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Forecasting Bank Credit Ratings

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Abstract

Purpose-This study presents an empirical model designed to forecast bank credit ratings. For this reason we use the long term ratings provided by Fitch in 2012. Our sample consists of 92 U.S. banks and publicly available information from their financial statements from 2008 to 2011. Methodology -First, in the effort to select the most informative regressors from a long list of financial variables and ratios we use stepwise least squares and select several alternative sets of variables. Then these sets of variables are used in an ordered probit regression setting to forecast the long term credit ratings. Findings-Under this scheme, the forecasting accuracy of our best model reaches 83.70% when 9 explanatory variables are used. Originality/value- The results indicate that bank credit ratings largely rely on historical data making them respond sluggishly and after any financial problems were already known to the public.

1. Introduction

Credit ratings agencies (CRAs) provide important financial information to market participants for various economic entities. For the purposes of this paper, these credit ratings form an assessment of the credit worthiness of the financial and banking institutions. Usually, stakeholders base their financial decisions on these ratings. In recent years there is an increased interest in credit ratings and their methodologies due to the existing interconnection between the world banking sector financial markets.

Rating agencies provide a rating scale of risks associated with the ability of banks to meet debt obligations on time. These ratings are used by investors, borrowers, issuers and governments in making investment and financial decisions. Consequently, changes in ratings lead to changes in capital allocation. The three major rating agencies are Moody's, Standard and Poor's and Fitch. The implementation of Basel II strengthened the demand for ratings and expanded the role of credit rating agencies.

They play a key role in the pricing of credit risk. However their integrity has been under consideration due to cases such as Enron and Lehman Brothers which had been assessed, by the rating agencies, with high ratings just a few days before their collapse. For this reason, they are often blamed for not being able to provide the market with the appropriate ratings required for important investment decisions. Such cases also occurred during the global financial crisis of 2008 and turn the interest in credit rating methodologies. It is generally accepted that when the credit rating of a bank is downgraded from the CRAs then things get worse for the specific banking institution and vice versa. This study seeks to find the most important factors contributing to the ratings of banks.

The remainder of the paper is organized as follows. Section 2 reviews the literature and section 3 describes the data. Section 4 presents the methodology and the empirical results and section 4 concludes the paper.

2. Literature Review

To date, the issue of bank ratings has been largely unexplored. A paper closely related to this study is Bissoondoyal-Bheenick and Treepongkaruna (2011) who analyze the quantitative determinants of bank ratings, provided by Standard & Poor's, Moody's, and Fitch for UK and Australian banks. They used an ordered probit model and find that accounting variables have more explaining power in banks' ratings rather than macroeconomic variables. Another paper Pagratis and Stinga (2007) conducted an order probit analysis in order to search how bank ratings by Moody's relate to bank characteristics. Variables for provisions, profitability, cost efficiency, liquidity, short-term interest rates and bank-size perform well in explaining ratings. Papadimitriou (2013) explored the clustering properties of the correspondence analysis map of 90 financial institutions using data from their public statement. The goal was to compare the clustering groups with the rating of the Fitch Rating Agency. Results showed that there is visible relation between the clustering and the ratings, though it is not useful as it is, since the regions corresponding to the ratings are highly overlapped.

Baesens Bart et al. compare 10 rating agencies, across different regions of banks of different size. Using ordinal logistic regression to estimate individual and long term rating they found that individual ratings can be accurately modeled from the hold out sample approximately 66% of the time but long term rating are more difficult to model. They also conclude that ratings of larger banks can be modeled more accurately than those of smaller banks.

