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Research of time series structural model in predicting Chinese listed companies financing problem

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Abstract. In recent years, improving the predictive ability of corporate defaults has become an important problem. Regarding characteristics of listed companies in this paper, we put forward time series structural model, and based on that we sampled 100 companies according to industry types, built the prediction model for the return sequences. Finally, we compared the time series structural model based on the predictive default distance of China's listed companies, and we can see the model has acceptable accuracy in practice.

Key words. Time series structural model, financing problem prediction, chinese listed companies, credit risk.

1. Introduction

Academic researches of the forecasting enterprise default are based on two major milestone results: the structural model on behalf of the Merton model and KMV model, and credit scoring.

The first researcher who contributed deep research on default prediction for large listed companies can be traced back to R. C. Merton[1]. He constructed the structure equations to price debt through appropriately simplifying the corporate capital

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structure and dynamic change of corporate values of companies; he matched the price of corporate debt and corporate equity with options. Then, the KMV[2] company developed an empirical estimator called "Probability of Default" on the basis of the Merton model, which is known as the estimation of expected default frequency (EDF), and can be seen as a consistent estimator for Probability of Default (PD), instead of using the cumulative normal distribution in the Merton model to calculate PD.

At present, the research of structural models for default prediction mainly focuses on the actual assessment and improvement in estimators. L. Lin, T. Lou, N. Zhan[3] used a small sample with 22 enterprises to adjust the parameters of the KMV model, which makes the model adapt to the situation better in China. Meanwhile, W. C. Lee[4] used a genetic algorithm to improve the best default point of the KMV model. A. C?mara ?? I. Popova ?? B. Simkins [5] applied several structural models to evaluate the default risk in the financial enterprises after the subprime crisis, and they found that the KMV model had better accuracy in default prediction. X. Chen, X. Wang, D.D. Wu[6] experimented with a large sample of 80 enterprises between 2004 and 2006 to build the KMV model and, in his research, it can be found that structural models cannot give early warning of default risk to small and medium-sized enterprises in China. Though structural models are seen as the most effective methods in the default prediction of large companies, they cannot avoid calculation of yield volatility which is also the key of these models.

Now, the majority of studies focus on the calculation of yield volatility in time series modeling, which relies on linearity and symmetry assumptions. However, several authors have discussed in detail the inadequacy of linear models in capturing asymmetries. Importantly, J.D. Hamilton[7] has settled that non-linear specifications should be seen as better candidate models than traditional linear approaches in capturing significantly stronger effects of oil shocks. J.S. Chiou , Y.H. Lee.[8] argued that most of the time series models experience structural changes that, when applied to real data, determine the break locations. At the same time, there is a general agreement in the literature that any inferences without consideration of regime switching phenomenon may as well lead to unreliable results for many financial time series, which can be found in the work of R. Yalamova[9]. Regimes switching models occur as an alternative to standard GARCH models in allowing dynamic variables' behavior to depend on the state that takes place at any given point in time.

In the research of T. Jagric[10][11], GARCH models work well to capture leptokurtosis and the volatility clustering generally observed in the financial time series but they demonstrate some inaccuracies in terms of changes of time scales.

In conclusion, it can be seen that the structural model puts on a good performance in the default prediction, but it has a number of parameters to estimate which directly influence the accuracy of the models. Time series analysis technology has been widely applied in the predicting field. The structure of the rest of this paper is as follows: The next section puts forward the prior research of the structural model. Section 3 describes our methods for default prediction in detail. Section 4 is about experiment studies; in this part, we will present several robust check results of structural models in Chinese actual practice. Then, the final section discusses the results with additional remarks.

2. Preliminaries

The structural model requires a mark-to-market value for listed companies' credit assessment, which describes the process of default as the explicit result of the deterioration with the companies' value. In this way, it can be simplified that the company owners' equity can be seen as a call option, and the liability as a put option.

2.1. Assumptions

The structural equation model usually needs to meet the following assumptions:

1. There are only two ways equity (with the value$S$) and debt (with the principal D and maturity$T$) for the company (with the value V) to finance.

2. At any$t \leq T$, the value of a company is equal to the sum of the debt value and equity value, which can be described as$V_t = S_t + D_t$.

