Adverse Selection in the Retail Credit Card Market in South Africa

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ABSTRACT

Adverse selection is a deterrent to the efficient functioning of markets that arises when one party to the transaction has more information than the other. In financial markets, adverse selection could lead to an overinvestment in the high risk customer pools resulting in unforeseen credit losses. This paper examines the results of preapproved credit limit increases for evidence of adverse selection.

Using an Econometrics approach, the research analyses campaign data from a large South African financial institution. Descriptive results are presented to reach the conclusion that: a) Respondents to credit limit increase solicitations are worse credit risks that Non Respondents, b) there are immediate credit quality changes following the acceptance of the offer and, c) the cardholder defaults following the limit increase.

Although this paper is closely aligned to research undertaken by Ausubel (1999) and Argawal et al. (2010), who also examine the existence of adverse selection in the credit card market, it provides additional evidence of adverse selection despite the use of robust screening techniques to minimise information asymmetries between the lender and the borrower.

DECLARATION

I, Elizabeth Lettie Segoale, 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.

Elizabeth Lettie Segoale

Signed at …………………………………………………

On the …………………………….. day of ………………………… 2014

DEDICATION

To my children

for their love, support and endless patience.

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I am thankful to God, who has given me the blessings and the strength to persevere in my studies.

- To my children Koketso, Kgethilwe and Kgotsofalang Segoale, who have allowed their mother to focus on her studies while putting themselves second. I love you immensely, my children, and thank you for walking this journey with me.

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1 CHAPTER 1: INTRODUCTION

1.1 Purpose of the study

The purpose of this research is to examine evidence of adverse selection on credit card customers by drawing data from a large South African financial institution. This is achieved through the adaptation of Ausubel's (1999) auction model of credit cards, to analyse randomized preapproved credit card limit increase offers to existing credit card customers. The study further evaluates whether customers with observable high risk attributes and liquidity constraints are prone to accepting credit offers at higher lending rates than low risk customers, an insight into Stiglitz & Weiss' (1981) adverse selection model.

1.2 Context of the study

Financial markets have shown to be vulnerable to the negative economic consequences of information asymmetry and adverse selection. In financial markets, Stiglitz & Weiss (1981) ignited discussions on how asymmetric information within credit markets influences economic policy and lending practices (Bebczuk, 2003; De Aghion & Morduch, 2004). Many credit policies and strategies have since been designed by banks to proactively mitigate the risks associated with information asymmetries. Consequently, an informed understanding of adverse selection within a South African credit card context is critical in determining optimal country specific remedies.

The South African retail banking sector is a highly concentrated banking industry with the largest four banks holding 86.4% of the total industry assets (SARB, 2009; Simbanegavi, 2009). Traditional Retail Banking (deposit taking and transactional banking) is the most intensely competitive market segment and a fundamental change in strategy and positioning is required to compete aggressively in this segment (PWC, 2013). The aggregated total outstanding debtors book of the banking sector in South Africa equalled R1, 223 billion in 2012 (y-o-y growth of 7.47% from 2011 to 2012). Over the 2012 year, retail banks collectively extended credit to the value of R354 billion, representing 82% of the total industry credit exposure (National Credit Regulator, 2012).

Key to the growth was the optimistic credit expansion in the unsecured lending categories with general loans and credit card advances registering double-digit rates of increase over twelve months (SARB, 2012). The credit card market alone reported a 15.29% (R 24.8 billion) increase from 2011, representing a 35% of the annual credit extension within the unsecured market (NCR, 2012).

The credit card market in South Africa is very competitive, with services ranging from the banks' offerings to airlines, retailers and cell phone providers; however the non-bank providers are backed by one of the banks. Additionally, the industry offers a myriad of attractive loyalty programs of which the customers evaluate rates and costs as the key criterion in their decision making.

Amongst the key changes experienced by the credit card regulation in South Africa, was the introduction of the National Credit Act 34, of 2005, which replaced the Usury Act. This evolution fundamentally changed the way banks structure their lending products. To mitigate the restrictions of the National Credit Act, 34 of 2005, banks adopted a strategy to shift away from the open market and increase their asset base through credit extension and retention of their existing customers.

Amongst the key drivers to this change was the assumption that information asymmetries may be less dominant where the lender has an established relationship with the customer (Elyasiani & Goldberg, 2004). Hence, there is reason to expect that a lender faces more adverse selection among new clients (those who have not previously done business with the institution). This period was characterised by internal growth through preapprovals of credit limits whereby intense screening was undertaken to minimise the observable and the hidden credit risk to existing customers.

Banks must address asymmetric information. The theory of asymmetric information was first introduced in Arkerlof's (1970) paper, 'The Market for "Lemons"': Quality Uncertainty and the Market Mechanism' in the motor vehicle industry and later adapted to other fields of study. Within credit markets, when a potential borrower goes to a bank and applies for a credit card, the borrower understands the possible outcomes of his venture better than the bank does and he knows about his own character (willingness and ability to pay the loan) better than the lender does.

In order to maximise their profits, lenders create different mechanisms to overcome the negative effects of incomplete information. Stiglitz & Weiss (1981) developed a credit rationing model where the interest rate is not used by the lender as a discriminating device as variations in the interest rate may affect the asset quality of the portfolio. Under this sort of imperfect information, Stiglitz & Weiss (1981) show that expected returns to the lender increase with the interest rate only up to a point. In their research, this phenomenon is caused by adverse selection.

The organisation under study is one of South Africa's major financial services providers' that offers an assortment of banking solutions. The bank's retail loans and advances grew by 3% to R 329 billion in 2012, and credit cards alone accounted for R 17.2 billion of the lending portfolio (NCR, 2012). The bank offers a variety of credit cards based on income and credit risk.

The study's approach to estimating the degree of adverse selection prevalent in the credit card market is methodologically similar to Ausubel (1999) and Agarwal, Chomsisengphet and Liu (2010).

1.3 Problem statement

1.3.1 *Main problem*

Imperfections in the credit markets induce a problem of adverse selection and affect investments and financing of banks in numerous ways. Adverse selection induces credit rationing which causes under investments or a 'conservative choice' of customers. Credit rationing can be mitigated by screening interventions when soliciting existing customers for credit limit increases. However, failure of these screening interventions results in attracting a high risk customer and increased default rates. The main problem investigated by this study is to examine evidence of adverse selection in limit increase pre-approvals to existing Credit Card customers where caution to eliminate high risk customers has been undertaken via robust screening techniques.

1.3.2 *Sub-problems*

- The first sub problem is that certain contractual agreements and incentives offered by the banks to credit cards customers when offering preapproved limits, influences the composition of the portfolio pool by broadening the high risk pool.
- The second sub-problem is that the poor credit quality of inferior solicited credit limit increases has a higher probability of default and result in higher bank losses.

1.4 Significance of the study

According to Brito & Hartley (1995), credit cards compete with precautionary money balances as a source of financing transactions and they compete with bank loans and other forms of financing by smoothing the consumption of income.

The process of credit extension, particularly in financial markets, has attracted economists' attention because it represents a challenge to the traditional business markets. In a typical market the seller is not interested in the behavioural qualities of the buyer; but only at exchanging the product at the right price. This occurs because it is an instant transaction and because both parties possess perfect information about the quality and the price of the homogeneous product being traded. Lenders, however, sell a loan contract for the principal and interest payment is deferred. This creates a need for lenders to quantify the behavioural risk of the customer.

The understanding of these behaviour patterns is critical for the banks as banks incur substantial losses resulting from underestimation of consumer credit risk. Conversely, the consumer is often burdened by bad credit records, sequestration and bankruptcy resulting from misjudgement of credit repayment commitments.

Over the last decades the insurance industry has been instrumental in utilising and generating evidence of adverse selection. The development of this pragmatic evidence of adverse selection was seen into other consumer credit markets including: credit cards (Ausubel, 1999; Calem & Mester, 1995); home mortgage and automobile loans (Edelberg, 2004); home equity credit (Agarwal, Ambrose, Chomsisengphet, & Liu, 2006) subprime automobile loans (Adams, Einav, & Levin, 2007); personal loans (Karlan & Zinman, 2010) and credit cards (Agarwal at al., 2010).

Previous research had primarily focussed on solicitations to an open market (new to bank customers) showing relatively less research exploring the extent of adverse selection on alternative existing customers whereby increased pre-screening and better credit risk segmentation strategies have been applied. According to Agarwal, Ambrose, Chomsisengphet (2007), financial institutions can reduce credit impairments by using discriminatory devices, supporting the findings by Karlan & Zinman (2009) that financial institutions can mitigate these losses by investing in screening and monitoring devices. Failure to apply these risk mitigating strategies can result in observed patterns of delinquency.

The study will seek to provide additional evidence by focusing specifically on credit limit extensions to existing customers, where current credit risk behaviour and historical default rates had been previously measured. Should adverse selection be present then adverse selection would be stronger if the bank reached out to customers with unknown risk (open market). The results should be utilized as the minimum measure of adverse selection in the credit card market.

Furthermore, the study aims to bridge the gaps by extending the literature on the dynamics of adverse selection, defining and identifying key credit risk characteristics within existing credit card customer segments within a South

African context. Lastly, the study will provide guidance to regulators and lenders, to the extent that law permits, to ask myriad questions so that the interest rate and the advanced limit increases initially quoted can be adjusted accordingly through robust and modified screening processes.

1.5 Delimitations of the study

a) Adverse selection and moral hazard are two fundamental problems that may arise in the presence of adverse selection, (Liu & Tan, 2008), this study limits its research to evidence of adverse selection.

b) The study is limited to existing credit card customers of the bank who had been eligible for a credit limit increase over the considered timelines. The study does not include new to bank customers, who did not have a credit card prior to the solicitations.

c) When assessing default rates, only customer initiated defaults (deterioration in credit quality caused by an increase in withdrawal of the credit limit by the customer) and not lender initiated (cut back of the credit line by the lenders due to credit risk mitigating strategies) will be considered.

d) Included in the sampling could be customers who received more than 1 credit limit increase over the 18 months performance period, these will be excluded and treated accordingly.

1.6 Definition of terms

Asymmetric information occurs when one party to a transaction is equipped with more or better information than the other party (Liu & Tan, 2008)

Adverse selection - generally refers to a market process where ‘good’ products are driven out of the market and ‘bad’ products are likely to be selected due to information asymmetries between the buyer and the seller (Liu & Tan, 2008)

Behaviour scoring - a scoring process where characteristics of a customers' recent credit behaviour are applied to determine their likelihood of default (Thomas, Ho, & Scherer, 2001)

Credit rationing – demand for loans exceeds supply at the prevailing interest rate (Afonso & St Aubyn, 1999)

Credit scoring - using the discriminatory power of credit models to differentiate between population groups(Thomas, 2000)

Default Definition – a point at which it is determined that the customer is unable to service existing financial obligations (Basel Committee on Banking Supervision (2001a)

Risk appetite – Risk appetite is the level and type of risk a firm is able and willing to assume in its exposures and business activities, given its business objectives and obligations to stakeholders (SSG, 2010)

Signalling – an action or feature co-evolved between sender and receiver, where both benefit on average from the extent of signals (Maynard-Smith & Harper, 2003)

Screening – a situation whereby the under-informed party can induce the other party to reveal their information, (Rothschild & Stiglitz, 1976).

1.7 Assumptions

The following assumptions have been made regarding the study:

a. The study will attempt to adequately address the empirical tests for adverse selection despite there having been previous studies such as Genesove (1993), where poor evidence of adverse selection was found in the used car market. Similarly, Chiappori and Salanie (2000) found no evidence in the French motor vehicle industry.

b. That sample data will comprise all information about the customers at the time of granting the credit limit increase, supported by subsequent data that will enable ease of performance monitoring.

c. Certain customers may have more than one credit card, so risk behaviour will be assessed at account level and at customer level, where the information is available.

2 CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This section of the study reviews the defining literature on adverse selection beginning with the primary contributions done by Akerlof (1970); Spence (1973) and Rothschild and Stiglitz (1976). The study progresses to further studies developed by a generation of scholars who acknowledge the pervasive effects of adverse selection, and extended this literature to other credit markets including the credit card industry.

2.2 Background Discussion

The premise of this research is underpinned by the theory of information as set out by Akerlof's (1970) research. He developed a model to explain the concept of information asymmetry in the market for 'Lemons' by using an analogy to illustrate how used motor vehicles price new ones out of the market in the presence of asymmetric information. In this type of market, used motor vehicles are overpriced whereas new motor vehicles are under-priced. Due to the presence of information asymmetries in the industry, adverse selection may be prevalent and could potentially induce market inefficiencies (Chen, 2005).

To enrich the studies on asymmetric information, optimal contracts were first distinguished for adverse selection in researches by Spence (1973) and Rothschild and Stiglitz (1976). Using the job market, Spence (1973) showed that under circumstances of uncertainty, the better - informed party can improve their market circumstances by making their private information known to the other party. Signalling refers to a strategy that can be adopted to mitigate problems associated with adverse selection. Spence proposes that to minimize information asymmetry, one party should signal the other and adjust their purchasing behaviour. Stiglitz, however illustrated that screening can be used effectively to capture the information of the uninformed party, a study that has proven to be fundamental to modern micro economic theory.

2.3 Adverse selection in Other Credit Markets

When projecting Akerlof's (1970) example into the credit lending market, we can assume that the bank, knowing the risk profile of the potential customer, will lend at an average interest rate in line with the risk profile of all borrowers. This 'shortcoming' will however drive differing behaviour with low risk customers negating the offer as this would often be higher than their expected rate, whereas high risk customers may perceive the average to be attractive and borrow aggressively.

Within financial markets, adverse selection exists when one party to a transaction is better informed about the risks of the transaction that the other lacks, and uses the information to their advantage when negotiating the deal (Cohen & Siegelman, 2010, p.39). Ever since Akerlof's (1970) influential article, adverse selection has come to be seen as amongst the most fundamental catalysts of market failure.

Following the concept of information asymmetry or 'lemon' market, many scholars enriched the literature across several fields of human science, with credit markets being the least explored area in light of the focus of theoretical literature. Given this set back in credit markets, scholars such as Edelberg (2004) in the home mortgage and automobile loans, Adams, Einav, and Levin (2007) in credit subprime, Karlan and Zinman (2009) in personal loans, Calem, Cannon, and Nakamura, (2011) in home equity, Ahlin and Waters (2012) in group lending made several attempts to identify the impact of adverse selection on various credit market variables. Central to their studies is the use of control variables (i.e. income, risk profile) and other observable variables to test for empirical evidence of adverse selection.

2.4 Adverse selection in the Credit Card Market

Extending the role of interest rates charged by credit lenders we can replicate these studies into the credit card market, through insights into Stiglitz and Weiss' (1981) model.

When making reference to the credit card market; fixing the interest rate to reflect an average interest rate is a challenge because within banking, the interest rate plays the dual rate of determining a market clearing equilibrium and also an instrument that determines the quality of the customer, and therefore the loan portfolio (Besley 1994, p.35). In his model, Stiglitz (1981) shows the existence of interest rates at which the expected return to the bank is maximised, and defines an equilibrium which is characterised by credit rationing.

Ausubel (1999) shows clear evidence of adverse selection on observable information and hidden information, which is measured through the portfolio composition of high risk respondents and subsequent increase in delinquencies, following a credit card pre-approval solicitation.

Complimenting Ausubel's research was Argawal et al findings that high risk customers who are financially distressed have limited access to credit and are prone to accepting loans at a higher interest charge. Both researchers observe a deterioration of the customer's credit quality particularly in the high risk segments.

Other peripheral studies of adverse selection within credit cards are evident in Calem and Mester (1995), who argued that credit card borrowers with high balances but low credit risk face high switching costs, highlighting evidence of adverse selection whereby lenders lower their interest rates to aggressively compete for customers. They concluded that adverse selection arises as a consequence of these search costs and switching costs.

However**,** Crook (2002), using Calem and Mester's (1995) hypothesis, used exploratory data to assess evidence of adverse selection when the market was competitive and found no evidence that suggests that those with large balances search differently to those with lower balances. However, it was evident that those households with poor credit histories search more that those with good credit histories. This study suggested a lesser adverse selection problem.

In summary, the above researchers advocate that adverse selection in the credit card market is often driven by five key drivers; these are the risk profile of the customer, interest rates, limit assignment, search costs and switching costs (although not mutually inclusive). These variables will be explored and applied extensively in the South African context to test for corresponding patterns of behaviour observed in previous researches.

2.5 Effects of information asymmetries

Theories show that information variations and consequent credit market failures can create inefficiency at various levels of the economy. These have historically and traditionally been seen through overinvestment (De Meza & Webb, 1987 ; Bernanke & Gertler, 1990) or poverty traps (Mookherjee & Ray, 2002). Wasmer & Weil, (2004) explored the impacts of credit market failures on the economy showing that these market failures constrain the availability of credit in the market.

2.6 Testing the Credit Market failures

In this study, financial losses and adverse selection will be tested via higher default rates of high risk customers, assuming that they are susceptible to borrow at high interest charges. In Ausubel (1999), customers who displayed poor credit qualities and accepted poor offers are significantly more likely to default. This is not surprising as prior studies that have explored the concept of adverse selection in consumer credit markets focussed extensively on cases where the presence of adverse selection is explained through rampant delinquency levels. Gross and Souleles (2002) measured adverse selection through observing the performance of credit cards issued during the period 1995 through 1997.The researchers monitored delinquency levels for a gradual deterioration using the levels of credit risk indicators at the time of issuance as the benchmark.

Klonner and Rai (2005) find significant evidence through observing the difference in the delinquency rates between early and late recepients before and following a policy shock. In McIntosh and Wydick (2007) credit expansion, whereby borrowers with better credit risk qualities are offered substantial loan amounts, the effect thereof increases the default rates but does not materially affect the reduction in the portfolio default from screening and incentive effects. Agarwal, et al. (2010) also, after controlling for a cardholder's risk attributes, demographics, and economic shocks, find that that cardholders who responded to poor quality offers, had a higher probability of default.

Using a different asset market, Agarwal et al. (2006) show that for the home equity market where collateral is available, ex ante screening for adverse selection increases default risks post the take up by 4 percent, with increased profits as a result of higher interest rates offsetting default levels.

The above illustrate that poor containment of adverse selection can result in adverse financial performance, particularly dependent on the prior screening performed to mitigate the risks, and the type of loan offered (secured or unsecured).

2.7 Mitigating adverse selection

To mitigate the adverse consequences of adverse selection, Akerlof (1970) proposed possible market solutions, such as warranties and guarantees, whereby the risk would be diversified between the two parties. Spence (1973) suggested signalling, Rothschild and Stiglitz (1976) recommended screening, Bester (1985) collateral requirements, and Besanko and Thakor (1987) recommended consigners as collateral.

To counter adverse selection, Jappelli and Pagano (1994) suggested credit registers to proactively manage the lending of loans to safe borrowers who had been priced out of the market, resulting in higher aggregate lending. McIntosh and Wydick (2007), through the use of bureau information in the screening process, contain the risks of adverse selection. Lastly, in an attempt to alleviate the origination of lower quality borrowers based on information asymmetries,Berndt and Gupta (2009) recommend additional regulations on the sale of loans, transparency in disclosure, and a loan clearinghouse as proactive techniques.

2.8 South African Context

Evidence of research into information asymmetries in the South African market can be traced in the low income loans (Ebert, 2001), agricultural commodities (Mashamaite & Moholwa, 2005), township property market (Motau, 2006); micro lending markets (Karlan & Zinman, 2009) and microfinance (Batabyal & Beladi, 2010) etc. Despite credit card markets being studied in the United States, Chinese markets and Italian markets, there is little evidence of studies related to the Credit Card market in South Africa.

2.9 Conclusion of Literature Review

A number of broad themes are evident in the review of adverse selection within a banking sector. Firstly, the relationship between credit lending (i.e. customer credit risk, interest rates, credit limits, switching costs and search costs) and adverse selection is conspicuous. Secondly, the dire consequences of adverse selection such as under-investment, over-investments, poverty traps, continue to threaten the financial stability within financial markets. Thirdly, the existence and availability of adverse selection - mitigating strategies and techniques are designed to curb banking financial exposures with the ultimate being to achieve information efficiency, because each type of information asymmetry induces market inefficiencies.

3 CHAPTER 3: RESEARCH PROPOSITION

To gain insight into the research problem being investigated, Ausubel (1999) illustrates the auction model as a useful conceptual framework for thinking about credit cards solicitations. This auction model of credit cards adopts the auction theory where the offer is seen as a sealed-bid auction, with the issuers assuming the roles of bidders, and the consumer assuming the role of auctioneers. This paper adopts a similar approach that allows for the theoretical prediction concerning adverse selection by using existing customer's responses to credit limit increase solicitations.

Proposition 1 (The Winner's Curse)

Existing credit card customers who display higher risk characteristics and utilisation are likely to respond to credit card limit increase solicitations.

Proposition 2 (Default)

Existing credit card customers who respond to credit card solicitations have a higher probability of default.

In essence, winning the auction presents bad 'news', the expected probability of default conditional on any solicitation being accepted, exceeds the unconditional expected probability of default. Based on the auction model, the lender should therefore increase the probability that he assigns to the customer defaulting.

To test the above propositions, the following hypotheses are tested:

3.1.1 *Hypothesis 1 (Observable information) - Proposition 1*

H1: There is a significant difference in the risk profile characteristics of non responders and responders to credit card solicitation.

3.1.2 *Hypothesis 2 (Observable information) – Proposition 2*

H2: There are immediate credit quality changes that are observable after the customer has accepted the credit limit increase offer.

3.1.3 *Hypothesis 3 (Hidden Information) – Proposition 2*

H3: The cardholder defaults as a consequence of a solicitation offer type indicator after controlling the consumer's demographic characteristics, the risk attributes observed by the lender at the time the card was issued.

4 CHAPTER 4: RESEARCH METHODOLOGY

The purpose of this section is to introduce the research strategy, practical techniques that will be applied and present the assumptions underpinning this research that will test the research hypothesis. Furthermore, it defines the scope and the research design and positions this specific research amongst existing research within the credit cards markets.

4.1 Research methodology / paradigm

Due to its reliance on numerical data (Charles & Mertler, 2002) the study applies a quantitative research design to quantify a comprehensive analysis that facilitates in determining the existence of adverse selection with the credit card market. In this process, variables will be isolated and causally related to determine the magnitude and the frequency of relationships.

Additionally, a deductive approach theory is considered in order to work out hypotheses, thus rejecting or accepting the hypotheses (Ghauri, 2005). This deductive approach will be instrumental in testing for the 3 hypotheses, as it allows for the use of statistical tools when analysing the data (i.e. testing measures of central tendency, standard deviations, etc.) Furthermore, to test for the hypothesis, t tests will be used.

4.2 Research Design

Bryman and Bell (2005) describe the purpose of a research design as being to provide a framework for the collection and analysis of data. The design selected is an Econometric methodology which is defined as the interaction of economic theory, observed data, and statistical methods to quantify relationships and apply the resulting outcomes appropriately (Verbeek, 2008, p 2).

Evidence of the Econometric studies are seen in the insurance industry (Abbring, Heckman, Chiappori, & Pinquet, 2003) where dynamic data is used to test adverse selection and Finkelstein and Poterba (2006) where a positive correlation test involves estimating two reduced-form econometric models and Sugawara and Omori (2013) where an econometric methodology is proposed to analyse selection problems in insurance.

Unlike natural sciences, certain features of economic data and economic systems which are used in econometrics unavoidably impose some limitations. According to Hong (2006):

- Firstly, as a simplification of reality, economic theory is critical in capturing the main factors, however observed data is an outcome of a myriad of factors, and some of them are unknown and unaccounted for.
- Secondly, an economy cannot be reversed nor repeated so the economic relationships change overtime (i.e. data observed are a single realization of economic variable).
- Lastly, data may be a challenge, as some of the economic variables are inherently immeasurable (i.e. correct customer base household expenses)

However, the Econometrics approach is appropriate for this research as it encapsulates time-series data against the Auction Model of Credit card to test the economic theory of adverse selection (which is presumed to lead to credit rationing) through postulating relationships amongst the dependent and independent variables.

