DETERMINANTS OF AUSTRALIAN LISTED PROPERTY TRUST BOND RATINGS

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ABSTRACT

Using artificial neural networks (ANN) and ordinal regression (OR) as alternative methods to predict LPT bond ratings, we examine the role that various financial and industry-based variables have on Listed Property Trust (LPT) bond ratings issued by Standard and Poor's from 1999-2006. Our study shows that both OR and ANN provide robust alternatives to rating LPT bonds and that there are no significant differences in results between the full models of the two methods. OR results show that of the financial variables used in our models, debt coverage and financial leverage ratios have the most profound effect on LPT bond ratings. Further, ANN results show that 73.0% of LPT bond rating is attributable to financial variables and 27.0% to industry-based variables, with the office LPT sector accounting for 2.6%, retail LPT sector 10.9% and stapled management structure 13.5%.

Keywords: Listed property trusts, bond rating, ordinal regression, artificial neural networks

INTRODUCTION

Bonds provide an important mechanism by which firms obtain new funds to finance new and continuing activities and projects. Bond issuance has been recognised by Listed Property Trusts (LPTs) as an important debt funding tool. Newell (2007) and PIR (PCA/IPD 2007) show the growth in debt levels of LPTs from only 15% in 1997 to 36% as at December 2006. Debt funding has been through direct bank borrowings and issuance of commercial mortgage-backed securities (CMBS) and unsecured bonds. For the period 1999-2006, bonds[1] worth a total of AU$10.5 billion were issued by LPTs (Property Council Australia 2007). In contrast, the Connect 4 Company Prospectuses database shows that LPTs raised AU$18.2 billion in equity raisings, excluding initial price offerings (IPOs). Chikolwa (2007a) also shows that LPTs issued CMBSs worth AU$9.3 billion over the same period.

In Australia, the bond ratings are assigned by Standard and Poor's, Moody's Investors Service and Fitch Ratings. The ratings inform the public of the likelihood of an investor to

[1] *This excludes commercial mortgage-backed securities.*

receive the promised principal and interest payments associated with the bond issue (Shin & Han 2001) The assigned ratings are important due to the implications they contain regarding the bond issue. Market yields correspond to bond ratings, which indicate an association between rating and risk. For instance, the success of an issue is dependent on obtaining a lower yield which is also influenced by high credit quality (Alles 2000; Kose et al. 2003). 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 (Altman & Rijken 2006; Shin & Han 2001). As such, studies of the rating process are of interest not only to bond holders, but also to investors.

Bond rating agencies assert that researchers cannot replicate their ratings quantitatively (Kim 2005) as they are the agency's opinion about an issue's potential default risk and that they rely heavily on a committee's analysis of the issuer's ability and willingness to repay its debt. However, 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). Kamstra et al. (2001) state that financial variables are able to explain about two thirds of a company's bond rating. Traditionally, statistical techniques such as multivariate discriminant analysis (MDA), multiple regression analysis (MRA), probit and logit models and more recently artificial neural networks (ANN) have been used to capture and model the expertise of the bond rating process.

To the best of our knowledge, only three studies have examined credit ratings using Australian data (Chikolwa 2007b; Gray et al. 2006; Matolcsy & Lianto 1995). Chikolwa (2007b) found that rating agencies use only a subset of variables they describe or indicate as important to rating CMBS [2] and showed the superiority of ANNs over ordinal regressions in predicting CMBS ratings. Gray et al (2006) find that interest coverage and leverage ratios have the most profound effect on credit ratings, using an ordered probit regression. Matolcsy and Lianto (1995) examine the incremental information content of bond rating revisions on stock prices, after controlling for accounting information, using a cross-sectional regression approach. Their finding that only rating downgrades have informational content is consistent with other studies.

This paper extends the analysis of Chikolwa (2007b) and Gray et al. (2006) by mainly applying ANN and OR as alternative methods for predicting ratings on bonds issued by Australian LPTs between 1999 and 2006. Tests are undertaken to compare the predictive power of ANN models and ordinal regression models. We find that both OR and ANN provide robust alternatives to rating LPT bonds and that there are no significant differences in results between the two full models. OR results show that of the financial variables used in our models, debt coverage and financial leverage ratios have the most profound effect on LPT bond ratings. Further, ANN results show that 73.0% of LPT bond rating is attributable to financial variables and 27.0% to industry-based variables; office

[2] *Only Loan-to-value (LTV) ratio was found to be statistically significant.*

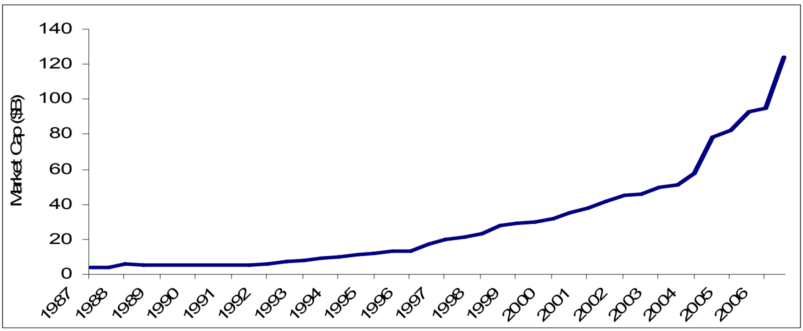
LPT sector accounting for 2.6%, retail LPT sector 10.9% and stapled management structure 13.5%.

