University of the Witwatersrand, Johannesburg

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The Impact of Macroeconomic Factors on the Risk of Default: The Case of Residential Mortgages

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DECLARATION

I, Koleka Mkukwana declare that the research work reported in this dissertation is my own, except where otherwise indicated and acknowledged. It is submitted for the degree of Master of Management in Finance and Investment at the University of the Witwatersrand, Johannesburg. This thesis has not, either in whole or in part, been submitted for a degree or diploma to any other universities.

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Date:

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1. ABSTRACT

Defaulted retail mortgage loans as a percentage of retail mortgage loans and advances averaged 9 percent over 2010 as reported in the SARB Bank Supervision Annual report. Banks are in the business of risk taking and as a result need to constantly evaluate and review credit risk management to attain sustained profitability. In credit risk modelling, default risk is associated with client-specific factors particularly the client's credit rating. However, Brent, Kelly, Lindsey-Taliefero, and Price (2011), have shown that variation in mortgage delinquencies reflect changes in general macroeconomic conditions. This study aims to provide evidence of whether macroeconomic factors such as the house price index, CPI, credit growth, debt to income ratio, prime interest rates, and unemployment, are key drivers of residential mortgage delinquencies and default in South Africa. In this study, data from an undisclosed bank is used to estimate three models that are supposed to capture the influence of several macroeconomic variables on 30 day, 60 day, and 90 day delinquency rates over the 2006-2010 period. In order to eliminate the potential bias introduced by those observations, a fourth model was estimated using aggregated banking industry published by the SARB. However, due to data constraints, only the severe mortgage delinquency state, that is the 90 day delinquency rate was modelled using this aggregate data. The SARB sample covers the period between 2008 and 2010. The choice of the date 2008 coincides with the introduction of the Basel 2 regulatory framework. Prior to 2008, the big four South African banks were governed by the Basel 1 framework, and measured their credit risk using the so-called Standardised Approach which has different loan categories and different default definitions compared to the Basel 2 Advanced Internal Ratings Approach adopted in 2008.

The findings suggest that the two samples (i.e. the data from the individual bank and the SARB data) imply different explanatory macroeconomic factors. Prime interest rates were found to be the only important variable in determining 30 day and 60 day delinquency rates for the individual bank. The house price index, CPI, credit growth, and prime interest rates were found to be the main determinants of the 90 day delinquency rates for the undisclosed bank, while the house price index, CPI, and credit growth, determine the 90 day delinquency rates for the big four banks.

Key Words: Risk, Credit Risk, Default Risk, Residential Mortgages, Profitability,

2. INTRODUCTION

A bank is a financial institution and like any other firm its main objective is maximization of profits and shareholders wealth. The severe 2007 - 2009 financial market meltdown and high defaulted exposures induced by the downturn in the housing sector and the bursting of the housing bubble, presented a challenge to the attainment of strong financial results. Attributable earnings for Absa's Retail banking declined by 21,1 percent to R2 863 million partially due to a sharp increase in impairments of 40,8 percent. (ABSA Group Annual Results December 2009). Similarly, the impairment charge for Nedbank Retail, South Africa's fourth largest bank by asset size, increased by 35,7 percent to R4 925 million mainly due to home loans defaulted advances, which increased by 58,5 percent on 2008. (Nedbank Group Annual Results December 2009). According to Nedbank, increasing impairments resulted in reduced earnings levels compared with the period ending at December 2008.

The financial meltdown combined with the high indebtedness of South African households highlighted the need for improved methodologies to better quantify banks' vulnerabilities to different types of economic shocks. In addition, high levels of non-performing loans undermine the bank's ability to function as intermediaries, which is matching the needs of a surplus (deficit) unit, either a business firm, government agency or an individual with the deficit (surplus) of another.

Banks are required to hold adequate credit impairments against non-performing loans to ensure that they are compensated for risks incurred and to protect depositors. The credit impairments limit the capital available for lending to the public, and thus constrain economic growth. Credit impairments are reserve accounts kept aside as provisions for loan losses. They divided into two categories namely; specific impairments, and portfolio impairments. Specific impairments are those that a bank views as being associated with a particular loan. While portfolio impairments are general provisions not allocated to a particular loan but are calculated based on average historical loan losses. Credit impairments appear on both the income statement and balance sheet. The balance sheet impairments are reduced from the total loans receivable (see line 4 in figure 2), this adjustment is done to ensure that the bank's assets are not overstated but show the portion of loans that will be collected. The balance sheet account is established and maintained by monthly charges against earnings. The charges appear on the income statement as an expense named the income statement charge (see line 10 in figure 3). The balance sheet impairment is increased by an amount equivalent to the amount charged against earnings as an income statement charge (see line 2 in figure 1 and line 10 in figure 3). Increases in impairments occur when (1) it has become apparent that a loan is more likely to be in part or wholly uncollectible; (2) an unanticipated write-off has occurred for which the bank did not set aside reserves; or (3) the amount of loans in the bank's portfolio has increased.

Figure 1 illustrates how the balance sheet impairments are calculated, while figures 2 and 3 below show how the income statement charge, and balance sheet impairments are reported in the respective financial statements. The figures reported do not reflect actual financial statements of the banks investigated.

Figure 1: Calculation of balance sheet impairments

	CALCULATION OF BALANCE SHEET IMPAIRMENTS	
1	Opening balance (begining 2009)	9 000
2	Add Income Statement charge	3 000
3	Add Recoveries	850
4	Less:Amounts written off in 2009	2 850
5	Closing balance (end 2009)	10 000

Figure 2: Balance sheet impairments example

BALANCE SHEET AS AT 31 DECEMBER 2009

ABC Bank

	R'm ASSETS				LIABILITIES AND EQUITY	
1	Cash		80 000	*9*	Deposits	740 000
2	Securities		200 000	*10*	Other Liabilities	190 000
3	Total Loans	640 000		*11*	Total Liabilities	930 000
4	Less: Balance Sheet Impairments	10 000				
5	Net loans		630 000			
6	Property		4 000	*12*	Owners Equity	70 000
7	Other Assets		86 000			
8	**TOTAL ASSETS**		1 000 000	*13*	**TOTAL LIABILITIES AND OWNERS EQUITY**	1 000 000

Figure 3: Income statement impairments example

INCOME STATEMENT FOR YEAR ENDING 31 DECEMBER 2009

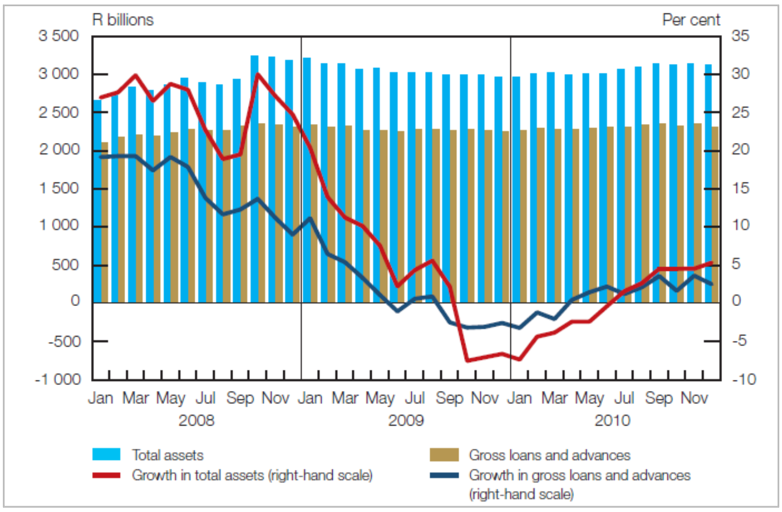
ABC Bank

	R'm		
	INTEREST INCOME		
1	Interest and fees on Loans	70 000	
2	Interest on Securities	18 000	
3	Other Interest Income	2 000	
	NON-INTEREST INCOME		
4	Service Charges	4 000	
5	Other non-interest income	6 000	
6	TOTAL INCOME	100 000	
	INTEREST EXPENSE		
7	Interest on deposits	40 000	
8	Other interest expense	20 000	
	NON-INTEREST EXPENSE		
9	Salaries	10 000	
10	Income Statement Charge	3 000	
11	Other non-interest expense	17 000	
12	TOTAL EXPENSES	90 000	
13	INCOME BEFORE TAX		10 000
14	Income tax		2 500
15	NET INCOME		7 500

According to the December 2010 Bank Supervision Annual report, the South African banking sector has 17 registered banks, 2 registered mutual banks and 13 registered international banks whose principal activities are to collect deposits from customers with excess funds and disburse loans to customers with insufficient. (South African Reserve Bank Supervision Annual Report 2010).

Figure 4 below provides a graphical representation of South African banking sector assets and loans to customers.

Figure 4: Total banking assets, gross loans and advances and respective growth rates



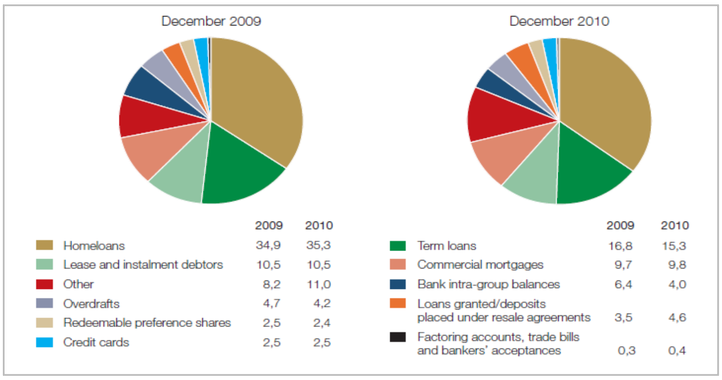
Source: SARB - Bank Supervision Annual Report 2010

The South African banking sector is dominated by four banks namely, Amalgamated Banks of South Africa (ABSA), First National Bank (FNB), The Standard Bank of South Africa (SBSA) and Nedbank. The four banks contributed 84, 6 percent to the balance-sheet size of the banking sector at December 2010, with loans and advances accounting 74 percent of these assets. (South African Reserve Bank (SARB) Supervision Annual Report 2010). The loans and advances asset category comprise of the following loan types;

i. Homeloans
ii. Term loans
iii. Other
iv. Lease and instalment debtors
v. Commercial Mortgages
vi. Loans granted/deposits placed under resale agreements
vii. Overdrafts
viii. Bank intra group balances
ix. Credit Cards
x. Redeemable preference shares
xi. Term loans
xii. Factoring accounts, trade bills and bankers' acceptances

Figure 5 shows the composition of the above loan types at December 2009 and 2010.

Figure 5: Total gross loans by product and respective growth rates



Source: SARB - Bank Supervision Annual Report 2010

The abovementioned loan types expose banks to the risks of not realising the expected returns on assets. According to Van Greuning and Bratanovic (2003), banking risk fall into four main categories namely, operational, financial, business, and event risks. Financial risks include liquidity, credit, solvency, interest rate, currency, and market price risks. Operational risks are related to a bank's overall organisation and functioning of internal systems, including computer related and other technologies; compliance with bank policies and procedure; and measures against mismanagement and fraud. Business risks are related with a bank's business environment, including macroeconomic and policy concern, legal and regulatory factors and the overall financial sector infrastructure and payment system. Lastly, event risks include all types of exogenous risks. Figure 6 shows the different risk types.

Figure 6: Banking risk categories

FINANCIAL RISKS	OPERATIONAL RISKS	BUSINESS RISKS	EVENT RISKS
BALANCE SHEET STRUCTRE	INTERNAL FRAUD	MACRO POLICY	POLITICAL
INCOME STATEMENT STRUCTURE	EXTERNAL FRAUD	FINANCIAL INFRASTUCTURE	CONTAGION
CAPITAL ADEQUACY	EMPLOYMENT PRACTICES AND SAFTY	LEGAL INFRASTRUCTURE	BANKING CRISES
CREDIT	CLIENTS, PRODUCTS AND BUSINESS SERVICES	LEGAL LIABILITY	OTHER EXOGENEOUS
LIQUIDITY	DAMAGE TO PHYSICAL ASSETS	REGULATORY COMPLIANCE	
MARKET	BUSINESS DISCRUPTION AND SYSTEM FAILURES	REPUTATTIONAL AND FIDUCIARY	
CURRENCY	EXECUTION, DELIVERY AND PROCESS MANAGEMENT	COUNTRY RISK	

Source: Van Greuning and Bratanovic (2003)

Although the other risks are all important and could cause bank runs if not efficiently managed, the study focuses only on credit risk. Credit risk is the dominant source of risk for most lending banks, since the balance sheet of lending banks mostly comprise of loans and advances. These findings are consistent with South African trends. Loans and advances represented, on average, 74 percent of banking sector total assets during 2010 (2009: 73 percent). (SARB Supervision Annual Report 2010). Among the different loan types, homeloans remain major constituents of gross loans and advances, accounting for 35, 3 percent at the end of December 2010 (December 2009: 34, 9 percent). Given these statistics, it is evident that poor credit models for home loans could adversely affect the financial position and performance of banks.

