Default Risk Indicator and Transition Matrix of Chinese Listed Companies

by

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An honors thesis submitted in partial fulfillment

of the requirements for the degree of

Bachelor of Science

Business Honors Program

NYU Shanghai

May 2017

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Abstract

Since 2008 financial crisis, default risk starts to catch investors' attention. Companies such as Lehman Brothers are thought to be safe but went bankruptcy overnight. The opinion that a firm can last forever starts to fade. The power of default affects not solely in US but globally. Chinese market has never experienced a debt default before 2014, but the Shanghai Chaori case broke the no-default history of Chinese market. The fact that Chinese market, which is highly regulated, starts to be influenced by default risk is noteworthy. This paper wants to dig out a way to measure the default risk in China and applies it to predict the future trend.

We start with the famous Altman Z-Score to see how well it captures the default risk in China. As Chinese companies seldom go bankruptcy, we use the Special Treatment as an indicator of financial distress. The results turn out that Z-Score only have a 70% of accuracy. To improve Z-Score, we use the Logistic Regression with a training sample consists of forty-nine distress companies and forty-nine healthy companies and obtain the L_{China} score. It perfectly classifies the two groups in the training sample and when comes to empirical study, it has an 87% of accuracy for 1122 companies over 12 years.

To analyze the L_{China} we introduce the Transition Matrix to capture the change of default risk. The default risk is decreasing in Chinese market but increasing in the global market. However, it is still a long way for Chinese market to become mature.

To conclude, L_{China} has done a better job to capture the default risk of Chinese market than Z-Score did. Generally, Chinese market has a higher volatility than the global market in terms of the financial stability of companies.

Acknowledgments

I would like to thank my thesis advisor Professor Jiawei Zhang for his useful advices and supervision. You guide me patiently through the thesis revising, data collection and analyzing. Without your help, it is impossible for me to finish this paper.

I would also like to thank the faculty advisor, Professor Marti G. Subrahmanyam, for creating this wonderful opportunity for us. This honor program is informative and I have learned a lot. Thank you for making this happen and flying back and forth to track our process.

Special thanks to Professor Edward I. Altman for giving me advice on how to approach this thesis and offering me great references and Professor Yakun Wang for meeting me in person and pointing out some potential flaws of my logic.

I would also like to thank all the professors who lecture us. Thank you for your time and carefully organized course. Your research experiences are valuable and point us a starting point.

Thank you my fellow students. It is a great year and all your thesis are amazing. I feel so lucky to be a part of this program.

Lastly, I would like to thank Lin Yu for staying up countless nights with me and helping me organizing thoughts. You are the best.

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Introduction

After 2008 financial crisis, people realize the devastating power of credit risk. One example is the Lehman Brothers, at the mid-September of 2008, the three biggest rating agency, Moody's, Standard & Poor's, and Fitch Ratings all maintained at least an A rating on AIG and Lehman Brothers. However, on September 15th Lehman Brothers declared bankruptcy. This inconsistency between ratings and real situation not only arouse the question of the rating standard, but also calls for a way to better estimate the default risk of a firm.

In the Lehman Brothers case, it is clear that the bankruptcy did not occur out of nowhere. The issuance of mortgage backed securities and collateralized debt obligation is the major reason for Lehman Brothers to bankrupt. They are unable to repay the obligation which leads to credit default. In other words, they do not have enough cash to repay these obligations. Therefore, to analyze default risk, financial statement is a great starting point as the balance sheet provides a screenshot for the firm's financial situation and the income statement as well as cash flow statement provides the insight of capital flow.

Default risk is also country sensitive, as the regulation will to some extend influence the default risk. For example, in China, a firm seldom goes bankruptcy but will be listed as Special Treatment instead. For some state-owned firms, government will even help them out of the financial distress.

Up to now, most of the researches are done by applying US market's data. Due to the urgent needs of a default risk measurement and the country sensitivity, the results obtained from the previous research may not be the best indicator for Chinese market. This paper mainly focuses on the Chinese companies that are listed on either Shanghai Stock Exchange or Shenzhen Stock Exchange. At first this paper evaluates how well does the most popular default risk indicator, Altman Z-Score, reflect the default risk of Chinese listed companies. Secondly, this paper will use the similar method Edward I. Altman applied to compute a default risk indicator based on financial data of Chinese listed companies. These two indicators will be evaluated based on how well they capture the default risk of Chinese listed companies. Lastly, we will present a default transition matrix based on the two indicators and analyze the transfer of default risk annually to evaluate whether this transition matrix can predict the default risk beforehand.