4.3 Research Population

4.3.1 *Population*

Brown (2006, p. 24), defines a population as "the entire group of people that a particular study is interested in." The study's population comprises a potential 1.9 million South African credit active Retail Credit card customers at a specific bank that are eligible for a credit limit increase over the lifetime of their credit card.

This customer database consists of time series data (continuous) that can be classified further into categorical and numerical variables. Within the categorical variables, there is nominal data (i.e. 'gender'), and ordinal data (i.e. delinquency code). Additionally, the numerical variables are classified into discrete variables (i.e. customer age) and continuous data (i.e. account balances).

At each observation (account level), the data can be sub-categorised into; customer demographics, affordability information, customer risk behaviour information, customer performance information, product information, pricing information and marketing information (i.e. credit limit increases information).To maintain the validity, reliability and accuracy of the population, new account information is appended on a monthly basis whereas obsolete and redundant information is archived.

From the 1.9m customers, the bank solicits on average 600 000 customers for a credit limit increase annually (estimate of 40 000 - 60 000 monthly) based on their credit risk behaviour, a strategy that has been adopted to increase revenue and strengthen customer retention since 2005.

4.3.2 *Research population*

The customer information in the database is updated monthly with a series of credit limit increases in instances whereby credit limit increases have been advanced (averaging 40 000 – 60 000 targeted leads per month). Key to determining the population that would be representative of these campaigns as well as test the hypothesis is identifying a population that:

- Represents the *consistency of credit rules* applied in soliciting customers for a credit limit increase from the inception of the campaigns, yet encompassing the most recently applied rules.
- Significant in size to *differentiate between bad and good performing accounts* (estimation of the bad rate)
- Meets the championed *response rate of 20%-30%,* to allow for post take up performance.
- Represents the *most recent performance with the 18 month outcome window falling within recent times*, creating relevance.
- Allows for practical data processing

For this research, the January 2011 campaign data with 40 000 leads and having the August 2013 month representing the most recent performance month is the most suitable population.

4.4 The research instrument

The study will use secondary data, whose primary data collection instrument was an application form (see Appendix A) which captures customer demographics, affordability information, product information, marketing consent information.

For credit limit increases (see Appendix B), a telephonic conversation is held with the potential customer where affordability information and consent to credit limit increase is confirmed.

4.5 Procedure for data collection

Collaboration was established with the bank's credit card department and the management information team to supply secondary data. Secondary data is defined as data collected by others, not specifically for the research question at hand (Stewart, 1984; Frankfort-Nachmias & Nachmias, 1992). The use of secondary data allows access to a large scale of data and allows the researcher to leverage on good technical skills that lead to data of high quality.

4.5.1 *The Application form – Appendix A*

The initial internal data collection touch point with all customers is through an application form which gathers customer demographics and affordability information. This data is stored in the data warehouse, where it is complimented by dynamic risk behaviour associated with each customer as the customer utilises the credit card on a monthly basis. This data is further merged against external credit bureau information (used uniformly by all South African financial institutions as the custodian of credit information) on a monthly basis allowing for a dynamic update of the overall customer credit behaviour.

4.5.2 *Routine Marketing Campaigns – Appendix B*

a) Purpose:

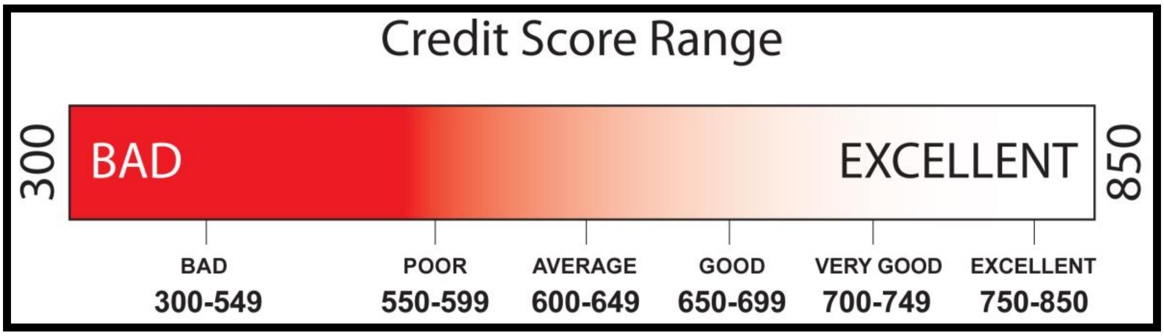
As part of routine marketing campaigns, the lender conducts large scale randomised trials of pre-approved credit limit increases to existing customers. These campaigns, in the form of credit limit increase invitations, are performed on a monthly basis designed to grow revenue and acquire annual automatic limit increases consent from customers. They are generated by targeting prime borrowers who have relatively good behaviour scores, credit bureau scores and transact within the agreed contractual terms.

For the customers to qualify for the campaign, the solicited accounts are required to meet the following criteria:

b) Existing Bank Customer:

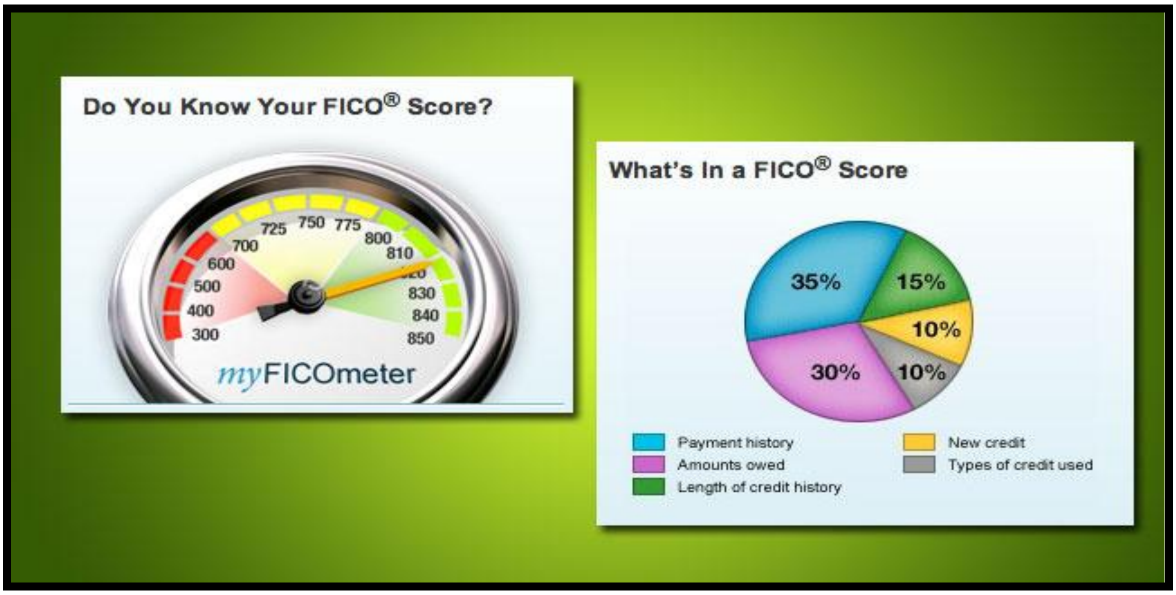
The customer ought to have a pre-existing credit card contractual agreement with an existing credit limit and need to have been active for a recommended period of time.

c) Above average credit bureau score



The credit score is a number assigned to you by external independent credit bureaus that determines your "creditworthiness" and influences the rates you get for mortgages, auto loans, and credit card terms.The recommended score should lie above 600.

d) Satisfactory Behaviour Score (FICO)



The behavioural score is a unique internal score calculated by the lender using the payment history, outstanding balances, new credit requests and length of credit history.These scores are used collectively to strengthen the lender's screening ability in discriminating between good and bad performing accounts going into the future. The cut off scores (decision to accept or reject credit limit increase) are predetermined by the screening models, together with adjustments based on business intuition (i.e. business risk appetite).

e) Size:

Offers of average 40 000 leads per month, across all product types (Silver, Gold, Platinum)

f) Expected Response Rate

Based on historical benchmark (20 – 30%) and expected return (Return on Equity) of 25%.

g) Pricing:

The pricing on the offers is based on risk, whereas the offered limit is based on affordability. The new limit is priced on the existing risk based pricing terms.

h) Duration:

Credit limit offers are valid for 6 to 8 weeks provided the customer's risk status and affordability does not deteriorate within the interval.

i) Medium of access:

The campaigns are submitted to an outbound contact centre to establish telephonic contact with the customer proactively selling the credit limit increase.

j) Data preservation:

The updated data is captured on the mainframe system, whereby updated information is stored in the data warehouse on a monthly basis.

4.6 Data processing, analysis and interpretation

4.6.1 *Data Processing:*

This section discusses the statistical methods that were used to analyse data in order to test each one of the hypotheses. The 40 000 January 2011 campaign leads were sourced from the Credit card Division in Microsoft Excel format and exported into SAS (Statistical Analysis Software) for processing and analysis.

This campaign data which consist of customer demographic variables(i.e. name, surname, address, language, current limit and recommended limit increase (risk limit)), was merged against the data warehouse customer data which has performance data (i.e. behaviour score, credit bureau score) and product information data (i.e. total current limit, debit interest rates) already in SAS format, using a unique account identifier , account key match variable, to obtain the full credit limit associated variables that will enable further analysis (see Appendix C, Databases)

Table 1: January 2013 Campaign leads Waterfall

January 2013 leads Waterfall - (09 January 2011 & 23 January 2013)			
Description	*Number*	*Variable Applied*	*% removed*
Number of leads received	40,000		
Duplications	-196	acc key match	-0.5%
	39,804		
Mismatch to the data warehouse	-305	acc key match	-0.8%
	39,499		
Limit increase could not be granted	-16	Current limit >= risk limit	0.0%
Total Research leads	***39,483***		***-1.3%***

4.6.2 *Data Analysis:*

a) The Model

Multiple Logistic Regressions will be performed to predict the bad rate within intermittent time frames, by looking at a series of predictor variables.

1. Regression 1 - Dependent variable = bad rate (bad at month 12), modelling for bad at month 12 =1.

2. Regression 2: Dependent variable = bad rate (bad at month 18), modelling for bad at month 18 = 1

A Logistic Regression is performed to predict the default at 12 months and 18 months post the limit increase based on multiple predictor variables. The independent variables used are: Credit Bureau Score, Behaviour Score, Purchase Limit Amount, Delinquent cycles count, Debit interest rate, Income Group code, customer behaviour score, utilisation, month on book, take up limit, limit increase indicator, Purchase limit amount log, month on book (sq) and take up log.

To test for the predictive power of the independent variables, various models will be designed. The variations in the models will be distinguished through their ability to yield a higher R squared, a higher Percent Concordant and where Multicollinearity is minimised. These predictor variables will be used to test for Demographics, Non Respondents and Respondents, and Default.

b) Demographics

Descriptive data is used to describe and analyse the campaigns. The campaign data is summarised using percentage groupings of each one of the credit risk related variables (see Appendix D, Grouping methodology)

To understand the campaign target market, a ***distributions analysis*** is performed on the following demographics: utilisation, month on book, card behaviour score, customer behaviour score, credit bureau score, debit balances, credit balances, limit, minimum limit and maximum limit.

c) **H1: Difference in the risk profile characteristics between Responders and Non Responders - (Winner's Curse)**

Following Ausubel (1999) and Agarwal et al (2010)'s previous studies on adverse selection, the absence of adverse selection results when there is no difference in the risk characteristics between the Respondents and Non Respondents.

To differentiate between Respondents and Non Respondents, a unique identifier (categorical variable = take-up) is derived. This variable is derived from testing for an increase in the movement of the existing current limit to the risk limit (campaign offered limit) in the January 2011 and February 2011 months.

To test for the difference in the statistical behaviour and whether the scores differ across a single variable of the Respondents and the Non Respondents, the ***Welch-Satterthwaite t-test*** is used to compare two distinct groups where the assumption of equal variances is not made.

The t- tests are performed on the 7 credit risk related numerical variables which are outputs from the Logistic Regression model (i.e. behaviour score, credit bureau score, number of cards, highest limit on bank cards, combined revolving limits, account age and utilization rate) to test whether these variables yield the rejection or the acceptance of equality.

d) H2: Observable credit quality changes after the customer has accepted the credit limit increase offer.

When assessing for observable credit quality changes, the Respondents and Non Respondents data is tracked over a 6 months, 12 months and 18 months performance window post the acceptance of the credit limit increase. The analysis looks at the point in time performance to assess a periodic change in the customer's ability to repay the new loan amount as well as to test for any additional debt burden that may be induced not only by the credit limit increase but also by economic distress.

The monitoring looks at the deterioration in performance of dynamic credit risk variables that are updated in the data warehouse on a monthly basis. The 4 variables include utilization rate, the credit bureau score, the card behaviour score and the customer behaviour score.

Similarly ***t tests*** are performed on the 4 variables (outputs from the Logistic regression) to test for the difference in scores over time across similar variables.

e) H3: The cardholder defaults as a consequence of a solicitation

To determine whether adverse selection can be decomposed into observable and hidden information, 3 default measures are monitored. This section focuses on the performance of 3 variables that indicate the customer's inability to sustain the repayment of ongoing debt (i.e. number of delinquent accounts, number of accounts charged off and number of bad accounts). The performance of these variables is monitored over 6 months, 12 months and 18 months across the Respondents and Non Respondents populations.

Again, ***t tests*** are performed on the 3 variables (from the Logistic Regression) and comparisons across Respondents and Non Respondents are measured.

4.7 Limitations of the study

The study uses selected data from a single large financial institution as a basis of the empirical research. However, this institution represents a typical South African bank within the South African economy which offers customers a myriad credit related solutions. As one of the major banks in South Africa, the bank's credit scoring and screening techniques are representative of the typical processes and methodologies followed by other banks. Despite these similarities, it remains important to understand that banks are governed by varying risk appetites which inform the degree of risk the banks are willing to accept. These diverging risk appetites need to be considered when applying the study to other banks as this will have an impact on the degree of adverse selection witnessed when doing comparative studies.

4.8 Validity and reliability

Reliability and validity could be seen as two different measurement instruments that illustrate the level of trustworthiness and credibility of a research. Bryman and Bell (2007) explain that reliability and validity are separated into internal and external concepts.

4.8.1 *External validity*

Although the credit card product offerings (interest rates and incentives) may vary across various banks, the generic use of the product by consumers allows for uniformity of offer across the banks.

The variables used in the research are generic variables with generic descriptions across the South African banks (i.e. delinquency, term, interest etc).This uniformity across these South African bank's measures allows the researcher to make connections between the data and the hypotheses that are being observed. Other South African banks, considering examining the existence of adverse selection in the solicitation of their credit products, can draw from this study.

4.8.2 *Internal validity*

Internal validity refers to what degree the researchers are able to agree and come to the same conclusions i.e. if there is a good match between their observations and theoretical thoughts that they expand throughout the research (Bryman & Bell, 2007). The bank's internal behavioural data and the external data from the credit bureaus are compiled on a monthly basis using consistent and uniform standards.

4.8.3 *Reliability*

Reliability in the context of a quantitative research is defined by Joppe (2002, p. 1) as "the extent to which results are consistent over time and an accurate representation of the total population under study is referred to as reliability and if the results of a study can be reproduced under a similar methodology, then the research instrument is considered to be reliable."

The bank's data is managed by a central Information Management team who test the data for uniformity, consistency and stability in the definition and the categorization of variables. Control measures such as checking the account number for uniqueness, ensuring that the number of record corresponds to those of the primary data source, understanding the month on month difference in number of records, etc., are closely managed. These measures of checking the data are repeated through several reiterations (1st, 2nd and 3rd) to test the stability of the data overtime. To test for the completeness of the data, these Management Information database variables are reconciled to the preceding data sources such as Enterprise data warehouse, Customer Information files, financial reporting files and the Product house systems.

Moreover, the primary data collection entry points (branches and the contact centres) are governed by Service level agreements which standardise and formalise the quality at which data is acquired.

5 CHAPTER 5: PRESENTATION OF RESULTS

The empirical results of the campaign analysis are presented in this chapter. This chapter commences by confirming the predictor variables from the Logistic Regression Model and uses the output for further analysis. Succeeding sections: 5.2, 5.3, 5.4 and 5.6 focus on the statistical analysis that tests for the presence of adverse selection.

5.1 The Model

To test for the predictive power of the independent variables in defining the dependent variable (12 and 18 months default) a Logistic Regression was performed. To test for the best fitting R Squared, Percentage Concordant and elimination of multicollinearity, and whether coefficients were highly significant, 13 models were designed.

The model selected for the **12 months** bad rate prediction is the **7 Factor Model 1** (illustrated in Table 2).

The model selected for the **18 months** bad rate prediction is the **7 Factor Model 1** (illustrated in Table 3)

The following Hypothesis was completed at a **5%** significance interval:

> H_o: The is no relationship between the dependent variables and the independent variables
>
> H_a: The is a relationship between the dependent variables and the independent variables

When testing for the independent variables to define the dependent variables (12 months and 18 months bad rate), the null hypothesis can be rejected as all variables are statistically significant at the 5% level.

Table 2: Logistic Regression 12 Months: Analysis of Maximum Likelihood Estimates

Parameter	Df	Est	Std Error	Wald Chi Squared	Pr>ChiSq
Intercept	1	2.1230	1.8854	1.2680	0.2601
Credit Bureau Score	1	-0.00966	0.00158	37.6015	<.0001
Behaviour Score	1	-0.0141	0.00206	47.0186	<.0001
Delinquent Cycles Co	1	0.8409	0.1916	19.2663	<.0001
Debit Interest Rate	1	0.2714	0.0370	53.7526	<.0001
Customer Behaviour Score	1	-0.00192	0.000527	13.3472	0.0003
Utilisation	1	2.0464	0.3494	34.3057	<.0001
Purchase limit Amount	1	0.5120	0.0914	31.3860	<.0001

R-Square 0.1317: Percent Concordant 75.6

- *Credit bureau score* - as the credit bureau score decreases, the bad rate increases (negative relationship)
- *Behavioural Score* - as the behavioural score decreases, the bad rate increases (negative relationship)
- *Delinquency cycles co* - as the delinquency cycles increases, the bad rate increases (positive relationship)

- *Debit interest rate -* as the delinquency cycles co increase, the bad rate increases (positive relationship)

- *Customer Behaviour Score* – as the customer behaviour score decreases, the bad rate increases (negative relationship)

- *Utilisation* - as the utilisation increases, the bad rate increases (positive relationship)

- *Purchase Limit Amount* as the purchase limit amount increases, the bad rate increases *(*positive relationship)

The model reports an R Squared (0.1317), Percentage Concordant (75.6) where multicollinearity has been eliminated. The null hypothesis can be rejected as all the variables are statistically significant at the 5% level

Table 3: Logistic Regression 18 Months: Analysis of Maximum Likelihood Estimates

Parameter	Df	Est	Std Error	Wald Chi Squared	Pr>ChiSq
Intercept	1	2.5717	1.5430	2.7776	0.0956
Credit Bureau Score	1	-0.00698	0.00122	32.6989	<.0001
Behaviour Score	1	-0.0125	0.00166	57.1153	<.0001
Delinquent Cycles Co	1	0.4760	0.1723	7.6341	0.0057
Debit Interest Rate	1	0.1975	0.0300	43.2959	<.0001

Customer Behaviour Score	1	-0.00210	0.000425	24.4058	<.0001
Utilisation	1	2.0872	0.2631	62.9488	<.0001
Purchase limit Amount	1	0.3878	0.0712	29.6454	<.0001

R-Square 0.1047: Percent Concordant 72.3

- *Credit bureau score* - as the credit bureau score decreases, the bad rate increases (negative relationship)
- *Behavioural Score* - as the behavioural score decreases, the bad rate increases (negative relationship)
- *Delinquency cycles co* - as the delinquency cycles increase, the bad rate increases *(* positive relationship)
- *Debit interest rate* - as the delinquency cycles co increase, the bad rate increases (positive relationship)
- *Customer Behaviour Score* – as the customer behaviour score decreases, the bad rate increases (negative relationship)
- *Utilisation* - as the utilisation increases the bad rate increases (positive relationship)
- *Purchase Limit Amount* as the purchase limit amount increases, the bad rate increases *(*positive relationship)

The selected model reports an R Squared (0.1047), Percentage Concordant (72.3) and multicollinearity has been eliminated. The null hypothesis can be rejected as all variables are statistically significant at the 5% level.

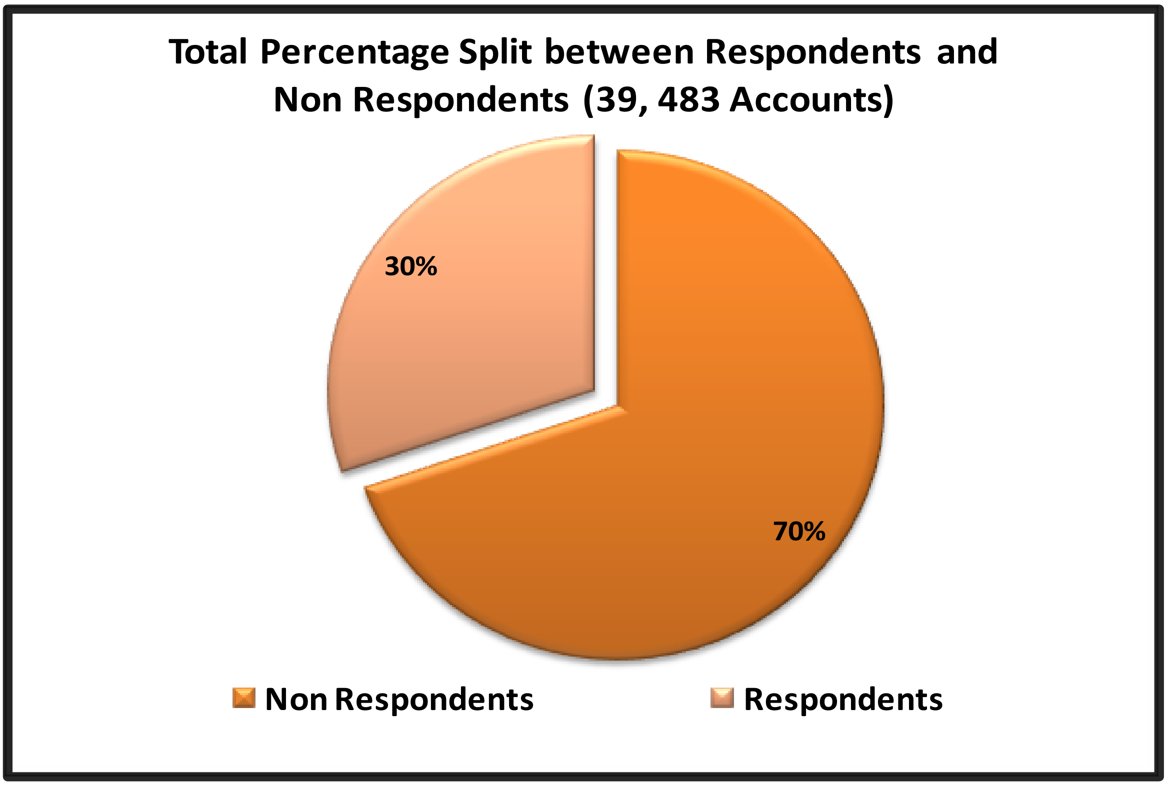
5.2 Demographics

The purpose of this section is to describe the campaign demographics. The data descriptions for utilization, month on book, card behaviour score, customer behaviour score, account debit balance, limit, minimum limit and maximum limit are continuous variables. The data variables are scaled with equal differences between the ranges, consistent with lender's business reports monitoring groupings that guide key strategic decisions. (Appendix D, Grouping methodology)

a) Respondents vs. Non Respondents

Figure 1 provides a view of the Respondents (taken up) and Non Respondents of the population.

