


Economic valuation as acceptance metric for credit contracts

The effect of introducing economic valuation as acceptance metric for credit contracts on overall portfolio profit: an example at an automotive leasing company



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ABSTRACT

Currently, Company X makes credit acceptance decisions based on the probability of default of an application. An application of which the PD is higher than the hurdle of █%, will be rejected. Through the deployment of such a measure, Company X tries to differentiate between good and bad applications. Although this is often a good method to keep risk in the portfolio on a target level, when using the PD risk measure solely the question arises whether these metrics alone capture the possible profit/loss contribution of credit contracts. In this case, this measure somewhat misses the real objectives of a credit provider. Finlay also mentioned this in his study 'Towards Profitability', saying that "The true objective for commercial lenders is to forecast financial measures, such as contribution to profit, and to make lending decisions on the basis of these forecasts." (Finlay, 2008).

Within Company X that is why the question arose whether there might be an alternative measure that does provide insight in the profit/loss contribution of a contract. An extensive literature review indicated that the ratio called "Risk Adjusted Return on Capital" (RAROC) may provide this insight. In order to make the calculation as complete as possible, aspects from several methods provided by the literature have been used. A combination of customer lifetime value and customer profitability is used to calculate the revenues and costs of a specific contract. Risk measures like the probability of default, loss given default and exposure at default together form the expected loss of contract. From a two model profit system, provided by Stewart (2011) it is learned that the aspects of profit, loss and risk costs have to be examined separately in the first stadium of the calculation. Based on these aspects, the RAROC is calculated as:

$$RAROC = \frac{\text{return} - \text{expected loss} - \text{expenses}}{\text{economic capital}}$$

The effectiveness of using RAROC as criterion for the credit acceptance policy is tested by analyzing a dataset of 58.337 unique financial lease applications submitted between 01-11-2013 and 31-12-2015. This study is carried out based on the following research question:

"Can economic valuation (Risk Adjusted Return on Capital) outperform probability of default as criterion for the credit acceptance decision, measured by an increase in overall portfolio profit?"

For all applications in the dataset the PD and RAROC are calculated. Three different hurdles are determined for both methods, and on this basis six different hypotheses were drawn. The first scenario is intended to compare the current situation (PD hurdle of ≤ █%) with the new situation (RAROC hurdle of ≥ 0%). Secondly, a scenario is supposed to compare both methods when the hurdle is set to point where the monetary profit is maximized; for the PD method this results in a hurdle of ≤ 70% and for the RAROC ≥ 0%. For scenario three the objective is to measure the effect when a hurdle is set to the point where the portfolio RAROC is the highest (PD hurdle of ≤ 45% and a RAROC hurdle of ≥ 30%).

Thousand portfolios were created for each scenario, using a Monte Carlo simulation. Of those thousand portfolios, the mean monetary profit and the mean portfolio RAROC for both methods are compared. For this analysis, Paired Samples T-test and Wilcoxon Signed Rank test have been performed.

The results of these test showed that, with the exception of the monetary profit in scenario 3, the RAROC method is able to outperform the PD method. Knowing this, the question can be answered with a yes, using RAROC as criterion for the credit acceptance policy can outperform probability of default, based on an increase in overall portfolio profit.

It can be concluded that implementing RAROC as criterion for the credit acceptance policy will have positive effects on both the monetary profit and the portfolio RAROC. Implementing this new method will concern a number of departments at Company X. Processes and workload on the departments credit applications, risk management, account receivables and controlling will likely change somewhat. This is mainly due to the increase in accepted credit contracts with the new method, which will result primarily in additional human resource needs. Although the implementation of the new method involves short- and long-term cost increases, it is still recommended to use the new method. The expected profit increases as well as the number of contracts and therefore an expected increase in market share shall ensure that the benefits exceed the disadvantages. In addition to implementing the method, it is also recommended to carry out further research. Future research should mainly be focused on the contract specific allocation of overhead costs and analyzing costs and profits in time buckets (e.g. monthly) in order to improve the accuracy of the RAROC method.

TABLE OF CONTENTS

Abstract	ii
1. Introduction	1
1.1. Research goal and question	2
1.2. Contribution	2
1.3. Theoretical framework.....	3
1.4. Research method	5
1.5. Thesis outline	6
2. Theoretical framework	7
2.1. Risk and return	7
2.2. Risk based criteria	8
2.3. Return based criteria.....	10
2.4. Risk and return based criteria	13
2.5. Summary of the discussed criteria	14
3. Method	16
3.1. Research design	16
3.2. Selection and sample	17
3.3. Data collection	17
3.4. Data editing.....	17
3.5. Measurement.....	20
3.6. Data analysis	21
3.7. Scenario analysis	25
3.8. Hypotheses.....	27
4. Results.....	28
4.1. Paired Samples Test for difference between mean monetary profit	28
4.2. Wilcoxon Signed Rank Test for difference between mean portfolio RAROC.....	29
4.3. Robustness testing	30
4.4. Results baseline scenario	30
5. Results Scenario Analysis	31
5.1. Paired Samples Test for difference between mean monetary profit	31
5.2. Wilcoxon Signed Rank Test for difference between mean portfolio RAROC.....	32
5.3. Robustness testing	33
5.4. Results additional scenarios.....	34
6. Portfolio impact analysis.....	35
7. Conclusion and discussion	37
7.1. Conclusion	37
7.2. Limitations.....	38

7.3. Future research	38
7.4. Practical implications	39
References	40
Appendix I - Time schedule.....	43
Appendix II – Histograms	44
Appendix III – Input variables	45
Appendix IV - Test of normality and descriptives	46

1. INTRODUCTION

This paper was written as a part of the graduation process for the Master of Business Administration with a specialization in Financial Management. The study was conducted in collaboration with and on behalf of a globally operating automotive leasing company. Because of the confidential information in this thesis the company will not be mentioned by name but referred to as “Company X”.

Company X offers products for automotive finance, insurance and leasing to individuals and small and medium businesses as well as large corporates. The core business of this firm can be summarized in offering financial or operational lease contracts. Financial lease is a form of car financing in which a customer pays a fixed installment each month for the whole contract duration, after which the car is fully owned by the customer. With this form of leasing, the customer is the economic owner, as he bears the risk of repair/maintenance/market value of the car. Operational lease differs from this, since the customer will only pay for the use of the car, and will not bear any of the risk of repair/maintenance/market value. Hence Company X will be the legal and economic owner of the car during or after contract period.

The automotive lease industry in The Netherlands has experienced a substantial growth – from 100.000 cars in 1983 to 713.200 in 2012 – during the past thirty years (Erich, 2013). This number has grown to 755.000 in 2015 (VNA, 2016). With this growth there have been both positive and negative consequences. Significant losses from loan defaults forms one of those negative consequences. Because of these losses, companies became more careful and are trying to increase the accuracy of credit decisions.

In order to make such credit decisions, the risk management department at Company X uses credit risk models to calculate the riskiness of a specific contract. “Credit risk models generally analyze risk in terms of a Probability of Default (PD) and a Loss Given Default (LGD). Both quantities (in this context) are predictive (as opposed to descriptive) statistical quantities representing future uncertain expectations of default and loss.” (Chisholm & Andersen, 2013). The PD is the probability that a given loan will go into default, and LGD is the likely loss (or expectation value of loss) that the lender will suffer if the loan goes into default.

If the PD passes a certain upper limit or cutoff score, it means that the risk of this contract is too high and therefore will not be accepted by the lender. This cutoff score is also called a “hurdle”. If the PD is higher than the hurdle rate then the loan is pointed as too risky, and the bank’s capital will not be allocated to the activity. The level of this hurdle is given in the credit acceptance policy designed by the local risk management department of Company X, see paragraph 2.2.1.

These credit risk models are applied in the following manner: a potential customer comes to Company X to submit an application for a lease contract. To submit an application, a certain set of personal/company information is required by Company X. This is appended with external data from data providers like Dun & Bradstreet and Graydon. This information is used in the calculation for predicting the PD. Based on the predicted PD, and a number of other factors from the acceptance policy, Company X decides whether or not a contract is proposed to the potential customer.

When a contract is proposed to a potential customer, the customer can make a final decision whether he/she accepts the proposal.

A proposed contract will be active after all parties accept the offer. All activated contracts together form a pool of contracts, which in this study is called the portfolio.

For years, the strategy of the risk management department aims to minimize risk. By applying the selection criteria mentioned in the acceptance policy, Company X succeeded to minimize the risk of the portfolio. This strategy, however, was internally called into question last year. [REDACTED]

The risk management strategy therefore needs to make a shift from minimizing risk towards optimizing risk. To optimize the level of risk in a portfolio there is sought for a better balance between risk and return. The current PD methodology, however, does not give sufficient insight into the return component to find this balance. Due to this shortcoming, the demand for an adjusted acceptance policy is emerged. With this premise Company X has conducted a preliminary examination into possible alternatives for the PD methodology. The preliminary examination has shown that it is desirable to have insight into the profit contribution per customer. It also showed that the profit contribution can be calculated using the risk adjusted return on capital (RAROC).

1.1. Research goal and question

Before Company X will use this method, they first want a comprehensive study into the effects of using RAROC instead of PD as criterion for the credit acceptance decisions. Also, Company X is curious whether or not a literature research suggest a better alternative than the RAROC. Finally, the question arises whether the overall portfolio profit increases when RAROC will be applied. These requirements are translated into the following research goal and research question.

1.1.1. Research goal

The goal of this study is to get a better insight in the effect of using RAROC as criterion for the credit acceptance decision instead of the currently used PD metric.

1.1.2. Research question

The goal of this study is translated to the following research question:

“Can economic valuation (Risk Adjusted Return on Capital) outperform probability of default as criterion for the credit acceptance decision, measured by an increase in overall portfolio profit?”

1.2. Contribution

The aforementioned goal of this study is twofold. On the one hand it helps Company X to get closer to the overall strategy of the company. On the other hand it contributes to the existing literature on the following aspects:

First contribution lies in the studied type of financing. The majority of the available literature on credit risk focusses on revolving credit. This study focusses on fixed term loans.

Why this is important can be motivated as follows. Basically, there are two ways to facilitate credit: fixed term loans and revolving credit. Automotive lease contracts are typical forms of fixed term loans, since the credit amount is payed back in monthly fixed payments. This is also called closed-end credit. For this type of credit three basic components are known when accepting a contract: credit amount, exact amount of time in which credit needs to be payed back and at what interest rate this credit is provided. This differs from revolving credit, or open-end credit, in which those components are not known when accepting a contract. A typical example of revolving credit is a credit card.

The majority of the available literature on credit risk focusses on revolving credit. The theory and models that are applicable to revolving credit are substantially different with respect to fixed term loans. This ensures that there is little literature available in the field of credit risk modeling for fixed term loans.

Another contribution to existing literature is that this paper combines diverse risk and return metrics. The existing literature that is available is mainly focused on static risk measures like PD or LGD without combining them into 'expected loss', or more advanced combinations with returns. This provides little guidance to find the balance between risk and return, which is necessary to optimize the risk level in a portfolio.

This study can contribute directly to the literature by discussing an acceptance decisioning model for fixed term loans that takes into account both risk and return. The added value of this study is mainly realized by the theoretical and empirical underpinning of using the RAROC for approval decisions in the leasing industry. The results of this study could form the basis for further research as well as guidance for leasing companies or banks to implement performance measures for credit approval decisions.

For Company X the contribution is more specific: this study offers tools to use RAROC for their credit approval decisions as a means to synchronize the risk department strategy with the overall strategy of the organization.

1.3. Theoretical framework

The Concise Oxford English Dictionary defines risk in multiple ways, among which: "hazard, a chance of bad consequences, loss or exposure to mischance" and "the possibility of financial loss".

Holton (2004) reviewed most of the existing definitions of risk in order to give the scientific world a generic definition to handle. He states that "If someone has a personal interest in what transpires, that person is exposed. Second, people don't know what will happen. In each situation, the outcome is uncertain. It seems that risk entails two essential components; exposure and uncertainty. Risk, then, is exposure to a proposition of which one is uncertain." It's notable that this definition contains two terms, risk and exposure, which are often used interchangeably. Risk and exposure have subtle differences in their meaning. According to Horcher (2011) risk refers to the probability of loss, while exposure is the possibility of loss. "Exposure to financial markets affect most organizations, either directly or indirectly."

Exposure contains the possibility of both loss and profit, of which the possibility of loss is the essence of risk.

Taking a closer look at risk, one can separate two types of risk: financial and non-financial risk.

