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An Empirical Analysis of Commercial Mortgage-Backed Securities Credit Ratings: Australian Evidence

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Abstract

The ultimate goal of structuring Commercial Mortgage-Backed Securities (CMBS) transactions is to obtain a high credit rating as this has an impact on the yield obtainable and the success of the issue. Though bond rating agencies claim that their ratings reflect each agency's opinion about an issue's potential default risk and rely heavily on a committee's analysis of the issuer's ability and willingness to repay its debt and therefore researchers would not be able to replicate their ratings quantitatively (Kim 2005), we follow previous researchers who gone ahead and replicated bond ratings on the premise that the financial variables extracted from public financial statements, such as financial ratios, contain a large amount of information about a company's credit risk (Huang et al. 2004). We use artificial neural networks (ANN) and ordinal regression (OR) as alternative methods to predict CMBS ratings. OR results show that rating agencies use only a subset of variables they describe or indicate as important to CMBS rating as some of the variables they use were statistically insignificant. Overall, ANN show superior results to OR in predicting CMBS ratings.

1. Introduction

Commercial mortgage-backed securities (CMBSs) have expanded the investment realm of both investors and issuers. They are seen as an alternative to direct investment in property offering advantages of liquidity, diversification, and being an alternative investment to other financial investments. CMBSs are bonds backed by a single commercial mortgage or, more generally, a pool of commercial mortgages (Jacob and Fabozzi 2003). In Australia, the expansion of the description of CMBSs as a form of securitisation of direct property assets, in addition to traditional definition of the securitisation of mortgages, has gained acceptance in the market (Jones Lang LaSalle 2001). CMBS securities also benefit from the standardised rating agency process that is directly analogous to the corporate bond markets. Corporate bond ratings inform the public of the likelihood of an investor receiving the promised principal and interest payments associated with the bond issue (Shin and Han 2001). However, issues of proprietorship have resulted in the methodology of rating mostly being shrouded in mystery. The methods and input variables used in rating are not fully disclosed to the public (Shin and Han 2001). Generally, the analysis undertaken by Standard and Poor's, Moody's Investors Service and Fitch Ratings in rating Australian CMBSs falls into three categories: property characteristics and cash flow analysis; portfolio level analysis; and transaction structure analysis, as elaborated in Appendix 1. The Appendix also includes factors considered and their weighting used by ABN AMRO (Roche 2002) in ranking CMBSs. Market yields correspond to bond ratings, which indicate an association between rating and risk. The higher the credit quality the lower will be yield and the more successful will be the issue (Alles, (2000); Kose et al, (2003). As such, studies of rating process are of interest not only to bond holders but also to investors.

Although bond rating agencies claim that their ratings reflect each agency's opinion about an issue's potential default risk and rely heavily on a committee's analysis of the issuer's ability and willingness to repay its debt and therefore researchers would not be able to replicate their ratings quantitatively (Kim 2005), researchers have still gone ahead and replicated bond ratings on the premise that the financial variables extracted from public financial statements, such as financial ratios, contain a large amount of information about a company's credit

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risk (Huang et al. 2004). Bond rating studies have traditionally used statistical techniques such as multivariate discriminant analysis (MDA), multiple regression analysis (MRA), probit and logit models to capture and model the expertise of the bond rating process. Recently, however, a number of studies have demonstrated that artificial neural networks (ANN) can be used as an alternative methodology to bond rating.

This study investigates several aspects of the use of ANN as a tool for predicting credit ratings of Australian CMBSs. Tests are undertaken to compare the predictive power of ANN models and ordinal regression models.

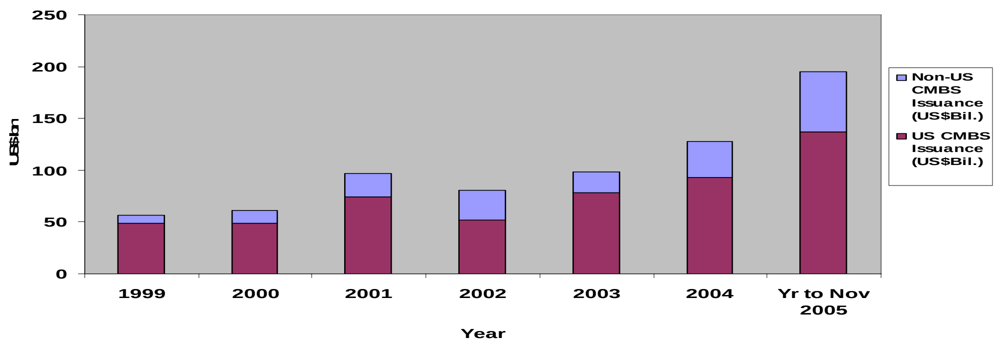
The paper is structured as follows. Section 2 reviews literature on the use of ANNs in various real estate applications and corporate bond rating studies respectively. Section 3 discusses the data and methodology. Section 4 presents the empirical results and analysis. Section 5 concludes and highlights future research direction.

2. An Overview of the Australian Commercial Mortgage-Backed Securities Market

The Australian CMBS market has undergone significant development since the first transactions came to the market in 1999, with a range of transaction types and issuers now accessing the market. The first CMBSs in Australia were done by Leda Holdings in 1999, the Longreach/Qantas head office securitisation and the David Jones flagship stores deals in 2000. As at the end of 2005 a total of 55 CMBSs had been issued with 137 tranches.

On the whole, global issuance of CMBSs has been on the increase with the USA leading the way. From 1999 to November 2005, CMBSs totalling US$532 billion had been issued in the USA compared to US$184 billion for the rest of the world during the same period as depicted in figure 1. There has also been an increase in the financing of commercial property through capital markets. Industry data show that in 2005 issuance of commercial CMBS in the United States was around US$170 billion, an 82 per cent increase over the previous year. Strong activity is also evident in Europe, where around US$56 billion of CMBS were issued in 2005, with around three quarters of this amount issued in the United Kingdom. In 2005, A$2.29 billion of newly rated notes were issued in Australia, an increase of 8.03% on the previous year.

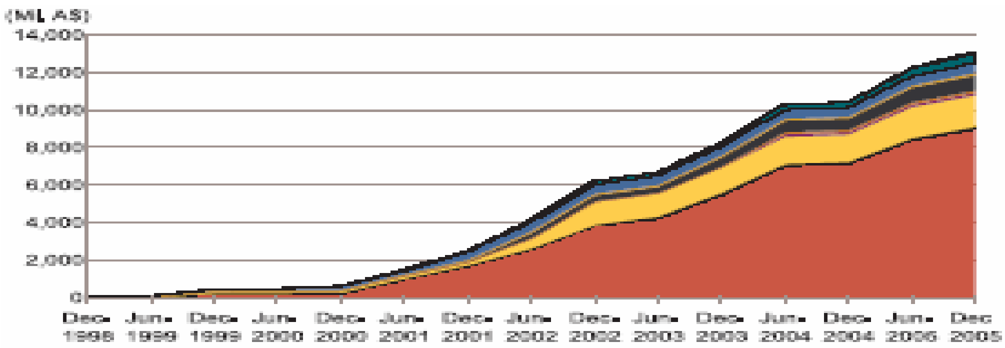
Figure 1: CMBS Global Issuance (January 1999-November 2005)



Source: Author's compilation from Commercial Mortgage Alert

The total cumulative Australian and New Zealand CMBS issuance volume since 1999 had reached A$12.6 billion as shown in figure 2 below. Total notes outstanding as at the end of 2005 was A$10.496 billion, arising from 16 credit lease and 31 CMBS transactions. Table 1 shows the number of tranches by sector issued from 1999-2005. With the overall Australian securitisation market approaching A$200 billion in debts outstanding, CMBS is still a relatively small asset class. Nevertheless, it remains both an important financing tool for commercial property owners and an alternative source of diversification for fixed income-investors. Appendix 2 shows some of the CMBSs issue by deal type and size.

