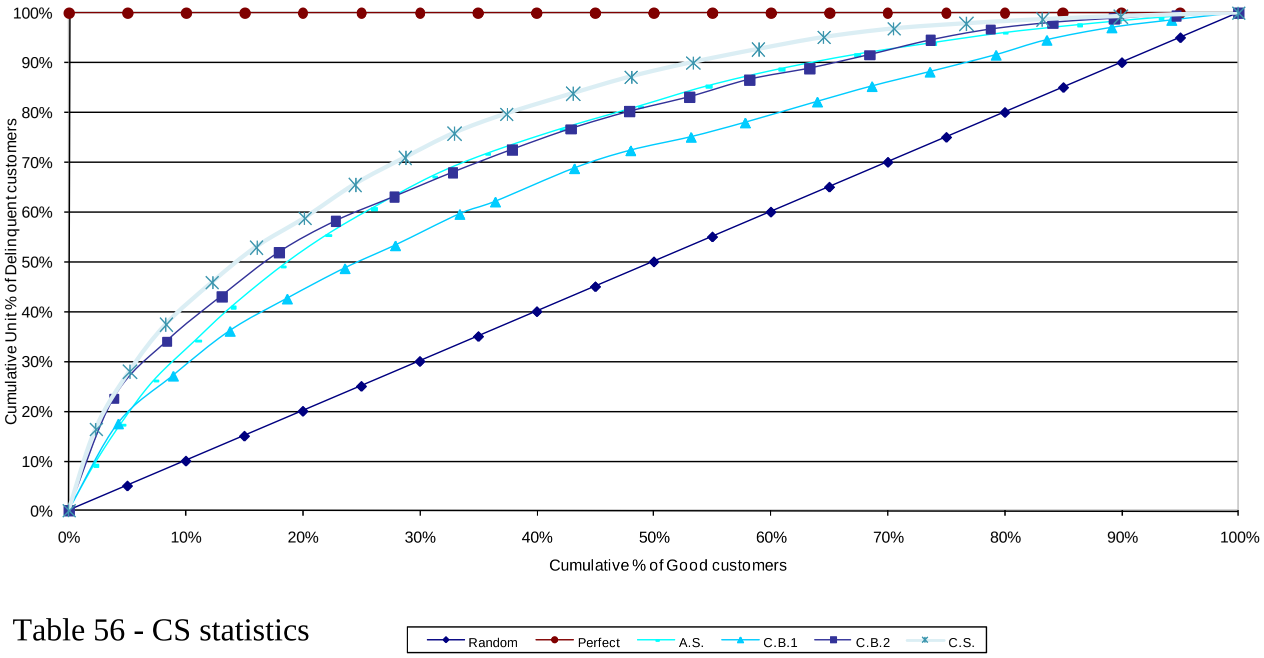
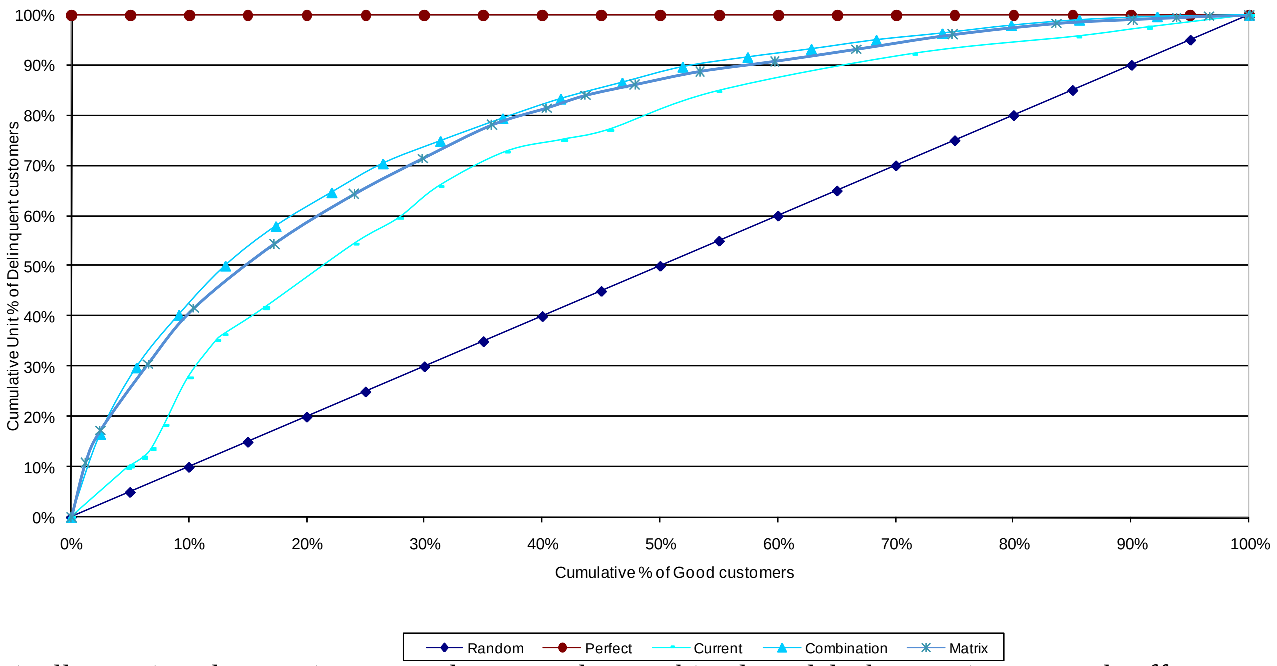


Table 56 - CS statistics

Bands	C.S. IV	C.S. wt. pattern	C.S. Default rate
1	0,2745	-1,9598	32,18%
2	0,1209	-1,3884	21,14%
3	0,0703	-1,1108	16,88%
4	0,0339	-0,7564	12,47%
5	0,0213	-0,6367	11,22%
6	0,0059	-0,3449	8,63%
7	0,0112	-0,4541	9,53%
8	0,0024	-0,2234	7,72%
9	0,0012	-0,1612	7,28%
10	0,0008	0,1381	5,50%
11	0,0052	0,3297	4,59%
12	0,0062	0,3871	4,34%
13	0,0146	0,6033	3,53%
14	0,0222	0,7532	3,05%
15	0,0274	0,8552	2,76%
16	0,0524	1,2328	1,91%
17	0,0926	1,7885	1,11%
18	0,1173	2,0596	0,85%
19	0,1429	2,3676	0,62%
20	0,2494	2,6581	0,47%
Total	1,2726	6,1373	6,27%

Figure 14 - Validation chart of Current vs. CS vs. Matrix



Finally, testing the matrix approach versus the combined model, the matrix approach offers promising results with results close to the combined model. On the contrary, the model used at the moment clearly presents some lack of stability and accuracy.

- Information value, weight of evidence and default rate

The information value of the different models can be classified as follows:

$$IV_{CombinedModel} > IV_{Matrix\ Approach} > IV_{Current\ Model}$$

For the weights of evidence, the distribution has been analyzed and they could be classified as follows (considering the monotonicity as the key criteria of comparison).

$$Wt_{CombinedModel} > Wt_{Matrix\ Approach} > Wt_{Current\ Model}$$

Analyzing the default rate of the different models, the combined model appears as the most accurate and stable.

The matrix approach appeared with a good potential for predicting bad loans. However, the main weakness of the matrix approach is the lack of stability.

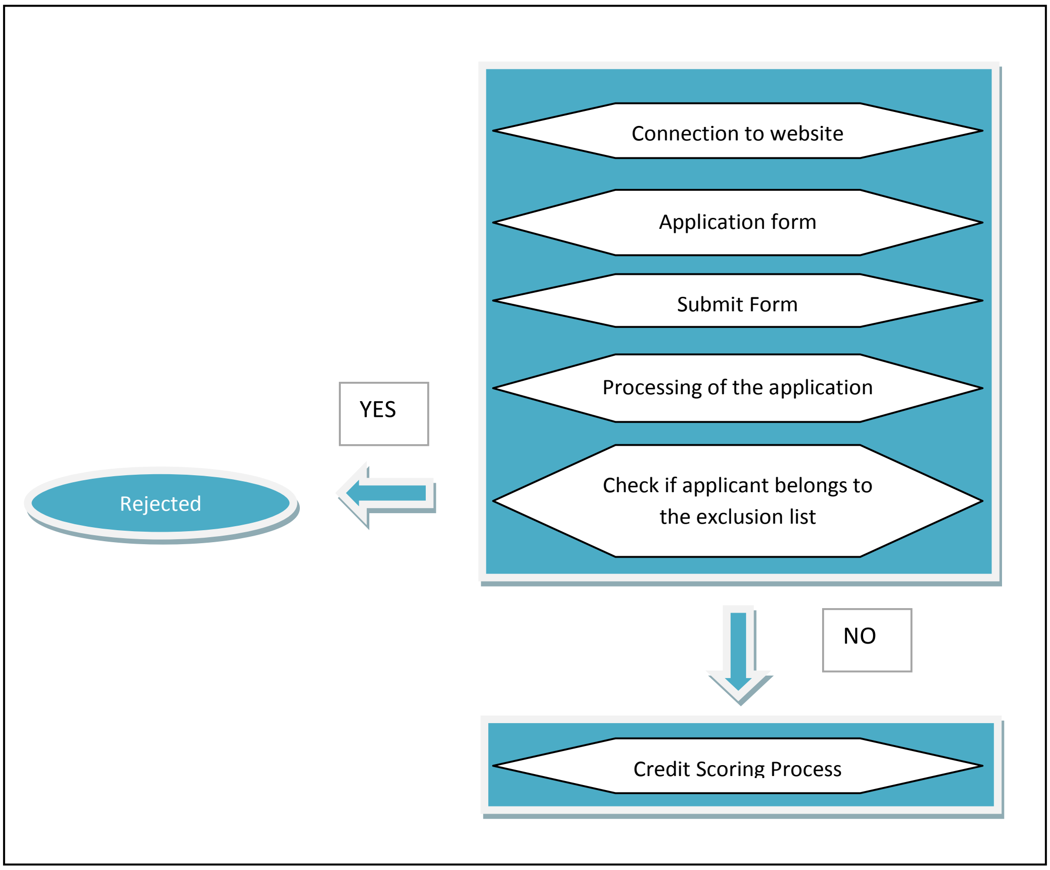
The matrix approach has the lowest default rate for the lowest risk segments and has one of the highest default rates for the highest risk segment. For middle segments, the combined score is most accurate and stable. The improvements in terms of predictability compared to the current system are impressive.

In conclusion, the model giving the best results is the combined scorecard.

5.3.2.2 Proposal of a possible scoring process

Before presenting the scoring process, the application process has to be reviewed. For example, a customer wants to order a credit card online. First, the applicant will go on the website of the bank, filled the application and submit it.

Figure 15 - Summary of the application process



The bank will process the application and reject the ones that are blacklisted or that have been listed as insolvent or with major financial problems.

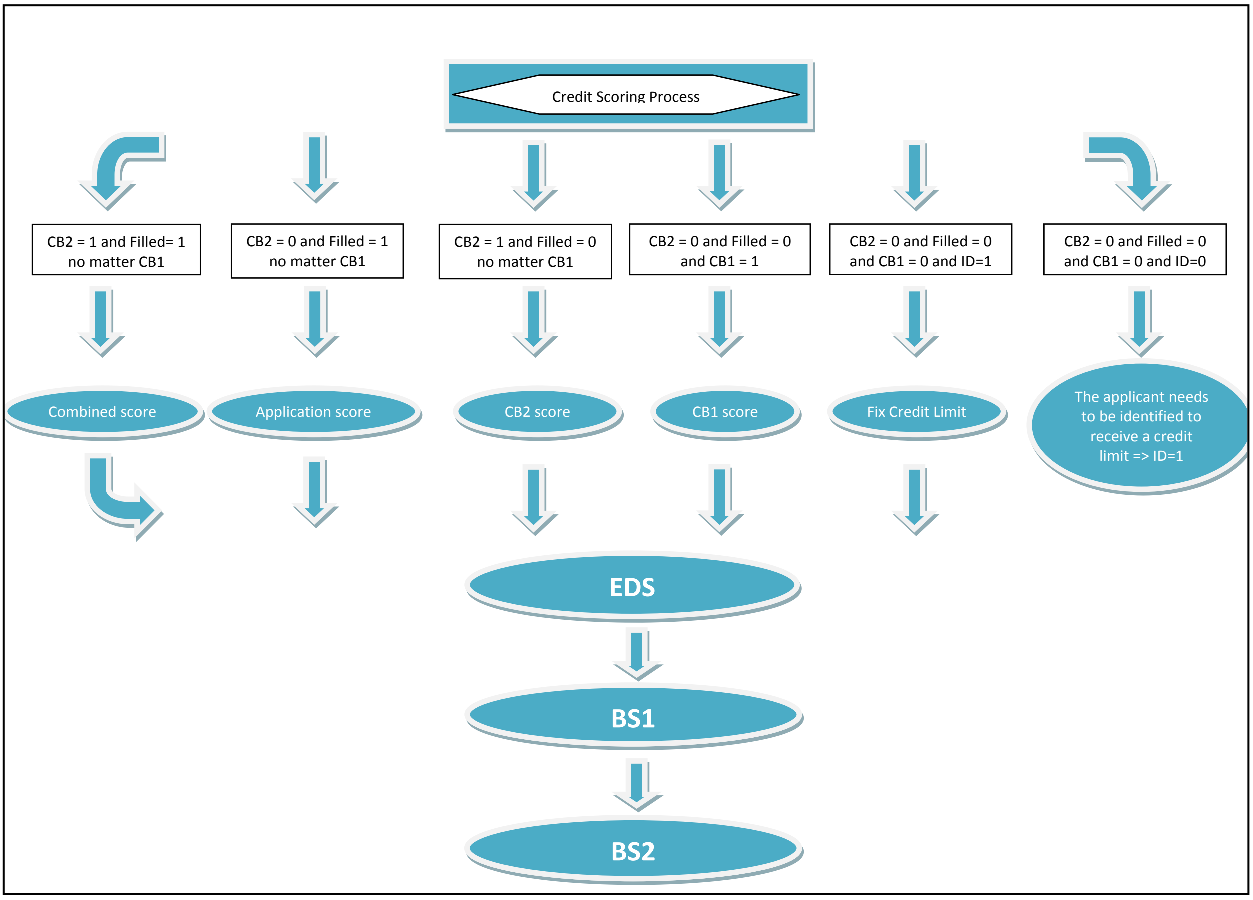
After this cleaning, this is when the credit scoring process will start to run. The process suggested in this report does not cover all areas of credit scoring but concentrates on credit risk aspects:

- An application scorecard to assign initial credit limits.
- Behavioural scorecards to increase credit limits.

However, the scoring process for initial credit limit will be somewhat more complex as applicants do not always have a score with Credit Bureau 2 and do not always fill the application.

For the following reasons, different applicant profiles have to be distinguished. As seen previously, the combined scorecard is the most efficient of all scorecards tested. Thus, all applicants that have filled the application and got scored with Credit Bureau 2 will be scored via the combined scorecard. For the rest of the portfolio, the model used will depend on the data available. It can be the application scorecard, the credit bureau 2 scores, the credit bureau 1 scores and a fix credit limit for applicants not identified and sending ID

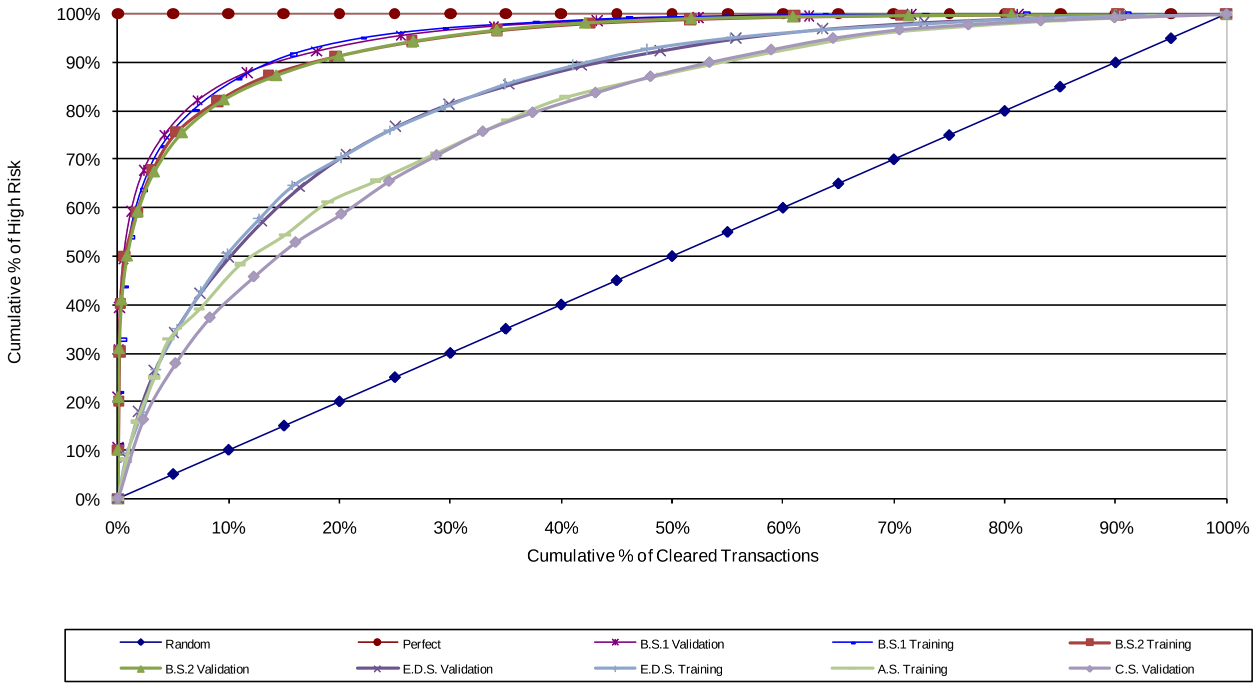
Figure 16 - Credit scoring flow chart



For the other models, the different applicants' profiles will not affect the models, i.e. early detection scorecard, behavioral scorecard 1 and behavioral scorecard 2. Indeed, the application scores and the credit bureau 2 scores have been imputed for the ones where it was missing. This means that all customers will get an early detection score, a behavioral score 1 and a behavioral score 2.

