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Discussion on IRB verification method -Application of ROC method in risk management

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ABSTRACT

A complete credit risk management system includes not only methods of default probability forecasting but also rigorous verification process which is an important guarantee on banking effective operation. The traditional testing method based on the '50%' critical point is not a reliable option. Criteria of ROC curve method is set to dynamic. The curve depicts the combination of false-alarm rate and the hit rates. Its result presented directly to the objective, and to avoid the conflicting between indicators. Through empirical analysis based on real data, ROC dynamic test is considered to be a more scientific test method.

KEYWORDS

ROC;
IRB;
Default probability;
Model verification

INTRODUCTION

The file of International Convergence of Capital Measurement and Capital Standards: A Revised Framework, published in Jun 2004, requires that 'Banks must have a sound system in order to validate the accuracy and consistency of rating systems, processes, and the estimation of all relevant risk components.'[1] A rigorous verification process is as importment as a scientific probility of default prediction method. However, existing research is still heavily focused on the prediction model itself. The study about verification methods is still relatively weak. Currently verification method used in most of the literature is the traditional '50%' critical point inspection method, such as the views mentioned by Zhou yabao and Liang hangman (2013)[2], Lan runrong and Chen xijun (2013)[3],Yang pengbo (2009)[4], Liu Xian-wei and Tao Ping (2011)[5]. In fact, 50% is not a probability of default that can be universally accepted. In many cases, even if the probability of default is 20%, it is still considered as an unaccepTABLE application. Therefore this traditional approach is not very reasonable.

In this paper writer verified the ability of prediction of two default prediction models respectively based on real data as well as using ROC curve method. Comparing two results, researchers proved that ROC curve method is a all-round way about model verification. This method has a better distinguish ability to seclect model. ROC curve allows decision-maker to be more flexible in choosing default criteria according to their own preferences between type I error and type II error. In other words, ROC curve method has advantage at both theoretical and practical ways.

THE RECEIVER OPERATING CHARACTER-

Four kinds of model forcasting results would be possible. They are summarized in TABLE 1

$Hit(C)$ means that the number of defaulters has been predicted correctly according to the benchmark C, and N_D is the total number of defaulters in the sample. $HR(C)=\frac{hit(C)}{N_D}$ means that the hit rate is the fraction of defaulters that was classified correctly by a given C. This indicator is a measurement of ability to estimate probility of default for our models.

$False(C)$ is the number of non-defaulters that were classified incorrectly as defaulters by using the 'C'. The total number of non-defaulters in the sample is denoted by N_{ND}. False alarm rate, $FAR(C)=\frac{false(C)}{N_{ND}}$, is the fraction of non-defaulters which were classified incorrectly by benchmark 'C'. This indicator describes the degree of false default-forcasting.

In a conventional verification method, 'C'is usually set to '50%'. However the standard of ROC curve is not tied to a particular critical point. In this way, 'C' is set to a dynamic benchmark by which probility value ranges from zero to one hundred percent. So judgement got by ROC curve parallels with the value of 'C'.

For each observation, model predicts the probability of default corresponding. These probabilities are sequentially determined as a cut-off point 'C'. We can calculate $HR(C)$ and $FAR(C)$ corresponds to each 'C'. We describe each pair of and on coordinate system and connect each point with a line. In fact, ROC curve reflects the pairing between $HR(C)$ and $FAR(C)$ under the different benchmark 'C'.

'A' denote the area enclosed by ROC curve. It can be calculated as $A=\int_0^1 HR(FAR)\,d(FAR)$. In order to compare forcasting ability amongst different models, we can transforme the size of 'A' to a statistic AUC. The value of AUC is between '0' and '1'. Comparing values of AUC according to each model is a convenient way to compare forcasting power among different models.

TABLE 1

situation probability	default	fulfill
bigger than C	Correct forcasting (hit)	False forcasting (false)
small than C	False forcasting (miss)	Correct forcastign (correct)

EMPIRICAL RESEARCH BASED ON ROC

To further illustrate the verification power of the new method, we built two different binary respond panel data models for estimating and forcasting based on real data. We applied two different ways separately, the conventional '50%'method and ROC curve method, to these two models for the sake of distinguishing different forcasting power. Comparing the results, we found that their performances on selecting the model vary due to different performancing on forcasting.

Data set

The necessary data for the statistical analysis was supplied by ICBC Fujian branch. The original data set consisted of about 78 medium-sized firm observations spanning the time period 2007 to 2011. Nearly three years of financial reports must be provided when clients apply for the loan. Credit rating in the past three years about loan applications would be evaluated according to historical data. So we actually get the data from 2005 to 2011. Enterprises which been awarded BBB-level and above are treated as default. However, due to obvious mistakes in the balance sheets and gain & loss accounts, the data set had to be reduced to 525 observations. All sample data is divided into two parts. One ranged from 2005 to 2009 was used for estimating which called the estimation sample. Another ranged from 2010 to 2011 was used for verification which called the test sample.

Methodology

According to the characteristics of the seleted financial ratio during the interal credit rating, all financial indexes could be classified into four categories : olvency status, financial benefit, development capacity, Asset operational condition.

