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INTERCONNECTIVITY AMONG ASSESSMENTS FROM RATING AGENCIES: USING CLUSTER AND CORRELATION ANALYSIS

Jaroslav KREJČÍŘ[1], Petr DOSTÁL[2], Karel DOUBRAVSKÝ[3]

Faculty of Business and Management, Brno University of Technology, Kolejní 2906/4, Brno 61200, Czech Republic
E-mails: [1]krejcir@fbm.vutbr.cz; [2]dostal@fbm.vutbr.cz; [3]doubravsky@fbm.vutbr.cz (corresponding author)

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Abstract. The aim of this paper is to determine whether there is a dependency among leading rating agencies assessments. Rating agencies are important part of global economy. Great attention has been paid to activities of rating agencies since 2007, when there was a financial crisis. One of the main causes of this crisis was identified credit rating agencies. This paper is focused on an existence of mutual interconnectivity among assessments from three leading rating agencies. The method used for this determines is based on cluster analysis and subsequently correlation analysis and the test of independence. Credit rating assessments of Greece and Spain were chosen to the determination of this mutual interconnectivity due to the fact that these countries are most talked euro-area countries. The significant dependence of the assessment from different rating agencies has been demonstrated.

Keywords: credit rating assessments, credit rating agencies, cluster analysis, correlation coefficient, test independence.

JEL Classification: G15, G24, C12, C60.

Introduction

The majority of developed economies worldwide have been going through varying periods of economic recession since 2007. One of the main villains of the crisis, which predated the recession, was identified as large credit rating agencies (Alsakka, Gwilym 2010; Furfine, Amato 2003). One of the factors criticized was the interconnectivity of the results published by such agencies (Alsakka, Gwilym 2013). Research problem of this paper is mutual interconnectivity of credit rating agency assessments. The aim of this paper is to determine whether there is a dependency among leading rating agencies assessments. Internationally most significant agencies are Standard & Poor's (from herein S&P), Moody's Investors Service (from herein Moody's) and Fitch Ratings (from herein Fitch). Particular agencies have their own system of denomination for their evaluations. For example, Moody's uses AAA as the best evaluation of long term liability fulfilment and CA as the worst. There is also a certain mark which serves to separate low and high risk investment, according to Moody's denominated as grade BAA3. For more details, the structure of credit rating agencies is elaborated on in (Crouhy *et al.* 2001; Jeon, Lovo 2013).

A big problem since 2007 has been shown to be that many financial institutions relied on external rating agencies a great deal and in many cases completely (Kräussl 2005; Hauck, Neyer 2014). For this reason, since 2009 regulation of these external evaluations has been increasing within the European Union. Directive 1060/2009 concerning such agencies was adopted on 16 September 2009 by the European Parliament and significantly impacts upon their operations and raises the level of transparency. This directive has been modified several times, most recently on 21 May 2013. This latest modification is very significant in relation to this article. One of its most significant goals is to lower dependency on external ratings and limit the influence of the biggest agencies (Kräussl 2005). To this end, among other means, is the rotation of agencies, which

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means that one agency can't publish long term evaluations of one issuer in the case of so called re-securitization (Jeon, Lovo 2013). This is based on the expectation that the new agency will evaluate the issuer differently to the previous assessor. In addition, it is also proposed that external evaluation will be carried out at least once by an agency with a lower than 10 % market share. Specifically noted in the text of the directive, is that such agencies with fewer than 50 analysts or a turnover of less than 10 million euro are at present given precedence.

In general, the agencies were especially criticized for the following reasons: Firstly, their inaccurate evaluation of new investment instruments of the financial market. Secondly, the influence of agencies on financial markets and the economy as a whole (Kräussl 2005). In this regard, the question arises whether the agencies influence each other. The answer to this question has an impact on the use of the agency rotation instrument. Thus it is appropriate to provide various instruments for the assessment of the mutually interconnected behaviour of such agencies. Various studies have been dedicated to this problem. For example, (Alsakka, Gwilym 2010) include not only the three biggest agencies but also two lesser Japanese agencies, Japan Credit Rating Agency (JCR) and Japan Rating & Investment Information (R&I). The results show the interconnectivity of their assessments. Similar conclusions could be inferred from (Becker, Milbourn 2010).

