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Risk Based Capital and Pricing for Reverse Mortgages Revisited

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Abstract

Demographic change is happening in developed countries with an ageing of the population. Individuals are financing retirement increasingly from superannuation savings and less from government pension support. A major asset that individuals have to fund their retirement is the residential home. The reverse mortgage is a product that allows retirees to access the value of their home to provide financing of retirement. Product providers need to assess the risks in offering reverse mortgage products including the "no negative equity" guarantee as well as the risks arising from termination of loans. Risk based capital and product sensitivity to future uncertainties need consideration following the recent financial crisis where interest rate spreads increased dramatically. This paper develops and implements a methodology to assess risk, pricing and capital requirements for reverse mortgage products for providers in the Australian market. A Vector Autoregressive Model (VAR) for financial variables including interest rates, house prices and CPI based on Australian data is used to better capture the interrelationship between economic variables. These economic variables are the most important in determining the timing and severity of losses to the issuer. The VAR model is flexible and straightforward to use in simulations. A typical reverse mortgage for a 65 year old is used to demonstrate the analysis. Termination rates and the impact on risk based capital are assessed based on US experience. Risk measures are used along with sensitivity analysis to assess pricing and capital for insurers and lenders. The effect of termination, mortality, and interest rate spreads is quantified.

Keywords: longevity risk, risk based capital, reverse mortgages, Vector Autoregressive Model

JEL Classifications: G22, C50

1 Introduction

Compulsory superannuation will not provide sufficient accumulated retirement assets for the large majority of older Australians and a substantial portion of wealth is in property. As at the end of 2005, total home equity (owner-occupied) was AUD$887 billion with those over the age of 60 accounting for AUD$345 billion (39%) of this amount (SEQUAL - Senior Australians Equity Release Association of Lenders Industry Submission [22]). Property is illiquid and many in the retirement age bracket are "asset-rich but cash poor". Australians are living longer and in order to maintain their standard of living will have to either sell their home, or borrow against this asset.

Home equity release products such as reverse mortgages allow retirees to convert a previously illiquid asset into cash payments which can be used for home improvements, regular income, debt repayment, aged care and medical treatments as well as a range of other uses which improve quality of life for retirees. The home equity release market has been growing quickly in Australia with close to 38,000 reverse mortgage loans outstanding totalling $2.5 billion as at the end of 2008 (SEQUAL/Deloitte December 2008 Reverse Mortgage Survey [23]). As more and more baby boomers move into retirement, it is important to fully understand risks associated with issuing products. Reverse Mortgages are financial products where loans are made against the value of an underlying property. The loans accrue interest and are only repaid once the house is sold. In Australia, these loans are non-recourse, that is there is a "no negative equity" guarantee on the products.

Recent events in financial markets have seen credit spreads widen significantly. Individuals have faced increasing mortgage repayments and financial intermediaries increased pressure on profits. House prices have shown volatility along with interest rates. These events highlight the need for careful analysis of risks in products such as reverse mortgages where house price and interest rate risks are the important risk factors.

The aim of this paper is to develop a model of economic variables to capture the interactions between macroeconomic variables which determine house prices based on Australian data for use in quantifying the major risks of a reverse mortgage. Loan termination rates are incorporated in order to quantify solvency (credit) risk. The models are used to examine the risks and pricing of reverse mortgages and to quantify risk based capital for providers in the Australian market for a reverse mortgage issued at age 65.

The model is a Vector Autoregressive Model (VAR) fitted to Australian data including the financial variables interest rates, house prices and CPI. These variables are most important in determining the timing and severity of the potential losses to an issuer. The model better captures the interrelationship between economic variables. The advantages of the VAR model is its flexibility, ease of estimation and use in simulation. An analysis of termination rates and the impact on risk based capital is provided based on US experience. Risk measures and sensitivity analysis are used to quantify the risk for insurers and lenders from termination and mortality. Sensitivity to interest rate spreads is also quantified.

The following section provides an overview of the reverse mortgage market in Australia

and the US. After that the simulation model details are presented. The application of the models to reverse mortgages is then outlined and results and implications discussed. Finally conclusions are drawn and the paper summarized.

2 Reverse Mortgage Product and Market Developments

The main features of a typical reverse mortgage contract are (CHOICE Test: Reverse Mortgages [9]):

Amount: The amount of money an individual can borrow will depend primarily on two factors; age and value of the home. Current products in the Australian market are usually structured so that as an individual's age increases, the loan-to-value (LVR) ratio increases, for example an individual aged 60 may borrow 15% of the value of their home whereas someone aged 80 or more can borrow up to 35% of the value of their home.

Repayment: Repayments are generally not made until an individual moves out of the house or dies. If the home is jointly owned, the loan is only repayable once the last surviving partner dies. However, some contracts allow a resident non-borrower to remain in the house even after all the borrowers have moved or died.

Proceeds: Depending on the contract, the borrower can access the proceeds of the reverse mortgage as a lump sum, annuity, a combination of both or a line of credit (drawdown). Most providers of reverse mortgages in the Australian market offer this level of flexibility as consumer needs vary.

Interest rates: Variable and Fixed interest rates are available with most lenders. Fixed-rate loans are usually available for terms between one and ten years. Some lenders also offer fixed rates for life or rates with a maximum cap. However, fixed rate loans may also come with break-fees for when a loan is repaid early. Variable rates are on average 1% above the standard variable home loan rate.

Fees: There are typically setup fees, ongoing fees and exit fees associated with reverse mortgages which vary from lender to lender.

Other contract features: In Australia, members of the industry body, SEQUAL must adhere to a policy of providing No Negative Equity Guarantees, that is all the reverse mortgages are non-recourse loans. Other contract features such as the process following the default of a loan will vary depending on the provider.

The major risks associated with reverse mortgage products are:

House Price Risk: The risk that deviations in house prices result in the lender sustaining a loss. This often occurs when loans are held for a longer period than expected and the accrued value of the loan exceeds the selling value of the underlying property. This is termed *crossover risk*. The point at which the accrued value of the loan exceeds the price of the underlying property is termed the *crossover point*. This is the most significant risk for the vast majority of reverse mortgage contracts as they are non-recourse.

Interest Rate Risk: The risk that fluctuations in interest rates results in losses for the lender. This may occur if borrowers decide to refinance especially if the loan is a fixed rate loan. Reverse mortgages may also expose lenders to interest rate spread changes.

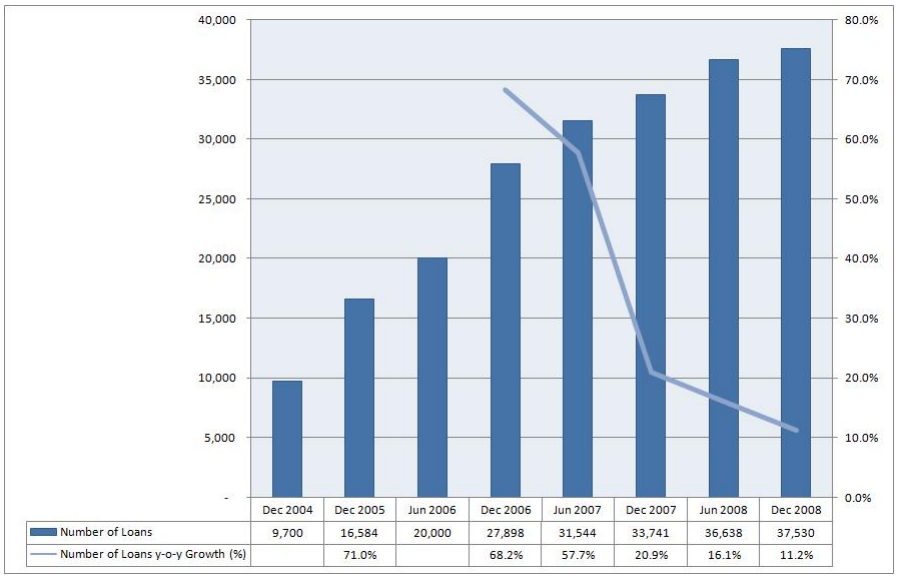
Longevity, Mortality, Mobility and Prepayment Risk: The risk that the rate at which borrowers terminate the loan differ from expectation. For example, increases in longevity increase the impact of crossover risk as the loan accumulates interest at a rate faster than the rate at which house prices appreciate. Prepayment risk may cause a larger than expected loss for the lenders.

Moral Hazard Risk: The risk that borrowers do not maintain their homes adequately. This may be more severe for loans with significant accrued interest close to the crossover point. Borrowers who have seen their equity stake decrease over time will have limited incentive to maintain the sale price of the home.

Other risks include those which affect the marketability of the product such as the role of bequest motives as well as reputation risks which may arise when default conditions on the loans are triggered.

2.1 Australian Market

The market for reverse mortgages in Australia has grown rapidly in the past four years by both number of loans and size of loans. As at December 2008, there were 37,350 loans on issue with a loan amount outstanding of AUD$2.48 billion. This compared with just 9,700 loans on issue with a loan amount outstanding of AUD$0.459 billion as at December 2004. Figures 1, 2 and 3 chart the growth of the market since December 2004 (SEQUAL website [23]).



	Dec 2004	Dec 2005	Jun 2006	Dec 2006	Jun 2007	Dec 2007	Jun 2008	Dec 2008
Number of Loans	9,700	16,584	20,000	27,898	31,544	33,741	36,638	37,530
Number of Loans y-o-y Growth (%)		71.0%		68.2%	57.7%	20.9%	16.1%	11.2%

Figure 1: Number of reverse mortgage loans on issue for Australia: Source SEQUAL

Growth has come from demographic changes, in particular retirement of the "baby boomer" generation. A relatively low savings rate and a low proportion of wealth

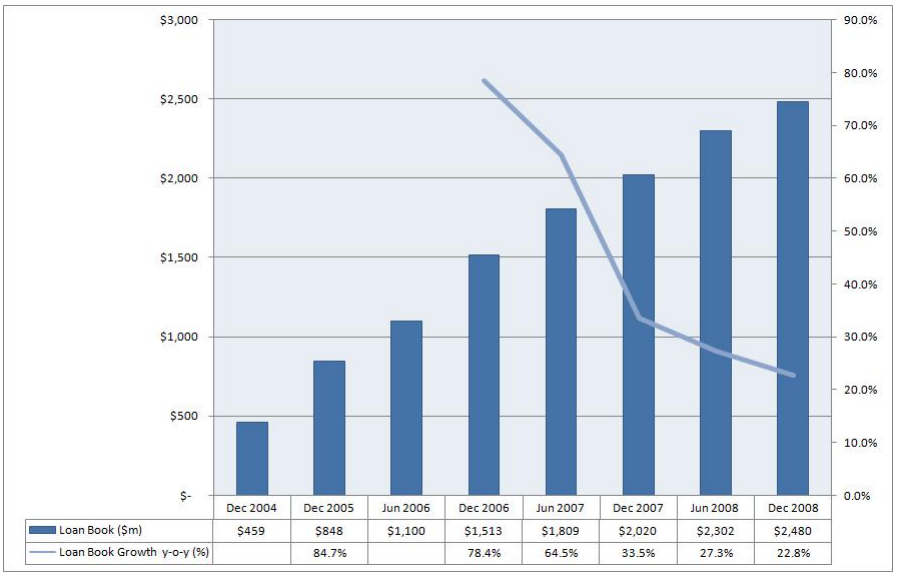


Figure 2: Total Reverse Mortgage Loan Amount Outstanding for Australia: Source SEQUAL

Figure 3: Average Reverse Mortgage Loan Size for Australia: Source SEQUAL

in superannuation has meant that baby boomers have a limited of wealth in liquid retirement assets. Figure 4 shows that the largest proportion of assets for those aged 65 and over is property (Source: Australian Bureau of Statistics 2007 [3]). Figure **??** shows the results for a study by SEQUAL and RFI, where 31% of respondents indicated that they expected to rely on their home as a source of retirement income. There has also been an increasing awareness from consumer education initiatives undertaken by lenders and the industry body SEQUAL.

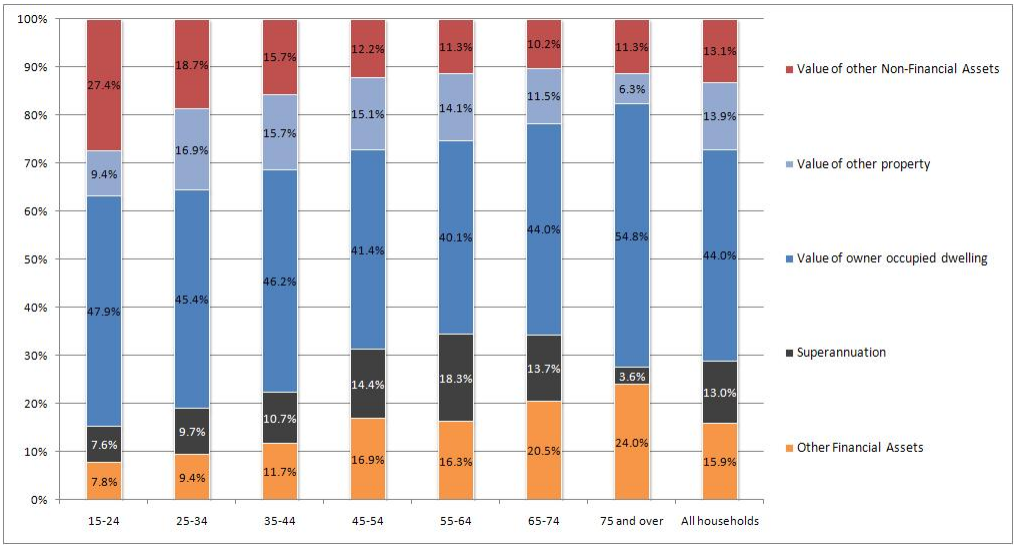


Figure 4: Asset Split for Australia by Age Group as at 2006: Source ABS

A barrier to the growth of the market identified by the SEQUAL/RFI survey is the treatment of lump sum loans in government eligibility tests for The Age Pension. Currently, Centrelink rules are that any amount over $40,000 will be counted for the assets test until it is spent, amounts below $40,000 are counted for the assets test if not spent within 90 days of withdrawal. Disqualification from receiving the pension may be a significant deterrent to taking on a reverse mortgage loan.

The regulatory body responsible for monitoring the standards of lenders as well as products is the Australian Securities and Investments Commission. In 2005, SEQUAL (Senior Australian Equity Release Association of Providers) was formed, which is now the industry's peak body for professional standards. SEQUAL requires members of the association to abide by certain rules such as the requirement that all members offer the No Negative Equity Guarantee, as well as for all members to belong to an ASIC approved External Dispute Resolution Scheme.

