Chikolwa, Bwembya (2006) ***An empirical analysis of structuring commercial mortgage-backed securities : Australian evidence***. In: Curtin Business School Doctoral Colloquium, 27-28 April 2006, Perth, WA.

Curtin Business School, Doctoral Colloquium

Fremantle, Western Australia, 27 to 28 April 2006

An Empirical Analysis of Structuring Commercial Mortgage-Backed Securities: 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. However, issues of proprietorship have resulted in the methodology of credit rating mostly being shrouded in mystery. The methods and input variables used in rating are not publicly disclosed. We use artificial neural networks (ANN) and multinominal logistic regression (MLR) as alternative methods to predict CMBS ratings. ANN shows superior results to MLR in predicting CMBS ratings.

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 publicly disclosed (Shin and Han 2001). 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.

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 alternative methodology to bond rating.

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

The paper is as follows. Section 2 presents an overview of the Australian CMBS market. Section 3 reviews literature on the use of ANNs in various real estate and corporate bond rating studies respectively. Section 4 discusses the data and methodology. Section 5 presents the empirical results and analysis. Section 6 concludes and highlights future research direction.

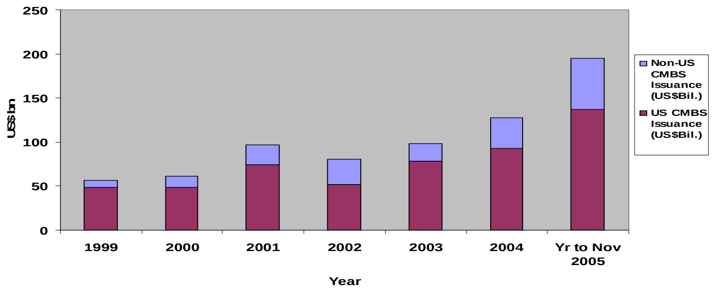
An Overview of the Australian Commercial Mortgage-Backed Securities Market

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. To date a total of 55 CMBSs have been issued with 137 tranches.

On the whole the 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.

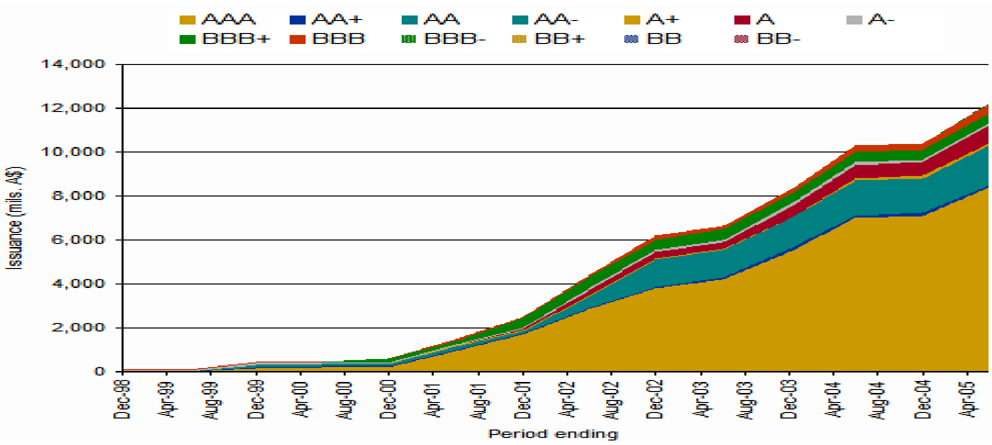
Figure 1: CMBS Global Issuance (January 1999-November 2005)



Source: Author's compilation from Commercial Mortgage Alert

The total cumulative Australian and New Zealand CMBS issuance volume since 1999 has reached A$12.6 billion as shown in figure 2 below. 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.

