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Analysis of Collective Behavior of Iran Banking Sector by Random Matrix Theory

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Abstract

Banked based financial sector of Iran leads us to focus on the banking industry and its components. One of the important aspects of this industry is its coupling structure. In this paper, we have analyzed the collective behavior of Iran banking sector by Random Matrix Approach (RMT). This technique is useful for splitting the information part of the correlation matrix from the random region. This research confirms good compliance with random matrix predictions. By removing the market mode of the system the average of the banking cross-correlation matrix changes. Then, by calculation of the participation ratio, node participation ratio and relative participation ratios of these banks, it is shown that the collective behavior of the system is so fragile. Also, by applying local and global perturbations on the banking sector, it is shown that this system is very sensitive to the global perturbation and the mean value of cross-correlations decreases rapidly that means some banks have crucial effects in the market.

Keywords: Iran banking sector, Random Matrix Theory, Collective Behavior, Perturbation

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Introduction

Many research shows the complexity of financial markets (Johnson et al, 2003; Stanley & Mantegna, 2000; Albert; Jeong & Barab_asi,2000; Namaki et al, 2019)

One of the most important characteristics of these complex systems is their collective behavior. This importance stems from the interactions and dependencies of their components. So, the analysis of these systems without considering their collective behavior doesn’t have good and complete outcomes (Mobarhan et al, 2016). The banking sector is one of the most important complex financial sectors of any countries. In Iran, historically this importance gets more attention. So, this matter leads us to analyze the behavior of this industry and the collective behavior of its components.

There are different methods for analyzing the collective behavior of complex systems (Li; Xu & He, 2016; Peron & Rodrigues, 2011). One of the best approaches for this purpose is the Random Matrix Theory (RMT). RMT was introduced and advanced by nuclear physicists to explain the energy levels of complex quantum systems (Wigner, 1951).

Using random matrix theory in finance goes back to 20-years ago. Potters et al used this theory and concluded that the largest eigenvalue of the correlation matrix is the representative of the market mode of the system (Bouchaud & Potters, 2000; Plerou et al, 1999; Mantegna & Stanley, 1999).

Plerou et al analyzed the stock market by random matrix theory (Plerou et al, 1999; Plerou et al, 2001). They computed the cross-correlation matrix of real data and compared the eigenvalues of this matrix with the eigenvalues of the random matrix. They concluded that most of the eigenvalues of the correlation matrix are in the bulk region of the random matrix, which is predictable by the RMT, and the others are not predictable by it.

Some of the researches have shown that eigenvectors corresponding to the eigenvalues outside the bulk region have specific and large deviations from the random matrix estimations (Plerou et al, 1999; Plerou et al,2002).

Also, the idea of Inverse Participation Ratio (IPR) has been presented for showing the importance of different components of the correlation matrix (Lim et al, 2009; Guhr, 1998). Some researchers have presented the notion of the largest eigenvalue of the coupling matrix as the market mode of the system (Lim et al, 2009; Laloux et al, 1999; Utsugi and Oshikawa, 2004; Plerou et al, 1999).

Namaki et.al have been used RMT for analyzing Tehran Stock Exchange (Namaki; Raei and Jafari, 2011). They have been analyzed cross-correlation of the stock market by RMT for comparing Tehran Price Index (TEPIX), as an emerging market versus the US market, as a mature one. They found most of the eigenvalues of cross-correlation are in the bulk region of random matrix and the largest eigenvalue has a systematic deviation from RMT prediction, which has a common effect on the whole market that be named market-wide effect. They found that the mean value of the distribution of cross-correlation coefficients under perturbation for Dow Jones Industrial Average, as a mature market is more vulnerable than Tehran stock exchange (TSE), as an emerging market.

Saeedian et.al (saeedian et al, 2019), have investigated 40 world stock markets with the highest GDP in the world. They have compared the collective behavior of this global market with the random matrix theory. They have concluded that the markets are highly correlated, and have a high degree of collective behavior. Lim et al (Lim et al, 2009) studied the effect of two types of perturbations on stocks. They have presented two types of local and global perturbations to find out the market reaction to them. In their research, they have emphasized that the local perturbation is a technical study and does not apply to real-world modeling, but global perturbation has a profound effect on the correlation matrix.

The goal of this paper is to study of the collective behavior of 21 banks of Iran stock market, then analyzing the reaction of this behavior to removing of the market effect, and finally measuring the robustness of these banks under local and global perturbations. The data of this study is composed of a price of 21 active banks in the market from March 2016 to March 2019.

In this paper, after the introduction, the models are explicated, then the results are shown and finally, we have presented the discussion and conclusions.

