UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

GORDON INSTITUTE
OF BUSINESS SCIENCE
University of Pretoria

Increasing the South African consumer's access to credit through the use of non-traditional sources.

Bradleigh Scott

27528376

A research project submitted to the Gordon Institute of Business Science, University of Pretoria, in partial fulfillment of the requirements for the degree of Master of Business Administration.

13 November 2008

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

ABSTRACT

In 2007, 12.5 million South African adults were classified as being unbanked and having limited access to financial services including credit. Of the 19 million consumers who have access to bank accounts and financial services products, 17.14 million are reported to be credit active. There is a need for government and/or credit providers to find new mechanisms for consumers to obtain access to financial services and allow them a chance to escape poverty.

Research was conducted on the data of a South African Municipality to determine whether there was a correlation between how consumers paid their municipal utility accounts and whether they had a good or bad credit bureau report. If the utility accounts show significant correlation to the credit bureau reports (which are based on data provided by credit grantors), then the utility accounts can be deemed to display 'credit-like' characteristics. This then provides evidence in support of the municipality providing their data to the credit bureau so that it can be used as additional data on which credit grantors can determine the credit risk of a consumer and possibly grant credit to someone who was previously denied.

The analysis conducted revealed a significant correlation between the payment behavior on the consumer's utility accounts to the data reflected on a credit bureau. It showed that the data provided displayed the same 'credit-like' characteristics as traditional credit accounts and supports the concept that the Municipality can provide their data to a credit bureau to be used in risk determination.

DECLARATION

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Bradleigh Scott

13 November 2008

ACKNOWLEDGEMENTS

I would like to express my gratitude for the immense patience, love and support from my wife Cathy over the last two years. I know she is looking forward to having her husband back.

Acknowledgement goes to my family and friends who have supported me in my decision to complete an MBA and have offered so much help and love in the process.

I would also like to thank Bev Mayers, Brenda Simpson, Jane Strydom, Lauren Kleynhans, Kevin Tait, Richard Madondo and Wen-Chi Kuo for their assistance in obtaining the data, compiling the stats or reviewing the research.

Acknowledgment must also be made to the Municipality for allowing me to utilise their data in this research and assistance with all my questions.

I'd like to thank my supervisor Gavin Price for deciphering my work and offering valuable advice. It was a pleasure to work with him.

I owe a debt of gratitude to my employer TransUnion for giving me the time, support and resources to complete both my MBA and this research project.

Finally I would like to thank the Lord, without whom I would not have stayed sane in the process.

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

TABLE OF CONTENTS

List of Tables

List of Equations

List of Figures

GLOSSARY OF TERMS

Age analysis buckets	Balances owing in current, 30 days, 60 days, 90 days and 120 days overdue.
Bads	‘Bads’ are generally defined as records that became seriously delinquent or written-off after a specific period.
Bad rate	Total number of bad accounts in relation to all accounts. Percentage of accounts on a credit book that will go into severe arrears. For example, 90 days past due.
Characteristic	Specific information obtained from a credit bureau report.
Credit Bureau scoring	Scores derived from the information available on a credit bureau report. Credit bureau scores are used on new applicants or existing accounts to make credit-related decisions.
Credit policy	The business rules around lending and the structuring of loans.
Credit scoring	A technology used by credit grantors to quantify, through the use of a statistically derived credit scorecard, the risk associated with extending credit to an individual.

Cut-off score	Any score value designated by the user above which and below which different decisions will be made on applicants or accounts.
Exclusion codes	Codes indicating why a score was not returned on a credit profile.
Expansion Risk Indicator	Risk indicator (1, 2, or 3) returned instead of an Empirica score for consumers whose credit files include header and enquiry information only.
Goods	'Goods' are generally defined as seasoned records (those that have sufficient history) that show no signs of delinquency and other derogatory behaviour during a specific period.
Minimum scoring criteria	The information a credit record must contain to be scored with a credit bureau scorecard. Minimum scoring criteria is put in place to ensure a credit record includes enough information to produce a reliable score.
Payment profile	This is a record housed on a credit bureau which represents a credit account with a credit supplier. It displays the payment behaviour of the consumer for the last 24 months. For example, is the consumer paying their account on time or are they constantly 3 months in arrears.
Retrospective	Retrospective is a process of determining what a

	consumer's credit report looked like on a specific date in the past 2 years.
Score	The numerical total of points awarded to a consumer. It is the total of the score points associated with each attribute in a scorecard.
Scorecard	A table with characteristics and their attributes, and the score associated with each attribute. A scorecard is used to derive a credit score for an applicant or existing account.

.

Chapter 1: Introduction to the Research Problem

"*The apartheid system severely distorted the South African financial system. A handful of large financial institutions, all linked closely to the dominant conglomerates, centralise most of the country's financial assets. But they prove unable to serve most of the black community, especially women. Nor do they contribute significantly to the development of new sectors of the economy. Small informal-sector institutions meet some of the needs of the black community and micro enterprise. They lack the resources, however, to bring about broad-scale development" (*African National Congress (ANC), 1994, section 4.7.1*).*

Before 1994, gross financial sector inefficiencies were supported by the apartheid government and policies were designed to protect and benefit the few (Kirsten, 2006). South Africa's legislation resulted in the majority of South Africans not having access to financial services (Coetzee, 1998). The term 'unbanked' is used to describe South Africans who do not have access to these services (South African Reserve Bank (SARB), 2003).

Post 1994, the South African government has worked hard to promote access to the financial services market for the previously disadvantaged (Kirsten, 2006) yet new innovative solutions are still needed. In relation to the ANC quote above it is argued that the efforts in making a meaningful contribution to economic development and reducing poverty to date can be disputed in that the country had not been that successful in providing access to financial services (Coetzee, Druschel, Cook, Brislin, Meagher and Pearson, 2005). Expanding access to financial services is an important objective in achieving the goal of poverty reduction. Financial services such as insurance and savings play an important role in limiting the effects of shocks to income caused by death or illness thus reducing the vulnerability to poverty. A sustainable route out of poverty however, usually requires the ability to utilise financial services to build capital (SARB, 2003). “Vulnerability is a cause of poverty and poverty is in turn a source of vulnerability. To achieve sustainable poverty reduction, poor people need to be able to effectively manage risk. It is through such management that households are able to reduce and mitigate risk and lessen the impact of shocks.” (Ardington and Leibbrandt, 2004, pg 1). A lack of effective risk management instruments and assets impact the ability of the poor to cope, and lead affected individuals to resort to short term coping strategies such as removing children from school, selling off productive assets and borrowing money from lenders at high interest rates thus increasing their vulnerability to poverty. These actions to avoid risk can perversely contribute to permanent deeper poverty (Ardington and Leibbrandt, 2004).

Globally, roughly 45% of the world’s population lives in poverty. Various spectra of poverty give rise to categories of the poor. This ranges from the ‘working poor’ who earn below minimum wage to the poorest of the poor (Arch, 2005), an estimated 1.4 billion people who live on less than $1.25 a day. The poverty rate alone for Sub-Saharan Africa in 2005 is measured at roughly 50% (The World Bank, 2008). The productive poor (working poor) are “fully capable both of integrating themselves into the mainstream of social and economic development and of actively contributing to improved economic performance at the national level” (Arch, 2005, pg 229). Many people though, have difficulty in accessing basic economic needs for growth, namely, money, banking and credit. These consumers are often part of the informal sector and are classified as the 'unbanked' (Arch, 2005).

In 2006 there were 15.27 million unbanked adults in South Africa (Hamlyn 2007). This figure is supported by a survey conducted by FinMark Trust (2007) which shows a reported 15.2 million unbanked adults in 2006 (49%) and 12.5 million unbanked adults in 2007 (39%). The access to financial services ranges from having no financial products at all to having an ATM card; or Mzansi, savings, transaction or post bank account. These adults do not have access to microloans, personal loans, mortgages, vehicle finance or overdrafts.

Mohamed (2005) mentions that access to credit for the poor should be increased significantly, however banks do not have enough information on which to make correct choices on to whom to lend money. Mohamed also mentions that having a bank account is a requirement for being able to access mainstream credit. No or insufficient credit history is also listed as the third most recorded reason for consumer's been denied credit (FinMark Trust, 2007). There is therefore a need, in some way, to enhance the information that is available to the banks to make decisions on those consumers who do not have a credit history and/or a bank account; thus allowing these consumers access to credit. Of the 19 million banked adults out of a total adult population of 31.6 million (FinMark Trust, 2008), 17.14 million are reported to be credit active (have an active credit record with a credit bureau in South Africa), (National Credit Regulator (NCR), 2008). Thus there is still much scope even within the banked population to gain access to formal credit.

Credit is traditionally granted to consumers based on the status of the consumer's credit bureau report (Political and Economic Research Council (PERC), 2007). In order to obtain credit, consumers should have at least one credit agreement listed on a bureau's database (PERC, 2007). Credit agreements are primarily obtained from South African Banks, Microlenders and Retailers. Currently consumers, who do not have existing agreements with these institutions, find it hard to obtain access to credit (PERC, 2007). This situation is referred as the 'credit Catch 22' where a consumer must have a credit history in order to qualify for credit. In situations where a consumer has no credit history, lenders generally rely on the operating assumption that the consumer is high-risk or that there is insufficient information in order to offer them an existing product and the consumer is generally rejected (Turner and Agarwal, 2008). A problem therefore exists on how a consumer with no credit history can break the 'credit Catch 22' situation and gain access to formal credit as is evident from the large numbers reported above.

A study has been conducted in the United States of America showing that non-traditional data like utility accounts (water, electricity, rates and taxes), telecommunications and rentals can be used to determine a consumer's credit worthiness and allow consumers access to credit (Turner, Stewart Lee, Schnare, Varghese and Walker, 2006). By enhancing the consumers' credit records with utility payment information, credit grantors would be able to use the information in decision making. The utility accounts are somewhat of a 'credit-like' nature as they involve the consumption of a service prior to payment, thus the payment information can be considered as predictive by potential creditors (PERC, 2007). The utility information allows lenders to utilise additional information in their credit decisions thus improving their ability to distinguish good from bad risk and translate to lower rates of delinquency (or default) for a given acceptance rate (Turner and Agarwal, 2008). This will in turn give consumers the ability to get study loans, home loans *et cetera.* (Hawkins, 2003) and allow them the opportunity to build capital and assist in escaping poverty (SARB, 2003). In light of the recent sub-prime crisis, the severity of the losses could have been lessened if lenders had access to “standardized, verifiable, non-financial data to assess credit risk, credit worthiness, and credit capacity” (PERC, 2007, p1). With such data, credit providers could have assessed who could have qualified for prime loans or who should have been disqualified because of a more complete picture of the consumer’s credit risk (PERC, 2007).

Proving that the utility data is ‘credit-like’ means that utility providers may have an incentive to report payment data to a credit bureau and thus provide incentives for their customers to pay their accounts (PERC, 2007). By accessing credit bureaux information a Municipality can also manage their own accounts and bad debt by setting deposit values and prioritising debt collections.

This research paper will seek to apply the theory in the above study in a South African context, and attempt to demonstrate that utility payment information supplied by a Municipality has ‘credit-like’ characteristics. This is done through comparing the payment behaviour of utility accounts to that of traditional credit accounts like home and vehicle loans and determining whether those consumers that conduct their utility accounts well, have good payment histories on their traditional credit accounts. On the other hand, those consumers who manage their utility accounts badly, have bad payment histories on their traditional credit accounts.

In confirming the above, and should Municipalities supply utility information to a credit bureau, the information supplied can be used by credit providers in making adequate credit decisions in the absence of traditional credit information. It can also be used to enhance decisions where only traditional credit information exists. Where consumers previously had no payment history on which credit grantors could make decisions, utility information may be captured and returned and used to grant access to credit for people who have never enjoyed it before. This will allow some consumers the ability to escape the ‘credit Catch 22’ and gain access to formal credit. In doing so consumers that may have been previously classified as ‘unbanked’ now have access to financial services previously denied, and assist as a mechanism in which the consumer can build up a credit history, build up capital and escape poverty. This is just one initiative that can be used as part of the wide spectrum of encompassing initiatives and programs needed to reduce poverty (Arch, 2005).

The remainder of this research report is structured as follows: Chapter 2 consists of the literature review that covers the theory base. Chapter 3 sets out the research hypotheses. The research method used is described in Chapter 4, while Chapter 5 presents the results of the research. These results are discussed in Chapter 6, with the conclusion being contained in Chapter 7.

Chapter 2: Literature Review

The literature review starts by defining the concept of the 'unbanked' and touches on the Financial Sector Charter which is seen as one step to address this problem. Attention is then turned to the concept of credit as a solution to assist the unbanked where the report examines the demand and supply of credit, the uses of credit, the concept of microfinance which has been used as a mechanism to assist the unbanked; as well as the various legal frameworks that have governed the issuing of credit since 1962. The next discussion is that of the dynamics of lending, encompassing the theory of credit risk, credit scoring, and credit bureaux. It includes information on the Fair Isaac Empirica credit scorecard and non-traditional credit bureaux data. The literature review then examines information surrounding municipal utility accounts incorporating municipal tariffs, deposit taking and credit control. The theory base then turns to the research conducted in the United States of America which demonstrated how utility account information has 'credit-like' characteristics and can be used in credit risk decisions. This chapter concludes by highlighting how this research will contribute to identifying a possible solution in assisting the unbanked in gaining access to financial services.

2.1 Unbanked

2.1.1 Defining the Unbanked

Arch (2005) defines the unbanked as being the poor who do not have access to basic economic needs for growth such as money, banking and credit. The Finmark Trust (2007) defines the unbanked through the use of the Financial

Services Measure (FSM) which classifies consumers into eight FSM tiers. Consumers are classified into a tier depending on the type of financial service products they have access to. A total of 15.2 million consumers falling into the first three tiers are classified as unbanked and do not have access to formal credit such as microloans, current accounts, mortgage bonds, overdrafts or vehicle finance. Table 2-1 depicts which financial products consumers in each tier have access to.