In the end, comparing the results of all scorecards, one can clearly state that the longer the observation period is, the better performing the model is. This statement is the key statement while defining scorecard's usage which is the topic of the next chapter of this thesis.

Figure 17 - Validation chart for all the scorecards



Chapter 6: Further application: How to find an equilibrium between credit risk scorings and profit

This chapter will be the second practical chapter in this PhD thesis. It will focus on implementing a scoring process that will take into account both the risk aspect and the profit aspect. Profit is a key element in the credit risk management process. Depending on the usage of the different scorecards, the bank has to find how to maximize net expected profits.

Therefore, the final step is to find how to optimize the use of such system for the bank. According to Ewert (1968), the main objective of any financial institution is to maximize the owner's wealth. The author will detail what profit means for the bank concerned in this thesis and illustrate this notion by presenting an income statement and defining its different components. The ultimate objective is to define the optimal credit policy by defining the key credit parameters that will affect the fully allocated margin of the company.

To optimize the scoring system developed in this thesis, the author presents different options: profit scoring, champion vs. Challengers testing, risk based pricing. The solution that is applied in this thesis is a testing process based on the champion vs. challenger approach. The credit lines have been anonymized to avoid any risk for the bank. The thesis presents the preliminary results of this test which will be a continuous testing process. The last solution presented is risk based pricing. Indeed, in this thesis, the bank is only playing with credit lines but interest rate is another valuable factor to consider. Once, the bank will have found the 'optimal' credit line, the next objective that the author would advice is to implement a risk based pricing model and to use the same testing approach.

In this chapter, the main questions that will be answered are:

- What is the optimal credit policy to minimize the losses and to maximize the profit?
- How to find the equilibrium between credit risk scorecards and profit?

Once those questions answered, the following issues stated earlier will be answered:

- How to find the optimal credit policy?

This thesis will intend to describe what the optimal credit policy for the bank should state.

- Profit vs. Default: how to find the equilibrium?

Knowing that a profitable customer is someone paying interest and having problems to repay, and thus, with a high probability of being delinquent, the frontier between risk and profit is rather small. This thesis will intend to propose methods to find the optimal strategy for the bank.

6.1 Profit

This purpose of this section is to define profit and how to take into account this notion while implementing the credit policy.

The first step is to define what profit means in the context of the research, both in terms of definition but also in the P&L itself and then how the credit policy will set the objective of the bank.

6.1.1 How to define profit and maximize it?

Banks might have different positions toward optimal credit policy and profit. Some banks will adopt a risk neutral position whereas other will follow the shareholder interest. For this research, the position was following the shareholder interest, i.e. get as much profitable as possible regardless of the loan loss amount.

As mentioned previously, the bank is not using the score models for rejecting applicants which is something not common in the industry. Most banks applied cut-off for acceptance and expect their portfolio to have a certain credit risk quality.

However, the view followed in this research is that:

- the bank gets as profitable as possible
- the bank minimizes the credit losses
- the rejection rate is strictly reduced to the minimum rate in order to satisfy regulators and auditors.

This philosophy is rather close to the philosophy of a subprime company and therefore involves higher risk than usual. This why finding the optimal way to use the scoring models, i.e. the optimal credit policy, is so crucial.

6.1.2 P&L of a Credit card business

The P&L (Profit and Loss) statement is also known as an income statement, statement of financial performance, earnings statement, operating statement or statement of operations (Helfert, 2001). Helfert (2001) gives the following definition:

“The income statement reflects the effect of management’s operating decisions on business performance and the resulting accounting profit or loss for the owners of the business over a specified period of time.“ The P&L statement starts with the revenues of the company and then all costs / expenses / tax that should be deduced to get the total contribution, also known as net income or fully allocated margin. The overall purpose of this financial statement is to reflect the financial position of the company to the management and the shareholders at a given time. Just below an example of an income statement.

Table 57 – Example of Income Statement

Income Statement (P&L) In thousands of EUR		YYYY
REVENUE		A=a1+...+a3
(1)	Interest	a1
(2)	Less Cost of Funding	a2
(3)	Balance Transfer Fee	a3
OCI		B=b1+...+b6
(3)	Interchange (Mastercard, Visa)	b1
(3)	Cash Advance Fee (ATM)	b2
(3)	Late Fee	b3
(3)	Overlimit Fee	b4
(3)	Commissions & Affilliate Income (Marketing related income)	b5
(3)	Other	b6
TOTAL REVENUE		A+B
COST		C=c1+c2
(11)	Impairment reserve	c1
(11)	Fraud reserve	c2
CONTRIBUTION		A+B+C
OPERATING COSTS		D=d1+...+d7
(8) (4)	Account Issuing (Credit bureaus...)	d1
(8) (4)	Marketing (Compaigns, promotions, coupons...)	d2
(8) (4)	Account Residency (Card processor costs...)	d3
(8) (4)	Operations (Call centers, printing services ...)	d4
(8) (4)	Collections (Collections agencies...)	d5
(7)	Headcount (Salaries, wages...)	d6
(9) (10)	Other (Information technology related expenses)	d7
PROFIT BEFORE TAX		A+B+C+D
(12)	Tax Savings	E
(1)	Incremental Treasury income (Bank placmeents)	F
TOTAL CONTRIBUTION		A+B+C+D+E+F

6.1.2.1 Revenue

In the credit card business, the revenues items will usually include:

- Interest (1): Interest income includes interest income earned on bank placements (including money market placements) and customer loans.

Interest income is charged on impaired loans to consumers based on the effective interest rate method.

Based on IAS 39 (International Accounting Standards), the effective interest rate is the rate that exactly discounts estimated future cash payments or receipts through the expected life of the financial instrument to the net carrying amount of the financial asset or liability (IAS, 2011). When calculating the effective interest rate, an entity shall estimate cash flows considering all contractual terms of the financial instrument (for example, prepayment, call and similar options) but shall not consider future credit losses. The calculation includes all fees and points paid or received between parties to the contract that are an integral part of the effective interest rate (IAS 18) (IAS, 2011).

- Fees and commission (3): Other fees and commission income consist of interchange fees from Visa / MasterCard, including account servicing fees, reminder fees charged to credit card customers.

- Other operating items (5): Other operating income includes all other income not recorded elsewhere.

6.1.2.2 Costs

In the credit card business, the costs items will usually include:

- Interest (2): Interest expense comprises interest paid on customer deposits. It can also include interest paid on loans made to other banks.

- Fees and commission (4): Other fees and commission expense consist of transaction and service fees, account handling fees paid to banks and fees paid to Visa/MasterCard.

- Other operating items (6): Other operating expense includes the net worth tax.

- Personnel expenses (7): Personnel expenses comprise wages, salaries, social security and other costs.

- General administrative expenses (8): General administrative expenses include administration expenses, operations expenses (including rental agreements, service agreements, customer acquisition costs...).

- Intangible assets (9): Computers / Software are stated at cost less accumulated amortisation and accumulated impairment losses.

Amortisation is recognised in profit or loss on a straight-line basis over the estimated useful life, and commences when the intangible asset is available for use and ceases at the earlier of the date the asset is classified as held for sale or the date it is derecognised (IAS 16) (IAS, 2011). As an example, for software, the estimated useful life could be three years.

Deferred tax is recognised using the balance sheet method, providing for temporary differences between the carrying amounts of assets and liabilities for financial reporting purposes and the amounts used for taxation purposes (IAS 12) (IAS, 2011).

Deferred tax assets and liabilities should be measured at the tax rates that are expected to apply to the period when the asset is realised or the liability is settled (liability method), based on tax rates/laws that have been enacted or substantively enacted by the end of the reporting period (IAS 12) (IAS, 2011). The measurement should reflect the entity's expectations, at the balance sheet date, as to the manner in which the carrying amount of its assets and liabilities will be recovered or settled (IAS 12) (IAS, 2011). A deferred tax asset should be recognised for an unused tax loss carry forward or unused tax credit if, and only if, it is considered probable that there will be sufficient future taxable profit against which the loss or credit carryforwards can be utilised (IAS 12) (IAS, 2011).

The carrying amount of deferred tax assets should be reviewed at the end of each reporting period and reduced to the extent that it is no longer probable that sufficient taxable profit will be available to allow the benefit of part or all of that deferred tax asset to be utilised. Any such reduction should be subsequently reversed to the extent that it becomes probable that sufficient taxable profit will be available (IAS 12) (IAS, 2011).

- Tangible assets - Property and equipment (10):

Recognition and measurement: Items of property, plant, and equipment should be recognised as assets when it is probable that: (IAS 16) (IAS, 2011):

- it is probable that the future economic benefits associated with the asset will flow to the entity, and the cost of the asset can be measured reliably. The asset is carried at cost less accumulated depreciation and impairment (IAS 16) (IAS, 2011). Cost includes expenditures that are directly attributable to the acquisition of the asset.

Depreciation: Depreciation is recognised in profit or loss on a straight-line basis over the estimated useful lives of each part of an item of property and equipment (IAS 16) (IAS, 2011).

Depreciation methods, useful lives and residual values are reassessed at the reporting date (IAS 16) (IAS, 2011).

- Impairment on financial assets (11): Every bank has to make a provision for credit loss. In addition, loans that are considered as uncollectible are written off.

- Income tax expense (12): Income tax expense consists of current and deferred tax.

Current tax is the expected tax payable on the taxable income for the year, using tax rates enacted or substantively enacted at the balance sheet date, and any adjustment to tax payable in respect of previous years. The Bank has at balance sheet date a result before taxes of EUR x, which generates a current income tax expense of EUR x*t, when applying the applicable tax rate in 2011 of t%.

6.1.2.3 Statement of comprehensive Income

In 2007, the International Accounting Standards Board issued a revised IAS 1: Presentation of Financial Statements. Under the revised version, business entities under IFRS must provide:

a Statement of Comprehensive Income or two separate statements comprising:

an Income Statement displaying components of profit or loss and a Statement of Comprehensive Income that begins with profit or loss (bottom line of the income statement) and displays the items of other comprehensive income for the reporting period (IAS1.81) (IAS, 2011).

The comprehensive income for a given period includes the net income for that period and other comprehensive income recognised in that period:

- "All items of income and expense recognised in a period must be included in profit or loss unless a Standard or an Interpretation requires otherwise" (IAS 1.88) (IAS, 2011).

- "Some IFRSs require or permit that some components to be excluded from profit or loss and instead to be included in other comprehensive income" (IAS 1.89) (IAS, 2011).

Table 58 – Definition of Statement of Comprehensive Income

The new income statement (Statement of Comprehensive Income) "The Statement of Comprehensive Income is similar to today's income statement in that it calculates a subtotal for net income and then has a section for other comprehensive income (OCI). However, everything above net income is divided into the same categories that the balance sheet is classified in — an operating section, an investing section, a financing section, income taxes, and discontinued operations. Within the OCI section, the entity must indicate to which category (operating, investing, or financing) the actual line items relate to. Line items are further identified by function and then nature. For example, cost of goods sold must be further subdivided into materials costs, labour costs, and overhead. Details for general and administrative expenses must also be disclosed. If these guidelines result in too lengthy of a statement, the entity can summarize the statement, but they must still present the details in the financial statement notes" (Benzacar, 2009).

Table 59 – Example of Statement of Comprehensive Income

STATEMENT OF COMPREHENSIVE INCOME In thousands of EUR		YYYY
Financial and operational income and expenses		A=a1+...+a6
(1)	Interest income	a1
(2)	Interest expense	a2
(3)	Commission income	a3
(4)	Commission expense	a4
(5)	Other operating income	a5
(6)	Other operating expense	a6
Administrative expenses		B=B1+B2
(7)	Personnel expenses	b1
(8)	General administrative expenses	b2
Depreciations and amortisations on (in)tangible assets		C=c1+c2
(9)	Depreciation and amortisation on tangible assets	c1
(10)	Depreciation and amortisation on intangible assets	c2
(11)	Impairment on financial assets	D
Result on activities before taxes		A+B+C+D
(12)	Income taxes Expense	E
Result for the year (Result on activities after taxes)		A+B+C+D+E
Other comprehensive income for the year		F
Total comprehensive income for the year		A+B+C+D+E+F

6.1.2.4 Regulatory / Prudential balance sheet requirement

Since 2007, under the circular CE 1606/2002 of the European Union, all traded companies have had to publish the financial results from the 1st of January 2005 in I.AS / I.F.R.S. International Financial Reporting Standards (IFRS) are accounting rules established by the International Accounting Standards Board (IASB) for traded companies or business entities owned by shareholders in order to harmonize financial results.

Just below a list of IFRS topics:

Table 60 – List of IFRS topic

Module	Name
IAS 1	Presentation of Financial Statements
IAS 2	Inventories
IAS 7	Cash Flow Statements
IAS 8	Accounting Policies, Changes in Accounting Estimates and Errors
IAS 10	Events After the Balance Sheet Date
IAS 11	Construction Contracts
IAS 12	Income Taxes
IAS 16	Property, Plant and Equipment
IAS 17	Leases
IAS 18	Revenue
IAS 19	Employee Benefits
IAS 20	Accounting for Government Grants and Disclosure of Government Assistance
IAS 21	The Effects of Changes in Foreign Exchange Rates
IAS 23	Borrowing Costs
IAS 24	Related Party Disclosures
IAS 26	Accounting and Reporting by Retirement Benefit Plans
IAS 27	Consolidated and Separate Financial Statements
IAS 28	Investments in Associates
IAS 29	Financial Reporting in Hyperinflationary Economies
IAS 31	Interests in Joint Ventures
IAS 32	Financial Instruments (Disclosure and Presentation)
IAS 33	Earnings per Share
IAS 34	Interim Financial Reporting
IAS 36	Impairment of assets
IAS 37	Provisions, Contingent Liabilities and Contingent Assets
IAS 38	Intangible Assets
IAS 39	Financial Instruments (Recognition and Measurement)
IAS 40	Investment Property
IAS 41	Agriculture
IFRS 1	First-time Adoption of International Financial Reporting Standards
IFRS 2	Share-based Payment
IFRS 3	Business Combinations
IFRS 4	Insurance Contracts
IFRS 5	Non-current Assets Held for Sale and Discontinued Operations
IFRS 6	Exploration for and Evaluation of Mineral resources
IFRS 7	Financial Instruments: Disclosures
IFRS 8	Operating segments
IFRS 9	Financial Instruments

Source: IAS (IAS, 2011).

As the author could not cover all items, she decided to focus on a specific item of IFRS which is the provision for loan losses as accounted in accordance with IFRS. The allowance for loan losses, also known as value adjustment, value impairment or loan loss provision, is an accounting estimate of credit losses inherent in an institution's loan portfolio that have been incurred as of the balance-sheet date. For more details, please refer to Chapter 6 – 6.2.3 Profit analyses.

IAS 39 “Financial Instruments: Recognition and Measurement” provides guidance regarding the calculation of value adjustment (IAS, 2011).

Table 61 – Extract from IAS 39

Para 58
An entity shall assess at the end of each reporting period whether there is any objective evidence that a financial asset or group of financial assets is impaired. If any such evidence exists, the entity shall apply paragraph 63 (for financial assets carried at amortised cost), paragraph 66 (for financial assets carried at cost) or paragraph 67 (for available-for-sale financial assets) to determine the amount of any impairment loss.

Para 59
A financial asset or a group of financial assets is impaired and impairment losses are incurred if, and only if, there is objective evidence of impairment as a result of one or more events that occurred after the initial recognition of the asset (a 'loss event') and that loss event (or events) has an impact on the estimated future cash flows of the financial asset or group of financial assets that can be reliably estimated. It may not be possible to identify a single, discrete event that caused the impairment. Rather the combined effect of several events may have caused the impairment. Losses expected as a result of future events, no matter how likely, are not recognised. Objective evidence that a financial asset or group of assets is impaired includes observable data that comes to the attention of the holder of the asset about the following loss events:
(a) significant financial difficulty of the issuer or obligor;
(b) a breach of contract, such as a default or delinquency in interest or principal payments;
(c) the lender, for economic or legal reasons relating to the borrower's financial difficulty, granting to the borrower a concession that the lender would not otherwise consider;
(d) it becoming probable that the borrower will enter bankruptcy or other financial reorganisation;
(e) the disappearance of an active market for that financial asset because of financial difficulties; or
(f) observable data indicating that there is a measurable decrease in the estimated future cash flows from a group of financial assets since the initial recognition of those assets, although the decrease cannot yet be identified with the individual financial assets in the group, including:
(i) adverse changes in the payment status of borrowers in the group (eg an increased number of delayed payments or an increased number of credit card borrowers who have reached their credit limit and are paying the minimum monthly amount); or
(ii) national or local economic conditions that correlate with defaults on the assets in the group (eg an increase in the unemployment rate in the geographical area of the borrowers, a decrease in property prices for mortgages in the relevant area, a decrease in oil prices for loan assets to oil producers, or adverse changes in industry conditions that affect the borrowers in the group).