Methods

1. Cross-correlation matrix

If $P_i(t)$ is the price of i_{th} asset at time t that we have held for the periodΔt, Return (R_t) is defined as follows:

$$R(t) = \ln P_i(t + \Delta t) - \ln P_i(t) \tag{1}$$

In this paper, we consider the Δt is one day and the daily prices of each stock are collected.

Since these stocks have different volatilities, we use normalized returns. $r_i(t)$ defined as follows.

$$r_i(t) = \frac{(R_i(t) - \langle R_i \rangle)}{\sigma_i} \tag{2}$$

In Eq. (2), σ_i is the standard deviation of the R_i, and $\langle ... \rangle$ denotes a time average over the period studied. The cross-correlation coefficient is defined as follows:

$$C_{ij} = \langle r_i(t) r_j(t) \rangle \tag{3}$$

Because the correlation matrix is symmetric, C_{ij} and C_{ji} are equal. The correlation coefficients are in the range of [-1,1].

1.1. Shuffled cross-correlation matrix

In any correlation matrix if off-diagonal elements are zero, it means that all elements of the market are independent of each other, but if they are non-zero, can be concluded that market elements are correlated with each other. In the shuffled correlation matrix (C_{sh}), with the random displacement of the off-diagonal elements of the correlation matrix, we eliminate any non-random correlation between the off-diagonal elements of the correlation matrix. That is the elimination of the collective mode of the market. Even though the correlation between the elements of the correlation matrix remains (Saeedian, 2019; Podobnik, 2010; Jamali, 2015).

2. Random matrix theory (RMT) and correlation matrix

The random matrix theory is applied based on the statistical properties of the eigenvalues and eigenvectors. By comparing the eigenvalues of the real correlation matrix and the random one, it has been seen that the most of the real matrix eigenvalues fall in the area of random matrix eigenvalues, which is called the bulk region. The bulk region represents the noise in the systems and the eigenvalues outside of that region are identified as information (Gopikrishnan, 1999; Saeedian, 2019; Laloux, 1999).

2.1. Inverse Participation ratio

Inverse Participation ratio is presented to measure the degree of collective behavior in the market. This ratio was first presented by Bell and Dean (Bell and Dean, 1970) in the field of nuclear physics and by some scholars (Guhr, 1998; Plerou, 2002) was entered to finance. The Inverse participation ratio is defined as follows.

$$P_k \equiv (\sum_{l=1}^{N} [u_k\,(l)]^4)^{-1} \tag{4}$$

Where u_k is eigenvector of k_{th} eigenvalue. $u_k(l)$, $l = 1, \dots, N$ are the components of u_k.

For the eigenvector, the value of PR is limited from above to N (number of stocks examined) and from below to units. Therefore, it can be concluded that the value of PR depends on N. Therefore, RPR has to eliminate the market size dependency and make it normalized?

2.2. Relative Participation Ratio

As mentioned above, the value of PR is depended to the size of the market. To normalize the value of PR, we define the Relative Participation Ratio (δ) as follows:

$$\delta = \frac{< P_{sh} > - < P >}{< P_{sh} >} \tag{5}$$

Where $< P >$ and $< P_{sh} >$ represent the average of PRs for all the eigenvectors of C and C_{sh} respectively.

When δ is close to 0, the collective behavior between the matrix components is weak, and vice versa, when this parameter gets distance from 0, the collective behavior between the components are more strong (Saeedian, 2019).

2.3. Node Participation Ratio

To determine the strength of each component of the market in the creation of collective behavior, node participation ratio is used, which is as follows:

$$N_l \equiv (\sum_{k=1}^{N} [u_k (l)]^4)^{-1} \quad (6)$$

N_l shows share of the lth market component in the collective behavior of the market. NPR reflects the independency of the stock from the market. Whatever NPR for the l_{th} stock is lower, that stock is more independent than the market, and vice versa (Saeedian, 2019).

3. Perturbing a correlation matrix

As mentioned, two types of perturbations are applied for the correlation matrices. Perturbation destroys some features of the correlation matrix, such as genuine correlations between companies. Each of which is described separately. First, the local perturbation is as follows (Lim, 2009):

1. Produce the Gaussian time series (white noise series) with the same length of the return series and then, we calculate their cross-correlations.

2.Randomly select one of the off-diagonal elements of the cross-correlation matrix, for example, C_{ij}.

3.Substitute the correlation obtained in step 1 instead of the element selected in step 2.

Because the correlation matrix is symmetric, the cross-correlation obtained from step 1 is embedded in both C_{ij} and C_{ji}. As mentioned global perturbation has a stronger and more inclusive effect than the local one (Lim, 2009). This perturbation is as follows:

1.Produce the Gaussian time series (white noise series) with the same length of return series.

2.Select an off-diagonal component of the cross-correlation matrix, for example, C_{ij}.

3.Find stock i and j in the return matrix.

