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VISUAL CORRELATION ANALYSIS OF FINANCIAL TIME SERIES

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Abstract. *The massive amount of financial time series data that originates from the stock markets generates huge quantity of complex data that is of interest to a large number of market participants. In order to gain a comprehensive understanding of the market mechanism investors require adequate solutions that can effectively handle the information. In this paper the concept of a minimum spanning tree (MST) is used to study patterns of comovements for a set of stocks from the South-East European emerging markets. It is presented how the MST and its related hierarchical tree evolve over time and describe the development of securities linkages. Over the sample period, 2007–2014, linkages between securities have changed, especially during the period of global financial crisis, what can have significant implications for investment decision-making.*

Key words: *correlation, minimum spanning tree, financial time series, emerging markets*

INTRODUCTION

Financial markets can be considered as complex systems characterized by a large number of elements correlated in a way that is difficult to identify and quantify. However, it is this correlation between the system elements that has a central role in investment theory and risk management, as it stands for a key factor in financial asset pricing and optimization of investment decisions. Efficient market hypothesis, as the most important paradigm of mathematical finance, rejects the possibility of predicting the price of securities. Specifically, financial time series, according to this theory, can be described by random process, so that it is impossible to predict their future values, because information from the financial market is instantly, fully, and continually reflected in the current prices of securities. In such conditions, prices and returns on financial assets can be considered uncorrelated. If, however, there are certain economic factors that can affect these values, then they exert impact on several financial instruments at the same time. The fact is,

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however, that financial markets are not perfectly efficient and that they exhibit numerous anomalies. Therefore, it can be concluded that the time series of financial asset prices carry a large amount of non-redundant information from which it is necessary to single out just that, which, through its specific impact, makes the market inefficient. The modeling of complex features of financial markets and various types of non-linear relations within it has recently used tools and procedures developed for the modeling of physical systems. Graphic presentation and analysis of financial markets is considered to be extremely useful, because of an intuitive way of showing the correlation structure of different securities and the possibility of identification of key factors, i.e. market segments.

Standard analysis of financial issues in econophysics is largely based on the minimum spanning tree. Minimum spanning trees are networks of nodes, which are connected with at least one edge, without a loop, in such a way that the sum of all edges is minimal. The application of this method in the graphic presentation of complex networks, such as financial markets, and the filtering of information about correlation between nodes was initiated by Mantegna [15]. Due to their simplicity, minimum spanning trees are today used in the study and presentation of the financial structure, such as the structure of financial markets [2, 17], currency markets [7], and the correlation of financial markets themselves [22, 3, 16].

Taking into account the possibility of portfolio diversification by investing in emerging capital markets [12, 8], as well as the participation of foreign investors in trading on markets in the region, this paper analyzes the correlation of securities traded on Belgrade, Zagreb, Ljubljana, and Skopje stock exchanges. The aim of the paper is to use methods of visualization to discover complex correlation between securities on these stock exchanges and point to their hierarchical clustering, as well as to analyze the impact of crisis on correlation of returns on securities analyzed. Therefore, this paper will first point to the complexity of financial time series, as an important characteristic that conditions the implementation of multidimensional models, and the second part of the paper will present the minimum spanning tree, as one of the network techniques for the analysis of financial data and extracting of information necessary for decision-making. In the third part of the paper, this specific technique will be applied to the selected sample of stocks, followed by the presentation of the correlation structure, on the basis of which the final part of the paper will provide appropriate conclusion and guidelines for the formation of investment strategies on markets in the region.

