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Transition and reversion of Japanese corporate rating structure under the recent credit crises

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Abstract. This study attempts to know the details of transition of rating structure under recent credit crises starting from BNP Paribas shock in August 2007 using Artificial Neural Network (ANN). This study checks the transition of recent bond rating structure under the credit crises based on accounting information giving Altman Z-score. Japanese corporate bond ratings are transformed to normally distributed variables using published 5-Year actual default probability, and are modelled as functions by key ratios giving Z-score. As remarkable findings, rating structure of S&P experienced serious shock in 2009 and reversion to the structure of training period in 2010. But time inconsistency of rating structures remains even in 2010. On the other hand, other agencies become more and more estranged under the crises.

Keywords: credit risk; bond pricing; risk management; artificial neural network

Introduction

The majority of previous research attempting to explain bond ratings systems are based on financial and other quantitative data. Among prior research using qualitative analyses, the most commonly assumed was a model where financial data of issuing corporations are set as explanatory variables. In these particular research horizons, pioneering theses were presented by Kaplan and Urwitz (1979), as cited earlier.

In addition, in previous researches including Altman (1968) and West (1973), a number of models were presented, which were designed to estimate rating transition probability by applying an ordered probit model or a logit model, to more complex ones designed to simultaneously estimate default probability and rating transition probability. Carty and Jerome (1994) and Cyert and Thompson (1968) were among those who attempted to analyze credit risks of corporations and banks. Analyses using actual data held by banks include those by Barkman (1981) and Betancourt (1999). Furthermore, analyses using panel data include those by Blume et al (1998). In comparison with studies on rating structure or predictions, the group of studies analyzing the differences in rating structures of each agency or time (or cross-sectional) consistency of informational content of rating information was a relatively small stream. This study belongs to this small stream, and focuses on the following points:

1. Are there any changes in rating structures for the period of credit crises starting from BNP Paribas shock in August 2007?
2. What kind of changes occurred on rating structures of each agency under the crises?

This study defines the rating structures by five parameters, inspired by Altman's Z-Score Model (Altman 1968). Procedure of estimating rating structures are consists of three steps. First, rating information are transformed into published actual default probability in five years. Next, Default probabilities are transformed into Z-values by probit function. Then, rating structures are estimated as nonlinear functions by Altman's five parameters using Artificial Neural Network (ANN).

The remainder of the paper is organized as follows. Section 2 depicts the error-back propagation method and cascade-correlation algorithm of ANN used in this study. In section 3, the data used are explained and the results of the analysis are revealed, followed by a discussion. Finally, findings are summarized in section 4.

Procedure for assuming a model in ANN

ANNs involve a variety of methods, of which Multi-Layer Perceptron (MLP) by Rumelhart, Hinton and Williams (1986) is the most frequently used and is used in this research. This is a feed-forward network with an arbitrary middle layer set up between the input and output layers.

MLP has a learning process whereby the weights between units are modified sequentially from the output end in such a manner that the output pattern, given a certain input pattern, would accord with target output. Error-Back Propagation (BP) is a well-known method to determine the weights systematically. Conceptually, BP can be summarized as follows:

(a) Set input pattern for learning and corresponding target output classes. At this time, set suitable initial values for the weights between layers.

(b) Compute input and output for each unit in the order of input layer, middle layer and output layer. All units receive input only from the immediately preceding layers, respectively, and send out output only to the immediately following layers, respectively. This sort of network is referred to as a feed-forward network.

(c) Compute the square error of the teacher signal, which is the target output corresponding to the input pattern and the output computed by the aforementioned procedure. As the Greek letter is used to express this square error, it is often referred to as the Delta rule or the Widrow-Hoff learning rule.

(d) Modify weights between network layers from the output layer toward the input layer in such a manner as to minimize this square error. This particular operation is the reason why the process is referred to as Error-Back Propagation.

(e) The process would end if the square error corresponding to all input patterns falls below a certain pre-set value. Otherwise, repeat the operations described in items (b) through (d).

However, BP is known to involve several problems. The most important of these is the slow pace at which BP learns from examples. Moreover, the weights are computed by fixing the number of nodes in the middle layer but the problem of arbitrariness of it could not be avoided.

As one of the approaches to improve these problems, Cascade-Correlation learning algorithm was developed by Fahlman and Lebiere (1991) and showed significant improvements. NeuralWorks Predict, a neural network tool by NeuralWare Inc. is the software which implements Cascade-Correlation learning algorithm. NeuralWorks Predict also outperforms other neural network tools in that it also builds in the stopping rules against over-fitting on empirical data. Moreover, NeuralWorks Predict assumes nonlinearity of the model and undertake some non-linear transformation for input variables in advance. Types of transformation used include log transformation, log-log transformation, exponential transformation, exponential transformation of exponent, square-root transformation, square, inverse number, inverse number of square root, and inverse number of square, depending on the complexity of the problem.

