DETERMINANTS OF COMMERCIAL MORTGAGE-BACKED SECURITIES CREDIT RATINGS: AUSTRALIAN EVIDENCE

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ABSTRACT. Using artificial neural networks (ANN) and ordinal regression (OR) as alternative methods to predict Commercial Mortgage-backed Securities (CMBS) credit ratings, we examine the role that various financial and industry-based variables have on CMBS credit ratings issued by Standard and Poor's from 1999–2005. Our OR results show that rating agencies use only a subset of variables they describe or indicate as important to CMBS credit rating as some of the variables they use were statistically insignificant. Overall, ANN show superior results to OR in predicting CMBS credit ratings.

KEYWORDS: Commercial mortgage-backed securities; Credit rating prediction; Ordinal regression; Artificial neural networks

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). CMBSs 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 (2001), Moody's Investors Service (2003) and Fitch Ratings (2005) in rating Australian CMBSs falls into three categories: property characteristics and cash flow analysis; portfolio level analysis; and transaction structure analysis, as elaborated in Ap-

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pendix 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, Lynch and Puri, 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 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. Maher and Sen (1997) show the following as reasons why predictability of credit rating is useful:

- It provides a firm some insight into the cost of going to the bond market to raise capital, which can be useful in comparing with other sources of funds;
- It can help investors decide where they want to place their money;
- It can provide a modified form of implicit evaluation of the firm in addition to the explicit evaluation of the bond issue; and
- An insight into factors consistent with establishing a firm's bond rating is useful in understanding the value of the firm.

Furthermore, security analysts and investors can use these ratings as the primary source of obtaining information about the quality and marketability of various issues and assess also market risk premium attached to the bonds while investment bankers use the ratings for determining commission rates on undertakings (Kim, 2005).

The paper is structured as follows. Section 2 presents an overview of the Australian CMBS market. Reviews of literature on the use of ANNs in various real estate applications and in corporate bond rating studies are presented in Section 3. Section 4 discusses the data and methodology. Empirical results and analysis are presented in Section 5. Finally, Section 6 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.

The total cumulative Australian and New Zealand CMBS issuance volume since 1999 had reached A$12.6 billion as shown in Figure 2 (Standard & Poor's, 2007). Total

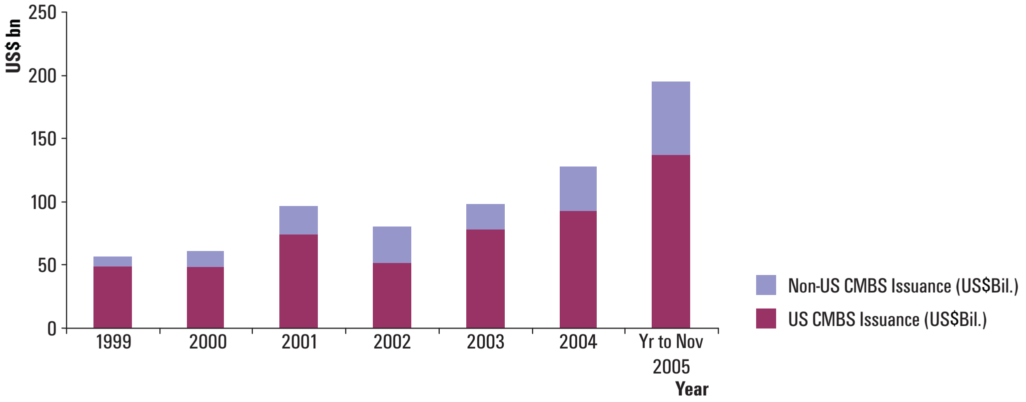

Figure 1. CMBS Global Issuance (January 1999-November 2005)
Source: Author's compilation from Commercial Mortgage Alert