Figure 2: Cumulative CMBS Issuance: Australia/New Zealand



Source: Standard and Poor's (2005)

Table 1: Number of Australian CMBS Issues by Tranches (2000-2005)

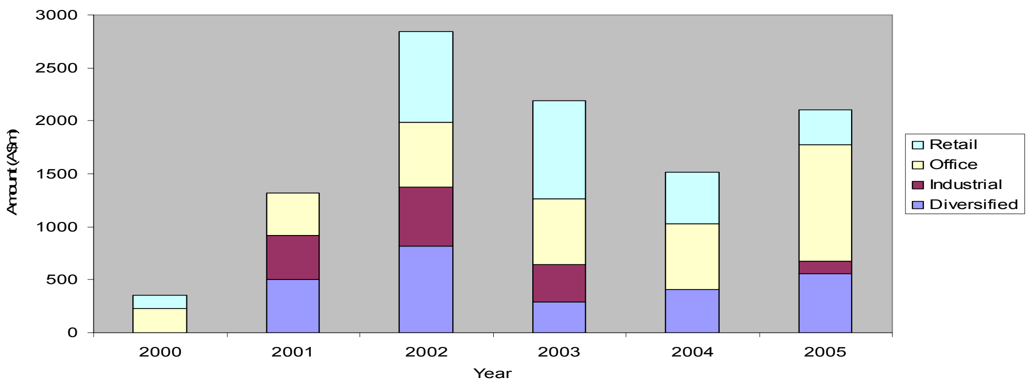
Sector	*2000*	*2001*	*2002*	*2003*	*2004*	*2005*	*2000-2005*
Diversified	1	2	11	7	7	14	42
Industrial	4	3	6	12	4	3	32
Office	0	3	4	5	9	10	31
Retail	0	0	15	9	0	8	32
Total	5	8	36	33	20	35	137

Source: Author's compilation from Standard and Poor's presale reports

Majority of the issues are in the single borrower multi-property category with over 95% of the total issuance to date. The CPIT 2006 Aurora Bonds CMBS is the only one single borrower single-property issuance to date. Two multi-borrower multi-property issues have been by MCS Capital Pty Limited and Challenger Capital Markets Ltd. ALE Finance Company Pty Ltd - Series 1 issuance is the only whole-business CMBS to date. The diversity of issuance transaction types show the maturity of the market as well as the arranger's confidence in trying out various CMBS structures to suit market needs.

However, as at the end of 2005 conduit-style CMBSs from large loans securitised in conduit programs which are common in the USA and Europe had not yet been undertaken in Australia.[1] A lot of the commercial mortgages continued to sit on bank balance sheets, and there was limited interest in pursuing securitisation of these assets. Since 2000, the most dominant CMBS issues have been in the office sector (A$3.6 billion), followed by the retail sector (A$2.7 billion). The diversified sector and the industrial sector have had A$2.6 billion and A$1.4 billion worth of CMBS issuance respectively. This is shown is figure 2.

Figure 3: Australian CMBS Issuance by Sector (1999-2005)



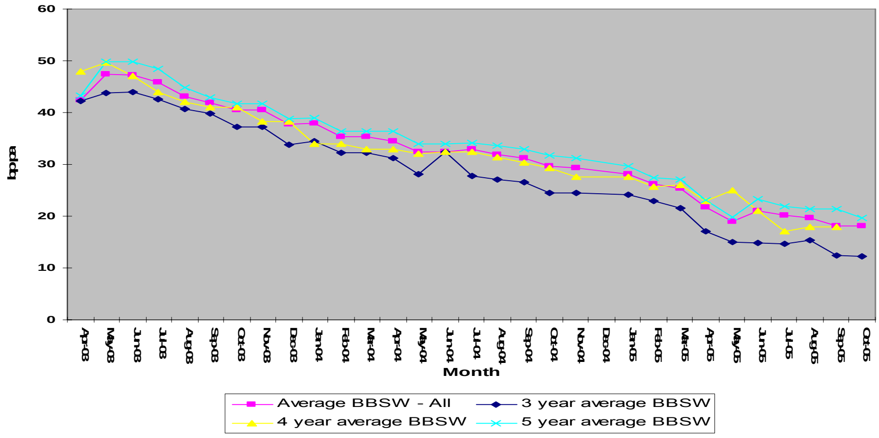
Source: Author's compilation from Standard and Poor's presale reports

Given the general appetite for fixed-income securities and the limited supply in the market, CMBS credit spreads have been contracting as shown in figure 4 below. In 2005 'AAA' five-year, interest only notes were priced at

[1] CMBS backed by reasonably large, well diversified pools of small-to medium-sized secured property loans.

20-25 bps (basis points) over three months' bank bill swap (BBSW), and three-year, interest-only notes at 17-20 bps over three-month BBSW. 'BBB' were priced at 60-95 bps over BBSW. These margins were lower than those of 2002, when they priced at least 20 bps wider for 'AAA' and 60 bps wider at 'BBB' level.

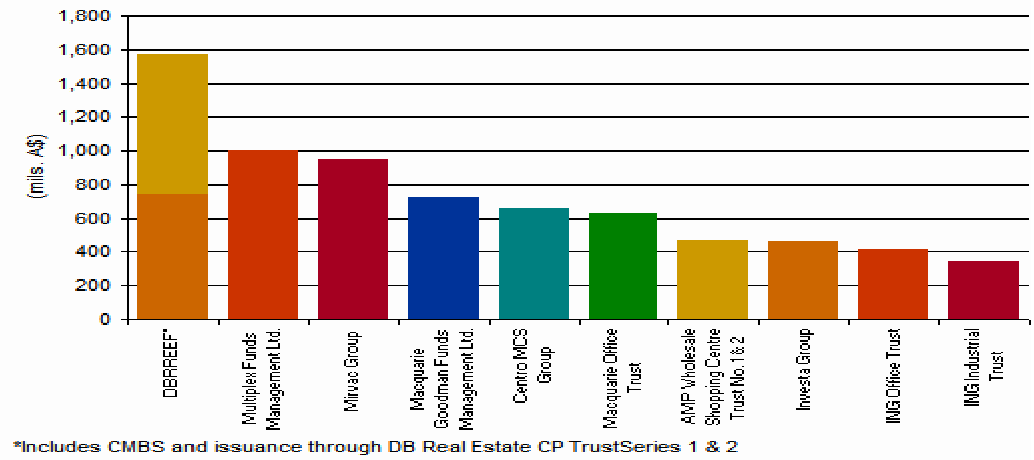
Figure 4: AAA Rated CMBS - Average Industrial Spread to Swap (Apr 2003- Oct 2005)



Source: Author's compilation from Property Australia magazine

Figure 5 shows the top 10 Australian CMBS issuers, all of which are Listed Property Trusts (LPTs). LPTs have a 65% market share. The single-purpose-vehicle-like characteristics of LPTs have helped in their establishment as major players in the CMBS market. Between 2001 and 2004, LPTs issued CMBSs worth over $3.7B via 27 issues (eg: Mirvac, Macquarie Goodman Industrial, ING Office, ING Industrial, Investa, Macquarie Office) and bonds worth over $4.8B via 40 issues (eg: Gandel, Commonwealth Property, GPT, Stockland, Westfield) (Newell and Tan 2005). This increased participation can partly be attributed to the high demand by institutional investors, mainly superannuation funds, for shares and bonds issued by LPTs in comparison to investing in direct property. The total contribution of asset allocation by Australian superannuation funds to property (both direct and indirect) declined from 17% in 1988 to 9% in 2000-2002, though the contribution of indirect property increased from 3% to 7% over the same period (InTech 2003). In 2005, 95% of superannuation funds had a specific allocation to property (either direct or indirect) averaging 10% (Newell 2006). With the drop in public bond issuance, bonds and CMBSs issued by LPT have been an attractive investment option for superannuation funds.

Figure 5: Top 10 Australian CMBS Issuers



Source: Standard and Poor's

The macroeconomic outlook for the Australian market remains benign, with historically low unemployment rates and a low interest environment expected to continue. These stable economic conditions are expected to foster resilience in the supply of securitisable financial receivables.

3. Prior Research in Artificial Neural Network Systems

ANNs are trainable analytical tools that attempt to mimic information processing pattens in the human brain. They are applied to a wide variety of pattern matching, classification, and prediction problems and are useful in many financial applications such as: stock price prediction, development of security trading systems, modelling foreign exchange markets, prediction of bond ratings, forecasting financial distress, and credit fraud detection and prevention. Comprehensive reviews of articles demonstrating the use of ANNs in various finance situations can be found in Fadlalla and Lin (2001); Coakley and Brown (2000); and Krishnaswamy et al. (2000).