The paper is structured as follows. Section 2 shows the significance of the bond markets as an unsecured funding source for LPTs. Next, Section 3 reviews literature on the use of ANNs in real estate and corporate bond rating studies. Section 4 discusses the data and methodology. The study results and their analyses are shown in Section 5. Concluding remarks and future research directions are shown in Section 6.

SIGNIFICANCE OF LISTED PROPERTY TRUST BONDS

The Australian LPT sector has grown significantly from AU$7 billion in 1992 to over AU$136 billion by market capitalisation as at December 2006, with total assets of over AU$140 billion, comprising over 3,000 institutional-grade properties in diversified and sector-specific portfolios (Newell 2007; PCA/IPD 2007). LPTs currently are the third largest sector on the stockmarket and representing over 10% of the total Australian stockmarket capitalisation, compared to only 5% of the total Australian stockmarket capitalisation in 2000 (UBS 2007). Figure 1 shows the growth in LPT market capitalisation since 1987.

Figure 1: Growth in Australian LPT market capitalisation: 1987-2006



Source: Newell (2007)

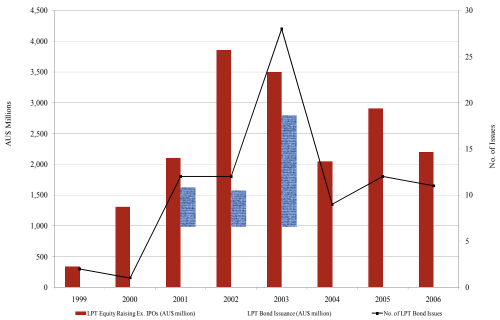
Diversified LPTs have a market share of 32% by market cap., office LPTs have 11%, retail LPTs 43% and industrial LPTs 12% (UBS 2007). Unlike US REITs, Australian LPTs do not have residential property in their portfolios.

The maturing nature of the LPT market has seen the increased sophistication of LPT debt management. Intense competition and pressure to add value to LPT returns have required LPT managers to be more sophisticated in capital and debt management (Blundell 2001).

A range of sophisticated debt products including CMBS, property trust bonds, hybrids and off-balance sheet financing have been used as a natural hedging strategy by LPTs with international property exposure and also to fund acquisitions. As at December 2006, LPTs had on average debt levels of 36% from 10% in 1995 (Newell 2007; PIR 2006) with some LPTs with 100% international property having debt levels in excess of 50%; eg: Rubicon America, Reckson NY Property, Galileo Shopping America (Newell 2006).

With regards to LPT bond issuance, the total cumulative issuance volume from 1999 to December 2006 reached AU$10.5 billion, with 87 issues as shown in Figure 2. Generally, annual LPT bond issuance has remained stable at around AU$1.5 billion, with the exception of the year 2003 when issuance nearly reached AU$2.8 billion. LPT bond issuance as a funding source can be compared to LPT equity raisings, excluding initial price offerings (IPOs). Although LPTs have raised more funds through issuing additional securities (AU$18.2 billion), bond issuance has featured prominently as well at an average of 65% of equity raisings. For instance in 2006, LPTs issued bonds worth AU$1.7 billion and raised AU$2.2 billion through issuance of additional securities.

Figure 2: Australian LPT bond issuance and equity raisings ex. IPOs: 1999-2006



Sources: Author's compilation from various Property Australia magazines and Connect 4 Company Prospectuses database (1999-2006)

To further emphasise the importance of issuance of bonds by LPTs as a funding source, we compare with the issuance of commercial mortgage-backed securities (CMBS) which is dominated by LPTs (Chikolwa 2007a; Standard & Poor's 2005)[3] from 2000 to 2006; see Table 1. Although more funds have been raised via CMBS (AU$14.3 billion) than LPT bonds (AU$10 billion), more LPT bonds (total number issued 85) have been issued in number than CMBSs (total number issued 66). Furthermore, in certain years (2001 and 2003) more funds were raised via LPT bonds than CMBS issuance.

Table 1: Australian LPT bond issuance and CMBS issuance: 1999-2006

Year	CMBS Issuance		LPT Bond Issuance	
	AU$ million	No. of Issues	AU$ million	No. of Issues
2000	$357	2	$100	1
2001	$1,320	5	$1,615	12
2002	$2,845	19	$1,570	12
2003	$2,191	14	$2,792	28
2004	$1,513	7	$905	9
2005	$2,102	8	$1,320	12
2006	$4,013	11	$1,650	11
Total	$14,340	66	$9,952	85

Sources: CMBS issuance: Chikolwa (2007a); LPT bonds: Author's compilation from various Property Australia magazines (1999-2006)

The Australian LPT bond market has remained competitive in comparison to their US equivalent, REITS unsecured debt offerings, with the two countries showing its increase in importance as a debt funding source. Table 2 shows LPT bond issuance and US REIT unsecured debt offerings by value and number from 1999-2006.