For financial risks no single one-sentence definition of risk is entirely satisfactory. Depending on context, one might arrive at notions such as “any event or action that may adversely affect an organization’s ability to achieve its objectives and execute its strategies” or, alternatively, “the quantifiable likelihood of loss or less-than-expected returns.”

Risk can be divided into a number of categories. First, the distinction is made between business and non-business risk. Non-business risk can then be subdivided into financial and operational risk. Since risk, in this thesis, is discussed in the context of finance, this theory section elaborates on financial risk only.

According to Woods & Dowd (2008), three main risk types can be encountered in the financial industry:

- Market risks: These are the financial risks that arise because of possible losses due to changes in future market prices or rates (Woods & Dowd, 2008).
- Credit risks: The risk of not receiving promised repayments on outstanding investments such as loans and bonds, because of the default of the borrower (McNeil, Frey & Embrechts, 2013).
- Financing, liquidity and cash flow risks: Financing risks affect an organization’s ability to obtain ongoing financing (Woods & Dowd, 2008).

All aspects that are discussed in this study are related to credit risk. According to Ammann (2013), credit risk can be defined as the possibility that a contractual counterparty does not meet its obligations stated in the contract, thereby causing the creditor a financial loss. Assessing credit risk is generally a task of the risk management department of a company. Since it is not realistic to have zero risk on providing loans, the core task of credit risk management is to find the cutoff amount of credit risk. This cutoff can be set by deciding whether the predicted amount of risk is acceptable or not. Although this may sound easy, finding a balance in how much risk can be accepted or not is a complicated process. For every company this cutoff value differs, since the context of each company is also different.

Credit risk is a widely discussed topic in the literature. Many authors have studied the effect of risk on company performance. Others have tried to create risk models to manage the amount of risk in a company or studied the effects and implications of such risk models. However, it is remarkable that little is written on credit risk in the leasing business, given the fact that, with approximately 755.000 cars and a turnover of 6 billion euro’s, this is an industry with considerable magnitude (VNA, 2016).

One of the goals of the proposed research is to add value to the existing literature on credit risk by giving theoretical applications of the topic on the automotive leasing industry. In order to accomplish this, a number of articles are reviewed to constitute the basis for this research. Starting with an article written by Hao, Alam and Carling (2010), who reviewed the literature on credit risk modeling. Hao et al. (2010) trace the developments of credit risk modeling in the past 10 years.

They stated that “During the past 10 years, most approaches in credit risk modeling involve the estimation of three parameters: the probability of default (PD), the loss given default (LGD) and the correlation across defaults and losses.” (Hao et al. 2010).

These three parameters were also studied in the context of automotive leasing, for example the study by Schmit (2005). This study presented the first results on the default and loss given default performance of automotive leases.

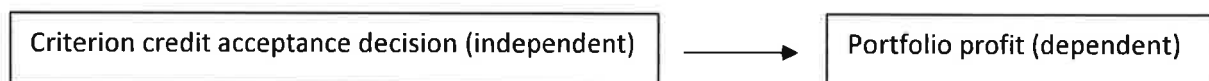
Although these models and parameters have been proven to be remarkably popular, they somewhat miss the real objectives of a credit provider. Finlay also mentioned this in his study ‘Towards Profitability’, saying that “The true objective for commercial lenders is to forecast financial measures, such as contribution to profit, and to make lending decisions on the basis of these forecasts.” (Finlay, 2008). This makes sense if one thinks about what the rationale of taking risks is if there are no rewards. Measuring risk disjointly from their returns can be very ineffective. “At worst, it might be a misspecification of the problem, if those classified as good or bad actually generate a loss or profit respectively, despite their eventual repayment classification.” (Finlay, 2010).

1.4. Research method

This study will test if using RAROC (combining forecasted returns with the risks as predicted by credit scoring models) as criterion for the credit acceptance decision can outperform the currently used PD metric, measured by an increase in overall profitability of an automotive leasing portfolio. Outperformance can be measured in terms of monetary portfolio profitability and the RAROC of the portfolio. Basically this can be summarized in the following test: comparing profit, in RAROC and monetary terms, of portfolio i and ii.

- i. Profit of all contracts accepted based on only risk measures (PD)
- ii. Profit of all contracts accepted based on economic valuation (RAROC)

These portfolios represent the independent variable, which is the criterion for credit acceptance decisions. Switching from portfolio i to ii is a change in the independent variable, which affects the dependent variable.



The above displayed conceptual model can be translated in the following hypothesis:

H1: $\mu_{MP} \text{ PD method (hurdle } \leq \blacksquare \%) \leq \mu_{MP} \text{ RAROC method (hurdle } \geq 0\%)$

H2: $\mu_{PR} \text{ PD method (hurdle } \leq \blacksquare \%) \leq \mu_{PR} \text{ RAROC method (hurdle } \geq 0\%)$

Hypothesis 1 can be read as: the mean monetary profit of the portfolio formed with a PD hurdle of $\blacksquare\%$ is lower compared to the mean monetary profit of the portfolio formed with a RAROC hurdle of 0%.

Hypothesis 2 can be read as: the mean portfolio RAROC of the portfolio formed with a PD hurdle of ■% is lower compared to the mean monetary profit of the portfolio formed with a RAROC hurdle of 0%.

The above presented hypotheses represent the current versus desired situation using a PD hurdle of ■% and a RAROC hurdle of 0%. This is the initial situation that the company wanted to test.

In order to test if these results still hold when different scenarios are tested, a scenario analysis is performed. For this scenario analysis, two additional scenarios are tested. Together with the baseline scenario this results in the following three scenarios that are tested:

1. Current versus desired situation – using a PD hurdle of ■% and a RAROC hurdle of 0%. This is the initial situation that the company wanted to test.
2. Maximal monetary profit – this scenario is aimed at comparing the two methods with a hurdle set to the specific value in which the monetary profit is maximized.
3. Maximal portfolio RAROC – The last scenario is aimed at comparing the two methods with a hurdle set to the point where the portfolio RAROC is the highest.

The hypotheses for the two additional scenarios are presented below.

H3: $\mu\text{MP PD method (scenario 2)} \leq \mu\text{MP RAROC method (scenario 2)}$

H4: $\mu\text{PR PD method (scenario 2)} \leq \mu\text{PR RAROC method (scenario 2)}$

H5: $\mu\text{MP PD method (scenario 3)} \leq \mu\text{MP RAROC method (scenario 3)}$

H6: $\mu\text{PR PD method (scenario 3)} \leq \mu\text{PR RAROC method (scenario 3)}$

The assumption is that it is more profitable to use the RAROC ratio instead of a single PD criterion in the credit acceptance decision. A summary of the different approaches is displayed below.

Table 1 | Application methods overview

<i>Elements</i>	<i>Current process (PD)</i>	<i>New process (RAROC)</i>
Expected loss	Only PD	Exposure at default x PD x Loss given default
Costs	Not included	Included
Returns	Not included	Included
Capital allocation	Not included	Included
Outcome	Static risk measure	Risk adjusted performance measure

1.5. Thesis outline

This thesis will proceed as follows: firstly there is an overview of the most important literature on credit approval methods in Chapter 2. In this section the components of the risk and return tradeoff will be discussed. Followed by a discussion into the research methodology of this study in Chapter 3. The results for the baseline scenario will be presented in Chapter 4. In Chapter 5 the results for the two additional scenarios will be presented. The impact of implementing the RAROC as acceptance method is discussed in Chapter 6. Chapter 7 discusses the conclusions of this study, as well as the limitations, further research, and practical implications.

2. THEORETICAL FRAMEWORK

This section reviews some of the most relevant literature on several topics related to this research. Starting with literature on, what is often called the first fundamental law of finance, the risk-return relationship. After this, focus switches to the two separate terms in this relationship. Finally ending with literature on applying the risk and return relationship to the credit decision making case.

2.1. Risk and return

One of the most familiar topics in financial matters is the risk-return relationship. The tradeoff between risk and return is a fundamental relationship in finance, which suggest that the expected return is positively related to the conditional variance (Wang & Yang, 2013). According to Ghysels, Santa-Clara and Valkanov (2005) this risk-return tradeoff is so fundamental in financial economics that it could well be described as the “first fundamental law of finance”.

This risk-return tradeoff often seems to be forgotten in the field of credit risk management (Beling, Covaliu & Oliver, 2005). This can partly be explained by the fact that credit risk, in most cases, is calculated in a risk department, where the focus is on risk instead of returns and risk is mostly minimized instead of optimized. Logically, the amount of credit risk would be balanced with the expected return. As Spuchlřáková, Valařková & Adamko (2015) stated “The aim of the credit risk management is to maintain the efficiency of the business activities and the continuity of the business.” Credit risk management should thus be synchronized with the business goals of the company, which in most cases is to maximize value. It is therefore inconsistent to take only risks into consideration when providing a loan. Ammann (2013) described this as follows: “Credit risk has long been recognized as a crucial determinant of prices and promised returns of debt. A debt contract involving a high amount of credit risk must promise a higher return to the investor than a contract considered less credit-risky by market participants. The higher promised return manifests itself in lower prices for otherwise identical indenture provisions.”

The risk-return tradeoff in the automotive leasing industry, in which Company X operates, is slightly more complicated than in most other markets. Although credit risk on loan contracts can vary between contracts, return will probably not vary to the same extent. If a highly risky contract would be priced with a risk adjustment, the contract would probably be far too expensive for anyone to accept. So to some extent lease contracts can take into account the risk-return tradeoff, but full incorporation of the tradeoff is less realistic. This doesn't mean that it is not useful to include return into the credit scoring model. “Common sense, however, would lead one to assume that even if full accounting information is not available, the inclusion of any additional account level information into the objective function of a credit scoring model should provide scope for improvement.” (Finlay, 2008).

In the following sections risk and return will first be discussed separately and finally some literature on the tradeoff will be presented.

2.2. Risk based criteria

In preparation of literature on risk based criteria, the following sections shortly describes the acceptance policy of Company X.

2.2.1. Acceptance policy

[REDACTED]

One of those guidelines aims to describe the credit acceptance policy as designed by local risk management for all financial lease applications. This policy contains the agreements that have been reached regarding the evaluation of credit applications as they reach the department of Central Credit Assessment (CCA). The role of the CCA is to evaluate the credit applications it receives.

Applications are submitted via diverse channels into the front office system. Missing information is added by contract management, after which the application is released for further processing. The business ruling system checks the application (after it is completed) and returns the system decision. Every file contains a data set as it is delivered by the front office system. In the mid office system several adapters add data to the application [REDACTED]

For all Financial Lease applications a credit scorecard is calculated, which is developed by local Risk Management. The final scores are stored in the file, and translated into classes of PD, which gives an indication of the chance that a customer will not meet his obligations in the coming year.

Reasons for rejection (acceptance policy) include but are not limited to:

- Low credit score (high PD) in combination with low collateralization
- Insufficient personal/company data
- High likelihood of fraud
- Negative registration at national credit register (BKR)
- Foreign organization
- The company (owners) are registered on sanction lists (anti-terrorism)

2.2.2. EAD, PD, LGD and EL

As can be seen in the above presented policy rules for credit applications acceptance, the only statistical measure that has influence in the credit granting policy at Company X is the PD metric.

The risk management department at Company X also uses (among others) this PD metric to estimate the risk within their portfolio. Provisions are based upon the outcome of these estimates. Following paragraphs will give more insight in the metrics that are currently in use at Company X.

The estimation of the average loss for a given set of exposures is called Expected Loss (EL). The EL can be divided into three main components, also called credit risk parameters: the Exposure at Default, the Probability of Default and the Loss Given Default (LGD): $EL = EAD \times PD \times LGD$.

The components, which are used in this formula, have been widely used in existing credit risk models. This is confirmed in the article written by Hao et al. (2010). They reviewed the literature on credit risk and traced the developments of credit risk modeling in the past 10 years.

They stated that "During the past 10 years, most approaches in credit risk modeling involve the estimation of three parameters: the probability of default, the loss given default and the correlation across defaults and losses" (Hao et al. 2010). Therefore the three components of the expected loss formula will be discussed subsequently.

The first part of the formula represents the exposure at default. EAD which is defined as the total exposure outstanding, which is calculated as the product between the total initial value and a depreciation rate (Schmit, Degouys, Delzelle, Stuyck & Wautelet, 2003).