The objective of the study is to quantify the impact of macroeconomic factors on the default risk of South African home loans. In their study of Mortgage Delinquency Migration, Gloy and Stokes (2007) argue that while mortgage delinquency is not a sufficient condition to insure default, it is a necessary condition for default as loans will generally progress through various states of delinquency prior to default. Therefore, they believe a better understanding of mortgage default should be obtainable through a better understanding of the dynamics of mortgage delinquency.

In this study, data from an undisclosed bank is used to estimate three models that are supposed to capture the influence of several macroeconomic variables on 30 day, 60 day, and 90 day delinquency rates over the 2006 - 2010 period. In order to eliminate the potential bias introduced by those observations, a fourth model was estimated using aggregated banking industry data published by the SARB. However, due to data constraints, only the severe mortgage delinquency state, that is the 90 day delinquency rate was estimated using aggregated data. Campbell and Dietrich (1983) stated that substantial explanatory power may be lost when national aggregates are used.

The analysis aims to provide information that will allow banks to improve assessments during underwriting to implement strategies that improve the default resolution process. If macroeconomic factors are found not to impact on residential default risk, then banks can focus on borrower specific factors as the sole determinants of credit risk. Alternatively, if macroeconomic factors are indeed found to impact on residential mortgage default risk, then focus should be stressed on those factors as well when modelling credit risk and not purely borrower specific variables. The inclusion of the borrower variables in the sample would lead to another research line which is beyond the scope of this paper. The paper consists of four chapters of discussion and analysis, where;

- Chapter 3 covers the literature review and research hypothesis.
- Chapter 4 presents the research methodology.
- Chapter 5 presents regressions and empirical findings of the study.
- Chapter 6 highlights conclusions and recommendations.

2.1 Problem Statement

Non-performing loans continued to grow in the first half of 2010, peaking at R123, 4 billion in May 2010. (SARB Quarterly Bulletin December 2010). Despite the establishment of The National Credit Act (NCA) in 2007, household debt remained at a high of 76, 5 percent in the second quarter of 2010 as reported in the SARB quarterly bulletin. The National Credit Act aims to solve specific problems in the existing consumer-credit market, including the prohibition of reckless lending by credit providers, the prevention and alleviation of the over indebtedness of consumers, and the prevention of the high costs of credit.

In credit risk modelling, default risk is associated with borrower-specific factors, particularly credit rating, but studies of Determinants of Mortgage Delinquency by Howard University have shown that variation in delinquency and default rates, over time reflect changes in borrower characteristics and changes in general economic conditions.

2.2 Purpose of the Study

The study aims to provide evidence of whether macroeconomic factors are key drivers of non-performing home loans in the South African banking sector. If macroeconomic factors are found not to impact on home loan default risk, then banks can focus on firm specific factors as the sole determinants of credit risk. Alternatively, if macroeconomic factors are indeed found to impact on residential mortgage default risk, then focus should also be stressed on those factors when modelling credit risk. The analysis will provide information that will allow banks to improve assessments during underwriting and assist in implementing strategies that improve the default resolution process.

2.3 Significance of the Problem

Given the interdependencies in the economy, accurate risk measures would support the capital allocation and strategic schemes of the bank in a globally competitive environment.

Risk managers would be interested in questions like "what would be the impact on default risk of the residential mortgage portfolio if there would be a 3 percentage points increase for example in prime interest rates. This is known as stress testing. This information would aid them in adapting credit risk policies and practises to control and avoid losses. An example of such a credit policy would be tightening the loan-to-value ratios to prohibit additional home loan lending when prime interest rates hit 3 percentage points and are higher than existing level of rates.

3. LITERATURE REVIEW

This chapter offers a review of the relevant theoretical foundation, existing empirical evidence upon which this study is based, and the research hypothesis. The first section describes the structure of the South African mortgage market. Section 2 introduces the concept of mortgage default which helps to explain the subsequent theoretical review provided in section 3. Finally, section 4 covers the research hypothesis.

3.1 The structure of South African mortgage market

Residential mortgage loans are extended by a number of banks and specialist mortgage lending institutions in South Africa. The largest of these, as illustrated in the graph below, are Nedbank, ABSA Bank, Standard Bank and First National Bank. At the end of 2010, home loans advanced by Absa, Standard Bank, First Rand and Nedbank where R248 million, R247 million, R149 million and R136 million respectively. (SARB Bank Return 900, 2010)

The overall home loans accounted 35, 3 percent of total gross loans and advances loans. South African Reserve Bank Supervision Annual Report 2010). Since 1999, specialist mortgage lenders such as SA Home Loans (SAHL) and Mortgage SA have successfully entered the residential mortgage market.

The South African big four banks target the low risk, upper income segment of the residential mortgage market. Since 1994 the objective of the national housing policy has been the provision of credit for low income households. The national housing policy aims to assist low income earners by increasing the engagement of banks in the high risk low income housing finance sector. The legislative pressure to serve the low income housing finance market has required formal banks to develop products without increasing their exposure and compromising returns.

A particular challenge is the fact that mortgage bonds are considered inappropriate for low income borrowers because of their limited understanding of mortgages. According to Marais, Botes, Pelser and Venter (2005), 22 percent of low-income home-owners default because they do not understand the regulations applicable to housing, or do not realise the consequences of non-payment. (Marais et al., 2005) quoted (Rust, 2002), that low-income home-owners do not seek appropriate advice in the event of hardship or a crisis.

The South African residential mortgage market over the last years has been dominated by variable interest rates, with less than 10 percent of all mortgages financed at a fixed rate. A fixed rate is a contracted rate between the bank and the borrower for a pre-determined period of time. A variable interest rate is a fluctuating rate based on the prime lending rate as determined from time to time. The features of the two types of rates are as follows;

- Fixed interest rates
  - o The rate will be fixed at a pre-determined rate for a specified period.
  - o These rates are not influenced by fluctuations in the mortgage prime lending rate.
  - o A fixed rate option contract may not be terminated prior to the expiry of the agreed term.
  - o A client may change to variable interest rate option; however it can be applied once the fixed rate option expires as per the agreement.
- Variable interest rates
  - o Fluctuations in the prime lending rate influence the variable interest rate.
  - o The interest rate option cannot be fixed for a pre-determined period.
  - o Banks determine the rates based on an individual's risk profile and property details.

3.2 The concept of mortgage default

Under the Advanced Internal Ratings Based approach, credit exposures are classified as either "current," "30 days past due," "60 days past due" or "90 plus days past due," where the latter classification represents exposures in default. A mortgage loan is current when the borrower has made all of the contractually required monthly payments. It is 30 days past due when the borrower has missed one monthly payment, it is 60 days past due when the borrower has missed two monthly payments, and it is 90-plus-days past due when the borrower has missed three or more monthly payments. The 90 plus days past due loan category consists of defaulted exposures entering the 90 plus day past due bucket for the first time, properties in possession, restructured loans, debt in counselling loans and loans in foreclosure process.

The mortgage contract gives the Bank the right to demand full payments of the loan when the counterparty fails to meet the contractual obligations. This means the bank will call the carrying amount due. Lending institutions understand that there could be genuine reasons for which the borrower is unable to make timely payments such as loss of job, or an accident that may have confined the borrower to bed. Thus, instead of running away from the banks, borrowers need to engage in a dialogue with the bank. Based on how genuine the borrowers' intent and case is, the bank may look for feasible solutions like restructuring debt or rescheduling the debt.

- The National Credit Act of 2005 which came into operation on June 2007 gives a consumer the right to apply for a debt review, to be declared over-indebted after his financial position has been evaluated, and to have his debts rescheduled. The consumer applies through a debt counsellor registered with the National Credit Regulator (NCR), the regulatory body of all debt counsellors. Debt rescheduling can occur by extending the period on the contract; this will bring down the monthly instalments commitment, though it will result to more interest payments in the long term. Another form of debt rescheduling is deferring the payment by seeking temporary relief from the bank for a few months; this may result to penalty charges for not paying within the time frames agreed upon earlier. Should the borrowers financial situation improve, the borrower can negotiate with the bank and revert to the old or higher monthly instalments or even prepay the loan, closing it early and saving excessive interest payments. Although rescheduling debt is a consumers right, the consumer may not apply for a debt review in respect of a particular credit agreement if the credit provider has already taken steps to enforce foreclosure. By 31 March 2010, the National Credit Regulator had registered 1 642 debt counsellors. The number of applications for debt counselling continued to grow during the period with between 7 000 and 8 000 new applications per month, reaching 161 749 applications at the end of the period, (Roestoff, Haupt, and Erasmus 2009). This statistics are proof of the over indebtedness of South African households.

- Borrowers can also consider restructuring the loan facility. Unlike the debt counselling option, debt restructuring is done directly with a bank and not through a debt counsellor who acts as an intermediary. However, defaulted clients do not automatically qualify for restructuring. The option to restructure is at the bank's discretion and a loan should possess certain qualities to qualify for a restructuring. These include factors like whether the client is making some form of payment or not. A client in a restructure is not removed from default but kept in default for a certain period of time while the bank monitors the consistency of payments. After a series of perpetual payments and commitment to the restructure arrangements, the bank then decides to take the client out of the 90 days past due to the current bucket, that is 0 - 30 days past due.

Based on the above discussions, a borrower may benefit from debt counselling and loan restructuring through retaining the asset, and the bank may also benefit because the revised agreements leads to a lower defaulted portfolio over time and prevents foreclosure. Standard Bank offers the EasySell programme, which is designed to help one sell your property in order to avoid foreclosure. Nedbank has a similar programme called the Nedbank Assisted Sales programme, where the bank uses estate agents to market and sell property. Similarly, FNB has a Quick Sell programme to help consumers who are over-indebted that their only option is to sell their properties for the best price they can obtain. If a borrower opts for Quick Sell but receives insufficient funds to cover what one owes the bank, FNB may provide a discount of up to 20 percent on your pre-sale outstanding loan amount. The discount depends on the extent of your arrears when you applied for Quick Sell. Absa also introduced a programme called Help you sell, where the bank assists the borrower to market the property through estate agencies or auctioneers. According to Lightstone, a company that researches the property market, the number of sales in execution has dropped significantly as a result of the bank's interventions to help distressed homeowners.

From the above discussions, it evident that there are other options available to lenders besides foreclosure to recover losses on default loans and it can take a substantial period of time to complete a foreclosure. However, if the borrower refuses to communicate with the bank and avoids any interaction with the bank to an extent that the bank does not get tangible commitment on payments, the bank servicers will typically start foreclosure proceedings.

Hayre, Saraf, Young, and Chen (2008) define foreclosure as a legal process, by which the property that serves as collateral on the loan is sold. Foreclosure occurs when the borrower defaults on the contractual obligations of the loan, usually by failing to meet the required capital or interest payments. Through the foreclosure process, the lender exercises his power to sell the property. Judgement for the amount due must first be obtained to serve as a basis for a writ of execution for a judicial sale.

Before or during the foreclosure process, the Bank may encourage the borrower to sell the property, even if the selling price is less than the mortgage amount. The mortgage lender may insist on a reserve price to protect his or her interests. The bank may also buy the property at the sale and set off the amount due under the mortgage against the purchase price. The proceeds can be used to satisfy the claim. If the servicer takes possession of the property, property is then classified as a Property in Possession. At this point, the lender may either tenant the property, with rental streams accruing to it, or sell the property by either private treaty or public auction. Banks usually take time to foreclose as this is an expensive exercise. When a lender forecloses on a property, significant costs arise.

Default risk on a residential mortgage loan is often in terms of any negative equity in the property at the time of default. The actual loss on a defaulted loan is however much greater than the negative equity. When a lender forecloses on a property, significant costs arise. Claurentie and Sirmans (2003) grouped the costs of foreclosing and liquidating properties into three categories namely; transaction costs, property costs and opportunity costs. Transaction costs include those involved with the foreclosure; attorneys' fees, trustees fees, sheriffs cost of sale, brokers commission and title charges. Property costs include those fees incurred by the lender to carry the property until liquidated: property taxes, hazard insurance, utilities, and repairs and maintenance. Opportunity costs include interest foregone on the investment value of the property.

Thus it appears that the cost of default comes not only from a decline in property prices that might produce negative equity, but also from the cost of the foreclosure and property liquidation process.