[3] *Listed Property Trusts have a 65% CMBS market share.*

Table 2: Australian LPT bond issuance and US REITS unsecured debt offerings: 1999-2006

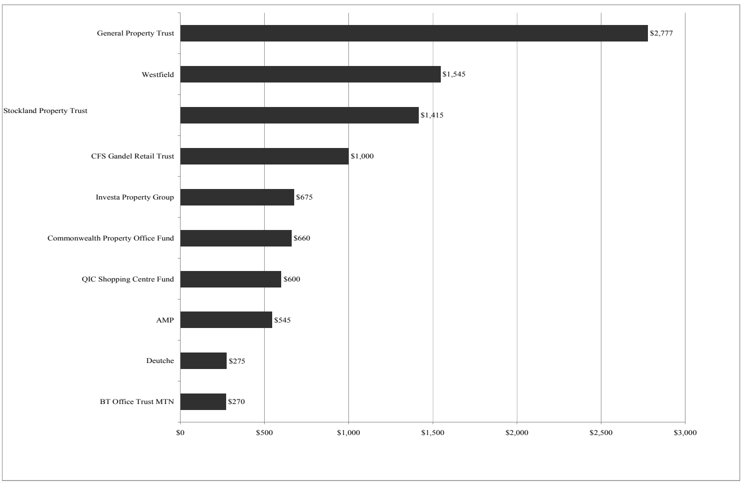
Year	LPT Bonds		US REIT Unsecured Debt Offerings	
	AU$m	No. of Issues	AU$m	No. of Issues
1999	$500	2	$10,337	69
2000	$100	1	$9,117	70
2001	$1,615	12	$12,864	44
2002	$1,570	12	$13,830	71
2003	$2,792	28	$14,163	68
2004	$905	9	$22,499	97
2005	$1,320	12	$21,230	105
2006	$1,650	11	$32,841	82
Grand Total	$10,452	87	$136,880	606

US$1 = AU$0.7692 as at 31 December 2006

Source: LPT bonds: Author's compilation from various Property Australia magazines (1999-2006); US REITS: NAREIT website

Figure 3 shows the top 10 LPT bond issuers who command a 93% market share and have issued bonds worth a combined total of AU$9.8 billion from 1999-2006. Major players in the LPT bond market include GPT (AU$2.8 billion), Westfield (AU$1.5 billion), Stockland (AU$1.4 billion) and CFS Gandel Retail Trust (AU$1 billion).

Figure 3: Top 10 Australian LPT bond issuers: 1999-2006

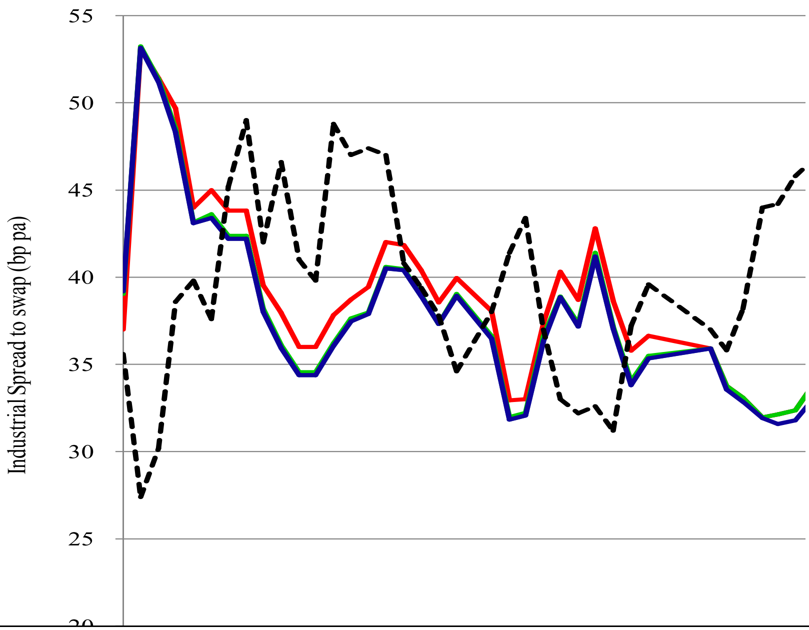


Source: Author's compilation from various Property Australia magazines (1999-2006)

An interesting feature is that of the top 5 LPT bond issuers, only the Investa Property Group have issued CMBSs with the remaining preferring only LPT bond issuance. Further, of the top 5 LPT bond issuers, Westfield, General Property Trust and Stockland are in the UBS Leaders 300 Index, emphasizing their ability to use their balance sheet to back bond issuance.

Figure 4 shows an inverse relationship between industry spread to swaps and 10-year government bond rates; as 10-year government bonds rates rise, industry spread to swaps tighten and vice versa. Generally, 1-3 year LPT bonds have been priced at 2-3bp above 5 year LPT bonds. There are no marked differences in swaps between 5 year and above LPT bonds.