According to Schmit (2003) lease contracts specify penalties and the conditions under which the lessee is considered to be in default. Each company can formulate their own definition of a company being in default. However, default is generally defined as the scenario in which a company decided to cancel an agreement because the counterparty has not paid the scheduled rentals. Company X composed different default reasons, besides payment arrears, such as cancellation due to a fraud or negative information provided by a credit enquiry agency. Probability of default is often estimated using the concept of mortality rate introduced by Altman. Within Company X the probability of default is modelled based on internal data. On certain points in time all healthy contracts are selected, and a list of potential predictors is gathered from the systems. This is modelled against all defaults in the following 12 months. As technique the binary logistic regression is used. A split is made between development sample and validation sample (generally random 70/30). As performance measures several statistics are used: ROC curve; Gini coefficient; Stability Index; and Kolmogorov-Smirnoff statistic.

According to Schuermann (2004), LGD is usually defined as ratio of losses to exposure at default. More specifically "LGD for a contract is calculated as one minus the recovery rate. The recovery rate is calculated as the discounted amounts recovered in comparison with the outstanding amount on the date of default" (Schmit, 2004). Company X calculates both measures in the same manner.

Using LGD, PD and EAD for measuring credit risk can be effective, since it can calculate important measures very accurately. However, one undeniable disadvantage of these methods is the absence of any indicators of profitability or returns of a specific contract. As stated in paragraph 2.1., this aspect shouldn't be ignored in the credit acceptance process. In order to overcome this disadvantage it is highly recommended to add some return aspects to this method, or consider to use a completely different method.

2.3. Return based criteria

The previous sub-chapter described what risk is and how it can be measured. This sub-chapter will pay attention to the return component of the famous risk-return tradeoff. Why it is relevant to take into account the return component in the credit granting process can be underpinned by the following quote: "Competitive predictors of the overall default frequency through macroeconomic indicators, loss rate estimation, an exact estimate of a default term structure, rating migration risk, or an accurate valuation of the relationship benefit have the potential to further increase profitability" (Blöchlinger & Leippold, 2006). In particular, the last section is notable, since it states that an accurate valuation of the relationship benefit has the potential to further increase profitability. To get more insight in customer value/profitability, a few ways of assessing value/profitability are discussed below. These methods will (partly) be used in a later stadium of this research.

2.3.1. Customer lifetime value

According to Pfeifer, Haskins & Conroy (2005) customer lifetime value (CLV) is the present value of the future cash flows attributed to the consumer relationship. In other words, it calculates the profitability of a customer.

"CLV is typically defined and estimated at an individual customer or segment level. This allows us to differentiate between customers who are more profitable than others rather than simply examining average profitability." (Gupta, Hanssens, Hardie, Kahn, Kumar, Lin & Sririam, 2006).

CLV is a well-known and a commonly used method for assessing customer profitability. However, just like the risk metrics discussed in the previous sub-chapter, it approached only one component of the risk-return tradeoff (except that one can use a risk-adjusted discount factor when discounting future cash flows).

2.3.2. Customer profitability

Besides CLV, Pfeifer et al. (2005) also discuss customer profitability (CP). They define CP as the difference between the revenues earned from and the costs associated with the customer relationship during a specified period.

"Consequently, the distinction between CLV and CP will be a distinction between value and profit in the financial sense.

Roughly speaking, value is what something is worth (the cash-equivalent price today that a buyer would be willing to pay to own the future cash-flow benefits springing from that asset) and profit is the difference between accrual-based revenues and accrual-based costs incurred in generating those revenues for a given period such as a quarter or a year. It is sometimes the case that unprofitable firms carry high valuations (under the expectation the company will generate a future stream of positive cash flows)" (Pfeifer et al., 2005).

Using CLV or CP as sole method for the credit acceptance process will result in the same disadvantages as using the PD method. It takes into account the profit component instead of the risk component, this however doesn't take into account the relationship between both components. Despite this problem, CLV and CP are described in this paper since they can give understanding in the way profitability and value can be calculated on a customer level. This knowledge will be applied in defining the various components in the new method.

2.3.3. Profit based scoring

With the exception of the abovementioned subjects, few literature on profit modelling in credit markets is available. According to Stewart (2011) this has to do with four struggle points, of which two are also applicable for the leasing industry. Starting with the challenge that no clear definition of profit on account level is available. This can be explained by the fact that assigning fixed and marginal costs to a specific contract is complex. Edelman, Crook & Thomas (2002) described this as: "Another challenge is the incremental change in marginal and fixed costs as new applications are accepted, that is, each new customer accepted results in changes to the average operational overhead of processing an account, with a corresponding knock on effect to the profitability of the account." Besides fixed and marginal costs, the time horizon is another challenging topic in defining profit on account level. Credit scoring models usually have a time scope of one or two years, while profitability is mostly measured over three to five years of time. "Therefore, there may be conflicts between short-term good/bad classifications and longer term profitability which lenders find difficult to reconcile in the operational environment (Finlay, 2008)." The second struggle point by Stewart (2011) is about the profit distributions, which have unique characteristics that make them difficult to model. For the automotive leasing industry this applies to different types of cars, maturities and interest rates.

Just like CLV and CP, Stewart (2011) tests a return based classification method. This method will shortly be explained since it contains some significant aspects that will be used later in this study. Stewart (2011) test whether a two model profit system, consisting of a combination of spend models (used in the credit card business) as a proxy for revenue and charge-off models as a proxy for cost, can be an effective and efficient alternative for standard binary classification models.

The two model profit system separates contracts into FICO (originally called Fair, Isaac and Company) categories, so that the profit and charge off relation is secluded. It then sets off profit against charge-off (costs) and score deciles. "FICO introduced analytic solutions such as credit scoring that have made credit more widely available." (FICO). This divides the accounts of a certain FICO category into ten different scores. So a score of 1 has low mean spendings whereas a 10 has high mean spendings.

For each score (0-10) the bad rates are almost the same, since the relation between revenue and costs is secluded by dividing it into FICO categories.

This gives the opportunity to see which contracts in a specific FICO range are likely to produce high revenues with a certain bad rate and which contracts are likely to produce little revenues with the same bad rate (Stewart, 2011).

The context in which this paper is written differs in certain respects. First of all, the profit model for credit cards must be able to predict whether a customer spends more money with the card in the future. "By definition, revolving credit is dynamic as repurchase may occur and hence the outstanding balance is to some extent open-ended" (Sanchez-Barrios, Andreeva & Ansell, 2016). In the automotive leasing industry, payment dates are known for the complete contract duration, also known as fixed term loans. Secondly, the model works with FICO scores, which are not used in the context of this research. So the model can't be directly implemented in this case, but some aspects are relevant for this specific topic. Starting with the fact that one can get more insight in contract profitability when profit can be partly separated from risk in a model. It also shows how costs and revenues can be combined into one model.

Performance can be measured with ratios as well. The most commonly used ratios to measure the performance of a company, business unit or single investment are the Return on Equity (ROE) and Return on Investment (ROI). The difference between these two ratios is that ROE takes into account the invested equity, whereas the ROI uses the complete invested capital.

Written as formulas we get:

$$RoI = \frac{\text{Return}}{\text{Invested Capital}}$$

$$RoE = \frac{\text{Return}}{\text{Invested Equity Capital}}$$

Although these ratios are widely used in practice, they also have some shortcoming. Both ratios do not take into account any risk. Because risk isn't considered in the calculation of these ratios, two investments with the same return looks similar. But one might be much riskier than the other, which is quite an important element to take into account. Banks and other loan providers are mostly risk averse, and they will thus never choose an investment which is riskier than another investment but generates the same profit. To overcome this problem, return has to be compared to the risk undertaken. In this way, it is possible to compare the performances of different investments and in this case different contract applications (Prokopczuk, Rachev, Schindlmayr & Trück, 2007).

As stated by Prokopczuk et al. (2007) return has to be compared by risk, this will be highlighted in the next section.

2.4. Risk and return based criteria

2.4.1. Relation between risk and returns

Previous sections described literature on both components of the risk-return tradeoff. Much literature can be found on these separate topics. But, up to now, there is little to none literature available in which the two factors are combined into one model. Most models choose to focus on one of the two components. In addition, the models that are reviewed during the literature phase are all specified for revolving credit instead of fixed term loans. This difference is described in the last paragraph of the previous sub-chapter.

One article that is comparable to this study is that of Blöchlinger and Leippold (2006). They studied the economic benefit of powerful credit scoring. In their paper they related the discriminatory power of a credit scoring model to the optimal credit decision to derive (a) the profit-maximizing cutoff and (b) the pricing curve. Though the objective is to some extent in line with the objective in this study, it is still a single factor model. It takes into account the default probability and the expected cash flows. But it doesn't take into account expected losses and other costs. Furthermore the model is an econometric model which is mathematically so complex that a practical application is difficult.

In contrast to a method where risk and return are compared after they have been modelled separately, there are some ratios used by banks in which these factors are combined in the numerator. One of these ratios is called the Risk Adjusted Return On Capital (RAROC). The RAROC is perceived as a solid method to use, this is also stated by Chłopek (2013).

In the conclusion of his study he states: "After a very reliable analysis of literature and real world examples, it can be said that whatever protection banks use there are always factors that could lead banks to failure. But banks can and have to reduce the risk as much as possible, and modern approaches like RAROC are very helpful in this." (Chłopek, 2013).

This ratio was introduced in the early 70's by Charles Sanford during his job at Bankers Trust (Guill, 2009). RAROC can be calculated as:

$$\text{RAROC} = \frac{\text{Risk-adjusted return}}{\text{Economic capital}} = \frac{\text{Return} - \text{expected loss} - \text{expenses}}{\text{Economic capital}}$$

The numerator of this ratio contains the risk adjusted return, which is calculated as the return minus expected loss and expenses. Economic capital is the denominator of this ratio, which is the amount of capital that serves as solvency or buffer capital (Laeven & Goovaerts, 2004). According to Risk Encyclopedia "Firms calculate economic capital at their own initiative and for exclusively proprietary purposes related to capital allocation and performance measurement."

“Today, almost all major banks and financial intermediaries have developed RAROC (Risk Adjusted Return On Capital) models to evaluate the profitability of various business lines, including their lending. RAROC is an answer to the demand by stockholders for improved performance, especially the maximization of shareholder value” (Chłopek, 2013). In this study, profitability will be measured on a contract level.

Since economic capital can also be used as allocated economic capital, the RAROC is able to measure performance on contract level. The objective of this study is in line with the statement of Chłopek (2013) and with the functioning of RAROC. Therefore RAROC will be used in this study as an alternative to the PD method.

The RAROC ratio incorporates all aspects that are considered important in the methods discussed above. Looking at the numerator of this ratio, it contains all risk methods discussed in this chapter. Value (CLV) and profitability (CP) of a customer will be combined in the return component of the numerator. What is learned from the model proposed by Stewart (2011) is also applicable for the RAROC method, since profit and risk are both incorporated in the RAROC. In conclusion, the RAROC is able to optimize risk for Company X instead of purely minimizing the risk.

2.5. Summary of the discussed criteria

This section provides a summary of all the above discussed criteria and methods of assessing return and risk.

PD/EAD/LGD – Risk based criteria - Risk metrics used to estimate risk within a portfolio

- i. Advantage - Provides accurate risk assessments.
- ii. Disadvantage - Does not provide a profitability indication.

CLV – Return based criteria - Present value of future cash flows attributed to the consumer relationship.

- iii. Advantage - Applicable at contract level, takes in consideration both revenue and costs. As well as revenues, this method also calculates the actual value that is added by a specific contract (for example strategic benefits when providing contracts to highly potential customers).
- iv. Disadvantage - Risk is not calculated on a contract basis. The cash flows are discounted by the cost of capital of a company. The risk factor herein is generic for the business line of the company, the risk level of a specific contract is thus not clear.

CP – Return based criteria - The difference between revenues earned and the cost associated with the customer relationship.

- v. Advantage - Is a very basic and clear method to calculate the profit per customer. Is applicable in almost every case.
- vi. Disadvantage - Does not take into account any risk. Since risk is not incorporated in the direct costs of a contract.

Two model profit system – Return based criteria - Combination of spend models (credit card business) as a proxy for revenues and charge-off models as a proxy for costs.

- vii. Advantage - Provides insight in the profitability of a contract as well as the risk class in which a contract has been classified.
- viii. Disadvantage - Focusses on credit card businesses, which is known for revolving credit instead of fixed term loans. So this is not directly applicable to this case.

ROI – Return based criteria - Ratio which divides return by the amount of invested capital.

- ix. Advantage - Calculates the profitability of a contract.
- x. Disadvantage - No risk measure or indicator is incorporated.

ROE – Return based criteria - Ratio which divides return by the amount of invested equity capital.

- xi. Advantage - Calculates the profitability of a contract.
- xii. Disadvantage - No risk measure or indicator is incorporated.

