Lex Humana, Petrópolis, v. 13, n. 2, p. 153-176, 2021, ISSN 2175-0947

RELATIONSHIP BETWEEN THE RATE OF FLUCTUATION SCALE AND INDEX CHANGES IN TEHRAN STOCK EXCHANGE

RELAÇÃO ENTRE A TAXA DE FLUTUAÇÃO DA ESCALA E AS MUDANÇAS DE ÍNDICE NA BOLSA DE VALORES DE TEERÃ*

Mohammad Heydari**
Southwest University, China

Fan Yanan***
University of Wrocław, Poland

Xiaoyang LI****
Southwest University, China

Zhou Xiaohu*****
Nanjing University of Science and Technology, China

Kin Keung Lai******
Shaanxi Normal University, China

Abstract: The objective of this study was to the relationship between the rate of fluctuation scale and index changes in Tehran Stock Exchange using the wavelet model. The method of this research is using data technique. One of the most widely used techniques in financial time series is neural network. Due to the comprehensiveness of this technique and the lack of some assumptions about the data, it has become more widespread compared to statistical data. However, noise in time series, especially in financial and economic time series, reduces the accuracy of neural network (NN) predictions. One method of descaling in time series is wavelet transform. The results showed that with constant inflation rate as a controlling variable of exchange rate fluctuation scales and stock price index, from 2005 to 2016, there is a negative and very coherent coherence in long-term scales. According to the results, it can be said that one of the most fundamental issues in terms of training guidelines is the economic situation and the adoption of investment strategies. Accordingly, this shows that in recent years, the long-term decline in the stock price index has reduced exchange rate fluctuations. The results of this research can be an educational guide for those who want to invest in the stock market.

* Artigo recebido em 22/04/2021 e aprovado para publicação pelo Conselho Editorial em 25/05/2021.
** Business College, Southwest University, Chongqing, China Email: MohammadHeydari1992@yahoo.com.
*** University of Wrocław, Wrocław, Poland Email: 15735925764@163.com
**** Business College, Southwest University, Chongqing, China Email: zjclxy@swu.edu.cn
***** Nanjing University of Science and Technology, Nanjing, Jiangsu, China Email: njustzxh@njust.edu.cn
****** International Business School, Shaanxi Normal University, Xi'an 710062, China Email: mskklai@outlook.com

Keywords: Fluctuation scale. Index changes. Tehran Stock Exchange. Wavelet model. Educational guide.

Resumo: O objetivo deste estudo foi a relação entre a taxa de escala de flutuação e as mudanças de índice na Bolsa de Valores de Teerã usando o modelo wavelet. O método desta pesquisa está usando a técnica de dados. Uma das técnicas mais utilizadas nas séries cronológicas financeiras é a rede neural. Devido à abrangência desta técnica e à falta de algumas suposições sobre os dados, ela se tornou mais difundida em comparação com os dados estatísticos. Entretanto, o ruído nas séries cronológicas, especialmente nas séries cronológicas financeiras e econômicas, reduz a precisão das previsões da rede neural (NN). Um método de descalcificação em séries cronológicas é a transformação wavelet. Os resultados mostraram que com uma taxa de inflação constante como variável de controle das escalas de flutuação cambial e índice de preços de ações, de 2005 a 2016, há uma coerência negativa e muito coerente nas escalas de longo prazo. De acordo com os resultados, pode-se dizer que uma das questões mais fundamentais em termos de diretrizes de treinamento é a situação econômica e a adoção de estratégias de investimento. Assim, isto mostra que, nos últimos anos, a queda de longo prazo do índice de preços das ações reduziu as flutuações cambiais. Os resultados desta pesquisa podem ser um guia educacional para aqueles que desejam investir no mercado de ações.

Palavras-chave: Escala de flutuação. Mudanças no índice. Bolsa de Valores de Teerã. Modelo Wavelet. Guia educacional.

Introduction

Issues in economy and finance fascinated statistical physicists all over the world (Dajcman, 2016). Fundamental issues pertain to the existence or not of the long, medium, or/and short-range power-law correlations in various economic systems, to the presence of financial cycles and on economic considerations, containing economic policy (Ausloos, 2017). Forecasting methods are classified into two general categories of primary and time series methods (Brooks, 2018). The variable's value (dependent variable) is determined concerning other variables (Independent variables) in structural methods. In contrast, in time series models, time intervals of a dependent variable are considered independent variables. In basic methods and predicting the dependent variable, predicting the variable or independent variables' value is also necessary (Brooks, 2018).