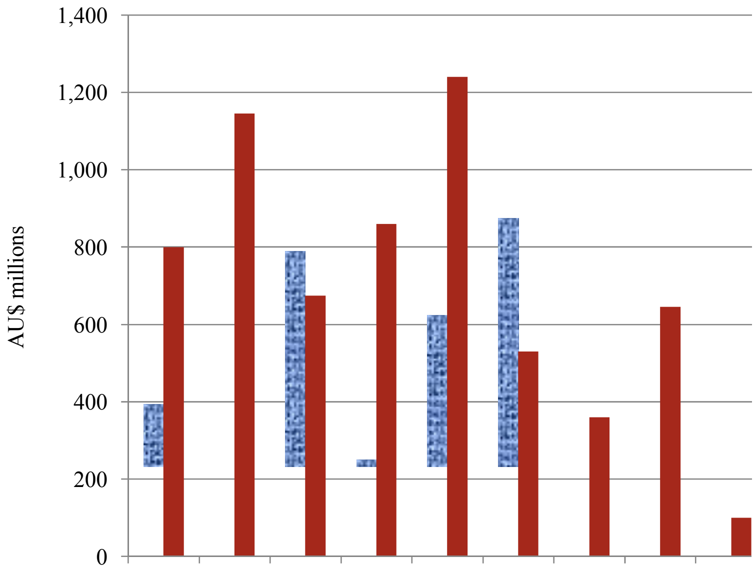
Figure 4: Australian LPT bond industry spread to swap and 10-year government bond rates: April 2003 - October 2006



Sources: Author's compilation from various Property Australia magazines (1999-2006) and RBA (2007

The sub-prime mortgage market events in the US are having an impact on the global bond markets and may have an impact on the refinancing prospects for maturing LPT bonds. Figure 5 presents the maturity profile of all the LPT bonds issued between 1999 and 2006. Nearly AU$3.3 billion worth of LPT bonds are maturing in 2008-2009, of which 45.9% are BBB rated bonds. As investors require greater compensation to invest in BBB rated bonds, refinancing will become more expensive.

Figure 5: Australian LPT bond maturity profile



Source: Author's compilation from various Property Australia magazines (1999-2006)

The macroeconomic outlook for the Australian market remains benign, with historically low unemployment rates and a low interest environment expected to continue. However, liquidity and valuation issues surrounding securitised debt backed by sub-prime mortgages in the US home market has resulted in the 'credit crunch' in the global financial system due to an increased perception of risk on the part of lenders. This has resulted in higher spreads on securitisable financial receivables and unsecured debt offerings.

LITERATURE REVIEW

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. 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. Frequently these studies are in the form of comparative analysis, with researchers contrasting them with the findings and perceived efficiency of ANNs. Salchenberger et al. (1992) and Tam and Kiang (1992) state that the main advantage ANNs have over statistical methods is that they do not require priori specification of a function form, but rather they attempt to learn from the training input-output examples alone.

Artificial neural networks in real estate studies

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), Lai and Fischer (2006), Pagourtzi et al. (2007); 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); predicting commercial mortgage-backed securities credit ratings: Chikolwa (2007b); and the impact of environmental characteristics on real estate prices: Kauko (2003).

Most of the studies, except for Worzala et al. (1995) and Lenk et al. (1997), show that ANNs have a superior predictive capacity over traditional statistical techniques. Worzala et al. and Lenk et al. noted that ANNs were not necessarily superior over traditional statistical techniques.

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 & James 1998a). This increased use of ANN methodology in the commercial real estate research gives credence to its extension to research in predicting ratings on bonds issued by LPTs.

Artificial neural networks in corporate bond studies

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).

Kim (2005) used an adaptive learning network (ALN) on a sample of 1080 observations (companies) primarily collected from the COMPUTSTAT database, Dunn 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. They further showed a prediction accuracy of 88% and 91% for investment grade and speculative bonds respectively.

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%.

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 further concluded 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 (Srinivasan & Bolster). 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.

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%).

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.

Dutta and Shekhar (1988) were the first to investigate the ability of neural networks (NNs) to predict 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.

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

DATA AND METHODOLOGY

Data

Our initial sample consists of all 87 Standard and Poor's rated bonds issued by Australian property trusts between 1999 and 2006 as found in the Property Australia magazine. After removing bonds that had incomplete financial information, our sample was reduced to 77. Concurrent and complete financial report information for the period 1999 to 2006 is obtained from the Aspect Fin Analysis database. We follow Gray et al (2006) definition of annual financial report as being contemporaneous with the rating if it relates to the financial year-end that occurs three to fifteen months prior to the rating. This ensures that any changes based on information released in the annual report are captured in the corresponding rating. Three-year averages of relevant financial ratios rather than the most recent observations are used in line with the 'rating through the cycle'[4] process which is adopted by credit rating agencies to capture the longer-term perspective (Carey & Hrycay 2001; Carey & Treacy 2000).

In order to have a reasonable number of observations in each rating class, the agency rating classes A, A+ and A3* are combined into a single rating class A, and the agency-rating classes BBB and BBB+ are combined into a single rating class BBB+. Further, the reclassification of tranches into three classes could enhance model performance because mathematical and statistical approaches have general limits in dealing with the ordinal nature of bond rating. It is known that as the number of bond classifications increases, the predictive power could likely decrease (Kwon et al. 1997). Table 3 provides summary statistics over time and by sector.

