The Impact of Borrower and Loan Characteristics on Mortgage Defaults in South Africa

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

Johannesburg, 2010

ABSTRACT

In South Africa, there is currently little research available on mortgage default and the determinants of default. The purpose of this research was to evaluate and distinguish between mortgage specific factors (including borrower and loan characteristics), driving mortgage default patterns in South Africa.

This study intended to provide guidance to the South African banking industry (i.e. banking institutions), the South African Reserve Bank (policy maker and regulator), and the broader South African population in general. In addition, the results of the study can be utilised by banking institutions as inputs into their origination scorecard, policy rules and risk-based pricing models.

Due to the sensitivities around financial institution's data in South Africa, the sample used for this study was all current (on book) mortgage loans from an anonymous (single) financial institution in South Africa. Also, due to the practical availability of data, the sample period covered all current loans from said financial institution from August 2006 to December 2008, with information covering each loans default or non-default status during that time period.

Based on the review of the literature surrounding mortgage defaults, five hypotheses were formulated. Only 1 of the 5 variables was found to be a good differentiator of mortgage default in South Africa. Current Loan-To-Value (LTV) was found to be the most critical and by far the largest contributor to the model's ability to differentiate defaults. It was found that the higher the Current LTV, the more likely those borrowers would default. This finding is in line with conventional wisdom in the mortgage industry, in that loan-to-value ratios are positively correlated with mortgage default.

The Age of the mortgage (i.e. account age in months since loan origination), Instalment to Income (ITI), Borrower age (years), Borrower Income and Balance Outstanding were found to be irrelevant in contributing to the model's ability to differentiate mortgage defaults. Also, Balance (Loan) Outstanding was found to be the variable having the least impact on the model's ability to differentiate

mortgage defaults.

In summary, given that Current LTV (loan characteristic), was found to be the only suitable variable in differentiating mortgage defaults, the conclusion is that only “Loan” characteristics (i.e. Loan to value) impact on mortgage defaults in South Africa. Furthermore, it is the “equity” theory that describes mortgage defaults, and not the “ability to pay” theory of default.

DECLARATION

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

Mohamed Hoosain Khan

Signed at …………………………………………………

On the …………………………….. day of ………………………… 2010

DEDICATION

This research report is dedicated to my wife Nadia, My dad Abdurahman, my mum Zainonisa, my brother Ashraf and my sister Mishal. Thank you for all the love and support you have given me. Without you, the completion of this research and ultimately my MBA would not have been possible.

ACKNOWLEDGEMENTS

I would like to express thanks and sincere gratitude to the following:

- Firstly, the Almighty for giving me the opportunity and ability to accomplish all that I have done,

- To my mum and dad who tirelessly, provided the moral support and guidance throughout this research. Thank you for your prayers that have help guide me along this journey,

- My supervisor, Chris Muller for your assistance, thoughts, feedback and all around help throughout this research. Thank you for allowing me to spend the long, and late hours at your home working on this research, and for putting up with me,

- To my friend and mentor Shaahien. Thanks for all the guidance and moral support throughout this journey,

- To my dear wife Nadia. You are my inspiration for accomplishing all that I have thus far. This research was as much your sacrifice as it was mine and for this, I thank you,

- To the Bank, for providing me with the data for the research,

- To everyone else that provided some sort of assistance in getting this research done.

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The purpose of this research was to evaluate and distinguish between mortgage specific factors (including borrower and loan characteristics), driving mortgage default patterns in South Africa.

1.2 Context of the study

The market for mortgage loans in South Africa has grown significantly since 2001, with the big four banks competing aggressively for share of market, in what is deemed to be a lucrative sub-portfolio on a risk-adjusted basis (Pillay 2007). The growth in this market was fuelled by an environment of declining and then low interest rates during the period 2003 to 2006. As a result, average year-on-year property price growth peaked at 32.2% during 2004 (Toit 2009).

However, during mid-June 2006, the upward trend of the interest rate cycle commenced. The 500 basis points increase in the prime lending (interest) rate between mid-2006 and mid-2008 placed strain on the South African economy in general, and mortgage holders in particular. Also, 2008 was the first year since 1999 that house prices dropped in real terms on an annual basis (Toit 2009).

As a result of the increase in interest rates; high food and fuel prices; and overall downturn in the economy (especially during 2008), banks in South Africa have experienced an increase in the size of their mortgage default portfolios. It is estimated that households currently owe banks approximately R1.2 trillion, of which the greater part constitutes mortgage advances (Botha 2009). Therefore, accurate forecasts of mortgage defaults are important in calculating the impact of defaults on bank's mortgage portfolios and the subsequent impact on bottom line profit, as well as the impact on the housing market in general.

1.3 Problem statement

1.3.1 *Main problem*

Identify the mortgage specific factors, including borrower, and loan specific factors, driving mortgage defaults in South Africa.

1.3.2 *Sub-problems*

The first sub-problem is to identify loan specific factors, contributing to mortgage defaults.

The second sub-problem is to identify borrower specific factors, contributing to mortgage defaults.

1.4 Significance of the study

In South Africa, there is currently little research available on mortgage default and the determinants of default. However, research conducted by Pillay (2007), found that the loan-to-value ratio was a good and significant predictor of default, thereby finding that the "equity" theory of default held true.

The data used in the research conducted by Pillay (2007) however, covered an environment of low interest rates in South Africa, where borrower characteristics i.e. borrower age, income etc. were not considered significant in determining mortgage default rates. This research aims to fill that gap, and evaluate mortgage default patterns covering both the "equity" theory (i.e. loan-to-value ratios and therefore loan specific factors) and the "ability to pay" theory (i.e. borrower characteristics) of default.

The study will provide guidance to the South African banking industry (i.e. banking institutions), the South African Reserve Bank (policy maker and regulator), and the broader South African population in general. In addition, the results of the study can be utilised by banking institutions as inputs into their origination scorecard models, policy rules and risk-based pricing models.

1.5 Delimitations of the study

- The data to be used in this research are records from one major financial institution in South Africa.
- Due to the sensitivities around this information, this data has been provided confidentially to the researcher, and no mention will be made of the financial institution providing the information.
- The research will be limited to mortgage performance data from September 2006 to December 2008. This was due to the availability of data provided from the financial institution concerned.
- Only borrowers that have missed at least 3 payments i.e. greater than or equal to 90 days in arrears will be considered under the definition of default.

1.6 Definition of terms

Table 1: Definition of Terms

Term	**Meaning**
Amortisation	Paying back of a loan over a specified period of time.
(Current) Loan-to-Value (LTV)	The current balance of a mortgage loan outstanding divided by the market value of that specific property.
Equity	If the LTV (described above) is less than 100%, positive equity exists, whereas if this ratio is >100%, negative equity is said to exist.
Trigger-event defaulters	Mortgage default occurring due to an unanticipated event e.g. loss of job or income, increase in family size etc.
Age of mortgage	The number of months / years since the mortgage loan was registered.
Instalment-to-Income ratio (ITI)	The ratio of monthly mortgage payments to the monthly income of the borrower.

1.7 Assumptions

- It is assumed that the data used in the research is accurate and representative of the population of the South African residential mortgage industry.

- It is assumed that any differences in origination strategies between the various banks offering mortgage products in South Africa, covering the period under study is not significant.

- It is assumed that there is sufficient data available to conduct a significant and valid study.

- It is assumed that any conclusions that will be drawn from the research will not be biased in anyway.

2 CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

In South Africa, there is currently little research available on mortgage default, and the determinants of default. Therefore, much of the literature relating to mortgage default is overseas based and as such, this review will rely heavily on the work and empirical findings of international studies.

According to Doling, Horsewood and Neuteboom (2007), the cost of repaying a mortgage loan, together with associated homeownership costs such as repairs, insurances, and property taxes constitute a major share of household's budget. Whilst the precise terms of loans will vary between and within countries, they will generally involve the making of payments at regular intervals over an extended period of time, normally between 10 and 25 years (Doling et al. 2007).

From a South African context, the majority of mortgage loans are characterised by variable interest rates that are linked to the prime lending rate. As such, they follow a "normal" amortisation process with an interest and capital portion forming part of the monthly mortgage instalments. As a result of this structure, the monthly mortgage instalments can vary depending on the upward or downwards movement of the prime lending rate. This could result in the borrower not being able to meet their monthly mortgage payments (especially if affected by rising interest rates), and thus poses an associated risk to the lender.

According to general banking practice in South Africa (and internationally), a borrower is deemed to be in default when they have missed at least 3 mortgage payments, i.e. 90 days in arrears. In light of this definition, this research will apply this concept when referring to default, and as mentioned in section 2.2, prepayment will not be considered as part of this definition.

2.2 Mortgage default modelling

Mortgage modelling as an area of research goes back many years. According to Capone (2001) the seeds of mortgage modelling as a research field go back at least to the Great Depression. He suggests that the increase in home mortgage foreclosure during that time brought national attention in the United States, to the issue of what factors influence the tendency of loans to default.

According to Capone (2001), throughout the life of a mortgage, a borrower holds both call and put options on a mortgage. He suggests that the mortgage can either be repurchased from the lender at par via payment in full (prepayment), completing a "call" option or it can be sold to the lender for the value of the underlying property via default, completing a "put" option. For the purpose of this research, only the "put" option of default will be considered, whereas factors leading to borrowers exercising the prepayment i.e. "call" option will be ignored and can be considered as an area for further research.

It should be noted however that the "put" option of default has differing ramifications in countries / regions where "non-recourse" lending versus "recourse" lending is observed. The difference between the two is than in the former, lending institutions do not have (legal) recourse to recover from the borrower any loan shortfall that resulted in exercising the "put" option. From a South African context however, mortgage lenders do have this right of recourse and will normally attempt to recover any shortfalls.

Given these differences, it is not surprising that the body of literature on mortgage default has divergent views around the causes of mortgage default. According to Whitley, Windram and Cox (2004), much of the literature uses one of two alternative theories of default to determine the likelihood of going into default on a mortgage i.e. the "equity" theory and the "ability to pay" theory. However, in many instances, researchers have examined the inter-relationship between the two and not viewed the above theories as mutually exclusive.

Delgadillo and Green Pimentel (2007) contend that previous studies have shown that home equity and loan-to-value (LTV) ratios have been reported to have a primary influence on the decision to default, whereas trigger events that limit a household's ability to pay were found to be important in determining the risk of default. In other words, borrowers' decision to default was based on whether equity existed in the property, only when a trigger event hampered their ability to service the mortgage debt.

This view is supported by Hayre, Saraf, Young and Chen (2008), who in their model of the determinants of mortgage defaults defined the following for a default to occur:

- The homeowner is unable to make the monthly payments typically due to the occurrence of some trigger event that impairs his ability to do so, and

- There is a lack of equity in the home, so that the homeowner is unable to refinance or sell the home without a loss.

Similarly, Van Order and Zorn (2000) mention that default on a mortgage can be viewed as the combination of some trigger event, which makes it no longer optimal for the owner of the house to continue owning, and negative equity, which makes it optimal to default rather than sell. According to Von Furstenberg (1969), there are two microeconomic elements of risk that can clearly be distinguished in home financing. First, there is the risk attached to the asset itself, which is influenced by anticipated price developments in the local real estate market, age and design of house, income and place of residence stability of the mortgagor.

Secondly, Von Furstenberg (1969) also assert that apart from the above "fundamental" factors, the financing terms of the mortgage or the expected strength of the equity shield, determine both how likely and how costly default will be. The contention of Von Furstenberg however, relates more to property and loan characteristics, but largely ignores the influence of borrower characteristics on the propensity to default.

In contrast, Vandell and Thibodeau (1985), in formulation of their theoretical model, recognises that a number of loan and non-loan related effects beyond equity in the unit could influence the default decision. These include:

- Payment levels relative to income,
- Current and expected neighbourhood and housing market conditions,
- Economic conditions,
- Wealth,
- Borrower characteristics as a proxy for variability in income or 'crisis' events, and
- Transaction costs incurred upon default.

According to Weagley (1987), lenders lend money based on characteristics of the borrower at the time of purchase. He also suggests that past research on mortgage default invariably used mortgage, borrower and property characteristics, obtained at the time of purchase, to model behaviour occurring months later. Weagley (1987) further contends that it was clear that the characteristics of the home, borrower and mortgage at the time of the decision to default may more accurately reflect factors associated with the default of the loan.

Given the somewhat divergent and in many instances convergent views of the determinants of mortgage default, the next section of this literature review will pay more attention to the two issues detailed above, i.e. the "equity" theory and the "ability to pay" theory of default .

2.3 "Equity" theory of default

According to Cooperstein, Redburn and Meyers (1991), a homeowners current equity in the home is the primary determinant of mortgage default. They also suggest that homeowners control the put option to "sell" their houses back to the lender at a price equal to the book value of the mortgage, while the lender is forced to accept the house in lieu of payment.

In the same vein, Whitley et al (2004) suggest that the equity theory of default holds that, when households default, they choose to do so voluntarily after a rational analysis of all future costs and benefits associated with continuing or not continuing to meet the contractual obligations of the mortgage. This view suggests that it is not a trigger event that causes "rational" borrowers to default; rather it is based more on a cost benefit analysis of continuing or discontinuing mortgage payments into the future. Without this trigger event, one can assume that the basis for evaluating this decision is based on the equity in the property. Kofner (2007) contend that under the "equity" theory the current loan to value (LTV), which measures the equity position of the borrower is considered to be the most important factor in default decisions.

Similarly, Harrison, Noordewier and Yavas (2004) suggest that conventional wisdom in the mortgage industry holds that loan-to-value (LTV) ratios are positively correlated with mortgage default. They contend further that mortgage underwriters and academicians have conventionally subscribed to the view that LTV ratios positively influence default rates. In support of this argument they mention that the greater the financial leverage (i.e. the higher the LTV ratio), the greater the debt service requirement and hence the higher the probability the borrower will ultimately encounter financial distress. They do concede however, that not all empirical studies of mortgage loan performance support this view.

This view is supported by Mints (2006) who found in a study conducted by Freddie Mac, that borrowers of loans with LTV of 95-99% were 5 times more likely to default than borrowers having loans of LTV's below 80%. Similarly, Pillay (2007) found that LTV ratios are a good and significant predictor of default in relation to other factors that impact on borrowers decision to default. Also, a back-test of the model developed by Pillay (2007) which compared expected defaults to actual defaults indicated that over a five year period, the expected defaults were a close approximation to the actual defaults.

In the same vein, von Furstenberg and Green (1974) mention that the original LTV ratio is an important risk characteristic, as it defines the strength of the equity shield protecting the mortgage from default in its initial years. They suggest further that the larger the initial down payment percentage, the greater and more unusual any decline in real estate prices can be and still not create an incentive to default. They conclude by mentioning that rational homeowners who have to move will contemplate default only if they expect their equity in their home, after sales commission, to be negative.

Similarly, Delgadillo and Green Pimentel (2007) suggest that the equity or put option holds that borrowers with enough equity in the property will never find themselves in default even if they lack the income to sustain mortgage payments. They claim that the borrower will sell the home off and redeem any remaining equity whereas if there is insufficient equity and even if borrowers can make the mortgage payment, default may still occur. Also, if the borrower expects that the lack of income is a temporary event and if equity exists in the property, they may also take the option of re-financing the loan to mitigate the temporary loss of income.

This view is supported by Hakim and Haddad (1999) who state that a homeowner would avoid exercising the default option by borrowing against the equity already accumulated, which presumes that property prices have risen since the time of purchase. In the same vein, they indicate that in a declining price environment however, equity is diluted and a homeowner may find it advantageous to pull out of the mortgage contract by defaulting.

Vandell and Thibodeau (1985) concluded in their “estimation of mortgage default using disaggregate loan history data” model that default risk is very dependent on the expected loan to value ratio. However, they also make mention of the fact that several non-equity factors overshadow the equity effect on default and help explain why some households with zero or negative equity may not default, whilst others with positive equity may.

On the basis of the literature review in section 2.3 and using the LTV ratio as a measure / proxy for equity in the property, the following hypothesis was formulated:

The current LTV ratio is a good predictor of mortgage default

2.4 Non-loan related characteristics

Capozza, Kazarian and Thomson (1997) found that similar to other empirical studies on default, LTV is an important determinant of default. They also found however, that the importance of LTV can be overstated if other relevant variables are excluded from the empirical specification. Capozza et al.(1997) mentioned that the full nature of the interaction between LTV and other determinants of default need to be explored in greater depth, with a particular reference to the role of borrower and property characteristics.

Similarly, Vandell and Thibodeau (1985) simulations showed that non-equity effects matter a great deal (in modelling mortgage default), and that the equity-effect per se is dwarfed by various non-loan related effects. In alignment with this view (and the view of others), the next section of this research will focus on borrower characteristics as a proxy for the “ability to pay” theory of default.

2.5 “Ability to pay” theory of default

Doling et al.(2007) state that critical to the viability of the system of house purchase as a whole, is the certainty that those borrowing are able to maintain the agreed repayment schedule. They further contend that during the repayment period however, the household may experience financial hardship in repaying the loan, either through a long-term reduction in income, or due to unanticipated and / or large increases in expenditure.

This long term reduction in income could be in the form of job loss, or a systemic contraction in an industry where borrowers derive their income (as evidenced by the state of the motor industry during 2008 in South Africa and worldwide). From an increase in expenditure perspective, this could be due to a number of factors i.e. rise in interest rates that mortgage loans are linked to, increase in family size etc.

Delgadillo and Green Pimentel (2007) also subscribe to the “ability-to-pay” theory which refers to borrowers defaulting because they are unable to meet their monthly mortgage payment, due to unexpected events that affect their ability to pay. Also, Whitley et al (2004) contend that the ability to pay theory of default suggests that individuals default involuntarily when they are unable to meet current payments.

According to Yang, Buist and Megbolugbe (1998), if the ability to pay problem arises and the property value (net of transaction costs) is greater than the unpaid balance of the mortgage, the borrower engages in a pre-foreclosure sale of the property. Otherwise, the ability to pay problem and a decline in property value below the unpaid mortgage value causes a default, mention Yang et al.(1998). Here, the combination of the “equity” theory and “ability to pay” theory results in default occurring, and not just the occurrence of a single event.

Harrison et al. (2004) propose that the correlation between LTV ratios and default risk is contingent upon the default cost to the borrower. Their view is that risky borrowers are defined as having lower default costs and are more likely to exercise the default option. In analysing an alternate source of default, Harrison et al. (2004) propose that default is triggered by a sufficient decline in the borrower’s future income and risky borrowers are defined as those with a high probability of a decline in future income.

Harrison et al. (2004) further suggest that the damage to the borrower’s credit rating can be used as a proxy of the default cost. This credit rating can be narrowed down to a credit score as a summary of borrower’s credit ratings. They contend that the most common credit score used throughout the residential mortgage underwriting industry is the FICO score, developed by Fair, Isaac and Company.

FICO scores are used by mortgage providers (and other loan providers) to predict the likelihood (at loan origination) that a borrower will default sometime in the future. Harrison et al. (2004) propose that borrowers characterised by marginal FICO scores (i.e. questionable borrowers requiring greatest underwriting review) are thus likely to suffer the most from any incremental or additional damage to their credit reputation.

After defining this borrower cost, Harrison et al. (2004) indicated the need to construct borrower risk profiles. The approach they took was to define risky borrowers as those with a higher probability of future income (or asset) decline. Harrison et al. (2004) concluded that self-employed borrowers and those with higher total debt ratios were expected to exhibit higher default probabilities.

As discussed by Ambrose and Capone (1998), allowing one's property to go to foreclosure is a two-step process. First, the borrower decides to technically default on the mortgage contract by missing a scheduled payment. They suggest that this can result from a decision by the borrower to exercise the implicit put option or from a decision to use mortgage delinquency to finance other expenditures. Foreclosure is thus the second part of the default process and occurs when the borrower is either unable to take action to avoid foreclosure or intentionally allows foreclosure to occur , mention Ambrose and Capone (1998).

They further suggest that it is important to understand the distinction between borrowers with differing default motivation, as they influence default outcomes. Ambrose and Capone (1998) suggest that ruthless defaulters optimise their behaviour by allowing foreclosure to occur, whereas borrowers in the trigger-event cohort may only go to foreclosure for reasons beyond their control. The distinction from this contention is that ruthless defaulters allow foreclosure to occur due to negative equity in the property whereas trigger-event borrowers simply don't have the income to continue the mortgage payments.

Burrows (1998) in their study of the social distribution of mortgage indebtedness concentrated on the characteristics of the head of each household as a measure of the overall household status. Burrows (1998) also mentions however, that valid sociological literature exists which critiques this procedure, and demonstrates the efficacy of the characteristics of other household members, especially female partners, on the overall socio-economic status of the household.

However, due to the problems of conceptualisation, measurement, data availability and statistical interpretation, Burrows (1998) however concludes that the results of the analysis were robust and add significantly to the knowledge of social distribution of mortgage indebtedness. In reference to past studies, Liu and Lee (1997) mention that mortgage loan defaults were believed to have a significant relationship with the characteristics of both mortgages and borrowers at the time of loan origination.

Importantly, Ambrose and Capone (1998) expected trigger-event defaulters to reveal themselves through the interaction of default outcomes and personal characteristics. As an example, they suggest that first-time buyers tend to be younger families having fewer saving and less well-established credit histories, thus making them riskier than older borrowers with well-established credit histories and greater savings / assets.

According to Burrows (1998), it is highly unlikely that the risk of being in mortgage arrears will be evenly distributed across households. It is much more likely that the risk of being in arrears will be associated with a complex range of factors, and the aim of his research was to disentangle those factors, and to estimate what relative importance should be attached to each.

In alignment with the above, the next section of this literature review will focus on personal borrower characteristics in order to obtain a view on those characteristics that could potentially describe defaulting borrowers in the "ability-to-pay" cohort.

2.5.1 *Age of Mortgage*

According to von Furstenberg and Green (1974) it is likely that the longer a family has resided at a given address and the longer it has met its payments on schedule, the greater the probability that the mortgage will not become delinquent in subsequent years. They further suggest that this theory holds for two reasons:

- The family would have had time to rebuild its liquid assets since the time the home was purchased, and
- It has revealed a pattern of stability, of neighbourhood attachment, and of financial responsibility that identifies it as a superior credit risk compared to more recent homebuyers.

According to von Furstenberg and Green (1974), since few families purchase homes in bad faith or planning only a brief stay, it is expected therefore that the delinquency rate will rise rapidly for the first one or two years and then decline gradually as the seasoning of the mortgage progresses. Also, the results of a study conducted by Delgadillo and Green Pimentel (2007) concluded that 75% of people that defaulted, were homeowners for less than 5 years.

In contrast though, the results of Vandell and Thibodeau (1985) mortgage arrears estimation model indicated that the age of the mortgage was insignificant in predicting mortgage arrears. They contend that dummy variables representing time since origination were inserted in their linear probability model, and were found to be insignificant.

According to Hayre et al.(2008), traditionally mortgage default rates have followed a pattern of being low initially, then increasing until they reach a plateau after a few years, and then beginning to decline once the loans have aged. They further contend that this pattern was captured by the Standard Default Assumption (SDA) curve which indicates that defaults increase linearly until month 30, remain stable until month 60, and then starts declining.

In contrast however, Hakim and Haddad (1999) using a log-normal, accelerated failure-time model, similar to the proportional hazard methodology commonly used, found that the default risk is highest when the mortgage age is between 45 and 78 months old. The explanation for the results of Hayre et al. (2008) is that this seasoning pattern results from traditional underwriting practices, where the borrower (traditionally) has to make a down payment, so that he has equity in the property, and he also has to satisfy the lender of his ability to make the monthly mortgage payments. This implies that there is unlikely to be default soon after the mortgage is taken out.

Hayre et al. (2008) further contend that the danger period is when loans are moderately seasoned, when a downturn in the housing market and an adverse personal event for the mortgagor could lead to the loan becoming delinquent. Also, after a few years, according to Hayre et al. (2008), it is likely that home prices would have increased (on average), thus increasing the borrowers equity stake and his financial situation is stable since he has been making regular payments for many years

On the basis of the literature review in section 2.4.1 the following hypothesis was formulated:

The Age of the mortgage (in months since loan origination) is a good differentiator of mortgage default

2.5.2 *Age of Borrower*

According to Epley and Liano (1999), empirical studies on residential mortgage lending activity relative to borrower age are almost nonexistent. This is due to the fact that reliable lender data that contain sufficient detail on the mortgage terms, including borrower age, are virtually nonexistent. They further contend that every loan officer is interested in the borrower characteristics of its customers to effectively package and market future mortgages.

Burrows (1998) in their study on the social distribution of mortgage arrears found that those aged below 45 (head of household) are more likely to be in default, whilst those aged over 55 are less likely to be in default. The analysis further concluded that only those in the youngest age group i.e. 18 to 24 significantly differed.

Burrows (1998) concluded that in relation to age, after all influences of other variables are considered, households with heads of households who are young adults (18 to 24) are significantly more likely to be in arrears than households with older heads of households. The results of a study conducted by Delgadillo and Green Pimentel (2007) indicated that the median age of mortgage default clientele was 36 years old. The study also concluded that primary reason for default was a reduction in income or job loss.

In contrast however, in a study conducted by Hakim and Haddad (1999), borrower's age in relation to mortgage default varied by region and was largely inconclusive. Liu and Lee (1997) empirical results found that the "young-buyer" cluster in their cluster analysis ranked as the highest likelihood of default, whilst the “owner-occupied” cluster represented the lowest likelihood of default.

On the basis of the literature review in section 2.4.3 the following hypothesis was formulated:

Borrower age (in years) is a good differentiator of mortgage default

2.5.3 *Instalment (Payment)-to-Income ratio (ITI)*

The instalment to income ratio is the ratio of monthly mortgage instalments to the monthly income of the borrower. According to Doling et al.(2007), given the common pattern in advanced economies for average housing costs to be high relative to average household income, it can be expected that for many individual households, housing cost-to-income will be high and expenditure on housing takes by far, the highest proportion of households income. According to Hayre et al.(2008), the higher the ITI ratio, the greater the proportion of the borrowers income that goes towards making mortgage payments, and hence the greater the strain a trigger event puts on the borrower’s ability to continue making these payments.

Webb (1982) formulates a potential delinquency model which alternatively defines a potential delinquent loan as a loan whose instalment to income ratio increases. He suggests that the benefit of this model lies in the fact that it can be applied without the need for experience data and allows for a convenient categorisation of the determinations of potential default i.e. borrower characteristics (which will determine changes in income) and mortgage terms (which will determine changes in payment).

The results of research conducted by Burrows (1998) concluded that households (mortgage) instalment to income ratios, was highly suggestive of a strong association between high multiples and increasing odds of being in default. In alignment with this view, Kofner (2007) mention that under the “ability-to-pay” model, the instalment-to-income ratio which captures the repayment capability of the borrower, plays a critical role in accounting for defaults.

In contrast however, Liu and Lee (1997) in their factor analysis found that no statistical significance existed in terms of risk classification for their “instalment-to-income” factor. They explained that the rationale for this was that the ITI ratio was already tightly controlled by financial institutions, and this restriction in range of this variable may have obscured its relevance to default risk.

In the same vein, Vandell and Thibodeau (1985) found that the payment burden effect of mortgages was found to have a negative relationship to default, likely due to stricter appraisal / underwriting standards which permitted high payment-to-income ratios only to those borrowers with ample additional resources to overcome default.

However, in a study conducted by Epley and Liano (1999), they found that in the long-run, instalment to income ratio especially for first time buyers were consistent with the existing literature and affect mortgage defaults positively. They did concede though that this ratio did not have an effect on defaults in the short run. The problem with “reduced” / “no” documentation loans mentioned earlier, is that uncertainty about the borrower’s true income relates to uncertainty about the payment-to-income ratio, thus making information about the borrower’s ability to handle mortgage payments more uncertain.

On the basis of the literature review in section 2.4.4 the following hypothesis was formulated:

Borrower Instalment-to-income ratio is a good differentiator of mortgage default

2.5.4 ***Borrower Income***

According to Weagley (1987), previous studies have concluded that if borrower incomes do not increase as fast as interest rates, a significant increase in the probability of default would follow in the early years of a mortgage. Doling et al.(2007) also conclude that a form of risk does exist, where individuals, in order to purchase their homes, take out loans to be repaid out of expected (future) flows of income.

Doling et al.(2007) concluded that even if anticipated future income flows remain as expected, unanticipated increased in housing costs and / or non housing costs – such as healthcare or additional children- may squeeze households budgets. Conversely they suggest that there is always the possibility that income flows may be lower than expected, for example as a result of unemployment, or loss of overtime earnings etc. Both expenditure increases and income reductions may, then, affect household's ability to meet loan repayments, say Doling et al.(2007).

They further contend that large homeownership sectors will incorporate households with a wide range of incomes, and it is those at the bottom end of the range who are most likely to experience financial difficulties. In contrast, Van Order and Zorn (2000) found that highest income borrowers (those at 200% or more of median income) are more likely to default than median-income borrowers (those at 81% to 120% of median) and about as likely as low-income borrowers (less than 60% of median).

According to a model developed by Yang et al. (1998), a default is realised only when house price decline is accompanied by declines in household income. They contend further that if declines in income reach the point at which mortgage expenses consumes too much of the household budget, the borrower must consider default (or prepayment) to reduce housing expenses.

Ford and Wilcox (1998) mention that as a consequence of the form of finance, sustainable home ownership requires secure, continuous employment and income. Also, the costs of credit are typically both variable and unpredictable over the lifetime of a mortgage and thus incomes must be able to accommodate upward fluctuations in interest rates (Ford and Wilcox 1998). Further, they mention that borrowers also have personal responsibility for property maintenance and insurance which set certain income requirements. Vandell and Thibodeau (1985) found however, that although the level of income does not seem to be important in terms of predicting default, the source of income does matter.

Ford and Wilcox (1998) identified some of the ways in which the interrelationship between the housing, labour and welfare markets are changing, and challenging the sustainability of home ownership. Doling et al.(2007) in their study corroborated the importance of the relationship between the housing markets and the labour markets. Their analysis supported the proposition that the sustainability of home ownership is founded on the ability of national economies to sustain households in full-time employment with relatively predictable incomes.

On the basis of the literature review in section 2.4.5 the following hypothesis was formulated:

Borrower Income is a good differentiator of mortgage default

2.6 Conclusion of Literature Review

In South Africa, there is currently little research available on mortgage default and the determinants of default. Therefore, much of the literature relating to mortgage default is overseas based. According to general banking practice in South Africa (and overseas), a borrower is deemed to be in default when they have missed at least 3 mortgage payments, i.e. 90 days in arrears.