In another text, a further possible approach is shown, namely cluster analysis. Due to the fact that at the moment within Europe there are not many minor credit agencies, the possibility of cluster analysis can be proved only with regard to the three biggest credit agencies. Long term data is only available from within these agencies.

1. Mathematical backgrounds

1.1. Clustering

Selected companies were grouped into clusters with the use of genetic algorithms (Deng *et al.* 2012; Zhang *et al.* 2013). Cluster analysis problems (De Roover *et al.* 2013; Saha, Maulik 2014) can be solved by means of genetic algorithms (Fung *et al.* 2014). These methods are widely used to solve sophisticated problems in different scientific fields, e.g. economics, operation research, psychology etc. (Long, Wu 2014; Wang, Kuo 2007), but in connection with assessment of credit rating agencies are little used. The advantages and basic concepts of the use of genetic algorithms in economic problems were described by (Dostál 2011, 2008; De Roover *et al.* 2013; Zheng *et al.* 2012).

The aim of a genetic algorithm as an optimization task is to divide a set of N existing objects into M groups. Each object is characterized by the values of K variables of a K-dimensional vector (Tenenhaus, A., Tenenhaus, M. 2014). The aim is to divide the objects into groups so that the variability inside those groups is minimized (De Roover *et al.* 2012; De Roover *et al.* 2013). The software MATLAB and its Global Optimization Toolbox (Hunt *et al.* 2001; Venkataraman 2002) are used for software applications that can be utilized to solve these types of problems. The input data are represented by coordinates $x_1, x_2, \ldots, x_K$ that characterize the objects. It is possible to define any number of groups. The fitness function is the sum of squares of distances between the objects and centroids. The coordinates of centroids $c_{j1}, c_{j2}, \ldots, c_{jK}$ ($j = 1, 2, \ldots, M$) are changed. The calculation assigns the objects to their centroids. The whole process is repeated until the condition of optimum (minimum) fitness function is reached. The process of optimization ensures that the defined coordinates $x_{i1}, x_{i2}, \ldots, x_{iK}$ ($i = 1, 2, \ldots, N$) of objects and assigned coordinates $c_{j1}, c_{j2}, \ldots, c_{jK}$ of groups have the minimum distances. The fitness function is expressed by following formula (Zheng *et al.* 2012):

$$f_{\min} = \sum_{i=1}^{N} \min_{j \in (1,2,\ldots,M)} \left(\sqrt{\sum_{l=1}^{K} (x_{il} - c_{jl})^2} \right), \qquad (1)$$

where N is the number of objects, M the number of groups, and K the dimension. In the course of research, following parameters had been tested: N = 39, M = 3 a successively tested one, two and three-dimensional tasks.

1.2. Two-dimensional data file

When it comes to statistical units measured (discovered), two symbols (two random numbers) X and Y, which are parts of the random vector (X, Y), we talk about so-called the *two dimensional data file*. In this article, a data file is formed by rating agencies assessments of the selected countries, respectively its division into clusters.

For the needs of this article the analysis of this two-dimensional data file is described through quantitative symbols. The symbols analyzed are of the quantitative type if their value may be expressed in numbers (measurable). The value of the correlation of the two quantitative signs X and Y may be expressed by various methods. If there is a functional dependency required, the regressive analysis method is used (Mathews 2005). If the common tendency of appearance of the values of certain entities is being observed, a so-called correlation coefficient is used (Tenenhaus, A., Tenenhaus, M. 2014).

Before the numerical processing of the unit of the data file it is advisable to show the data using a two-dimensional grid system, when each and every pair (x_i, y_i), corresponds to a point on the grid, which is called a *correlation diagram*. This diagram indicates the nature of the data as linear, nonlinear and non-homogenous and the presence of remote values.