Para 63
For financial assets carried at amortised cost, if there is objective evidence that an impairment loss on loans and receivables or held-to-maturity investments carried at amortised cost has been incurred, the amount of the loss is measured as the difference between the asset's carrying amount and the present value of estimated future cash flows (excluding future credit losses that have not been incurred) discounted at the financial asset's original effective interest rate (ie the effective interest rate computed at initial recognition). The carrying amount of the asset shall be reduced either directly or through use of an allowance account. The amount of the loss shall be recognised in profit or loss.

Para 64
An entity first assesses whether objective evidence of impairment exists individually for financial assets that are individually significant, and individually or collectively for financial assets that are not individually significant (see paragraph 59). If an entity determines that no objective evidence of impairment exists for an individually assessed financial asset, whether significant or not, it includes the asset in a group of financial assets with similar credit risk characteristics and collectively assesses them for impairment. Assets that are individually assessed for impairment and for which an impairment loss is or continues to be recognised are not included in a collective assessment of impairment.

Source: IAS (IAS, 2011).

To summarize, the basic principles for recording the reserve for loans based on IFRS are as follows:

1) A reserve can only be recorded if and when it is probable than a loss has been incurred at the date of the financial statements

2) An entity should first assess for impairment loans that are individually significant before moving to a collective assessment

3) The focus of the pool approach is generally on the historical loss experience for the pool.

In section 2.3, the author will use the loan loss reserve to estimate a profit indicator.

6.1.3 The optimal credit policy

The Credit Policy formalises and articulates the Bank's objectives to measure, monitor, and manage credit risk. For more details, please refer to Chapter 2. The aim of this section is to describe the three main parameters that should be set within the policy and that will influence the profit of the firm.

6.1.3.1 Acceptance / Rejection criteria

When the scorecard system is finalized, the lender will have to decide how to use the score.

In fact, some customers with their application or behavioural score will be classified as "good" customers whereas they are never revolving. The lender will have different options:

- The easiest is simply to reject those customers. In fact, they are always paying on time and they don't represent a high portion of the total profit of the bank.

- Others options that could be considered as a compromise between rejecting them and accepting them is to propose to those customers products that could satisfy them and this time, bring profit.
- The lender may also accept them knowing that they are not profitable but considering them as business costs accepted by the bank or decide to assign specific fees or rates to those customers. Some of those customers will turn into profitable ones, while the rest will possibly stop their contract.

In addition, for credit card companies, giving credit card to customers who pay on time is not a major issue; as long as they use the card, the bank will still get the interchanges which over time will cover for cost of the card. So knowing who is not profitable is not a must.
In the case studied, the bank was applying this third option.

In summary, There are two types of account: those bringing profit to the bank (or at least fulfilling their contractual engagement / the "good" customer), and the ones generating net losses.

Most banks will use credit scoring models to reject high risk profile customers and to detect the low risk customers to assign them higher limits.
However, as explained previously, in this Ph.D thesis, the bank was accepting all customers without bad marks regardless of their risk profile and was using credit scoring to assign credit line in respect of their risk profile.

6.1.3.2 Credit lines

Initially, credit lines were granted by credit officers based on their own judgements. According to Witkowska (2006), the drawbacks of such method were: the costs for training the credit officers, wrong decisions in granting the credit, the time needed to review the applicant's profile / to categorize them / to take the final decision and the fact that more than one agent might work on a case. For those reasons, credit institutions started to work on automating credit decisions.

The past years have seen the explosion of the use of statistics to predict credit risk, and for taking decision on granting credits. Credit scoring models have been more and more used to predict the credit risk of the portfolio and to assign the credit lines.

On the credit line assignment process, there are two possible issues from a credit policy stand point:

- If the credit line is too strict, applicants might decide to stop their contract and go to a competitor.
- By contrast, by assigning high credit limits, the bank will take high credit risk.

The bank has to find the optimal credit limit for the different risk profiles of the applicants. The next section of this chapter focuses on this issue.

6.1.3.3 Interest rates

In the United States, the average credit card rate for March 2009 was 13.89% (Indexcreditcards, no date). In Germany, the average interest rate is 14.56% based on 28 credit cards' competitors.

The interest rate can be fixed or variable (Modern-banking, 2009).

Usually, most banks have mentioned in their terms and conditions that the interest can be modified by the bank. Indeed, most credit card companies will use techniques such as risk based pricing (also called differential pricing) to fix their interest rate schedule.

The Chapter 6 Section 6.2.5 of this thesis presents a technique to optimize interest rate that is called risk based pricing.

6.2 Methods to optimize profit vs. Losses

This purpose of this section is to present different methods that can be used for profit optimization.

6.2.1 Profit scoring

On the question:"How to maximize profit?" one option is to build new tools such as profit scoring. The concept of profit scoring is not really different from those for developing other scorecards. The main difference is in the outcome definition, with profit scoring, the aim is to predict who is profitable and who is not whereas with other scorecards, the aim is to predict if the customer will default or not.

The main difficulty to develop a profit scorecard is the definition of the different terms. The dependent variable has to be clearly defined, i.e. the calculations of profit/loss and their parameters. The outcome should be binary so based on the profit and loss calculations, each account should get one of those two status "good" and "bad". The cut off between those two statuses will depend on the strategy chosen by the bank. Thomas et al. suggested the following strategies:

- Accept all loans where the expected income is greater than the expected cost.
- Accept all loans where the expected income is greater than the expected cost by a fixed amount.
- Accept all loans where the expected income is greater than the expected cost by a fixed percentage.
- Accept all loans where the expected profit is at least a fixed percentage of the amount of the loan.

According to Thomas et al., parameters that have to be taken into account in the profit calculation are administrative and funding costs, timing of early payment, cross-selling opportunities, acquisition costs, overhead-type costs (recover our system development costs), NPV (Net Present Value) calculation and the risk of allocation of costs if no measurements are possible.

The principle of a profit scorecard is similar to any other scorecards. It follows the same process.

When the profit scorecard is finalized, the lender will have to decide how to use the score. In fact, in some cases, some customers with their application or behavioral score will be classified as "good" customers whereas with their profit score they will be classified as "bad". There are then different actions that can be taken:

- The bank can decide not to do anything and just accept the cost as some might become profitable over time. Another option is to assign interest rates or fees to those customers.
- The bank can also decide to reject those. In fact, they are always paying on time and they don't represent a high portion of the total profit of the bank.
- The bank can also decide to offer them another products more adapted to their needs and to the bank's expectation.

As mentioned previously, the bank that provided the data for this thesis was accepting all valid applications without major credit juridical issues which mean that the third option was the one applied by the company.

Technically, implementing a profit scoring does not present any particular difficulty than any other type of scorecards. The binary outcome: defaulters and non defaulters of other scorecards is just replaced by the outcome: profitable and non-profitable The major issue and also the reason why this subject has not been discussed in depth is that it is complex to get a complete definition of profit/loss, to get some clear decision rules regarding doubtful cases and fulfil the assumptions that are required for the profitability assessment.

6.2.2 Champion vs. Challenger testing

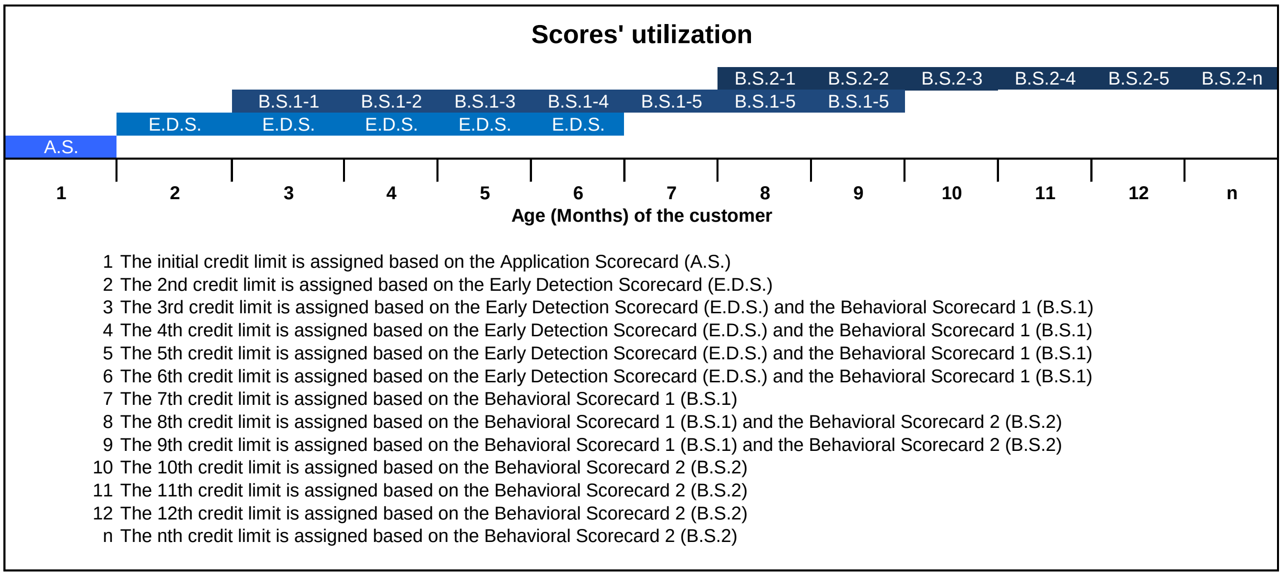
This section is focussing on credit strategies and the testing plan that goes with it to find the optimal credit policy for the bank. Getting figures to illustrate this point are really difficult as testing such strategies are costly for the bank. In an ideal world, banks would do such tests but most of them are reluctant to perform them as they could be rather costly, even though the outcome might lead to higher income. Anyway, the result is not so interesting because it will vary from bank to bank depending on their product specificities. The main point is to show that champion versus challenger strategies are indispensable to find the optimal credit policy even though having great tools with a high predictive power.

6.2.2.1 Credit scoring framework

Four scorecards have been developed: an AS (Application Scorecard), an E.D.S. (Early Detection Scorecard based on the first day transaction), a first BS (Behavioural Scorecard for the 6 first months the customer is using the card) and a second BS (Behavioural Scorecard for the 6 next rolling months).

The scoring process presented in this section will include the 4 models. However, after developing scorecards, one is force to conclude that those are only tools and it is the way we use it which is the key element. For this PhD thesis, presenting the process and giving some details about the scores are findings that will interest researchers or bankers. However, their usage is really the key element to get an efficient credit scoring process. Depending on the way scorecards are used, the results might be the opposite of what is expected even though the common objective of every institution is to identify the optimal credit policy or the most profitable credit policy.

Figure 18 - Scorecards time frame



Typically, the scores would work as follows:

Four risk profiles need to be defined. Those profiles are necessary in order to make the process flexible and manageable, a 20 points/dimensions system would be rather complex and not easily explainable to the management. There could be many changes over time so defining groups will allow fast changes. An E.D.S. of 14 pts is now included in the medium high risk category but the system should be set up such as an E.D.S. of 14 pts can move to high risk easily if necessary. Those categories will be created for each scorecard, i.e. E.D.S., BS1 and BS2 except for the AS where the initial credit limit will define the risk profile.

Three risk profiles are defined based on the risk level associated with it:

- Low refers to a default rate equal to or below 1%.
- Medium refers to a default rate between 1% and 5%.
- High refers to a default rate above 5%.

At months 1, 2, 7 and 10 and plus, the increases will be based only on one score. The risk profiles Low and Medium-Low will be eligible for increases. This decision will depend on the risk appetite of the bank, some may decide to only increase the Low risk profile, and others may increase all segments.

At months 3, 4, 5, 6, 8 and 9, the system will be a little bit more complex. For months 3, 4, 5 and 6, the bank has access to the E.D.S. of the customers. The BS1 is only fully efficient after 6 billing months which means month 7. However, it can be calculated from month 3 as it means two billing months and therefore, one payment's information. Early indications of bad behaviour should be considered even though month 7 is not reached.

For the following reason, for months 3, 4, 5 and 6, a combined profile is established called EDS_BS1 where:

Table 62 - Risk segmentation for EDS_BS1

EDS	BS1	EDS_BS1
	Low	Low
	Medium	Low
Low	High	Medium
	Low	Low
	Medium	Medium
Medium	High	High
	Low	Medium
	Medium	High
High	High	High

For months 8 and 9, the bank has access to the BS1 and BS2 of the customers. As BS1 has a higher information value, although it is not significantly different, the bank can decide to take into account the BS1 score for a longer period. Thus, the BS1 at month 7 will still be used for 3 months, i.e. months 7, 8 and 9.

As for EDS_BS1, a combined profile is established called BS1_BS2 where:

Table 63 - Risk segmentation for BS1_BS2

BS1	BS2	BS1_BS2
	Low	Low
	Medium	Low
Low	High	Medium
	Low	Low
	Medium	Medium
Medium	High	High
	Low	Medium
	Medium	High
High	High	High

The process described covers the full life cycle of a customer and allows controlling the credit exposure. The process is dynamic; the risk profile definitions can be adjusted, the usage of the scorecards can be modified, the despatch of the increases is flexible. The increases of the credit limit should be regular, but not too regular in order to avoid that the fraudsters can understand the system.

6.2.2.2 The champion: the current strategy

Since the 1990s, champion and challenger strategies have been more and more used in the credit area but also recognized as one of the best solution for decision taking due to its simple concept.

The champion strategy without having access to historical data or performing tests will be the strategy that based on past experience and specificities of the portfolio appeared as the optimal one. With some slightly modifications, the one shown in the next section was the one applied within the bank. The champion strategy is the strategy that 'sounds' the most correct based on past experience and the data available, if possible. It is the 'best' strategy to achieve the objective of the bank.

However, there could be more than one strategy that 'sounds 'correct and allows reaching the objectives of the bank. Those strategies are the challengers. Those challenger strategies are usually more aggressive or more conservative, the aim being to find the optimal way to reach the target.

Once the tests performed, the conclusion might be that the challenger's strategy is the most appropriate and therefore, that this challenger strategy replaced the champion strategy and consequently became the new champion strategy.

Just below a practical example justifying the use of Champion vs. Challenger testing, let's imagine a bank is facing two possible options:

Option 1

Considers that with a certain application score, the system assign a credit limit x and with a perfect early detection score, i.e. 20 points, the credit limit becomes x+1000. The default rate associated with this scoreband is 1%. So taking 100 customers getting a perfect early detection score, one of those is expected to default. The total amount at risk would be x+1000. Therefore, the increase of the amount at risk due to the increase is expected to be 1000.

Option 2

Considers that with a certain application score, the system assigns a credit limit x/4 and with a good early detection score, i.e. 16, the credit limit becomes x/n+100 where n>0 and <10. The default rate associated with this scoreband is 10%. So taking 100 customers getting a good early detection score, ten of those are expected to default. The total amount at risk would be 10*(x/n+100). Therefore, the amount at risk due to the increase is expected to be 10*100=1000.

Without any other information (except that the bands are equal sized) and deciding on the best option, one would consider that the first option is the most secure and would probably increase the best segment from x to x+1000.

Further on, assume that:

- the average balance of a customers over time will be (2/3)x
- a credit limit of x+1000 is much higher than the average usage
- the x/n customers are more prone to revolve than the x customers
- Churn, interests and losses are the three elements to consider while seeking the optimal credit policy.

Under those assumptions and taking case 2, the x/n customers will be motivated to keep using the card, so less churn and more future income as they are prone to revolve; the x customers will stay with their initial limit which does not prevent them for reaching the average long term loan balance.

One would then consider that the 2nd case is the best option.

However, the best way for a financial institution to find out the optimal credit policy is to test the different possible assumptions implementing champion versus challenger strategy.

6.2.2.3 The challengers: the strategies to be tested

In the credit card industry, credit strategies can have different action scopes (Thomas et al., 2001):

- Line Management
- Authorizations
- Outbound Calls, Contact Confirmation, Data Verification, Email, etc…
- Flag/Monitor for Subsequent Review
- Repricing, new interest rate, new terms, etc…

The strategies selected will depend on the objectives of the bank which include:

- Blocking account usage before an excessive number of risky transactions are approved
- Reducing the time interval between detection and alert of the customer to the potential fraud
- Minimizing the inconvenience to profitable customers
- Limiting ongoing exposure

Strategies dealing with line management are mostly focusing on financial aspects such as reducing the amount at risk or the loan loss rate. The purpose is to decrease the delinquent balances or fraudulent balances.

Strategies dealing with the interest rates generally centre on financial aspects as above but more on the profit side (such as the increase in the interests and the utilization).

Strategies more directed at communication (such as outbound calls, contact confirmation, data verification and e-mail), on authorizations and on flag/monitor for subsequent review have different purposes. It can aim at testing different ways to treat delinquent customers or customers overlimit. One can also test different modalities to set up authorization, i.e. in case of a customer exceeds the maximum amount authorized or a certain number of transactions, a merchant will ask an authorization for the transaction. Same when a card is reissued, one can test different ways of communication to find out where to send the new cards.

In this PhD thesis, the main focus is credit scoring and therefore, the credit line management.

On the technical side, to put in place such strategies, systems will need to be modified. Systems will need to allow the user to randomly select accounts. To do so, most systems have random number allocated to each account. This might be a two- or three-digit number. However, the best systems will have more than one random number allocated. This is useful in reallocating test groups. Moreover, if the test is to be valid, we need to have a statistically significant number of “bads” (fraudulent) accounts of at least 30 or so and preferably 2-3 times that. So, giving 500 accounts, if the default unit rate is approximately 10% we likely would have enough but if it is much lower than we would likely need many more accounts. Test and sampling strategy has to follow the next rules:

- The more alternative credit strategies will be implemented, the more samples will be needed and the longer the observation period will have to be.
- Need to generate enough random digits to selected samples.
- Need to define a sampling process.

Below is an example on how to implement credit strategies.