In contrast, in the time series methods, a variable's interruptions predict the same variable's future value. Due to the simplicity of time series models, this method has been significantly expanded, especially in the financial and economic spheres. Forecast models are divided into two general categories of statistical algorithms and artificial intelligence models. Statistical algorithms are GARCH, ARIMA. These models' need is the linear relationship (Except the GARCH model) of data sustainability, which is usually not the case in financial markets (Zhang, Patuwo and Hu, 2015). Artificial intelligence (AI) models also include neural networks, fuzzy systems, genetic algorithms, among which the neural network (NN) is widely used according to its features. The existence of some advantages has led to the superiority of AI models compared to statistical models. The advantage of the "NN" compared with econometric models is the lack of a need for sustainable time series and existing linear relationships. In other words, the neural network ANNs[1] can determine any linear and nonlinear relationship because of comprehensiveness (Zhang, et al., 2015).

Innovation and the main difference between the present research and other similar researches are continuous wavelet transformation (CWT) and partial wavelet coherence (PWC) study between variables. On the other hand, in evaluating the relationship between the stock price indicator and the exchange rate scales, other variables such as inflation and interest rates are also helpful (Broze, Gourieroux and Szafarz, 2017). For this purpose, to eliminate the effects of the inflation rate on the relationship between the stock price index and the exchange rate scales, the inflation variable is introduced as a control variable in the model. The method used in this sketch, with the inclusion of the control variable, is the PWC so that we can find a more consistent relationship between the stock price indicator and the exchange rate fluctuations scales by keeping the effect of the inflation rate in different time horizons using a partial and PWC and a fuzzy difference (Los, 2014).

Therefore, this research applies a wavelet transform using the Daubechies wavelet to decompose the time series. The hypothesized model mixtures several statistical algorithms and soft computing strategies like GARCH, wavelet transform, continuous wavelet, partial wavelet coherence, and ARIMA. Besides applying wavelet-associated data representation, using the prior study to determining data processing by the utilizing ARIMA algorithm for forecasting liner decomposed time series by wavelet transform.

Conceptual overview in literature

Wavelet theory has been widely used as a research method in scientific analysis (Iori et al., 2017). In many conditions, wavelet analysis has been used as a research tool, and in most cases, the results are satisfactory and have been more appropriate than previous studies. Wavelet analysis significantly affects most disciplines, such as math, statistics, signal analysis, image analysis, data compression, geophysics, and numerical analysis (Skjeltorp, 2018).

This study focuses on the third application of Wavelet transformation and its use in reducing data loss. Cao et al. (2015) compared the linear methods of Fama and nonlinear methods of these two methods of Capital Asset Pricing Model (CAPM) and (Neural Network). They believed that factors that differed from those in developed countries affected the stock returns in developing countries. The results show that CAPM has a linear model for Fama and French in the CAPM model and has a higher ability to predict stock returns. This difference is statistically significant by using the Diebold-Mariano Test. These results were confirmed for the nonlinear methods of the two models. Compared with linear and nonlinear methods, the "NN" also has a higher ability to predict stock returns than other methods (Cao, et al., 2015).

The contribution of chaos theory and economic time series analysis

The concept of Lyapunov's appearance before the emergence of chaos theory was used to determine the stability of linear and nonlinear systems. Lyapunov's power calculation is done by measuring the amount of stretching or curvature occurring in each system. Several methods for calculating the Lyapunov exponentiation, including direct methods and the Jacobian Matrix system, can be pointed out. Finally, the inverse of the maximum calculated Lyapunov exponent can indicate the definite and random boundary of the linked series; therefore, it is possible to predict the amount, or, in other words, the number of predictable days in this study (Wolf, 2019).

Some of these tests measure the randomness of the process, while others test one of the chaotic process characteristics (Iori et al., 2018). The first group of these tests are indirect tests, and the group is usually random; the second BDS is direct tests. In indirect tests, such as a waste test, linear regression, or nonlinear regression is used. Consequently, the rejection of the randomized hypothesis of waste sentences does not necessarily mean that a process is chaotic. This is due to the linear and nonlinear modeling used in the test (Fama, 2015).

Conceptual modeling: definition, purpose, and benefits multi-scale method

The multi-scale method is widely utilized in analysing time series of financial markets, and it can provide market information for different economic entities that focus on different periods (Maslow, 2017). We can detect each time series's topological relationship by constructing multi-scale networks of price fluctuation correlation in the stock market. Past studies have not referred to the issue that the initial fluctuation correlation networks are fully connected networks and more information exists within these networks currently being utilized. We use Currency exchange data from the Central Bank of the Islamic Republic of Iran and stock index information from the TSE as a case study. First, we decompose the initial stock price fluctuation series into different time scales. Second, we construct the stock price fluctuation correlation networks at different time scales. Third, we remove the edges of the network according to thresholds and analyse the network indicators. By mixing the multi-scale algorithm with the multi-threshold algorithm, we bring to light the implicit information of fully connected networks (Famer and Joshi, 2015; Maslow, 2017).