Table 2-1: FSM Tiers (Finmark Trust, 2007)

Tier	*Miscellaneous Products*
1	None
2	Informal loan/Development agency loan/Co-op/village bank account/Pawn shop loan, Store account (no card)
3	ATM card, Mzansi/savings/transaction/post bank account/Lay by
4	Loan from microlender/employer, retail savings book, store credit card, retail account Home loan from mashonisa
5	Cell phone banking, credit/debit/loyalty/other clubcard, loan for house (not bank), personal loan (not informal)
6	Current/cheque/fixed deposit/notice deposit/call account, bond/mortgage
7	Money market account, petrol/garage card
8	Overdraft, vehicle/car finance

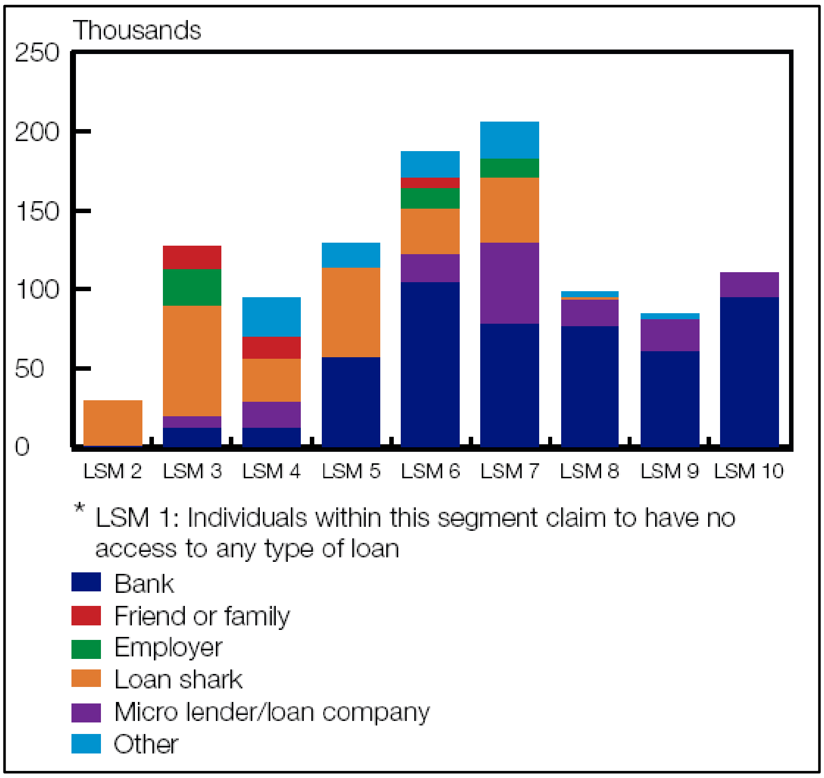
In addition a study conducted by the Department of Trade and Industry (Hawkins, 2003) demonstrates that the Life Style Measure (LSM) can also be used to define the unbanked. Consumers in LSM one to three are largely excluded from financial services products and formal credit and are therefore also classified as unbanked. Table 2-2 presents the level of access to financial services for each LSM type. The LSM is a marketing research tool used to segment the South African population using criteria like degree of urbanisation and ownership of items like cars and major appliances (South African Advertising Research Foundation (SAARF), 2006).

Table 2-2: Spectrum of Provision and Access to Products. Adapted from Hawkins (2003) and the South African Advertising Research Foundation (2007).

	Consumer Access to financial products									
	LSM 1	LSM 2	LSM 3	LSM 4	LSM 5	LSM 6	LSM 7	LSM 8	LSM 9	LSM 10
Income per month	1003	1210	1509	1924	2674	4400	6880	9304	12647	19974
Financial services products	Excluded			On the Margins: Restricted access to credit/ Premium charged		Included				Super Included

The table above also shows that a consumer's average income is low for the lower LSM types. Ardington and Leibbrandt (2004) demonstrate that income is also an important criterion for gaining access to financial services. Formal employment and a steady income are often an initial requirement in order to gain access to financial services. As income increases, an increase in access to and utilisation of financial products is observed. Figure 2-1 depicts the types of loans that the various LSM groups utilise, LSM 1-3 primarily use loans from their employer, friends or family, or loan sharks.

Figure 2-1: Source of Loan Finance (South African Reserve Bank, 2003).



2.1.2 Financial Sector Charter

One major initiative to address the needs of the unbanked is the Financial Sector Charter launched in 2003. It is an agreement among major players in the financial sector to provide banking services to low income populations and assist unbanked South Africans to have access to financial products (Ardington and Leibbrandt (2004). The charter sets out targets that need to be met including allowing 80% of people in the LSM 1-5 to have access to transaction and savings products (Kirsten, 2006).

2.2 Credit

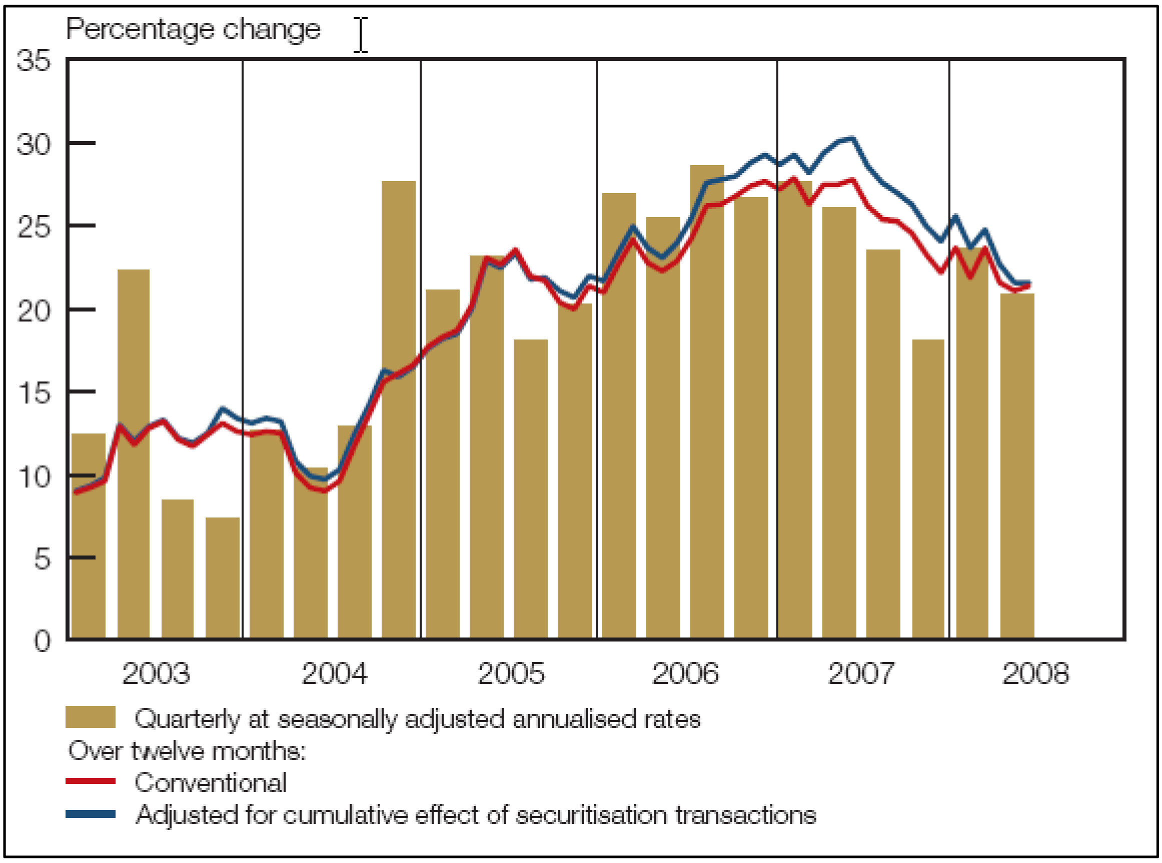
2.2.1 Demand and Supply of Credit

Global research estimates that 500 million people own small or micro businesses and only 10 million of these entrepreneurs have access to financial services such as credit. The research also estimates that fewer than 2% of the poor have access to financial services. Demand for credit, deposit-taking, savings and insurance products is estimated to exceed 100 million persons in need of nearly $22 billion in funds (Arch, 2005).

Consumer credit plays an increasingly important role within households as a financial planning instrument as well as an asset on the balance sheet of financial institutions. However, despite the increasing importance of consumer credit; some households are still rationed in financial markets. Rationing is used as a mechanism to allocate resources in credit markets which may result in some credit applications being excluded from credit, despite being equally creditworthy as those granted a loan (Jacobson and Roszbach, 2003).

Despite the fact that the there may be a huge demand for credit based on the above information it is still impacted by the financial services industry's ability to supply credit. Reports from the South African Reserve Bank (SARB), (2008a) show that the twelve months leading to February 2007 saw a growth rate as high as 27.8% in loans and advances to the domestic private sector (these consist of instalment-sale credit agreements, leasing finance, mortgage, overdrafts, credit card and general advances) but the last three quarters of 2007 have followed a downward trend with an adjusted and annualised rate of 18.1% in the final quarter (Figure 2-2) "The slowdown followed the gradual tightening of monetary policy since June 2006, accompanied by tighter lending standards set by the National Credit Act from June 2007" (SARB, 2008a, p.32). The number of loan advances still remains low into 2008 due to the tightening of credit conditions because of weaker consumer and business confidence about short-term economic prospects (See Figure 2-2) (SARB, 2008b).

Figure 2-2: Total Loans and Advances to Private Sector (SARB, 2008b)



2.2.2 Uses of Credit

Credit has many uses and benefits that the unbanked population do not have access to, the greatest being the ability to assist the unbanked as a tool in order to build capital and escape poverty (SARB, 2003). Credit can be used to help consumers manage risk or cope with losses or costs resulting from the occurrence of a risky event. It can be used instead of other methods often used by the poor like taking children out of school, selling productive assets or borrowing money from lenders at high interest rates which increase the individual's vulnerability to poverty (Ardington and Leibbrandt, 2004). Credit also enables millions of consumers to buy millions of Rands worth of goods each day (Klein and Richner, 1992). Not only is credit safe and convenient in that consumers need not carry large sums of cash, it gives the consumer the ability to arrange a consumption plan best suited to the individual earning pattern, for example: financing real estate, food, clothing and vehicles (Klein *et al*., 1992). Although many consumers over-utilise credit, the fact that millions of consumers use credit everyday is strong evidence that it is a useful tool (Klein *et al*., 1992). Credit is also used to maintain consumption at a specific level that is consistent with permanent income; a student for example may desire to maintain consumption at a higher level than what their current income allows (Roszbach, 2004). Swart (1999) further lists the uses of credit as enabling the consumer to buy goods and/or services at a lower price than in a few years time because of inflation; as well as enabling the consumer to earn a higher rate of return on borrowed money than the cost of the money borrowed.

2.2.3 Microfinance

Microfinance is a means to provide financial services to low-income people including the very poor (Bebula, 2007). Arch (2005) and Daniels (2004) further define microfinance as a sector of formal and non-formal financial institutions offering micro-savings, micro-credit and micro-insurance products and services. The services are targeted at micro-entrepreneurs, small farmers and the poor. Table 2-3 below depicts the use of the R29 billion disbursed through Microloans.

Table 2-3: Micro Lending in the SA Credit Market (Bebula, 2007)

Type	**Percentage**
Micro Enterprise	4%
Housing	11%
Education	12%
Consumption	73%

Microloans are better suited to the needs of lower-income borrowers as the loans needn't be secured by assets such as a home, instead the risk is covered in the price of the loan or in some cases the pension/provident fund benefits are used to secure the loan. It is also a better option for lenders as they do not have to evict households in the event of non-payment (Tomlinson, 2006). Tomlinson further states that although about 3 million people (who never had access to formal credit before) have now been granted access to finance, microloans are still made primarily to salaried individuals with regular rather than irregular incomes.

2.2.4 Regulatory Framework

2.2.4.1 Usury Act and Amendments

The Usury Act 73 of 1968 led to the vast majority of South Africans not having legal access to formal credit. The Act limited pricing and restricted credit product offerings. In 1992, the first exemption notice was issued to the Usury Act and exempted small loans from interest-rate restrictions (Kirsten, 2006). The exemption notice removed interest rate ceilings on small loans under R6000 and payable under 36 months (Daniels, 2004). The issue of microloans then became possible, and due to a huge demand, nearly R15 billion was disbursed in 1999. The exemption led to a separate, largely unregulated sector of credit provision to people on the periphery of the banking system (Kirsten, 2006).

2.2.4.2 MFRC and NLR

In 1999, a further exemption was issued on the Usury Act which revised the small loan amount to R10 000 and provided for the establishment of the Micro

Finance Regulatory Council (MFRC) to manage the microfinance sector and govern the way that microloans are administered and repayments collected (Daniels, 2004). In 2002 it became compulsory for microlenders to register loans on the National Loans Register (NLR), a database used to record all loans granted by lenders registered with the MFRC (Kirsten, 2006). The NLR database is used to coordinate lender behaviour and determine a consumer's level of indebtedness. The NLR is hosted by two South African Credit Bureaux: TransUnion Credit Bureau and Experian (Coetzee *et al.*, 2005).

2.2.4.3 National Credit Act (NCA)

The credit industry in South Africa is now governed under the National Credit Act 34 (2005). The Act seeks to "promote and advance the social and economic welfare of South Africans, (and to) promote a fair, transparent, competitive, responsible, efficient, effective and accessible credit market and industry" (Singh, 2006, p.2). The Act which replaced the Usury Act of 1968 and the Credit Agreements Act of 1980 commenced on the 1st June 2006. The Act provides for the registration of credit bureaux and credit providers as well as to regulate the granting of credit by credit providers to ensure that unfair credit practices and reckless credit granting are prohibited and that responsible credit granting is promoted (National Credit Act, 2005). Under the Act, the National Credit Regulator (NCR) was established to monitor the "consumer credit market and industry to ensure that prohibited conduct is prevented or detected and prosecuted" (National Credit Act, 2005, p.48). The Act aims to redress imbalances in the consumer credit market and create a market where consumers have access to credit at affordable rates. It also seeks to address some of the problems in the microlending industry caused by the banking sector not meeting the needs of low-income earners (Kirsten, 2006).

One of the National Credit Act (2005) provisions requires credit grantors to conduct proper affordability assessments (through whichever method the credit provider deems appropriate) on credit applicants to ensure that they are not currently over-indebted.

It must also be noted that the provision of services such as telecommunications and utilities are viewed as 'incidental' credit by the NCA (National Credit Act, 2005) because interest is charged when the account is not paid on or before the required payment date (City of Johannesburg, 2005). These providers are excluded from having to conduct affordability assessments (National Credit Act, 2005).

2.3 The Dynamics of Lending

2.3.1 Credit Risk

Credit risk is defined as the risk that a financial contract cannot be concluded according to the original terms because the credit receiver has defaulted (Valsamakis, Vivian and du Toit, 2003). Consumers are able to gain access to credit because credit grantors can identify which consumers will pay their accounts and which will default (Klein *et al*., 1992).

Capon (1982) stated that the conceptual framework for judgmental credit decisions consists of the three 'c's' of credit: character (character of the consumer), capacity (repayment ability) and capital (how much is being requested). This list is expanded by Thomas (2000) to include collateral (what the applicant is willing to contribute from their own resources) and condition (the market conditions at the time of application).

Over the last two decades there has been remarkable growth in the availability and use of consumer credit. For some time, the decision to grant credit was based on human judgement to assess the risk of default. This growth in volume has led to the rise of more formal, objective methods (credit scoring) to help credit grantors assess the associated risk with a consumer's credit application (Chye, Chin and Peng, 2004).