3.3 Theoretical review

This literature review explores research from different authors who analyse the factors that explain movements in residential delinquency rates and default rates. Early studies on mortgage default amongst others include the studies by Herzog and Earley (1970), Campbell and Dietrich (1983). While this thesis aims to examine the relationship between delinquency rates and macroeconomic variables, earlier studies by Herzog and Earley (1970) and Campbell and Dietrich (1983) focused on loan, borrower and property characteristics as determinants of past due loans.

Herzog and Earley (1970) used twelve independent variables to explain variation in delinquency risk namely; (1) loan purpose, (2) the presence and absence of junior financing, (3) loan-to-value ratio, (4) loan type, (5) initial term to maturity, (6) monthly mortgage payment to borrower income ratio, (7) borrower occupation, (8) marital status, (9) number of dependents, (10) geographical region, (11) borrower age, and (12) type of lender . To ascertain the influence of these variables, the authors classified the loans as being current (no payments missed), delinquent (ninety days or more) and in foreclosure. Using the loan status as the dependant variable, the authors then developed a linear probability function where the dependant variable, loan status was assigned a value of zero if loan was in current status, and a value of one if it was either ninety or more days delinquent or in foreclosure. In cases where negative values or values greater than 1 arise, Herzog and Earley (1970) argue that it is not possible to assign a probability interpretation to them. Therefore the authors chose to call the regression functions risk equations and to call the results of these equations risk indices. Herzog and Earley (1970) further stated that if equations have good discriminating power, lower values for the results demonstrate low risk while high values indicate high risk. The analysis was performed on separate samples of loans sourced from the United States Savings and Loan League (USSLL), the Mortgage Bankers Association (MBA) and the National Association of Mutual Savings banks (NAMSB).

The general regression equation was as follows:

$$R_a = a_1 + a_2 RLS + a_3 T + a_3 RPI + O_i + DN_i + SM_i + AB_i + P_i + FJ + TLD_i + TLN + R_i + e_t \qquad (1)$$

where the variables with subscripts are used to show the presence of two or more dummy classes and symbols are defined as follows: (RLS) loan to value ratio; (T) term to maturity, (RPI) monthly payment to income ratio; (O) borrower occupation; (DN) number of dependants; (SM) is marital status; (AB) borrower age; (P) loan purpose; (FJ) indicates the presence and absence of junior financing; (TLD) type of lender; (TLN) type of loan; and (R) region.

Herzog and Earley (1970) claimed that due to scarcity of data and other technical issues it was not possible to include variables which contained more than a few dummy variables. Instead of using all variables, the indices were based on the five variables including RLS, T, P, FJ, and RPI.
The regression results of risk indices for delinquency risk, foreclosure risk, and straight foreclosure risk are given in table 11 of Appendix A.

The authors found borrowing for refinancing purposes and the presence of junior financing to be the most important variable affecting the incidence of serious loan delinquency. Refinancing is the process of acquiring new loans to pay off an existing loan. Junior financing is a class of debt that, in the event of insolvency, is prioritized lower than other classes of debt.
At a significance level of one percent, the loan to value was found to have a positive and significant influence on delinquency risk in loan statuses. However, the term of maturity showed a negative relationship in all three loan statuses and was statistically significant in only four of six equations. Term to maturity is the time remaining before a contract expires. The longer the term, the higher the chances of the loan becoming delinquent. Occupation was found to be significant. The authors stated that in general, professional persons, executives, and managers showed the least delinquency and self-employed persons and salesmen the most. The variable region proved to be significant in determining variation in delinquency risk. The study therefore showed differences amongst the regions. Loan type was also a significant variable. The number of dependants showed a positive significant relationship for the USSLL sample and was insignificant in the MBA and NAMSB samples.
The mortgage payment-to-borrower income variable was found not to have a significant relationship for delinquency risks. Herzog and Earley (1970) explain that this occurred because both lenders and borrowers watch this ratio carefully. The authors added that lenders and borrowers avoid situations where the ratios exceed critical limits unless there is assurance that payments will be made from non income sources. In addition, the study revealed that most loans within the observed samples had mortgage payment-to-borrower income ratios below 25 percent. Marital status was found not to be statistically significant in all samples; however the risk coefficients were uniformly lower for married than for single borrowers. Borrower age showed mixed results, so no generalisation was justified.

According to Campbell and Dietrich (1983) a default occurrence is based on an optimization model of consumer choice. The authors claim that, at each point in time of the life of a mortgage, borrowers observe a set of state variables and choose one of four utility maximizing actions; default, delay payment, prepayment, or continue to pay mortgages.

The authors assume that the utility maximizing choice can be represented as a probability function of the state variables given as follows;

$$P\,(s_i\ I\ x) = f_i(x) \qquad (2)$$

where the sum of the probabilities of all n elements in s for a given x is equal to unity; $\sum_{t=1}^{n} P\,(S_i\ I\ x) = 1$; and s_i represents the *ith* choice variable of the representative borrower.

Thus Campbell and Dietrich (1983) estimate a multinomial logit using regional aggregates constructed from cross sectional and time series data. The time series data included the index of mean housing prices for new and existing single family dwellings, the index of nominal disposable income, the rate of unemployment, and the current mortgage rate in the region. Cross sectional data included current loan to value, age of mortgage and a dummy variable which assumes a value of 1 when a home is new, 0 otherwise.

Campbell and Dietrich (1983) quoting a study by McFadden (1973) show that under a reasonable set of assumptions, the consumer's choice can be described by a logit function. For default, delinquent and prepay, the logit function is given as follows;

$$P_i = e^{\beta i} \;/\,(1+ e^{-\beta 1X} + e^{-\beta 2X} + e^{-\beta 3X}) \qquad (3)$$

The logit function for continuing to make payments is given as follows;

$$P_4 = 1/\ (1+ e^{-\beta 1X} + e^{-\beta 2X} + e^{-\beta 3X}) \qquad (4)$$

Where β_1 represents a vector of coefficients relating the probability of choice i to the variables in X. Combining equations (3) and (4) the following is obtained;

$$P_i/P_4 = e^{-\beta 1X} \qquad (5)$$

Transforming equations (5) into a linear log equation gives;

$$Log(P_i/P_4) = e^{-\beta 1X} \qquad (6)$$

The authors used the weighted least squares method procedure to estimate the regression model. The general regression equations are stated below:

$$LPDEF = a_1 + a_2CLTV + a_3CPTY + a_4UNEM + a_5CROR + a_6\,DUMNEW + a_7DUM85 + a_8DUM90 + a_9DUM95 + e_t \qquad (7)$$

$$LPDEL = b_1 + b_2CLTV + b_3CPTY + b_4UNEM + b_5CROR + b_6\,DUMNEW + b_7DUM85 + b_8DUM90 + b_9DUM95 + e_t \qquad (8)$$

$$LPPRE = c_1 + c_2CLTV + c_3CPTY + c_4UNEM + c_5CROR + c_6\,DUMNEW + c_7DUM85 + c_8DUM90 + c_9DUM95 + e_t \qquad (9)$$

$$LPDEF_a = d_1 + d_2CLTV + d_3CPTY + d_4UNEM + d_5CROR + d_6\,DUMNEW + d_7DUM85 + d_8DUM90 + d_9DUM95 + d_{10}Age + d_{11}Age^2 + e_t \qquad (10)$$

$$LPDELa = f_1 + f_2CLTV + f_3CPTY + f_4UNEM + f_5CROR + f_6DUMNEW + f_7DUM85 + f_8DUM90 + f_9DUM95 + f_{10}Age + f_{11}Age^2 + e_t \qquad (11)$$

$$LPPREa = g_1 + g_2CLTV + g_3CPTY + g_3UNEM + g_4CROR + g_5\,DUMNEW + g_6DUM85 + g_7DUM90 + g_8DUM95 + g_9Age + g_{10}Age^2 + e_t \qquad (12)$$

where dependent variables with subscripts are used to show the presence of age variables, the other variables are defined as follows: (LPDEF) log of probability of default in a given year; (LPDEL) log probability of delinquency in a given year; (LPPRE) log of probability of prepayment and/or insurance cancellation in a given year; (CLTV) current loan-to-value ratio; (CPTY) current payment-to-income ratio; (UNEM) rate of unemployment; (CROR) ratio of the current mortgage rate to contract rate on the mortgage at the beginning of a year; (AGE) age of the mortgage at the beginning of a year; (AGESQ) age of the mortgage squared; (DUMNEW) a dummy variable which assumes a value of 1 when a home is new, 0 otherwise; (DUM80) a dummy variable which assumes the value of 1 if a loan has an initial loan-to-value ratio less than or equal to 80%, 0 otherwise. The variables (DUM85), (DUM90), and (DUM95) have a similar interpretation.

Following correlation results showing strong collinearity between age and household monthly income; a total of six models were estimated. Three models show regression results when the age variables are omitted while the other three models show results with the age variables included. The regression results with the t statistics are provided in table 12 of Appendix A.
The regression results suggest that the loan-to-value ratio, the unemployment rate, the age of the mortgage and ratio of current to original mortgage rate all have negative effects (significant at 1 percent level).

More recent studies on mortgage delinquencies include Rebelo and Vaz Caldas (2010) and Brent et al., (2011).
Brent et al., (2011) examine mortgage delinquency rates for loans in each state and Washington, DC from 2004 through to 2009. Like Herzog and Earley (1970), models are estimated for different delinquency buckets including, 30 day, 60 day, 90 day, and 90 plus days delinquency rates. However, Brent et al., (2011) calculate a delinquency rate for each delinquent bucket instead of using a linear probability function. The authors' extend the work of Herzog and Earley (1970) by further categorizing data by prime and subprime loans to capture differences in the performance of these loans, and by introducing new independent variables including borrower race, adjustable rate mortgages, no-income verification, a house price index and unemployment. The models use independent variables that represent: 1) borrower characteristics; 2) loan characteristics; and 3) economic conditions and shocks to income to explain variation in Y, which represent the degree of delinquency. The authors use a two-way fixed effects model to examine cross-sectional time series data on mortgage delinquency rates in the US.

The general regression equation estimated by Brent et al., (2011) is given below:

$$D_r = \beta_1 + \beta_2 whpet + \beta_3 blpct + \beta_3 hispct + \beta_4 asnpct + \beta_5 ntvpet + \beta_6 fempct + \beta_7 credscr + \beta_8 income + \beta_9 nonoccp + \beta_{10} nivst + \beta_{11} spread + \beta_{12} pctrefi + \beta_{13} lien2nd + \beta_{14} pctadj + \beta_{15} depct + \beta_{16} unempl + \beta_{17} numpermt + \beta_{18} hpidx + \beta_{19} prbusvc + e_t \qquad (13)$$

where Dr represents the delinquency rate for each loan class and variables are defined as follows: (whpet) white borrowers;(blpct) African American borrowers; (hispct) Hispanic borrowers; (asnpct) Asian borrowers;(ntvpet) Native American borrowers; (fempct) female borrowers; (credscr) credit score; (income) personal income; (nonoccp) non-owner occupied loans; (pctadj) adjustable rate loans;(depct) denial rate; (unempl) unemployment rate; (numpermt) number of building permits; (hpidx) house price index; and (prbusvc) growth rate of persons employed in professional and business services. The authors estimated six models; the regression results of the estimated models, with standard errors are given in tables 13 through to table 15 of Appendix A.

The findings suggest that factors that determine 30 and 60 day delinquency rates differ from those that determine 90 day and 90 plus day delinquency rates. Borrower income was found to have a significant negative influence on delinquency rates. Brent et al., (2011) found that income reduces all delinquency rates for prime borrowers, except 30-day delinquency rates. Amongst the loan characteristics, the variables no-income verification, refinance loans and adjustable rate mortgages were found to be statistically significant. The findings relating to the refinance loans independent variable are consistent with findings by Herzog and Earley (1970). Refinance entails paying off an existing loan using proceeds from a new loan. No-income verification loans reduce delinquency rates, while adjustable rate mortgages increase 90-day delinquency rates for prime loans and 90 plus day delinquency rates for prime and subprime loans. The authors stated that no-income verification loans are primarily approved for borrowers with very high credit scores and sizeable down payments. Refinance loans increase 30-day and 60-day delinquency rates and reduce 90-day and 90 plus day delinquency rates. When considering the results for economic conditions, growth in the house price index was found to reduce delinquency rates. Unemployment and denials proved to increase all delinquency rates, except 30-day delinquency rates. The variable denials refer to application denial rates, increased denial rates are increased applications from less credit worthy borrowers. However, borrower race does not consistently explain delinquency rates.