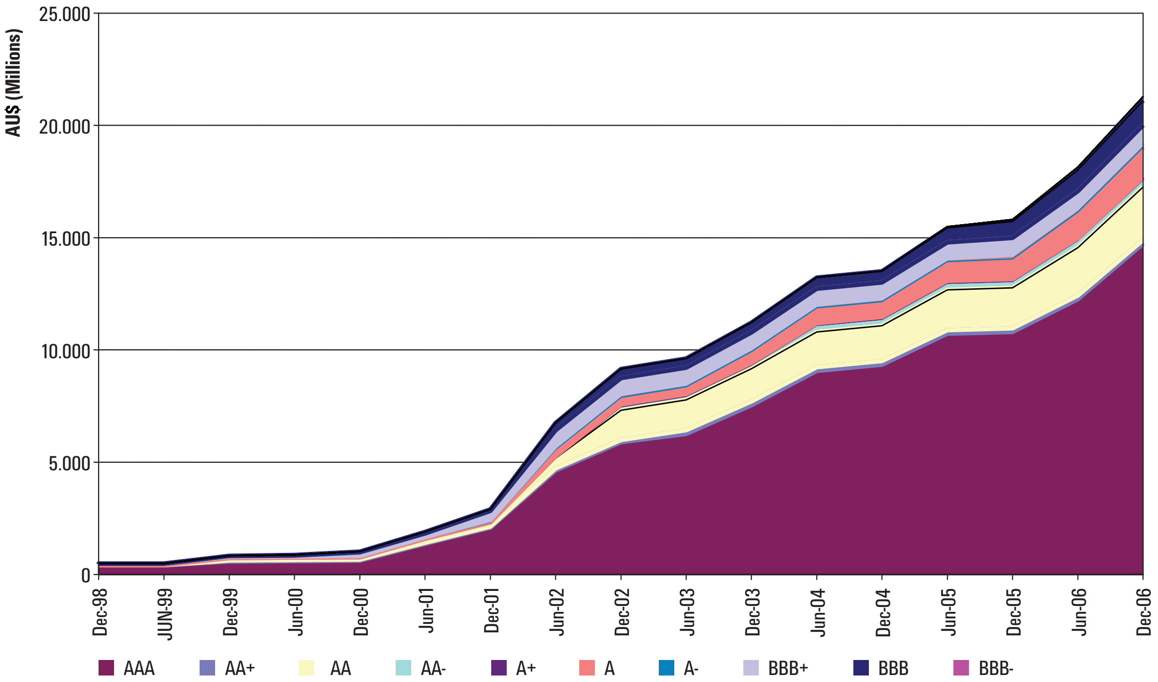

Figure 2. Cumulative CMBS issuance: Australia/New Zealand
Source: Standard and Poor's (2007)

Table 1. Number of Australian CMBS issues by sector (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

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.

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. Conduit CMBSs are backed by reasonably large well diversified pools of small-to medium-sized secured property loans. 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 3.

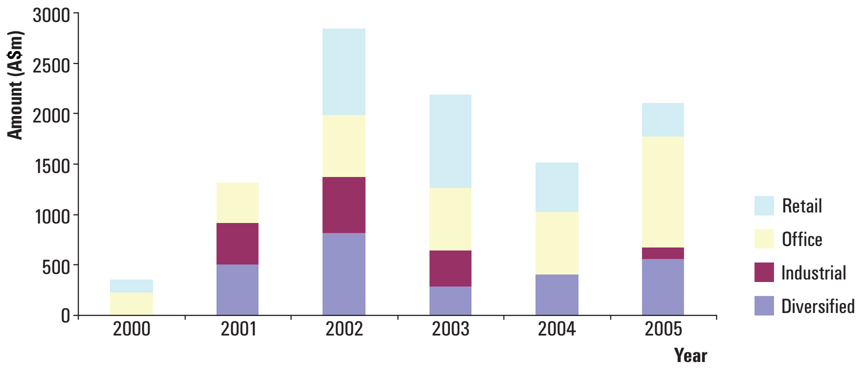

Figure 3. Australian CMBS issuance by sector (1999-2005)
Source: Author's compilation from Standard and Poor's presale reports

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. 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 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, 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.

