

https://dspace.org/

# Credit risk pricing through South African economic cycles.

**Brink, Duan De Bruin.**

**2014-08-12**
http://hdl.handle.net/10539/15152

Downloaded from a DSpace repository. https://dspace.org/

# Credit risk pricing through South African economic cycles

**Duan De Bruin Brink**

**A research report submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of Master of Business Administration**

**Johannesburg, 2013**

# ABSTRACT

Banks have been struggling since the 2008 global financial collapse to generate consistent and reasonable shareholder returns in the wake of a sluggish economic landscape. This research investigated whether banks are successful in adapting to changes in the economy, by comparing the realised returns generated before and after the financial collapse, at an individual loan account level. Banks that have superior credit risk pricing models, driven by a pro-active credit risk department, will survive the onslaught of future economic downturns and come out stronger and more competitive. Individual loan data was collected from a credit provider to establish whether credit departments are pro-active in assessing credit risk and pricing for it accurately, in the context of a changing economic environment. Based on the results, banks are not successful in pricing through economic cycles. Banks need to continuously measure and back-test the realised returns of loans and loan portfolios using simple techniques like internal rates of return, driven by real cash flows instead of relying mainly on the financial results produced by accounting standards, which can be biased and judgemental.

# DECLARATION

I, _____, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration in the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

---

Duan De Bruin Brink

Signed at ……

On the …….. day of …… 2013

# DEDICATION

I dedicate this research to my newborn son, Zian. You made this journey special.

# ACKNOWLEDGEMENTS

This research would not have been possible without the guidance of Chris Muller. Chris Muller is an incredibly smart and patient person who mentored me throughout this research. The very late nights and walks around the golf course opened my eyes to new possibilities.

Eric Schaling played an important role in getting the research concluded, without his assistance this research would never been finalised.

# TABLE OF CONTENTS


**ABSTRACT ..... II**

**DECLARATION ..... III**

**DEDICATION ..... IV**

**LIST OF TABLES ..... VIII**

**LIST OF FIGURES ..... VIII**

**CHAPTER 1: INTRODUCTION ..... 9**

PURPOSE OF THE STUDY ..... 9
CONTEXT OF THE STUDY ..... 9
PROBLEM STATEMENT ..... 12
SIGNIFICANCE OF THE STUDY ..... 13
DELIMITATIONS OF THE STUDY ..... 17
DEFINITION OF TERMS ..... 18
ASSUMPTIONS ..... 19

**CHAPTER 2: LITERATURE REVIEW ..... 20**

2.1. INTRODUCTION ..... 20
2.2. DEFINITION OF TOPIC, OR BACKGROUND DISCUSSION. ..... 22
2.3. EVALUATE WHETHER CREDIT RISK WAS APPROPRIATELY PRICED ..... 23
2.3.1 CREDIT RISK AND PRICING ..... 23
2.3.2 CREDIT RETURNS ..... 26
2.3.3 HYPOTHESIS ..... 29
2.4. CONCLUSION OF LITERATURE REVIEW ..... 30
2.4.1 HYPOTHESIS ..... 32

**CHAPTER 3: RESEARCH METHODOLOGY ..... 34**

3.1 RESEARCH METHODOLOGY ..... 34
3.2 RESEARCH DESIGN ..... 35
3.3 POPULATION AND SAMPLE ..... 35
3.3.1 POPULATION ..... 35
3.3.2 SAMPLE AND SAMPLING METHOD ..... 35
3.4 THE RESEARCH INSTRUMENT ..... 36
3.5 PROCEDURE FOR DATA COLLECTION ..... 36
3.6 DATA ANALYSIS AND INTERPRETATION ..... 37

3.7 LIMITATIONS OF THE STUDY ..... 39
3.8 VALIDITY AND RELIABILITY ..... 39
3.8.1 EXTERNAL VALIDITY ..... 39
3.8.2 INTERNAL VALIDITY ..... 40
3.8.3 RELIABILITY ..... 40

**CHAPTER 4: PRESENTATION OF RESULTS ..... 42**

4.1 DEMOGRAPHIC PROFILE OF RESPONDENTS ..... 42
4.2 RESULTS PERTAINING TO HYPOTHESIS ..... 47
4.3 SUMMARY OF THE RESULTS ..... 50

**CHAPTER 5: DISCUSSION OF THE RESULTS ..... 51**

5.1 DEMOGRAPHIC PROFILE OF RESPONDENTS ..... 51
5.2 DISCUSSION PERTAINING TO HYPOTHESIS ..... 51
5.3 CONCLUSION ..... 53

**CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS ..... 54**

6.1 CONCLUSIONS OF THE STUDY ..... 54
6.2 RECOMMENDATIONS ..... 54
6.3 SUGGESTIONS FOR FURTHER RESEARCH ..... 55

**REFERENCES ..... 56**

**APPENDIX A ..... 60**

CONSISTENCY MATRIX ..... 60

# LIST OF TABLES

**Table 1: Differences between cash and accrual principals of accounting** 14

**Table 2: Results of hypothesis test by risk grade** ..... 50

# LIST OF FIGURES

Figure 1: Number of liquidations and insolvencies relating to individuals and partnerships ..... 19

Figure 2: Sample size per month of loan issued ..... 42

Figure 3: Distribution of monthly gross income overlaid with loan advanced ... 43

Figure 4: Collection rate as a percentage of total contractual instalment ..... 44

Figure 5: Distribution of sample by province ..... 45

Figure 6: Distribution of sample age category ..... 45

Figure 7: Distribution of loans issued pre and post the financial collapse by initial risk grade ..... 46

Figure 8: Mean monthly gross income, loan advanced and age by risk initial risk grade ..... 47

Figure 9: Realised rate of return pre and post the financial collapse by initial risk grade ..... 48

# CHAPTER 1: INTRODUCTION

## Purpose of the study

The purpose of this research is to evaluate whether South African credit providers are accurately pricing for credit risk through economic cycles with reference to the recent global financial collapse.

## Context of the study

If credit providers understood, measured and reported the real returns of their loan portfolios through economic cycles and took pro-active and corrective action when returns are not optimal, would we have been able to avoid the 2008 financial bubble from forming and bursting?

The evolution of credit through the ages of mankind has been a catalyst of growth and has allowed mankind to attain almost everything his heart desired. Henry Ford realised that producing great and affordable cars was not sufficient. He also had to provide financing (Bryan 1993). This desire of mankind to own earthly things is one of the reasons why credit has evolved over the ages, and for economies to grow (Greiner and Fincke 2009). The use of credit cards during the 1960s extended the application of credit to various products (Kočenda and Vojtek 2009). Credit has matured from simple barter transactions, to the current, more sophisticated, credit default swaps.

The evolution of credit, however, has not come without an unintended constraint on growth in certain instances, which caused serious havoc in the financial world between 2008 and 2010, and is still being felt throughout the world with some countries still being plagued by unsustainably high levels of debt (Gill and Pinto 2005).

Although credit plays a major role in assisting the world economy to grow, it can result in undesirable after effects such as protracted periods of recession or depression, as was the case in the recent financial meltdown due to the sub-

prime lending practices. Also, sub-prime lending mainly thrives in stable markets, where good economics are at play and unemployment levels are low (Marron 2007).

This problem was amplified by banks accounting for revenues from day one of the loan agreement (whether the customer was initially assessed as good or bad), while only accounting for the bad debts when the default event actually occurred, which is in line with the current IFRS (International Financial Reporting Standards) rules. Default is commonly referred to as having missed 3 instalments or being 3 instalments in arrear (Hand and Henley 1997; Blessis 2002). This research instead suggests a more pro-active and prudent method of accounting for bad debts, which is to account for bad debts when it is anticipated to occur, based on the level of credit risk assessment done at inception of the loan combined with the subsequent risk migration or transition throughout the life of the contract period. Today's risk is tomorrow's potential losses (Blessis 2002), but, it should read, today's risk should be today's losses.

Greedy bankers coupled with complacent borrowers, made the credit problem extremely toxic. The probability of future credit crises and bubbles can be reduced if these two pitfalls are appropriately dealt with. The sub-prime crisis could have been avoided if proper risk assessments had been made and adhered to, in order to keep greed and complacency in check. Furthermore, certain banks would not have gone under, if they had had sufficient reserves (either in the form of provisions or equity) to protect themselves against the onslaught of the sub-prime crisis. These reserves should have been raised earlier on in the contract, instead of only accounting for it when the default event actually occurred. This research did not attempt to discuss the level of equity a bank is required to hold to prevent insolvency, but rather focused mainly on credit risk pricing.

Credit from a credit provider's perspective can best be described as a coin which has two sides: risk and return. The veil, under which credit hides, can be better understood if we measure the appropriate variables through innovative models and then execute robust credit pricing strategies to ensure that banks

remain strong through economic cycles.

Managing a credit loan portfolio is complicated by the tension between the credit managers and marketing managers (Trench *et al* 2003). The banking industry is mainly organised around minimising risks or reducing losses (Blessis 2002), although greed does sometimes overshadow this belief in times of short term focus. The risk department therefore seeks to minimise credit losses, whereas the marketing department seeks to grow customers.

Bankers are therefore predominantly utility maximisers (i.e. risk efficiency orientated), rather than pure profit maximisers (Beazer 1975). Banks have motives to develop risk-based practices and risk models (Blessis 2002). Regulators require these, because they focus on systemic risk, the risk that the entire bank industry could fail (Blessis 2002) and cause economic havoc. Measuring risk is very important to banks, as they are effectively risk machines; they accept it, transform it and embed services with it (Blessis 2002). This single minded objective of risk reduction is, however, short-sighted, as it ignores the bigger picture of creating value for all stakeholders, including the customer.

Appropriately measuring the risk-return profile of loan portfolios ensures that lenders:

- take risks more consciously,
- can anticipate adverse changes,
- protect themselves against unexpected events and
- gain expertise in pricing for risk (Blessis 2002).

This leads to optimal and competitive credit pricing strategies amongst all players in the credit industry, which will see them thriving through economic cycles. Optimal and competitive pricing policies are considered to be those that are highly optimised in serving the needs of the organisations' clients on the one hand and shareholders on the other. Lenders should strive towards an optimal model as it eliminates waste, or in credit terms, bad debts, and ultimately achieves sustainable shareholder returns, as well as satisfied

customers. When pricing is optimal, it seeks to price through economic cycles. This ensures that returns remain fairly robust through boom or bust cycles. This is a proactive approach in setting credit risk pricing instead of reacting to the economic environment. Banks that have an optimal pricing strategy can therefore anticipate economic cycles better than those that do not have such a strategy.

Simply put, if an optimal pricing strategy works effectively, attrition rates drop in respect of economically profitable customers as they are competitively priced, while simultaneously banks' bad debt ratios drop, as the potentially bad customers are not given credit in the first place, if an optimum return can not be generated on them. This creates a healthy economic landscape, where economic growth is sustainable and enduring at the micro and macro level. It reduces short term economic growth burnout and ensures companies remain strong and viable over the long haul, very similar to jogging a marathon instead of sprinting it at full speed.