Figure 2: Cumulative CMBS Issuance



Source: Standard and Poor's (2005)

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

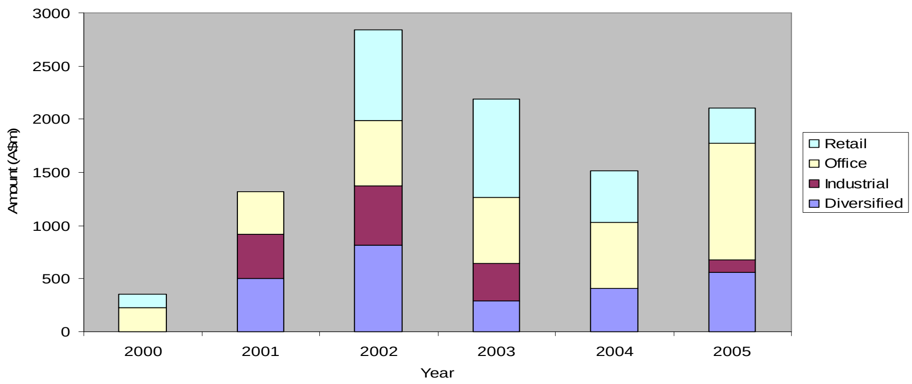
Sector	2000	2001	2002	2003	2004	2005
Diversified	1	2	11	7	7	14
Industrial	4	3	6	12	4	3
Office	0	3	4	5	9	10
Retail	0	0	15	9	0	8
TOTAL	**5**	**8**	**36**	**33**	**20**	**35**

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

Most Australian CMBS transactions are structured as single-borrower, secured loan-style deals unlike the USA and Europe which also have conduit-style CMBSs from large loans securitised in conduit programs. A lot of the commercial mortgages continue to sit on bank balance sheets, and there has been 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.

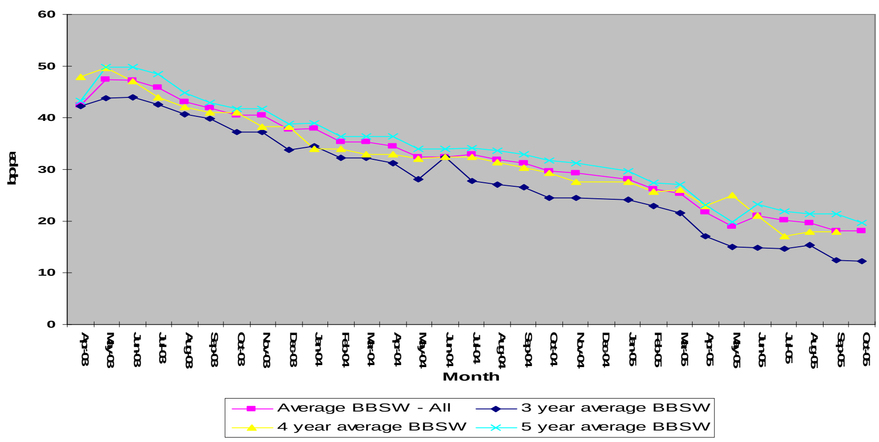
Figure 3: Australian CMBS Issuance by Sector (1999-2005)



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 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

In Australia, Listed Property Trusts (LPTs) actively participate in CMBSs with a 65% market share. The single-purpose-vehicle-like characteristics of LPTs have helped in their establishment as major players in the CMBS market. LPTs issued $3.8 billion in property related CMBS debt during the year 2002, compared with A$1.5 billion in 2001 (Standard & Poor's 2003). This 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). With the drop in public bond issuance, bonds and CMBSs issued by LPT have been an attractive investment option for superannuation funds.

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.

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. According to Salchenberger et al. (1992) and Tam and Kiang (1992), ANNs have several advantages over statistical methods. 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.

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.

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. The 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); and Huang et al. (2004).

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 ML (Multinomial Logit) 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%.

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 MLR.

Methodology and Data

In this study, the ANN was trained with back propagation algorithm using part of the sample called a training sample and tested the prediction accuracy of the bond rating of another sample which is called a testing (holdout) sample. The results are compared with the prediction accuracy of the MLR method.

Description of MLR 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). MLR has been considered appropriate as it accommodates the categorical 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; $p_i = P\ (Y_i = r);\ i$=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:

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

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

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

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.