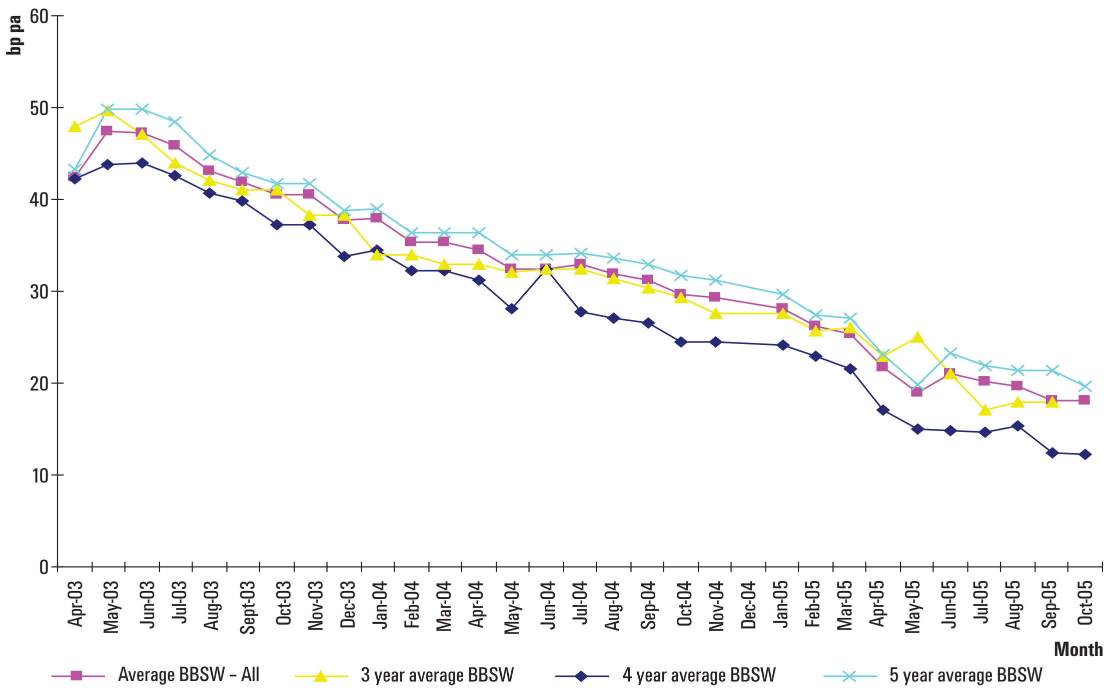

Figure 4. AAA Rated CMBS - average industrial spread to swap (Apr 2003-Oct 2005)
Source: Author's compilation from Property Australia magazine