Literature Review

Although the default risk did not catch investors' attention until the 2008 financial crisis, many studies have been trying to capture and identify default risk as early as in 1900s. One of the forerunners, R.F. Smith, noticed the difference of financial ratios between continuing and discontinuing firms (Smith, 1935). This study provides the insight that default risk can be quantified by using financial ratios. William Beaver took advantage of this idea and did empirical studies to test the usefulness of ratio analysis in identifying business failure (Beaver, 1966). The result demonstrated the mean of financial ratios between successful and failure companies varied a lot and using financial ratio to distinct discontinuing companies from continuing companies is viable.

Inspired by Beaver's idea, Edward I. Altman conducted the well-known research in 1968, he quantified the default risk by giving weight to financial ratios and computed the world famous Altman Z-Score (Altman, 1968). This score includes leverage, profitability, market capitalization and so on to summarize the financial situation of companies. Although the method was straightforward, Z-Score actually predicted the default risk before some companies went bankruptcy during 2008 financial crisis. This score is still regarded as the golden number when identifying default risk and is used worldwide.

Detailed look at Altman Z-Score

Altman Z-Score uses data on company financial statements to judge the financial health of the company and estimate the bankruptcy risk in two years. He defines default companies as either recognized as receivership or fit the provisions of the US National Bankruptcy Act (NBA). The data samples he chose are one group of thirty-three bankruptcy companies which are filed a bankruptcy petition under NBA and another group of thirty-three healthy companies within a certain asset size range randomly (Altman 1968). Afterwards, a discriminant analysis was applied and below is the formula for Z-Score

$$\textbf{Z-Score} = \mathbf{1.2A + 1.4B + 3.3C + 0.6D + 1.0E}$$

Where:

A = working capital / total assets

B = retained earnings / total assets

C = earnings before interest and tax / total assets

D = market value of equity / total liabilities

E = sales / total assets

Generally, a score below 1.8 means a high possibility of bankruptcy while a score over 3 can be considered as healthy. The result is convincing with a 6% Type I error and a 3% Type II error for the training set. Besides the statistical significance, Altman revisited Z-Score in 2000 by doing empirical analysis between 1976 and 1999 (Altman, 2000). He stated Z-Score has an accuracy of 80%-90% which strongly demonstrated that financial ratio can explain the default risk.

Default Risk Research of Chinese market

Some researches regarding the financial distress in China has also been done. Altman and Heine developed a Z_{China}, a four-variable model similar to Z-Score in 2007 right after the Bankruptcy Law came out on June 1st 2007 (Altman and Heine, 2007). This model has an accuracy of about 80%.

Besides the discriminant analysis used in Z-Score, scholars also test the usefulness of other statistical methods. Chen tested various classification methods and found out Logit and Neural Network models are the best choices when identifying the default risk in China (Chen, 2006). His research also confirms that financial ratios such as Earnings Before Interest and Tax to Total Assets (EBITTA), Total Debt to Total Assets (TDTA), Price to Book (PB), are significant indicators of default risk in China.

Applicability of Altman Z-Score for Chinese Listed Companies

Altman's model is entirely based on the sample of US companies. However, in the Chinese financial database, Wind, Altman Z-Score is used to predict the default risk of Chinese listed companies. Does Z-Score have the universality to predict bankruptcy regardless of the country? To test the applicability of Altman Z-Score for Chinese Listed Companies, we collected Z-Score of all Chinese listed companies which were listed before 2002[1].

Data and Results

There are total 1122 listed companies listed before 2002[2] and we collect the Z-Score from 2002 to 2015. As Chinese companies seldom bankrupt or delist, we regard Special Treatment (ST)[3] as a sign of default. Companies are forced to declare ST when the financial situation went South.

