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Correlation study of the Athens Stock Exchange

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Abstract

We study the year-after-year properties of three different portfolios traded in the Athens Stock Exchange (ASE) for the time period 1987–2004. We use the minimum spanning tree (MST) technique and the random matrix theory (RMT), which make it possible to examine at the same time the temporal evolution of the portfolios and of the market as a whole. The first four moments of the distribution of correlations and the normalized tree lengths of the MST show a similar behaviour for all three portfolios. However, by studying topological properties of the MST, such as the node degree k, we are able to identify changes to the MST associated to each portfolio that are due to a crisis in the market, like the one that happened during the period 1999–2001. We also see that, while the effect of the market to the information content of the correlation matrix for all three portfolios is almost the same, the market is affected differently by different economic sectors at different time periods.

Keywords: Econophysics; Emerging market; Minimum spanning tree; Random matrix theory

1. Introduction

There has been an increased interest recently in applying techniques that are well known in physics to the study of financial and economic time series [1,2]. The fact that financial markets behave as a complex system with huge amounts of available data has resulted in bringing in new approaches developed in physics during the past decades such as, network structures and characterizations, which help us towards our understanding of the dynamics of economic systems, and give rise to econophysics. The study of correlations in the parameters of a system is of great importance for a variety of physical phenomena. The calculation or the explicit measurement of a correlation function can provide a wealth of information, for example, about the structure of the system. Similarly the study of correlations between different stocks, based on analyzing the properties of their correlation matrix, regarding the fluctuations in their price, is of considerable importance for understanding the behaviour of financial markets.

For these reasons there is much recent empirical and theoretical work focused on how to extract and use this information by applying a variety of methods [4–9,14–21]. But while most of this work concerns the US and other mature markets, there is little published work about emerging markets or new markets in general.

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In this paper we use two different approaches, the minimum spanning tree (MST) technique and the random matrix theory (RMT), to analyse the correlation matrix of the Athens Stock Exchange (ASE) for the time period 1987–2004. We chose to study this specific market because it experienced a booming situation, starting from a relatively low activity of the 1980s, following the general global rise of the 1990s, and eventually joining the European Monetary System in the early 2000s. Thus the ASE has characteristics in several different phases, and it is interesting to see if the current findings agree with the behaviour of other mature markets. Additionally, the 17-year period we study also includes the critical bear market of the period 1999–2001 which gives us the opportunity to check what changes happens to the market during such periods.

For better interpretation of our results we use three different portfolios. The first one consists of the 26 stocks that have been traded without interruption in the ASE during the period 1987–2004. The second portfolio consists of 26 stocks that are randomly chosen each year, and the third portfolio consists of all stocks that were traded in the ASE each year, and therefore, their number is not constant.

The paper is organized as follows: in Section 2 we present our data set in more detail and we discuss some specific aspects about the Greek stock market, in Section 3 we discuss the methods that we use to create the correlation matrix and extract information from it, in Section 4 we present our results obtained from the analysis of the data set, and in Section 5 we draw our conclusions.

2. Data

For the present study we use daily closing prices of stocks traded at the ASE for the years 1987–2004. During these years the Greek stock market evolved rapidly. This evolution, of course, emerged through different phases that in general were a reflection of the evolution of the Greek economy. Starting with the first year of the data set the number of stocks changed dramatically, with new stocks entering the market every year, while several stocks that failed fulfilling the economic criteria for trading in the ASE were removed. Therefore, the total number of stocks each year varies from 49 stocks in the year 1987 to 320 stocks in the year 2004.

The stocks traded in the ASE are classified according to their economic activity in 10 different economic sectors. Those economic sectors are reported in Table 1, following the classification found in the www.ase.gr.

3. Methodology

In this section we describe the methodology that we use for the treatment of the data. Recent empirical and theoretical analyses have shown that useful economic information can be detected in a correlation matrix using a variety of methods [1,2,4–9,14–21]. In this paper we use two different approaches, one based on the MST technique [4–9,20,21], and one based on RMT [14–20]. For a complete review on these methods see also Coronnello et al. [20].

Table 1
The economic sectors of activity for the stocks traded at the ASE

	Sector
1	Primary sector
2	Financial services
3	Commerce
4	Hotel—restaurant services
5	Transport—communication services
6	Health—public care services
7	I.T.—real estate—commerce services
8	General services
9	Manufacturing
10	Constructions

The classification that we use here is the same classification that is provided by the ASE in the web-page www.ase.gr.

Let $P_i(t)$ be the daily closing price of stock i at day t. A similarity measure between the synchronous time evolution of a pair of stocks, i and j, is given by the correlation coefficient that is defined as

$$\rho_{ij} = \frac{\langle r_i r_j \rangle - \langle r_i \rangle \langle r_j \rangle}{\sqrt{(\langle r_i^2 \rangle - \langle r_i \rangle^2)(\langle r_j^2 \rangle - \langle r_j \rangle^2)}}, \tag{1}$$

where $\langle \ldots \rangle$ means a time average over the investigated time period. Here r_i is the logarithmic return defined by $r_i = \ln P_i(t) - \ln P_i(t - \Delta t)$. If two stocks, i and j, are completely correlated (anti-correlated) then $\rho_{ij} = +1(-1)$, while if the two stocks are completely uncorrelated then $\rho_{ij} = 0$. In our case $\Delta t = 1$ day. The correlation coefficients between all pairs of stocks form a $n \times n$ symmetric matrix, the correlation matrix **C**. We will describe now the basic aspects of these two different methods, widely used in the literature to extract meaningful information from a correlation matrix.