4.Place two Gaussian-distributed time series in the return matrix in column i and j.

5.From the modified return matrix, recalculate the new cross-correlation matrix.

Steps 4 and 5 create a global perturbation that is related to the pair of stocks selected in Step 2.

In the steps described above, we selected an off-diagonal member of the correlation matrix randomly. To further organization of the perturbation actions, we define the following two methods for selecting cross-correlations:

1.Top-ranked method: The largest correlations are selected at first and then the smaller ones are selected.

2.Bottom-ranked method: The smallest correlations are selected at first and then the larger ones are selected.

The important point is that the local perturbation only perturbs the two selected stocks, but the effect of global perturbation is pervasive and affects the entirety of the cross-correlation matrix.

Results

The purpose of the methods presented in this study is to compare the collective behavior of banks in Iran capital market, also we have investigated the impact of removing the holistic effect on the market. Finally, we have measured the robustness of these banks to the perturbation. For have a better view, we can see in fig. (1) Color images of correlation matrix C. As expected, the correlation of these banks is weak. But one of the interesting thing about this matrix is the negative cross-correlation of some of the banks, which is not a common behavior in the other world markets.

In fig. (2), by comparing the distribution of correlation coefficients of random matrix and real matrix C, it is obvious that the majority of these real coefficients conform with the random one. We can conclude that most statistical features of cross-correlation C follow the random matrix properties.

In fig. (3), we can see the eigenvalues of the correlation matrix. It is obvious, one of the eigenvalues is outside the bulk region that is the representative of the information part of matrix or Market wide-effect.

In fig. (4), we remove the market-wide effect from C .It is seen that removing the market-wide effect just changes the average of PDF of correlation coefficients to some extent.

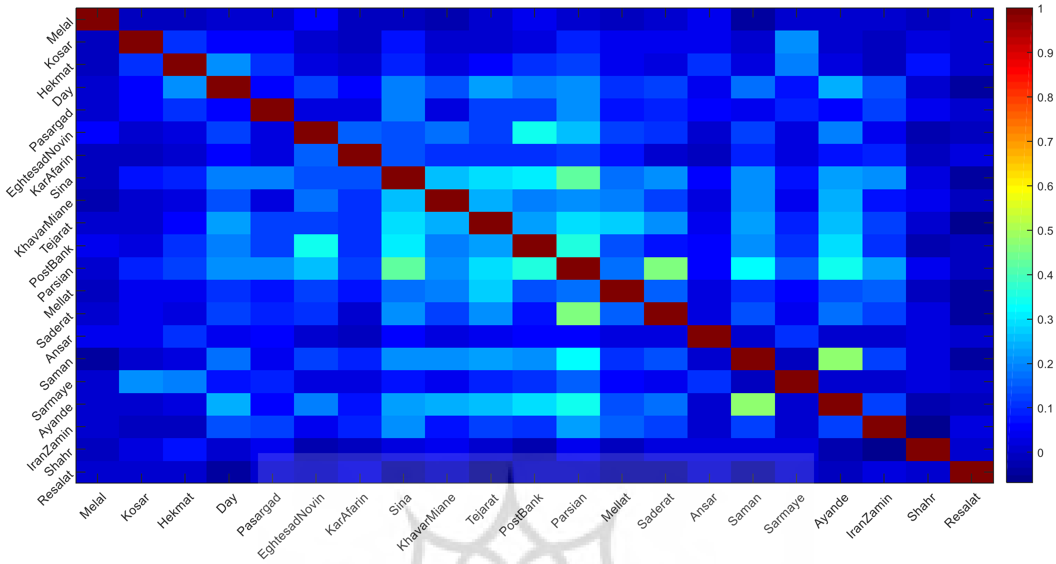

Figure 1. Color image of the cross-correlation matrix.