[4] *This is described as a rating assessment in a worst case scenario, in the bottom of a presumed credit quality cycle.*

Table 3: Distribution of sample observations over time, rating class and sector

	A	A-	A+	A3*	BBB	BBB+	***Total***
			Panel A: LPT Bond Rating by Year				
1999	1					1	***2***
2000	1						***1***
2001	2	7				3	***12***
2002	4	2	3	1		2	***12***
2003	4	19				5	***28***
2004	1	4				4	***9***
2005	3	3				6	***12***
2006	1	4			2	4	***11***
Total	***17***	***39***	***3***	***1***	***2***	***25***	***87***
			Panel B: LPT Bond Rating by Sector				
Diversified	3	15	3		2	16	***39***
Office		6		1		9	***16***
Retail	14	18					***32***
Total	***17***	***39***	***3***	***1***	***2***	***25***	***87***

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). The primary reference for modelling bond ratings which has been utilised directly or with minor variations is the Kaplan and Urwitz (KU) (1979) model. The KU model uses financial ratios relating to leverage, coverage, liquidity, profitability, and size. Rating agencies list qualitative factors such as management ability, value of intangible assets, financial flexibility, operating efficiency, industry risk, accounting quality and market position as being important in their rating process (Moody's Investor Service 2002). 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).

Consistent with information provided by Standard and Poor's (2007) and Moody's Investor Service (2002) and with the approach used by Gray et al. (2006), we model LPTs credit rating as a function of its financial characteristics given by interest coverage, profitability and leverage and industry characteristics. Credit ratings tend to be highly sensitive to the firm's interest coverage ratio- firms with higher coverage ratios are likely to have higher credit ratings. Profitability is another signal of the firm's ability to generate cash to meet its financial obligations- a high profitability ratio is more likely to be associated with a better credit rating. Cash flow or debt coverage ratios, such as free cash flows relative to total debt, are important in credit analysis as they provide an indication of the firm's present ability to service its debt and meet its financial obligations. A low cash-flow-to-debt ratio may be symptomatic of higher risk and a signal of weak prospects. High cash flow relative to total debt is associated with higher credit ratings. Further, higher leverage factors, measured as debt to total assets, reduce the cushion the firm has with respect to any incremental changes in its fortunes. Higher leverage is associated with lower credit ratings. In addition, long-term debt leverage is generally higher for firms with lower ratings.

Blume et al (1998) hypothesises that a firm with higher equity beta is expected to have a lower credit rating as it will be less able to service its debt for given accounting ratios as its equity risk increases. However, there have been inconsistent results in prior literature of using equity beta as a predictor variable in credit rating. Earlier studies (KU) found it to be a significant variable in credit rating prediction, while recent studies (Crabtree & Maher 2005; Gray et al. 2006; Maher & Sen 1997) have all found it to be insignificant. As such, our models do not include beta as a predictor variable.

The log of assets provides a robust measure of firm size, while at the same time providing a rational proxy for information asymmetry in view of the fact that information asymmetry typically decreases as a firm size increases (Krishnaswami et al. 1999). As such, we hypothesise that bonds issued by large LPTs by asset size should command higher ratings.

Rating agencies suggest that credit ratings should depend, in part, on the firm's business environment. Numerous industry characteristics including competitiveness, barriers to entry, exposure to technological change, regulatory environment and vulnerability to economic cycles can have a significant influence on the level of business risk a firm faces (Gray et al. 2006; Iskander & Emery 1994). For instance, Moody's Investor Service (2003) find competitive pressures, characteristics of the catchment areas, and expectations of future developments to have a greater impact in their rating of retail LPTs and vacancy rates, tenant demand trends, and future stock additions on office LPTs. Retail LPTs exhibit more cash flow stability than office or industrial LPTs, given Australia's relatively steady consumer spending trends as well as the long-term nature of their lease structures. Consequently, an office LPT is expected to generate stronger debt coverage ratios at a given level. A more stable and predictable cash flow should translate into a lower level of business risk and hence a lower credit risk. To control for possible LPT sector effects, indicator variables (0,1) for each LPT sector in the sample are included. An LPT sector dummy (0,1) is added as an independent variable to the benchmark model for two (i.e. n - 1) groups.

Stapled securities account for over 75% of the LPT market capitalisation, compared to only 29% in 2004 (Newell 2006). Tan (2004) show that the adoption of this internal management structure has enabled a closer alignment of unit holders and manager interests, no fee leakage and a lower cost of capital. Further, Newell (2006) state that the adoption of the internal management structure has not increased LPT risk levels.

However, Standard and Poor's (2007) assert that LPTs exposure to non-lease-related income may constrain their credit rating, as these activities carry much higher business risk than traditional, passive asset management, which reduces the firm's percentage of income-producing assets and its debt capacity at all rating levels. To control for possible LPT stapled-structure effects, indicator variables (0,1) for each LPT stapled-structure in the sample are included. An LPT stapled-structure dummy (0,1) is added as an independent variable to the benchmark model for one (i.e. n - 1) group.

Descriptive statistics regarding the sample are provided in Panel A and variable definitions in Panel B of Table 4.

Table 4: Descriptive statistics and variable definitions

Variable	*Minimum*	*Maximum*	*Mean*	*Std. Dev.*
Panel A: Descriptive Statistics				
DA	0.08	0.38	0.23	0.07
OCD	0.08	0.52	0.24	0.08
NS	1.05	3.74	2.27	0.78
TA	8.89	9.96	9.56	0.29
LS_1	0.00	1.00	0.18	0.39
LS_2	0.00	1.00	0.32	0.47
SS	0.00	1.00	0.68	0.47

Panel B: Variable Definitions	
DA	3-year average of total debt divided by 3-year average of total assets.
OCD	3-year average of operating cash flow divided by 3-year average of total debt.
TA	Natural log of 3-year average of total assets.
NS	3-year average of net tangible assets per share.
LS_1	Indicator variable set equal to 1 if the bond is backed an office LPT, 0 otherwise.
LS_2	Indicator variable set equal to 1 if the bond is backed an retail LPT, 0 otherwise.
SS	Indicator variable set equal to 1 if the bond is backed a LPT with a stapled structure, 0 otherwise.