Figure 1: Percentage split of the Respondents and Non Respondents

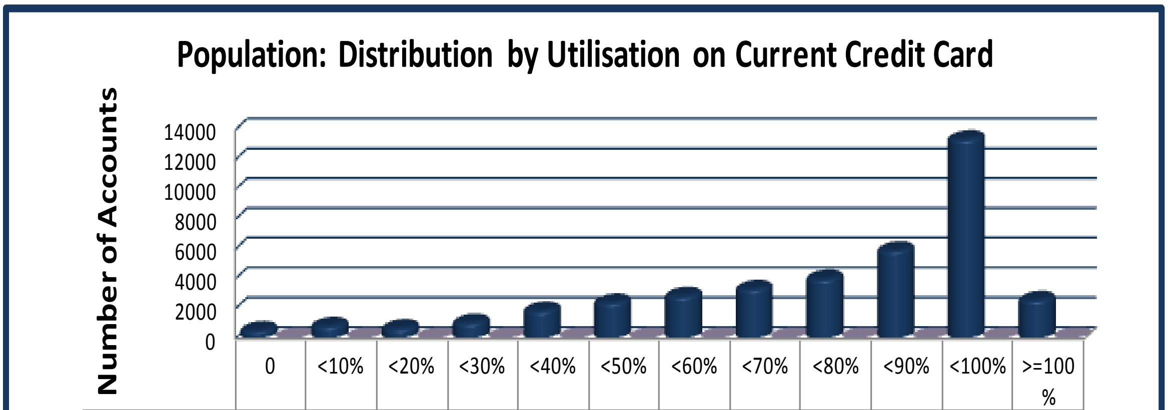


Respondents are customers who have accepted the lender's offer to increase their current credit limit. Conversely, Non Respondents are customers who have deferred the acceptance of the limit offer to a future period or have declined the offer. The Respondents yielded a 30% take up rate, consistent with the lender's expectations.

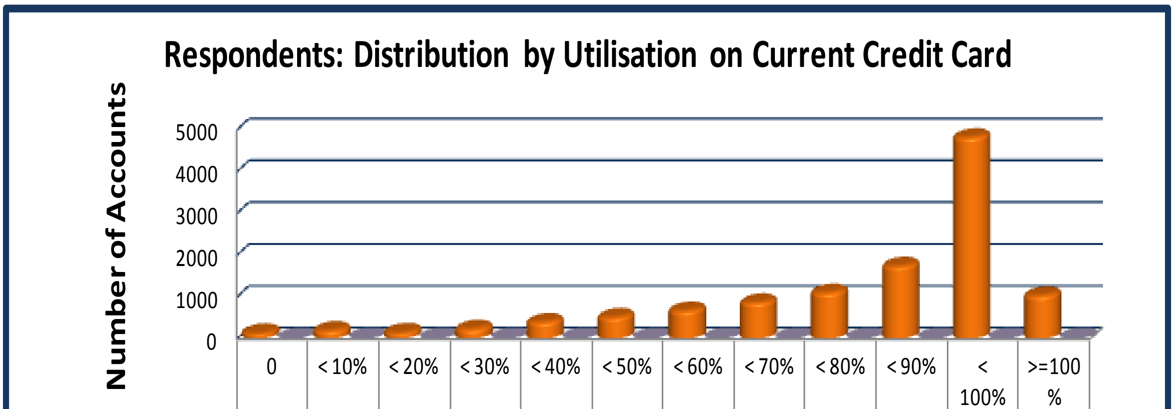
b) Utilisation on existing credit card

Figure 2 provides a view of the utilisation breakdown of the population

Figure 2: Distribution of Utilisation (Existing Account)



	0	<10%	<20%	<30%	<40%	<50%	<60%	<70%	<80%	<90%	<100%	>=100 %
No of Accounts	544	849	692	1067	1863	2407	2853	3328	4010	5912	13376	2582
% Distribution	1.38%	2.15%	1.75%	2.70%	4.72%	6.10%	7.23%	8.43%	10.16%	14.97%	33.88%	6.54%



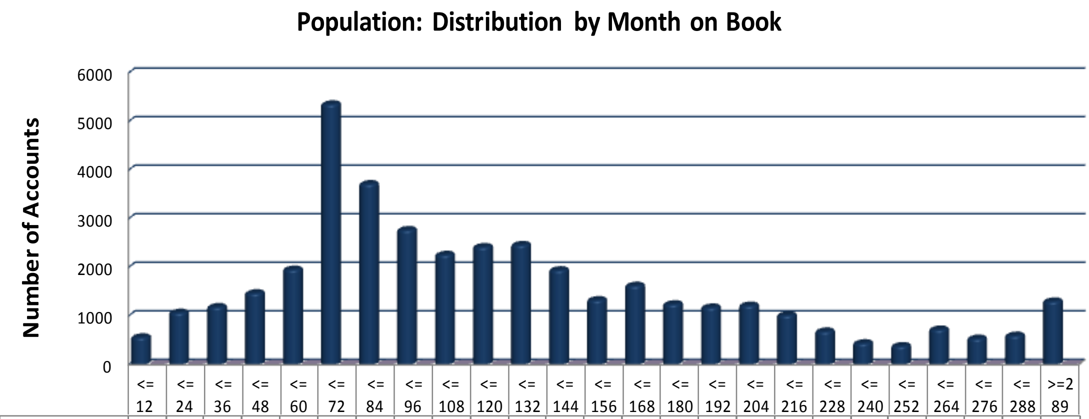
	0	< 10%	< 20%	< 30%	< 40%	< 50%	< 60%	< 70%	< 80%	< 90%	< 100%	>=100 %
No of Accounts	141	203	153	240	402	522	677	871	1108	1745	4825	1041
% Distribution	1.18%	1.70%	1.28%	2.01%	3.37%	4.38%	5.68%	7.30%	9.29%	14.63%	40.45%	8.73%

The utilisation percentage is the amount of all outstanding balances divided by the sum of each credit card limit. The total population indicates that 40.42% of the accounts solicited for the campaign were already over a 90% utilisation rate whereas 49.18% of the respondent population was over 90% utilised - a notable increase of 22.67% in the respondent population. In soliciting the eligible accounts, the lender focussed on accounts that were highly utilised with the highest distribution above the 80% mark utilisation. This is further reinforced in the Respondents population.

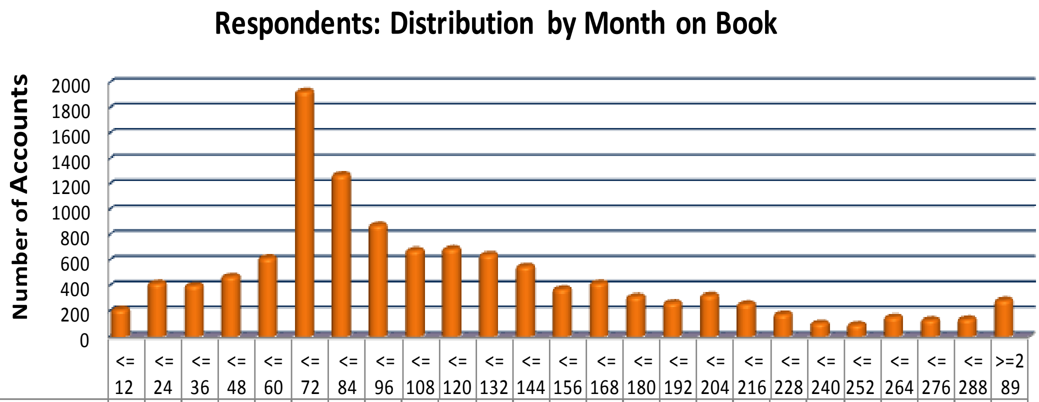
c) Month On Book (Account Age)

Figure 3 provides a view of the month on book breakdown of the population

Figure 3: Distribution of Months on Book



	<= 12	<= 24	<= 36	<= 48	<= 60	<= 72	<= 84	<= 96	<= 108	<= 120	<= 132	<= 144	<= 156	<= 168	<= 180	<= 192	<= 204	<= 216	<= 228	<= 240	<= 252	<= 264	<= 276	<= 288	>=2 89
No of Accounts	564	1071	1188	1472	1958	5360	3718	2773	2262	2423	2464	1946	1329	1626	1245	1178	1217	1018	685	442	383	723	537	598	1303
% Distribution	1.43	2.71	3.01	3.73	4.96	13.5	9.42	7.02	5.73	6.14	6.24	4.93	3.37	4.12	3.15	2.98	3.08	2.58	1.73	1.12	0.97	1.83	1.36	1.51	3.30



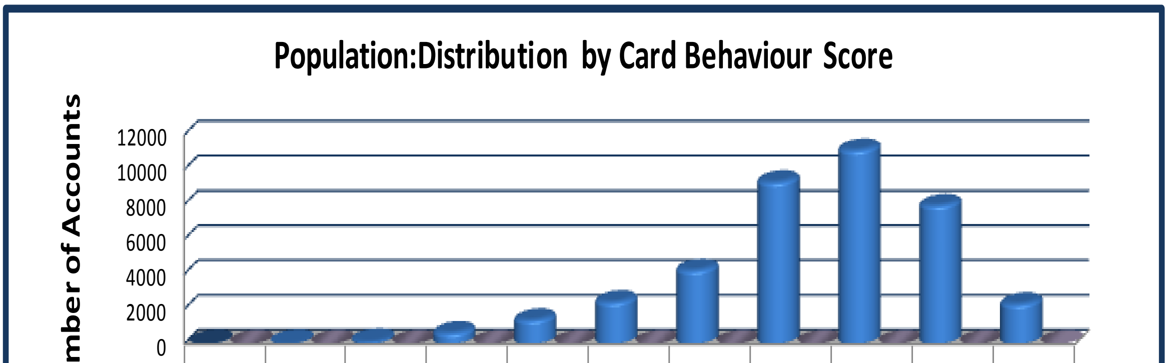
	<= 12	<= 24	<= 36	<= 48	<= 60	<= 72	<= 84	<= 96	<= 108	<= 120	<= 132	<= 144	<= 156	<= 168	<= 180	<= 192	<= 204	<= 216	<= 228	<= 240	<= 252	<= 264	<= 276	<= 288	>=2 89
No of Accounts	218	424	407	478	624	1937	1278	882	683	695	649	557	379	425	319	270	328	261	181	109	97	158	136	143	290
% Distribution	1.83	3.55	3.41	4.01	5.23	16.2	10.7	7.39	5.73	5.83	5.44	4.67	3.18	3.56	2.67	2.26	2.75	2.19	1.52	0.91	0.81	1.32	1.14	1.20	2.43

The month on book (average age) measures the amount of time the account has been open in months. Below the month on books of less than 120 (5 years), the percentage distribution is consistently higher for respondents than it is for the total population. For the total population, 42.28 % falls above 120 months whereas for the respondent's population, 36.07% falls above 120 months. The campaign highest month on book distributions were seen in accounts greater than falling in between 72 and 96 months in both populations.

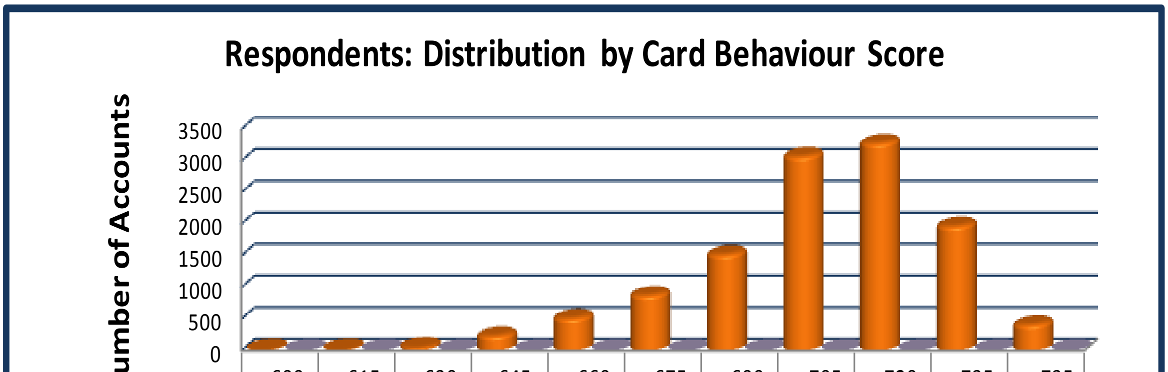
c) Card Behaviour Score

Figure 4 provides a view the behaviour score distribution of the population

Figure 4: Distribution of Behaviour Score



	<600	<615	<630	<645	<660	<675	<690	<705	<720	<735	>=735
Series1	19	38	147	627	1377	2412	4221	9293	11114	7944	2291
Series2	0.05%	0.10%	0.37%	1.59%	3.49%	6.11%	10.69%	23.54%	28.15%	20.12%	5.80%



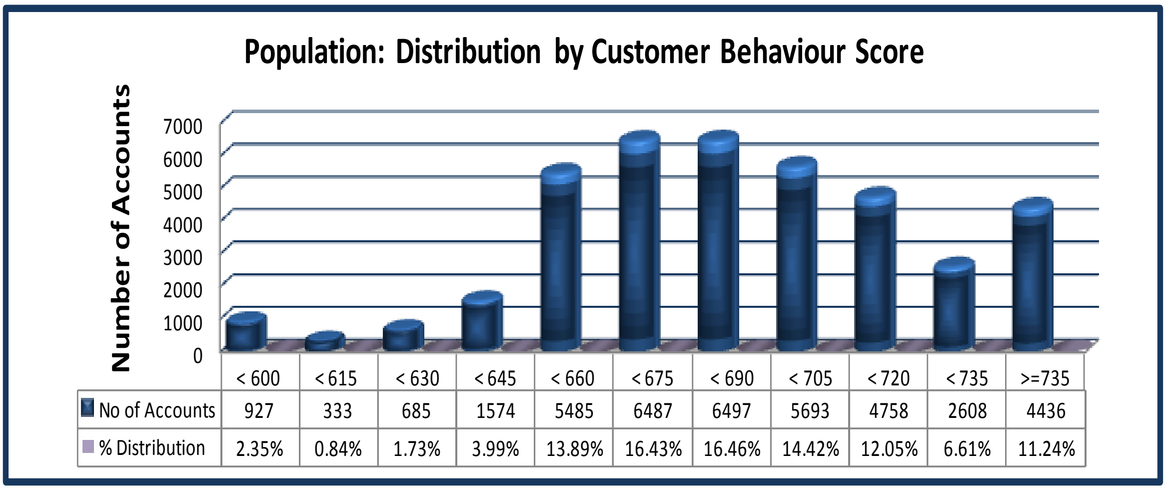
	<600	<615	<630	<645	<660	<675	<690	<705	<720	<735	>=735
No of Accounts	10	12	51	234	511	872	1518	3071	3276	1964	409
% Distribution	0.08%	0.10%	0.43%	1.96%	4.28%	7.31%	12.73%	25.75%	27.46%	16.47%	3.43%

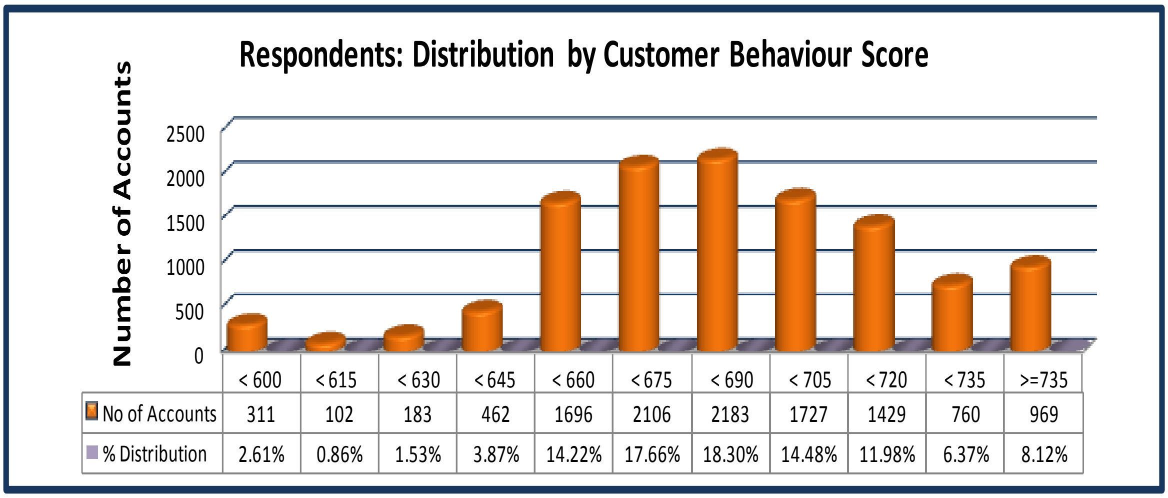
The card behaviour is a monthly measure of the credit performance specific to the repayment of the credit card account only. This credit performance includes the ability to honour repayments timeously and managing the card credit limit within the contractual agreement. Above the score of 705, the respondent population displays a distribution consistently lower than the total population. Of the 19 accounts that were solicited with a score below 600 (lowest score ranges), over 50% of the respondents accepted the offer which is inconsistent and much higher than the 30% campaign take up rate.

d) Customer Behaviour Score

Figure 5 provides a view the Customer behaviour score distribution of the population

Figure 5: Distribution of Customer Behaviour Score



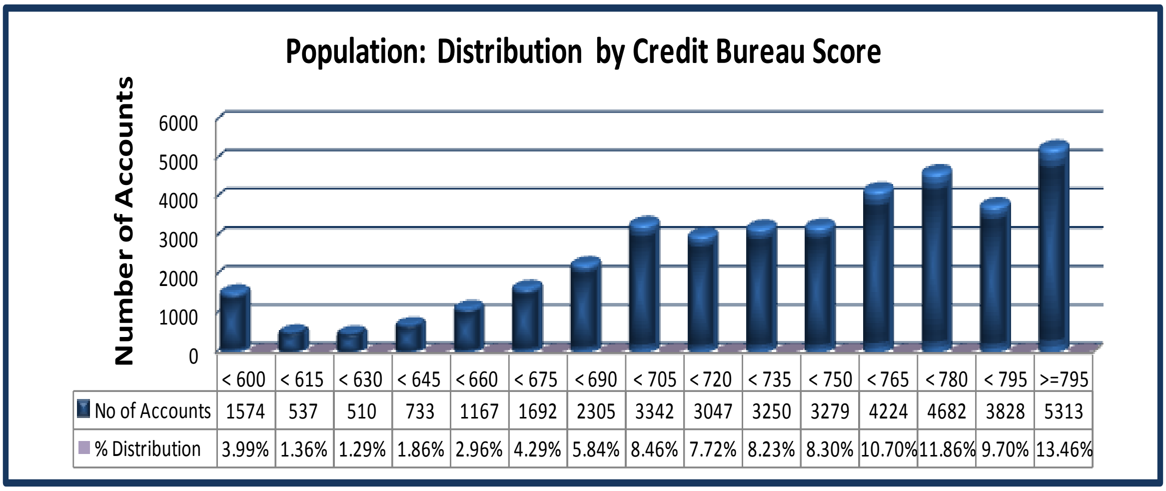


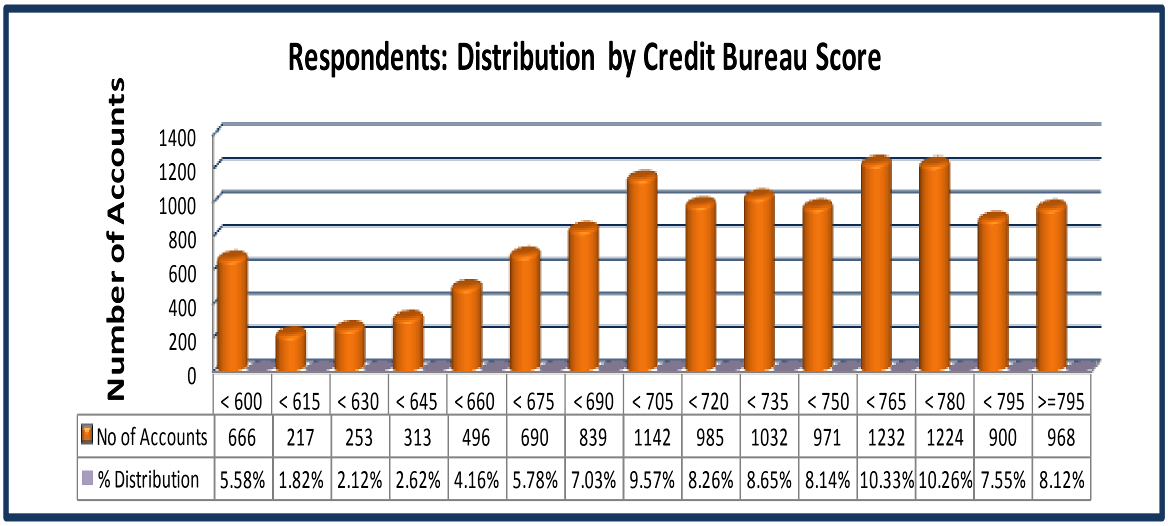
The customer behaviour score is an internal credit risk score that aggregates the credit performance of all risk products (i.e. Mortgage loan, Vehicle asset, Personal loans, etc.). This score aggregates delinquency levels, utilisation levels across multiple bank products. A similar pattern to the card behaviour score is witnessed whereby the respondents distribution remains lower to the total population above the 705 score.

e) Credit Bureau Score

Figure 6 provides a view the Credit Bureau Score distribution of the population

Figure 6: Distribution of Credit Bureau Score



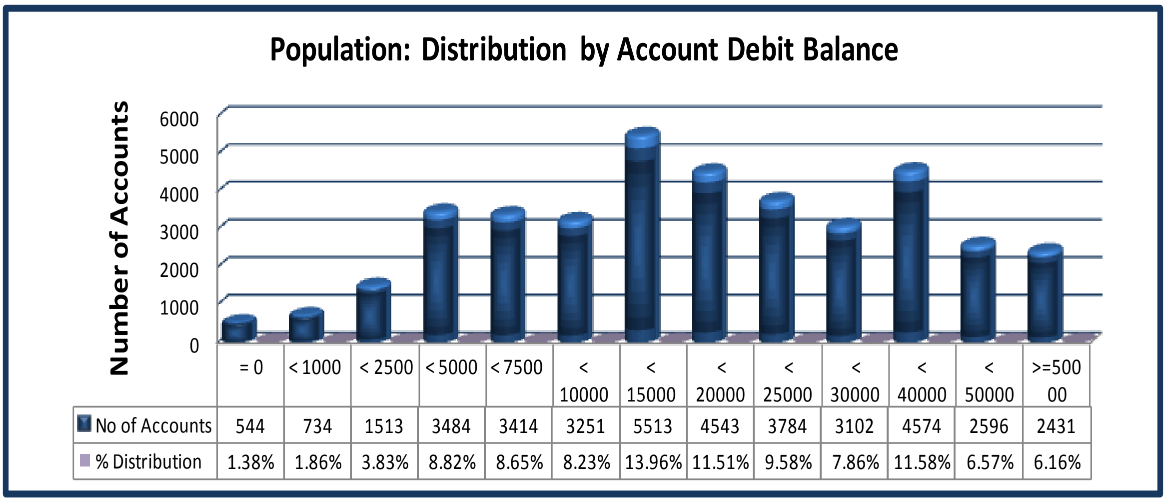


The credit bureau score incorporates the credit risk performance of all lending products. These include products offered by the lender, and all other credit providers. Below the score of 735 (poor and good scores) the credit bureau percentage distribution is consistently higher for the respondent population, whereas above the 735 score (exceptional), the total population reports a higher distribution.