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TABLE 2

	no- random effects			random effects		
	Odds	Std Dev	P>z	Odds	Std Dev	P>z
Debt Asset ratio	1.892	0.571	0.052	4.18	1.432	0.012
Current ratio	0.185	0.073	0.002	0.032	0.004	0.000
Rate of Return on Common Stockholders' Equity	0.582	0.127	0.121	0.132	0.031	0.000
Current Assets Turnover	0.421	0.182	0.003	0.019	0.002	0.001
Rate of Capital Accumulation	0.971	0.143	0.084	0.254	0.027	0.002
Quick ratio	0.296	0.174	0.004	1.344	1.003	0.054
Currency Ratio of main business	0.402	0.193	0.000	0.093	0.008	0.000

TABLE 3

		Rate of correct	Type Ⅰ error	type Ⅱ error
no- random effects	estimation sample	74.418	0.737	0.230
	test sample	64.116	0.375	0.358
	total	71.619	0.630	0.265
random effects	estimation sample	93.158	0.631	0.039
	test sample	78.621	0.875	0.175
	total	93.976	0.704	0.076

Learned from Zhengda Chuan (2010)[6], we were established binary response panel data models which contain random effects and no- random effects in order to compare the function of different test methods. Value of the dependent variable Y is '0' and '1'which '0' indicates the performance business meanwhile '1' indicates the default business. Backward selection methods as implemented in GLLAMM[7] were applied to check whether the model could be reduced to a lower number of input variables. All remaining input variables are Debt Asset ratio, Rate of Capital Accumulation, Rate of Return on Common Stockholders' Equity, Current Assets Turnover, Currency Ratio of main business, Current ratio, Quick ratio. We exhibit the estimating values of parameters in TABLE 2.

Verified result comparing

We applied two different ways separately, the conventional '50%'method and ROC curve method, to two forcasting models for verification. comparing and analysis two verified results, this paper try to exhibit the advantage of new method on verification and model choosing.

TABLE 3 shows the analysis result about forcasting by the conventional method.

Meanwhile we applied ROC dynamic verification method to forcasting results. Three ROC curves got by calculating are showed in Figure 1.

TABLE 4 exhibits verification AUC results in different sample range which got by ROC method.

Analysis on results got by two methods

According to the empirical results, the advantages and disadvandages of two models apperead contradictory places on different indicators under traditional test methods. TABLE 4 shows that, according the correct

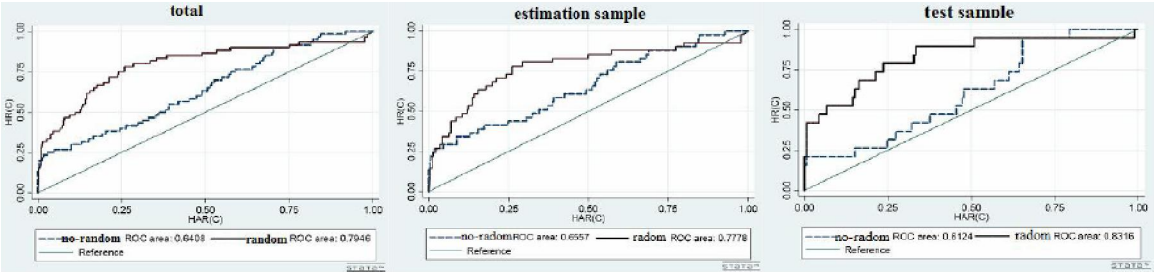

Figure 1

rate and type II error, models with random effects are superior in every sample interval than no-random effects model. At the same time, according type a & error, the conflict result is presented between the two models. The results show that the random effects model, with type I error rate 0.631, is superior to no-random effects model which with type II error rate 0.737 on the estimate sample interval. on the test sample interval and all-range sample interval, the type I error of the model with random effects are 0.875 and 0.704 separately. This indicates that the model with random effect is not as good as no-random effect model on type I error indicator.

The biggest distinction between ROC dynamic method and the '50%' method is that ROC has advantage at comprehensiveness. Traditional methods chooses '50%' as a critic point to judge whether defaults or not. However ROC method uses every default probility that model calculated to descript ROC curve. Obviously ROC method is more suitable for judging advantage of model. As showed in Figure 2, the area of ROC showed by the random effect model is biger than which showed by no-random effect model. TABLE 5 also confirms the same conclusion clearly. The areas of ROC curves enclosed of the model with random effect are 0.7778, 0.8316 and 0.7946 in three different sample ranges. They are all bigger than the areas of ROC curves enclosed of no-random effect model in same sample ranges.

TABLE 4

estimation sample		test sample		total	
No-random	random	No-random	random	No-random	random
0.6557	0.7778	0.6124	0.8316	0.6408	0.7946

CONCLUSION

The traditional '50%' method uses correct rate, type I error and type II error to Verificate the forcasting power of credit rating model. However as mentioned above, this way has a deficiency and shortcoming. The gap between '49.999%' and '50.001%' is Almost negligible, but represent the situation of fulfill and default respectively. When there are two or several defaults prediction models to be identified and selected, '50%' inspection standard does not have effective recognition capability. In another way, this three indicator also showed the one-sidedness and mechanical properties when '50%' criterion was adopted. Furthermore three indicators may appear conflicting results that would be an impact on making the right judgments of model selection.

ROC dynamic methods discussed in this article is just to overcome the shortcomings of traditional methods. It verifies predictive ability of the model overall. ROC area contains all probability of default. It is an important for models choicing. Thus ROC method avoids conflicting situation between the indicators.

In a coordinate system ordinate variable is hit rate, and the horizontal axis represents the false alarm rate. So we could get the type I error and type a & error from different criterion. That means judgement about type I error and type II error is no longer a constant mechanical. Considering two indicators dynamically is making selection of model more comprehensive and reasonable. Importantly we can choose loose or strict criteria according to our own preferences.

Another important advantage of ROC method is that we can pick quickly a more accurate model up by obveration of gap between different ROC curves showed in the same coordinate system. Meanwhile we can choose a criterion for judging conveniently and quickly.

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