Although the issue of credit ratings of banks has been largely unexplored, substantial papers can be found in predicting bond ratings. Ederington (1985), Mingo et al. (1973), Belkaoui (1980) used statistical methods such us logistic regression and multivariable discriminant analysis (MDA) to predict bond ratings. In these studies different sets of variables were used and the prediction results were between 50% and 70%.Many studies on bond credit rating prediction with neural networks (Dutta et al. (1988); Surkan et al. (1990); Kim (1992)) show more promising results than statistical methods. Moody and Utans (1995) used neural network to predict bond ratings of firms that had a rating from S&P. Using 10 input variables to predict 16 S&P subratings they achieved to predict 36.2% of the ratings correctly. Using a 5-class and 3-class subratings their model predicted correct 63.8% and 85.2% respectively. Maher and Sen (1997) used neural networks and logistic regression to compare each method performance on predicting bond ratings for the period 1990-92. Their best model was a neural network model with 70% accuracy on a holdout sample. Kwon et al. (1997) compared an ordinal pairwise partitioning (OPP) to back propagation neural networks to the conventional neural networks modeling approach as well as MDA. They used 126 financial variables for Korean companies in the period 1991-1993. They obtained an accuracy of 71-73% via neural networks with OPP, 66-67% via conventional neural networks and 58-61% via MDA. Zan Huang et al. (2004) applied back propagation neural networks (BPNN) and SVMs to corporate credit rating prediction for the United States and Taiwan markets and found prediction accuracy around 80% via SVM. Wun et al. used SVM to classify Taiwan's issuer credit ratings and found that it performed better than the BPNN model with an accurate rate of 84.62%.

The aim of this paper is τo find the most important variables that contribute to long term ratings of USA banks as they are assigned by Fitch.

3. The Data

For our analysis we use a cross-section of 92 U.S. banks for which we could find freely available long-term ratings from Fitch. The ratings we attempt to forecast pertain to the year 2012. In doing so, we collect for each one of the 92 banks in our sample 46 individual variables and ratios for four years prior to our target rating (2008 to 2011) that come from their publicly reported financial statements. Thus, in order to forecast the credit rating of a bank in 2012 we include in our regressors set for each variable its previous four years values: e.g., the Net Operating Income of 2011 (NOI11) and three years prior to that NOI10, NOI09 and NOI08. In this way, we effectively use 184 variables for each bank to forecast bank ratings. All financial data come from the database of the FDIC (Federal Deposit Insurance Corporation). The variables are reported in Table 1.The dependent variable is ordinal and has six categories that are grouped in our case in three categories. They are assigned integer values from 0 to 2, such that lower values indicate a lower rating. The three rating categories (with assigned values in brackets) are: AA, A (2), BBB (1), BB, B, CCC (0).

Table 1: List of independent variables

Assetsand Liabilities	**Incomeand Expense**	**Performane Ratios**	**Condition Ratios**
Total employees (TOEM)	Total interest expense (TIE)	Yield on earning assets (YOEA)	Loss allowance to loans (LATL)
Total assets(TASSET)	Provision for loan and lease losses (PLLL)	Net interest margin (NIM)	Net loans and leases to deposits (NLLTD)
Cash and due from depository institutions (CASH)	Total noninterest income (TNI)	Net operating income to assets (NOIA)	Net loans and leases to core deposits (NLLCD)
Net loans & leases (NLL)	Service charges on deposit accounts (CHARGE)	Return on assets (ROA)	Equity capital to assets (EQCTA)
Loan loss allowance (LLA)	Trading account gains & fees (TRACC)	Return on equity (ROE)	Core capital (leverage) ratio (LEV)
Goodwill and other intangibles (GOI)	Additional noninterest income (ANI)	Assets per employee (ASSPE)	Tier 1 risk-based capital ratio (T1RBC)
Total deposits(TD)	Total noninterest expense (TNE)		Total risk-based capital ratio (TRBCR)
Interest-bearing deposits (IBD)	Salaries and employee benefits (SAL)		
Trading liabilities(TL)	Pre-tax net operating income (PTNOI)		
Subordinated debt (SD)	Securities gains (SEC)		
Total bank equity capital (TBEC)	Net income attributable to bank (NIA)		
Long-termassets(LTA)	Cash dividends (DIVDS)		
Average Assets (AA)	Net operating income (NOI)		
Volatile liabilities (VL)			
Loans and leases held for sale (LLHFS)			

Unused loan commitments (ULC)			
Tier 1 (core) risk-based capital (T1CRC)			
Tier 2 risk-based capital (T2RBC)			
Total unused commitments (TUC)			
Derivatives (DER)			