Table 5 provides the bivariate correlations that exist between the data items.

Table 5: Spearman correlation coefficients

	TA	*DA*	*OCD*	*NS*	*LS_1*	*LS_2*	*SS*
TA	1.000						
DA	0.180	1.000					
OCD	-0.028	-.745(**)	1.000				
NS	.610(**)	-0.083	-0.154	1.000			
LS_1	-.350(**)	.363(**)	-.265(*)	-.514(**)	1.000		
LS_2	0.015	0.101	0.099	-.274(*)	-.327(**)	1.000	
SS	.662(**)	-0.089	0.027	.772(**)	-0.177	-.408(**)	1.000

**Indicates significance at the 1% level, * indicates significance at 5% level.

A number of models are used. Our benchmark Model 1 includes NTA per share (NS), total debt/total assets (DA), operating cash flows/total debt (OCD) and log of total assets (TA) as independent variables. Model 2 tests whether the office LPT sector (LS_1) has an impact on bond rating. We further test whether the retail LPT sector (LS_2) has an impact on bond rating in Model 3. In model 4, we test the combined effect of LPT sector (LS_1 and LS_2) have on LPT bond rating. Finally, Model 5 has all the independent variables in Models 1 and 5 in addition to the stapled-structure (SS) variable. LPT bond rating is the dependent variable in all the models.

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

Description of OR model

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

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:

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

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

where:

r = bond rating category;

p_i = $P\ (Y_i = r)$;

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

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

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

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

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

$$p_i = \frac{1}{1+e^{-\beta X_i}} \tag{3}$$

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

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

Y_i = BBB+ if Y_i^* is $\leq \beta_1$

Y_i = A- if $\beta_1 \leq Y_i^* \leq \beta_2$

Y_i = A if $Y_i^* \geq \beta_2$

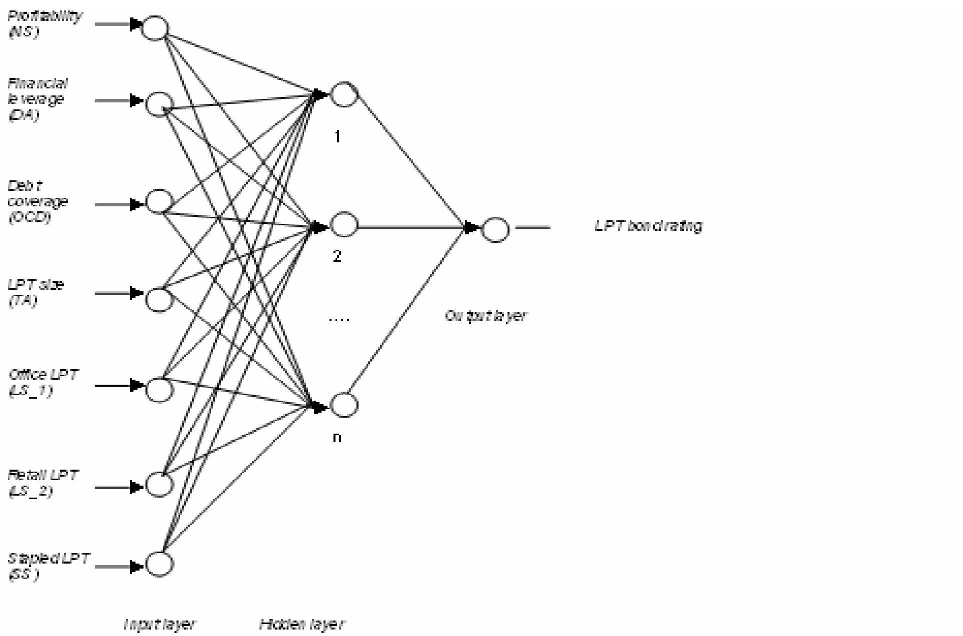
OR regressions were carried out in SPSS® version 15.0 (SPSS Inc. 1968).

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 LPT bond rating.

Figure 5: Structure of a LPT bond 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. NS, DA, OCD, TA, LS_1, LS_2 and SS variables) to output measures (LPT bond rating). The weighted summation function typically used in a feed-forward/back propagation neural network is:

$$Y_j = \sum_{j}^{n} X_i W_{ij} \tag{4}$$

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:

$$Y_T = \frac{1}{1 + e^{-y}} \tag{5}$$

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

Alyuda Forecaster XL® (Alyuda Research Inc. 2001) was used for the ANN experimentation. In the case of our 4-7 input and 3 output network, the hidden units were automatically set at 9 (model 1), 12 (model 2), 33 (Model 3), 33 (model 4) and 6 (model 5).

EMPIRICAL RESULTS AND ANALYSIS

OR results

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.