Our estimation model is depicted by:

$$CMBS_{rating} = \beta_0 + \beta_1(LTV) + \beta_2(DSCR) + \beta_3(SIZE) + \beta_4(TENURE) \qquad (4)$$

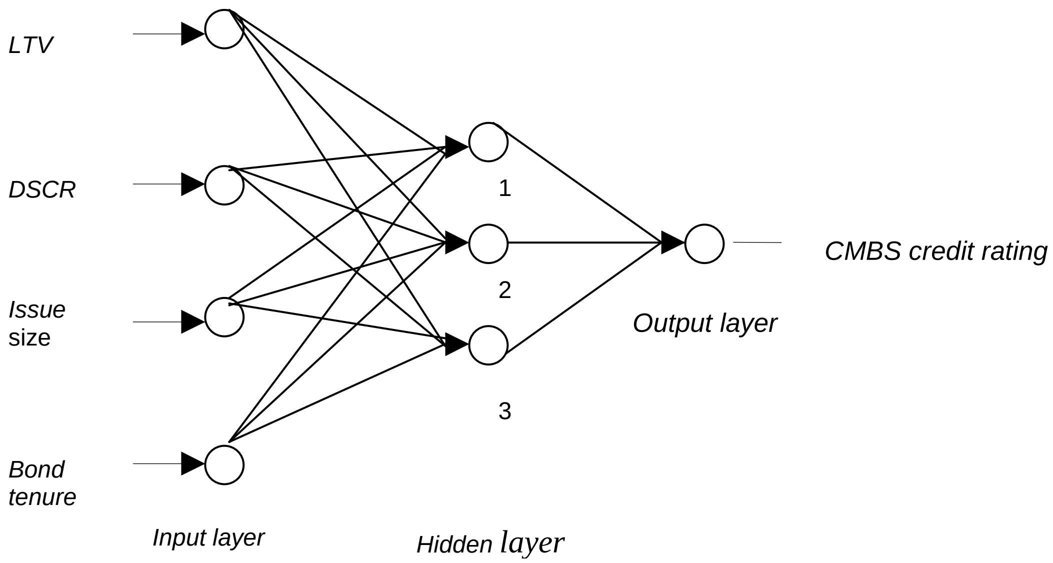
where LTV =Loan-to-value ratio; DSCR=Debt service coverage ratio; SIZE=Size of issue; and TENURE=Bond duration. $\beta_0,\ \beta_1,.\ \beta_k$ are fixed (but unknown) parameters.

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) 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 W_{ij} the weights assigned to the input values for each of the 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 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)

Data

Based on Standard and Poor's RatingsDirect database, our dataset comprised a total of 55 CMBS were issued with a total of 137 tranches from July 1999 to December 2005 with ratings ranging from AAA, AA, A, BBB+, BBB, BBB- , to NR. 120 tranches and 17 tranches were randomly selected as training and hold out samples respectively. Details of the individual rating categories in each sample are shown in table 2.]

Table 2: Observations per CMBS rating

Rating	*Training Sample*	*Hold Out Sample*
A	17	3
A-	1	1
AA	25	3
AAA	62	3
BBB	10	4
BBB-	3	2
BBB+	1	1
NR	1	0
Grand Total	**120**	**17**

Descriptive statistics of the data used in the experiments is shown in table 3 below. To control for the influence of the large values of issued amounts in the analysis, log numbers were used.

Table 3: Descriptive Statistics

	Issued Amount (A$m)	*Bond Tenure (Years)*	*DSCR***	*LTV***
Mean	75.42653285	4.087591241	2.094744526	0.460584
Standard Error	6.621709609	0.108403087	0.043321231	0.008508
Standard Deviation	77.50512387	1.268825607	0.507062011	0.099586
Minimum	0.435	1	1.2	0.31
Maximum	350	7	3.5	0.76

Alyuda Forecaster XL® (Alyuda Research Inc. 2001) was used for the ANN experimentation. It automatically sets the number of data to be used in the training and test sets. It also sets the best number of hidden units to use. In this case, 8 hidden units where set for a 6 input and 1 output network.

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

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 grand 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 1.

The main criterion used to quickly assess the risk of CMBS deals are the loan-to-value (LTV) ratio and the debt service coverage ratio (DSCR) (Fabozzi and Jacob 1997). In addition, the interest coverage ratio (ICR) is also frequently used. 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.

LTV, DSCR, bond tenure and size of issue, are selected as independent variables with bond rating as the dependent variable in the MLR and ANN analyses.

Empirical Results and Analysis

Prediction Accuracy Analysis

MLR was able to correctly predict an overall 79.2% of the CMBS rating as shown in table 4.