In determining credit risk, two types of errors can be made. A *Type 1 error* occurs when someone who is a high credit risk is identified as being creditworthy and is extended credit placing the lender and borrower at risk. A *Type 2 error* occurs when someone who is creditworthy is identified as being highly risky and is rejected credit or offered a lower amount of credit (Lee, Turner, Varghese and Walker, 2008).

2.3.2 Credit Scoring

Mester (1997, p3) defined credit scoring as a statistical method that can be used to "predict the probability that a loan applicant or existing borrower will default or become delinquent". Utilising historical data and statistical techniques, the effects of various applicant characteristics are isolated to determine the effects on delinquencies and defaults. This method produces a 'score' that the bank or retailer can use to rank the loan application in terms of risk (Mester, 1997).

In most scoring models, a higher score indicates lower risk. A simple form of a credit scorecard splits variables into a few categories and assigns weights to each category. A score is produced by summing the weights corresponding to the cells in which the application data falls onto each categorised variable. The credit application is then classified as potentially good or bad depending on the comparison to a threshold (Hand and Adams, 2000).

Some of the benefits of utilising credit scoring include: reduced discrimination, as the models provide objective analysis of a consumer's creditworthiness; allowing for increased speed and consistency in the loan application process; and improving the discrimination between potential good and bad accounts (Chye *et al.*, 2004). These quantitative methods of credit management assist with increasing the credit grantors' profits (through granting credit to more creditworthy consumers) and reducing losses (by denying credit to non-creditworthy consumers) (Rosenberg and Gleit, 1994).

2.3.2.1 Fair Isaac Empirica Credit Scorecard

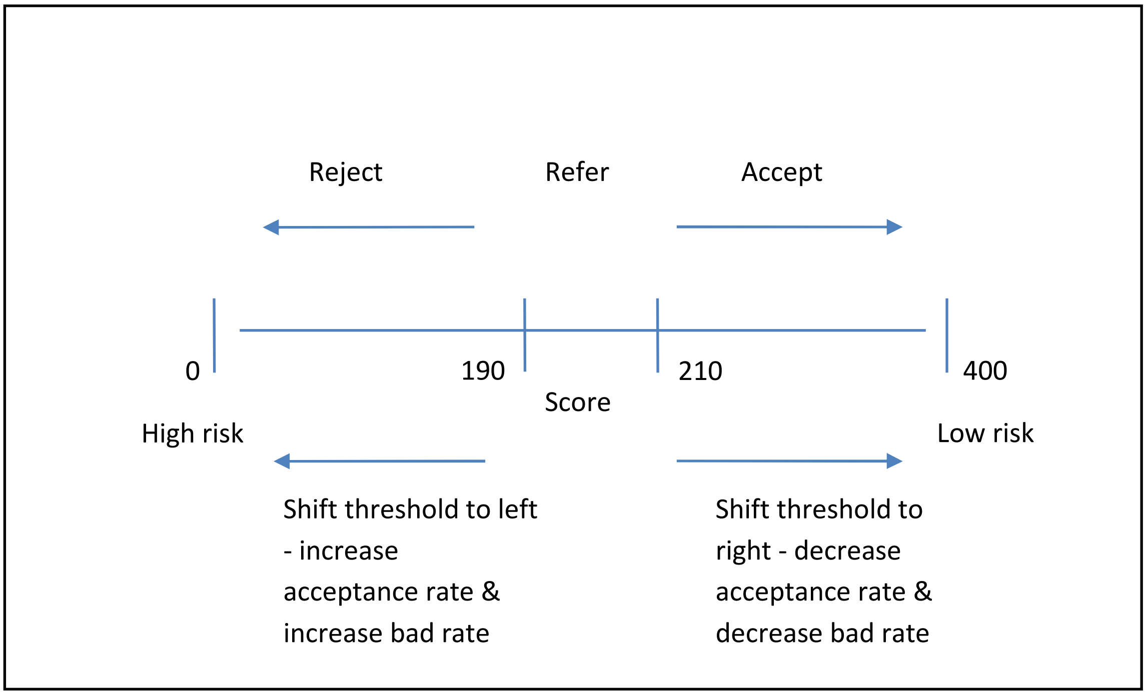
Bill Fair and Earl Isaac began the first scoring consultancy in the early 1950s which later became Fair Isaac (Thomas, 2000). Fair Isaac, utilising consumer credit information from TransUnion Credit Bureau (TransUnion), developed a credit risk scorecard and Expansion Risk Indicator scorecard called Empirica (TransUnion Credit Bureau and Fair Isaac, 2003a). Empirica predicts the likelihood that the consumer will default (be in an arrears position greater than 90 days) on an account within the next 12 months. According to TransUnion and Fair Isaac an Expansion Risk Indicator is created when a consumer has little or no monthly payment history reflected against the consumer's credit bureau report. The Expansion Risk Indicator produces an Expansion Risk

Indicator (1, 2 or 3) which denotes the risk associated with the consumer and is calculated utilising demographic and enquiry information. An Expansion Risk Indicator of one indicates a noticeably higher risk whilst an indicator of three indicates a lower risk. The Empirica score ranges from low 300s to below 900. A high score indicates a prediction of lower risk than a lesser score. When a consumer is scored either an Empirica score is generated, an Expansion Risk Indicator is generated or the consumer is allocated an Exclusion code. The exclusion code is an exception code which provides a reason as to why the consumer could not be scored for example the consumer is deceased or is under administration (TransUnion Credit Bureau and Fair Isaac, 2003b). Empirica is used by clients to assess debtors' risk during the account origination process, evaluate debtors with no previous measureable credit experience and manage existing debtors' credit limits and collection obligations (TransUnion Credit Bureau and Fair Isaac, 2007).

2.3.2.2 Acceptance Rates and Bad Debt Rates

Credit scoring involves decisions regarding score cut-off strategies and the trade-off between approval rates and bad rates. Many companies that use scorecards set minimum score levels (thresholds) at which they are willing to accept credit. If they set the minimum score at which they accept a loan at a lower score (higher risk), they accept more credit applicants but run the risk of their bad rate increasing (predicted rate at which accounts granted will go bad). The higher the minimum score is set, the fewer applicants are accepted and the bad rate decreases (Siddiqi, 2006), (see Figure 2-3).

Figure 2-3: Score Cut-off Decisions – Trade-off Between Acceptance Rate and Bad Rate (Adapted from Siddiqi, 2006).



2.3.3 Credit Bureaux

Klein (2001) describes credit bureaux as for-profit businesses that make opportunities for credit, employment, housing and insurance available and more affordable to consumers. They elicit the provision of such opportunities by creating accountability and in doing so, are part of the foundation of civil society.

According to Avery, Calem, Canner and Bostic (2003) the primary purpose of a credit bureau is the collection of data to facilitate credit evaluation. They gather information on an individual's history of credit, leases, non-credit related accounts and money-related public records. All this information is compiled into a credit report. A credit report generally contains the following five types of information:

i. Identifying information e.g. names, ID number, addresses.

ii. Detailed information reported by creditors e.g. accounts from banks and retailers.
iii. Public record information e.g. monetary judgments granted by a court.
iv. Information reported by collection agencies.
v. The identity of individuals or companies that have accessed an individual's credit report.

South African credit bureaux are regulated by the National Credit Act 34 of 2005. The Act stipulates that a credit bureau cannot hold information such as race, political affiliation, medical status and religion. The Act further stipulates that credit bureaux may only release credit information if it is for a prescribed purpose for example: the investigation of fraud, setting a limit for service provision, developing a credit scoring system and granting of credit.

The largest credit bureau in South Africa is TransUnion Credit Bureau (Firer, Ross, Westerfield and Jordan, 2004) which has a base of over 40 million consumers, with 15 million classified as credit active as per the credit active definition defined by the National Credit Regulator (Sajiwan, 2008). The National Credit Regulator defines a credit active consumer as having at least one credit account or a civil court judgment, administration order or a default (Heymans, 2007).

2.3.3.1 Credit Bureau Payment Data

A consumer's credit bureau profile consists mainly of credit accounts (Avery *et al.*, 2003). Each account contains the following information:

i. Account status (open account, closed account *et cetera.*).

ii. Account dates (date account was opened, date account was last paid).

iii. Account balance (opening balance/credit limit, current balance, instalment, amount past due).

iv. Type of account (home loan account, instalment account, revolving account).

v. Name and type of creditor (credit card company, retailer, insurer).

vi. Payment performance

  a. Last payment status (zero months in arrears, one month in arrears, handed over for collection, repossession).

  b. Worst ever status (zero months in arrears, one month in arrears, handed over for collection, repossession).

  c. Up to 48 months history of payment performance.

2.3.3.2 Non – traditional Credit Bureau Data

The Information Policy Institute (2005, p.8) lists possible categories of data that are considered as potential sources of non-traditional data. These categories might be sufficiently “credit-like to have predictive value for lending decisions”. These data categories include: utility payments (water, electricity and gas), Telecommunication (fixed line, cellular), auto liability insurance, homeowner’s insurance, rental payments, child care payments and healthcare payments. Turner and Agarwal (2008) give three criteria needed in order for non-traditional data to be used to predict credit risk:

i. *They must be ‘credit-like’ vs. ‘cash-like’*. Transactions that involve the provision of goods or services in advance of payment exhibit similar properties to that of an ordinary credit transaction. In addition, where the transactions occur repeatedly over time and at regular intervals, they exhibit ‘credit-like’ properties.

ii. *There must be sufficient coverage*. The greater the population of non-traditional accounts, the greater the impact to the predictability of credit scoring models.

iii. *The data furnishers must be concentrated*. This relates to collection of information, and that the search, contracting, data testing and verification, and transaction costs increase as the number of data furnishers supplying particular data grow.

2.4 Municipality Accounts

Unlike traditional credit accounts, municipalities do not need proof of employment or proof of an income in order to obtain municipal services (eThekwini Municipality, 2007). It is thus easier for the poor to open a utility account and have this reported to a credit bureau.

2.4.1 Municipal Tariffs

The Municipal Systems Act 32 of 2000 (Municipal Systems Act, 2000, p.70) states that a municipal council must adopt and implement a tariff policy on the levying of fees for municipal services supplied by the municipality. The tariff policies must allow for the amount an individual pays to be in proportion to their use of a service. It should also allow for poor households to have access to basic services through:

i. “Tariffs that cover only operating and maintenance costs;

ii. Special tariffs or life line tariffs for low levels of use or consumption of services or for basic levels of service; or

iii. Any other direct or indirect method of subsidisation of tariffs for poor households".

2.4.2 Deposits

eThekwini and City of Johannesburg's Credit Control Policy (eThekwini Municipality, 2007; City of Johannesburg, 2005) states that deposits are due and payable for the registration of new customers or existing customers who have changed addresses. The deposit is calculated as two months of the projected consumption value. This can be reduced to one month if the consumer agrees to a direct debit order or increased to three months based on the payment history on the property concerned. The municipality can review the deposit held if the consumer's payments are irregular and unacceptable (three late payments in five months). Should this occur, the consumer will be requested in writing to increase the deposit value held by the municipality (eThekwini Municipality, 2007).

2.4.3 Credit Control

A municipality must collect all monies that are owed to it and adopt, maintain and implement a credit control and debt collection policy (Municipal Systems Act, 2000). The Act further stipulates that an "amount due for municipal service fees, surcharge on fees, property rates and other municipal taxes, levies and duties is a charge upon the property in connection with which the amount is owing and enjoys preference over any mortgage bond registered against the property" (Municipal Systems Act, 2000, p.100). All accounts are billed in arrears on a monthly basis (eThekwini Municipality, 2007). If consumers fail to pay their utility accounts the municipality may restrict or disconnect the supply of water and/or electricity (City of Johannesburg, 2005).

2.5 Utilisation of Utility Accounts Research

Research conducted in the United States of America (Turner *et al*., 2006) showed that between 35 and 54 million Americans do not have access to credit. As a result many of these consumers are forced to seek loans from 'loan sharks' who charge interest at rates as high as 500%. Without the lack of reliable credit, these consumers are disadvantaged in not being able to build assets like homes and small businesses (Turner *et al*., 2006). The above research examined 8 million consumers who had at least one reported utility or telecommunications account. The set of 8 million consumers were run through a set of generic Credit Bureau credit risk scorecards at two points in time: 31st March 2005 and 31st March 2006. The consumers were run against the various scorecards with and without the utility trades included in their profile. The intervening year was used as the 'performance period' to evaluate the models' predictability. The credit scorecard performance was measured using the Kolmogorov-Smirnov (K-S) statistic. The research revealed the following:

i. Consumers outside of the credit mainstream have similar risk profiles as those in the mainstream when including utility accounts into their credit assessments.
ii. Utility account data makes extending credit easier. Banks and retailers now have access to more information which will assist in determining the consumer's creditworthiness.

iii. Minorities and the poor are able to benefit from the use of utility data by banks and retailers.
iv. The use of utility data can decrease the credit risk of consumers as more credit information is available on the bureau's database.
v. The availability of additional data can improve scoring models.
vi. The additional data can reduce bad loans.
vii. Utility companies can access bureau data to identify which utility applications are likely to go bad.

Further quantitative analysis conducted (Lee *et al.*, 2008) examined the longer-term effects of utilising non-traditional data in credit scoring. The analysis could find no evidence of deteriorations of credit scores over time for those consumers with non-financial payment data on file; and no evidence that those consumers who open new accounts after having only non-financial accounts became overextended and experienced declines in credit scores.

2.6 Conclusion of Literary Review

There are still a large number of South Africans who do not have access to financial services. This includes gaining access to credit which can be used by these citizens as a means to escape poverty. Although much work has been done through financial charters, new financial products and revisions of South African law, more initiatives are needed to assist in reducing the number of unbanked people. One of the issues identified has been that credit grantors often lack sufficient information on which to make credit risk decisions. They also usually require proof of formal employment in order to grant loans.

Municipal utility account information is viewed as a means to enhance credit bureau profiles with 'credit-like' information. This can be used by credit grantors in making a decision in the absence of traditional credit information. The fact that it is difficult for consumers to be refused a utility account assists in breaking the 'credit Catch 22' situation. Demonstrating that utility accounts possess credit-like characteristics and can be used in credit decisions is the focus of this paper.

The following chapter lays out the research hypotheses that are designed to test the 'credit-like' nature of the municipal utility account.

Chapter 3: Research Hypotheses

The literature review identifies that utility account information should have the same 'credit-like' characteristics as that of traditional credit data currently housed by a credit bureau. The following hypotheses are designed to test the theory that utility accounts are 'credit-like' in nature and can be used in credit scoring to differentiate between good and bad paying consumers. This is primarily done by comparing the utility account classification (good or bad) to that of a credit bureau risk scorecard based on credit bureau data. If the utility accounts that are classified as bad correlate with the credit bureau information then it can be deduced that utility account information displays 'credit-like' characteristics.