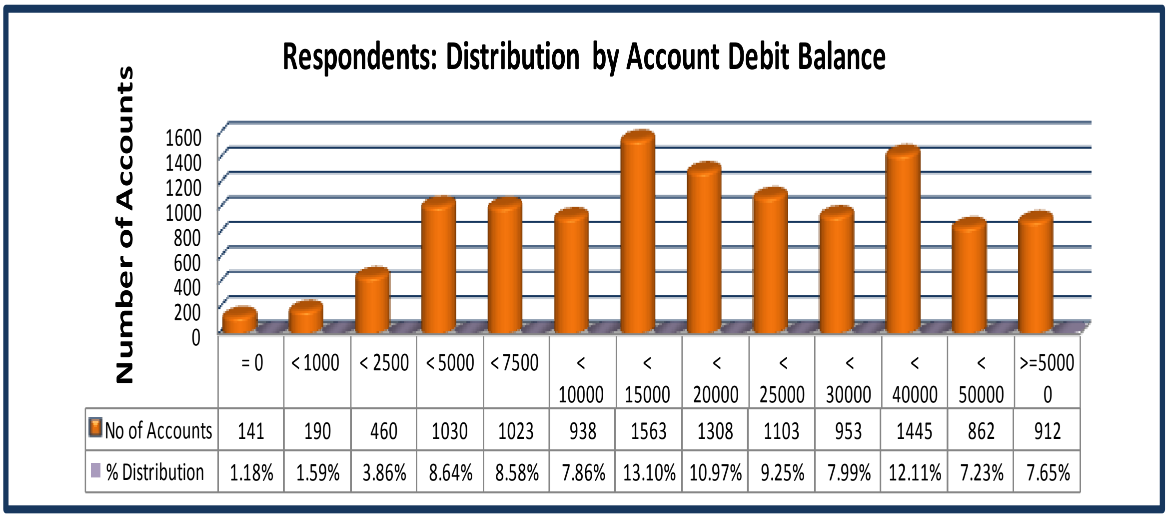
f) Account Debit Balance

Figure 7 provides a view of the Account Debit Balance distribution of the population

Figure 7: Distribution of Account Debit Balance



	= 0	< 1000	< 2500	< 5000	< 7500	< 10000	< 15000	< 20000	< 25000	< 30000	< 40000	< 50000	>=50000
No of Accounts	544	734	1513	3484	3414	3251	5513	4543	3784	3102	4574	2596	2431
% Distribution	1.38%	1.86%	3.83%	8.82%	8.65%	8.23%	13.96%	11.51%	9.58%	7.86%	11.58%	6.57%	6.16%



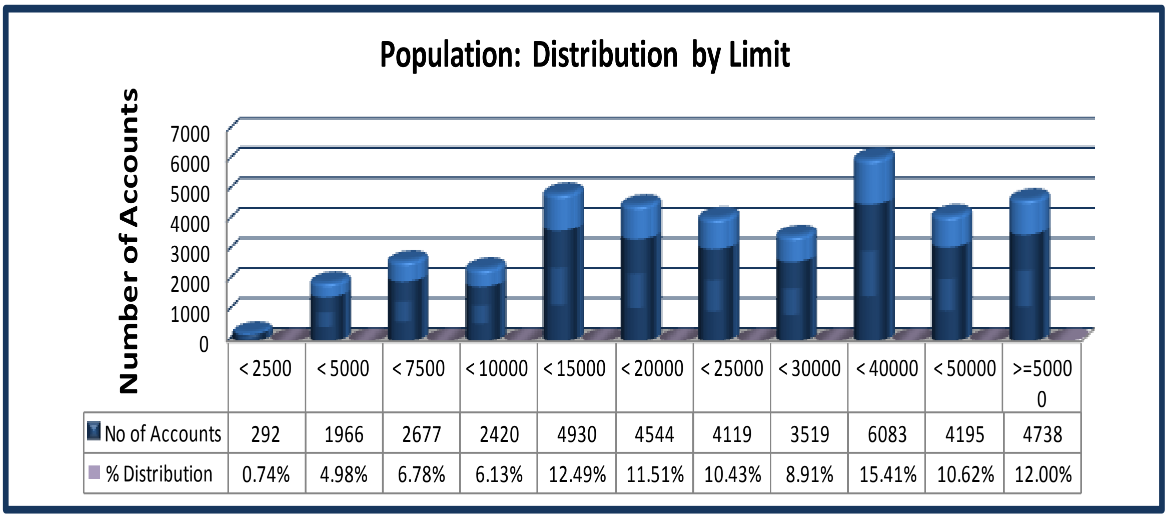
	= 0	< 1000	< 2500	< 5000	< 7500	< 10000	< 15000	< 20000	< 25000	< 30000	< 40000	< 50000	>=50000
No of Accounts	141	190	460	1030	1023	938	1563	1308	1103	953	1445	862	912
% Distribution	1.18%	1.59%	3.86%	8.64%	8.58%	7.86%	13.10%	10.97%	9.25%	7.99%	12.11%	7.23%	7.65%

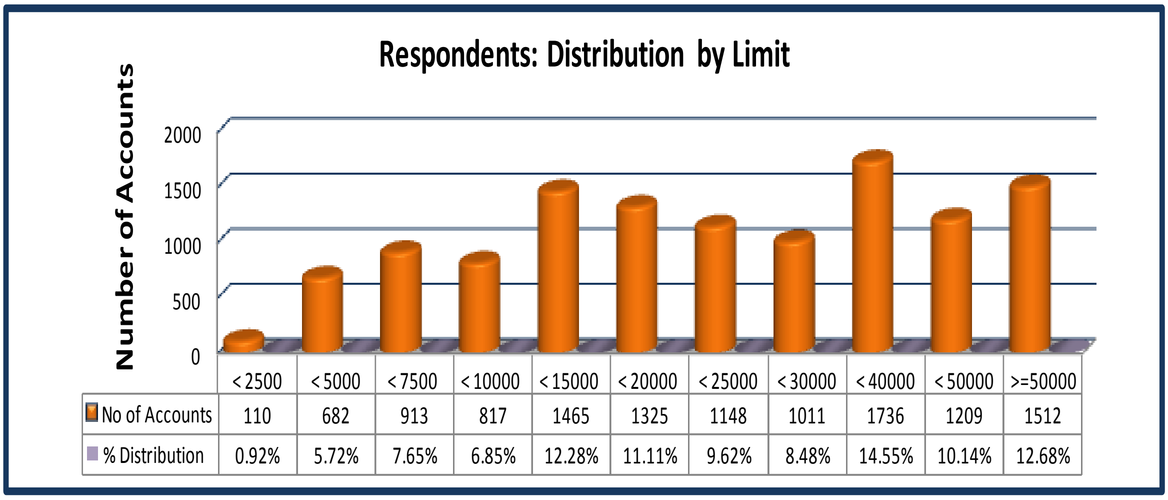
The account debit balance represents the customer’s outstanding balance on the credit card account. Above the R30 000 debit balance, the respondent population has a distribution higher than that of the total population.

g) Limit

Figure 8 provides a view of the Limit distribution of the population

Figure 8: Distribution of Limit



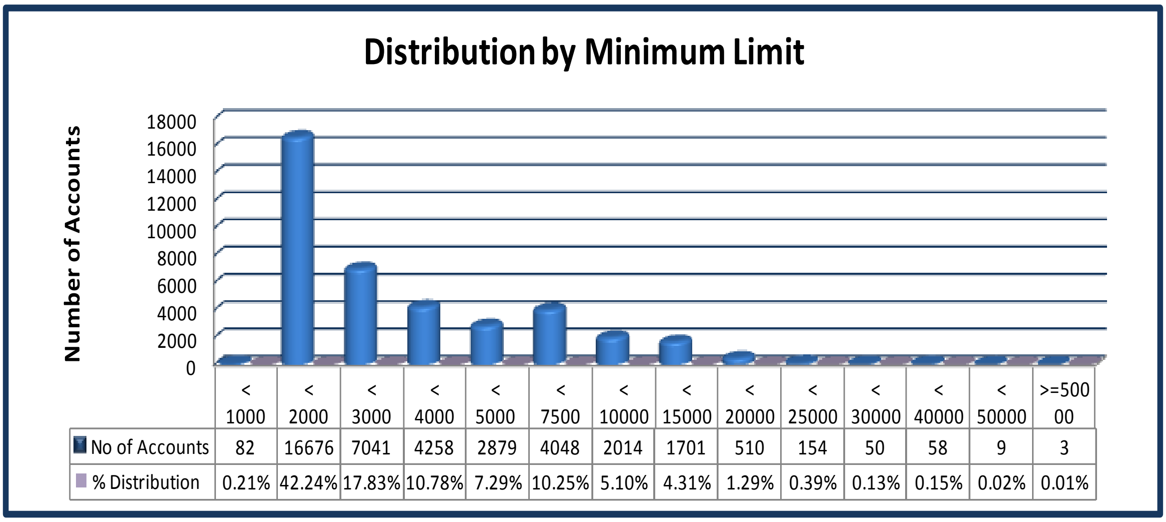


The limit represents the current credit facility that is loaded on the credit card. The distribution of the limits on the respondent population is consistently higher than the total population below the R10 000 limit. However, at the highest end of the limit, above R50 000, the respondent population shows yet again a distribution of 12.68% higher than 12.00% of the population.

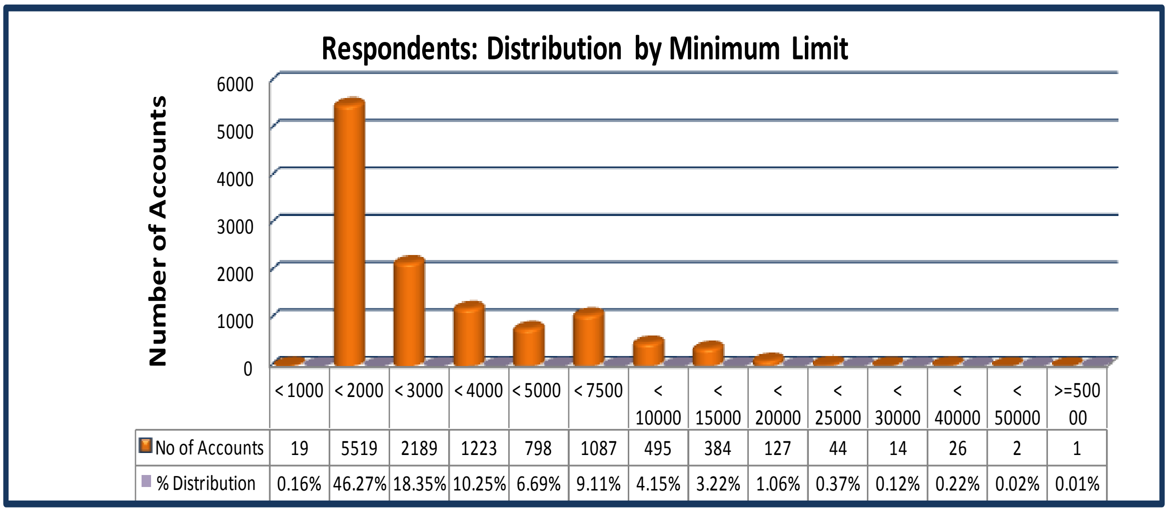
h) Minimum Limit

Figure 9 provides a view of the Minimum Limit distribution of the population

Figure 9: Distribution of Minimum Limit



	< 1000	< 2000	< 3000	< 4000	< 5000	< 7500	< 10000	< 15000	< 20000	< 25000	< 30000	< 40000	< 50000	>=50000
No of Accounts	82	16676	7041	4258	2879	4048	2014	1701	510	154	50	58	9	3
% Distribution	0.21%	42.24%	17.83%	10.78%	7.29%	10.25%	5.10%	4.31%	1.29%	0.39%	0.13%	0.15%	0.02%	0.01%



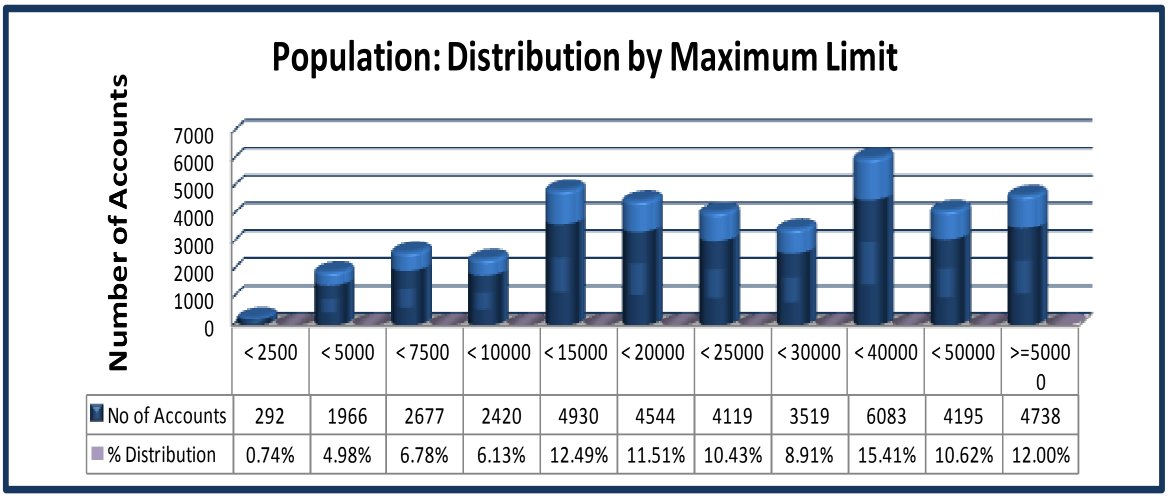
	< 1000	< 2000	< 3000	< 4000	< 5000	< 7500	< 10000	< 15000	< 20000	< 25000	< 30000	< 40000	< 50000	>=50000
No of Accounts	19	5519	2189	1223	798	1087	495	384	127	44	14	26	2	1
% Distribution	0.16%	46.27%	18.35%	10.25%	6.69%	9.11%	4.15%	3.22%	1.06%	0.37%	0.12%	0.22%	0.02%	0.01%

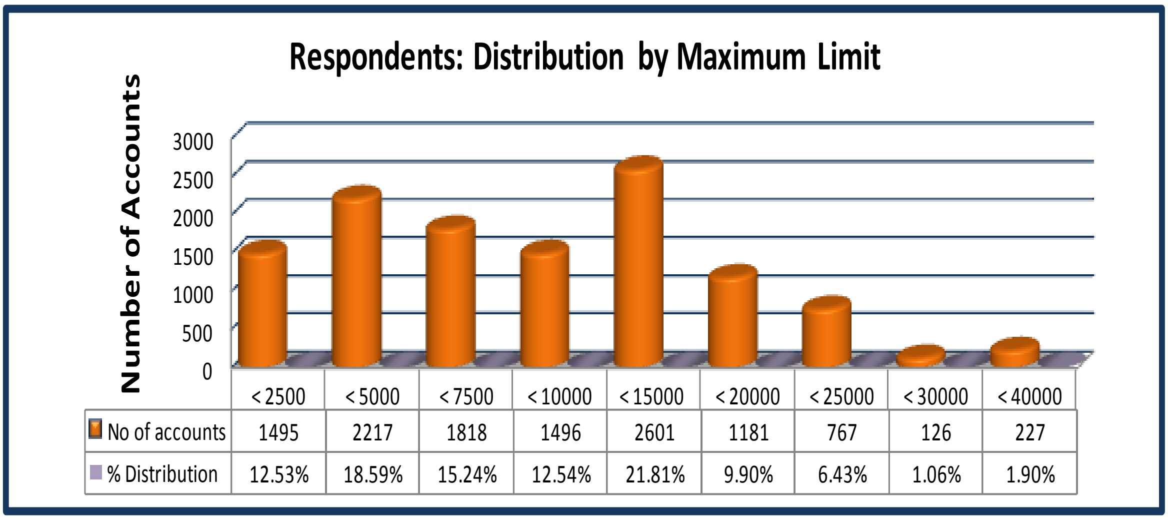
The minimum limit represents the lower limit that can be offered by the campaign. The minimum limit is higher on the respondent population particularly in the lower limits. The largest distribution of the minimum limit assigned falls below the R3 000 limit. Although a slight difference in the percentage distribution, the distribution across the two populations is similar.

i) Maximum Limit

Figure 10 provides a view of the Maximum Limit distribution of the population

Figure 10: Distribution of Maximum Limit





The maximum limit is a limit that is offered by the campaign. This is the highest limit that can be offered on a specific account, having taken into consideration the risk profile and the customer's repayment ability (affordability).

- **Summary:**
  - **Population summary :** The campaign targeted highly utilised customers, with good credit ratings (seen in the Card Behaviour

score, Credit Bureau Score and Customer Behaviour scores are above 660) and offered limits based on affordability.

- **Respondents' summary**: Respondents are highly utilised, have lower credit risk scores and have been assigned limits with caution to mitigate the affordability risk once the limit increase has been accepted.

5.3 Results pertaining to Hypothesis 1

H1: There is a significant difference in the risk profile characteristics between non responders and responders to credit card solicitation.

To understand the Winner's curse, this section analyses each of the two campaigns independently. Isolating the two campaigns in this section allows for a better understanding of the consistency of the data and execution of these ongoing campaigns.

The ***Welch-Satterthwaite t-test*** is used to compare the two distinct groups where the assumption of equal variances is not made. The variables applied for this analysis are continuous in nature. The equality test were done and indicated that the scores were not equal and a summary of the output in reported in Table 4, Table 5,Table 6 and Table 7 below.

The following Hypothesis was completed at a **5%** significance interval:

H_o: The means between the Respondents and the Non Respondents are equal

H_a: The means between the Respondents and the Non Respondents are not equal

Campaign 1: The null hypothesis is rejected across 5 of the 8 variables (i.e credit bureau score, card behaviour score, and customer behaviour score, months on book and utilisation).The tests yielded the rejection of equality between the Respondents and the Non Respondents, at the 0.0001% level.

Across the 3 other variables, the variance in the means is notable, showing an economic difference in the responses between the two populations rather than a statistical difference. Table 2 summarises the Winner's curse – Campaign 1

Campaign 2: Similarly, the null hypothesis is rejected across 5 of the 8 variables (i.e. credit bureau score, card behaviour score, and customer behaviour score, months on book and utilisation).The tests yielded the rejection of equality between the Respondents and the Non Respondents, at the 0.0001% level.

Across the 3 other variables, the variance in the means is notable, showing an economic difference in the responses between the two populations rather than a statistical difference. Table 4 summarises the Winner's curse – Campaign 2

Summary: The null hypothesis is rejected on 5 of the 8 variables at the 0.0001% level. The other 3 variables report a notable economic difference.

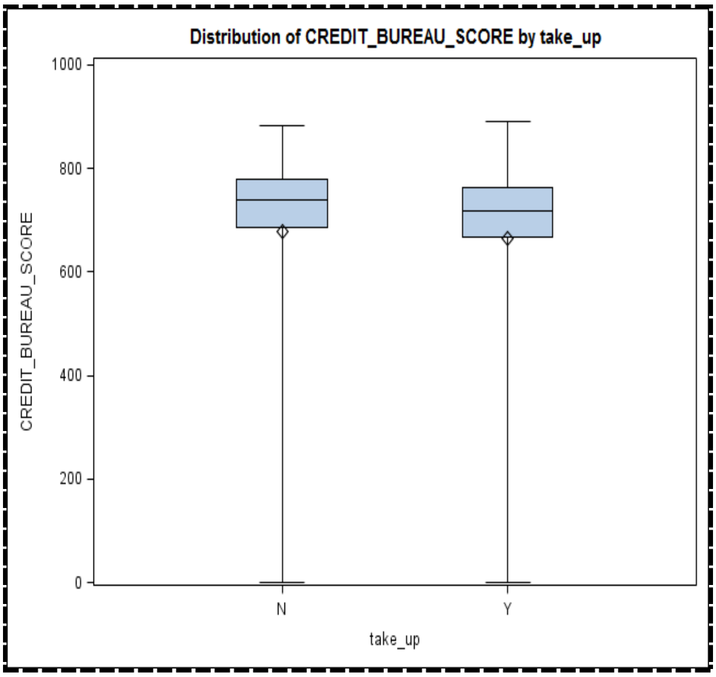
Table 4: The Winner's Curse – Campaign 1

Continuous Variable	**Respondents**	**Non Respondents**	**t test**
Credit Bureau Score	665	678	< 0.0001
Card Behaviour Score	682	690	< 0.0001
Customer Behaviour Score	675	681	< 0.0001
Number of bank Cards	1.2864	1.2681	*0.0058*
Highest Limit on Cards	R 27 359	R 27479	*0.6981*

Combined Revolving Limits	R 29 787	R 29 426	*0.3238*
Month on Book	113	126	< 0.0001
Utilisation Rate	0.7842	0.7247	< 0.0001
Observations: Non Respondents ***14 215*** : Respondents: ***5 430***			

Table 5: Comparison of scores across variables: Campaign 1

Box Plot: **Credit Bureau Score**

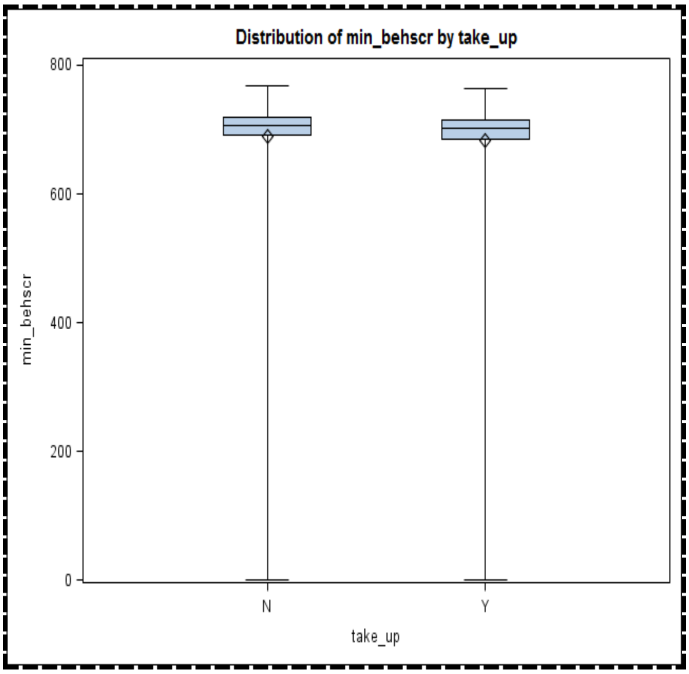


Non Respondents: the range of the means is between 0 and 891. The average mean is 677.

Respondents: the range of the means is between 0 and 882. The average mean is 665.

Indication: there is difference in means between the two populations

Box Plot: Card Behaviour Score

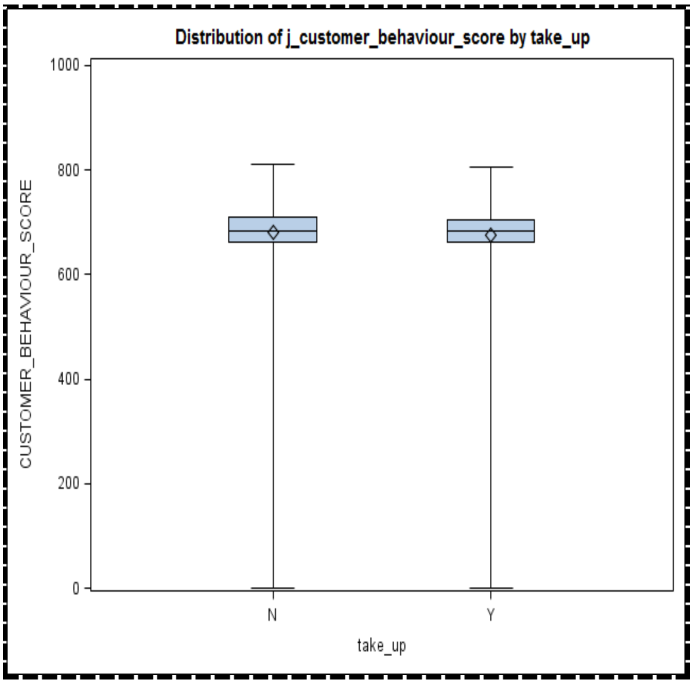


Non Respondents: the range of the means is between 1 and 768. The average mean is 689.

Respondents: the range of the means is between 1 and 764. The average mean is 682.