2.2 USA Market

The size of the US market has seen a significant expansion in the past few years as shown in Figure 6, driven by similar factors to those in Australia. According to Ginnie Mae, the key drivers of growth in the US HECM market are attributable to an increasing rate of baby boomers entering retirement, an estimated 35 million people over age 65

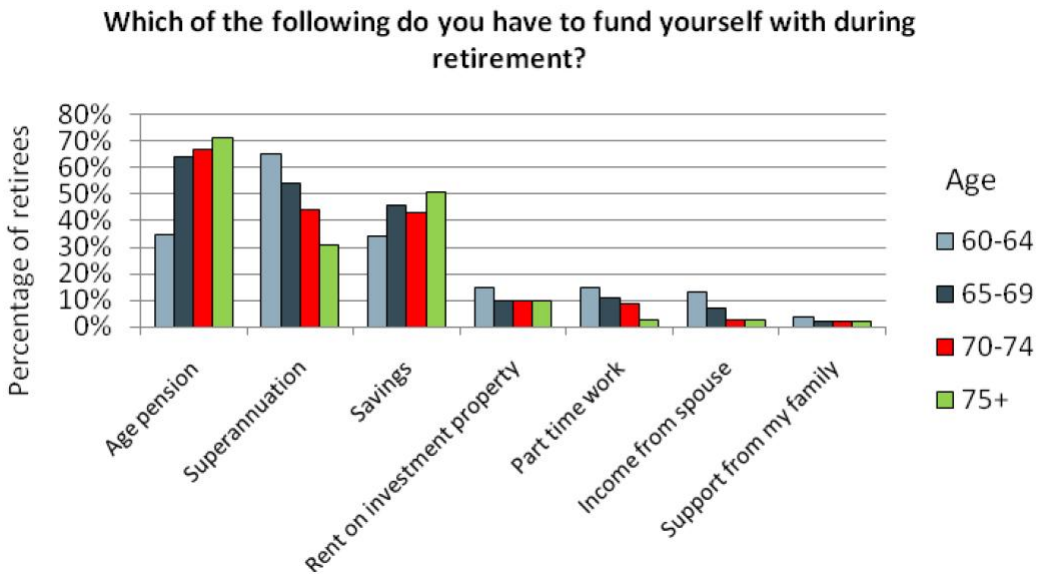


Figure 5: Australian SEQUAL/RFI Survey

by 2010, and 50 million by 2020 (US Census Bureau) and a 80% homeownership rate for this population during these periods.

There are several reverse mortgage products in the United States but the predominant reverse mortgage product has been the Home Equity Conversion Mortgage (HECM) which was issued as part of an initiative undertaken by the United States Department of Housing and Urban Development (HUD) in 1989. As of May 2007, the HECM accounted for approximately 90% of the market (National Reverse Mortgage Lenders Association Press Release (NRMLA) 2007 [19]). To encourage the development of the market, the US government insures all reverse mortgages which comply with the HECM programme rules. The rules include a "No Negative Equity guarantee" to the borrowers, so the loan is non-recourse. This guarantee or insurance is provided by HUD's Federal Housing Administration (FHA). When the accumulated value of the loan exceeds the selling price of the house, the lender files a claim to HUD for benefits. Alternatively, the lenders also have the option to "assign" the loan to HUD once the loan balance grows to equal 98% or more of the loan's *maximum claim amount* which is the lesser of the original appraised value of the property or the maximum insurable mortgage under the FHA's program.

There is also a peak industry body, the National Reverse Mortgage Lenders Association (NRMLA), which oversees the issuance of HECMs as well as other reverse mortgage products. This association performs a similar role to SEQUAL in Australia whereby they hold members of the association to certain product standards as well as serving as an educational resource.

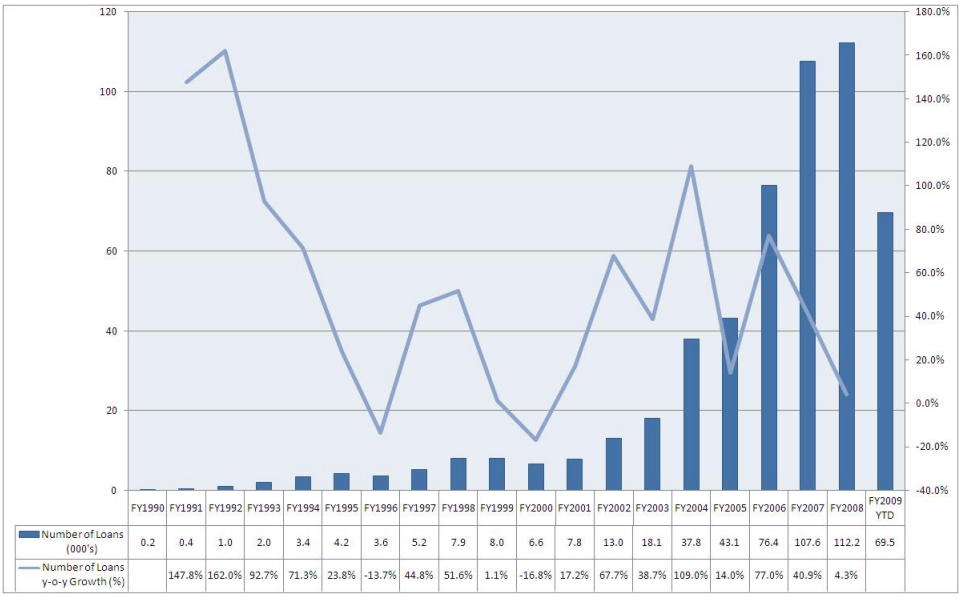


Figure 6: US Reverse Mortgage Market. Source: National Reverse Mortgage Lenders Association

3 Simulation Models for Reverse Mortgage Risks

3.1 House Prices and Interest Rates

House price and interest rate models typically used assume house prices follow a geometric Brownian motion model and interest rates follow an Ornstein Uhlenbeck or Vasicek mean-reverting process. Wang, Valdez and Piggott (2007) [29] model house prices as log-normal and estimate the growth rate and volatility using quarterly median house prices from the eight capital cities in Australia. They allow for idiosyncratic house price risk and systematic house price risk. A one-factor stochastic Vasicek model was used for the dynamics of the short rate.

Similar modeling approaches have been used by Chinloy and Megbolugbe (1994) [8] as well as Ma, Kim and Lew (2007) [16]. This approach makes it straightforward to perform simulations and it allows straightforward pricing of the "no negative equity" insurance premium as it can be priced using an option pricing formula. Often these models assume independence between house prices and interest rates. Rodda, Lam and Youn (2004) [21] develop a stochastic model of interest rates and house prices to determine the size and frequency of HECM claims.

A vector autoregression (VAR) is a multivariate model where values of modeled variables are explained by a combination of lags of the variable itself as well as lags of other variables. They were popularised by Sims (1980) [25] as a useful tool in empirical macroeconomic analysis. The general specification of a Gaussian VAR(p) process for an $(n \times 1)$ vector $\mathbf{y_t}$ is:

$$\mathbf{y_t} = \mathbf{c} + \mathbf{\Phi_1 y_{t-1}} + \mathbf{\Phi_2 y_{t-2}} + \cdots + \mathbf{\Phi_p y_{t-p}} + \varepsilon_\mathbf{t}$$

with $\varepsilon_\mathbf{t} \sim$ i.i.d. $\mathcal{N}(\mathbf{0}, \mathbf{\Omega})$ (Hamilton 1994 [11])

Vector Autoregressions have been used by McCue and Kling (1994) [18] as well as Brooks and Tsolacos (1999)[5] for estimating house prices. McCue and Kling (1994) modeled the behaviour of a system of macroeconomic variables which included real estate returns. Macroeconomic variables explained about 60% of the variation in equity REITs series. Nominal interest rates had the most significant influence. Brooks and Tsolacos (1999) [5] estimated an unrestricted VAR model showing interest rates and inflation were significant in explaining house price returns. They found that the most significant influence on real estate series were the lagged values of the real estate series themselves. VAR models capture the autoregressive effect of historical values.

Otto (2007) [20] estimated an autoregressive distributed lag model for modelling the growth rate of house prices:

$$\begin{aligned}\Delta \log P_t^h = \mu \quad &+ \quad \sum_{i=1}^{k} \gamma_i \Delta \log P_{t-i}^h + \sum_{i=1}^{k} \lambda_{1i} \log \frac{R_{t-i}^h}{P_{t-i}^h} + \sum_{i=1}^{k} \lambda_{2i} i_{t-i} \\ &+ \quad \sum_{i=1}^{k} \lambda_{3i} \pi_{t-i} + \nu_t\end{aligned}$$

where P_t^h is the price of a house at time t, R_t^h is the rent per period at time t, i_t is the nominal interest rate at time t, and π_t is the nominal inflation rate at time t. Otto (2007) [20] found that this model explains at least 40% of the variation in house prices for five of the eight capital cities. Interest rates had a negative effect and inflation had a positive effect for all the state capitals.

Abelson et al (2005) [1] estimated a vector error correction model using several economic variables. They also estimate a short-run asymmetric error correction model to determine the difference in the speed of house prices adjusting back to long-run equilibrium relationships. They first estimate a long-run price equation by estimating a cointegration vector, θ in the equation:

$$\log P(t) = a_0 + \theta x_t + \sum_{j=-k}^{k} \delta_j \Delta x_{t-j} + \nu_t$$

where P_t is the real house price and x_t is a vector of time series which include the following variables: $\log(Allords_t)$: the real All Ordinaries index, R_t: the real mortgage interest rate (quarterly yield), $\log(GDI_t)$: real household disposable income per capita, $\log(ER_t)$: the trade-weighted exchange rate, $\log(CPI_t)$: the consumer price index, $\log(UE_t)$: the unemployment rate, and $\log(H_t)$: the detached housing stock per capita. They find that long run house prices were determined significantly by real disposable income, real interest rates, equity prices, CPI and the supply of housing. There was a strong negative relationship between the real mortgage rate and real house prices. with a 1% rise/fall in the real mortgage rate leading, on average, to a 5.4% fall/rise in house prices.

3.2 Loan Termination Rates

Lenders of reverse mortgages face the risk that loans are terminated earlier than expected. Termination rates of reverse mortgages have received little research atten-

Table 1: Data Sources

Data Period	Mar-1982 to Dec-2008	
Variable	Source	Series Name
Standard Variable Mortgage Rate	Reserve Bank of Australia	F05
NSW CPI	Australian Bureau of Statistics(ABS)	6401.01
Sydney House Median Rental Index	Real Estate Institute of Australia	REMF5
Female Mortality Rates	ABS	Life Tables 2005-2007
US Termination Rates	Szymanoski (2007)	N/A

tion. Little data on terminations rates exist. The original assumptions of the HECM program in the US, before data was available, were that termination rates were 1.3× the underlying female mortality rate for each age bracket. Only recently has enough loan experience been available to assess the observed termination rates. Szymanoski *et al* (2000) [27] models termination rates to determine the effects of variables including age, house appreciation rate, income and other liquid assets.

4 VAR Model for Australian Application

The VAR modeling framework was adopted because it captures the relationships between the variables better and is straightforward to use in simulations. The variables modeled were the main factors impacting interest rates and house prices:

- dMR: Difference in standard variable mortgage rate
- $RlnH$: Return for Real Log Sydney House Prices
- $LnCPI$: Log change in NSW CPI Index
- $RlnR$: Return for Real Sydney Rental Index

Variables modeled and a brief description of data sources is shown in Table 1.

Residex produce residential property indices for all the major capital cities in Australia using a repeat-sales method not dissimilar from that used to estimate the Case Shiller index in the United States. As Residex is one of the only freely available, sophisticated method and long-dated series on real estate this is used for estimating house price changes.

4.1 Model Estimation

After a detailed analysis of the data and model fitting and diagnostic checking, a VAR(2) was found to be the most suitable model for capturing the relationship between

Table 2: VAR Univariate Tests

Variable	Lag	LMP Statistic
dMR	2	0.4782
$RlnH$	2	0.2339
$LnCPI$	2	0.4094
$RlnR$	2	0.2339

Table 3: VAR Model Selection

VAR Process	SBC	LMP Statistic	Royston's Test p-value
VAR(1)	-8.4307	0.0009	0
VAR(2)	-8.3770	0.1182	0
VAR(3)	-8.2602	0.0576	0
VAR(4)	-8.1544	0.3648	0
VAR(5)	-8.0768	0.4920	0

the variables. The Vector Autoregression was estimated using the software package MATLAB. The `vare` function from the "Spatial Econometrics Toolbox" was used. The Li-Mcleod Portmanteau test for serial correlation was used with the function `arres` from "ARfit: A Matlab package for the estimation of parameters and eigenmodes of multivariate autoregressive models". The residuals were modeled with a t location-scale distribution or a Normal distribution. The distribution fit tool in MATLAB `dfittool` was used to estimate the parameters. Model selection was based on the Akaike Information Criterion as well as the Schwarz Bayesian Criterion. The model was simulated for 5000 runs with each run comprising 200 time periods and the simulated paths compared for reasonableness against the historical data using the simulated and empirical cumulative density function.

Loan termination rates were modeled using multiples of the underlying female mortality rate. The female mortality rate was fitted with a cubic polynomial and parameters estimated with ordinary least squares. Multiples of 1 were applied beyond age 93.

4.2 Model Fitting and Diagnostics

Univariate tests were applied to the series to determine the order of autoregression. If the series all have the same order then a VAR model can be used, otherwise a Vector Error Correction Model must be estimated. Table 2 confirms that an autoregression of order 2 is appropriate for all the variables.

The lags and the tests for serial correlation are shown in Table 3. The Schwarz-Bayesian Criterion (SBC) and the p-values of the modified Li-McLeod portmanteau (LMP) statistic (1981) [13] are shown for different lag lengths for each variable.

Table 4: VAR estimates: dMR

Variable		Coefficient	t statistic	t probability
dMR	lag1	0.1958	1.9363	0.0558
dMR	lag2	0.4023	3.5646	0.0006
$RlnH$	lag1	0.0273	1.0755	0.2849
$RlnH$	lag2	0.0488	1.9667	0.0521
$LnCPI$	lag1	-0.0235	-0.3080	0.7588
$LnCPI$	lag2	0.0444	0.6248	0.5336
$RlnR$	lag1	-0.0030	-0.3291	0.7428
$RlnR$	lag2	-0.0006	-0.0628	0.9501
constant		-0.0012	-1.2570	0.2118
midrule R^2	0.2916			

Although the SBC selection criterion supports a lag 1 vector autoregressive process, p-values from the Li-Mcleod portmanteau statistic indicate that a VAR(1) violates the assumption of no serial correlation in the residuals. A VAR(2) is the first lag length at which the residuals are serially uncorrelated. Royston's Test for Multivariate Normality shows that the errors are not multivariate normal under all models which requires further analysis.