Unlike Herzog and Earley (1970) and Brent et al., (2011), Rebelo and Vaz Caldas (2010) use an ordered probit model to estimate the influence of credit, social and economic variables on the probabilities of mortgage default in Portuguese households. Rebelo and Caldas (2010) estimate four models where the dependant variable takes one of four values depending on the degree of delinquency. (Y = 0) represents delayed and one month overdue instalments; (Y = 1) represents two month overdue instalments; (Y = 2) includes pre-litigation, three overdue instalments; lastly (Y = 3) includes clients in litigation and over three overdue instalments. According to Rebelo and Vaz Caldas (2010), the multinomial logit which allows for more than two categories suffers from the "independence of irrelevant alternatives" assumption. To address this issue the authors add that the order probit allows the dependent variables to assume values which are ordinal or ranking. The authors define the general regression equation as follows:

$$y = f\ (x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}) +\ e \qquad (14)$$

where e represents the statistical error and variables are: age (x_1), marital status (x_2), job contract (x_3), education level (x_4), place of residence (x_5), household size (x_6), household monthly income (x_7), monthly net income per capita, number of banking loans (x_8), effort rate (x_9), and loan guarantee (x_{10}).

Following correlation results showing a significant linear association between household size and household monthly income, the authors estimated four ordered probit regression models. Model 1 included socio-economic variables x_1, x_2, x_3, x_4, and x_5 as well as x_6 and x_7. Model 2 included model 1 variables and additional bank involvement variables x_8, x_9 and x_{10}. Model 3 included social-economic variables as per model 1 but replacing x_6 and x_7 with $x_{7a} = \frac{x_7}{x_6}$ (per capita income). Model 4 included model 3 variables with the addition of bank involvement variables x_8, x_9 and x_{10}. The regression results of the four estimated probit models, with standard errors are given in table 16 of Appendix A.
According to Rebelo and Vaz Caldas (2010), the loan capacity related variables namely number of banking loans, financial effort rate, and the ratio between loan amount and guarantee or real estate value influence the ranking of default probabilities. However, regarding the social and economic variables, only dummies, such as marital status, place of residence, family size, and monthly income were relevant. The type of job contract as well as qualifications do not influence default probabilities while age only influences default probabilities associated with more than 3 overdue instalments. The findings relating to occupation, marital status proved to be inconsistent to earlier studies by Herzog and Earley, while findings pertaining to place of residence, age, monthly income where in line with earlier findings.

Based on the above literature review, it is possible to summarize that determinants of defaults on a mortgage loans are related to household socio-economic and behavioural characteristics as well as to the external or macroeconomic environment.

However, this thesis models the default rates for South African loans for the period 2006 through to 2010 using only macroeconomic variables. As mentioned earlier, this study estimates four models using data from a big bank in South Africa (models 1, 2 and 3) and published aggregated data model 4. Data from a big bank in South Africa was used to estimate models for 30 day, 60 day, and 90 plus day delinquent loans, while published aggregated data was used to model 90 plus day in delinquency mortgage loans for the big four banks.

3.4 Research Hypothesis

Mortgage delinquency rates and default rates are driven primarily by how households are tied to business cycles. Increases in prime interest rates lead to increases in mortgage payments and could constrain the liquidity of borrowers. As prices of consumables including transport costs and food prices increase, consumers tend to enter into arrears in the bond repayments to meet basic needs. Increasing unemployment rates result in negative shocks to income that impact on borrower's ability to pay a mortgage. Decreasing house prices impair the borrower's equity position, which in turn increases delinquency risk because homeowners are in a worse position to refinance or sell if a trigger event occurs. The greater the proportion of the borrower's income that goes toward making debt payments, the greater the strain a trigger event puts on the borrower's ability to continue making mortgage payments. Excessive borrowing leads to over indebtedness and thus default.

Based on the above, the hypothesis statement is formulated as follows:

> *Depressed economic conditions including high interest rates, high inflation, high unemployment, and low real estate prices, high debt to income ratios impair home owner's ability to meet contractual monthly mortgage payments and may lead to default. The aforementioned tough economic conditions are generally unpredictable negative shocks which reduce the consumers' income.*

4. RESEARCH METHODOLOGY

This chapter offers a brief description of the research population, research sample and research methodology.

4.1 The research population

The population of the study is defined as all residential mortgage loans and advances underwritten by the South African retail banking sector.

4.2 The research sample

Separate samples of loans were obtained from the South African Reserve Bank (SARB) and from one of the four big South African banks. For confidentiality reasons, the name of the bank is not disclosed. The four banks contributed 84, 6 percent to the balance-sheet size of the banking sector at December 2010, with loans and advances accounting 74 percent of these assets and, residential mortgages accounting 35,3 percent of loans and advances. (South African Reserve Bank Supervision Annual Report 2010). Specifically, of the 35, 3 percent in residential mortgages, Standard bank has the largest portfolio of residential mortgages at 34 percent followed by ABSA, FirstRand and Nedbank at 30 percent, 18 percent, and 17 percent respectively.

4.3 Data Analysis

Monthly data concerning current, past due and foreclosed mortgages were gathered from one of the big four banks in South Africa. The sample period was January 2005 until December 2010. The default rates data is aggregated data of the big four banks, extracted from the South African Reserve Bank Annual Report for the period between January 2008 and December 2010. The start period January 2008 was selected to ensure consistency in the data due to the introduction of the Basel 2 regulatory framework, details are as follows:

i. Prior to 2008, the big four South African banks measured their credit risk using the Standardised Approach. Under this approach, credit risk exposures are classified as either “standard,” “special mention,” “substandard”, “doubtful” or “loss.” Specifically, defaulted advances included accounts classified as “substandard,” “doubtful” or “loss.” However, on 1 January 2008, the big four banks adopted the Advanced Internal Ratings-Based (AIRB) approach for the calculation of the minimum capital requirement for credit risk. Under the AIRB approach credit exposures are classified as either “current,” “30 days in arrears”, “60 days in arrears” or “90 plus days in arrears", where the latter classification represent defaulted advances. The impact of the amendment to the definition of overdue accounts is not discussed in this paper.

ii. The classification of loans and advances types was narrow under the Standardised approach and consisted of few loan categories. Loans and advances were classified as either "mortgage loans," "instalment sales and leases," "and "other loans and advances," where mortgages loans included farm loans, residential mortgages, and commercial mortgages.

iii. Lastly, the credit exposure under the Standardised approach included both the on-balance sheet exposure and off-balance sheet exposure. Off-balance sheet refer to exposure where the borrower has not utilised the exposure although the credit has been granted. However, the impact of the above mentioned issues on data is not discussed in this report.

The choice of macroeconomic variables used in the study was motivated by Herzog and Earley (1970), Brent et al., (2011), and Rebelo and Vaz Caldas (2010).

The data for prime interest rates, the Absa house price index, and the consumer price index were extracted from Reuters, while the data for debt to income ratio, credit growth, and unemployment were sourced from Statistics South Africa.

All variables were computed by indexing[1] the variable being either a number or a percentage. Since we would not expect variation in any dependent variable to add a constant amount to delinquencies or default rate, rather, variations in a dependent variable influence delinquencies by a constant percentage. For ease of interpretation of regression coefficients, the variables where then transformed by taking logarithms[2] of the indexed number or percentage. Following the logarithm transformation, the log linear regression model is expressed as a follows;

$$ln\, y_t = \beta_1 + \beta_2\, lnx_2 + \ldots + \beta_n lnx_n + e_t \qquad (15)$$

where, $\beta_2 \ldots \beta_n$ are partial slope coefficients[3]. Each partial slope coefficient measures the partial elasticity of the dependant variable with respect to the explanatory variable in question, holding all other variables constant.

A trend analysis showing the original and transformed data for each independent variable is provided in the paragraphs that follow. Figure 7 shows delinquency rates and default rates for loans classified as 30-day, 60-day and 90-day past due between 2005 and 2010. Delinquency rates were at their lowest towards the final quarter of 2005. As the recession became evident in 2009, 30 day

[1] Such that $V_1 = 100$, $V_t = (V_{t-1} * V_t)/ V_{t-1}$, where V_1 = value (balance or percentage) at month 1 and V_t is value at t

[2] Such that $\ln(Dratio_{dt}) = D_t$

[3] Such that the partial derivative of ln Y with respect to ln X is $\beta_n = \frac{\delta \ln Y}{\delta \ln X_n} = \frac{\delta Y/Y}{\delta X_n/X_n} = \frac{\delta Y}{\delta X_n} \cdot \frac{X_n}{Y}$

delinquency rates rose to a high of 4 percent as new clients were migrating from performing to delinquent. By the end 2009, the 90 days delinquency rates had increased to 13 percent.

Figure 8 shows the same delinquency and default rates using transformed data. The original ratios and transformed ratios exhibit similar trends over the sample period.

Figure 9 shows aggregated delinquency and default rates for residential mortgage loans between the periods 2008 and 2010. During the sample period, default rates showed an increasing trend, increasing from 2.67 percent in January 2005 to 8.67 percent in December 2010, a 225 percent increase. However, default ratios flattened between the final quarters of 2009 and 2010.

Figure 7: 30 day, 60 day, and 90 day delinquency rates

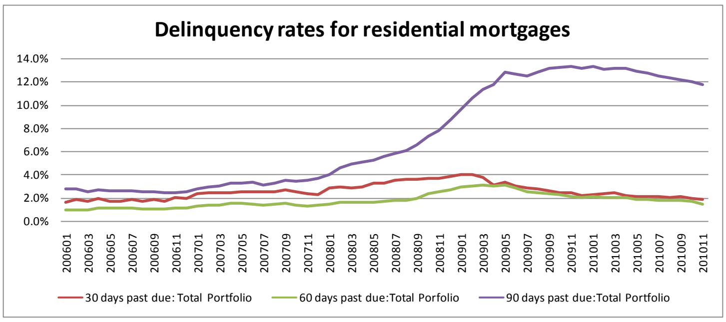


Figure 8: Transformed 30 day, 60 day, and 90 day delinquency rates

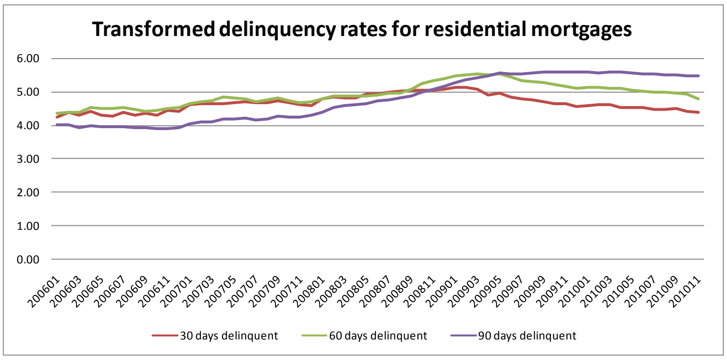


Figure 9: Default rates for aggregated data

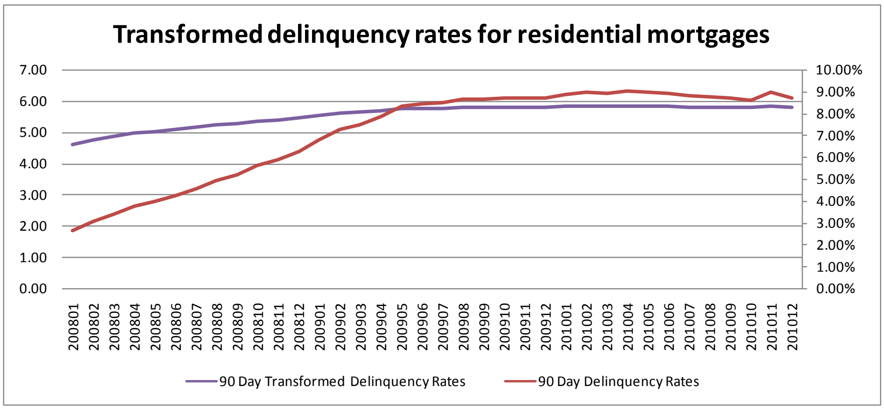


Figure 10 captures the prime interest rates. Prime interest rates are interest rates changes linked to the repo rate. Prime interest rates at 10, 5 percent were at their highest at December 2008, and showed a decreasing trend in the last quarter of 2010.
Figure 11 captures the debt to income ratio (DTI) ratio. The debt to income ratio (DTI) is the ratio of mortgage payments and other debt payments to income of the borrower. The debt-to-income ratio reached a high of 82, 0 percent in the March 2008 and trended gradually downwards to 77, 6 percent in December 2010.

Figure 12 captures credit growth. The variable credit growth is the value total mortgages credit extended to households including residential mortgages.

Figure 13 captures the consumer price index (CPI). The CPI is the official measure of inflation in South Africa. From 2005 until 2010, the average inflation rate in South Africa was 5.2 percent, reached a high of 13.50 percent in August 2008 and a low of 1.5 percent in September 2010.