1. MULTIDIMENSIONAL ANALYSIS AND DATA MINING FRAMEWORK FOR FINANCIAL TIME SERIES ANALYSIS

Huge quantity of complex data that is generated on the financial markets is of interest to a large number of market participants. Analysis of financial market information attracted particular public attention in the years of the global financial crisis of 2007-2008, as well as during the European debt crisis of 2010, when a large number of financial instruments lost significant value [14]. Given that the effects of the shocks on the stock exchange are transmitted through international financial markets [6] and increasingly affect the global economy [10], the methods for managing information in the monitoring and analysis of financial markets are becoming essential for a large number of stakeholders, especially investors. However, the analysis and understanding of the relations on the financial market requires the processing of huge amounts of data, which is becoming increasingly challenging, taking into account that in periods of intense trading on financial markets every second generates 50,000 new pieces of data on changes in financial asset prices [29]. One can, therefore, conclude that the processing of data collected over longer time intervals goes beyond the analysts' capabilities, while the mathematical and statistical models are less and less reliable basis for timely investment decision-making. Visualization methods commonly used as an analysis tool, such as a line graph with a time axis and a price axis, cannot be used to display a large number of time series because they are not transparent [24]. The complexity of financial data, accompanied by investors' aspiration to receive information constantly, timely, and in easily accessible and visually acceptable manner caused the emergence of multi-dimensional data models and sophisticated visualization techniques. Business intelligence systems, with OLAP (Online Analytic Processing) tools, analytical techniques, data warehouses and data visualization, are good source of information in modern business, including investment decision-making. Business Analytics covers a range of applications and techniques for collecting, storing, analyzing data and providing access to data, to help users bring adequate and timely decisions. All the tools and techniques can be classified into several categories: information and knowledge discovering, decision support and intelligent systems and visualization. Business analytics tools and techniques include reporting (formatted reports to a wide range of users), *ad hoc* query and analysis, statistical analysis and data mining [27]. OLAP is a set of activities performed by users of business intelligence systems. These activities include generating queries and their results, graphics, statistical analysis, multidimensional analysis and data visualization. OLAP tools enable discovering of knowledge hidden in existing data, discovering patterns and trends in the historical data, predicting future events and values based on current trends, discovering deviations from the trends and their relation to sudden turbulent movements and so on [23].

Several technologies are used for analyzing financial and accounting data stored in a data warehouse, among which the most frequent is OLAP technology. OLAP multidimensional model, along with specific aggregation techniques, ensures the organization of large data series, which allows an easy and prompt interpretation [26]. It uses data structures, called cubes, which are organized in multidimensional databases. The process of defining the structure of cubes is called multidimensional modeling.

Data cube is a multidimensional model that provides a new approach to the organization of data. The number of dimensions may be 3 as in the regular cube as shown in Figure 1, or greater depending on the particular problem and data [28]. Financial time series data can be presented by data cube whose edges are defined as dimensions of the data, and each cell in the cube is identified by specific values of each dimension. The basic architecture of the dimensional model is the star schema (see Fig. 1). Star schema contains two types of tables – fact table and dimension tables.

Data cube Stocks is formed, with each cell representing a combination of values from dimensions. The contents of each cell are measures: stock prices and continuously compounded returns. Data in dimensions are organized in hierarchies with different levels of aggregation. Stock dimension has levels: All sectors, Sector and Stock. Regions dimension has levels: All regions, Region and Country. Time dimension has levels: year, quarter, month and day. Data cube was created using Oracle Analytic Work Space Manager over Oracle 12c database [30].

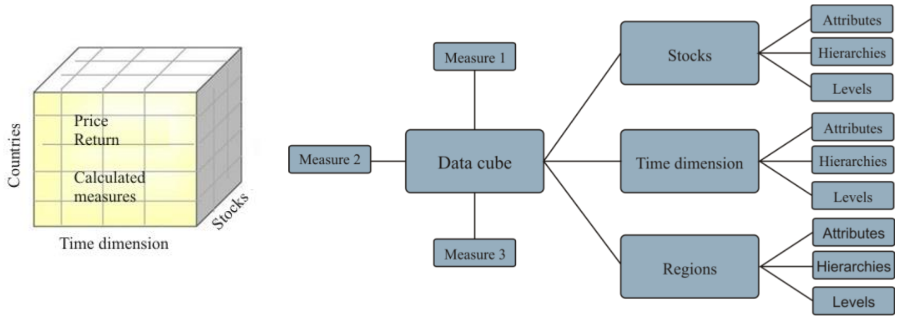

Fig. 1 Data Cube and Multidimensional Data Model

Data cube Stocks consists of data on the securities of the South-East European emerging stock markets. Stocks stand for the most liquid securities on the analyzed markets, and most of them are components of the Stoxx Balkan 50 Equity Weight index basket. In this paper the following stocks are analyzed:

- From the Belgrade Stock Exchange AIKB (AIK banka a.d. Beograd), ALFA (Alfa plam a.d. Vranje), ENHL (Energoprojekt holding a.d. Beograd), KMBN (Komercijalna banka a.d. Beograd) from the financial sector, and AERO (Aerdorom Nikola Tesla a.d. Beograd), FITO (Galenika Fitoframacija a.d. Zemun), GMON (Goša montaža a.d. Velika Plana), IMLK (Imlek a.d. Beograd), JESV (Jedinstvo a.d. Sevojno), MTLC (Metalac a.d. Gornji Milanovac), SJPT (Sojaprotein a.d. Bečej) from the non-financial sector,
- From the Zagreb Stock Exchange ADRIS (Adris grupa d.d.), HRTELEKOM (Hrvatski telekom d.d.), INA (INA-industrija nafte d.d.), LEDO (Ledo d.d.), PODRAVKA (Podravka prehrambena industrija d.d.) from the non-financial sector,
- From the Ljubljana Stock Exchange GORENJE (Gorenje d.d. Velenje), KRKA (Krka d.d. Novo Mesto), MERCATOR (Mercator d.d. Ljubljana), PETROL (Petrol d.d. Ljubljana), TELEKOMSI (Telekom Slovenije d.d. Ljubljana) from the non-financial sector, and
- From the Skopje Stock Exchange KMBMK (Komercijalna banka a.d. Skopje) from the financial sector, and ALKALOID (Alkaloid a.d. Skopje), GRANIT (Granit a.d. Skopje), PETROLMK (Makpetrol a.d. Skopje), TELMK (Makednosnki Telekom a.d. Skopje) from the non-financial sector.

The data period is 8 years long – from January 2007 until the end of December 2014.

2. Capital Market Visualization Using Minimum Spanning Tree Network

The widely used approach to analyses is describing the structure of a market by constructing Minimum Spanning Tree. This graph shows the interconnection among the securities, detecting clusters and mutual relationships in a financial market. The process starts with finding a matrix based on the Pearson correlation coefficient between each pair of time series of stock returns. The correlation matrix is than transformed into the distance matrix using the following formula [15]

$$d_{i,j} = \sqrt{2(1-\rho_{i,j})} \tag{1}$$

where $\rho_{i,j}$ is correlation coefficient between returns on stocks i and j respectively.

These distances are then used for constructing a network that connects the individual stocks based on the levels of correlation.

Let G = (V, E) be a connected, undirected graph with a set of nodes V (stocks) and a set of edges E (distances between nodes). Each edge $e \in E$ has non-negative length $\ell(e)$, i.e. the function set is $\ell : E \rightarrow R+$ for the length or weight of the edges.

What needs to be found is a subset T of edges of graph G so that all nodes from V remain connected when edges of T are used and the sum of the lengths of the edges in T is minimum in all such sets T. It is easy to see that the subgraph (V, T) of graph G is the tree, i.e. the connected non-cyclic graph. This graph is called the minimum spanning tree (MST) of the graph G. For the solution to this problem, two greedy algorithms can be used – Prim's and Kruskal's algorithms.

Greedy algorithms usually have a simple form and are used to solve optimization problems, such as discovering MST, discovering the shortest path in a graph, or discovering the sequence of some operations. The abstract formulation of optimization problems contains standard characteristic elements, with the following meaning:

- Set C of all possible (available or allowable) candidates – e.g. edges of the graph.
- Function that checks whether a particular set S of the selected candidates is a solution to the problem, i.e. whether a set of edges is a link between two selected nodes of the graph.
- Objective function that gives the value to any solution to the problem. This is the function to be optimized (minimized or maximized) – e.g. total length of the spanning tree or the length of path between two nodes.

Solving the optimization problem is the search for a set of candidates that represents the solution to the problem and optimizes the value of the objective function. The initial assumption is that the underlying problem has at least one solution, i.e. that there is a subset $S \subseteq C$, which is the solution to the problem.

In the case of MST, candidates are edges of the graph, i.e. C = E. S set of the selected edges is the solution to the problem if the edges of S make the spanning tree of G, i.e. connect all the nodes of V. The S set of edges is allowed if it does not have cyclic connection. Depending on the algorithm used, there is or there is no limitation that the set will give the tree for V, i.e. that (V, S) is a connected graph. The problem solution might be a tree, or an unconnected graph – spanning forest with several connected components (trees), which are not interconnected.