3.1. The MST analysis

This method was used first to extract taxonomy information from economic data by Mantegna [4]. It is based on the idea that the correlation coefficient between a pair of stocks can be transformed to a distance between them by using an appropriate function as a metric. An appropriate function for this transformation is

$$d_{ij} = \sqrt{2(1 - \rho_{ij})}, \quad 0 \leqslant d_{ij} \leqslant 2, \tag{2}$$

where small values of the distance d_{ij} imply strong correlation for the pair of stocks, i and j, and vice versa. Applying this function to all elements of the correlation matrix **C** we transform it to a distance matrix, **D**. This distance matrix is used to create the MST by using an easy to implement algorithm [3].

The MST is a simply connected graph that links all n stocks with $(n - 1)$ edges in such a way that the sum of all stock distances is the minimum. This measure is very useful in identifying clustering of stocks that belong to the same economic sector. The MST for the ASE is shown in Fig. 1 for 176 stocks for the year 1997. The use of MST as a filtering technique reduces drastically the information space, from the $n(n - 1)/2$ correlation elements originally contained in the correlation matrix to the $(n - 1)$ tree edges.

Since the MST uses the elements of the correlation matrix to create a network, it was shown by Bonanno et al. [6] that this network can be characterized by its topological properties, such as the node degree distribution k_i, where k_i is the number of the nodes that are connected directly to node i. Onnela et al. [8,9] analysed some dynamical properties of the MST, such as the normalized tree length, the single step survival ratio, and the multi-step survival ratio, using a portfolio of 447 stocks traded at the NYSE from 1980 to 1999.

The normalized tree length, defined as

$$L(t) = \frac{1}{n - 1} \sum_{d_{ij} \in D} d_{ij}^t, \tag{3}$$

where t denotes the time when the tree is constructed, $(n - 1)$ is the number of edges of the tree, and d_{ij} the distance elements present on the distance matrix **D**.

The single step survival ratio of tree edges is defined as

$$\sigma(t) = \frac{1}{n - 1} |E(t) \cap E(t - 1)|, \tag{4}$$

where $E(t)$ is the set of edges of the MST at time t , $\cap$ is the intersection operator and $| \ldots |$ gives the number of elements in the set.

Accordingly, the multi-step survival ratio at time t is defined as

$$\sigma(t, k) = \frac{1}{n - 1} |E(t) \cap E(t - 1) \cap \ldots E(t - k + 1) \cap E(t - k)|, \tag{5}$$

where only the edges that are constantly present on the tree after k time steps survive.