[1] We chose Year 2002 because Wind database has a comprehensive financial data collection after 2002.
[2] Except 4 banks as Z-Score does not apply to banks.
[3] A Chinese regulation towards companies with a financial disorder. A *ST refers to a more severe risk of delisting.

Although delist does happen several times, restructuring is a more common situation in China. Therefore, regarding ST companies as default is not 100% precise but this treatment does indicate some financial distress inside the company. The potential problem of using ST as a sign of default will be discussed in the conclusion section. We collect all of the data in Wind, but it only shows the current ticker of the company. To identify the actual ST list situation, we found the ST implementation and cancellation file to adjust these tickers into the correct ones for each year.

For Z-Score, we use 1.81 as the threshold: companies with a score lower than or equal to 1.81 are predicted as ST while companies with a score higher than 1.81 are predicted as non-ST. Therefore, we can compute the Type I and Type II[4] error of Z-Score's application on Chinese Listed Companies:

	Number Correct	**Per cent Correct**	**Per cent Error**	**Total**
Type I	770.7[5]	69.6%	30.4%	1018
Type II	60.3	58.0%	42.0%	104
Total	831.0	68.5%	31.5%	1122

Compared to the empirical study done by Altman, both Type I and Type II error are substantially higher when Z-Score applied to the Chinese market. To see whether Z-Score has the predictability, we use the Z-Score in year t-1 to predict the default on year t. The chart below shows the Type I and Type II error of 1 year leading prediction:

[4] Type I error are companies are actually non-default but the prediction shows default; Type II error are companies are actually default but the prediction shows non-default.
[5] Number correct takes the average of the number of correct predictions over 14 years.

	Number Correct	Per cent Correct	Per cent Error	Total
Type I	716.0[6]	70.3%	29.7%	1018
Type II	59.46	57.2%	42.8%	104
Total	775.46	69.1%	30.9%	1122

The result does not improve much with a slightly better Type I error but a slightly worse Type II error. Therefore, Z-Score actually fails to distinct unhealthy companies in Chinese market as it works in US market.

Default Risk Indicator for Chinese Listed Companies

As the result above shows, if we keep applying Altman Z-Score for Chinese listed companies, on the average, our prediction is wrong for around 30% of the time. The high error rate calls for the need of creating a Chinese market specific default risk indicator. China is an emerging market with strict government regulations. The average company size in China is relatively smaller and the group of state-owned enterprise is definitely a Chinese characteristic. In this paper, we will first analyze the financial ratios first and take these Chinese characteristics into consideration later to see whether the result can be improved.

Data Sample and Collection

From 2002 to 2015, forty-nine companies are listed as ST/*ST for more than 7 years. We regard these companies with high default risk and use them as the sample for default group[7]. The selection of non-default companies is on a random base in order to reduce the selection bias. We

[6] Number correct takes the average of the number of correct predictions over 14 years.
[7] Full list of these companies and their tickers are in Appendix I.

first find 708 companies which have never been listed as ST/*ST for entire 14 years. Out of them, we use a random number table to select forty-nine companies as the sample for non-default group[8]. The average total asset for default group is ￥0.55 billion RMB and the average market capitalization is ￥2.17 billion RMB while for non-default group, the average total asset is ￥14.70 billion RMB and the average market capitalization is ￥13.30 billion RMB. However, we will not deliberately adjust for this huge difference as the size of a company may be a key factor when identifying default risk.

As for financial ratios, we choose the exact same set of ratios as Altman Z-Score uses mainly for two reasons. First, as previous research of Chen shows, debt ratio, profitability and market capitalization covey the default risk (Chen, 2006). Although the form of the ratio may vary, for example, EBIT/Sales and Net Income/Sales both measure the profitability. Therefore, we focus more on the category of the ratio such as profitability, leverage, solvency rather than the ratio within a category. Altman Z-Score uses ratio covers almost every financial aspect regarding default risk and therefore is a great starting point. Second reason is about the availability of data. The ratios in Z-Score are available in Wind from 2002 to 2015 for all the 1122 companies listed after 2002. While some other ratios such as matured debt to cash are not available for the whole time horizon we choose. Therefore, we use the following six financial ratios:

- Working capital/Total asset
- Retained Earnings/Total assets
- Earnings before interest and taxes/Total assets
- Earnings before interest and taxes/Total assets
- Market value equity/Book value of total debt

[8] Full list of these companies and their tickers are in Appendix I.