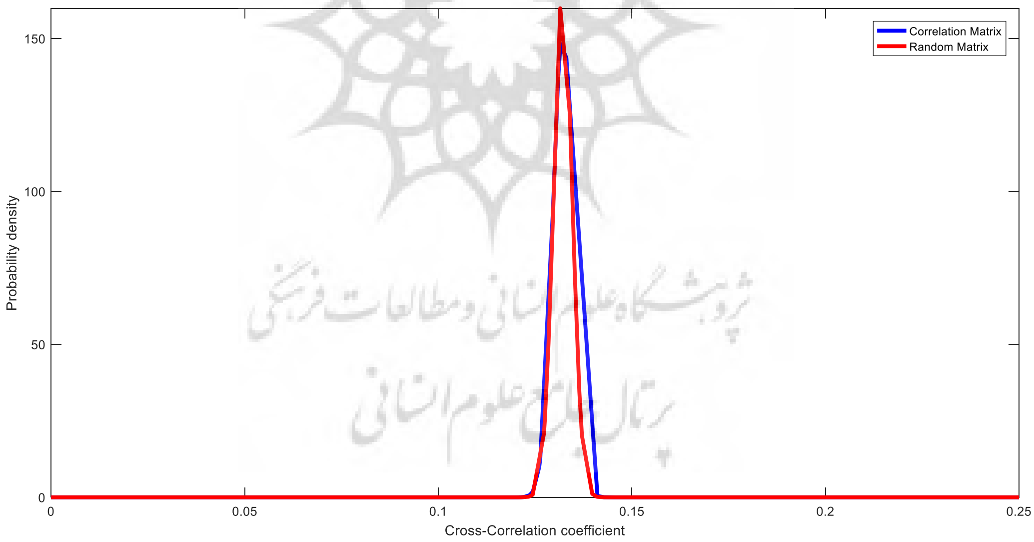

Figure 2. comparing the distribution of correlation coefficients of random matrix and real matrix for active banks in TSE.

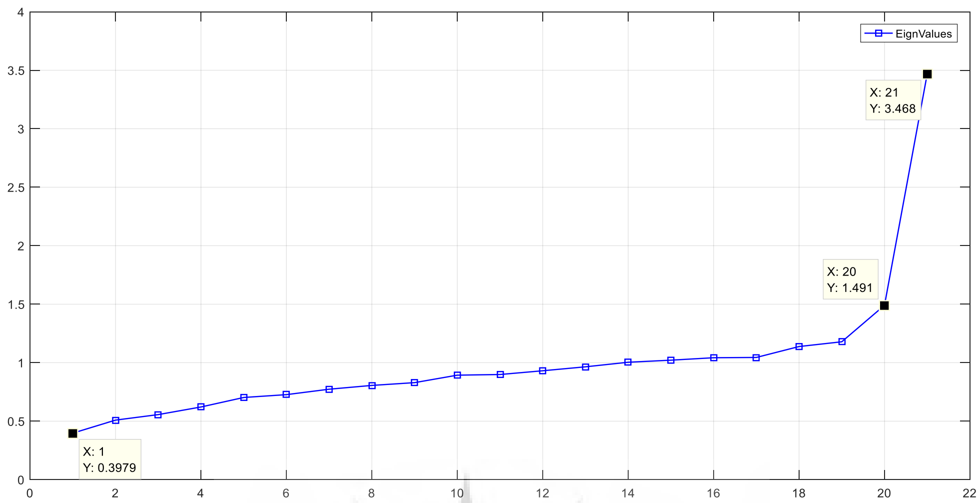

Figure 3. The eigenvalues of the correlation matrix are shown. That is obvious that the largest eigenvalue is 2.5 times of the previous eigenvalue, indicating that this eigenvalue contains market information.

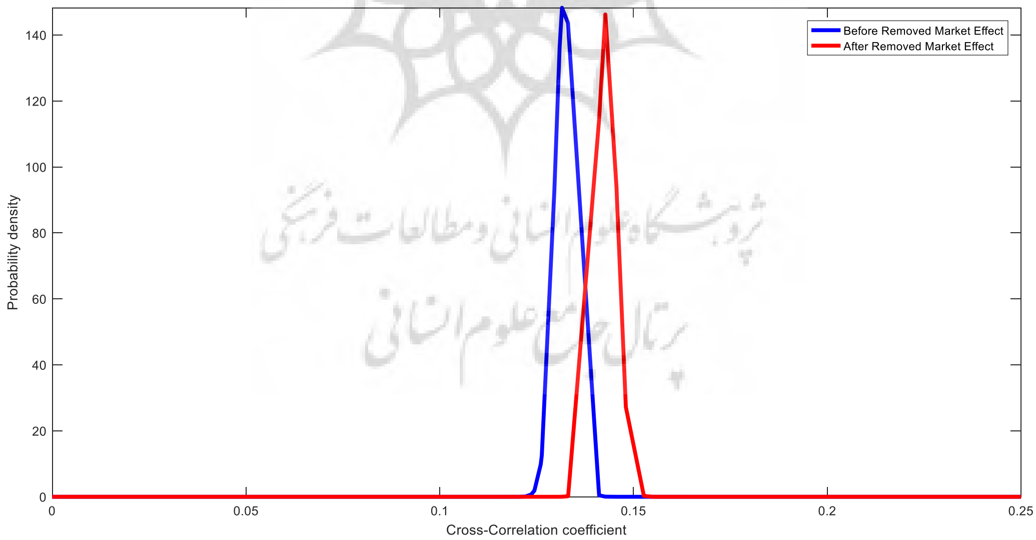

Figure 4. This figure shows that by removing the market-wide effect, only the average of market cross-correlation matrix changes.