Table 4: MLR prediction

Observed	Predicted								
	A	AA	AAA	Aaa*	BBB-	BBB	BBB+	NR	Percent Correct
A	13	3	1	0	0	0	0	0	76.5%
AA	2	18	5	0	0	0	0	0	72.0%
AAA	2	5	54	0	0	0	0	0	88.5%
Aaa*	0	0	0	1	0	0	0	0	100.0%
BBB-	0	1	0	0	0	2	0	0	.0%
BBB	1	0	0	0	0	9	0	0	90.0%
BBB+	0	0	0	0	0	1	0	0	.0%
NR	0	0	1	0	1	0	0	0	.0%
Overall Percentage	15.0%	22.5%	50.8%	.8%	.8%	10.0%	.0%	.0%	79.2%

Other important statistics of the MLR model are presented in table 5. It can be seen from looking at the coefficients that amount issued, DSCR, and LTV are all significant at 0.05 level, with bond tenure being insignificant.

Table 5: Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	213.69	53.559	7	0
Issued Amount A$m	187.568	27.437	7	0
Bond Tenure (Years)	161.254	1.124	7	0.993
DSCR	180.07	19.939	7	0.006
LTV	182.038	21.908	7	0.003

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

ANN was able to correctly predict 92% and 90% for the training and test sets respectively of the CMBS rating in both the training and the test sets as shown in table 7.

Table 7: Summary of ANN results results

	Training set	Test set
# of rows:	100	20
CCR:	92.00%	90.00%
Average AE:	n/a	n/a
Average MSE:	n/a	n/a
Tolerance type:	n/a	n/a
Tolerance:	n/a	n/a
# of Good forecasts:	92 (92%)	18 (90%)
# of Bad forecasts:	8 (8%)	2 (10%)

Table 8: Comparison of ANN and MLR predictions

Rating	ANN Prediction	MLR Prediction
AAA	98.36%	76.5%
Aaa*	100.00%	0%
AA	92.00%	88.5%
A	82.35%	100%
BBB+	100%	0%
BBB	100%	72%
BBB-	66.67%	0%
NR	0%	0%
Total	**91.67%**	**79.2%**

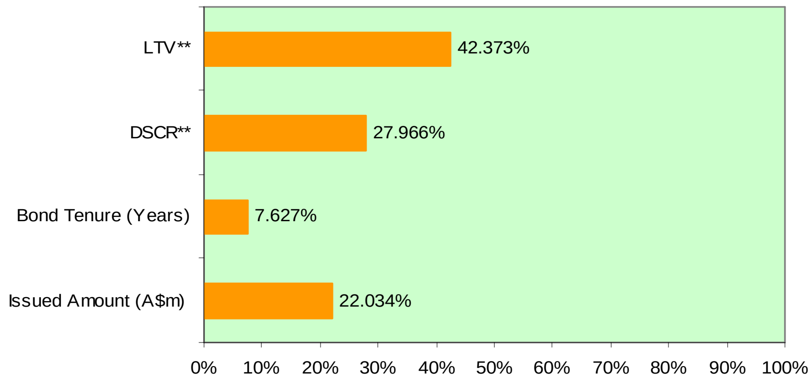
ANN had better predictions across all rating classes than MLR except for the A rating as shown in table 8.

Variable Contribution Analysis

Though literature states that LTV, DCSR and ICR are important property ratios which impact on the achievable credit rating for a CMBS issue, no study has shown the relative contribution of each of these input parameters to a CMBS rating. This study thus evaluates the relative importance of each property input variable in the CMBS rating neural network model.

The results of the relative importance of different property inputs in our neural network model are shown in figure 6.

Figure 6: CMBS Variable Contribution Results



Our study has shown that LTV has the largest contribution of 42.37% in CMBS rating. This supports earlier studies which have listed LTV has being the most important variable in CMBS rating. The other variables contributions are: DSCR 27.97%; CMBS issue size 22.03%; and CMBS tenure 7.62% respectively.

Discussion and Future Directions

Previous research done on predicting corporate bonds using ANN and other statistical methods has used financial ratios, on the premise that they contain a large amount of information about a company's credit risk, as the key variables. In this study, we extended the application of neural networks to the problem of predicting CMBS ratings and compared the results with the more traditionally used MLR. Property ratio of LTV and DSCR where seen as containing adequate information on the property credit risk.