Much of the literature on mortgage default uses one of two alternative theories to determine the likelihood of going into arrears on a mortgage i.e. the “equity” theory and the “ability to pay” theory. However, in many instances, researchers have examined the interrelationship between the two, and not viewed the above theories as mutually exclusive.

Typically, default on a mortgage can be viewed as the combination of some trigger event, which makes it no longer optimal for the owner of the house to continue owning, and negative equity, which makes it optimal to default rather than sell. The literature on the topic indicates a number of loans and non-loan related effects beyond equity in the unit could influence the default decision. These include:

- Payment levels relative to income,
- Current and expected neighbourhood and housing market conditions,
- Economic conditions,
- Wealth,
- Borrower characteristics as a proxy for variability in income or ‘crisis’ events, and
- Transaction costs incurred upon default.

From the “equity” theory of default perspective, a homeowner’s current equity in the home is the primary determinant of mortgage default. This view suggests that it is not a trigger event that causes “rational” borrowers to default; rather it is based more on a cost benefit analysis of continuing or discontinuing mortgage payments into the future. Under the “equity” theory the current loan to value (LTV), which measures the equity position of the borrower, is considered to be the most important factor in default decisions. However, it was noted that the full nature of the interaction between LTV and other determinants of default need to be explored in greater depth, with a particular reference to the role of borrower and property characteristics.

The “ability-to-pay” theory of default refers to borrowers defaulting because they are unable to meet their monthly mortgage payment, due to unexpected events that affect their ability to pay. It is important to understand the distinction between borrowers with differing default motivation, as they influence default outcomes. Ruthless defaulters optimise their behaviour by allowing foreclosure to occur, whereas borrowers in the trigger-event cohort may only go to foreclosure for reasons beyond their control

Importantly, it is expected that trigger-event defaulters reveal themselves through the interaction of default outcomes and personal characteristics. Also, mortgage loan defaults were believed to have a significant relationship with the characteristics of both mortgages and borrowers at the time of loan origination.

Research has shown that is likely that the longer a family has resided at a given address and the longer it has met its payments on schedule, the greater the probability that the mortgage will not become delinquent in subsequent years. This theory holds for two reasons:

- The family would have had time to rebuild its liquid assets since the time the home was purchased, and

- It has revealed a pattern of stability, of neighbourhood attachment, and of financial responsibility that identifies it as a superior credit risk compared to more recent homebuyers.

Empirical studies on residential mortgage lending activity relative to borrower age are almost nonexistent. This is due to the fact that reliable lender data that contain sufficient detail on the mortgage terms, including borrower age, are virtually nonexistent. In studies concluded however, with regards to borrower age, it was found, after all influences of other variables were considered, households with heads of households who are young adults (18 to 24) are significantly more likely to be in arrears than households with older heads of households. Other empirical studies however found that the relationship between borrower age and default was largely inconclusive.

The instalment to income ratio (ITI) is the ratio of monthly mortgage payments / debt obligations to the monthly income of the borrower. The higher the ITI ratio, the greater the proportion of the borrowers income that goes towards making mortgage payments, and hence the greater the strain a trigger event puts on the borrower's ability to continue making these payments. Under the "ability-to-pay" model, the instalment-to-income ratio which captures the repayment capability of the borrower plays a critical role in accounting for defaults.

Previous studies have concluded that if borrower incomes do not increase as fast as interest rates, a significant increase in the probability of default would follow in the early years of a mortgage. Even if anticipated future income flows remain as expected, unanticipated increased in housing costs and / or non housing costs – such as healthcare or additional children- may squeeze household’s budgets. If declines in income reach the point at which mortgage expenses consumes too much of the household budget, the borrower must consider default (or prepayment) to reduce housing expenses.

As a consequence of the form of finance, sustainable home ownership requires secure, continuous employment and income. Also, the costs of credit are typically both variable and unpredictable over the lifetime of a mortgage and thus incomes must be able to accommodate upward fluctuations in interest rates.

Based on the review of the literature around mortgage defaults, the following hypotheses were formulated:

Hypothesis 1: *The LTV ratio is a good differentiator of mortgage default*

Hypothesis 2: *The Age of the mortgage (in months since loan origination) is a good differentiator of mortgage default*

Hypothesis 3: *Borrower Age (in years) is a good differentiator of mortgage default*

Hypothesis 4: *Borrower Instalment-to-income ratio is a good differentiator of mortgage default*

Hypothesis 5: *Borrower Income is a good differentiator of mortgage default*

3 CHAPTER 3: RESEARCH METHODOLOGY

This study lent itself to a quantitative paradigm because of the requirement to estimate the relationships between property related factors (i.e. LTV), borrower characteristics (i.e. Borrower Income, Customer Age etc) and mortgage default. Given the hypotheses enumerated in section 2.6, a regression incorporated into a 'Scorecard (i.e. scoring) and Ranking' model was used to estimate the relationships mentioned above.

Although much research has been done in this field, the majority of the research is overseas based (using data from abroad), and relatively few studies have been conducted in South Africa utilising data from South African mortgage institutions. Due to the existence of the vast body of literature on mortgage default and modelling (albeit overseas based), a quantitative as opposed to a qualitative paradigm was deemed necessary.

3.1 Research methodology /paradigm

As mentioned in section 3 above, a quantitative paradigm was used for this research. A quantitative approach was suitable for this research as the aim of this research was to test a theory by specifying narrow hypotheses, and the use of post positivist claims for developing knowledge (Creswell 2008). Also, hypotheses are tested through a deductive approach and the use of quantitative data permits statistical analysis, which provides answers which have a much firmer basis than the lay person's common sense or intuition or opinion (Burns 2000). It was therefore essential that the process and results of this research had a strong quantitative foundation, to ensure applicability of results across various spectrums (policy makers, regulators, consumers and mortgage institutions).

Also, according to Remenyi, Williams, Money and Swartz (1998), for quantitative research it is usually obvious what evidence is required and this evidence may usually be collected in a tight structure. This research is appropriate for the theory as the data that was collected was clearly defined (i.e.

mortgage arrears data including borrower and property characteristics) and was collected within a tight structure (i.e. observed mortgage performance data from a leading South African financial institution).

3.2 Research Design

The researcher extracted mortgage data from the database of an anonymous South African financial institution. This data was then analysed in order to test the hypotheses identified at the end of section 2.6. This approach was appropriate for this study as the testing of hypotheses require the analysis of actual (empirical) mortgage performance data.

3.3 Population and sample

3.3.1 *Population*

The population for this research was all current (not fully amortised) residential mortgage loans in South Africa.

3.3.2 *Sample and sampling method*

Due to the sensitivities around financial institution's data in South Africa, the sample used for this study was all current (on book) mortgage loans from an anonymous (single) financial institution in South Africa. Also, due to the practical availability of data, the sample period covered all current loans from said financial institution from August 2006 to December 2008, with information covering each loans default or non-default status during that time period.

Each data point (and therefore each borrower) in the sample had the following attributes:

- Account Number,
- Property Value,

- Current LTV,
- Borrower Income,
- Borrower Age,
- Borrower Instalment-to-Income (ITI),
- Account age since loan origination (in months),
- Borrower Employment status,
- Borrower default status at a point in time.

3.4 Procedure for data collection

The data was provided (anonymously) to the researcher.

3.5 Data analysis and interpretation

The data analysis method(s) used in the research are indicated below:

- Descriptive Statistics;
- Logistic Regression
- Scorecard and Ranking model utilising a regression technique / equation

Initially, the data was analysed using descriptive statistics in order to summarise the large quantities of data, using measures that are easily understood by an observer (Burns 2000). Descriptive statistics therefore consists of graphical and numerical techniques for summarising data. Given the volume of data used in the research, descriptive statistics was (initially) an appropriate analysis method for summarising and understanding the data.

Logistic regression is frequently used by researchers as a tool for constructing models that classify observations into two or more categories (Hadjicostas 2006). Also, according to Peng, Lee and Ingersoll (2002) many research problems call for the analysis and prediction of a dichotomous outcome, which traditionally were addressed by either ordinary least squares regression (OLS) or linear discriminant function analysis. They assert further that both techniques were subsequently found to be less than ideal for handling dichotomous outcomes due to their strict statistical assumptions i.e. linearity, normality etc. Therefore, the distinction between logistic regression and a linear regression is that the dependant variable in a logistic regression model is binary or dichotomous.

The general linear (multiple) regression equation has the following form (Albright, Winston and Zappe 2006):

$$Y = B_0 + B_1X_1 + B_2X_2 + \ldots.\ B_kX_k \qquad \textbf{\textit{Equation 1}}$$

In order to test the hypotheses identified in section 2.6, initially a binary logistic regression model was used, regressing the default status of a customer (represented as either a '1' i.e. in default, or '0' i.e. not in default) against the property and borrower characteristics (independent variables), identified in the hypotheses. Although the logistic regression function was used at the outset, the researcher could not get appropriate results, either by maximum likelihood method, nor by Excel Solver using 'true' positives divided by the full pool of defaults expected. The use of the logistic regression technique was terminated at this point.

$$\textbf{\textit{Borrower Score}} = B_0 + B_1\text{Current\_LTV} + B_2\text{Account\_Age} + B_3\text{Borrower\_Age} + B_4\text{ITI} + B_5\text{Borrower\_Income}\ldots.\ B_kX_k \qquad \textbf{\textit{Equation 2}}$$

Using the general regression function above (equation 2), an in-sample Scorecard and Ranking procedure was employed to determine the appropriate co-efficient for the property and borrower related variables / characteristics. This technique assigned a 'score' to each customer. The score was then ranked from highest to lowest (i.e. in descending order), with those customers with the highest score being most likely to default.

Microsoft Excel Solver was then used to optimise these results by 'floating' the defaulted loans to the top of the complete list, by changing the co-efficient of the input variables.

The objective function used in the Solver routine named "Model_Success", called for the minimisation of the following equation:

Area / Number of Defaults / Size of Sample **_Equation 3_**

where,

Area = Previous Area + (Rank * Default Status) **_Equation 4_**

As can be seen in *Equation 4*, the value for "Area" equals the cumulative sum of the customer ranking multiplied by the default status. It should be noted that the default status could only take on the value of "0" (not in default) or "1" (in default). Thus, given the structure of *Equation 4*, "Area" would increase given a default status = "1", whilst a default status ="0" would have no impact on the "Area" i.e. multiplication by zero. Thus, in order to minimise this value, customers in default would need to be higher up the ranking than those not in default. Given that the value for "Number of Defaults" and "Size of Sample" in *Equation 3* was fixed (for each month), the only way of minimising this equation was for the value of "Area" to be as low as possible. Therefore, the lower the sum of the rank of the defaults, the better the Solver routine had performed.

The Microsoft Excel Solver routine would repeatedly attempt to change the value of the co-efficient (of the variables) until *Equation 3* could not be minimised any further. At this point the Microsoft Excel Solver routine would terminate with the appropriate co-efficient.

A summary of the workings of the model are as follows:

- For a particular month i.e. December 2008, determine those accounts that were not in default the previous month, i.e. November 2008.

- Using those identified non-defaulted accounts in November 2008 (for example), determine the population of accounts that (newly) defaulted in

December 2008. This was to ensure that the model was based on new accounts into default and did not include historical and therefore 'old' defaults.

- Using Excel Solver, optimize the co-efficient of the variables to minimize the objective function (see above for description of the objective function)

- Once the objective function could not be minimised any further, the Solver procedure would terminate with the corresponding results i.e. variable's co-efficient.

Table 2: Example 1 of scoring and ranking model

Ranking	Default status	Area	Cumulative Area
1	1	1	1
2	0	0	1
3	1	3	4
4	1	4	8
5	0	0	8
.	1	0	8
.	0	0	8
.	0	0	8
9999	0	0	8
10000	1	10,000	10,008

Table 3: Example 2 of scoring and ranking model

Ranking	Default status	Area	Cumulative Area
1	1	1	1
2	0	0	1
3	1	3	4
4	1	4	8
5	0	0	8
.	1	0	8
.	0	0	8
.	0	0	8
9999	1	9,999	10,007
10000	1	10,000	20,007

Tables 2 and 3 are two examples of the mechanics of the Scoring and Ranking model. Both tables have the same variables with the only difference between them is that in Table 2, 1 default was ranked very high i.e. rank 10,000. In Table 3, two defaults were ranked high i.e. at rank 9,000 and 10,000 respectively. It is evident from the illustration in the tables above, the impact on 'Cumulative Area' (variable minimised in Equation 4) of having a default customer (status = 1) lower down in the ranking.

The data used in this research was warehoused in a Microsoft Access database. In building the Scorecard and Ranking model, inputs into the model were done via Microsoft Excel. The interface between the Excel input sheet and the Microsoft Access database i.e. the regression and scorecard ranking, was done via a Visual Basic for Applications (VBA) code (Refer to Appendix C for the code).

Furthermore, given the large volume of data that existed per month, in order to build an appropriate sample to pass through the model, a technique to group the data was deemed necessary. In order to achieve this, a method to 'Regime' certain variables was employed. As a result, 2 regimes were used in the model. Refer to section 4.8.1 and 4.8.2 for the characteristics of the 2 regimes.

3.6 Limitations of the study

Albeit that the data represents residential mortgage information from one financial institution only, the researcher deems the data representative of the entire population, due to the large market share that this financial institution holds in the residential mortgage space.

Given that the sample data represents residential mortgage performance over a period during which South Africa experienced rising and high interest rates, caution should be used when applying the results of this study to an environment of low interest rates. The research conducted by Pillay (2007) however, analysed mortgage defaults over a period of sustained, low interest rates, and this study builds on the recommendation of Pillay (2007) to examine mortgage defaults in an inflationary interest rate environment.

3.7 Validity and reliability

According to Kalof, Dan and Dietz (2008), assessment of research findings is centred around issues of validity and reliability. Reliability is concerned with consistency, and research findings are considered reliable if similar findings are revealed in repeated applications of the research (Kalof et al. 2008).

According to Kalof et al.(2008), validity is concerned with congruence between the details of the research, the evidence, and the conclusions drawn by the researcher. The primary reason for considering issues around validity and reliability is that they are the most important criteria used to evaluate research, and should indicate how well the research will be accepted by a critical audience of peers and assessors (Remenyi et al. 1998)

3.7.1 *External validity*

External validity is the ability to generalise from a study to a larger population (Kalof et al. 2008). Whilst the sample data represents residential mortgage information from one South African financial institution only, the researcher deems the data representative of the entire population due to the large market share that this financial institution holds in the residential mortgage space. Also, given the large sample data, the researcher deems it representative of the broader mortgage industry.

3.7.2 *Internal validity*

Internal validity refers to the extent to which the study is drawing appropriate conclusions from the data at hand (Kalof et al. 2008). In generating the hypotheses for this study, triangulation of various studies conducted overseas where employed, where conclusions were drawn utilising regression techniques. In order to ensure / improve internal validity, a robust Scoring and Ranking model was used to ensure that no causal inferences were drawn incorrectly from the data. Also, the results of the descriptive statistics and the Scoring and Ranking model were compared to test for similarities and / or any differences.

3.7.3 ***Reliability***

Reliability is concerned with consistency, and research findings are considered reliable if similar findings are revealed in repeated applications of the research (Kalof et al. 2008). To maximise reliability of the study, a sound Scorecard and Ranking model was used to test the hypotheses. Two regimes (instead of one) were chosen to test whether similar results would have been obtained using different regimes of the data.

4 CHAPTER 4: PRESENTATION OF RESULTS

4.1 Introduction

The purpose of this chapter is to present the results of the data analysis. The first part of this chapter introduces the descriptive statistics while the second part discusses the result of the Scoring and Ranking model.

4.2 Portfolio Analysis

4.1.1 *Mortgage Portfolio Growth*

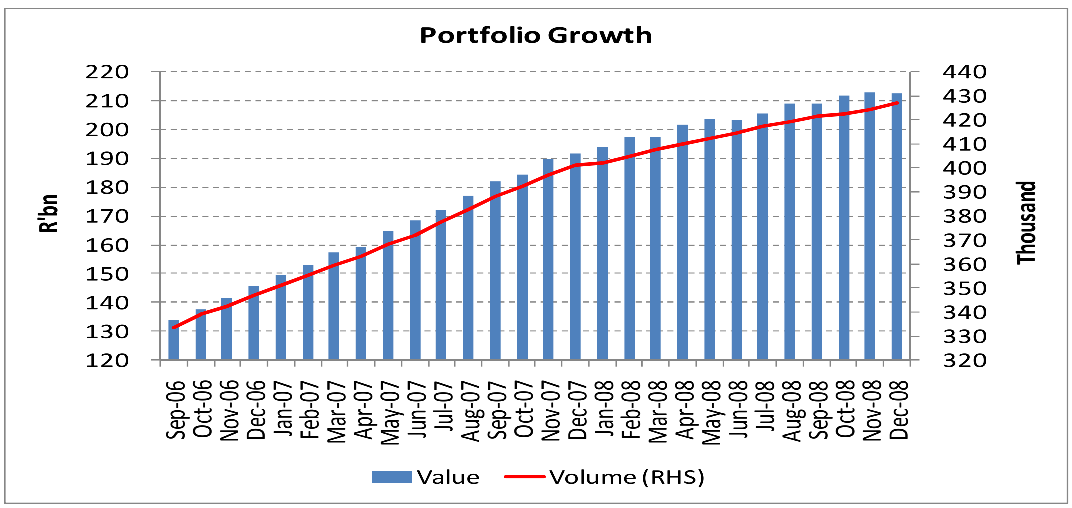


Figure 1: Mortgage Portfolio Growth

The mortgage portfolio of the financial institution concerned experienced steady growth (in absolute terms) from R133 billion in September 2006 to R212 billion in December 2008. During this period, the number of customers increased from 333,778 to 427,008 customers.

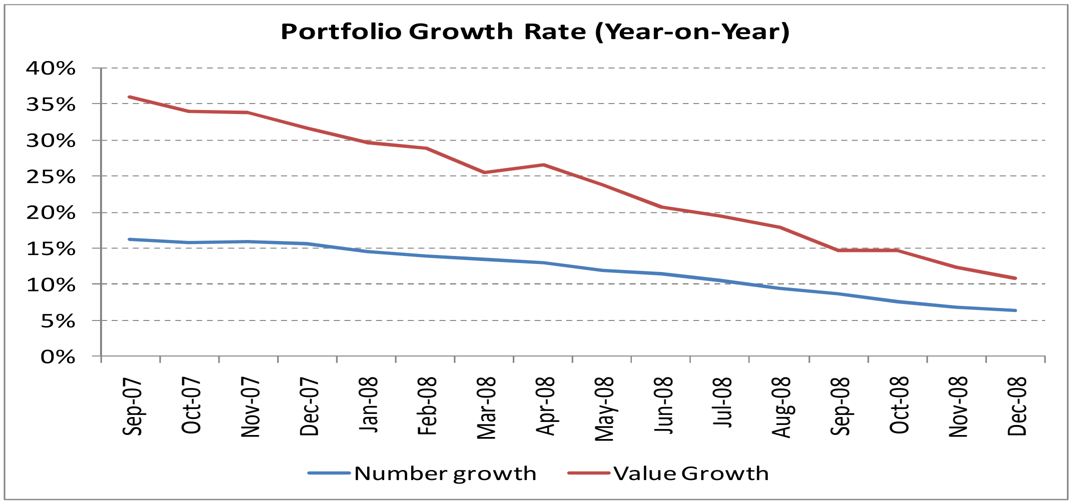


Figure 2: Year-on-Year growth rate

From a year-on-year growth perspective however, the mortgage portfolio experienced declining growth rates from a high in September 2007 (16% and 36% in number and value respectively), to a low in December 2008 (6% and 11% in number and value respectively). It should be noted that due to data constraints (data only available from September 2006 onwards); year-on-year growth rates could only be determined from September 2007 onwards.

4.1.2 *Mortgage Default Growth*

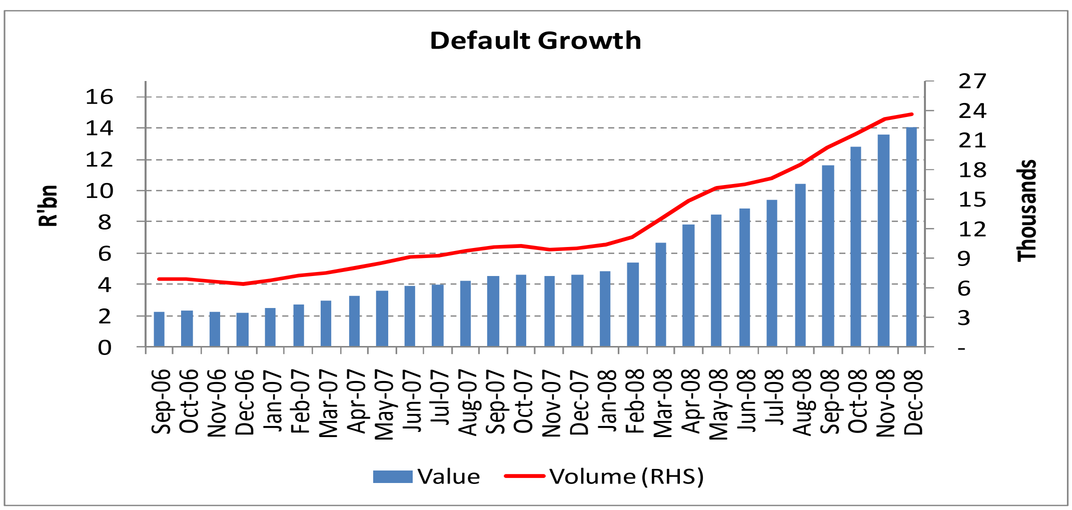


Figure 3: Mortgage Default Growth

Mortgage defaults grew from R2.2 billion in September 2006 to R14.0 billion in December 2008. In terms of number, 6,859 customers were in default in September 2006. This number grew to 23,624 customers by December 2008.

This growth in mortgage defaults was expected, given the inflationary interest rate environment in South Africa from mid 2006 onwards and the recessionary conditions experienced in late 2007 (and beyond).

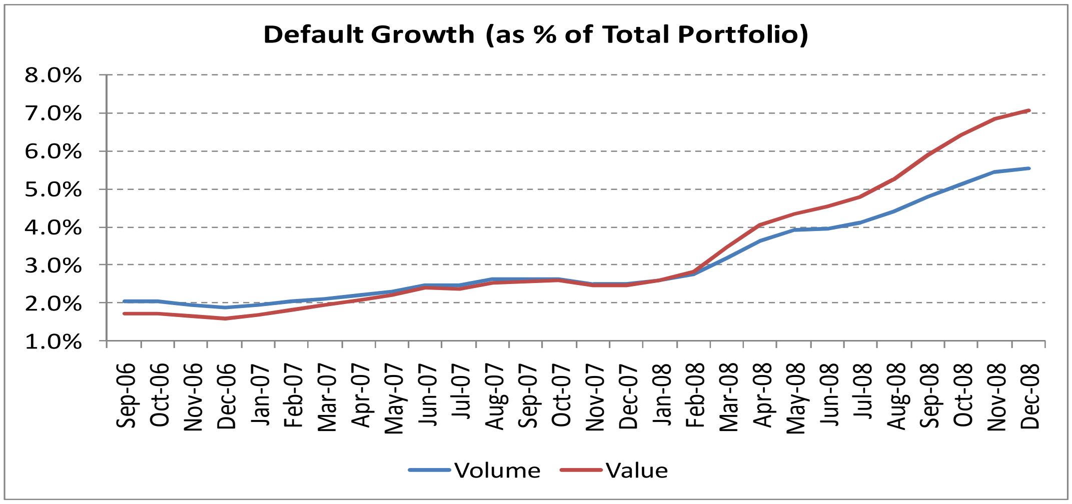


Figure 4: Default Growth as % of Total Portfolio

The figure above illustrates mortgage defaults as a percentage of the total mortgage portfolio per month (in number and by value). As at September 2006, 2.1% (number) and 1.7% (value) of the total portfolio was in default. This percentage grew to 5.5% (number) and 7.1% (value) by December 2008. According to figure 4, the number and value in default as a percentage of the total portfolio was on a similar trajectory until February 2008, after which the gap between value and number widened.

4.2 Results pertaining to Current LTV

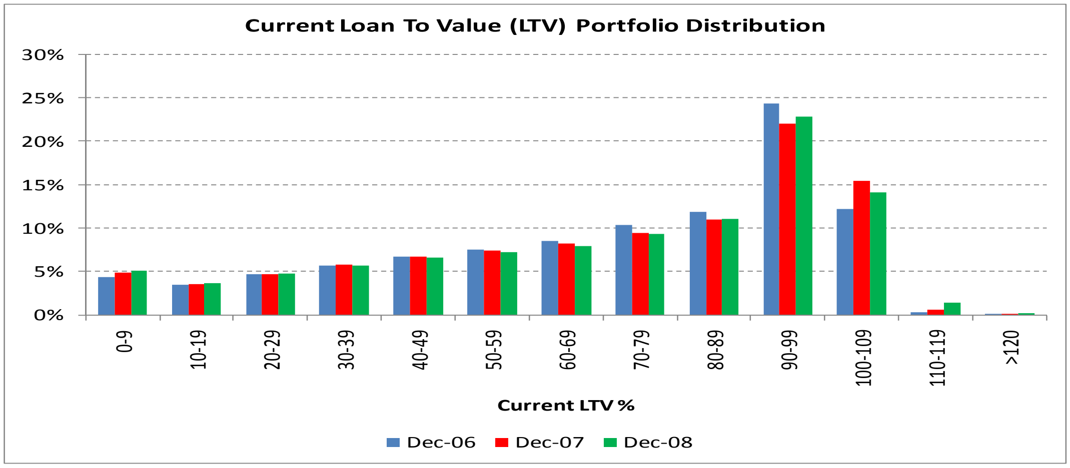


Figure 5: Current LTV Portfolio Distribution (number)

The figure above shows the Current LTV distribution of the mortgage portfolio for December 2006, 2007 and 2008 respectively. The highest proportion of the portfolio (23%) existed within the 90 - 99% category. On average, approximately 49% of the portfolio had a Current LTV of greater than or equal to (>=) 80%. Also, approximately 14% (average) of the portfolio (across the 3 months) were within the 100% - 109% category. (Refer to Appendix C for September 2006 to December 2008 graphs)

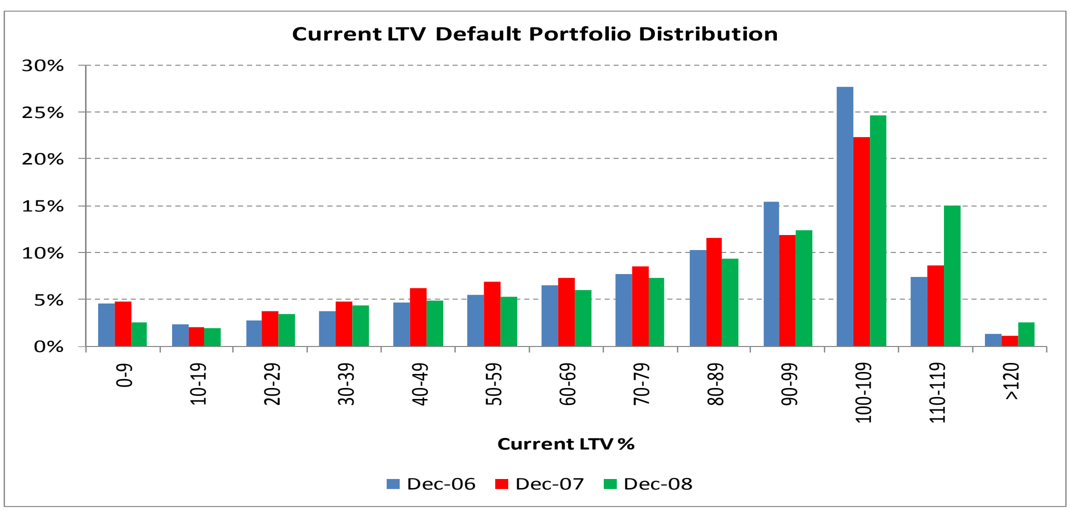


Figure 6: Current LTV Default Portfolio Distribution

The highest proportion (average of 25% across the 3 months) of defaults was within the 100 - 109% Current LTV category. On average, approximately 61% of the default portfolio had a Current LTV of greater than or equal to (>=) 80%. However, given that the portfolio was skewed towards the higher Current LTV's, it was expected that the default portfolio would have a similar bias. It was therefore necessary to introduce a measure to determine the actual *default rate* per Current LTV category. The figure below is a distribution of this default rate per Current LTV category. This distribution is arrived at by dividing the total number of defaults per Current LTV category, by the total number of customers within a particular Current LTV category.

For example,

Number of *defaulted* customers in Current LTV 100-109 = 3,547

Number of *portfolio* customers in Current LTV 100-109 = 5,932

Thus, default rate for Current LTV 100-109 category = 3,547 / 5,932

= 60%

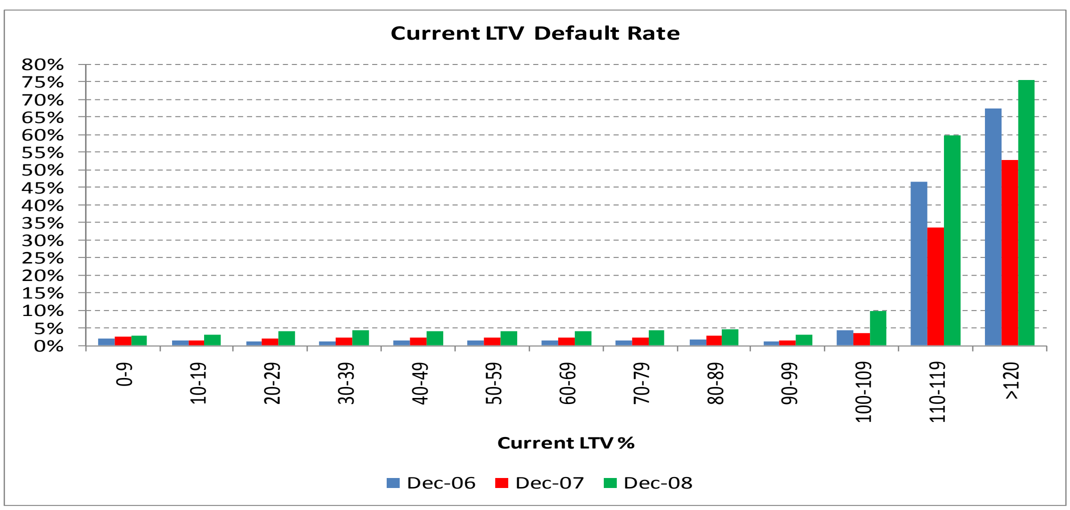


Figure 7: Current LTV default rates

The graph above indicates that the highest default rates were in the >= 110% band. 65% (average) of the entire portfolio within the >120% band were in default and 47% (average) of the entire 110 - 119% band were in default. Also, the default rates within each Current LTV band ticked up in December 2008 relative to December 2007 and December 2006 respectively.