1.3. Pearson correlation coefficient

Expresses the strength of the relationship between the symbols analyzed (numbers) X and Y is the correlation coefficient. Another characteristic which describes the strength of the relationship of the symbols analyzed is the *correlation coefficient*. Selective co-variance is calculated according to the following relationship:

$$C_{XY} = \frac{1}{n-1}\left[\sum_{i=1}^{n} x_i y_i - n\overline{xy}\right], \tag{2}$$

where x_i, y_i represent the values identified of the observed symbols X, Y and $\overline{x}$, $\overline{y}$, selected averages (arithmetical averages) calculated from the values measured. If this covariance equals zero, the symbols identified do not correlate (there is no linear relationship between them). When the covariance is not zero, the correlation between the symbols identified exists. The strength of this correlation is impossible to determine from covariance because covariance is not normative. If the value of the strength of the correlation needs to be determined then the selective coefficient (also called Pearson's correlation coefficient) is calculated based on the relationship (De Roover *et al.* 2013)

$$r_{XY} = \frac{C_{XY}}{s_x s_y}, \tag{3}$$

where s_x, s_y are selective relevant anomalies calculated from the values measured. If the correlation coefficient equals zero, the symbols observed do not correlate (there is no linear relationship). If the correlation coefficient is different from zero, the correlation between the symbols exists. Based on the value which the correlation coefficient gains it's possible to say that the relationship is strong ($|r_{xy}|$ is close to one), average ($|r_{xy}|$ is close to one and a half) and weak (($|r_{xy}|$ is close to zero).

1.4. Cross correlation

Cross correlation is the standard method for measuring to what extent the two rows correlate. Let's take two rows x_i and y_i, where $i = 1, 2,..., n$. Cross correlation r_{xy} with the delay d is defined using the relationships (2), (3)

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})\cdot(y_{i-d} - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n}(y_{i-d} - \overline{y})^2}}, \tag{4}$$

where d is the delay and equates to $d = 1, 2,..., n$. In this calculation the question arises what to do if is the row index is lower than zero or bigger or equal to n. The most common approaches ignore these situations.

1.5. Test of independence of the two quantitative symbols

Because when calculating the selective correlation coefficient (estimate of the real correlation coefficient ρ) we base our calculations on the values measured, so this estimate is connected to certain inaccuracies because it's based on statistics, which are random values. Thanks to the correlation coefficient r_{xy} it is possible to test whether the symbols observed are stochastically linearly independent or dependent. So the correlation coefficient ρ is equal or different to zero. Null hypothesis of the test of independency is put in the following formula:

$$H_0 : \rho = 0, \tag{5}$$

And it shows that the symbols observed are independent. An alternative hypothesis which is put in this formula shows that these symbols are dependent. As a testing criterion we use statistics (random value)

$$t = \frac{r_{xy}\sqrt{n-2}}{\sqrt{1-r_{xy}^2}}, \tag{6}$$

which has student's t-distribution.

For the selected level of significance α is for the test the critical field

$$W_\alpha = \left\{ t : |t| \geq t_{1-\frac{\alpha}{2}}(n-2) \right\}. \tag{7}$$

When the value of the tested criteria in the critical field is carried out, the null hypothesis is refused at the α100% level of significance of the null hypothesis, and an alternative is accepted (Mathews 2005).

2. Case study

In the following part, the procedure described is demonstrated with regard to Greece and Spain. As input data we used the data of three rating agencies from a given time. All the agencies analysed the same time period for each state, first in one and then in the other. In the case of Greece, it was from 13 November 1995 to 18 December 2012. In the case of Spain, it was form 18 August 1994 to 16 October 2012. Given the different results of the rating evaluations of particular agencies (for each state and each agency) each was subjected to cluster analysis. The cluster analysis was calculated in environment MATLAB with using Global Optimization Toolbox (Venkataraman 2002) and the script DPGA.m (Dostál 2008) was created. Because cluster method according to (1) is based on genetic algorithm, the number of population was set to 10 000. The number of clusters given the number of available data was set to 3. Then the rating evaluation was split into three clusters and