Figure 14 captures the Absa House Price Index. This index provides a measure of typical price inflation for houses issued by Absa. Nominal house deflation averaged 2, 9 percent in 2009. However, house prices peaked around mid-year and slowed down significantly to an average of 2, 6 percent year on year in the second half of 2010.

Figure 15 captures unemployment. The number of unemployed individuals showed an increasing trend since September 2007, however declined in September 2008.

Figure 10: Prime interest rates 2006 - 2010

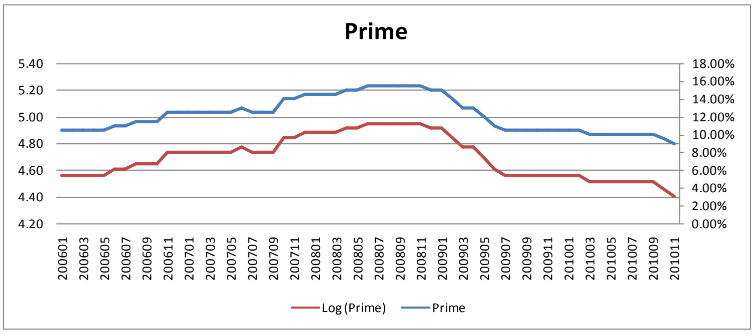


Figure 11: Debt to income ratio 2006 - 2010

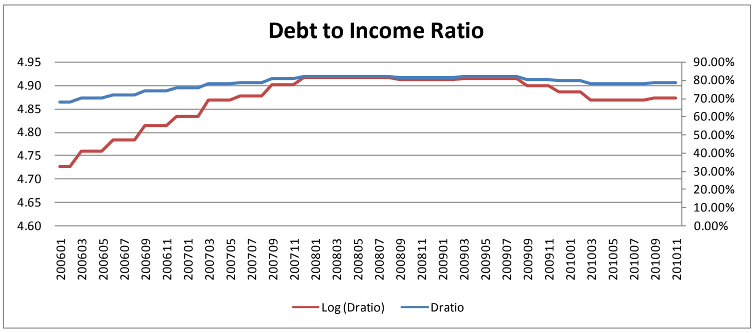


Figure 12: Credit growth: loans and advances 2006 – 2010

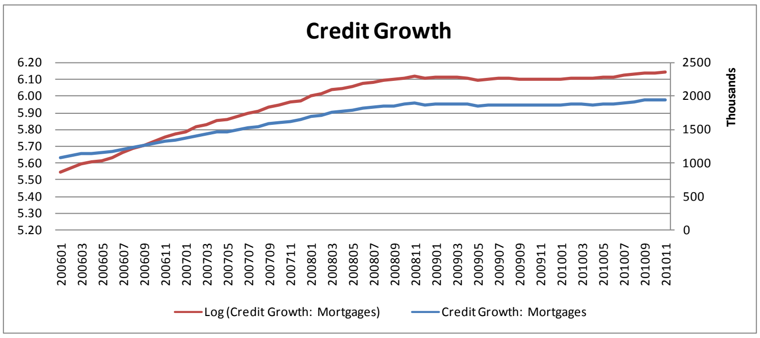


Figure 13: CPI 2006 – 2010

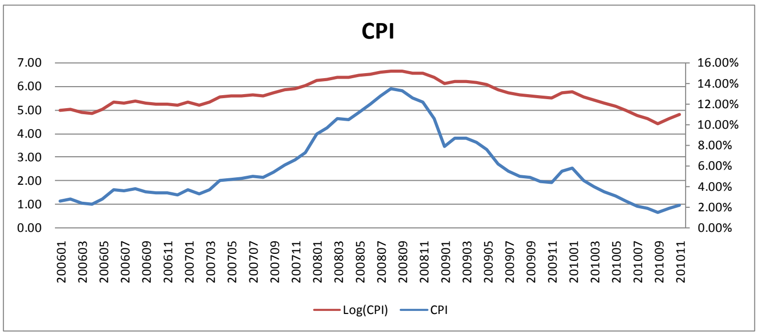


Figure 14: Absa house price index 2006 - 2010

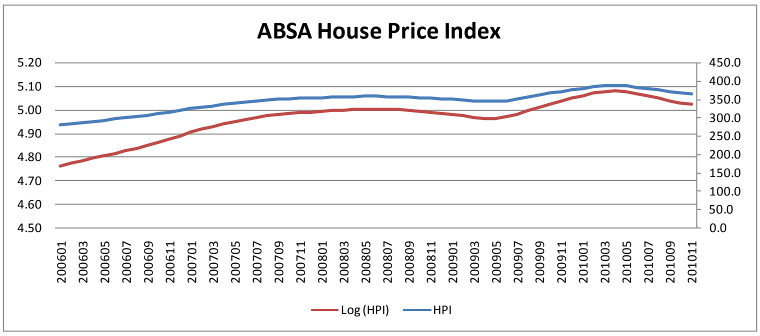


Figure 15: Unemployment 2006 – 2010

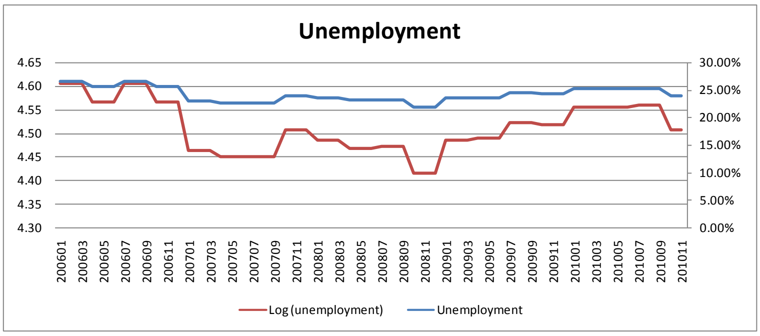


Table 1 presents the descriptive statistics for the data including sample mean, standard deviation, minimum, and maximum values of the dependent variables and independent variables in the regression.

Table 1: The descriptive statistics for the data

Descriptive Statistics										
	30 days delinquent	*60 days delinquent*	*90 days delinquent*	*Aggregated default ratios*	*Prime*	*HPI*	*Unemployment*	*Debt-to-income*	*CPI*	*Credit Growth*
Mean	108.6747518	142.7506106	146.9958007	0.071524617	111.171	143.6871	91.2568	130.469	325.8945	394.7425
Standard Error	3.577150862	6.340455733	11.64945234	0.003458673	2.331921	1.516474	0.63265	0.870284	24.48597	8.607002
Median	103.3682944	130.4967757	112.5263371	0.084428665	113.6364	146.3455	90.56604	132.4459	266.6667	434.3153
Mode	#N/A	#N/A	#N/A	#N/A	113.6364	#N/A	100	136.4393	188.8889	#N/A
Standard Deviation	27.47661713	48.70196459	89.48114131	0.020752036	17.91183	11.64825	4.859476	6.684778	188.0803	66.11163
Sample Variance	754.964489	2371.881355	8006.87465	0.000430647	320.8336	135.6818	23.6145	44.68625	35374.21	4370.748
Kurtosis	-0.554180914	-0.316476046	-1.741087529	-0.749886493	-1.23226	-0.12881	-0.88771	0.552021	-0.39309	-0.86619
Skewness	0.638497122	0.734442292	0.287591756	-0.886864918	0.361315	-0.76347	0.245867	-1.22298	0.872988	-0.79121
Range	99.57186616	173.3505158	220.2095774	0.063301396	59.09091	44.30421	17.35849	23.62729	666.6667	207.7608
Minimum	69.09018098	77.10630436	49.57095511	0.026681832	81.81818	116.7983	82.64151	112.812	83.33333	256.1794
Maximum	168.6620471	250.4568202	269.7805325	0.089983228	140.9091	161.1025	100	136.4393	750	463.9402
Sum	6411.810355	8422.286025	8672.752239	2.574886214	6559.091	8477.537	5384.151	7697.671	19227.78	23289.81
Count	59	59	59	36	59	59	59	59	59	59

We use the E-views statistical package to analyse the data. Tables 2 and 3 present the correlation coefficient between delinquency rates and the macroeconomic variables for the two samples, the undisclosed bank data, and SARB aggregated bank data.

Table 2: Correlation matrix (Aggregated bank data)

Correlation Matrix							
	DRATIO	**CPI**	**DINCOME**	**ABSAHP**	**CREDIT**	**EMPLO**	**PRIME**
DRATIO	1.0000						
CPI	0.9486	1.0000					
DINCOME	0.5867	0.7000	1.0000				
ABSAHP	0.4551	0.6503	0.7356	1.0000			
CREDIT	0.8596	0.8521	0.3128	0.3440	1.0000		
EMPLO	-0.0445	0.1544	0.2106	0.7037	0.0071	1.0000	
PRIME	-0.8214	-0.9090	-0.7865	-0.6574	-0.6072	-0.1427	1.0000

Table 3: Correlation matrix (Undisclosed bank)

Correlation matrix									
	30 days delinquent	*60 days delinquent*	*90 days delinquent*	*Prime*	*HPI*	*Unemployment*	*Debt-to-income*	*CPI*	*Credit Growth*
30 days delinquent	1								
60 days delinquent	0.730844886	1							
90 days delinquent	0.241255167	0.758668973	1						
Prime	0.743076661	0.154391991	-0.368541261	1					
HPI	0.395189853	0.550215512	0.733793682	0.063956	1				
Unemployment	-0.74834694	-0.419396402	-0.013556903	-0.67686	-0.39589	1			
Debt-to-income	0.763193156	0.688493589	0.488150495	0.509507	0.801089	-0.71722	1		
CPI	0.858779641	0.424395736	-0.009288872	0.877536	0.279112	-0.6552	0.663011	1	
Credit Growth	0.597814499	0.748323388	0.781552498	0.164891	0.911921	-0.44832	0.864156	0.429477	1

4.4 Econometric Methodology

4.4.1 Univariate characteristics of data

The report uses the ordinary least squares (OLS) regression model to estimate the influence of macroeconomic factors on mortgage delinquencies. The OLS methodology was chosen as an estimator because it is linear, unbiased, and has a minimum variance amongst all linear unbiased estimators of a parameter. From the data provided the OLS regression estimate is given as follows:

$$Y_t = \beta_1 + \beta_2 x_2 + \ldots + \beta_n x_n + e_t \qquad (16)$$

where y_t represents the dependent variable, β_1 is the constant, β_n is the slope of coefficients, and X_n the explanatory variables macroeconomic variables and e_t are the residuals which are independent and identically distributed random variables with $E[e_t] = 0$ and $E[e^2_t] = \sigma^2_e$.

Defaulting on a mortgage represents the ultimate consequence of past decisions to delay payment. As such, a better understanding of the probability of default is obtainable from better understanding the probability of delinquency that is induced by the sequence. A total of four OLS models were then run using the different loan delinquency statuses as the dependent variable. The mortgage delinquency statuses include 30 days, 60 days, and 90 days delinquent loans. The last model uses SARB aggregated data to estimate default risk using the ratio of default to mortgage loans as the dependent variable.

The choice of macroeconomic variables used in the study was motivated by studies by Herzog and Earley (1970), Brent et al., (2011), and Rebelo and Vaz Caldas (2010). These include employment, debt to income ratio, inflation, credit growth, house prices, and prime interest rates. Early studies by Herzog and Earley (1970) suggest employment determines a mortgage delinquency status. The findings may suggest that declining employment rates result in negative shocks to income that impact on borrower's ability to pay a mortgage. Therefore, employment rate and mortgage default rate should be inversely related.

The debt to income ratio (DTI) is the ratio of the monthly mortgage payments and other debt payments to the monthly income of the borrower. The higher the DTI ratio, the greater the proportion of the borrower's income that goes toward making debt payments, and hence the greater the strain a trigger event puts on the borrower's ability to continue making mortgage payments. Thus debt to income ratio should be directly related to mortgage delinquency and default ratio.

Another factor that determines delinquency status and default risk is inflation which is measured by the consumer price index. As prices of consumables including transport costs and food prices increase, consumers tend to enter into arrears in the bond repayments to meet basic needs.

The variable credit growth is the annual percentage change in overall credit extended to households including residential mortgages. This variable is expected to have a negative relationship with the 30 days delinquent rates. This relationship may signify that borrowers acquire new credit facilities like overdrafts and credit cards to reduce their mortgage debt to keep their accounts in current. Thus they acquire additional credit to pay off existing credit. Borrowers may benefit from the credit relief in short term; however, over time excessive borrowing will lead to over indebtedness and thus default. Thus the same variable is expected to have a significant positive relationship with defaulted loans.

Increases in house prices improve the borrower's equity position, which in turn reduces delinquency risk because homeowners are in a better position to refinance or sell if a trigger event occurs.