Indication: there is difference in means between the two populations

Box Plot : Customer Behaviour Score



Non Respondents: the range of the means is between 0 and 810. The average mean is 680.

Respondents: the range of the means is between 0 and 807. The average mean is 674.

Indication: there is difference in means between the two populations

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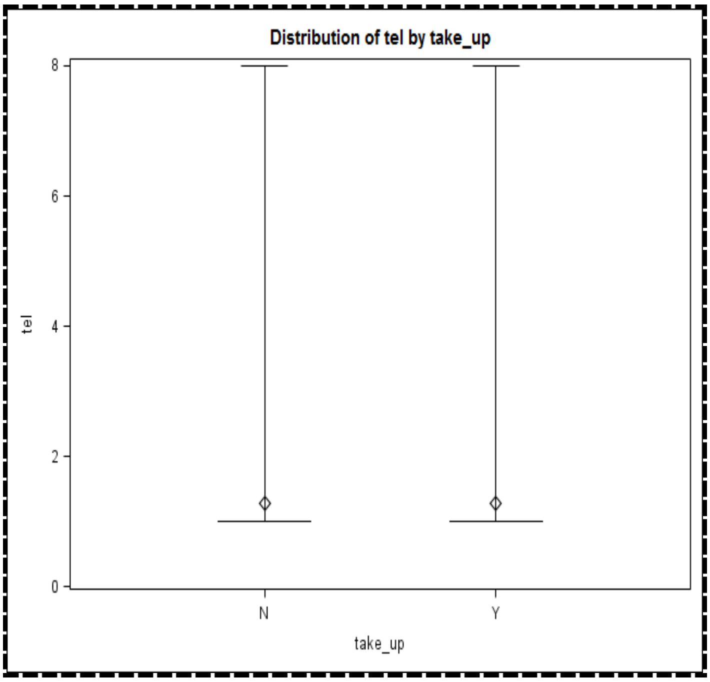
Box Plot : **Number of cards**



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Non Respondents: the range of the means is between 1 and 8. The average mean is 1.26

Respondents: the range of the means is between 1 and 8. The average mean is 1.28.

Indication: there is a slight difference in means between the two populations

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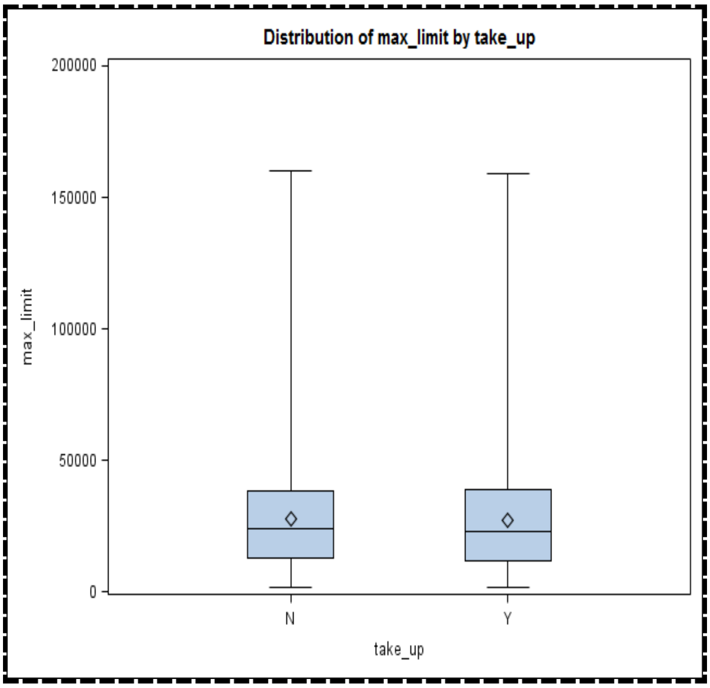
Box Plot : **Maximum Limit**



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Non Respondents: the range of the means is between R 1 440 and R 160 000. The average mean is R27 359.

Respondents: the range of the means is between R1 500 and R 159 250. The average mean is R27 478.

Indication: there is a slight difference in means between the two populations

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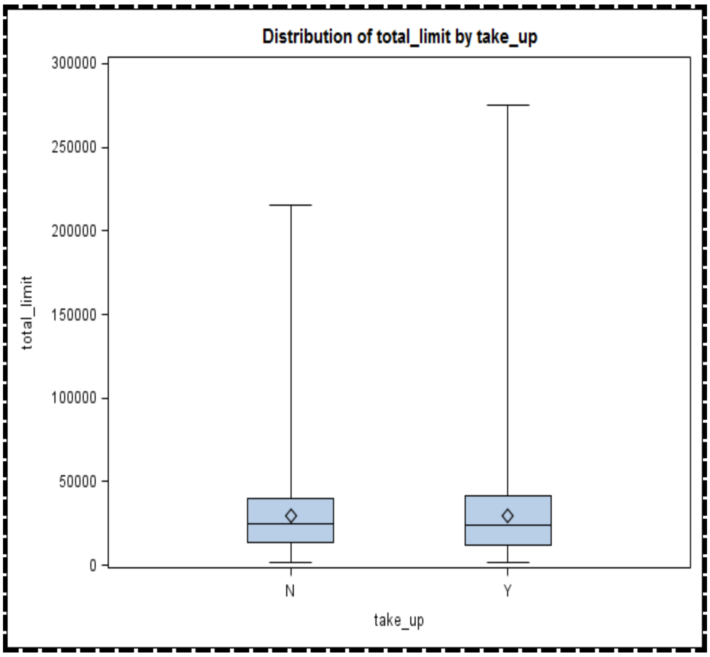
Box Plot :**Total Limits**

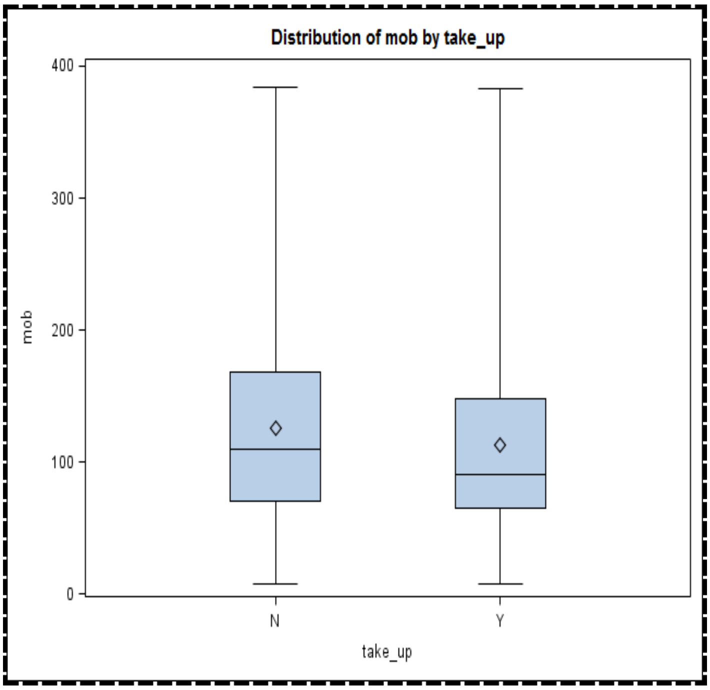


Non Respondents: the range of the means is between R 1 440 and R 215 501. The average mean is R29 425

Respondents: the range of the means is between R1 500 and R 275 501. The average mean is R29 787.

.**Indication:** There is a slight difference in means between the two populations

Box Plot :**Month on Book**

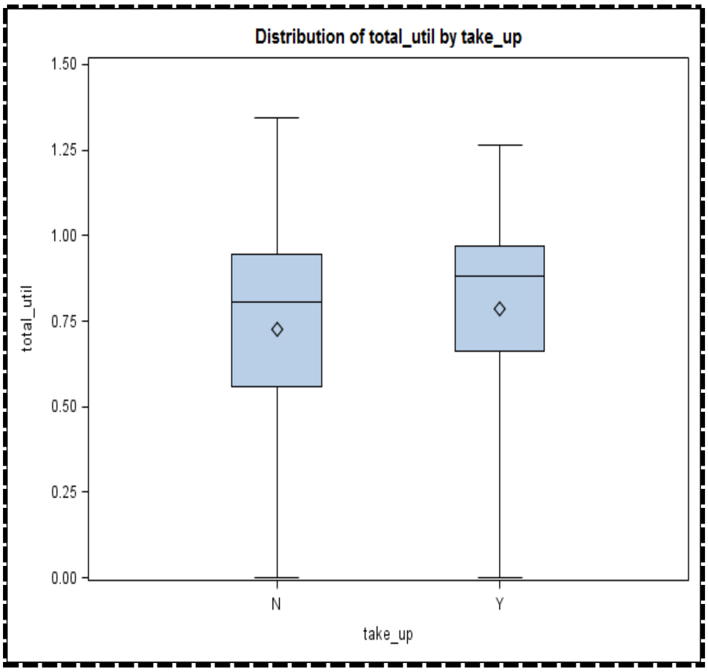


Non Respondents: the range of the means is between 8 and 384. The average mean is 125.

Respondents: the range of the means is between 8 and 383. The average mean is 113.

Indication: there is a difference in means between the two populations

Box Plot: Utilisation



Non Respondents: the range of the means is between 0 and 126%. The average mean is 78%.

Respondents: the range of the means is between 0 and 134%. The average mean is 72%.

Indication: there is a difference in means between the two populations

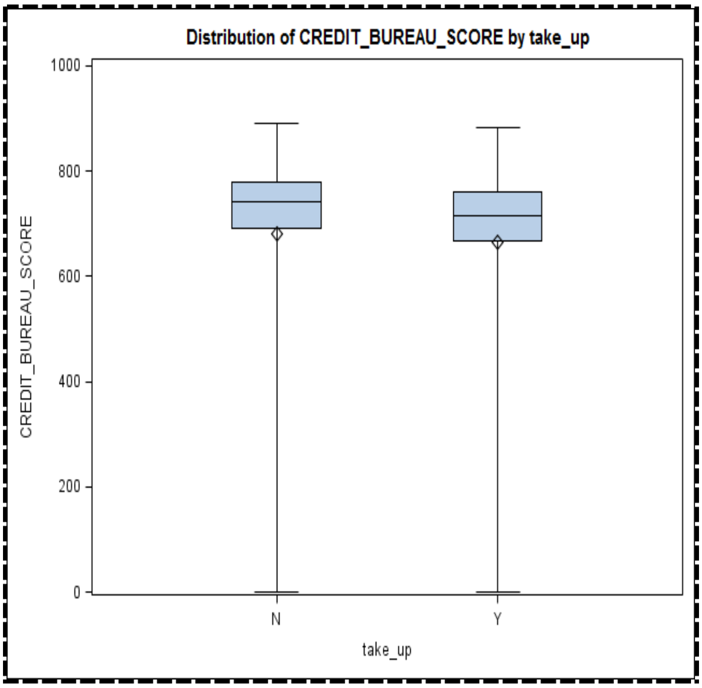
Table 6: The Winner's Curse – Campaign 2

Continuous Variable	Respondents	Non Respondents	t test
Credit Bureau Score	666	682	< 0.0001
Card Behaviour Score	686	691	< 0.0001
Customer Behaviour Score	678	684	< 0.0001
Number of bank Cards	1.2953	1.2992	*0.6763*

Highest Limit on Cards	R 27 962	R 27 904	*0.8456*
Combined Revolving Limits	R 30 675	R30 375	*0.4014*
Month on Book	113	129	< 0.0001
Utilisation Rate	0.7718	0.6949	< 0.0001
Observations: Non Respondents ***13 340*** : Respondents: ***6 898***			

Table 7: Comparison of scores across variables: Campaign 2

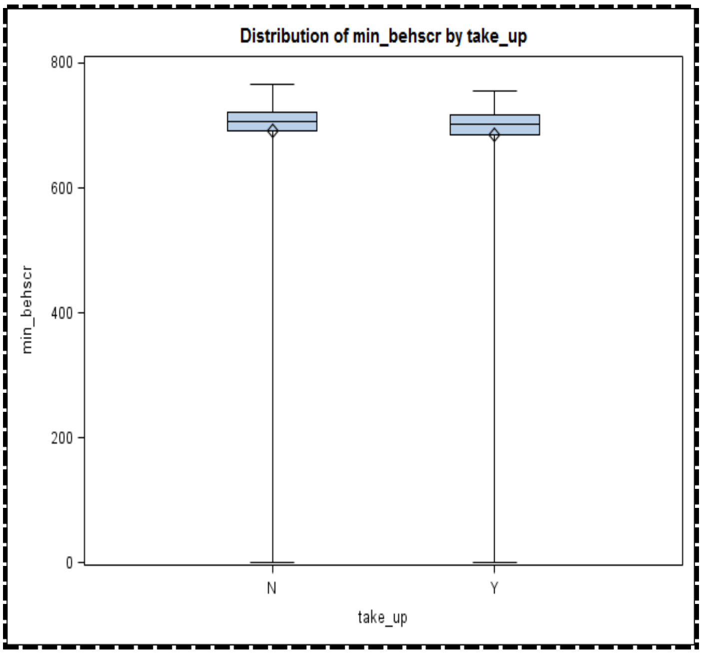
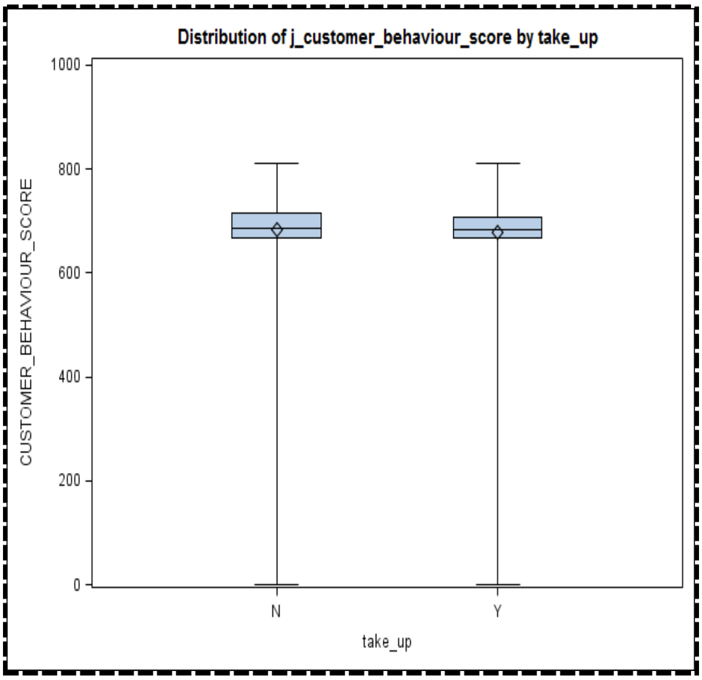
Box Plot: **Credit Bureau Score**

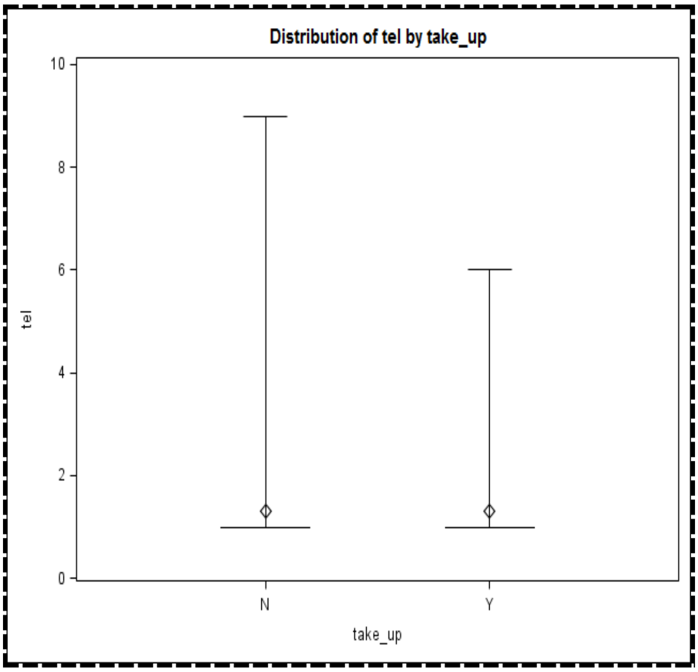
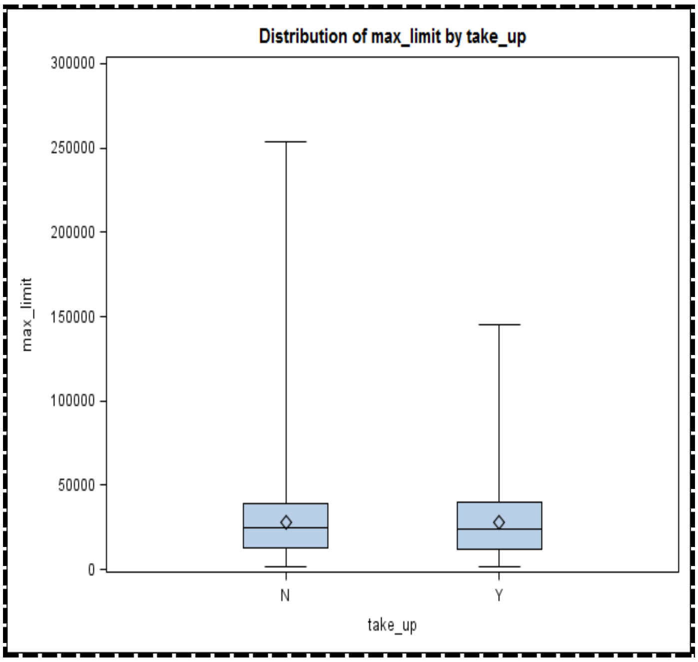


Non Respondents: the range of the means is between 0 and 891. The mean score 682.

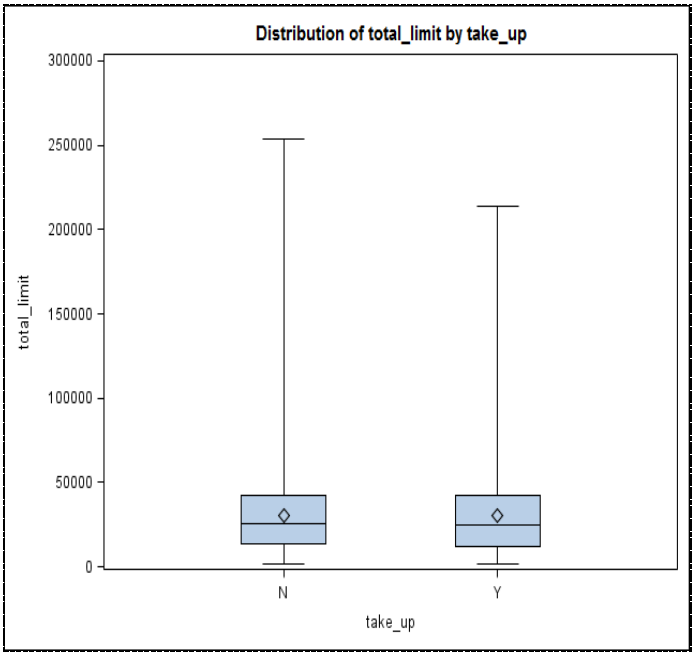
Respondents: the range of the means is between 0 and 882. The mean score is 666.

Indication: difference in means between the two populations

Box Plots: **Behaviour Score** 	**Non Respondents:** the range of the means is between 1 and 765. The mean score is 691. **Respondents**: the range of the means is between 1 and 756. The mean score is 756. **Indication:** difference in means between the two populations
Box Plots **: Customer Behaviour Score** 	**Non Respondents:** the range of the means is between 0 and 810. The mean score is 684. **Respondents**: the range of the means is between 0 and 810. The mean score 677. **Indication:** difference in means between the two populations

Box Plot: **Number of cards** 	**Non Respondents:** the range of the means is between 1 and 9. The average mean is 1.29. **Respondents**: the range of the means is between 0 and 6. The average mean is 1.29. **Indication:** There is a slight difference in means between the two populations.
Box Plot**: Maximum Limit** 	**Non Respondents:** the range of the means is between R1 500 and R254 000. The average mean is R 27 904. **Respondents**: the range of the means is between R 1 440 and R145 400. The average mean is R27 962. **Indication:** There is a slight difference in means between the two populations.

BoxPlot: **Total Limit**

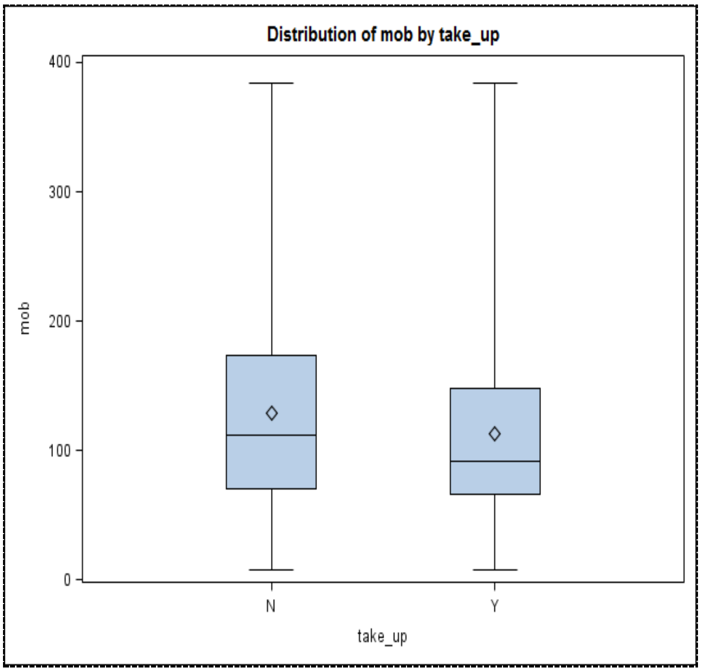


Non Respondents: the range of the means is between R1 500 and R254 000. The mean score is R30 374.

Respondents: the range of the means is between R1 440 and R213 450. The average mean is R30 674.

Indication: There is a slight difference in means between the two populations.

Box Plot: **Month on Book**

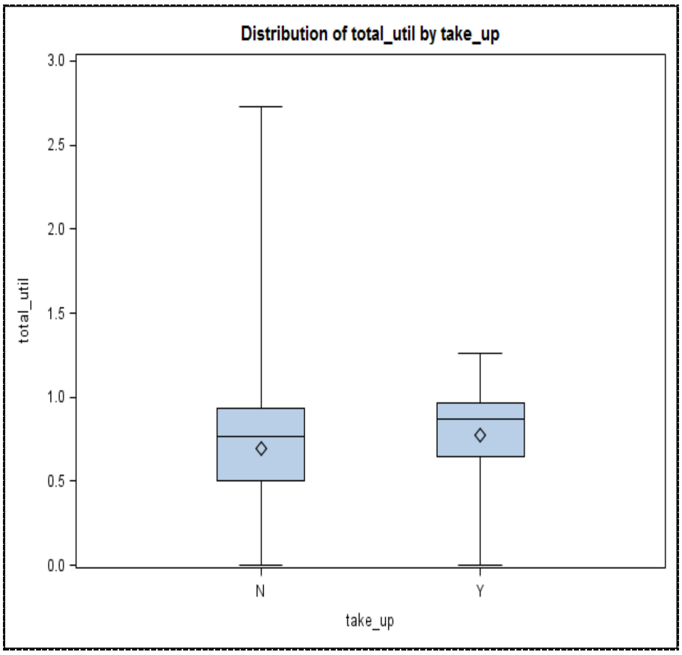


Non Respondents: the range of the means is between 8 and 384. The average mean is 128.

Respondents: the range of the means is between 8 and 384. The average mean is 112.

Indication: there is a difference in means between the two populations.

Box Plot: **Utilisation**



Non Respondents: the range of the means is between 0 and 272%. The average mean is 69%.

Respondents: the range of the means is between 0 and 126%. The average mean is 77%.

Indication: there is a difference in means between the two populations

5.4 Results pertaining to Hypothesis 2

H2 : There are immediate credit quality changes that are observable after the customer has accepted the credit limit increase offer.