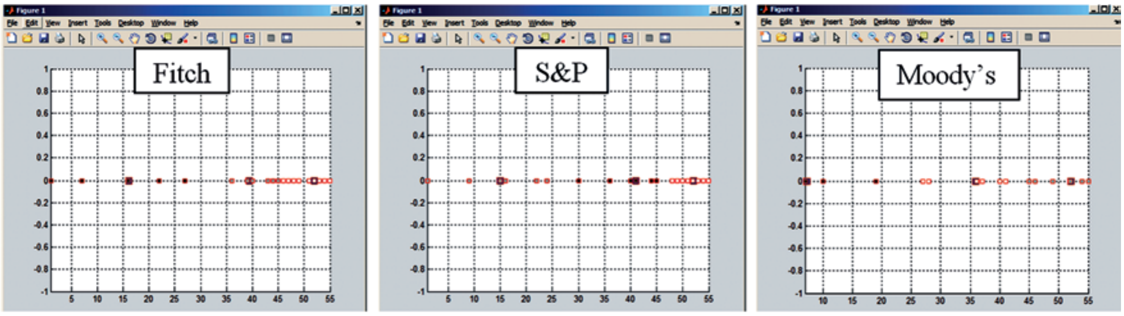

Fig. 1. Greece: Results of cluster analysis for selected agencies (Source: own processing)

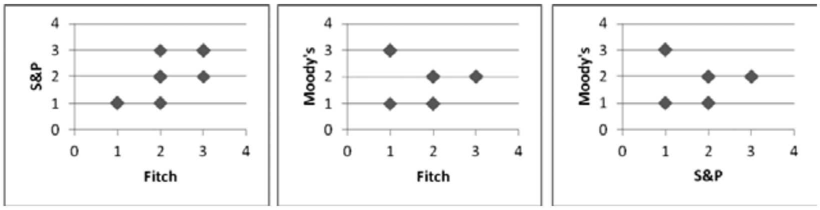

Fig. 2. Correlation diagrams of rating evaluation of Greece from two agencies (Source: own processing)

thus acquired numerical (uniform) evaluation of the countries was subjected to further detailed correlation analysis. Results of cluster analysis for Greece are seen in Figure 1.

From Figure 1, it can be seen that there are three different clusters represented by white, grey and blue squares. Each cluster is determined by coordinates of its centroid. Because the issue is one-dimensional (squares lie on horizontal axis, see Fig. 1), there is only one coordinate of each centroid, see Table 1. Cluster ID had assigned to rating agency assessments and these results entered into the correlation analysis.

Based on the correlation diagram (see Fig. 2), it could be seen that in the evaluation of Greece by particular agencies that there is a rather weaker dependency (points are not clearly spread around the line). Given the fact that the graph doesn't consider the shift of the sequence (rating evaluations), in the following tables there are values of the cross correlation in accordance with relationship (4).

From Table 2, it can be seen that the most significant correlation is 0.951 for $d = 0$ which means that at zero shift exists between the evaluation of Fitch and S&P there is a strong linear relationship. It could thus be stated that the results of their evaluations are the same at the given time for the given state (So if a positive evaluation of one agency is seen then a positive evaluation of a different agency can be expected).

From Table 3 it is evident that the most significant correlation is 0.480 where d = –1, which means at this shift, there exists between the evaluation of Fitch and Moody's a medium-strength positive linear relationship. It could thus be stated that if Moody's gives a positive evaluation, Fitch's evaluation will also be positive, but there is a one period delay in reaching the same conclusion.

From Table 4, it can be seen that the biggest correlation is 0.468 where d = –3, which means that at this shift there exists between S&P a Moody's a medium-strength linear relationship. It could thus be stated that if Moody's evaluates positively, S&P will also evaluate positively, but with a three period delay.