In fig. (5), we present PR and PR_{sh} and it can be seen that since these indices behave so similar to each other, the collective mode of the market is not very strong. Also, the RPR (δ) in this study is 0.29 that is near zero and indicates a weak degree of collective behavior (Saeedian, 2019).

Fig (6) shows the share of each bank in the collective behavior by using Eq. (6) and we measure the contribution of each bank to the collective behavior. In fig. (6) Banks with lower NPR are more independent than the general trend of the market and conversely, banks with higher NPR depend on the other banks. As it can be seen the E. Novin has the most NPR and Ansar Bank has the lowest NPR.

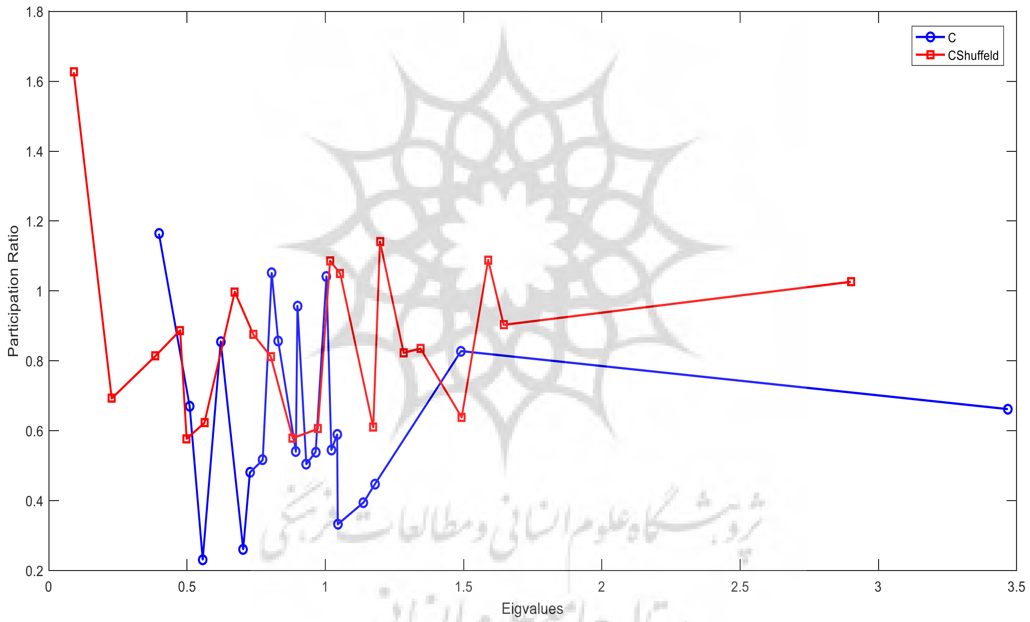

Figure 5. Comparison of PR for the correlation matrix and shuffled one. Whatever the difference between them is lower, the collective behavior of the market is weaker.

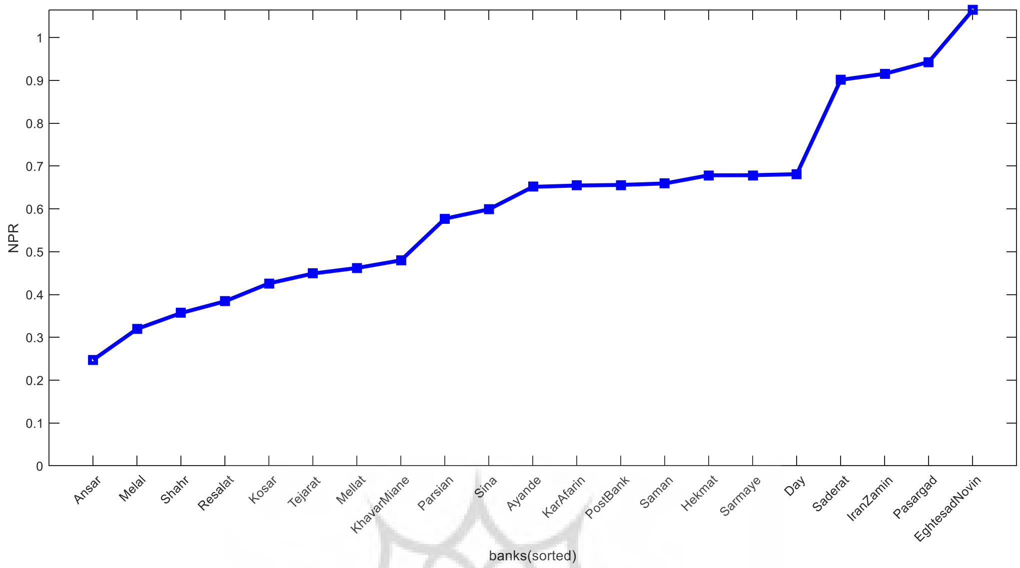

Figure 6. NPR of banks has been shown. It can be seen E. Novin bank has the most NPR and the Ansar bank has the lowest NPR.