The results pertaining to Hypothesis 2 are displayed in Table 8, Table 9 and Table 10. This section uses dynamic risk measures (i.e. utilisation rate, credit bureau score, card behaviour score and the customer behaviour score variables - all continuous variables) to measure the difference in the Respondents and the Non Respondents risk performance at 6 months, 12 months and 18 months following the limit increase. A point in time snapshot of the above variable was undertaken at the respective time periods and t test performed to assess for the difference in the means following the taken up period.

The following Hypothesis was completed at a **5%** significance interval:

H_o: There are no immediate credit quality changes after the customer has accepted the limit increase.

H_a: There are immediate credit quality changes after the customer has accepted the credit limit increase.

The null hypothesis is rejected across the 4 variables (i.e. utilisation rate, credit bureau score, card behaviour score, and customer behaviour score) over the 6 months, 12 months and 18 months performance periods. Across the 3 timeframes, the tests yielded the rejection of equality between the Respondents and the Non Respondents, at the 0.0001% level.

Table 8: Performance 6 months after credit limit increase

Continuous Variable	Non Respondents	Respondents	t test
Utilisation Rate	65.79%	72.12%	< 0.0001
Credit Bureau Score	667	654	< 0.0001
Card Behaviour Score	678	672	< 0.0001
Customer Behaviour Score	675	678	< 0.0001
Observations: Non Respondents ***27 538*** : Respondents: ***11 928***			

The 6 months performance which is the earliest indicator of customer financial distress following the credit limit increase indicates the following:

Utilisation: Respondent population has utilisation of 72.12% higher than the Non Respondents of 65.75%. This performance remains the same when compared to the utilisation at the time of the offer with the Respondents still highly utilised despite the increase in limits. Both the Respondents and the Non Respondents show a reduction in utilisation of 6.49% and 7.14% respectively from the time of offer. The gap in utilisation between the Respondents and the Non Respondents over the 6 months remained marginally the same at 9.09% and 9.72%, despite an increase in the Respondents limit.

Credit Bureau Score: The Respondents score of 654 shows deterioration from the average of 665 that was measured at the time of the credit limit offer. The Non Respondents score shows deterioration from 680 at the time of offer to 668. However, when benchmarked, the Respondents reports a lower credit bureau score of 654 against 667 of the Non Respondents. The 6 monthly comparative score from the time of offer indicates that Respondents and the Non Respondents scores have deteriorated by 1.65% and 1.91% respectively. Similarly, the gap in the Respondents and the Non Respondents scores has decreased from 2.29% to 1.99%.

Card Behaviour Score: The Respondent score is 672 against the Non Respondents of 678 .The Respondents show deterioration in the Card Behaviour score of 1.74% and the Non Respondents of 1.75% over the 6 months period. The difference in the scores between the two populations remained at 9%.

Customer Behaviour Score: The Respondents scores show a deterioration from 676 to 660 (2.37% reduction) whereas the Non Respondents show a deterioration from 682 to 675 (1.03% reduction) over the 6 months period. The Respondents still have a lower customer behaviour score of 660 when compared to the Non Respondents of 675. The comparative gap in the scores over the last 6 months has increased from 0.9% to 2.3%.

t tests: simple t tests on each one of these 4 variables on a 6 months performance window yielded the rejection of equality between the Respondents and the Non respondents, at the 0.0001% level. The null hypothesis is rejected as the differences between the Respondents and Non Respondents are statistically significant.

Table 9: Performance 12 months after credit limit increase

Continuous Variable	Non Respondents	Respondents	t test
Utilisation Rate	60.70%	68.74%	< 0.0001
Credit Bureau Score	665	651	< 0.0001
Card Behaviour Score	637	628	< 0.0001
Customer Behaviour Score	667	648	< 0.0001
Observations: Non Respondents ***27 538*** : Respondents: ***11 928***			

The 12 months performance measures factors in the effect of the customer's personal responsibility in managing their creditworthiness as well as external economic factors that could affect their credit risk and affordability. This midterm performance review window highlights the following:

Utilisation: Twelve months following the credit limit increase the Respondent population has a utilisation of 68.74% higher than the Non Respondents of 60.70%. Over the last 12 months, the Respondents utilisation reduced from 77% to 68% (11.69%). Similarly, the Non Respondents had a higher reduction percentage of 14.29% from 70% to 60% over 12 months. The gap in the utilisation % between the Respondents and Non Respondents increased from 9.09% to 11.76%

When benchmarked against the 6 months performance period, the Respondents report a further drop in utilisation of 5.6% from 72% to 68% and the Non Respondents of 7.7% from 65% to 70%.

Credit Bureau Score: The Respondents credit bureau score over the 12 month performance period deteriorated by 2.11% from 665 to 651. The Non Respondent's scores reduced from 680 to 665, a 2.21% deterioration, slightly higher than the Respondents. The gap in the credit bureau scores between the Respondents population and the Non Respondents population narrowed from 2.30% to 2.15%.

Comparisons to the 6 months performance period highlight a slight reduction of 0.5% from 651 to 654 in the Respondents and 0.3% in the Non Respondents population.

Card Behaviour Score: The Respondents scores have deteriorated by 8.19% from 684 to 628.The Non Respondents scores deteriorated by 7.68% from 690 to 637. However, the Respondents still have a lower Card Behaviour score of 628 relative to the Non Respondents of 637. The difference in the gaps between the two populations increased from 0.9% to 1.4%.

When benchmarking against the 6 months performance, the Respondents show a further deterioration in the scores of 6.5% from 672 to 628. The Non Respondents report a reduction of 6% from 678 to 637.

Customer Behaviour Score: The Respondents scores show a deterioration from 676 to 648 (4.14% reduction) whereas the Non Respondents show a deterioration from 682 to 667 (2.20% reduction) over the 12 months period. The Respondents still have a lower customer behaviour score of 648 when compared to the Non Respondents of 667. The comparative gap in the scores over the last 12 months has increased from 0.9% to 2.9%.

When compared against the 6 months performance, the customer behaviour scores have deteriorated by 1.8% from 660 to 648 for the Respondents by 1.2% from 675 to 667.

t tests: simple t tests on each one of these 4 variables on a 12 months performance window yielded the rejection of equality between the Respondents and the Non respondents, at the 0.0001% level. The null hypothesis is rejected as the difference between the Respondents and Non Respondents are statistically significant.

Table 10: Performance 18 months after credit limit increase

Continuous Variable	**Non Respondents**	**Respondents**	**t test**
Utilisation Rate	55.57%	61.47%	< 0.0001
Credit Bureau Score	665	651	< 0.0001
Card Behaviour Score	600	575	< 0.0001
Customer Behaviour Score	641	620	< 0.0001
Observations: Non Respondents ***27 538*** : Respondents: ***11 928***			

The 18 variables measure the long term performance of these accounts taking all credit risk related factors into account:

Utilisation: The Respondents utilisation of 61% remains higher than the Non Respondents of 55%, similar to the time of the offer. Both the Respondents and the Non Respondents show a reduction in utilisation of 20.78% and 21.43% respectively from the time of offer. The gap in utilisation between the Respondents and the Non Respondents over the 18 months remained marginally the same at 9.09% and 9.84%, despite an increase in the Respondents limit.

A comparison to the 12 months performance period shows a significant drop in utilisation of the Respondents from 68% to 61%, (10.3%) and 60% to 55% (8.3%) of the Non Respondents.

Credit Bureau Score: Insignificant change in the bureau scores between the 12 months on book and the 18 months on book performance.

Card Behaviour Score: The Respondent score is 575 against the Non Respondents of 600 .The Respondents show deterioration in the Card Behaviour score of 15.94% and the Non Respondents of 13.04% over the 18 months period. The difference in the scores between the two populations increased from 0.9% to 4.3%.

Comparatives to the 12 months performance data show a deterioration of 8% from 628 to 575 for the Respondent population.

Customer Behaviour Score: The Respondents scores show a deterioration from 676 to 620 (8.28 % reduction) whereas the Non Respondents show a deterioration from 682 to 641 (6.01% reduction) over the 18 months period. The Respondents still have a lower customer behaviour score of 620 when compared to the Non Respondents of 641. The comparative gap in the scores over the last 12 months has increased from 0.9% to 3.4%.

t tests: simple t tests on each one of these 4 variables over an 18 months performance window yielded the rejection of equality between the Respondents and the Non respondents, at the 0.0001% level. The null hypothesis is rejected as the difference between the Respondents and Non Respondents are statistically significant.

5.5 Results pertaining to Hypothesis 3

H3: The cardholder defaults as a consequence of a solicitation offer type indicator after controlling the consumer's demographic characteristics, the risk attributes observed by the lender at the time the card was issued.

This section displays the results for Hypothesis 3 in Tables 9, 10, 12. The analysis uses a time series approach to monitor the change in the Respondents and Non Respondents over a specific period. It focuses on delinquencies which are used to define defaults, following the credit limit increase. Default performance is measured into 6 months, 12 months and 18 months post the limit offer. The analysis uses the following variables: delinquency number, charge off number and bad number which are continuous in nature.

Table 11: Performance 6 months after credit limit increase: Default

Continuous Variable	Non Respondents	Respondents	t test
Delinquency Number	829	532	< 0.0001
Delinquency %	3.01%	4.46%	
Charge Off Number	48	9	0.0054
Charge Off %	0.17%	0,08%	
Bad rate number	207	119	0.0190
Bad rate	0.75%	1%	
Observations: Non Respondents ***27 538*** : Respondents: ***11 928***			

The 6 months default performance quantifies the number of accounts that show early indications of distress through missing repayments.

Delinquency number: A credit card is considers delinquent if the cardholder goes past 30 days without making the required minimum payment. Comparing the delinquency across the two populations, the Respondents are at 4.46% and the Non Respondents at 3.01%.

Charge off Number: is a declaration by the lender that the amount of debt is unlikely to be collected. Although the lender's policy rules allow for charge off at 180 days of delinquency, accounts can be charged off at any level of delinquency should the card owner show no ability to service the debt. The Respondents in charge of rate is 0.08% and the Non Respondents 0.17%.

Bad number: is the number of good accounts (those that have not defaulted beyond 90 days nor been charged off/number of bad accounts (those that have defaulted). The Respondent's bad rate is 1.00% whereas the Non Respondents is 0.75%

t test: of the 3 variables, the null hypothesis can only be rejected for the delinquency number at the 0.0001% level. The other two variables are economically quite substantial.

Table 12: Performance 12 months after credit limit increase: Default

Continuous Variable	Non Respondents	Respondents	t test
Delinquency Number	989	709	< 0.0001
Delinquency %	3.59%	5.94%	
Charge Off Number	160	90	0.058
Charge Off %	0.58%	0.75%	
Bad rate number	420	284	< 0.0001
Bad rate	1.53%	2.38%	
Observations: Non Respondents ***27 538*** : Respondents: ***11 928***			

The 12 months default performance measures the customer's ability to repay the limit over a prolonged period.

Delinquency number: The Respondents have a higher default rate at 12 months on book of 5.95%, relative to the Non Respondents of 3.59%.

Charge off Number: The Respondents charge off is 0.75% and the Non Respondents is 0.58%.

Bad number: The Respondents bad rate of 2.38% exceed the Non Respondents bad rate of 1.53%.

t test: of the 3 variables, the null hypothesis can only be rejected for the delinquency number and the number of ‘bads’ at the 0.0001% level. The charge off variables difference remains economically substantial.

Table 13: Performance 18 months after credit limit increase: Default

Continuous Variable	Non Respondents	Respondents	t test
Delinquency Number	781	610	< 0.0001
Delinquency %	2.84%	5.11%	
Charge Off Number	525	252	0.1843
Charge Off %	1.91%	2.11%	
Bad rate number	793	508	< 0.0001
Bad rate	2.88%	4.26%	
Observations: Non Respondents ***27 538*** : Respondents: ***11 928***			

The 18 months default performance measures accounts that are considered irrecoverable by the lender. The lender's charge off policy is 180 days. The probability of charge off increases post the 180 days.

Delinquency number: The Respondents have a higher default rate at 18 months on book of 5.11%, relative to the Non Respondents of 2.84%.

Charge off Number: The Respondents charge off is 2.11% and the Non Respondents is 1.91%.

Bad number: The Respondents bad rates of 4.26% exceed the Non Respondents bad rate of 2.88%.

t test: of the 3 variables, the null hypothesis can only be rejected for the delinquency number and the number of 'bads' at the 0.0001% level. The charge off variables difference remains economically substantial.

When assessing the 6 months, 12 months and the 18 months default performance, the null hypothesis can be rejected for the delinquency number and bad rate number at a level below 0.05% significance level.(***marginal difference in the charge off number) .

6 CHAPTER 6: DISCUSSION OF THE RESULTS

In this section, the research findings are evaluated against the research proposition and hypothesis, formulated in Chapter 3.

6.1 Introduction

Figure 11: A comparison of the differences' between the research and the research by Ausubel (1999) and Argawal et al.(2010)

	This Research	**Ausubel (1999)**	**Agarwal, et al. (2010)**
Product	Credit Card	Credit Card	Credit Card
Customer Type	Existing	New	New
Type of Offer	Limit increase	New limit assignment	New limit assignment
Population size	40 000	2 059 876	2 137 635
Response Rates	30%	0.7%	0.3%
No: Respondents	12 000	15 123	6 448

Variables Used	Month on Book, Credit Bureau Score, Card Behaviour Score, Customer Behaviour Score, Number of Bank Cards, Highest Limit On Bank Cards, Credit Limit, Revolving Balance, Revolving Limits, Utilization rate, Debit interest rate, Delinquency Rate, Charge Off Rates,	Month on File, Credit Bureau Score, Number of bank cards; Highest Limit on Bank Cards, Preliminary Revolving Balances; Preliminary Revolving Limits, Preliminary Utilisation Rate, Mortgage Balance, Number of Delinquencies in the last 12 months, Income, Gold, Credit Limit, Revolving Balance, Revolving Limit, Utilisation Rate, Debt Burden, Delinquency rates, Charge Off rates, Charge Off Balances, Activity Rate and Bankruptcy rate.	Total Revolving limits, total credit cards utilisation rate, credit withdrawn as a fraction of total credit availability on all credit cards, account age, month on file Delinquency (30+ past due), FICO score
Performance Periods	6 months, 12 months, 18 months	21 months and 27 months	12 months and 24 months
Outcome	Presence of Adverse Selection	Presence of Adverse selection	Presence of Adverse selection

The table above summarises the salient features between this research and previous research. The key difference is the choice of the targeted customer, who is influential in determining the variables that would best define the performance and the credit measures of that population.

The current research, unlike previous researches done by Ausubel (1999) and Agarwal, et al. (2010), applies robust screening rules as the lender already has an existing relationship with the customer. This is reinforced in the choice of internal variables such as Card behaviour score and Customer behaviour score which are unique to this study as these are derived from the customer’s historical information. By implication, there should be a lesser degree of adverse selection in this research population as the lender understands the customer better than the lenders in comparative studies.

6.2 Discussion pertaining to hypothesis 1 : Winner’s Curse

The first hypothesis will be addressed and discussed in this section: ***H1: There is a significant difference in the risk profile characteristics between non responders and responders to credit card solicitation.***

According to Ausubel (1999) in the absence of adverse selection, there should be no difference in the characteristics of the respondents and non respondents.

6.3 Demographics

The outputs from the Respondents vs. Non Respondents together with the Winner’s curse outputs were used to test this hypothesis. The campaign take up of 30% is significantly higher than Ausubel (1999) of 7% and Agarwal, et al. (2010) of 3% due to the targeted market. With this study focussing on existing customers, a better response rate was achieved as there is an already existing relationship with the customer, better contact ability, operational ease of loading the limit, and the design of the selection criteria.

The summary of the risk characteristics distribution indicate that, based on the utilisation rate, the Respondents are 49.18% above 90% utilisation and 40.42% for the total population. Respondents are more utilised, increasing their propensity to take credit. The month on book for the Respondents over 120 months (5 years) is 36.07% and 42.28% for the total population indicating that the Respondents account age is younger than the total population. Above the 705 score the Card Behaviour Score and the Customer Behaviour scores, are consistently lower than those of the total population. This indicates that the Respondents were high risk customers as their credit performance internally was already showing signs of financial strain. The Credit Bureau score of the Respondents' population is towards lower scores.

Respondents have higher account balances above R30 000 reinforcing their consisted need for credit. The Respondents Limits are primarily below R10 000 indicating that the customer has low affordability as there is often a correlation between the limit offered and the consumer's ability to repay the limit. Respondents have, on average, lower limits than the total population. The minimum limit is higher on the Respondents population, particularly in the lower limits, the maximum limits show the inverse.

6.4 Winner's Curse

When looking at the comparisons in distributions in Table: 2 and Table: 4 the results constitute overwhelming evidence of adverse selection.

Campaign 1: Similar to Ausubel (1990)'s research, comparisons done on 8 variables indicate striking evidence of adverse selection seen in the Respondents averaging month on book of 126, whereas Non Respondents averaged 113 months on book. This is an indication that the Respondents, on average had markedly shorter credit histories than Non Respondents, by a margin of 13 months. Responders had a mean credit bureau score of 665 whereas the Non Respondents had a mean credit score of 678. A higher score for the credit bureau score, card behaviour score and the customer behaviour score, corresponds to a better credit risk.

The highest limit on the bank cards for Respondents averaged R 27 359, whereas for the Non Respondents averaged R27 479. The credit limit assigned on existing cards is a measure of the credit worthiness of the consumer as perceived by the current lender. The aggregate revolving balances for Responders averaged R 29 787 whereas Non Responders averaged R29 426. Respondents are much more borrowed up than Non Respondents, which could explain one of the reasons as to why they have responded, and also explaining why they pose a greater risk of default than the Non Respondents.

Campaign 2: The results for Campaign 2 are qualitatively similar where Table 4 illustrates that Respondents averaged month on book of 113 whereas the Non Respondents averaged 129. The Respondents mean scores across credit bureau score, card behaviour score, and customer behaviour score, all risk performance measures, are lower than the Non Respondents, thus corresponding to a high credit risk. The Respondents highest limit on bank cards is R 27 962 whereas, Non Respondents R 27 904.The Respondents Revolving balances averaged R30 675 whereas the Non Respondents averaged R 30 375. In this campaign, the Respondents' are much more borrowed that the Non Respondents.

The collective t tests across the Respondents and Non Respondents indicate that the null hypothesis is rejected across 5 of the 8 variables (i.e. credit bureau score, card behaviour score, and customer behaviour score, months on book and utilisation).The tests yielded the rejection of equality between the Respondents and the Non Respondents, at the 0.0001% level. Given the above observations, the lender is susceptible to adverse selection.

Across the 3 (number of bank cards, highest limit on bank cards and combined revolving limits) other variables, the variance in the means is notable, showing an economic difference in the responses between the two populations rather than a statistical difference. This finding, however, is similar to Ausubel (1999)'s research where the number of delinquencies in the last 12 months and the number of existing bank credit cards, were almost similar in the two populations (no statistical significance)

This study is aligned to Agarwal, et al. (2010) where Respondents to inferior offer type exhibit poorer credit quality characteristics than those responding to superior types. In the context of this study, inferior products are lower limit offers on higher interest rates (Risk Based Pricing). When benchmarked against Agarwal, et al., (2010)'s research, similarities include the lower FICO scores, higher credit limits on existing lines, average length of credit histories is shorter, and higher delinquency indices.

In summary, this research is consistent with both Ausubel (1990) and Agarwal, et al. (2010) whose results show that the risk characteristics of the Responders are statistically different from those of the Non Responders. Similar to Agarwal, et al. (2010), the results indicate that higher risk customers, assuming that the consumer are aware of their own credit risk types, have fewer external options for acquiring funds to smooth consumption. These customers who are high risk are often charged a higher risk based interest rate.

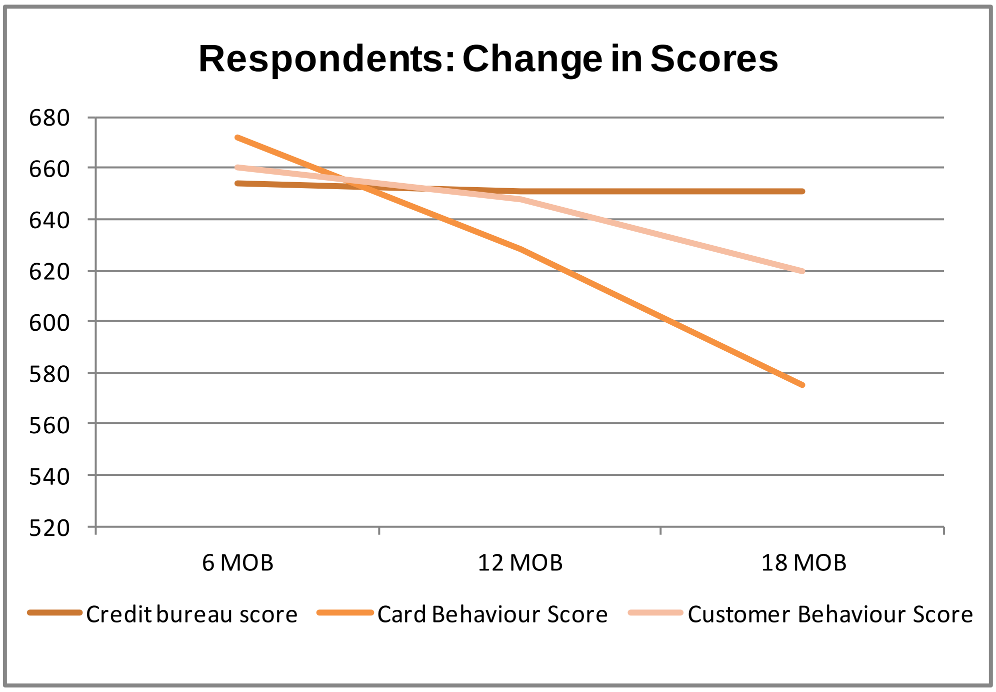
6.5 Discussion pertaining to Hypothesis 2

The second hypothesis will be addressed and discussed in this section: ***H2: There are immediate credit quality changes that are observable after the customer has accepted the credit limit increase offer.***

In addition to the credit bureau score, this research introduces two additional internal credit measures that the lender had available when targeting their existing customer base. The lender observes the Card behaviour score and the Customer Behaviour scores, which are measures of internal credit risk performance.

Figure 12 and Figure 13 below illustrate the gradual deterioration of the credit bureau score, card behaviour score and the customer behaviour score.