Table 3-1: Definition of Symbols Used in Hypothesis Testing

Symbol	Definition
x	1st variable of analysis
y	2nd variable of analysis
H_0	Null hypothesis
H_1	Alternative hypothesis
r	Calculated correlation coefficient from the ordered pairs
n	Number of ordered pairs
t	Student t-distribution statistic
t_c	Critical t-score

3.1 Hypothesis 1

There is a negative correlation between the Fair Isaac Empirica score and the Municipality's rate payers who have been classified as bad and have substantial credit bureau data. A negative correlation is tested because the lower the Empirica score the higher the risk.

- $H_0: P \geq 0$
- $H_1: P < 0$

Where P = population correlation coefficient

3.2 Hypothesis 2

There is a negative correlation between Fair Isaac's Expansion Risk Indicator and the Municipality's rate payers who have been classified as bad accounts with little Credit Bureau data. A negative correlation is tested because the lower the Expansion Risk Indicator the higher the risk.

- $H_0: P \geq 0$
- $H_1: P < 0$

Where P = population correlation coefficient

3.3 Hypothesis 3

There is a negative correlation between the Empirica score and the average outstanding value. The higher the Empirica score, the lower the risk and outstanding value on the Municipal account.

- $H_0: P \geq 0$
- $H_1: P < 0$

Where P = population correlation coefficient

3.4 Hypothesis 4

There is a positive correlation between the worst ever status reported on the Credit Bureau and the severity of the Municipal account. Worst ever status refers to the worst status reported on any of the consumer's payment profile entries.

- $H_0: P \leq 0$
- $H_1: P > 0$

Where P = population correlation coefficient

3.5 Hypothesis 5

There is a negative correlation between the retrospective Empirica score and Municipality's rate payers who have been classified as good and bad accounts. This hypothesis is designed to show that an Empirica score generated a year ago would have predicted that the consumer would be currently in arrears on their utility account.

- $H_0: P \geq 0$
- $H_1: P < 0$

Where P = population correlation coefficient

Chapter 4: Research Methodology

4.1 Research Design Overview

The quantitative descriptive research method will be used to analyse secondary data. Descriptive research is used to "describe the characteristics of a population" (Zikmund, 2003, p.55). Zikmund also describes secondary data as data assembled for another project other than this one.

All consumer utility accounts from a South African Municipality have been obtained. Permission was granted from the Municipality for their data to be used for this research, however the Municipality has requested that they remain anonymous.

The data was then formatted and run against TransUnion Credit Bureau's consumer database and an Empirica credit risk score developed by Fair Isaacs was generated for each consumer. The data obtained from TransUnion along with the Empirica score and Municipality data was used to test the hypotheses in Chapter 3. Permission was granted by TransUnion to utilise their data and the Empirica scorecard in this research. Data was run against the live database as well as the Bureau's retro database. A retrospective run was done to determine what the consumers' profiles and credit scores reflected a year ago (1^{st} October 2007).

4.2 Population and Sampling

The population is all the consumer utility accounts of the Municipality that were successfully matched to TransUnion Credit Bureau's database. The population dataset was obtained from a medium sized South African municipality with over

200,000 citizens (Statistics South Africa (StatsSA), 2001). 35,597 records were originally obtained from the Municipality and 15,683 records could be successfully matched to the Credit Bureau. The final dataset in the analysis was not sampled and instead a census was used as it was possible to analyse the complete enumeration of the entire population instead of only a portion of the population (Iman, 1994).

4.3 Data Collection Process

4.3.1 Municipality Data Collection

Two files were obtained from the Municipality. One file contained the account holder details and the second contained the age analysis for each account. The fields received are contained in Table 4-1. A total of 35,597 consumer records were received. The two files were matched together utilising the account number.

Table 4-1: Fields Supplied by the Municipality

Account Details File	Account Age Analysis File
Account Number	Account Number
ID number	Account Holder's Name
Account Holder's Surname	Erf Number
Account Holder's Initial	Type of Service
Postal Address	Total Balance
Outstanding balance	Age Analysis value Oct 2008
	Age Analysis value Sept 2008
	Age Analysis value Aug 2008
	Age Analysis value July 2008
	Age Analysis value June 2008
	Age Analysis value May 2008 and older

4.3.2 TransUnion Credit Bureau Data Collection

The Municipal data was formatted into a standard TransUnion Credit Bureau batch input layout needed to obtain the credit profiles of the consumers from the Bureau's consumer database. One extract from TransUnion's live database was requested (to test hypotheses one to four) and one retrospective extract was requested (to test hypothesis five). Data was extracted as of the 1st October 2007 in the retrospective extract to determine what the consumers' profiles looked like at this point in time and what Empirica score would have been assigned. Of the 35,597 records that were processed through the Bureau, only 15,683 records could be matched. The main contributor to the low match rate on the Credit Bureau was the lack of RSA Identity numbers (ID numbers) captured or ID numbers captured incorrectly on the Municipal database. There were a total of 17,598 ID number errors (See Appendix 1 for full Bureau batch statistics). The data extract also contained a number of corporate entries. Not all the consumers who had a valid ID number could be successfully matched to the Credit Bureau as these consumers may have never applied for credit or other related services and therefore do not have an entry on the Bureau's database.

4.4 Data Formatting

The majority of the accounts had money outstanding in the 30 day age bucket. The Municipality confirmed that this was because the month of September had just been billed and the majority of the account holders were still to pay their accounts. With this in mind and with the Municipality in agreement, the age analysis was adjusted so that the 30 day age bucket was shifted to reflect as current. This resulted in a shift of all the age analysis buckets so that 90 days became 60 days *et cetera.*

4.5 Hypothesis Testing

Table 4-2: Definition of Symbols Used in Hypothesis Testing

Symbol	Definition
x	1st variable of analysis
y	2nd variable of analysis
H_0	Null hypothesis
H_1	Alternative hypothesis
r	Calculated correlation coefficient from the ordered pairs
n	Number of ordered pairs
t	Student t-distribution statistic

The testing of the identified hypotheses was conducted using Microsoft Excel. All the hypotheses were tested by calculating the Coefficient of Correlation to determine whether there is indeed a relationship between the two variables in each hypothesis. The two sample one-tail Student t-distribution test was used to determine whether the correlation is significant or not. The Student t-distribution statistic was compared to the Critical t-score. A confidence level of 95% was used in each hypothesis test except for Hypothesis 2, where a confidence level of 79% was also tested.

4.5.1 Coefficient of Correlation

The Coefficient of Correlation describes the strength of the linear relationship between two variables. The Coefficient can assume any value from -1.00 to +1.00. The value -1.00 denotes a perfect negative correlation whilst +1.00 denotes a perfect positive correlation (Lind, Mason and Marchal, 2000). The formula represented in Equation 4-1 was used to determine the Coefficient of Correlation (r).

Equation 4-1: Coefficient of Correlation

$$r = \frac{n \sum xy - (\sum x)(\sum y)}{\sqrt{[n \sum x^2 - (\sum x)^2][n \sum y^2 - (\sum y)^2]}}$$

4.5.2 Student t-distribution Test

The t-test is utilised to test the significance of the Correlation Coefficient (Lind *et al.*, 2000). The formula represented in Equation 4-2 was used to determine the Student t-distribution statistic (t).

Equation 4-2: Student t Distribution Test

$$t = \frac{\mathrm{r}}{\sqrt{\frac{1 - \mathrm{r}^2}{\mathrm{n} - 2}}}$$

4.5.3 Determining the Bad Rate

The Municipality cuts off the supply of service if money is owed in 30 days; however the account is handed over for collection if there is an amount owing in 90 days and older and the amount is over R100. As agreed with the Municipality, accounts that had amounts reflected in 90 days and older with a minimum of R100 outstanding in these age buckets were classified as bad accounts. The formula represented in Equation 4-3 was used to calculate the bad rate in each hypothesis test.

Equation 4-3: Bad Rate Calculation

$$\frac{\boldsymbol{Total\ number\ of\ bad\ accounts}}{\boldsymbol{Sum}\ (\boldsymbol{Bad} + \boldsymbol{Good\ accounts})}$$

4.6 Hypothesis Testing Approach

The following steps were taken to test each hypothesis:

Hypothesis 1, 2 and 5:

i. The Empirica score or Expansion Risk Indicator for each consumer was obtained from TransUnion Credit Bureau.
ii. The number of good and bad accounts was determined from the Municipal data for each consumer assigned an Empirica score or Expansion Risk Indicator.
iii. The collective bad rate was calculated for all the consumers for each Empirica score or Expansion Risk Indicator.
iv. The Coefficient of Correlation was calculated using the Empirica score and the associated bad rate as the two analysis variables (Hypothesis 1 and 5) or the Expansion Risk Indicator and associated bad risk as the analysis variables (Hypothesis 2).
v. The Student t-distribution statistic was calculated and compared against the Critical t-score. If the Student t-distribution statistic was greater than the Critical t-score (in the case of positive correlations) or less than the Critical t-score (in the case of negative correlations); the null hypothesis was rejected.

Hypothesis 3:

i. The Empirica score for each consumer was obtained from TransUnion Credit Bureau.

ii. The total outstanding balance for each consumer was obtained from the Municipality data and averaged for all the consumers with the same Empirica score.

iii. The Coefficient of Correlation was calculated using the Empirica score and the average outstanding balance as the two analysis variables.

iv. The Student t-distribution statistic was calculated and compared against the Critical t-score. If the Student t-distribution statistic was greater than the Critical t-score (in the case of positive correlations) or less than the Critical t-score (in the case of negative correlations); the null hypothesis was rejected.

Hypothesis 4:

i. The aggregated variable of the worst ever reported payment profile status was obtained for each consumer with at least one payment profile line from TransUnion Credit Bureau.

ii. The number of good and bad accounts from the Municipal data for each assigned worst ever payment profile status was determined. The worst ever payment profile status refers to the worst status reported on any of a consumer's accounts within the last 24 months (TransUnion Credit Bureau, 2004).

iii. The order of worst ever statuses was ranked based on the criteria given by the National Credit Regulator (2007) The order of increasing severity of the statuses follows the pattern reflected in Table 4-3.

iv. The collective bad rate per ranking allocated was calculated.

v. The Coefficient of Correlation was calculated using the ranked worst ever payment profile status and the associated bad rate as the two analysis variables.

vi. The Student t-distribution statistic was calculated and compared against the Critical t-score. If the Student t-distribution statistic was greater than the Critical t-score (in the case of positive correlations) or less than the Critical t-score (in the case of negative correlations); the null hypothesis was rejected.

Table 4-3: NCR's Order of Increasing Severity for Status Codes

Status Code	Description
C	Account closed
D	Account in dispute
G	Insurance policy cancelled by client
H	Insurance policy cancelled by supplier
K	Deceased claim paid out
M	Disability paid out
P	Account paid up
S	Account surrendered
T	Early settlement by customer
V	Loan settled in cooling off period
Z	Consumer is deceased
0	0 months in arrears
1	1 month in arrears
2	2 months in arrears
E	Terms extended
3	3 months in arrears
4	4 months in arrears
5	5 months in arrears
6	6 months in arrears
7	7 months in arrears
8	8 months in arrears
9	9 months in arrears
F	Insurance policy lapsed
I	Credit card revoked
J	Goods repossessed
L	Account handed over for collection
W	Account written off

Further tests conducted

Two additional tests were conducted to determine what relationship exists between the consumer's age and income and the Municipal accounts reported as bad. The consumer's age was determined through analysing the first six digits of the valid RSA ID number which represents the date of birth of the consumer. The estimated income was calculated using TransUnion Credit Bureau's Income Estimator product which statistically calculates the consumer's estimated income based on the payment information available to the Bureau (TransUnion Credit Bureau, 2007).

The following steps were then followed:

i. The number of good and bad accounts was determined from the Municipal data for each consumer assigned to an age group or income band.
ii. The collective bad rate for all the consumers was calculated for each age group or income band.
iii. The Coefficient of Correlation was calculated using the age group or income band and the associated bad rate as the two analysis variables.
iv. The Student t-distribution statistic was calculated and compared against the Critical t-score to determine the significance of the correlation.

4.7 Potential Limitations

There were a number of limitations to the research methods employed. The most significant of these are discussed below.

The first limitation was that access to the data of only one Municipality was granted and obtained for this research project. The results and conclusions of this research report are therefore only applicable to the Municipality analysed and not to all other South African municipalities.

The second limitation was that the accounts determined as bad in this research report contain consumers who have disputed their utility bill with regards to the Municipality's estimate of electricity and water usage. Some of these consumers have part-paid their accounts in anticipation of a correct calculation of the consumers usage and adjustment of the amount outstanding. Unfortunately, these consumers could not be identified and removed from the data analysed.

Another limitation was that, on review of some of the accounts, the age analysis reflected overdue amounts in 90 days and older, yet credit amounts were reflected in the current, 30 day or 60 day buckets. This reveals ineffectual age analysis management where payments are not correctly allocated to the respective age buckets. This may have resulted in some consumers having been incorrectly classified as bad accounts.

A large number of the Municipal records had incomplete information captured on the rate payer with which to match to the Credit Bureau. This resulted in a reduction in the number of records analysed in this study. The analysis would have been more effective if the correct information, like Identity number, was captured on all account holders and the consumers successfully matched to the Credit Bureau.

Chapter 5: Results

Table 5-1: Definition of Symbols Used in Hypothesis Testing

Symbol	Definition
r	Calculated correlation coefficient from the ordered pairs
n	Number of ordered pairs
t	Student t-distribution statistic
t_c	Critical t-score

5.1 Good/Bad Rates

The table below reflects the total good and bad accounts for the full dataset supplied by the Municipality based on their good/bad definition.

Table 5-2: Good/Bad Distribution for all the Municipal Accounts

Account Classification	Total Number of Accounts	% of Total Accounts
Bad	23,721	67%
Good	11,876	33%
Grand Total	**35,597**	**100%**

The table below reflects the total good and bad accounts for the records successfully matched against the Credit Bureau based on the Municipality's good/bad definition. This dataset was the final dataset used to test the hypotheses.

Table 5-3: Good/Bad Distribution for all the Accounts Matched to the Credit Bureau

Account Classification	Total Number of Accounts	% of Total Accounts
Bad	10,016	64%
Good	5,667	36%
Grand Total	**15,683**	**100%**

5.2 Hypothesis 1 Test Results

Table 5-4 below summarises the associated bad rate for each Empirica score (for illustrative purposes the Empirica scores have been grouped). It also provides the total number of bad and good accounts. Table 5-5 shows the results of the hypothesis test indicating that the null hypothesis was rejected. A graphical representation of the correlation between the two variables tested is provided in Figure 5-1.