RAROC – Risk and Return based criteria - Divides the risk adjusted return by the economic capital which is held for a specific contract.

- xiii. Advantage - Gives insight in both risk and return. Is an clear and relatively easy applicable method. Commonly used in the banking industry, so benchmarking is possible.
- xiv. Disadvantage - Does not provide a method to calculate overhead allocation to a specific contract, so overhead must be taken into account at a next stadium.

The next chapter will describe in which way it will be analyzed if applying RAROC as acceptance metric, instead of the current PD method, turns out in an increase in overall portfolio profit.

3. METHOD

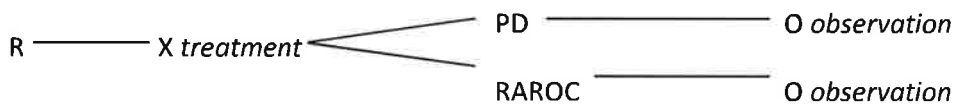
This chapter provides information on how data is collected, how the data has been adjusted, how the measurements are defined and conceptualized, whether the results maintain if different scenarios are tested, the impact of this change on the portfolio and, finally, what are the expectations.

3.1. Research design

The objective of this study is to get a better insight in credit acceptance policies and to explore an alternative of accepting policy based on the widely used (Sousa, Gama & Brandão, 2016) PD metric. It will be tested if a RAROC method can outperform a single PD metric, measured by an increase in overall portfolio profit. The literature has been reviewed for examples of such performance testing. This led to the article of Řezáč & Řezáč (2011) which states that the quality of credit scoring models in most cases is tested by a GINI coefficient. Finlay (2008), however, mentioned that a continues model using a financial measure such as profit may well appear worse if traditional measures of model performance such as GINI are applied. This can be explained logically by the fact that a GINI is especially suitable for binary classification models while profit is a continues variable. For this reason, it was decided not to use GINI but to establish an alternative method to assess the performance of the two models (PD and RAROC).

To test if there is a significant difference between the effects of the two models, the derived data set will be analyzed with the regular PD metric and once with the RAROC. Since this contains a two-group analysis where a treatment is administered and the consequences will be observed, a two-group experimental design is applied in this study.

This research design can be graphically explained in the following way:



The graph starts with an R (random assignment) followed by an X (treatment) and both lines ends with O (observation). In this design, one group gets the RAROC treatment and the other group is the comparison group and gets the PD treatment (Trochim, 2006). In this study the comparison group is the dataset in which the PD metric is handled as acceptance metric, which can also be called the standard treatment. The second treatment group is the dataset in which the RAROC method is applied as acceptance metric. This research design is focused on determining whether the two datasets are different, in profit terms, after switching from acceptance models.

Trochim (2006) states that “The posttest-only randomized experiment is strong against the single-group threats to internal validity because it's not a single group design! It's strong against the all of the multiple-group threats except for selection-mortality.” Threats to the internal validity are moderate to non-existent because the threat of selection-mortality does not apply in this study since data is collected from an existing database.

3.2. Selection and sample

The target population in this study are financial lease contracts in the automotive industry. Within this population, the sample frame includes all financial lease applications which are registered in the database of Company X. [REDACTED]

3.3. Data collection

For this study data is collected unobtrusive from databases at Company X. Company X works with internally developed software to handle credit applications. When a client applies for a credit contract, personal and company information is entered into the system. The software then assesses this application and decides whether it is approved or not, or in some cases recommends to process this application manually. For both accepted and rejected contracts data will be stored in databases. Information will be extended during the contract period for accepted contracts.

The required data applicable for the analysis can be derived from the software. [REDACTED], there are two main sources of data. When exported from the systems, data will be clearly presented in Excel. Each variable, for example credit amount, contract duration etc., is displayed in a separate column. [REDACTED]

3.4. Data editing

3.4.1. Applied filters and demarcations

[REDACTED]

3.4.2. Data adjustments and corrections

As mentioned above, data is gathered from two systems, data from both systems contains application information at the time of application. For all accepted contracts, information will be updated and extended during the contract period. It is possible that the up to date information is more complete or more accurate than the information gathered at the time of application.

Therefore, it was decided to supplement the data for a number of variables on the basis of the software systems which do not only keep track of data at the application at time, but during the entire contract period. This is the case for credit amount, down payment and the final term for accepted contracts. Data from system 1 and 2 for these factors is compared to data on the invoice that is sent to the customer. In case of any differences in the two sources, data on the invoice is leading.

In the past few years Company X improved the accuracy of predicting the probability of default. Adjustments to the method were implemented in the acceptance system after they were validated. Due to these changes, the PD at application is calculated in various ways throughout the years. This will give a small bias in the comparison of various contracts over time. To correct for this bias, the PD is recalculated according to the current PD model for all contracts included in the dataset. It has been assured that only historic data was used that was available at t.

The current model calculates the PD based on three main categories, which are the bureau score, customer score and contract score. The scores of these main categories are calculated by summing up several variables which are multiplied by a specific coefficient. Eventually the bureau score, customer score and contract scores will be multiplied with a coefficient and then added up, resulting in a log odd. This log odd is transformed into a PD.

3.4.3. Data additions

There are missing certain variables in the current data set that are required in order to carry out the analysis of this study, among which the calculation of a contract RAROC. To be able to calculate a RAROC for each contract, the dataset needs to be supplemented with some extra data consisting of subvention rates, effective interest rates on sourced capital and dealer commissions. This information is provided by the financial controlling department at Company X.

3.4.4. Additional calculations

Performing additional calculations is the last part of the data editing process. In order to perform the desired analysis, the RAROC for each contract in the dataset needs to be calculated. The RAROC is calculated using the following formula:

$$\text{RAROC} = \frac{\text{Risk-adjusted return}}{\text{Economic capital}} = \frac{\text{Return} - \text{expected loss} - \text{expenses}}{\text{Economic capital}}$$

In this formula, it is seen that the RAROC is calculated based on four components: return; expenses; expected loss; and economic capital. These components, however, cannot be extracted directly from the data. Therefore, each component is decomposed into several variables. Each component will be explained subsequently.

Return:

Interest income lifetime - Due to differences in lease objects (cars), the contract duration, down payment and the balloon amount, the interest rate varies per contract.

The effective interest rate which will be charged to the customer can theoretically range from [REDACTED]. It is possible that the charged interest rate is 0%, for example when Company X launches some temporary attractive deals. Due to those deals, more cars will be sold. Therefore in some cases a leasing company can get subvention from the car importer or dealer for contracts signed during those temporary deals. When subvention is granted, the income rate will be supplemented to a certain rate so that Company X still makes money on those deals. The effective interest rate (including subvention or not) then is multiplied with the average earning assets (AEA) and the contract duration in years, resulting in the lifetime interest income.

Expenses:

Interest expense lifetime - The lifetime interest expense is calculated by multiplying the effective interest rate on sourced capital by the liability amount and the contract duration in years. The effective interest rate on sourced capital contains a base rate and a spread and is based on the starting date of the contract and the contract duration in months.

Direct cost lifetime - Direct costs of a contract are costs that are directly attributable to one specific contract. These include for example costs incurred for printing, signing and sending a contract. [REDACTED]

Commission lifetime - Financial lease contracts can be granted directly by Company X or through intermediaries such as a car dealer. When a contract is granted through an intermediary, this intermediary gets a commission from Company X for selling contracts. This commission is an intermediary-specific predetermined percentage of the unearned interest (at application time this is equal to the lifetime interest income) on the contract in question.

Expected loss:

Expected loss fraud lifetime - Is calculated by multiplying the probability of fraud by the AEA. It is assumed that the full exposure will be lost in case of fraud (LGD 100%).

Expected loss default lifetime - Is calculated by multiplying the lifetime PD by the LGD at application and the AEA.

Economic capital

Economic capital - This can be calculated by multiplying the assets (in this case the credit amount) by the risk weight and the capital ratio. The EBA has set the risk weight on 57,1425% and the capital ratio to 10,5%. For example, the required amount of equity for a contract with a credit amount of €100,- is €6,- ($100 * 57,1425\% * 10,50\%$) (European Banking Authority, 2012).

Outcome:

Profit or loss - Is calculated by subtracting the sum of costs from the sum of returns.

Risk adjusted return on capital - Is calculated by dividing the profit or loss by the contract duration in years and the amount of equity held in the specific contract.

As can be seen in the above formula, the RAROC takes into account a few more variables compared to the PD metric. This should give a better insight in whether a contract is good or not. It is composed of two main components: risk and return. However, in the formula this will be scaled into return and expenses. The return side consists of all sources of revenue which originates from this contract. This includes interest income, subvention income, cross selling's, value chain benefits and strategic interests. Because of the subjectivity of the last three components, cross selling's to strategic interests, these components will be set to zero in this study.

The cost side consists of interest expenses, direct contract costs, dealer commission and risk costs (expected loss given default and expected loss given fraud). Overhead will deliberately not be included in the calculation, since the overhead does not change by accepting or rejecting an individual application (sunk cost). It should therefore not be of influence on the accept/reject decision.

The difference between revenues and costs is the, so called, contribution to the profit. This is divided by the amount of equity that (shareholders of) the company is required to hold on that particular contract. Ultimately, this calculation results in the RAROC. For the contract specific RAROC's, peak shaving is applied for extreme values, these are cut off at a RAROC of 100%. Since this where just a few contracts, data will not be influenced.

3.5. Measurement

As stated in the beginning of this chapter, the performance of credit risk models is often measured by a GINI score. According to Finlay (2008), this would make the performance of a profit model seem worse. Additionally, the risk department wants to get their strategy in line with the profit oriented strategy of the company. For this reason it was decided to test the quality of the model by comparing the portfolio profits generated by both models.

Portfolio profit is a, so called, index measure. "An 'index' is a measure which combines several different pieces of information" (University of Twente). In this study, profit is the index measure. Profit combines different pieces of information.

3.5.1. Dichotomy of the measurement

"Economist and accountants differ on the proper definition of profit" (Kimball, 1998). Kimball wrote a paper on different ways of measuring performance in banking, including economic profit (monetary profit) and RAROC. [REDACTED]. Firstly profit is measured in terms of cash, in this case called the portfolio monetary profit. Secondly, profit is measured by a ratio, in this case the portfolio RAROC.

3.5.2. Measuring monetary profit

The way in which profit is calculated is a critical point in this study. Calculating profit slightly different can result in conflicting conclusions. However, literature doesn't provide a standard way of calculating portfolio profit for leasing companies. Therefore the calculation of profit will be similar to the way profit contribution (numerator of the RAROC) for a contract specific RAROC is calculated. This is calculated as follows: interest income and subvention income minus interest expense, direct costs, commissions, expected loss from fraud and expected loss from credit default. The profit contribution for all contracts in the portfolio will be added up. This will result in the overall profit contribution of the portfolio. Eventually the total overhead costs will be subtracted from the profit contribution, which leads to the overall monetary portfolio profit. This can be summarized in the following formula.

$$\text{Portfolio monetary profit} = \sum_{i=1}^n \text{profit contributions}_i - \text{overhead costs}$$

3.5.2. Measuring portfolio RAROC

Additionally the monetary profit can be expressed as a ratio measure by dividing it by the required equity that Company X has to hold for the exposure. This can be summarized in the following formula.

$$\text{Portfolio RAROC} = \frac{\sum_{i=1}^n \text{profit contributions}_i - \text{overhead costs}}{\sum_{k=1}^n \text{economic capital}_k}$$

3.6. Data analysis

The decision whether an application is accepted in the current situation, as explained in the introduction, depends on the PD level. If the PD level exceeds the hurdle then the application will be rejected. For the RAROC method this is the other way around. If the RAROC is higher than the hurdle rate then the loan is pointed as value adding, and bank capital ought to be allocated to the activity.

Company X currently works with a PD hurdle of █%. Every application with a PD higher than █% will automatically be rejected. When Company X is willing to implement the RAROC method, they will handle a 0% RAROC hurdle. This means that every application with a RAROC of 0% or higher will be accepted.

A hurdle of 0% means that every contract which has a profit contribution of more than zero is accepted. This ensures that all contracts which contribute to the portfolio profit will be included in the portfolio. As a result, the portfolio profit and the amount of contracts in the portfolio is maximized with this hurdle. Overhead costs therefore will be covered over more contracts, which reduces the impact of overhead costs on a specific contract. The bottom line is that a hurdle of 0% is most suited to the company's strategy, since it maximizes profit while it meets the required prescribed minimum ROE.

