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Credit ratings patterns for BRICS industrial companies

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Abstract

The main goal of this paper is to study interconnections between credit ratings and financial indicators of industrial companies from BRICS countries. We use method of patterns, one of the modern methods of nonlinear modeling, to identify groups of heterogeneous objects with different influence on ratings. Additionally, in this research, we evaluate Tobit regression model for selected groups and establish some credit rating patterns for the BRICS industrial companies. Our results of Tobin model, may have practical implementation in short-term financial management.

Keywords: Credit rating; Time-series patterns; Time series analysis; Data mining; Cluster analysis

1. Introduction

The successful development and the financial stability of industrial company (here and after – IC) in the long run is strongly connected with macroeconomic and micro financial factors determined by the degree of development of financial market in a country. Any innovative activity is constructed on a solid basis of macro prudential and financial environment.

Nomenclature		
2	Data and methodologies (page 3)	Fig. 1, Fig. 2

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3	Results (page 4)	Table 1
4	Summary and conclusions (page 5)	Fig. 3

1.1. Credit ratings patterns for IC's

Innovative developments in BRICS countries commonly reveal an improvement or deterioration in the credit-worthiness of a company. Although rating agencies primarily meant to utilize credit ratings of IC's to signify the current credit quality, especially for IC's from emerging economies.

All these factors are interconnected, and the analysis of this relationship is difficult, but interesting problem. To solve it we use the method of pattern analysis, such method is rather new area of data analysis associated with a search for relationships among different objects and suggests constructing their classification and solving the problem to study heterogenic objects in dynamics.

If we point to a more formal side, then we should say that pattern method consists of three consecutive stages as follows:

- First step, information search, primary statistical processing of data and selection the basic system of indicators;
- Secondly, - construction of the feature space of the objects and clustering them to find samples of patterns;
- Final, to study the objects behavior in dynamics using dynamic and regression analysis of patterns.

We take into account that in the context of short-term prediction of financial risks and watching over the level of rating changes, it is important to take into account the homogeneity of objects. One of the aims of our work was to build up a cluster analysis based on different IC's from BRICS. The first step was to identify the nature of time-related patterns of credit ratings IC's, and further we apply some simple nonlinear techniques. The second important task of our experiment was a selection of such groups of objects (ICs) in time. After this, we built a Tobin's regression model. As a result of our work and the final computational experiment, the collected observations were divided into 13 groups by its credit ratings' patterns and by means of regression analysis. The most significant factors were determined. In addition, the small influence of the credit ratings' in time has been discovered, and the level of financial capabilities of each group relative to other groups from the entire sample was singled out.

1.2. Literature review

The problem of finding patterns for hetero- and homogeneous objects is based on fundamental research, in particular, which can be singled out in [1, 3, 6]. In this article authors discuss the issue of changes in credit ratings over time and raise the problem about the degradation of credit ratings in time. It should be noted that the majority of studies [4-5] in this direction did not answer the question "of what happens to the level of credit ratings over time and how they are influenced by changes in financial performance" relatively to what happened to the company over the same period of time. Academicians and practitioners often use the homogeneous Markov chain [2], to describe the dynamics of credit ratings. But in fact, this process does not correspond to actual changes of credit ratings. The issue of separation of intercountry samples was made to step away from the homogeneity assumption of the Markov chain transition matrix [7].

We should note that today's opportunities for studying and constructing credit risk maps allow us to use long panel datasets to identify those areas of pattern recognition with automatic data processing using computer algorithms [8]. Most of the authors, who obtained estimates of different patterns, use methods of simple clustering. Such actions [9-10] like the construction of classification for different categories of objects by the identifying level of descriptive statistics assist to match these time-related patterns to actual economic groups.

This article offers a different approach to track credit rating patterns while accounting for time series movements within credit rating changes, rather than cross-rating dependencies. We substantiate this nonlinear model with clustering homogeneous objects through some statistical tests, associate it with market and financial variables, and demonstrate its economic importance.

2. Data and methodologies

The dataset was collected from 2006 to 2016 for industrial companies from BRICS countries; the number of observations is 12,170. The sample included 114 industrial companies with different credit ratings, from high investment grades to speculative ones. Data source: Bloomberg, IMF.