3. The value of the company follows the geometric Brownian motion or $dV = uVdt + \sigma_u VdZ$.

4. Before maturity, bond holders cannot force companies to bankruptcy. Yet, at the maturity T, if the value of the company can cover the debt principal, it means that the company has the payment ability; otherwise, the value of the company is not enough to pay back the principal, which is$V < D$, and it incurs a default.

5. When a default occurs, bond holders have more priority than shareholders. So they can get the full value $V$of the company; otherwise, bond holders only earn their principals$D$.

According to these assumptions, the share holders' profit and loss can be thought of as a call option of the company's value where the strike price is D, and the bond holders' profits and losses can be thought of as a put option that is the risk-free bond Dminus the company's value. Based on this, one can predict the default through pricing the value of equity and debt.

2.2. Models

According to the Black and Scholes option price, we can get the following relationship:

$$S = VN(d_1) - De^{-rT}N(d_2) \tag{1}$$

$d_1 = \frac{\ln(V/D)+(r+\sigma_V^2/2)\times T}{\sigma_V\sqrt{T}}$,$d_2 = d_1 - \sigma_V\sqrt{T}$,$N(*)$is the cumulative probability distribution function of standard normal distribution.

According to the sensitivity analysis$\sigma_s = \frac{V}{S}(\frac{\partial V}{\partial S})\sigma_V$, there is$\frac{\partial V}{\partial S} = N(d_1)$, which then leads to:

$$\sigma_s = \frac{V}{S}N(d_1)\sigma_V \tag{2}$$

Because the value $V$of the company and its volatility cannot be evaluated easily, we can calculate the value S and the volatility σ_s of equity from capital market, leading us to V and $\sigma_v$through simultaneous equations (??)1) and (??)2) the two equations. Therefore, it can be seen that S and σ_s are the key indicators for the model's accuracy. Furthermore, with the effect on the financial market, Scan be obtained directly, so the calculation of σ_s becomes the core for the structural model.

2.3. Kernel Parameters

In recent research, Garch (1,1) is always used to estimate σ_s, the details of which can be found in the references [14]. We give the model below:

$$r_t = \sqrt{h_t e_t}$$

$$\begin{aligned} h_t &= \alpha_0 + \alpha_1 r_{t-1}^2 + \beta_1 h_{t-1} \\ e_t &\sim iidN(0,1) \end{aligned} \tag{3}$$

3. Empirical analyses

3.1. Data and Parameters

In this paper, we use the CSMAR database (http://www.gtarsc.com/) as a data source, and select listed companies in China which appeared on the market before 2009 and have not been off since 2009. There are 1697 listed companies (including 184 ST companies), all of which belong to 13 industry groups.

This article mainly aims at the financing problem prediction of the listed companies because financial listed companies have more liquidity with the assets and liabilities than the ordinary corporate entities, whose credit risk may cause shocks in the financial system. There are many regulatory factors to restrict, so the financing problem cannot be predicted only through the market information. Based on these, we do not take these financial listed companies in our experiment, but we sampled the rest of the listed companies randomly according to industry categories, finally enabling us to select 100 sample enterprises (including 50 ST enterprises and 50 enterprises that were not ST).

We use the following way to estimate several key parameters in the model:

First: period. The structural model considers only the default prediction problem which will be due in the next year. This section uses the listed companies' market data in 2009 to predict the financing problem in 2010, and in Section 4 we use the market data in 2010 to validate the model's results.

Second: risk-free rate. In this section, we use the one-year deposit rate of 2.25% in 2009 as the risk-free rate.

Then: equity value. There are two kinds of shocks of a listed company in China for long time-tradable and non-tradable shares. There mainly are two ways to calculate the equity value: (??)1) equity value = tradable shares×market price + non-tradable shares×conversion ratio; (??)2)equity value = tradable shares×market price + non-tradable shares×net assets per share. This paper adopts the second calculation method.

Finally: default point. This paper follows the KMV model to determine the default point. Long-term debt is the debt with maturity of more than one year and is written as LT for short; short-term is the debt which matures within a year, written as ST for short. Then, the default point can be determined in accordance with the following standards.
$$\begin{array}{ll} DP = ST + 0.5 \times LT & LT/ST < 1.5 \\ DP = ST + (0.7 - 0.3 \times ST/LT) \times LT & LT/ST \geq 1.5 \end{array}$$

3.2. GARCH Structural Model

According to the closed price of a stock, we can get the yield sequences by $r_t = \log(\frac{p_t}{p_{t-1}})$ in 2009, with $p_t$on behalf of the day's closing price and p_{t-1}on behalf of the precious's closing price. Here, take the stock with code 000713 as an example; its daily closing yield sequence is shown in Figure 1 below:

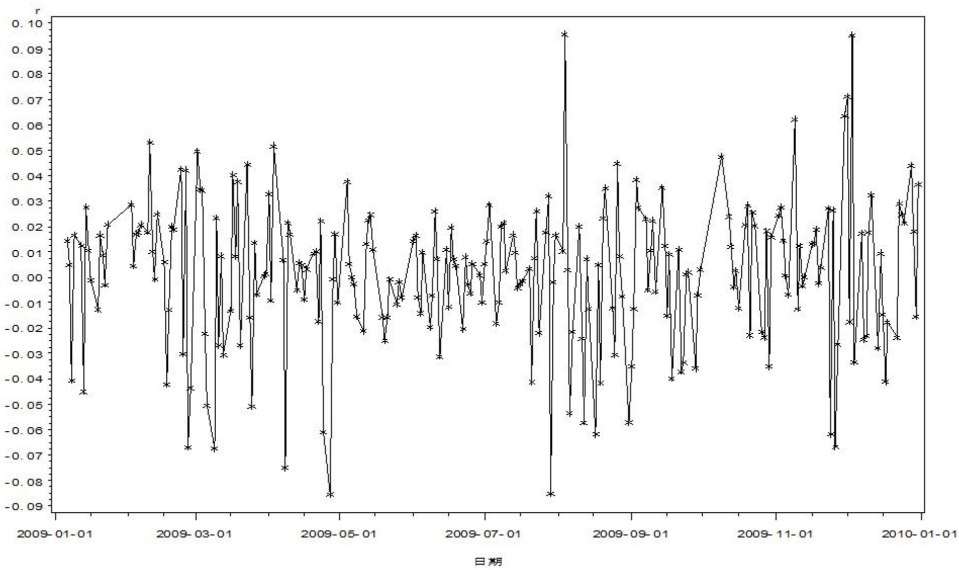

Fig. 1. Return series figure

Take the autocorrelation test with $r_t$andr_t^2; the results are shown in Table 1 and Table 2. From Table 1 we can see that there is no autocorrelation ofr_t, and from Table 2 we can see there exists an auto-correlation ofr_t^2.

Table 1.Autocorrelation of r_t

Name of Variable=r														
Mean of Working Series 0.001461														
Standard Deviation 0.02847														
Number of Observations 241														
Autocorrelations														
Lag	Covariacnce	Correlation	1	9	8	7	6	5	4	3	2	1	0	1	2
0	0.0008106	1.00000	|										|	*	*
1	(0.0000051)	-0.00634	|										|		
2	(0.0000480)	-0.05918	|									*	|		
3	0.0000240	0.02960	|										|	*	
4	(0.0001320)	-0.16281	|							*	*	*	|		
5	(0.0000823)	-0.10155	|								*	*	|		
6	0.0000981	0.12107	|										|	*	*
7	(0.0000463)	-0.05711	|									*	|		
8	0.0000080	0.00992	|										|		
9	0.0000247	0.03047	|										|	*	
10	(0.0000286)	-0.03533	|									*	|		

Table 2. Autocorrelation of r_t

Name of Variable=r2															
Mean of Working Series 0.000813															
Standard Deviation 0.01394															
Number of Observations 241															
Autocorrelations															
Lag	Covariacnce	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2
0	0.0000019	1.00000	|										|	*	*
1	0.0000001	0.04228	|										|	*	
2	0.0000003	0.17692	|										|	*	*
3	0.0000002	0.09358	|										|	*	*
4	0.0000003	0.16606	|										|	*	*
5	0.0000008	0.42210	|										|	*	
6	0.0000002	0.08719	|										|	*	*
7	0.0000001	0.05674	|										|	*	
8	(0.0000002)	- 0.09734	|								*	*	|		
9	0.0000001	0.02649	|										|	*	
10	0.0000000	0.02469	|										|		

Table 3. LM Tests of r_t

Q and LM Tests for ARCH Disturbances				
Order	Q	P>Q	LM	P>LM
1	0.5454	0.4602	0.5634	0.4529
2	7.4276	0.0244	7.3402	0.0255
3	9.5662	0.0226	8.8753	0.0310
4	16.0044	0.0030	12.9619	0.0115
5	16.3866	0.0058	12.9691	0.0237
6	18.5835	0.0049	13.3627	0.0376
7	19.5461	0.0066	13.5569	0.0596
8	22.0221	0.0049	18.8789	0.0155
9	22.2924	0.0080	18.9054	0.0260
10	22.5574	0.0125	19.4069	0.0354
11	22.6075	0.0201	19.4680	0.0532
12	22.6440	0.0309	19.4951	0.0773

From Table 3, we can find that there exists a high-order ARCH effect, so it can be fit with the GARCH (1,1) model. The result of GARCH (1,1) is shown in Table 4.