The main difference between the various greedy algorithms for solving problems in MST is in the method of choice of edges to be added. Prim's algorithm builds a tree that grows, while Kruskal's algorithm greedily makes a forest that gradually merges into a tree. Both algorithms are careful not to make a cyclic graph by adding nodes.

Prim's algorithm - The authors of this algorithm are Prim in 1957 [19] and Dijkstra in 1959 [4], although it was later discovered that Jarnik in 1930 formulated a similar procedure.

The algorithm starts from any node – the root of the tree. At the beginning, the set W has a single edge, with any node as an element, and the set T is empty. At each step, the existing tree (W, T) increases, adding to a set T a new edge that touches W, and adding to a set W another node of that edge, which was not in W. In this way, there is a tree that grows until it connects all the nodes in V.

Function of choice in Prim's algorithm has the following form – at each step, for the current tree (W, T), function of choice selects the shortest edge e = {u, v}, such that $u \in$

V \ W and v ∈ W, i.e. node u belongs to the current tree, and node v is the unclassified node from the set of all nodes W. Algorithm adds node into a set W, and edge {u, v} into a set T. At any time, edges in set T make a minimum spanning tree of a graph. The algorithm continues until all nodes are connected, or until the sets W and V are equalized.

Prim’s algorithm performs well, i.e. for the connected, undirected graph G with the cost function ℓ, the algorithm returns a set of edges T, so that (V, T) is the minimum spanning tree of graph G. The algorithm in the loop runs exactly |V| - 1 times, because, at each iteration, one node is added to set W.

For a graph G, there can be several minimum spanning trees. This is due to the possibility that, at some point, there may be more edges e of minimum length ℓ(e), attached to the current set of nodes W.

Kruskal’s algorithm - This algorithm was formulated by Kruskal in 1956 [13]. As with Prim’s algorithm, in the set of edges T, MST of graph G is created. The difference is that every iteration uses the whole set of graph nodes. At the beginning, the set of edges is empty and all nodes are unconnected, and then, at each step, an edge with the smallest length is added. Prior to the algorithm, all the edges are sorted by weight (cost) in ascending order, and at each next step, the shortest remaining edge is chosen, taking care not to make a cyclic edge. In this way, the subgraph is formed, comprising a number of nodes, and may not be connected.

The difference in relation to Prim’s algorithm is that here the next edge is added without checking whether nodes of this edge touch some of the already connected nodes. So, the basic difference is in the choice of the edge to be added at each step. Prim’s algorithm always starts from the already connected nodes (at the beginning from the arbitrary node). All the edges that touch the already connected nodes are checked, and the edge with the lowest weight added. When the edge is selected, the node belonging to that edge is added.

In Kruskal’s algorithm, at each step, edge with the lowest weight is added, regardless of whether its nodes are already connected, thus forming a forest – of mutually unconnected trees. It can be concluded that Prim’s algorithm starts from nodes, while Kruskal’s algorithm is based on the edges of a minimum weight (cost). The condition for the implementation of Prim’s algorithm is that the graph is connected.

The choice of the algorithm depends on the characteristics of the graph, number of vertices and edges. Prim's algorithm is significantly faster in the case of a really dense graph with many more edges than vertices. Kruskal performs better in typical situations (sparse graphs) because it uses simpler data structures.

In this paper Prim’s algorithm is used, where the creation of the tree relied on the use of *spantree* function from R package “vegan” [18]. After creating MST, dendrograms were created based on the calculation of the distance between all nodes using *cophenetic* function from the same package and clustering.

Since data for the analysis is in the data cube Oracle R Enterprise was used for creating MST and dendrograms. Oracle R Enterprise integrates R with Oracle Database, enabling execution of R commands and scripts for statistical and graphical analyses on data stored in Oracle Database. Using Oracle R Enterprise to prepare and analyze data in an Oracle Database instance has many advantages for an R user. Some of the advantages are: eliminating data movement, operating on database-resident data, keeping data secure, using the memory and processing power of the database, using current data, preparing data in the database and execution of R Scripts in the database.