Maximal overlap discrete wavelet transform algorithm (MODWT)

Here, we utilized the MODWT to process the original stock price fluctuation series. Compared with other wavelet methods, the MODWT algorithm has several valuable characteristics. First, the general discrete wavelet algorithm demands that the data's length is equal to 2^n (n is a positive integer), while the MODWT algorithm does not have this limit. Second, we can obtain more information from low-frequency series when we utilize the MODWT algorithm. We decompose the stock price fluctuation series into different time-scale time series. The Eq. is as follows:

(5)

$$X_t = \sum_{J=1}^{J0} D_{J0} + S_{J0}$$

In Eq. (5), X_t denotes the original stock price fluctuation series. J, which is from 1 to $J0$, denotes that the number of time series is $J0$. Here, we set $J0$ as 6. Some authors prove that six wavelets transform levels are suitable for us to gain enough information from the financial time series (Tiwari, Oros, Albulescu, 2014; Dajcman, 2013). Dj denotes the wavelet transform coefficient between scale 2^j and $2^{j+1}$$(j = 1, \ldots, J0)$. The D_1 for one to two months, D_2 for two to four months, D_3 for four to eight months, D_4 for eight to sixteen months, D_5 for sixteen to thirty-two months represent long-term levels. S_6 is the trend level, denoting the trend of the original signal. Here we obtain six-time scales or time levels. We give these maximal overlaps discrete wavelet transforms decomposition figure in Fig. 1:

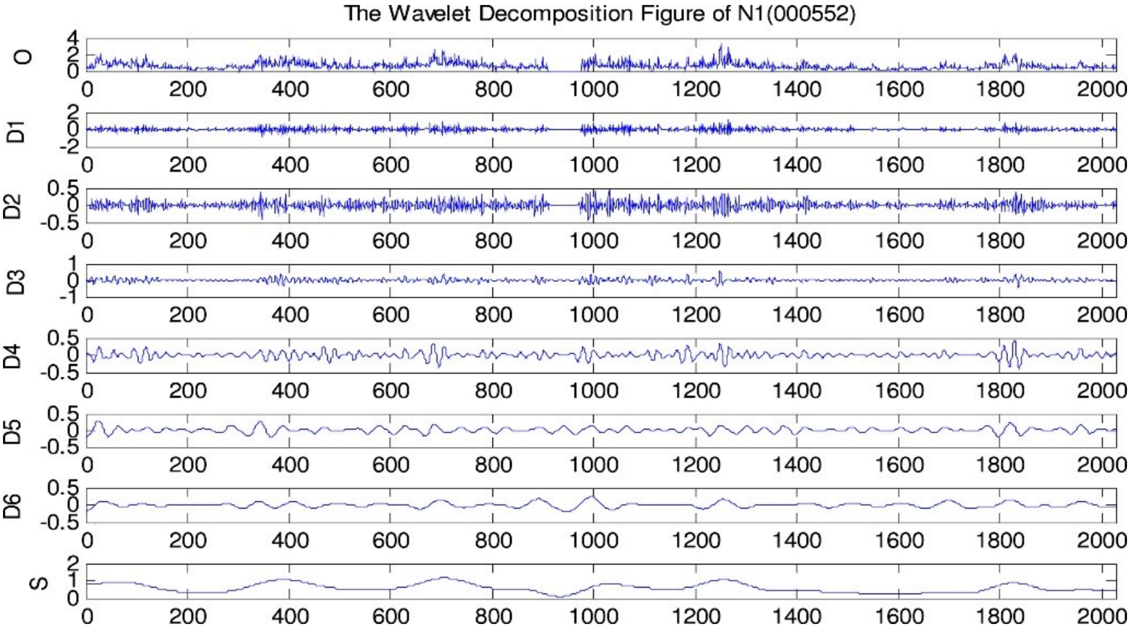

Fig 1. The wavelet decomposition figure of N_1 (000552)

As it is evident from figure 1, the O series on the top is the original stock price fluctuation series, and the D_1–D_6 levels denote different wavelet decomposition series at different scales. S denotes the trend level. As the time scale grows, the frequency of stock price fluctuation slows.