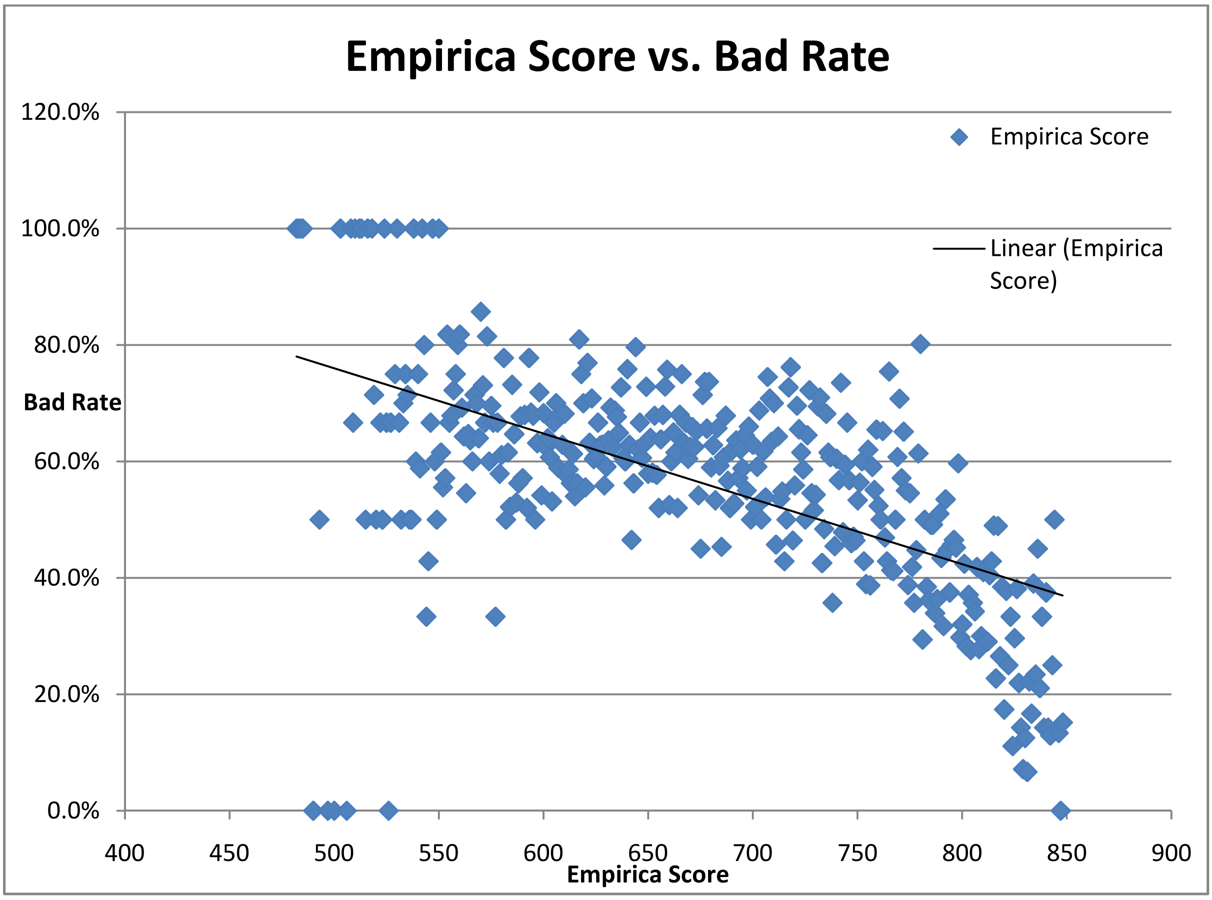
Table 5-4: Hypothesis 1 – Empirica Score vs. Bad Rate

Variable X Empirica Score	Bad	Good	Grand Total	Variable Y Bad Rate
482-501	6	5	11	54.5%
502-521	20	6	26	76.9%
522-541	83	40	123	67.5%
542-561	153	64	217	70.5%
562-581	232	120	352	65.9%
582-601	316	183	499	63.3%
602-621	402	238	640	62.8%
622-641	549	302	851	64.5%
642-661	557	300	857	65.0%
662-681	409	234	643	63.6%
682-701	373	272	645	57.8%
702-721	369	237	606	60.9%
722-741	367	274	641	57.3%
742-761	541	487	1,028	52.6%
762-781	569	464	1,033	55.1%
782-801	414	543	957	43.3%
802-821	321	602	923	34.8%
822-841	125	381	506	24.7%
842-861	16	90	106	15.1%
Grand Total	**5,822**	**4,842**	**10,664**	**54.6%**

Table 5-5: Hypothesis 1 - Calculations and Results

r	-0.580
n	345
t	-13.191
t_c	-1.649
Result	**Reject H_0**

Figure 5-1: Empirica Scores vs. Bad Rate



5.3 Hypothesis 2 Test Results

Table 5-6 below summarises the associated bad rate for each Expansion Risk Indicator. It also provides the total number of bad and good accounts. Table 5-7 shows the results of the hypothesis test indicating that the null hypothesis was not rejected with a confidence level of 95% and rejected with a confidence level of 79%.. A graphical representation of the correlation between the two variables tested is provided in Figure 5-2.

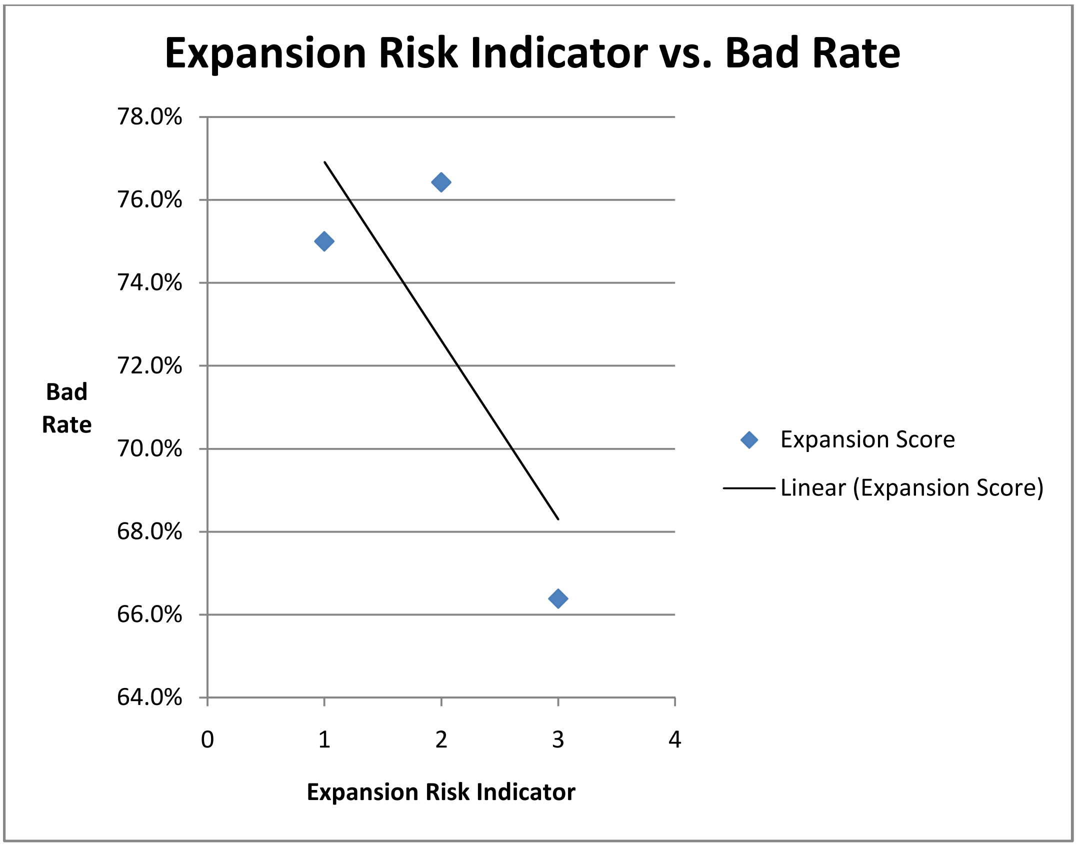
Table 5-6: Hypothesis 2 - Empirica Expansion Risk Indicator vs. Bad Rate

Variable X				**Variable Y**
Empirica Expansion Risk Indicator	**Bad**	**Good**	**Grand Total**	**Bad Rate**
1	36	12	48	75.0%
2	94	29	123	76.4%
3	160	81	241	66.4%
Grand Total	**290**	**122**	**412**	**70.4%**

Table 5-7: Hypothesis 2 - Calculations and Results

	95% Confidence Level	**79% Confidence Level**
r	-0.793	-0.793
n	3	3
t	-1.302	-1.302
t_c	-6.314	-1.289
Result	**Do not reject H_0**	**Reject H_0**

Figure 5-2: Expansion Risk Indicator vs. Bad Rate



5.4 Hypothesis 3 Test Results

Table 5-8 below summarises the average total balance for each Empirica score (for illustrative purposes the Empirica scores have been grouped). Table 5-9 shows the results of the hypothesis test reflecting that the null hypothesis was rejected. A graphical representation of the correlation between the two variables tested is provided in Figure 5-3.

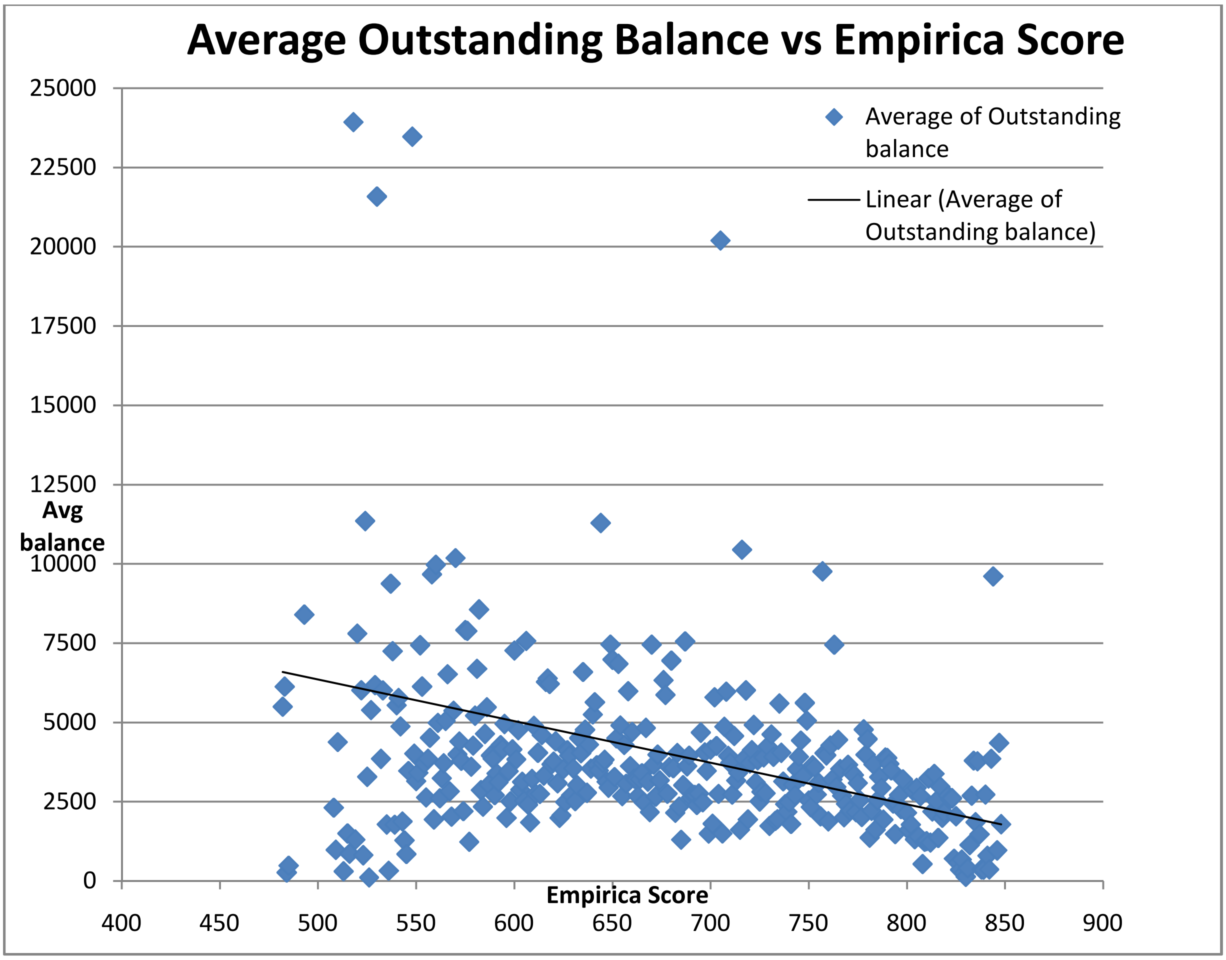
Table 5-8: Hypothesis 3 – Average Outstanding Balance vs. Empirica score

Variable X Empirica Scores	Variable Y Average of Total balance
482-501	2,917.28
502-521	5,657.07
522-541	7,487.27
542-561	5,805.29
562-581	4,551.84
582-601	4,015.47
602-621	3,937.26
622-641	3,714.74
642-661	5,360.89
662-681	3,648.72
682-701	3,063.14
702-721	5,395.13
722-741	3,090.17
742-761	3,614.58
762-781	3,387.12
782-801	2,540.03
802-821	1,992.33
822-841	1,634.81
842-861	1,488.76
Grand Total	**3,589.90**

Table 5-9: Hypothesis 3 - Calculations and Results

r	-0.282
n	345
t	-5.439
t_c	-1.649
Result	**Reject H_0**

Figure 5-3: Average Outstanding Balance vs. Empirica Score



5.5 Hypothesis 4 Test Results

Table 5-10 summarises the associated bad rate for each worst ever Credit Bureau payment profile status. It also provides the total number of bad and good accounts. Table 5-11 shows the results of the hypothesis test reflecting that the null hypothesis was rejected. A graphical representation of the correlation between the two variables tested is provided in Figure 5-4.