At the core of the pattern method, a valuation procedure was performed using simple-weighted clustering method: mean and median values were determined by numeric meaning of credit ratings of each entity. After this, the obtained results were sequentially clipped from the total sample (in-to-out) and divided into several subsamples. See formula (1) below in 2.1.

2.1. Simple-weighted clustering process and method of anomalous clusters

This method consists of application of a strategy of sequential data depletion, in our case - one cluster. The initial step is to point the apex from the center of collected datasets. That means to measure all observations to different bias sample selections, which are taken as the center of the biggest cluster for detailed clustering. Then the each cluster formed for itself and for industry, it is formed bias selection for calculating measure between credit ratings.

The distance from every sample-bias to the center - is less than the distance to the center of the another sample selection and it shows the aggregate level of ratings and company financial performance in the industry. Then the second point near the center of the bias selection replaces the center of the cluster, and the next iteration occurs.

$$
\begin{aligned}
& r_k(t+1) = r_k(t) + \alpha_t * h_{vk}(t) \\
& \times \begin{cases} \left([x(t) - r_v(t)] + [r_v(t) - r_k(t)] \left(\dfrac{d_{vk}}{\Delta_{vk}\lambda} - 1 \right) \right), & \text{for } r_v(t) \text{ between } x(t) \text{ and } r_k(t); \\ \left([x(t) - r_v(t)] - [r_v(t) - r_k(t)] \left(\dfrac{d_{vk}}{\Delta_{vk}\lambda} - 1 \right) \right), & \text{for } r_k(t) \text{ between } x(t) \text{ and } r_v(t); \\ \left([x(t) - p] + [p - r_k(t)] \left(\dfrac{d_{vk}}{\Delta_{vk}\lambda} - 1 \right) \right), & \text{otherwise} \end{cases}
\end{aligned} \tag{1}
$$

where $r_k(t)$ r_v (t) is a numeric value of the credit rating;

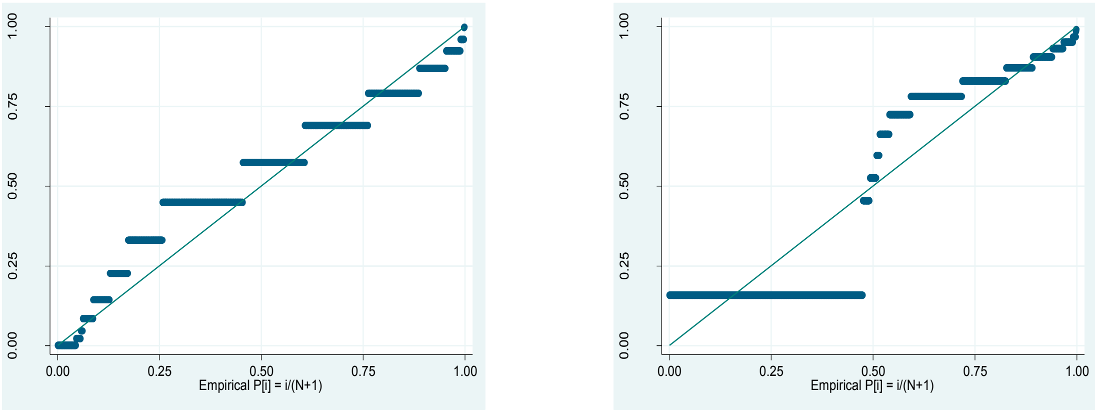
p - probability of entering the border zone;

a_t - the result of determining the hit in the group, is 0 or 1;

$h_v k(t)$ - the level determined for the transition to the neighboring group.