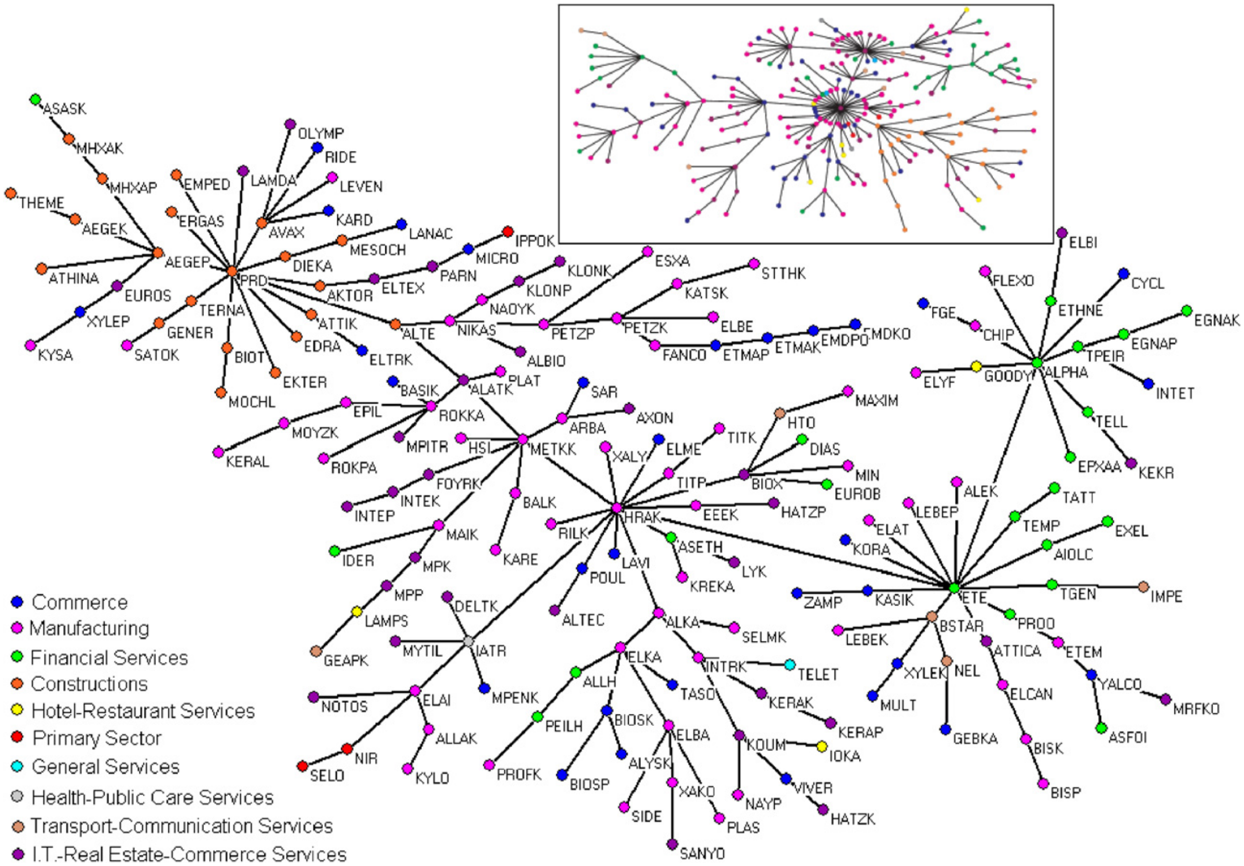

Fig. 1. Minimum spanning tree (MST) obtained by considering the daily logarithmic return time series of all stocks traded in the Greek stock market (Athens Stock Exchange, ASE) in year 1997. The different colours represent the different sectors of economic activity. The existence of stocks that behave as hubs, having more connections than the average, is evident. Inset: MST obtained using all stocks traded in ASE for the year 2000, which is in the middle of the 1999–2001 crisis period.

3.2. Random matrix theory

RMT is a tool that was originally developed and used in nuclear physics by Wigner, Dyson, Mehta, and others [10–13] in order to explain the statistics of the energy levels of complex quantum systems. Recently, it has also been applied to studies of economic data [14–20]. RMT is very useful in financial applications because it allows us to compute the effect of uncertainty in the estimation of the correlation matrix and, therefore, it can be applied very effectively in portfolio management [15,18,19].

Let us suppose that we have a portfolio of n stocks that are described by n time series of T time records and that the returns of these stocks are independent Gaussian random variables with zero mean and variance σ^2. The correlation matrix of this set of variables in the limit $T \to \infty$ is simply the identity matrix. RMT allows us to prove that in the limit $T, n \to \infty$, with a fixed ratio $Q = (T/n) \geqslant 1$, the eigenvalue spectral density of the covariance matrix is given by

$$\rho(\lambda) = \frac{Q}{2\pi\sigma^2\lambda}\sqrt{(\lambda_{\max} - \lambda)(\lambda - \lambda_{\min})}, \tag{6}$$

where $\lambda_{\min}^{\max} = \sigma^2(1 + 1/Q \pm 2\sqrt{1/Q})$. The spectral density is different from zero in the interval $\lambda_{\min} \leqslant \lambda \leqslant \lambda_{\max}$. In the case we are dealing with a correlation matrix, we have $\sigma^2 = 1$. The application of RMT in the investigation of financial correlation matrices leads to the immediate observation that the largest eigenvalue is totally incompatible with Eq. (6), and the corresponding eigenvector is the "market" itself.

When we use the term "market" we refer to the average behaviour of all stocks traded at the Athens Stock Exchange, which is exemplified by the behaviour of the general index. Therefore, the eigenvector corresponding to the largest eigenvalue describes the common behaviour of all stocks comprising the portfolio being investigated.

The fact that the largest eigenvalue is totally inconsistent with the "pure noise" hypothesis of the RMT leads to the assumption that the components of the correlation matrix that is orthogonal to the eigenvector corresponding to the first eigenvalue is pure noise. This hypothesis allows us to subtract the contribution of the first eigenvalue λ_1 from the nominal value $\sigma^2 = 1$ so we can compute new boundary values $\tilde{\lambda}_{\min}$ and $\tilde{\lambda}_{\max}$ by using the new value $\tilde{\sigma}^2 = 1 - \lambda_1/n$ in Eq. (6).

Using the above technique we find that more eigenvalues fall outside the interval $\tilde{\lambda}_{\min} \leqslant \lambda \leqslant \tilde{\lambda}_{\max}$ that is given by the random matrix formalism and, therefore, these eigenvalues may also be used to extract useful economic information stored in the correlation matrix. The remaining large number of eigenvalues is inside the interval between $\tilde{\lambda}_{\min}$ and $\tilde{\lambda}_{\max}$, and thus one cannot conclude whether any information is contained in the corresponding eigenspace.

A method suggesting the way to extract information about the economic sectors that is stored in the eigenvectors of the correlation matrix, proposed in Ref. [17], is the following: we first compute the correlation matrix and afterwards we remove the effect of the largest eigenvalue. We then calculate the spectrum ranking the eigenvalues, such that $\lambda_k > \lambda_{k+1}$. The eigenvector corresponding to λ_k is denoted as $\boldsymbol{u}^k$. The set of investigated stocks is partitioned in S sectors, $s = 1, 2, \ldots, S$ according to their economic activity. We then use a $S \times n$ projection matrix $\boldsymbol{P}$ with elements

$$P_{si} = \begin{cases} \frac{1}{n_s} & \text{if stock } i \text{ belongs to sector } s, \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

Here n_s is the number of stocks belonging to sector s. For each deviating eigenvector $\boldsymbol{u}^k$ we compute

$$X_s^k = \sum_{i=1}^{n} P_{si}[u_i^k]^2. \tag{8}$$

This number gives a measure of the contribution of a given sector s into the composition of eigenvector $\boldsymbol{u}^k$. Thus, when a given eigenvector has a large value of X_s^k for only one (or few) sector s, one can say that the eigenvector is attributed to that specific economic sector.

4. Characteristics and evolution of the ASE

In this section we apply the previously described methodology to the ASE data, in order to investigate the properties and evolution of the Greek stock market. We use data spanning the time period 1987–2004. In Figs. 1 and 2 we show the MST and the associated hierarchical tree obtained for all stocks traded at the ASE the year 1997 for illustrative purposes. We choose this specific year because it is close to the middle of the data set. The number of stocks traded that year was 176, which is an adequate number to produce a meaningful picture of the tree structure of the market.