The estimated model for the vector of variables, $\mathbf{y_t}$, is:

$$\widehat{\mathbf{y_t}} = \widehat{\mathbf{W}} + \widehat{\mathbf{A_1}}\mathbf{y_{t-1}} + \widehat{\mathbf{A_2}}\mathbf{y_{t-2}} + \varepsilon$$

where:

$$\mathbf{y_t} = \begin{pmatrix} dMR_t \\ RlnH_t \\ LnCPI_t \\ RlnR_t \end{pmatrix} \widehat{\mathbf{W}} = \begin{pmatrix} -0.0012 \\ -0.0042 \\ 0.0041 \\ 0.0019 \end{pmatrix}$$

$$\widehat{\mathbf{A_1}} = \begin{pmatrix} 0.1958 & 0.0273 & -0.0235 & -0.0030 \\ -1.4206 & 0.2838 & -0.0298 & 0.0572 \\ 0.5124 & 0.0466 & 0.3191 & -0.0053 \\ -0.6814 & -0.0459 & 0.0095 & -0.2281 \end{pmatrix}$$

$$\widehat{\mathbf{A_2}} = \begin{pmatrix} 0.4023 & 0.0488 & 0.0444 & -0.0006 \\ -0.8355 & 0.3898 & 0.6724 & 0.0239 \\ 0.1083 & 0.0123 & 0.2004 & -0.0049 \\ 1.0084 & -0.2407 & 0.2440 & 0.1000 \end{pmatrix}$$

Overall, the model provides a reasonable fit to the data with R^2 in the range of 0.29 to 0.48 for the variables.

Table 4 shows the estimated equation for the change in mortgage rates (dMR). There is a significant autoregressive component from the previous period's rate changes.

Table 5: VAR estimates: $RlnH$

Variable		Coefficient	t statistic	t probability
dMR	lag1	-1.4206	-3.7132	0.0003
dMR	lag2	-0.8355	-1.9564	0.0534
$RlnH$	lag1	0.2838	2.9578	0.0039
$RlnH$	lag2	0.3898	4.1523	0.0001
$LnCPI$	lag1	-0.0298	-0.1031	0.9181
$LnCPI$	lag2	0.6724	2.5006	0.0141
$RlnR$	lag1	0.0572	1.6853	0.0952
$RlnR$	lag2	0.0239	0.7203	0.4731
constant		-0.0042	-1.1570	0.2502
R^2	0.4862			

Table 6: VAR estimates: $LnCPI$

Variable		Coefficient	t statistic	t probability
dMR	lag1	0.5124	3.7124	0.0003
dMR	lag2	0.1083	0.7031	0.4837
$RlnH$	lag1	0.0466	1.3468	0.1813
$RlnH$	lag2	0.0123	0.3629	0.7175
$LnCPI$	lag1	0.3191	3.0600	0.0029
$LnCPI$	lag2	0.2004	2.0662	0.0415
$RlnR$	lag1	-0.0053	-0.4343	0.6651
$RlnR$	lag2	-0.0049	-0.4101	0.6827
constant		0.0041	3.1915	0.0019
R^2	0.4862			

Observed patterns for mortgage rate changes show half of the observations equal to zero, but when rate changes occur, they occur in clusters with rate rises or reductions happening in successive quarters. Real growth in house prices as well as the long-run effect of inflation are both positively related to changes in the mortgage rate. Only real growth in house prices has a significant effect on mortgage rates.

Table 5 shows the estimated equation for real house prices. There is a significant negative relationship with changes in the mortgage rate, a significant autoregressive component and a positive relationship with inflation and the real rental growth rate. Lagged variables of real house price growth have a significant role in determining subsequent growth rates, consistent with other Australian studies.

The estimated equation for $LnCPI$ indicates a significant autoregressive effect. Changes in previous period's mortgage rates also have a significant positive impact. $RlnR$ does not have significant explanatory power for dMR, $RlnH$ and $LnCPI$. The model still includes $RlnR$ since other studies show rental prices are significant in determining house

Table 7: Granger Causality F-test p-values

		Independent Variable			
		dMR	$RlnH$	$LnCPI$	$RlnR$
Dependent Variable	dMR	0.000	0.005	0.822	0.947
	$RlnH$	0.000	0.000	0.019	0.228
	$LnCPI$	0.000	0.165	0.000	0.861
	$RlnR$	0.672	0.500	0.934	0.026

Table 8: Residuals Fit Tests

		t location-scale	Normal
dMR Residuals Fit	Parameters	3	2
	Log Likelihood	418.244	411.967
	AIC	-830.488	-819.934
	SBC	-822.554	-814.645
$LnCPI$ Residuals Fit	Parameters	3	2
	Log Likelihood	383.644	379.597
	AIC	-761.288	-755.194
	SBC	-753.354	-749.905
$RlnR$ Residuals Fit	Parameters	3	2
	Log Likelihood	182.133	161.530
	AIC	-358.266	-319.060
	SBC	-350.333	-313.771

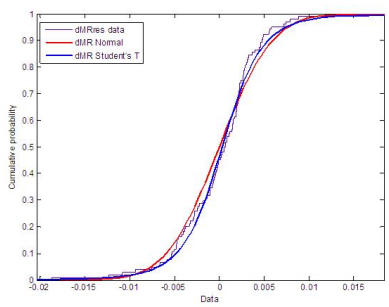
prices.

The joint significance for the lags of variables are shown in Table 7.

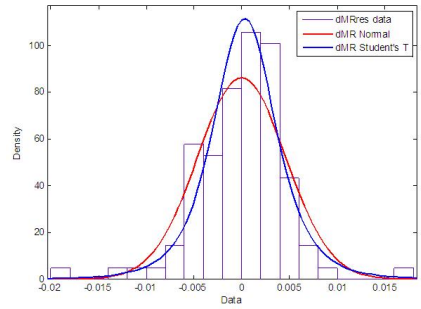
4.3 Residual Fits

The diagnostic tests for multivariate normality show that the errors are not multivariate normal. The normal distribution did not capture the leptokurtic nature of 3 of the 4 residuals series, with a t distribution providing a better fit in these cases. The residuals for dMR exhibited clear leptokurtosis with the normal distribution providing a poor fit for the data. In particular, the normal distribution fails to capture the "peakedness" of the data around zero. The t distribution provides a much better fit for data in the proximity of the mean as well as allowing for fatter tails. Table 8 show both the Akaike information criterion and the Schwarz Criterion have lower values under the t distribution than the Normal distribution.

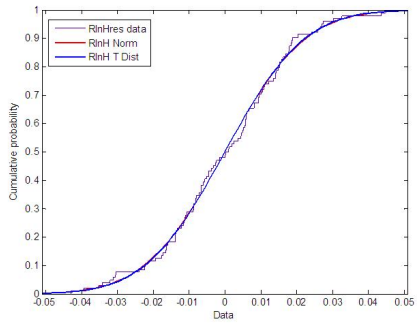
The residuals of $RlnH$ are captured well by the Normal distribution. A t distribution does not differ much from the Normal distribution as shown in Figures 7c and 7d. The residual fits for $LnCPI$ and $RlnR$ are similar to that for dMR with a t distribution



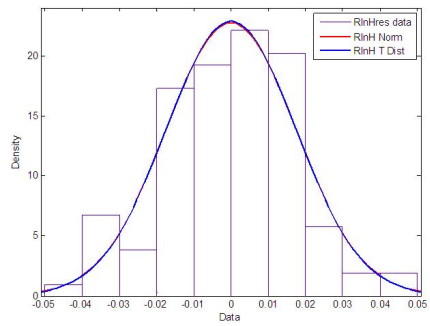
(a) dMR Residuals CDF



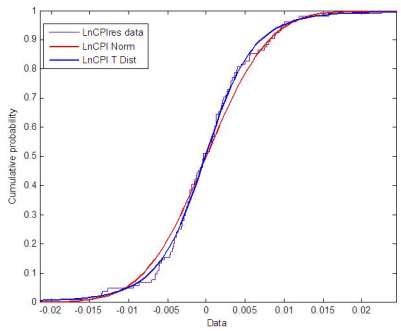
(b) dMR Residuals PDF



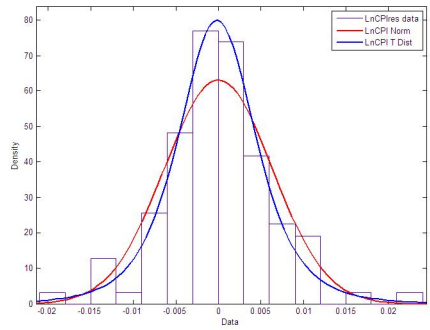
(c) $RlnH$ Residuals CDF



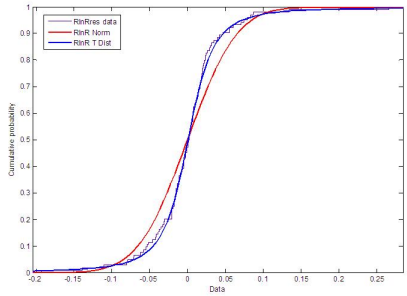
(d) $RlnH$ Residuals PDF



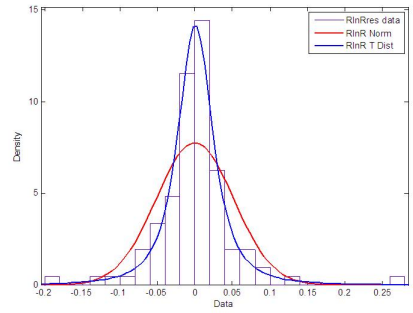
(e) $LnCPI$ Residuals CDF



(f) $LnCPI$ Residuals PDF



(g) $RlnR$ Residuals CDF



(h) $RlnR$ Residuals PDF

Figure 7: Residual Fits

better capturing the features of the residuals than a Normal distribution (Figures 7e through 7h and Table 8).

Table 9: Residuals Correlation Matrix

	dMRres	RlnHres	LnCPIres	RlnRres
dMRres	1.000	-0.003	0.112	0.089
RlnHres		1.000	-0.291	0.151
LnCPIres			1.000	-0.127
RlnRres				1.000

Table 10: Residuals Correlation Matrix (Associated p-values)

	dMRres	RlnHres	LnCPIres	RlnRres
dMRres		0.9743	0.2566	0.3678
RlnHres			0.0027	0.1270
LnCPIres				0.1993
RlnRres				

Table 11: Simulated House Prices: Annualised Geometric Mean at different percentiles

	Independent Residuals	T-Copula Residuals	% Difference
Min	1.0152	1.0217	0.64%
0.5th P	1.0404	1.0434	0.28%
1st P	1.0450	1.0465	0.14%
5th P	1.0571	1.0573	0.01%
10th P	1.0632	1.0630	-0.02%
25th P	1.0746	1.0729	-0.15%
50th P	1.0866	1.0835	-0.28%
75th P	1.0991	1.0948	-0.39%
90th P	1.1107	1.1043	-0.58%
95th P	1.1180	1.1100	-0.71%
99th P	1.1296	1.1198	-0.86%
99.5th P	1.1368	1.1237	-1.15%
Max	1.1610	1.1614	0.03%

4.4 Residual Dependence

Tables 9 and 10 shows that the estimated error covariance matrix does not display statistically significant correlations for 5 of the 6 relationships. Because of this an assumption of independence in the errors was made.

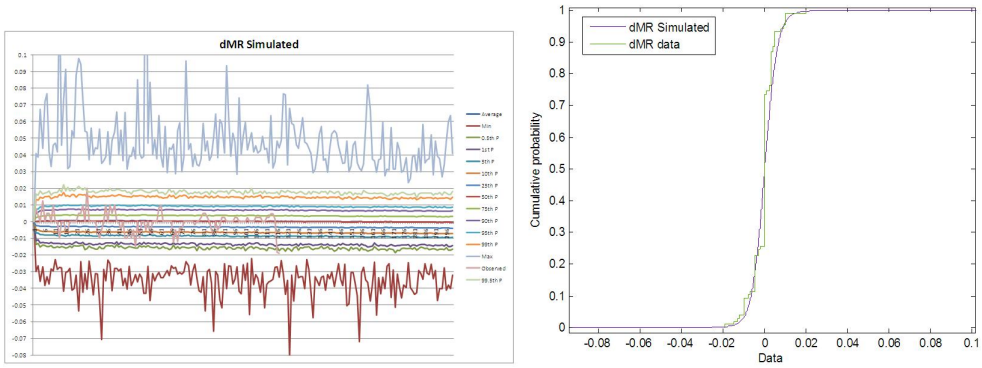
An alternative model was estimated with a t-copula for dependence between the marginals in order to generate fatter tails for some of the simulated variables. Residual scatterplots under the two assumptions are compared in the Appendix. Tables 11 and 12 show that the geometric mean of rates at various percentiles were relatively unchanged by this assumption.

Table 12: Simulated Mortgage Rates: Annualised Geometric Mean at different percentiles

	Independent Residuals	T-Copula Residuals	% Difference
Min	1.0337	1.0413	0.74%
0.5th P	1.0551	1.0523	-0.26%
1st P	1.0577	1.0560	-0.16%
5th P	1.0706	1.0686	-0.18%
10th P	1.0788	1.0760	-0.26%
25th P	1.0956	1.0931	-0.22%
50th P	1.1199	1.1170	-0.26%
75th P	1.1512	1.1471	-0.35%
90th P	1.1824	1.1782	-0.36%
95th P	1.2053	1.1991	-0.51%
99th P	1.2515	1.2433	-0.65%
99.5th P	1.2707	1.2659	-0.37%
Max	1.3822	1.4258	3.15%

4.5 VAR Simulated Paths

The mortgage rates were simulated with a starting observation of 10%. Figures 8a and 8b show the simulated values for dMR. The maximum (minimum) values of the simulation are far greater (smaller) than the observed maximum (minimum) values. Historical data is consistent with the simulated percentiles. The average/median change in interest rates is also consistent with the simulated changes. The simulated distribution tends to slightly overestimate the number of observations immediately to the left of zero and underestimates the number of observations immediately to the right of zero.