4.3 Results pertaining to Account Age

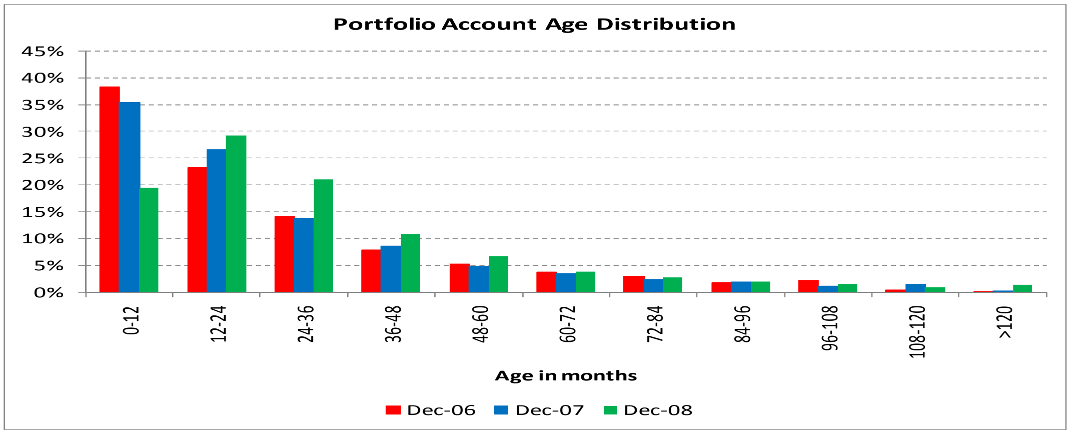


Figure 8: Account Age portfolio distribution (number)

The figure above illustrates the Account age distribution of the mortgage portfolio for December 2006, 2007 and 2008 respectively. Account age represents the age in months (at a point in time) since mortgage registration. As at December 2006 and 2007 respectively, the highest proportion of customers were within the 0 – 12 months old band. However, as at December 2008 this proportion shifted to the 12 – 24 months old category. (Refer to Appendix C for September 2006 to December 2008 graphs)

As indicated in the Table below, approximately 75% of the portfolio was less than 36 months old as at December 2006 and 2007. This proportion however reduced to 69.8% as at December 2008.

Table 4: Portfolio Account Age segmentation

	December 2006 (% of portfolio)	December 2007 (% of portfolio)	December 2008 (% of portfolio)
<= 36 months old	75.6%	75.7%	69.8%
>36 months old	24.4%	24.3%	30.2%

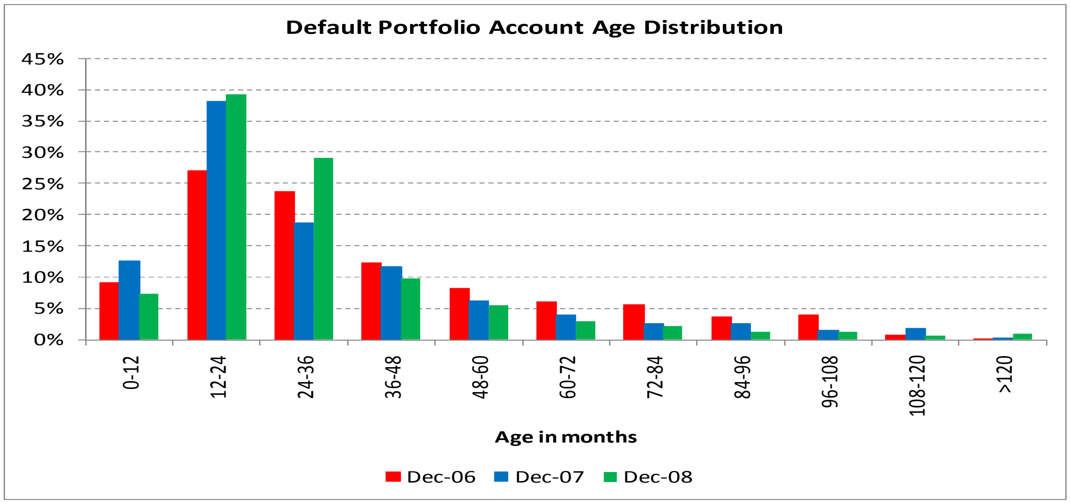


Figure 9: Default Account Age Distribution (number)

The figure illustrates the Account age distribution of the default portfolio for December 2006, 2007 and 2008 respectively. For all 3 points in time, the highest proportion of defaults was within the 12 – 24 months old category. During December 2008 and 2007, the proportion of defaults within the 12 – 24 months old category was 38% and 39% respectively. Also by December 2008, the 24 – 36 month old band accounted for 29% of all defaults.

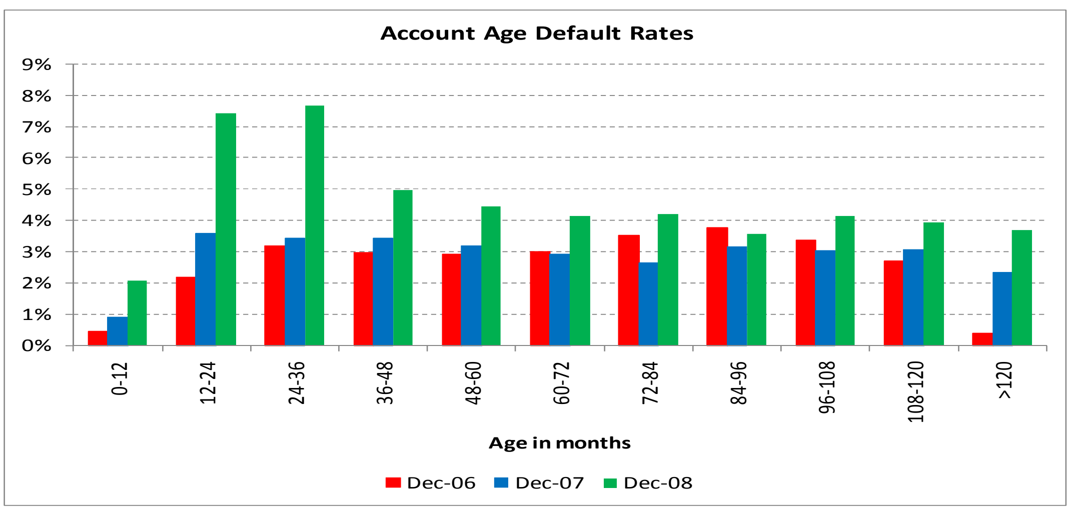


Figure 10: Account age default rates

Similar to the Current LTV variable, given that the portfolio was skewed towards the younger accounts i.e. <= 36 months old, it was expected that the default portfolio would have a similar bias. It was therefore necessary to introduce a measure to determine the actual default rate per Account age category. Figure 10 is a distribution of this default rate per Account age category. Once again, this distribution is arrived at by dividing the total number of defaults per category by the total number of customers within a particular category.

As at December 2006, the age band experiencing the highest default rate was the 72 – 96 months old one. As at December 2007 however, this proportion was more evident in the 12 – 48 months old band. However as at December 2008, it is clear that the 12 – 36 months old bands experienced the highest default rate (~7% of that category).

4.4 Results pertaining to Customer Age

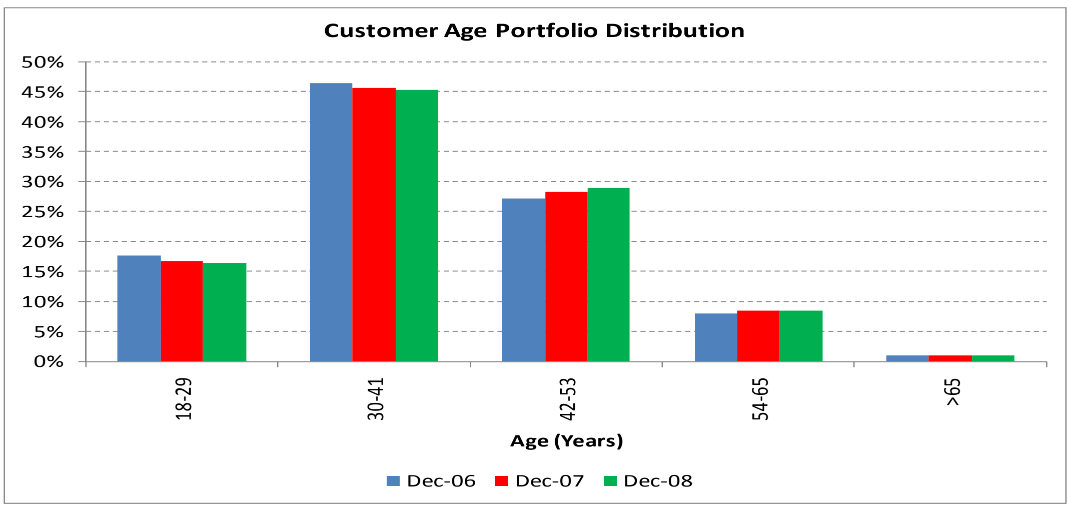


Figure 11: Customer Age portfolio distribution

The figure above illustrates the Customer Age distribution of the mortgage portfolio for December 2006, 2007 and 2008 respectively. Customers in the 30 – 41 years old category comprise approximately 46% (on average) of the portfolio. On average, 91% of the portfolio was less than 54 years old, whilst customers less than 30 years old comprised 17% of the portfolio. (Refer to Appendix C for September 2006 to December 2008 graphs)

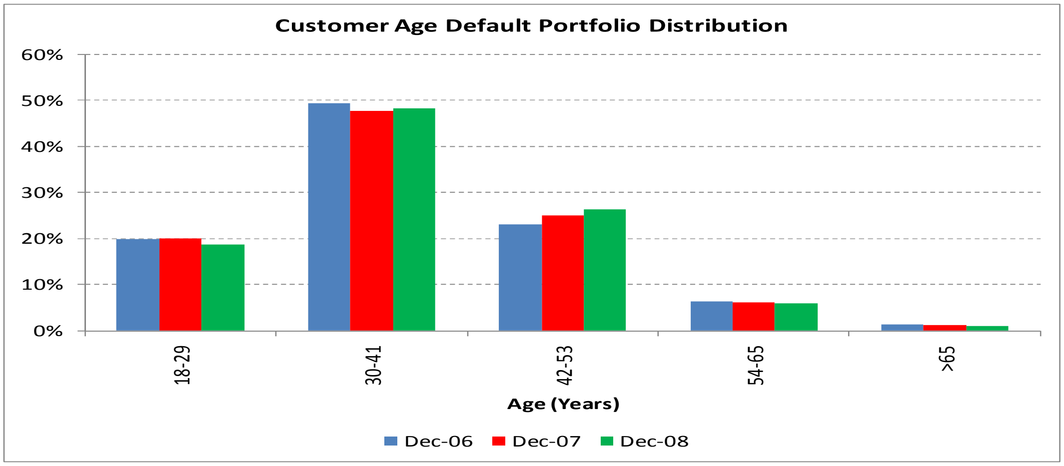


Figure 12: Customer Age default distribution

Similar to the Customer Age portfolio distribution, the highest proportion of customers within the *default* distribution exist within the 30 – 41 years old age category. Also 93% of the default portfolio was less than 54 years old, whilst customers less than 30 years old comprised 19% of the default portfolio. Similar to the variables discussed previously, given that the portfolio was skewed towards the 30 – 41 years old (age) customers, it was expected that the default portfolio would have a similar bias. The figure below is therefore a distribution of the *default rate* per Customer Age category.

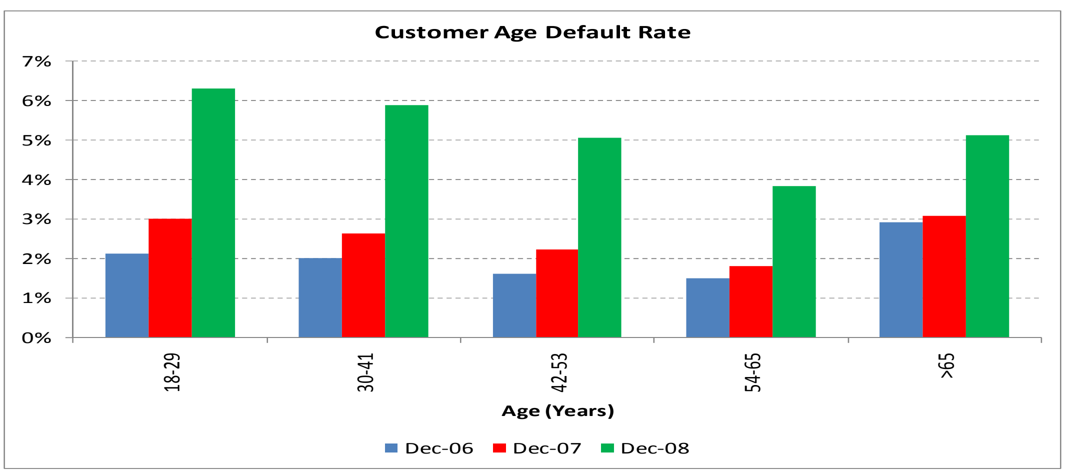


Figure 13: Customer Age default rates

As at December 2008, the 18 – 29 Customer Age category had the highest default rate (6.3%). As the age of customers increase, the default rate gradually decreases, reaching a low in the 54 – 65 years old age category. However, customers older than 65 years old (thereafter) exhibit an increasing default rate (when compared to the trends up to 65 years old).

4.5 Results pertaining to Instalment-To-Income (ITI)

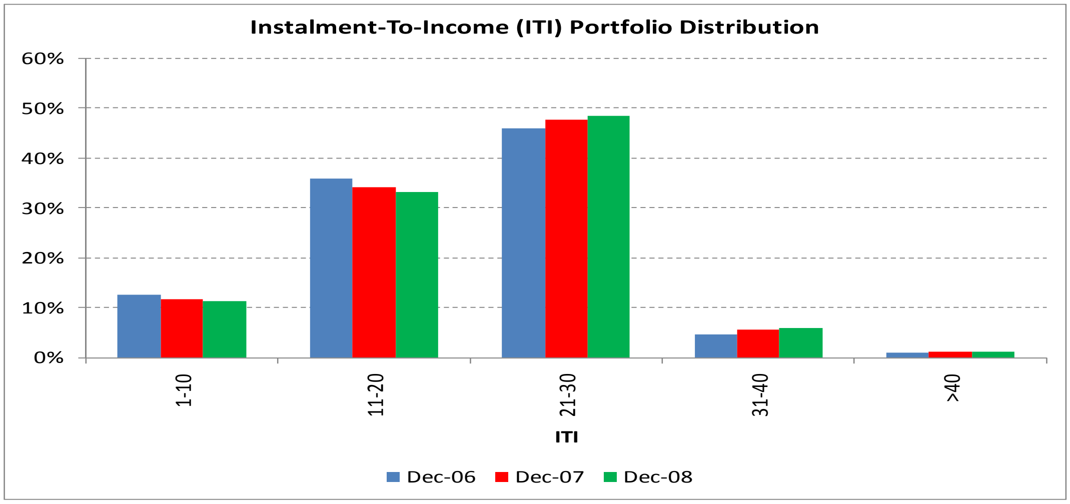


Figure 14: ITI Portfolio Distribution

The figure above illustrates the ITI distribution of the mortgage portfolio for December 2006, 2007 and 2008 respectively. ITI is the ratio of customer's monthly instalments to their income. The highest proportion (47%) of customers exist within the 21 – 30 ITI category, whilst 93% of the portfolio had an ITI of less than or equal to (<=) 30%. Consequently, 7% of the portfolio had an ITI of greater than 30%. (Refer to Appendix C for September 2006 to December 2008 graphs)

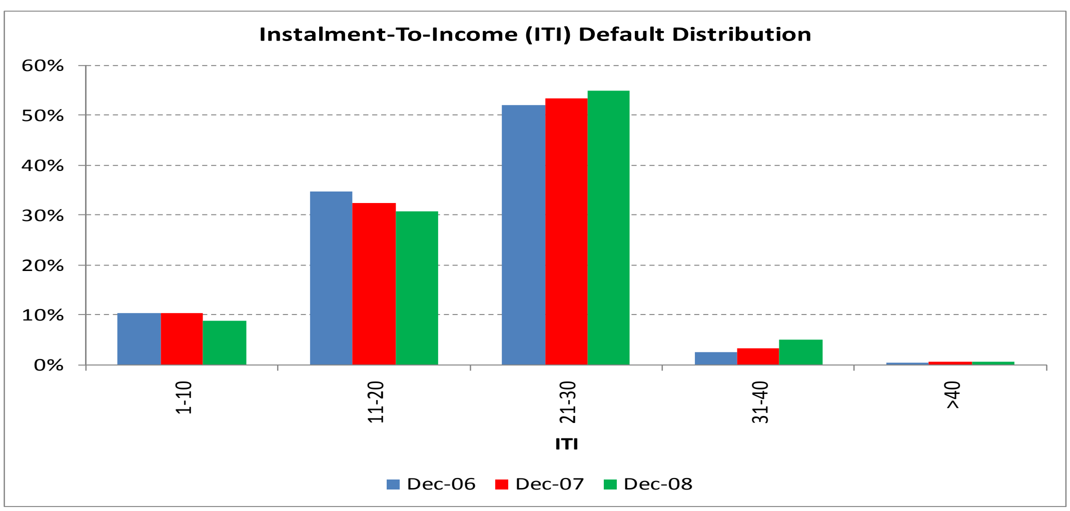


Figure 15: ITI Default Distribution

Similar to the portfolio ITI portfolio distribution, the highest proportion of customers within the *default* portfolio existed within the 21 – 30 ITI category.

The proportion of defaults within this category grew from 52% in December 2006, to 55% in December 2008. On the contrary, the proportion of defaults in the 11 -20 ITI categories declined from 35% to 31% during the same period.

Similar to the variables discussed previously, given that the portfolio was skewed towards the 21 – 30 ITI categories, it was expected that the default portfolio would have a similar bias. It was therefore necessary to introduce a measure to determine the actual default rate per ITI category. The figure below is a distribution of this default rate per ITI category. This distribution was arrived at by dividing the total number of defaults per ITI category by the total number of customers within that particular ITI category.

E.g. Number of *defaulted* customers in ITI category 21 – 30 = 12,986

Number of *portfolio* customers in ITI category 21 – 30 = 206,620

Thus, default rate for ITI category 21 – 30 = 12,986 / 206,620

= 6.3%

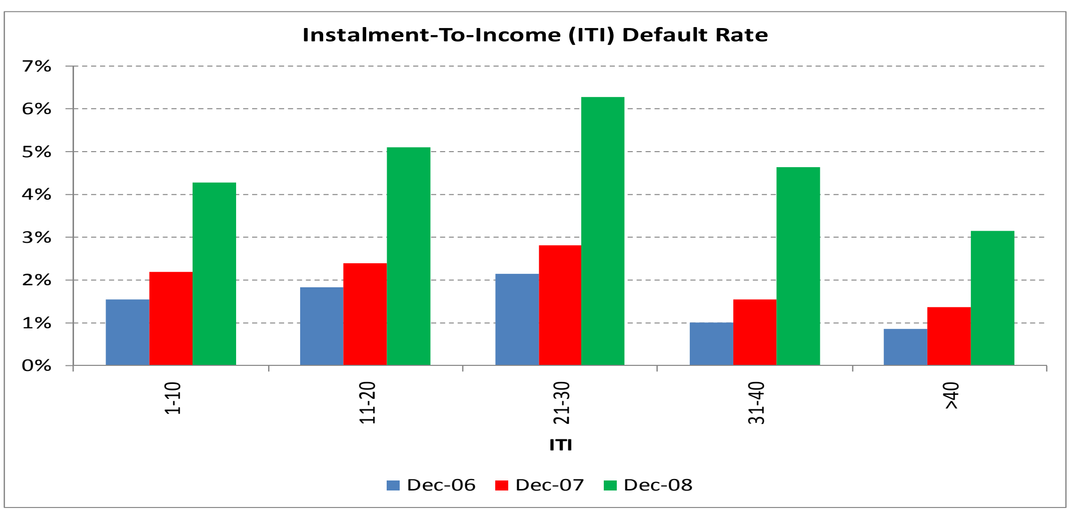


Figure 16: ITI Default Rates

As at December 2008, customers within the ITI 21 – 30 categories had the highest default rate. As illustrated in figure 19, the default rate increases from the ITI 1 – 10 category, reaches a peak in the ITI 21 – 30 category and declines thereafter.

4.6 Results pertaining to Borrower Income

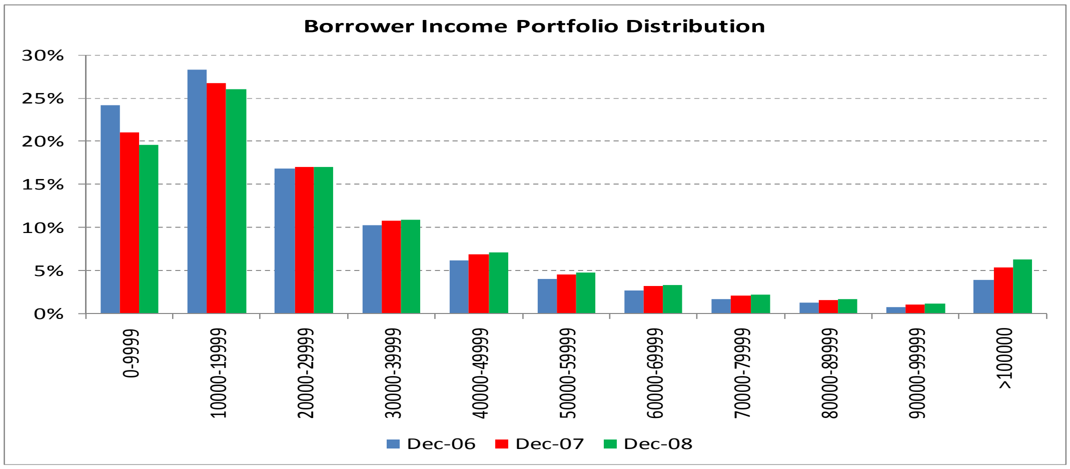


Figure 17: Borrower Income (per month) Portfolio Distribution

The figure above illustrates the borrower income distribution of the mortgage portfolio for December 2006, 2007 and 2008 respectively. The highest proportion of customers occured within the R10,000 – R19,999 income bands. As at December 2006, 52.5% of the portfolio had incomes of < R20,000. This number reduced to 47.7% and 45.7% in December 2007 and December 2008 respectively. (Refer to Appendix C for September 2006 to December 2008 graphs)

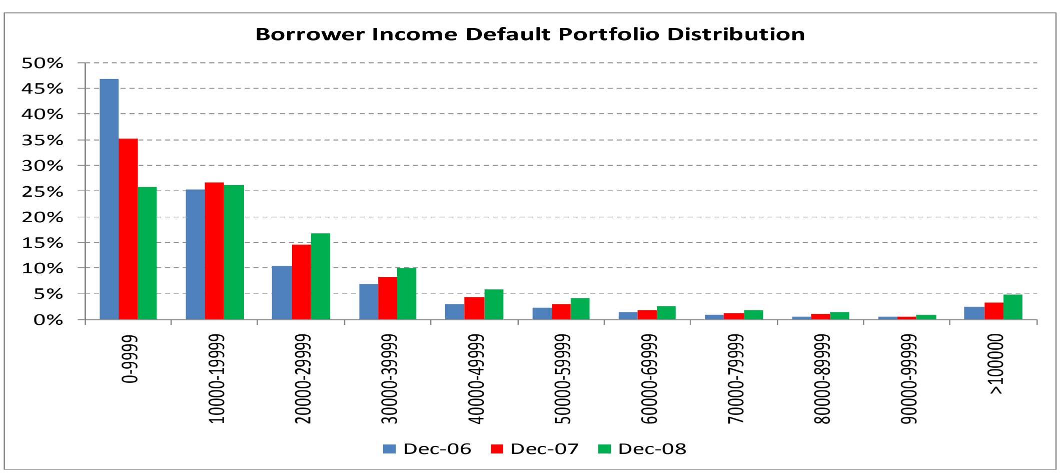


Figure 18: Borrower Income (per month) Default Distribution

The highest proportion of *defaults* as at December 2006 and December 2007 existed within the 0 – 9,999 income band. By December 2008 however, customers within the 0 – 9,999 band and the 10,000 – 19,999 band each accounted for 26% of the total defaults. As at December 2006, customers within the < 20,000 income band accounted for 72% of all defaults. This reduced to 62% and 52% for December 2007 and December 2008 respectively.

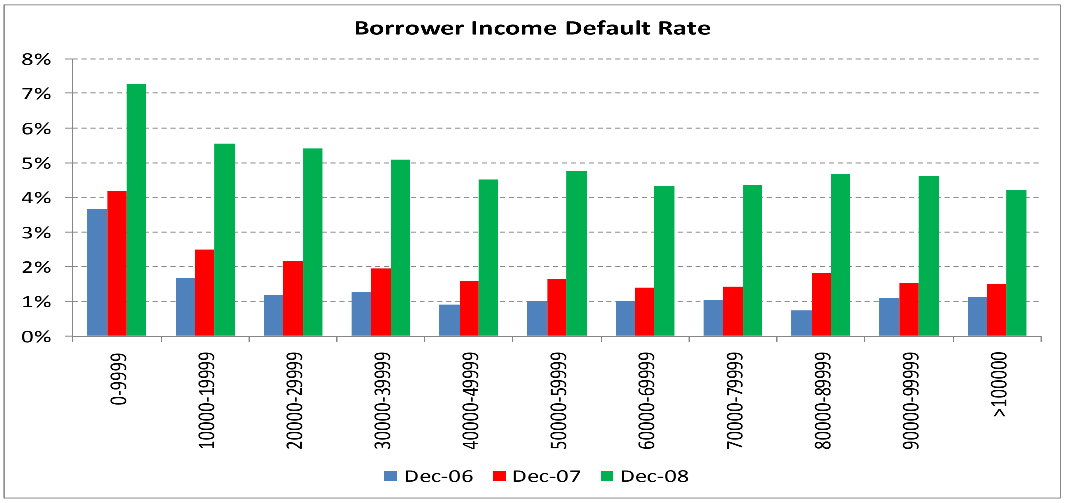


Figure 19: Borrower Income (per month) default Rates

The figure above illustrates the borrower income default rate. As at December 2006, 2007 and 2008 the 0 – 9,999 income band had the highest default rate. Figure 22 further illustrates that the default rate gradually reduces from a peak in the 0 – 9,999 category and then has a slight up tick around the 80,000 – 99,999 income range.

4.7 Results pertaining to (loan) Balance Outstanding

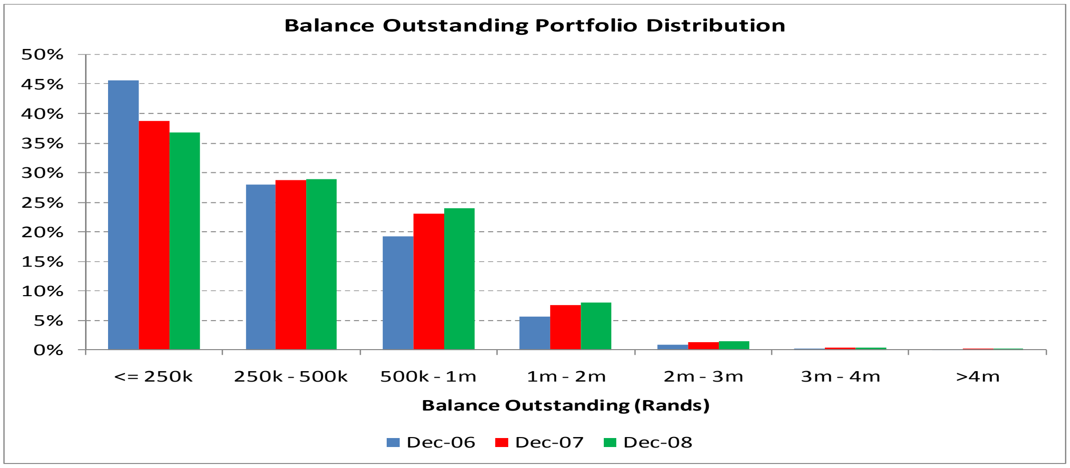


Figure 20: Balance Outstanding Portfolio distribution

The figure above illustrates the Balance Outstanding distribution of the mortgage portfolio for December 2006, 2007 and 2008 respectively. The highest proportion of customers existed within the <= R250,000 category. As at December 2006, 46% of the portfolio had a Balance Outstanding of <=R250,000. By December 2008, this proportion reduced to 37%. (Refer to Appendix C for September 2006 to December 2008 graphs)

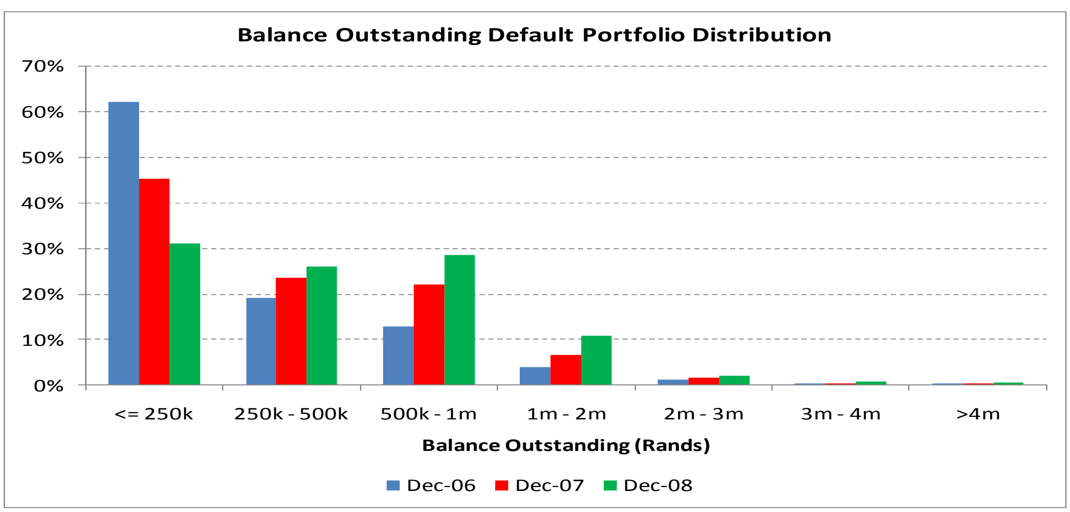


Figure 21: Balance Outstanding Default Distribution

Similar to the portfolio distribution above, the highest proportion of defaults occurred within the <=R250,000 category. This proportion however reduced from 61% in December 2007 to 31% by December 2008. Subsequently the proportion of defaults in the R500k – R1m category increased from 13% in December 2006 to 29% by December 2008. During this period however, the overall mortgage portfolio growth in this category was 5% i.e. 19% (Dec 06) to 24% (Dec 08).