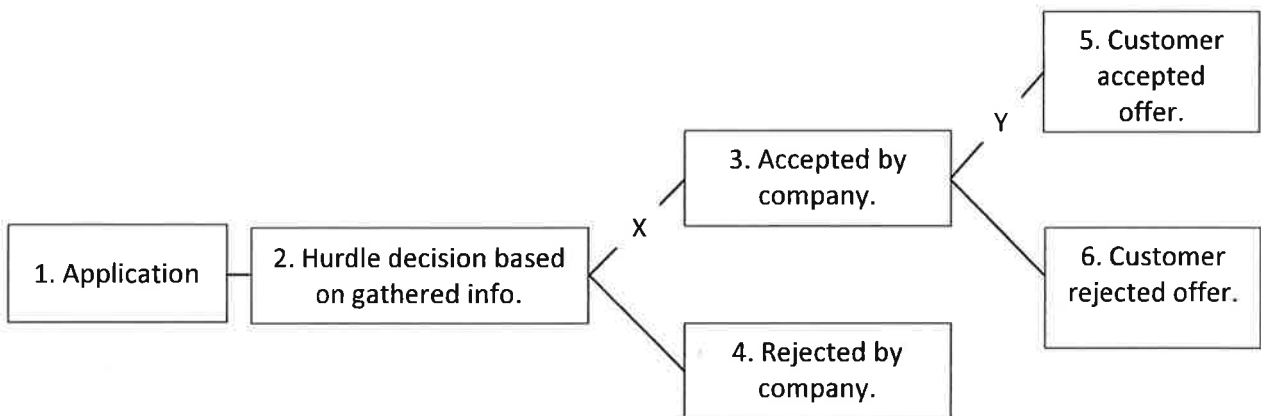
3.6.1. Baseline scenario current versus desired

The initial situation which is tested is the current versus desired situation. In this case this means that a portfolio drawn up on the basis of a ■% PD hurdle is compared with a portfolio formed by a 0% RAROC hurdle. As aforesaid it is compared on the basis of monetary profit and the portfolio RAROC.

3.6.2. Forming a portfolio

The introduction briefly explains how a portfolio is created. A portfolio is the collective name for all contracts that are active. The process in which is decided if an application will be an active contract depends on three factors. Figure 1 demonstrates this process.

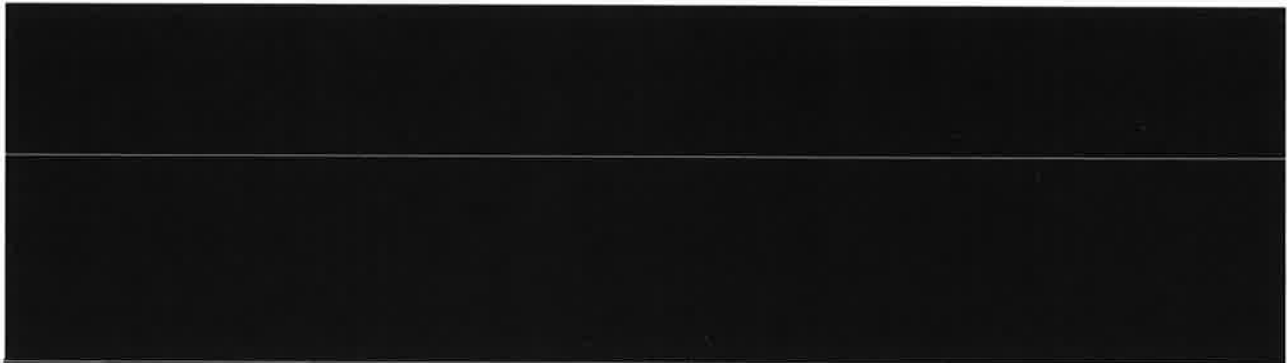
Figure 1 | Portfolio formation process



An application for a lease contract is submitted by the customer (step 1). The application is entered in a digital system, and all the necessary information is collected. The necessary calculations, like the PD or in the new situation a RAROC, are carried out on the basis of this information. Subsequently, it is decided on the basis of the hurdle whether an application is accepted by the company (step 2). In Figure 1, X represents the acceptance rate. An offer will be sent to all customers whose application is accepted by the company (step 3). Finally, the customer must decide whether to accept this offer. In Figure 1, Y represents the hit ratio. The hit ratio is the ratio between the number of accepted applications by the company and the number of offers accepted by the customer. If the customer accepts the offer (5), the status of the application will change to active contract and the contract is included in the portfolio.

Basically, the same process is simulated for the analysis. The data set contains all application that will be analyzed. For every contract the PD and RAROC are calculated. Subsequently, the company decision based on the hurdle is simulated in Excel. For the current situation a PD hurdle of ■% is applied and for the desired situation a RAROC hurdle of 0%. All application that are not selected will be filtered from the data. The customer decision, also called the hit ratio (Y), is simulated on the basis of a randomizer. This randomizer simulates the customer decision following a probability distribution based on historical data. Applications that were selected by both the company and the randomizer made up the portfolios that are analyzed.

For both portfolios the monetary profit and portfolio RAROC is calculated (according to the formulas presented in paragraph 3.5.2. and 3.5.2.). Table 2 shows an example of a formed portfolio. This portfolio is formed based on a RAROC hurdle of 0%.

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Respectively the columns contains the year, number of applications, number of active contracts, monetary profit, required equity, portfolio RAROC, the mean PD of the portfolio and the sum of expected losses.

The table can be read as follows: between 11-2013 and 12-2015 58.337 applications were submitted. Of these, 26.306 were accepted by both the company and the customer and formed the total portfolio.

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3.6.3. Monte Carlo Simulation

There is still one thing that needs to be done to be able to compare the two portfolios. The portfolio presented in Table 2 is formed according to the process presented in Figure 1. As described earlier, a part of this process depends on the client decision. Because this is unknown in this simulated portfolio it is simulated by using a randomizer. Due to the use of a probability distribution in this randomizer, every portfolio that will be generated is slightly different. The comparison is therefore never exactly equal which forms a potential bias. To prevent this, a Monte Carlo Simulation is carried out.

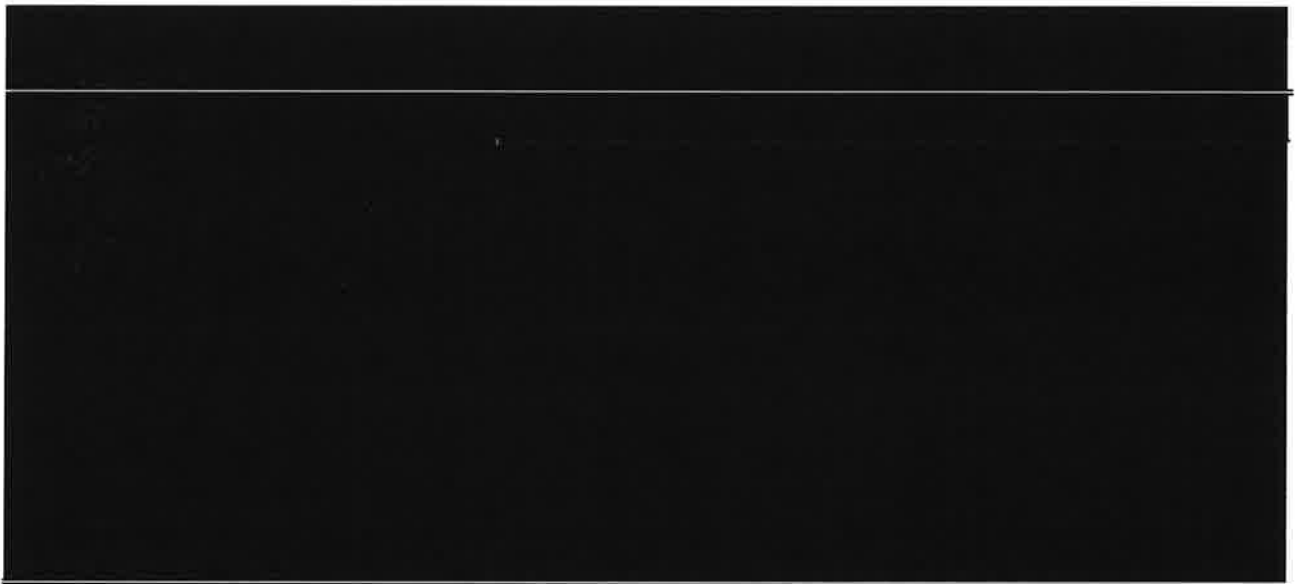
The name Monte Carlo Simulation comes from the Monte Carlo casino in Monaco, France. Casino's work with randomness and repetition of processes in lots of their activities. A Monte Carlo Simulation is "a type of simulation which relies on repeated random sampling and statistical analysis to compute results" (Raychaudhuri, 2008).

In this study the Monte Carlo Simulation is used to repeat the formation process of a portfolio 1.000 times. Subsequently, for the variables presented in Table 2 the mean values are calculated for all 1.000 portfolios. These averages together form the final portfolio and . By performing this step, the probability of coincidence is thereby minimized.

3.6.4. Portfolio analysis

Differences between the portfolio representing the current situation and the portfolio representing the desired situation is tested based on the mean monetary profit and the mean portfolio RAROC. These variables consists of scale numeric data. For the analysis, there is made use of the Paired Sample T-test and the Wilcoxon Signed Rank test. A Paired Sample T-test is a statistical test for testing differences between two means with normal distributed data. The Wilcoxon Signed Rank test is also a statistical test for testing differences between two group, but only for data that is not normally distributed (University of Twente).

The portfolios formed based on the method described in the previous paragraphs are tested for normal distribution to choose the appropriate statistical test. In order to test the data for normal distribution, the Skewness and Kurtosis are calculated via SPSS. Subsequently, SPSS is used to perform a Kolmogorov-Smirnov Test and a Shapiro-Wilk test. The results of those tests are shown in Table 3 and Table 4.



For both tests, the results in Table 3 and Table 4 show that the monetary profit is normally distributed ($p=,20 \geq \alpha=,05$). The test however indicates that the portfolio RAROC is not normally distributed ($p=,00 \leq \alpha=,05$). Since the monetary profit means are normally distributed, a paired samples T-Test is performed. A Wilcoxon Signed Rank test is performed for the portfolio RAROC means, since these means aren't normally distributed.

3.6.5. Robustness testing

Robustness testing is the process in which the robustness or correctness of test cases in a test procedure are verified. In this study the term robustness testing is used for verifying the correctness of the results of the Wilcoxon Signed Rank test. This test is used since the test for normality pointed out that the portfolio RAROC variable contained not normally distributed data. However, a lot of criticism is given for the Kolmogorov-Smirnov and the Shapiro-Wilk test. This criticism is examined by, among other Mohd Razali and Bee Wah (2011). They stated that "When the normality assumption is violated, interpretation and inferences may not be reliable or valid. The three common procedures in assessing whether a sample of size n come from a population with a normal distribution are: graphical methods (histograms, boxplots, Q-Q-plots), numerical methods (skewness and kurtosis indices) and formal normality tests" (Razali & Wah, 2011). In this quotation, three common procedures are appointed. Of those three, two are already performed.