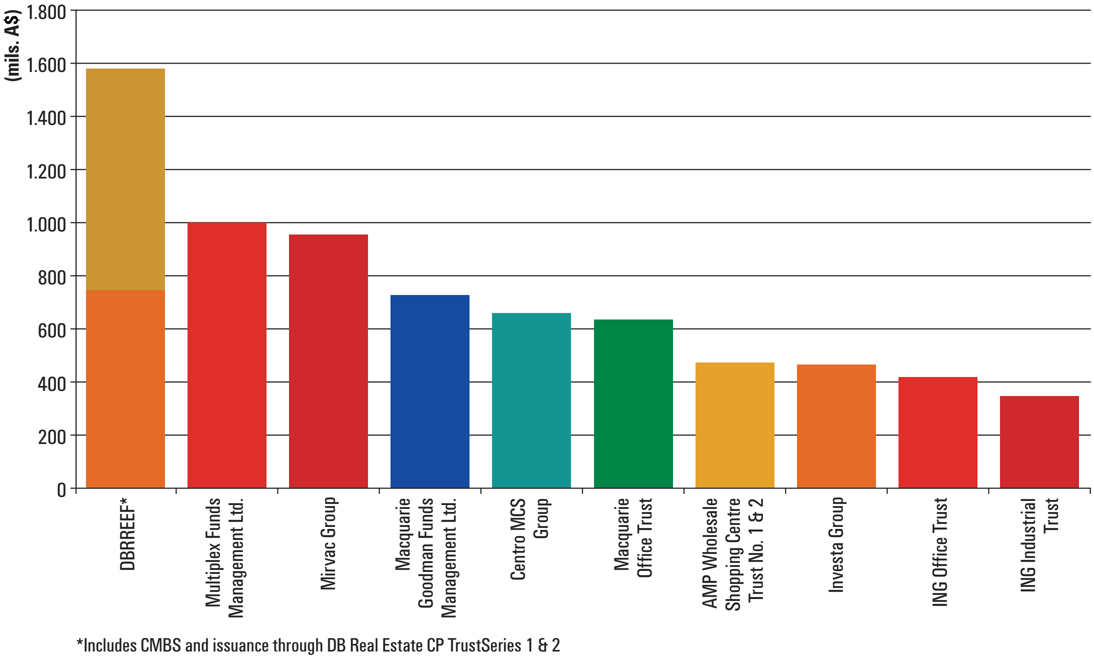

Figure 5. Top 10 Australian CMBS issuers
Source: Standard and Poor's (2005)

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 patterns 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 Investor Service, Standard and Poor's, and Fitch Ratings, 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 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. Financial figures on bonds issued by 256 companies were 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, Moody's Investor Service (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, Kennedy and Suan, 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:

$$\log_{it}(p_i) = \log\left[\frac{p_i}{1-p_i}\right] = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + + \dots \beta_n X_{in} \quad (1)$$

where: r = bond rating category; $p_i = P\ (Y_i = r)$; $i = 1 \dots n$, where n is the sample size; and $X_{i1,\dots,}\ X_{in}$ are predictor variables.

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

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

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.

$$Y_i = \text{BBB if } Y_i^* \text{ is} \leq \beta_1$$

$$Y_i = \text{A if } \beta_1 \leq Y_i^* \leq \beta_2$$

$$Y_i = \text{AA if } \beta_2 \leq Y_i^* \leq \beta_3$$

$$Y_i = \text{AAA if } Y_i^* \geq \beta_3$$

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

4.3. Description of ANN model

This subsection contains a gentle introduction to the fundamental theory of ANN. Consider the following model:

$$y_t = g(x_t; \theta) + \varepsilon_t \tag{4}$$

where $g(\bullet)$ denotes a continuous differentiable function, x_t is a $k \times 1$ vector of explanatory variables, which could include the lagged dependent variables, y_{t-1} for some i, θ is a $l \times 1$ vector of parameter and ε_t is a sequence of independently, identically distributed random variables. In general, the explicit function form of g is unknown. However, it is possible to find a universal approximator, so that the function g can be estimated as accurately as one wish. One such approximator is

$$F(x_t;\gamma) = \phi_0 + \sum_{i=1}^{q} \beta_i G(x_t;\gamma_i) \tag{5}$$

where

$$G(z;\nu;c) = \frac{1}{1+\exp(-\nu[z-c])} \tag{6}$$

is the well known logistic function. (Hornik, Stinchcombe and White, 1989, 1990) (see also (Cybenko, 1989), (Carroll and Dickinson, 1989), (Funahashi, 1989)) showed that for any continuous function $g(x_t; \theta)$, every compact subset K of R^k and every $\delta > 0$, there exists a $F(x_t; \gamma)$ such that

$$\sup_{x \in K} \| F(x_t;\gamma) - g(x_t;\theta) \| < \delta \tag{7}$$

Following these results, it is straightforward to show that the accuracy of the approximation is determined by the number of hidden layer units, namely, q and the parameter vector γ, given a set of k inputs, namely, the $k \times 1$ vector x_t. The choice of q can be somewhat arbitrary, it is often a matter of striking a balance between accuracy and over-fitting. Given q, the parameter vector γ can be estimated using non-linear least squares:

$$\hat{\gamma} = \arg\min_{\gamma \in \Lambda} \sum_{t=1}^{T} (y_t - F(x_t;\gamma))^2 \tag{8}$$

Obviously, the computational complexity of this minimisation problem grows as the number of hidden layer units grows. Several studies (See (Weeraprajak, 2007) for a comprehensive review) have suggested that the computational burden can be reduced if it is possible to separate the function $F(\bullet)$ into linear and non-linear components. In this case, the parameters associated with the linear component can be estimated using conventional least squares estimator, which has a closed form solution and the parameters in the non-linear component can be estimated using the non-linear least squares estimator. This implies the number of parameters required to be estimated by the non-linear estimator is reduced and hence improve computation efficiency.