- Total Equity/Total Debt and Sales/Total assets

Below is the result of logistic regression and the explanations of these six ratios.

Logistic Regression Result

Uses the ratios above, we apply a logistic regress for total ninety-eight companies, assigning the default group with 1 and non-default group with 0. The regression result is shown below:

$$\mathbf{L_{China} = -48 + 2.02*X_1 + (-27.61)*X_2 + (-18.04)*X_3 + 0.026*X_4 + 0.14*X_5 + (-2.27)*X_6}$$

- X_1 = *Working capital/Total assets*: This ratio measures the liquidity of a firm. Working capital refers to the difference between current asset and current liability, which can be considered as net current asset. If the net current asset is low, when debt matures or some financial emergency occurs, the firm lacks the ability to cash in asset which may lead to default.
- X_2 =*Retained Earnings/Total assets*: Retained earnings is an accumulated number which relates to the reinvestment. Generally, a long-lived company will have higher retained earnings than new companies and high reinvestment companies will have higher retained earnings than dividend paying companies. Therefore, high retained earning companies either have a better sustainability or have better investment choices. These abilities will keep companies away from bankruptcy.
- X_3 =*Earnings before interest and taxes/Total assets:* This ratio indicates the profitability of a company, especially how well a company can turn the money invested into profit. The better the profitability, the less likely for a company to default.

- X_4 =*Market value equity/Book value of total debt:* This ratio measures the volatility of assets when the stock price changes. If the market cap-to-debt is too high, a slight change in stock price will do huge damage to the value of asset and thus the firm has higher default risk.
- X_5 = *Total Equity/Total Debt:* Equity-to-Debt ratio is a measure of financial leverage, generally the higher level of debt, the more default risk a company undertakes.
- X_6 = *Sales/Total assets:* This ratio also shows the profitability but sales demonstrate more on productivity. Sales is also the indicator of growth thus this ratio convey the information of the expansion of the company.

Below is the Wald test for the regression coefficients. As we can see, all the coefficients have at least 99.5% of significance. Therefore, the regression result is statistically significant.

	Wald Chi-Square	**Pr > Chi2**
Intercept	0.000	0.996
X_1	0.000	0.996
X_2	0.000	0.994
X_3	0.000	0.994
X_4	0.000	0.999
X_5	0.000	0.997
X_6	0.000	0.995

The classification of training set is also desired:

from \ to	**0**	**1**	**Total**	**% correct**
0	49	0	49	100.00%
1	0	49	49	100.00%
Total	49	49	98	100.00%

100% companies of the default group have been classified into default group and 100% companies of the non-default group have been classified into no-default group. Therefore, the logistic regression result seems to be solid.

However, this result is obtained through an average data, an empirical study is implemented below to see how well does the work in the dynamic situation as we apply the score to the annual data.

Empirical Results

Empirical Test on Chinese Listed Companies

To see how well the L_{China} indicates the default risk in a dynamic situation, we get the financial ratios and default situation data from 2002 to 2015. For each year, we applied the formula:

$$\mathbf{P_{default} = 1/(1+Exp(-L_{China}))}$$

The cutoff point is 50% for classifying default and non-default group. If the company has a $P_{default}$ <50%, we will classify the company as non-default while a $P_{default}$ over 50% indicates high default risk. Below is the consolidated result or the Type I and Type II error:

	Number Correct	**Per cent Correct**	**Per cent Error**	**Total**
Type I[9]	901.4[10]	88.5%	11.5%	1018
Type II	85.3	82.0%	18.0%	104
Total	986.6	87.9%	12.1%	1122

For the same set of data used to evaluate Z-Score, L_{China} significantly reduce both the Type I and Type II error. Type I error drops 18.9% from 30.4% to 11.5% while Type II error drops 24.0% from 42.0% to 18.0%.

[9] Annual Type I & Type II error is shown in the appendix.
[10] Number correct takes the average of the number of correct predictions over 14 years.