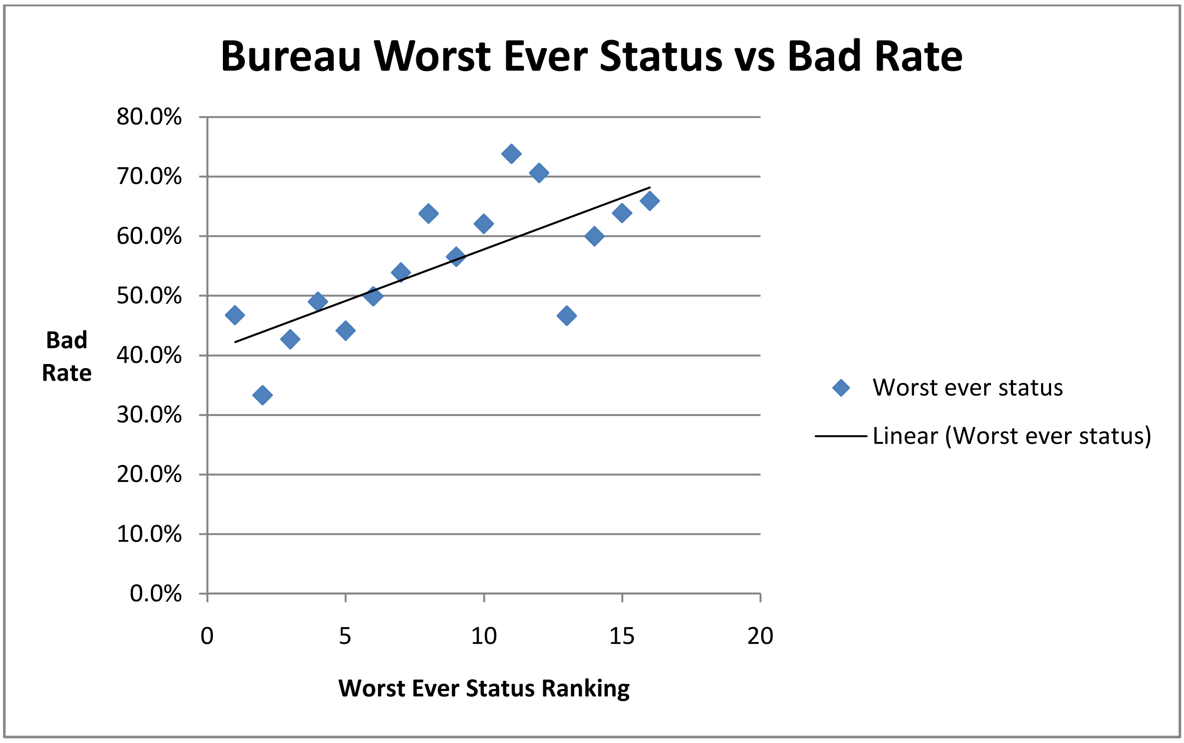
Table 5-10: Hypothesis 4 – Credit Bureau Worst Ever Status vs. Bad Rate

Variable X					**Variable Y**
Ranking	**Worst Ever Status**	**Bad**	**Good**	**Grand Total**	**Bad Rate**
1	0 months in arrears	1,227	1,397	2,624	46.8%
2	H – Insurance policy cancelled by supplier	3	6	9	33.3%
3	1 month in arrears	744	998	1,742	42.7%
4	2 months in arrears	596	620	1,216	49.0%
5	E – Terms extended	34	43	77	44.2%
6	3 months in arrears	319	320	639	49.9%
7	4 months in arrears	289	247	536	53.9%
8	5 months in arrears	194	110	304	63.8%
9	6 months in arrears	125	96	221	56.6%
10	7 months in arrears	77	47	124	62.1%
11	8 months in arrears	172	61	233	73.8%
12	9 months in arrears	332	138	470	70.6%
13	I – Credit card revoked	7	8	15	46.7%
14	J – Goods repossessed	33	22	55	60.0%
15	L – Handed over for collection	485	274	759	63.9%
16	W- Account written off	1,033	534	1,567	65.9%
	Grand Total	**5,670**	**4,921**	**10,591**	**53.5%**

Table 5-11: Hypothesis 4 - Calculations and Results

r	0.733
n	16
t	4.037
t_c	1.761
Result	**Reject H_0**

Figure 5-4: Bureau Worst Ever Status for a Consumer vs. Bad Rate



5.5 Hypothesis 5 Test Results

Table 5-12 below summarises the associated bad rate for each retro Empirica score (for illustrative purposes the Empirica scores have been grouped). It also provides the total number of bad and good accounts. Table 5-13 shows the results of the hypothesis test reflecting that the null hypothesis was rejected. A graphical representation of the correlation between the two variables tested is provided in Figure 5-5.

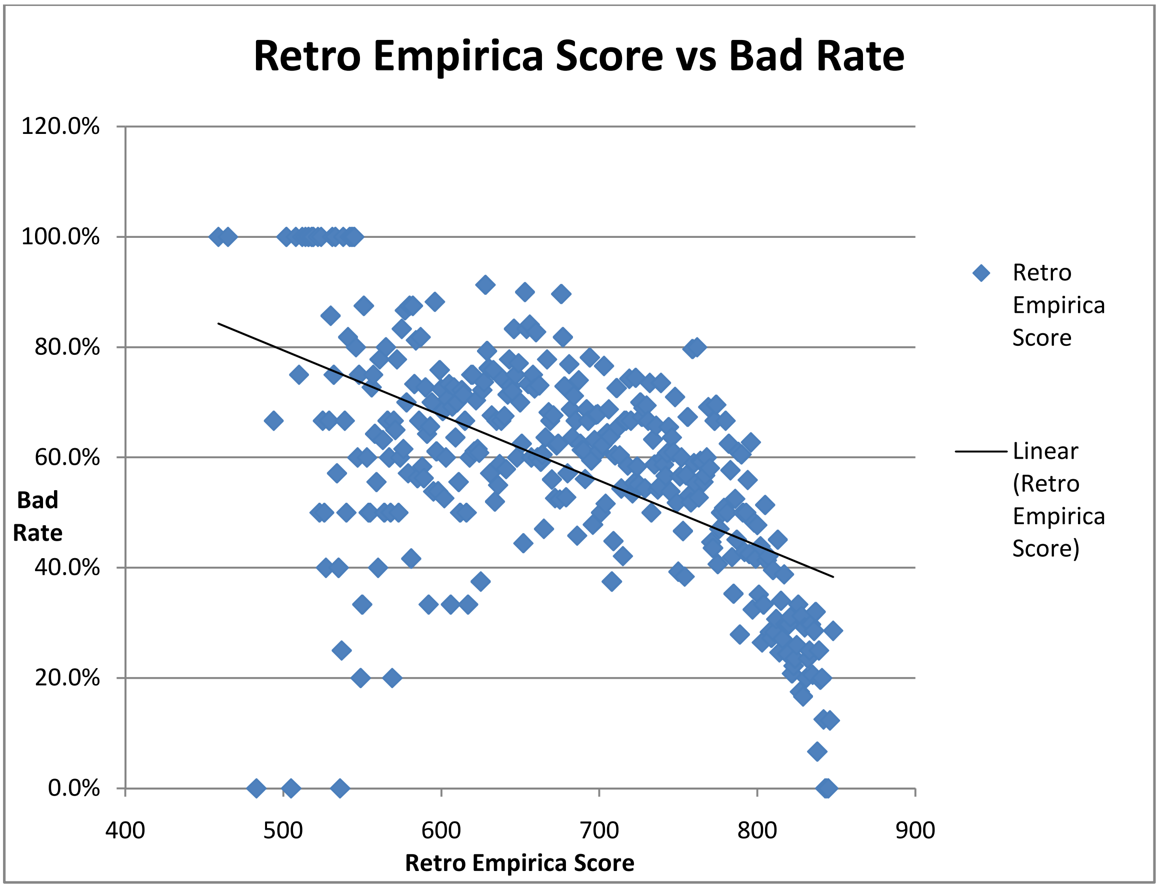
Table 5-12: Hypothesis 5 - Retro Empirica Score vs. Bad Rate

Variable X Retro Empirica Score	Bad	Good	Grand Total	Variable Y Bad Rate
459-478	4	0	4	100%
479-498	2	2	4	50%
499-518	11	2	13	85%
519-538	32	22	54	59%
539-558	76	34	110	69%
559-578	132	77	209	63%
579-598	184	99	283	65%
599-618	225	129	354	64%
619-638	298	144	442	67%
639-658	377	142	519	73%
659-678	412	197	609	68%
679-698	516	290	806	64%
699-718	535	351	886	60%
719-738	563	352	915	62%
739-758	690	535	1,225	56%
759-778	654	447	1,101	59%
779-798	549	534	1,083	51%
799-818	430	798	1,228	35%
819-838	175	530	705	25%
839-858	37	173	210	18%
Grand Total	**5,902**	**4,858**	**10,760**	**55%**

Table 5-13: Hypothesis 5 - Calculations and Results

r	-0.562
n	330
t	-12.300
t_c	-1.652
Result	**Reject H_0**

Figure 5-5: Retrospective Empirica Score vs. Bad Rate



5.6 Additional analysis conducted results

The following results reflect the results of some additional analysis that was conducted on the Municipal and Bureau data.

5.6.1 Income vs. Bad Rate

Table 5-14 below summarises the associated bad rate for each income band (for illustrative purposes the incomes bands have been grouped). It also provides the total number of bad and good accounts. Table 5-15 shows the results of the statistical analysis. A graphical representation of the correlation between the two variables tested is provided in Figure 5-6.

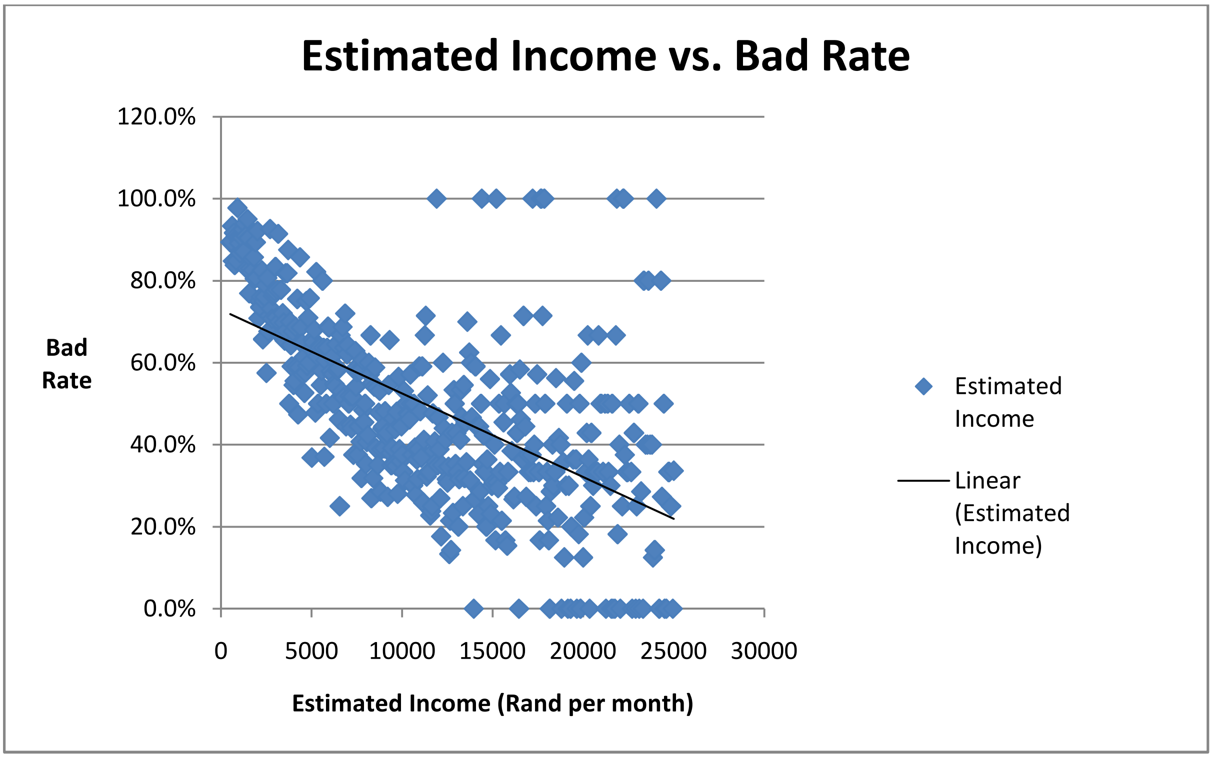
Table 5-14: Income vs. Bad Rate

Income Bands (Rand per month)	Bad	Good	Grand Total	Bad Rate
R 500 – R 999	722	84	806	90%
R 1,000 – R 1,999	724	109	833	87%
R 2,000 – R 2,999	613	207	820	75%
R 3,000 – R 3,999	450	172	622	72%
R 4,000 – R 4,999	376	211	587	64%
R 5,000 – R 5,999	373	242	615	61%
R 6,000 – R 6,999	301	234	535	56%
R 7,000 – R 7,999	267	267	534	50%
R 8,000 – R 8,999	225	263	488	46%
R 9,000 – R 9,999	197	271	468	42%
R 10,000 – R 10,999	175	230	405	43%
R 11,000 – R 11,999	152	240	392	39%
R 12,000 – R 12,999	113	216	329	34%
R 13,000 – R 13,999	109	145	254	43%
R 14,000 – R 14,999	95	149	244	39%
R 15,000 – R 15,999	55	105	160	34%
R 16,000 – R 16,999	65	90	155	42%
R 17,000 – R 17,999	54	73	127	43%
R 18,000 – R 18,999	42	90	132	32%
R 19,000 – R 19,999	32	65	97	33%
R 20,000 – R 20,999	34	63	97	35%
R 21,000 – R 21,999	18	42	60	30%
R 22,000 – R 22,999	21	42	63	33%
R 23,000 – R 23,999	22	38	60	37%
R 24,000 – R 25,000	666	1,315	1,981	34%
Grand Total	**5,901**	**5,901**	**10,864**	**54%**

Table 5-15: Income vs. Bad Rate - Calculations and Results

r	-0.592
n	418
t	-14.990
t_c	-1.648

Figure 5-6: Estimated Income vs. Bad Rate



5.6.2 *Age vs. Bad Rate*

Table 5-16 below summarises the associated bad rate for each age group (for illustrative purposes each age has been grouped). It also provides the total number of bad and good accounts. Table 5-17 shows the results of the statistical analysis. A graphical representation of the correlation between the two variables tested is provided in Figure 5-7.