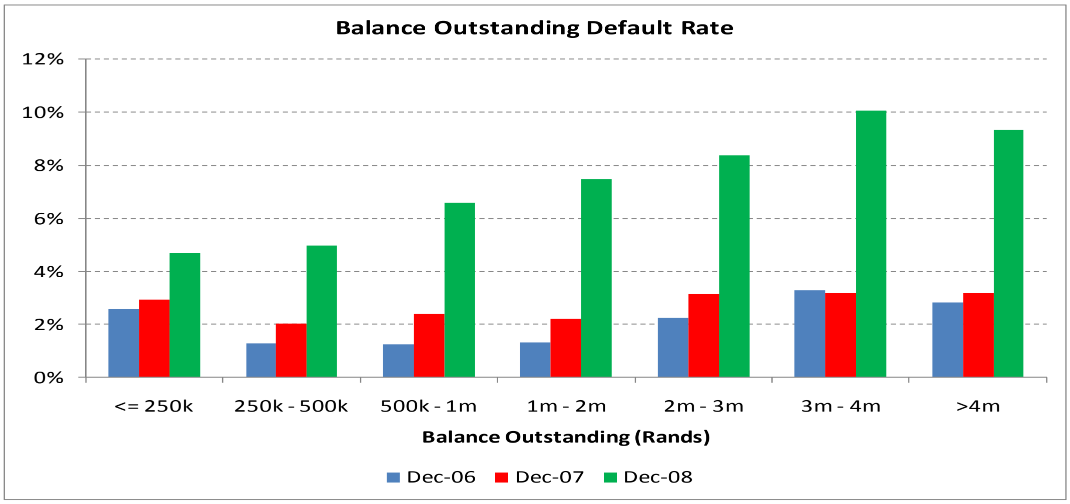


Figure 22: Balance Outstanding Default Rates

As at December 2006 and December 2007, the <=R250k, the R3m – R4m and the >R4m categories had the highest default rate. By December 2008 however this proportion was evident in the R3m – R4m which had a default rate of 10%. Also, the > R4m and the R2m – R3m category had default rates of 9% and 8% respectively.

4.8 Model Results

4.8.1 *Regime 1*

Given the large volume of data that existed per month, a technique to be able to group the data was necessary, in order to build an appropriate sample to pass through the model. In order to achieve this, a technique to 'Regime' certain variables was employed. The Employment Status indicator variable was included as part of the regimes.

The first regime used to develop the model was:

Table 5: Regime 1 Characteristics

Regime 1	
Employment status	Self- Employed
Clean Slate	TRUE
Customer Age Category	<= 35 years old
Current LTV	>= 98%

The 'Clean Slate' variable was introduced into the data to allocate a state to a particular customer who had previously either defaulted or not. Thus, in running the model for the month of November 2008 (for example), had a customer at any time defaulted (i.e. been more than 90 days in arrears), that customer would have had a 'Clean Slate = False' state. Had a customer not previously defaulted, they would have had a 'Clean Slate = True' state.

Thus for Regime 1, only those customers that fit the profile of being self-employed, younger than 36 years old, never defaulted previously and had a Current LTV >= 98% were included in the sample. The figure below illustrates the size (number of customers) and number of defaults per month for Regime 1.

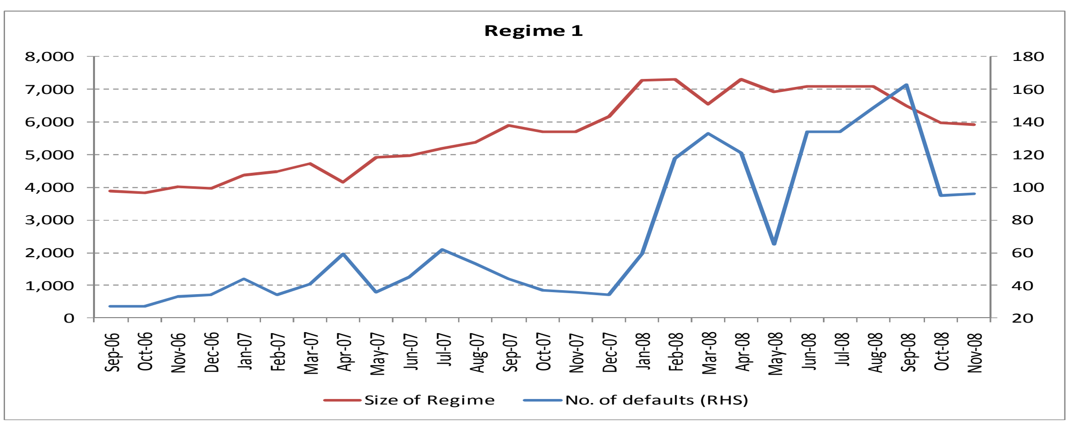


Figure 23: Number of customers and defaults (Regime 1)

Regime 1: Co-efficient

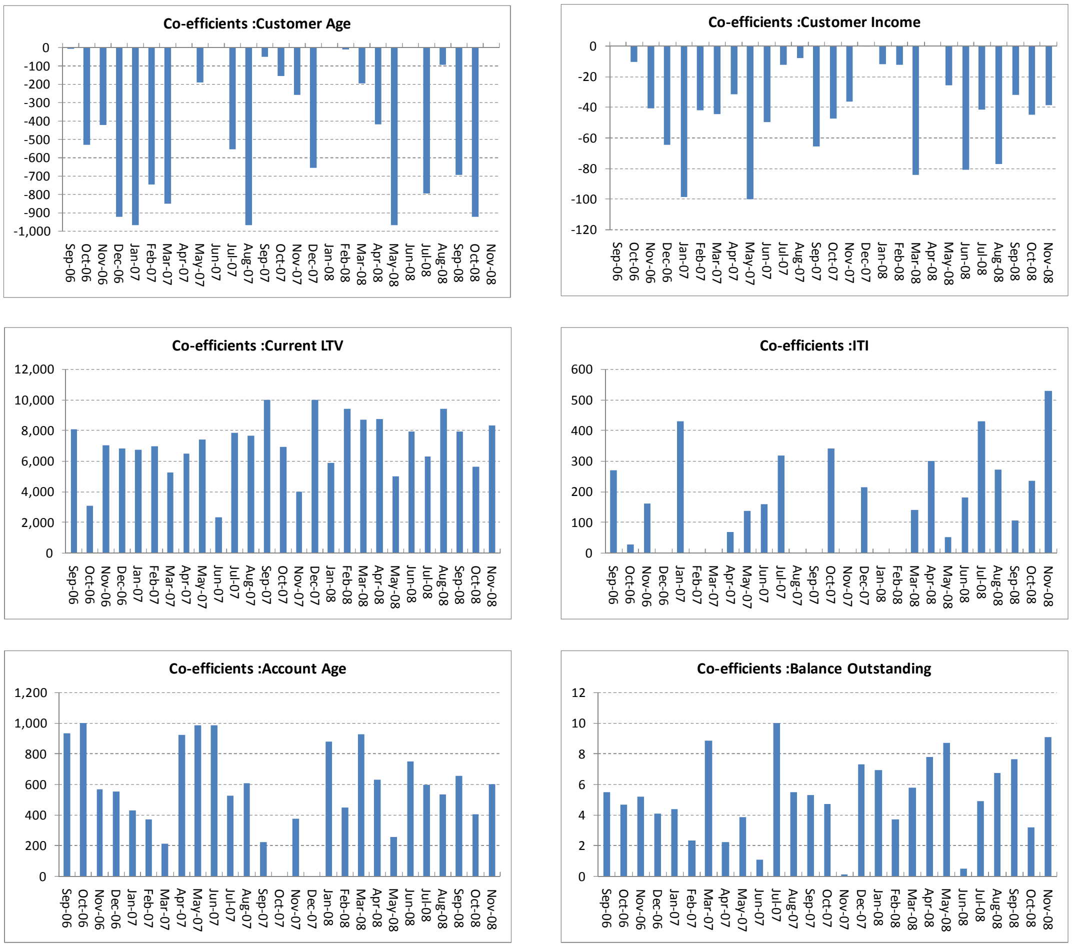


Figure 24: Co-efficient (Regime 1)

The co-efficient for Customer Age and Borrower Income are negative whilst those for Current LTV, ITI, Account Age and Balance Outstanding are positive (Regime 1). The implication of this, is that those variables with a negative co-efficient suggest that the lower the value of those variables the more likely the customer will default. Conversely, those variables with a positive co-efficient suggest that the higher the value of those variables the more likely a customer will default.

Proportional Contribution

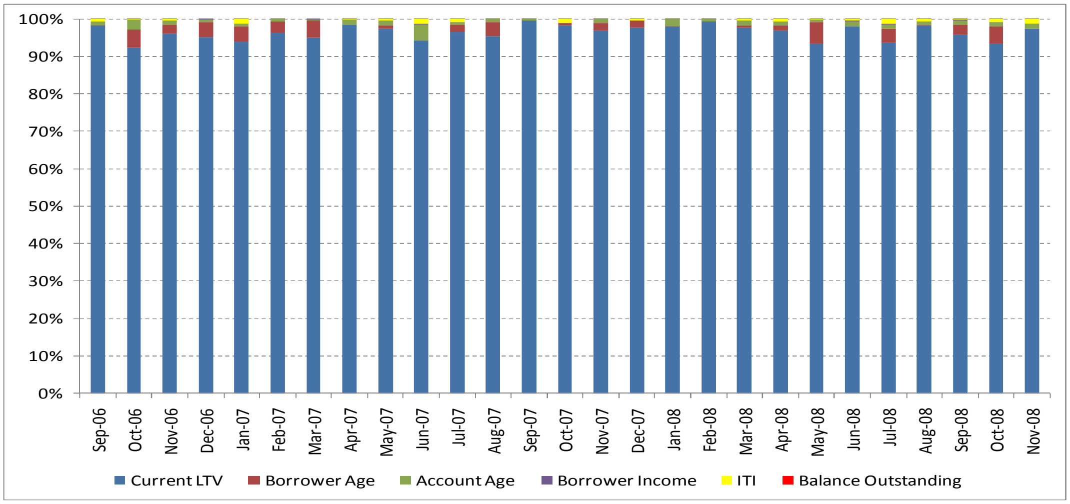


Figure 25: Variables proportional contribution (Regime 1)

The figure above illustrates the proportional contribution of the variables to the model outcome. The table below shows the average co-efficient, score and proportional contribution of each variable. As evident, 'Current LTV' (96.4%) is the biggest proportional contributor to the model. The 2nd and 3rd largest contributors are 'Borrower Age' (2%) and 'Account Age (1.1%) respectively. The contributions of ITI, Borrower Income and the Balance Outstanding variables contribute less than 1% to the model outcome.

Table 6: Co-efficient, Scores and % Contribution

	Co-efficient	Score	% Contribution
Current LTV	7017.6	707,172	96.4%
Borrower Age	423.2	13,078	2%
Account Age	573.0	6,822	1.1%
ITI	160.5	3,414	0.47%
Borrower Income	40.9	447 (logged)	0.07%
Balance Outstanding	5.2	70 (logged)	0.01%

Regime 1: Goodness of Fit

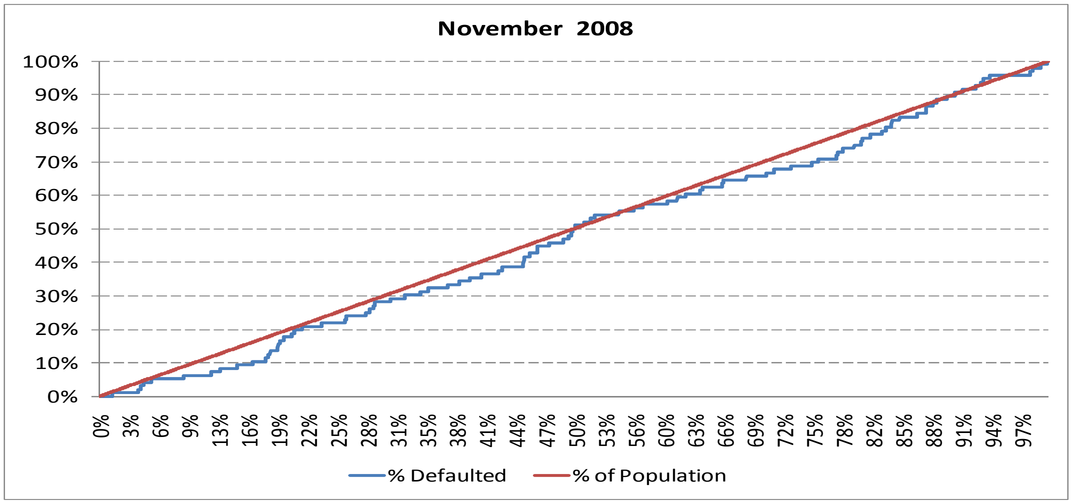


Figure 26: Random ranking (Regime 1)

The figure above illustrates a percentage default versus percentage of population graph as a result of a *random* ranking of the Regime 1 data for November 2008. If a line was drawn through the '50%' value on the x-axis, 50% of the defaults would have been represented in 50% of the total data for this regime (and month). Therefore, the goodness of fit test for the model lies in attempting to exceed this value. In other words, the model would be required to exceed (by far) this ratio of 50% of defaults being represented in 50% of the total data (due to a pure random ranking of customers).

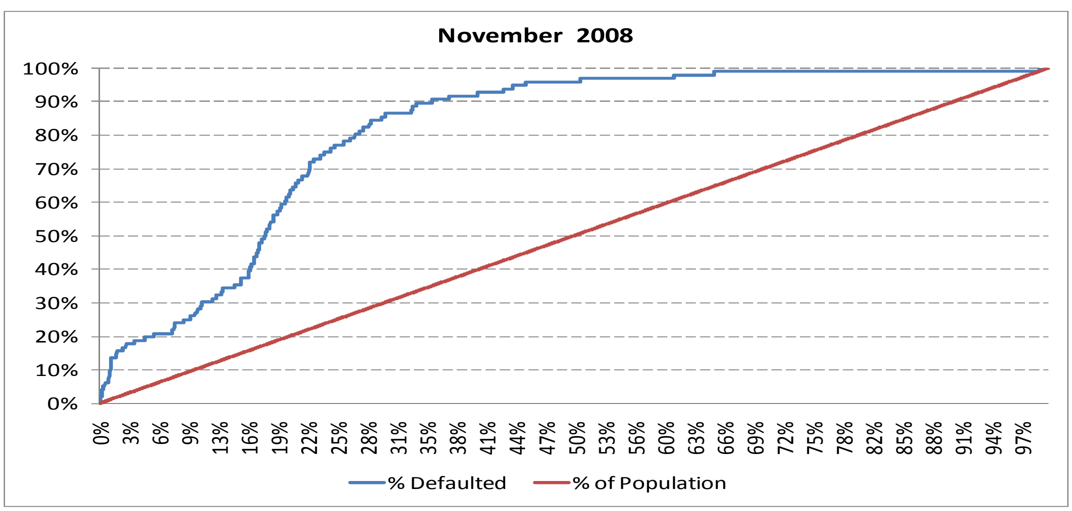
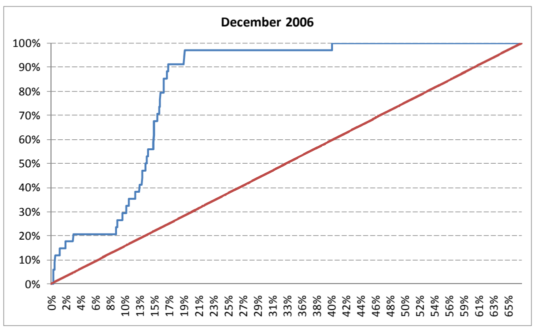


Figure 27: Model ranking (Regime 1)

Figure 27 illustrates a percentage default versus percentage of population graph as a result of the Scorecard *model* ranking of the Regime 1 data (November 2008). The figure above indicates that the model was able to distinguish / predict 96% of the defaults in 50% of the total data. Similarly, the model predicted 90% of defaults in 34% of the total data. The model achieves this by ranking customers in descending order based on the ‘score’ the model assigns to each customer. Customers with the higher scores are more likely to default than those with lower scores.



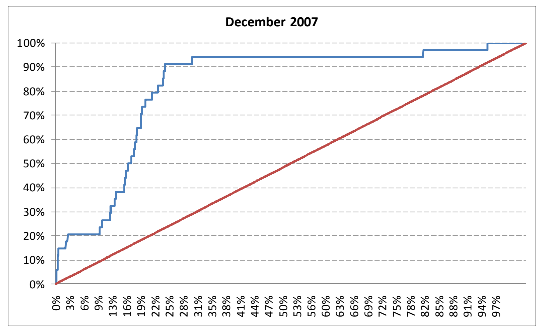


Figure 28: December 2006 and 2007 model ranking (Regime 1)

As evident in the graphs above, 90% of the defaults for December 2006 were predicted using 17% of the total data. Also, 100% of the defaults for this month were predicted with 40% of the total data. Similarly for December 2007, 90% of the defaults were predicted utilising 24% of the data.

4.8.2 *Regime 2*

The second regime used to pass through the model had the following characteristics:

Table 7: Regime 2 Characteristics

Regime 1	
Employment status	Self- Employed
Clean Slate	TRUE
Customer Age Category	> 35 years old
Current LTV	>= 98%

For Regime 2, only customers that fit the profile of being self-employed, older than 36 years old, never defaulted previously and had a Current LTV >= 98% were included in the sample. The difference between Regime 1 and Regime 2 is that customers in Regime 1 were less than or equal to 35 years old whereas in Regime 2, only customers greater than 35 years old were considered.

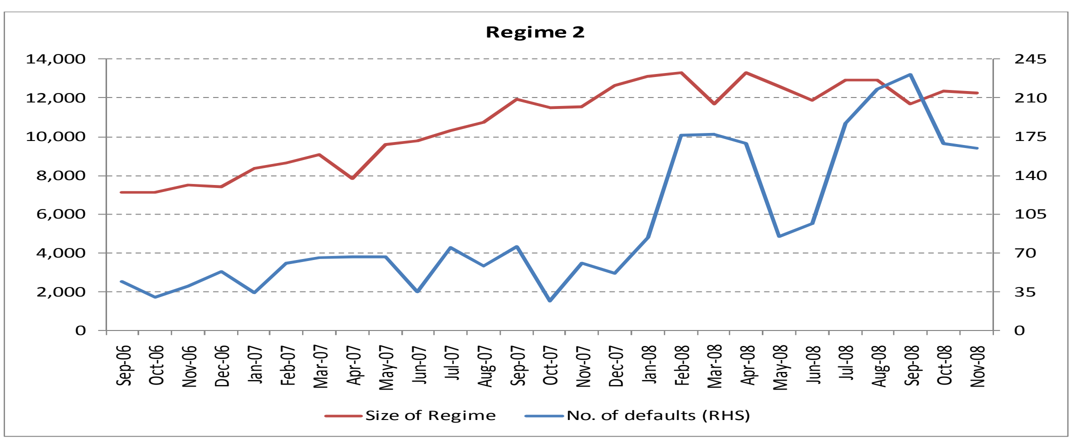


Figure 29: Number of customers and defaults (Regime 2)

The figure above shows the size (number of customers) and number of defaults for Regime 2 (per month).

Regime 2 Co-Efficient

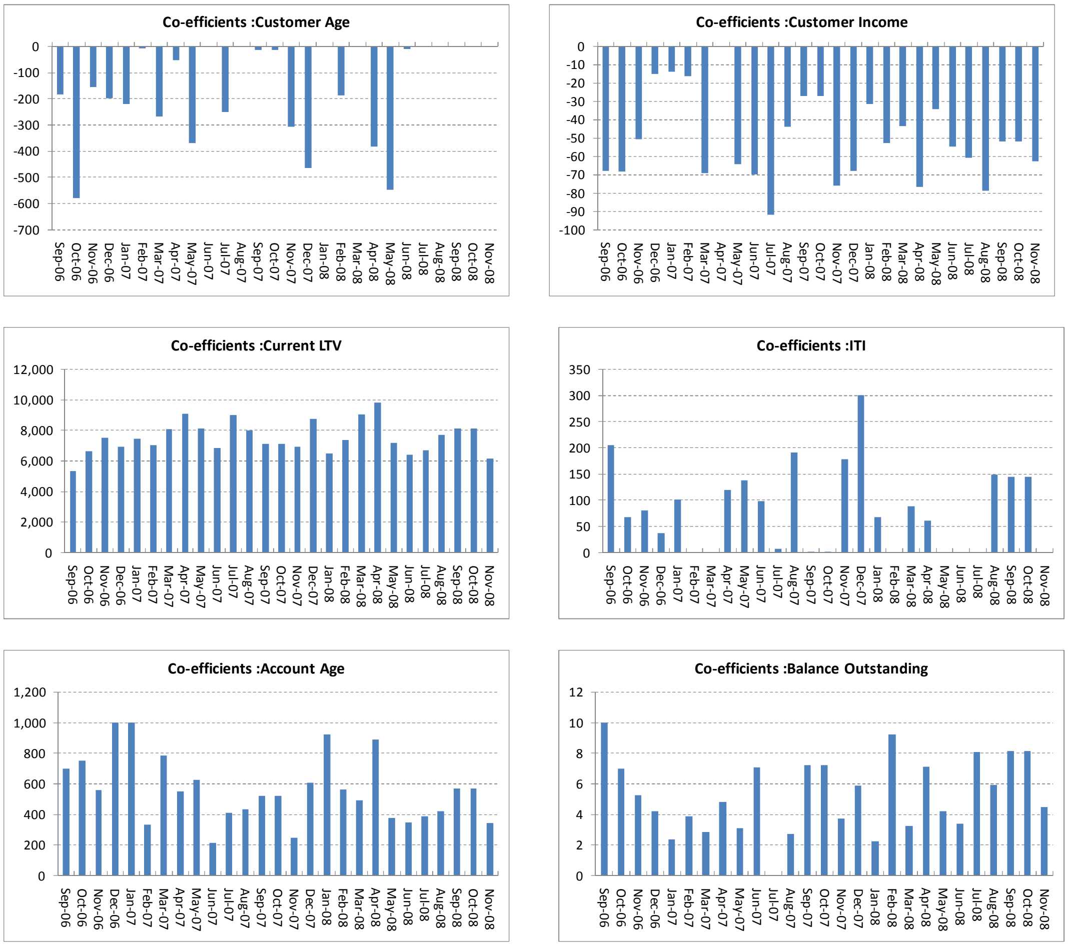


Figure 30: Co-Efficient (Regime 2)

Similar to Regime 1, the co-efficient for Customer Age and Borrower Income are negative whilst those for Current LTV, ITI, Account Age and Balance Outstanding are positive. The implication of this is that those variables with a negative co-efficient suggest that the lower the value of those variables the more likely the customer will default. Conversely, those variables with a positive co-efficient suggest that the higher the value of those variables the more likely a customer will default.

Proportional Contribution

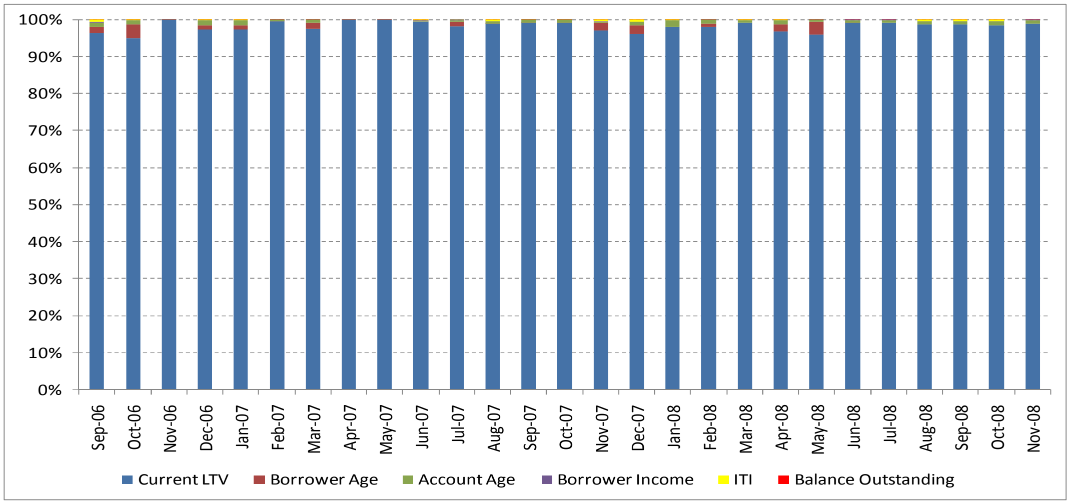


Figure 31: Variables proportional contribution (Regime 2)

The figure above illustrates the proportional contribution of the variables to the model outcome. The table below shows the average co-efficient, score and proportional contribution of each variable. Similar to Regime 1, the 'Current LTV' variable is the biggest proportional contributor (98.2%) to the model. Also, the 2nd and 3rd largest contributors are the 'Customer Age' (0.8%) and 'Account Age' (0.8%) variables respectively. The ITI, Borrower Income and Balance Outstanding variables contribute less than 0.5% to the model outcome.

Table 8: Co-efficient, Score and % Contribution

	Co-efficient	Score	% Contribution
Current LTV	7,521.7	14,824,866	98.2%
Borrower Age	156.5	7,191	0.8%
Account Age	562.7	6,501	0.8%
ITI	80.8	1,683	0.19%
Borrower Income	50.5	566 (logged)	0.07%
Balance Outstanding	5.2	71 (logged)	0.01%

Regime 2: Goodness of Fit

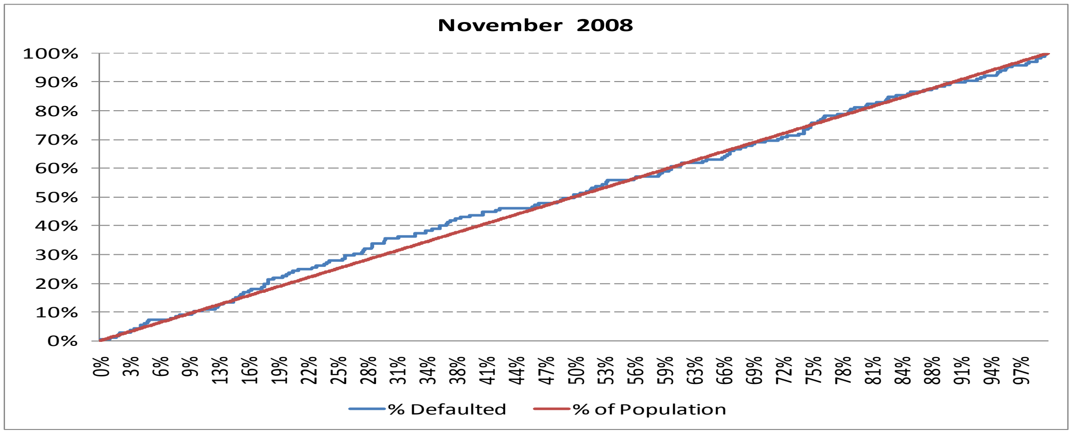


Figure 32: Random Ranking (Regime 2)

Similar to figure 26, the chart above illustrates a percentage default versus percentage of population graph, as a result of a *random* ranking of the Regime 2 data (November 2008). As indicated by the graph, 50% of the defaults are represented in 50% of the total data for this regime. Therefore, the goodness of fit test for the Regime 2 model lies in attempting to exceed this value. Thus the model would be required to (far) exceed this ratio of 50% of defaults being represented in 50% of the total data (due to a pure random ranking of customers).

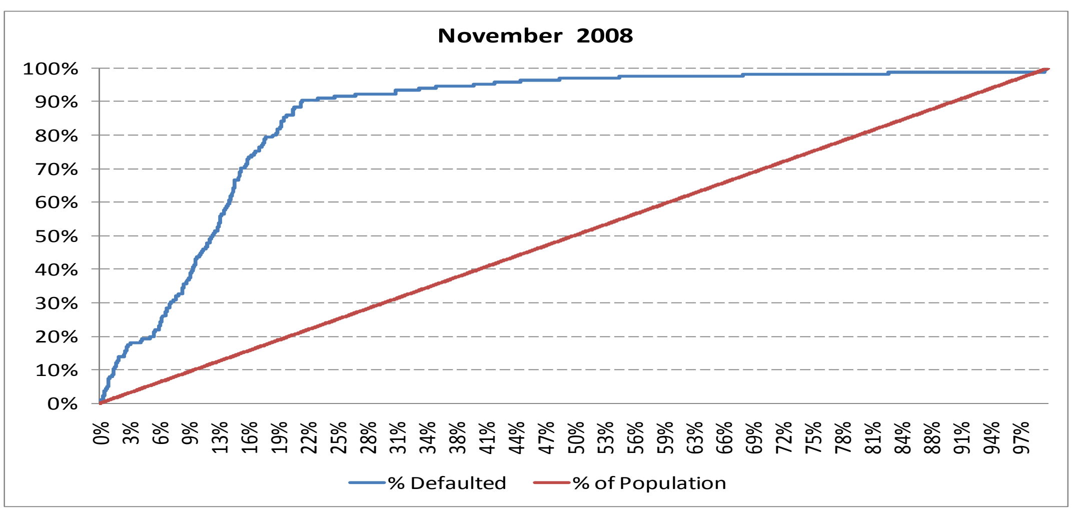


Figure 33: Model Ranking (Regime 2)

The figure above shows the percentage default in relation to the percentage of population graph, as a result of the Scorecard *model* ranking of the Regime 2 data (November 2008). The graph illustrates that the model was able to predict 97% of the defaults in 50% of the total data. Similarly, the model predicted 90% of defaults in 22% of the total data. The model achieves this by ranking customers in descending order based on the ‘score’ the model assigns to each customer. Customers with the higher scores are more likely to default than those with lower scores.