3. Results of Correlation Analysis of Emerging Financial Markets

Effects of diversification of portfolio investment generated on emerging markets have been pointed out as the most important feature of financial globalization during the nineteen-nineties [1]. Emerging markets, as a special group of capital markets, were for the first time defined in 1981 by the World Bank, in order to form the Third World Equity Fund. Given the fact that there was no single definition of these markets, the basic criterion for classification was GDP per capita. Today, however, classification of capital markets based on the development level cannot be linked to economic indicators. Emerging markets and frontier markets, which have since emerged as a subgroup of emerging markets, are usually considered separately from the developed markets due to the political environment and their specifics – depth and width, regulatory and institutional infrastructure. These new capital markets in transition countries in Europe, South America, Asia, Middle East, and Africa offered investors unusually high returns, compared to developed markets, and a lower level of volatility [9]. The main differences between the developed and frontier markets, which can be characteristic of the analyzed capital markets, are reflected in: level of information efficiency, investor basis, homogeneity of assets, liquidity of stocks, and type of investors interested in these markets. Specific functioning of these markets prevented the establishment of relationships with other world markets, protecting them from the impact of global developments. However, connections between the financial markets caused the spillover of crisis to emerging markets and to different types of financial assets [5]. In this way, the emerging markets during the financial crisis 2007-2008 lost 50% of market capitalization, while frontier markets lost 60% [21]. In Europe, this financial crisis turned into a sovereign debt crisis in several countries, which did not pass unnoticed on emerging markets, although debt crisis spillover can use various channels, so that the research results are different [11, 25]. Therefore, in this paper, the time series of returns on stocks from emerging financial markets were divided into three periods: pre-crisis period, which includes trading in 2007, period during the crisis – from 2008 to the end of 2010, and period after the crisis – from 2011 until the end of 2014.

Based on the statistical characteristics (Table 1), it can be concluded that the probability distribution of correlation coefficients in all the observed periods deviates from normal distribution. The mean value of the correlation coefficient in all three periods under consideration does not change significantly and retains a relatively low value. Standard deviation also has similar values in the entire observation period. However, the maximum values of the correlation coefficient in the period before, during, and after the crisis amounted to 0.38, 0.65, and 0.33, respectively. The values of skewness and kurtosis are lower in the crisis period, indicating that the probability distribution curve is wider during the crisis, but it can be concluded that, among the stocks analyzed, negative correlation prevails.

Table 1 Statistical properties of the distribution of cross-correlation coefficients before, during, and after the crisis.

Period	Mean cross-correlation	Standard deviation	Skewness	Kurtosis
Before	0.10619	0.26774	2.84353	6.77291
During	0.18690	0.27178	1.96439	3.32018
After	0.10151	0.26048	3.02269	7.69843

Source: authors' calculation

Looking at the minimum spanning tree graph in the period before the crisis (Fig. 2), regardless of the fact that this period covers only one year, it can be concluded that there are several centers – stocks, around which returns on other stocks gravitate. The largest number of stocks (6) is related to the ALKALOID and PETROLMK, as well as to SJPT and MERCATOR (5). All hubs belong to the non-financial sector, as well as the largest number of stocks that gravitate towards them. Distance values between returns on the stocks analyzed are in the range from 1.11 to 1.48, and stocks can be grouped into several clusters.

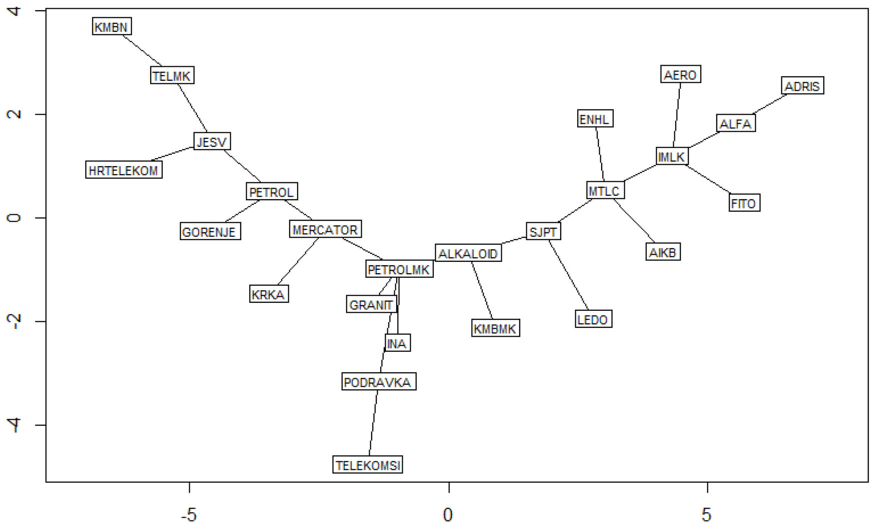

Fig. 2 Minimum spanning tree before the crisis for 25 stocks from emerging markets