Neural networks are regarded by many authoritative commentators as a useful addition to standard statistical techniques, and are in fact themselves based on statistical principles. Frequently these studies are in form of comparative analysis, with researchers contrasting the findings and perceived efficiency of ANNs with more tried and tested statistical methods. Although Salchenberger et al. (1992) and Tam and Kiang (1992) state that ANNs have several advantages over statistical methods, the results of these studies were less than expected because the real data in application is usually unevenly distributed among classes and these applications are limited in dealing with the ordinal nature of bond rating. Unlike statistical models, a neural network does not require priori specification of a function form, but rather attempts to learn from training input-output examples alone.

3.1 Artificial Neural Network Systems in Real Estate Research

ANN has recently earned a popular following amongst real estate researchers covering aspects such as real estate valuation: Tay and Ho (1991); Evans and Collins (1992); Worzala et al. (1995); Kauko (2004); examination of the impact of age on house values: Do and Grudnitski (1992); prediction of house value: McGreal et al. (1998); Nguyen and Cripps (2001) and Lai (2005); forecasting commercial property values: Connellan and James (1998a) and Connellan and James (1998b); and the impact of environmental characteristics on real estate prices Kauko (2003).

McGreal et al. (1998); Nguyen and Cripps (2001); and Lai (2005); all demonstrated the superiority of ANN over MRA in predicting house values. Worzala et al. (1995) and Lenk et al. (1997), however, noted that ANNs where not necessarily superior. Connellan and James (1998b) also show the superiority of ANNs over MRA in predicting commercial property values.

The increased use of neural networks by academic and commercial analysts in real estate studies is motivated by their recognition of complex patterns of multivariate property data (Connellan and James 1998a). This increased use of ANN methodology in the commercial real estate research gives credence to its extension to research in predicting CMBS bond ratings.

3.2 Artificial Neural Network Systems in Corporate Bond Rating Research

Bond ratings are subjective opinions on the likelihood of an investor receiving the promised interest and principal payments associated with bond issues. They are published by bond rating agencies such as Moody's, Standard and Poor's, and Fitch, in the form of a letter code, ranging from AAA-for excellent financial strength-to D for entities in default.

Rating agencies and some researchers have emphasized the importance of subjective judgement in the bond rating process and criticized the use of simple statistical models and other models derived from artificial intelligence to predict credit ratings, although they agree that such analysis provide a basic ground from judgement in general (Huang et al. 2004). Qualitative judgement, which includes accounting quality, operating efficiency, financial flexibility, industry risk, and market position, is still difficult to measure though. Literature on bond rating prediction has demonstrated that statistical models and artificial intelligence models (mainly neural networks) achieved remarkably good prediction performance and largely captured the characteristics of the bond rating process.

In this sense, various quantitative methods have been applied to bond rating. Statistical methods such as multivariate discriminant analysis (MDA), multiple regression analysis (MRA), probit and logit models have been used in order to capture and model the expertise of the bond rating process.

Several studies show that ANNs can be applied to bond rating: Dutta and Shekhar (1988); Surkan and Singleton (1990); Maher and Sen (1997); Kwon et al. (1997); Daniels and Kamp (1999); Chaveesuk et al. (1999); Yesilyaprak (2004); Huang et al. (2004) and Kim (2005).

Dutta and Shekhar (1988) were the first to investigate the ability of neural networks (NNs) to bond rating. Their sample comprised bonds issued by 47 companies randomly selected from the April 1986 issues of Value Line Index and the Standard and Poor's Bond Guide. They obtained a very high accuracy of 83.3% in discerning AA from non-AA rated bonds. However, the sample was so small that it simply amounted to showing the applicability of neural networks to bond rating.

Surkan and Singleton (1990) also investigated the bond rating abilities of neural networks and linear models. They used MDA, and found that NNs outperformed the linear model for bond rating application.

Maher and Sen (1997) compared the performance of neural networks with that of logistic regression. NN performed better than a traditional logistic regression model. The best performance of the model was 70% (42 out of 60 samples).

Kwon et al. (1997) compared the predictive performance of ordinal pairwise partitioning (OPP) approach to back propagation neural networks, conventional (CNN) modelling approach and MDA. They used 2365 Korean bond-rating data and demonstrated that NNs with OPP had the highest accuracy (71-73%), followed by CNN (66-67%) and MDA (58-61%).

Chaveesuk et al. (1999) compared the predictive power of three NN paradigms- back propagation (BP), radial basis function (RBF) and learning vector quantisation (LVQ)- with logistic regression models (LRM). Bond issues of 90 companies were randomly selected from the 1997 issues listed by Standard and Poor's. LVQ (36.7%) and RBF (38.3%) had inferior results to BP (51.9%) and LRM (53.3%). BP only performed slightly better than LRM. They concluded came that assignment of bond ratings is one area that is better performed by experienced and specialised experts since neither NN nor LRM produced accurate results.

Daniels and Kamp (1999) modelled the classification of bond rating using NN with one hidden layer; and a linear model using ordinary least squares (OLS). Financial figures on bonds issued by 256 companies where selected from Standard and Poor's DataStream. The percentage of correct classification ranged from 60-76% for NN and 48-61% for OLS.

Yesilyaprak (2004) compared ANNs and MDA and multinomial logit (ML) techniques for predicting 921 bonds issued by electric utility (367), gas (259), telephone (110) and manufacturing companies (185). ANNs (57 – 73 %) performed better than both MDA (46 – 67 %) and ML (46 – 68 %) in predicting the bond rating in three samples. ML (68 %) performed better in predicting the bond rating (in one sample (electric utility).

Huang et al. (2004) compared back propagation neural networks and vector support machine learning techniques for bond rating in Taiwan and the United States. The data set used in this study was prepared from Standard and Poor's CompuStat financial data. They obtained a prediction accuracy of 80%.

Kim (2005) used an adaptive learning network (ALN) on a sample of 1080 observations (companies) primarily collected from the CMPUTSTAT database, Dun and Bradstreet database, and Standard and Poor's bond manuals to predict their rating. The overall performance of the model shows that the trained ALN model was successful in predicting 228 (84%) out of 272 cases. The further showed a prediction accuracy of 88% and 91% for investment grade and speculative bonds respectively.

In summary, most studies on ANNs showed promising results than those of other classification methods. The current study attempts to extend the use of ANNs to predict ratings on CMBSs. The predictive capacity of ANNs is further compared to that of OR.

4. Methodology and Data

4.1 Hypotheses

In this paper we hypothesise that loan-to-value ratio (LTV) is negatively related to CMBS credit rating whereas debt-to-service coverage ratio (DSCR) is positively related. The incidence of default rises with increase in LTV; that is, if all other factors are held constant, the probability of default for a loan increases as the LTV increases, but not equal. Unlike the LTV, where the probability of default increases as the LTV rises, the incidence of default is a decreasing function of the DSCR. However, the relationship between the DSCR and the probability of default is weaker than the relationship between the LTV and default. Our motivation for the specified hypothesis stems from Fabozzi and Jacob (1997) and Geltner and Miller (2001), among others, who state that LTV and DSCR are the two mostly widely used commercial mortgage underwriting criteria. Descriptions of LTV and DSCR are found in Section 4.5

We further hypothesise that CMBS issues with a well diversified portfolio both on a property composition and geographic location basis will attract higher credit ratings. The diversity of a portfolio of assets will have an impact on the volatility of the pool's expected loss. By diversifying the mix and location of property, one can mitigate a pool's expected losses. Property diversity mitigates the risk of fall in asset value of the single largest property in the pool. Geographic diversity mitigates the risk single market decline and may reduce any losses associated with this type of risk. In support of our hypotheses, Ovnerud-Potter (2003) asserts that CMBS deals also benefit from portfolio diversification.

Additional hypotheses are that size of issue and note tenure are positively and negatively related to the success of bond issues respectively. Larger bond issues are done by bigger firms with strong track records who fall under stricter regulatory regimes such as the Australian Securities and Investment Commission and the Managed Investment Scheme provisions of the Corporations Act 2001, among others, should attract higher credit ratings. Longer note tenures increase the incidence of default and should therefore attract lower credit ratings.

To test the hypotheses, ordinal regressions are applied to the CMBS sample whereas prediction of accuracy in bond rating for ANN evaluates their contribution to the model.