The other methods used in this study for analyzing the stability of the banking system are local and global perturbations. In fig. (7) global and local perturbations are applied to C and at each stage the number of perturbed correlation coefficients increases. Namaki et.al have shown the global perturbation has a greater effect on the mean values of C than the local perturbation. Because in global perturbation, the correlation of each component in the matrix C is replaced by Gaussian time series, so effect on the whole market while in the local ones, only the relations between the two components are replaced by a coefficient generated by the Gaussian time series (Namaki et al, 2011).

As mentioned in the section (2.3) there are two methods top-ranked and bottom-ranked to make the perturbation. In the fig. (8) The two methods of global perturbations are compared which shows, they are not significantly different from each other in TSE.

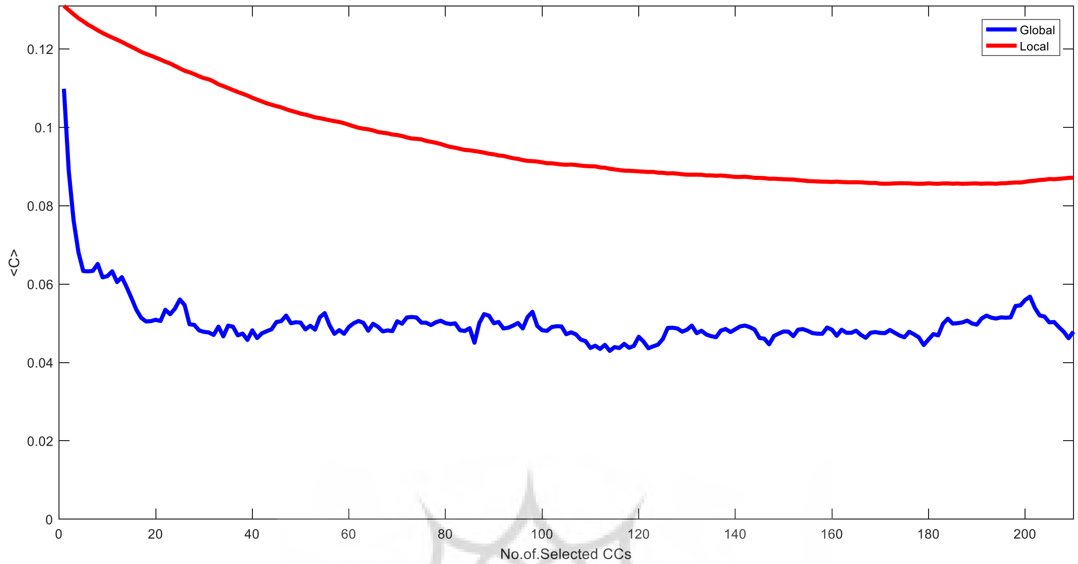

Figure 7. Comparison of mean values of cross-correlation matrix perturbed by local and global perturbations. The X-axis shows the number of correlation coefficients selected to be perturbed. As the number of perturbed correlation coefficients increases, the mean values of the correlation coefficients decreases.

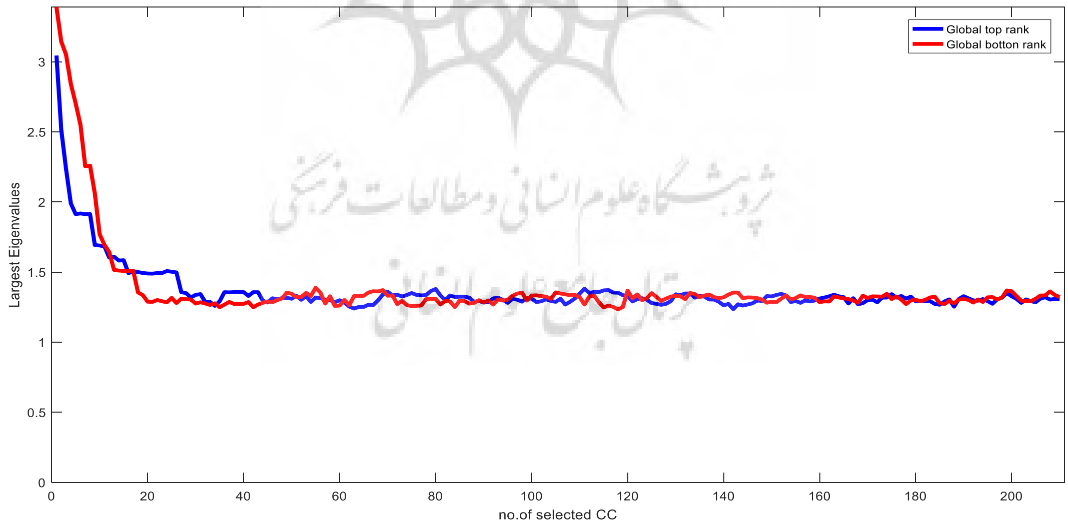

Figure 8. Comparison of the largest eigenvalues with global perturbation using Top-Ranked and Bottom Ranked methods.