Therefore, companies that do not have an optimum risk-return model, risk gaining potentially bad business in the short-term coupled with high attrition rates of good clients and eventually losing ground over the long term, when the credit risks materialise into greater than expected credit losses, while good customers are now being served by the competitors (Blessis 2002).

Properly modelling and measuring returns of loan portfolios is therefore crucial in developing credit risk based pricing strategies (Blessis 2002) that remain stable through economic cycles. Companies that accurately price for credit risk will realise consistent returns across all loan portfolio, whether loans were issued before, during or after economic cycle changes.

## Problem statement

Do South African credit providers accurately price for credit risk through economic cycles, with reference to the recent global financial collapse?

## Significance of the study

The study fills a gap in that the measurement of realised returns of loan portfolios using IRR (internal rates of return) will be less judgemental and vague and more robust and reliable than traditional methods of measuring returns, in order for banks to report whether the pricing of credit risk at inception of the contract was appropriate.

For the purposes of this research, realised returns are the effective yield earned on the applicable loan portfolio, which includes interest, insurance, initiation fees and monthly service fees. Realised returns exclude operating costs, interest costs and taxes. The reason why these items are excluded is due to the high level of judgement involved in allocating these items to the various loan portfolios. Therefore, for the sake of comparability and to eliminate bias, they have been excluded from measuring returns. Realised returns for this research were revenue charged less bad debt costs incurred. Revenue charged is the charge to the client (consisting of interest, insurance, initiation fees and monthly service fees), while bad debts are the unrecoverable portion of the loan.

The traditional models utilised by banks to calculate realised returns are risk-adjusted return on capital (RAROC) and shareholder value added (Blessis 2002). RAROC measures the income net of expected losses and costs divided by economic capital applied to that loan portfolio (Blessis 2002). Shareholder value measures the return given to shareholders in excess of their minimum required return.

However, both the above models rely on the accrual principals of accounting standards and not the cash principals of the IRR (internal rate of return) methodology. The most significant difference between the accrual principals and cash principals is the timing of recognising bad debt costs.

**Table 1: Differences between cash and accrual principals of accounting**

| Cash principal | Accrual principal |
|---|---|
| Objective | Biased |
| Focus on both risk and returns | Focus mainly on risk |
| Provision for bad debts raised from inception of contract, resulting in non-erratic yields over the life of the contract | Provision for bad debts only raised when default event arises, resulting in profits being overstated upfront, while bad debts are overstated towards the end of the contract, resulting in erratic yields over the life of the contract |
| Time value of money considered | Time value of money not considered |
| Direct link to credit pricing | Indirect link to credit pricing |
| Forward looking | Backward looking |

The timing of recognising bad debt costs and the value thereof is crucial to understanding and measuring the returns of loan portfolios and therefore the evaluation of whether the credit risk pricing was priced through economic cycles. Under the accrual principals which is based on accounting standards (IAS 39 - *Financial Instruments: Recognition and Measurement*) and regulated by IFRS, bad debts arise from:

- writing off the outstanding balance of the loan to the income statement (bad debts written off) when the loan cannot be recovered and
- calculating a provision for doubtful debts (or impairment provisions) and recognising the movement in this provision in the income statement when the customer starts showing signs of default.

In the first instance, the actual bad debts written off is based on the bank's experience of bad debt clients, which are based on certain prescribed rules and

are generally triggered at a specific point of that loan i.e. the client has not made a repayment over the past twelve months. When that point is triggered, the unrecoverable portion of the loan is written off and recorded as a bad debt expense in the income statement.

Secondly, provisions for doubtful debts are raised by the bank when the client is displaying doubtful behaviour, i.e. the client is unable to make all of his monthly contractual repayments and starts missing a few repayments or only makes partial repayments, but stays active enough not to warrant a write off yet. The bank has some doubt whether they will be able to recover the entire unpaid loan by the end of the contract and starts to raise a provision for the value of the loan that is likely to be unrecoverable towards the end. Banks assess the recoverability of the loan continuously, and either increase or decrease the provisions for doubtful debts against potentially doubtful loans based on the performance of the loans and recognise this movement in the provision for doubtful debts in the income statement. If the provision increases, the bad debt expense in the income statement is increased and vice versa.

It is clear from the above that the amount and the point in time when bad debts are written off or provided for is subjective and can differ widely between banks and even between loan portfolios based on the rules applied by the banks.

The accrual principal is a subjective and biased way of recognising and accounting for bad debt costs. The accrual principal of recognising bad debts creates distorted values of the risk and returns of loan portfolios throughout the life of the contract and hence the true profitability of loan portfolios at a given point in time.

The accrual principal also makes it difficult to accurately measure whether credit pricing was priced for through economic cycles. It also does not take into consideration the time value of money. The accrual principal is also backward looking, i.e. the bank will not raise a provision for doubtful debts until the client starts performing poorly, although the bank would have assessed the client upfront at the loan application stage, that this client is potentially high risk.

The suggested method of measuring the true performance of loan portfolios uses the cash principals of IRR methodology in order to determine whether the credit pricing was optimal or not.

Companies adopting a credit risk pricing approach which prices through economic cycles will also reduce the impact of cross-subsidisation between low risk and high risk customers. Cross-subsidisation punishes low risk customers for instance, by over-charging them relative to their risk, to the benefit of high risk customers who are undercharged relative to their risk (Blessis 2002). Cross subsidisation generally results in higher than expected attrition rates, especially in competitive markets and higher than expected bad debt ratios.

Each line of business or loan portfolio should be measured on its own risks and on its own returns. This ensures enterprise wide risk management objectives at a group level are met, and forces banks to behave like portfolio managers (Ong 1999). Ensuring that all customers are appropriately priced for through economic cycles, will result in satisfied customers, strategic positioning of the credit product and fair credit pricing policies.

The study provides guidance to credit risk committees of banks in assessing whether their credit risk pricing models are developed to be robust through economic cycles, to ensure banks remain sustainable in the long term.

Most research in credit risk and return has been focused on corporate and government bonds, with very little research in the consumer loan credit industry sector. This research provides insights into credit risk and returns in the consumer credit lending industry of South Africa. Also, most research already conducted focuses mainly on risk, whereas the returns are of a secondary focus.

## Delimitations of the study

- This research will only focus on the consumer credit sector in South Africa.

- Only one company is used for the data analysis.

- Returns will be measured up until the end of contractual period plus some additional period (on average 20 to 36 months after the initial loan period), which in the case of this research was between 43 and 59 months since the inception of the loan. *Bank One* found that using 36 months since inception is a sufficient indicator of profitability (Trench *et al* 2003).

- The potential positive or negative effect of customers acquired as part of a strategic intent to grow market share was not excluded from the sample.

## Definition of terms

*Arrears* – Balance of instalments missed to date

*CAPM* – Capital asset pricing model

*CD* – Contractual delinquency

*Economic profit* – Profit after tax adjusted for the cost of equity

*EVA* – Economic value added. Returns given to shareholders in excess of their minimum required return

*IAS* – International Accounting Standards

*IFRS* – International Financial Reporting Standards

*IRR* – Internal rate of return

*Loans issued after the financial crisis* – Loans issued between 1 January 2008 and 30 September 2008 with repayments up to May 2012

*Loans issued before the financial crisis* – Loans issued between 1 June 2007 and 31 December 2007 with repayments up to May 2012

*NCA* – National Credit Act

*NPV* – Net present value

*RAROC* – Risk-adjusted return on capital. RAROC measures the income net of expected losses and costs divided by economic capital applied to that loan portfolio

*RIRR* – Realised IRR (based on the actual repayments) or realised returns

*STATS SA* – Statistics South Africa

*TIRR* – Theoretical IRR (based on the contractual obligation and terms) or contractual returns

## Assumptions

The cost of funding, operating costs and taxes will not be brought into the equation of measuring returns. It is assumed that these factors have an equal impact on all loans and loan portfolios within a company pre or post a financial crisis.

It is assumed that banks are able to price through economic cycles. Banks employ extremely sophisticated processes and techniques to gather economic data. Highly skilled people are tasked to analyse and interpret this data and to implement a pricing strategy in response to the findings of the economic data.

For the purpose of this research it is assumed that the financial bubble hit its peak at the end of 2007 where appetite for credit risk was insatiable. This is supported by the level of liquidation and insolvencies of individuals and partnerships ramping up during early 2008 and peaking towards the end of 2009 as can be noted in the graph below (STATS SA 2012).

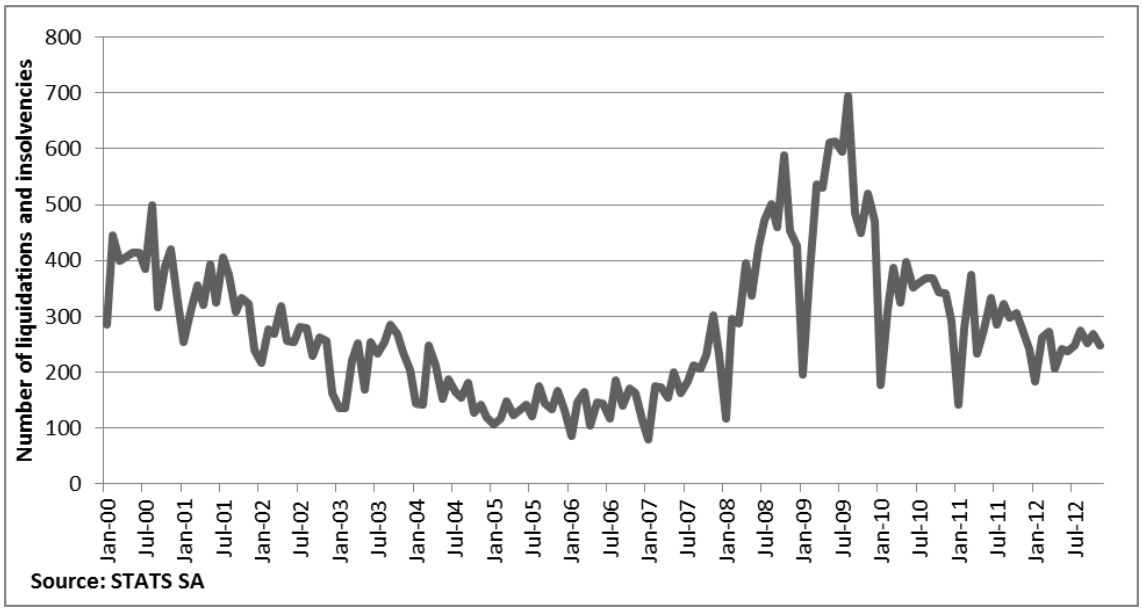


**Figure 1: Number of liquidations and insolvencies relating to individuals and partnerships**

# CHAPTER 2: LITERATURE REVIEW

## 2.1. Introduction

Mankind has gone from very simple methods of lending to more sophisticated credit lending practices. Some of the earliest documented methods of credit scoring were measuring the 5 C's of a client (Savery 1977):

- Character (integrity)
- Capacity (sufficient cash flow to service the debt)
- Capital (net worth)
- Collateral (security offered against the debt)
- Conditions (of the borrower and the economy)

The above methods were initially judgemental, subjective, labour intensive and more an art than a science. Credit scoring began in 1960 when credit cards matured and automation became critical (Kočenda and Vojtek 2009). The advancement of credit granting, due to the sheer volume of transactions, required lending organisations to adopt a more sophisticated and automated credit scoring approach, in assessing the credit risk of a particular client (Thomas 2010). Automated credit scoring is less labour intensive, consistent, uniform and unbiased (Marron 2007), resulting in efficiencies and creating economies of scale to the credit provider.