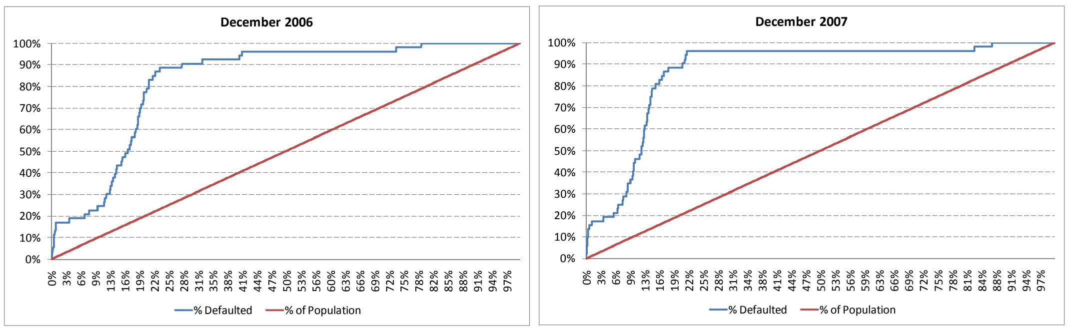


Figure 34: December 2006 and 2007 model ranking (Regime 2)

As evident in the graph above, 90% of the defaults for December 2006 were predicted using 28% of the total data. Similarly for December 2007, 90% of the defaults were predicted utilising 21% of the data.

4.9 Summary of the results

The mortgage portfolio of the financial institution concerned experienced steady growth from R133 billion (333, 7778 customers) in September 2006 to R212 billion (427,008 customers) by December 2008. At the same time mortgage defaults grew from R2.2 billion in September 2006 (6,859 customers) to R14 billion by December 2008 (23,624 customers). As a percentage (in number) of the total portfolio, 2.1% of the portfolio was in default in September 2006, compared to 5.5% by December 2008.

The highest Current LTV proportion (23%) of the portfolio was within the 90 - 99% category. Similarly, the highest Current LTV proportion (25%) within the default portfolio was in the 100 – 109% category. A Current LTV value above 100% indicates that the balance outstanding on the mortgage exceeds the underlying asset value i.e. the property being mortgaged. Also 80% of the default portfolio had a Current LTV > 80%.

As at December 2006 and 2007, the highest proportion of customers was within the 0 – 12 months Account age category. However by December 2008 this shifted to the 12 – 24 months old category. Also, 75% of the portfolio was less than 36 months old at December 2006 and 2007. By December 2008, this reduced to 69.8% indicating a slight maturing of the portfolio. From a default point of view however, the 12 – 24 months old Account Age category showed the highest proportion of defaults.

Customers within the 30 – 41 years old age category comprised 46% of the total portfolio, whilst those less than 30 years old made up 17% of the portfolio. Similarly, the highest default category were customers within the 30 – 41 years old age category, however from a default rate perspective, customers within the 18 – 29 year old band showed the highest default rate.

The highest proportion of customers existed within the ITI 21 – 30% category. From a default point of view this band showed the highest proportional defaults as well as the highest default rate.

From a customer income perspective, the R10, 000 – R19, 999 category had the highest number of customers. The highest number of defaults and the highest default rate however occurred within the <= R9, 999 income category.

4.9.1 *Regime 1*

The co-efficient for Customer Age and Customer Income were negative indicating that the lower the value of these variables the more likely a customer will default. The co-efficient for Current LTV, ITI, Account Age and Balance Outstanding were positive indicating that the higher the value of these variables the more likely a customer will default.

Current LTV (96.4%) was the biggest proportional contributor to the model. The 2nd and 3rd largest contributors were Borrower Age (2%) and Account Age (1.1%) respectively. The contributions of ITI, Borrower Income and the Balance Outstanding variables contributed less than 1% to the model outcome.

For November 2008, the model was able to distinguish / predict 96% of the defaults in 50% of the total data. Similarly, the model predicted 90% of defaults in 34% of the total data. The model achieved this by ranking customers in descending order based on the 'score' the model assigns to each customer. Customers with the higher scores are more likely to default than those with lower scores. Also, 90% of the defaults for December 2006 were predicted using 17% of the total data. Also, 100% of the defaults for this month were predicted with 40% of the total data. Similarly for December 2007, 90% of the defaults were predicted utilising 24% of the data

4.9.2 *Regime 2*

Similar to Regime 1, the co-efficient for Customer Age and Customer Income were negative whilst the co-efficient for Current LTV, ITI, Account Age and Balance Outstanding were positive.

Current LTV was the biggest proportional contributor (98.2%) to the model. Also, the 2nd and 3rd largest contributors were the Customer Age (0.8%) and Account Age (0.8%) variables respectively. The ITI, Borrower Income and Balance Outstanding variables contributed less than 0.5% to the model outcome.

For November 2008, the model was able to predict 97% of the defaults in 50% of the total data. Similarly, the model predicted 90% of defaults in 22% of the total data. Also, 90% of the defaults for December 2006 were predicted using 28% of the total data. For December 2007, 90% of the defaults were predicted utilising 21% of the data.

5 CHAPTER 5: DISCUSSION OF THE RESULTS

5.1 Introduction

The purpose of this chapter is to evaluate, discuss and interpret the results presented in chapter 4, in relation to the literature and hypotheses discussed and formulated in chapter 2. The structure of this chapter will comprise a discussion and interpretation of each variable and its impact on the model's ability to differentiate defaults.

5.2 Interpretation of results relating to Current LTV

According to the descriptive statistics (section 4), the highest proportion of defaults (25%) existed within the 100 – 109% Current LTV band, whilst the highest default rate existed within the >=110% category. This was expected as a Current LTV > 100% indicates a negative equity position for the borrower. This is consistent with the views of Cooperstein, Redburn and Meyers (1991), Whitley et al (2004), Kofner (2007), Harrison, Noordewier and Yavas (2004), and Pillay (2007).

The is however in contrast to the view of Vandell and Thibodeau (1985) who make mention that apart from Loan-to-Value (LTV), that several non-equity factors overshadow the equity effect on default and help explain why some households with zero or negative equity may not default, whilst others with positive equity may. Similarly, Vandell and Thibodeau (1985) mention that in mortgage default modelling, the 'equity-effect' per se is dwarfed by various other non-related factors.

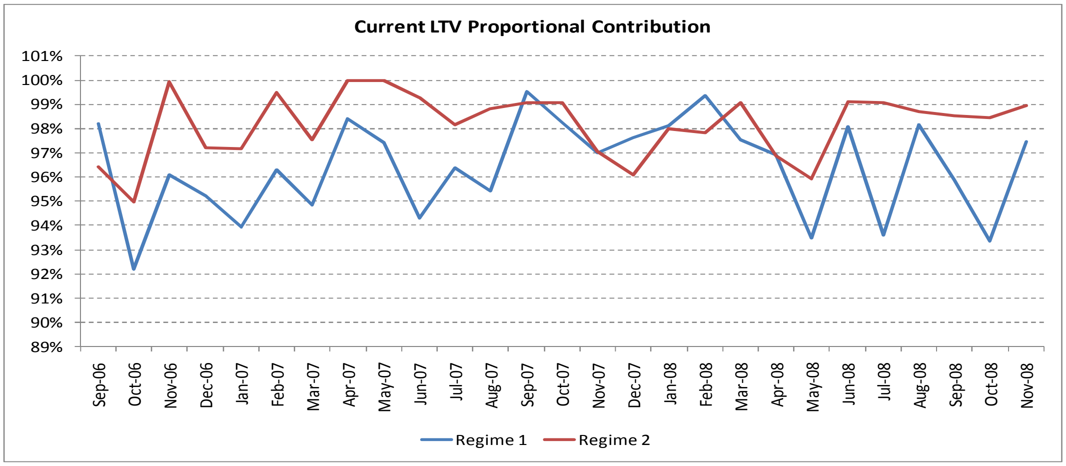


Figure 35: Current LTV Proportional Contribution

For both Regime 1 and 2, the results of the model indicated a positive co-efficient for the Current LTV variable. This indicates that the higher the value of this variable, the more likely that a default event will occur i.e. a customer with a Current LTV =100% is more likely to default than one with an LTV = 80%. This is also consistent with the results of the descriptive statistics and some of the views mentioned above. In terms of the proportional contribution to the model, for both Regime 1 and 2, the Current LTV variable contributed 97% (on average) to the total model outcome (in terms of the scorecard and its associated ranking).

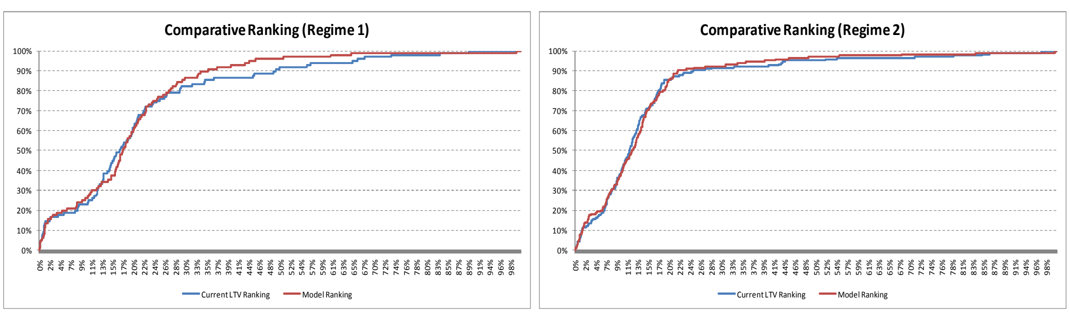


Figure 36: Comparative Ranking (Model and Current LTV only)

The figure above illustrate the comparative ranking of defaults (November 2008) for both, the Scorecard and Ranking model incorporating all the variables, as well as the ranking of defaults using the Current LTV (in descending order) variable only. As can be seen from the graph, and given its high contribution to the model (97%), the Current LTV variable on its own is a close approximation to the Scorecard and Ranking model of defaults. This suggests that a close approximation to the ‘best fit’ of defaults could have been obtained by simply ranking the Current LTV variable only. The implication of this is that the other variables could have been excluded with a very similar model outcome, which raises questions about the validity of the other variables used.

5.2.1 *Conclusion relating to Current LTV*

Given the insights gained from the descriptive statistics, the sign of the co-efficient (i.e. positive) and its major contribution to the scorecard model, the *Current LTV variable is a good differentiator of mortgage defaults.*

5.3 Interpretation of results relating to Account Age

The highest proportion of customers occurred within the 0 – 12 months old band (December 2006 and 2007), whilst by December 2008, this proportion shifted to the 12 – 24 months old category. Given the low interest rates experienced in South Africa during 2005 and 2006, and the easy availability of mortgage finance at the time, it was expected that the average Account age of the portfolio would be younger, during these years, and subsequently increasing once the upward trend of the interest rate cycle manifested in more defaults and more stringent lending criteria.

Proportionally, customers within the 12 – 24 months old category demonstrated the highest defaults. This is in line with the findings of Furstenberg and Green (1974), who stated that the delinquency rate will rise rapidly for the first one or two years and then decline gradually as the seasoning of the mortgage progresses. This trend was however expected given that the portfolio was skewed towards ‘younger’ customers.

As at December 2006, customers within the 72 -96 months old age category experienced the highest default rate. By December 2007 and 2008, this was evident in the 12 – 48 months and 12 – 36 month categories respectively. This indicates that over time, the account age categories experiencing the higher default rates became younger. This phenomenon can be explained by the assertion of Hayre et al. (2008), who mentioned that the danger period is when loans are moderately seasoned, when a downturn in the housing market and an adverse personal event could lead to the loan becoming delinquent. During 2007 and 2008, the South African mortgage industry experienced such a downturn (Toit 2009) as also evident by the declining year-on-year growth rates (refer to figure 2).

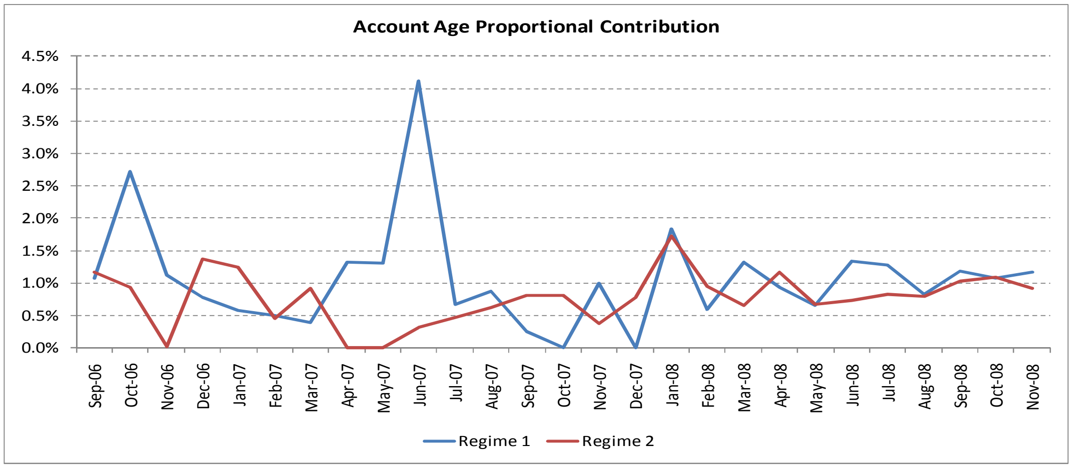


Figure 37: Account Age Proportional Contribution

For Regime 1 and 2, the results of the model indicated a positive co-efficient for the Account Age variable. However, in terms of the proportional contribution to the model this variable's contribution for Regime 1 and 2, was 1.1% and 0.9% respectively. (in terms of the scorecard and its associated ranking). This indicates that for Regime 1 (i.e. younger borrowers), Account age (i.e. the age of the loan since mortgage registration) is slightly more relevant in its contribution towards ranking defaults than for Regime 2 (i.e. older borrowers). However, from a model perspective, the validity of this variable is called into question in that its contribution to the total customer *score* was found to be negligible.

This can be explained by the fact that over time (i.e. when a mortgage seasons) it is likely that house prices increase (on average), thus increasing the borrowers equity stake which makes customers less likely to default. Similar to the findings of Hayre et al. (2008), it is not the relatively young age of the mortgage that potentially results in a default, but the fact that the Current LTV reduces (with equity increasing) over time, which makes customers less risky.

5.3.1 *Conclusion relating to Account Age*

Given the above, the *Account Age variable is not a good differentiator of mortgage defaults.*

5.4 Interpretation of results relating to Borrower Age

Whilst customers in the 30 – 42 years old age category comprised 46% of the portfolio, those in the < 30 years old band comprised 17% of the total portfolio. From a default rate perspective, customers in this category (i.e. < 30 years old) showed the highest default rate, with the default rate reducing as the age of customers increase. This validates the study of Burrows (1998) who concluded that households with heads of households who are young adults (18 to 24) are significantly more likely to be in arrears than households with older heads. However this in contrast to the findings of Delgadillo and Green Pimentel (2007) who indicated that the median age of mortgage default clientele was 36 years old.

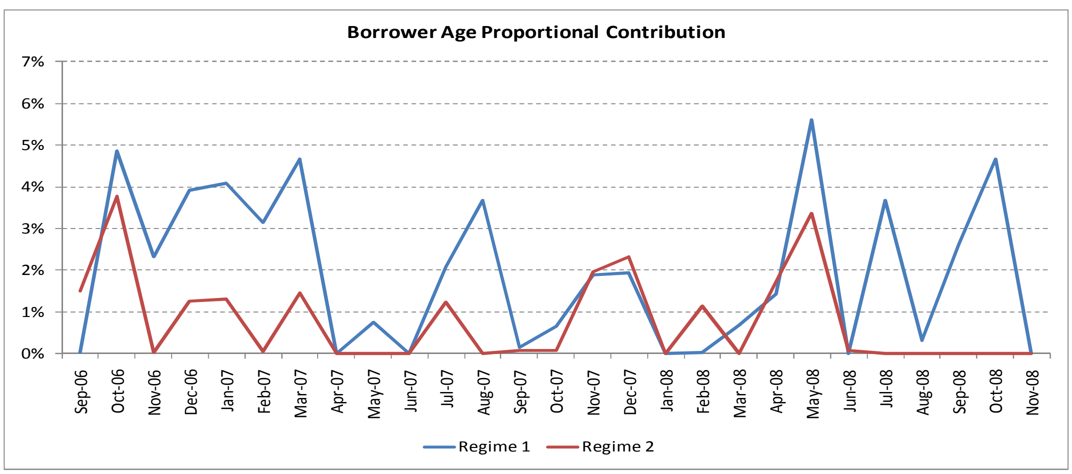


Figure 38: Borrower Age Proportional Contribution

For both Regime 1 and 2, the results of the model indicated a positive co-efficient for the Borrower Age variable However, in terms of the proportional contribution to the model this variable’s contribution for Regime 1 and 2, was 2% and 0.8% respectively. (in terms of the scorecard and its associated ranking). This indicates that for Regime 1 Borrower age is slightly more relevant in its contribution towards ranking defaults than for Regime 2 .However, from a model perspective, the validity of this variable is called into question in that its contribution to the total customer *score* was found to be negligible. These findings are similar to those of Hakim and Haddad (1999), who found that borrower's age in relation to mortgage default varied by region and was largely inconclusive.

5.4.1 *Conclusion relating to Borrower Age*

Given the above, the *Borrower Age variable is not a good differentiator of mortgage defaults.*

5.5 Interpretation of results relating to Instalment-to-Income (ITI)

The highest proportion of customers (total portfolio) and the highest proportion of defaulted customers existed within the 21 – 30% ITI category. Similarly, customers in this band showed the highest default rate, whilst declining as the ITI increased thereafter. This (lower default rate as ITI increases) contradicts the finding of Hayre et al.(2008), Burrows (1998) and Kofner (2007), who found that the higher the ITI ratio, the greater the proportion of the borrowers income that goes towards making mortgage payments, and hence the greater the strain a trigger event puts on the borrower's ability to continue making these payments.

From a proportional model contribution perspective, for both Regime 1 and 2, the ITI variable contributed only 0.3% (on average) to the total model outcome (in terms of the scorecard and its associated ranking). Thus, the validity of this variable is called into question in that its contribution to the total customer *score* was found to be negligible. This 'lack of validity' confirms the findings of Liu and Lee (1997), who found that (in their factor analysis) no statistical significance existed in terms of risk classification for their "instalment-to-income" factor

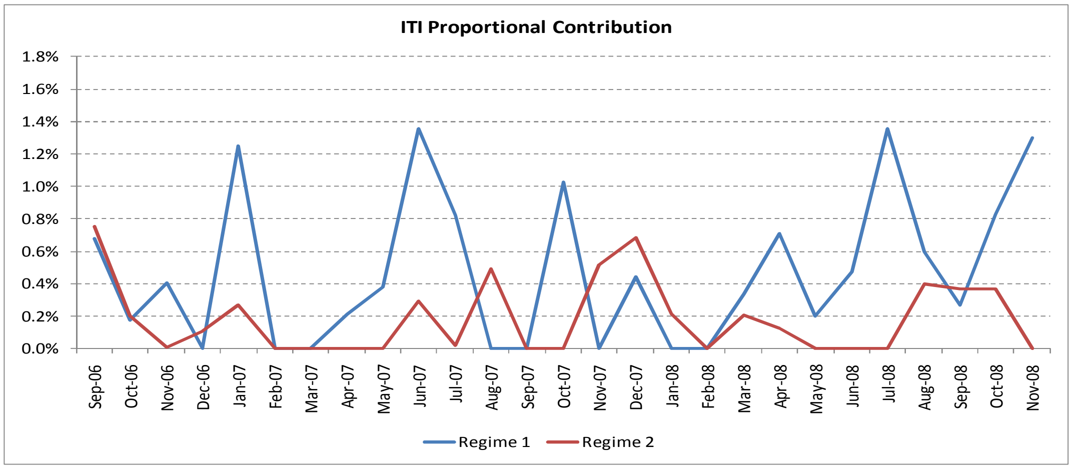


Figure 39: ITI Proportional Contribution

The rationale for this they mention is that this ratio is already tightly controlled by financial institutions, and this restriction in range of this variable may obscure its relevance to default risk.

Normally, this ITI ratio is capped at 30% by financial institutions and customers with an ITI > 30% would normally have gone through a rigorous credit underwriting procedure before their mortgage loan was granted. This explains why 93% of customers had an ITI < 30%. Given these tight underwriting standards, it explains why customers with higher ITI's show lower default rates than those in the 21 – 30% band.

5.5.1 *Conclusion relating to ITI*

Given the above, the *ITI variable is not a good differentiator of mortgage defaults.*

5.6 Interpretation of results relating to Borrower Income

The highest proportion of customers occurred within the R10, 000 – R19, 000 income bands. However from a default perspective, the highest proportion of customers existed within the <= R9, 000 income band. This category also showed the highest default rate. This can be explained by the fact that the majority of mortgages (from a South African context) are 'variable rate' mortgages. Variables rate mortgages are mortgages whose interest rates are linked to the prime lending rate. Therefore, un-anticipated increases in the cost of credit (i.e. interest rates) and other expenses will have an effect on household's ability to repay their mortgage, especially in the lower income brackets. This demographic (i.e. lower income) has much less disposable income available to accommodate sudden and unexpected income and expenditure shocks. This view is also held by (Ford and Wilcox 1998).

This is in contrast to the view held by Vandell and Thibodeau (1985) however, who found that although the level of income does not seem to be important in terms of predicting default, the source of income does matter. However, for both Regime 1 and 2, the results of the model indicated a negative co-efficient of the Borrower Income variable. This indicates that the lower the value of this variable, the more likely that a default event will occur. This is however inconsistent with the results of the descriptive statistics and views mentioned above. The implications of the negative co-efficient however, is in contrast to the findings of Van Order and Zorn (2000) who found that highest income borrowers (those at 200% or more of median income) are more likely to default than median-income borrowers (those at 81% to 120% of median) and about as likely as low-income borrowers (less than 60% of median).

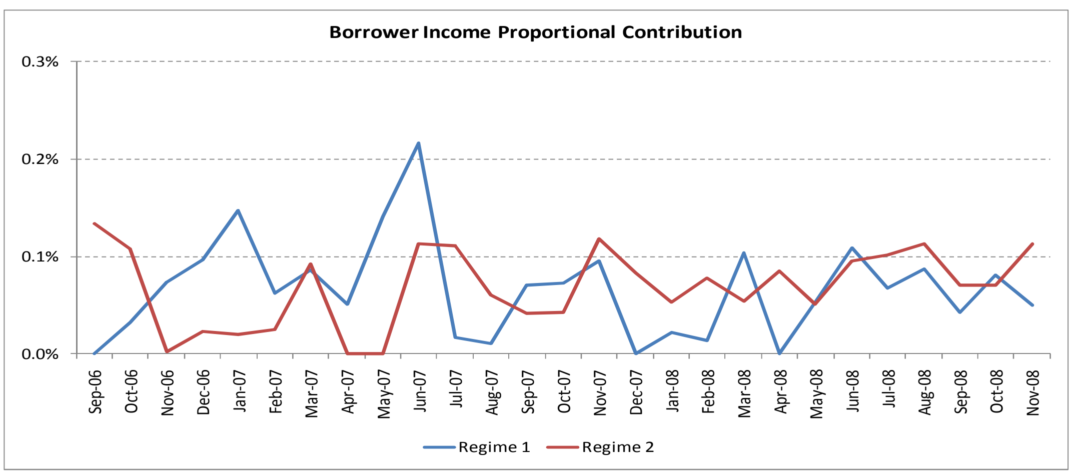


Figure 40: Borrower Income Proportional Contribution

From a proportional contribution perspective, for both Regime 1 and 2, the Borrower Income variable contributed 0.1% (on average) to the total model outcome (in terms of the scorecard and its associated ranking).

5.6.1 *Conclusion relating to Borrower Income*

Given the above, the *Borrower Income variable is not a good differentiator of mortgage defaults.*

5.7 Interpretation of results relating to Outstanding (loan) Balance

There is very little in the literature regarding the Balance Outstanding variable, and its associated impact on the ability to differentiate mortgage defaults. In formulating the scorecard model on paper (at the outset of the research), this variable repeatedly manifested itself as a significant contributor in predicting defaults.

An example of this formulation on paper (the process thereof) as follows:

- A sample of customers was randomly selected and without knowing their default status, the researcher (manually) predicted which ones would have defaulted, based on their respective characteristics i.e. Current LTV, Borrower Income, ITI, and Account & Customer Age.

More often than not, one of the reasons why a customer was chosen as a defaulted one was due to a combination of the above variables (in varying levels), but also as a result of a relatively high balance outstanding. Therefore, when building the Excel and Solver model this variable was included, even though it's importance was not apparent in the review on the literature on the subject of mortgage default modelling.

From a descriptive statistics perspective, the highest proportion of customers occurred within the <=R250k Balance Outstanding band. As expected, this category also showed the highest proportion of defaults. However this proportion reduced from 62% in December 2006 to 31% by December 2008. As at December 2006 and December 2007, the <=R250k, the R3m – R4m and the >R4m categories had the highest default rate. By December 2008 however this proportion was evident in the R3m – R4m which had a default rate of 10%. Also, the > R4m and the R2m – R3m category had default rates of 9% and 8%

respectively. This increase in the default rate can be attributed to the fact that the absolute value impact (of an increase in the interest rate) on borrower's instalments ,is much higher for the higher Balance Outstanding mortgages than on the 'smaller' Balance Outstanding loans.

Table 9: Difference in monthly instalments for varying Balances Outstanding

Balance Outstanding	*Instalment at 10%*	*Instalment at 11%*	*Instalment at 12%*	*Difference in Instalment (10% - 12%)*
R250,000	R2,412	R2,580	R2,752	R340
R500,000	R4,825	R5,160	R5,505	R680
R2,000,000	R19,300	R20,644	R22,021	R2,721
R4,000,000	R38,600	R41,288	R44,043	R5,443

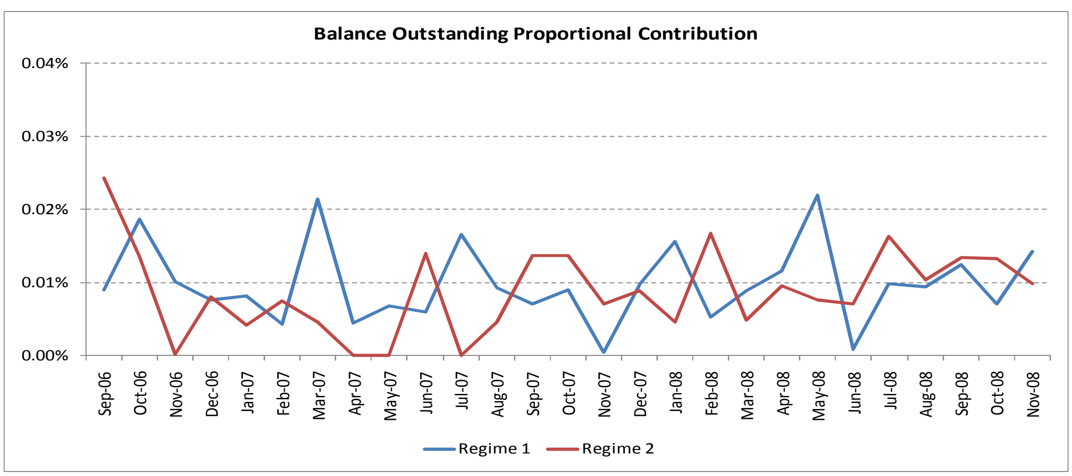


Figure 41: Balance Outstanding Proportional Contribution

For both Regime 1 and 2, the results of the model indicated a positive co-efficient of the Balance Outstanding variable. This indicates that the higher the value of this variable, the more likely that a default event will occur. From a proportional contribution perspective, for both Regime 1 and 2, this variable contributed 0.01% (on average) to the total model outcome (in terms of the scorecard and its associated ranking). As mentioned above, given the lack of literature around the impact of Balance Outstanding on the ability to differentiate mortgage defaults, it is difficult to validate these findings against previous research. What is evident however is that according to the scorecard and ranking model employed in this research, this variable was by far the smallest contributor, to the model's ability to differentiate mortgage defaults.

5.7.1 *Conclusion relating to Balance Outstanding*

Given the above, the *Balance Outstanding variable is not a good differentiator of mortgage defaults.*

5.8 Conclusion

Based on the review of the literature surrounding mortgage defaults, five hypotheses were formulated. Only 1 of the 5 variables was found to be a good differentiator of mortgage default. Additionally a new variable (not in the original hypotheses) was also found not to be a good differentiator of defaults.

For both Regime 1 and 2, the results of the model indicated a positive co-efficient for the *Current LTV* variable. In terms of the proportional contribution to the model, for both Regime 1 and 2, the Current LTV variable contributed 97% (on average) to the total model outcome. Given its high contribution to the model (97%), the Current LTV variable on its own was a close approximation to the Scorecard and Ranking model of defaults. This suggests that a close approximation to the 'best fit' of defaults could have been obtained simply by ranking the Current LTV variable only (and excluding the other variables). The implication of this is that the other variables could have been excluded with a very similar model outcome which raises questions about the validity of the other variables.

Therefore given the insights gained from the descriptive statistics, the sign of the co-efficient (i.e. positive) and its contribution to the scorecard model, the

Current LTV variable is a good and by far the most relevant differentiator of mortgage defaults.

For Regime 1 and 2, the results of the model indicated a positive co-efficient for the *Account Age* variable. However, in terms of the proportional contribution to the model for both Regime 1 and 2, the Account Age variable contributed only 0.9% (on average) to the total model outcome (in terms of the scorecard and its associated ranking). Thus, the validity of this variable is called into question in that its contribution to the total customer *score* was found to be negligible. Given the above, the *Account Age variable is not a good differentiator of mortgage defaults.*

For both Regime 1 and 2, the results of the model indicated a positive co-efficient for the *Borrower Age* variable. However, in terms of the proportional contribution to the model for both Regime 1 and 2, the Borrower Age variable contributed only 1.4% (on average) to the total model outcome (in terms of the scorecard and its associated ranking). Thus, the validity of this variable is called into question in that its contribution to the total customer *score* was found to be negligible. Given the above, the *Customer Age variable is not a good differentiator of mortgage defaults.*

From a proportional model contribution perspective, for both Regime 1 and 2, the *ITI* variable contributed only 0.3% (on average) to the total model outcome (in terms of the scorecard and its associated ranking). Therefore, the validity of this variable is also called into question in that its contribution to the total customer *score* was found to be negligible. Given the above, the *ITI variable is not a good differentiator of mortgage defaults.*

For both Regime 1 and 2, the results of the model indicated a negative co-efficient of the *Borrower Income* variable. From a proportional contribution perspective, for both Regime 1 and 2, the Borrower Income variable contributed 0.1% (on average) to the total model outcome (in terms of the scorecard and its associated ranking). Given the above, the *Borrower Income variable is not a good differentiator of mortgage defaults.*

There was very little in the literature regarding the Balance Outstanding variable, and its associated impact on the ability to differentiate mortgage defaults. However in formulating the scorecard model on paper (i.e. manually), this variable repeatedly manifested itself as a potential contributor to predicting defaults.