Different time scales and correlation network

After setting the TSE fluctuations scale rate and stock exchange price index changes as nodes, the stock price fluctuation relation as edges, and the correlation coefficients as weights, we now get seven stock price fluctuation correlation networks at different time scales. These seven correlation networks are fully connected. According to the time scales, we calculated the fluctuation correlation of different stock prices at different time scales, and we utilize the Pearson Correlation Coefficient to count these relationships. The equation for counting the Pearson Correlation Coefficient is as follows:

(6)

$$r_{xy}^{t} = \frac{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2}\sqrt{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}}$$

x_i and y_i are the observed values in different time scale series, and x and y are the mean values of amounts of different time scale series; n is the number of observations in the sequence, which is 2027. D denotes the level of time scales.

(7)
$r_{xy}^{t} \in [-1,\ 1]$

Which denotes the correlation of each company's stock price fluctuation at different time scales, and t denotes the level of time scales. Moreover, we test the significance of all Pearson Correlation Coefficients, and then we eliminate those results whose coefficients are not significant. After dealing with these results, we construct a correlation network. There are only 13 negative numbers in the calculation result, which are at the $D_5/D_6/S$ level, so we eliminate these numbers for the convenience of later calculations. It is worth mentioning that these negative numbers do not pass the significance test.

Figure 2 denotes the correlation of stock price fluctuation in this sample. It is evident, as the time scale level enhances, the general correlation of stock price fluctuation increases. In Figure 2, as the time scale level enhances, the number of squares whose color is warmer enhances. We can see that as the time scale level increases, the correlations between each company become tighter.

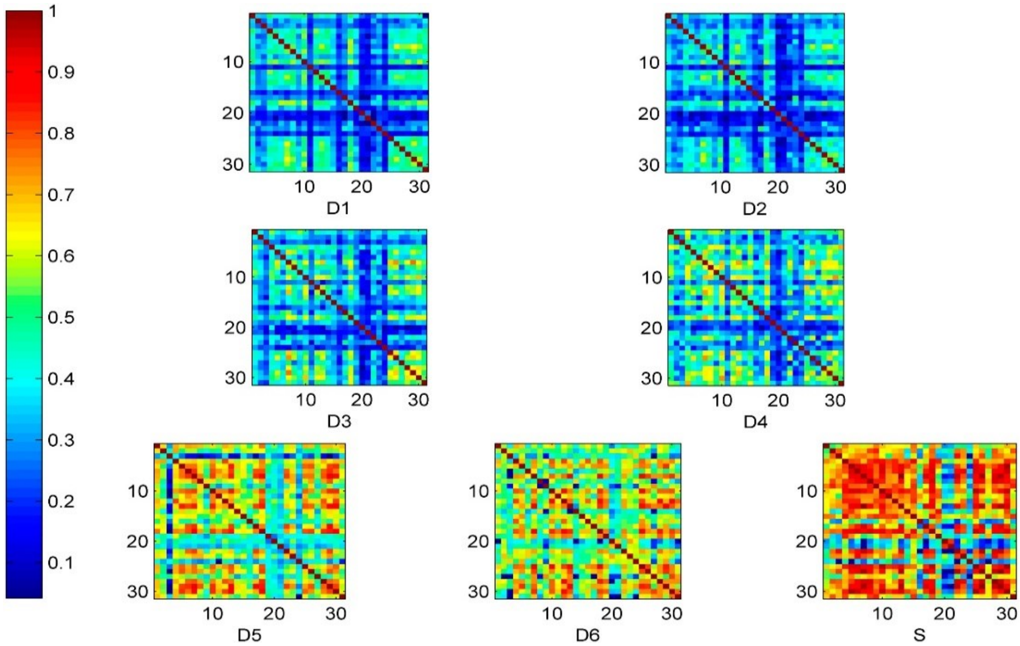

Fig 2. Correlation of stock price fluctuation in the sample

After constructing the correlation network, we begin to remove the edges according to weights to obtain more information from the fully connected network. Based on the correlation coefficients' weight in TSE fluctuations scale rate and stock exchange price index changes, we eliminate small to large edges (There is an interval every 0.05). We set each weight where we delete the edges as thresholds.

Here, we chose several indices to depict a multi-threshold network's characteristic: the closeness of this sample, the transmission of fluctuation, and the medium of fluctuations scale rate and stock exchange price index changes. We select these indices because they consider both nodes and edges, which more clearly reflect the correlation of stock price fluctuation.

Methodology

Methods and type of research

One of the most widely used techniques in financial time series is neural network. Due to the comprehensiveness of this technique and the lack of some assumptions about the data, it has become more widespread compared to statistical data (Iori et al., 2017).