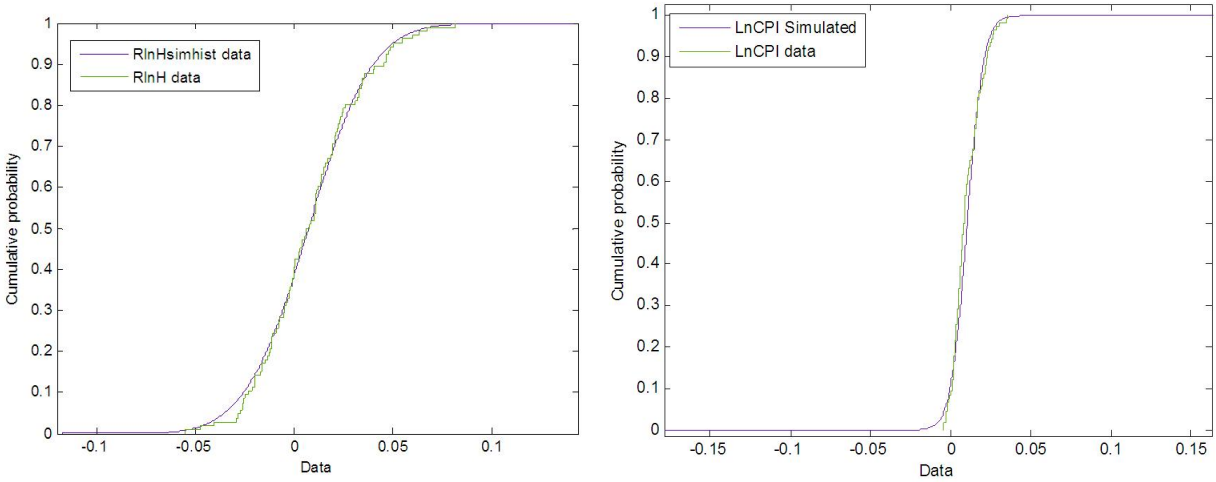
(a) dMR Simulated (b) dMR Simulated CDF

Figure 8: dMR Residual Fits

The simulated mortgage rates in Figure 11a are reasonable and within the bounds of expectation. A modification was made to the simulation process to deal with negative simulated paths. As negative/zero mortgage rates clearly don't make sense,

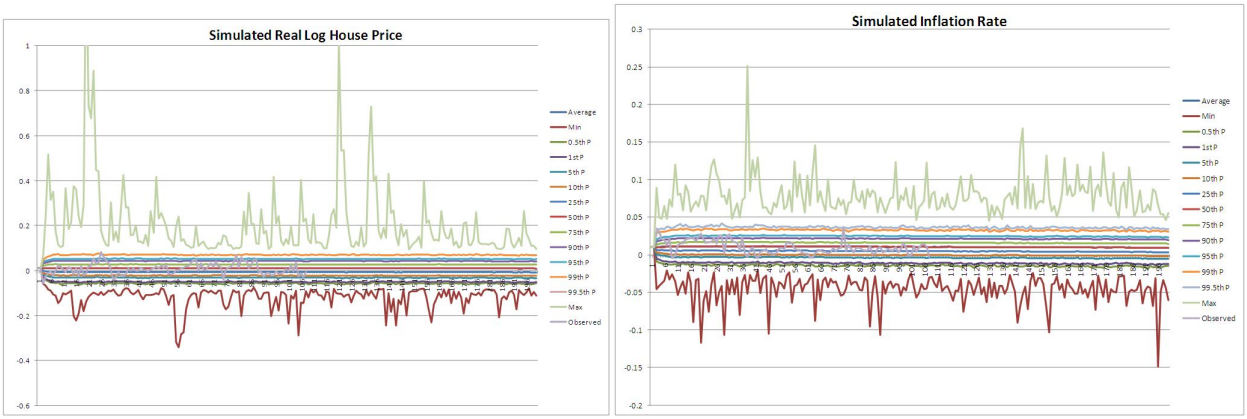
simulated paths where the minimum mortgage rate was below 5bps were not included. The median interest rate, whilst exhibiting slight curvature, appears generally stable over 200 quarters. The upper percentiles of the distribution also provide a good base for conducting scenario analysis where scenarios involve sustained high mortgage rate environments.

The simulated house price was constructed by multiplying the base house price by the real house price growth rate, exp^{RlnH} and the inflation rate, exp^{LnCPI}. The simulated distribution for $RlnH$ and $LnCPI$ both capture the features of the empirical distribution (Figures 9a and 9b). Although the maximum (minimum) values of the distributions are again much larger (smaller) than the observed values, the simulated percentiles are consistent with observed data (Figures 10a and 10b).



(a) $RlnH$ Simulated CDF (b) $LnCPI$ Simulated CDF

Figure 9: $RlnH$ and $LnCPI$ Simulated CDF



(a) $RlnH$ Simulated (b) $LnCPI$ Simulated

Figure 10: $RlnH$ and $LnCPI$ Simulated

The simulated house prices are presented in Figure 11b. The median simulated house price tracks the observed median house price reasonably well. Overall, the simulated

results have captured a reasonable range of results as shown in Table 13.

Table 13: Mean Annual Simulated Housing Returns

	Returns
Min	1.52%
0.5th P	4.04%
1st P	4.50%
5th P	5.72%
10th P	6.33%
25th P	7.46%
50th P	8.67%
75th P	9.92%
90th P	11.08%
95th P	11.80%
99th P	12.96%
Max	16.11%

5 Solvency and Shortfall for Reverse Mortgages

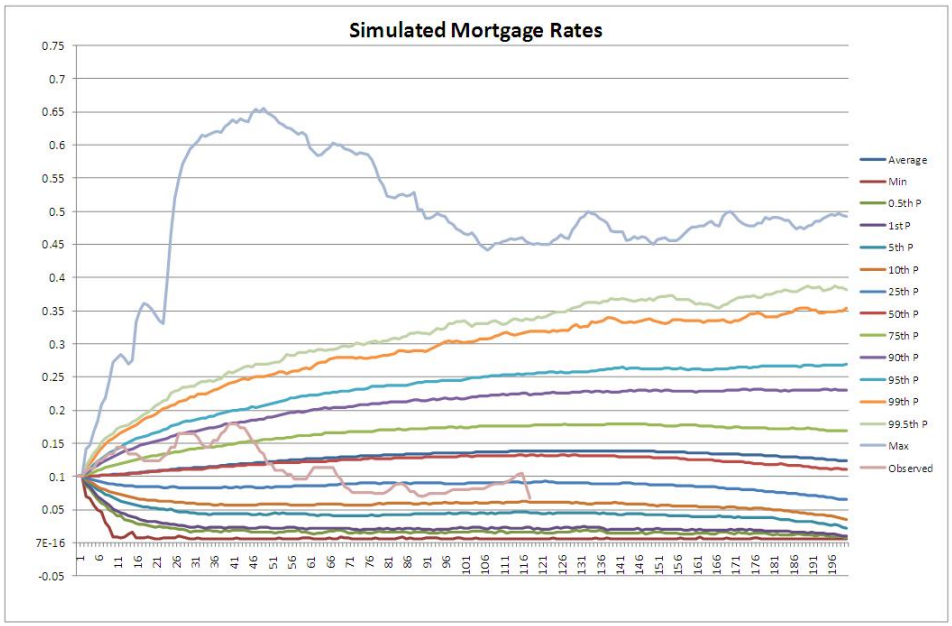
The application of the model will be for the analysis of reverse mortgages for borrowers aged 65. Details are shown in Table 14.

Table 14: Loan Parameters

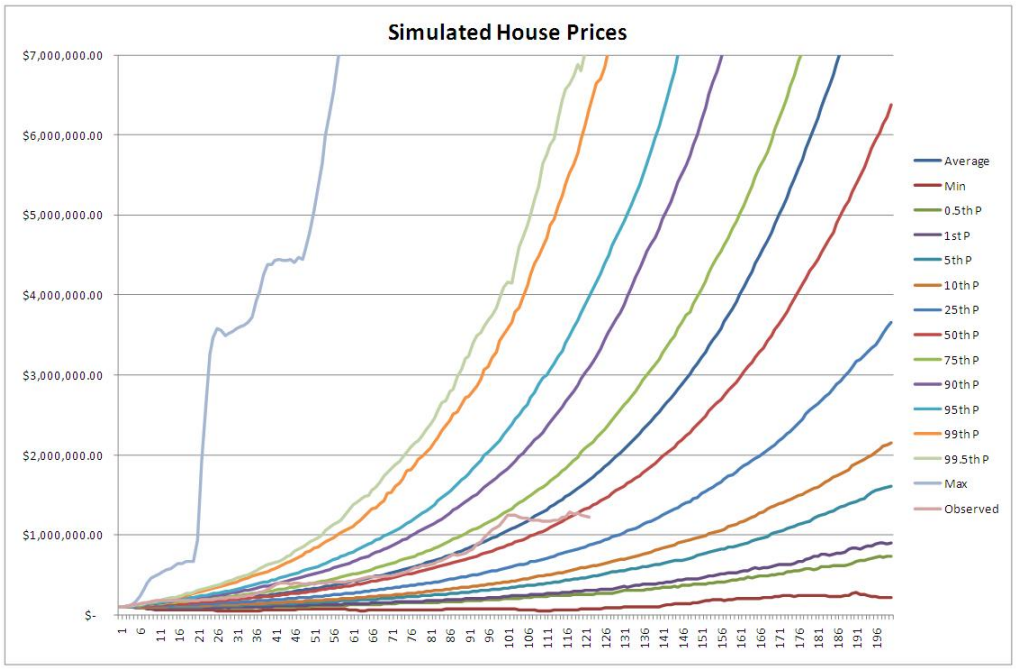
Parameter	Assumption
Initial House Price	$100,000
Loan to Value Ratio	15%
Age of Borrower	65
Pricing	1% above Standard Variable Mortgage Rate

5.1 Solvency

The models have been developed to quantify the credit loss a lender of reverse mortgages is expected to face and to calculate the reserving rate or insurance premium they would need to pay to mitigate against the credit loss. In order to do this the perspective considered is that of a hypothetical insurer which provides insurance to the lender against any credit losses. The "default event" for the lender is when the loan outstanding first exceeds the house price. This is the major risk of most Australian



(a) Simulated Mortgage Rates



(b) Simulated House Prices

Figure 11: Simulated Mortgage Rates and House Prices

equity release products. The analysis is based on quantifying the cost to purchase insurance against the default event.

Claims occur when the total value of the loan outstanding exceeds the underlying value of the home and the insurer meets the difference between the value of the loan and the proceeds from the sale of the house. The insurer must hold enough capital at the beginning of the policy to meet its future obligations with a high level of solvency. The lender pays premiums to the insurer either as a lump sum at the beginning of the period, or an income stream for the duration of the policy. The shortfall for the insurer is the present value of future cash inflows (premiums) minus the present value of future cash outflows (claims). Simulation was used to quantify the shortfall the insurer faces. This is the solvency or credit risk associated with the reverse mortgage loan. Sensitivities of the shortfall to changes in investment return and termination assumptions were assessed for a range of scenarios.

Termination rates were included for a range of scenarios to reflect variation in mortality and mobility rates. The US experience with reverse mortgage products shows that observed multiples to female mortality were substantially higher than 1.3x across all ages and sex. As reverse mortgages have a relatively short history in Australia, observed termination data are not available for Australia. The effect of changes in the termination rate is assessed using the US data from Szymanoski. Termination rates were based on the underlying female mortality rate from the Australian Bureau of Statistics (ABS). Multiples were applied to the underlying female mortality rate to derive the termination rates in Figure 12 and Figure 13.

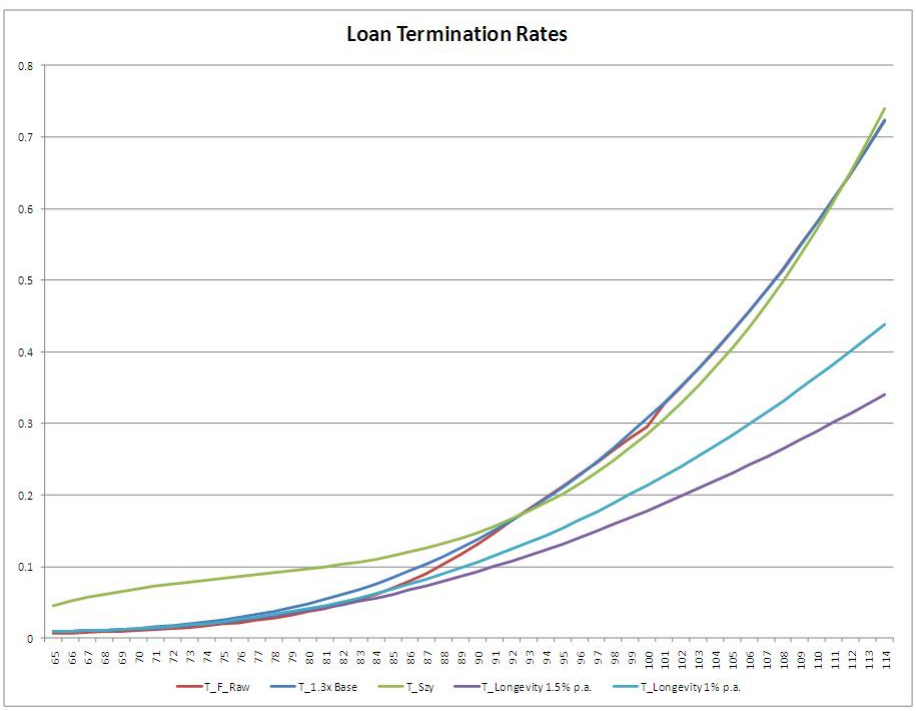


Figure 12: Loan Termination Rates

The series "T_F_Raw" represents the underlying female mortality rate taken from the ABS extrapolated using a cubic polynomial to a terminal age of 115. The series

"T_1.3x Base" represents the base case assumption of termination rates being 1.3x the underlying female mortality up until age 93. The series "T_Szy" represents termination rates taken from US data. Multiples of termination rates to the female mortality rate from the US data were applied to Australian data to arrive at the termination rate. The series "T_Longevity 1.5% p.a." and "T_Longevity 1% p.a." represent termination rates with constant longevity improvement rates of 1.5% and 1% p.a. across all age groups. These improvement rates are an indicative range based on historical data from the Australian Government Actuary [2].

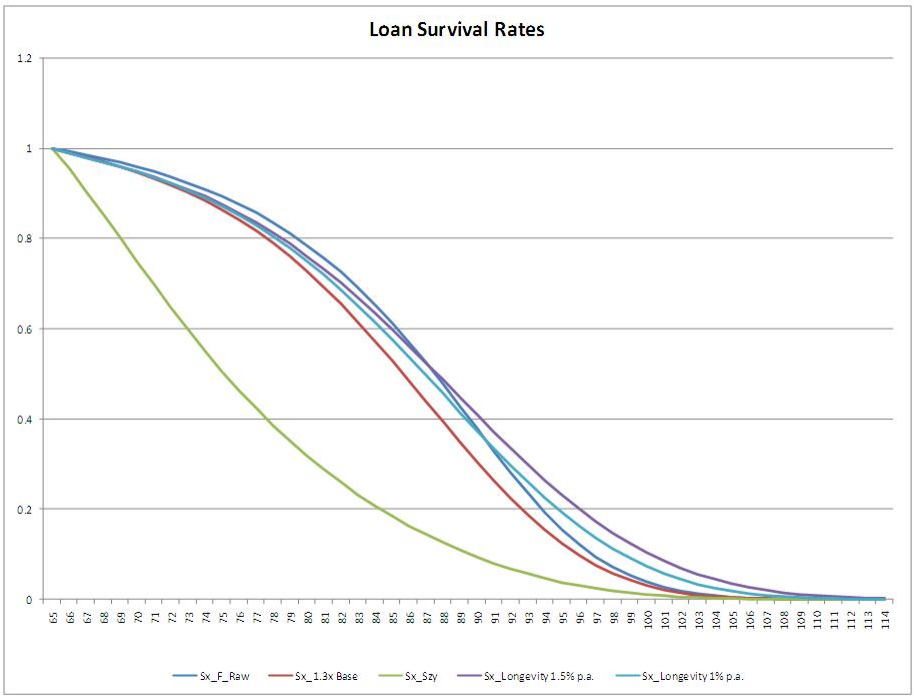


Figure 13: Loan Survival Rates

5.2 Insurer Shortfall: Base Case

The base case scenario is for a portfolio of homogeneous loans that totals $100,000 on lives aged 65. Termination rates are 1.3x female mortality until age 93, at which point they revert to the female mortality rate and the spread between the variable mortgage rate and the investment return is equal to a constant 150bps. Figure 14 shows a typical cash flow stream for the insurer with a large negative cash flow when the total loan value outstanding exceeds the underlying house prices, followed by a series of smaller cash flows as the remaining loans lapse over time. There are no premiums charged under this base case.