By examining the hierarchical tree figure we can see that the correlation in the market is significant and there is some evident clustering of stocks belonging to the same economic sector (shown with the same colour). A well-formed cluster is that of stocks belonging to the construction economic sector (orange). This observation is, of course, confirmed also by the MST, but by examining the topology of MST we can get even more information about the market. For example, we can clearly see that there are some stocks behaving as hubs, having many more links than the average node. We can also see that almost all stocks belonging to the financial sector (green) are directly connected either to the stock of the National Bank of Greece (ETE) or to the stock of Alpha Bank (ALPHA). These are the two largest banks in Greece, and their stock result in two of the most connected hubs of the network.

From the MSTs in Fig. 1 an interesting observation is given by the comparison between the MST of a normal trading period and the MST of a crisis period. That is, during crisis periods we can identify some star-

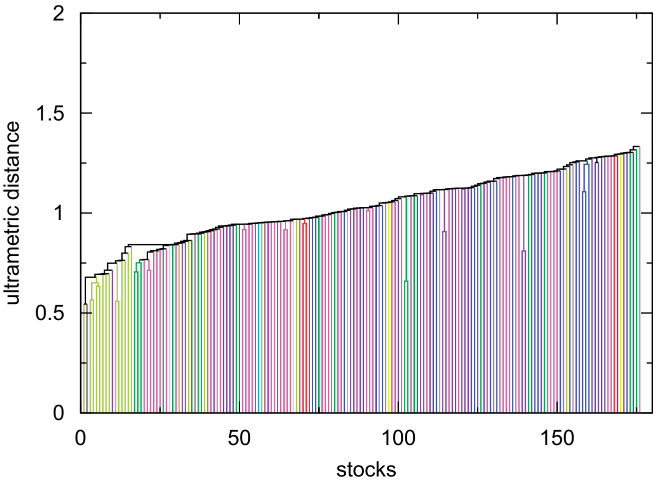

Fig. 2. Hierarchical tree associated to the MST of Fig. 1, obtained by considering the daily logarithmic return time series of all stocks traded in the Greek stock market in year 1997. The different colours represent the different sectors of economic activity.

like topologies of stocks having a very large number of connections. This behaviour is absent or not so pronounced in the trees that were created using years with normal trading activity.

In order to capture the evolution of the market in more detail we study the behaviour of three different portfolios year-after-year. The first portfolio consists of the 26 stocks that have been traded without interruption in the ASE during the period 1987–2004. The second portfolio consists of 26 stocks that are randomly chosen each year, and the third portfolio consists of all stocks that were traded in the ASE each year, and therefore, their number is not constant.

In Fig. 3 we present a plot of the distribution of the correlation coefficients, between all stocks traded in the market the year 2004. The correlation coefficients are obtained by the correlation coefficient matrix, considering only the non-diagonal elements of the upper or lower triangular matrix. On the same plot we also show the first four moments of the distribution, namely the mean correlation coefficient

$$\lambda_1(t) = \frac{1}{n(n-1)/2} \sum_{i<j} \rho^t_{ij}, \tag{9a}$$

the variance

$$\lambda_2(t) = \frac{1}{n(n-1)/2} \sum_{i<j} (\rho^t_{ij} - \lambda_1(t))^2, \tag{9b}$$

the skewness

$$\lambda_3(t) = \frac{1}{n(n-1)/2} \sum_{i<j} (\rho^t_{ij} - \lambda_1(t))^3 / \lambda_2^{3/2}(t), \tag{9c}$$

and the kurtosis

$$\lambda_4(t) = \frac{1}{n(n-1)/2} \sum_{i<j} (\rho^t_{ij} - \lambda_1(t))^4 / \lambda_2^2(t). \tag{9d}$$

These moments are calculated for all three different portfolios under investigation, for each year inside the period 1987–2004. We found that all moments of the correlation coefficient matrix have an almost identical value each year for all three portfolios. This could suggest that in the case of the ASE all stocks are on the average affected the same by the price movement of other stocks.