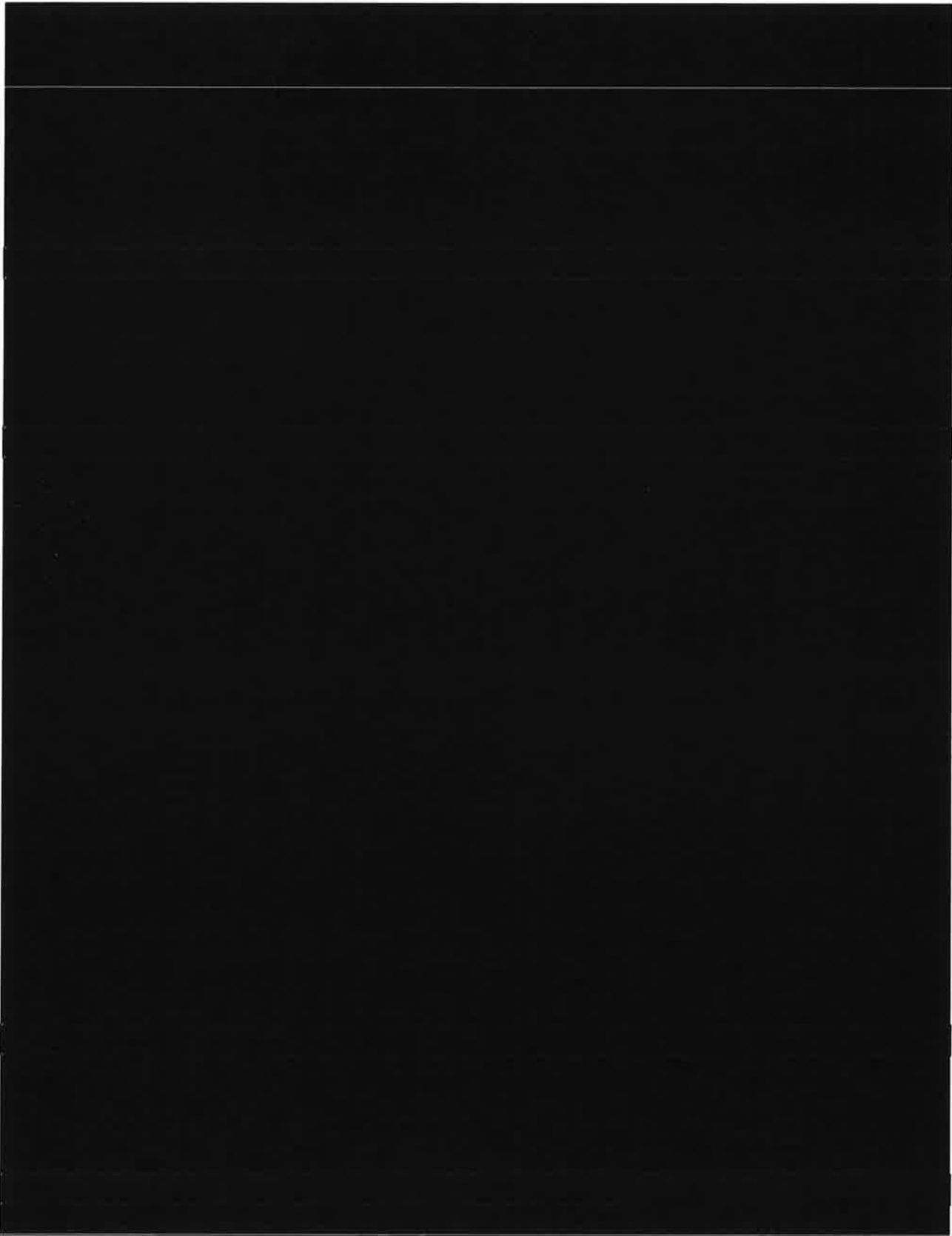
For the sake of the reliability of this study, the final procedure will be performed as well. For this reason, histograms are plotted to assess the normal distribution, see Appendix II. The dependent variables for three scenarios, has been objectively reviewed and based on this it has been chosen to carry out a parametric Paired Sample T-test to verify the non-parametric Wilcoxon Signed Rank test.

3.7. Scenario analysis

It is difficult to determine whether the RAROC method can outperform the PD method based on one scenario. Therefore an additional scenario analysis is performed to ensure the validity of this study. In this analysis, the results are tested in two additional scenarios. Together with the baseline scenario, the results are tested in the following three different scenarios:

4. Current versus desired situation – using a PD hurdle of ■% and a RAROC hurdle of 0%. This is the initial situation that the company wanted to test.
5. Maximal monetary profit – this scenario is aimed at comparing the two methods with a hurdle set to the specific value in which the monetary profit is maximized.
6. Maximal portfolio RAROC – The last scenario is aimed at comparing the two methods with a hurdle set to the point where the portfolio RAROC is the highest.

To see what hurdles needs to be used to maximize the monetary profit and the portfolio RAROC for both methods a portfolio is formed for every hurdle. In this way the hurdle can be set for each situation. Table 5 presents the results of this process.



Based on Table 5, the following hurdles can be set:

1. Current versus desired situation: PD hurdle \leq ■% - RAROC hurdle \geq 0%
2. Maximal monetary profit: PD hurdle \leq 70% - RAROC hurdle \geq 0%
3. Maximal portfolio RAROC: PD hurdle \leq 45% - RAROC hurdle \geq 30%

For each of these three scenarios there will be formed two portfolio. One portfolio for the PD method with the corresponding hurdle for that scenario and another portfolio for the RAROC method. Eventually there are 6 different portfolios that will be tested against each other.

The portfolios formed based on the two additional scenarios are tested for normal distribution to choose the appropriate statistical test. Test result of the Skewness, Kurtosis, Kolmogorov-Smirnov test and Shapiro-Wilk test can be find in the appendix.

3.8. Hypotheses

The expected outcome of the tests mentioned in the previous paragraph are expressed in different hypotheses. Due to the fact that the RAROC method uses much more information in its calculations, it is expected that this method outperforms the PD method in all scenarios on both variables. These expectations are translated to the hypotheses presented in Table 6. Hypothesis 1 for example, can be understood as: it is expected that the mean monetary profit of the portfolio formed with a ■% PD hurdle is lower than the monetary profit of the portfolio formed with a 0% RAROC hurdle

Table 6
Scenario comparisons current versus new method.

Scenario	PD hurdle	RAROC hurdle	Purpose	Dependent variable	Hypotheses
1	\leq ■%	\geq 0%	Current vs desired	Monetary profit (MP) Portfolio RAROC (PR)	H1: μ MP PD method \leq μ MP RAROC method H2: μ PR PD method \leq μ PR RAROC method
2	\leq 70%	\geq 0%	Comparing max. monetary profit	Monetary profit (MP) Portfolio RAROC (PR)	H3: μ MP PD method \leq μ MP RAROC method H4: μ PR PD method \leq μ PR RAROC method
3	\leq 45%	\geq 30%	Comparing max. portfolio RAROC	Monetary profit (MP) Portfolio RAROC (PR)	H5: μ MP PD method \leq μ MP RAROC method H6: μ PR PD method \leq μ PR RAROC method

4. RESULTS

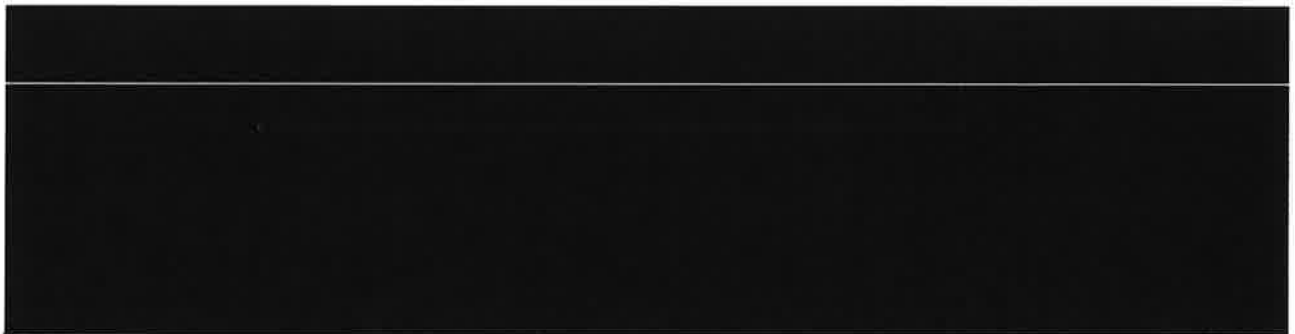
The data analysis methods described in the previous chapter has been performed and the results of the baseline scenario are given in this chapter. The first paragraph presents the results of the parametric tests, subsequently the results of the non-parametric test are presented. The third paragraph shows the results from the robustness testing. Finally, concluding remarks are given in the fourth paragraph.

4.1. Paired Samples Test for difference between mean monetary profit

A paired samples t-test is a parametric test that is performed to test the differences in monetary profit for the current versus the desired situation. Table 7 shows some descriptives of this variable. It first describes the tested pairs, in this case the monetary profit in the first scenario (1 – MP) for both the PD portfolio with a hurdle of █% and the RAROC hurdle with a hurdle of 0%. █ These are the means based on 1000 simulated portfolios for each method. The remaining columns gives the N, standard deviation and the standard error mean.



With the figures presented in Table 7, the paired samples t-test is performed. Results of this test are presented in Table 8. The first column describes the test scenario. The mean difference between the monetary profit of the two methods is presented in the second column.



█
█
█ This means that the monetary profit is higher █ when using the RAROC method.

4.2. Wilcoxon Signed Rank Test for difference between mean portfolio RAROC

As stated before, a Wilcoxon Signed Rank test is used for testing the differences in the portfolio RAROC's for the two methods. Because data for this variable was not normally distributed, a non-parametric test was performed. Table 9 shows the descriptive statistics of this test, Table 10 the ranks and Table 11 the final results.



The Wilcoxon Signed Rank test calculates the difference between two measurements for each research unit. A research unit represents one portfolio, therefore the N=1000 since the Monte Carlo simulation formed 1000 portfolios for both methods. The differences are ranked as negative or positive. The third column of Table 10 shows the amount of negative and positive ranks counted in the test. In this case, the portfolio RAROC for the PD method is lower than for the RAROC method in each portfolio drawn.

Table 10

Ranks

		N	Mean Rank	Sum of Ranks
1 - PR (PD ≤ 20% vs AR ≥ 0%)	Negative Ranks	0 ^a	0,00	0,00
	Positive Ranks	1000 ^b	500,50	500500,00
	Ties	0 ^c		
	Total	1000		

a. RAROC - Portfolio RAROC < PD - Portfolio RAROC

b. RAROC - Portfolio RAROC > PD - Portfolio RAROC

c. RAROC - Portfolio RAROC = PD - Portfolio RAROC

Table 11

Test Statistics Wilcoxon Signed Ranks Test

	1 - PR (PD ≤ 20% vs AR ≥ 0%)
Z	-28,545 ^a
Asymp. Sig. (2-tailed)	,000

a. Based on negative ranks.

As can be seen in Table 11, a Wilcoxon Signed Rank test showed that a change in the acceptance method did elicit a statistically significant change in the portfolio RAROC for the baseline scenario (1. Z = -28,545, p = ,000). In other words, the portfolio RAROC is higher when applying a RAROC method in the baseline scenario.

4.3. Robustness testing

The results of the non-parametric test revealed a statistically significant change in the portfolio RAROC. In this paragraph the results are presented for the robustness test. A robustness test was performed to see if the results still hold when a parametric test is used in the same particular situation. Table 12 presents the statistics of the paired samples and Table 13 shows the results of the paired samples t-test.



Like the Wilcoxon Signed Rank test, the paired samples t-test shows that the portfolio RAROC in the baseline scenario is higher for the RAROC methodology than for the PD method. In Table 13 it is shown that a paired samples t-test succeeded to reveal a statistically reliable difference between the mean portfolio RAROC for the PD method [redacted] and the RAROC method [redacted] in scenario 1, $t(999) = -769,78$, $p = 0,00$, $\alpha = .05$.

4.4. Results baseline scenario

All the results presented in this Chapter are summarized in Table 14. For hypotheses 1 and 2 there was enough evidence to reject the null hypothesis and accept the expected alternative hypothesis.

Table 14
Results summary

Scenario	PD hurdle	RAROC hurdle	Dependent variable	Hypotheses	Result
1	\leq [redacted] %	$\geq 0\%$	Monetary profit (MP)	H1a: μ_{MP} PD method \geq μ_{MP} RAROC method	Rejected
			Portfolio RAROC (PR)	H2a: μ_{PR} PD method \geq μ_{PR} RAROC method	Rejected

5. RESULTS SCENARIO ANALYSIS

The scenario analysis method described in Chapter 3 has been performed and the results will be given in this chapter. This chapter is written in the same format as the previous chapter.

5.1. Paired Samples Test for difference between mean monetary profit

Table 15 shows the paired samples statistics for the two additional scenarios. Pair 2 represents the scenario where the hurdle is set to the level where monetary profit is maximized. Subsequently, pair 3 represents the scenario where the hurdle is set to the level where portfolio RAROC is maximized.