The shortfall quantile function is shown in Figure 15 with the values re-ordered from largest to smallest to determine loss percentiles and conditional tail expectations. The distribution of the shortfall has a heavy tail where the losses are extreme, with the largest shortfall at -$12,587 and the 99th percentile at -$7,734. Without premiums or

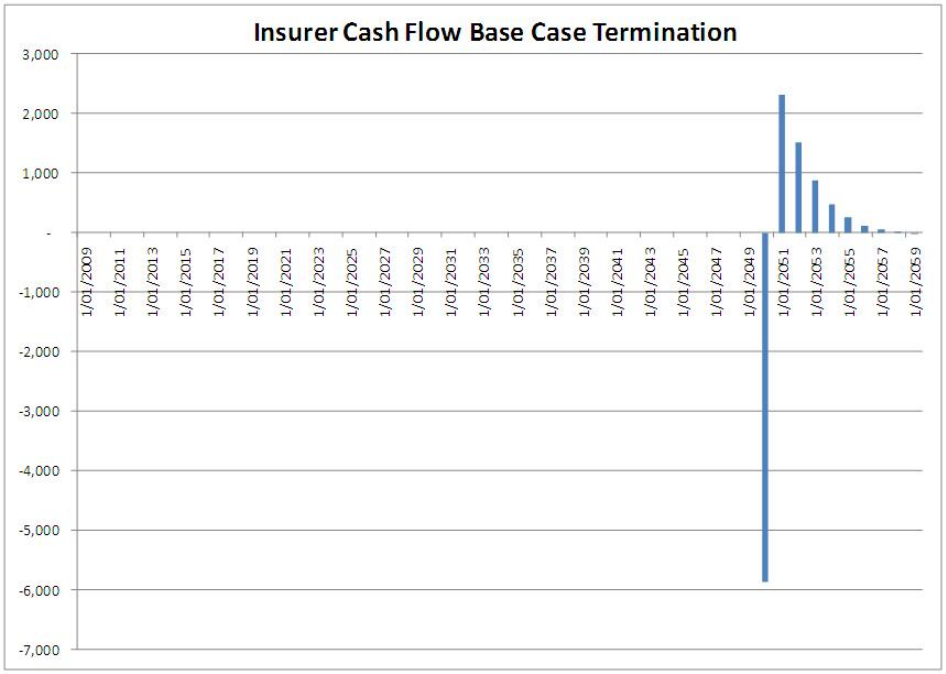


Figure 14: Insurer Cash Flow Profile

capital, an insurer can expect to sustain a loss of more than $7,734 with a probability of 1%.

There is a significant density at zero. A large proportion of these cases are where the value of the loan doesn't exceed the value of the house so that no loss is incurred. There were 150 observations above zero representing the instances where a loss occurs, but the house prices appreciates to the extent that the insurer has a positive surplus when all the loans have terminated.

Table 15: Base Case Premium

Age	65
LVR	15%
Investment Return	Constant 150bps below mortgage rate
Loan Termination	1.3x Female Mortality until age 93, revert to female mortality after age 93
Required Insurer Probability of Survival/Solvency	99%
Upfront Premium	2% of Loan
Quarterly Premium	70bps of Loan Outstanding

Table 16: Insurer Shortfall: Base Case

	Shortfall	Shortfall as a % of Original Loan
Min	-$12,587.43	83.9%
0.5 P	-$8,788.92	58.6%
1st P	-$7,728.00	51.5%
5th P	-$4,747.48	31.6%
10th P	-$3,008.70	20.1%
25th P	-$655.75	4.4%
50th P	-$0.33	0.0%
75th P	$-	0.0%
90th P	$-	0.0%
Max	$9,111.29	-60.7%

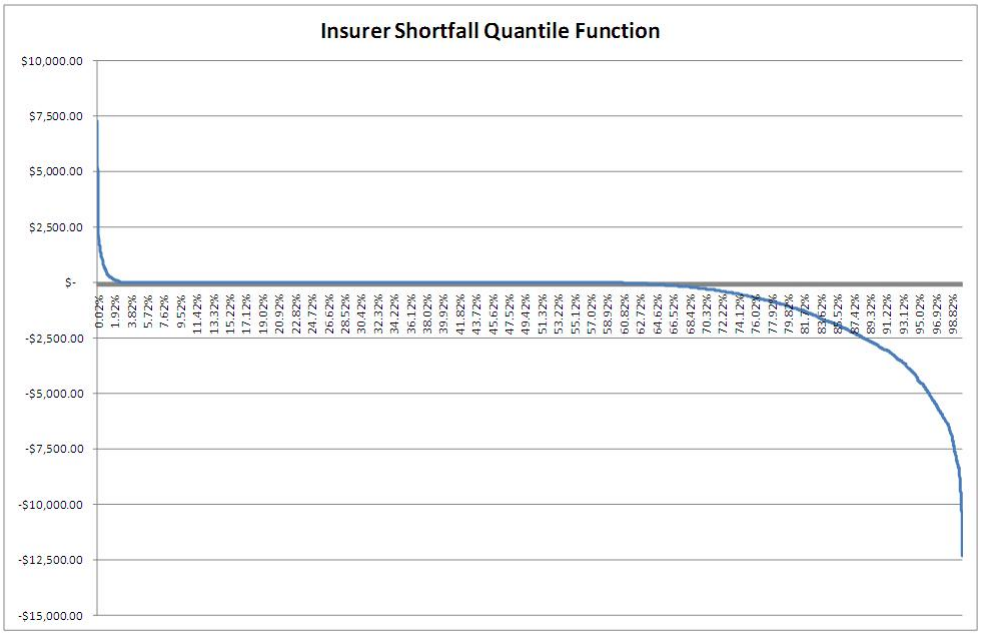


Figure 15: Insurer Shortfall Quantile Function

Figure 16 shows the risk measures for both Value-at-Risk (VaR) and Tail Value-at-Risk (TVaR). VaR measures the shortfall as at pre-determined percentages and is often used in practice to quantify extreme risks. The criticism of VaR as a risk measure is the lack of information on losses beyond the pre-determined percentile. TVaR is used to address this issue through quantifying the conditional loss beyond the pre-determined percentile.

In the base case the expected shortfall is -$9,007, given that the shortfall has exceeded the 99th percentile. The VaR shortfall at the 99th percentile equals -$7,728, a 14% difference from TVaR at the 99th percentile.

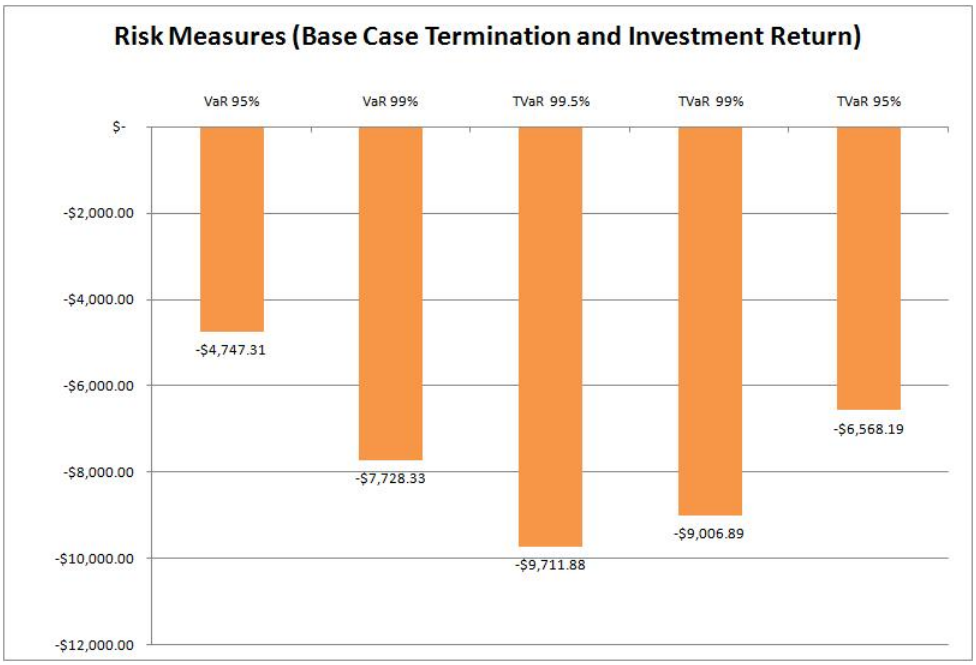


Figure 16: Risk Measures (Base Case Termination)

5.3 Insurer Shortfall: Sensitivity to Investment Return Spread

The sensitivities of both VaR and TVaR to changes in the base case investment return spread of 150bps are of interest. The spread is assumed constant across the 50 years of the simulation. The spread between mortgage rates and an underlying cash rate is affected by a variety of factors related to the lender's cost of funding as well as the perceived riskiness of the mortgage.

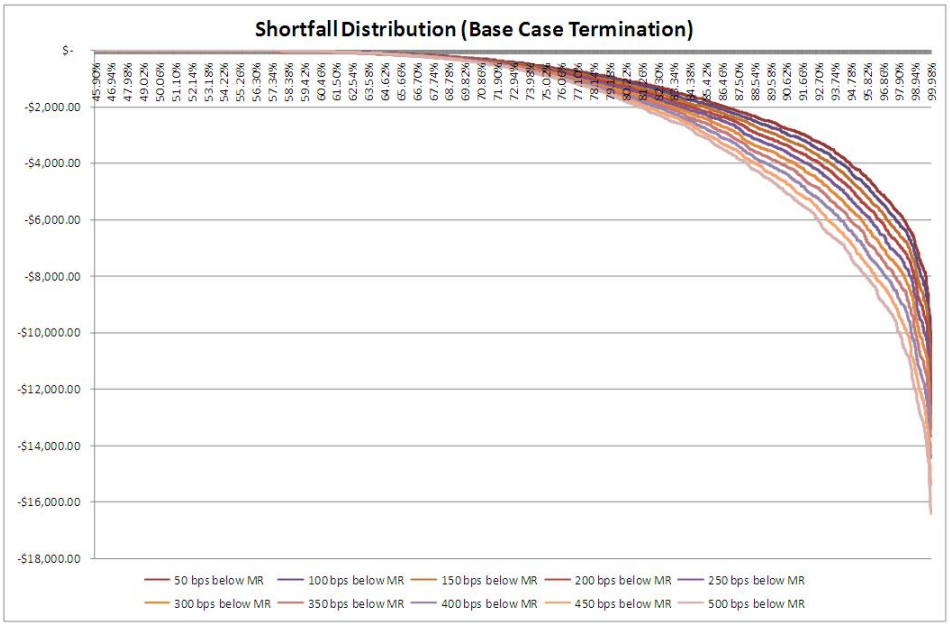


Figure 17: Shortfall Sensitivity to Investment Return (Base Case Termination)

Figure 17 shows the shortfall distribution. The proportional effect of changes is relatively constant for different percentiles of the distribution. VaR at the 90th, 95th and 99th percentile respond very similarly to changes in the investment assumption. For every 50bps increase in the spread, VaR increases by approximately 6-7%.

The maximum spread between 90 day bank bills and the standard variable mortgage rate over the past 20 years has been between 475 and 500 bps. Data during the credit crunch and the subsequent financial crisis show that the investment spread between mortgage rates and the underlying cash rate increased from an average of 150bps to levels approaching 250bps to 300bps. This increase largely reflected the increased cost of credit to Australian banks. The subsequent effect on the loss distribution is to increase VaR by 15% to 20% on average.

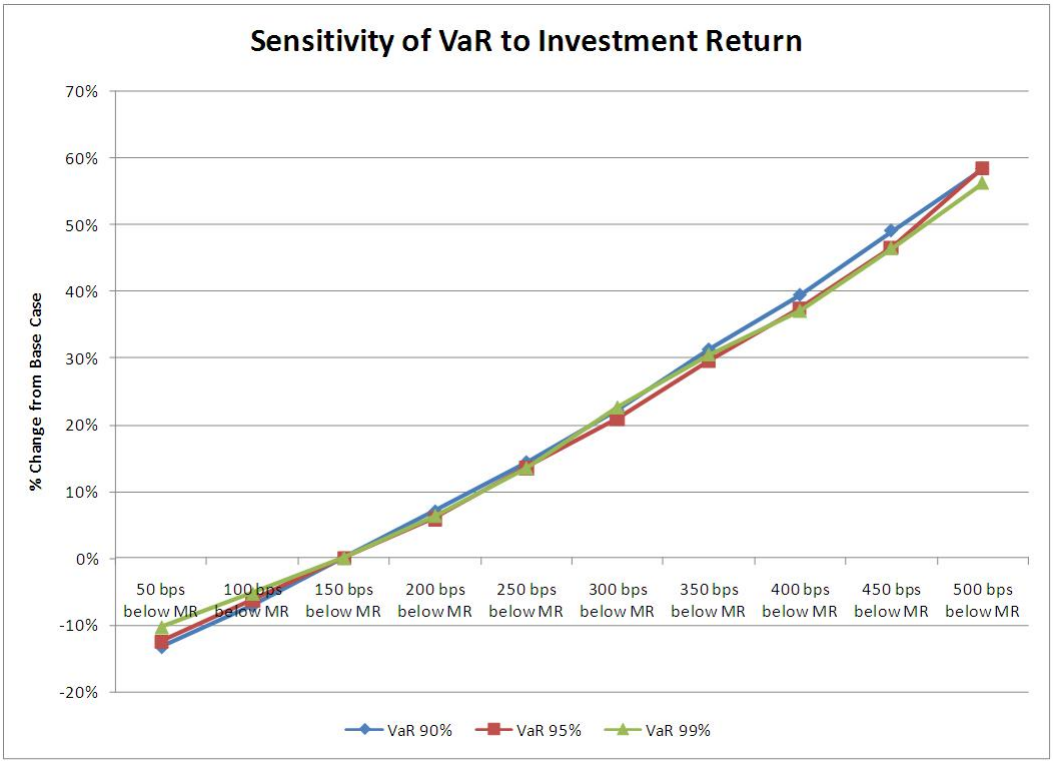
Figure 18 shows the effects of changes in investment spread assumptions on TVaR are similar to those on VaR with an increase of 5-6% for an increase of 50bps in the spread. Assuming the current spread of 250bps will persist in the long-term, this increases the base case TVaR at 99% by 12%.