The objective is to evaluate the strategies on a representative sample and over a period long enough to draw accurate conclusions. Let's consider 5000 new active customers per month.

Knowing that the default unit rate is 9% after 6 months of eligibility and 7% after 3 months and that to be eligible 3 more months are needed. The test's results cannot be expected before at least 6 months. Let's take 7% default unit rate and a 6 months observation period, 5 samples of 1000 customers each (incl. 60 expected to become delinquent) can be extracted.

As strategies will both affect initial and subsequent credit limits, the sampling process has to be automated in 2 steps: create a random digit and run a program that will select 5 samples of 1000 customers randomly and flag them with a flag named Test that will take the following values Test1-Test5.

Once the scorecards have run on the applicant, transaction or statement file, the score will be connected with a different credit limit matrix where the credit limits to be tested will be inserted.

The samples have to be selected randomly and it is recommended to repeat the test at least one more month in case the sample would be biased or not representative. Three times would be a good option.

The Test1 sample should be the control sample that will receive reference credit limits.

In this PhD thesis, 4 strategies will be implemented. Once the technical side clarified, the bank needs to define the possible strategies of credit lines to be tested:

First step: the bank needs to find the optimal initial credit limit that will be set based on the application score of the customers. The examples used are illustrated with a conservative range of initial credit limit. Most banks will have a higher range of credit lines.

Three options are then presented:

Table 64 - Low initial credit limit

Pt	A.S.-1	A.S.-2	A.S.-3	A.S.-4	A.S.-5
1	x	x	x	x	6*x
2	x	x	x	x	6*x
3	x	x	x	x	6*x
4	x	x	x	x	6*x
5	x	x	x	x	6*x
6	x	x	x	x	6*x
7	x	x	x	x	6*x
8	x	x	x	x	6*x
9	x	x	x	x	6*x
10	x	x	x	x	6*x
11	2*x	x	x	x	6*x
12	2*x	x	x	x	6*x
13	4*x	x	x	x	6*x
14	4*x	x	x	x	6*x
15	4*x	x	x	x	6*x
16	4*x	x	x	x	6*x
17	10*x	x	2*x	x	6*x
18	10*x	2*x	2*x	x	6*x
19	20*x	2*x	4*x	x	6*x
20	30*x	2*x	4*x	x	6*x

Table 65 - Medium initial credit limit

Pt	A.S.-1	A.S.-2	A.S.-3	A.S.-4	A.S.-5
1	x	x	x	x	6*x
2	x	x	x	x	6*x
3	x	x	x	x	6*x
4	x	x	x	x	6*x
5	x	x	x	x	6*x
6	2*x	x	x	x	6*x
7	2*x	x	x	x	6*x
8	2*x	x	x	x	6*x
9	2*x	x	2*x	x	6*x
10	2*x	x	2*x	x	6*x
11	4*x	x	2*x	x	6*x
12	6*x	x	2*x	x	6*x
13	6*x	x	2*x	x	6*x
14	6*x	x	2*x	x	6*x
15	10*x	x	2*x	x	6*x
16	10*x	x	2*x	x	6*x
17	20*x	x	4*x	x	6*x
18	20*x	2*x	4*x	x	6*x
19	30*x	2*x	6*x	x	6*x
20	40*x	2*x	10*x	x	6*x

Table 66 - High initial credit limit

Pt	A.S.-1	A.S.-2	A.S.-3	A.S.-4	A.S.-5
1	x	x	x	x	6*x
2	x	x	x	x	6*x
3	x	x	x	x	6*x
4	x	x	x	x	6*x
5	2*x	x	x	x	6*x
6	2*x	x	x	x	6*x
7	2*x	x	x	x	6*x
8	2*x	x	x	x	6*x
9	4*x	x	2*x	x	6*x
10	4*x	x	2*x	x	6*x
11	6*x	x	2*x	x	6*x
12	6*x	x	2*x	x	6*x
13	8*x	x	2*x	x	6*x
14	8*x	x	2*x	x	6*x
15	20*x	x	2*x	x	6*x
16	20*x	x	2*x	x	6*x
17	30*x	x	6*x	x	6*x
18	30*x	2*x	6*x	x	6*x
19	40*x	2*x	8*x	x	6*x
20	40*x	2*x	20*x	x	6*x

Second step: the bank has to test what is the optimal speed for increasing credit limits. As the bank used three risk profiles (high, medium and low), those three cases will not be treated in the same way, as the risks associated with them differ.

For the low risk segment:

This segment is the lowest risk segment of the bank. Three types of speed can be tested for the different types of initial credit limits.

Table 67 – Increases in speed for the low risk segment

Initial credit limit	Increases speed
	Slow
	Medium
Low	Fast
	Slow
	Medium
Medium	Fast
	Slow
	Medium
High	Fast

A bank will not be able to test all and will select the ones that best fits the portfolio targeted by the bank. Considering this example, where the bank is assigning conservative initial credit limits and limited to 4 strategies, the strategies picked could be:

- Medium Initial + Medium increase's speed (which is the champion strategy)
- Medium Initial + Fast increase's speed
- High Initial + Medium increase's speed
- Low Initial + Fast increase's speed

However, the risk appetite of the bank will also enter as a criterion of decision for the strategies.

For the medium risk segment:

This is the medium risk segment of the bank. The speed for increasing should be normally lower than the one tested above. This is why in the increases' speeds below slow/2, Medium/2 and Fast/2 have been included. It just means that the speed has been reduced by half.

It means that instead of 9 months to reach the maximum credit limit, it will take 18 months.

The reason is that the risk is twice and even higher for this segment.

Table 68 – Increases in speed for the medium risk segment

Initial credit limit	Increases speed
	Slow
	Medium
	Fast
	Slow/2
	Medium/2
Low	Fast/2
	Slow
	Medium
	Fast
	Slow/2
	Medium/2
Medium	Fast/2
	Slow
	Medium
	Fast
	Slow/2
	Medium/2
High	Fast/2

The bank should probably test the following:

- Medium Initial + Slow increase's speed
- Medium Initial + Medium increase's speed
- High Initial + Slow increase's speed
- Low Initial + Medium increase's speed

For the high risk segment:

This segment will not be eligible for any increases.

Table 69 – Increases in speed for the high risk segment

Initial credit limit	Increases speed
Low	
Medium	
High	-

Graphical displays of the different increases' speed would be as follows:

Figure 19 - Fast Increases trend chart for well behaved customers

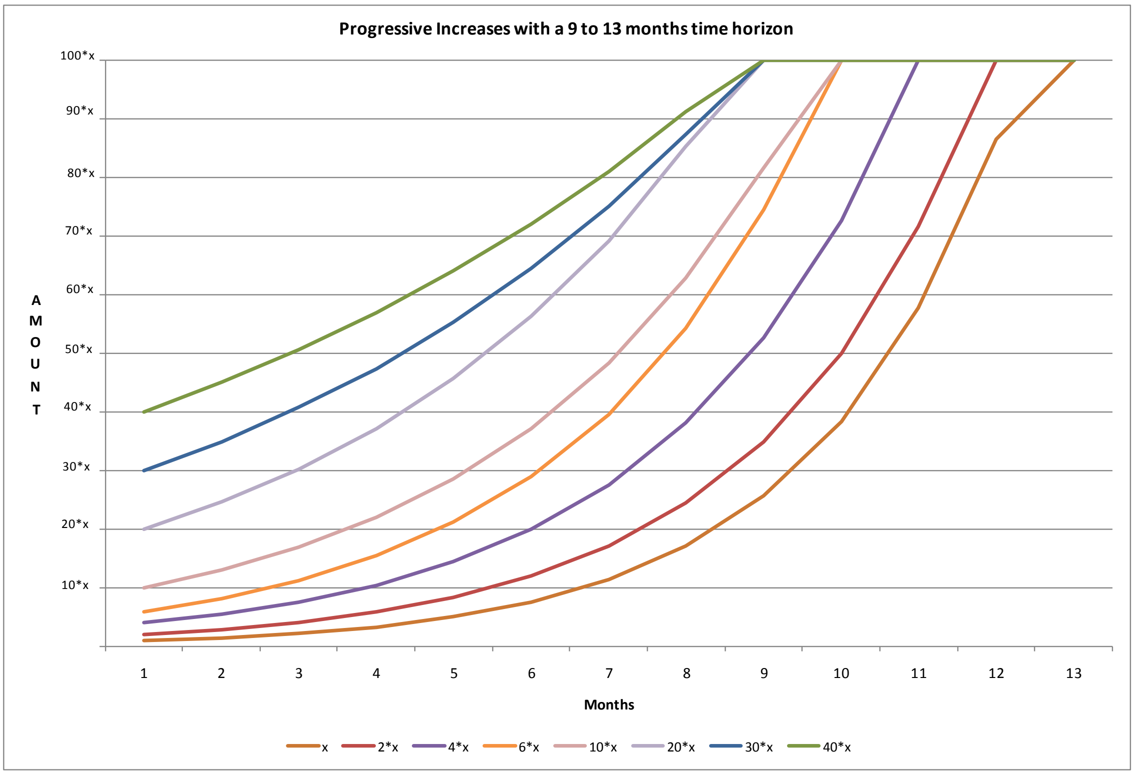


Figure 20 - Medium Increases trend chart for well behaved customers

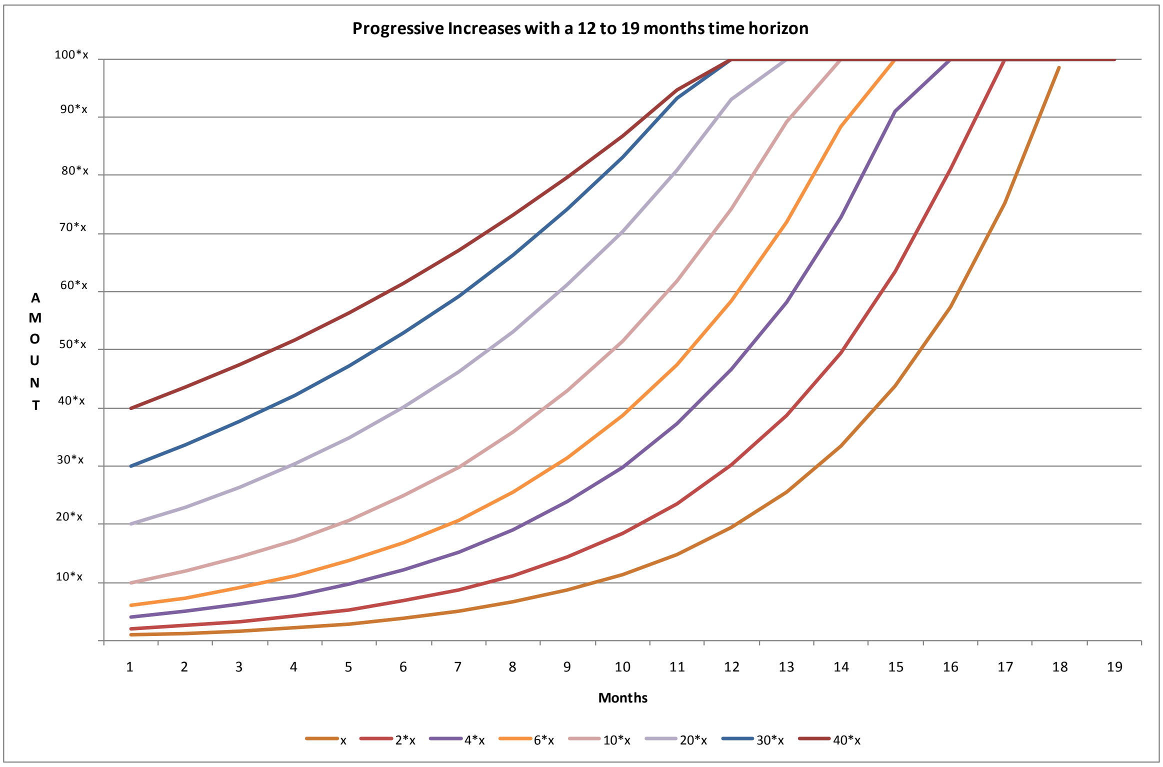
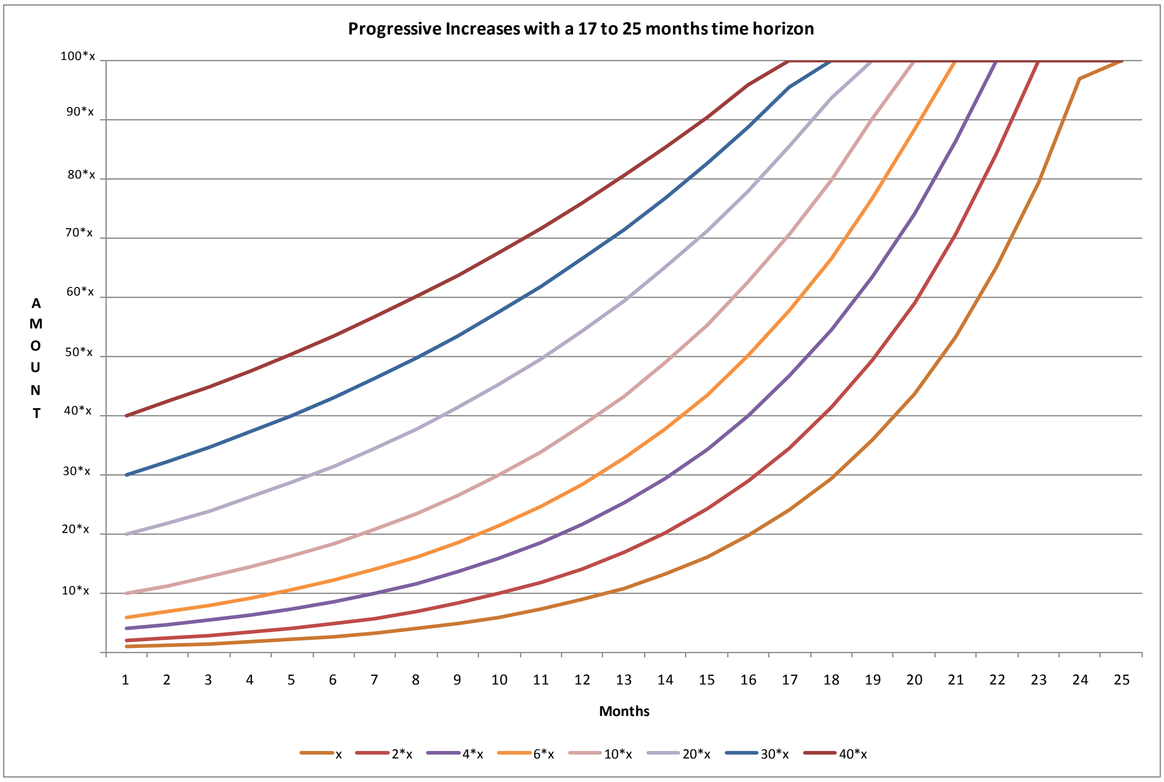


Figure 21 - Slow Increases trend chart for well behaved customers



Performing tests is the only way to find out the optimal credit policy for a bank. The next step is to evaluate which strategy is giving the best result. Different performance reports as well as key performance indicators will be used to make the final decision.

The next section presents the method used for evaluating the strategies.

6.2.3 Profit analysis

In this section, the author presents an indicator, which is a ratio of the monthly per card value adjustment vs. the monthly per card interest income, that can be used for analysing the profitability of the business and that the bank is using.

6.2.3.1 Value adjustment

Value adjustment is also known as value impairments. Value adjustments are recorded in the P&L and on the balance sheet as described previously. In the credit card industry, value adjustment is commonly assessed at the end of each billing cycle, which is often the end of the month as credit cards can be used through the month, and applied to the ending balance.

The finance department is usually responsible for assessing value adjustment and to define it in the credit and fraud loss policy or loan loss reserve procedure or loan loss procedure or impairment procedure....

Basically, a value adjustment is due to an impairment of the value of the asset. The bank proceed to a value impairment for an account when the account shows clear signs that a loss event will occur and that this will cause a decrease of future loan cash flows.

Examples of objective evidences of the occurrence of a loss are:

- Significant financial difficulties with the obligor
- Default/delinquency or other severe breaches of contract
- Agreed deferral of payments, interest reduction
- Debt negotiation, or bankruptcy procedures

In the credit card business, a common practice in loan loss calculation is to group accounts presenting the same risk exposure. Indeed, credit lines are usually small loans and credit card holders tend to behave the same way and therefore presenting clear significant delinquent patterns.

Example of value impairments would be:

- For accounts in bankruptcy filing: 100 % value impairment
- For accounts considered as fraudulent: 99 % value impairment
- For accounts in default-status high where high could be 210 days or more past due: 65% value impairment.
- For accounts in default-status medium where medium could be 90 days past due to 210 days past due: 50 % value impairment.
- For accounts in default-status low where low could be 60 days past due: 45 % value impairment.
- For pre-delinquent account, i.e. 0 to 30 days past due: If the percentage of this group increases by 20% on average over the last three months, the percent increase in number of clients multiplied with the aggregate balance of these clients will be subject to the probability of reaching 60 days past due, and adjusted for the applicable value impairment adjustments.
- For Normal accounts: only accounts with a credit limit above EUR x, and a balance of 100 % or more of their ending limit, and paying only minimum amount are concerned: If the percentage of this group increases by 20% on average over the last three months, the percent increase in number of clients multiplied with the aggregate balance of these clients will be subject to the probability of becoming 60 days past due, and adjusted for the applicable value impairment adjustment.

Those are just examples; there are many ways of estimating value impairments. Value impairments calculation might also use economic data provided by external source, but also use historical and seasonal data. As each bank is responsible for assessing the value of its portfolio, the degree of complexity of its loan loss calculation will depend on the expected precision in the forecast.