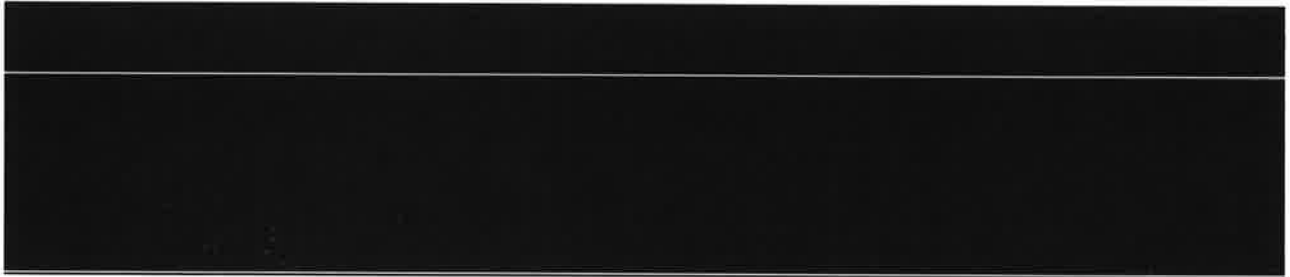


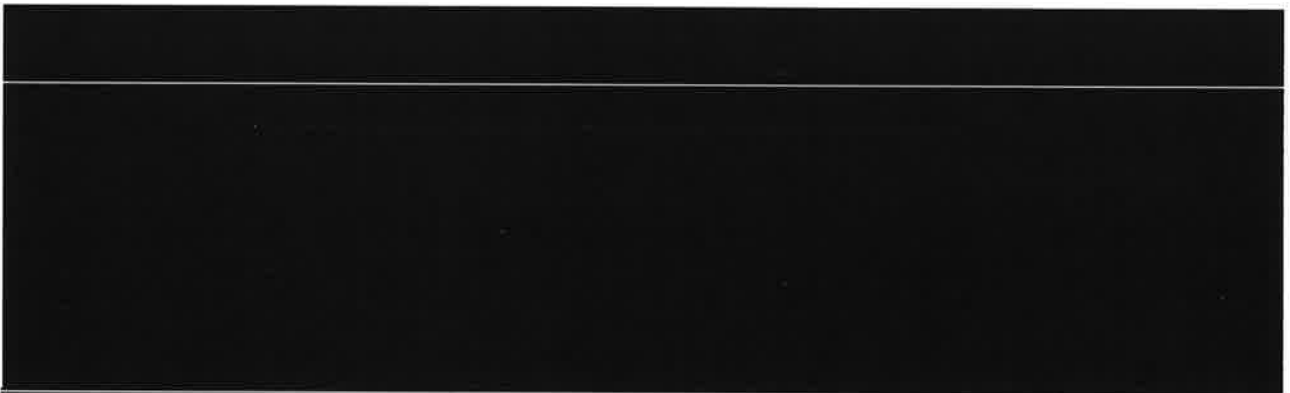
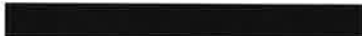




Table 16 gives the results for the paired samples t-test performed for the two additional scenarios. When looking at the results in Table 16, one thing stands out:  , which means that the monetary profit is higher for the RAROC method. However, the mean monetary profit is lower for the RAROC method in scenario 3 (1.921.237).



For scenario 2 a paired samples t-test also succeeded to reveal a statistically reliable difference between the mean monetary profit for the PD method  and the RAROC method  , $t(999) = -462,57$, $p = 0,00$, $\alpha = .05$. Again, this means that the monetary profit is higher when using the RAROC method.

Scenario 3, however, shows contradictory results compared to the other scenarios. A paired samples t-test succeeded to reveal a statistically reliable difference between the mean monetary profit for the PD method [REDACTED] and the RAROC method [REDACTED], $t(999) = 1560,87$, $p = 0,00$, $\alpha = .05$. In this scenario the mean monetary profit for the PD method is significantly higher than the monetary profit for the RAROC method.

5.2. Wilcoxon Signed Rank Test for difference between mean portfolio RAROC

As stated before, a Wilcoxon Signed Rank test is used for testing the differences in the portfolio RAROC's for the two methods. Table 17 shows the descriptive statistics of this test, Table 18 the ranks and Table 19 the final results



Just like the baseline scenario, all ranks are positive for the two additional scenarios. This can be seen in Table 18. The positive ranks means that the portfolio RAROC is lower for the PD method compared to the RAROC method.

Table 18

Ranks

		N	Mean Rank	Sum of Ranks
2 - PR (PD ≤ 70% vs AR ≥ 0%)	Negative Ranks	0 ^a	0,00	0,00
	Positive Ranks	1000 ^b	500,50	500500,00
	Ties	0 ^c		
	Total	1000		
3 - PR (PD ≤ 45% vs AR ≥ 30%)	Negative Ranks	0 ^a	0,00	0,00
	Positive Ranks	1000 ^c	500,50	500500,00
	Ties	0 ^c		
	Total	1000		

a. RAROC - Portfolio RAROC < PD - Portfolio RAROC

b. RAROC - Portfolio RAROC > PD - Portfolio RAROC

c. RAROC - Portfolio RAROC = PD - Portfolio RAROC

It is tested if the difference presented in Table 18 is significant. The results of this test can be seen in Table 19.

Table 19

Test Statistics Wilcoxon Signed Ranks Test

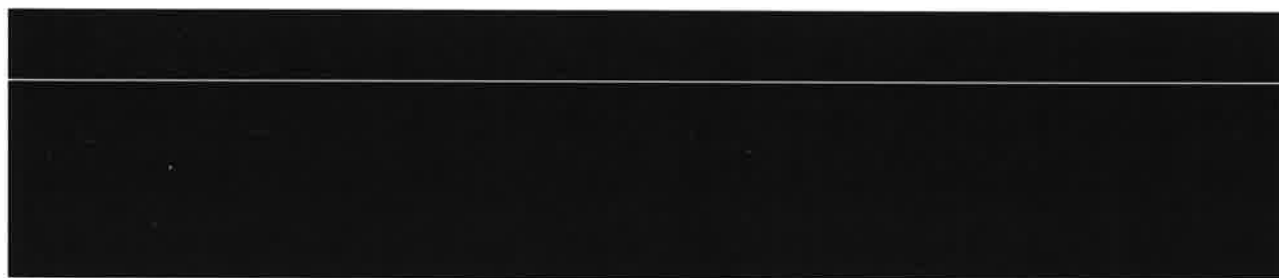
	2 – PR (PD ≤ 70% vs AR ≥ 0%)	3 – PR (PD ≤ 45% vs AR ≥ 30%)
Z	-29,065 ^a	-28,446 ^a
Asymp. Sig. (2-tailed)	,000	,000

a. Based on negative ranks.

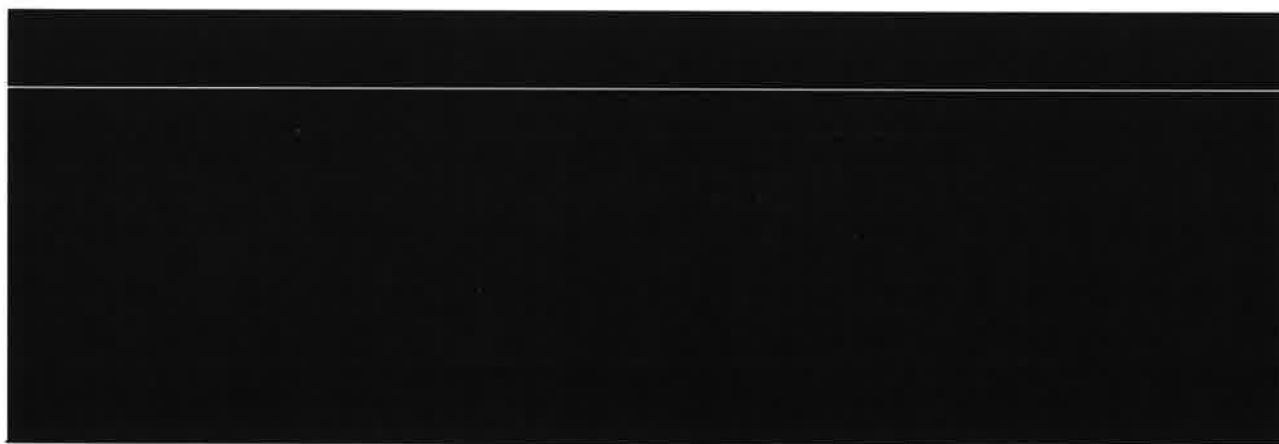
As can be seen in Table 19, a Wilcoxon Signed Rank test showed that a change in the acceptance method did elicit a statistically significant change in the portfolio RAROC in both scenarios (2. $Z = -29,065$, $p = ,000$) (3. $Z = -28,446$, $p = ,000$). In other words, the portfolio RAROC is higher when applying a RAROC method in both the additional scenarios.

5.3. Robustness testing

Just as for the baseline scenario a robustness test is carried out for the two additional scenarios. The results of this test can be seen in Table 20, 21 and 22. Starting with Table 20 presenting the paired samples statistics.



The test results of the paired samples t-test for both additional scenarios are presented in Table 21.



Like the Wilcoxon Signed Rank test, the paired samples t-test shows that the portfolio RAROC in both scenarios is higher for the RAROC methodology than for the PD method. In Table 21 it is shown that a paired samples t-test succeeded to reveal a statistically reliable difference between the mean portfolio RAROC for the PD method [REDACTED] and the RAROC method [REDACTED], $t(999) = -323,43$, $p = 0,00$, $\alpha = .05$. And for scenario 3 this is also the case, PD method [REDACTED], RAROC method [REDACTED], $t(999) = -1123,69$, $p = 0,00$, $\alpha = .05$.

5.4. Results additional scenarios

All the results presented in this chapter are summarized in Table 22. For hypotheses 3,4 and 6 there was enough evidence to reject the null hypothesis and accept the expected alternative hypothesis. For hypothesis 5, however, there was insufficient evidence to reject the null hypothesis. This means that the monetary profit in scenario 3 is higher for the PD method in comparison with the method RAROC.

Table 22
Results summary

Scenario	PD hurdle	RAROC hurdle	Dependent variable	Hypotheses	Result
2	$\leq 70\%$	$\geq 0\%$	Monetary profit (MP)	H3a: $\mu\text{MP PD method} \geq \mu\text{MP RAROC method}$	Rejected
			Portfolio RAROC (PR)	H4a: $\mu\text{PR PD method} \geq \mu\text{PR RAROC method}$	Rejected
3	$\leq 45\%$	$\geq 30\%$	Monetary profit (MP)	H5a: $\mu\text{MP PD method} \geq \mu\text{MP RAROC method}$	Accepted
			Portfolio RAROC (PR)	H6a: $\mu\text{PR PD method} \geq \mu\text{PR RAROC method}$	Rejected

6. PORTFOLIO IMPACT ANALYSIS

The results presented in the previous chapters showed a significant difference in both the monetary profit and portfolio RAROC for all three scenarios, except for the mean monetary profit in the third scenario. This is enough information to be able to answer the research question. However, it does not say so much about the changes that are involved in the change of the acceptance method and hurdles. Therefore, these changes will be discussed in this section.

Apart from the increase in profits and portfolio RAROC, the new RAROC method also shows its effects in terms of the risk in the portfolio. In order to map this change, the portfolio risk indicators used by company are applied to the different scenarios. The result of this mapping is presented in Table 23, where the expected loss, the probability of default and the portfolio size are calculated for each scenario.



In this table, it can be seen that the amount of expected loss in the current situation is estimated at [REDACTED] for the 26 months incorporated in this study. The mean probability of default in the portfolio is calculated at [REDACTED]% and the portfolio contains 24.278 contracts. Some significant changes can be seen when these figures are compared to those of the newly suggested method (RAROC with a hurdle of 0%). In this scenario, the expected loss is [REDACTED] with a mean PD of [REDACTED]. The number of contracts in the portfolio increased to 26.448.

The expected loss increases with [REDACTED] when the RAROC method is applied as acceptance metric and is used with a hurdle of 0%. Although it seems that these differences can have a significant impact on the portfolio, this is put into perspective as it is already included in [REDACTED] profit increase.

The mean probability of default in the portfolio rises from [REDACTED]% to [REDACTED]% and the amount of contracts in the portfolio increases from 24.278 to 26.448. A mean probability of default of [REDACTED]% is still in line with the policy of Company X, therefore it does not causes any strategic or policy conflicts. The increase in the number of contracts included in the portfolio causes mostly positive effects. This manifests itself primarily in the fact that more contracts contribute to the allocation of overhead costs. As a result, the relative impact of overhead costs decreases allowing the portfolio RAROC to rise.

An increase in the number of contracts in the portfolio is accompanied by an increase in work volume. This can have a negative effect on the personnel costs of Company X, since it is most likely that they need additional personnel.

Altogether, changes in the characteristics of the portfolio are explicable and the impact is incalculable. Table 23 can also be used to explain the increase in portfolio profit and the RAROC of the portfolio. This can be explained by the following three reasons:

1. Contracts in the portfolio are slightly more risky, and in general this means more profitable;
2. The amount of contracts is increased by 2.170 contract which all contributes to the monetary profit;
3. In the proposed situation, overhead costs will be allocated to 27.448 contracts instead of 24.278 which allows the portfolio RAROC to rise.