4.2 Description of OR Model

There is a general consensus on the inappropriateness of least squares methods to rate bonds as they ignore their ordinal nature (Kamstra et al. 2001). OR has been considered appropriate as it accommodates the ordinal nature of the bond rating in the analysis.

The model is similar to the general multiple linear regression model but defines Y_i and estimates β differently.

The logistic model computes the probabilities that an observation will fall into each of the various rating categories. The observation is classified into the category with the highest probability. This probability is estimated by the logistic model as:

$$\text{logit}(p_i) = \log\left[\frac{p_i}{1-p_i}\right]$$

$$= \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots\ldots \beta_n X_{in} \qquad (1)$$

where

r = bond rating category;

p_i = $P(Y_i = r)$;

i = 1…n, where n is the sample size; and

$X_{i1,\ldots,}$ X_{in} are predictor variables.

The β s are estimated by maximising the log-likelihood function:

$$\sum_{i=1}^{N} P(\beta; Y_i) = \sum_{i} \ln\left(\frac{1}{1-e^{-\beta X_i}}\right) \quad (2)$$

where β is the vector of the parameters to be estimated. Once β's are estimated, p_i is estimated by

$$p_i = \frac{1}{1+e^{-\beta X_i}} \quad (3)$$

The observation is assigned to the bond rating category with the highest predicted probability. These predictions are compared to the actual bond rating assigned to the issue to calculate classification accuracy for the model.

The observed value on Y_i depends on whether or not a particular threshold has been crossed.

Y_i = BBB if Y_i^* is ≤ β_1

Y_i = A if $\beta_1 \le Y_i^* \le \beta_2$

Y_i = AA if $\beta_2 \le Y_i^* \le \beta_3$

Y_i = AAA if $Y_i^* \ge \beta_3$

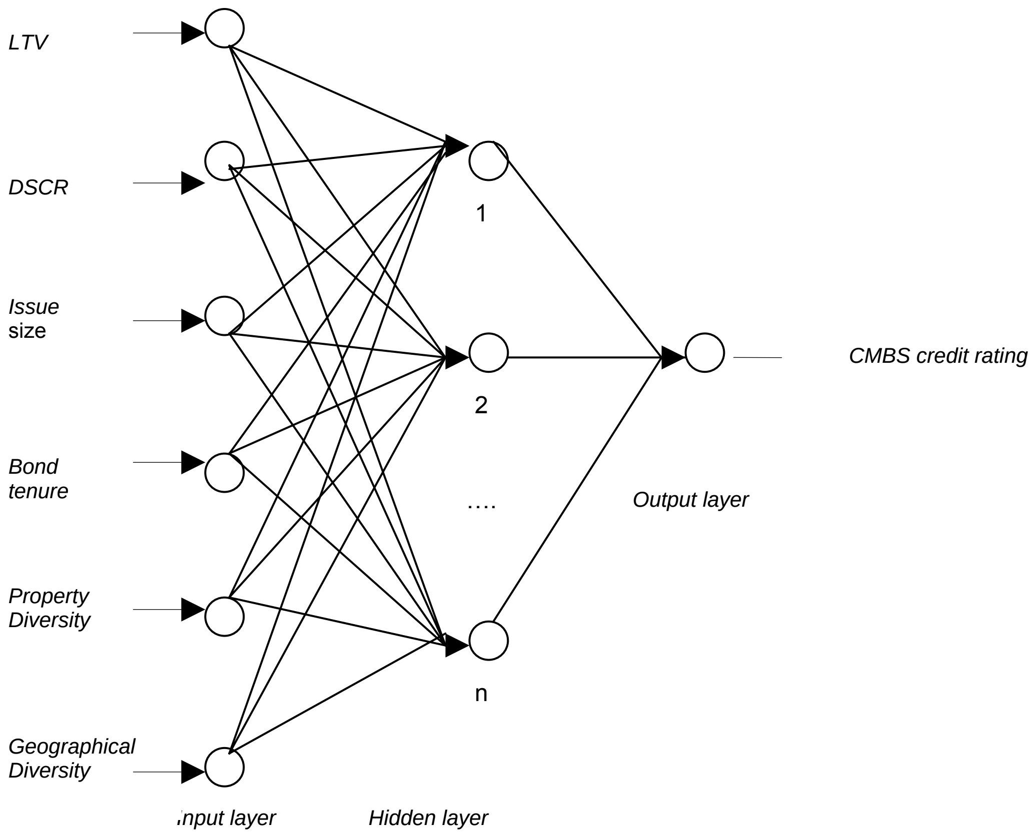
OR regressions were where carried out in SPSS® version 13.0 (SPSS Inc. 1968)

4.3 Description of ANN Model

ANN models have three primary components as shown in Figure 5:

1) The input layer;
2) The hidden layer(s), commonly referred to as the 'black box'; and
3) The output measure(s) layer, the estimated CMBS rating.

Figure 5 Structure of a CMBS rating neural network



The hidden layer(s) contain two processes: the weighted summation functions; and the transformation functions. Both of these functions relate the values from the input data (e.g. LTV; DSCR; issue size; bond tenure, property diversity, geographical diversity) to output measures (CMBS rating). The weighted summation function typically used in a feed-forward/back propagation neural network is:

$$Y_j = \sum_{j}^{n} X_i W_{ij} \qquad (3)$$

where $\mathbf{X}_i$ is the input values and $\boldsymbol{W}_{ij}$ the weights assigned to the input values for each of the $\boldsymbol{j}$ hidden layer nodes. A transformation function then relates the summation value(s) of the hidden layer(s) to the output variable value(s) or $\boldsymbol{Y}_j$. This transformation function can be of many different forms: linear functions, linear threshold functions, step linear functions, sigmoid functions or Gaussian functions. Most software products utilise a regular sigmoid function such as:

$$Y_T = \frac{1}{1 + e^{-y}} \qquad (4)$$

This function is preferred due to its non-linearity, continuity, monotonicity, and continual differentially properties (Do and Grudnitski 1992).

Alyuda Forecaster XL® (Alyuda Research Inc. 2001) was used for the ANN experimentation. In the case of our 6 input and 4 output network, the hidden units where automatically set at 29 (model 1), 28 (model 2) and 23 (Model 3).

4.4 Data

Based on Standard and Poor's Ratings Direct database, our dataset comprised all the CMBSs issued between July 1999 and December 2005 totalling 55. The issues had a combined total of 137 tranches and ratings ranging from AAA, AA, A, BBB+, BBB, BBB- , to NR. In this study, all A and BBB rated tranches were grouped into two groups that is A-rated and BBB-rated respectively. The reclassification of tranches into four classes could enhance model performance because mathematical and statistical approaches have general limits in dealing with ordinal nature of bond rating. It known that as the number of bond classification increases, the predictive power could likely decrease (Kwon et al. 1997). We further excluded unrated tranches, to leave us with 118 tranches (training sample) and 17 tranches (test sample) respectively. Details of the individual rating categories in each sample are shown in Table 2.

Table 2: Observations per CMBS Rating

Rating	*Training Sample*		*Test Sample*	
	Count	*Proportion*	*Count*	*Proportion*
A	17	14%	4	23%
AA	25	21%	3	18%
AAA	62	53%	3	18%
BBB	14	12%	7	41%
Total	118	100%	17	100%

Descriptive statistics of the data used in the experiments is shown in Table 3.

Table 3: Descriptive Statistics

Training Sample

	Issued Amount (A$m)	*Bond Tenure (Years)*	*DSCR***	*LTV***	*Property Diversity*	*Geographical Diversity*
Mean	79.87	3.97	2.14	0.46	0.29	0.48
Standard Error	7.36	0.12	0.05	0.01	0.02	0.01
Standard Deviation	79.90	1.31	0.51	0.10	0.18	0.15
Minimum	1	1	1.28	0.31	0.08	0.2
Maximum	350	7	3.5	0.76	1	1

Test Sample

	Issued Amount (A$m)	*Bond Tenure (Years)*	*DSCR***	*LTV***	*Property Diversity*	*Geographical Diversity*
Mean	47.59	4.94	1.81	0.48	0.32	0.51
Standard Error	13.33	0.06	0.09	0.02	0.04	0.06
Standard Deviation	54.96	0.24	0.36	0.07	0.18	0.26
Minimum	3	4	1.2	0.36	0.11	0.21
Maximum	190	5	2.7	0.61	0.55	0.78

Appendix 3 provides bivariate training sample correlations that exist between the data items.