Table 4: OR results

Variable (Expected Sign)	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*
A-	37.741	37.959	66.040	98.773	115.803
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
	[13.224]	[13.062]	[23.116]	[26.309]	[10.888]
A	39.160	39.378	68.050	101.774	120.730
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
	[14.029]	[13.856]	[24.007]	[26.981]	[11.505]
Profitability (NS)	1.026	1.011	2.974	6.663	18.749
(+)	(0.014)	(0.022)	(0.000)	(0.000)	(0.000)
	[5.996]	[5.272]	[23.300]	[31.959]	[19.956]
Financial leverage (DA)	-18.475	-18.206	-22.858	-47.179	-108.561
(-)	(0.007)	(0.010)	(0.002)	(0.000)	(0.000)
	[7.234]	[6.665]	[9.352]	[18.071]	[13.025]
Debt coverage (OCD)	11.565	11.509	14.048	23.334	51.465
(+)	(4.729)	(0.030)	(0.020)	(0.005)	(0.004)
	[0.030]	[4.685]	[5.445]	[7.893]	[8.320]
LPT size (TA)	3.513	3.539	6.933	10.771	13.002
(+)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
	[9.443]	[9.377]	[21.043]	[26.800]	[12.387]
Office LPT (LS_1)		0.115		-7.731	-23.554
		(0.874)		(0.000)	(0.000)
		[0.025]		[21.822]	[14.660]
Retail LPT (LS_2)			-3.547	-8.588	-16.273
			(0.000)	(0.000)	(0.000)
			[24.257]	[30.982]	[19.318]
Stapled LPT (SS)					13.295
					(0.000)
					[15.774]
Chi-Square	21.908	21.935	50.956	83.183	123.581
*Pseudo R-Square	0.131	0.132	0.306	0.499	0.741

The primary control variables (NS, DA, OCD and TA) are all significant at the .05 level in the predicted direction. The industry-based variables (LS_1, LS_2 and SS) are each found to be significant when added individually and together to the benchmark model. In results not shown in this study, we find year of bond issue and size of bond issue to be statistically insignificant. All the models are significant at the .05 level with Likelihood Ratios ranging between 21.9 and 123.5. Our results are comparable to other studies (Blume et al. 1998; Crabtree & Maher 2005; Gray et al. 2006) that have found debt coverage (OSD), leverage (DA) and profitability (NS) to provide explanatory power in the credit rating process. In addition, the significance of the log of total assets (TA) suggests that larger LPTs will command higher credit ratings, confirming information asymmetry supposition by Krishnaswami et. al (1999).

The benchmark model 1 had a low pseudo R-square of 0.131 and adding the LPT sector variables individually only raised the pseudo R-square to 0.132 and 0.306 respectively (models 2 and 3). A marked difference in pseudo R-square (0.499) was noted when the two LPT sector variables (LS_1 and LS_2) were added to the benchmark model together (model 4). Overall, model 5 which incorporated all the industry-based variables (LS_1, LS_2 and SS) showed the best pseudo R-square result at 0.741

These results are consistent with the interpretation that retail LPTs have more stable cash flows than office LPTs and the bonds they issue should command higher ratings. Further, despite Standard and Poor's (2007) assertion that LPTs with exposure to non-lease-related income may constrain their credit rating, we find that the bonds issued by LPTs with stapled management structures command higher credit ratings. A possible explanation would be the higher anticipated returns from LPTs with stapled management structures. To investigate the effects of these industry-based predictability measures on bond ratings further, we examine the incremental effect each variable has on bond rating prediction accuracy.

The predictive capacity increased from the model 1 (56%) to the full model 5 (91%). The other models had the following prediction accuracy rates: model 2 (60%), model 3 (71%) and model 4 (91%). Table 5 compares the prediction accuracies across bond rating classes for all the models. The benchmark model 1 has a higher predictive capacity for the lower rated bonds (BBB+ and A-) and performs poorly for the higher rated notes (A). Models 2 and 3 shows that bonds issued by an office LPT are more likely to be rated BBB and those issued by retail LPTs rated A-. Further, our full model shows 73% likelihood of the bonds being rated either BBB+ or A-.

Table 5: OR classification accuracy of models 1-5

	BBB+	*A-*	*A*	*Correctly Predicted (%)*
Model 1	22/24 (92%)	21/32 (66%)	0/21 (0%)	56%
Model 2	22/24 (92%)	21/32 (66%)	3/21 (14%)	60%
Model 3	20/24 (83%)	26/32 (81%)	9/21 (43%)	72%
Model 4	22/24 (92%)	30/32 (94%)	18/21 (86%)	91%
Model 5	23/24 (96%)	28/32 (88%)	19/21 (90%)	91%

ANN results

Analysis were done using the five models on our initial 77 sample which was divided into 54 (70%) as training and 23 (30%) test samples. Results of the model prediction accuracies and variable contribution are shown below.

Prediction accuracy analysis

All the models had 96% prediction accuracy for the training sample; see Table 6. The predictive capacity of models increased from 52% (models 1) to 83% (model 5) for the test set emphasising the importance of the inclusion of industry-based variables in the models. The other models had the following results for their test samples: model 2 (61%), model 3 (70%) and model 4 (78%).