4. Methodology and empirical results

4.1 Feature Selection

In order to identify the variables that contribute the most to the assigned bank ratings of our sample we follow a thorough variable selection procedure. For the total of 184 regressors we first calculate the correlations, $r_{i,R}$, where i refers to each individual variable and R is the ratings dependent variable. Next, as a prefiltering step, we create six alternative groups of regressors as follows: In group 1 we include all variables with $|r_{i,R}| \geq 0.5$ along with all their lags. E.g., if NOI10 has a correlation greater than 0.5 then in group 1 we include all time instances of this variable: NOI11, NOI10, NOI09 and NOI08. This group includes 20 variables. In a similar manner, in group 2 we do the same with for $|r_{i,R}| \geq 0.4$.This group includes 44 variables. For group 3 all variables with $|r_{i,R}| \geq 0.4$ are included without their corresponding time instances: if only NOI10 has a correlation above 0.4 then only this variable is selected in group 3. In this group there are 15 variables. In group 4 we include the 5 variables with the highest positive correlation and the 5 variables with the highest negative correlation for a total of 10 variables. In group 5 we select the 30 variables with the highest correlation. Finally, in group 6 we have all 184 explanatory variables of our sample. Table 2 summarizes the number of variables in each group.

Table 2. Number of variables in each regressor group

Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
20 variables	44 variables	15 variables	10 variables	30 variables	184 variables

The next step is to identify from each one of the above groups the most significant variables in terms of the ratings. This is done in each group by:

a) A combinatorial exhaustive search methodology of all possible sets of 4 variables. We then select the one set that produces the highest R^2 in a regression on the ratings dependent variable.

b) Selecting in the same manner as above an augmented regressor set with 8 variables.

c) We select using a stepwise forward method of least squares the set of variables with p-value greater than 0.1.

Table 3 reports the corresponding R^2 for each of the above methods of selection and for all six groups of variables and Table 4 summarizes the variables selected from each method.

Table3: R^2 values for the optimum set of regressors for the six groups of variables.

Regressor Selection	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Combinatorial 4	0.49	0.54	0.54	0.53	0.53	0.59
Combintorial 8	0.53	0.61	0.57	0.49	0.60	0.70
Stepwise-forward	0.40	0.55	0.55	0.46	0.53	0.71
	(4)	(5)	(5)	(3)	(4)	(11)

* The numbers in the parentheses indicate the variables selected by the stepwise-forward criterion.

Table 4: Variables selected from each method.

STEPLS-Combinatorial 4

Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
NOIA10	NOI10	NOI10	L_TASSET11	L_TASSET11	L_TASSET11
PTNOI10	L_TASSET11	L_TASSET11	L_TASSET10	L_TASSET10	TIE11
NOIA8	IBD11	IBD11	NOIA10	NOIA10	SEC8
ROA08	AA10	AA10	TNE11	TNE11	PTNOI10

STEPLS- Combinatorial 8

Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
NIA10	L_TASSET11	L_TASSET11	NOI10	L_TASSET11	L_TASSET11
ROA10	IBD11	IBD11	AA10	L_TASSET10	L_TASSET10
PTNOI10	AA10	AA10	IBD11	TNE11	SEC8
ROA09	PTNOI10	L_TASSET10	NIA10	TNI10	LTA8
NOIA8	TNI11	NOIA10	PTNOI10	DIVDS11	YOEA11
ROA08	TNI9	L_TASSET9	ROA10	ROE09	NIM10

NIA11	ROE08	L_TASSET8	NOIA10	PTNOI9	NOIA10
ROA11	NOIA8	TNI11	PLLL10	PTNOI10	TBEC9

Stepwise Forward

Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
NOI10	NOI10	NOI10	NOI10	TNE11	NOI10
NIA10	L_TASSET11	L_TASSET11	IBD11	L_TASSET11	L_TASSET11
ROA10	IBD11	IBD11	AA10	L_TASSET10	TIE11
NOIA10	AA10	AA10		NOIA10	L_TASSET10
	L_TASSET10	L_TASSET10			SEC8
					GOI8
					ASSPE10
					LTA8
					TRL11
					SD11
					T2RBC8