Credit scoring models had to be developed at the macro level, rather than the individual level, as companies cannot possibly model future actions of any one individual (Marron 2007). Companies employ various forms of credit risk scoring, but the most common form is performing an application score for new clients and a behavioural score for existing clients (Rosenberg and Gleit 1994; Altman and Saunders 1997). Some of the criteria used in application scoring in setting an appropriate risk grade are: Length of time at current residential

address; length of time with current employer; salary; number of dependents; other loan commitments; occupation and rented or owned home (Blessis 2002; Kočenda and Vojtek 2009).

Behavioural scoring uses an existing client's repayment history, in setting the risk grade. Certain banks also incorporate bureau scores (Marron 2007), which are independent credit rating agencies, together with the application and behaviour scoring in setting a credit score. These scoring techniques, or scorecards, attempt to maximise profits (Crook *et al* 2007). However, if scoring of credit only focuses on minimising credit losses, it would not by implication mean that you will be maximising profits given the level of risk. Banks, however, have been finding it difficult to offer a reasonable return to their shareholders during times of economic uncertainty, and have been trying to price through economic cycles to ensure investment viability in the long run.

The above type of scoring is commonly referred to as discriminative techniques (Rosenberg and Gleit 1994). Discriminative scoring is applied by organisations when there are discrete and identifiable groups of customers; otherwise segmentation destroys valuable predictive information (Rosenberg and Geit 1994). Regression techniques are commonly used to group similar customers. Grouping of loans consists of date of origination, type of customers, product families and risk grades (Blessis 2002).

There are two types of errors that occur with scoring: Type 1 errors are where you accept bad credit, resulting in loss of capital and interest. Type 2 errors are where you reject good credit and results in lost opportunity. The cost of type 2 errors is lower than type 1 errors (Blessis 2002).

The company that will be used for this research uses discriminative techniques, although other techniques for scoring also exist, namely: decision trees, neural networks, dynamic programming, linear programming, integer programming and Markov chains (Rosenberg and Geit 1994; Hand and Henley 1997).

## 2.2. Definition of topic, or background discussion.

A shareholder's main aim is to maximise its return on investment. Companies achieve this by investing capital into those businesses, divisions or loan portfolios that generate the highest return on their investment. Part of making higher returns may require companies to take on higher risks. This requires companies, especially those in the lending industry, to understand and manage risks, while maximising returns and delivering these returns consistently through economic cycles. Loss making business, divisions or loan portfolios is therefore an inherent part of taking risks. This requires banks to properly manage risks whilst ensuring that quality and sustainable returns are generated, in order to generate an economic profit.

The goal of risk management is to enhance and maintain the risk-return profile of transactions and portfolios of banks (Blessis 2002) in order to achieve shareholder's objective. The overarching goal is to determine the appropriate credit price given the level of credit risk (Thomas, Oliver and Hand 2005) to ensure that returns are consistent through economic cycles.

This can be achieved by adopting a robust method of measuring the performance of loan portfolios. Continuous feedback systems could then be employed to compare realised returns (revenue net of bad debts) with the initial risk assessment. This feedback loop will then be able to confirm whether the company is appropriately pricing for credit risk through economic cycles. It is important to have continuous feedback loops, to improve the predictive power of scorecards (Hand 2005).

Classic portfolio optimisation theory suggests that you can minimise risk given the level of return and/or maximise return given the level of risk (Blessis 2002). *Bank One* managed to develop and implement such an optimisation model (Trench *et al* 2003). *Bank One* used customer payment profiles to develop such models, collecting terabytes of data (Trench *et al* 2003). *Bank One*'s project focused around the initial credit granting process, as they found that profitability is superior when the upfront credit pricing was optimal, rather than focusing on the collection strategy. *Bank One* admitted that they failed not on "price-

increasing" strategies, but rather "price-decreasing" strategies, which resulted in increased attrition rates (Trench *et al* 2003). The variables that were used by *Bank One* will be similar to those being used in this research:

- initial credit score assigned to customers,
- initial amount lent,
- contractual and realised repayments,
- balances throughout the contract period,
- delinquency status (or level of arrears) and
- interest rates.

The relationship between risk and return and its trade-off is referred to as economic capital management or capital allocation. Capital allocation is used for performance management, product pricing and employee remuneration. RAROC is the most widely used tool for capital allocation, as it ensures effective use of shareholders' funds (Milne and Onorato 2007).

## 2.3. Evaluate whether credit risk was appropriately priced

The purpose of this research was to evaluate whether South African credit providers are accurately pricing for credit risk through economic cycles with reference to the recent global financial collapse.

### *2.3.1 Credit risk and pricing*

Credit risk is the probability of default and is explained by expected and unexpected losses (Bank of Japan 2005). When a customer starts missing his repayments, he goes into default. A customer goes into default if the debt outstanding exceeds the assets due to:

- negative income shocks (loss of job, divorce, large once-off health costs

or large increased interest rates) and/or

- mismanagement of expenses (Crook and Bellotti 2010).

The granting of credit in South Africa is governed by the National Credit Act (NCA) and the underpinning requirement of the NCA is to ensure that the customer can afford the credit given by the credit provider. The NCA currently governs credit agreements originated since June 2007 in South Africa. Banks therefore assess a customer's credit risk to ensure that he can afford the loan and whether the bank is willing to accept such risk.

Most customers applying for credit are assessed for credit risk. This initial risk assessment requires a customer to be risk graded. The common practice in the credit industry is to classify credit risk into low, medium or high risk customers (Hand and Henley 1997). The number of risk grading amongst lenders generally varies from two to twenty, and average around five risk grades (Willam and Carey 2000). The initial risk assessment occurs at the point of granting the credit and is done by:

- application scoring and/or
- behavioural scoring and/or
- bureau scoring.

Companies use a combination of the above types of risk assessment techniques to assign a credit score or grading for the customer. Credit pricing is set according to the level of risk and can be set by adjusting the:

- Amount of credit extended and/or
- Type of credit (revolving or non-revolving) and/or
- Period of the loan and/or
- Interest rate charged (and/or other fees charged) and/or
- Secured or unsecured loan

Risk assessments can be automated or manual. However, in today's technological and high volume driven economy, most banks have an automated process, especially those banks dealing with high volume retail customers.

The main aim of credit risk assessments is to manage the level of risk a bank is willing to take. This could in some instances work against the shareholders' main aim of maximising returns. Management has to play a careful balancing act between meeting the required shareholder returns, without exposing themselves to undesirable levels of risk, while ensuring the business remains robust through economic cycles. Various banks can pursue different pricing strategies, be it to minimise losses, maximise profits or grow market share for instance. Risk levels generally increase when banks are trying to break into a new market. Long term strategies such as customers for life, could also result in lower than expected initial returns relative to the risk taken, compared to potential longer term profitable customers.

Credit risk is managed by credit providers on a top-down and/or bottom up basis. Top-down styles would generally include:

- how banks should strategically position different businesses,
- how different loan portfolios compare,
- how should management be compensated,
- what are projected ranges of profits/losses for the future,
- impact of operating costs and efficiency ratios,
- chance of unexpected losses and
- how should banks strategically divest or invest (Ong 1999).

Examples of bottom up approaches would include:

- how to assess risk and return profiles of loan portfolios on a day-to-day basis and

- how to structure and approve loan facilities to specific borrowers and
- how to price fairly for risk (Ong 1999)

Banks also operate in a space where the product they offer is the same. One of the key differentiating factors and strategies a bank can employ is pricing appropriately for risk through economic cycles.

Banks who do not appropriately apply credit risk pricing model fall into the trap of following the herd in order to win a customer. This is a short term view of winning a customer for the sake of outperforming your peers, which can have detrimental consequences, as the recent sub-prime crisis revealed. Lending organisations, who price appropriately for the level of risk taken through economic cycles, will be strategically well positioned and will ensure that returns generated are consistent and robust through economic cycles.

### *2.3.2 Credit returns*

The most common method of measuring returns of a particular loan portfolio is the yield charged to the customer (Altman and Saunders 1997). This is essentially all the annualised revenues (interest, insurance, initiation fees and monthly service fees) charged to a particular customer, expressed as a % of the loan outstanding. This method is referred to as the accrual method, as the income earned by the credit provider is the amount charged to the customer and therefore accrued for in the financial records of the credit provider, which is reflected as revenue on the income statement.

Realised returns is the yield charged to the customer (as noted above), after deducting the cost of bad debts. The current basis of accounting for the realised returns by credit providers uses the accrual method. The accrual of bad debts consists of the actual bad debt written off and the amount provided for potential bad debts that might materialise in the future. Bad debts accounted for in the financial records of the credit provider, using the accrual method, is dependent on accounting rules and policies set by management.

The drawback of measuring realised returns using the accrual method is that

the amount charged to the customer is not always recovered in cash or even worse, the capital might not be recovered. The method used in this research is to measure realised returns of the various loan portfolios using an IRR model based on the actual cash flows over the period of the loan. The actual cash flows received over the period of the loan is then discounted, using the principals of time value money to derive the IRR. The IRR is therefore a cash basis of measuring and accounting for the realised returns. The higher the IRR the higher the risk-adjusted return generated from the customer and vice versa. The IRR can be a theoretical/contractual IRR or a realised IRR. A theoretical IRR assumes that the customer will behave in terms of the contract and not miss any instalment when due. This contractual IRR would therefore equate to the credit price charged to the customer, whereas the realised IRR is based on actual repayments made by the client which represents the realised return.

The proposed method of measuring returns on a realised IRR basis is more prudent compared to the current accounting practice of earning revenue as the current method realises revenue when it is charged to the customer and only accounting for bad debts based on management's rules. The method of accounting for revenue and bad debts in this research, adjusts the credit price for the non-recoverability of the revenue and capital portion of the loan from inception of the contract instead of the date that default event occurs. This reduces the overstatement of revenue and hence profits, at the beginning of the contract, and also reduces the likelihood of only accounting for bad debts towards the end, ensuring that profits are earned consistently and evenly as a realised return over the life of the contract. This ensures that the pricing of credit risk and the earning of credit returns are consistent through economic cycles.