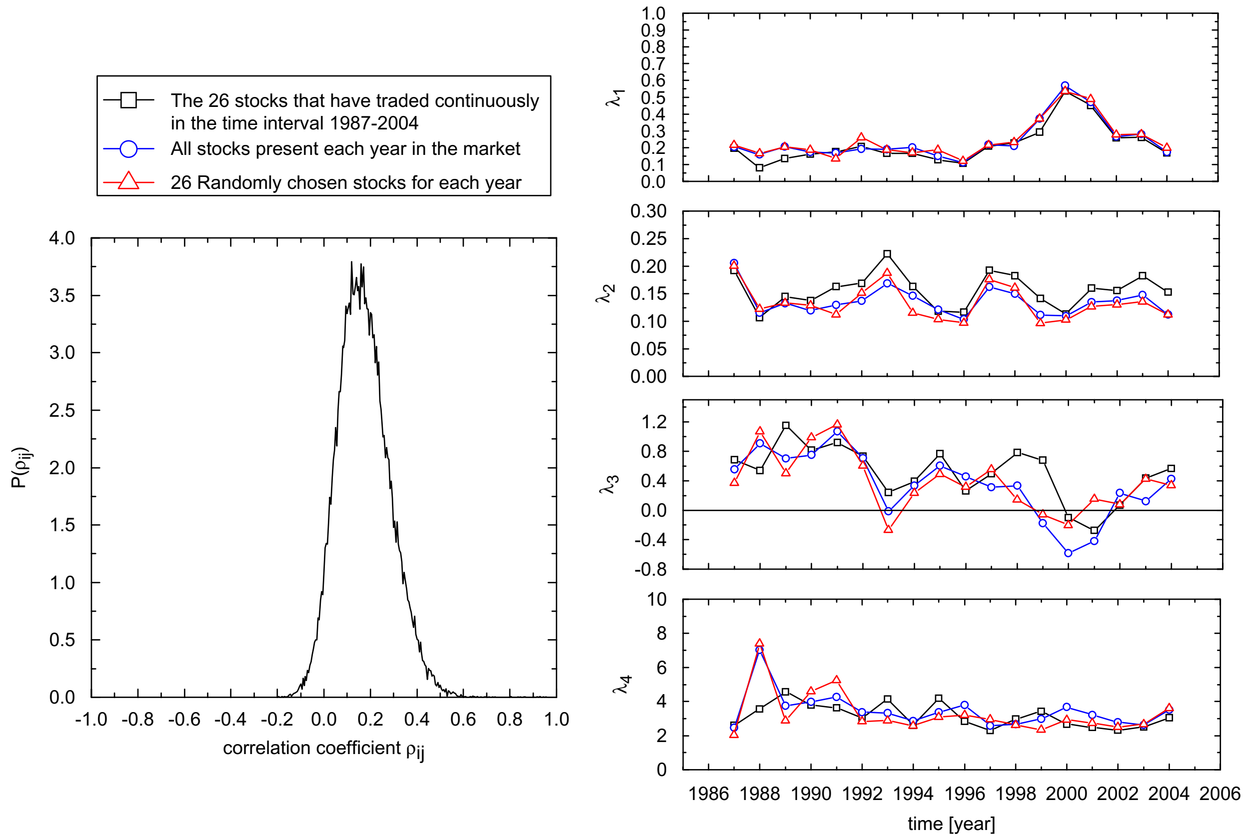

Fig. 3. Left: Plot of the distribution of the correlation coefficients, between all stocks traded in ASE for the year 2004. Right: Plots of the first four moments of the correlation coefficient distribution, plotted as a function of time for the range of 1987–2004.

A very interesting observation is that for the years 1999, 2000 and 2001 the mean value of the correlation coefficient matrix increased dramatically, as it almost tripled its value for the year 2000. During these years there was a sudden decline in the Greek stock market (as in the rest of the world). This large increase of the mean correlation value suggests that during this crisis period all stocks were so highly correlated that the market was moving as a whole.

This behaviour of the market can also be observed by examining the normalized tree length of the MST (Fig. 4) that is obtained for every year and for each portfolio separately. As we can see during the crisis period of 1999–2001 the tree shrinks considerably, which means that the distances between the stocks are rapidly decreasing. It is also interesting to note that the normalized tree length has similar values for all three different portfolios, the same way the mean value of the correlation coefficient matrix does.

In order to get more information from the MSTs we examine the distribution of the degree k, which is the number of links that are connected to each node of the network. We consider only the portfolios having all the stocks that are present each year at the ASE and we calculate the distribution of the degree for each year. We find that for all years the distribution is well approximated by a power law for one decade in k and then it is followed by a set of some isolated points with higher degree. In order to get better statistics instead of using the k-distribution for every year separately, we used the aggregated k-distribution for all the MSTs and we fitted the data using a power law function (Fig. 5a). The value that we find for the exponent is $a = 1.86 \pm 0.06$. Our finding is close to the value $\alpha = 2.2$ observed by Vanderwalle et al. [21] that studied the scale-free behaviour of the tree for 6358 stocks traded for one year at the NYSE, NASDAQ and AMEX. A similar value $\alpha = 2.1$ was observed by Onnela et al. [9] by studying 447 stocks traded at the NYSE from 1980 to 1999. It is, however, somewhat different than the value $\alpha = 2.6$ found in Ref. [6] by Bonanno et al. that studied the closing prices of

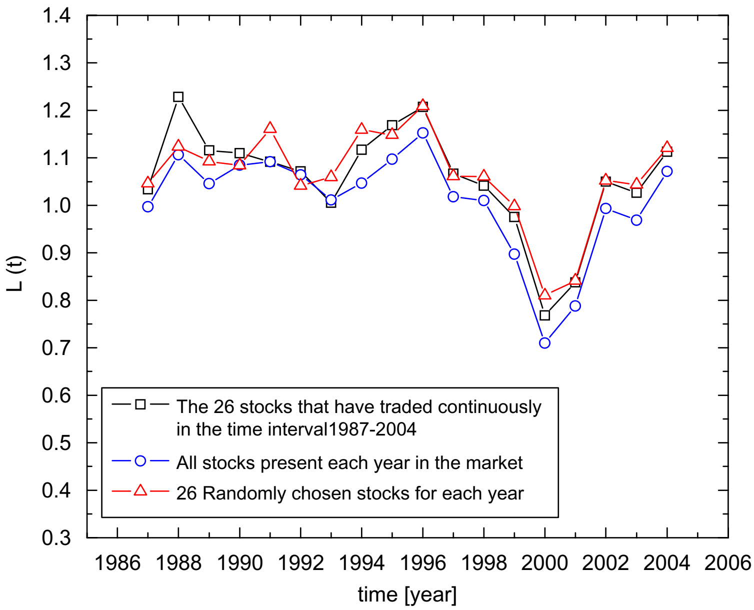

Fig. 4. Normalized tree length, $L(t)$, of the MST, as it is obtained separately for each investigated portfolio.