Table 1. Greece: coordinate of centroids (Source: own processing)

Agency	Coordinate of centroid		
	Cluster no.1	Cluster no.2	Cluster no.2
Fitch	16.1	39.4	51.9
S&P	15.0	41.0	52.0
Moody's	7.3	35.9	52.1

Table 3. Correlation coefficient of evaluation of Greece from Fitch and Moody's (Source: own processing)

d	–15	–14	–13	–12	–11	–10	–9	–8	–7	–6	–5
r_{xy}	0.289	0.288	0.286	0.285	0.283	0.282	0.280	0.278	0.308	0.337	0.366
d	–4	–3	–2	–1	0	1	2	3	4	5	6
r_{xy}	0.396	0.425	0.454	0.480	0.444	0.378	0.313	0.248	0.182	0.117	0.052
d	7	8	9	10	11	12	13	14	15		
r_{xy}	–0.014	–0.048	–0.083	–0.119	–0.154	–0.190	–0.226	–0.262	–0.298		

Table 4. Correlation coefficient evaluation of Greece from S&P and Moody's (Source: own processing)

d	−15	−14	−13	−12	−11	−10	−9	−8	−7	−6	−5
r_{xy}	0.366	0.364	0.363	0.361	0.360	0.358	0.357	0.355	0.354	0.382	0.411
d	−4	−3	−2	−1	0	1	2	3	4	5	6
r_{xy}	0.439	0.468	0.436	0.402	0.368	0.305	0.243	0.180	0.118	0.055	−0.007
d	7	8	9	10	11	12	13	14	15		
r_{xy}	−0.070	−0.103	−0.105	−0.108	−0.142	−0.176	−0.210	−0.243	−0.277		

Table 5. Test of independence for the level of significance α = 0.05 (Source: own processing)

Agencies	r_{xy}	Testing Criteria	Criteria Value	Hypothesis H_0
Fitch, S&P	0.951	24.739	0.031	Reject
Fitch, Moody's	0.480	4.377	0.031	Reject
S&P, Moody's	0.468	4.237	0.031	Reject

Due to the fact that while calculating the correlation coefficient we based it on the values measured, this estimate is open to some uncertainty because it's based on statistics with random variables. With the help of selective correlation coefficient r_{xy} we can thus test (5)–(7), if the features observed are stochastically linearly independent or dependent respectively.

From Table 5, it could be seen that for all the pairs of agencies, there is a null hypothesis (5) which is rejected and an alternative hypothesis received. It is thus confirmed that the evaluations of the agencies are mutually dependent.

Results of cluster analysis for Greece are seen in Figure 3. From Figure 3, it can be seen that there are also three different clusters represented by white, grey and blue squares. Each cluster is determined by coordinate, see Table 6. Cluster ID had assigned to rating agency assessments and these results entered into the correlation analysis.

Similarly to Greece, from these correlation diagrams (see Fig. 4) it's evident that between the evaluations on Spain by the agencies there is a rather weaker dependency (points are not clearly spread around the line). Given the fact that the graph doesn't consider the shift of the sequence (ratings evaluations), in the following tables there are values of the cross correlation in accordance with relationship (4).

Table 6. Spain: coordinate of centroids (Source: own processing)

Agency	Coordinate of centroid		
	Cluster no.1	Cluster no.2	Cluster no.2
Fitch	42.1	56.9	63.7
S&P	42.9	59.9	63.9
Moody's	39.8	60.9	67.0

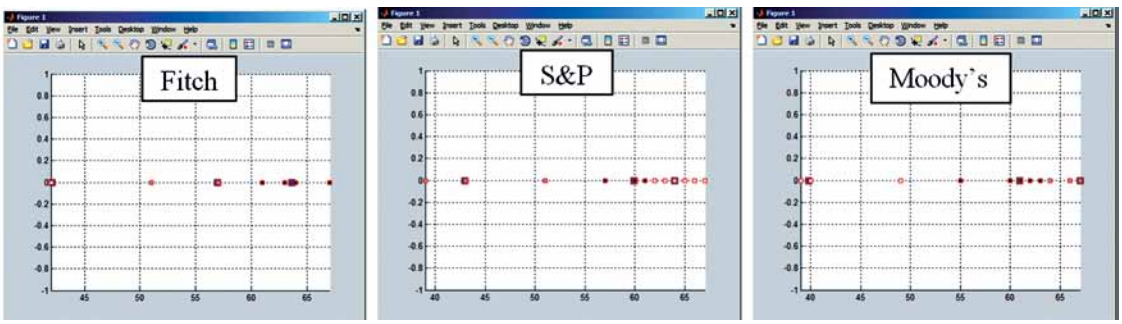

Fig. 3. Spain: Results of cluster analysis for selected agencies (Source: own processing)