4.2 Ordered Probit Models

The above selection procedure results in 18 different sets of regressors. These sets are next used in an ordered probit model and they are compared in terms of bank rating forecasting accuracy. In an ordered probit model the dependent variable y represents ordered observations or in other words a ranking variable. In our case this is the credit rating assigned by Fitch for each individual banking institution for the year 2012. This dependent variable is modeled by a latent variable y_i^* that has a linear relation with the vector of explanatory variable $\boldsymbol{x_i}$ as follows:

$$y^* = x_i^{'}\beta + \varepsilon_i$$

Where ε_i is independently and identically distributed. The actual y_i is fitted from y_i^* where:

$$y_i = \begin{cases} 0 & if\ y_i^* \leq \gamma_1 \\ 1 & if\ \gamma_1 < y_i^* \leq \gamma_2 \\ 2 & if\ \ \gamma_2 < y_i^* \end{cases}$$

And the probabilities of having each value of y are given by:

$$Prob(y_i = 0\ |x_i, \beta, \gamma) = F(\gamma_1 - x_i^{'}\beta)$$

$$Prob(y_i = 1\ |x_i, \beta, \gamma) = F\left(\gamma_2 - x_i^{'}\beta\right) - \ F\left(\gamma_1 - x_i^{'}\beta\right)$$

$$Prob(y_i = 2\,|x_i, \beta, \gamma) = F(\gamma_3 - x_i'\beta) - F(\gamma_2 - x_i'\beta)$$

F is the cumulative distribution function of ε. The marginal values γ are estimated with the β coefficients by maximizing the log-likelihood function:

$$Logl(\beta, \gamma) = \sum_{i=1}^{N}\sum_{j=0}^{N} \log\big(Prob(y_i = j|x_i, \beta, \gamma)\big) \cdot 1(y_i = j).$$

The last term corresponds to an indicator function which takes the value 1 if the condition is true and 0 if the condition is false.

4.3 Empirical Results

We use the ordered probit method to find the best forecasting model. The prediction evaluation of each model is shown in Table 5. Each column corresponds to each one of the six groups of the prefiltered regressors and each row presents the results for the corresponding selection criterion. According to these results, the best accuracy for all regressor selection criteria is achieved for group 6 for the stepwise forward method and the combinatorial selection of eight regressors.

Table 5. Rating forecasting accuracy

Regressor Selection	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Combinatorial 4	69.57%	70.65%	70.65%	68.48%	68.48%	**71.74%**
Combintorial 8	68.48%	75.00%	76.09%	71.74%	71.74%	**81.52%**
Stepwise -forward	65.22%	71.74%	71.74%	71.74%	68.48%	**81.52%**

According to these results the best rating forecasting accuracy is achieved in group 6 when the regressor selection criterion is the combinatorial method that selects in total eight explanatory variables. The accuracy is 81.52% and the variables used are: the logs of total assets for 2010 and 2011, securities gains (losses) over total interest income of 2008, long-term assets (5+ years) of 2008 over total assets, yield on earning assets of 2011, net interest margin of 2010, net operating income to assets of 2010 and total bank equity capital over total assets for 2009. Finally, the best forecasting accuracy of bank rankings are achieved when in the list of the eight explanatory variables, selected from group 6 and the combinatorial method, we also include the long-term assets over total assets for 2009. The forecasting accuracy reaches 83.70%.

Table 6: Comparison of predicted to real rating categories

	Rating category 0	Rating category 1	Rating category 2
predicted 0	14	1	0
predicted 1	3	21	5
predicted 2	0	6	42

In the rating category AA, A (2), 42 of the 47 observations were correctly classified. In the category BBB (1), BB, B and CCC (0), 21 of the 28 and 14 of the 17 observations were correctly classified.

5. Conclusion

We examine 184 publicly available financial variables of U.S. banks from 2008 to 2011 in order to fit a model that will forecast the next year's long term rating of Fitch. In doing so, we prefilter this extensive list of possible regressors and produce six groups of variables. From each one of these groups we select three sets of explanatory variables by applying the combinatorial method for four and eight selected variables and the stepwise forward method. This results in eighteen sets of explanatory variables that are used in an ordered probit framework to forecast Fitch's long term ratings for 2012. According to the results the optimum model that reaches an 83.70% forecasting accuracy is the one that includes nine financial variables. The results indicate that the assessment of credit ratings is largely relying on historical data. Thus, it is not surprising that bank downgrading was announced rather late and after their financial problems were already visible to all investors and policy makers. Also it is most easy to forecast banks with high rating rather than banks with a low rating. The most important variables contributing to long term ratings of banks are size, performance ratios and asset quality.

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