One year leading prediction also experiences a more significant improve:

	Number Correct	**Per cent Correct**	**Per cent Error**	**Total**
Type I	910.0[11]	89.4%	10.6%	1018
Type II	92.4	88.8%	11.2%	104
Total	1002.4	89.3%	10.7%	1122

Type I error drops 19.1% from 29.7% to 10.6% while Type II error drops 31.6% from 42.8% to 11.2%. For annual Type I error, the minimum is 8.3% and the maximum is 14.1% while for annual Type II error, the minimum is 13.1% and the maximum 45.2%. Therefore, this model tends to have a higher Type II error which means to classify non-ST firms as ST firms. However, for Chinese listed companies, L_{China} overall has a much better accuracy in comparison with Altman Z-Score and it can fairly predict the default a year beforehand.

Potential Explanations for Type I and Type II error

Although L_{China} improves the prediction 13% error rate is unneglectable. As all the results above come from ratio analysis, this 13% error may exist due to off-balance sheet information. Below are 3 potential explanations for the error rate.

i. *Industry:* In this paper, we treat all the industry equally, assign the ratios with same weight and sign. However, each industry may have different emphasize on financial ratios. For example, manufacturing business generally has a high fixed asset, therefore, the working capital is low due to the nature of the business. A further study can separate the industry and apply Logit regression respectively to see whether the result will vary.

ii. *Company Property*: State-owned enterprise is a Chinese characteristic which refers to the firms with more than half of the shares are held by either local or central government.

[11] Number correct takes the average of the number of correct predictions over 14 years.

Extreme cases such as Petro China has 86% of its shares held by central government. For these companies, as long as the government did not default, they will remain healthy. Therefore, the Type II error occurs may result from a bad financial situation but a solid company property. In year 2014, the Type II error reaches the all-time high of 45.4%. However, if we examine the total 14 wrongly classified companies, 10 of them are either local or central government owned. If we eliminate them, the Type II error drops to 12.9%. Therefore, company property does play an important role when identifying default risk.

iii. *Restructuring:* This is a key factor affects the default risk prediction in Chinese market. Generally, when a firm is in distress, it will try its best to stay listed. Restructuring is the most popular method for a Chinese company in the hope to turn the bad financial situation around. Extreme examples such as Xiange Qing, a former major player in foodservice industry, restructured five times during 2013 and finally went into internet industry. The frequent restructures indicate the board was at loss of what to do and chose an industry which seems to boom (Yao, 2013). Although Xiange Qing was suspended in 2014, the stock price went up cause investors regard restructuring as good news. Therefore, when a company is considering a restructuring, a Type I error will occur.

Due to these potential problems the L_{China} may not include, we try to analyze the default risk dynamically. Specifically, we will not only analyze the score, but the transition of the score to see whether some of the default risk is conveyed through the transition.

Default Risk Transition Matrix

Default risk is not a static value, every change in the fundamentals or environment will also affect the possibility of default. Thus, a dynamic analysis is required when evaluating default risk. It is not the current state matters the most but how the company reaches current state and where it will head to. Standard & Pool has developed a method for this aim. Each year, they will release a “Annual Global Corporate Default Study and Rating Transitions” with the annual review of the global default trend. Specifically, they will generate a Rating Transition Matrix. The basic concept of this matrix is to track how the rating of companies change over time. This is an extremely useful tool for evaluating the transfer of default risk and even provide an insight of whether the market is getting risker or not. We will apply this transition matrix on the L_{China}. But first, we need to assign a rating for the L_{China} to produce a neat result.

Rating Method

We want to rate all the companies with score 1 to 10 as 1 refers to the companies with highest default risk and 10 refers to companies with lowest default risk. Below is the formula we use to assign rating for the L_{China}:

$$\mathbf{R_C = 10*(1 - \text{Percentile of } L_{China} \text{ out of all 1122 companies})}$$

We round up R_C so that all the ratings are integer and the range is strictly from 1 to 10. This rating demonstrates a relative position of a company regarding all the 1122 companies. This approach aims to capture the sudden change of financial situation. A significant rise or drop definitely represent an abrupt turning of the basis of a company which may be caused by restructuring or accounting fraud.