At the level of distance between 1.3 and 1.35 it is possible to divide the tree into 11 clusters, but two large groups of stocks are being observed (Fig. 3). The remaining stocks do not form clear clusters. The first cluster consists mainly of the stocks from the Serbian capital market, while the second cluster contains the Slovenian and Macedonian stocks. The stocks from the Croatian capital market do not form a clearly visible cluster.

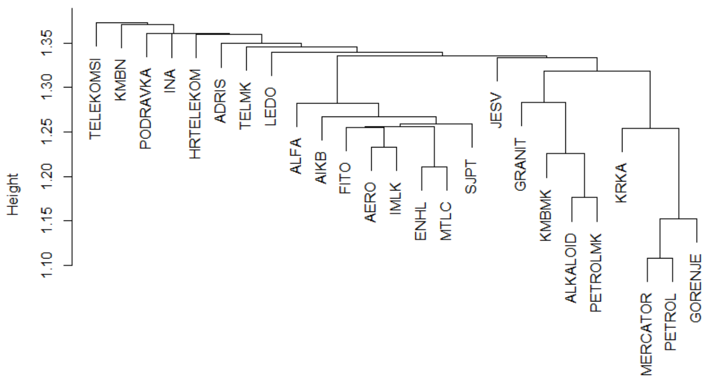

Fig. 3 Hierarchical tree of 25 stocks from emerging markets before the crisis

The crisis period is characterized by concentration of stocks around three hubs, as follows: AIKB (5), SJPT (4), and FITO (4) (Fig. 4). These stocks are traded on the Belgrade Stock Exchange and belong to different sectors: issuer of stocks AIKB belongs to the financial sector, while issuers of stocks SJPT and FITO belong to the non-financial sector (manufacturing industry sector). To AIKB, as a central hub, SJPT and FITO gravitate, as well as stocks from the financial sector of other stock exchanges, so it cannot be argued that the hierarchical structure is determined by sector. During the crisis, there is a more pronounced positive correlation between returns on the observed stocks, with regard to the fact that the distance value ranges from 0.84 to 1.50.

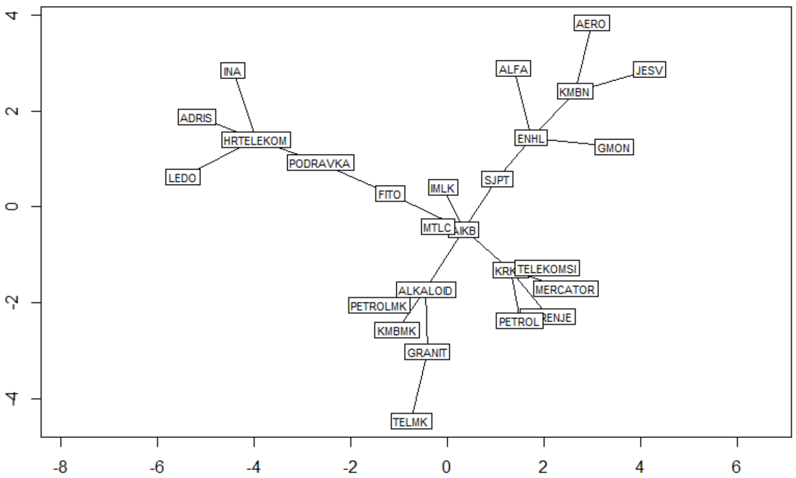

Fig. 4 Minimum spanning tree during the crisis for 26 stocks from emerging markets