Banks are required to grade the client at inception of the loan in order to account for realised returns on the proposed bases. Once the client is graded, all the loans in a similar grade would then be grouped together to form a loan portfolio. The future cash flows of each loan portfolio then needs to be forecast by management, based on historical repayment profiles of similar loan portfolios, given the level of initial risk assessment. The IRR of the loan portfolio in which the applicable loan is grouped under, is then used to account

for the realised return in financial records of the credit provider.

The individual loans making up the loan portfolio would migrate over the life of the contract to an appropriate loan portfolio, based on the actual performance of that loan.

Each loan should be assessed on a monthly or quarterly basis to determine whether the risk has changed from the previous assessment done. As loans move into better graded loan portfolios, provision for bad debts would reduce proportionately and vice versa.

For the purpose of this research, future cash flows will not be projected, as the actual cash flows are already known. Each individual loan's discount rate (or realised return) in the dataset can be calculated based on the actual cash flows, up until the date when cash repayments cease. The individual IRR of the loan portfolio, is then used to determine the realised return of the loan portfolio. The theoretical IRR (or credit price charged) of the loan portfolio is also calculated, using the theoretical aggregated cash repayments in accordance to contractual repayments.

The difference between the credit price charged and the realised return represents the bad debt ratio, which is the unrecovered portion of the total capital lent by banks and total revenue charged over the loan period. A high bad debt ratio, would imply that the bank has to charge a higher credit price in order to realise a minimum and consistent shareholder return through economic cycles. Therefore, bank's credit pricing strategies are robust if they can accurately forecast this bad debt ratio through economic cycles, in order to achieve a consistent realised return. Note that the basis of calculating the realised returns for this research is a cash basis of calculating the bad debt ratio, compared to the current accounting accrual method. The cash basis is considered superior, as it is unbiased and not driven by rules or policies set by management, but rather the true underlying performance of the loan (Audzeyeva *et al* 2012).

It is important to note that repayments included in determining the realised

returns will in some instance go past the contractual loan period, due to certain customers not being able to make all the repayments within the contractual loan period. This is likely to occur when the customer starts going into default. Loans included in the dataset for this research reached maturity date and additional payments post the research date are not foreseen and are unlikely to have an impact on the realised returns.

Banks obtaining a consistent return that is priced for through economic cycles could indicate the following:

- Customer is correctly priced
- Bank is strategically positioned
- Minimum shareholder returns are generated
- Attrition rates of economically profitable customers are low
- Bad debt ratios are continuously kept in check
- Bank has a strong brand and loyal customer base

The realised returns of loans issued before and after the financial collapse grouped by loan portfolio will be compared to each other in order to determine whether a consistent return was generated through economic cycles. For the purpose of this research, loans issued before the financial crisis consisted of loans issued between 1 June 2007 and 31 December 2007, whereas loans issued between 1 January 2008 and 30 September 2008 were classified as loans issued post the financial crisis. The actual repayment period used to calculate the realised return will be taken from the same period, which is from the loan issuance date up to May 2012, to ensure comparability through the same economic cycle.

### *2.3.3 Hypothesis*

Ha = Realised returns of loan portfolios, grouped according to the initial risk

assessments, are not consistent through economic cycles.

H0 = Realised returns of loan portfolios, grouped according to the initial risk assessments, are consistent through economic cycles.

## 2.4. Conclusion of Literature Review

This research attempts to overcome barriers faced by previous research or businesses. Profit scoring is considered to be complex scoring models and yet to be successfully tried, if applied correctly, could enable the lender to drive the long term bottom line of the company (Schreiner 2005).

The overarching goal for lenders is to optimise decisions linked to shareholder value creation, rather than trying to manage default risk alone, which on its own does not guarantee profit maximisation, but rather loss avoidance or reduction (Thomas, Oliver and Hand 2005). The goal is therefore one that is of a long term nature, and therefore pricing for credit through economic cycles will ensure shareholder returns are maximised. Evolved risk based practices are those where banks apply risk-adjusted performance measures (i.e. measuring both risk and return congruently) (Blessis 2002). Boegelein (2006) asks why there has been so little research in modelling continuous financial measures and why are rudimentary models of binary classifications in terms of default rates so much more applied. Boegelein (2006) also remarks that no research exists where a profit maximisation approach has been successfully or unsuccessfully applied by lending organisations. Perhaps it is a lack of appropriate data or the unwillingness of banks to depart with their models, as their credit models provide a competitive advantage (Hand and Henley 1997). This lack of measuring the proper variables defeats the shareholders' main aim of maximising returns to ensure returns remain robust through economic cycles.

Credit pricing models that are able to accurately price for credit risk, whether high or low, through economic cycles, result in profitable portfolios where the desired returns are consistent and robust, while keeping defaults in check. They also allow for greater market share, as the pricing is more competitive. They

also result in lower losses and higher revenue (Blöchlinger and Leippold, 2006).

Credit pricing models that are not robust and which do not price through economic cycles result in mispriced credit assets. Banks that misprice loans starts losing critical mass, driving up operating costs relative to revenue, further watering down profits. Strategically positioned banks will be those banks that have credit pricing models that price through economic cycles which ensures that market penetration and share remains optimised. Credit scoring and pricing is thus a core competence of all great banks.

Good and bad customers are normally defined by banks by their delinquency state, instead of classifying customers in order of their realised return. The possibility of slow payers generating a fair return is ignored in the rudimentary method of classifying customers based on delinquency. Classifying customers in order of delinquency becomes a “moot” point when determining the profitability of these accounts (Boegelein 2006). Defaults ignore strategy, instead lenders should be more interested in whether a customer is profitable or not (Hand and Henley 1997).

The development of IT and complicated modelling techniques and cost of storage has allowed companies in the US during the mid-1990’s to use more sophisticated models (Marron 2007). Risk-based pricing ensures that a competitive price is charged given the level of risk (Thomas, Oliver and Hand 2005). Therefore, risk-based pricing allows lenders to turn high risk customers profitable. It also allows organisations to grow market share in two areas:

- previous individuals that were deliberately excluded due to high risk, are now included on the basis of profitability, and

- low-risk customers are offered more competitive prices, allowing these customers to consume more credit, which reduces attrition rates.

The ultimate goal of lending organisations is to maximise the risk-return profile of loan portfolios (Ong 1999), in order to maximise shareholder return. By incorporating the results of the risk-return profile back into the credit scorecards through continuous feedback loops, ensures that companies remains

competitive in setting the credit pricing policy, for both high and low risk customers. This ensures that decisions are made for the long term benefit of the company and ensures companies endure through economic cycles. Maximum profit need not monotonically be related to risk alone, as low risk customers might be unprofitable if they repay their credit cards on time, whereas high risk customers might be profitable, if they are charged a high rate which is recovered (Hand and Henley 1997). Micro lenders have proven that reasonable returns can be generated by potentially risky clients, although losses can be potentially higher too (Blessis 2002). This requires banks to correctly measure the return given the level of risk, which would thus enhance credit scoring and ensure robustness.

The past decade revealed that banking practices have changed from minimising default to maximising profit (So and Thomas 2008), however, very little research suggest that banks have been successful in its application. Profit scoring would allow organisations to have a tool that aligns default rates to the overall company objective: robust shareholder returns (Thomas 2000). The development of profit scoring models could lead to major impacts on the credit industry and consumers. Organisations that successfully apply profit scoring techniques can cherry pick and go after the most economically profitable customers to ensure that returns are consistent through economic cycles.

Credit modelling in the 21st century will move towards business objectives linked directly to shareholder value, rather than default risk alone, which allows for profit maximisation and increasing market share (Thomas, Oliver and Hand 2005).

A great deal of research is required to incorporate default and profitability (Thomas 2010) in order to measure and ensure returns are robust through economic cycles, this research overcomes some of these obstacles.

### *2.4.1 Hypothesis*

Ha = Realised returns of each loan portfolio, grouped according to the initial risk

assessments, are not consistent through economic cycles.

H0 = Realised returns of each loan portfolio, grouped according to the initial risk assessments, are consistent through economic cycles.

# CHAPTER 3: RESEARCH METHODOLOGY

## 3.1 Research methodology

A quantitative methodology was applied to this research. Banks face quantitative issues in setting credit pricing. A quantitative method is the best research method for researching credit pricing, due to the investigation into internal rate of returns, which was effortlessly quantifiable with the data available.

The findings of this research, using the suggested method, are clear and unambiguous. The data was readily available and computation was not protracted. However, there might be certain factors affecting credit pricing other than the quantitative variables being used in this research. Some of these could be the social issues and political unrest for instance, which could result in a different outcome to confirm whether credit pricing in South Africa is robust through economic cycles. However, it is widely accepted that internal rates of return, being a quantitative method, is the most effective method for this research.

The quantitative non-parametric method which will be applied to this research will be a *Mann-Whitney U* test. Applying this test, the difference between the realised returns of similar risk grades will be compared, in respect of loans issued before and after the financial collapse. The return of loans will be calculated using actual cash flows from inception of the contract (commencing from June 2007 to September 2008) up to May 2012. Contracts commencing from June 2007 to December 2007 are classified as loans issued pre the financial collapse and contracts issued from January 2008 to September 2008 as post the financial collapse.

The null hypothesis should be rejected where the realised return of loans issued pre and post the financial collapse is not similar and hence, the pricing of credit risk was not sufficiently robust through economic cycles. Each risk grade will be

measured separately as pricing and risk varies across risk grades.

## 3.2 Research Design

The methodical approach that was adopted in this research is a mathematical model to determine whether the credit risk of each loan portfolio was appropriately priced for through economic cycles. The IRR is the most effective tool of measuring returns as it is objective and only uses real cash flows and is not influenced by management and judgement. IRR is a simple mathematical model as the number of variables required for this mathematical model is limited to the initial loan amount and the repayments made over the loan period.

The *Mann-Whitney U* test was able to determine whether the credit pricing of the loan portfolios were different pre and post the financial collapse.

## 3.3 Population and sample

### *3.3.1 Population*

The population consist of short term credit retail providers in South Africa.

### *3.3.2 Sample and sampling method*

The cluster sample method will be applied for this study which is also referred to as a convenient sample (Albright *et al* 2006). Convenience sampling is a non-probabilistic technique based on sampling units due to the ease of access to these units (Yu and Cooper 1983).

The sample selected consisted of approximately 90 000 loans, which originated between June 2007 and September 2008, with repayments recorded up to May 2012. The majority of the customers were awarded a loan with a repayment period of 24 months and therefore an additional tolerance of 21 months was given to customers who were late payers.

## 3.4 The research instrument

The instrument that was used to analyse the data is an internal rate of return (IRR). An internal rate of return is a mathematical model which is the effective annual compounded rate of return, measured over the period of investment or in this case the loan. The IRR is effectively the discount rate used to make subsequent cash inflows equal the initial outflow (loan issued at inception of contract). It is therefore where the future benefits discounted is equal to the initial outflow, and is where the net present value (NPV) is nil.