Superior predictive results where obtained from the ANN analysis in comparison to MLR. ANN correctly predicted 92% and 90% CMBS rating for the training and test sets respectively whereas MLR had 72.9%, confirming results obtained in earlier studies on predicting corporate bond rating using the two methodologies. It was further reviewed that LTV ratio was the most important factor influencing CMBS rating followed by DSCR, issue size and CMBS tenure, respectively.

These results are important as they contribute to CMBS rating methodology being more explicit. An explicit rating methodology 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.

Acknowledgement

The author gratefully acknowledges the support of Standard and Poor's for access to their RatingsDirect database.

References

Alles, L. 2000, *Asset Securitisation in Australia: How and Why it Works*, Curtin Business School, Perth.

Alyuda Research Inc. 2001, 'Forecaster XL', Fremont, CA.

Belkaoui, A. 1980, 'Industrial Bond Ratings: A New Look', *Finanncial Management*, vol. 9, no. 3, pp. 44-51.

Chaveesuk, R., Srivaree-ratana, C. and Smith, A. 1999, 'Alternative Neural Network Approaches to Corporate Bond Rating', *Journal of Engineering Valuation and Cost Analysis*, vol. 2, no. 2, pp. 117-131.

Coakley, J. R. and Brown, C. E. 2000, 'Artificial Neural Networks in Accounting and Finance: Modelling Issues', *Intelligent Systems in Accounting, Finance and Management*, vol. 9, no. 2, pp. 119-144.

Connellan, O. and James, H. 1998a, 'Estimated Realisation Price (ERP) by Neural Networks: Forecasting Commercial Property Values', *Journal of Property Valuation and Investment*, vol. 16, no. 1, pp. 71-86.

Connellan, O. and James, H. 1998b, 'Forecasting Commercial Property Values in the Short Term', in *RICS Cutting Edge Conference 1998*, RICS Research, Leicester.

Daniels, H. and Kamp, B. 1999, 'Application of MLP Networks to Bond Rating and House Pricing', *Neural Computing and Applications*, vol. 8, no. 8, pp. 226-234.

Do, A. Q. and Grudnitski, G. 1992, 'A Neural Network Approach to Residential Property Appraisal', *Real Estate Appraiser*, vol. 58, no. 3, pp. 38-45.

Dutta, S. and Shekhar, S. 1988, 'Bond Rating: A Non-Conservative Application of Neural Networks', in *Proceedings of the IEEE International Conference on Neural Networks*, San Diego, pp. II443-II450.

Evans, A. H. J. and Collins, A. 1992, 'Artificial Neural Networks: An Application to Residential Valuation in the UK', *Journal of Property Valuation and Investment*, vol. 11, no. 2, pp. 195-203.

Fabozzi, F. J. and Jacob, D. P. 1997, *The Handbook of Commercial Mortgage-backed Securities*, Frank Fabozzi Associates, New Hope.

Fadlalla, A. and Lin, C. 2001, 'An Analysis of the Applications of Neural Networks in Finance', *Interfaces*, vol. 31, no. 4, pp. 112-122.

Fischer, D. 2004, *Income Property Analysis*, D. Fischer, Perth.

Huang, Z., Chen, H., Hsu, C., Chen, W. and Wu, S. 2004, 'Credit Rating Analysis with Support Vector Machines and Neural Networks: A Market Comparative Study', *Decision Support Systems*, vol. 37, pp. 543-558.

InTech 2003, *Institutional Listed Property Exposure*, JB Were Investment Series.

Jacob, D. P. and Fabozzi, F. J. 2003, 'The Impact of Structuring on CMBS Class Performance', *Journal of Portfolio Management*, vol. Special Real Estate Issue, pp. 76-86.

Jones Lang LaSalle 2001, *Commercial Mortgage Backed Securities: The New Kid on the Block*, Sydney.

Kamstra, M., Kennedy, P. and Suan, T.-K. 2001, 'Combining Bond Rating Forecasts Using Logit', *The Financial Review*, vol. 36, no. 2, pp. 75-96.