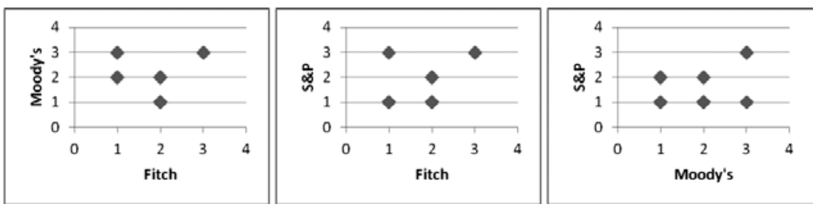

Fig. 4. Correlation diagrams of the rating evaluations of Spain for pairs of agencies (Source: own processing)

Table 7. Correlation coefficient of ratings evaluation of Spain for Fitch and Moody's (Source: own processing)

d	−12	−11	−10	−9	−8	−7	−6	−5	−4	−3	−2
r_{xy}	−0.091	−0.161	−0.231	−0.300	−0.370	−0.440	−0.510	−0.579	−0.455	−0.331	−0.207
d	−1	0	1	2	3	4	5	6	7	8	9
r_{xy}	−0.083	0.041	0.094	0.147	0.200	0.253	0.187	0.121	0.055	−0.011	−0.018
d	10	11	12								
r_{xy}	0.041	0.100	0.159								

Table 8. Correlation coefficient for the ratings evaluation of Spain for Fitch and S&P (Source: own processing)

d	−12	−11	−10	−9	−8	−7	−6	−5	−4	−3	−2
r_{xy}	−0.123	−0.197	−0.271	−0.345	−0.425	−0.505	−0.470	−0.436	−0.250	−0.064	0.122
d	−1	0	1	2	3	4	5	6	7	8	9
r_{xy}	0.308	0.494	0.600	0.706	0.584	0.463	0.284	0.105	−0.074	−0.127	−0.180
d	10	11	12								
r_{xy}	−0.233	−0.286	−0.339								

Table 9. Correlation coefficient for the ratings evaluation of Spain for Moody's and S&P (Source: own processing)

d	−12	−11	−10	−9	−8	−7	−6	−5	−4	−3	−2
r_{xy}	0.202	0.157	0.112	0.067	0.080	0.093	0.106	0.119	0.132	0.238	0.343
d	−1	0	1	2	3	4	5	6	7	8	9
r_{xy}	0.356	0.369	0.318	0.267	0.216	0.165	0.115	0.033	−0.048	−0.031	−0.059
d	10	11	12								
r_{xy}	−0.041	−0.024	−0.006								

Table 10. Test of independence for the level of significance α = 0.05 (Source: own processing)

Agencies	r_{xy}	Testing Criteria	Criteria Value	Hypothesis H_0
Fitch, S&P	−0.579	−4.320	0.031	Reject
Fitch, Moody's	0.706	6.064	0.031	Reject
S&P, Moody's	0.369	2.413	0.031	Reject

From Table 7 it can be seen that the most significant correlation is –0.579 thus $d = -5$, which means at this shift there exists between the evaluation of Fitch and Moody's a medium-strength negative linear relationship. It could thus be stated that if Moody's evaluates positively then Fitch will evaluate negatively, but with a five period delay.

From Table 8, it can be seen that the most significant correlation is 0.706 where $d = 2$, which means that at this shift there exists between S&P a Fitch a strong positive linear relationship. In could thus be stated that if Fitch evaluates positively, then S&P will evaluate positively as well but with a two period delay.

From Table 9, it can be seen that the most significant correlation is 0.369 where $d = 0$, which means that at this shift there exists between S&P a Fitch a medium-strength positive linear relationship. In could thus be stated that if Fitch evaluates positively, then S&P will evaluate positively as well. With the help of the selective correlation coefficient r_{xy} it's possible as in the case of Greece to test (5)–(7) whether the features observed are stochastically linearly independent.