The height of dendrogram indicates that the distances between the clusters are lower comparing to the pre-crisis period, as in the period after the crisis (Fig. 5 and 7), but also that there is a greater range of distances between the clusters (around 0.7) during the crisis period in contrast to the period before and after the crisis (about 0.3). During the crisis the most similar group is the group of Slovenian stocks (TELEKOM, KRKA, MERKATOR, PETROL, GORENJE), which is followed by a cluster of Serbian stocks (ENHL, SJPT, AIKB, KMBN) and a cluster of Macedonian stocks (ALKALOID, PETROLMK, GRANIT and KMBMK). A cluster of the Croatian stocks (INA, HRTELEKOM, ADRIS, LEDO, PODRAVKA) can be observed, but the distance within the cluster significantly differs from the previous clusters of stocks. At the level of just over 1.3 it is possible to divide the tree and get the three clusters, and, if GMON is excluded from analysis, two clusters. In the hierarchical structure under this term, one cluster consists of the stocks from Zagreb stock exchange and a second cluster of the remaining stocks.

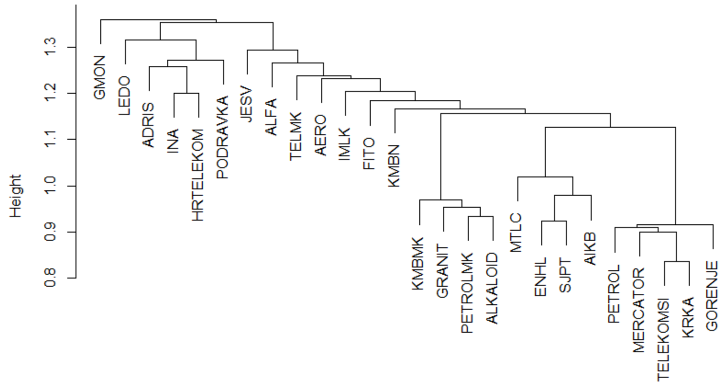

Fig. 5 Hierarchical tree of 26 stocks from emerging markets during the crisis

In post-crisis period, financial institutions retain the role of central hubs (Fig. 6). The biggest hubs are AIKB and KMBN (5), followed by NTLC, ENHL, and KRKA (4). Both stocks whose issuers belong to financial sector and stocks whose issuers belong to non-financial sector gravitate to these centers. The hierarchical structure is less dispersed, and distance values are in the range from 1.16 to 1.48, based on which one can conclude that the correlation of returns in the period after the crisis is largely negative.

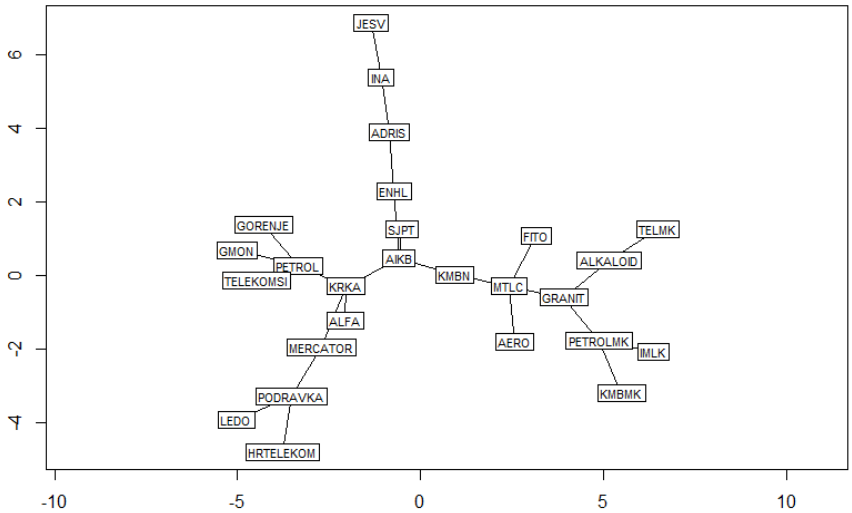

Fig. 6 Minimum spanning tree after the crisis for 26 stocks from emerging markets

The height of the hierarchical tree is similar to the dendrogram before the crisis (Fig. 7). In the period after the crisis, with the exception of the cluster consisting of the Slovenian stocks (TELEKOM, KRKA, MERKATOR, PETROL, GORENJE), there are no clearly visible clusters.