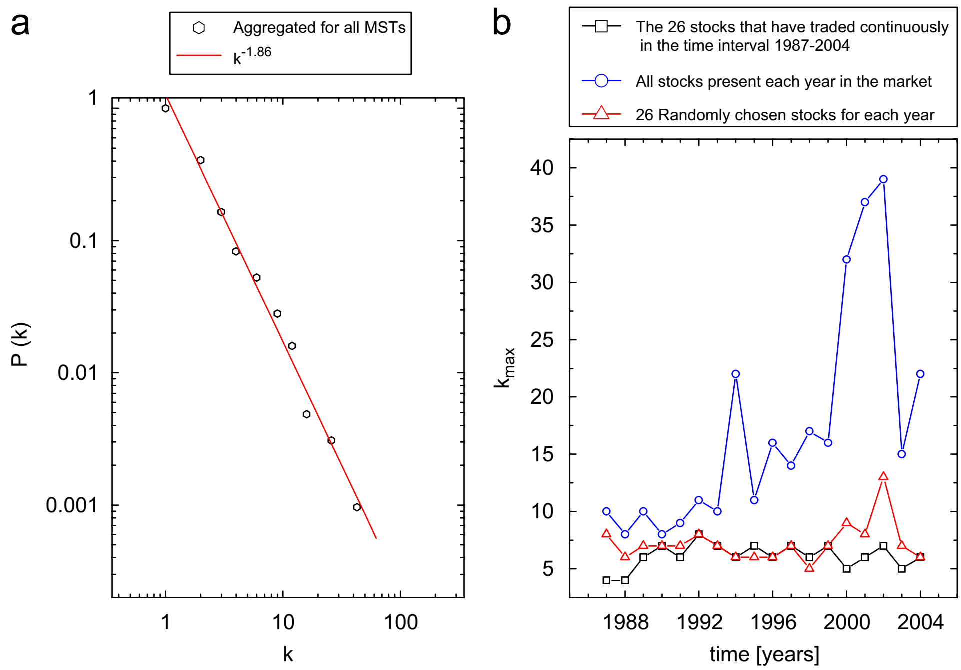

Fig. 5. (a) Distribution of the degree k aggregated from the MSTs of all years in the range 1987–2004, using logarithmic binning. The value of the slope of the straight red line is −1.86. The fit quality is good and power law behaviour is strongly supported. (b) Plot of the temporal evolution of the maximum number of links, k_{max}, of the most connected stock in the MST. We see that during the bear market of 1999–2001 the value of k_{max} increased significantly.

1071 stocks traded continuously at the NYSE from 1987 to 1998. In Fig. 5a we plot the distribution of the aggregated k-distribution for all the MSTs together with the function

$$f(k) = k^{-a}. \tag{10}$$

From the best fits of the annual k-distributions we have observed that during the crisis period of 1999–2002 the value of the exponent decreases and takes the average value $\alpha = 1.68 \pm 0.1$. A similar behaviour was observed by Onnela et al. [9], where they found that near black Monday the exponent takes the value $\alpha = 1.8 \pm 0.1$.

From the above discussion it is evident that the MST can be strongly influenced during a crisis period. We can more clearly understand this by examining the temporal evolution of the maximum number of links k_{max} of the most connected stock in the MST. This plot is shown in Fig. 5b, where one can see that during the crisis years k_{max} behaves differently for the three considered portfolios.

We observe that k_{max} increases dramatically for both cases, i.e. for the case of the portfolio consisting of all stocks traded in the market and the case of the portfolio of 26 randomly chosen stocks. Now, if we combine this with our previous findings that the MST during the crisis period shrinks, we can conclude that the MST has a star-like structure. This kind of MST is also observed if one performs this analysis using high frequency intraday data. For example, in Ref. [20] Coronnello et al. found a star-like structure in the MST that was obtained starting from 5-min price returns of 92 stocks traded at the London Stock Exchange.

On the other hand the tree corresponding to a portfolio consisting of all 26 stocks traded without interruption in the ASE from 1987 to 2004 does not seem to have any influence in the k_{max} value. This finding suggests that those stocks probably form a more stable tree. This hypothesis is also supported by examining the plots of the single step and the multi-step survival ratios that are shown in Fig. 6. From these plots we see that the links of the MST created by these 26 stocks have higher multi-step survival ratio comparing to the MSTs of the other two portfolios. Furthermore, we observe that this MST has a higher survival ratio during the crisis period of 1999–2001, which means that during this crisis the largest part of this tree remained unchanged.

Of course, as it is expected, the MST that is created for each year using the portfolio of 26 randomly selected stocks leads to an almost zero survival ratio, but it is interesting to note that the same holds true (very low survival ratio) for the MST created by all stocks that are traded each specific year in the market. This reveals that the addition or removal of stocks has a strong effect on the dynamics of the market. The new stocks that are added or the stocks that are being removed seem to result in a strong reconfiguration of the market. This reconfiguration suggests that the market is a constantly evolving complex system.