Figure 12: Respondents Change in Scores



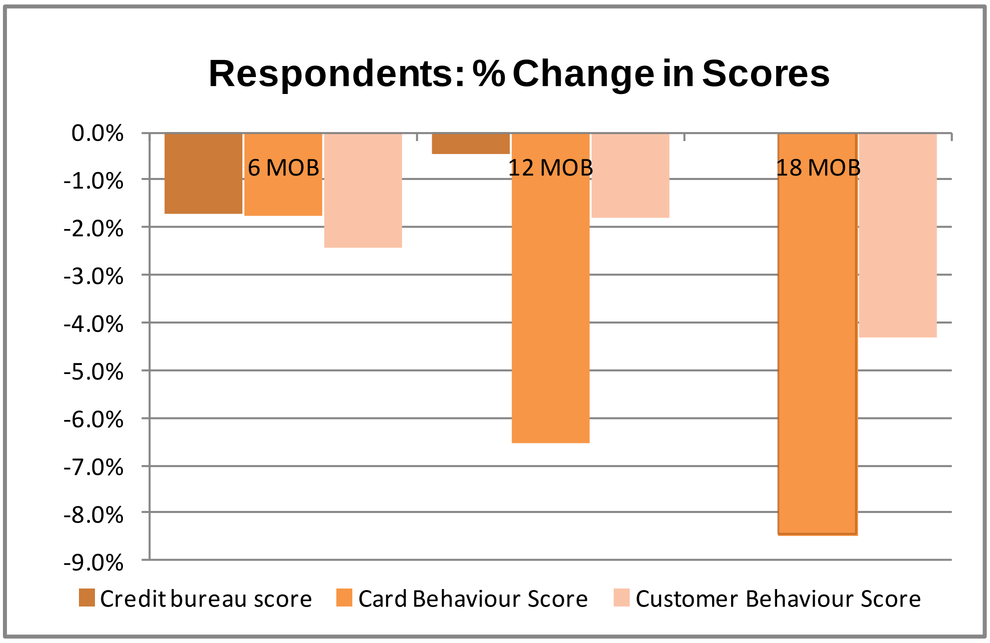
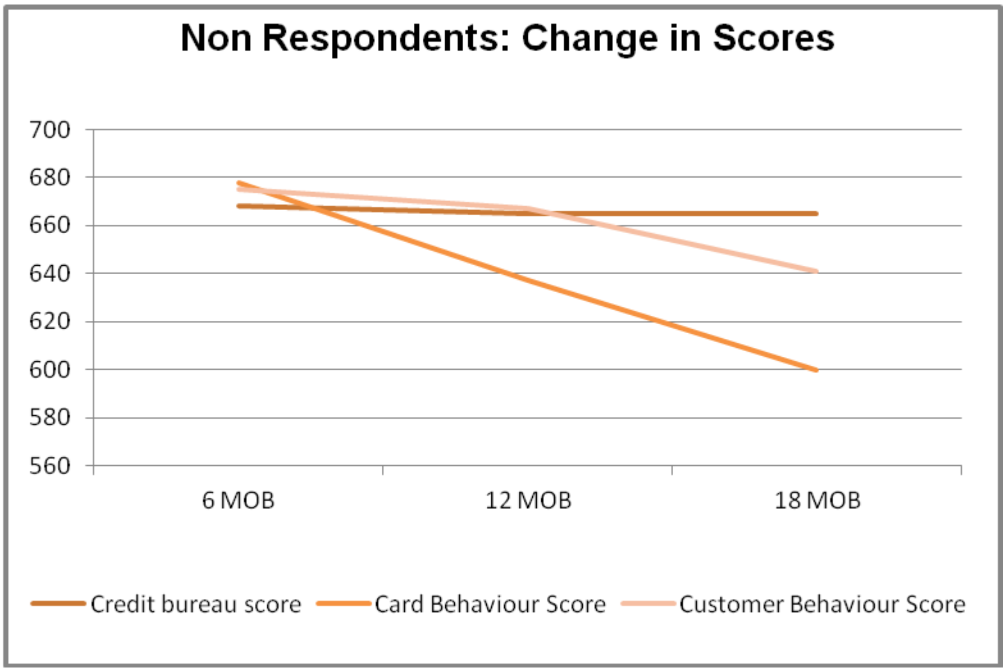
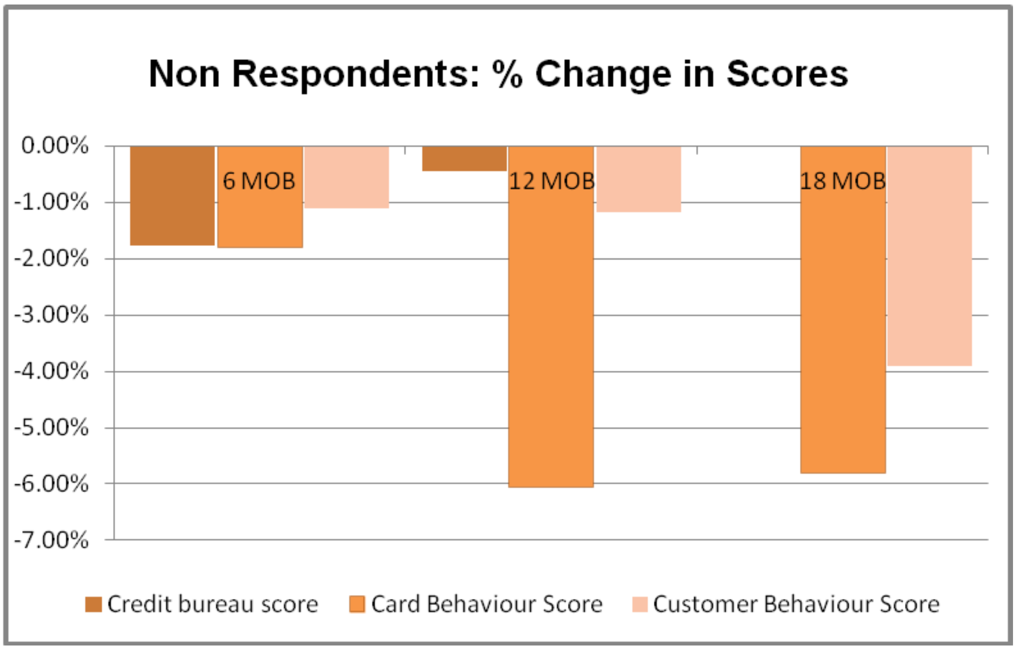


Figure 13: Non Respondents Change in Scores





The Respondents credit bureau score shows a reduction of 1.7% (6MOB), 0.5% (12MOB) and 0% (18MOB) whereas the Non Respondents credit bureau score shows a reduction of 1.76% (6MOB), 0.4%(12MOB) and 0.0%(18MOB). Both populations show a reduction in the credit bureau score over the 18 months following the credit limit increase. For both populations, this is an early indication of financial distress with scores of a gradual decline. However, the credit bureau score shows little volatility over this period as the score is not immediately susceptible to economic or customer credit risk behaviour changes as it incorporates multiple credit risk drivers. The Respondent population, however, reflects a steeper deterioration in the credit bureau score than the Non Respondents.

The Respondents Card behaviour score shows a reduction of 1.8% (6MOB), 6.5% (12MOB) and 8.4% (18MOB). The Non Respondents card behaviour score shows a reduction of 1.8% (6MOB), 6.0% (12MOB) and 5.8 % (18MOB). This, being the most dynamic of the risk indicators, shows a significant reduction in both populations. This is the best measure of risk as this is directly related to the specific product on which the credit limit was done. The deterioration in the Respondents exceeds that of the Non Respondents.

Lastly, the Respondents customer behaviour score shows a reduction of 2.4% (6MOB), 1.8% (12 MOB) and 4.3% (18MOB).The Non Respondents scores show a reduction of 1.1% (6MOB), 1.2% (12MOB) and 3.9% (18MOB). Again, the Respondents reduction in the scores exceeds the Non Respondents scores.

The statistical t test on each one of these 4 variables over the 18 months performance window yielded the rejection of equality between the Respondents and the Non respondents, at the 0.0001% level. The null hypothesis is rejected as the difference between the Respondents and Non Respondents are statistically significant.

Although not specifically measured in either Ausubel (1990) and Agarwal, et al. (2010)'s research, these findings are consistent with prior studies of Gross and Souleles (2002) and Agarwal et al. (2008) - card holders with a lower credit limit, higher utilisation rate, higher number of open credit cards, higher balance transfers, are more likely to default. The overall propensity of the Respondents to default is signalled in the early deterioration of the scores, signalling the presence of adverse selection.

6.6 Discussion pertaining to Hypothesis 3

The third hypothesis will be addressed and discussed in this section: ***H3: The cardholder defaults as a consequence of a solicitation offer type indicator after controlling the consumer's demographic characteristics, the risk attributes observed by the lender at the time the card was issued.***

The adverse selection which was examined in Section 6.3 and Section 6.4 was observable to a credit card issuer at the time that the consumer responded to the credit limit increase solicitation. These credit limit solicitations with inferior credit risk characteristics, generate inferior observable characteristics (i.e. higher utilised had poorer credit scores)

The default measures were supported by the review of delinquencies, charge off and bad rate over the 18 months period as well as logistic regression that used specific input variables to predict the probability of default at 12 months and 18 months on book.

Into the 18 months performance window, the Respondents have a higher default of 5.11% on delinquencies, relative to the Non Respondents of 2.84%, a charge off of 2.11% relative to the Non Respondents is 1.91% and overall bad rate of 4.26%, which exceeds the Non Respondents bad rate of 2.88%.

t test: of the 3 variables, the null hypothesis can only be rejected for the delinquency number and the number of 'bads' at the 0.0001% level. The charge off variables difference remains economically substantial.

6.7 Conclusion

This research is instrumental in using offers of credit limit increases made to existing credit card customers to examine the existence of adverse selection in the South African credit card market. Firstly, a descriptive analysis was used to differentiate the Respondents to the Non Respondents and to understand the underlying variations in the two populations. Additionally, this descriptive allowed for a better understanding of the targeted population that was used as part of the empirical research. The Winner’s curse focussed on significance in the statistical differences between the Respondents and the Non Respondents whose results were complimentary in rejecting the null hypothesis, confirming that the Respondents have inferior credit risk characteristics in comparison to the Non Respondents. These results showed overwhelming evidence of adverse selection.

Lastly, adverse selection is tested by estimating the likelihood of a card holder to default while controlling for information on the cardholder’s risk attributes observed by the lender at the time the card was issued. Evidence of increased delinquency indices, charge off and bad rate, and strong correlation between the dependent and independent variables in determining the bad rate, provide strong evidence of adverse selection.

7 CHAPTER7:CONCLUSIONS AND RECOMMENDATIONS

7.1 Introduction

This chapter summarises the major research findings and makes recommendations based on the research results.

7.2 Conclusions of the study

The purpose of this research was to examine the existence of adverse selection in the Credit card market using data from a large South African Banking institution.

The first hypothesis was:

H1: There is a significant difference in the risk profile characteristics between non responders and responders to credit card solicitation.

The literature indicated that adverse selection exist where there is information asymmetry between the lender and the borrower. This research endorses the findings from comparative research (although targeting a different customer base) with Respondents showing inferior credit bureau, card behaviour score, customer behaviour score, number of bank cards, combined revolving limits, lower months on book and utilisation when compared to the Non Respondents.

The second hypothesis was:

H2: There are immediate credit quality changes that are observable after the customer has accepted the credit limit increase offer.

This research introduced an additional component of detecting early default on accounts that have accepted a credit limit increase. The systematic deterioration in the credit bureau score, the card behaviour score as well as the customer behaviour score serve as early indicators of unforeseen losses and are key in indicating that the lender is susceptible to adverse selection.

The third hypothesis was:

H3: The cardholder defaults as a consequence of a solicitation offer type indicator after controlling the consumer's demographic characteristics, the risk attributes observed by the lender at the time the card was issued.

Default measures such as delinquency levels, charge off levels and bad rates show losses incurred by the lender as a consequence of the solicitations. In the above measure, Respondents have signalled a high propensity to default. Consistent with previous researchers, Gross and Souleles (2002), Ausubel (1999), Agarwal, et al. (2008) and Agarwal, et al. (2010), this research finds that cardholders with lower limits, higher utilisation, higher revolving balances carry a higher propensity to default.

The combined results of the 3 hypotheses show strong and robust evidence of adverse selection within a bank's credit lending process to existing customers where undesired results occur, due to information asymmetries (access to different information) between the lender and the borrower. These information asymmetries between the lender and the borrower have made it difficult for the lender to differentiate between good credit risk and bad credit risk. The existence of adverse selection has been examined in the above study where bad risk customers were more probable in acquiring credit limit increases than good risk customers.

Despite prior screening and a cautious selection of a better risk customer, adverse selection still manifests in the pre-approved credit lending process. If the lender had reached out to lower risk customers, adverse selection would be rampant. These results could be interpreted as a minimal test of adverse selection.

7.3 Recommendations

Based on the research findings, a number of recommendations can be made to understanding and managing adverse selection within the credit card market.

When identifying pockets of growth opportunities using pre-approved limit solicitation, lenders should consider the following:

- Fully understand the credit risk position of the customer, using robust screening and signalling techniques. This implies the implementation of scorecards and investing in screening enablers that can better differentiate between good and bad customers.

- Use of effective risk based pricing to mitigate credit losses. Poor differentiation between good risk and bad risk customers often results in misaligned pricing between good and bad customers.

- Regulators and lenders should hold the borrower and lender equally responsible for this through implementing stricter controls within the National Credit Act.

7.4 Suggestions for further research

- A more useful way of looking at information asymmetries within the credit card market would be to conduct a similar study making specific reference to the terms on which the credit limits extension was done. This should include interest rates, the repayment periods, etc.

- Extend the study into finer demographics (i.e. age, gender, product type, salary, banks, etc. of the campaign populations)

- Understand the severity of adverse selection within the various customer contact channels when campaigning.

- Understand the extent of adverse selection where a lender offers an existing transactional customer (with a cheque or savings account) multiple bank products simultaneously (i.e. home loans, personal loans, credit card, etc.)

Resources and time permitting, lenders should not only use statistical data to establish the customer's credit risk. Although credit scoring performance tools are good in understanding historical behaviour, future behaviour can be established via direct contact with the customer prior to making the offers. A thorough needs analysis complemented by an understanding of current income and expense commitment can be used in addition to statistical models to understand a customer's credit risk performance.

8 RESEARCH PLANNING

8.1 Time-table

Table 14: Time-plan for completion of research report by Elizabeth Segoale

	date	date	date	date	date	date	date
Finalise proposal	13/09/13						
Gain approval	30/09/13						
Gather data		30/11/13	30/11/13	30/11/13			
Do data analysis			31/12/13	31/12/13	31/10213		
Write report					15/01/2014	17/01/2014	
Finalise report							30/01/14

8.2 Consistency matrix

Table 15: Consistency matrix

Research problem: The main problem of this study is to examine evidence of adverse selection in limit increase preapprovals to existing Credit Card customers where caution to eliminate high risk customers has been undertaken via robust screening techniques.					
Sub-problem	**Literature Review**	**Hypotheses or Propositions or Research questions**	**Source of data**	**Type of data**	**Analysis**
The first sub problem is that certain contractual agreements and incentive effects offered by the banks to credit cards customers when offering preapproved limits, influences the composition of the portfolio pool by broadening the high risk pool.	(Arkerlof, 1970) Ausubel, 1999); (Agarwal, Chomsisengphet, & Liu, 2010)	• There is a significant difference in the risk profile characteristics between non responders and responders to credit card solicitation.	One of the 4 Big Banks	Secondary, time series data	Analysis of Variance(ANOVA) Logistic Regression

Research problem: The main problem of this study is to examine evidence of adverse selection in limit increase preapprovals to existing Credit Card customers where caution to eliminate high risk customers has been undertaken via robust screening techniques.					
Sub-problem	**Literature Review**	**Hypotheses or Propositions or Research questions**	**Source of data**	**Type of data**	**Analysis**
The second sub-problem is that the poor credit quality of inferior solicited credit limit increases, have a higher probability of default and result in higher bank losses	Stiglitz & Weiss (1981); (Ausubel, 1999); (Gross & Souleles, 2002); (Klonner & Rai, 2005); (McIntosh & Wydick, 2007); (Agarwal, Chomsisengphet, & Liu, 2010)	• There are immediate credit quality changes that are observable after the customer has accepted the credit limit increase offer and, if so, whether these differ by solicitation offer types.	One of the 4 Big Banks	Secondary, time series data	Analysis of Variance(ANOVA) Time series Analysis
The second sub-problem is that the poor credit quality of inferior solicited credit limit increases, have a higher probability of default and result in higher bank losses	Stiglitz & Weiss (1981); (Ausubel, 1999); (Gross & Souleles, 2002); (Klonner & Rai, 2005); (McIntosh & Wydick, 2007); (Agarwal, Chomsisengphet & Liu, 2010)	• The cardholder defaults as a consequence of a solicitation offer type indicator after controlling the consumer’s demographic characteristics, the risk attributes observed by the lender at the time the card was issued.	One of the 4 Big Banks	Secondary, time series data	Analysis of Variance(ANOVA) Time series Analysis

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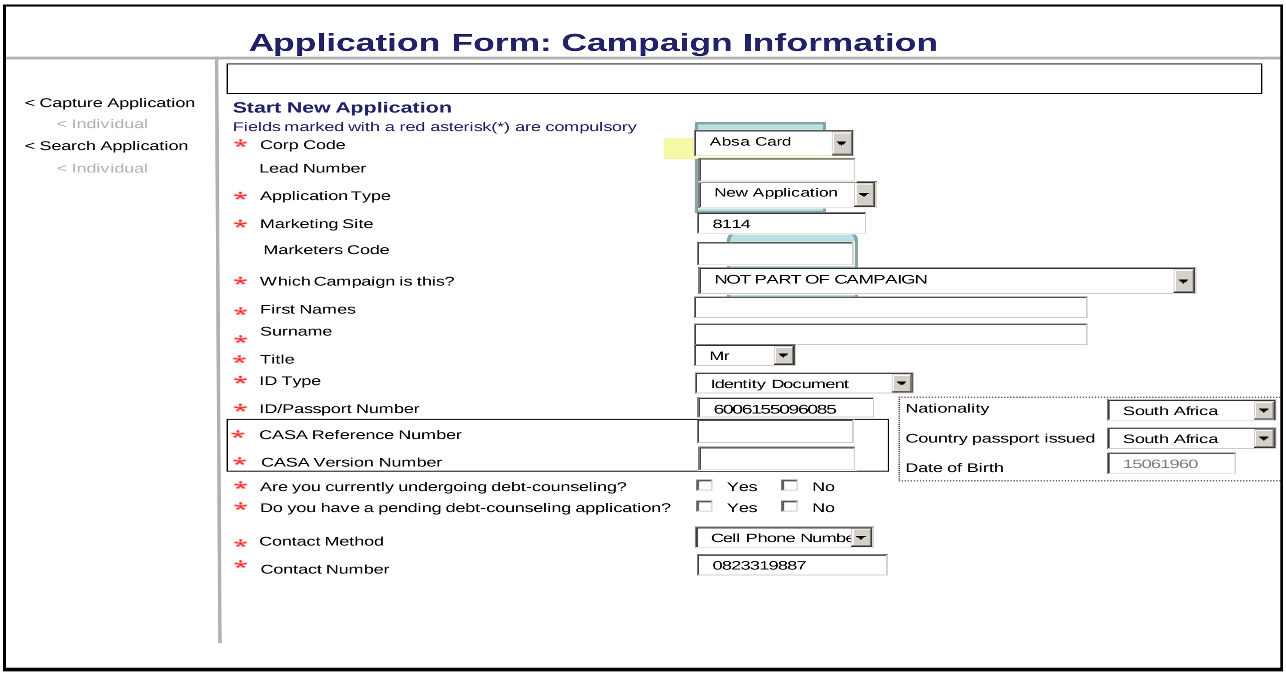
APPENDIX A: Electronic application form: Campaign information



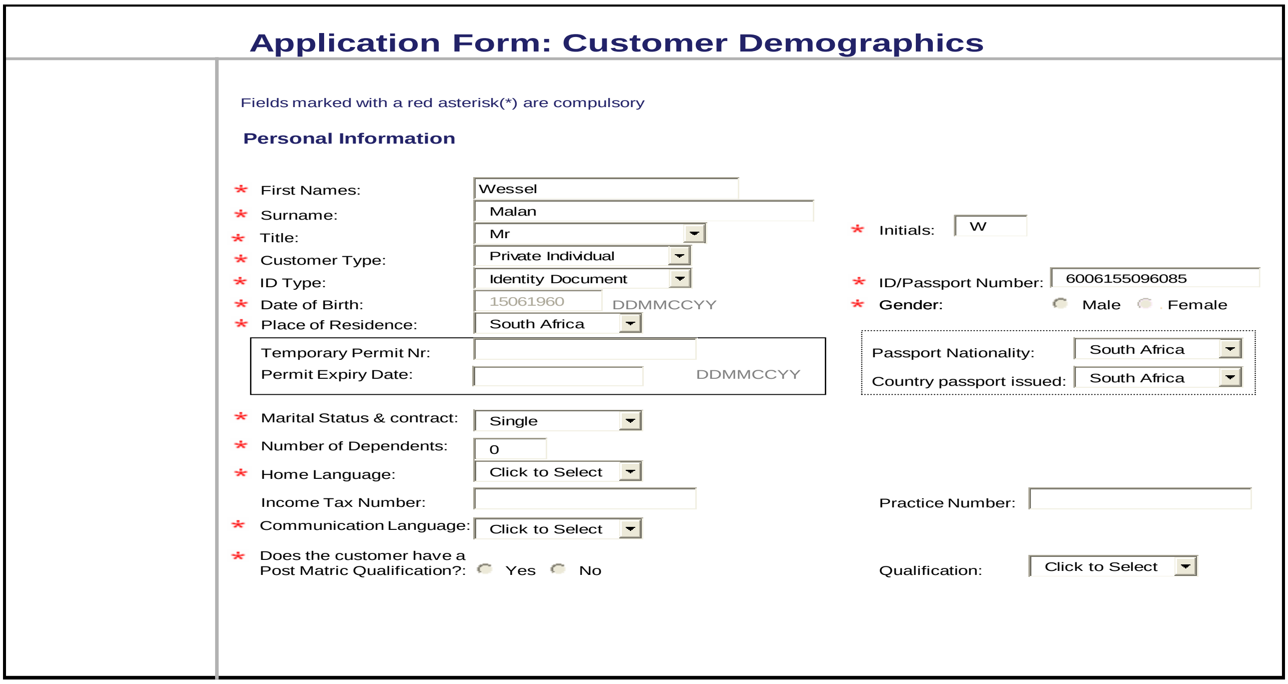
Application Form: Campaign Information

< Capture Application
< Individual
< Search Application
< Individual

Start New Application
Fields marked with a red asterisk(*) are compulsory

- * Corp Code: Absa Card
- Lead Number:
- * Application Type: New Application
- * Marketing Site: 8114
- Marketers Code:
- * Which Campaign is this?: NOT PART OF CAMPAIGN
- * First Names:
- * Surname:
- * Title: Mr
- * ID Type: Identity Document
- * ID/Passport Number: 6006155096085
- * CASA Reference Number:
- * CASA Version Number:
- Nationality: South Africa
- Country passport issued: South Africa
- Date of Birth: 15061960
- * Are you currently undergoing debt-counseling? Yes No
- * Do you have a pending debt-counseling application? Yes No
- * Contact Method: Cell Phone Numbe
- * Contact Number: 0823319887

Customer Demographics



Application Form: Customer Demographics

Fields marked with a red asterisk(*) are compulsory

Personal Information

- * First Names: Wessel
- * Surname: Malan
- * Initials: W
- * Title: Mr
- * Customer Type: Private Individual
- * ID Type: Identity Document
- * ID/Passport Number: 6006155096085
- * Date of Birth: 15061960 DDMMCCYY
- * Gender: Male Female
- * Place of Residence: South Africa
- Temporary Permit Nr:
- Permit Expiry Date: DDMMCCYY
- Passport Nationality: South Africa
- Country passport issued: South Africa
- * Marital Status & contract: Single
- * Number of Dependents: 0
- * Home Language: Click to Select
- Income Tax Number:
- Practice Number:
- * Communication Language: Click to Select
- * Does the customer have a Post Matric Qualification?: Yes No
- Qualification: Click to Select

Customer Affordability Details

Application Form: Affordability Information

General Information

Fields marked with a red asterisk(*) are compulsory

* Stayed at Current Address Since: ______ CCYYMMDD
* Have you ever previously undergone debt-counseling?: ☐ Yes ☐ No
  Debt-counseling clearance date: ______ CCYYMMDD
* Do you have any other credit cards?: ☐ Yes ☐ No
* Do you have an Absa Credit Card?: ☐ Yes ☐ No
* With Employer Since: 200402 CCYYMMDD

Personal Monthly Income and Expenses

* Total Monthly gross income ______
* Source of Income [Click to Select]
* Total Net Income ______
* Total Fixed debit Installments ______
* Total living Expenses ______
* Surplus ______

☐ Yes ☐ No

APPENDIX B: Credit Limit Increase Telephonic Scripting

I can assist you with a limit increase now - can I continue ? (CLIENT MUST confirm YES wants to apply now)

<Client preferred name> in order for me to assess your new credit limit and to ensure I'm speaking to the correct person, I need to confirm:

- Your full names?
- Your id number? (Agent can confirm the date of birth and the customer to confirm the rest of the id number). For irate customers, the agent can negotiate with customer by confirming the first two numbers and the customer confirming the next two until the full id number is confirmed)
- Are you currently under Debt Counselling? (Customer must confirm NO)

- **Total monthly gross income:**
- **Total monthly net income:**
- **Total monthly fixed debit instalments**:

- **Total monthly living expenses:** <Client preferred name> is this affordability information given correct?