The graphical representation of the basic ANN model with the three primary components, namely the input layer (the input/explanatory variables, x_t), the hidden layer (black box) with multiple units, $G(x_t, \gamma_i)$ and the output measure layer (the estimated CMBS rating in this case) can be found in Figure 6.

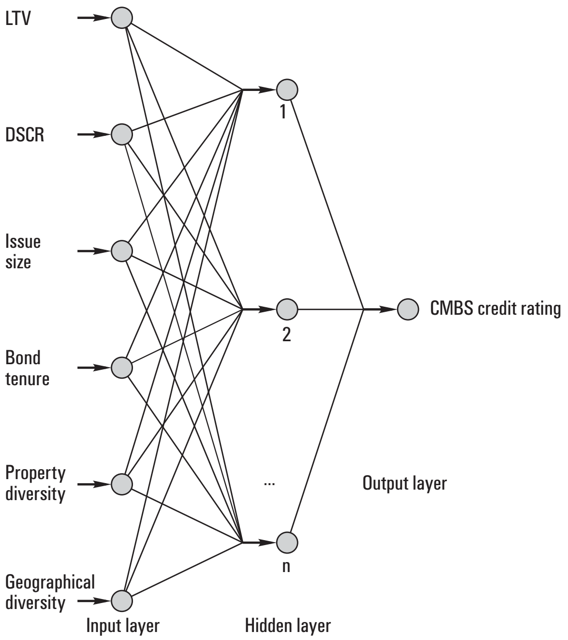

Figure 6. Structure of a CMBS rating neural network

The hidden layer(s) contain two processes: the weighted summation function (the linear component); and the transformation function (the nonlinear component). 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).

Alyuda Forecaster XL® (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, Han and Lee, 1997).

We further excluded unrated tranches, to leave us with 118 tranches (training sample) and 17 tranches (test sample) respectively. Zhang et al. (1998) indicate that literature offers little guidance in selecting the training and test samples, with most authors selecting them based on the rule of 90% vs. 10%, 80% vs. 20% or 70% vs. 30%, etc. They emphasise that the critical issue is to have both the training and the test sets representative of the population or underlying mechanism. The division of training and test sets should depend on the problem characteristics, the data type and the size of the available data. 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%

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

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

Appendix 2 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 (2003), 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. Standard and Poor's (2001) as well state that their basis of rating is the relative risk of the collateral and the ability of the collateral to generate income. 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:

$$\mathrm{HHGR} = \sum_{j=1}^{8} \left(\frac{x_j}{x} \right)^2 \tag{9}$$

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

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].

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 1a to 6a 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 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

The log-likelihood test in this case failed as the estimation of the general model failed to converge. Subsequently we do not believe the test is valid in this case, leading us to conclude that statistical approaches used in corporate bond rating studies have limited replication capabilities in predicting CMBS credit ratings.

5.2. ANN

5.2.1. Prediction accuracy analysis

As pointed out in section 4.5 and following the approach taken to test the explanatory power of OR models to predict credit ratings by composing models with various independent variables, the same approach was adopted using ANN. Three models were run starting with the basic model with two independent variables being LTV and DSCR. Some researchers (Fabozzi and Jacob, 1997) and rating agencies (Moody's Investor Service, 2003) regard these as the most important variables in determine a CMBS credit rating. The second model included bond tenure (TENURE) and log of issue size to the independent variables in Model 1. Finally, Model 3 had all the independent variables used in Models 1 and 2 in addition to portfolio diversity variables. Tranche rating is the dependent variable in all the models.

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 7. 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.