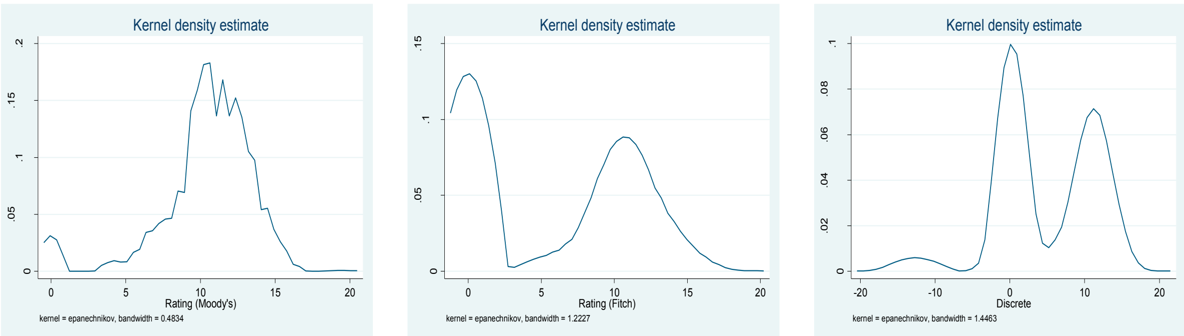
We obtained 13 credit rating patterns (see figure 3 on page 6) for ICs that had similar quantitative estimates as a result of clustering and identified their median values. The frequency of data and distribution of credit ratings are presented in figures 1 and 2.

Such methods at each step consider a partition $r_k(t+1)$ and perform its local transformation in the direction of improving the value of the mean and median criteria. Only the last point from the cluster center, out of all the possible local transformations, divides one object from the class of other objects. According to the procedure, the class of truly identified (homogenous) objects only for one group. An object, which is found on the border criteria – is maximized, and if it is positive, this object transfers to the closest group. If not, the splitting occurs to the final result.



(a) (b)

Fig. 1. Frequency of credit ratings – for Moody's (a) and Fitch (b)



(a) (b) (c)

Fig. 2. Distribution of IC's credit ratings – for Moody's (a); Fitch (b) and Average (c)

When we estimate the Tobin model we need to take into account the clustering groups – it serves us a censoring procedure for each group of IC's objects. We note that the entire sample consists of thirteen different sets of observations. The first set contains the observations for which the value of Y is 1 and higher. For these observations we know only the values of the X variables and the fact that Y* is less or equal to 1. The second set consists of all observations for which the values of both X and Y* are known and higher (from 2 to 3), and the similar process was done for the following 11 groups. The likelihood function of the Tobit consists of each of these two parts.

3. Results

We found that the intensity of occurrence of credit ratings' among ICs from BRICS were different. It occurs that the investment grades were subsequently downgraded into a speculative ratings class (the problem of downgrading ratings in time). Moreover, for ICs that started with a speculative credit rating and which have been upgraded, rather than for ICs that are still in the same broad investment or speculative grade category. Tobin model showed that the coefficients of the ratings-based factors and their significance levels are only slightly affected by addition of macroeconomic factors to the model specification. This implies that the information obtained from the macro variables is incremental to that contained in a ICs credit rating history alone.

Table 1. Tobin's model results

Variable name/ Group	PG1	PG2	PG3	PG4	PG5	PG6	PG7	PG8	PG9	PG10	PG11	PG12	PG13
Relation_to_y	0.005	0.016	0.067	-0.179	-0.023		0.653	0.174 *		0.460 *	-0.017	0.104	-0.161 **
TOTALASSETS	0.034	0.022	0.003	0.000	0.008	-0.021	0.005	-0.001	0.005	0.005 ***	0.001	0.002	0.000
Discrete	-0.000	-0.000	0.000	0.000	-0.000	0.003	0.002	-0.001 ***	0.000 *	0.000	-0.000	-0.002 ***	-0.001 ***
EbM^2	-0.353	0.912	-3.348	0.956	1.152 *	4.424 *	-2.047	0.067	1.343	-2.155	0.521	0.179	0.406 ***
EbInt^2	-0.000	0.000	0.000	0.000	-0.000	0.013 **	-0.000	-0.000	0.002	-0.000	-0.000	0.001	-0.000
DebtBookCap	0.524	-0.099	0.300	-0.238	0.261	-1.129 *	0.460	-0.364	-0.036	-0.433	0.021	0.180	-0.027
RCFDebt	0.077	-0.135	0.052	-0.091	-0.008	-2.098 ***	0.510	-0.033	-0.616	-0.152	0.195	0.023	0.159
CurrentRatio	-0.225 ***	0.116	-0.114	-0.048	0.042	0.012	0.108	-0.290 ***	0.237	0.088	0.466 *	0.003	-0.017
RatingMoodys	-0.179 ***	-0.093 ***	-0.075 ***	-0.087 ***	-0.118 ***	-0.079	-0.195 ***	-0.086 ***	-0.065 ***	-0.054 ***	-0.110 ***	-0.111 ***	-0.124 ***
Country_du1	-1.494 ***	0.099	-0.823 ***	-0.334 *	0.050			-0.247 *		-0.085	-0.584 *	-0.288 **	-0.139
Country_du2	-0.245	0.845 ***	-0.271					-0.110				-0.049	
Country_du3	-0.286 *			-0.083	0.110		0.304	0.127				-0.047	-0.047
Country_du4	0.005	0.210	-0.774 ***		0.414 ***			-0.011		-0.070	-0.146	0.358	0.263 *
Country_du5			0.152	-0.035	0.288	-0.171					0.171		0.148
Date_dummy 2008	0.009	0.241 *	0.007	0.146	-0.018	-0.032	-0.041	0.053		-0.168 *	-0.082	0.029	0.090
Cons	2.825 ***	0.947 *	1.668 ***	1.699 ***	1.502 ***	1.588 **	1.861	2.142 ***	0.772	1.020 ***	0.811	1.623 ***	1.926 ***