6.2.3.2 Interest Income

Interest income is the calculated interest on loans.

6.2.3.3 Profitability Ratio

The graph below presents the latest trends in terms of value adjustments vs. interest income for the bank. The data are analysed on a yearly basis and on a cumulative basis. The ratio also is analysed for the entire portfolio and by strategies

The indicator used in this analysis is a ratio of the monthly per card value adjustment vs. the monthly per card interest income. The ratio has been estimated with respect to the age of the vintage as well as the monthly value adjustment.

The ratio can be interpreted as follows:

- A ratio of 1.0 means that for a given month, that vintage has generated as much value adjustments as to cancel out interest income (before funding costs and all other costs)
- A ratio of less than 1.0 means that for a given month, the vintage generated less value adjustments than annual interest income. For example, a ratio of 0.2 implies 20€ of value adjustment generated for 100€ in interest (before funding costs and all other costs).

As funding costs and other costs are not considered, the interpretation of the ratios should be as follows:

- A ratio between 0 and 0.75 is indicating a positive ratio between value adjustments vs interest income related to the vintage and acceptable performance in terms of contribution to the total income of the bank.
- A ratio between 0.75 and 1 should be considered as an alarm call signifying that the interest income from the relevant vintage will not cover all losses and costs of corrective measures needed to be implemented in order to reduce losses.
- A ratio above 1 is not acceptable for the bank as it means that the bank is certainly losing money on the relevant vintage.

6.2.4 Practical application

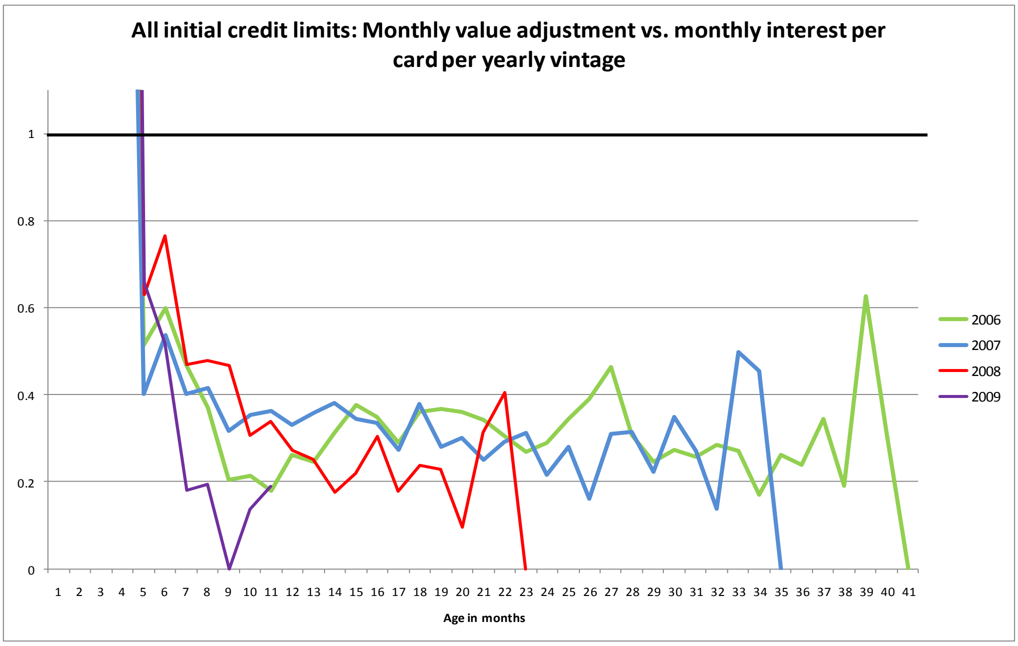
6.2.4.1 Profit analysis of before and after implementation of the scoring process

The scoring system started to be implemented in June 2008 and was finalised in January 2009.

From the graph, it appears that 2008 is on a good way to consistently beat 2007 and 2006 in relative profitability in the medium and long term. It can also be expected that 2009 will develop more favourably than 2008 and therefore 2007 and 2006.

Clearly the new scoring system has improved the overall profit of the bank.

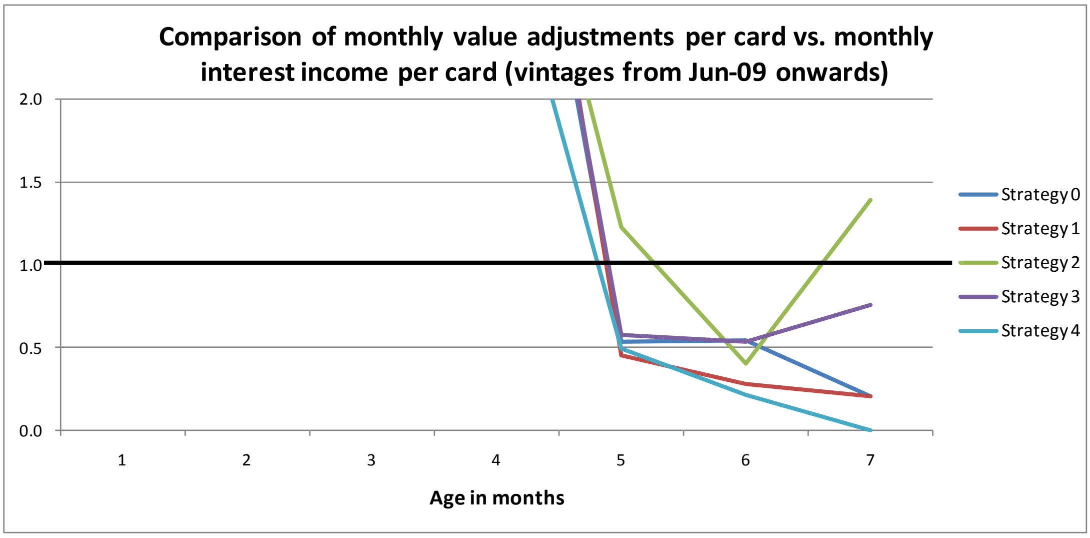
Figure 22 - Monthly value adjustment vs. monthly interest per card per yearly vintage



6.2.4.2 Profit analysis of a Champion vs. Challengers test

Based on the preliminary results that were available at that time, the strategy 4 is giving the best result which is high initial limits and slow increases.

Figure 23 - Monthly value adjustment vs. monthly interest per card per yearly vintage



Based on those results, the bank has decided to take on more risk and to test more aggressively credit lines.

6.2.5 Another way to maximize profit: Risk Based Pricing

Risk based pricing considers the credit risk aspect but also the profitability.

6.2.5.1 Definition

The objective of risk base pricing is to adjust the interest rate in function of the risk profile of the customer as well as his profitability. As in credit scoring, the outcome will be if the customer is delinquent or not but the portfolio will also be segmented into levels of profitability and for each of those segments the interest rate will vary. The target is to find interest rate where the income will be sufficient to cover the loss or even to earn profit. The customer will then receive the appropriate interest rate corresponding to his risk profile and which does not prevent the bank to make profit. Basically, low risk customers will receive a low interest rate and high risk customers will receive a high interest rate. Risk based pricing facilitates to give loan and makes sure that the risk taken is worth it or that at least the bank will earn enough to cover the losses (Thomas et al. 2002).

According to Thomas et al. (Thomas et al. 2002), the main issues raised while implementing risk based pricing are:

- Adverse selection. Applicants for a credit card are scored via scorecards developed with data from the past. Therefore, all banks will not assign the same risk to the same applicant. The first possibility is that he might receive a better offer from another bank. The bank has them to take into account the highest rate that an applicant will accept which is also the best rate that can be offered considering his risk profile. Analysis has to be performed in order to figure out the best take-up rate. The second possibility which is also the most probable is that other banks will offer even higher rate and that the applicant could have taken the card with an even higher rate. Before fixing the take-up rate, the economic context and the competitive market are parameters that should not be neglected as for any other product.

- Good portfolio. For the low risk portfolio, the rate offered by the bank might be lower than the minimum rate to cover the losses and to make profit. Indeed, low risk customers might not be satisfied by the optimal rate offered by the bank. Therefore, to get those customers, the bank might have to do a commercial effort. As mentioned above, the economic context and the competitive market are parameters not to neglect while fixing the take-up rate.
- Communication issue: Communication wise, the main issue is to explain why the customer is not receiving the rate advertised on the website but a higher rate to both banking employees and applicants.

As for credit scoring, it has taken many years for banks to understand the importance of linking the risk to the cost of a loan and to find the optimal price to sell it in order to cover this cost. According to Thomas et al., it is surprising that financial institutions have not concentrated on this before especially considering that "credit scoring is an ideal technique for setting risk-based prices or interest rates" (Thomas et al. 2002).

The product concerned in this thesis is fairly basic. Based on the scores, three groups of lenders have been segmented: the low risk category, the medium risk category and the high risk category. Nevertheless, it has to be clear that this product is not designed for gold card lenders. The portfolio is mostly containing lenders who would hardly get a credit in another institution. This is why risk based pricing would be a plus. The low risk segment that also contains mostly non or occasional revolvers should be eligible for a lower interest rate that would possibly make them revolved. On the contrary, the high risk segment that contains lenders that would hardly get a credit anywhere else and that contains also intense revolvers should be eligible for higher interest rate.

6.2.5.2 Example of model

Basically, the issue is to know if an applicant should be granted a credit or not and especially which interest rate he should be given based on the score he got assigned. Thomas et al. (Thomas et al. 2002) have worked on this issue and presented a possible model for risk based pricing based on the hypothesis that a scoring system was in place where:

For a given score s: $\max_i\left\{\left(L(i)q(G\backslash s) - Dq(B\backslash s)\right)a_s(i), 0\right\}$.

Where

p_G: Proportion of goods

p_B: Proportion of bads

$p(s\backslash G)$: Probability a good has a score less than s

$p(s\backslash B)$: Probability a bad has a score less than s

$p(s) = p(s\backslash G)p_G + p(s\backslash B)p_B$: Proportion of score below s

$q(G\backslash s) = \frac{p(s\backslash G)}{p(s)}$: Conditional probability that a consumer with score s will be good

$q(B\backslash s) = \frac{p(s\backslash B)}{p(s)}$: Conditional probability that a consumer with score s will be bad

i: interest rate charged

i(s): i is a function of s

s: Credit score

D: Cost of default which is independent of i

L(i): Profit which is a function / monotonically dependent of i

The main weakness of this equation is that it does not take into account the fact that some customers from a certain score band might not accept to be charged an interest rate with their credit card. For example, in the case of an increase of the interest rate for a specific score band, only the ones with no other option will accept it, i.e. the riskier. The ones with better option will leave and thus the default rate of the overall score band will worsen. Credit card holders follow adverse selection principle.

The optimal interest rate for a score s is the result of the following equation, i.e. by differentiating with respect to i and setting the derivative to 0 to find the maximum (Thomas et al. 2002).

$$\max_{i}\{\left(L(i)q(G\backslash s,i)-Dq(B\backslash s,i)\right)a_s(i),0\}.$$

where

$a_s(i)$: Fraction of those with credit score s who will accept interest rate i,

$q(G\backslash s,i)$: Fraction of acceptors with score s when the interest rate is i who are good.

$q(B\backslash s,i)$: Fraction of acceptors with score s when the interest rate is i who are bad.

$$-L'(i)q(G\backslash s)a_s(i)+\left(L(i)q'^{(G\backslash s,i)}-Dq'(B\backslash s,i)\right)a_s(i)=\left(L(i)q(G\backslash s)-Dq(B\backslash s)\right)a'_s(i)$$

Thomas et al. (Thomas et al. 2002) make the following assumptions:

- $a_s(i)=e^{-\propto(s)(i-i^*)}$: Everyone accepts an interest rate i* and the subsequent drop-off is exponential, and that there is no effect of interest rate on the fraction of goods who accept.
- $L(i)=\frac{R}{(1+i)^T}-\frac{R}{(1+i^*)^T}$: There is one payment of R at time T with the interest charged being i, while the real cost of capital i*.

$$\frac{R}{(1+i)^{T+1}} q(G\backslash s) e^{-\propto(s)(i-i^*)} = -(\frac{R}{(1+i)^{T}} q(G\backslash s) - Dq(B\backslash s) \propto (s) e^{-\propto(s)(i-i^*)}$$

$$\Leftrightarrow$$

$$\frac{q(G\backslash s)}{(1+i)^{T}} (\propto (s) + \frac{1}{1+i}) = -Dq(B\backslash s) \propto (s)$$

Thomas et al. (Thomas et al. 2002) recommended solving this equation for each score bands in order to find the optimal interest rate that should be charged.

Other profit function might include bank's choice variables such as credit ceiling, fees for merchants on transactions, rewards for direct debit, interest rate penalties on late payers, length of interval between penalty jumps, credit ceiling responses to good behaviour etc (Thomas et al. 2002).

6.2.5.3 Practical application

The main focus of this research is credit scoring and therefore, not much time have been devoted to risk based pricing. However, even though not having a sophisticated model, basics rules have been suggested that could help the bank to make more profit.

A simple solution is just to play with the interest rate: if a customer lapses into delay, he will receive his first penalty; i.e. an increase of the interest; if he receives a second penalty, the interest rate will be increased a second time and the same process will be repeated until he will reach the maximum interest rate.

By contrast, if he clears all payments due, he will benefit from a reduction in his interest rate.

Another parameter that could be used is the amount of interest paid by the customer: if a customer has never incurred any penalty and has never revolved, i.e. paid interest, the interest rate will be decreased.

The penalty criterion will affect those customers that display risky behaviour and barely react to interest rate adjustments.

On the contrary, it will favour customers with a low risk profile and that do not revolve. By lowering the interest rate, they might be willing to use the revolving facility.

Chapter 7: Qualifications & Extensions to this research

The previous chapters describe in detail the subject matter of this thesis. Step by step, the reader comes to understand the credit risk management process created by the author.

This chapter aims to answer the following questions:

- What is the outcome of this research?
- How might this research be extended?

The objective is to state clearly the main contribution of this thesis as well as to discuss some additional areas of research related to it. The chapter will focus mainly on ways in which the research adds to our knowledge.

7.1 Qualifications to the thesis

The real value of this PhD thesis lies in the credit scoring system developed and explored in the dissertation. However, there are several other features that make this PhD thesis a unique piece of work.

7.1.1 The literature review

The literature review presented embraces all major related papers. About 500 references are listed, covering the late 1950s until the present day.

The literature review focused mostly on the credit scoring history, statistical techniques used for classification purposes and the different issues faced in credit scoring.

7.1.2 The models and level of detail

From a practical view, this research includes an application on real data which is rare. Indeed most companies are extremely reluctant to divulge their data and allow the results to get publicly released.

Some of the models described in this thesis are innovative. Indeed, the author combined an application scorecard with a credit bureau score and showed that the resulting model outperformed the application scorecard and the credit bureau score while treated independently.

The behavioral scorecards described are another key element of this thesis. Application scorecards have been covered in different papers whereas the behavioral scorecard has typically been ignored by researchers.

The details of the data available, the equations, and the results are unique.

7.1.3 The scoring process

The presentation of a scoring process with this level of detail is something very rarely encountered, and never in a form similar to this dissertation. The scoring process described in this research has the advantage that at each point in time, customers will get assigned a score representing their default probability. The process was constructed so as to be as dynamic as possible and to reflect changes of behaviour.

Most researchers that have presented scoring models have not revealed in detail how to use them. This thesis emphasizes that scorecards are just tools and it is the way they will be used that will make the difference. This is where champion vs. challenger testing is essential as are the evaluation criteria used for selecting the new champion.

7.1.4 Credit granting

In most papers, scorecards are used for accepting/rejecting applicants but few have focused on the credit granting element. This thesis, by contrast, has concentrated on this aspect. This thesis describes a scoring system for assigning appropriate lines to credit applications with the aim of maximizing the bank's (sum of expected discounted stream of) profits.

However, there is, furthermore, a major, wider social issue in correctly granting credit lines. This involves trying to identify the screening process for potential borrowers that could be deemed to maximize social welfare. Profits of the lender undeniably form one element in social welfare. But there are other considerations: the levels of welfare of the borrowers themselves form another part. Lenders' and borrowers' interests are therefore to some extent aligned. It is no kindness to lend to someone who could not afford to repay; and the principles governing a socially efficient allocation of credit will doubtless have much in common with those that maximize the lender's welfare.

Furthermore, the experience of the 2008-2009 financial crisis illustrates the fact that there can be very large negative externalities involved in the consequences of misguided credit granting.

7.2 Possible extensions to the thesis

This thesis is surely original for the reasons listed above. However, the author is well aware that this PhD thesis could have been extended with further research.

7.2.1 Logistic regression vs. other statistical techniques

The first possible extension would have been to compare the result of the logistic regression with the results of other statistical techniques. For instance, if it had been technically possible, the author would have compared the results of the logistic regression with the results of different types of neural networks as well as decisional trees.

7.2.2 Credit-Fraud-Collections process

Going beyond the scope of this research, it would have been illuminating to extend the current credit process to collection and fraud by incorporating a collection scorecard and fraud scorecard. The system would have then covered credit/collection/fraud and therefore could have been even more efficient in optimizing the expected net profit. In addition, implementing a collection scorecard could help in improving the performance of the collection department.

7.2.3 Strategies testing results

Given more time, the author would have presented the results of the strategies testing. However, currently, the bank is still performing tests and what is optimal today, might not be optimal tomorrow. External factors might change, and the business might change.