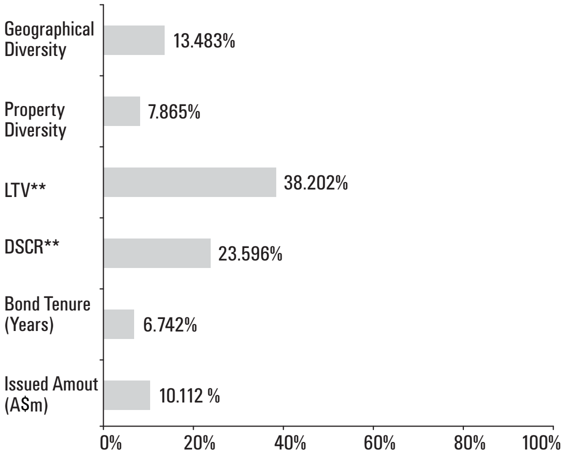

Figure 7. CMBS rating variable contribution

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 Ranking 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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SANTRAUKA

KOMERCINE HIPOTEKA UŽTIKRINTŲ VERTYBINIŲ POPIERIŲ KREDITO REITINGŲ EMPIRINĖ ANALIZĖ: AUSTRALIJOS PAVYZDYS

Bwembya CHIKOLWA, Felix CHAN

Sisteminant komercine hipoteka užtikrintų vertybinių popierių prekybos sandorius, svarbiausias tikslas – gauti aukštą kredito reitingą, nes tai daro poveikį pelningumui ir emitento sėkmei. Kredito reitingų agentūros teigia, kad jų vertinimai išreiškia kiekvienos agentūros nuomonę apie potencialią emitento nemokumo riziką ir daugiausia remiasi emitento gebėjimo bei noro grąžinti savo skolą analize, kurią atlieka komitetas, taigi tyrinėtojams jų reitingų kiekybiškai replikuoti nepavyktų. Tačiau tyrinėtojai replikavo obligacijų reitingus, remdamiesi prielaida, kad finansiniai koeficientai turi daug informacijos apie įmonės kredito riziką. Prognozuodami komercine hipoteka užtikrintų vertybinių popierių reitingus, kaip alternatyvius metodus naudojame dirbtinius neuroninius tinklus ir ranginę regresiją. Ranginės regresijos rezultatai rodo, kad reitingų agentūros naudoja tik tą kintamųjų poaibį, kuriuos jos apibūdina arba nurodo kaip svarbius komercine hipoteka užtikrintų vertybinių popierių reitingui, nes kai kurie iš naudojamų kintamųjų statistiškai nereikšmingi. Apskritai dirbtinių neuroninių tinklų rezultatai, prognozuojant komercine hipoteka užtikrintų vertybinių popierių reitingus, geresni nei ranginės regresijos.

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 ranking 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

Sources:
1. Moody's Investor Service (2003).
2. Standard and Poor's (2001).
3. Fitch Ratings (2005).
4. Roche (2002).

APPENDIX 2. Training sample correlations

Variable	Issued amount (A$m)	Bond tenure (years)	DSCR**	LTV**	Property diversity	Geographical diversity	Rating*
Issued amount (A$m)	1.000						
Bond tenure (years)	0.037	1.000					
DSCR**	0.236(**)	0.070	1.000				
LTV**	-0.465(**)	0.037	-0.689(**)	1.000			
Property diversity	0.025	0.108	-0.146	0.203(*)	1.000		
Geographical diversity	-0.089	-0.216(*)	-0.042	0.073	0.194(*)	1.000	
Rating*	0.505(**)	0.030	0.669(**)	-0.861(**)	-0.138	-0.063	1.000