	PG1 to PG2	PG1 to PG3	PG1 to PG4	PG1 to PG5	PG1 to PG6	PG1 to PG7	PG1 to PG8	PG1 to PG9	PG1 to PG10	PG1 to PG11	PG1 to PG12	PG1 to PG13
Average score (mean) relative to group 1	0,307	0,557	0,342	0,11	0,184	-0,024	0,439	0,041	0,268	0,492	-0,141	0,004

4. Summary and conclusions

This article offers an alternative approach to credit ratings pattern analysis. Our results showed that Tobin's model tracks time-series movements within credit rating changes in time. The proposed homogeneous objects of one cluster is validated through the Kruskal-Wallis test and Mann-Whitney (U-test), and it is found to be statistically and economically significant.

Although, our analysis show us that different industrial companies (according to sample selected groups) shows various results. The greatest impact of our selection bias shows that industrial companies do not vary from one country to another, but has different financial performance.

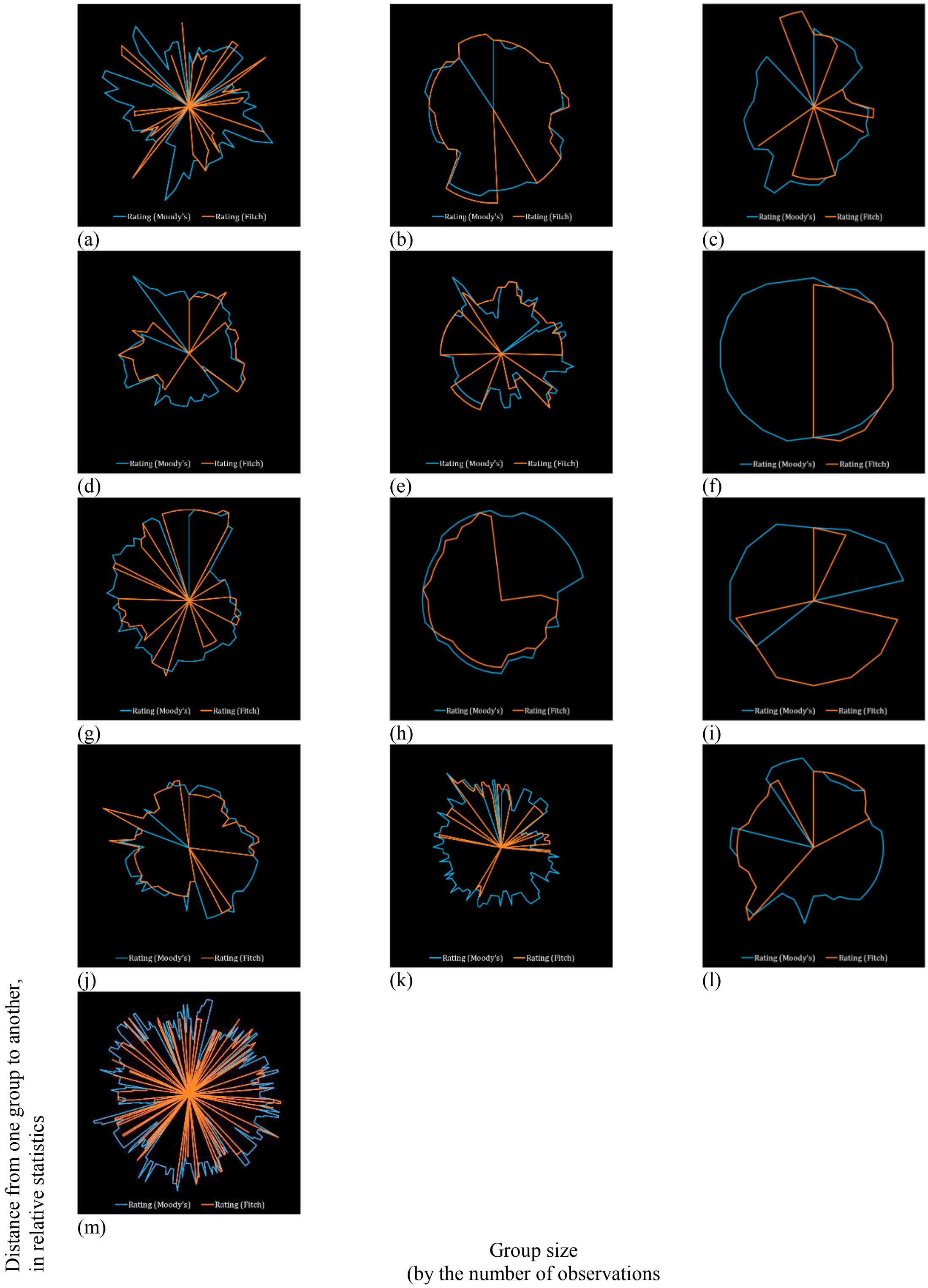


Fig. 3. (a) PG1; (b) PG2; (c) PG3; (d) PG4; (e) PG5; (f) PG6; (g) PG7; (h) PG8; (i) PG9; (j) PG10; (k) PG11; (l) PG12; (m) PG13

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Appendix A. Numeric scale

A.1. Table 1. Rating scale of credit ratings (for Moody's scale)