4.5 Selection of Variables

Bond rating recognises the following areas of attention: profitability; liquidity; asset protection; indenture provisions; and quality of management. Bond rating models use independent variables, often calculated as ratios, which are predominantly derived from public financial statements. The assumption is that financial variables extracted from public financial statements, such as financial ratios, contain a large amount of information about a company's credit risk (Huang et al. 2004). Financial ratios used relate to leverage, coverage, liquidity, profitability, and size. Financial and property ratios referred to are in appendix 3. Rating agencies list qualitative factors such as management ability, value of intangible assets, financial flexibility, operating efficiency, industry risk, accounting quality and market position. However, most of these qualitative factors are likely reflected in the quantifiable data such as financial and non-financial variables, and could be assessed indirectly from analysing these quantifiable data (Kim 2005).

According to Moody's, the credit risk of CMBSs depends the characteristics of the underlying properties, loan structure, loan-to-value (LTV) ratio and the debt service coverage ratio (DSCR) and portfolio diversification (Ovnerud-Potter 2003). Standard and Poor's as well state that their basis of rating is the relative risk of the collateral and the ability of the collateral to generate income (Eastham 2001). The main criterion used to quickly assess credit risk of CMBS deals are the loan-to-value (LTV) ratio and the debt service coverage ratio (DSCR) (Fabozzi and Jacob 1997). The LTV is calculated by dividing the total amount of the notes issued by the current market value of all the properties. The DSCR is calculated by dividing the total net passing income of the properties by the debt-servicing amount. The debt-servicing amount is derived by multiplying credit rating agencies' stressed interest rate assumption by the notes' issuance amount.

Credit rating agencies establish a stabilised net cash flow and an 'assessed capital value', which are used as the basis of the debt-sizing calculations. The appropriate LTV and DSCR are applied to those values. The capitalisation rate used to determine the 'assessed capital value' is a function of the risk and return of the asset, reflecting its age, quality, location, and competitive position within the market (Standard & Poor's 2004).

Following Hedander (2005) who used a diversity scoring system based on the Herfindahl Index to measure diversity on a geographic and property type concentration basis in Australian listed property trusts, we adopt a similar procedure to measure diversity in Australian CMBS portfolios. This index effectively converts a pool of issues of uneven size into a measurement of diversity, as if all issues were the same size. A totally focussed CMBS issue has an index equal to one, while the index for a diversified CMBS issue is closer to zero. Appendix 4 shows property and geographical diversity details, among others.

The Herfindahl Geographic Region Index (HHGR) for each respective CMBS issue is calculated as follows:

$$HHGR = \sum_{j=1}^{8} \left(\frac{x_j}{x}\right)^2$$

where	j	=	Geographic region: the states in Australia (New South Wales, Victoria, Queensland, South Australia, Western Australia, Northern Territory, Australian Capital Territory (ACT) and Tasmania,
	x_j	=	Percentage of asset type in portfolio
	x	=	Total portfolio composition

We wish to acknowledge use of other factors in CMBS rating to deal with transaction and legal risk but have not considered them in this study as there are common or standard features that have been set up to mitigate these risks in all issues.

A number of models are used. Model 1 includes LTV and DSCR as independent variables. Model 2 has an addition of bond tenure and the log of issue size to the independent variables in Model 1. Finally, Model 3 has all the independent variables in Models 1 and 2 in addition to portfolio diversification variables. Tranche rating is the dependent variable in all the models.

5. Empirical Results and Analysis-

5.1 OR

The results of the ordinal regression analyses are shown in Table 4. To empirically specify the model, three tests were used: the standard technique of likelihood ratio test, the significance of the individual coefficients, explanatory power (pseudo R-Square) and the accuracy of the predicting rate. From the observed significance levels, only LTV is related to CMBS credit ratings being significant at .05 level of confidence in all three models but with anomalous positive coefficients implying that high LTV ratios command higher credit ratings. A negative coefficient for LTV was hypothesised as higher LTV increase the level of default and result in lower credit ratings. Log of issued amount (SIZELN) had the anticipated positive coefficient sign whereas bond tenure (TENURE) and level of property diversity (PD) had the anticipated negative coefficients. DSCR, TENURE, PD and geographic diversity (GD) appear not be related to the rating being insignificant at .05 level of confidence. This is an interesting finding as prior literature has stipulated that LTV and DSCR are the two main predictors of CMBS default risk (Fabozzi and Jacob 1997). However, recent research by An (2006), Deng et al. (2005) and Grovenstein et al. (2004), among others, find little statistically significant relationship exists between original LTV and DSCR and CMBS default risk, supporting our results. They attribute this to the endogenous nature of original LTV and DSCR to the underwriting process. Lenders frequently respond to higher perceived overall risk (based on a multidimensional analysis including factors other than LTV and DSCR) by limiting the amount they will lend thereby lowering the loan-to-value ratio and increasing the debt service coverage ratio.

The low pseudo R-square in all three models (ranging from 0.018 to 0.039) indicate that there are other factors affecting CMBS bond rating, giving credence to use of other investigative techniques into their rating such as ANN. It should also be noted that addition of variables SIZELN and TENURE (model 2) to the basic model of DSCR and LTV increased the predictive power from 0.018 to 0.033. The full model with all the variables (model 3) showed an over double increase in the predictive power (0.018 to 0.039) over the basic model though there was a marginal increase over model 2 (0.033 to 0.039).

The inclusion of additional variables to the basic model increased chi-square from 7.036 (model 1) to 9.778 and 11.495 (model 2 and 3) respectively though significance levels decreased. Models 1 and 2 chi-square were significant at the 0.05 level and model 3 at the 0.10 level.

These results imply that rating agencies use only a subset of variables they describe or indicate as important to CMBS rating. Further, the suggested variables do not generally (with exception of LTV and to some extent DSCR) discriminate among credit ratings. This is exemplified by figures 1 to 6 in Appendix 5. There is a strong relationship between CMBS rating and LTV, whereas a weak relationship exists with DSCR. The other variables show no relationship to CMBS rating.

Table 4: OR Results

Variable (Expected Sign)	*Model 1*			*Model 2*			*Model 3*		
A	1.980	(0.310)	[1.031]	3.861	(0.100)	[2.700]	4.115	(0.088)	[2.914]
AA	3.053	(0.118)	[1.952]	4.959	(0.035)	[4.428]	5.221	(0.031)	[4.664]
AAA	5.515	(0.006)	[2.006]	7.481	(0.002)	[9.545]	7.757	(0.002)	[9.768]
DSCR (+)	0.471	(0.321)	[0.983]	0.622	(0.207)	[1.593]	0.801	(0.122)	[2.393]
LTV (-)	6.268	(0.011)	[6.548]	8.307	(0.003)	[9.004]	9.512	(0.001)	[10.401]
SIZELN (+)				0.590	(0.122)	[0.331]	0.693	(0.077)	[3.130]
TENURE (-)				-0.079	(0.565)	[2.394]	-0.087	(0.553)	[0.353]
PD (-)							-1.255	(0.230)	[1.438]
GD (+)							-0.949	(0.446)	[0.580]
Chi-Square	7.036	(0.030)		9.778	(0.044)		11.495	(0.074)	
*Pseudo R-Square	0.018			0.033			0.039		

*We utilise McFadden's pseudo R-Square based on Ederington (1985) who recommend it as being the most attractive intuitively as well as theoretically of all others. Regression coefficients provided with significance levels (in parenthesis) and Wald chi-square [in brackets].

Table 5 shows the number of ratings correctly predicted. The best results was obtained by model 3 which included all the variables at 53% (63 out of 118 cases) followed by models 1 and 2 at 52% (61 out of 118 cases) each.