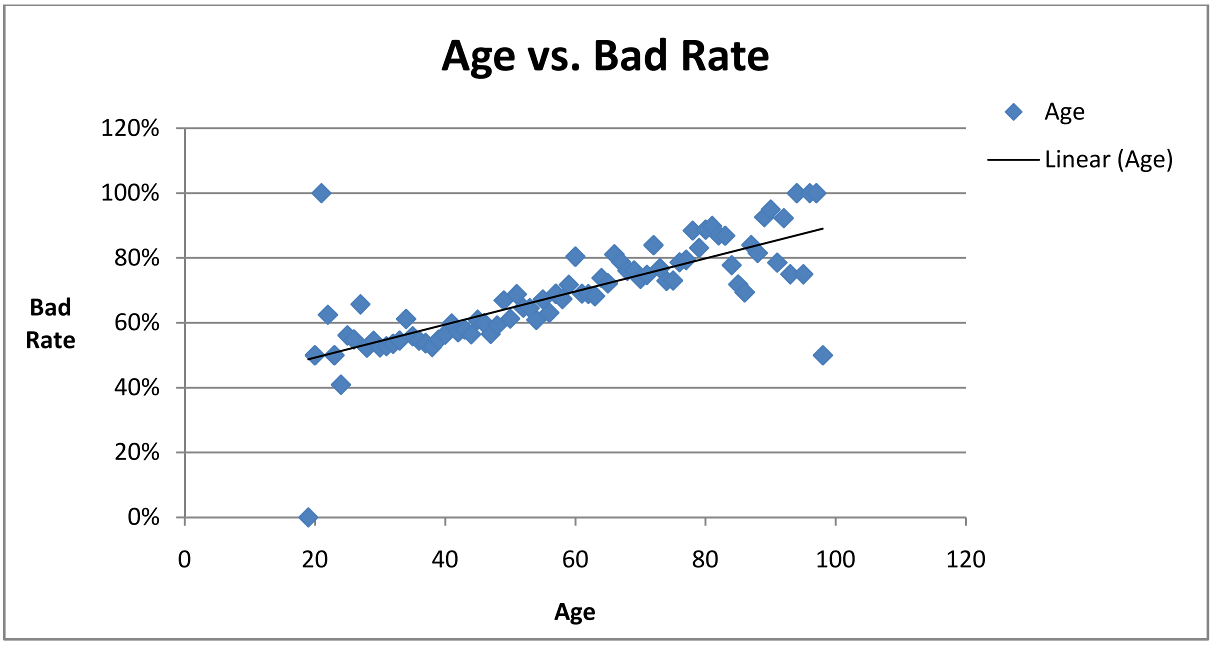
Table 5-16: Bad Rate per Age Group

Age Groups	Bad	Good	Grand Total	Bad Rate
19-24	28	28	56	50%
25-29	297	229	526	56%
30-34	670	541	1,211	55%
35-39	1,183	996	2,179	54%
40-44	1,341	989	2,330	58%
45-49	1,324	860	2,184	61%
50-54	1,160	654	1,814	64%
55-59	1,039	501	1,540	67%
60-64	836	312	1,148	73%
65-69	706	210	916	77%
70-74	497	154	651	76%
75-79	435	103	538	81%
80-84	277	42	319	87%
85-89	125	33	158	79%
90-94	75	8	83	90%
95-99	9	2	11	82%
Grand Total	**10,002**	**5,662**	**15,664**	**64%**

Table 5-17: Age Group vs. Bad Rate - Calculations and Results

r	0.740
n	80
t	9.709
t_c	1.665

Figure 5-7: Bad Rate for Each Age Group



5.6.3 Empirica Exclusion Code

Table 5-18 below provides a breakdown of the reasons why a consumer could not be scored with either a Live Empirica Score of Expansion Risk Indicator.

Table 5-18: Empirica Exclusion Code and Associated Bad Rate

Exclusion Code	Bad	Good	Grand Total	Bad Rate
Consumer is Deceased	781	164	945	83%
Consumer is under administration	100	61	161	62%
Consumer has insufficient information on file	3,023	478	3,501	86%
Grand Total	**3,904**	**703**	**4,607**	**85%**

Chapter 6: Discussion of Results

This chapter discusses the results presented in Chapter 5 and provides insight into the hypotheses laid out in Chapter 3. The chapter is structured as follows: firstly the results of the good and bad rates are reviewed. This is followed by the findings for each hypothesis. Where possible the findings are compared to the literature in Chapter 2. The chapter concludes with the findings of additional tests conducted on the Municipality and Credit Bureau data.

6.1 Good/Bad Rates

A total of 67% of all the utility account information received from the Municipality was classified as bad and had an amount greater than R100 outstanding for over 90 days. The Municipality confirmed that their bad rate was high but stated that this is due to two main reasons; the first being that consumers do not pay their accounts for all the same reasons as any other credit account (for example, lack of finances, general refusal to pay), the second is where consumers dispute the assessment rates calculated and either pay a portion of the amount owed (pending further reconciliation) or do not pay the amount in its entirety.

Analysis of the dataset of account holders successfully matched to the Credit Bureau reveals that 64% were classified as bad accounts based on the Municipality's definition. This bad rate is significantly higher than the bad rate generally accepted by the credit industry. If the bad rates were to be this high for credit providers they would have gone out of business.

6.2 Hypothesis 1: Empirica Score vs. Bad Rate

The hypothesis test revealed a negative correlation between the Fair Isaac Empirica score and the Municipality's accounts which were classified as bad (as graphically presented in Figure 5-1). The lower the score the higher the risk therefore the negative correlation shows that the higher the risk, the more likely it is that the consumer has a bad utility account.

The Student t-distribution test (Table 5-5) revealed that the correlation is significant and less than the Critical t-score. The null hypothesis was therefore rejected because the correlation was < 0 and significant. The negative correlation confirms the notion that consumers who do not pay their utility accounts and are credit active tend to have bad credit profiles. It can also be suggested that, if there is a correlation between negative Credit Bureau profiles and negative Municipality profiles, the Municipality accounts display credit-like characteristics (PERC, 2007). A total number of 10,664 records were analysed in this hypothesis test which is lower than the 15,683 records matched to the Credit Bureau. The main reason for this is that the Empirica score is generated only on consumers with sufficient credit information on which to adequately determine risk (TransUnion Credit Bureau and Fair Isaac, 2003b). The remaining consumers either received an Expansion Risk Indicator (412 records) or Exclusion Code (4,607 records).

It can also be noted that the records analysed in this hypothesis have a lower overall bad rate (54.6%) compared to the general population (64%) indicating that consumers who are credit active on the Credit Bureau are less risky than consumers with no credit history reported on the Credit Bureau.

6.3 Hypothesis 2: Expansion Risk Indicator vs. Bad Rate

The second hypothesis test revealed a high negative correlation between the Expansion Risk Indicator and the Municipality's accounts which were classified as bad (as reflected in Figure 5-2). The lower the score the higher the risk therefore the negative correlation shows that the higher the risk, the more likely it is that the consumer has a bad utility account.

The Student t-distribution test (Table 5-7) revealed that the correlation is statistically not significant and is within the Critical t-score. The null hypothesis was therefore not rejected. It is unclear as to why the t-distribution was within the Critical t-score. One contributing factor may be that the number of ordered pairs is only 3 and that this is not significant enough in order to statistically evaluate the correlation or the confidence level is too strict. If the confidence level is set at 79%, the null hypothesis is rejected as the t-distribution is below the Critical t-score.

It is observed that the total bad rate (70.4%) is far higher than that in hypothesis 1 (54.6%). A conclusion is therefore made that consumers with a credit record but without sufficient payment account information are generally more risky than consumers with payment information on a credit account. Consumers rated with an Expansion Risk Indicator of 3 (classified as less risky) still have a staggeringly bad rate of 66.4% whereas consumers rated in Hypothesis 1 in the Empirica band 842-861 (classified as less risky) have a combined bad rate of 15.1%.

The test is therefore not conclusive that consumers who have a good Expansion Risk Indicator will be good rate payers but casual observation shows that consumers who receive an Expansion Risk Indicator (70.4% bad rate) are in general more likely to default than consumers who receive an Empirica score (54.6%) .

A further observation to note is that the number of records analysed were only 412 as opposed to the 10,664 records analysed in Hypothesis 1. There are therefore fewer records on which to statistically evaluate.

6.4 Hypothesis 3: Average Outstanding Balance vs. Empirica Score

The result of this test shows that there is a negative correlation between the Empirica scores generated and the total outstanding balance on the Municipal accounts. Even though the correlation is rather low, visual inspection of Figure 5-3 reveals a downward slope. The lower the score the higher the risk therefore the negative correlation shows that the higher the risk, the higher the amount owed on the utility account.

The Student t-distribution test (Table 5-9) revealed that the correlation is significant and less than the Critical t-score. The null hypothesis was therefore rejected because the correlation was < 0 and significant. This test differs to the one conducted in Hypothesis 1 in that Hypothesis 1 tested that there was an amount outstanding over 90 days, whereas this test looks at the total value outstanding and whether or not there is a correlation. A possible conclusion to this test is that there is a correlation between the total balance outstanding and the bad rate. This seems rather logical in that accounts in arrears, for example 4 months in arrears, should generally have a greater outstanding amount than someone who is not in arrears.

It must be noted that both the outstanding balance and the age bucket in which money is owed both correlate with Empirica, adding to the evidence that these accounts reflect similar characteristics to traditional credit accounts. Both types of accounts have consumers who are provided with a good or service in advance of payment, are regularly billed and can generate outstanding balances in age buckets over 90 days (Turner and Agarwal, 2008).

A further observation is that the amount outstanding seems to bear less importance than the age buckets in which the amount is owed. This is determined by comparing the correlation to Empirica of Hypothesis 1 and 3. Hypothesis 1 reveals a correlation of -0.580 and Hypothesis 3 a correlation of -0.282.

6.5 Hypothesis 4: Credit Bureau Worst Ever Status vs. Bad Rate

When reviewing the results of Hypothesis 4, a strong positive correlation between the worst ever status reported on any of a consumer's payment profile lines against the Municipal bad rate is noted (as reflected in Figure 5-4). The Student t-distribution test (Table 5-11) revealed that the correlation is significant and greater than the Critical t-score. The null hypothesis was therefore rejected because the correlation was > 0 and significant. The worst ever status is an aggregate variable on the Credit Bureau which determines what the worst status is on the combined payment profiles for each consumer within the last 24 months.

It is noted that the results of this Hypothesis reveal a stronger correlation to the bad rate (0.733) than the results of Hypothesis 1 where Empirica was correlated to the bad rate (-0.580). This may be due to the fact that the Empirica scorecard is calculated on more information than just the worst ever payment profile status and should be a better statistical risk assessment.

6.6 Hypothesis 5: Retro Empirica Score vs. Bad Rate

The hypothesis results reveal a negative correlation between the retrospective Fair Isaac Empirica score and the Municipality's accounts which are classified as bad (as reflected in Figure 5-5). The lower the score the higher the risk therefore the negative correlation shows that the higher the risk, the more likely it is that the consumer has a bad utility account.

The Student t-distribution test (Table 5-13) revealed that the correlation is significant and less than the Critical t-score. The null hypothesis was therefore rejected because the correlation is < 0 and significant. The negative correlation shows that the Empirica scorecard which predicts credit risk, could predict whether the consumer was likely to default on their municipal account in the future; thus adding to the evidence that the utility account has credit behaviour. It can also be suggested that because there is a correlation between the negative Credit Bureau profiles and negative Municipality profiles the Municipality accounts display credit-like characteristics (PERC, 2007). A total number of 10,760 records were analysed in this hypothesis test which is higher than the 10,664 records utilised in testing Hypothesis 1 because consumers may have had old accounts removed from their credit profile over the last year, and hence are no longer reported as credit active.

Like Hypothesis 1, there is a difference between the number of records that received a retrospective Empirica score (10,760) and the total number of records matched to the Credit Bureau (15,683). This is again because some consumers lack adequate information on which to determine risk and were therefore assigned either an Expansion Risk Indicator or Exclusion Code.

6.7 Additional Data Analysis Conducted

In addition to the hypotheses stipulated in Chapter 3, two additional tests were conducted. The first looks at the relationship between the consumer's estimated income and the Municipality's bad rate. The second looks at the relationship between the consumer's age and the Municipality's bad rate.

6.7.1 Estimated Income vs. Bad Rate

The estimated income derived from TransUnion Credit Bureau's Income Estimator product was compared with the Municipalities bad rate to determine whether any correlation exists. The results reveal that a negative correlation exists between income and the Municipal bad rate; therefore consumers who earn more income are less likely to default on their municipal accounts (as graphically presented in Figure 5-6). The Student t-distribution test (Table 5-15) revealed that the correlation is significant and less than the Critical t-score. What is interesting to note is the large range between the bad rates of consumers in the lower income bands to that of consumers in the higher income bands. The bad rate ranges from 90% (in the income band: R 500 - R 999) to 34% (in the income band: R 24,000 – R 25,000). These results seem logical in that consumers who earn more have more disposable income in order to pay their municipal accounts.

A total of 10,864 consumers could be allocated an estimated income. This is because the income is calculated on the consumers with sufficient payment profile information and 4,819 consumers could therefore not be assigned an income.

6.7.2 Age vs. Bad Rate

The second test conducted determined whether there is a relationship between the consumer's age and the Municipal definition of bad. The general observation in credit scoring is that the younger you are the more risky you are. The results however show a strong positive correlation between age and the bad rate, therefore the older you are the more inclined you are to default (as graphically presented in Figure 5-7). The Student t-distribution test (Table 5-17) revealed that the correlation is significant and greater than the Critical t-score. It is unclear as to why this is so, and further analysis would need to be conducted to determine the possible reasons. It is a credit industry accepted premise that with age comes maturity and therefore better management of accounts, so the results of this test go against the norm.

Further, it is noted that a bad rate of 89% is assigned to consumers who fall in the age bracket 90-99. It is suspected that some of these consumer are deceased hence the failure to pay their utility accounts.

6.8 Empirica Exclusion Code Analysis

A review was done on the Exclusion Codes generated on Empirica. These are consumers who could not be scored with either an Empirica score or Expansion Risk Indicator. Table 5-18 reveals that 945 consumers were listed as deceased with a combined bad rate of 83%.

A total of 161 consumers were reported as being under administration and having a court administration order or notice reported on their credit profile. There are a total of 3,501 consumers with a combined bad rate of 86% who could not be assigned any score because they lack any information needed on which to make a decision. Consumers who received an Exclusion Code (85% bad rate) appear to be far more risky than consumers who receive an Empirica Score (54.6% bad rate). 86% of the consumers who had a profile on the Credit Bureau but were not credit active were classified as bad. It reveals that consumers who are credit active are generally better payers than consumers who are not credit active.

Chapter 7: Conclusion

This research aimed to demonstrate that utility payment information supplied by a municipality has ‘credit-like’ characteristics. It attempted to do this through comparing the payment behaviour of utility accounts to that of traditional credit accounts like home loans and vehicle loans. It looked at whether those consumers who conduct their utility accounts well, have good payment histories on their traditional accounts; on the other hand, those consumers who manage their utility accounts badly have bad payment histories on their traditional credit accounts.

The results discussed in Chapter 6 revealed that there was a correlation between the Credit Bureau’s live and retrospective Empirica scores and payment profile information to the Municipalities utility accounts. Consumers who had bad Credit Bureau profiles tended to have bad municipal accounts. The results also demonstrated that, not only those consumers who owed amounts over R100 and older than 90 days were more likely to have a bad credit record, but consumers with high outstanding balances on the utility account were also more likely to have a bad credit record.

What was evident was that the bad rate on consumers who were credit active happened to be better than that for consumers who were not credit active. This poses the question of whether consumers who are credit active are more responsible than those who are not credit active.