5.4 Insurer Shortfall: Sensitivity to Termination Rates

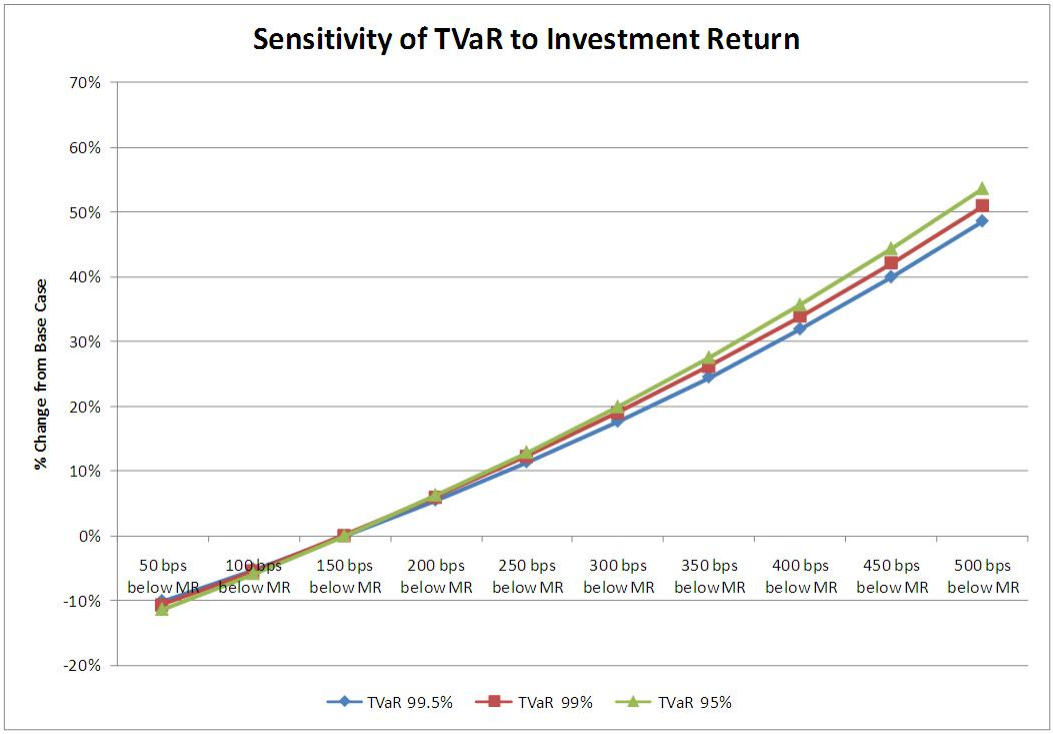
The shortfall, VaR and TVaR figures are calculated using the base case cash rate spread of 150bps below the standard variable mortgage rate. Figure 19 shows the timing of the default event relative to the number of loans outstanding when the default event occurs. The vast majority of default events occur after 20 years when the surviving members of the cohort are aged 85. The time to default is a function of initial loan values, interest rates and house prices. By the time the cohort has reached age 85, 60% of the cohort's loans are still active using base case termination rates.

Using Szymanoski's termination rates from US data, less than 20% of the cohort's loans are still active, resulting in a lower claim amount. Longevity improvements impact defaults which occur during ages 90 to 100. The percentage of loans outstanding at age 96 is approximately 10% using base case termination rates whilst approximately 20% of loans are outstanding for the same age assuming a 1.5% p.a. improvement in longevity. Figure 20 shows the shortfall sensitivity to termination rates.

The effect of termination rates on VaR at different percentiles is shown in Figure 21a and for TVaR in Figure 21b. Using Szymanoski's US data reduces VaR by 60% to 70% relative to base case scenarios. The effect of longevity improvements become less pronounced as the VaR percentile is increased. TVaR is far less sensitive to longevity improvements when compared with VaR although just as sensitive to Szymanoski's US data.



(a) VaR Sensitivity to Investment Return (Base Case Termination)



(b) TVaR Sensitivity to Investment Return (Base Case Termination)

Figure 18: Risk Measures: Sensitivity to Investment Return

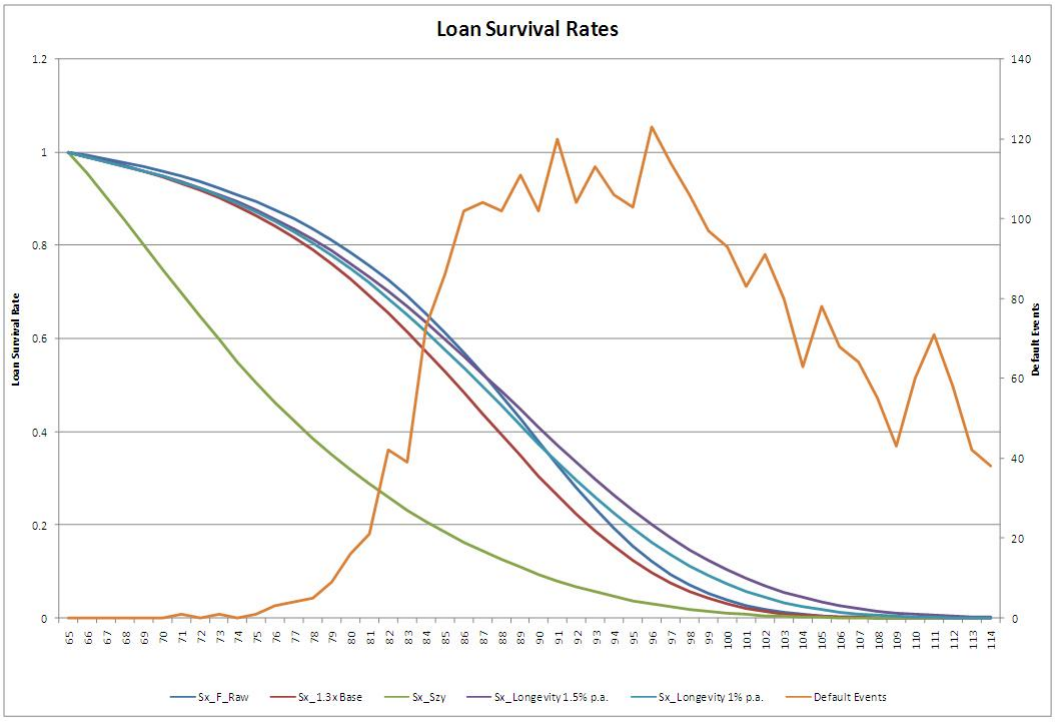


Figure 19: Loan Survival Rates vs Default Events

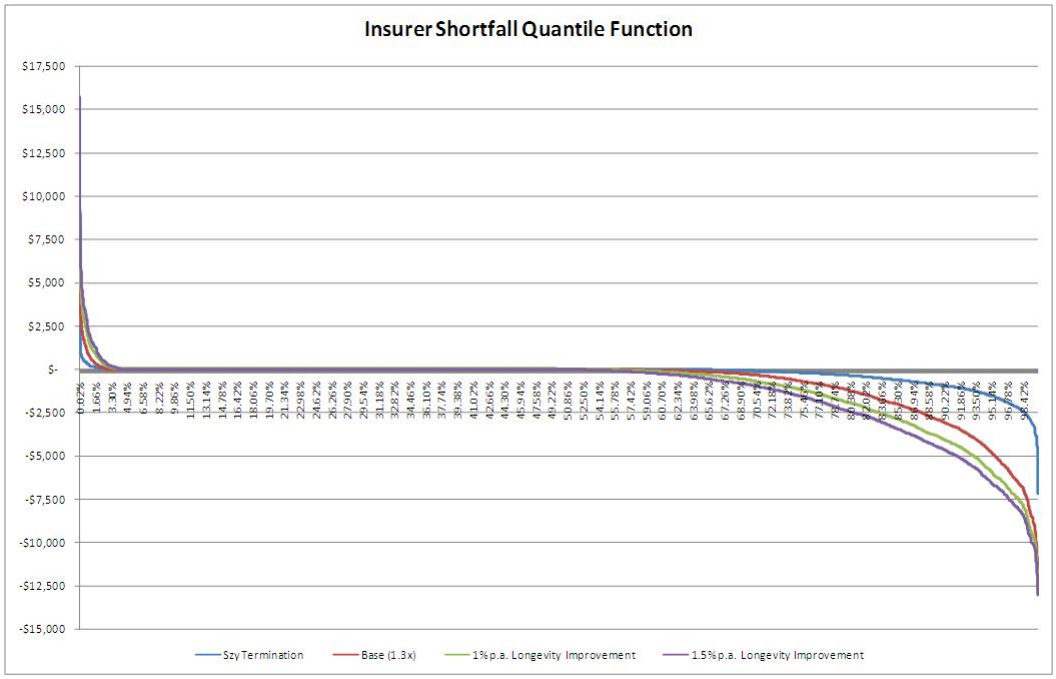
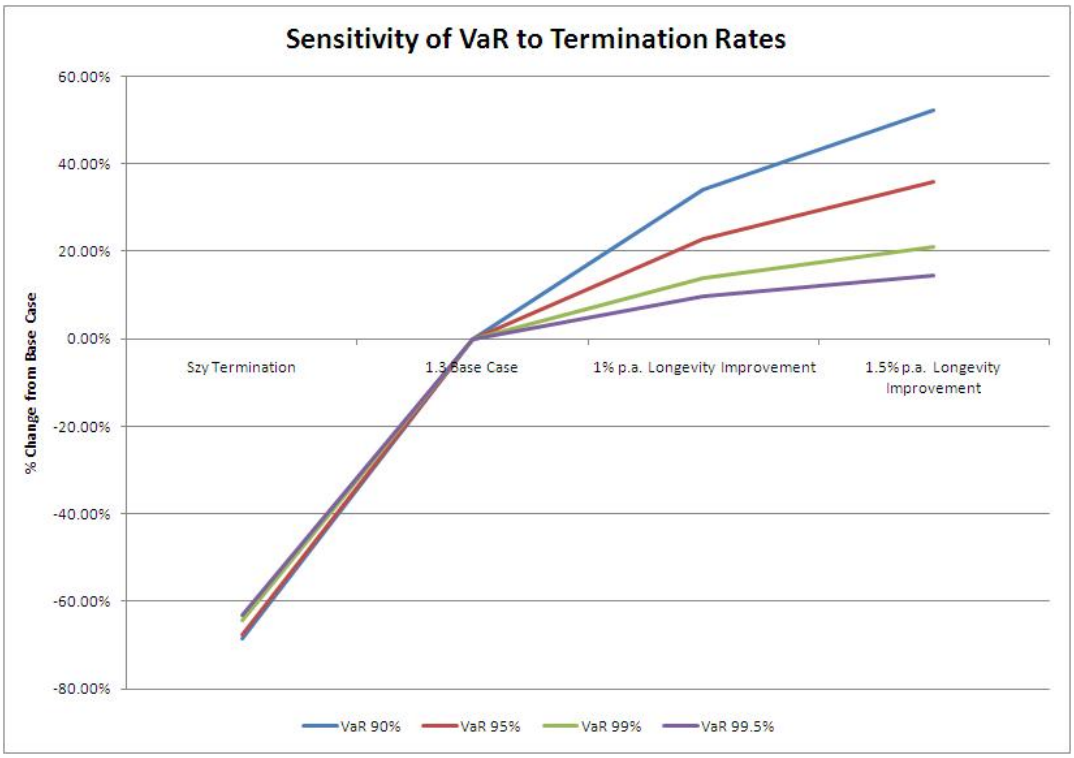
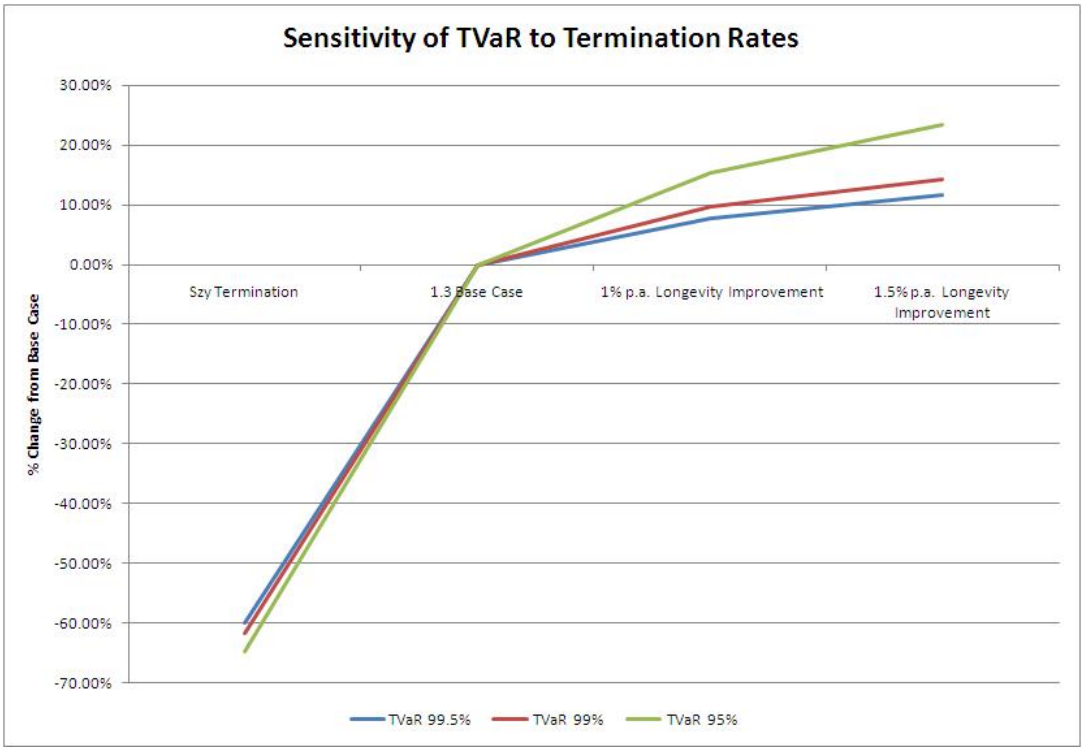


Figure 20: Shortfall Sensitivity to Termination Rates



(a) VaR Sensitivity to Termination Rates



(b) TVaR Sensitivity to Termination Rates

Figure 21: Risk Measures: Sensitivity to Termination Rates

6 Premium and Capital Requirements

The premium for the credit/loan loss insurance depends on the probability of solvency. The premium is assumed to consist of an upfront lump sum component equal to 2% of the loan and an annual premium calculated as a fixed percentage of the loan outstanding. If there is a claim, the policy is terminated and no more premium revenue is received. If there isn't a claim, premiums terminate once all loans have been terminated. Under the base case termination and investment scenarios, the probability of solvency was 99.3%.

6.1 Base Case Premium Scenario

Under the base case scenario, a quarterly premium of between 60bps and 70bps provides a positive VaR at the 99% level of confidence. The base case chosen is an upfront premium equal to 2% of the loan amount with a quarterly premium of 70bps payable in advance. VaR sensitivity to the annual premium is shown in Figure 22.