Design of research

Because the wavelet transforms and the continuous wavelet transforms (CWT) require high data values, monthly data was used from October 1997 to March 2017. Currency exchange data from the Central Bank of the Islamic Republic of Iran and stock index information from the TSE have been extracted. To calculate the stock price index, change rate from the following Eq. (8):

(8)

$$R_t = \left(\frac{TEPIX_t - TEPIX_{t-1}}{TEPIX_{t-1}} \right) \times 100$$

R_t is the monthly stock price index, $TEPIX_t$ stock price index at the end of the month, and $TEPIX_{t-1}$ stock price index at the end of the previous month.

The following Eq. (9) was also used to extract currency fluctuations:

(9)

$$\Delta e_t = \left(\frac{e_t - e_{t-1}}{e_{t-1}} \right) \times 100$$

That the exchange rate at time t and e_{t-1} is the exchange rate at time *t-1*. To implement the model, the first time series of both variables of exchange rate scales and stock price index in five horizons of 1 to 2 months, 2 to 4 months, 4 to 8 months, 8 to 16 months, and 16 to 32 months analyzed via discontinuous wavelet with the using Discontinued Maximum Overlap (MODWT) technique. The mother wavelet is a Daubechies wavelet, which is a (DWT) with minimal asymmetry were selected.

Participants

This case's closeness reflects the clustering degree of nodes, namely, the network's integrity and closeness. The Eqs. are as follows:

(10)

$$C_i = \frac{2E_i}{k_i\left(k_i - 1\right)}$$

(11)

$$C' = \frac{1}{n}\sum_{i=1}^{n} C_i$$

Eq. (10) is the clustering coefficient of the network, and Eq. (11); is the closeness of stock exchange (TSE) fluctuations scale rate and stock exchange price index. The character k_i denotes the number of stocks connected with a node in the network, and E_i is the number of edges between two nodes. i is from 1 to n, and n is any positive integer.

Instrument of research and procedure

The transmission of fluctuation denotes the transmission of stock price fluctuation in networks. A more significant number offers a long distance between any two nodes in the network and is an average number of the total distance between any two nodes in the network. A smaller number in the indicator offers that one company's fluctuation easily influences another firm's network. The equation is as follows:

(12)

$$1 = \frac{1}{N\left(N-1\right)}\sum_{i \neq j \in V} d_{ij}$$

Here, d_{ij} denotes the shortest distance between node i and node j in the network, as it is the smallest number of edges connecting these two nodes in the network.

Medium listed of fluctuations scale rate and stock exchange price index changes

The medium of fluctuations in scale rate and stock exchange price index changes represents a node's importance. It denotes the number of shortest paths passing through a node in the network. A high level of medium tells us that this node is essential in the network.

(13)

$$b_{ij}(k) = g_{ij}(k) / g_{ij}$$

(14)

$$CAB_k = \sum_{i}^{n} \sum_{j}^{n} b_{ij}(k), i \neq j \neq k$$

CAB_k is the medium of fluctuations in scale and stock exchange price index changes $(i < j)$. g_{ij} denotes the total number of shortest paths between node i and j.$g_{ij}(k)$ denotes the number of shortest paths through node k between node i and j.

Statistic Analysis

During the threshold filtering process, we count the number of nodes and edges at every threshold. The following figure is the distribution of nodes and edges of five time-scale networks when we remove edges based on weights from small to large. The X-axis denotes the threshold level when we filter the edges, and the Y-axis shows the number of nodes in the network. As denoted, that changing trend of edges is relatively smooth. Also, this trend of different time scales differs red line of short-run level decline more advanced than other lines D_3 level of medium-term is the same with D_2 level of short-run scale before weight 0.35. The whole trend of different lines is based on their time scales. Based on Figures. 3 and 4, we find that the number of edges decreases during the initial phase of setting thresholds, while the number of nodes does not change. This indicates that the distribution of edge quantity is relatively average in this period, and there are not too many edges between several nodes.

During this process, we can see that the change in node quantity is usually analogous at different time scales: in the starting phase, the number of nodes does not change much, and as the scale level grows, the quantity reduces sharply.