7. CONCLUSION AND DISCUSSION

In this chapter, the conclusions that can be drawn after analyzing and describing the findings are given. Furthermore, this section shows how the study contributes to the risk appetite literature, and in particular to the existing risk-return models for automotive leasing industries. Additionally, the research limitations, practical implications and future research will be discussed in this section.

7.1. Conclusion

The current PD method doesn't provide enough information about a contract to be able to make correct decisions regarding good or bad contracts. Making lending decisions solely based on risk enlarged the chance on a type 1 error (incorrectly rejected profitable contracts) and a type 2 error (incorrectly accepted loss-giving contracts).

The question whether an economic valuation (Risk Adjusted Return on Capital) can outperform probability of default as criterion for the credit acceptance decision, measured by an increase in overall portfolio profit can be answered based on the results of the 6 tested hypotheses. Even though the results are not fully unanimous, it can be concluded that the RAROC outperforms the PD as criterion for the credit acceptance decision. Only in scenario 3, where a conservative RAROC hurdle is tested against a non-conservative PD hurdle, the PD criterion outperforms RAROC in terms of monetary profit. However, this result does not have profound implications. Since the portfolio RAROC in scenario 3 is still higher when using the RAROC instead of the PD as a criterion for the credit acceptance decisions. The research question of this study can therefore be answered with yes, RAROC can outperform PD as criterion for the credit acceptance decision on both the monetary profit and the portfolio RAROC.

Using RAROC as criterion for the credit acceptance decision increases the understanding of good or bad contracts. Where the PD methodology only considers the probability that a customer does not pay on time or not at all, RAROC takes into account much more variables. It is true that a higher PD results in a higher expected loss, and it is therefore more likely that a contract is not sufficiently profitable. This is however purely an assumption, since the PD method doesn't provide any information about profitability. This is exactly the point at which the RAROC method is able to increase performances. Just like the PD method, RAROC takes into account the expected loss, but also addresses the anticipated costs, benefits and the required amount of equity need for the loan. Contracts with a high PD will not be accepted in the present situation. The new methodology will examine whether the expected profit exceeds the expected losses. If this is the case, the contract will still be accepted.

7.2. Limitations

Some limitations can be appointed for this study, of which most of the limitations result from deliberately made choices regarding this study. Starting with the limitations that didn't arise from these decisions.

- The generalizability of this study is hard to estimate. In theory, the results of this study can be useful for other companies. In practice this depends on the internal processes of those companies, which are unknown for outsiders.
- Limited input from literature, since literature specifically for the automotive leasing industry is very restricted.

- Due to the time restrictions, the study was limited to 3 scenarios, comparing 3 different hurdles for both methods. A hurdle, however, can range between -100 to 100%.
- For contracts that didn't become active at Company X (rejected by Company X or not activated by the client), a number of variables were based on assumptions. Although these assumptions are based on high quality data from other contracts, this can result in a very small bias.
- Cross selling's and strategic benefits and value chain benefits were set to zero because of the subjectivity of those variables. It can, however, make a positive difference if these variables are filled in properly, which could support our hypothesis even further
- No suitable method has been found to deal with the incremental change in marginal and fixed costs as new applications are accepted. Therefore, overhead costs were allocated on a portfolio level instead of on a contract basis.

7.3. Future research

Future research in the field of credit risk management, and in particular credit acceptance decisions, should study several more alternatives for the PD method and the effects of applying those methods. In addition, most literature in this field is aimed at revolving credit and very little is studied for fixed term loans.

In order to increase the applicability of such studies, it is highly recommended to aim future research at finding suitable methods to deal with the incremental change in marginal and fixed costs as new applications are accepted. Finding accurate ways to allocate overhead costs for both revolving credit and fixed term loans would be a major achievement in this field.

This study is aimed at analyzing financial lease contract. Future research can expand this to other products like private lease, hire purchase and operational lease contracts. Since each product have to deal with other variables and considerations, it would be very useful to study the effects of implementing RAROC as criteria for the credit acceptance decision for those products.

Since this study only analyzed the effects of three scenarios on two full years of data, future research could extend these scopes. To a certain extent, it is valuable to analyze a longer period of time. The understanding of the RAROC method can thereby be increased by including more scenarios in the analysis.

Future research could also study the effect of introducing time buckets to the RAROC method. In this study the timeframe in which a contract is analyzed is the complete contract duration. All costs and profits are calculated for the complete lifetime of the concerned contract. By splitting these calculations into the costs and profits per time bucket (e.g. monthly) cash flows of a specific contract can be approached much more accurately.

7.4. Practical implications

Switching from a PD to a RAROC criterion for the credit acceptance decision concerns a number of departments at Company X, and most likely in every company implementing it.

[REDACTED]

Because the new method will not solely take the PD into account, it is possible that the percentage of defaulters will experience a small increase. This will result in extra work for the employees on the department for account receivables.

The new criterion for the credit acceptance decision will also handle other monitoring variables. In the current situation the portfolio is monitored by the mean PD, LGD etcetera. When implementing the RAROC as criterion, these measures needs to be expanded with the portfolio RAROC. This needs to be implemented in the weekly, monthly and yearly reports provided by both the risk management department as the controlling department.

REFERENCES

- Alam, M., Hao, C., & Carling, K. (2010). Review of the literature on credit risk modeling: development of the past 10 years. *Banks and Bank Systems*, 5(3), 43-60.
- Ammann, M. (2013). *Credit risk valuation: methods, models, and applications*. Springer Science & Business Media.
- Beling, P., Covaliu, Z., & Oliver, R. M. (2005). Optimal scoring cutoff policies and efficient frontiers. *Journal of the Operational Research Society*, 56(9), 1016-1029.
- Blöchlinger, A., & Leippold, M. (2006). Economic benefit of powerful credit scoring. *Journal of Banking & Finance*, 30(3), 851-873.
- Chłopek, P. S. (2013). Raroc as a credit risk approach. *Nauki o Finansach*, (3 (16)), 64-76.
- Erich, M. (2013). *Assetvisie Autoleasemaatschappijen, Autolease op weg naar 2020*. ING Economisch Bureau
- European Banking Authority. (2012). *Assessment of SME proposals for CRD IV/CRR*.
- FICO. (n.d.). *FICO At a Glance*. Retrieved February 2, 2016, from FICO: <http://www.fico.com/en/about-us>
- Finlay, S. (2010). Credit scoring for profitability objectives. *European Journal of Operational Research*, 202(2), 528-537.
- Finlay, S. M. (2008). Towards profitability: A utility approach to the credit scoring problem. *Journal of the Operational Research Society*, 59(7), 921-931.
- Ghysels, E., Santa-Clara, P., & Valkanov, R. (2005). There is a risk-return trade-off after all. *Journal of Financial Economics*, 76(3), 509-548.
- Guill, G. D. (2009). *Bankers Trust and the birth of modern risk management*. Wharton School, University of Pennsylvania, April.
- Gupta, S., Hanssens, D., Hardie, B., Kahn, W., Kumar, V., Lin, N., ... & Sriram, S. (2006). Modeling customer lifetime value. *Journal of Service Research*, 9(2), 139-155.
- Holton, G. A. (2004). Defining risk. *Financial Analysts Journal*, 60(6), 19-25.
- Horcher, K. A. (2011). *Essentials of financial risk management (Vol. 32)*. John Wiley & Sons.
- Kimball, R. C. (1998). Economic profit and performance measurement in banking. *New England Economic Review*, 35-53.
- Laeven, R. J., & Goovaerts, M. J. (2004). An optimization approach to the dynamic allocation of economic capital. *Insurance: Mathematics and Economics*, 35(2), 299-319.

- Pfeifer, P. E., Haskins, M. E., & Conroy, R. M. (2005). Customer lifetime value, customer profitability, and the treatment of acquisition spending. *Journal of Managerial Issues*, 11-25.
- Prokopczuk, M., Rachev, S. T., Schindlmayr, G., & Trück, S. (2007). Quantifying risk in the electricity business: A RAROC-based approach. *Energy Economics*, 29(5), 1033-1049.
- Raychaudhuri, S. (2008, December). Introduction to monte carlo simulation. In *Simulation Conference, 2008. WSC 2008. Winter* (pp. 91-100). IEEE.
- Razali, N. M., & Wah, Y. B. (2011). Power comparisons of shapiro-wilk, kolmogorov-smirnov, lilliefors and anderson-darling tests. *Journal of Statistical Modeling and Analytics*, 2(1), 21-33.
- Řezáč, Martin, and František Řezáč. "How to measure the quality of credit scoring models." *Finance a úvěr: Czech Journal of Economics and Finance* 61.5 (2011): 486-507.
- Risk Encyclopedia. (n.d.). *Economic Capital*. Retrieved February 3, 2016, from Risk Encyclopedia: http://www.riskencyclopedia.com/articles/economic_capital/
- Sanchez-Barrios, L. J., Andreeva, G., & Ansell, J. (2016). Time-to-profit scorecards for revolving credit. *European Journal of Operational Research*, 249(2), 397-406.
- Schmit, M. (2004). Credit risk in the leasing industry. *Journal of banking & finance*, 28(4), 811-833.
- Schmit, M. (2005). Is automotive leasing a risky business?. *Finance*, 26(2), 35-66.
- Schmit, M., Degouys, C., Delzelle, D., Stuyck, J., & Wautelet, F. (2003). Credit risk in the Leasing Business. *Prieiga per Internetą*:< http://www.leaseurope.org/pages/Studies_and_Statements/Studies/PartII-rev.pdf>. Žiūrėta:[2006 02 03].
- Schuermann, T. (2004). What do we know about Loss Given Default?.
- Sousa, M. R., Gama, J., & Brandão, E. (2016). A new dynamic modeling framework for credit risk assessment. *Expert Systems with Applications*, 45, 341-351.
- Spuchlíáková, E., Valášková, K., & Adamko, P. (2015). The Credit Risk and its Measurement, Hedging and Monitoring. *Procedia Economics and Finance* , 675–681.
- Stewart, R. (2011). A profit-based scoring system in consumer credit: making acquisition decisions for credit cards. *Journal of the Operational Research Society*, 62(9), 1719-1725.
- Thomas, L. C., Edelman, D. B., & Crook, J. N. (2002). Credit scoring and its applications. *Siam*.
- Trochim, W.M. (2006, October 10). *Two-Group Experimental Designs*. Retrieved January 27, 2016, from Social Research Methods: <http://www.socialresearchmethods.net/kb/expsimp.php>
- University of Twente. (n.d.). *Keuze Toets*. Retrieved January 28, 2016, from University of Twente: <https://www.utwente.nl/bms/m-winkel/keuze%20toets/>

University of Twente. (n.d.). *Operationalization*. Retrieved January 28, 2016, from University of Twente:
<https://www.utwente.nl/bms/m-winkel/sites/apartsitesmeth/operationalization/>

Vereniging van Nederlandse Autoleasemaatschappijen. (2016, April 4). *Autoleasemarkt in cijfers 2015*.
Retrieved April 21, 2016, from *Vereniging van Nederlandse Autoleasemaatschappijen*:
<https://www.vna-lease.nl/website/iedereen/feiten-cijfers/infographics-2015>

Wang, J., & Yang, M. (2013). On the risk return relationship. *Journal of Empirical Finance*, 21, 132-141.

APPENDIX I - TIME SCHEDULE

The image displays a Gantt chart with the following structure of tasks:

- Task 1: A single long horizontal bar at the top.
- Task 2: A horizontal bar starting at the same time as Task 1 but ending earlier.
- Task 3: A horizontal bar starting later than Task 2 and ending later than Task 1.
- Task 4: A horizontal bar starting at the same time as Task 1 and ending earlier than Task 2.
- Task 5: A horizontal bar starting later than Task 4 and ending later than Task 1.
- Task 6: A single long horizontal bar starting at the same time as Task 1 and ending later than Task 5.
- Task 7: A horizontal bar starting later than Task 6 and ending later than Task 1.
- Task 8: A horizontal bar starting later than Task 7 and ending later than Task 1.
- Task 9: A horizontal bar starting later than Task 8 and ending later than Task 1.
- Task 10: A horizontal bar starting later than Task 9 and ending later than Task 1.
- Task 11: A horizontal bar starting later than Task 10 and ending later than Task 1.

APPENDIX II – HISTOGRAMS

APPENDIX III – INPUT VARIABLES

Input variables:

The table contains 7 rows of data. Each row consists of two columns. The first column contains a single cell per row, and the second column contains a single cell per row. All text within these cells is completely obscured by black redaction bars.

APPENDIX IV - TEST OF NORMALITY AND DESCRIPTIVES