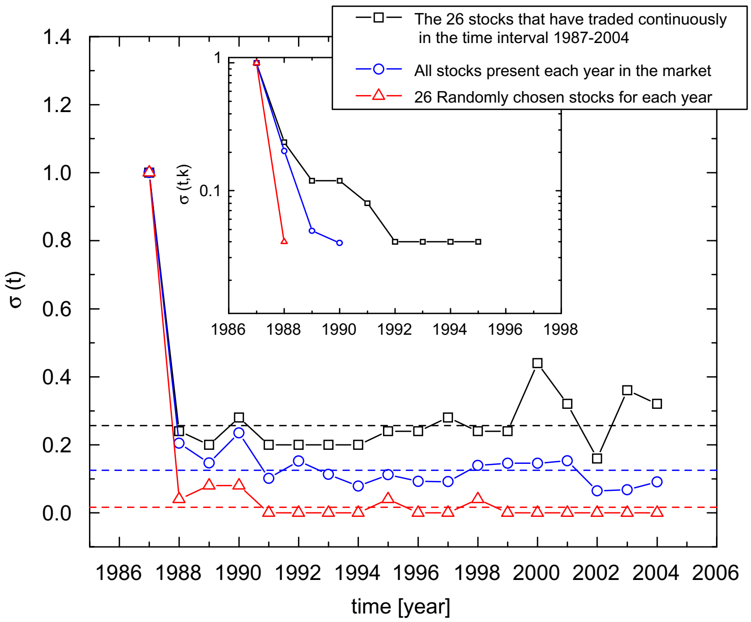

Fig. 6. Single step survival ratio, $\sigma(t)$, of the MSTs for all three different portfolios calculated for the time period 1987–2004. Inset: The multi-step survival ratio, $\sigma(t, k)$, of the MSTs for the same portfolios, calculated for the same time period.

So far we have studied the way that the correlations between stocks can be used to extract information about the market and how the market structure is affected by changes in the stock correlations. We will now investigate the reverse effect, namely how the market affects the correlation matrix itself. A straightforward way to do this is by using the RMT technique.

As it was described in Section 3 it has been shown [14,17] that the largest eigenvalue of the correlation matrix carries economic information from the whole market and affects strongly the information that can be extracted from the remaining eigenvalues. Therefore, one should first remove this contribution by using the normalization $\tilde{\sigma}^2 = 1 - \lambda_1/n$ in Eq. (6). In Fig. 7 we show the contribution of the market to the information content of the correlation matrix for the data for every year, as it is described by the value λ_1/n.

From Fig. 7 we can make two interesting observations. Firstly, we see that for every year the contribution of the market is the same to each of the investigated portfolios. This means that no matter what way was used to select the stocks to be included in the three portfolios, the portfolio will be affected by changes in the market the same way. Secondly, we can see that during the crisis period of 1999–2001 the effect of the market becomes dominant to the correlation matrix in such a way that for the year 2000 almost 60% of the information carried out in the correlation matrix is due to the market. This is a verification that during a crisis period the stocks are strongly correlated and the market moves as a whole.

Another interesting finding arises when we examine the contribution of each economic sector to the eigenvector that corresponds to the largest eigenvalue of the correlation matrix. Since this eigenvector corresponds to the entire market as a whole, we expect to find an almost homogenous contribution from all economic sectors present in the market. But as we can see from Fig. 8 this is not the case. At least for the early years of the Athens stock market we can clearly see that there are specific sectors that seem to play a more significant role. One can argue here that this effect arises because in the early years of the market all sectors were not present, but from Fig. 8 we can see that even the sectors that were present those years do not contribute evenly to the market. Instead, some sectors (like the financial sector or the construction sector) contribute more. This effect fades out year after year and for the later years we can see that the contribution of all sectors becomes homogenous. This is an interesting finding because it could be a signal of maturity of the market. But no information can be deduced if this is something common for all emerging markets or if it is a characteristic of the Greek stock market.

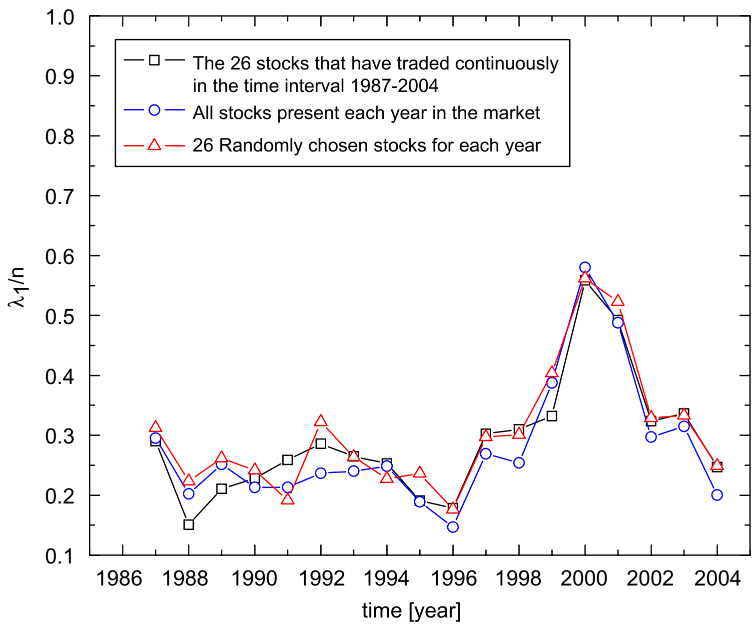

Fig. 7. The contribution of the market to the information content of the correlation matrix as a function of time for each year in the period 1987–2004, as it is described by the value λ_1/n.