7.2.4 Additional behavioral scorecards

To fine-tune the process described in this thesis, the behavioural scoring part might have been extended by testing a three months behavioral scorecard as well as a 12 months behavioral scorecard. The process would have then been significantly more complex. The sponsor of this PhD was not looking for a complex approach but for something oriented toward their business and easy to apply and understand.

7.2.5 Pros and Cons of quality indicators

One more topic that has occurred to the author during this research concerns the advantages / disadvantages of the different quality indicators (Gini, K.S., IV) used to evaluate scorecards. The author has not found in the literature any proof that one statistic is unambiguously superior to another. In order to evaluate and to rank them, the author would have applied them to evaluate their strengths and weaknesses.

7.2.6 Decision criteria for selecting a strategy

Another possible enhancement of this research would be to define the extent to which each of the key performance indicators should affect the choice of the final strategy. The difficulty is that each credit card company markets a different portfolio. Nevertheless, an application to data presenting the tracking of strategies such as those described in this paper could lead to a guideline on how to pinpoint the optimal credit policy.

7.2.7 Interest rate

In the United States, retail interest rates are subject to regulatory control by the authorities. Using risk based pricing for setting interest rates is rather complex and constrained by law.

In Germany, retail interest rates cannot exceed a certain level, although, within the authorized range, the interest rate is within the discretion of individual firms. Furthermore, in highly competitive markets, firms will be price takers, with interest rates exogenous.

As the bank providing the data was new in the market, the bank decided to set the same interest for all customers. Therefore, the interest rate did not affect the relative behaviour of the customers as it was neutral. In this context, implementing a scoring system to set credit lines was not biased by risk based pricing methods. Maximizing the discounted present value of the stream of net expected profits was then only relying on optimizing the credit lines granting process. Losses due to defaults were the main risk incurred. Therefore having a process for setting credit lines was first priority.

Nevertheless, in order to maximize the discounted present value of the stream of net expected profits, rates of interest would, in some circumstances, constitute another choice variable to consider. After defining the optimal lines, the bank would then focus on risk based pricing for setting retail interest rates.

7.3 Regulation / policy implications

Another aspect that could have been explored at greater length in this research is the regulatory and supervision aspects.

7.3.1 Regulation of the Credit Card business

Historically, banks involved in the credit card business have been accused of unfair trade practice. In the credit card industry, customers have been subject to abuses like interest rates rises of which the customers were informed only at short notice, after having made purchases at lower interest rates. At the time, such action by the credit card firm was clearly unfavourable to the customer’s interest. Nevertheless, the credit card business was not completely unregulated. Two examples are: (i) the Truth in Lending Act in the United States in 1868 and (ii) the fact that European credit card companies must provide their annual percentage rate (APR).

There were clear indications that the credit card sector needed to be regulated like any other banking activity. Banks are now subject to various regulatory requirements such as minimum capital requirements, minimum liquidity ratios and rules on provision, and publishing their results.

However, one can debate in which extent the credit card business needs to be regulated. Opponents of banking regulations have warned that an excess of regulation would limit access to credit, raise interest rates, and risk penalizing customers in other ways, such as reducing loyalty / rewards program.

Nowadays, merchants have raised concerns about interchanges and asked for more regulation. However, banks and consumers disagree, as they may both benefit from the interchanges that are charged to the merchants, by permitting lower annual fees, cash rebates and other loyalty / marketing offers.

7.3.2 Entry Barriers

The credit card industry has no serious impediment to entry except regulatory requirements.

The Contestable Markets Theory described by Baumol et al. in 1982, introduced the idea that a new entrant could introduce a business freely and without any entry barriers (Baumol et al., 1982).

The credit card industry functions broadly as described by Baumol et al.. Any new firm is free to start a business and to leave it, with no sunk costs. Further, the entrant is assumed to have access to an incumbent’s technology (there is no learning by doing, for example) and the incumbent cannot alter his prices faster than his customers can migrate to a rival. Under perfect contestability, an incumbent firm can make no abnormal profit and if its average cost is horizontal, it prices at marginal cost (Morris & al., 1986). Within retail banking, in practice, however, asymmetric information and switching costs may well prevent perfect contestability.

From a practical standpoint, most banks will have the possibility to issue credit cards via the Visa or MasterCard networks, the two largest credit card issuers. The rest of the required infrastructure for launching credit card is usually common to other traditional banking activities and would require a minimal level of unrecoverable investment.

Nevertheless, as stated earlier, the low level of entry barriers have pushed regulators to enforce regulation and supervision of the credit card business. Credit card banks have now to meet a set of regulatory requirements to maintain their banking licence.

7.3.3 More competition: pros and cons

The next question that can be raised is if the credit card industry should continue to be a free market or not.

The credit card market is already full of players. So, new entrants will compete with major credit card companies. Those new entrants will differentiate themselves from the major ones by tempting customers with attractive offers or by focusing on some niche of the market, usually ignored by the big ones. One might therefore infer that the credit card industry is highly competitive. However, the number of firms is not a reliable guide to the extent and character of competition as contestability theory illustrates. In the credit card industry, card processors and card issuers are rather limited. As an example, the leading credit card issuers are Visa, MasterCard, Amex and Diners which appears as highly concentrated. But in practice, cards from a specific card issuer can be issued by many different banks and lenders (except for Amex which is issuing its own card). To reinforce the point, the number of players does not necessarily indicate quality of competition as a sole supply can be faced by third parties.

The new regulations in place enforce control of banking activities and are designed to impose costs and diminish the risk of failure and financial instability. However, there is a big controversy around this topic. Recently, the Economist (2012) has pointed out substantial weaknesses in the 2010 Dodd-Frank Act in the US and also that the implementation of this regulation has lead to massive costs and was much too complex, in practice. The 1999 repeal of Glass-Seagall was, however, a key contributor to the financial crisis some years later. If not thought carefully, the new regulations and the removal of old regulations can have grave unintended consequences.

Although, one question that can be raised is this: To make this market even fairer and more competitive, should regulators also impose price controls? The view of the author is that interfering in fees, interchanges, interest rates or credit lines, might lead to the end of the credit card market depending on the form that interferences took. For instance, capping interest rates or credit lines or fees might end competition in the market and could be deleterious for the market as banks might no longer be able to differentiate their product. In many countries, however, interest rates or credit lines or fees are subject to relatively high levels, although banks are free to set parameters below these ceilings, and to employ their own preferred techniques for controlling risk.

Enforcing reductions in fees imposed on merchants (“Interchanges”) as advocated by retailing interest groups, would be fiercely resisted by both consumers’ bodies and credit card companies. However, other possible avenues of regulation may prove advisable.

Focusing specifically on the topic of this thesis, the recent financial crisis has pushed banks to restrict access to credit. The immediate effect of the crisis on banks has been to tighten their credit policy by granting credit to borrowers presenting a good credit history whereas the poor credit ones find they may be denied credit.

However, regulators' interest should now be turned to the question of how in practice to improve the allocation of credit and reducing undesired consequences such as fewer people end up with loans they cannot repay. The advantages of such an approach would be to strengthen financial stability and at the same time bring efficiency benefits for lenders and borrowers. This would reduce risk, improve insurance effect of loans and help enhance social welfare by directing loans to people that need them most.

7.3.4 Subprime Lending

A subprime credit card is a type of credit card granted to applicants with a bad credit history or no credit history. This type of product will differ from the traditional credit card as it will grant lower credit lines with higher interest rate and fees. In the United States, annual interest rates applied to subprime credit cards can reach 30%. Recently, Morran (2011) indicated that the average interest rate of subprime credit card is around 20%, which is 2.4% higher than the average of 2010. He also indicated that the average credit lines increased from $300 to $500 but still remain low. Further, credit line increases were found to be more frequent in 2011, occurring twice a year if payments were made on time.

Subprime cards are issued by all types of issuers, both key players in the industry and new entrants targeting this particular segment of the market. Morran (2011) gives the examples of Capital One and HSBC who started issuing subprime loans again, arguing that their sole interest was to make available credit to a larger portion of the population. The fact is that subprime credit card users are paying more interest and fees than other users and covers a very heterogeneous group.

However, it is important to warn customers about this facility when seeking for a credit. Indeed, after recent events, the topic of subprime lending has become more and more controversial and a subject of suspicion. The subprime credit card industry is accused of predatory lending practices. Customers may not really understand the various features and costs associated with their loans, as was discussed in Chapter 1 – Section 1.3.2.

The product used for building the scoring system presented in this thesis is not different from a subprime credit card, as the interest rate and fees are rather high and credit lines are rather small. One could raise ethical questions about this type of lending. Nevertheless, this could provoke the response that offering some credit to almost everyone is often justifiable. The author's view is that with an efficient credit scoring system, the bank should be able to grant the appropriate amount to the appropriate customer and therefore, the interest of both borrowers and the bank would be met. Assume that individuals' consumption needs and income are subject to stochastic shocks, denying banking facilities to them would lead to a serious loss of welfare.

Conclusion

This PhD thesis focuses on credit risk in relation with the credit card business and applying credit scoring techniques on credit card data.

The first chapter of this thesis introduced the reader to the banking industry and the credit card business. The main activities of a bank are described as well as the type of risk it has to deal with and also the regulations that they are subject to.

The second chapter furnishes the main notions of risk management needed for developing the analysis of this thesis. Identifying the optimal credit line and the optimal credit policy for a lender is the central aim of this PhD thesis. So, the author focuses on credit risk and particularly upon credit scoring. The different types of scorecards are described. Application scorecards and behavioral scorecards form the centerpiece of this thesis.

In the third chapter, the different statistical techniques are reviewed by a detailed scrutiny of the literature in this field. The different techniques, reports and indicators used to evaluate and monitor scorecards are described. This critical survey of a very extensive literature points to the use of logistic regression as a modelling technique, and information value combined with validation charts and weights of evidence as evaluation tools.

The fourth chapter points out various issues faced with credit scoring such as the ability to understand statistics as well as technical concerns that have been raised by researchers. The chapter also lists a number of areas of possible improvements in the application to credit scoring.

The fifth chapter presents an application on real data provided by a credit card company. After reviewing the literature, the author confirms that the data used for this application follows minimum requirements even though the quality might be enhanced if simple measures were taken. As for the application scorecards, the combined scorecard of internal information with credit bureau information has proved to improve the model performance. With behavioral scorecards, the implementation of an early detection scorecard creates room for greater success in predicting credit risk, as opposed to relying on the application scorecard once the first transaction has been performed. The long term behavioral models appear much more accurate in predicting credit risk than any other models. This illustrates the fact that additional data should normally help to improve a model's predictive powers.

In the sixth chapter, in order to contain its losses and thereby help to raise the lender's profit, the author employs the champion vs. challenger approach. Indeed, performing test on real data is seen to be the best way of pinpointing an optimal credit policy.

As mentioned initially, the central contributions of this PhD thesis are the application on real data and the level of detail covered. Indeed, models presented here are innovative and the presentation of a scoring process with this level of detail is, to the best of the author's knowledge, unrivalled. However, no thesis gives the last word on any subject. There is always room for extensions and further research. Several of the possibilities here are described in Chapter 7.

The basic principle of financial institutions is to pass the temporary surpluses of some agents to allow other agents to balance their temporary deficits. An agent's income is subject to idiosyncratic shocks, as is his or her marginal utility of consumption. Forcing people to limit their spending to their income in any period, in any state of the world, is grossly inefficient. Improving the technology that a lender uses to allocate credit between agents has very considerable social benefits. It will also enable the lender to avoid costly mistakes.

The financial crisis that erupted in 2008 occurred largely because lending criteria had been misapplied, and, in retrospect, far too lax; its consequences are that they are now probably much too tight. Understanding how these grievous errors can arise, and how they might be better avoided in future, is of paramount importance. It is hoped that the detailed microeconomic analysis of the mechanics of a particular lender's credit allocation process can play some part in this endeavour.

Appendix

Appendix 1 – References List

Modeling technique	Type of reference	Reference
Discriminant analysis	**General**	Durand (1941), Myers & Forgy (1963), Boggess (1967), Morrison (1969), Lane (1972), Bates (1973), Chang & Affifi (1974), Apilado et al. (1974), Eisenbeis (1977, 1978), Grablowsky & Talley (1981), Taffler (1982), Moses & Liao (1987), Falbo (1991), Overstreet & Bradley (1994), Rosenberg & Geit (1994), Trevino & Daniels (1995), Hand et al. (1996), Lee, Jo & Han (1997), Kim, Kim, Kim, Ye & Lee (2000), Kim & Oommen (2008).
	Financial data	Churchill (1941), Merwin (1947), Myers & Forgy (1963), Hills (1967), Altman (1968, 1988 and 1993), Hoskins (1968), Altman et al. (1974), Altman et al. (1977), Altman & Eisenbeis (1978), Deakin (1972), Edmister (1972), Bates (1973), Apilado et al. (1974), Blum (1974), Eisenbeis (1977), Taffler & Tisshaw (1977), Bidelbeek (1979), Misha (1984), Gombola et al. (1987), Piesse & Wood (1992), Lussier (1995), Altman et al. (1995).
	Credit Scoring	Bardos (1998), Desai et al. (1996), Martell and Fits (1981), Overstreet, Bradley & Kemp (1992), Reichert et al. (1983) Titterington (1992), Lee et al (2002).
Logistic regression	**General**	Lachenbruch (1975), Orgler (1970), Orgler (1971), Cox (1972), Breslow (1974), Dawes (1974, 1979), Dawid (1976), Fitzpatrick (1976), Wainer (1976, 1978), Gunst & Mason (1977), Laughlin (1978), Darroch et al. (1980), Haggstrom (1983), Garthwaite & Diskey (1988), Lucas (1992), Lai & Ying (1994), Henley (1995), Djebarni & Al-Abed (1998), Flagg, Giroux &Wiggins (1991), Kay, Warde & Martens (2000), Laitinen & Laitinen (2000), Lau (1987), Suh, Noh & Suh (1999), Vellido, Lisboa & Vaughan (1999), Wong, Bodnovich & Selvi (1997), Zavgen (1983), Gentry et al. (1985), Keasey & Watson (1987), Aziz et al. (1988), Cox & Snell (1989), Hosmer & Lemeshow (1989), Platt & Platt (1990), Ooghe et al. (1995), Crook (1996), Mossman et al. (1998), Charitou & Trigeorpis (2002), Becchetti and Sierra (2002).
	Credit Scoring	Banasik (1996), Berkowitz & Hynes (1999), Henley (1995), Joanes (1993), Laitinen (1999), Westgaard & van der Wijst (2001).
Probit regression		Badu & Daniels (1997), Badu et al (2002), Boyes et al. (1989), Crook (2001), Banasik, Crook & Thomas (2003); Greene (1998); Guillen & Artis (1992), Loviscek & Crowley (1990), Tsaih et al (2004), Wallace (1978; 1981).
Neural Networks	**General**	Jacobs (1988), Tang et al. (1991), Kuan & White (1994), Lee et al. (1993), Coats & Fant (1993), Cheng & Titterington (1994), Ripley (1994), Hill et al. (1994), Kuan & Liu (1995), Lachtermacher & Fuller (1995), Drossu & Obradovic (1996), Boussabaine & Duff (1996), Wong et al. (1997), Zhang, Patuwo & Hu (1998), Gruca & Klemz (1998), Vellido et al. (1999), Lau et al. (2001), Tkacz (2001), Papadas & Hutchison (2002), Heravi et al. (2004), Santin et al. (2004), Delgado (2005), Nakamura (2005), Hippert et al. (2005), Longhi et al. (2005), Longhi et al. (2005), Erbas & Stefanou (2008), Anderson & Rosenfeld (1988), Cheng & Titterington (1994), Haykin (1994), Stern (199), Vellido et al. (1999), Zhang, Patuwo, & Hu (1998).
	Credit Scoring	Gallant(1988), Nelson & Illingworth (1990), Eberhart & Dobbins (1990), Kim & Scott (1991), Davis et al. (1992), Jensen (1992), Salchenberger, Cinar & Lash (1992), Tam & Kiang (1992), Deng (1993), Robins (1993), Rosenberg & Gleit (1994), Altman et al. (1994), Kerling & Poddig (1994), Podding (1994), Piramuthu, Shaw & Gentry (1994), Richeson, Zimmermann & Barnett (1994), Borrowsky (1995), Lacher et al. (1995), Williamson (1995), Sharda & Wilson (1996), Torsun (1996), Desai et al. (1996), Glorfeld (1996), Jagielska & Jaworski (1996), Glorfeld & Hardgrave (1996), Hand & Henley (1997), Desai et al. (1997), Arminger, Enache & Bonne (1997), Brill (1998), Piramuthu (1999), Barney, Graves & Johnson (1999), Zhang, Hu, Patuwo, & Indro (1999), Yang et al. (1999), West (2000), Malhotra & Malhotra (2003), Lee et al. (2002), Kim & Sohn (2004), Lee & Chen (2005), Blochlinger & Leippold (2006),Seow &
Time varying model	**General**	Anderson & Goodman (1957), Cyert et al. (1962), Bierman & Hausman (1970), Metha (1970), Dirickx & Wakeman (1976), Long (1976), Corcoran (1978), Van Kuelen et al. (1981), Frydman (1984), Frydman et al. (1985), Srinivasan & Kim (1987b), Edelman (1992), Clemen et al. (1995).
K-nearest neighbor	**General**	Fix and Hodges (1952), Cover & Hart (1967), Chatterjee & Barcun (1970), Hand (1986), Henley & Hand (1996), Tam & Kiang (1992).
Recursive partitioning	**General**	Raiffa and Schlaifer (1961), Metha (1968), Sparks (1972), Breiman et al. (1984), Frydman, Altman & Kao (1985), Makowski (1985), Coffman (1986), Carter & Catlett (1987), Safavian & Landgrebe (1991), Boyle et al. (1992), Davis, Edelman & Gammerman (1992), Altman et al. (1994), Zakrzewska (2007).
Mathematical programming	**General**	Kendall (1966), Rao (1971), Pye & Tezel (1974), Hand (1981), Showers and Chakrin (1981), Kolesar and Showers (1985), Hardy and Adrian (1985), Joachimsthlaer & Stam (1990), Glover (1990), Ziari et al. (1997); Gehrlein and Wagner (1997), Hamsici & Martinez (2008).
	Credit Scoring	Hardy & Adrian (1985) , Gehrlein & Wagner (1997).
Genetic algorithms	**General**	Efron (1977), Fogarthy & Ireson (1993), Desai et al. (1997), Yobas et al. (2000).
	Credit Scoring	Ong et al. (2005).
Rough sets / Fuzzy Logic method	**General**	Pawlak, Grzymala-Busse, Slowinski & Ziarko (1995).
	Credit Scoring	Hoffman et al. (2002); Hoffman et al. (2007).
Multi-variate adaptative splines	**General**	DeGooijer, Ray & Krager (1998), Friedman & Roosen (1995), Griffin, Fisher, Friedman & Ryan (1997), Nguyen-Cong, Van & Rode (1996), Ohmann, moustakis, Yang & Lang (1996), Lee & Chen (2005), Friedman (1991).
Support Vector Machine		Vapnik (1995, 2000), Burges & Schölkopf (1997), Schölkopf et al. (1996, 1998), Vapnik et al. (1997), Joachims (1998), Pontil & Verri (1998), Baudat et al. (2000), Scholkopf & Smola (2000), Cristianini & Shawe-Taylor (2000), Zhang (2000), Kecman (2001), Weston et al. (2001), Guyon et al. (2002), Yu et al. (2003), Frohlich & Chapelle (2003), Gestel et al. (2003), Baesens et al. (2003), Huang et al. (2004), Mao (2004), Schebesch & Stecking (2005), Schebesch (2005), Somol et al. (2005), Lai et al. (2006), Huang et al. (2007), Zhou et al. (2009).
Comparison	**Traditionnal vs. Modern ones**	Lee & Chen (2005), Lee et al. (2002), Zekic-Suzac et al. (2004), Malhotra & Malhotra (2003), Ong, Huang, & Tzeng (2005), Abdou et al. (2008), Arminger, Enache & Bonne (1997), Gilbert et al. (1990).