Table 5: OR Classification Accuracy of Models 1-3

Model 1

Actual CMBS Rating	*Predicted CMBS Rating*		
	AAA	BBB	*Total*
A	17	0	17
AA	23	0	23
AAA	59	0	59
BBB	17	2	19
Total	116	2	118

Model 2

Actual CMBS Rating	*Predicted CMBS Rating*		
	AAA	BBB	*Total*
A	17	0	17
AA	23	0	23
AAA	58	1	59
BBB	16	3	19
Total	114	4	118

Model 3

Actual CMBS Rating	*Predicted CMBS Rating*		
	AAA	BBB	*Total*
A	17	0	17
AA	23	0	23
AAA	59	0	59
BBB	15	4	19
Total	114	4	118

5.2 ANN

5.2.1 Prediction Accuracy Analysis

The predictive capacity of ANNs decreased from 93% (models 1 and 2) to 91% (model 3) for the training set and test and increased from 70% (model 1) to 80% (model 2 and 3) for the test set as shown in Table 6. Further

Tables 7 shows the classification of accuracy within individual rating categories. Appendix 6 shows the error distribution.

Table 6: Summary of ANN Results

Model	Training Sample		Test Sample	
	No. of Good Predictions	No. of Bad Predictions	No. of Good Predictions	No. of Bad Predictions
Model 1	93(95%)	5(5%)	14(70%	6(30%)
Model 2	93(95%)	5(5%)	16(80%)	4(20%)
Model 3	91(93%)	7(7%)	16(80%)	4(20%)

Table 7: ANN Classification Accuracy

Model 1

Actual CMBS Rating	Predicted CMBS Rating			
	AAA	AA	A	BBB
AAA	55	3	1	0
AA	0	22	1	0
A	1	5	11	0
BBB	0	0	0	19

Model 2

Actual CMBS Rating	Predicted CMBS Rating			
	AAA	AA	A	BBB
AAA	59	0	0	0
AA	2	21	0	0
A	1	3	11	2
BBB	1	0	0	18

Model 3

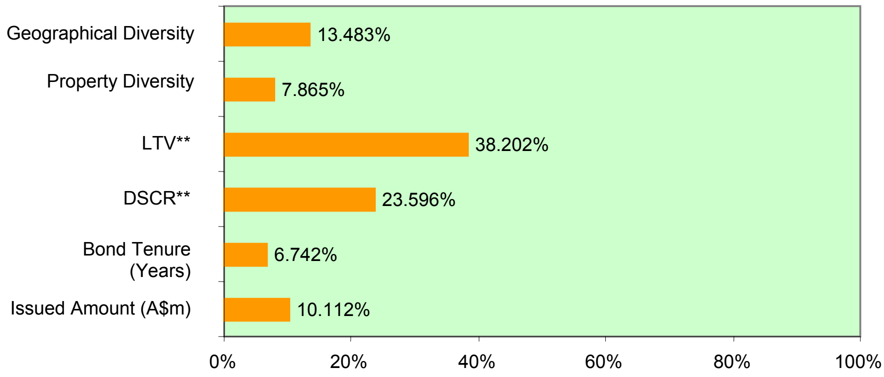
Actual CMBS Rating	Predicted CMBS Rating			
	AAA	AA	A	BBB
AAA	57	0	2	0
AA	1	20	2	0
A	1	3	12	1
BBB	1	0	0	18

5.2.2 Variable Contribution Analysis

Though earlier literature and publications by credit rating agencies state that LTV and DCSR are important property ratios which impact on the achievable credit rating for a CMBS issue, to the best of our knowledge no study has empirically examined the relative contribution of each of these input parameters to a CMBS rating. This study thus evaluates the relative importance of different factors considered in the CMBS rating using a neural network model.

The results of the relative importance of these variables in our full neural network model (model 3) are shown in Figure 6. We do not show the results of the other two models but suffice to state that the following order of importance was revealed though at various percentages: LTV, DSCR, Issued Amount and Bond Tenure.

Figure 6: CMBS Rating Variable Contribution



Our study has shown 62% of CMBS rating is attributable to LTV (38.2%) and DSCR (23.6%); supporting earlier studies which have listed the two as being the most important variables in CMBS rating. The other variables contributions are: CMBS issue size 10.1%; and CMBS tenure 6.7%, geographic diversity 13.5% and property diversity 7.9% respectively.

Our results are comparable to those stated in the ABN AMRO CMBS Rating Model. Under the model all the property-based factors added up to 75% (asset quality (15%); refinancing risk (20%); lease expiry profile (15%); credit quality of income (15%) and tenancy concentration (10%). All these factors are captured by LTV and DSCR in our model, which have a combined total weighting of 62%. In our model, diversification accounted for 21% whereas the ABN AMRO model had 15%. Differences between our model and the ABN AMRO model with the remaining factors makes difficult to complete the comparisons comprehensively. Our model captures bond tenure and amount issued. The ABN AMRO model captures management experience and growth strategy.

One drawback observable from Figure 2 is that no signs are attached to the calculated weights. Thus the interpretation of the relative weights can be inferred from OR analysis.

6. Conclusion, Limitations and Future Directions

Superior predictive results were obtained from the ANN analysis in comparison to OR. ANN correctly predicted 95% and 91% CMBS rating for the training and test sets respectively whereas OR had 52-53% for the training set across the three models, confirming results obtained in earlier studies on predicting corporate bond rating using the two methodologies. Further, ANNs offer better results classifying across rating classes, while OR perform better only at the AAA class level and perform poorly for lower classes.

While our study has empirically tested variables propagated by credit rating agencies as being important to CMBS rating and found all but LTV to statistically insignificant using OR, we conclude that statistical approaches used in corporate bond rating studies have limited replication capabilities in CMBS rating and that the endogeneity arguments raise significant questions about LTV and DSCR as convenient, short-cut measures of CMBS default risk. However, ANNs do offer promising predictive results and can be used to facilitate implementation of survey-based CMBS rating systems. This should contribute to making the CMBS rating methodology become more explicit which is advantageous in that both CMBS investors and issuers are provided with greater information and faith in the investment.

However, before these results can be generalised, field studies need to be conducted to compare the interpretation of the bond-rating process we have obtained from our models with bond-rating experts. Deeper market structure analysis is also needed to fully explain the differences we found in our models. Further still, though our results cannot be viewed as definitive due to the small sample size, the can form a basis for future studies. Over time with more CMBS issuances, a larger sample size will enable analysis of various issues backed by different property classes to check for differences, if any.

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Appendix 1 Factors Considered in Rating Australian CMBSs

Moody's *CMBS Rating Approach*[1]	*Standard and Poor's CMBS Rating Approach*[2]	*Fitch Ratings CMBS Rating Approach*[3]	*ABN AMRO CMBS Rating Model*[4]
▪ *Property Characteristics Analysis* -Sustainable cash flow -Quality grade -Property type -Tenant quality ▪ *Loan Structure Analysis* -Amortisation profile -Floating rate loans -Seasoning and Delinquencies -Cross-Collateralisation and Cross-Defaulting -Other loan features ▪ *Loan-to-Value and Debt-Service Coverage Ratios Analysis* -Current, Balloon and Target LTV -Actual and Hurdle DSCR ▪ *Portfolio Level Analysis* -Portfolio diversification -Other overall considerations (legal environment, quality of service, liquidity, tail periods, commingling risk, insurances)	▪ *Property Based Analysis* -Location -Tenancy (tenant profile, lease maturity risk) -Lease -Market rental rates and expenses -Building quality assessment -Supply and demand considerations -Management ▪ *Transaction Structure Analysis* -Term of debt - Amortisation profile - Hedging strategy -Cash trap mechanisms	• *Rating Analysis* ▪ Quantitative Analysis -Adjustment to Net Operating Income (rent recognition, vacancy, other income, management fee, real estate taxes, insurance) -Capital items consideration (leasing costs, replacement reserves) -Interest rate adjustment (mortgage constant to reflect long-term conventional financing) -Debt Service Coverage Ratio -Loan-to-Value Ratio -Amortisation credit ▪ Qualitative Analysis -Sponsor/manager's track record -Overleverage and Subordinate Debt -Collateral quality (location, access and visibility; design and construction quality; tenant quality; economic and market trends; leaseholds -Environmental issues -Pool-related adjustments (loan and geographic diversity) • *Structural Issues* -Balloon payments -Liquidity -Servicer's experience -Cross-Collateralisation and Cross-Default -Control of property cash flow -Property releases -Low Debt Service Reserve -Management replacement -Insurance coverage • *Legal Features* -Special-purpose entity -Representations and Warranties	▪ *Asset Quality (15%)* -Location -Age -Condition -Tenant retention ▪ *Refinancing Risk 20%)* -Refinancing risk -Ownership structure ▪ *Leasing Expiry Profile (15%)* -Percentage of lease expiring over debt term -Amount of future cash flow to amortise debt ▪ *Management (10%)* -Track record -Growth strategy ▪ *Tenancy Concentration (10%)* -Credit worthy of tenant -Lease profile ▪ *Number of Assets in Pool (15%)* -Diversification -Number of assets in pool