The final determinant of delinquency status and default rate included in the model specification is the prime interest rate. Prime interest rates are interest rates changes linked to the repo rate. The variable is expected to have a significant negative influence on default risk. Jumps in prime interest rates lead to increases in mortgage payments and could constrain the liquidity of borrowers.

The hypothesized relationship between each of the five independent variables and the independent variables is summarized in Table 4.

Table 4: Independent variables and direction of influence

Direction of Influence		
Independent Variable	**Direction of Influence**	
	Direct (+)	**Inverse (-)**
CPI	●	
Debt to income ratio	●	
House prices		●
Credit growth (short term effect)		●
Credit growth (long term effect)	●	
Unemployment		●
Prime interest rates	●	

Regression models involving time series data sometimes give results that are spurious or of dubious value, in the sense that superficially the results look good but on further investigation they look suspect. In addition, an OLS model provides unreliable estimators when variables are non-stationary. It is thus important to test for stationarity in time series data. Stationary models can yield time series plots that closely resemble those from non-stationary models having a stochastic trend. (Koop, 2006, p148). Therefore looking at time series plots alone is not enough to tell whether a series has a unit root. Given an AR (p) model, $\Delta Y_t = \alpha Y_{t-1} + x_t'\varphi + \beta_1 \Delta Y_{t-1} + \beta_2 \Delta Y_{t-2} + \ldots + \beta_p \Delta Y_{t-p} + v_t$, (Koop, 2006) suggests the following as ways of identifying whether a time series variable, Y, is stationary or has a unit root:

In the AR (p) model, if $\alpha = 1$, then Y has a unit root. If | α | < 1 then Y is stationary.

If Y has a unit root then its autocorrelations will be near one and will not drop much as lag length increases.

If Y has a unit root, then it will have a long memory. Stationary time series do not have long memory.

If Y has a unit root then the series will exhibit trend behaviour (especially if a is non-zero).

If Y has a unit root, then ΔY will be stationary. For this reason, series with unit roots are often referred to as difference stationary series.

Thus, the hypothesis of stationarity can be evaluated by testing whether the absolute value of α is strictly less than one. The null and alternative hypotheses may be written as;

$$H_0 : \alpha = 0$$
$$H_1 : \alpha < 0 \qquad (17)$$

and evaluated using the t statistic for α:

$$t\alpha = \alpha/(se(\alpha)) \qquad (18)$$

where, α^ is the estimate of α, and $se(\alpha^\wedge)$ is the coefficient standard error. If the variables in the distributed lag model are stationary, then OLS estimates are reliable and the statistical techniques of multiple regressions (e.g. looking at P-values or confidence intervals) can be used in a straightforward manner. Using the E-views statistical software, we employ the Augmented Dickey Fuller (ADF Test) test for unit root (Dickey & Fuller, 1981). E-views allow users to automatically select the lag length, or specify a fixed positive integer value. In the report lag selection is automatically performed by E-views. The ADF tests were performed on all variables including dependent variables and independent. The results are presented in the chapter 5.

5. REGRESSION AND EMPIRICAL FINDINGS

Chapter 5 presents regressions and empirical findings of the study. Table 5 below shows the ADF test results for SARB aggregated data.

Table 5: Augmented Dickey-Fuller Unit Root Results: Aggregated Data

Variables	*Default ratio*	*Absa House Price Index*	*Δ(Absa House Price Index)*	*Consumer Price Index*	*Credit Growth*	*Debt-to-income ratio*	*Δ (Debt-to-income)*	*Unemployment*	*Δ (Unemployment)*	*Prime interest rates*	*Δ(Prime interest rates)*
Regression coefficient	-0.1008	0.0318	0.7412	-0.0492	-0.1424	-0.1339	0.5360	-0.1160	-1.0025	0.0026	-0.7707
Augmented Dickey-Fuller test statistic	-10.4986	1.5336	-3.5692	-3.8502	-4.3839	-1.5527	-5.1897	-1.3701	-5.4541	0.0797	-4.4791
P-value	0.0000	0.9989	0.0136	0.0057	0.0014	0.4956	0.0002	0.5855	0.0001	0.9595	0.0011
Augmented Dickey-Fuller Critical value at 1%	-3.6329	-3.6999	-3.6999	-3.6329	-3.6329	-3.6329	-3.6537	-3.6329	-3.6394	-3.6329	-3.6394
Augmented Dickey-Fuller Critical value at 5%	-2.9484	-2.9763	-2.9763	-2.9484	-2.9484	-2.9484	-2.9571	-2.9484	-2.9511	-2.9484	-2.9511
Augmented Dickey-Fuller Critical value at 10%	-2.6129	-2.6274	-2.6274	-2.6129	-2.6129	-2.6129	-2.6174	-2.6129	-2.6143	-2.6129	-2.6143

The ADF statistic value for Default ratio is -10.49859, the associated one-sided p-value is 0.0000, and less than 0.05, thus we reject the null hypothesis and conclude that the series has no unit root. In addition, the statistic ADF value $t\alpha$ is less than the critical values so that we reject the null at 1%, 5%, and 10% critical values.

The p-value associated with ABSAHP variable is 0.9989 and greater than 0.05 indicating that the series has a unit root; in addition the ADF value $t\alpha$ at 1.5336 is greater than the critical values so we fail to reject the null at 1%, 5%, and 10% critical values and conclude that the series has a unit root or non-stationary. When we apply first differencing, the ADF statistic value $t\alpha$ at -3.5692 is greater than the 1% however less than 5% and 10% critical values. Thus we reject the null hypothesis at 1% and fail to reject the null at 5% and 10% critical values.

The ADF statistic value for CPI is -3.8502, the associated one-sided p-value is 0.0057, and less than 0.05, thus we reject the null hypothesis and conclude that the series has no unit root. Furthermore, the statistic ADF value $t\alpha$ is less than the critical values so that we reject the null at 1%, 5%, and 10% critical values.

The variable credit growth has an ADF statistic value $t\alpha$ is -4.3839, the associated one-sided p-value is 0.0014, and less than 0.05, thus we reject the null hypothesis and conclude that Credit has no unit root. In addition, it is important to note that the statistic ADF value $t\alpha$ is less than the critical values so that we reject the null at 1%, 5%, and 10% critical values.

The variable debt to income ratio proved to have a unit root as shown in the ADF results above. ADF value $t\alpha$ at -1.5527 is greater than the critical values at 1%, 5%, and 10% significant levels. In addition, the p-value is greater than 0.05. Performing first differencing we get results shown in table 5 above. The p-value is less than 0.05 and the ADF statistical value $t\alpha$ at -5.189674 is less than the critical values so we reject the null at 1%, 5%, and 10% critical values and conclude that change in debt to income has no unit root.

The ADF unit root test results on unemployment show that the p-value associated with this variable is 0.2210 and greater than 0.05 indicating that the variable has a unit root. In addition the ADF value

t_α at -2.168 is greater than the critical values, so we fail to reject the null at 1%, 5%, and 10% critical values and conclude that the series has a unit root or is non-stationary. After first differencing, the series proved to be stationery; the ADF statistic value $t\alpha$ at -6.1161 is less than critical values at 1%, 5%, and 10% significant levels and the p-value is less than 0.05.

The unit root test results for the variable Prime show the p-value at 0.9595, which is greater than 0.05 indicating that the variable has a unit root. In addition the ADF value $t\alpha$ at 0.0797 is greater than the critical values so we fail to reject the null at 1%, 5%, and 10% critical values and conclude that the series has a unit root or is non-stationary. We perform first differencing on the series. After first differencing, the variable proved to be stationery; the ADF statistic value $t\alpha$ at -4.4791 is less than critical values at 1%, 5%, and 10% significant levels and the p-value is less than 0.05. We conclude that change in prime has no unit root.

The table below shows ADF results for the undisclosed bank.

Table 6: Augmented Dickey-Fuller Unit Root Results: Undisclosed Bank

Variables	30 day delinquent	Δ(30 day delinquent)	60 day delinquent	Δ(60 day delinquent)	90 day delinquent	Δ(90 day delinquent)	Absa House Price Index	Consumer Price Index	Δ(Consumer Price Index)	Credit Growth	Debt-to-income ratio	Δ (Debt-to-income)	ΔΔ(Debt-to-income)	Unemployment	Δ (Unemployment)	Prime interest rates	Δ(Prime interest rates)
Regression coefficient	-0.0650	-1.212852	-0.0359	-0.4763	-0.0062	-0.5022	-0.0058	-0.0329	-0.5633	-0.0203	-0.0503	-0.2987	-2.7049	-0.1265	-1.0053	0.0009	-0.7278
Augmented Dickey-Fuller test statistic	-1.5863	-9.564053	-1.6393	-3.8650	-0.7524	-4.2727	-3.1808	-1.2458	-4.6388	-4.1878	-2.3523	-1.9515	-22.9689	-2.2099	-7.4556	0.0320	-5.4839
P-value	0.4831	0.0000	0.4562	0.0041	0.8246	0.0012	0.0267	0.6485	0.0004	0.0016	0.1599	0.3070	0.0001	0.2051	0.0000	0.9574	0.0000
Augmented Dickey-Fuller Critical value at 1%	-3.5482	-3.5504	-3.5504	-3.5504	-3.5504	-3.5504	-3.5600	-3.5504	-3.5504	-3.5504	-3.5550	-3.5550	-3.5550	-3.5482	-3.5504	-3.5482	-3.5504
Augmented Dickey-Fuller Critical value at 5%	-2.9126	-2.9135	-2.9135	-2.9135	-2.9135	-2.9135	-2.9177	-2.9135	-2.9135	-2.9135	-2.9155	-2.9155	-2.9155	-2.9126	-2.9135	-2.9126	-2.9135
Augmented Dickey-Fuller Critical value at 10%	-2.5940	-2.5945	-2.5945	-2.5945	-2.5945	-2.5945	-2.5967	-2.5945	-2.5945	-2.5945	-2.5956	-2.5956	-2.5956	-2.5940	-2.5945	-2.5940	-2.5945

The ADF unit root test results on all the dependent variables for the undisclosed bank reveal that variables have a unit root. This is evident in the p-values which are all greater than 0.05. After first differencing, all dependent variables proved to be stationery; the ADF statistic value tα less than critical values at 1%, 5%, and 10% significant levels and the p-values less than 0.05. The ADF test performed on the independent variables show that only the variables credit growth and Absa house price index, of the six variables proved to be stationery. Credit growth is stationery, with an ADF statistic value tα of 4.1878, and a p-value of 0.0016. However, variables CPI, unemployment, and prime became stationery upon first differencing, while debt to income ratio became stationary on second differencing.

Having tested for unit roots in variables and performed differencing where necessary, we then run the OLS regression model. The OLS regression results are discussed in the section 5.1.

5.1 Estimation results and evaluation

The regression results are given on table 7 below.

Table 7: Regression Results: Aggregated Data

Variables	*Δ(Absa House Price Index)*	*Consumer Price Index*	*Credit Growth*	*Δ (Debt-to-income)*	*Δ (Unemployment)*	*Δ(Prime interest rates)*
Regression coefficient	-2.5783	4.8492	-2.9931	1.3089	-0.4762	-0.3178
Standard Error	1.2311	0.2847	0.7173	1.1625	1.1882	0.2273
T-Statistic	-2.0943	17.0324	-4.1729	1.1260	-0.4008	-1.3981
P-Value	0.0492	0.0000	0.0005	0.2735	0.6928	0.1774
R^2	0.9432					
Adjusted R^2	0.9262					

The estimated regression model is as follows:

$$D_t = -3.12 + 1.31\Delta\, DtoIncome - 2.99Credit + 4.85CPI - 2.58\Delta ABSAHP_{t-8} - 0.32\Delta Prime_{t-3}\ 0.48\Delta UNEMP_{t-2} + e_t \quad (19)$$

The analysis of the results focuses on identifying macroeconomic factors that explain default ratios rates for residential loans. R^2 exceeds 0.94, indicating that about 94 percent of the movements in the default ratios can be explained by the model. Credit growth, CPI, and Absa house price index are the only variables that significantly explain default rates and exhibit the expected direction. The variables prime interest rates, debt to income ratio, and unemployment were not significant; debt to income exhibited the expected direction of influence while prime and unemployment showed an unexpected negative relationship.

The regression results suggest the following:

- Default ratios increase as the change in the debt to income ratio for bond holders increases. An increase in the debt income ratio suggest that debt has increased more relative to income and therefore consumers heavily indebted find it hard to meet monthly payments and therefore they default. Although the variable exhibited the expected positive influence on default rates, it's insignificant at a 5% level. The results are consistent with findings by Herzog and Earley (1970), who found mortgage payment-to-borrower income to be insignificant in explaining delinquency risks. They argued that both lenders and borrowers avoid situations where the ratios exceed critical limits unless there is assurance that payments will be made from non-income sources. However, the argument does not seem reasonable in the case of South Africa. Prior the introduction of the National Credit Act (NCA) in 2005, many South African households were heavily indebted with their expenses well exceeding their incomes. The NCA was government's measure to curb incidents of debt. Its purpose is to ensure that lenders refrain from granting consumers credit they do not afford.