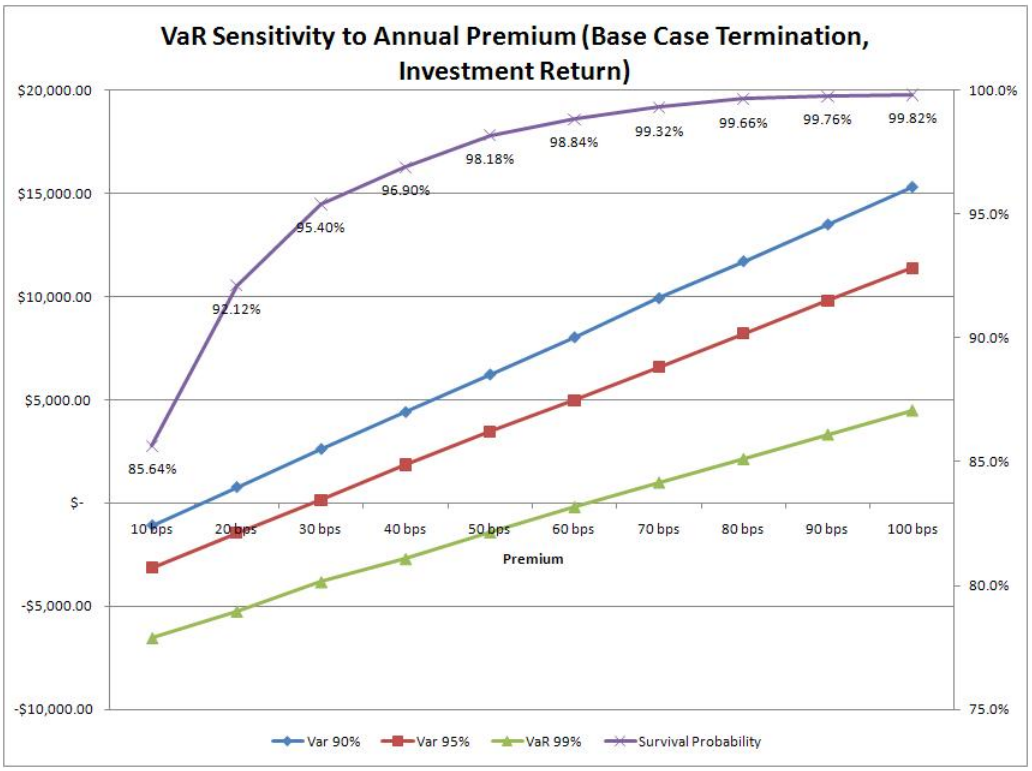


Figure 22: VaR Sensitivity to Annual Premium

The risk measures for the insurer's shortfall distribution are shown in Figure 23. TVaR at 95% is positive.

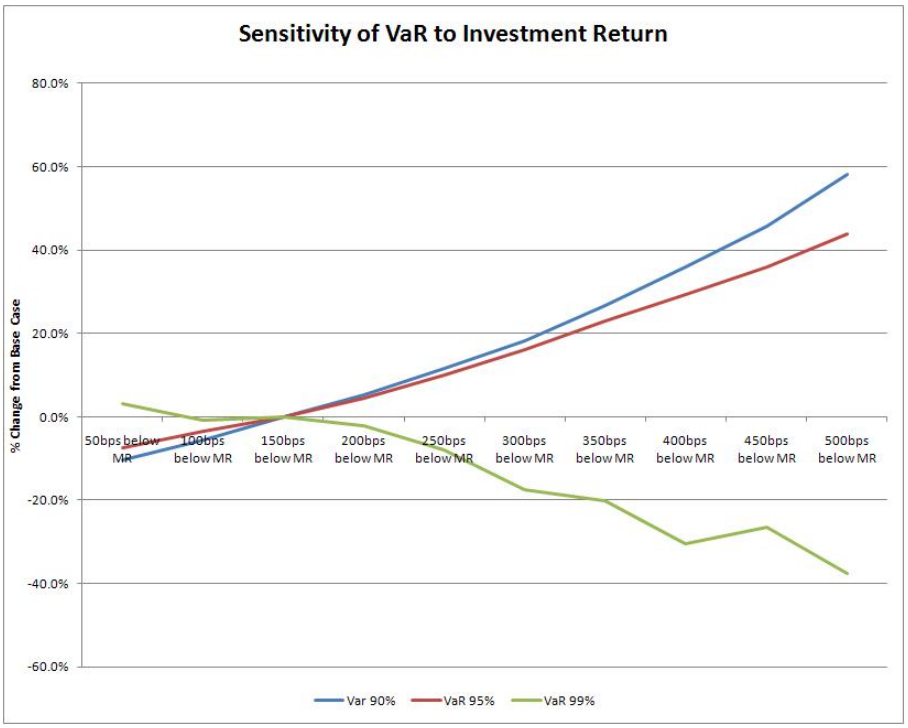
Figure 23: Risk Measures: 70bps Annual Premium

6.2 Sensitivity to Investment Return Spread

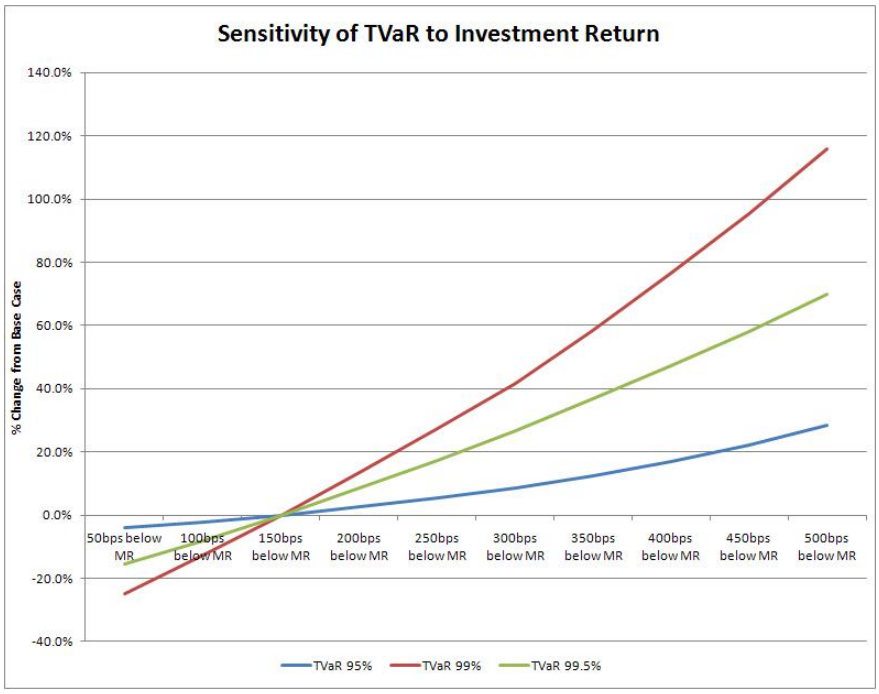
The sensitivity of risk measures to investment return spreads exhibits different patterns at different percentiles of the shortfall are shown in Figure 24. For decreases in the investment rate, the 90th and 95th percentile of the shortfall, which were surpluses, also increase. This reflects an increase in the present value of premiums greater than the increase in the present value of claims. Less capital needs to be held to achieve the same probability of solvency for a decrease in the investment rate spread. At the 99th percentile of the shortfall, which was a surplus, a decrease in the investment rate results in further decreases to the 99th percentile. Losses were sufficiently large at these percentiles to more than offset the increase in the present value of the premiums. The net effect of the investment rate decrease was to decrease the 99th percentile shortfall. Higher levels of capital must be held in order to achieve the same probability of solvency.

The values of TVaR or conditional expected loss are consistent with those for VaR. Losses in the tails (99th and 99.5th percentile) were less impacted by the increase in the present value of the premium since they decrease with the decrease in the investment return, a more negative shortfall as investment returns decreased. However, the TVaR at the 95th percentile increased with a decrease in the investment return, indicating a higher surplus with a decrease in the investment return. The shortfall distribution shown in Figure 25 illustrates a crossover between the shortfall scenarios. Where the investment return is lower (higher), there is a steeper (more gradual) descent toward a loss and a lower (higher) break-even probability.

Table 17 shows the probability of solvency is not as sensitive to changes in the investment return spread assumption. As the investment assumptions are varied from 50bps to 500bps below the standard variable mortgage rate, the probability of survival changes by a maximum of 0.8%. The shortfall function under various investment return



(a) VaR Sensitivity to Investment Return



(b) TVaR Sensitivity to Investment Return

Figure 24: Risk Measures: Sensitivity to Investment Returns

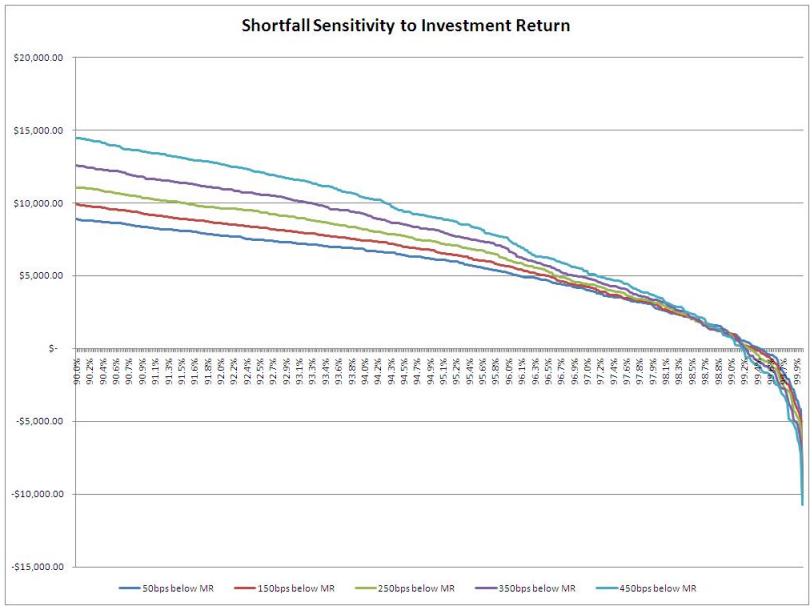


Figure 25: Shortfall Distribution 70bps p.a.

assumptions tends to have similar values at the break-even point.

6.3 Sensitivity to Termination Rates

The shortfall sensitivity to termination rates is shown in Figure 26. An increase in termination rates early on results in higher surpluses as well as a higher break-even point.

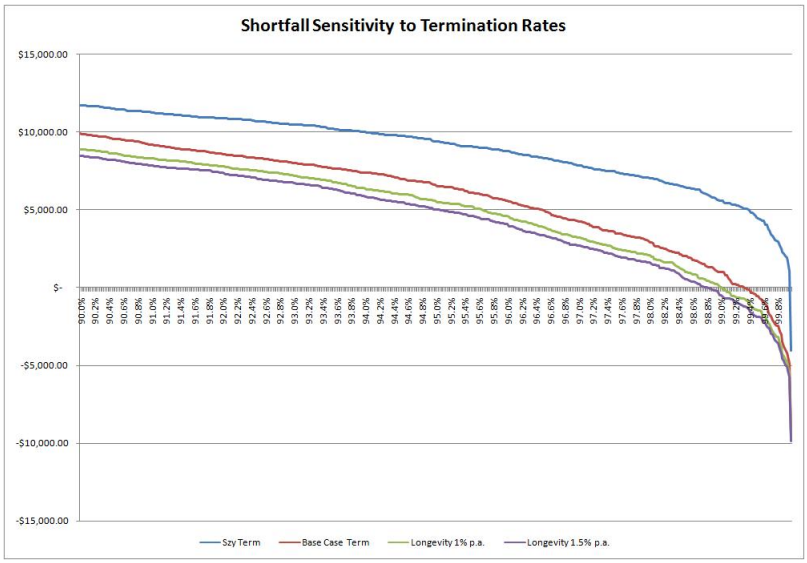


Figure 26: Shortfall Sensitivity to Termination Rate

The probability of solvency for a range of premiums is determined using different termination rates for an investment return spread of 150bps below the standard variable

Table 17: Probability of Solvency: Sensitivity Analysis

		Spread below MR		
		50bps	500bps	bps Difference
Premiums	10bps	85.6%	86.4%	80bps
	20bps	92.3%	92.3%	0bps
	30bps	95.6%	94.9%	70bps
	40bps	97.1%	96.8%	40bps
	50bps	98.2%	97.9%	30bps
	60bps	99.0%	98.8%	20bps
	70bps	99.4%	99.1%	30bps
	80bps	99.7%	99.4%	20bps
	90bps	99.7%	99.6%	10bps
	100bps	99.9%	99.8%	10bps

mortgage rate. Termination rates derived from Szymanoski's data result in much higher probabilities of solvency for lower premiums. Assuming an annual premium of 10bps, the probability of solvency using Szymanoski's data is 95.08% for the insurer. The insurance premiums required to replicate this probability of solvency are, close to 30bps p.a. assuming base case termination rates, between 30bps per quarter and 40bps per quarter assuming longevity improvements of 1% p.a. and between 40bps per quarter and 50bps per quarter assuming longevity improvements of 1.5% p.a.

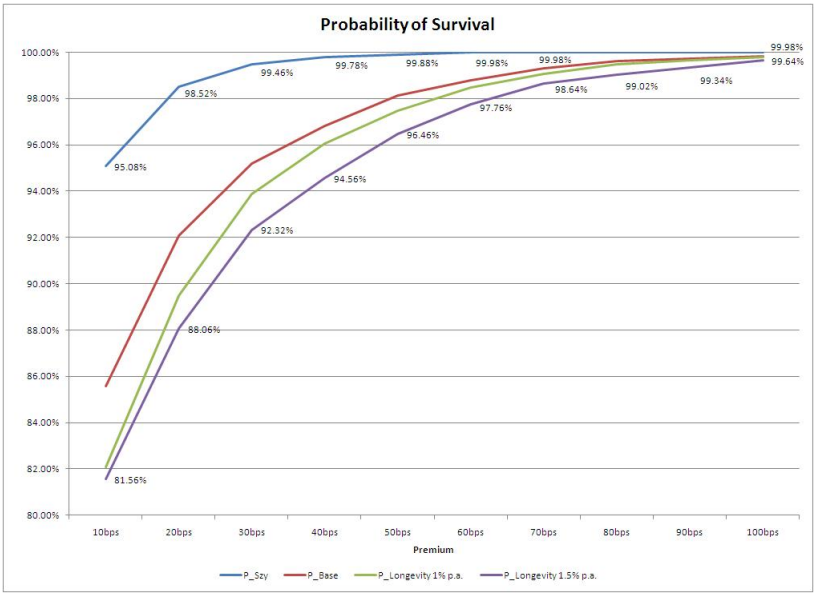


Figure 27: Probability of Solvency

The sensitivity for the base case scenario to the independence assumptions were also examined and the results shown in Table 19. The largest effect is at the extremes of the distribution with minimum and maximum values fluctuating by 5% to 15%. The

Table 18: Probability of Solvency: Sensitivity Analysis

	P_Szy	P_Base	P_Longevity 1% p.a.	P_Longevity 1.5% p.a.
10bps	95.08%	85.56%	82.08%	81.56%
20bps	98.52%	92.06%	89.50%	88.06%
30bps	99.46%	95.18%	93.86%	92.32%
40bps	99.78%	96.82%	96.04%	94.56%
50bps	99.88%	98.14%	97.48%	96.46%
60bps	99.98%	98.80%	98.46%	97.76%
70bps	99.98%	99.30%	99.06%	98.64%
80bps	99.98%	99.62%	99.46%	99.02%
90bps	99.98%	99.72%	99.66%	99.34%
100bps	99.98%	99.82%	99.80%	99.64%

Table 19: Simulated Insurer Shortfall Sensitivity to Residual Correlations

	Independent Residuals	T-Copula Residuals	% Difference
Min	-12,587.43	-13,534.67	7.52%
0.5th P	-8,788.92	-8,353.05	-4.95%
1st P	-7,728.90	-7,437.77	-3.76%
5th P	-4,747.48	-4,673.15	-1.56%
10th P	-3,008.70	-3,101.01	3.06%
25th P	-655.75	-642.76	-1.98%
50th P	-0.33	-0.34	3.37%
75th P	-	-	0%
90th P	-	-	0%
95th P	-	-	0%
99th P	767.97	800.61	4.25%
99.5th P	1,538.43	1,553.95	1.00%
Max	9,111.29	8,636.59	-5.21%

minimum value assuming a t-copula dependence structure increases the size of the shortfall by 8%. Between the 0.5th and 99.5th percentile, the values differ by between 0% to 5%.