Kauko, T. 2003, 'Residential Property Value and Locational Externalities', *Journal of Property Investment & Finance*, vol. 21, no. 3, pp. 250-270.

Kauko, T. 2004, 'Towards the 4th Generation - An Essay on Innovations in Residential Property Value Modelling Expertise', *Journal of Property Research*, vol. 21, no. 1, pp. 75-97.

Kose, J., Lynch, A. W. and Puri, M. 2003, 'Credit ratings, Collateral, and Loan Characteristics: Implications for Yield', *The Journal of Business,* vol. 76, no. 3, pp. 371-409.

Krishnaswamy, C. R., Gilbert, E. W. and Pashley, M. M. 2000, 'Neural Network Applications in Finance: A Practical Innovation', *Journal of Financial Practice and Education,* vol. 10, no. 1, pp. 75-84.

Kwon, Y. S., Han, I. and Lee, K. C. 1997, 'Ordinal Pairwise Partitioning (OPP) Approach to Neural Networks Training in Bond Rating', *Intelligent Systems in Accounting, Finance and Management,* vol. 6, no. 1, pp. 23-40.

Lai, P. P. 2005, 'An Exploration of Neural Networks and Its Application to Taipei's Housing Price', in *10th Asian Real Estate Society Annual Conference*, Sydney.

Lenk, M. M., Worzala, E. M. and Silva, A. 1997, 'High-Tech Valuation: Should Artificial Neural Networks Bypass the Human Valuer', *Journal of Property Valuation and Investment,* vol. 15, no. 1, pp. 8-26.

Maher, J. L. and Sen, T. K. 1997, 'Predicting Bond Ratings Using Neural Networks: A Comparison with Logistic Regression', *Intelligent Systems in Accounting, Finance and Management*, vol. 6, pp. 59-72.

McGreal, S., Adair, A., McBurney, D. and Patterson, D. 1998, 'Neural Networks: The Prediction of Residential Values', *Journal of Property Valuation and Investment,* vol. 16, no. 1, pp. 57-70.

Nguyen, N. and Cripps, A. 2001, 'Predicting Housing Value: A Comparison of Multiple Regression Analysis and Artificial Neural Networks', *Journal of Real Estate Research,* vol. 22, no. 3, pp. 313-336.

Rowland, P. J. 1993, *Property Investments and Their Financing,* The Law Book Company Limited, Sydney.

Salchenberger, L. M., Cinar, E. M. and Lash, N. A. 1992, 'Neural Networks: A New Tool for Predicting Thrift Failures', *Decision Sciences,* vol. 23, no. 4, pp. 899-915.

Shin, K. and Han, I. 2001, 'A Case-Based Approach using Inductive Indexing for Corporate Bond Rating', *Decision Support Systems,* vol. 32, no. 1, pp. 41-52.

SPSS Inc. 1968, 'SPSS 13.0', Chicago, IL.

Standard & Poor's 2003, *Australian Property Trusts*, Standard & Poors, Melbourne.

Standard & Poor's 2005, *Australia & New Zealand CMBS Performance Watch*, Standard & Poor's, Melbourne.

Surkan, A. J. and Singleton, J. C. 1990, 'Neural Networks for Bond Rating Improved by Multiple Hidden Layers', in *Proceedings of the IEEE International Conference on Neural Networks*, Revised edn, San Diego, pp. 163-168.

Tam, K. Y. and Kiang, M. Y. 1992, 'Managerial Applications of Neural Networks: The Case of Bank Failure Predictions', *Management Science,* vol. 38, no. 7, pp. 926-947.

Tay, D. P. H. and Ho, D. K. H. 1991, 'Artificial Intelligence and the Mass Appraisal of Residential Apartments', *Journal of Property Valuation and Investment*, vol. 10, no. 2, pp. 525-540.

Worzala, E. M., Lenk, M. M. and Silva, A. 1995, 'An Exploration of Neural Networks and Its Application to Real Estate Valuation', *Journal of Real Estate Research*, vol. 10, no. 2, pp. 185-202.

Yesilyaprak, A. 2004, 'Bond Ratings with Artificial Neural Networks and Econometric Models', *American Business Review,* vol. 22, no. 1, pp. 113-123.

Appendix 1: 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)