- Default rates increase as the percentage of credit growth increases. These findings are consistent with expectations. Expansion of loan portfolios may lead to new loans being originated without adequate screening and risk management. When the criteria for granting loans relaxes, credit quality decreases. The introduction of the National Credit Act in 2007 coupled with the need to gain market share led to banks writing new loans aggressively and which eventually compromised asset quality. Nedbank whose strategy was to grow market share during 2007/8, continues to feel the effects of the business written in the 2007/8 vintages, with the defaulted portfolio remaining at elevated levels.
- Default ratios increase as the CPI increases. These findings are in line with expectations. As prices of consumables including transport costs and food prices increase, consumers tend to enter into arrears in the bond repayments to meet basic needs. The results suggest that, over time, consumers battle to catch-up on overdue instalments and eventually default.
- Default ratios decrease as the house prices increases. These findings are as expected. The results may suggest that house prices increases, improve the borrower's equity position thus reducing default risk because homeowners are in a better position to sell if faced with financial distress.
- Default ratios decrease as the change in prime interest rates increase. Prime interest rate exhibited an unexpected negative influence on default rates, given the predominance of flexible mortgage interest rates. South African interest rates were relatively low and stable over the sample period. The results may suggest that due to few variations over the sample period, the model could not access adequately the impact of interest rate changes on default risk.
- Default ratios decrease as change in unemployment increase. Unemployment exhibited an unexpected direction of influence on default rates; in addition, the variable is insignificant. The result could indicate that the profile of the borrowers is skilled and educated, as South African unemployment is characterised mainly with the unskilled population.

Table 8 below shows the regression results for the 30 days delinquency rates.

Table 8: Regression Results: 30 Day Delinquency Rates

Variables	*Δ(Absa House Price Index)*	*Consumer Price Index*	*Credit Growth*	*ΔΔ (Debt-to-income)*	*Δ (Unemployment)*	*Δ(Prime interest rates)*
Regression coefficient	-0.2635	0.0222	0.1310	-0.1797	-0.8961	1.0220
Standard Error	0.3735	0.0125	0.2014	0.6453	0.3908	0.2993
T-Statistic	-0.7055	1.7770	0.6503	-0.2785	-2.2927	3.4140
P-Value	0.4840	0.0820	0.5187	0.7819	0.0264	0.0013
R^2	0.3885					
Adjusted R^2	0.3105					

The regression equation for 30 day delinquent rates is as follows:

$$D_t = 0.61 - 0.18\Delta\Delta\, Dincome + 0.13Credit + 0.02\Delta CPI - 0.26ABSAHP_{t-5} + 1.02\Delta Prime_{t-3} - 0.15\Delta UNEMP_{t-3} + e_t \qquad (20)$$

The regression results for 30 days delinquent rates suggest the following:

- The R^2 reading for the regression is at a low 39 percent, indicating that about 39 percent of the variation in the log of 30 days delinquency rates is explained by the logs of prime, debt to income ratio, CPI, credit growth unemployment and Absa house price index. The low degree of explanation implies that there may be other omitted variables that influence 30 days delinquency rates including but not limited to client specific variables like loan to value, borrower occupation, borrower age, and marital status.
- The variable prime lagged three months is the only variable that exhibited the correct sign and proved to be significant at a 5 percent level of significance. The partial regression coefficient for prime suggests that a percent increase in the change of prime increases 30 day delinquency rates by 1.02 percent, ceteris paribus. According to Absa, early cycle delinquencies experienced over 2010 improved as a result of lower rates. Therefore the regression results seem reasonable.
- When the change in the change of log debt to income ratio increases by a percent, 30 days delinquent rates decrease by 0.18 percent, ceteris paribus. The regression results seem unreasonable, higher debt relative to income should increase the chances of a borrower becoming delinquent.
- The partial regression coefficient for credit growth suggests that a percent increase in log of credit growth increases 30 day delinquency rates by 0.13 percent, ceteris paribus. This positive relationship is not expected for the 30 days delinquent loans but should hold for the severely delinquent loan bucket, 90 plus days delinquent. This may signify that borrowers acquire new credit facilities like overdrafts and credit cards to reduce their mortgage debt to keep their accounts in current. Borrowers may benefit from the credit relief in short term; however, over time excessive borrowing will lead to over indebtedness and thus default.
- With a p value of 0.08, CPI proved to be insignificant at a significance level of 5 percent. However the 30 days delinquent rates increase as CPI increases, this seems reasonable as higher inflation encourage borrowers to miss mortgage payments so as to meet basic needs.
- Absa house price index is also insignificant at 5 percent level of significance. The partial regression coefficient for house prices suggest that a percent increase in house prices decreases 30 days delinquent rates by 0.26 percent, ceteris paribus. The inverse relationship seems reasonable since increases in house prices improve the borrower's equity position, which in turn reduces delinquency risk because homeowners are in a better position to refinance or sell if a trigger event occurs. The results are consistent with findings by Brent et al., (2011).

- The results show that an increase in unemployment lagged three periods' reduces the 30 day delinquency rates. The results do not seem reasonable; an unemployed borrower has no or less income to service his contractual obligations, thus increasing the probability of becoming delinquent on the loan. The regression results for the 60 days delinquency rates are presented on table 9 below.

Table 9: Regression Results: 60 Day Delinquency Rates

Variables	*Δ(Absa House Price Index)*	*Consumer Price Index*	*Credit Growth*	*ΔΔ (Debt-to-income)*	*Δ (Unemployment)*	*Δ(Prime interest rates)*
Regression coefficient	*-0.0392*	*0.0105*	*-0.0142*	*-0.4934*	*0.1166*	*0.6410*
Standard Error	*0.3103*	*0.0124*	*0.1237*	*0.6331*	*0.3680*	*0.2970*
T-Statistic	*-0.1263*	*0.8475*	*-0.1144*	*-0.7793*	*0.3168*	*2.1584*
P-Value	*0.9000*	*0.4011*	*0.9094*	*0.4398*	*0.7528*	*0.0361*
R^2	*0.2037*					
Adjusted R^2	*0.0999*					

The regression equation for 60 day delinquent rates is as follows:

$$D_t = 0.28 - 0.49\Delta\,\Delta Dincome - 0.014\Delta Credit + 0.0105\Delta CPI_{t-4} - 0.039\Delta ABSAHP_{t-5} + 0.641\Delta Prime_{t-4} + 0.117\Delta UNEMP_{t-4} + e_t \quad (21)$$

The regression results for 60 days delinquent loans suggest the following:

- The R^2 for model is 20 percent and suggests that about 20 percent of the variation in the log of 60 days delinquency rates is explained by the logs of prime, debt to income ratio, CPI, credit growth unemployment and Absa house price index. The low degree of explanation implies that there may be other omitted variables that influence 60 days delinquency rates including but not limited to client specific variables like percent of non-owner occupied loans, percent of refinance loans, percent denials and number of housing permits issued as found by Brent et al., (2011).
- The variable prime lagged four months is the only variable that exhibited the correct sign and proved to be significant at a 5 percent level of significance. The partial regression coefficient for prime suggests that a percent increase in change of prime increases 60 days delinquent rates by 0.64 percent, ceteris paribus.
- When the change of the change in the debt to income ratio increases by a percent, 60 days delinquent rates decrease by 0.49 percent, ceteris paribus. The regression results seem unreasonable, higher debt relative to income should increase the chances of a borrower becoming delinquent.
- Regression results show that 60 days delinquent rates decrease as credit growth increases. This negative relationship is expected for the 60 days delinquent loans. This may signify that borrowers acquire additional credit to pay off existing credit to benefit from the credit relief in short term; however, over time excessive borrowing will lead to over indebtedness and enter severe delinquent buckets.

- The variable CPI proved to be insignificant at a significance level of 5 percent. However the 60 days delinquent rates increase as CPI increases, this seems reasonable as higher inflation pushes borrowers to miss mortgage payments so as to meet basic needs.
- Absa house price index is also insignificant at 5 percent level of significance. The partial regression coefficient for house prices suggest that a percent increase in house prices decreases 60 days delinquent rates by 0.04 percent, ceteris paribus. The inverse relationship seems reasonable since increases in change in house prices improve the borrower's equity position, which in turn reduces delinquency risk because homeowners are in a better position to refinance or sell if a trigger event occurs. The results are consistent with findings by Brent et al., (2011).
- The results show that an increase in unemployment lagged four periods' increases the 60 day delinquency rates. The variable exhibited the expected relationship; an unemployed borrower has no or less income to service his contractual obligations, thus increasing the probability of becoming delinquent on the loan. However, the variable proved to be insignificant at a significance level of 5 percent.

The regression results for the 90 days past due loans are presented in table 10 below.

Table 10: Regression Results: 90 Day Delinquency Rates

Variables	*Δ(Absa House Price Index)*	*Δ(Consumer Price Index)*	*Credit Growth*	*ΔΔ (Debt-to-income)*	*Δ (Unemployment)*	*Δ(Prime interest rates)*
Regression coefficient	-0.5792	0.0196	0.2365	0.1262	-0.5014	0.3995
Standard Error	0.1995	0.0081	0.0745	0.4430	0.2519	0.1932
T-Statistic	-2.9028	2.4273	3.1761	0.2848	-1.9909	2.0673
P-Value	0.0057	0.0192	0.0027	0.7771	0.0525	0.0444
R^2	0.2976					
Adjusted R^2	0.2060					

The regression equation for 90 day delinquent rates is as follows:

$$D_t = 1.66 + 0.24\Delta Credit_{t-3}\, t + \ 0.02\Delta CPI_{t-5} - 0.58\Delta ABSAHP + 0.40\Delta Prime_{t-3} - 0.50\Delta UNEMP_{t-3} + e_t \qquad (22)$$

The regression results for 90 days delinquent rates suggest the following:

- The R^2 for model is 30 percent and suggests that about 30 percent of the variation in the log of 90 days delinquency rates is explained by the logs of prime, changes in the debt to income ratio, CPI, credit growth, unemployment and the Absa house price index. The low degree of explanation may mean that the model has omitted variables that influence 90 days delinquency rates including but not limited to client specific variables like borrower race and other macroeconomic variables, like number of building permits and percentage of denials.
- The variable prime lagged three months exhibited the correct sign and proved to be significant at a 5 percent level of significance. The partial regression coefficient for prime

suggests that a percent increase in change of prime increases 90 days delinquent rates by 0.40 percent, ceteris paribus.

- When the change in the change of debt to income ratio increases by a percent, 90 days delinquent rates decrease by 0.13 percent, ceteris paribus. Although, the variable is insignificant, the direction of influence seems reasonable, higher debt relative to income increase the chances of a borrower becoming delinquent. Similarly, Herzog and Earley (1970) found the mortgage payment-to-borrower income to be insignificant in explaining delinquency risks. They explained that this occurred because both lenders and borrowers watch this ratio carefully. The authors added that lenders and borrowers avoid situations where the ratios exceed critical limits unless there is assurance that payments will be made from non-income sources.
- Regression results show that 90 days delinquent rates increase as credit growth increases. This positive relationship is reasonable for the 90 days delinquent loans. This may signify that borrowers acquire additional credit to pay off existing credit to benefit from the credit relief in short term; however, over time excessive borrowing lead to over indebtedness thus borrowers enter severe delinquent loan buckets.
- The variable CPI proved to be significant at a significance level of 5 percent. The 60 days delinquent rates increase as CPI increases, this seems reasonable as higher inflation pushes borrowers to miss mortgage payments so as to meet basic needs.
- Absa house price index is also significant at 5 percent level of significance. The partial regression coefficient for house prices suggest that a percent increase in change of house prices decreases 90 days delinquent rates by 0.58 percent, ceteris paribus. The inverse relationship seems reasonable since increases in house prices improve the borrower's equity position, which in turn reduces delinquency risk because homeowners are in a better position to refinance or sell if a trigger event occurs. The results are consistent with findings by Brent et al., (2011), Herzog and Earley (1970).
- The results show that an increase in change in unemployment lagged three periods’ reduces the 90 day delinquency rates. The results do not seem reasonable; an unemployed borrower has no or less income to service his contractual obligations, thus increasing the probability of becoming delinquent on the loan.