Rating grade	Aa3-Aaa	A1	A2	A3	Baa1	Baa2	Baa3
Numerical scale	1	2	3	4	5	6	7
1-year default rate1, %	0%	0.07%	0.05%	0.05%	0.13%	0.17%	0.25%
Rating grade)	Ba1	Ba2	Ba3	B1	B2	Ca-B3	
Numerical scale	8	9	10	11	12	13	
1-year default rate, %	0.44%	0.71%	1.36%	1.97%	2.95%	12.9%	

A.2. Table 2. Descriptive statistics

Variable name/ Group	Notation	Average	Maximum	Minimum	Standard deviation
Credit rating (average, in numeric scale)	Relation_to_y	8,128	24,423	3,146	4,441
Total assets, growth (%)	TOTALASSETS	5,000	10,851	2,384	3,985
Position towards the center of cluster (difference between groups)	Discrete	12,000	37,175	3,616	4,950
EBIT margin, (%) in square	EbM^2	2,261	7,935	0,402	0,232
EBIT/interest expenses, (%) in square	EbInt^2	0,173	0,520	0,067	0,094
Debt/Book capitalization, (%)	DebtBookCap	0,350	0,455	0,416	0,697
Retained cash flow (RCF)/Debt, (%)	RCFDebt	9,000	25,324	3,232	4,321
Liquidity ratio, growth (%)	CurrentRatio	1,712	1,607	1,168	2,194

Dummy group	RatingMoodys	- a dummy variable for Moody's credit rating
	Country_du1 Country_du2 Country_du3 Country_du4 Country_du5	- a dummy variable for BRICS country: 1 – Brazil 2 – Russia 3 – India 4 – China 5 – South Africa
	Date_dummy 2008	- a dummy variable for financial crisis