** 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)

				Property Details							Financial details			Tenant/Lease details				No. of assets		
					Capital value			Net income ($m)			Gearing								Diversity	
Sector	Issue	Issued amount (A$m)	Note tenure (years)	Total lettable area (m²)	Market value (AU$m)	S&P stressed value (AU$m)	Capital value discount (%)	Market Net income (AU$m)	S&P net income (AU$m)	Net income sdiscount (%)	DSCR	LTV	LF	CQI	TC	WALE	OR	TA	PD	GD
All																				
	Min	0	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	7	1.008.603	1.880	1.660	22,9%	142,20	120,30	22,5%	3,50	76,0%	13,3%	100,0%	100,0%	30,0	100,0%	101	100,0%	1,00
	Average	75	4	349.805	760	672	11,0%	62,00	56,28	9,0%	2,14	45,1%	3,1%	37,5%	45,8%	7,8	97,2%	21	29,8%	0,47
Diversified																				
	Min	1	3	97.316	265	228	7,3%	21,00	19,50	3,0%	1,29	32,0%	1,9%	17,9%	42,0%	3,6	91,3%	7	9,7%	0,32
	Max	350	6	588.200	1.430	1.255	20,2%	123,87	107,80	13,4%	3,50	68,0%	4,4%	56,0%	67,0%	10,0	99,0%	25	60,2%	0,51
	Average	62	4	284.666	688	606	12,0%	56,79	50,97	9,3%	2,10	46,1%	3,2%	39,5%	50,9%	7,1	97,0%	19	35,5%	0,40
Industrial																				
	Min	5	1	500.844	454	399	3,0%	46,00	37,80	2,0%	1,46	33,0%	2,0%	24,2%	24,3%	4,1	94,0%	26	8,0%	0,48
	Max	185	5	1.008.603	1.147	885	22,9%	92,26	84,10	17,8%	3,10	68,0%	3,3%	24,2%	25,0%	6,3	99,0%	39	14,0%	0,79
	Average	60	3	787.841	808	701	12,2%	74,79	67,53	9,8%	2,40	42,6%	2,5%	24,2%	24,9%	5,4	97,6%	34	10,2%	0,63
Office																				
	Min	10	1	49.650	495	473	4,4%	34,40	29,30	5,4%	1,28	32,0%	1,2%	13,3%	39,0%	4,1	83,0%	1	11,9%	0,26
	Max	350	5	431.691	1.880	1.660	16,4%	142,20	120,30	22,5%	2,40	62,0%	3,4%	75,0%	79,9%	8,0	99,5%	21	100,0%	1,00
	Average	133	3	310.142	1.220	1.084	10,9%	96,40	83,27	13,6%	2,04	41,0%	2,2%	44,3%	54,2%	5,7	96,4%	13	26,3%	0,49
Retail																				
	Min	0	3	91.152	200	200	0,0%	17,90	17,90	0,0%	1,20	35,0%	2,0%	0,0%	20,1%	4,0	93,0%	2	11,0%	0,20
	Max	240	7	533.343	1.380	1.100	20,3%	92,80	85,40	13,9%	3,30	76,0%	13,3%	100,0%	100,0%	30,0	100,0%	101	64,0%	0,78
	Average	61	5	189.845	524	468	0,10	41,76	39,06	5,9%	2,09	0,48	0,04	0,30	0,45	13,9	0,98	20	0,37	0,45

LF: Liquidity facility (% of stressed value)
WALE: Weighted average lease expiry (years)
TC: Tenancy concentration (Top 5 tenants as % of total gross income)
PD: Property diversity (% of portfolio value)

CQI: Credit quality of income (% of income from investment grade tenants)
OR: Occupancy rate (%)
GD: Geographic diversity Herfindahl index
TA: Total number of properties

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

APPENDIX 5. Variable scatter plots

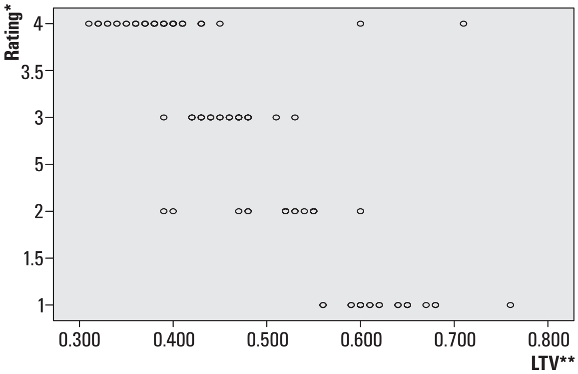

Figure 1a. CMBS rating vs. LTV
(Strong relationship)