The model used to calculate the IRR is to solve "*r*":

$$\mathrm{NPV} = \sum_{n=0}^{N} \frac{C_n}{(1+r)^n}$$

where the NPV is nil; *C* is the cash flow in period *n* and *N* being the total number of periods. It should be noted that the re-investment rate of the interim cash flows generated over the life of contract was either re-invested back into other similar loan profiles or where a similar return was not generated on these cash flows, then these excess cash flows were regularly given back to shareholders by way of a dividend, preventing banks from generating a return lower than the return calculated by the IRR formula.

The IRR can be calculated using the initial amount lent together with the actual repayments made by the customer to determine the realised return, whereas the contractual payments per the contract can be used to calculate the contractual credit price.

The research measured the realised return of loans grouped by the initial risk assessment, split between loans issued pre and post the financial collapse.

## 3.5 Procedure for data collection

All the data for this research was collected from one bank in South Africa. The data was collected electronically from the data warehouse of the particular

bank. The particular bank gave the researcher authority to access their data warehouse for the purposes of this research.

## 3.6 Data analysis and interpretation

The data that was relevant to determine the realised return was:

- initial capital lent to the client
- initial risk grading or assessment
- actual monthly repayments from inception of contract up to the point where the monthly repayments no longer alters the risk adjusted return of the loan. Based on preliminary discussions with the particular bank, on average, loans take approximately an additional 12 months beyond the contractual loan period, to either
    - be settled in full or
    - the client completely ceases to pay or
    - the repayments become so insignificant that the repayments eventually do not cover additional interest.

For the purposes of this research an additional 21 months subsequent to the contractual period, was included in the calculation of the realised return.

Due to the returns not following a normal distribution, a non-parametric test was used for this research. The returns of credit risk based products vary wildly due to a collection of returns being -100% (as a result of bad debt write-offs) and another collection of returns achieving the desired price charged, with the balance of the loans somewhere in between. The test statistic which will be used will be a *Mann-Whitney U* test. A *Mann-Whitney U* test is a non-parametric test to assess whether a sample from an independent observation is larger or smaller than the other sample. The *Mann-Whitney U* test is a rank order test. This creates asymmetrical distributions, which voids the assumptions made with independent sample t-tests, the most important being a standard normal

distribution under the null hypothesis.

The method to calculate the *Mann-Whitney U* test is as follows:

1. Rank all the returns from pre and post the financial collapse per risk grade in descending order

2. Sum the ranks of the returns for both samples per risk grade (where $R_1$ is the sum of the ranks from pre the financial collapse and $R_2$ post the financial collapse)

3. Calculate the *U* for both samples per risk grade (where $n_1$ is the sample size from pre the financial collapse and $n_2$ post the financial collapse)

    - $U_1 = R_1 – n_1 \times (n_1 – 1)/2$
    - $U_2 = R_2 – n_2 \times (n_2 – 1)/2$

4. Calculate the mean and standard deviations *U*

    - $m_U = (n_1 \times n_2) / 2$

    - $\sigma_U = ((n_1 \times n_2 \times (n_1 \times n_2 + 1)) / 12)^{0.5}$

5. Calculate the *z* statistic (where *U* is the smaller of $U_1$ or $U_2$)

    - $z = (U - m_U)/ \sigma_U$

6. The returns pre and post the financial collapse, grouped according to the initial risk grade, will be significantly different where the *z* statistic is greater than 1,96.

7. The null hypothesis will be rejected where the returns are significantly different pre and post the financial collapse.

The major assumptions in using the *Mann-Whitney U* test are:

- All returns are independent of each other
- The returns are ordinal type data (i.e. using a ranking or order system)
- The distribution of the returns grouped by loan portfolio, pre and post are equal (i.e. there is symmetry between the two samples by loan portfolio)

The above assumptions were tested and did not fail.

## 3.7 Limitations of the study

- Credit returns do not consider client acquisition strategies, which in certain instances can create short-term losses in order to gain market share.
- Credit returns ignore operating costs, taxes and interest cost, and could affect the bottom line result.
- The type of credit offering could impact returns, for instance repayments on secured loans are less volatile than unsecured loans.
- The sample only consisted of one bank in South Africa.
- The returns could have been affected by change in management or by a change in systems.

## 3.8 Validity and reliability

### *3.8.1 External validity*

External validity examines whether or not the observation can be applied or generalised across measures, persons and settings (Calder *et al* 1982).

The population upon which inference is made upon is limited to the credit retail sector of South Africa. The sample selected to represent this population was

limited to one credit provider, which has a large share of the target market or population. Although the research was confined to the credit retail sector in South Africa, the outcome of this research can be applicable to other credit providers as they too have the same dilemma of determining whether credit pricing is appropriately priced for through economic cycles. Banks in other sectors have similar credit pricing processes, although targeted towards different risk groups, and therefore this study has the ability to generalise across different credit providers.

### *3.8.2 Internal validity*

Internal validity addresses whether or not the measurement makes a difference or not, and whether there is sufficient evidence to support the claim (Calder *et al* 1982; Onwuegbuzie 2000).

The core focus of this study is around the internal rate of return, which is a measurement to support the claim. Regression analysis will not be utilised to determine whether there are any cause and effect relationships, and therefore internal validity poses a lesser problem for this research.

Internal rate of return, however, can be affected due to a number of variables not contained within this research. IT system changes, management compensation and changes to collection processes can affect realised rates of return. However, limited changes were made by the company under review.

This study will not attempt to understand the variables affecting the internal rate of return, as the purpose of this study is to establish whether the credit price is robust or not.

### *3.8.3 Reliability*

Reliability is the extent to which research produces the same outcome under stable circumstances on all instances (Bell 2006). Consistency will be achieved by measuring the internal rate of return, by including additional repayments beyond the agreed contract period. This will ensure that internal rates of return

would be the consistent and robust, whether it was measured during boom or bust economic cycles.

# CHAPTER 4: PRESENTATION OF RESULTS

## 4.1 Demographic profile of respondents

A sample of 87 982 loans were obtained. Fifty seven percent of loans were advanced to female customers. 36 685 loans of the sample were granted between June 2007 and December 2007 (pre financial collapse) and 51 297 loans were granted between January 2008 and September 2008 (post financial collapse).

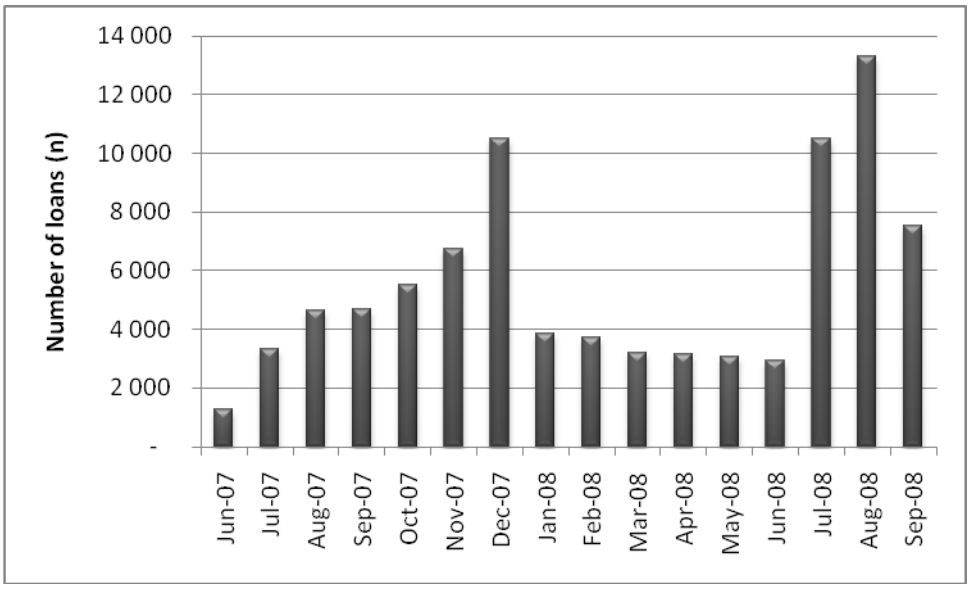


**Figure 2: Sample size per month of loan issued**

The mean gross income per month earned by the loan applicants were R4 524 with a mean loan value of R5 178. A total of R456m was lent across the sample size. Below is a distribution of the loans advanced overlaid by the monthly gross income.

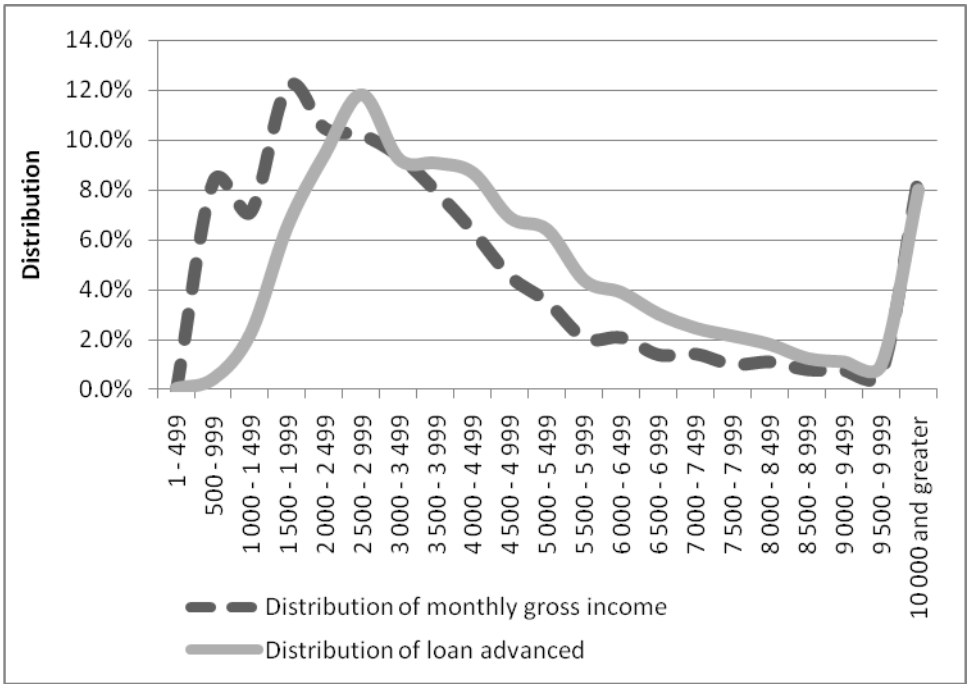


**Figure 3: Distribution of monthly gross income overlaid with loan advanced**

Most of the loans issued above R10 000 related to the medium to very low risk graded loans.

Ninety five percent of the loans in the sample had a fixed contractual loan repayment period of 24 months and there were no contractual periods over 36 months.

Most of the actual loan repayments ceased from 4 years since inception of the loan and asymptotes from there onwards, as can be seen from the graph below. Any additional repayments that might have been received after 4 years would have been highly unlikely and due to the time value of money, would have had very little impact on the realised return.