For both Regime 1 and 2, the results of the model indicated a positive co-efficient of the *Balance Outstanding* variable. From a proportional contribution perspective, for both Regime 1 and 2, this variable contributed 0.01% (on average) to the total model outcome (in terms of the scorecard and its associated ranking). Given the lack of literature around the impact of Balance Outstanding on the ability to differentiate mortgage defaults, it was difficult to validate these findings against previous research.

What was evident however was that according to the scorecard and ranking model employed in this research, this variable was by far the smallest contributor, to the model's ability to differentiate mortgage defaults. Given the above, the *Balance Outstanding variable is not a good differentiator of mortgage defaults.*

6 CHAPTER 6: CONCLUSIONS AND RECOMMENDATION

6.1 Introduction

The first part of this chapter summarises the findings and conclusions of this research, in relation to the context specified at the beginning. The second part of this chapter deals with any recommendations to the stakeholders identified earlier. The last part of this chapter highlights suggestions for further research.

6.2 Conclusions of the study

The purpose of this research was to evaluate and distinguish between mortgage specific factors driving mortgage default patterns in South Africa. This was further disaggregated into identifying borrower and loan specific factors, driving mortgage default rates.

Contextually, during mid-June 2006, the upward trend of the interest rate cycle commenced. The 500 basis points increase in the interest rate between mid-2006 and mid-2008 placed strain on the South African economy in general, and mortgage holders in particular. This resulted in 2008 being the first year since 1999 that house prices dropped in real terms on an annual basis. As a result of this environment of increasing interest rates; high food and fuel prices; and overall downturn in the economy (end 2007 and onwards) banks in South Africa experienced an increase in the size of their mortgage default portfolios. Therefore, accurate forecasts of mortgage defaults were important in calculating the impact of defaults on bank’s mortgage portfolios, on their bottom line profit, as well as the impact on the housing market in general.

6.3 Variables contributing to Effective Mortgage Default Modelling

The following six variables were identified and hypothesised as those contributing directly to mortgage defaults:

Hypothesis 1:

The LTV (Current) ratio is a good differentiator of mortgage defaults.

Hypothesis 2:

The Age of the mortgage (in months since loan origination) is a good differentiator of mortgage defaults.

Hypothesis 3:

Borrower age (in years) is a good differentiator of mortgage defaults.

Hypothesis 4:

Borrower Instalment-to-income ratio is a good differentiator of mortgage defaults.

Hypothesis 5:

Borrower income is a good differentiator of mortgage defaults.

Although the Balance Outstanding variable was not that evident (from the review of the literature) as a differentiator of mortgage defaults, the researcher introduced this variable into the model after insight gained from the descriptive statistics, and attempting to 'manually' (at the outset of the research when investigating an appropriate model) predict defaults.

Thus, the 6^{th} hypothesis:

Balance (Loan) Outstanding is a good differentiator of mortgage defaults.

Current LTV was also found to be the critical and by far the largest contributor to the model's ability to differentiate defaults. It was found that the higher the Current LTV, the more likely that the Borrower would default. This finding is in line with conventional wisdom in the mortgage industry, in that loan-to-value ratios are positively correlated with mortgage default.

The Age of the mortgage (i.e. account age in months since loan origination), Instalment to Income (ITI), Borrower age (years), Borrower Income and Balance Outstanding were found to be irrelevant in contributing to the model's ability to differentiate mortgage defaults. These 5 elements combined, contributed 3.6% and 2.7% for Regime 1 and 2 respectively to the total model outcome, thereby rendering them largely irrelevant. Also, Balance (Loan) Outstanding was found to be the variable having the least impact on the model's ability to differentiate mortgage defaults.

In summary, given that Current LTV (loan characteristic), was found to be the only dependable variable in differentiating mortgage defaults, the researcher concludes that only "Loan" characteristic impact on mortgage defaults in South Africa. The researcher also concludes that it is the "equity" theory that singularly describes mortgage defaults, and not the "ability to pay" theory of default.

6.4 Recommendations

As indicated in Chapter 1, this study aimed to provide guidance to the South African banking industry (i.e. banking institutions), the South African Reserve Bank (policy maker and regulator), and the broader South African population in general. In addition, it was mentioned that the results of the study can be utilised by banking institutions as inputs into their origination scorecard models, policy rules and risk-based pricing models.

From a South African Reserve Bank (SARB) perspective, this study can provide guidance in terms of the level of risk in the various Banks' mortgage portfolios. In other words, if certain portfolios are concentrated towards riskier ones, this can aid the Reserve Bank in identifying these pockets and insisting on a higher capital requirement for those lending institutions. This is to ensure that depositors have a certain degree of protection when depositing their money with a Bank. The SARB can also use this research to institute caps on mortgage portfolio's to ensure that certain levels (in terms of borrower and loan characteristics) are not breached.

From a banking industry perspective, the results of this research can provide input into Basel II risk rating models by segmenting the portfolio into various risk categorise. The benefit of this, is that it can aid Banks in achieving the Basel II "Advanced" risk rating approach rather than the "Standardised" one which requires Banks to hold a lower level of capital. Additionally, Banks will have a better understanding of their portfolios which will aid in identifying lower risk segments for cross-sell opportunities.

Also, local Banks can use this research to aid in developing origination scorecard models, where historic default (as modelled by this research) characteristics can be used as inputs into these origination models. Also, from a risk-based pricing perspective, Bank's will have a better idea of which customers to price higher than others.

In terms of adding value to the broader South African public, the results of this research can aid the public in firstly understanding the mortgage industry, the various characteristics of mortgages to understand and look out for when making the decision to purchase a home. If the public understand those factors that contribute largely to defaults, they will be better informed in terms of making a home purchase decision, which could have a stabilising effect on the economy in general. The findings of this research will also assist the public in having a better understanding of their relative risk which will aid them in obtaining the best pricing on their mortgage loan.

6.5 Suggestions for further research

One of the outcomes of research (apart from adding to the body of knowledge on a particular topic) is areas for further research. The following are recommended areas for further research, in the area of mortgage default modelling:

An important area often over-looked in this field, is the purpose for which a home is bought. It may be that the default profile of an owner-occupied home (owner lives on the property) versus a buy-to-let home (bought for the purpose of letting out to tenants) will be different.

Another potential area for further research, is the impact that mortgage originators (3rd party mortgage loan 'middle-men') have had on the mortgage industry in general (from a pricing and structural perspective) as well as the performance (from a default perspective) of these loans relative to those originated through Bank's branch networks.

The model used in this research can also be expanded to include more characteristics of homeowners as inputs into the model:

- Race of homeowner (especially within a South African context)
- First time home buyer or not
- The number of dependants the head of the household has
- Term of the mortgage i.e. different contract maturities
- Social class of head of household
- Female versus male household heads.

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APPENDIX A

Microsoft Excel Model Input Screen

Co-efficients - Changing Variables

Betas	
BetaAge	0.00
BetaBtv	8,150.21
BetaIncome	-51.88
BetaITI	145.27
BetaLifeMonths	566.96
BetaBalance	8.11

Regimes : Input Variables

Regimes	
TheDate	31 Oct 2008
Employment	S
CleanSlate	TRUE
AgeLow	36
AgeHigh	100
LtvCutOff	98

Model Output

Model Success	17.0%

APPENDIX B

Visual Basic for Applications (VBA) Code

```
Option Explicit
Dim wsp As Workspace
Dim db  As Database
Dim rs  As Recordset
Function ModelSuccess(TheDate As Date, _
                Employment As String, _
                CleanSlate As Boolean, _
                AgeLow As Long, _
                AgeHigh As Long, _
                LtvCutoff As Double, _
_                 BetaBtv As Double, _
                BetaITI As Double, _
                BetaIncome As Double, _
                BetaAge As Double, _
                BetaLifeMonths As Double, _
                BetaChangeLtv1 As Double, _
                BetaChangeLtv2 As Double, _
                BetaBalance As Double)

   Dim Intersection    As Recordset
   Dim Guesses         As Recordset
   Dim NextMonth       As Date
   Dim Query           As String
   Dim x
   Dim qGuesses        As String
   Static Table        As CollectionX
   Dim sl              As StrucLoan
   Dim i               As Long
   Dim PrevCumDefaults As Long
   Dim Area            As Double
   Dim NumberOfDefaults As Long
```

```
            If Table Is Nothing Then
    InitialiseMe
        NextMonth = MyEoMonth(TheDate, 1)
        Query = ""
    Query = Query + "Select MS3.*, MSD.Default_Status As
FinalDefaultStatus "
        Query = Query + "From MortgageStatus As MS3 "
        Query = Query + " Inner Join MortgageStatus As MSD On
MS3.Acc_Num = MSD.Acc_Num "
        Query = Query + "Where "
    Query = Query + "    MS3.Date=#" & Format(TheDate, "yyyy/mm/dd") & "#
AND "
    Query = Query + "    MSD.Date=#" & Format(NextMonth, "yyyy/mm/dd") &
"#        AND "
        Query = Query + "                MS3.Default_status=""0""
AND "
        Query = Query + "    MS3.[Employment Status]='" & Employment & "'
AND "
        Query = Query + "        MS3.CleanSlate=" & CleanSlate & "
AND "
        Query = Query + "    MS3.Cust_Age<=" & Format(AgeHigh, "0") & "
AND "
    Query = Query + "      MS3.Cust_Age>" & Format(AgeLow, "0") & "
AND "
        Query = Query + "    MS3.Current_LTV>=" + Format(LtvCutoff, "0") +
"          AND "
    Query = Query + "    MS3.Current_LTV>=" + Format(LtvCutoff, "0") + " "
        Set Guesses = db.OpenRecordset(Query)
        Set Table = New CollectionX
        With Guesses
      .MoveFirst
      Do While Not .EOF
        Set sl = New StrucLoan
          sl.BalToVal = !Current_LTV
          sl.CurDate = !Date
          sl.CustomerAge = !Cust_Age
```

```
            sl.DateLastReg = !Last_Reg
            sl.DefaultStatus = IIf(!FinalDefaultStatus.Value = "0", 0, 1)
            sl.Income = !Income
            sl.ITI = !ITI
            sl.Life = (sl.CurDate - sl.DateLastReg) / 365.25 * 12
            sl.Balance = !Bal
                        Table.Add sl
                  .MoveNext
      Loop
   End With
End If
                  For Each sl In Table
   With sl
      .Logistic = BetaAge * .CustomerAge + _
               BetaBtv * .BalToVal + _
               BetaIncome * Log(.Income) + _
               BetaITI * .ITI + _
               BetaLifeMonths * .Life + _
               BetaBalance * Log(.Balance) + _
               BetaChangeLtv1 * .LtvChange1 + _
               BetaChangeLtv2 * .LtvChange2
   End With
Next
                  Table.Sort New derefLogistic, "Descending"
                  i = 0
Area = 0
NumberOfDefaults = 0
For Each sl In Table
   i = i + 1
   With sl
      .Rank = i
      If i = 1 Then
         .CumDefaults = .DefaultStatus
      Else
         .CumDefaults = PrevCumDefaults + .DefaultStatus
      End If
```

```
                .PctDefault = .CumDefaults / .Rank
            NumberOfDefaults = NumberOfDefaults + .DefaultStatus
                'Area = Area + .PctDefault * (Log(i + 1) - Log(i))
            'Area = Area + .PctDefault * (1)
            Area = Area + .Rank * .DefaultStatus
                PrevCumDefaults = .CumDefaults
        End With
    Next
        ModelSuccess = Area / NumberOfDefaults / Table.Size
                    Beep
End Function
Sub ModelSuccessDump()
    Dim TheDate As Date
    Dim Employment As String
    Dim CleanSlate As Boolean
    Dim AgeLow As Long
    Dim AgeHigh As Long
    Dim LtvCutoff As Double
    Dim BetaBtv As Double
    Dim BetaITI As Double
    Dim BetaIncome As Double
    Dim BetaAge As Double
    Dim BetaLifeMonths As Double
    Dim BetaBalance As Double
    Dim BetaChangeLtv1 As Double
    Dim BetaChangeLtv2 As Double
    Dim Intersection    As Recordset
    Dim Guesses         As Recordset
    Dim NextMonth       As Date
    Dim Query           As String
    Dim x
    Dim qGuesses        As String
    Static Table        As CollectionX
    Dim sl              As StrucLoan
    Dim i               As Long
    Dim PrevCumDefaults As Long
```

```
Dim Area            As Double
Dim ws              As Worksheet
Dim r               As Long
TheDate = Range("TheDate")
Employment = Range("Employment")
CleanSlate = Range("CleanSlate")
AgeLow = Range("AgeLow")
AgeHigh = Range("AgeHigh")
LtvCutoff = Range("LtvCutoff")
BetaBtv = Range("BetaBtv")
BetaITI = Range("BetaITI")
BetaIncome = Range("BetaIncome")
BetaAge = Range("BetaAge")
BetaLifeMonths = Range("BetaLifeMonths")
BetaBalance = Range("BetaBalance")
BetaChangeLtv1 = Range("BetaChangeLtv1")
BetaChangeLtv2 = Range("BetaChangeLtv2")
                If Table Is Nothing Then
  InitialiseMe
      NextMonth = MyEoMonth(TheDate, 1)
      Query = ""
  Query = Query + "Select MS3.*, MSD.Default_Status As FinalDefaultStatus "
      Query = Query + "From MortgageStatus As MS3 "
      Query = Query + " Inner Join MortgageStatus As MSD On MS3.Acc_Num = MSD.Acc_Num "
      Query = Query + "Where "
  Query = Query + "    MS3.Date=#" & Format(TheDate, "yyyy/mm/dd") & "# AND "
  Query = Query + "    MSD.Date=#" & Format(NextMonth, "yyyy/mm/dd") & "#        AND "
      Query = Query + "                    MS3.Default_status=""0"" AND "
      Query = Query + "    MS3.[Employment Status]='" & Employment & "' AND "
```

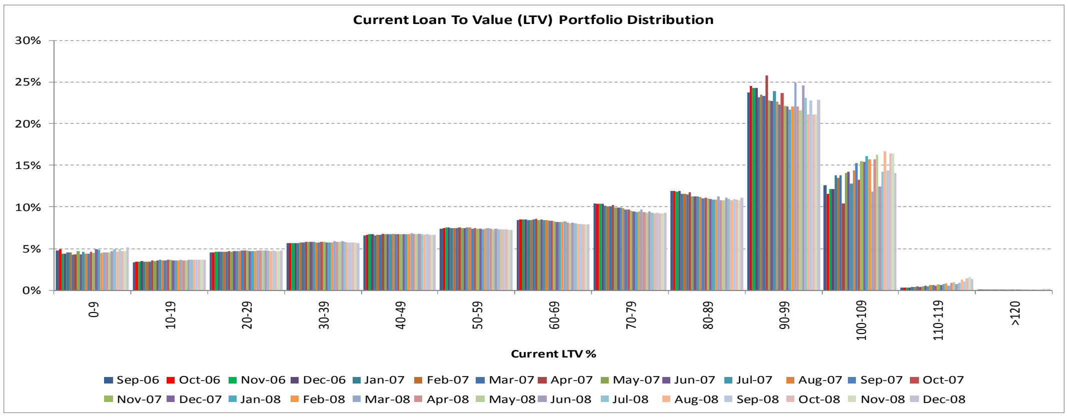
```
            Query = Query + "        MS3.CleanSlate=" & CleanSlate & "
AND "
            Query = Query + "    MS3.Cust_Age<=" & Format(AgeHigh, "0") & "
AND "
      Query = Query + "       MS3.Cust_Age>" & Format(AgeLow, "0") & "
AND "
            Query = Query + "    MS3.Current_LTV>=" + Format(LtvCutoff, "0") +
"          AND "
      Query = Query + "    MS3.Current_LTV>=" + Format(LtvCutoff, "0") + " "
            Set Guesses = db.OpenRecordset(Query)
            Set Table = New CollectionX
            With Guesses
         .MoveFirst
         Do While Not .EOF
            Set sl = New StrucLoan
               sl.BalToVal = !Current_LTV
               sl.CurDate = !Date
               sl.CustomerAge = !Cust_Age
               sl.DateLastReg = !Last_Reg
               sl.DefaultStatus = IIf(!FinalDefaultStatus.Value = "0", 0, 1)
               sl.Income = !Income
               sl.ITI = !ITI
               sl.Life = (sl.CurDate - sl.DateLastReg) / 365.25 * 12
               sl.Balance = !Bal
               sl.LtvChange1 = !BalToValChg1
               sl.LtvChange2 = !BalToValChg2
                           Table.Add sl
                     .MoveNext
         Loop
      End With
   End If
                     For Each sl In Table
      With sl
         .Logistic = BetaAge * .CustomerAge + _
                  BetaBtv * .BalToVal + _
                  BetaIncome * Log(.Income) + _
```

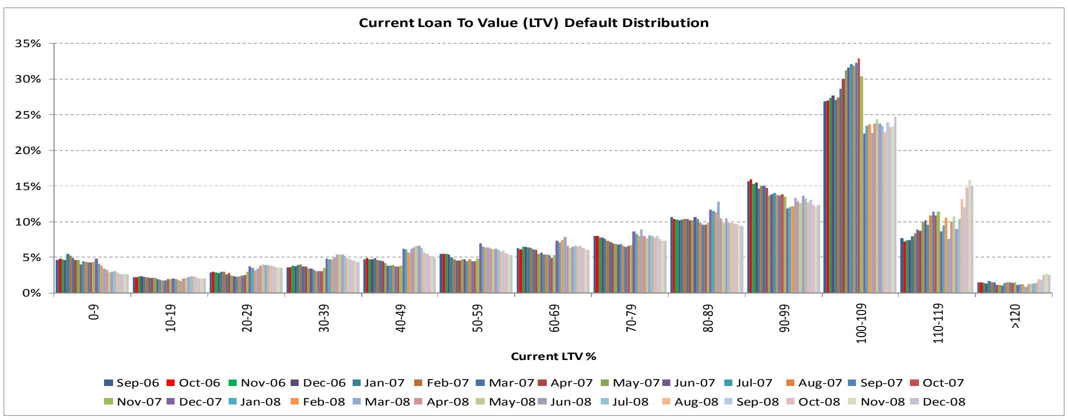
```
                BetaITI * .ITI + _
                BetaLifeMonths * .Life + _
                BetaBalance * Log(.Balance) + _
                BetaChangeLtv1 * .LtvChange1 + _
                BetaChangeLtv2 * .LtvChange2
    End With
Next
                    Table.Sort New derefLogistic, "Descending"
                    i = 0
Area = 0
For Each sl In Table
    i = i + 1
    With sl
        .Rank = i
        If i = 1 Then
            .CumDefaults = .DefaultStatus
        Else
            .CumDefaults = PrevCumDefaults + .DefaultStatus
        End If
                .PctDefault = .CumDefaults / .Rank
                Area = Area + .PctDefault * (Log(i + 1) - Log(i))
                PrevCumDefaults = .CumDefaults
    End With
Next
    Set ws = Worksheets.Add
    r = 1
ws.Cells(r, 1) = "Rank"
ws.Cells(r, 2) = "PctDefault"
ws.Cells(r, 3) = "Logistic"
ws.Cells(r, 4) = "DefaultStatus"
ws.Cells(r, 5) = "Balance"
ws.Cells(r, 6) = "BalToVal"
ws.Cells(r, 7) = "Income"
ws.Cells(r, 8) = "Life"
ws.Cells(r, 9) = "ITI"
ws.Cells(r, 10) = "CustomerAge"
```

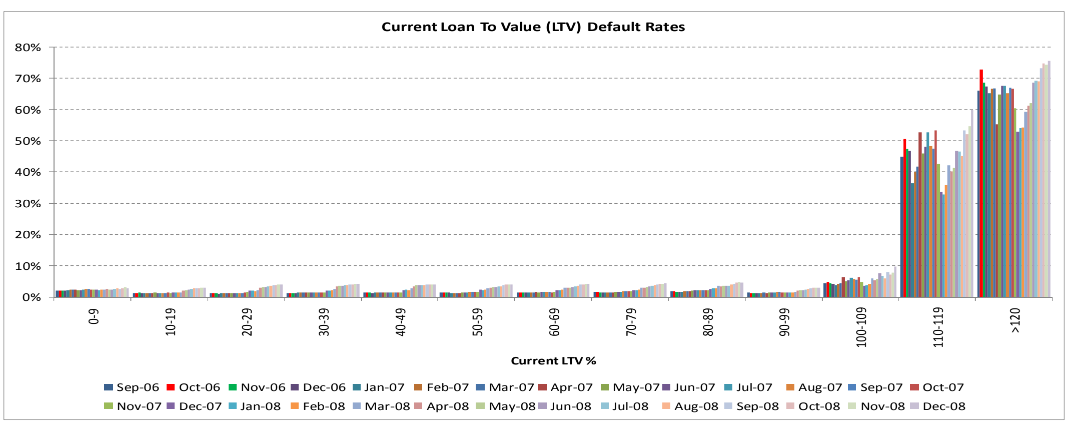
```
        ws.Rows(1).Font.Bold = True
          r = 2
        For Each sl In Table
        ws.Cells(r, 1) = sl.Rank
        ws.Cells(r, 2) = sl.PctDefault
        ws.Cells(r, 3) = sl.Logistic
        ws.Cells(r, 4) = sl.DefaultStatus
        ws.Cells(r, 5) = sl.Balance
        ws.Cells(r, 6) = sl.BalToVal
        ws.Cells(r, 7) = sl.Income
        ws.Cells(r, 8) = sl.Life
        ws.Cells(r, 9) = sl.ITI
        ws.Cells(r, 10) = sl.CustomerAge
            r = r + 1
    Next
End Sub
```

APPENDIX C: DESCRIPTIVE STATISTICS

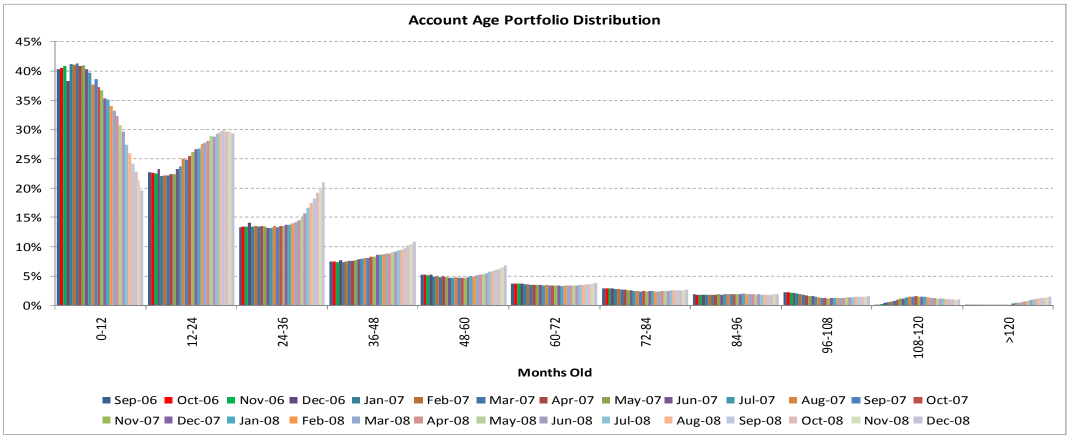
Current LTV Graphs

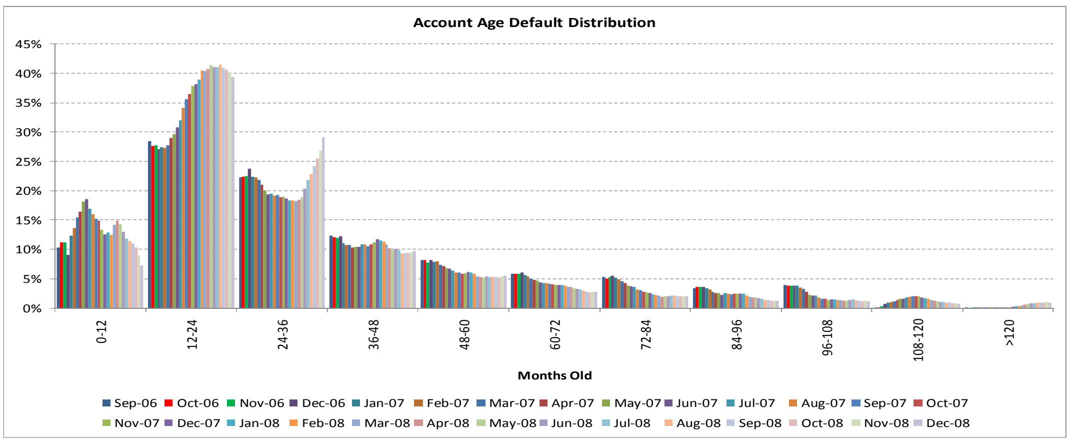


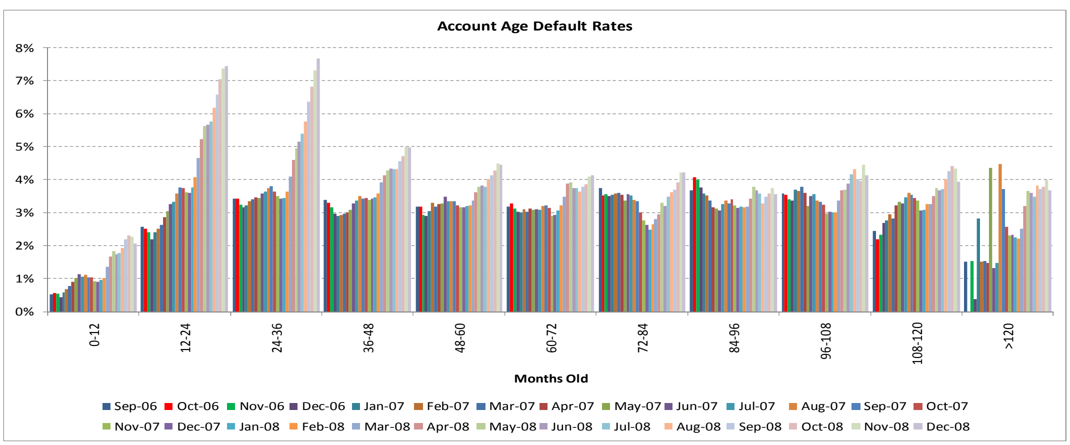




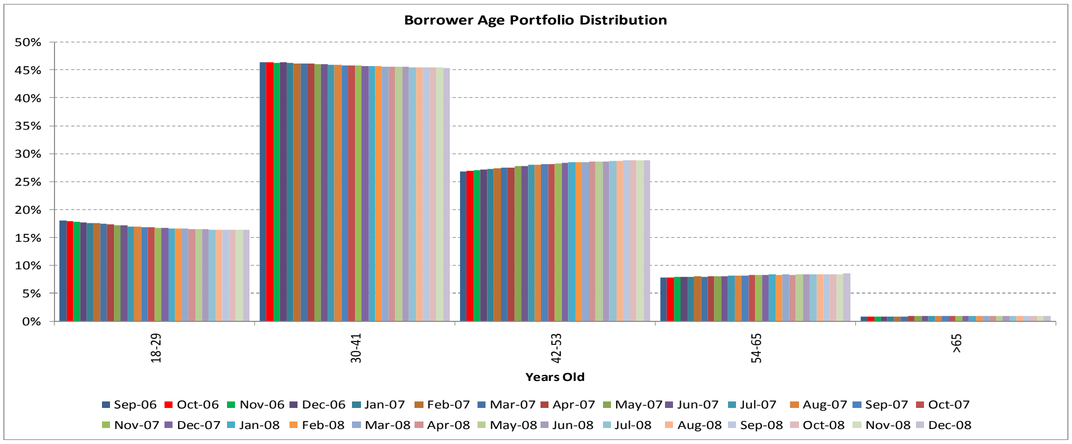
Account Age Graphs (Months since loan registration)

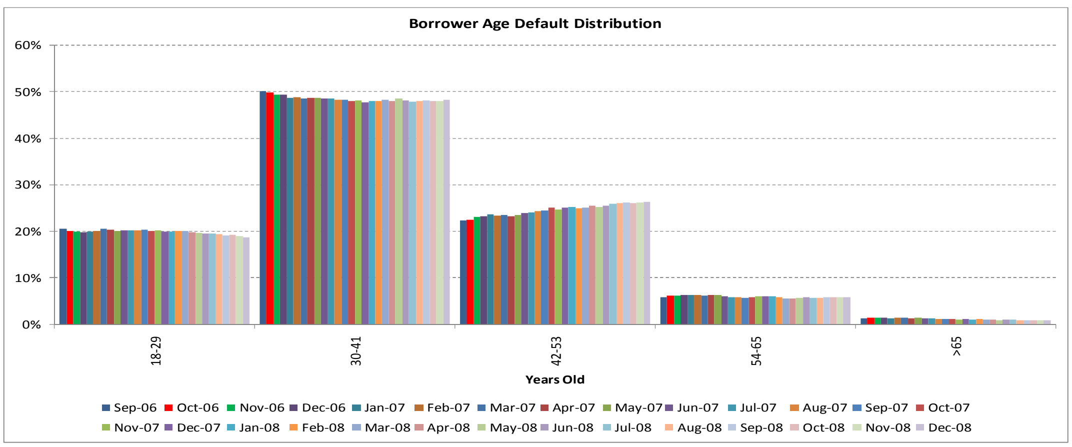


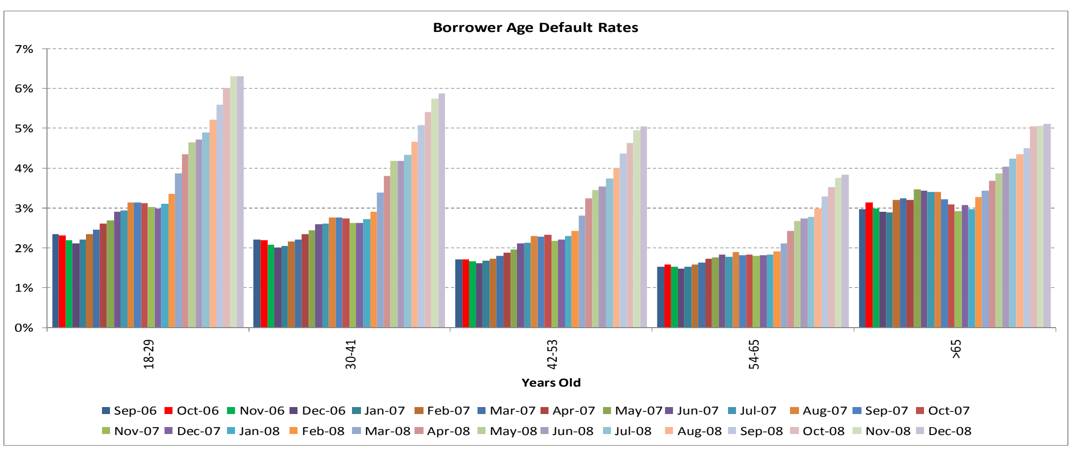




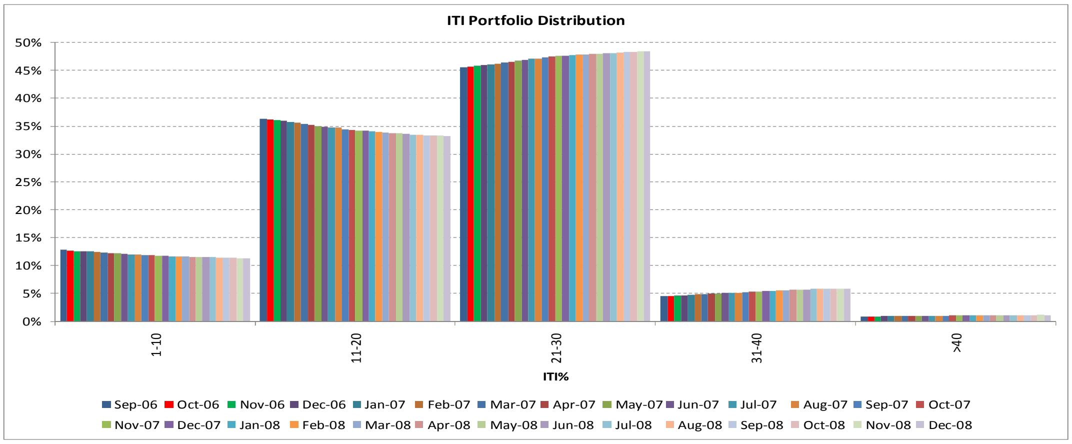
Borrower Age graphs (Years Old)