Lex Humana, Petrópolis, v. 13, n. 2, p. 153-176, 2021, ISSN 2175-0947
© Universidade Católica de Petrópolis, Petrópolis, Rio de Janeiro, Brasil

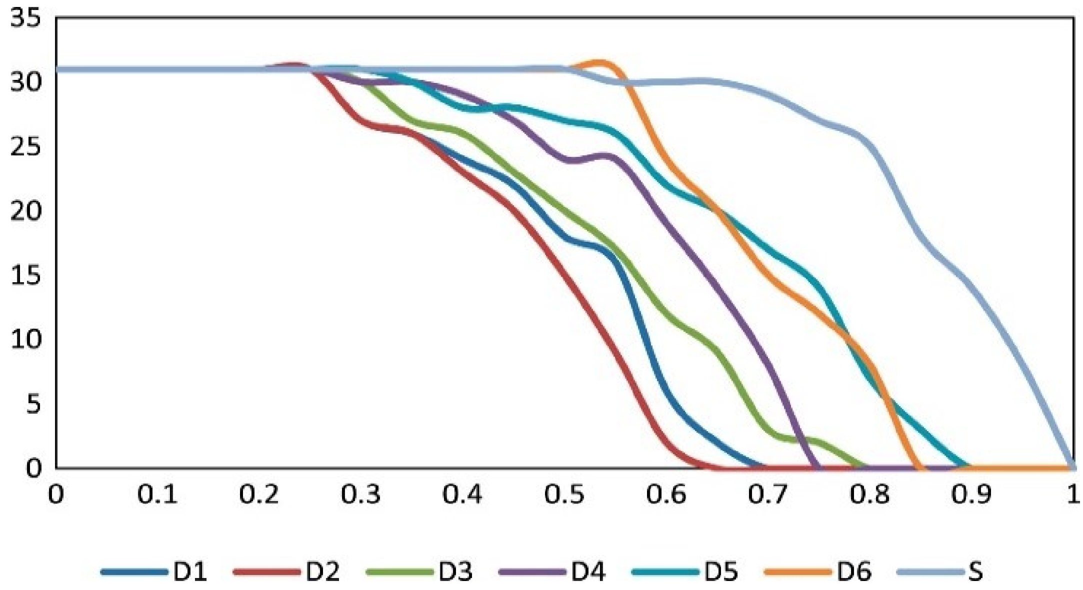

Fig 3. The changing number of nodes when setting the thresholds

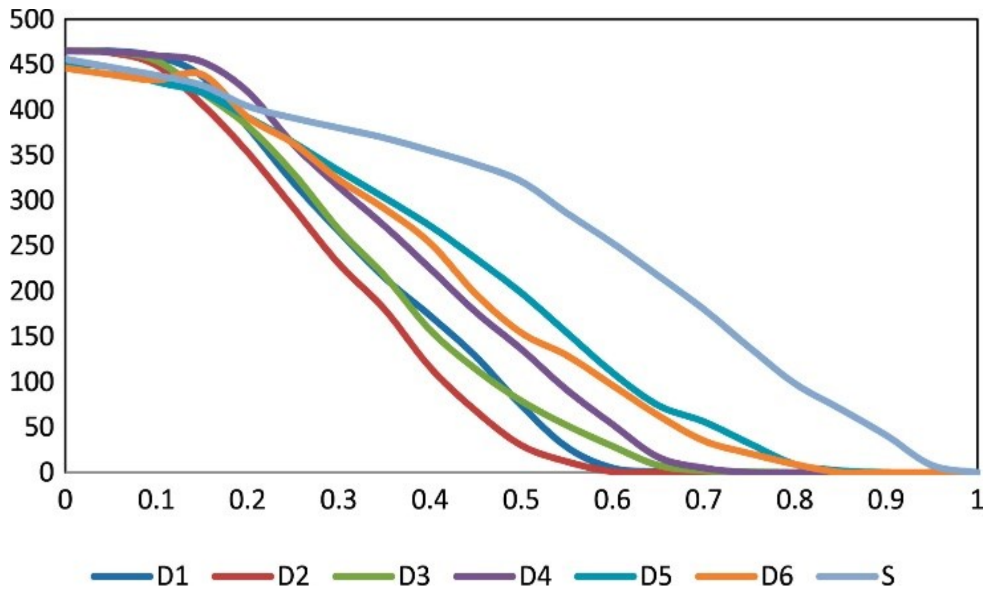

Fig 4. The changing number of edges when setting the thresholds

The X-axis has the same meaning as abscissa in Figure 3, and the Y-axis declares the closeness of fluctuations scale rate and stock exchange price index changes. Based on the overall trend, in the initial phase, this index's change is comparably smooth. As we remove more edges, the network structure is damaged, and network indicators fluctuate (See Fig. 5).