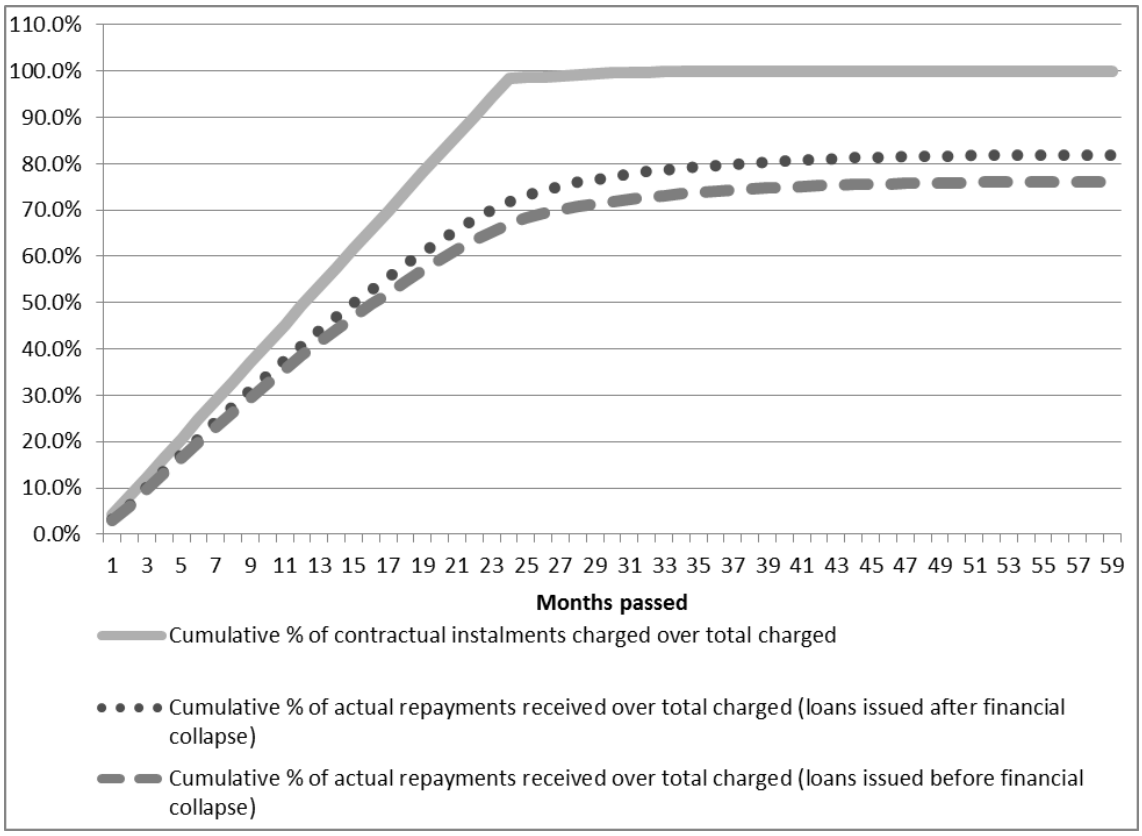


**Figure 4: Collection rate as a percentage of total contractual instalment**

By month 24 (by when the loan should have been contractually repaid), only 66.9% of the contractual instalments were collected in respect of loans issued pre the financial collapse, compared to an improved 71.7% in respect of loans issued post the financial collapse. This increased to 76.1% by year 5 since inception of the loan for loans issued pre the financial collapse and 81.8% for loans issued post the financial collapse. It should be noted that the difference between the contractual repayments charged and actual repayments received, represents bad debts.

Most of the loan applications were issued in Kwazulu-Natal (23%), followed by Gauteng (17%), with the lowest representation from Northern Cape (3%). Below is a distribution of the number of loans issued across the various South African provinces.

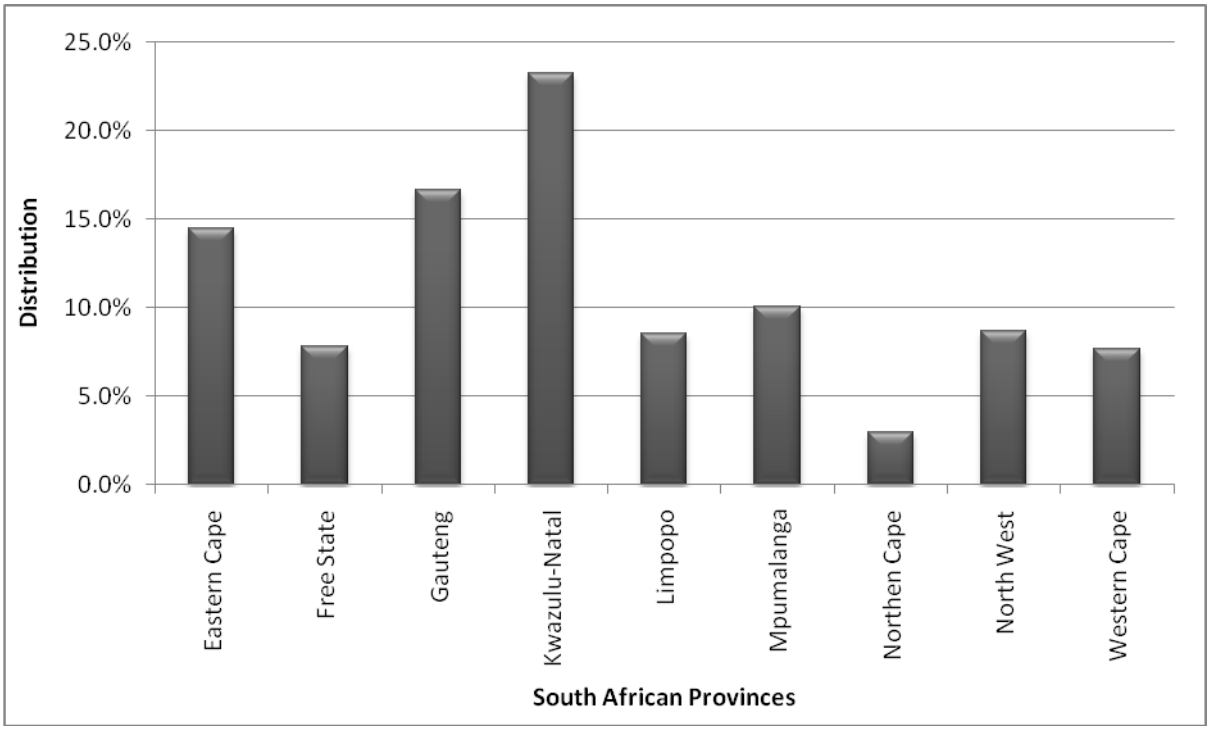


**Figure 5: Distribution of sample by province**

The age group between 25 to 28 represented 16% of the sample, gradually reducing to 0% by the age category 69 and older. The following is the distribution of the age group

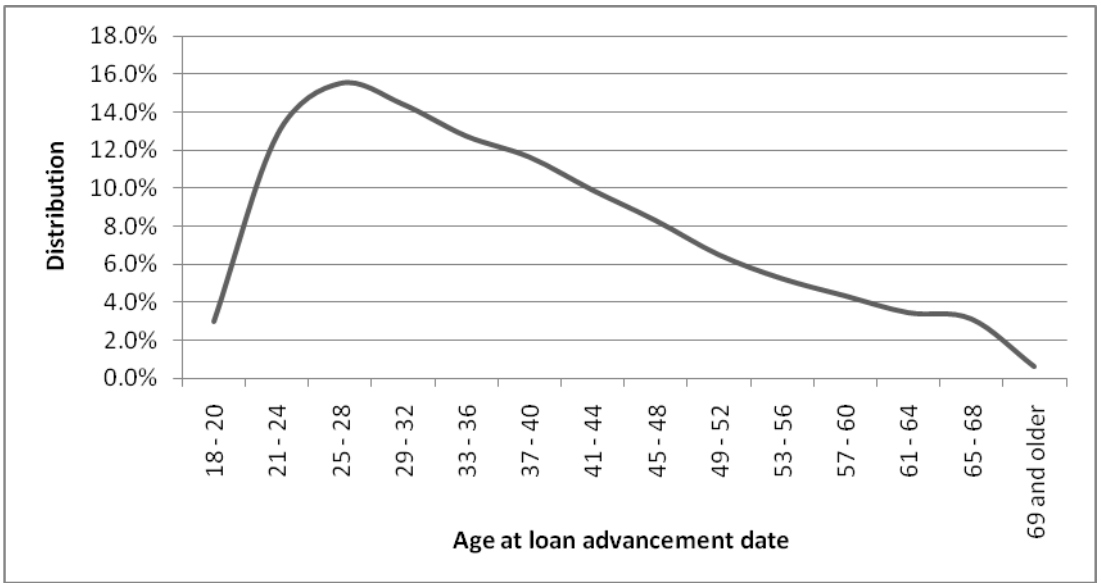


**Figure 6: Distribution of sample age category**

There were 7 loan portfolios or risk grades, ranging from very low risk, low risk, low to medium risk, medium risk, medium to high risk, high risk and very high risk. The graph below shows the distribution of loans by portfolio. Most of the loans issued pre the financial collapse fell in the high risk (35%) category, dropping to 20% post the financial collapse. The distribution shifted post the financial collapse, with 23% of the loans originating from the medium to high risk category.

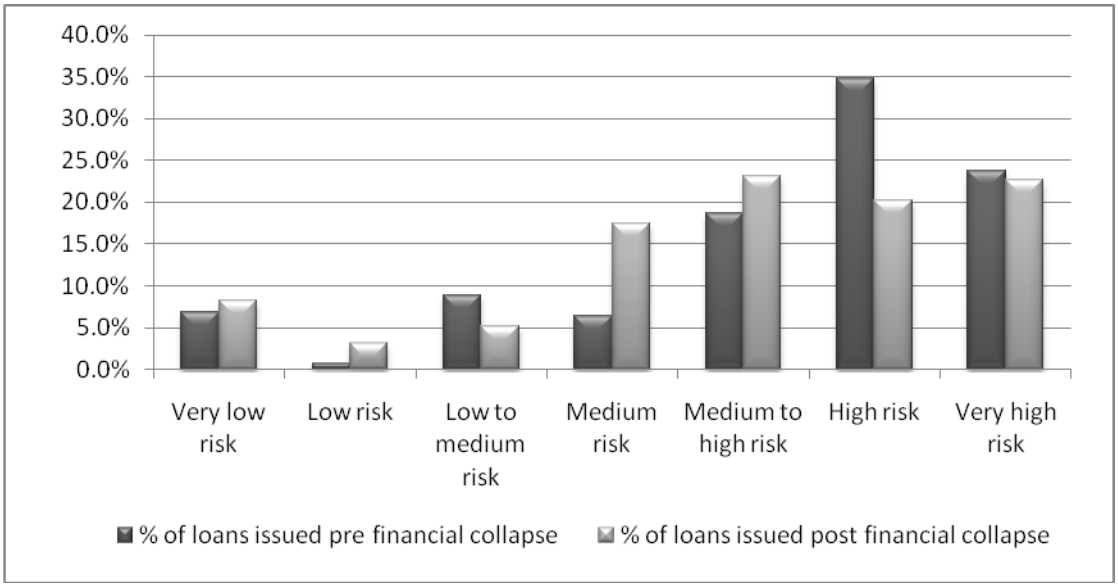


**Figure 7: Distribution of loans issued pre and post the financial collapse by initial risk grade**

The low risk customers were on average 11 years older than the high risk customers. The loan value and income were also higher for low risk customers and compared to high risk customers. The following graph represents the mean monthly gross income, loan advanced and age by risk grade.