By demonstrating that the utility accounts held by the Municipality have ‘credit-like’ characteristics it can be used as evidence in support of the Municipality supplying the data to the Credit Bureau and been used by credit providers in making adequate credit decisions in the absence of traditional credit information (Turner *et al*., 2006 and PERC, 2007). It could also be used to enhance decisions where only traditional credit information exists. Where consumers previously had no payment history on which credit grantors could make decisions, utility information could be captured and returned and used to grant access to credit. This in turn may be used as one initiative in allowing consumers the ability to escape the ‘credit Catch 22’ and gain access to formal credit (Turner and Agarwal, 2008). Thus consumers that may have been previously classified as ‘unbanked’ now have access to financial services previously denied, and assist as a mechanism in which the consumer can build up a credit history build up capital and escape poverty (Arch, 2005). The addition of the Municipality data can also assist with assessing the consumer’s ability to afford the credit. The data assists in completing the profile of the consumer’s monthly expenditure commitment and whether the consumer has spare capacity with which to service new debt.

The research results also show that the Credit Bureau data can be used by the Municipality to determine who is more likely to be a bad risk and default on their municipal account. The Municipality can utilise the Bureau to determine risk on the opening of a utility account by a consumer. A higher deposit could be charged for consumers predicted to be a high risk. The Municipality can also use the Credit Bureau score as a mechanism for collection prioritisation (TransUnion Credit Bureau and Fair Isaac, 2007). Those consumers who have a bad score can be handed over sooner for collection if the consumer starts to default on 30 days, as the amount will most likely age to 90 days or older.

Certain results have highlighted the need for additional research in this field. The following areas require additional study:

i. Due to the fact that the data of only one South African municipality was used in the research, there is a need to obtain data from additional municipalities to determine whether the results observed with this Municipality are repeated in others.
ii. Further research is required as to why older utility account holders tend to be worse payers than younger account holders as demonstrated in Chapter 5.
iii. The research conducted by Turner, Stewart Lee, Schnare, Varghese and Walker (2006) mentioned that rental information can also be used as a non-traditional data source on which to grant credit. Analysis of this data can be explored further to assess its credit-like nature.
iv. In addition to the rental data mentioned above, the use of school fee payment information can also be looked at as a non-traditional data source. Currently certain South African schools provide payment information on bad account payers to Credit Bureaux, however analysis on the good payers of school fees versus consumers with good credit bureau profiles could be analysed to see if there is a strong correlation. This could go to assisting consumers who don’t have a credit record but pay their child’s school fees gaining access to credit.

In closing, the study lends itself to the following recommendations:

i. That the Credit Bureau actively pursues obtaining utility information from South African municipalities in order to enhance a consumer's credit record.

ii. That the municipalities actively capture vital information on their account holders like ID number, surname, and full forenames. This can assist the Bureau in successfully matching the account to an existing consumer's credit report or alternatively create a new credit profile on the Bureau for the consumer. The National Credit Act also requires that any entity submitting data to a credit bureau needs to supply an SA identity number (or passport and data of birth), surname and forename.

REFERENCES

Ardington, C. and Leibbrandt, M. (2004) *Financial Services and the Informal Economy*. African Development and Poverty Reduction: The Macro-Micro Linkage, Forum Paper 2004. Available from http://www.commerce.uct.ac.za/Research_Units/DPRU/DPRU-Conference2004/Papers/Financial_Services_Ardington.pdf (Accessed on 10 September 2008).

African National Congress (ANC) (1994) *The Reconstruction and Development Programme: A Policy Framework*. Available from http://www.anc.org.za/rdp/rdp4.html (Accessed on 13 September 2008).

Arch, G. (2005) Microfinance and Development: Risk and Return from a Policy Outcome Perspective. *Journal of Banking Regulation*, 6(3), 227-245.

Avery, R.B., Calem, P.S., Canner, G.B. and Bostic, R.W. (2003) An Overview of Consumer Data and Credit Reporting. *Federal Reserve Bulletin*, 89(2), 47-73.

Bebula, X. (2007) *The South African Micro Enterprise Sector Analysis*. Republic of South Africa Department of Trade and Industry 2007 Annual Business Summit. Available from: http://www.thedti.gov.za/smme/07AnnualBusinessSummit.htm (Accessed on 1 September 2008).

Capon, N. (1982) Credit Scoring Systems: A Critical Analysis. *Journal of Marketing*, 46(2), 82-91.

Chye, K.H., Chin, T.W. and Peng, G.C. (2004) Credit Scoring Using Data Mining Techniques. *Singapore Management Review*, 26(2), 25-47.

City of Johannesburg (2005) *Credit Control and Debt Collections Policy*. Available from http://www.joburg-archive.co.za/bylaws/credit_control_annexd.pdf (Accessed on 2 November 2008).

Coetzee, G. (1998) *Regulation and Supervision of MicroFinance Institutions: The Experience in South Africa*. University of Pretoria: Department of Agricultural Economics, Extension and Rural Development.

Coetzee, G., Druschel, K.A., Cook, L.D., Brislin, N.W., Meagher, J.P. and Pearson, R.V. (2005) *The Evolution of the South African Microfinance Sector from 1992 to 2004: The Role of the Microfinance Regulatory Council*. ECI Africa and IRIS Centre of the University Research Corporation International.

Daniels, R. C. (2004) Financial Intermediation, Regulation and the Formal Microcredit Sector in South Africa. *Development Southern Africa*, 21(5), 831-849).

eThekwini Municipality (2007) *eThekwini Credit Control Policy*. Available from http://www.ethekwini.gov.za/durban/government/munadmin/treasury/income_expend/revenue_man (Accessed on 25 May 2008).

FinMark Trust (2007) *FinScope South Africa 2007: Survey Highlights Including FSM Model.* Available from http://www.finscope.co.za/_documents/2008/Brochure_FSSA07.pdf (Accessed on 31 May 2008).

FinMark Trust (2008) Finscope Press Release: *The Number of People Banked in South Africa Has Increased 20 Percent – but Use of Products Remains Limited.* Available from http://www.finscope.co.za/documents/_2008/PR_SA07_banked.pdf (Accessed on 29 May 2008).

Firer, C., Ross, S.A., Westerfield, R.W. and Jordan, B.D. (2004) *Fundamentals of Corporate Finance*. 3rd South African ed. Berkshire: McGraw-Hill Education.

Hamlyn, M. (2007) Half of SA Adults 'Unbanked'. *Fin24.com*, September 11. Available from http://www.fin24.com/articles/default/display_article. aspx?ArticleId=1518-25_2181386 (Accessed on 25 May 2008).

Hand, D.J. and Adams, N.M. (2000) Defining Attributes for Scorecard Construction in Credit Scoring. *Journal of Applied Statistics*, 27(5), 527-540.

Hawkins, P. (2003) *The Cost, Volume and Allocation of Consumer Credit in South Africa*. Department of Trade and Industry: South Africa. Available from http://www.thedti.gov.za (Accessed on 30 May 2008).

Heymans, M. (mheymans@ncr.org.za), 13 August 2007. *CB Synoptic Report and Submission Date.* Email to B. Scott (bscott@transunion.co.za).

Iman, R.L. (1994) *A Data-based Approach to Statistics*. California: Wadsworth Publishing Company.

Information Policy Institute. (2005) *Giving Underserved Consumers Better Access to the Credit System: The Promise of Non-Traditional Data.* Available from http://www.infopolicy.org/pdf/nontrad.pdf (Accessed on 29 May 2008).

Jacobson, T. and Roszbach, K. (2003) Bank Lending Policy, Credit Scoring and Value-At-Risk. *Journal of Banking & Finance*, 27, 615-633.

Kirsten, M. (2006) *Policy Initiatives to Expand Financial Outreach in South Africa*. Development Bank of Southern Africa. Available from:

www.dbsa.org/Research/ Documents/Policy%20Initiatives%20to%20expand%20outreach.doc (Accessed on 28 August 2008).

Klein, D.B. (2001) Credit-Information Reporting. *Independent Review,* 5(3), 325-344.

Klein, D.B. and Richner, J. (1992) In Defence of the Credit Bureau. *CATO Journal*, 12(2), 393-411.

Lee, A., Turner, M., Varghese, R. and Walker, P. (2008) *You Score, You Win: The Consequences of Giving Credit Where Credit is Due*. Chapel Hill, North Carolina: PERC Press.

Lind, D.A, Mason, R.D and Marchal, W.G. (2000) *Basic Statistics for Business and Economics.* 3rd ed. Singapore: McGraw-Hill Higher Education.

Mester, L.J. (1997) What's the Point of Credit Scoring? *Business Review (Federal Reserve Bank of Philadelphia)*, September-October, 3-16.

Mohamed, S. (2005) The Poor Need Banks for Savings and Credit. *Polity.org.za.* Available from http://www.polity.org.za/article.php? a_id =76794 (Accessed on 20 May 2008).

Municipal Systems Act (2000) Act No. 32 of 2000.

National Credit Act (2005) Act No. 34 of 2005.

National Credit Regulator (NCR) (2007) *FORM 44: Sect 70(5) Quarterly Synoptic Report – Credit Bureaux (Version 1.4 - 24/10/2007).*

National Credit Regulator (NCR) (2008) *Credit Bureaux Monitor*, March 2008, Quarter 1. Available from http://www.ncr.org.za/pdfs/publications/NCR%20CB%20Monitor-Q3.pdf (Accessed on 08 November May 2008).

Political and Economic Research Council (PERC) (2007) *The Promise of Non Financial Data: How Using Energy Utility and Telecoms Payment Data Can Help Millions Build Assets*. Policy Brief: Vol.7, No.1. Available from http://www.infopolicy.org/ publications/ADI%20II%20Policy% 20Brief. pdf (Accessed on 01 May 2008).

Rosenberg, E. and Gleit, A. (1994) Quantitative Methods in Credit Management: A Survey. *Operations Research*, 42(4), 589-613.

Roszbach, K. (2004) Bank Lending Policy, Credit Scoring, and the Survival of Loans. *The Review of Economics and Statistics,* 86(4), 946-958.

Sajiwan, M. (MSajiwan@transunion.co.za), 15 May 2008. *NCR Synoptic Report Quarter 1 2008.* Email to Z. Mtimkulu (zmtimkulu@ncr.org.za).

Siddiqi, N. (2006) Credit Risk Scorecards, *Developing and Implementing Intelligent Credit Scoring.* Hoboken, New Jersey: John Wiley & Sons,Inc.

Singh, A. (2006) *Releasing New Credit Energy in South Africa. A Guide to the National Credit Bill*. Pinegowrie: Ananda Consulting Services cc.

South African Advertising Research Foundation (SAARF) (2006) Living Standards Measure. Available from http://www.saarf.co.za/ (Accessed on 13 September 2008).

South African Advertising Research Foundation (SAARF) (2007) *LSM Presentation 2007.* Available from http://www.saarf.co.za/ (Accessed on 31 May 2008).

South African Reserve Bank (SARB) (2003) Financial Development and the Unbanked. *Labour Markets and Social Frontiers*, 3.

South African Reserve Bank (SARB) (2008a) *Quarterly Bulletin No 237: March 2008*. Available from http://www.reservebank.co.za/. (Accessed on 30 May 2008).

South African Reserve Bank (SARB) (2008b) *Quarterly Bulletin No 249: September 2008*. Available from http://www.reservebank.co.za/. (Accessed on 14 September 2008).

Statistics South Africa (StatsSA) (2001) Census 2001. Available from http://www.statssa.gov.za/census01/HTML/C2001Interactive.asp (Accessed on 30 October 2008).

Swart, N. (1999) *Personal Financial Management*. Kenwyn: Juta & Co,Ltd.

The World Bank (2008) *New Data Show 1.4 Billion Live On Less Than US$1.25 A Day, But Progress Against Poverty Remains Strong*. Available from http://web.worldbank.org/WBSITE/EXTERNAL/NEWS/0,,contentMDK:21881954~pagePK:64257043~piPK:437376~theSitePK:4607,00.html (Accessed on 13 September 2008).

Thomas, L.C. (2000) A Survey of Credit and Behavioural Scoring: Forecasting Financial Risk of Lending to Consumers. *International Journal of Forecasting*, 16, 149-172.

Tomlinson, M.R. (2006) *Are Title Deeds a Silver Bullet for Accessing Credit?* Graduate School of Public and Development Management of the University of the Witwatersrand, and the Development Bank of Southern Africa.

TransUnion Credit Bureau (2004) *Aggregate Process Documentation*.

TransUnion Credit Bureau (2007) *Business & Functional Specification for Income Estimator and BCC (Version 1.1).*

TransUnion Credit Bureau and Fair Isaac (2003a) *Empirica User Guide*.

TransUnion Credit Bureau and Fair Isaac (2003b) *Sellers Guide for Empirica: The Third Generation*.

TransUnion Credit Bureau and Fair Isaac (2007) *Empirica Product Sheet*.

Turner, M. A., Stewart Lee, A., Schnare, A., Varghese, R. and Walker, P.D. (2006) *Give Credit where Credit is due: Increasing Access to Affordable Mainstream Credit Using Alternative Data*. Political and Economic Research Council and the Brookings Institution Urban Markets Initiative. Available from http://www.infopolicy.org/pdf/alt-data.pdf (Accessed on 31 May 2008).

Turner, M, A. and Agarwal, A. (2008) Using Non-traditional Data for Underwriting Loans to Thin-file Borrowers: Evidence, Tips and Precautions. *Journal of Risk Management in Financial Institutions,* 1(2), 165-180.

Valsamakis, A.C., Vivian, R.W. and du Toit, G.S. (2003) *Risk Management.* 2nd ed. Sandton: Heinemann Higher and Further Education.

Zikmund, W.G. (2003) *Business Research Methods*. 7th ed. Thomson South-Western.

APPENDIX

Appendix 1

TransUnion Credit Bureau Batch Match & Input Data Quality Statistics

	Amount	%
Total Number of Records Submitted to TransUnion	**35,597**	
RSA ID Errors		
RSA Identity Number Errors Total	**17,598**	**49%**
Blank RSA Identity Number	7,423	42%
Miscellaneous RSA ID No errors	10,175	58%
Address Errors		
Total Residential Address Errors	**12,590**	**35%**
Blank Residential Address Errors	57	0%
Invalid Residential Addresses	0	0%
Miscellaneous Residential Address Errors	12,533	100%
Forename Errors		
Forename Errors	**3,888**	**11%**
Surname Errors		
Total Surname Errors	**798**	**2%**
Headers Rejected because Surname Field Blank	0	0%
Miscellaneous Errors in Surname	798	100%
Results of Fixing Routines		
Total Number of Input Header Records Rejected Prior to Match Attempts	1,368	4%
Total Number of Errors Fixed	1,830	5%
Match Results		
Total Number of Input Header Records Passed to TransUnion Search and Match Routines	34,229	96%
Number of Positively Matched Headers	15,683	46%
Number of NO Matches Found	18,546	54%
Output Results		
Total Number of Records in Output	**15,683**	**44%**