Table 4. Statistic of GARCH(1,1)

GRACH Estimates				
SSE	0.19538		Obs	241.00000
MSE	0.00081		Uncond Var	0.00088
Log Likelihood	523.90461		Total R-Square	.
SBC	(1025.87000)		AIC	-1039.80920
Normality Test	8.89240		P>Chisq	0.01170

From table 4, the GARCH (1, 1) model gets through the test and has a small AIC. So it can be said that GARCH (1, 1) has a solid fitting effect on the volatility of sequencer_t.

By continuing to take the LM test with the sequence residual error, it can be found that the residual error has no ARCH effect. Thereby, we can get the yield sequence volatility model as follows: $\sigma_t^2 = 0.0000894 + 0.1670\varepsilon_{t-1}^2 + 0.7313\sigma_{t-1}^2$.

Based on the aggregation formula of the GARCH model, the predicted earnings volatility model can be obtained as follows:$\sigma_{t+h,t}^2 = 0.0000894 \times \frac{1-(0.167+0.7313)^h}{1-(0.167+0.7313)} + (0.167 + 0.7313)^h \sigma_t^2$. So the total volatility is equal to $\sigma^2 = \sum_{h=1}^{252} \sigma_{t+h,t}^2$in future years, which is obtained by cumulating the everyday's volatility.

4. Robust Check

According to the modeling process in the third part, we determine the parameters using Matlab. Based on simultaneous equations (??)1) (??)2), we can solve the asset $V$and its volatilityσ_V.

Although calculations of default probability in structural models are very different, now researchers generally agree that the calculation method of KMV is more suitable. The KMV model uses the default distance which can be seen in equation (??)6) to judge for the possibility of default.

$$DD = \frac{V - DP}{V \times \sigma_v} \tag{4}$$

On the one side, there is great difficulty in collecting the information of a company's actual default; on the other side, it is a regulation that if there are any financial struggles or abnormal situations which can cause investors difficulty in judging a listed company's prospects and may cause interests to be impaired, its stock must be granted special treatment with a "ST" mark in China. Therefore, in these robust checks, we use "ST" to represent the breach of companies. In order to validate the model, we do the paired T tests. The results are shown in Table 5.

Table 5. Pair T-test of time series model

Variable	St_type	N	Lower CL Mean	Mean	Upper CL Mean	Lower CL Std Dev	Std Dev	Upper CL Std Dev	Std Err
dd_ga	0	50	2.4404	2.5571	2.6736	0.3428	0.4103	0.5113	0.0580
dd_ga	1	50	0.3057	0.4717	1.6378	0.4881	0.5843	0.7281	0.0826
dd_ga	$diff(1-2)$		2.1347	2.0863	1.2856	0.4430	0.5048	0.5869	0.1010

As can be seen from the tables above, at the 95% confidence interval, the model can identify ST enterprises from good enterprises, so it can be said that the model has effective judgment in default prediction with the listed companies in China. Thus, it can be inferred that the structural model is effective in the risk assessment with Chinese listed companies.

5. Conclusion

Credit risk management is one of the most important problems commercial banks face. Normally, the optimal way of credit risk management is to forecast the default accurately before the loan. In recent years, the structural models dominate the studies and are widely used in practice to forecast the default risk of the listed companies because this model can estimate the company's market value by mark-to-market.

This paper deeply discusses the methods for estimating parameters of the structural equation model, putting forward the time series structure model. Through time series analysis, we can capture the core parameters for prediction sequences reconstruction, and that gave a lot of improvement in the default prediction, which can be verified with the China's listed company.

Still, just as with other structural models, the time series structural model still cannot wholly avoid the estimation of the value of equity, so it has a strong dependence on market environment, which limits its applications with the small and medium-sized enterprises. lected such that the total cost should be minimum and within specified limits.

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