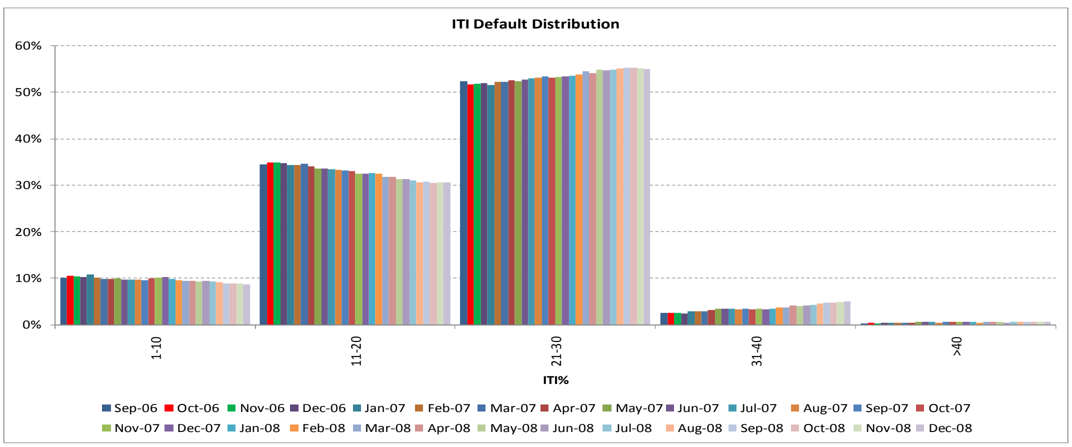


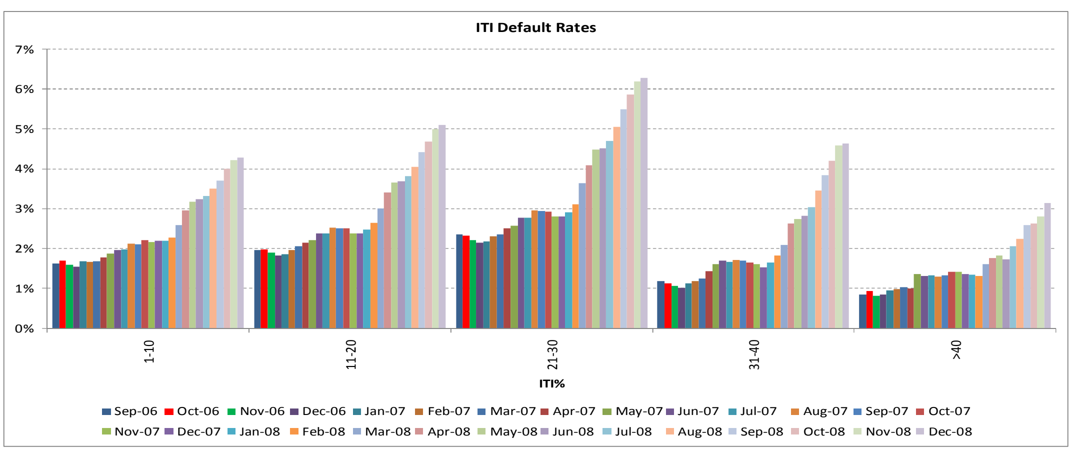




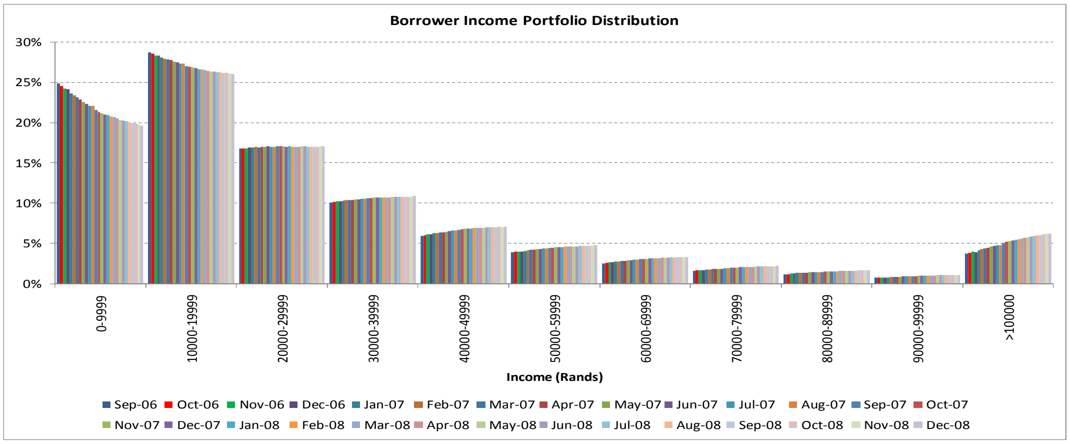
Instalment to Income (ITI) graphs

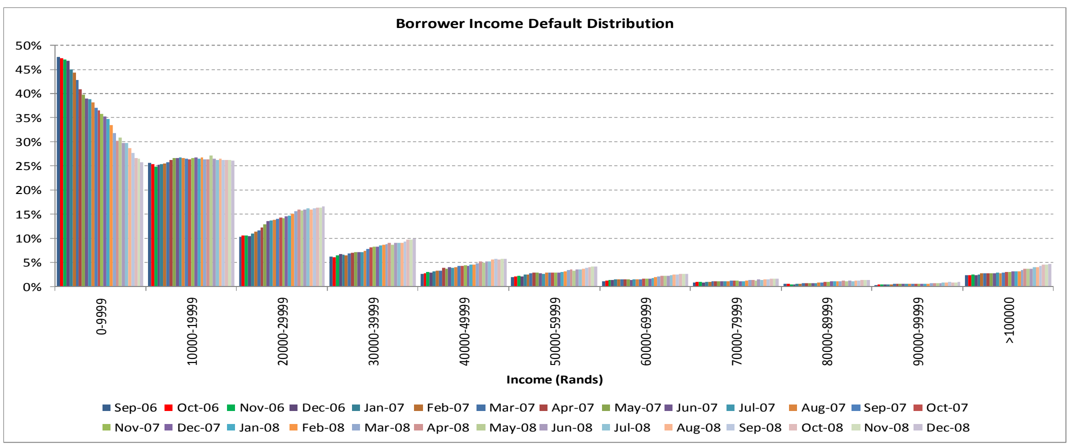


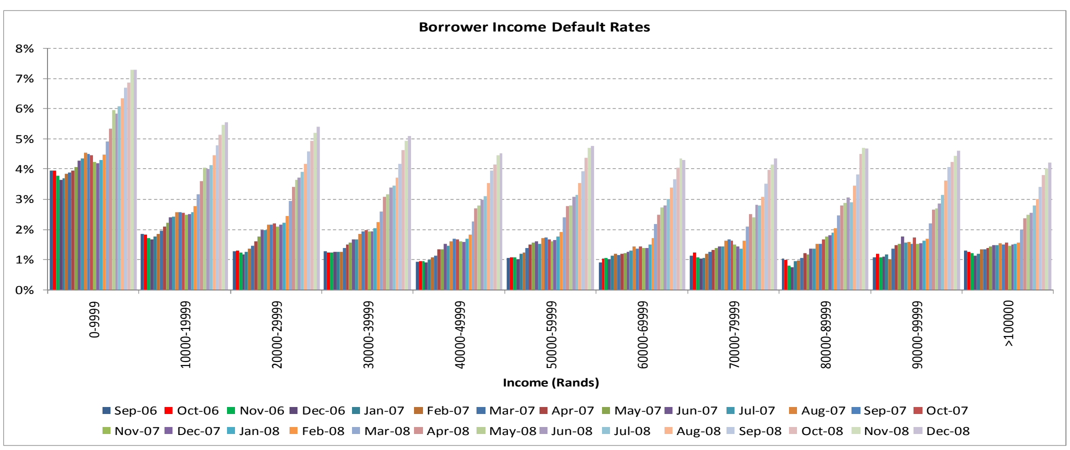




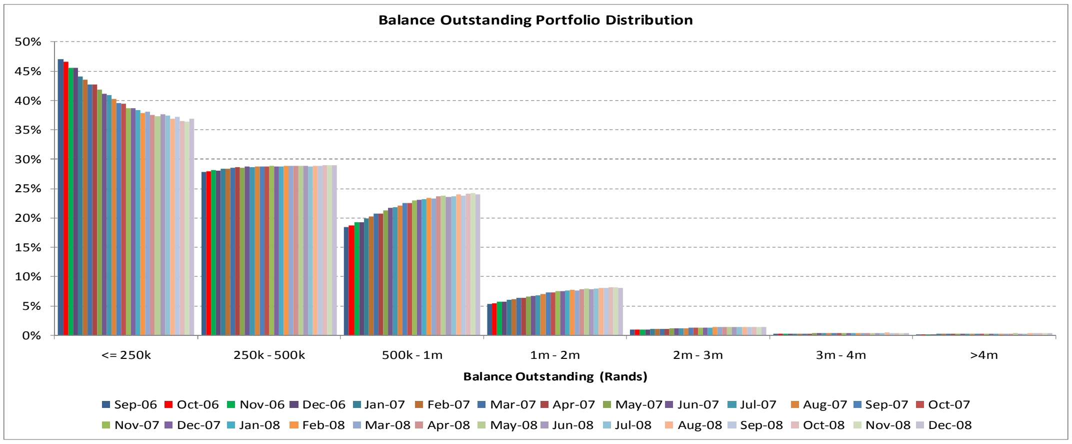
Borrower Income graphs

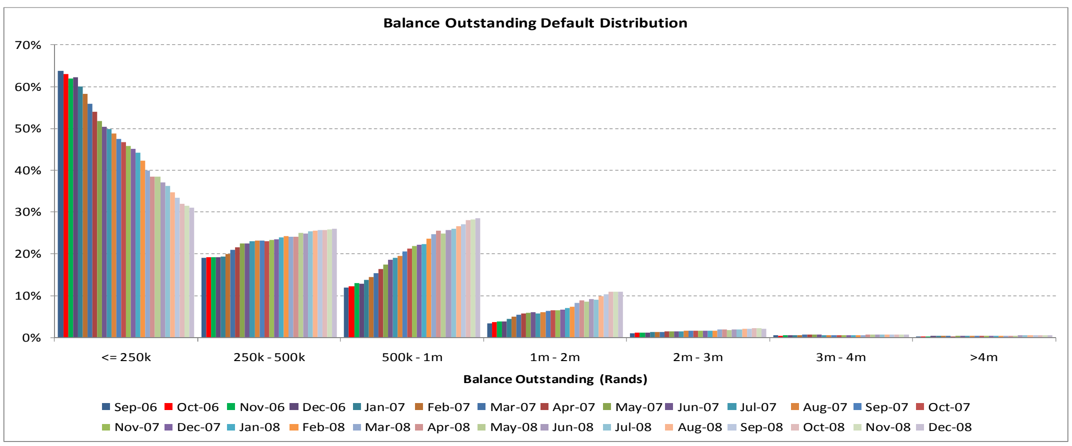


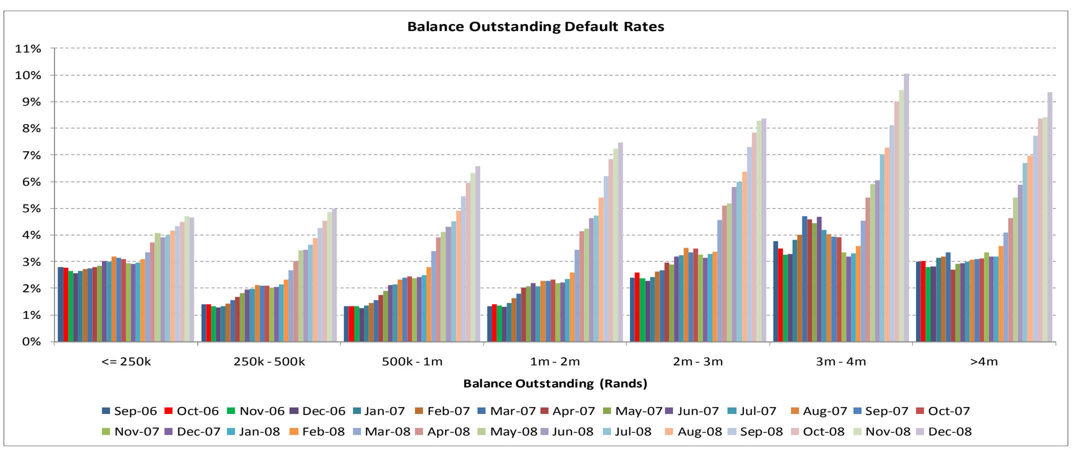




Balance Outstanding Graphs







APPENDIX D

Regime 1 Co-efficient, Scorecard and Proportional Contribution

	Sep-06	Oct-06	Nov-06	Dec-06	Jan-07	Feb-07	Mar-07	Apr-07	May-07	Jun-07	Jul-07	Aug-07	Sep-07
Co-efficient													
Current LTV	8,073.39	3,072.66	6,559.31	6,829.63	6,744.45	6,974.43	5,248.20	6,518.10	7,432.28	2,320.81	7,825.63	7,672.11	10,000.00
Borrower Age	5.92	532.08	482.06	923.79	966.40	747.35	849.76	-	189.16	-	555.60	965.89	48.73
Account Age	933.07	999.86	646.42	553.16	427.79	370.38	215.41	925.52	986.40	987.54	527.16	607.03	223.75
Borrower Income	-	10.21	43.91	64.46	98.84	42.06	44.55	31.36	100.00	49.50	12.35	7.95	65.66
ITI	270.35	27.88	117.45	-	430.99	-	0.00	67.44	137.38	158.48	316.87	-	-
Balance Outstanding	5.50	4.65	4.81	4.11	4.37	2.31	8.84	2.21	3.87	1.09	10.00	5.51	5.29
Model Score *(Coefficient * Value of variable)*													
Current LTV	814,657	309,647	612,691	688,742	681,491	704,362	530,253	656,975	750,849	234,481	787,921	773,739	1,009,722
Borrower Age	181.70	16,314.43	14,812.33	28,343.80	29,674.33	22,934.20	26,099.69	-	5,819.97	-	17,096.78	29,734.34	1,499.93
Account Age	8,880	9,134	7,138	5,588	4,187	3,611	2,162	8,823	10,075	10,229	5,468	7,050	2,511
Borrower Income	-	109.90	473.10	694.94	1,069.25	455.89	483.69	340.67	1,089.78	539.53	134.77	86.78	718.24
ITI	5,628	585	2,575	-	9,053	-	0	1,436	2,914	3,373	6,726	-	-
Balance Outstanding	74.26	62.89	64.84	55.53	59.14	31.31	119.84	29.92	52.56	14.86	135.88	74.87	72.00
Total	829,421	335,853	637,754	723,425	725,534	731,395	559,119	667,604	770,800	248,637	817,483	810,685	1,014,523
Proportional Contribution													
Current LTV	98.22%	92.20%	96.07%	95.21%	93.93%	96.30%	94.84%	98.41%	97.41%	94.31%	96.38%	95.44%	99.53%
Borrower Age	0.02%	4.86%	2.32%	3.92%	4.09%	3.14%	4.67%	0.00%	0.76%	0.00%	2.09%	3.67%	0.15%
Account Age	1.07%	2.72%	1.12%	0.77%	0.58%	0.49%	0.39%	1.32%	1.31%	4.11%	0.67%	0.87%	0.25%
Borrower Income	0.00%	0.03%	0.07%	0.10%	0.15%	0.06%	0.09%	0.05%	0.14%	0.22%	0.02%	0.01%	0.07%
ITI	0.68%	0.17%	0.40%	0.00%	1.25%	0.00%	0.00%	0.22%	0.38%	1.36%	0.82%	0.00%	0.00%
Balance Outstanding	0.01%	0.02%	0.01%	0.01%	0.01%	0.00%	0.02%	0.00%	0.01%	0.01%	0.02%	0.01%	0.01%

	Oct-07	Nov-07	Dec-07	Jan-08	Feb-08	Mar-08	Apr-08	May-08	Jun-08	Jul-08	Aug-08	Sep-08	Oct-08	Nov-08
Co-efficient														
Current LTV	6,907.75	4,025.85	10,000.00	5,894.10	9,432.85	8,691.23	8,768.19	4,993.28	7,918.19	6,292.68	9,433.34	7,917.28	5,613.77	8,316.62
Borrower Age	154.00	257.93	653.48	2.40	10.49	193.16	416.82	967.28	-	793.96	96.27	693.20	923.46	0.00
Account Age	-	374.77	0.00	881.84	446.97	929.96	630.92	256.85	749.05	598.89	535.18	653.97	405.90	603.94
Borrower Income	47.30	36.39	0.30	11.94	12.22	84.11	-	25.96	80.73	41.59	76.99	32.01	45.06	38.85
ITI	342.15	-	214.58	-	0.00	141.11	301.10	50.23	180.99	431.55	272.94	105.90	237.27	528.66
Balance Outstanding	4.71	0.12	7.31	6.94	3.72	5.80	7.79	8.71	0.50	4.92	6.73	7.63	3.16	9.10
Model Score *(Coefficient * Value of variable)*														
Current LTV	695,682	407,380	1,009,588	595,881	953,871	875,302	885,939	506,289	799,519	635,387	957,768	801,331	569,771	844,409
Borrower Age	4,736.45	7,935.27	20,106.91	75.27	329.07	6,057.36	13,091.11	30,373.28	-	24,926.19	3,021.50	21,753.95	28,433.60	0.00
Account Age	-	4,219	0	11,155	5,768	11,850	8,575	3,536	10,892	8,709	8,043	9,909	6,541	10,147
Borrower Income	518.05	399.11	3.27	131.11	134.38	926.53	-	286.76	892.12	459.55	850.96	353.47	497.42	429.18
ITI	7,264	-	4,578	-	0	3,033	6,457	1,074	3,866	9,217	5,826	2,264	5,059	11,253
Balance Outstanding	64.09	1.63	99.59	94.58	50.68	79.10	106.26	118.87	6.76	67.05	91.85	103.99	43.10	123.91
Total	708,265	419,935	1,034,376	607,337	960,154	897,248	914,168	541,678	815,176	678,766	975,601	835,715	610,344	866,361
Proportional Contribution														
Current LTV	98.22%	97.01%	97.60%	98.11%	99.35%	97.55%	96.91%	93.47%	98.08%	93.61%	98.17%	95.89%	93.35%	97.47%
Borrower Age	0.67%	1.89%	1.94%	0.01%	0.03%	0.68%	1.43%	5.61%	0.00%	3.67%	0.31%	2.60%	4.66%	0.00%
Account Age	0.00%	1.00%	0.00%	1.84%	0.60%	1.32%	0.94%	0.65%	1.34%	1.28%	0.82%	1.19%	1.07%	1.17%
Borrower Income	0.07%	0.10%	0.00%	0.02%	0.01%	0.10%	0.00%	0.05%	0.11%	0.07%	0.09%	0.04%	0.08%	0.05%
ITI	1.03%	0.00%	0.44%	0.00%	0.00%	0.34%	0.71%	0.20%	0.47%	1.36%	0.60%	0.27%	0.83%	1.30%
Balance Outstanding	0.01%	0.00%	0.01%	0.02%	0.01%	0.01%	0.01%	0.02%	0.00%	0.01%	0.01%	0.01%	0.01%	0.01%

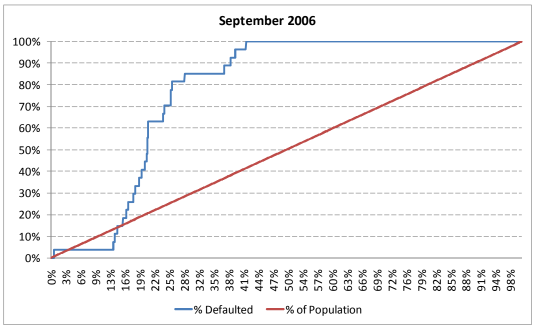
APPENDIX E

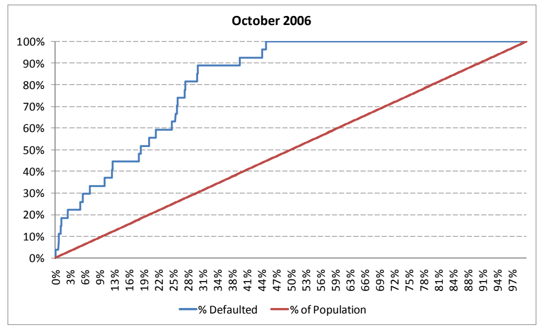
Regime 2 Co-efficient, Scorecard and Proportional Contribution

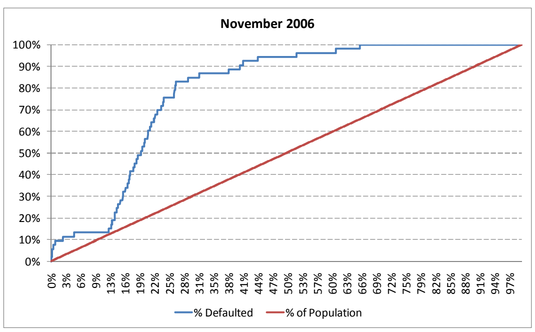
	Sep-06	Oct-06	Nov-06	Dec-06	Jan-07	Feb-07	Mar-07	Apr-07	May-07	Jun-07	Jul-07	Aug-07	Sep-07	Oct-07	Nov-07	Dec-07	Jan-08	Feb-08	Mar-08	Apr-08	May-08	Jun-08	Jul-08	Aug-08	Sep-08	Oct-08	Nov-08
Co-efficient																											
Current LTV	5,360.24	6,647.05	7,469.62	6,926.00	7,439.03	7,036.70	8,097.30	9,076.04	8,139.79	6,811.63	9,016.64	7,964.64	7,120.33	7,120.33	6,951.90	8,764.33	6,518.10	7,372.67	9,051.13	9,794.57	7,155.43	6,423.86	6,707.13	7,681.80	8,150.21	8,150.21	6,140.51
Borrower Age	182.91	577.92	177.95	197.62	219.82	7.07	267.15	51.73	367.15	-	249.61	1.66	12.78	12.78	306.90	463.18	-	187.14	0.00	381.11	548.93	11.00	-	-	-	-	-
Account Age	699.24	751.27	610.41	1,000.00	1,000.00	335.34	785.55	548.70	625.77	214.27	411.77	432.09	520.95	520.95	247.13	608.32	925.52	565.06	490.44	888.81	376.86	349.63	387.16	420.83	566.96	566.96	343.28
Borrower Income	67.86	68.29	45.60	15.00	13.90	16.16	68.95	0.00	64.28	70.04	91.66	43.89	27.17	27.17	76.02	67.92	31.36	52.58	43.57	76.71	34.21	54.84	60.84	78.69	51.88	51.88	62.66
ITI	205.24	67.55	80.59	37.61	100.72	0.00	0.00	119.51	138.13	98.53	8.15	191.58	0.02	0.02	177.72	300.76	67.44	0.00	89.04	60.70	-	-	-	148.68	145.27	145.27	-
Balance Outstanding	9.98	6.99	4.60	4.21	2.39	3.88	2.84	4.82	3.10	7.06	-	2.69	7.23	7.23	3.73	5.87	2.21	9.25	3.22	7.12	4.19	3.36	8.10	5.94	8.11	8.11	4.48
***Model Score** (Coefficient * Value of variable)*																											
Current LTV	538,895.67	667,288.93	26,236,177.34	695,702.57	748,319.22	707,466.49	814,333.75	205,485,571.84	150,614,277.41	685,118.96	903,961.37	799,506.80	715,240.16	713,279.68	699,709.26	879,965.29	655,621.82	741,601.63	906,766.34	984,660.66	721,573.80	644,059.19	673,535.83	775,674.26	820,414.34	822,366.86	620,311.13
Borrower Age	8,382.43	26,536.73	8,174.25	9,077.14	10,086.75	324.29	12,247.52	2,374.17	16,874.73	-	11,486.75	76.15	588.80	588.06	14,113.39	21,327.21	-	8,601.68	0.00	17,545.45	25,268.36	505.98	-	-	-	-	-
Account Age	6,508.63	6,618.52	6,074.63	9,854.46	9,535.34	3,210.80	7,672.45	5,052.89	6,254.87	2,196.02	4,258.08	5,024.74	5,807.26	5,810.66	2,720.62	7,173.34	11,515.56	7,213.19	6,066.40	11,913.24	5,065.29	4,720.67	5,590.49	6,284.73	8,542.83	9,090.67	5,758.66
Borrower Income	748.75	755.33	507.71	166.32	154.29	179.68	767.85	0.01	717.84	782.80	1,025.71	490.99	304.31	304.81	853.74	763.57	352.78	591.97	491.45	865.13	386.49	620.22	688.07	890.36	587.78	587.54	710.14
ITI	4,221.55	1,393.79	1,667.70	776.05	2,076.54	0.00	0.00	2,476.14	2,868.22	2,046.53	169.16	3,981.05	0.39	0.39	3,713.24	6,291.66	1,411.00	0.00	1,862.23	1,272.27	-	-	-	3,126.95	3,054.61	3,055.44	-
Balance Outstanding	135.76	95.20	62.83	57.45	32.67	52.93	38.73	65.80	42.45	96.64	-	36.90	99.02	99.06	51.11	80.55	30.26	127.03	44.13	97.68	57.54	46.05	111.15	81.53	111.24	111.26	61.46
Total	558,893	702,689	26,252,664	715,634	770,205	711,234	835,060	205,495,541	150,641,036	690,241	920,901	809,117	722,040	720,083	721,161	915,602	668,931	758,136	915,231	1,016,354	752,351	649,952	679,926	786,058	832,711	835,212	626,841
Proportional Contribution																											
Current LTV	96.4%	95.0%	99.9%	97.2%	97.2%	99.5%	97.5%	100.0%	100.0%	99.3%	98.2%	98.8%	99.1%	99.1%	97.0%	96.1%	98.0%	97.8%	99.1%	96.9%	95.9%	99.1%	99.1%	98.7%	98.5%	98.5%	99.0%
Borrower Age	1.5%	3.8%	0.0%	1.3%	1.3%	0.0%	1.5%	0.0%	0.0%	0.0%	1.2%	0.0%	0.1%	0.1%	2.0%	2.3%	0.0%	1.1%	0.0%	1.7%	3.4%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
Account Age	1.2%	0.9%	0.0%	1.4%	1.2%	0.5%	0.9%	0.0%	0.0%	0.3%	0.5%	0.6%	0.8%	0.8%	0.4%	0.8%	1.7%	1.0%	0.7%	1.2%	0.7%	0.7%	0.8%	0.8%	1.0%	1.1%	0.9%
Borrower Income	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	0.1%	0.1%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
ITI	0.8%	0.2%	0.0%	0.1%	0.3%	0.0%	0.0%	0.0%	0.0%	0.3%	0.0%	0.5%	0.0%	0.0%	0.5%	0.7%	0.2%	0.0%	0.2%	0.1%	0.0%	0.0%	0.0%	0.4%	0.4%	0.4%	0.0%
Balance Outstanding	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

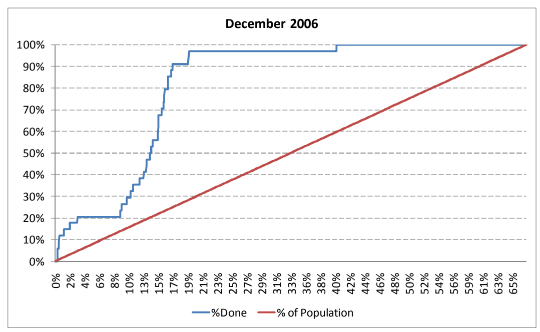
APPENDIX F:

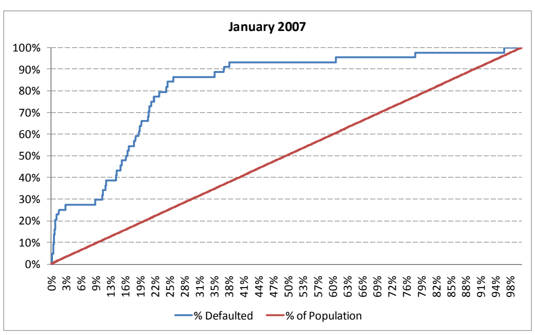
Regime 1 Graphs

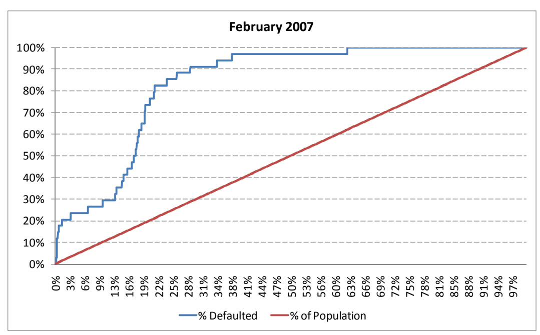


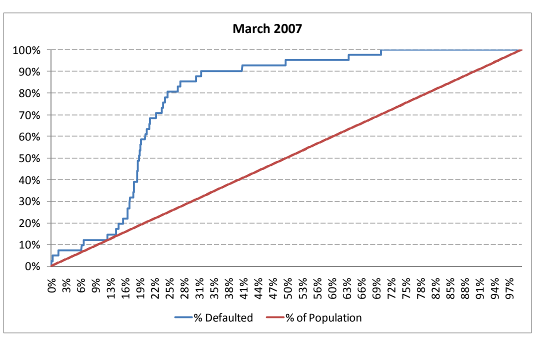


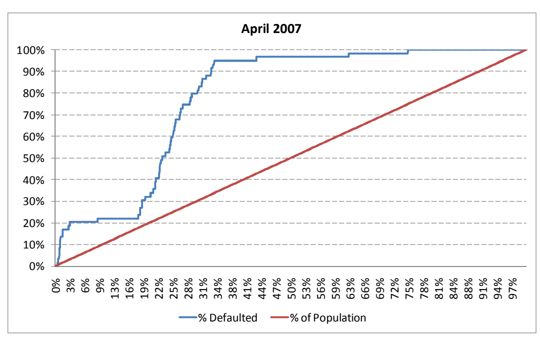


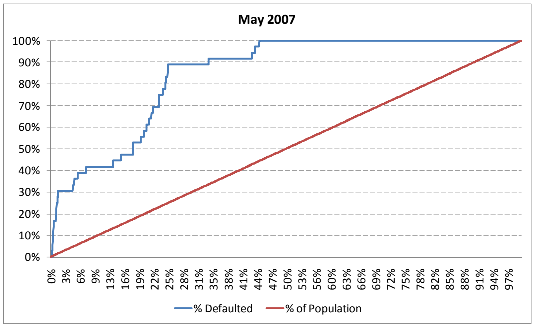











May 2007
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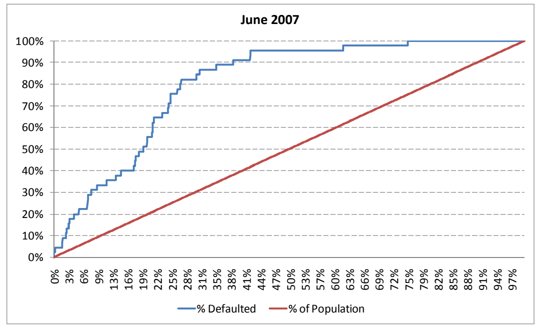
% of Population


June 2007
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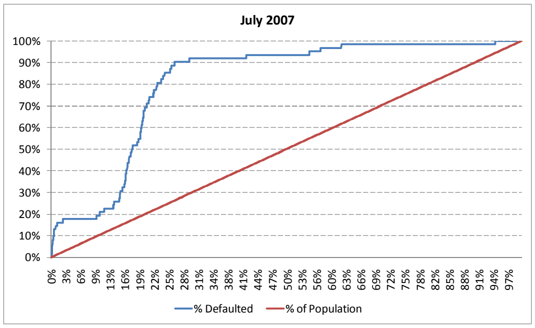
% of Population


July 2007
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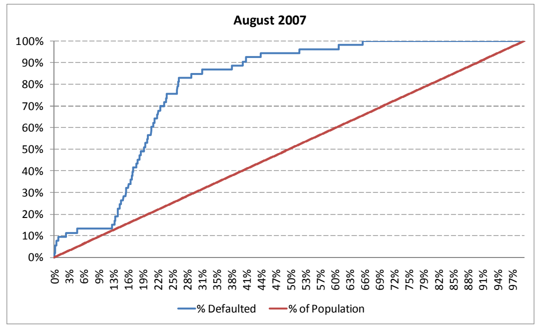
% of Population


August 2007
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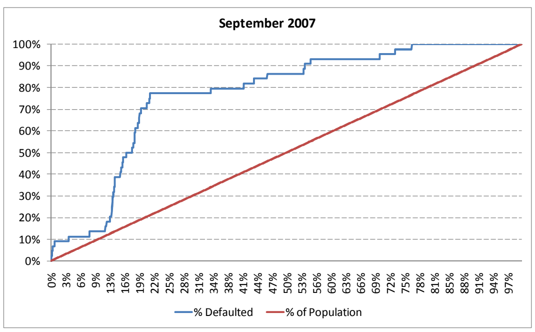
% of Population


September 2007
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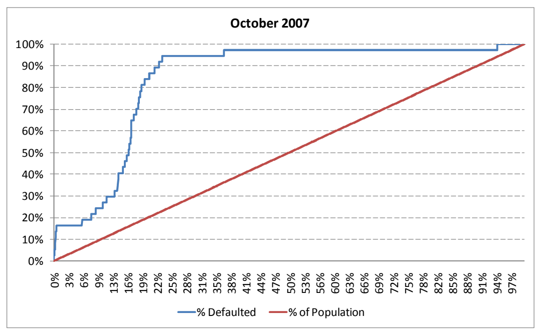
% of Population


October 2007
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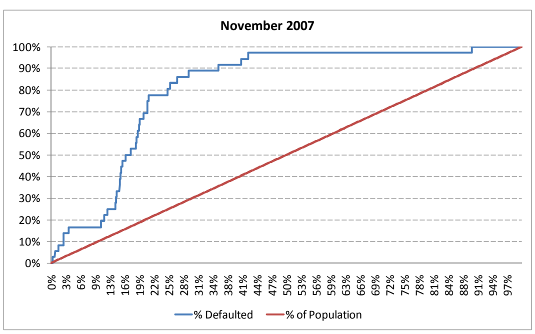
November 2007
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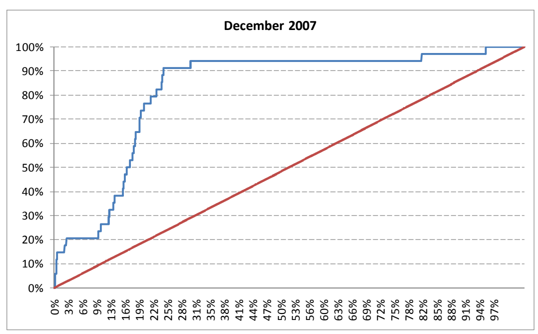
December 2007
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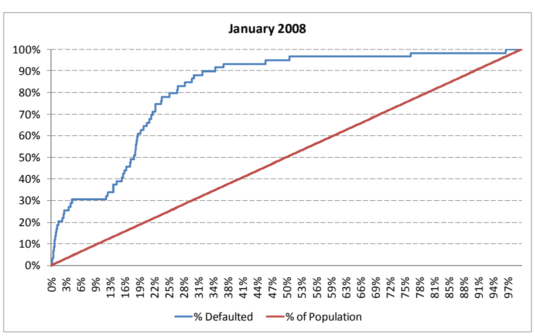
% of Population


January 2008
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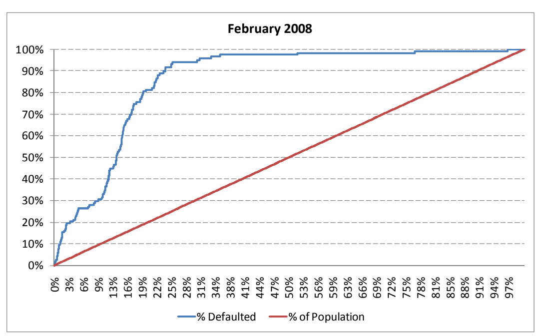
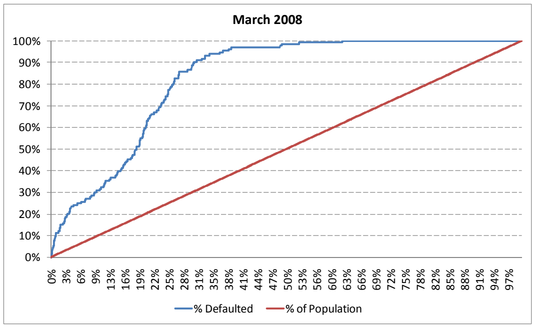
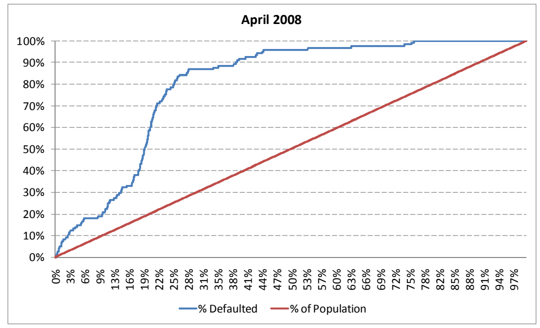
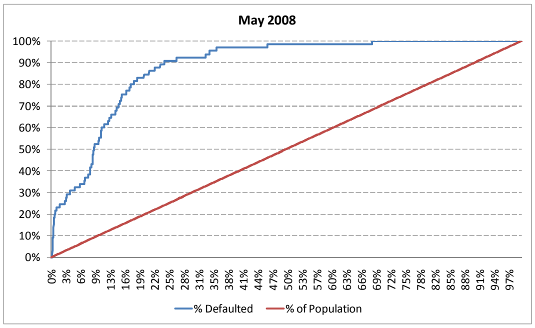
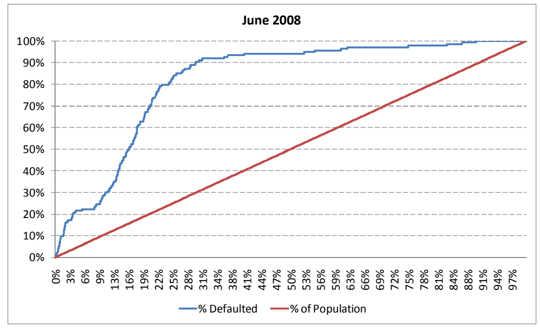
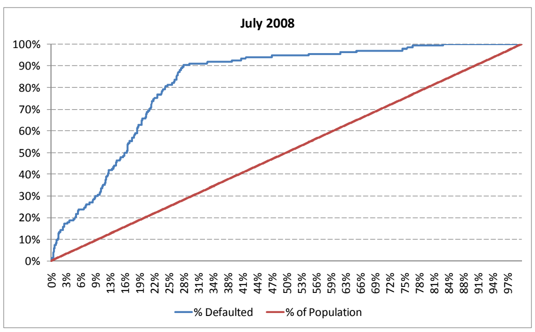

February 2008
% Defaulted
% of Population

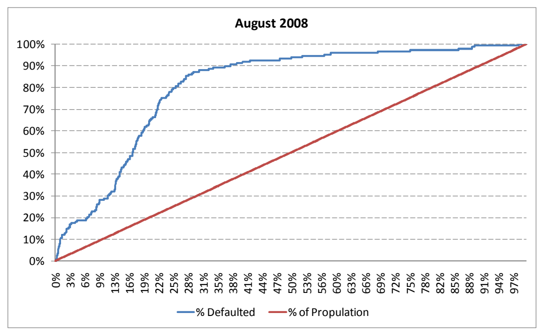

March 2008
100% 90% 80% 70% 60% 50% 40% 30% 20% 10% 0%
% Defaulted
% of Population

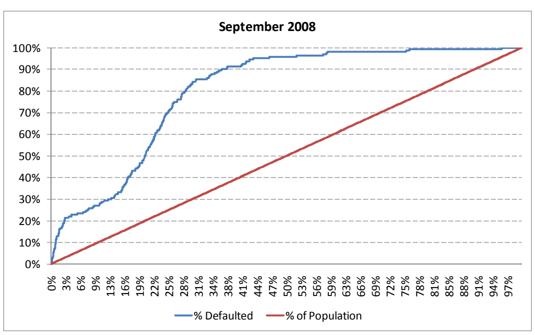

April 2008
100% 90% 80% 70% 60% 50% 40% 30% 20% 10% 0%
% Defaulted
% of Population

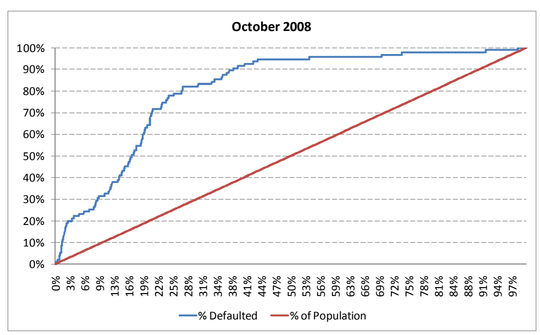

May 2008
100% 90% 80% 70% 60% 50% 40% 30% 20% 10% 0%
% Defaulted
% of Population

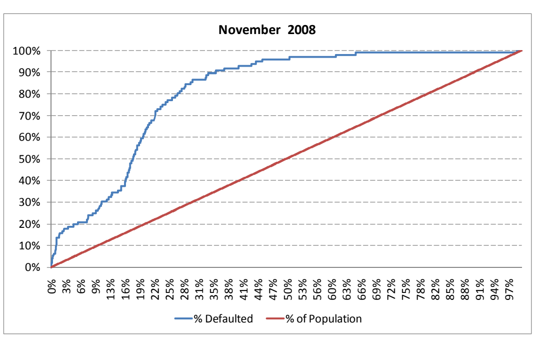

June 2008
100% 90% 80% 70% 60% 50% 40% 30% 20% 10% 0%
% Defaulted
% of Population


July 2008
100% 90% 80% 70% 60% 50% 40% 30% 20% 10% 0%
% Defaulted
% of Population


August 2008
100% 90% 80% 70% 60% 50% 40% 30% 20% 10% 0%
% Defaulted
% of Propulation

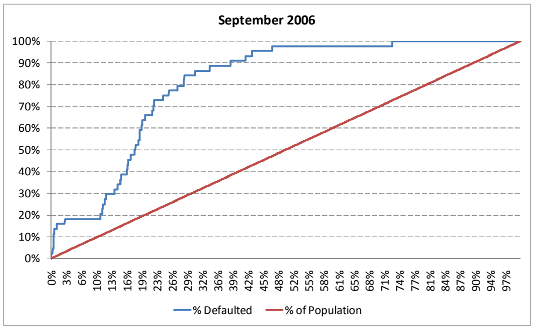

September 2008
100% 90% 80% 70% 60% 50% 40% 30% 20% 10% 0%
% Defaulted
% of Population

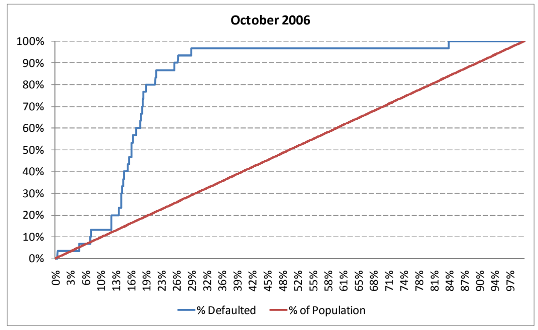

October 2008
100% 90% 80% 70% 60% 50% 40% 30% 20% 10% 0%
% Defaulted
% of Population

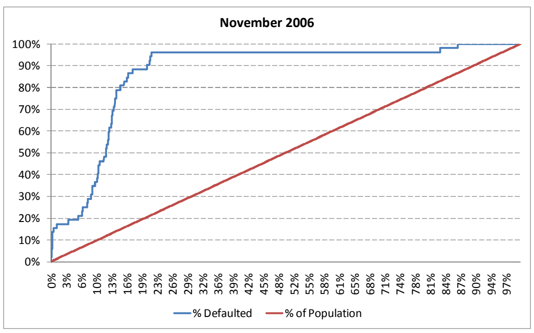

November 2008
100% 90% 80% 70% 60% 50% 40% 30% 20% 10% 0%
% Defaulted
% of Population

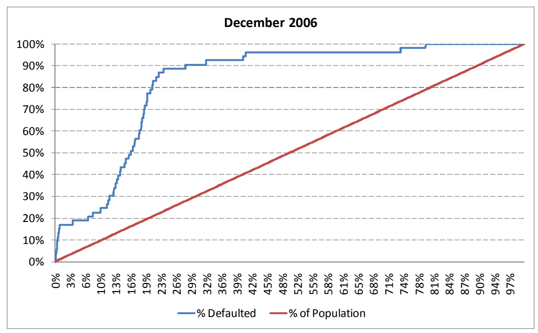
APPENDIX G:

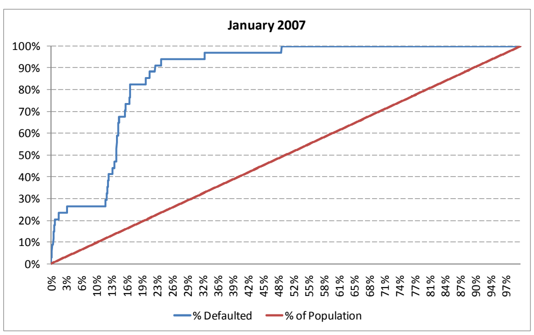
Regime 2 Graphs

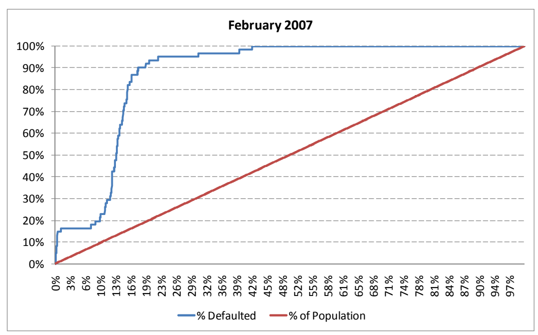


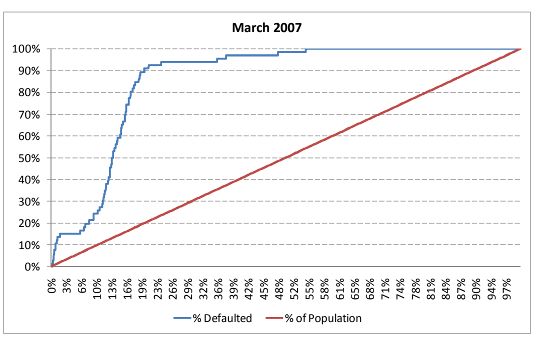


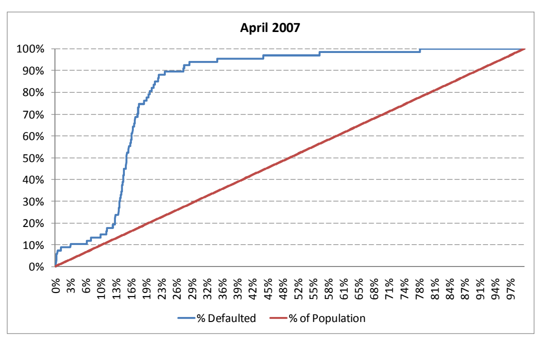


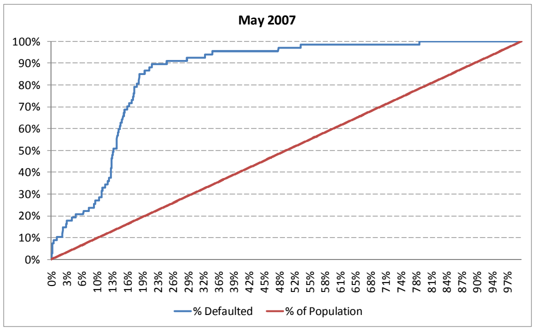


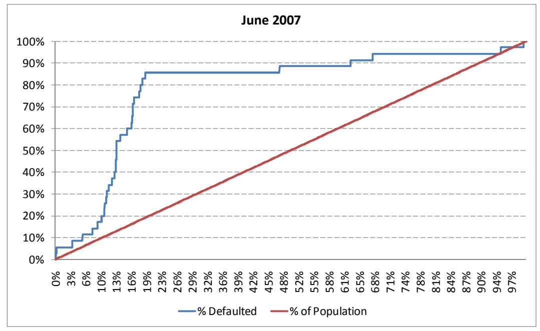









May 2007
% Defaulted
% of Population


June 2007
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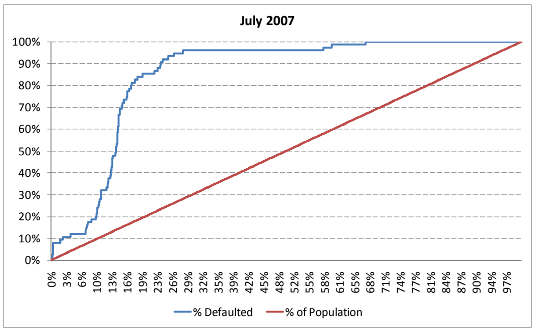
% of Population


July 2007
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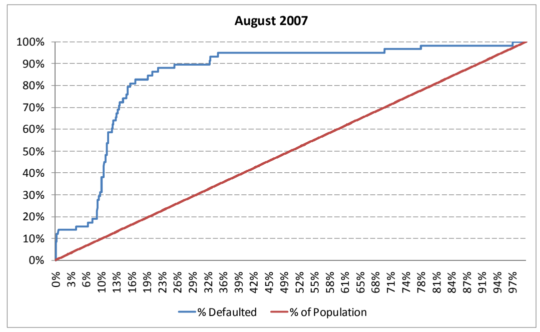
August 2007
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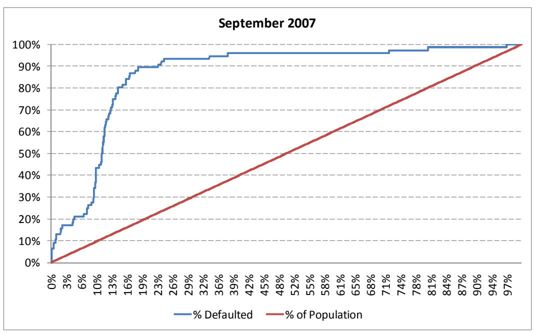
% of Population


September 2007
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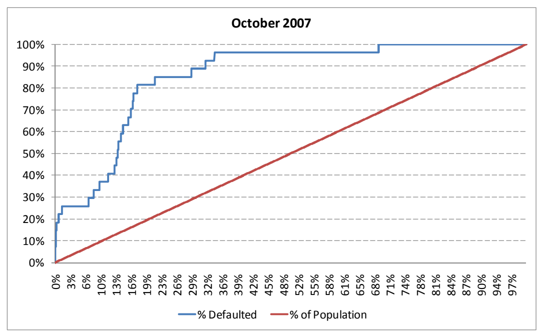
October 2007
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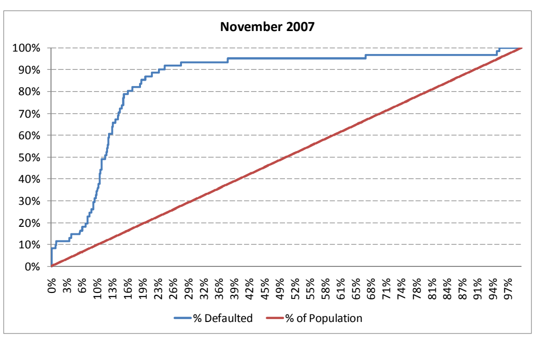
November 2007
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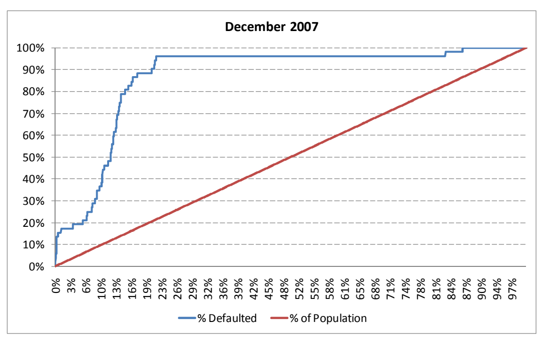
December 2007
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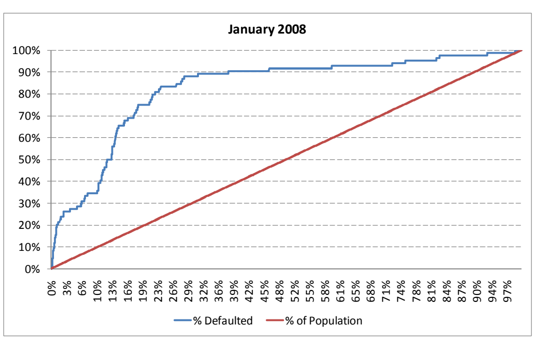
January 2008
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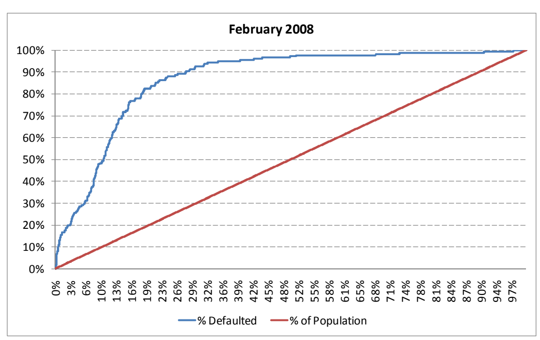
February 2008
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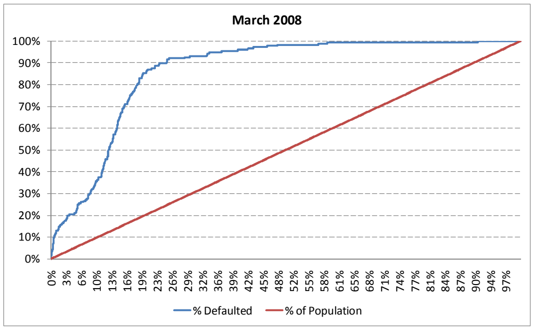
% of Population


March 2008
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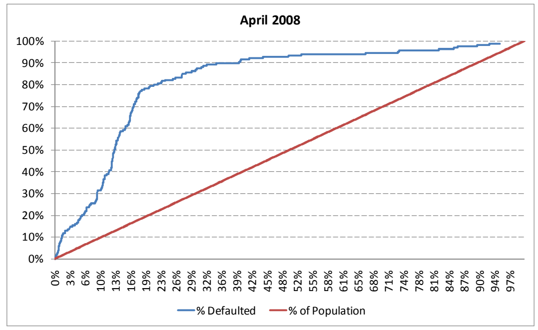
April 2008
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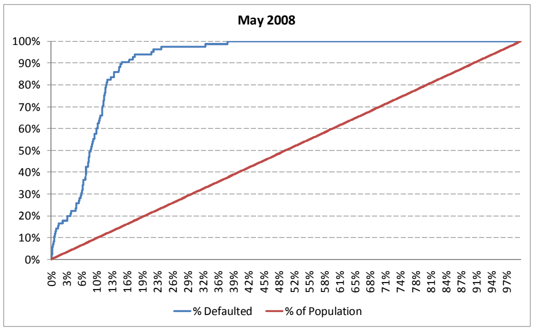
May 2008
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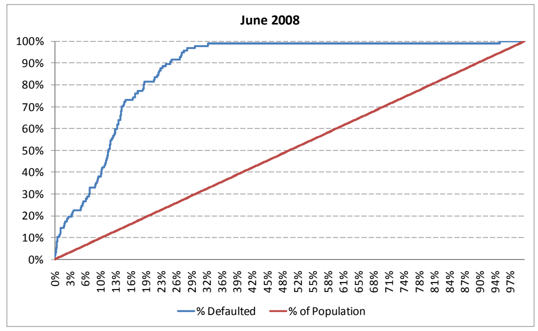
% of Population


June 2008
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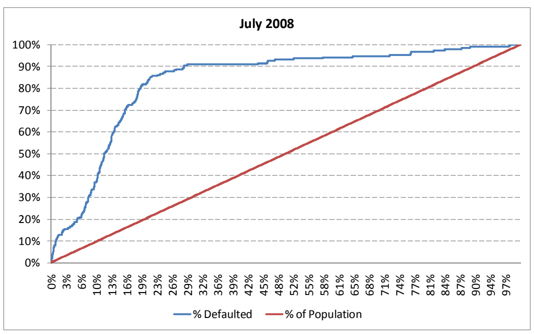
July 2008
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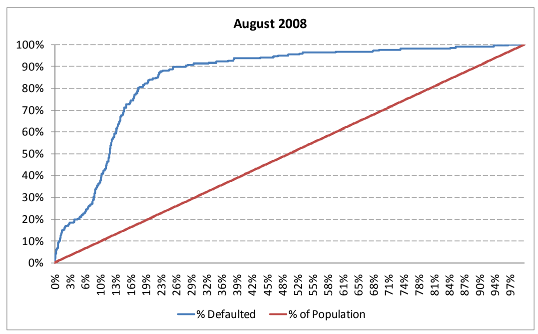
August 2008
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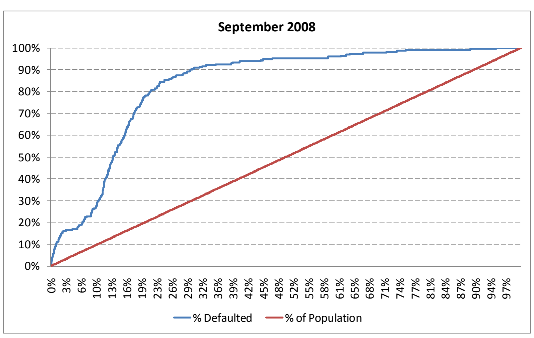
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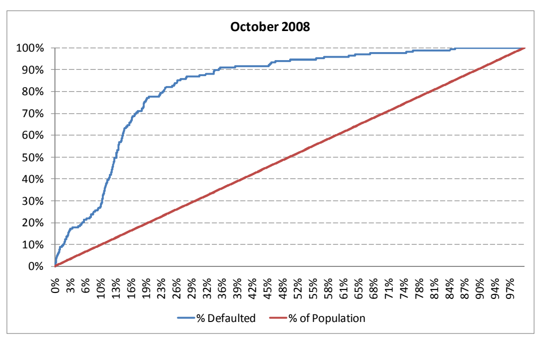
October 2008
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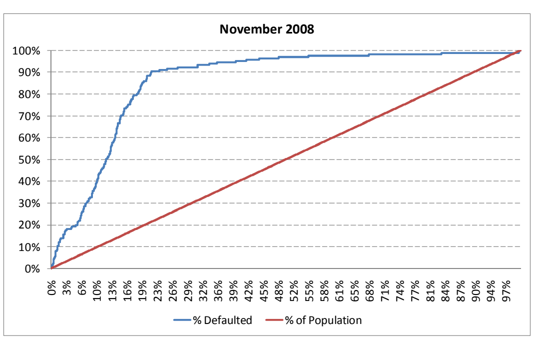
November 2008
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% of Population