Analysis

Data set

We extracted companies listed on the Tokyo Stock Exchange that were given long-term bond ratings from U.S. rating agencies (S&P, Moody's) and Japanese agencies (JCR,R&I) simultaneously at the end of March from 2005 to 2010. For companies with no long-term bond rating, we used the issuer credit rating. R&I does not publish long-term bond ratings and only publishes issuer credit ratings. JCR does not publish issuer credit ratings and only publishes long-term bond ratings. S&P publishes only issuer credit ratings. Moody's publishes both issuer credit ratings and long-term bond ratings. However, in practice, for companies that receive both ratings, there are no differences in their ratings. As a result, we collected 175 samples.

Table. 1. Number of samples.

2005	*2006*	*2007*	*2008*	*2009*	*2010*
32	34	30	31	31	17

Actual 5 year cumulative default probability 5YDP is collected from each agency's site. Default probability corresponding to each rating and Z-value corresponding to each default probability are shown below. $P(\tilde{Z} | \tilde{Z} < Z - value) = 5\text{YDP}$ $\tilde{Z} \sim N(0,1)$ Z-value corresponding to 5YDP = 0%, or 100% is assumed to be –6 or 6, respectively.

Table. 2. Actual 5 year default probability and Z-value.

	S&P		*Moody's*		*JCR*		*R&I*	
	5Y DP	*Z-value*	*5Y DP*	*Z-value*	*5Y DP*	*Z-value*	*5YDP*	*Z-value*
AAA	0.10%	-3.09023	0.00%	-6.0000	0.00%	-6.0000	0.00%	-6.0000
AA	0.30%	-2.74778	0.00%	-6.0000	0.00%	-6.0000	0.04%	-3.35279
A	0.60%	-2.51214	0.29%	-2.75888	0.23%	-2.83379	0.65%	-2.48377
BBB	3.00%	-1.88079	0.69%	-2.46243	1.01%	-2.32261	1.12%	-2.28352
BB	11.30%	-1.21073	3.91%	-1.76123	9.65%	-1.30175	7.60%	-1.4325
B	25.40%	-0.66196	8.64%	-1.36326	36.59%	-0.34273	22.73%	-0.74777
CCC or lower	50.90%	0.022562	100.00%	6.0000	100.00%	6.0000		

Z-values above are output variables of ANN in this study and Input variables are 5 financial ratio described below. Financial data corresponding to each rating information are those of the nearest fiscal term collected from Nikkei Needs. The choice of 5 input variables is inspired by the Z-Score model (Altman(1968)). Working Capital/Total Assets (WC/TA) is a proxy for the fort term liquidity of the firm. Retained Earnings/Total Assets (RE/TA), EBITDA/Total Assets (EBTD/TA), and Market Value of Equity/Total Liabilities (MV/TL) variables proxy for historic, current and future profitability, respectively. Net Sales/Total Assets (NS/TA) is a turnover ratio of Total Assets as a proxy for firm's efficiency at using its total assets.

Robustness of rating structure before and under the credit crises

Explanatory power of ANN models on rating structure is measured by correlation between actual (Table 2) and estimated Z-values, AIC and BIC. Z-values in test period (i.e. credit crises, 2008~2010) are estimated by models in training period (2005-2007 or -2008) and transition of rating structures can be recognized by decrease of explanatory power during test periods.

Table. 3. Transition of rating structure under the credit crises 2007~2010.

		Training period 2005~2007				*Training period 2005~2008*		
		2005~2007	*2008*	*2009*	*2010*	*2005~2008*	*2009*	*2010*
S&P	*correlation*	0.9844	0.7452	0.6515	0.8900	0.9838	0.6678	0.8238
	AIC	-141.33	50.57	66.35	26.22	-196.73	65.39	33.51
	BIC	-133.18	51.34	67.12	20.93	-187.01	66.16	28.22
Moody's	*correlation*	0.9086	0.8066	0.4944	0.6361	0.9754	0.5792	0.9291
	AIC	164.38	94.89	125.46	78.80	75.22	117.57	56.25
	BIC	172.54	116.81	117.77	75.62	84.95	118.34	50.96
JCR	*correlation*	0.9824	0.2986	0.5389	0.2690	0.9889	0.6126	0.7473
	AIC	138.59	160.50	143.33	99.03	95.57	141.77	78.65
	BIC	146.74	161.27	144.10	93.74	105.30	142.54	73.36
R&I	*correlation*	0.9792	0.6276	0.4951	0.7968	0.9782	0.5386	0.5976
	AIC	-154.78	44.57	52.07	30.37	-202.34	62.19	41.06
	BIC	-146.63	45.34	52.84	30.37	-192.62	62.96	35.77