After these findings, we will present dendrogram and heat maps in fig. (9) and fig. (10). both are derived from the clustering algorithm (Cattell, 1943). Banks are clustered in Ward's method (Ward, 1963). This dendrogram is a two-dimensional graph in which the Y-axis shows the degree of Similarity of the components to each other and the X-axis shows the degree of dissimilarity of the components to each other. In this case, there are two main clusters that the distance between them is high. So we conclude that the banking sector in TSE is composed of two completely separate clusters, each of them is correlated in its own cluster and the weak correlation with the other cluster is obvious. In fig. (10) Heat map has been shown. Color bar represents a range of correlation coefficient. Banks with higher cross-correlation have warmer colors and vice versa.

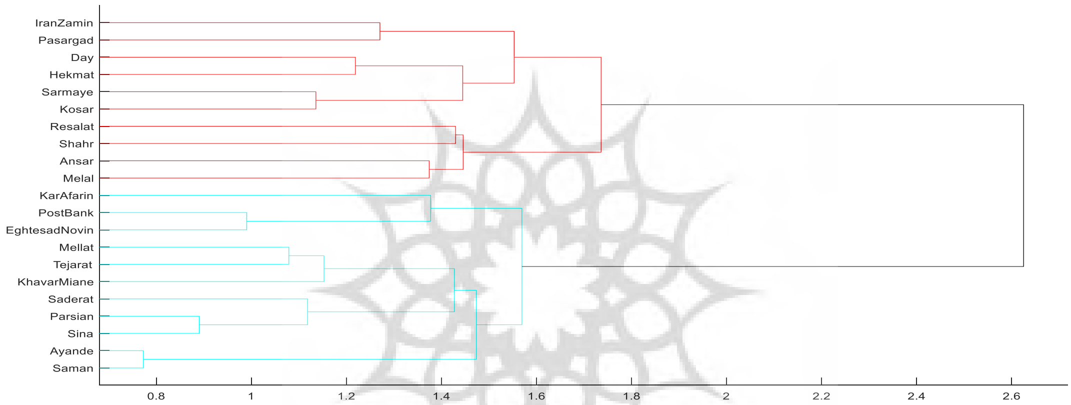

Figure 9. Comparison of Bank Clusters by Dendrogram. The high distance between clusters indicates the weak correlation between the main clusters of the banks.

Figure 10. Heat maps of banks clustered by ward method and shows that Ayande and Saman bank has the strongest correlation which is also approved in the dendrogram.

Conclusion

In this paper, we have studied the collective behavior of Iran banking sector via Random Matrix Theory (RMT). By using this technique, it is found that a large portion of the eigenvalues of the correlation matrix conforms to the random matrix. As mentioned, the largest eigenvalue of the correlation matrix has a common effect on the whole market and by removing this effect from the banking sector, only a little change in the mean value of the distribution of the correlation matrix occurs that confirms the degree of weak collective behavior of this market. By using the Participation Ratio (PR), we check the collective behavior of this system and we have concluded that the banking network doesn’t have a strong collective behavior. Also, it is obvious that the E. Novin bank has the most and Ansar bank has the least NPR. By perturbing the network, it is seen that the mean of correlation coefficients decreases to half of the initial values very fast and after that, it continues in a steady state. This technique is useful for analyzing different networks based on various characteristics.

References

Wigner, E. P. (1951, October). On the statistical distribution of the widths and spacings of nuclear resonance levels. In *Mathematical Proceedings of the Cambridge Philosophical Society* (Vol. 47, No. 4, pp. 790-798). Cambridge University Press.

N. F. Johnson, P. Je_eries, P. M. Hui, et al., Financial market complexity, OUP Catalogue (2003).

Stanley, H. E., & Mantegna, R. N. (2000). *An introduction to econophysics*. Cambridge University Press, Cambridge.

A. Namaki, A. Shirazi, R. Raei, G. Jafari, Network analysis of a financial market based on genuine correlation and threshold method, Physica A: Statistical Mechanics and its Applications 390 (21-22) (2011) 3835-3841.

Albert, R., Jeong, H., & Barabási, A. L. (2000). Error and attack tolerance of complex networks. *nature*, *406*(6794), 378-382.

Bouchaud, J. P., & Potters, M. (2000). *Theory of financial risks* (Vol. 4). From Statistical Physics to Risk Management: Cambridge University Press, Cambridge.