7 Conclusions

Reverse mortgages and other home equity release schemes are becoming more significant as a means of funding retirement needs. Issuers of reverse mortgages must have the capability to assess the risks in these loan products in order to price and risk manage their portfolio of loans. A regulator must also be confident that the appropriate capital is held against the risks. The major risk arises from the appreciation of house prices

exceeding the value of the loan accrued with interest. Margins included in loans to cover this risk may be inadequate to cover the risk since it depends on loan termination rates from disability and mortality. The risks in reverse mortgages has both a loan loss and a life insurance component.

This paper has developed a more robust modeling framework for assessing the risks of reverse mortgage products. Losses arising from the credit risk associated with the "no negative equity" guarantee for reverse mortgages is assessed using a Vector Autoregression framework. A VAR framework better captures the interrelationship between interest rates and house prices. These are the variables that determine the severity of the potential loss. The major advantage of the VAR framework is its flexibility and its popularity as a tool for macroeconomists (Sims 1981). Another advantage is the ease of estimation and simulation with packaged programs available for most statistical software programs. Termination rates allowing for longevity improvements and recent US experience are also included since these are important in determining the timing of any potential loss. Sensitivities to the model assumptions are assessed for the potential shortfall. The analysis is based on reverse mortgages for a portfolio of 65 year old borrowers. The analysis can be readily extended to other ages.

Sensitivities were assessed for changes in the investment return spread and the loan termination rates. A 100bps to 200bps decrease in investment rates were found to decrease VaR at the 99th percentile by 8%-20% respectively from the base case scenario. For a 1% longevity improvement per annum across all ages, the premium required for a 99% chance of survival is 70bps. For an additional 0.5% in longevity improvement per annum across all ages, the premium required for the same 99% chance of survival is 80bps, an additional 10bps. In the base case, 70bps per quarter results in a probability of survival of 99.3%. If termination rates were similar to Szymanoski's US data, the quarterly premium would be closer to the midpoint of 20bps and 30bps.

The analysis shows that both termination rates and changes in investment return spreads have a significant impact on the level of capital required to insure against credit losses. Australian lenders who wish to conduct internal reserving to a 99% probability of sufficiency in meeting the credit losses would need to set aside 60-70bps each quarter for the loan to a 65 year old based on the modeling. Market premiums are in the range of 20bps to 30bps. Early Australian termination data have been similar to the US experience. If emerging data from Australian reverse mortgages continues this trend then a premium of 20bps to 30bps per quarter could provide for a 99% probability of solvency for the insurer.

As the reverse mortgage market grows in Australia as demographic change forces changes to retirement funding, APRA will need to focus more on risk-based capital requirements for lenders. For APRA, product providers would be required to hold enough in assets to meet obligations. Mono-line insurers offering credit insurance for these products would need internal models and adequate pricing and capital. Where lenders opt to reserve for the credit loss internally, the future losses would need to be adequately provisioned and capital held against unexpected losses. The Vector Autoregression framework provides a basis for internal models for assessing the value of these loans for both insurers and lenders.

The sensitivities to the termination rates highlights the need for further research of loan termination rates and in particular, a segmentation of termination causes. In 2008, death and aged care combined accounted for less than 5% of terminations in Australia (SEQUAL). 25% repaid the loan voluntarily, 20% repaid through the sale of a property, 5% refinanced and 45% of repayments listed other reasons. Given the age profile of the Australian reverse mortgage market with 30% of policyholders above the age of 80, mortality will be expected to play an increasing role in termination rates. With better data a model which captures mobility, morbidity as well as qualitative information on planned loan use would be relevant. The relationship between other liquid assets belonging to the homeowner, house price appreciation, and illness could also be assesed.

8 Acknowledgements

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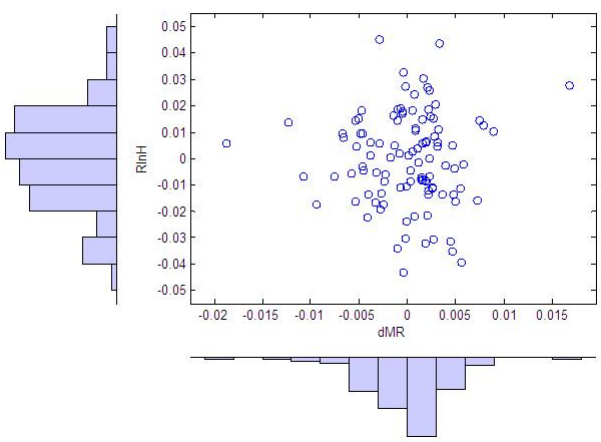
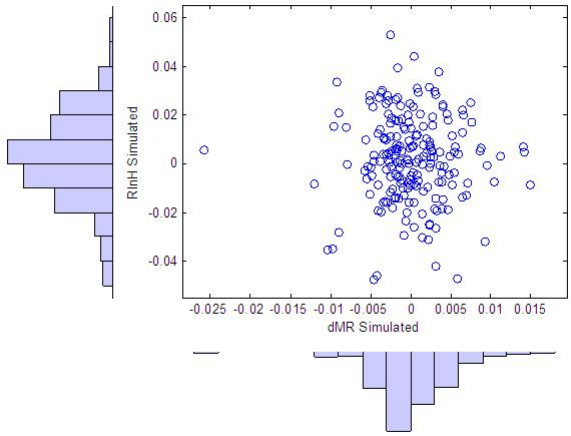
9 Appendix

9.1 Residual Independence Checks

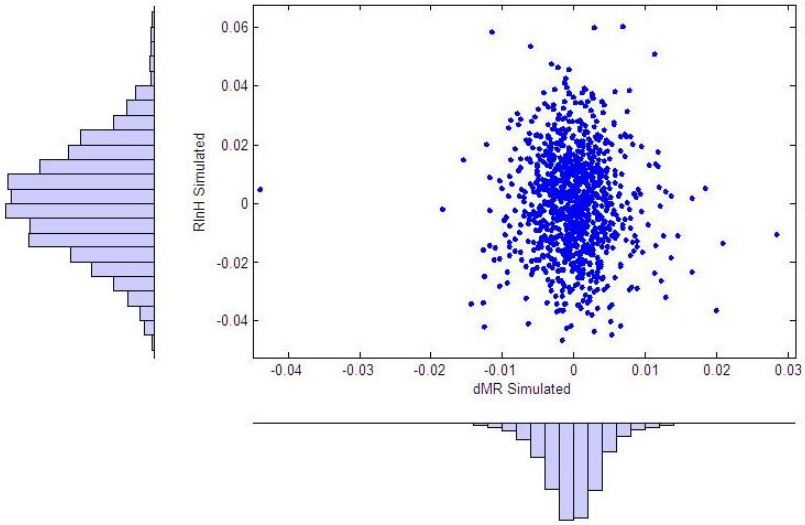
Scatterplots of residuals for dMR and $RlnH$ are shown in Figure 28a. There is no correlation pattern and appear random. The simulations assuming independence shown in Figure 28b captures the range of observations as well as the spread of observations. Simulations using the t-copula shown in Figure 28c produce more extreme observations relative to the residuals simulated assuming independence.



(a) dMR vs $RlnH$ Actual Residuals



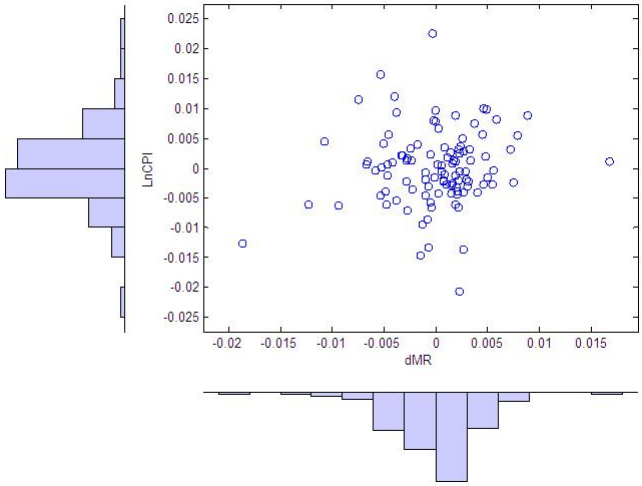
(b) dMR vs $RlnH$ Simulated Residuals (Independent)



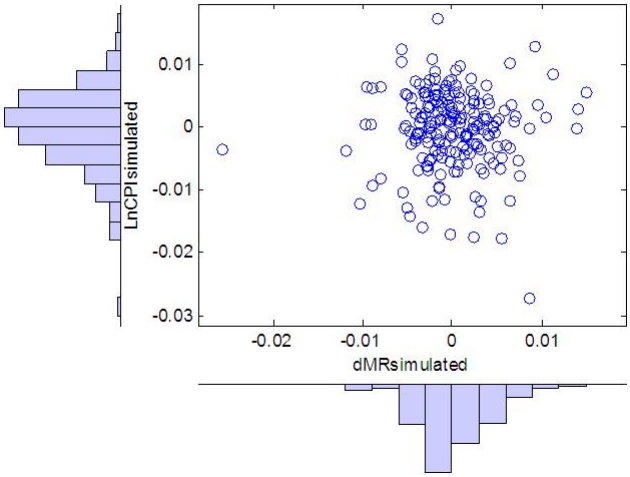
(c) dMR vs $RlnH$ Simulated Residuals (t-copula)

Figure 28: dMR vs $RlnH$ Residual Checks

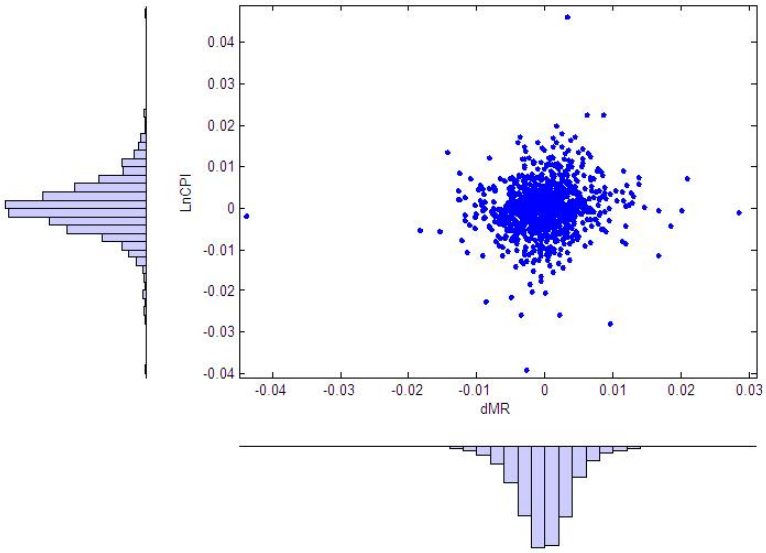
The scatterplots of residuals for dMR and $LnCPI$ shown in Figure 29 are similar to those for dMR and $RlnH$.



(a) dMR vs $LnCPI$ Actual Residuals

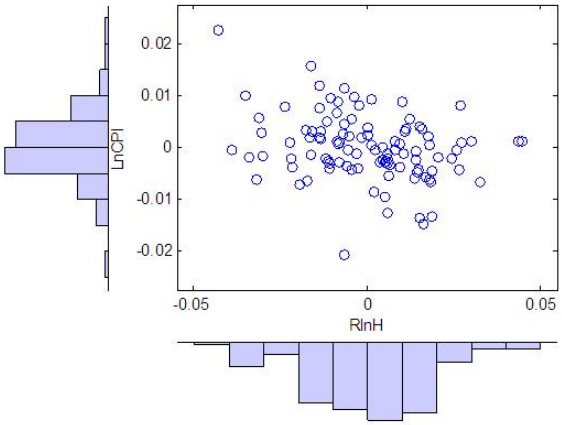


(b) dMR vs $LnCPI$ Simulated Residuals (Independent)

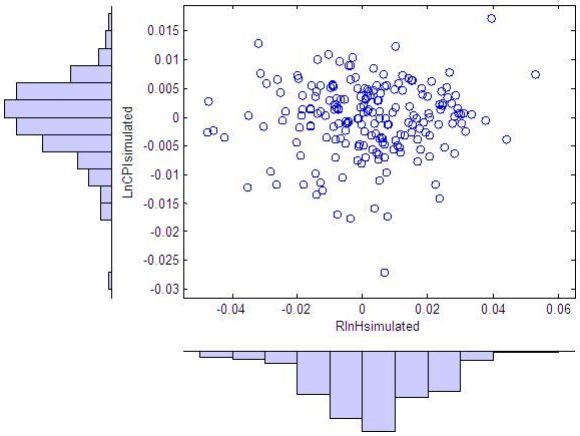


(c) dMR vs $LnCPI$ Simulated Residuals (t-copula)

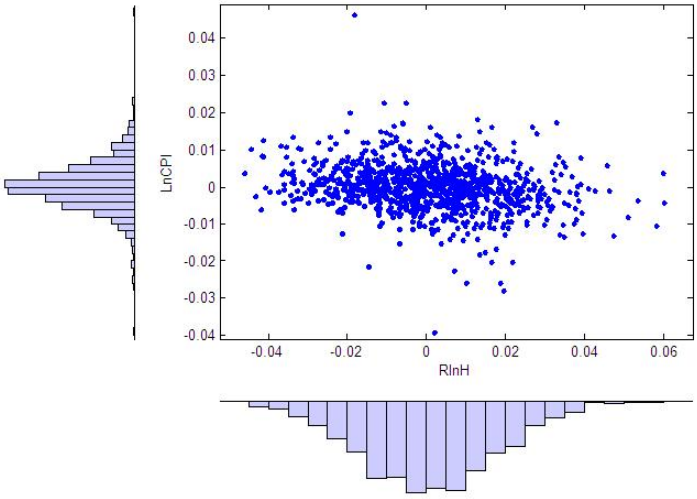
Figure 29: dMR vs $LnCPI$ Residual Checks



(a) $LnCPI$ vs $RlnH$ Actual Residuals



(b) $LnCPI$ vs $LnCPI$ Simulated Residuals (Independent)



(c) $LnCPI$ vs $RlnH$ Simulated Residuals (t-copula)

Figure 30: $LnCPI$ vs $RlnH$ Residual Checks

Scatterplots of residuals for $LnCPI$ and $RlnH$ shown in Figure 30a appear to exhibit a negative relationship. The simulated residuals assuming independence in Figure 30b have captured a reasonable range, but the slope may not have been captured. The simulated residuals using the t-copula in Figure 30c have captured the slope as well as producing fatter tails.

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