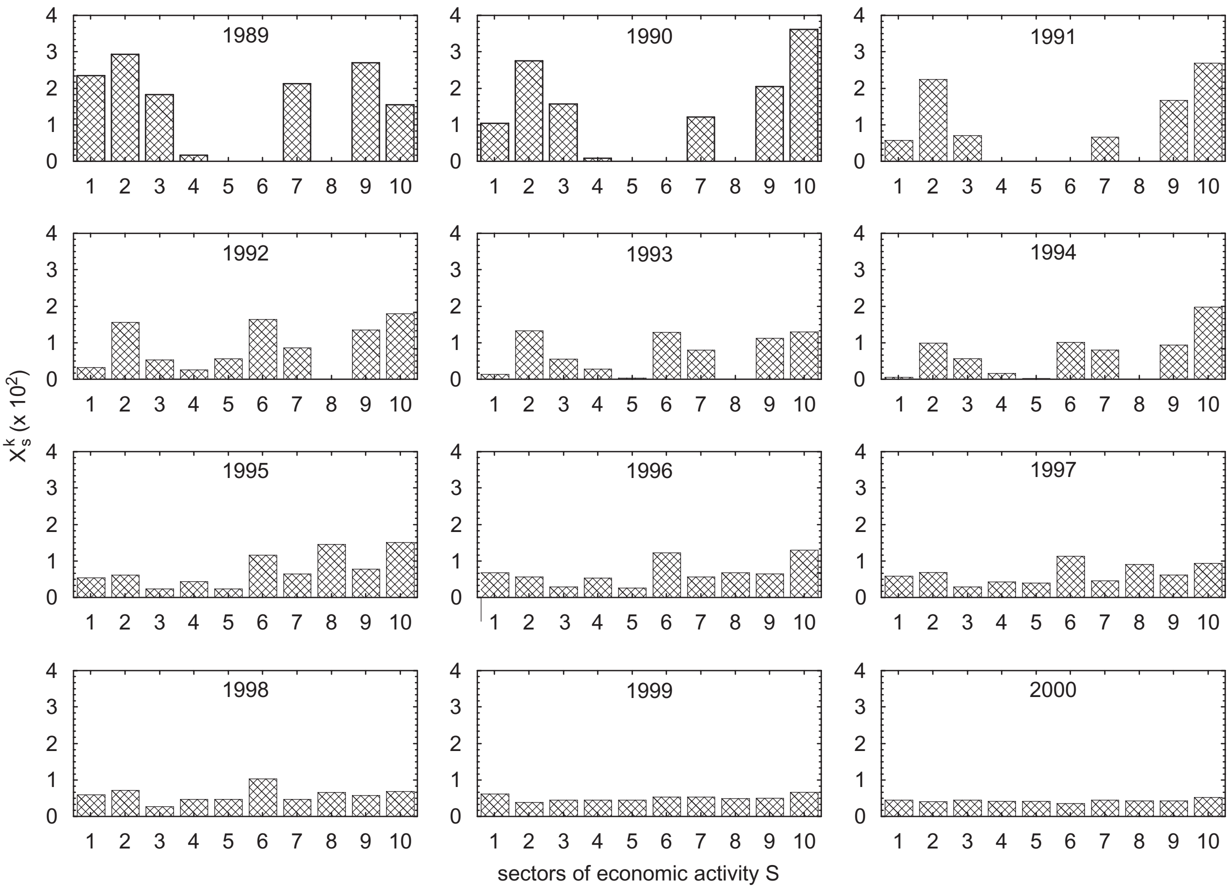

Fig. 8. The contribution of each economic sector to the eigenvector that corresponds to the largest eigenvalue of the correlation matrix for different years. We can see that at the early years the different economic sectors do not contribute evenly to the market, but some sectors (e.g. the financial sector or the constructions sector) contribute more. This effect fades out with time, and eventually the contribution of all sectors becomes homogenous.

5. Conclusion

We have studied the temporal evolution of the Greek stock market using the MST clustering technique and the RMT to extract information from the correlation matrix of the system using three different portfolios of stocks. Our analysis showed that the mean value of the correlation coefficient matrix each year and the associated normalized tree length $L(t)$ are almost identical each year for all portfolios considered, which leads us to suggest that in the case of the Greek stock market all stocks are (on the average) affected the same way by the price movements of other stocks.

We also studied for each year the distribution of the degree k, which is the number of links that are connected to each node of the network. This analysis was performed to the portfolio that contains all stocks that were present on the market each year, and we found that the aggregated k-distribution for all the MSTs is well approximated by a power law for more than one decade with an average exponent $a = 1.86 \pm 0.06$.

An interesting observation is that the behaviour of the market is completely different during a crisis period. During such crisis we find that the correlations between stocks become stronger and the MST shrinks. In addition, the value of the power law exponent decreases and becomes $\alpha = 1.68$, while the maximum number of links $k_{\max}$ of the most connected stock in the MST becomes higher. This leads to a star like structure for the MST, similar to what is observed if one performs this analysis using high frequency intraday data.

Next, we analysed how the market affects the correlation matrix itself by studying the value of λ_1/n, where λ_1 is the largest eigenvalue of the correlation matrix. We found that for every year the contribution of the market is the same to each of the investigated portfolios. This has implications to the way one selects a trading portfolio, since it means that this portfolio will be affected by changes in the market the same way as any other portfolio. We also find that during a crisis period the effect of the market becomes dominant to the correlation matrix and this is verification that during such periods stocks are largely correlated and the market moves as a whole.

Finally, we examined the contribution of each economic sector to the eigenvector that corresponds to the largest eigenvalue of the correlation matrix and we found that for the early years of the Greek stock market there are specific sectors that seem to play more significant role than others, while for the later years the contribution of all the economic sectors to the "market" becomes homogenous. This could be a signal that such a market is becoming more mature since the almost equal contribution from all economic sectors to the eigenvector that corresponds to the largest eigenvalue of the correlation matrix is verified for the case of mature markets, such as the NYSE and LSE [17,20].

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