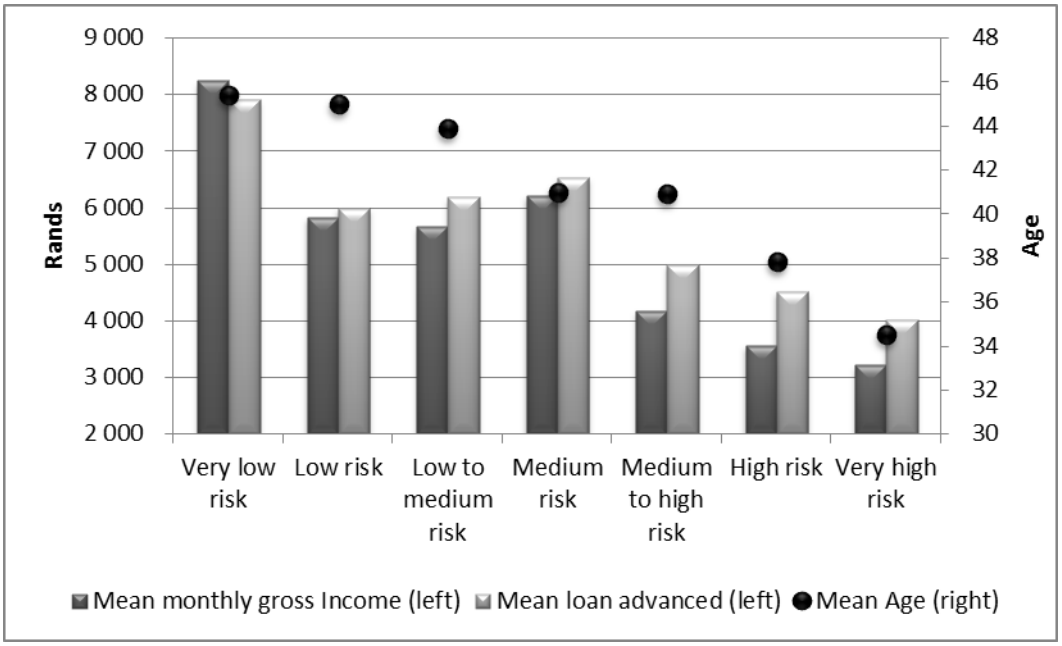


**Figure 8: Mean monthly gross income, loan advanced and age by risk initial risk grade**

## 4.2 Results pertaining to Hypothesis

As noted before, when realised returns, split before and after significant changes in economic cycles, resulted in significantly different outcomes, could indicate that credit pricing and risk grading was not done in view of potential changes in economic cycles. Returns that remain consistent or similar through economic cycles could indicate that the upfront credit pricing and risk grading was accruate and sufficiently robust to ensure that returns remain sustainable and consistent through economic booms and busts.

It is important to note that the repayment period to measure the realised return of loans issued pre or post the financial collapse was conducted over the same period, being the period since inception of the loan (ranging between June 2007 and September 2008) up to May 2012. Therefore the main contributor to the variance of the return pre and post the financial collapse is largely driven by the credit pricing and risk grading at inception of the loan contract and not the

repayments.

The realised return earned on each loan in the sample was calculated individually using the IRR methodology. The realised return of each individual loan was then grouped according to the initial risk assessment and whether the loans were issued pre or post the financial collapse. Below is the median realised return by risk grade split between loans issued pre and post the financial collapse.

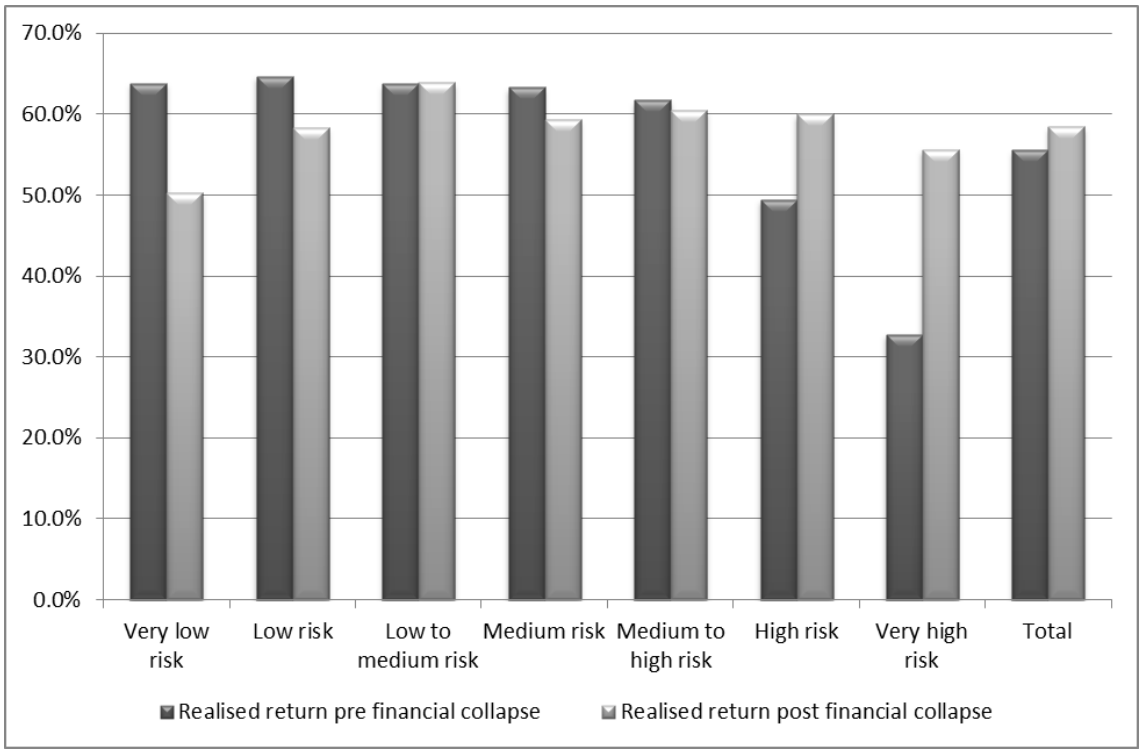


**Figure 9: Realised rate of return pre and post the financial collapse by initial risk grade**

The median realised return generated on loans issued post the financial collapse of 58.4% were 2.8% better than the loans issued pre the financial collapse of 55.6%. The realised returns generated on very low risk customers reduced from 63.8% to 50.3% pre and post the financial collapse respectively, whereas the realised returns of very high risk customers swung the other direction, improving from 32.8% to 55.8% pre and post the financial collapse respectively. The improvement in the realised returns of very high risk

customers could be explained by the unwillingness of the bank to accept high risk customers post the financial bubble, therefore making credit granting more stringent. This is evident in Figure 8 above where there was a reduction of loans issued in the high risk graded categories, compared to an increase in the percentage of low to medium risk graded loans, when the financial collapse occurred during the beginning of January 2008. Banks were much more cautious when the global financial collapse occurred, resulting in a tightening of credit granting, especially in the high risk graded customers.

This research statistically tests whether the credit pricing was robust through economic cycles. This was done by comparing the realised returns of loans issued pre and post the financial collapse with each other. If the realised returns remained consistent through the economic cycle, irrespective of whether the loan was issed pre or post the financial bubble, then it is assumed that the credit pricing policy applied was appropriate and priced through economic cycles. If however, there is sufficient evidence to show that there was a significant difference in the pre and post returns realised, grouped according to the initial risk assessment, then the null hypothsis would be rejected.

The difference between the pre and post realised returns were compared against each other using a *Mann-Whitney U* test. This test was the most appropriate for testing whether two populations are similar, as the individual realised returns of loans, grouped according to initial risk grade, were not normal distributions. The *Mann-Whitney U* test, being a non-parametric test was the most appropriate test for distributions that are not normal.

The *Mann-Whitney U* test was applied, by comparing the individual returns loans issued pre and post the financial collapse. The *Mann-Whitney U* test then evaluates differences between returns using a rank order system. The method described in chapter 3.6 above was strictly applied to each risk grade. The outcome of the test was to determine the Z score and the P value, in relation to the variance between the realised returns, split between pre and post the financial collapse. The credit pricing is robust through economic cycles where the Z value is smaller than 1.96. This implies that there are no differences

between the returns of loans issued pre and post the financial collapse, and the null hypothesis is not rejected. It would, however, indicate that the difference is significant, where the Z value is greater than 1.96.

From the seven loan portfolios tested, there were only two loan portfolios, where the null hypothesis is not rejected. The *Low Risk* and *Medium to High Risk* graded loans were correctly priced through economic cycles. In respect of the other five risk grades, as well as the consolidated loan portfolio, the null hypothesis is rejected. On an overall basis, the credit risk pricing was not robust through economic cycles.

**Table 2: Results of hypothesis test by risk grade**

| *Risk grade* | *Mann-Whitney U test : Z value* | *P value* | *Accept or reject null hypothesis* | *Where the realised returns consistent through the economic cycle?* |
|---|---|---|---|---|
| Very low risk | 17.88 | 0.00 | Reject null hypothesis | No |
| Low risk | 1.85 | 0.06 | Do not reject null hypothesis | Yes |
| Low to medium risk | 2.79 | 0.01 | Reject null hypothesis | No |
| Medium risk | 3.01 | 0.00 | Reject null hypothesis | No |
| Medium to high risk | 1.74 | 0.08 | Do not reject null hypothesis | Yes |
| High risk | 18.70 | 0.00 | Reject null hypothesis | No |
| Very high risk | 19.19 | 0.00 | Reject null hypothesis | No |
| **ALL** | **22.32** | **0.00** | **Reject null hypothesis** | **No** |

## 4.3 Summary of the results

The null hypothesis is rejected due to the Z value, of the consolidated loan portfolio, being more than 1.96, indicating that there was a significant difference between the realised returns of loans issued pre and post the financial collapse. The credit risk pricing was not sufficiently robust enough to ensure that the realised returns of loans remained consistent through economic cycles.

# CHAPTER 5: DISCUSSION OF THE RESULTS

## 5.1 Demographic profile of respondents

The profile of the sample was to a large extent expected. It was expected that the proportion of risk taken in the higher risk bands to reduce post the financial collapse in January 2008, as banks had to respond with the increase in bad debts (as a result of the deterioration in actual repayments received, relative to the contractual amounts required), especially in the high risk bands.

It was interesting to note that there was some form of relationship between the monthly gross income earned by the applicants and the loan given to the client, given the level of risk.