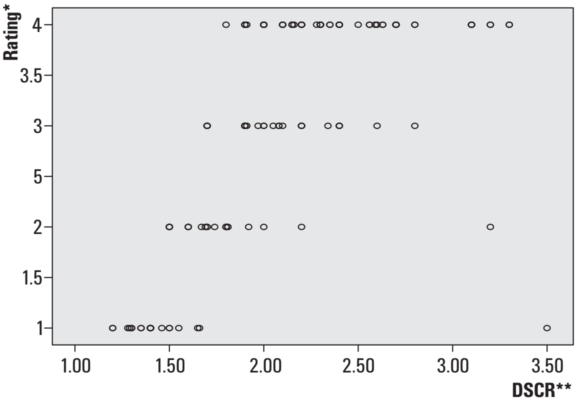

Figure 2a. CMBS rating vs. DSCR
(Weak relationship)

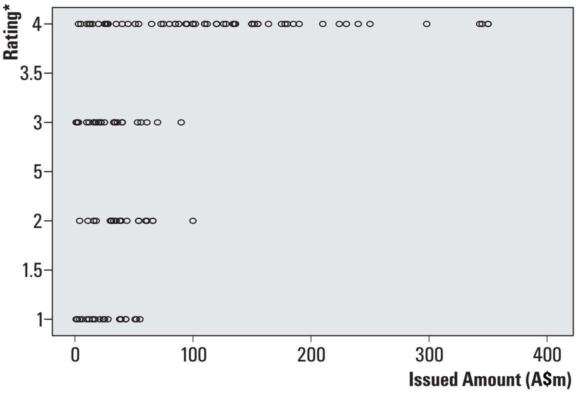

Figure 3a. CMBS rating vs. Issued amount
(No relationship)

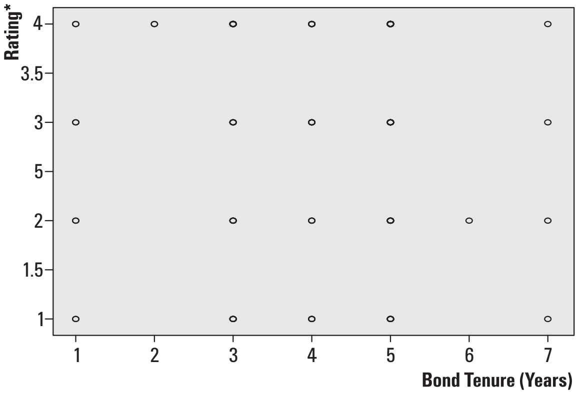

Figure 4a. CMBS rating vs. Bond tenure
(No relationship)

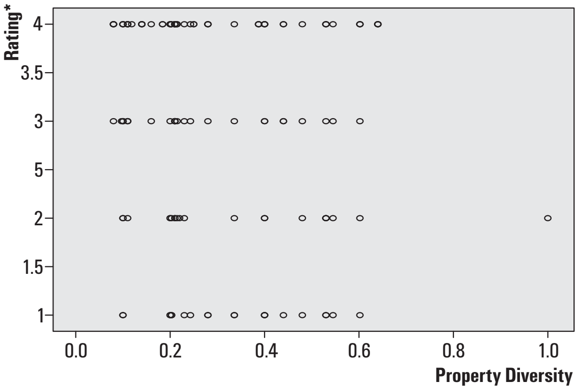

Figure 5a. CMBS rating vs. Property diversity
(No relationship)

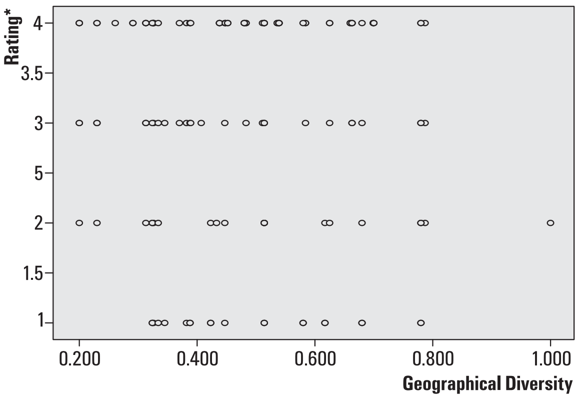

Figure 6a. CMBS rating vs. Geographical
diversity (No relationship)

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%