6. CONCLUSION

Like any other firm, the fundamental objective of bank management is to maximize profits and shareholders' returns. As a result, Bank strategies are more focused on growing asset portfolios and gaining market share. However the art of striking a balance between risk and portfolio growth still remains a challenge as seen in the rising default rates between 2006 and 2010. As evident in the recent financial crises, increasing default rates affect banks profitability and the economy at large. In such a context, banks require improved methodologies to better quantify banks' vulnerabilities to different types of economic shocks. Risk managers would be interested in questions like "what would be the impact on default risk of the residential mortgage portfolio if there would be a 3 percentage points shock for example in interest rates. This information would aid them in adapting credit risk policies and practises to control and avoid losses. An example of such a credit policy would be tightening the loan-to-value ratios to prohibit additional home loan lending when interest rates hit 3 percentage points and are higher than existing level of rates.

The study revealed early delinquency rates and severe delinquency rates are affected by different macroeconomic conditions. Prime interest rates were found to the main determinants of 30 day and 60 day delinquencies for the individual bank. Such results would aid the banks in implementing loan modifications by extending the term of mortgages exposed to negative interest rate shocks. This would bring borrowers to current status and thus prevent foreclosures.

The house price index, consumer price index, prime, and credit growth were found to be the main determinants of 90 day delinquency rates for the individual bank, while the house price index, CPI, and credit growth, determine the 90 day delinquency rates for the big four banks.

7. APPENDIX **A**

Table 11: Regression Results: Risk Indexes

Regression Results: Risk Indexes						
Sample Data						
	Delinquency Risk Equations		Foreclosure Risk Equations		Straight Foreclosure Risk Equations	
Variables	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Constant	0.3026		0.0943		0.1574	
Loan-to-value (RLS)	0.1694	0.0420	0.0704	0.0532	0.0400	0.0160
Term -to-maturity (T)	-0.0003	0.0001	0.0049	0.0001	0.0012	0.0004
Loan purpose (P1)	0.4148	0.0139	0.0852	0.0190	0.0285	0.0053
Loan purpose (P2)	0.1191	0.0247	0.0484	0.0302	0.0244	0.0098
Loan purpose (P3)	0.1641	0.0133	0.0560	0.0167	0.0274	0.0053
Prescence and abscenec of junior financing (FJ)	0.1830	0.0136	0.0741	0.0221	0.0579	0.0052
Aggregated Published Data						
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Constant	0.3589		0.1198		0.1331	
Loan-to-value (RLS)	0.1824	0.0487	0.0432	0.0201	0.0473	0.1670
Term -to-maturity (T)	-0.0046	0.0001	0.0005	0.0001	0.0023	0.0008
Loan purpose (P1)	0.0513	0.0141	0.0872	0.0187	0.0293	0.0054
Loan purpose (P2)	0.1570	0.0140	0.0541	0.0231	0.0513	0.0063
Sample and Aggregated Data						
	Coefficient	t-stat	Coefficient	t-stat		
Constant	0.2972					
Loan-to-value (RLS)	0.4451	0.0812	-0.0168	0.1022		
Term -to-maturity (T)	-0.0055	0.0002	0.2916	0.0002		
Monthly payment to income ratio (RPI)	-0.1002	0.1808	0.0005	0.2167		

Source: Herzog and Earley (1970)

Table 12: Regression Results: Default, Delinquencies, and Prepayments

Regression Results												
	Age Variables Included						Age variables ommitted					
	Log of probability of Default (LPDEF)		Log of probability of Delinquency (LPDEL)		Log of probability of Prepayment (LPPRE)		Log of probability of Default (LPDEF)		Log of probability of Delinquency (LPDEL)		Log of probability of Prepayment (LPPRE)	
Dependent Variables	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Constant	-5.62	27.08	-3.06	19.43	2.43	14.52	-7.28	29.51	-5.76	31.74	-1.82	9.55
Current loan-to-value ratio (CLTV)	0.58	3.70	-1.40	12.09	-2.95	22.16	1.23	7.38	-0.39	3.33	-1.44	11.31
Current payment-to-income ratio (CPTY)	0.03	0.29	-3.74	5.44	-11.00	14.35	3.82	3.73	5.30	6.86	2.41	2.96
Rate of unemployment (UNEM)	0.10	16.94	0.05	10.04	-0.05	8.40	0.11	17.44	0.06	13.38	-0.03	5.52
Ratio of the current mortgage rate to contract rate on the mortgage (CROR)	-0.33	2.70	-0.44	4.91	-1.20	12.64	-0.40	3.14	-0.81	8.87	-1.58	17.56
Age of the mortgage at the beginning of a year(AGE)							0.40	13.24	0.55	20.01	0.81	35.27
Age of the mortgage squared (AGESQ)							-0.03	12.67	-0.04		-0.05	28.33
Dummy variable which assumes a value of 1 when a home is new, 0 otherwise (DUMNEW)	0.32	11.14	0.13	5.59	0.10	3.94	0.22	7.21	-0.10	4.06	-0.24	9.60
Dummy variable which assumes the value of 1 if the loan has an initial loan-to-value ratio greater than 80 and less than or equal to 85%, 0 otherwise (DUM85)	-0.28	2.92	-0.06	0.83	0.28	3.19	-0.36	3.83	-0.14	1.97	0.18	2.35
Dummy variable which assumes the value of 1 if the loan has an initial loan-to-value ratio greater than 85% and less than or equal to 90%, 0 otherwise (DUM90)	-1.04	20.48	-0.49	12.78	0.44	10.31	-1.15	22.70	-0.65	17.80	0.22	5.86
Dummy variable which assumes the value of 1 if the loan has an initial loan-value ratio greater than 90%, 0 otherwise (DUM95)	-0.20	3.50	-0.22	4.81	0.17	3.39	-0.30	5.24	-0.33	25.24	0.01	0.26
R^2		0.25		0.21		0.34		0.28		0.31		0.48

Source: Campbell and Dietrich (1983)

Table 13: Regression Results: 30 Day Delinquency Rates

Regression Results						
30 day delinquency rate						
	Prime loans			Subprime loans		
Variable	coefficient	t-stat	Significance level	coefficient	t-stat	Significance level
whpet	-0.0099	-1.1800		-0.0074	-0.3900	
blpct	-0.0010	-0.1800		0.0038	0.2900	
hispct	0.0015	0.1700		-0.0018	-0.0900	
asnpct	-0.0019	-0.1000		0.0024	0.0500	
ntvpct	0.0045	0.1400		0.1110	1.5100	
fempct	-0.0411	-1.0000		-0.0414	-0.4400	
credscr	-0.0066	-0.6400		0.0017	0.0700	
income	0.0000	0.1800		0.0001	2.5700	0.0500
nonoccpt	-0.0054	-1.0300		-0.0246	-2.0500	0.0500
nivst	-0.0470	-3.7800	0.0100	-0.0839	-2.9600	0.0100
spread	0.0130	1.6500		0.0252	1.4100	
pctrefi	0.0201	3.7100	0.0100	0.0552	4.4700	0.0100
lien2nd	0.0028	0.3700		0.0272	1.5500	
pctadj	0.0058	0.6600		0.0181	0.9000	
denpct	-0.0025	-0.4600		0.0032	0.2600	
unempl	0.0378	1.6000		-0.0561	-1.0400	
numpermt	0.0007	0.5600		0.0067	2.4900	0.0500
hpidx	-0.0105	-9.9800	0.0100	-0.0132	-5.5300	0.0100
probusvc	0.0012	0.1800		-0.0101	-0.6700	
R^2	0.9928			0.9801		

Source: Brent, Kelly, Lindsey-Taliefero, and Price (2011)

Table 14: Regression Results: 60 Day Delinquency Rates

Regression Results						
60 day delinquency rate						
	Prime loans			Subprime loans		
Variable	coefficient	t-stat	Significance level	coefficient	t-stat	Significance level
whpet	0.0037	0.6000		0.0104	0.7500	
blpct	0.0059	1.3800		0.0204	2.1600	
hispct	-0.0080	-1.2000		-0.0113	-0.7700	
asnpct	-0.0067	-0.4700		0.0079	0.2500	
ntvpct	-0.0191	-0.8000		-0.0113	-0.2100	
fempct	-0.0001	0.0000		-0.0205	-0.3000	
credscr	0.0014	0.1800		-0.0061	-0.3600	
income	0.0000	-2.8100	0.0100	0.0000	-0.4000	
nonoccpt	-0.0038	-0.9700		-0.0149	-1.7200	0.1000
nivst	-0.0270	-2.9600	0.0100	-0.0694	-3.4100	0.0100
spread	0.0065	1.1300		0.0017	0.1300	
pctrefi	0.0000	0.0000		0.0263	2.9500	0.0100
lien2nd	-0.0075	-1.3300		-0.0084	-0.6700	
pctadj	0.0082	1.2600		0.0132	0.9100	
denpct	0.0086	2.1500	0.0500	0.0295	3.3100	0.0100
unempl	0.0519	2.9900	0.0100	0.0855	2.2100	0.0500
numpermt	-0.0005	-0.5400		0.0038	1.9500	0.1000
hpidx	-0.0038	-4.9700	0.0100	-0.0069	-4.0100	0.0100
probusvc	0.0024	0.5000		-0.0001	-0.0100	
R^2	0.9624			0.9925		

Source: Brent, Kelly, Lindsey-Taliefero, and Price (2011)

Table 15: Regression Results: 90 Day Delinquency Rates

Regression Results						
90 day delinquency rate						
	Prime loans			Subprime loans		
Variable	coefficient	t-stat	Significance level	coefficient	t-stat	Significance level
whpet	0.0094	0.4300		0.0115	0.1700	
blpct	0.0234	1.5600		0.0408	0.9000	
hispct	-0.0386	-1.6400		-0.0282	-0.4000	
asnpct	-0.0076	-0.1500		0.2624	1.7200	0.1000
ntvpct	-0.1241	-1.4800		0.0448	0.1800	
fempct	0.0581	0.5400		-0.1519	-0.4700	
credscr	0.0013	0.0500		-0.0058	-0.0700	
income	-0.0002	-4.3600	0.0100	-0.0001	-0.7700	
nonoccpt	-0.0064	-0.4700		-0.0548	-1.3200	
nivst	-0.0521	-1.6100		-0.3008	-3.0800	0.0100
spread	0.0159	0.7800		0.0486	0.7900	
pctrefi	-0.0354	-2.5000	0.0500	0.0419	0.9800	
lien2nd	-0.0271	-1.3500		-0.0535	-0.8800	
pctadj	0.0402	1.7500	0.1000	0.0988	1.4200	
denpct	0.0329	2.3200	0.0500	0.1373	3.2100	0.0100
unempl	0.2760	4.4900	0.0100	0.5867	3.1600	0.0100
numpermt	-0.0022	-0.7100		0.0160	1.6800	0.1000
hpidx	-0.0039	-1.4100		-0.0370	-4.4800	0.0100
probusvc	0.0072	0.4100		-0.0229	-0.4400	
R^2	0.8631			0.9712		

Source: Brent, Kelly, Lindsey-Taliefero, and Price (2011)

Table 16: Regression Results: Marginal Effects for Ordered Probit

Regression Results: Marginal effects for Ordered Probit (at the means of the variables)								
	Model 2				Model 4			
Variable	Y=0	Y=1	Y=2	Y=3	Y=0	Y=1	Y=2	Y=3
Age (X1)	0.0010	0.0015	0.0007*	-0.0032	0.0006	0.0010	0.0005*	-0.0020*
Marital status (X2)	0.0533*	0.0854*	0.0458*	-0.1844**	0.0539*	0.0863*	0.0465*	-0.1867*
Job contract (X3)	-0.01490	-0.02200	-0.10200	0.04700	-0.01660	-0.02450	-0.01130	0.05240
Education (X4)	0.00070	0.00110	0.00050	-0.00230	-0.00220	-0.00330	-0.00160	0.00700
Residence place (X5)	-0.1027*	-0.1123*	-0.0322*	0.2471*	-0.10360	-0.1129*	-0.0322*	0.2488*
Household size (X6)	-0.0370*	-0.0562*	-0.0272*	0.1204*				
Monthly net income (X7)	0.0000*	0.0001*	0.0001*	-0.0002*				
Monthly net income per-capita (X7a)					0.0001*	0.0002*	0.0001*	0.0004*
# banking loans (X8)	-0.0197*	-0.0300*	-0.0145**	0.0641*	-0.0196**	-0.0299*	-0.0145**	0.0640*
Effort rate (X9)	-0.7864*	-1.1970*	-0.5793*	2.5628*	-0.8173*	-1.2435*	-0.6037*	2.6646*
Loan/real guarantee (X10)	-0.2396*	-0.3648*	-0.1765*	0.7810*	-0.1485*	-0.2260*	-0.1097**	0.4842*
Statitical Significance	* Statistical significanct at 1% level; ** Statistical significanct at 5% level; *** Statistical significanct at 10% level							

Source: Rebelo and Vaz Caldas (2010)

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