Appendix 2 – Transaction categories

Category	SubCategory
Airlines	1 Airlines, air carriers.
Amusement & entertainment	1 Amusement parks, carnivals, circuses, fortune tellers, 2 Aquariums, dolphinariums, zoos, and seaquariums, 3 Athletic fields, commercial sports, professional sports clubs, sports promoters, 4 Bands, Orchestras, and miscellaneous entertainers - not elsewhere classified, 4 Bowling alleys 5 Clubs - Country clubs, membership (athletic, recreation, sports), private golf courses, 6 Dance halls, schools, and studios, 7 Gambling Transactions, 8 Golf courses, public, 9 Motion picture theaters, 10 Pool and billard establishments, 11 Recreation services - not elsewhere classified, 12 Theatrical producers (except motion pictures), ticket agencies, 13 Tourist attractions and exhibits, 14 Video amusement game supplies, 15 Video entertainment rental stores, 16 Video game arcades / establishments.
Automobile / vehicle rentals	1 Car rental Agencies, 2 Automobile rental agencies - not elsewhere classified 3 Motor home and recreational vehicle rental, 4 Truck rentals.
Automobiles & vehicles	1 Auto store, home supply stores, 2 Automobile and truck dealers - (used only) – sales, 3 Automobile and truck dealers - sales service, Repairs, Parts, and leasing, 4 Automotive parts, accessories stores, 5 Automotive tire stores, 6 Boat dealers, 7 Camper dealers, Recreational and utility trailers, 8 Fuel dispenser, automated, 9 Miscellaneous automotive, aircraft, and farm equipment dealers - not elsewhere classified, 10 Motor homes dealers, 11 Motorcycle shops and dealers, 12 Service stations (with or without ancillary services), 13 Snowmobile dealers
Business services	1 Advertising services, 2 Automobile parking lots and garages, 3 Business services - not elsewhere classified, 4 Cleaning and maintenance, janitorial services, 5 Commercial art, graphics, photography, 6 Computer programming, data processing, and integrated systems design services, 7 Consulting, management, and public relations services, 8 Consumer credit reporting agencies, 9 Detective agencies, protective agencies, security services including armored cars, guard dogs, 10 Employment agencies, temporary help services, 11 Equipment rental and leasing services, furniture rental, tool rental, 12 Exterminating and disinfecting services, 13 Photo developing, photofinishing laboratories, 14 Quick copy, reproduction, and Blueprinting services, 15 Stenographic and secretarial support services, 16 Truck stop transactions.
Clothing stores	1 Accessory and apparel stores – Miscellaneous, 2 Alterations, mending, seamstresses, tailors, 3 Children's and infants' wear stores, 4 Family clothing stores, 5 Furriers and fur shops, 6 Men's and Boy's Clothing and accessories stores, 7 Men's and women's clothing stores, 8 Shoe stores, 9 Sports apparel, riding apparel stores, 10 Wig and toupee shops, 11 Women's accessory and specialty stores, 12 Women's ready to wear stores.
Contracted service	1 Agricultural cooperatives, 2 Air conditioning, heating and plumbing contractors, 3 Carpentry contractors, 4 Concrete work contractors, 5 Contractors, special trade - not elsewhere classified, 6 Electrical contractors, 7 General contractors - Residential and commercial, 8 Horticultural and Landscaping services, 9 Isolation, Masonry, Plastering, Stonework, and tile setting contractors, 10 Roofing and siding, Sheet metal work constructors, 11 Vetinary services.
Government services	1 Bail and bond payments, 2 Court costs including alimony and child support, 3 Fines, 4 Government services - not elsewhere classified, 5 Intra-Government purchases - Government only, 6 Postal services - government only, 7 Tax payments.
Hotels & motels	1 Lodging - Hotels, Motels, Resorts
Order / telephone order providers	1 Catalog Merchants, 2 Combination catalog and retail merchants, 3 Inbound telemarketing merchants, 4 Insurance services, 5 Other direct marketers - not elsewhere classified, 6 Travel related arrangement services, 7 Continuity / subscription merchants.

Category	SubCategory
Miscellaneous stores	1 Antique reproduction stores, 2 Antique shops - sales, repairs and restoration services, 3 Art dealers and galleries, 4 Artist supply stores, craft shops, 5 Bars, cocktail lounges, discotheques, nightclubs, and taverns - drinking places (alcoholic beverages), 6 Book stores, 7 Bicycle shops - Sales and Service, 8 Camera and photographic supply stores, 9 Card, Gift, Novelty, and Souvenir Shops, 10 Cigar stores and stands, 11 Clock, jewelry, watch, and silverware store, 12 Computer software stores, 13 Cosmetic stores, 14 Crystal and glassware stores, 15 Door to door sales, 16 Drapery, Upholstery, and window coverings stores, 17 Drug stores, pharmacies, 18 Eating places, restaurants, 19 Electric razor stores - sales and service, 20 Electronic sales, 21 Equipment, furniture, and home furnishings stores (except appliances), 22 Fabric, needlework, piece goods, and sewing stores, 23 Fast food restaurants, 24 Fireplace, fireplace screens and accessories stores, 25 Floor covering stores, 26 Florists, 27 Fuel dealers - Coal, fuel oil, liquefied petroleum, wood, 28 Game, Toy, and Hobby shops, 29 Hearing aids, sales, services, supply stores, 30 Household appliance stores, 31 Leather goods and luggage stores, 32 Miscellaneous and specialty retail stores, 33 Miscellaneous house furnishing specialty shops, 34 Music stores - Musical instruments, pianos, sheet music, 35 New dealers and newsstands, 36 Office, school supply, and stationery stores, 37 Orthopedic goods - artificial limb stores, 38 Package stores, beer wine, and liquor, 39 Pawn shops, 40 Pet shops - Pet food and supplies, 41 Record shops, 42 Religious goods stores, 43 Salvage and wrecking yards, 44 Second hand stores, used merchandise stores, 45 Sporting goods stores, 46 Stamp and coin stores - philatelic and numismatic supplies, 47 Swimming pools - sales and supplies, 48 Tent and awning shops, 49 Typewriter stores - rentals, sales, service.
Personal service providers	1 Barber and beauty shops, 2 Buying / Shopping club, Services, 3 Carpet and Upholstery cleaning, 4 Cleaning, Garment, and Laundry services, 5 Clothing rental - Costumes, uniforms and formal wear, 6 Dating and escort services, 7 Debt, Marriage, Personal - counseling service, 8 Dry cleaners, 9 Funeral service and crematories, 10 Hat cleaning shops, shoe repair shops, shoe shine parlors, 11 Health and beauty spas, 12Laundry services - Family and commercial, 13 Massage parlors, 14 Other services - not elsewhere classified, 15 Photographic studios, 16 Tax preparation service.
Professional services and membership organizations	1 Accounting, auditing, and bookkeeping services, 2 Architectural, engineering, and surveying services, 3 Associations - civil, social, and fraternal, 4 Attorneys, legal services, 5 Automobile associations, 6 Child care services, 7 Chiropodists, podiatrists, 8 Chiropractors, 9 Colleges, universities, professional schools, and junior colleges, 10 Dental and medical laboratories, 11 Dentists, Orthodontists, 12 Doctors - not elsewhere classified, 13 Health practitioners, medical services - not elsewhere classified, 14 Hospitals, 15 Nursing and personal care facilities, 16 Opticians, optical goods, and eyeglasses, 17 Optometrists, Ophthalmologists, 18 Organizations, charitable and social service, 19 Organizations, membership - not elsewhere classified, 20 Organizations, political, 21 Organizations, religious, 22 Osteopathic physicians, 23 Professional services - not elsewhere classified, 24 Schools and educatioal services - not elsewhere classified, 25 Schools, business and secredtarial, 26 Schools, correspondence, 27 Schools, Elementary and secondary, 28 Schools, trade and vocational, 29 Testing laboratories (non-medical).
Repair services	1 Air conditioning and refrigeration repair shops, 2 Appliance repair shops, electrical and small, 3 Automotive body repair shops, 4 Automotive paint shops, 5 Automotive service shops, 6 Car washes, 7 Clock, jewelry, and watch repair shops, 8 Electronic repair shops, 9 Furniture - Reupholstery and repair, refinishing, 10 Miscellaneous repair shops and related services, 11 Tire retreading and repair shops, 12 Towing services, 13 Welding repair.
Retail stores	1 Bakeries, 2 Building materials, lumber stores, 3 Candy, nut, confectionery stores, 4 Dairy products stores, 5 Department stores, 6 Discount stores, 7 Duty free stores, 8 Freezer, Locker meat provisioners, 9 Glass, Paint, Wallpaper stores, 10Grocery stores, supermarkets, 11 Hardware stores, 12 Home supply warehouse stores, 13 Lawn and garden supply stores, 14 Miscellaneous food stores - convenience stores, markets, specialty stores, and vending machines, 15 Miscellaneous general merchandise stores, 16 Mobile Home dealers, 17 Variety stores, 18 Wholesale clubs.
Service providers	1 Campgrounds and trailer parks, 2 Caterers, 3 Insurance sales, underwriting, and premiums, 4 Lodging - Hotels, motels, resorts - not elsewhere classified, 5 Member Financial institution - Automated cash service providers disbursements, 6 Member financial institution - Manual cash disbursements, 7 Member financial institution - merchandise and services, 8 Money transfer - Member financial institution, 9 Money transfer – Merchant, 10 Payment transaction provider - money transfer for a purchase, 11 Payment transaction provider - Member financial institution - payment transaction, 12 Payment transaction provider - Merchant - Payment transaction, 13 Quasi cash - member financial institution, 14 Quasi cash – merchant, 15 Real estate agents and managers – rentals, 16 Recreational and sporting camps, 17 Remote stored value load - Member financial institution, 18 Remote stored value load – Merchant, 19 Securities - Brokers / dealers, 20 Timeshares, 21 Value purchase - Member financial institution.
Transportation	1 Railroads – freight, 2 Transportation - suburban and local commuter passenger, including ferries, 3 Passenger railways, 4 Ambulance services, 5 Limousine and taxicabs, 6 Bus line, 7 Motor freight Carriers, Trucking - Local-Long Distance, Moving and Storage companies, 8 Local delivery, 9 Courier services - Air and Ground, Freight forwarders, 10 Public Warehousing - Farm products, Refrigerated Goods, Household Goods storage, 11 Cruise lines, 12 Boat leases and boat rentals, 13 Marinas, Marine service / supplies, 14 Air carriers, airlines - not elsewhere classified, 15 Airports, Airport Terminals, Flying fields, 16 Bridge and road fees, tolls, 18 Transportation services - not elsewhere classified, 19 Travel agencies and tour operators.
United-Kingdom	1 U.K. Petrol stations, electronic hot file, 2 . .supermarkets, electronic hot file.

Category	SubCategory
Utilities	1 Cable, Satellite, and other pay television and radio services, 2 Computer network / information services, 3 Key-entry Telecom Merchant providing single local and long-distance phone calls using a central access number in a non-face=to-face environment using key entry, 4 Telecommunication Equipment including telephone sales, 5 Telecommunication Services including but not limited to prepaid phone services and recurring phone services., 6 Telegraph – Merchant, 7 Utilities - Electric, gas, heating oil, Sanitary, Water.
Wholesale Distributors and Manufacturers	1 Books, Periodicals, and newspapers, 2 Chemicals and allied products - not elsewhere classified, 3 Commercial equipment - not elsewhere classified, 4 Commercial Footwear, 5 Computer maintenance, repair, and services - not elsewhere classified, 6 Computers, computer peripherical equipment, software, 7 Construction Materials - not elsewhere classified, 8 Dental / Laboratory / Medial / Ophtalmic Hospital Hospital equipment and supplies, 9 Drugs, drug proprietors, and druggists sundries, 10 Durable goods - not elsewhere classified, 11 Electrical parts and equipment, 12 Florists' supplies, nursery stock, and flowers, 13 Hardware equipment and supplies, 14 Industrial supplies - not elsewhere classified, 15 Information retrieval services, 16 Men's, Women's, and children's uniforms and commercial clothing, 17 Metal service centers and offices, 18 Miscellaneous publishing and printing, 19 Motion picture and video tape production and distribution, 20 Motor vehicle supplies and new parts, 21Nondurable goods - not elsewhere classified, 22 Office and commercial furniture, 23 Office, photographic, photocopy, and microfilm equipment, 24 Paints, varnishes, and supplies, 25 Petroleum and petroleum products, 26 Pier goods, Notions and other dry goods, 27 Plumbing and heating equipment, 28 Precious stones and metals, watches and jewelry, 29 Sanitation, Polishing, and specialty cleaning preparations, 30 Stationery, Office Supplies, printing and writing paper, 31 Typesetting, Plate Making, and related services.

Category	SubCategory
Geographical areas	Afghanistan, Albania, Algeria, American Samoa, Andorra, Angola, Anguilla, Antarctica, Antigua and Barbuda, Argentina, Armenia, Aruba, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bermuda, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Bouvet Island, Brazil, British Indian Ocean Territory, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Canada, Cape Verde, Cayman Islands, Central African Republic, Chad, Chile, China, Christmas Island, Cocos (Keeling) Islands, Colombia, Comoros, Congo, Cook Islands, Costa Rica, Côte D'Ivoire, Croatia, Cyprus, Czech Republic, Democratic Republic of the Congo, Denmark, Djibouti, Dominica, Dominican Republic, East Timor, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Estonia, Ethiopia, Falkland Islands(Malvinas), Faroe Islands, Fiji, Finland, France, French Guiana, French Polynesia, French Southern Territories, Gabon, Gambia, Georgia, Germany, Ghana, Gibraltar, Greece, Greenland, Grenhere classified, 22 Office and commercial furniture, 23 Office, photographic, photocopy, and microfilm equipment, 24 Paints, varnishes, and supplies, 25 Petroleum and petroleum products, 26 Pier goods, Notions and other dry goods, 27 Plumbing and heating equipment, 28 Precious stones and metals, watches and jewelry, 29 Sanitation, Polishing, and specialty cleaning preparations, 30 Stationery, Office Supplies, printing and writing paper, 31 Typesetting, Plate Making, and related services.s, beer wine, and liquor, 39 Pawn shops, 40 Pet shops - Pet food and supplies, 41 Record shops, 42 Religious goods stores, 43 Salvage and wrecking yards, 44 Second hand stores, used merchandise stores, 45 Sporting goods stores, 46 Stamp and coin stores - philatelic and numismatic supplies, 47 Swimming pools - sales and supplies, 48 Tent and awning shops, 49 Typewriter stores - rentals, sales, service.ama, Papua New Guinea, Paraguay, Peru, Philippines, Pitcairn, Poland, Portugal, Puerto Rico, Qatar, Reunion, Romania, Russian Federation, Rwanda, Samoa, San Marino, Sao Tome and Principe, Saudi Arabia, Senegal, Serbia and Montenegro, Seychelles, Sierra Leone, Singapore, Slovakia, Slovenia, Solomon Islands, Somalia, South Africa, Spain, Sri Lanka, St.Helena, St.Kitts-Nevis, St.Lucia, St.Pierre and Miquelon, St.Vincent and the Grenadines, Sudan, Suriname, Svalbard and Jan Mayen, Swaziland, Sweden, Switzerland, Syrian Arab Republic, The Republic of China (Taiwan), Tajikistan, United Republic of Tanzania, Thailand, Togo, Tokelau, Tonga, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Turks and Caicos Islands, Tuvalu, U.S. Minor Outlying Islands, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Vanuatu, Holy See (Vatican City State), Venezuela, VietNam, British Virgin Islands, U.S. Virgin Islands, Wake Island, Wallis and Futuna, Western Sahara, Yemen, Zambia and Zimbabwe.