Based on our results, at the D_1 level, when we filter the threshold from 0.55 to 0.6, some nodes like N_4, N_5, N_6, N_8, N_{12}, N_{13}, N_{14}, N_{27}, N_{28}, N_{30} disappear, and N_7, N_{10}, N_{18}, N_{26}, N_{29}, N_{30} remain. These remaining nodes form a *"core group"* of a network, also a market about share price fluctuation. The "Core Group" does not mean that it may influence other nodes in this stock price fluctuation network. However, it does mean that nodes in this group have an extremely close relationship with each other. As threshold filtering continues and the last group is eliminated, closeness becomes zero, just as other time scale networks (see Fig. 6).

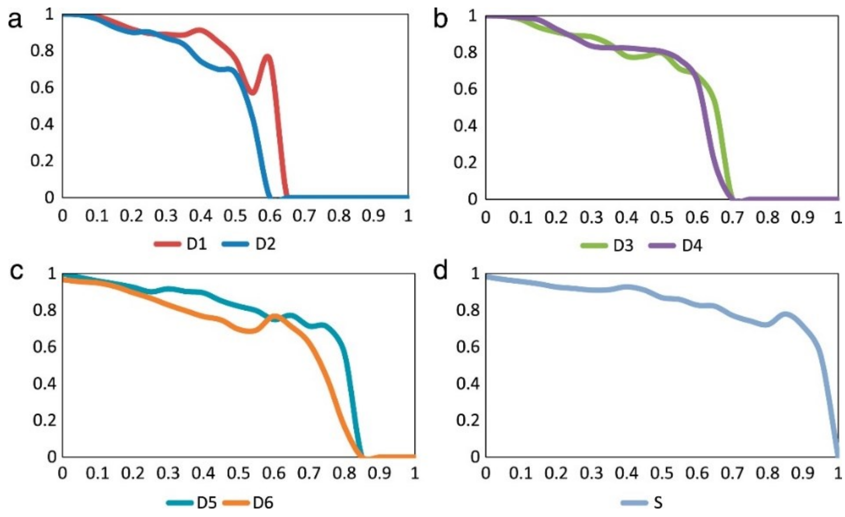

Fig 5. Change of closeness of sample at different time scales

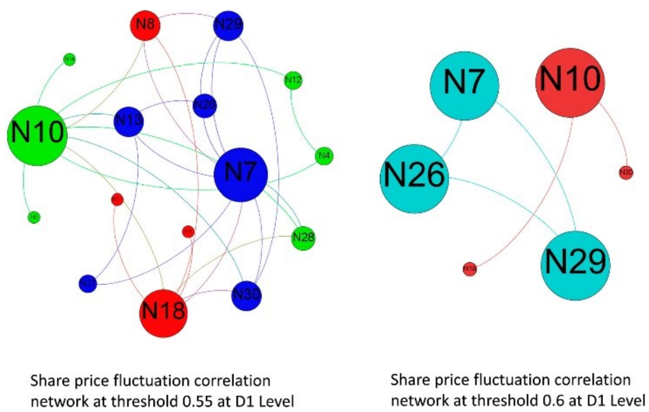

Fig 6. Share price fluctuation correlation network at threshold 0.55 and 0.6 at the D_1 level

The X-axis has a similar meaning as the abscissa in Figure. 8, and the Y-axis indicates the transmission of fluctuation. Based on the overall trend, this indicator is initially one at all scales because it is all fully connected. All nodes need just one step to associated with other nodes in the network. As the threshold level grows, more edges are eliminated, and the distance between nodes enhances. Thus, the amount of transmission of stock price fluctuation enhances gradually, and after exceeding a certain threshold level, the amount reduces sharply to zero.

Moreover, at the D_5 level, no rapid-increasing point can be seen because of the flatter curve. Therefore, we can say that some essential nodes and edges' disappearance causes the collapse of the "Bridge" in networks. The disappearance of the "Bridge" is due to the enhanced distance between nodes, namely the transmission of fluctuation. Through observing the process, these disappearing nodes are eliminated. As the table indicates, after removing the nodes and edges connected with these nodes, the fluctuation's value has a considerable enhance. Thus, we can call the nodes and edges connected with these nodes' "Bridges" of these networks.

Results

In this section, the analysis of variance and covariance and wavelet correlation of non-scales related to two variables of exchange rate scales and stock price indicator are discussed. Figure 7 demonstrates the variance of the percentage of exchange rate scales and stock price index, as indicated in figure 7 and Table 1; the variance of the stock price indicator shows higher volatility than the variance of exchange rate fluctuations scales. Also, both variables are more variance in short-term scales and decreased variance on a larger scale.