It is also of importance to note that an additional ten percent of repayments are made subsequent to the contractual period. This would improve the overall rate of return and it is therefore important not to exclude these repayments from calculating the realised returns.

## 5.2 Discussion pertaining to Hypothesis

The realised returns of loans issued just after the financial collapse compared to the loans issued just before the financial collapse performed better overall. It should be noted that the same collection period was used to measure the realised returns. Therefore, the most significant impact on the realised return was therefore the initial risk assessment done and the related credit pricing thereof, and not the repayments as such.

In order to prevent fluctuations in realised returns through economic cycles, credit departments' main focus and drive should revolve around the point of giving credit, compared to trying to collect the credit extended (Trench *et al* 2003). If the process of giving credit is not aligned to the current and

foreseeable economic climate and changes therein, then realised returns will not be robust and could lead to banks failing. Banks should therefore have continuous feedback mechanisms to ensure that the initial credit scoring was appropriate (Hand 2005). Banks, like Lehman Brothers, failed on two levels, firstly they had loans on their balance sheet which only generated a return during boom times. Secondly, they failed because when those high risk loans, or sub-prime loans, had to be impaired, the banks did not have sufficient equity or reserves to cover themselves against such high levels of impairment expenses.

Minimising credit losses are no longer the holy grail, but rather balanced and enduring profits appears to be the more superior approach (Blessis 2002). Instead of maximising profits as suggested by Beazer (1975), a balance between risk and return which can endure through economic cycles appears to be superior. Measuring the risk-return profile is now easier to measure than in the past. Blessis (2002) agrees that measuring, predicting and reacting appropriately to the risk-return profile is of strategic importance, resulting in banks taking risks more consciously to protect themselves against changing market forces.

The cash principal of measuring returns fits in nicely with being able to do a balanced risk-return profile that is unbiased and not as subjective as the current accrual basis of measuring returns.

Boegelein (2006) considers ranking loans using a delinquency state as rudimentary. Using realised returns would be a much improved method of ranking customers which allows companies to make superior and strategic choices in extending credit. The over-arching goal is to set an appropriate price for the level of risk taken (Thomas, Oliver and Hand 2005). This is more effectively achieved by moving from purely credit scoring to profit scoring techniques (Thomas 2000). Whether banks are successful in applying profit scoring techniques is still up for debate.

## 5.3 Conclusion

Adopting an appropriate measurement technique to quantify the risk-return profile and to account for it as such, will lead to optimal lending practices to ensure that changes in the economic environment do not have a significant impact on realised returns. This model will satisfy both regulators in the credit industry and accounting standard bodies. The hypothesis reflects shortcomings in banks' credit departments, as returns still fluctuate too much through economic cycles.

# CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

## 6.1 Conclusions of the study

The increase in competition in the South African banking industry during recent years, makes it hard for banks to make the right choices around the level of credit to be extended and the pricing thereof. Banks have to ensure that the credit they makes available is affordable, but also sufficiently robust to generate a decent return for shareholders. These factors make it hard for banks to price through economic cycles. A bank also does not necessarily want to be the first mover in anticipation of a change in economic cycles, if it turns out that the move was premature in the expected changes in the economic landscape. It has to play a very careful balancing act between risk and return. Capital reserves are a crucial buffer when the risk outweighs the returns. If the realised risk is greater than the realised return, coupled with high levels of gearing can result in the bank becoming insolvent or illiquid in a very short time frame.

Very few banks responded quickly and effectively to the change in the economic landscape. Those that were pro-active and were able to adapt to the changes survived the 2008 financial collapse.

## 6.2 Recommendations

Firstly, banks should move towards a credit underwriting model which will prevent major fluctuations in realised returns. This includes accurately assessing the credit upfront, by giving the right level of debt, with appropriate loan repayment periods and charging a reasonable rate to generate a return that remains consistent through economic cycles.

Secondly, returns reported by companies in their financial statements have to

be aligned to the initial risk grade. Companies are not raising sufficient provisions against high risk customers at the inception of the contract, resulting in losses only being reported when the customer becomes bad. It is recommended that the final realised rate of return earned on high risk customers, should be the rate that should be earned through the income statement throughout the entire life of the loan. This will ensure that returns reflect the level of risk taken by the bank from day 1 of the loan. This will prevent companies from reporting high rates of return upfront and low rates of return towards the end of the loan. It will also prevent companies from paying excessive management incentives upfront, only to find that the returns were not sustainable in the long run.

## 6.3 Suggestions for further research

Future research can be conducted to understand which variables had the most significant impact on the realised returns, irrespective of the initial risk assessment. Understanding the drivers of the realised return is critical for banks to price for credit more accurately. It will ensure that banks remain competitive and have enduring profits that remain robust through economic cycles.

# REFERENCES


Albright, S.C., Winston, W.L. and Zappe, C.J. (2006) *Data Analysis and Decision Making with Microsoft Excel*, Third edition, Pacific Grove: Brooks/Cole-Thomson Learning.

Altman, E.I. and Saunders, A. (1997) Credit risk measurement: developments over the last 20 years, *Journal of Banking & Finance*, vol. 21, no. 11-12, pp. 1721-1742.

Audzeyeva, A., Summers, B. and Schenk-Hoppé, K. R. (2012) Forecasting customer behaviour in a multi-service financial organisation: a profitability perspective, *International Journal of Forecasting*, vol. 28, no 2, pp. 507 – 518.

Bank of Japan (2005), *Advancing credit risk management through internal rating systems*, accessed 2 March 2012, from www.boj.or.jp/en/research/brp/ron_2005/data/fsk0509a.pdf

Beazer, W.F. (1975) *Optimization of bank portfolios*, Lexington Books, University of Michigan.

Bell, J. (2006) *Doing your Research Project*, 4th edition, Open University Press, Maidenhead.

Blessis, J. (2002) *Risk management in banking*, John Wiley and Sons, New York.

Blöchlinger, A. and Leippold, M. (2006) Economic benefit of powerful credit scoring, *Journal of Banking & Finance*, vol. 30, no. 3, pp 851-873.

Boegelein, L. (2006) *Credit model validation – Evolving practices and*

*challenges, PRMIA*, Athens.

Bryan F.R. (1993) *Henry's Lieutenants*, Wayne State University Press, Detroit.

Calder, B. J., Phillips, L. W. and Tybout, A. M. (1982) The Concept of External Validity, *The Journal of Consumer Research*, 9(3), pp. 240-244.

Crook, J. and Bellotti, T. (2010) Time varying and dynamic models for default risk in consumer loans, *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, vol. 173, no. 2, pp. 283-305.

Crook, J.N., Edelman, D.B. and Thomas, L.C (2007) Recent developments in consumer credit risk assessment, *European Journal of Operational Research*, vol. 183, no. 3, pp. 1447–1465.

Finlay, S. (2010) Credit scoring for profitability objectives, *European Journal of Operational Research*, vol. 202, no. 2, pp. 528-537.

Gill I.S. and Pinto B. (2005), *Public Debt in Developing Countries: Has the Market-based Model Worked?*, World Bank Publications, Washington.

Greiner A. and Fincke B. (2009) *Public debt and economic growth*, Springer, Berlin.

Hand, D.J. (2005) Good practice in retail credit scorecard assessment, *The Journal of the Operational Research Society*, vol. 56, no. 9, pp. 1109-1117.

Hand, D.J. and Henley, W.E. (1997) Statistical classification methods in consumer credit scoring: a review, *Journal of Royal Statistical Society*, vol. 160, no. 3, pp. 523-541.

Kočenda, E. and Vojtek, M. (2009) *Default predictors and credit scoring models*

*for retail banking*, CESifo Working Paper Series, accessed 3 September 2010, www.cesifo-group.org/wp

Marron, M. (2007) 'Lending by numbers': credit scoring and the constitution of risk within American consumer credit, *Economy and Society*, vol. 36, no. 1, pp. 103-133.

Milne, A. and Onorato, M. (2007) *Apples and Pears? The relationship between risk capital and required returns in financial institutions,* accessed 2 March 2012 from *http://ssrn.com/paper=962362*

National Credit Act (Act no 34 of 2005), *Government Gazette (Republic of South Africa)*, vol. 489, no. 28619.

Ong, M.K. (1999) *Internal Credit Risk Models – Capital allocation and performance measurement*, Risk Books, Indiana University.

Onwuegbuzie, A. J. (2000) *Expanding the Framework of Internal and External Validity in Quantitative Research*, Annual Meeting of the Association for the Advancement of Educational Research (AAER), Ponte Vedra, http://eric.ed.gov/, pp. 1-61.

Rosenberg, E. and Gleit, A. (1994) Quantitative methods in credit management: a survey, *Operations Research*, vol. 42, no. 4, pp. 589-613.

Schreiner, M. (2005) Can scoring help attract profit-minded investors to microcredit?, *Financial Sector Development Conference*, Germany.

So, M.C. and Thomas L.C. (2008) Modelling the profitability of credit cards by Markov decision, *Discussion Papers in Centre for Operational Research*, Management Science and Information Systems, CORMSIS-09-09.

Southampton: University of Southampton.

STATS SA (2012) *Liquidations and insolvencies*, accessed 14 November 2012, http://www.statssa.gov.za/timeseriesdata/excel_format.asp

Thomas, L.C. (2000) A survey of credit and behavioural scoring: forecasting financial risk of lending to consumers, *International Journal of Forecasting*, vol. 16, no. 2, pp. 149-172.

Thomas, L.C. (2010) Consumer finance: challenges for operational research, *Journal of the Operational Research Society*, vol. 61, no. 1, pp. 41-52.

Thomas, L. C., Oliver, R. W. and Hand, D. J. (2005) A survey of the issues in consumer credit modelling research, *The Journal of the Operational Research Society*, vol. 56, no. 9, pp. 1006-1015.

Trench, M.S., Pederson, S.P., Lau, E.T., Ma, L., Wang, H. and Nair S.R. (2003) Managing credit lines and prices for Bank One credit cards, *Interfaces*, vol. 33, no. 5, pp. 4-21.

William, F.T. and Carey, M. (2000) Credit risk rating systems at large US banks, *Journal of Banking & Finance*, vol. 24, no. 1-2, pp. 167-201.

Yu, J. and Cooper, H. (1983) Quantitative Review of Research Design Effects on Response Rates to Questionnaires, *Journal of Marketing Research*, 20(1), pp. 36-44.

# APPENDIX A

## Consistency matrix

| Main problem | Literature Review | Hypotheses | Source of data | Type of data | Analysis |
|---|---|---|---|---|---|
| Do South African credit providers accurately price for credit risk through economic cycles with reference to the recent global financial collapse? | • Blessis (2002)<br>• Thomas *et al* (2005)<br>• Trench *et al* (2003) | Realised returns of loan portfolios, grouped according to the initial risk assessments, are not consistent through economic cycles. | Transaction database of pre-selected credit provider. | Continuous cross sectional numeric data. | Mann-Whitney U test |