You qualify for a credit limit of R......Would you like to take up this limit or do you accept this limit? (Response must be a confirmed "YES") Thank You and Congratulations!……………………..Your limit will be increased within 3 working days providing that your Credit Card Account is in order at the time of the processing of the Limit Increase.

<Client preferred name> should your affordability change in future, (a change in either your income or expenses), you can call *???????* and go through the affordability assessment to obtain a limit increase which is subject to a credit assessment.

If you have any queries in future please call *????????* which is also printed on the back of your credit card. Thank you for your time and *?????* wishes you a great day.

APPENDIX C: Databases

Taken Up data - database

#	Variable	Variable type	Type	Len	Format		Label
1	ID_key_match	Identifier	Char	13			
2	ACC_key_match	Identifier	Char	16			
3	c_current_limit	Continuous	Num	8	BEST12.		
4	AutoCLI_limit	Continuous	Num	8	BEST12.		
5	c_risk_limit	Continuous	Num	8	BEST12.		
6	CAMPAIGN	Categorical	Num	8	BEST12.		
7	TOTAL_CREDIT_LIMIT	Continuous	Num	8			
8	LIMIT_INCREASE_IND	Categorical	Char	1	$1.		LIMIT_INCREASE_IND
9	CREDIT_BUREAU_SCORE	Discrete	Num	8		4	CREDIT_BUREAU_SCORE
10	BEHAVIOUR_SCORE	Categorical	Num	8		4	BEHAVIOUR_SCORE
11	ACCOUNT_BALANCE	Continuous	Num	8		17.2	ACCOUNT_BALANCE
12	TOTAL_BUDGET_BALANCE_AMT	Continuous	Num	8		17.2	TOTAL_BUDGET_BALANCE_AMT
13	PURCHASE_LIMIT_AMT	Continuous	Num	8		16	PURCHASE_LIMIT_AMT
14	BUDGET_LIMIT_AMOUNT	Continuous	Num	8		9	BUDGET_LIMIT_AMOUNT
15	OPEN_DATE	Date	Num	8	DATETIME20.		OPEN_DATE

16	DELINQUENT_CYCLES_COUNT	Discrete	Num	8	5	DELINQUENT_CYCLES_COUNT
17	ACCOUNT_TYPE_CODE	Categorical	Char	5	$5.	ACCOUNT_TYPE_CODE
18	BUDGET_INTEREST_RATE	Continuous	Num	8	9.3	BUDGET_INTEREST_RATE
19	CREDIT_INTEREST_RATE	Continuous	Num	8	9.3	CREDIT_INTEREST_RATE
20	DEBIT_INTEREST_RATE	Continuous	Num	8	8.3	DEBIT_INTEREST_RATE
21	CARD_ACCOUNT_STATUS_CODE	Categorical	Char	3	$3.	CARD_ACCOUNT_STATUS_CODE
22	j_credit_limit	Continuous	Num	8		CREDIT_LIMIT
23	CURRENT_BALANCE	Continuous	Num	8		CURRENT_BALANCE
24	RISK_GRADE	Categorical	Char	3	$3.	RISK_GRADE
25	j_current_limit	Continuous	Num	8	BEST12.	
26	j_risk_limit	Continuous	Num	8	BEST12.	
27	INCOME_GROUP_CODE	Categorical	Num	8	3	INCOME_GROUP_CODE
28	NUMBER_OF_CARD	Discrete	Num	8		
29	UTILISATION_RATE	Categorical	Num	8		
30	CUSTOMER_BEHAVIOUR_SCORE	Discrete	Num	8	13	CUSTOMER_BEHAVIOUR_SCORE
31	RISK_GRADE_CODE	Categorical	Num	8	3	RISK_GRADE_CODE
32	f_credit_limit	Continuous	Num	8		CREDIT_LIMIT
33	f_current_limit	Continuous	Num	8	BEST12.	
34	f_risk_limit	Continuous	Num	8	BEST12.	
35	take_up	Categorical	Char	1		

Performance data - database

#	Variable	Variable Type	Type	Len	Format	Label
1	ID_key_match	Identifier	Char	13		
2	ACC_key_match	Identifier	Char	16		
3	c_current_limit	Continuous	Num	8	BEST12.	
4	AutoCLI_limit	Continuous	Num	8	BEST12.	
5	c_risk_limit	Continuous	Num	8	BEST12.	
6	CAMPAIGN	Categorical	Num	8	BEST12.	
7	TOTAL_CREDIT_LIMIT	Continuous	Num	8		
8	LIMIT_INCREASE_IND	Categorical	Char	1	$1.	LIMIT_INCREASE_IND
9	CREDIT_BUREAU_SCORE	Continuous	Num	8	4	CREDIT_BUREAU_SCORE
10	BEHAVIOUR_SCORE	Discrete	Num	8	4	BEHAVIOUR_SCORE
11	ACCOUNT_BALANCE	Continuous	Num	8	17.2	ACCOUNT_BALANCE
12	TOTAL_BUDGET_BALANCE_AMT	Continuous	Num	8	17.2	TOTAL_BUDGET_BALANCE_AMT
13	PURCHASE_LIMIT_AMT	Continuous	Num	8	16	PURCHASE_LIMIT_AMT
14	BUDGET_LIMIT_AMOUNT	Continuous	Num	8	9	BUDGET_LIMIT_AMOUNT
15	OPEN_DATE	Date	Num	8	DATETIME20.	OPEN_DATE
16	DELINQUENT_CYCLES_COUNT	Discrete	Num	8	5	DELINQUENT_CYCLES_COUNT
17	ACCOUNT_TYPE_CODE	Categorical	Char	5	$5.	ACCOUNT_TYPE_CODE
18	BUDGET_INTEREST_RATE	Continuous	Num	8	9.3	BUDGET_INTEREST_RATE
19	CREDIT_INTEREST_RATE	Continuous	Num	8	9.3	CREDIT_INTEREST_RATE

20	DEBIT_INTEREST_RATE	Continuous	Num	8		8.3	DEBIT_INTEREST_RATE
21	CARD_ACCOUNT_STATUS_CODE	Discrete	Char	3	$3.		CARD_ACCOUNT_STATUS_CODE
22	j_credit_limit	Continuous	Num	8			CREDIT_LIMIT
23	CURRENT_BALANCE	Continuous	Num	8			CURRENT_BALANCE
24	RISK_GRADE	Categorical	Char	3	$3.		RISK_GRADE
25	j_current_limit	Discrete	Num	8	BEST12.		
26	j_risk_limit	Discrete	Num	8	BEST12.		
27	INCOME_GROUP_CODE	Categorical	Num	8		3	INCOME_GROUP_CODE
28	NUMBER_OF_CARD	Discrete	Num	8			
29	UTILISATION_RATE	Continuous	Num	8			
30	CUSTOMER_BEHAVIOUR_SCORE	Discrete	Num	8		13	CUSTOMER_BEHAVIOUR_SCORE
31	RISK_GRADE_CODE	Categorical	Num	8		3	RISK_GRADE_CODE
32	f_credit_limit	Continuous	Num	8			CREDIT_LIMIT
33	f_current_limit	Continuous	Num	8	BEST12.		
34	f_risk_limit	Continuous	Num	8	BEST12.		
35	take_up	Categorical	Char	1			
36	cbs_m6	Identifier	Num	8		4	
37	bs_m6	Identifier	Num	8		4	
38	cyc_delq_m6	Categorical	Num	8		5	
39	acc_type_m6	Categorical	Char	5	$5.		
40	acc_status_m6	Categorical	Char	3	$3.		
41	limit_m6	Continuous	Num	8			
42	bal_m6	Continuous	Num	8			
43	rg_m6	Categorical	Char	3	$3.		
44	cust_bs_m6	Continuous	Num	8		13	
45	rg_code_m6	Categorical	Num	8		3	
46	cbs_m12	Continuous	Num	8		4	
47	bs_m12	Continuous	Num	8		4	
48	cyc_delq_m12	Categorical	Num	8		5	
49	acc_type_m12	Categorical	Char	5	$5.		
50	acc_status_m12	Categorical	Char	3	$3.		
51	limit_m12	Continuous	Num	8			
52	bal_m12	Continuous	Num	8			
53	rg_m12	Categorical	Char	3	$3.		
54	cust_bs_m12	Continuous	Num	8		13	
55	rg_code_m12	Categorical	Num	8		3	
56	cbs_m18	Continuous	Num	8		4	
57	bs_m18	Continuous	Num	8		4	
58	cyc_delq_m18	Categorical	Num	8		5	
59	acc_type_m18	Categorical	Char	5	$5.		
60	acc_status_m18	Categorical	Char	3	$3.		
61	limit_m18	Continuous	Num	8			
62	bal_m18	Continuous	Num	8			
63	rg_m18	Categorical	Char	3	$3.		
64	cust_bs_m18	Continuous	Num	8		13	
65	rg_code_m18	Categorical	Num	8		3	

Bad Definition- database

#	Variable	Variable Type	Type	Len	Format	Label
1	ID_key_match	Identifier	Char	13		
2	ACC_key_match	Identifier	Char	16		
3	c_current_limit	Continuous	Num	8	BEST12.	
4	AutoCLI_limit	Continuous	Num	8	BEST12.	
5	c_risk_limit	Continuous	Num	8	BEST12.	
6	CAMPAIGN	Categorical	Num	8	BEST12.	
7	TOTAL_CREDIT_LIMIT	Continuous	Num	8		
8	LIMIT_INCREASE_IND	Categorical	Char	1	$1.	LIMIT_INCREASE_IND
9	CREDIT_BUREAU_SCORE	Discrete	Num	8	4	CREDIT_BUREAU_SCORE
10	BEHAVIOUR_SCORE	Discrete	Num	8	4	BEHAVIOUR_SCORE
11	ACCOUNT_BALANCE	Continuous	Num	8	17.2	ACCOUNT_BALANCE
12	TOTAL_BUDGET_BALANCE_AMT	Continuous	Num	8	17.2	TOTAL_BUDGET_BALANCE_AMT
13	PURCHASE_LIMIT_AMT	Continuous	Num	8	16	PURCHASE_LIMIT_AMT
14	BUDGET_LIMIT_AMOUNT	Continuous	Num	8	9	BUDGET_LIMIT_AMOUNT
15	OPEN_DATE	Date	Num	8	DATETIME20.	OPEN_DATE
16	DELINQUENT_CYCLES_COUNT	Discrete	Num	8	5	DELINQUENT_CYCLES_COUNT
17	ACCOUNT_TYPE_CODE	Categorical	Char	5	$5.	ACCOUNT_TYPE_CODE
18	BUDGET_INTEREST_RATE	Continuous	Num	8	9.3	BUDGET_INTEREST_RATE
19	CREDIT_INTEREST_RATE	Continuous	Num	8	9.3	CREDIT_INTEREST_RATE
20	DEBIT_INTEREST_RATE	Continuous	Num	8	8.3	DEBIT_INTEREST_RATE
21	CARD_ACCOUNT_STATUS_CODE	Categorical	Char	3	$3.	CARD_ACCOUNT_STATUS_CODE
22	j_credit_limit	Continuous	Num	8		CREDIT_LIMIT
23	CURRENT_BALANCE	Continuous	Num	8		CURRENT_BALANCE
24	RISK_GRADE	Categorical	Char	3	$3.	RISK_GRADE
25	j_current_limit	Continuous	Num	8	BEST12.	
26	j_risk_limit	Continuous	Num	8	BEST12.	
27	INCOME_GROUP_CODE	Categorical	Num	8	3	INCOME_GROUP_CODE
28	NUMBER_OF_CARD	Discrete	Num	8		
29	UTILISATION_RATE	Continuous	Num	8		
30	CUSTOMER_BEHAVIOUR_SCORE	Discrete	Num	8	13	CUSTOMER_BEHAVIOUR_SCORE
31	RISK_GRADE_CODE	Categorical	Num	8	3	RISK_GRADE_CODE
32	f_credit_limit	Continuous	Num	8		CREDIT_LIMIT
33	f_current_limit	Continuous	Num	8	BEST12.	
34	f_risk_limit	Continuous	Num	8	BEST12.	
35	take_up	Categorical	Char	1		
36	cbs_m6	Continuous	Num	8	4	
37	bs_m6	Continuous	Num	8	4	

38	cyc_delq_m6	Categorical	Num	8		5
39	acc_type_m6	Categorical	Char	5	$5.	
40	acc_status_m6	Categorical	Char	3	$3.	
41	limit_m6	Continuous	Num	8		
42	bal_m6	Continuous	Num	8		
43	rg_m6	Categorical	Char	3	$3.	
44	cust_bs_m6	Continuous	Num	8		13
45	rg_code_m6	Categorical	Num	8		3
46	cbs_m12	Continuous	Num	8		4
47	bs_m12	Continuous	Num	8		4
48	cyc_delq_m12	Categorical	Num	8		5
49	acc_type_m12	Categorical	Char	5	$5.	
50	acc_status_m12	Categorical	Char	3	$3.	
51	limit_m12	Continuous	Num	8		
52	bal_m12	Continuous	Num	8		
53	rg_m12	Categorical	Char	3	$3.	
54	cust_bs_m12	Continuous	Num	8		13
55	rg_code_m12	Categorical	Num	8		3
56	cbs_m18	Continuous	Num	8		4
57	bs_m18	Continuous	Num	8		4
58	cyc_delq_m18	Categorical	Num	8		5
59	acc_type_m18	Categorical	Char	5	$5.	
60	acc_status_m18	Categorical	Char	3	$3.	
61	limit_m18	Continuous	Num	8		
62	bal_m18	Continuous	Num	8		
63	rg_m18	Categorical	Char	3	$3.	
64	cust_bs_m18	Continuous	Num	8		13
65	rg_code_m18	Categorical	Num	8		3
66	bad_m6	Categorical	Char	1		
67	bad_m12	Categorical	Char	1		
68	bad_m18	Categorical	Char	1		

APPENDIX D: Grouping Methodology

Grouping Methodology

util_bucket	*% Utilization*	
0	0	if util = 0 then util_bucket = 0;
1	<10%	else if util < 0.1 then util_bucket = 1;

2	<20%	else if util < 0.2 then util_bucket = 2;
3	<30%	else if util < 0.3 then util_bucket = 3;
4	<40%	else if util < 0.4 then util_bucket = 4;
5	<50%	else if util < 0.5 then util_bucket = 5;
6	<60%	else if util < 0.6 then util_bucket = 6;
7	<70%	else if util < 0.7 then util_bucket = 7;
8	<80%	else if util < 0.8 then util_bucket = 8;
9	<90%	else if util < 0.9 then util_bucket = 9;
10	<100%	else if util < 1 then util_bucket = 10;
11	>=100%	else util_bucket = 11;

mob_gp	*Month_On_Book*	
1	<= 12	if mob <= 12 then mob_grp = 1;
2	<= 24	else if mob <= 24 then mob_grp = 2;
3	<= 36	else if mob <= 36 then mob_grp = 3;
4	<= 48	else if mob <= 48 then mob_grp = 4;
5	<= 60	else if mob <= 60 then mob_grp = 5;
6	<= 72	else if mob <= 72 then mob_grp = 6;
7	<= 84	else if mob <= 84 then mob_grp = 7;
8	<= 96	else if mob <= 96 then mob_grp = 8;
9	<= 108	else if mob <= 108 then mob_grp = 9;
10	<= 120	else if mob <= 120 then mob_grp = 10;
11	<= 132	else if mob <= 132 then mob_grp = 11;
12	<= 144	else if mob <= 144 then mob_grp = 12;
13	<= 156	else if mob <= 156 then mob_grp = 13;
14	<= 168	else if mob <= 168 then mob_grp = 14;
15	<= 180	else if mob <= 180 then mob_grp = 15;
16	<= 192	else if mob <= 192 then mob_grp = 16;
17	<= 204	else if mob <= 204 then mob_grp = 17;
18	<= 216	else if mob <= 216 then mob_grp = 18;
19	<= 228	else if mob <= 228 then mob_grp = 19;
20	<= 240	else if mob <= 240 then mob_grp = 20;
21	<= 252	else if mob <= 252 then mob_grp = 21;
22	<= 264	else if mob <= 264 then mob_grp = 22;
23	<= 276	else if mob <= 276 then mob_grp = 23;
24	<= 288	else if mob <= 288 then mob_grp = 24;
25	>=289	else mob_grp = 25;

bs_grp	Behaviour_Score_Group	
1	< 600	if behaviour_score < 600 then bs_grp = 1;
2	< 615	else if behaviour_score < 615 then bs_grp = 2;
3	< 630	else if behaviour_score < 630 then bs_grp = 3;
4	< 645	else if behaviour_score < 645 then bs_grp = 4;
5	< 660	else if behaviour_score < 660 then bs_grp = 5;
6	< 675	else if behaviour_score < 675 then bs_grp = 6;
7	< 690	else if behaviour_score < 690 then bs_grp = 7;
8	< 705	else if behaviour_score < 705 then bs_grp = 8;
9	< 720	else if behaviour_score < 720 then bs_grp = 9;
10	< 735	else if behaviour_score < 735 then bs_grp = 10;
11	>=735	else bs_grp = 11;

custbs_grp	Customer_Behaviour_Score_Group	
1	< 600	if j_customer_behaviour_score < 600 then custbs_grp = 1;
2	< 615	else if j_customer_behaviour_score < 615 then custbs_grp = 2;
3	< 630	else if j_customer_behaviour_score < 630 then custbs_grp = 3;
4	< 645	else if j_customer_behaviour_score < 645 then custbs_grp = 4;
5	< 660	else if j_customer_behaviour_score < 660 then custbs_grp = 5;
6	< 675	else if j_customer_behaviour_score < 675 then custbs_grp = 6;
7	< 690	else if j_customer_behaviour_score < 690 then custbs_grp = 7;
8	< 705	else if j_customer_behaviour_score < 705 then custbs_grp = 8;
9	< 720	else if j_customer_behaviour_score < 720 then custbs_grp = 9;
10	< 735	else if j_customer_behaviour_score < 735 then custbs_grp = 10;
11	>=735	else custbs_grp = 11;

cbs_grp	Credit_Bureau_ScoreGroup	
1	< 600	if credit_bureau_score < 600 then cbs_grp = 1;
2	< 615	else if credit_bureau_score < 615 then cbs_grp = 2;
3	< 630	else if credit_bureau_score < 630 then cbs_grp = 3;
4	< 645	else if credit_bureau_score < 645 then cbs_grp = 4;
5	< 660	else if credit_bureau_score < 660 then cbs_grp = 5;
6	< 675	else if credit_bureau_score < 675 then cbs_grp = 6;
7	< 690	else if credit_bureau_score < 690 then cbs_grp = 7;
8	< 705	else if credit_bureau_score < 705 then cbs_grp = 8;
9	< 720	else if credit_bureau_score < 720 then cbs_grp = 9;

10	< 735	else if credit_bureau_score < 735 then cbs_grp = 10;
11	< 750	else if credit_bureau_score < 750 then cbs_grp = 11;
12	< 765	else if credit_bureau_score < 765 then cbs_grp = 12;
13	< 780	else if credit_bureau_score < 780 then cbs_grp = 13;
14	< 795	else if credit_bureau_score < 795 then cbs_grp = 14;
15	>=795	else cbs_grp = 15;

db_grp	*Debit_Balances*	
0	= 0	if bal_db = 0 then db_grp = 0;
1	< 1000	else if bal_db < 1000 then db_grp = 1;
2	< 2500	else if bal_db < 2500 then db_grp = 2;
3	< 5000	else if bal_db < 5000 then db_grp = 3;
4	< 7500	else if bal_db < 7500 then db_grp = 4;
5	< 10000	else if bal_db < 10000 then db_grp = 5;
6	< 15000	else if bal_db < 15000 then db_grp = 6;
7	< 20000	else if bal_db < 20000 then db_grp = 7;
8	< 25000	else if bal_db < 25000 then db_grp = 8;
9	< 30000	else if bal_db < 30000 then db_grp = 9;
10	< 40000	else if bal_db < 40000 then db_grp = 10;
11	< 50000	else if bal_db < 50000 then db_grp = 11;
12	>=50000	else db_grp = 12;

ct_grp		
0	= 0	if bal_ct = 0 then ct_grp = 0;
1	< 1000	else if bal_ct < 1000 then ct_grp = 1;

		if purchase_limit_amt = 0 then lim_grp = 0;
lim_grp	*Limit_ Group*	else if purchase_limit_amt < 1000 then lim_grp = 1;
2	< 2500	else if purchase_limit_amt < 2500 then lim_grp = 2;
3	< 5000	else if purchase_limit_amt < 5000 then lim_grp = 3;
4	< 7500	else if purchase_limit_amt < 7500 then lim_grp = 4;
5	< 10000	else if purchase_limit_amt < 10000 then lim_grp = 5;
6	< 15000	else if purchase_limit_amt < 15000 then lim_grp = 6;
7	< 20000	else if purchase_limit_amt < 20000 then lim_grp = 7;
8	< 25000	else if purchase_limit_amt < 25000 then lim_grp = 8;
9	< 30000	else if purchase_limit_amt < 30000 then lim_grp = 9;

10	< 40000	else if purchase_limit_amt < 40000 then lim_grp = 10;
11	< 50000	else if purchase_limit_amt < 50000 then lim_grp = 11;
12	>=50000	else lim_grp = 12;

lim_min_grp	Minimum_ Limit_Group	if limit_offer_min = 0 then lim_min_grp = 0;
1	< 1000	else if limit_offer_min < 1000 then lim_min_grp = 1;
2	< 2000	else if limit_offer_min < 2000 then lim_min_grp = 2;
3	< 3000	else if limit_offer_min < 3000 then lim_min_grp = 3;
4	< 4000	else if limit_offer_min < 4000 then lim_min_grp = 4;
5	< 5000	else if limit_offer_min < 5000 then lim_min_grp = 5;
6	< 7500	else if limit_offer_min < 7500 then lim_min_grp = 6;
7	< 10000	else if limit_offer_min < 10000 then lim_min_grp = 7;
8	< 15000	else if limit_offer_min < 15000 then lim_min_grp = 8;
9	< 20000	else if limit_offer_min < 20000 then lim_min_grp = 9;
10	< 25000	else if limit_offer_min < 25000 then lim_min_grp = 10;
11	< 30000	else if limit_offer_min < 30000 then lim_min_grp = 11;
12	< 40000	else if limit_offer_min < 40000 then lim_min_grp = 12;
13	< 50000	else if limit_offer_min < 50000 then lim_min_grp = 13;
14	>=50000	else lim_min_grp = 14;

		if limit_offer_max = 0 then lim_max_grp = 0;
lim_max_grp	*Limit_Maximum_ Group*	else if limit_offer_max < 1000 then lim_max_grp = 1;
2	< 2500	else if limit_offer_max < 2500 then lim_max_grp = 2;
3	< 5000	else if limit_offer_max < 5000 then lim_max_grp = 3;
4	< 7500	else if limit_offer_max < 7500 then lim_max_grp = 4;
5	< 10000	else if limit_offer_max < 10000 then lim_max_grp = 5;
6	< 15000	else if limit_offer_max < 15000 then lim_max_grp = 6;
7	< 20000	else if limit_offer_max < 20000 then lim_max_grp = 7;
8	< 25000	else if limit_offer_max < 25000 then lim_max_grp = 8;
9	< 30000	else if limit_offer_max < 30000 then lim_max_grp = 9;
10	< 40000	else if limit_offer_max < 40000 then lim_max_grp = 10;
11	< 50000	else if limit_offer_max < 50000 then lim_max_grp = 11;
12	>=50000	else lim_max_grp = 12;