From Table 10 it could be seen that for all the pairs of agencies, there is a null hypothesis (5) which is rejected and an alternative hypothesis received. It is thus confirmed that the evaluation of the agencies are mutually dependent.

3. Discussion

With the help of cluster analysis, there were in the case of Greece and Spain results discovered which confirmed conclusions already provided from other studies. The data used came from, in the vast majority, the period before greater regulation of rating agencies was introduced. This means that rating agencies were influenced only by market forces and their position on the market. From these results it could be inferred that the rating evaluations from the three biggest rating agencies is mutually dependent. Considering the statistically-proven mutual dependency of those evaluations it is not realistic to expect different evaluations when applying so-called rotation of agencies where market forces are in place.

Based on the previous findings, this effort to launch the rotation of agencies seems to be very problematic. It either won't bring any differences in evaluations of particular agencies or is thus useless or, on the contrary, there will arise significant differences which in the end could cause confusion on the financial markets and consequently destabilize the economy in the short run. Consequently this could lead to a loss of trust in ratings agencies and the gradual marginalization of this field. Or based on pressure on the part of the regulator, there could be unrealistic evaluations made. The effort of the regulator to implement in the free market other ratings agencies, could theoretically lead to the efforts of those agencies to try to manipulate the regulator in their favour and thus gain a higher market at the expense of domineering agencies. Due to the fact that this regulator is mostly interconnected with national authorities, it can't be ruled out that they will publish fully authentic evaluations. Well-established agencies are, in their effort to keep their market share, able to produce evaluations in accordance with the requirements. This is the worst case scenario for the economy. It could lead to misleading signals being given to the financial markets. Despite the fact that the aim of the external ratings agencies is to limit the external rating evaluation as much as possible, it still has a great impact on financial markets. This situation might deepen the discrepancy between the expectations and real results of the evaluated issuers. The ultimate result, after the ruined expectations of the financial markets because of improper information, could be a financial crisis and a consequent economic recession. For this reason, we need to pay proper attention to the problem of rating evaluations and subject them to further investigation and analysis as soon as we acquire the first date after the new measures have been implemented.

The described methods (cluster analysis based on the genetic algorithm and subsequently correlation analysis) can be used not just for sophisticated problems in economics, operation research, etc. but also with a success in connection with assessment of credit rating agencies. Each method has its pros/cons. The first limitation of described methods is the sensitivity to the lack of information (input data). Described clustering is based on genetic algorithm then the second limitation is the choice of a number of a population which depends on experiences of a user.

Conclusions

External rating assessments by rating agencies have been getting increasingly regulated in recent years. One of the new measures implemented by the regulators is the so-called rotation of rating agencies. The aim is to increase the credibility of rating assessments. It is necessary to know whether before the implementation of this measure, the assessments of rating agencies were mutually independent. In this article, this dependency has been examined using cluster and consequently correlation analysis. As a case study, the rating evaluation of Greece and Spain was selected due to their importance to the European economy. This rating assessment of Greece and Spain was done by Standard & Poor's, Moody's and Fitch. Thanks to the cluster and correlation analysis, it was discovered that the assessment from different rating agencies are mutually dependent. This finding is confirmed by the findings of other studies. It's open to question whether the implementation of the rotation of agencies measure will contribute to the stabilization of financial markets or their destabilization.

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Jaroslav KREJČÍŘ. Ph.D. student at the Department of Economics, Faculty of Business and Management, Brno University of Technology. Research interest: macroeconomics.

Petr DOSTÁL. Professor at the Department of Informatics, Faculty of Business and Management, Brno University of Technology. Research interest: soft computing and artificial intelligence such as fuzzy logic, artificial neural networks, evolutionary algorithms, and the theory of chaos in business and public services.

Karel DOUBRAVSKÝ. Assistant professor at the Department of Informatics, Faculty of Business and Management, Brno University of Technology. Research interest: statistical analysis, data mining, decision analysis and fuzzy modelling.