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Appendix 2 Training Sample Correlations

Variable		Issued Amount (A$m)	Bond Tenure (Years)	DSCR**	LTV**	Property Diversity	Geographical Diversity	Rating*
Issued Amount (A$m)	Pearson Correlation	1	.037	.236(**)	-.465(**)	.025	-.089	.505(**)
	Sig. (2-tailed)		.673	.006	.000	.777	.307	.000
Bond Tenure (Years)	Pearson Correlation	.037	1	.070	.037	.108	-.216(*)	.030
	Sig. (2-tailed)	.673		.420	.666	.211	.012	.727
DSCR**	Pearson Correlation	.236(**)	.070	1	-.689(**)	-.146	-.042	.669(**)
	Sig. (2-tailed)	.006	.420		.000	.090	.626	.000
LTV**	Pearson Correlation	-.465(**)	.037	-.689(**)	1	.203(*)	.073	-.861(**)
	Sig. (2-tailed)	.000	.666	.000		.018	.401	.000
Property Diversity	Pearson Correlation	.025	.108	-.146	.203(*)	1	.194(*)	-.138
	Sig. (2-tailed)	.777	.211	.090	.018		.024	.112
Geographical Diversity	Pearson Correlation	-.089	-.216(*)	-.042	.073	.194(*)	1	-.063
	Sig. (2-tailed)	.307	.012	.626	.401	.024		.471
Rating*	Pearson Correlation	.505(**)	.030	.669(**)	-.861(**)	-.138	-.063	1
	Sig. (2-tailed)	.000	.727	.000	.000	.112	.471	

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Appendix 3 Financial and Property Ratios

No.	Category	Description	Operating and Financial Ratio	Property Ratio	Variable
1	Size	Tangible fixed assets	Total assets	Property value	V
2	Coverage	Total size of debt	Total debt	Debt	D
3	Leverage	Long term capital intensiveness	Total debt/Total assets	Loan-to-value	D/V
4	Profitability	Short term capital intensiveness	Short term debt/Total assets	Break even	(OE+PMT)/GI
5	Liquidity	Total liquidity of the firm	Current assets/Current liabilities	Debt service coverage	PMT/NOI
6	Coverage	Measure of company's ability to pay bond holders	Pre-tax interest expense/Income	Interest coverage	(NOI-PMT)/NOI
7	Indenture provision	Subordination status	(0-1)		
8	Efficiency	Quality of management	Net operating income/Sales	Operating expenses ratio	NOI/GI

Source: Author's compilation from Belkaoui (1980); Rowland (1993) and Fischer(2004)

Appendix 4 CMBS Summary Details (1999-2005)

Sector	Issue	Issued Amount (A$m)	Note Tenure (Years)	Property Details: Total Lettable Area (m²)	Property Details: Capital Value: Market Value ($m)	Property Details: Capital Value: S&P Stressed Value ($m)	Property Details: Capital Value: Capital Value Discount (%)	Property Details: Net Income ($m): Market Net Income ($m)	Property Details: Net Income ($m): S&P Net Income ($m)	Property Details: Net Income ($m): Net Income Discount (%)	Financial Details: Gearing: DSCR**	Financial Details: Gearing: LTV**	Financial Details: Liquidity Facility (% of stressed value)	Tenant/Lease Details: Credit Quality of Income (% of income from investment grade tenants)	Tenant/Lease Details: Tenancy Concentration (Top 5 tenants as % of total gross income)	Tenant/Lease Details: Weighted Average Lease Expiry (Years)	Tenant/Lease Details: Occupancy Rate (%)	No. of Assets: Total No. of Assets	No. of Assets: Diversification: Property (% of portfolio value)	No. of Assets: Diversification: Geographical
All																				
	Min	0.435	1	49,650	200	200	0	18	17.90	0	1.20	32.0%	1.16%	0%	20%	3.6	83.0%	1	8.0%	0.20
	Max	350.00	7.00	1008603.00	1880.00	1660.00	22.9%	142.20	120.30	22.5%	3.50	76.0%	13.3%	100.0%	100.0%	30.00	100.0%	101.00	100.0%	1.00
	Average	75.37	4.13	349804.88	760.34	671.92	11.0%	62.00	56.28	9.0%	2.14	45.1%	3.1%	37.5%	45.8%	7.82	97.2%	20.79	29.8%	0.47
Diversified																				
	Min	1.00	3.00	97316.00	265.40	227.60	7.3%	21.00	19.50	3.0%	1.29	32.0%	1.9%	17.9%	42.0%	3.60	91.3%	7.00	9.7%	0.32
	Max	350.00	6.00	588200.00	1429.60	1255.00	20.2%	123.87	107.80	13.4%	3.50	68.0%	4.4%	56.0%	67.0%	10.00	99.0%	25.00	60.2%	0.51
	Average	62.10	4.35	284666.20	688.05	606.29	12.0%	56.79	50.97	9.3%	2.10	46.1%	3.2%	39.5%	50.9%	7.05	97.0%	18.70	35.5%	0.40
Industrial																				
	Min	5.00	1.00	500844.00	454.00	398.50	3.0%	46.00	37.80	2.0%	1.46	33.0%	2.0%	24.2%	24.3%	4.10	94.0%	26.00	8.0%	0.48
	Max	185.00	5.00	1008603.00	1147.00	885.00	22.9%	92.26	84.10	17.8%	3.10	68.0%	3.3%	24.2%	25.0%	6.30	99.0%	39.00	14.0%	0.79
	Average	60.13	3.48	787841.30	808.31	701.19	12.2%	74.79	67.53	9.8%	2.40	42.6%	2.5%	24.2%	24.9%	5.40	97.6%	34.30	10.2%	0.63
Office																				
	Min	10.00	1.00	49650.00	495.00	473.00	4.4%	34.40	29.30	5.4%	1.28	32.0%	1.2%	13.3%	39.0%	4.10	83.0%	1.00	11.9%	0.26
	Max	350.00	5.00	431691.00	1880.00	1660.00	16.4%	142.20	120.30	22.5%	2.40	62.0%	3.4%	75.0%	79.9%	8.00	99.5%	21.00	100.0%	1.00
	Average	132.59	3.07	310142.04	1219.77	1084.28	10.9%	96.40	83.27	13.6%	2.04	41.0%	2.2%	44.3%	54.2%	5.66	96.4%	13.33	26.3%	0.49
Retail																				
	Min	0.44	3.00	91152.00	200.00	200.00	0.0%	17.90	17.90	0.0%	1.20	35.0%	2.0%	0.0%	20.1%	4.00	93.0%	2.00	11.0%	0.20
	Max	240.00	7.00	533343.00	1380.00	1100.00	20.3%	92.80	85.40	13.9%	3.30	76.0%	13.3%	100.0%	100.0%	30.00	100.0%	101.00	64.0%	0.78
	Average	60.63	4.89	189845.03	524.43	467.90	0.10	41.76	39.06	5.9%	2.09	0.48	0.04	0.30	0.45	13.85	0.98	20.22	0.37	0.45

Appendix 5 Variable Scatter Plots

Figure 1 CMBS Rating vs. LTV (Strong relationship)

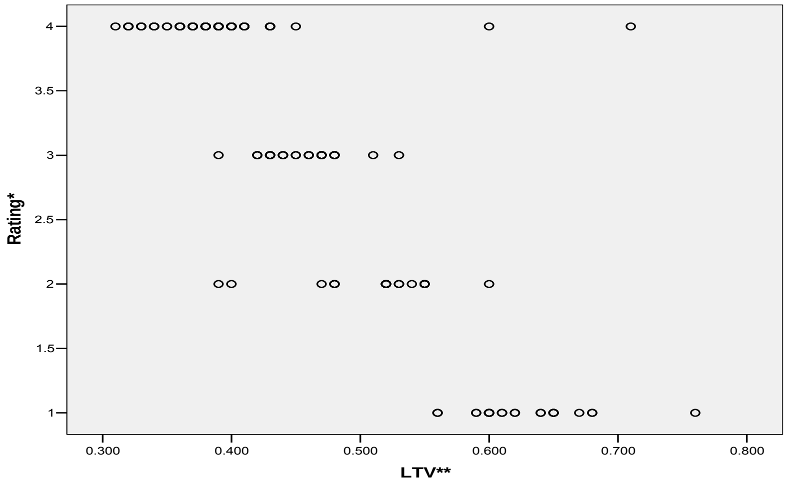


Figure 2 CMBS Rating vs. DSCR (Weak relationship)