Insight of the Default Risk Matrix

After rating, there are around 112 companies for each score. Below is the average transition rate from 2002 to 2015 with the row indicates the rating at year t-1 and the column indicates the rating at year t:

To\From	1	2	3	4	5	6	7	8	9	10
1	79.2%	14.4%	2.9%	1.3%	0.5%	0.4%	0.6%	0.2%	0.1%	0.3%
2	12.5%	54.5%	17.9%	6.6%	3.4%	2.2%	1.5%	0.8%	0.1%	0.3%
3	2.5%	22.1%	44.2%	16.0%	7.0%	3.6%	2.2%	1.2%	0.8%	0.3%
4	1.4%	4.5%	22.9%	39.7%	18.7%	7.3%	3.6%	1.1%	1.2%	0.1%
5	0.8%	1.8%	7.1%	23.3%	34.2%	19.0%	7.7%	3.8%	1.6%	0.4%
6	0.6%	0.8%	2.1%	8.2%	23.7%	35.9%	19.1%	6.9%	2.0%	0.5%
7	0.3%	0.6%	1.4%	2.3%	8.4%	22.4%	35.7%	21.5%	6.8%	1.2%
8	1.0%	0.3%	0.8%	1.4%	2.6%	6.5%	22.3%	40.4%	20.8%	3.8%
9	0.7%	0.3%	0.4%	1.1%	1.3%	2.1%	5.8%	21.8%	48.7%	17.8%
10	1.0%	0.6%	0.3%	0.1%	0.2%	0.7%	1.6%	2.4%	17.9%	75.1%

The first cell of 79.2% means 79.2% of 1R companies will remain 1R the next year and the last cell of the second column means 1.0% of 1R companies become 10R companies the next year. This matrix also demonstrates several interesting properties:

1. The diagnose cells have the highest rate compare to the same column:

   This property is easy to understand as a company with 3R will most likely to remain a 3R next year. These company experience an average financial year with no significant gain or loss. However, generally a medium rated companies such as 4R or 5R are more volatile than 1R and 10R companies as only 34.2% 5R firms remain 5R the next year while 79.2% of 1R remain 1R. For extreme rating such as 1R, they can only head to one direction as 1R is the lowest rating.

2. More than 75% likely a company will remain in a [-1, +1] rating range:

   Generally, the transition is slight, as it is highly possible for one company to drop or increase 1R. This is reasonable as one company's financial situation can fluctuate during one year. Especially for medium rated companies which are most volatile due to the possibility move to both directions. However, move over 2 rating within a year is less likely to happen as it requires a bigger change.

3. Big leap change is possible and black swan happens more than one expect:

   Although a leap over 2 rating is less possible, a sudden rise or drop happens more often than one expects. 1% of the 1R companies jump directly to 10R the next year. Normally, we assume the transition to far ratings will gradually reduce. However, the huge leaps turn out to happen more frequent than expected. This heavy tail is notice worthy cause it may include the restructuring. This can also be an indicator of accounting manipulation.

4. Companies generally have a tendency to move up:

   For each rating, the possibility of moving one rating up is normally higher than moving one rating down. For example, 5R has 23.7% possibility to move to 6R while a 18.7% possibility to move to 4R. This phenomenon demonstrates a trend of better financial situation for Chinese market.

All the analysis above only focuses on the Chinese market solely. We separate Chinese market is to get the most accurate result for Chinese market but not distinct it from the global market. In fact, we expect the L_{China} will help to better compare Chinese market and the Global market.

Chinese and the Global Market

After looking at the transition matrix itself, we will analyze it in a comparative way. We want to compare the Chinese Default Risk Transition Matrix with the Global Rating Transition Matrix to see what characteristics they share in common and what is unique in Chinese market. Below is the Global Rating Transition Matrix of 2015[12]:

To\From	CCC/C	B	BB	BBB	A	AA	AAA
NR	18.7%	13.3%	9.1%	6.4%	3.2%	2.1%	0.0%
D	25.7%	2.4%	0.2%	0.0%	0.0%	0.0%	0.0%
CCC/C	49.7%	4.6%	0.2%	0.0%	0.0%	0.0%	0.0%
B	5.9%	76.0%	6.9%	0.0%	0.0%	0.0%	0.0%
BB	0.0%	3.6%	80.0%	4.9%	0.0%	0.0%	0.0%