Appendix 3 – CS Detail Coarse Display

dev1_scr	#acct	#good	#bad	#cumgood	#cumbad	prob good	prob bad	wt. pattern	%cumgood	%cumbad	IV
									0%	0%	
1	112	9	103	9	103	0,008	0,081	-2,377	1%	8%	0,175
2	110	11	99	20	202	0,009	0,078	-2,136	2%	16%	0,147
3	134	19	115	39	317	0,016	0,091	-1,740	3%	25%	0,130
4	117	16	101	55	418	0,013	0,080	-1,782	5%	33%	0,118
5	113	33	80	88	498	0,028	0,063	-0,825	7%	39%	0,029
6	161	44	117	132	615	0,037	0,092	-0,917	11%	48%	0,051
7	125	48	77	180	692	0,040	0,061	-0,412	15%	54%	0,008
8	131	46	85	226	777	0,038	0,067	-0,553	19%	61%	0,016
9	108	52	56	278	833	0,044	0,044	-0,013	23%	66%	0,000
10	138	65	73	343	906	0,054	0,057	-0,055	29%	71%	0,000
11	161	76	85	419	991	0,064	0,067	-0,051	35%	78%	0,000
12	124	63	61	482	1.052	0,053	0,048	0,093	40%	83%	0,000
13	163	104	59	586	1.111	0,087	0,046	0,628	49%	87%	0,025
14	109	72	37	658	1.148	0,060	0,029	0,727	55%	90%	0,023
15	116	79	37	737	1.185	0,066	0,029	0,819	62%	93%	0,030
16	117	83	34	820	1.219	0,069	0,027	0,953	69%	96%	0,041
17	118	98	20	918	1.239	0,082	0,016	1,650	77%	98%	0,109
18	113	98	15	1.016	1.254	0,082	0,012	1,938	85%	99%	0,136
19	108	98	10	1.114	1.264	0,082	0,008	2,343	93%	100%	0,174
20	87	81	6	1.195	1.270	0,068	0,005	2,664	100%	100%	0,168
Total	2.465	1.195	1.270								1,380

val1_scr	#acct	#good	#bad	#cumgood	#cumbad	prob good	prob bad	wt. pattern	%cumgood	%cumbad	IV
									0%	0%	
1	1.218	826	392	826	392	0,023	0,163	-1,960	2%	16%	0,275
2	1.320	1.041	279	1.867	671	0,029	0,116	-1,388	5%	28%	0,121
3	1.345	1.118	227	2.985	898	0,031	0,094	-1,111	8%	37%	0,070
4	1.628	1.425	203	4.410	1.101	0,040	0,084	-0,756	12%	46%	0,034
5	1.524	1.353	171	5.763	1.272	0,038	0,071	-0,637	16%	53%	0,021
6	1.623	1.483	140	7.246	1.412	0,041	0,058	-0,345	20%	59%	0,006
7	1.711	1.548	163	8.794	1.575	0,043	0,068	-0,454	24%	66%	0,011
8	1.672	1.543	129	10.337	1.704	0,043	0,054	-0,223	29%	71%	0,002
9	1.620	1.502	118	11.839	1.822	0,042	0,049	-0,161	33%	76%	0,001
10	1.708	1.614	94	13.453	1.916	0,045	0,039	0,138	37%	80%	0,001
11	2.136	2.038	98	15.491	2.014	0,057	0,041	0,330	43%	84%	0,005
12	1.865	1.784	81	17.275	2.095	0,050	0,034	0,387	48%	87%	0,006
13	1.984	1.914	70	19.189	2.165	0,053	0,029	0,603	53%	90%	0,015
14	2.064	2.001	63	21.190	2.228	0,056	0,026	0,753	59%	93%	0,022
15	2.062	2.005	57	23.195	2.285	0,056	0,024	0,855	65%	95%	0,027
16	2.197	2.155	42	25.350	2.327	0,060	0,017	1,233	71%	97%	0,052
17	2.261	2.236	25	27.586	2.352	0,062	0,010	1,788	77%	98%	0,093
18	2.366	2.346	20	29.932	2.372	0,065	0,008	2,060	83%	99%	0,117
19	2.409	2.394	15	32.326	2.387	0,067	0,006	2,368	90%	99%	0,143
20	3.645	3.628	17	35.954	2.404	0,101	0,007	2,658	100%	100%	0,249
Total	38.358	35.954	2.404								1,273

Appendix 4 – E.D.S. Detail Coarse Display

dev1_scr	#acct	#good	#bad	#cumgood	#cumbad	prob good	prob bad	wt. pattern	%cumgood	%cumbad	IV
									0%	0%	
1	503	41	462	41	462	0,008	0,093	-2,441	1%	9%	0,207
2	503	70	433	111	895	0,014	0,087	-1,842	2%	18%	0,135
3	504	65	439	176	1.334	0,013	0,088	-1,930	3%	27%	0,145
4	502	95	407	271	1.741	0,019	0,082	-1,474	5%	35%	0,093
5	504	110	394	381	2.135	0,022	0,079	-1,295	8%	43%	0,074
6	503	120	383	501	2.518	0,024	0,077	-1,180	10%	51%	0,063
7	502	145	357	646	2.875	0,029	0,072	-0,920	13%	58%	0,040
8	503	157	346	803	3.221	0,031	0,069	-0,810	16%	65%	0,031
9	503	217	286	1.020	3.507	0,043	0,057	-0,296	20%	70%	0,004
10	504	224	280	1.244	3.787	0,044	0,056	-0,243	24%	76%	0,003
11	504	258	246	1.502	4.033	0,051	0,049	0,028	30%	81%	0,000
12	502	273	229	1.775	4.262	0,054	0,046	0,156	35%	86%	0,001
13	503	311	192	2.086	4.454	0,061	0,039	0,463	41%	89%	0,010
14	504	335	169	2.421	4.623	0,066	0,034	0,665	48%	93%	0,021
15	502	386	116	2.807	4.739	0,076	0,023	1,183	55%	95%	0,062
16	503	420	83	3.227	4.822	0,083	0,017	1,602	64%	97%	0,106
17	504	445	59	3.672	4.881	0,088	0,012	2,001	72%	98%	0,152
18	502	449	53	4.121	4.934	0,088	0,011	2,117	81%	99%	0,165
19	503	472	31	4.593	4.965	0,093	0,006	2,704	90%	100%	0,234
20	504	487	17	5.080	4.982	0,096	0,003	3,336	100%	100%	0,308
Total	10.062	5.080	4.982								1,855

val1_scr	#acct	#good	#bad	#cumgood	#cumbad	prob good	prob bad	wt. pattern	%cumgood	%cumbad	IV
									0%	0%	
1	1.200	526	674	526	674	0,008	0,086	-2,395	1%	9%	0,188
2	1.493	759	734	1.285	1.408	0,011	0,094	-2,113	2%	18%	0,175
3	1.610	949	661	2.234	2.069	0,014	0,085	-1,785	3%	27%	0,126
4	1.765	1.162	603	3.396	2.672	0,017	0,077	-1,491	5%	34%	0,089
5	2.172	1.543	629	4.939	3.301	0,023	0,081	-1,249	7%	42%	0,072
6	2.342	1.758	584	6.697	3.885	0,026	0,075	-1,045	10%	50%	0,051
7	2.575	1.998	577	8.695	4.462	0,030	0,074	-0,905	13%	57%	0,040
8	2.827	2.274	553	10.969	5.015	0,034	0,071	-0,733	16%	64%	0,027
9	3.297	2.765	532	13.734	5.547	0,041	0,068	-0,499	21%	71%	0,013
10	3.439	2.998	441	16.732	5.988	0,045	0,057	-0,230	25%	77%	0,003
11	3.580	3.212	368	19.944	6.356	0,048	0,047	0,020	30%	81%	0,000
12	3.953	3.644	309	23.588	6.665	0,055	0,040	0,321	35%	85%	0,005
13	4.676	4.370	306	27.958	6.971	0,065	0,039	0,512	42%	89%	0,013
14	4.949	4.708	241	32.666	7.212	0,070	0,031	0,825	49%	92%	0,033
15	4.770	4.574	196	37.240	7.408	0,068	0,025	1,003	56%	95%	0,044
16	5.398	5.245	153	42.485	7.561	0,079	0,020	1,388	64%	97%	0,082
17	6.209	6.100	109	48.585	7.670	0,091	0,014	1,878	73%	98%	0,145
18	5.912	5.848	64	54.433	7.734	0,088	0,008	2,368	81%	99%	0,188
19	5.990	5.943	47	60.376	7.781	0,089	0,006	2,693	90%	100%	0,223
20	6.439	6.415	24	66.791	7.805	0,096	0,003	3,442	100%	100%	0,320
Total	74.596	66.791	7.805								1,836

Appendix 5 – BS1 Detail Coarse Display

dev1_scr	#acct	#good	#bad	#cumgood	#cumbad	prob good	prob bad	wt. pattern	%cumgood	%cumbad	IV
									0%	0%	
1	505	1	504	1	504	0,000	0,110	-6,412	0%	11%	0,705
2	506	5	501	6	1.005	0,001	0,110	-4,796	0%	22%	0,521
3	505	9	496	15	1.501	0,002	0,108	-4,198	0%	33%	0,449
4	505	10	495	25	1.996	0,002	0,108	-4,091	0%	44%	0,435
5	505	34	471	59	2.467	0,006	0,103	-2,817	1%	54%	0,273
6	503	60	443	119	2.910	0,011	0,097	-2,188	2%	64%	0,188
7	506	98	408	217	3.318	0,018	0,089	-1,615	4%	73%	0,115
8	505	160	345	377	3.663	0,029	0,075	-0,957	7%	80%	0,044
9	504	214	290	591	3.953	0,039	0,063	-0,493	11%	86%	0,012
10	506	272	234	863	4.187	0,049	0,051	-0,038	16%	92%	0,000
11	504	349	155	1.212	4.342	0,063	0,034	0,623	22%	95%	0,018
12	505	411	94	1.623	4.436	0,074	0,021	1,286	29%	97%	0,069
13	505	451	54	2.074	4.490	0,082	0,012	1,934	38%	98%	0,135
14	504	462	42	2.536	4.532	0,084	0,009	2,209	46%	99%	0,164
15	505	485	20	3.021	4.552	0,088	0,004	2,999	55%	100%	0,250
16	506	494	12	3.515	4.564	0,089	0,003	3,529	64%	100%	0,306
17	504	499	5	4.014	4.569	0,090	0,001	4,414	73%	100%	0,394
18	505	502	3	4.516	4.572	0,091	0,001	4,931	82%	100%	0,445
19	505	504	1	5.020	4.573	0,091	0,000	6,034	91%	100%	0,549
20	504	504	0	5.524	4.573	0,091	0,000	12,941	100%	100%	1,181
Total	10.097	5.524	4.573								6,256

val1_scr	#acct	#good	#bad	#cumgood	#cumbad	prob good	prob bad	wt. pattern	%cumgood	%cumbad	IV
									0%	0%	
1	948	10	938	10	938	0,000	0,105	-6,735	0%	11%	0,708
2	949	19	930	29	1.868	0,000	0,104	-6,085	0%	21%	0,633
3	912	44	868	73	2.736	0,001	0,097	-5,176	0%	31%	0,501
4	870	96	774	169	3.510	0,001	0,087	-4,281	0%	39%	0,366
5	1.152	258	894	427	4.404	0,003	0,100	-3,437	1%	49%	0,334
6	1.439	561	878	988	5.282	0,007	0,098	-2,642	1%	59%	0,242
7	1.660	905	755	1.893	6.037	0,011	0,085	-2,013	2%	68%	0,148
8	2.135	1.485	650	3.378	6.687	0,019	0,073	-1,368	4%	75%	0,074
9	3.043	2.408	635	5.786	7.322	0,030	0,071	-0,861	7%	82%	0,035
10	4.083	3.565	518	9.351	7.840	0,045	0,058	-0,265	12%	88%	0,004
11	5.406	5.021	385	14.372	8.225	0,063	0,043	0,374	18%	92%	0,007
12	6.345	6.056	289	20.428	8.514	0,076	0,032	0,848	26%	95%	0,037
13	6.902	6.728	174	27.156	8.688	0,084	0,020	1,461	34%	97%	0,094
14	7.523	7.421	102	34.577	8.790	0,093	0,011	2,093	43%	99%	0,170
15	7.363	7.310	53	41.887	8.843	0,091	0,006	2,732	52%	99%	0,233
16	8.029	8.000	29	49.887	8.872	0,100	0,003	3,426	62%	99%	0,331
17	7.443	7.419	24	57.306	8.896	0,093	0,003	3,540	72%	100%	0,319
18	7.646	7.636	10	64.942	8.906	0,095	0,001	4,444	81%	100%	0,419
19	7.292	7.284	8	72.226	8.914	0,091	0,001	4,620	90%	100%	0,416
20	7.790	7.787	3	80.013	8.917	0,097	0,000	5,667	100%	100%	0,550
Total	88.930	80.013	8.917								5,622

Appendix 6 – BS2 Detail Coarse Display

dev1_scr	#acct	#good	#bad	#cumgood	#cumbad	prob good	prob bad	wt. pattern	%cumgood	%cumbad	IV
									0%	0%	
1	501	2	499	2	499	0,000	0,101	-5,546	0%	10%	0,557
2	502	3	499	5	998	0,001	0,101	-5,140	0%	20%	0,515
3	503	2	501	7	1.499	0,000	0,101	-5,550	0%	30%	0,559
4	501	5	496	12	1.995	0,001	0,100	-4,623	0%	40%	0,459
5	502	20	482	32	2.477	0,004	0,097	-3,209	1%	50%	0,300
6	502	54	448	86	2.925	0,011	0,090	-2,142	2%	59%	0,171
7	501	72	429	158	3.354	0,014	0,087	-1,811	3%	68%	0,131
8	502	111	391	269	3.745	0,022	0,079	-1,285	5%	76%	0,073
9	503	186	317	455	4.062	0,037	0,064	-0,559	9%	82%	0,015
10	501	236	265	691	4.327	0,046	0,054	-0,142	14%	87%	0,001
11	502	309	193	1.000	4.520	0,061	0,039	0,444	20%	91%	0,010
12	501	350	151	1.350	4.671	0,069	0,030	0,814	27%	94%	0,031
13	502	389	113	1.739	4.784	0,077	0,023	1,210	34%	97%	0,065
14	503	428	75	2.167	4.859	0,084	0,015	1,715	43%	98%	0,118
15	501	460	41	2.627	4.900	0,090	0,008	2,391	52%	99%	0,197
16	501	476	25	3.103	4.925	0,094	0,005	2,920	61%	99%	0,259
17	503	491	12	3.594	4.937	0,097	0,002	3,685	71%	100%	0,347
18	501	493	8	4.087	4.945	0,097	0,002	4,095	80%	100%	0,390
19	502	498	4	4.585	4.949	0,098	0,001	4,798	90%	100%	0,466
20	502	499	3	5.084	4.952	0,098	0,001	5,088	100%	100%	0,496
Total	10.036	5.084	4.952								5,161

val1_scr	#acct	#good	#bad	#cumgood	#cumbad	prob good	prob bad	wt. pattern	%cumgood	%cumbad	IV
									0%	0%	
1	5.175	89	5.086	89	5.086	0,000	0,100	-6,356	0%	10%	0,635
2	5.695	141	5.554	230	10.640	0,000	0,109	-5,984	0%	21%	0,652
3	5.509	380	5.129	610	15.769	0,001	0,101	-4,913	0%	31%	0,492
4	6.250	1.134	5.116	1.744	20.885	0,002	0,101	-3,817	0%	41%	0,376
5	7.172	2.552	4.620	4.296	25.505	0,005	0,091	-2,904	1%	50%	0,249
6	9.625	4.948	4.677	9.244	30.182	0,010	0,092	-2,254	2%	59%	0,186
7	11.680	7.538	4.142	16.782	34.324	0,015	0,081	-1,712	3%	68%	0,114
8	17.053	12.937	4.116	29.719	38.440	0,025	0,081	-1,165	6%	76%	0,065
9	22.785	19.325	3.460	49.044	41.900	0,038	0,068	-0,590	10%	82%	0,018
10	26.791	24.255	2.536	73.299	44.436	0,047	0,050	-0,052	14%	87%	0,000
11	31.064	29.022	2.042	102.321	46.478	0,057	0,040	0,344	20%	91%	0,006
12	35.878	34.325	1.553	136.646	48.031	0,067	0,031	0,785	27%	94%	0,029
13	39.678	38.517	1.161	175.163	49.192	0,075	0,023	1,191	34%	97%	0,062
14	41.643	40.882	761	216.045	49.953	0,080	0,015	1,673	42%	98%	0,108
15	49.412	48.967	445	265.012	50.398	0,096	0,009	2,390	52%	99%	0,208
16	47.255	47.056	199	312.068	50.597	0,092	0,004	3,155	61%	100%	0,277
17	53.611	53.494	117	365.562	50.714	0,104	0,002	3,815	71%	100%	0,389
18	47.619	47.538	81	413.100	50.795	0,093	0,002	4,064	81%	100%	0,371
19	48.135	48.097	38	461.197	50.833	0,094	0,001	4,833	90%	100%	0,450
20	51.247	51.234	13	512.431	50.846	0,100	0,000	5,969	100%	100%	0,595
Total	563.277	512.431	50.846								5,282

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