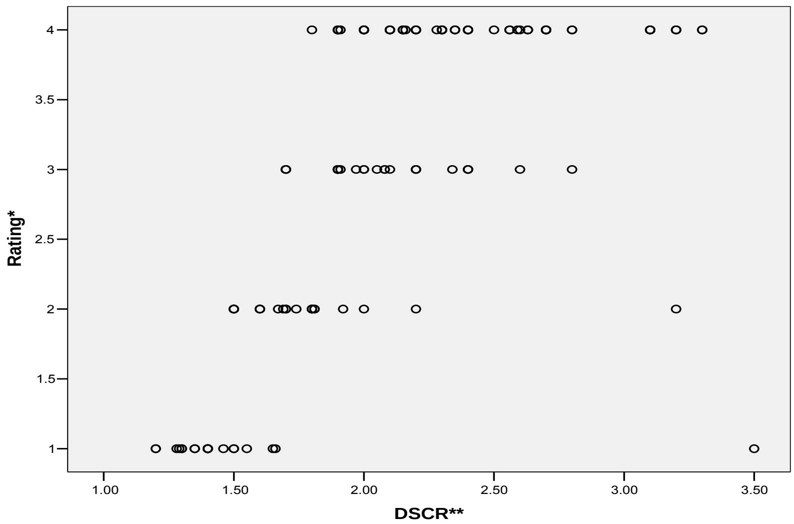


Figure 3 CMBS Rating vs. Issued Amount (No relationship)

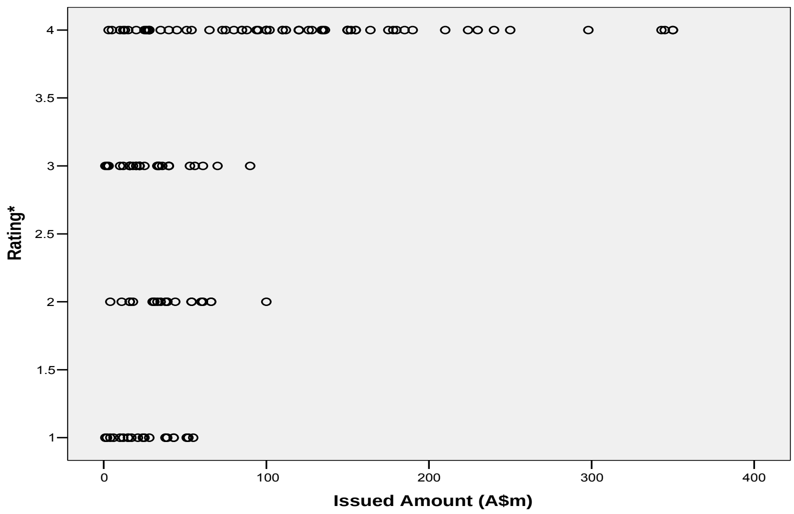


Figure 4 CMBS Rating vs. Bond Tenure (No relationship)

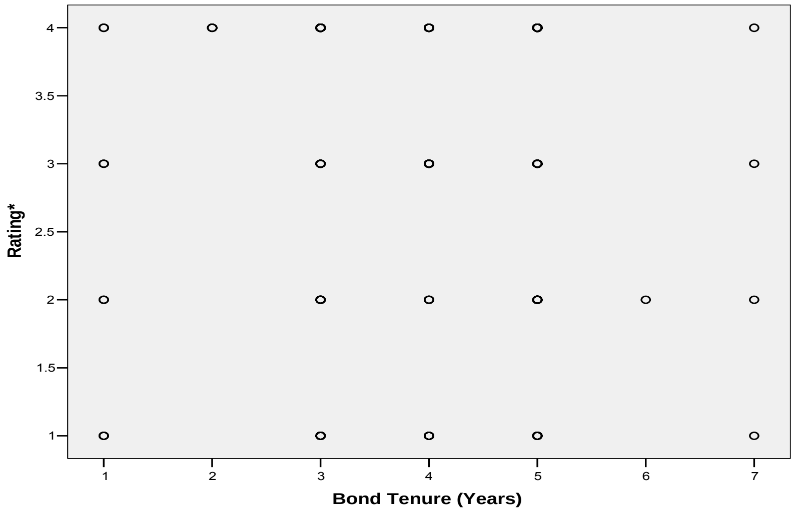


Figure 5 CMBS Rating vs. Property Diversity (No relationship)

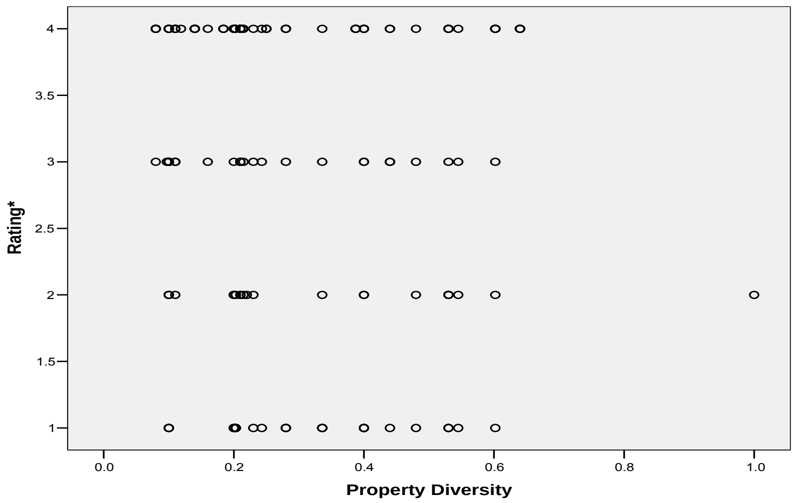
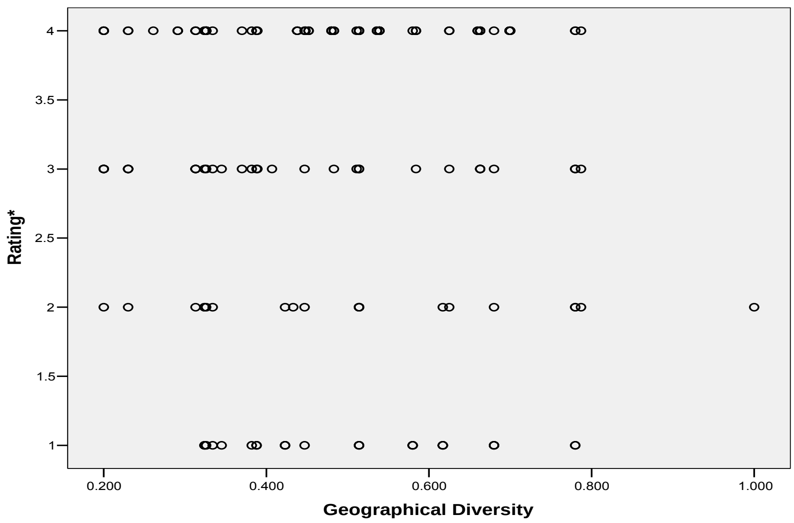


Figure 6 CMBS Rating vs. Geographical Diversity (No relationship)



Appendix 6 ANN Error Distribution

Model 1

Class	# Cases	# Errors	% Errors
AAA	59	4	6.78%
AA	23	1	4.35%
A	17	6	35.29%
BBB	19	0	0.00%
Total	118	11	9.32%

Model 2

Class	# Cases	# Errors	% Errors
AAA	59	0	0.00%
AA	23	2	8.70%
A	17	6	35.29%
BBB	19	1	5.26%
Total	118	9	7.63%

Model 3

Class	# Cases	# Errors	% Errors
AAA	59	2	3.39%
AA	23	3	13.04%
A	17	5	29.41%
BBB	19	1	5.26%
Total	118	11	9.32%