[12] Data comes from "2015 Annual Global Corporate Default Study And Rating Transitions"

BBB	0.0%	0.2%	3.6%	85.6%	5.5%	0.0%	0.0%
A	0.0%	0.0%	0.0%	3.1%	89.9%	4.4%	0.0%
AA	0.0%	0.0%	0.0%	0.1%	1.4%	93.3%	0.0%
AAA	0.0%	0.0%	0.0%	0.0%	0.0%	0.3%	100.0%

Compare it with the Chinese Default Risk Transition Matrix of 2015:

To\From	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	82.1%	15.2%	0.9%	0.0%	0.9%	0.0%	0.9%	0.0%	0.0%	0.0%
2	10.7%	53.6%	15.2%	9.7%	6.3%	0.9%	2.7%	0.0%	0.9%	0.0%
3	0.9%	20.5%	44.6%	18.6%	4.5%	6.3%	1.8%	0.9%	1.8%	0.0%
4	0.9%	6.3%	25.9%	36.3%	13.4%	8.9%	4.4%	2.7%	1.8%	0.0%
5	0.0%	0.0%	7.1%	27.4%	38.4%	16.1%	6.2%	2.7%	1.8%	0.0%
6	0.9%	0.9%	5.4%	7.1%	28.6%	35.7%	13.3%	4.5%	2.7%	0.9%
7	0.0%	1.8%	0.0%	0.0%	3.6%	25.0%	41.6%	19.6%	7.1%	1.8%
8	1.8%	0.0%	0.0%	0.0%	2.7%	7.1%	23.0%	46.4%	14.3%	4.5%
9	1.8%	0.0%	0.9%	0.9%	1.8%	0.0%	4.4%	22.3%	53.6%	14.3%
10	0.9%	1.8%	0.0%	0.0%	0.0%	0.0%	1.8%	0.9%	16.1%	78.6%

The overall structure is similar, with the highest rate on the diagnoses and most of the companies generally moves one rating. However, Chinese market also has several unique characteristics:

1. The move between ratings is more volatile in Chinese market:

   In the Global Transition Matrix, the rating normally moves only one rating away but in Chinese Transition Matrix, the rating moves more volatilely, moves of 2 or 3 ratings happens quiet often. The emerging nature of Chinese market may contribute to this difference. The restructuring in Chinese market may also be one of the reasons that cause the rating to fluctuate.

2. Opposite tendency:

   While the Chinese rating has a tendency to move up, global rating moves down. For global default transition, the top companies remain top and the unhealthy companies gradually get worse. This may be caused by the developed market. The top is locked by the business giants that accounts for a large market share. Their position is relative steady and the rating is not likely to change. But small business comes and goes. As for China, except some state-owned enterprise, small portion of companies have a dominated market share but overall, the whole market is growing. Therefore, the trend is in opposite direction.

Conclusion

Although Altman Z-Score is regarded as the golden rule to identify the bankruptcy risk, it may not have the same magical power when apply to Chinese market. On average, it will misclassify 30% non-default companies as default and let 40% default companies escape. Therefore, this paper uses financial ratio analysis to find a default risk indicator specifically for Chinese listed companies. Thanks to the former research on the Chinese financial ratio evaluation, we create a L_{China} by logistic regression. The score proves to be statistically significant and perfectly classify the training data with 100% accuracy. L_{China} also performs well in empirical study regarding to 1122 companies with a time horizon of 14 years. L_{China} greatly reduce the error rate to 12.7%. When doing a one year leading prediction, L_{China} performs even better, with an error rate of 10.7%. Therefore, L_{China} to a large extent, captures the default risk of Chinese listed companies. Our model uses ST as an indicator of default which may have some drawbacks. First, it is a legal regulation rather than a true reflection of the financial situation. Second, some companies are listed as ST because of faking financial data and this is hard to be captured by the financial ratios. However, ST does provide an insight of the financial distress of a company.

For the Type I error and Type II error, different user may weigh the importance of these two errors differently. For example, if a bank wants to loan out money, they will care more about Type II error which is to classify distressed companies as non-default because the loss can be significantly large. In this case, the constant in the L_{China} can be adjusted to decrease the Type II error.