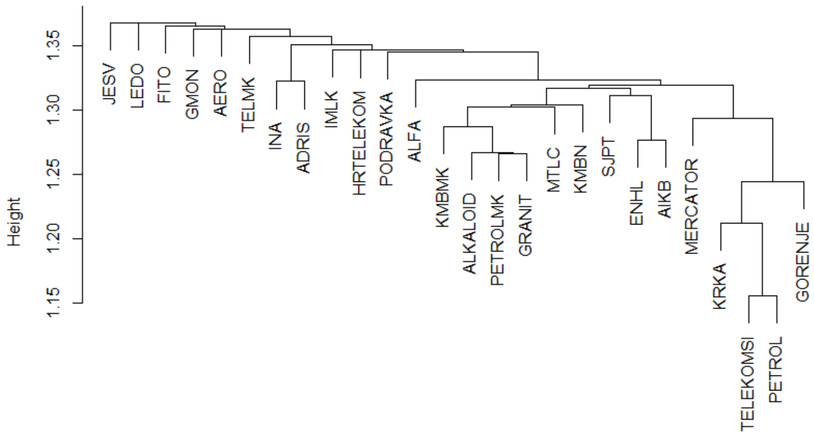

Fig. 7 Hierarchical tree of 26 stocks from emerging markets after the crisis

CONCLUSION

The massive amount of financial time series data that originates from the stock markets is of interest to a large number of market participants. The complexity of financial data, accompanied by investors' aspiration to receive information constantly, timely, and in easily accessible and visually acceptable manner caused the emergence of multi-dimensional data models and sophisticated visualization techniques. Business intelligence systems, with OLAP tools, analytical techniques, data warehouses and data visualization, are good sources of information in modern business, including investment decision-making. The widely used approach to analyses is describing the structure of a market by constructing MST, which represents the interconnection among the securities, enables detecting clusters and mutual relationships in a financial market.

Considering possible diversification effects of investing in emerging markets, correlation structure of the stocks from the four South-East European emerging markets using MST method is presented in this paper. Although the observed markets are located in the same geographic region, during the periods without shocks on the capital markets, selected stocks do not reflect significant correlation. However, in the period of the global financial crisis markets show certain interdependence, especially on the movement of the returns in financial sector. In terms of investment decision-making these results can provide useful insights as to which stocks could be included in a portfolio to improve its performance. Since the main objective of investors is to diversify the portfolio, selecting stocks that are in different clusters (far away from each other) would be beneficial. This analysis is especially relevant in crisis periods, when investors prefer to have a well-diversified portfolio.

Since the characteristics of emerging markets are reflected in numerous anomalies, such as information inefficiency, homogeneity of assets and illiquidity of stocks, several directions for the future research can be observed. The analyzed technique should be modified in order to adjust to the distribution of the continuously compounded returns, which is usually not Gaussian. On the other hand, the non-linear correlations between financial time series can be observed using different correlation measures, such as the Spearman's rank correlation and the Kendall tau correlation. Observing the correlation with developed stock market and causal relationship will enable investors to discover key markets that drive trading and spillovers.

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VIZUELNA KORELACIONA ANALIZA FINANSIJSKIH VREMENSKIH SERIJA

Obiman broj podataka u finansijskim vremenskim serijama sa tržišta kapitala generiše ogromnu količinu kompleksnih podataka koji su od interesa za veliki broj učesnika na tržištu. Da bi na sveobuhvatan način razumeli tržišni mehanizam, investitori zahtevaju adekvatna rešenja kojima mogu efikasno manipulisati podacima. U ovom radu korišćen je koncept minimalnog obuhvatnog stabla (MOS) u cilju otkrivanja obrazaca promene korelacija u skupu akcija sa novonastalih tržišta jugoistočne Evrope. Pokazan je način na koji MOS i odgovarajuće hijerarjisko stablo evoluiraju tokom vremena i opisuju razvoj međuzavisnosti između akcija sa posmatranih tržišta. Tokom perioda posmatranja, 2007-2014, veze između akcija su se menjale, posebno u periodu globalne finansijske krize, što može imati značajne implikacije na donošenje investicionih odluka.

Ključne reči: *korelacija, minimalno obuhvatno stablo, finansijske vremenske serije, novonastala tržišta*