Based on the results above, S&P, Moody's and R&I: Explanatory power decreased remarkably at 2009 and improved at 2010. This fact can be interpreted that rating structure experienced serious transition in 2009 and reversion to the structure of training period in 2010. But time inconsistency of rating structure remains even in 2010.

JCR: Explanatory power measured by correlation continued to decrease from 2009 to 2010. But based on AIC and BIC, more plausible measure in case of nonlinear model like ANN, Explanatory power decreased remarkably at 2009 and improved at 2010. This fact can be interpreted that rating structure experienced serious transition in 2009 and reversion to the structure of training period in 2010. Fact concerning correlation can be interpreted to show extreme nonlinearity of ANN model.

Sensitivity analysis

In order to analyze the more details on transition of rating structure, sensitivity analyses are carried out on ANN models of each year or period.

Table. 4. Sensitivity Analysis (average gradient/standard deviation of gradient).

	S&P					*Moody's*				
	WC/TA	*RE/TA*	*EBTD/TA*	*MV/TL*	*NS/TA*	*WC/TA*	*RE/TA*	*EBTD/TA*	*MV/TL*	*NS/TA*
2005	0.0855	-0.4416	-0.0615	-0.3454	-0.0659	-0.5786	-0.1055	-0.8248	0.0948	-0.2009
2006	-0.0515	-0.0045	-0.2392	0.0576	-0.1496	0.6112	0.2565	-0.1092	0.2159	0.6959
2007	-0.3855	-0.1766	-0.0605	-0.1133	-0.2358	-0.2745	-0.0331	-0.4999	-0.1322	0.6267
2008	-0.3680	-0.2062	-0.3752	0.2482	-0.0807	0.0275	-0.2220	-0.4979	-0.0632	0.2671
2009	0.3472	-0.2524	-0.1403	-0.2741	0.0890	-0.0985	-0.3547	-0.2656	-0.1370	1.0266
2010	-0.0680	-0.2178	-0.2659	0.0734	-0.0119	0.1245	-0.5461	-0.8394	0.5862	0.3652

	JCR					*R&I*				
	WC/TA	*RE/TA*	*EBTD/TA*	*MV/TL*	*NS/TA*	*WC/TA*	*RE/TA*	*EBTD/TA*	*MV/TL*	*NS/TA*
2005	-0.3665	-0.2477	-0.5465	-0.2476	-0.2519	0.0351	-0.6838	-0.5549	0.1738	-0.2363
2006	-0.0925	-0.4186	-0.2031	-0.2677	0.1769	-0.2796	-0.0629	-0.6270	0.5071	0.3314
2007	-1.1233	-0.1582	-0.4796	-0.8288	0.5515	-0.0351	0.1372	-0.3961	-0.2569	0.4451
2008	-0.9031	0.0469	-0.2342	-0.1685	0.3039	-0.7199	-0.1762	-0.2788	-0.3915	-0.0272
2009	-0.7149	-0.5166	0.0044	-0.3235	-0.0666	-0.2757	0.0017	-0.0239	-0.8594	-0.0270
2010	-0.8916	-1.2259	0.8318	-1.1481	0.7755	-0.7219	-0.8740	0.4542	-0.9861	0.2189

Exposures fluctuate in both training and test period. These facts imply the consistency with the results in table3. Remarkably, S&P experienced relatively less fluctuation and seems to revert to the structure of training period. Other agencies show the high volatility and less time consistency under crises than S&P.

Conclusions

This study attempts to know the details of transition of rating structure under recent credit crises starting from BNP Paribas shock in August 2007 using ANN. As results, rating structure of S&P seems to revert to that before crises in 2010 and JCR becomes more and more estranged under the crises. The points to be aware of is over-fitting problem accompanying ANN. To solve this problem, the same analyses are carried out on many models which were structured on randomly selected data subsets and similar facts are found.

The frameworks of study can be widely used in the cases where many agencies (evaluators) publish the rating information in categorical data form. It can be a versatile method that allows us to make a quantitative comparison and discuss validity of rating information with the aim of bringing about efficient investment decision-making and asset pricing.

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