To analyze the dynamic of default risk, we introduce the Default Risk Transition Matrix. Some major discovery is that companies tend to move within 1 rating change and the heavy tail exists due to the characteristics of Chinese market. When compare default risk in China with the world, it turns out China is still in a growing path thus the transition is more volatile.

Appendix I

List of Companies in Default Group

Ticker	Company Name	Ticker	Company Name
000008.SZ	神州高铁	000892.SZ	欢瑞世纪
000010.SZ	美丽生态	000921.SZ	海信科龙
000017.SZ	深中华 A	600083.SH	博信股份
000030.SZ	富奥股份	600234.SH	*ST 山水
000035.SZ	中国天楹	600313.SH	农发种业
000048.SZ	康达尔	600338.SH	西藏珠峰
000156.SZ	华数传媒	600381.SH	青海春天
000403.SZ	ST 生化	600385.SH	山东金泰
000409.SZ	山东地矿	600515.SH	海航基础
000505.SZ	*ST 珠江	600556.SH	ST 慧球
000509.SZ	华塑控股	600603.SH	*ST 兴业
000555.SZ	神州信息	600608.SH	上海科技
000557.SZ	西部创业	600617.SH	国新能源
000561.SZ	烽火电子	600681.SH	百川能源
000587.SZ	金洲慈航	600691.SH	阳煤化工
000603.SZ	盛达矿业	600698.SH	湖南天雁
000613.SZ	大东海 A	600715.SH	文投控股
000620.SZ	新华联	600751.SH	天海投资
000622.SZ	*ST 恒立	600793.SH	宜宾纸业
000633.SZ	*ST 合金	600817.SH	*ST 宏盛
000656.SZ	金科股份	600847.SH	万里股份
000670.SZ	*ST 盈方	600870.SH	厦华电子
000691.SZ	ST 亚太	600891.SH	秋林集团
000693.SZ	ST 华泽	600892.SH	大晟文化
000863.SZ	三湘印象		

List of Companies in non-Default Group

Ticker	Company Name	Ticker	Company Name
000002.SZ	万科 A	600073.SH	上海梅林
000009.SZ	中国宝安	600112.SH	天成控股
000028.SZ	国药一致	600160.SH	巨化股份
000066.SZ	长城电脑	600196.SH	复星医药
000401.SZ	冀东水泥	600226.SH	升华拜克
000421.SZ	南京公用	600255.SH	鑫科材料
000503.SZ	海虹控股	600287.SH	江苏舜天
000513.SZ	丽珠集团	600316.SH	洪都航空
000528.SZ	柳工	600345.SH	长江通信
000534.SZ	万泽股份	600382.SH	广东明珠
000548.SZ	湖南投资	600511.SH	国药股份
000564.SZ	供销大集	600557.SH	康缘药业
000582.SZ	北部湾港	600583.SH	海油工程
000597.SZ	东北制药	600626.SH	申达股份
000610.SZ	西安旅游	600637.SH	东方明珠
000627.SZ	天茂集团	600663.SH	陆家嘴
000652.SZ	泰达股份	600686.SH	金龙汽车
000665.SZ	湖北广电	600718.SH	东软集团
000690.SZ	宝新能源	600750.SH	江中药业
000709.SZ	河钢股份	600794.SH	保税科技
000731.SZ	四川美丰	600810.SH	神马股份
000768.SZ	中航飞机	600831.SH	广电网络
000807.SZ	云铝股份	600863.SH	内蒙华电
000987.SZ	越秀金控	600881.SH	亚泰集团
600026.SH	中远海能		

Appendix II

Annual Type I and Type II error for L_{China} Score's Empirical Study

Year	2002	2003	2004	2005	2006	2007	2008
Type I	11.8%	10.3%	11.2%	13.7%	12.6%	9.2%	12.7%
Type II	14.9%	16.7%	14.7%	18.0%	15.8%	20.9%	13.1%

Year	2009	2010	2011	2012	2013	2014	2015
Type I	11.9%	8.6%	8.3%	9.4%	12.4%	13.6%	14.1%
Type II	16.3%	17.3%	16.7%	22.6%	27.9%	45.2%	19.5%

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