Namaki, A., Raei, R., & Jafari, G. R. (2011). Comparing Tehran stock exchange as an emerging market with a mature market by random matrix approach. *International Journal of Modern Physics C, 22*(04), 371-383.

Namaki, A., Jafari, G. R., & Raei, R. (2011). Comparing the structure of an emerging market with a mature one under global perturbation. *Physica A: Statistical Mechanics and its Applications*, *390*(17), 3020-3025.

Namaki, A., Raei, R., Asadi, N., & Hajihasani, A. (2019). Analysis of Iran Banking Sector by Multi-Layer Approach. *Iranian Journal of Finance*, *3*(1), 73-89.

Li, S., Xu, T., & He, J. (2016). Determination of collective behavior of the financial market. *SpringerPlus*, *5*(1), 1-9.

Peron, T. D. M., & Rodrigues, F. A. (2011). Collective behavior in financial markets. *EPL (Europhysics Letters)*, *96*(4), 48004.

Plerou, V., Gopikrishnan, P., Rosenow, B., Amaral, L. A. N., & Stanley, H. E. (1999). Universal and nonuniversal properties of cross-correlations in financial time series. *Physical review letters*, *83*(7), 1471.

Plerou, V., Gopikrishnan, P., Rosenow, B., Amaral, L. A. N., & Stanley, H. E. (2001). Collective behavior of stock price movements—a random matrix theory approach. *Physica A: Statistical Mechanics and its Applications*, *299*(1-2), 175-180.

Lim, G., Kim, S., Kim, J., Kim, P., Kang, Y., Park, S., ... & Kim, K. (2009). Structure of a financial cross-correlation matrix under attack. *Physica A: Statistical Mechanics and its Applications*, *388*(18), 3851-3858.

Laloux, L., Cizeau, P., Bouchaud, J. P., & Potters, M. (1999). Noise dressing of financial correlation matrices. *Physical review letters*, *83*(7), 1467.

Utsugi, A., Ino, K., & Oshikawa, M. (2004). Random matrix theory analysis of cross-correlations in financial markets. *Physical Review E*, *70*(2), 026110.

Plerou, V., Gopikrishnan, P., Amaral, L. A. N., Meyer, M., & Stanley, H. E. (1999). Scaling of the distribution of price fluctuations of individual companies. *Physical review e*, *60*(6), 6519.

Mobarhan, N. S., Saeedi, A., Roodposhti, F. R., & Jafari, G. R. (2016). Network trending; leadership, followership and neutrality among companies: A random matrix approach. *Physica A: Statistical Mechanics and its Applications*, *462*, 858-863.

Mantegna, R. N., & Stanley, H. E. (1999). *Introduction to econophysics: correlations and complexity in finance*. Cambridge university press.

Mehta, M. L. (2004). Random matrices, volume 142 of Pure and Applied Mathematics.

Guhr, T., Müller–Groeling, A., & Weidenmüller, H. A. (1998). Random-matrix theories in quantum physics: common concepts. *Physics Reports*, *299*(4-6), 189-425.

Saeedian, M., Jamali, T., Kamali, M. Z., Bayani, H., Yasseri, T., & Jafari, G. R. (2019). The emergence of the world-stock-market network. *Physica A: Statistical Mechanics and its Applications*, *526*, 120792.

Podobnik, B., Wang, D., Horvatic, D., Grosse, I., & Stanley, H. E. (2010). Time-lag cross-correlations in collective phenomena. *EPL (Europhysics Letters)*, *90*(6), 68001.

Jamali, T., & Jafari, G. R. (2015). Spectra of empirical autocorrelation matrices: A random-matrix-theory–inspired perspective. *EPL (Europhysics Letters)*, *111*(1), 10001.

Gopikrishnan, P., Plerou, V., Amaral, L. A. N., Meyer, M., & Stanley, H. E. (1999). Scaling of the distribution of fluctuations of financial market indices. *Physical Review E*, *60*(5), 5305.

Bell, R. J., & Dean, P. (1970). Atomic vibrations in vitreous silica. *Discussions of the Faraday Society*, *50*, 55-61.

Plerou, V., Gopikrishnan, P., Rosenow, B., Amaral, L. A. N., Guhr, T., & Stanley, H. E. (2002). Random matrix approach to cross-correlations in financial data. *Physical Review E*, *65*(6), 066126.

Pan, R. K., & Sinha, S. (2007). Collective behavior of stock price movements in an emerging market. *Physical Review E*, *76*(4), 046116.

Cattell, R. B. (1943). The description of personality: Basic traits resolved into clusters. *The journal of abnormal and social psychology*, *38*(4), 476.

Ward Jr, J. H. (1963). Hierarchical grouping to optimize an objective function. *Journal of the American statistical association*, *58*(301), 236-244.

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