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	52(96%)	2(4%)	12(52%)	11(48%)
Model 2	52(96%)	2(4%)	14(61%)	9(39%)
Model 3	52(96%)	2(4%)	16(70%)	7(30%)
Model 4	52(96%)	2(4%)	18(78%)	5(22%)
Model 5	52(96%)	2(4%)	19(83%)	4(17%)

Further, Tables 7 shows the classification of accuracy within individual rating categories, with highest being for the *A* rating class at 76.2% - 95.2%. This is followed by the *A-* rating class which has a range of 87.5% - 93.8% and finally the BBB+ rating class at 58.3% - 91.7%. These results are comparable to those obtained in OR; see Table 5. ANN predicts better at higher rating classes (A and A-) than at the lower class (BBB+), which is the opposite for OR.

Table 7: ANN classification accuracy

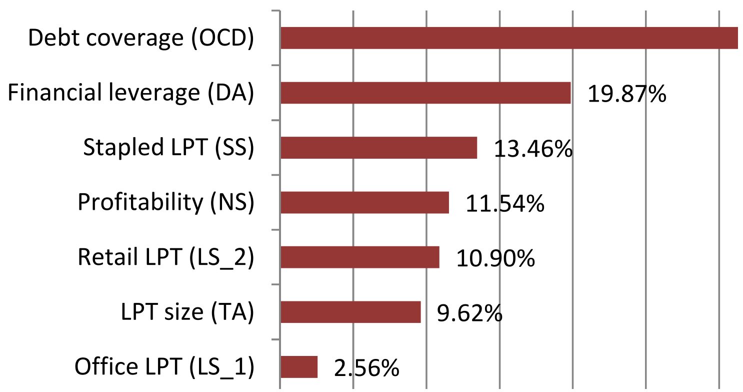
	BBB+	A-	A	Correctly Predicted (%)
Model 1	14/24 (58%)	30/32 (94%)	20/21 (95%)	83%
Model 2	16/24 (67%)	30/32 (94%)	20/21 (95%)	86%
Model 3	22/24 (92%)	30/32 (94%)	16/21 (76%)	88%
Model 4	22/24 (92%)	28/32 (88%)	20/21 (95%)	91%
Model 5	20/24 (83%)	30/32 (94%)	21/21 (100%)	92%

Variable contribution analysis

Though earlier literature and publications by credit rating agencies state that financial variables are important in the credit rating of firms and unsecured bonds issued by firms, to the best of our knowledge, no study has empirically examined the relative contribution of both financial and industry-based variables in LPT bond rating. This study thus evaluates the relative importance of different factors considered in the LPT bond rating using a neural network model.

Garson (1991) developed a means whereby connection weights within a neural network can be interpreted allowing the effect of various input nodes to be examined and ranked according to their relative importance. This is intrinsically done in Alyuda Forecaster XL®. The results of the relative importance of these variables in our full neural network model, (model 5) are shown in Figure 6. We do not show the results of the other four models, but suffice to state that the following order of importance was revealed though at various percentages: OCD, DA, NS, SS, LS_2, LS_1 and TA.

Figure 6: LPT bond rating variable contribution



Our study has shown 27.0% of LPT bond rating is attributable to industry-based variables; office LPT sector (LS_1) accounting for 2.6%, retail LPT sector (LS_2) 10.9% and stapled management structure (SS) 13.5%. Unlike Gray et al. (2006) who found industry-based variables insignificant in rating Australian firms using probit regression, results of our OR and ANN analysis indicate that industry-based variables are important in determining LPT bond ratings. A possible explanation is that LPTs core business is property investment. Financial variables contribute 73.0% to LPT bond rating, with debt coverage (OCD) being the dominant variable at 32.0%. This is followed by financial leverage (DA: 19.9%), profitability (NS: 11.5%) and LPT size (TA: 9.6%).

One drawback observable from Figure 6 is that no signs are attached to the calculated weights. Thus the interpretation of the relative weights can be inferred from OR analysis.

CONCLUSION, LIMITATIONS AND FUTURE DIRECTIONS

The sub-prime mortgage market events in the US have resulted in a 'credit crunch' in the global financial system due to an increased perception of risk on the part of lenders. This has had an impact on the refinancing prospects for maturing LPT bonds and further resulted in no new issuances due to high spreads on securitisable financial receivables and unsecured debt offerings. As such, studies on bond ratings are of great importance for the resuscitation of this source of funding.

This study examines the extent to which various financial and industry variables have on Listed Property Trust (LPT) bond ratings issued by Standard and Poor's from 1999-2006. Ordinal regression (OR) results show that of the financial variables used in our models, debt coverage and financial leverage ratios have the most profound effect on LPT bond ratings. Further, we find industry-based variables of LPT sector and stapled management structure to significantly affect bond rating.

We also examine predictive accuracies of OR and Artificial Neural Networks (ANN) as alternative methods to rating LPT bonds. Empirical analyses indicate that both OR and ANN provide robust alternatives to rating LPT bonds and that there are no significant differences in results between the two full models. Inclusion of industry-based variables increases the predictive accuracies of both the OR and ANN models. In addition, ANN results show that 73.0% of LPT bond rating is attributable to financial variables and 27.0% to industry-based variables.

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, though our results cannot be viewed as definitive due to the small sample size, they can form a basis for future studies.

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