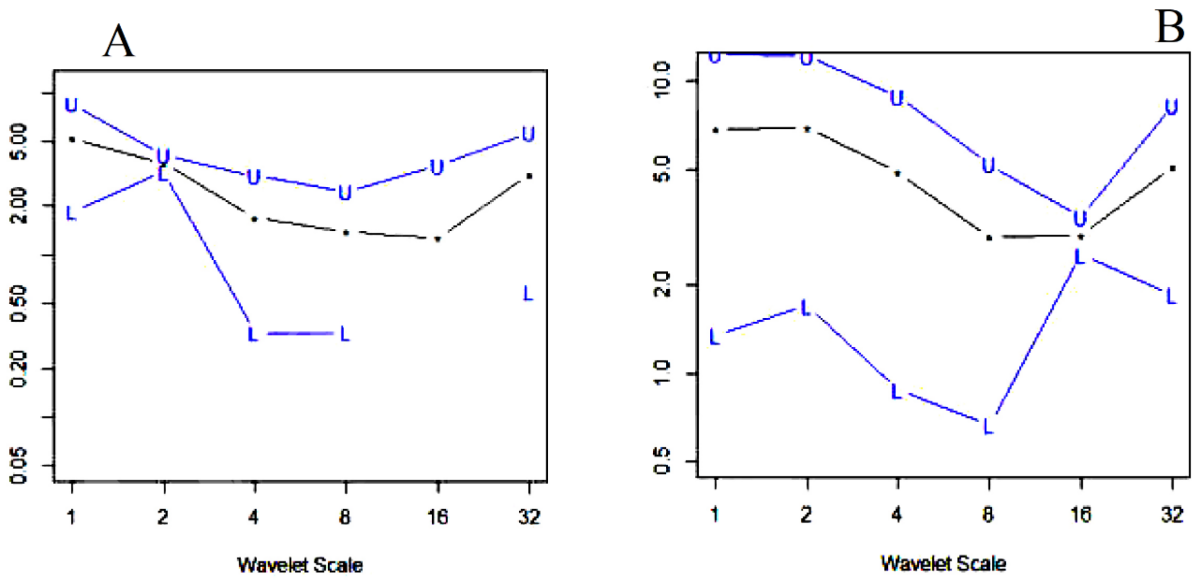

Fig 7. Stock price variance (A) and the variance of the percentage change in the exchange rate (B)
Source. Research findings

Table 1
Wavelet variance of exchange rate fluctuations scales and stock price index

Analyzed Scales[2]	Exchange rate fluctuations	Stock price fluctuations
D_1	20.5	85.6
D_2	65.3	95.6
D_3	7.1	86.4
D_4	3.1	93.2
D_5	3.14	5.05

Source. Research findings

Covariance and wavelet correlation

Figure 8; shows covariance and figure 9; wavelet correlation for the exchange rate scales and stock price indicator. Table 2 also shows covariance coefficients and wavelet correlation coefficients.

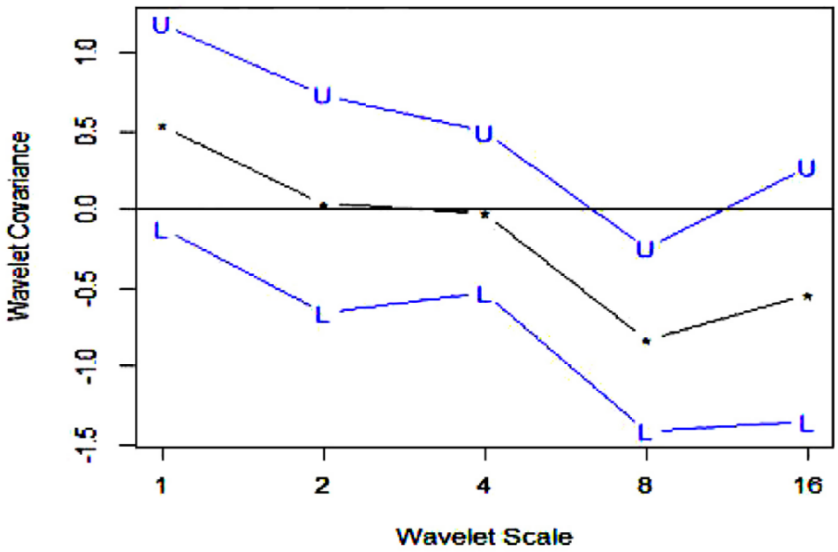

Fig 8. The covariance of the exchange rate scale and stock price indicator
Source. Research findings

[2] D_1 for one to two months, D_2 for two to four months, D_3 for four to eight months, D_4 for eight to sixteen months, D_5 for sixteen to thirty-two months.

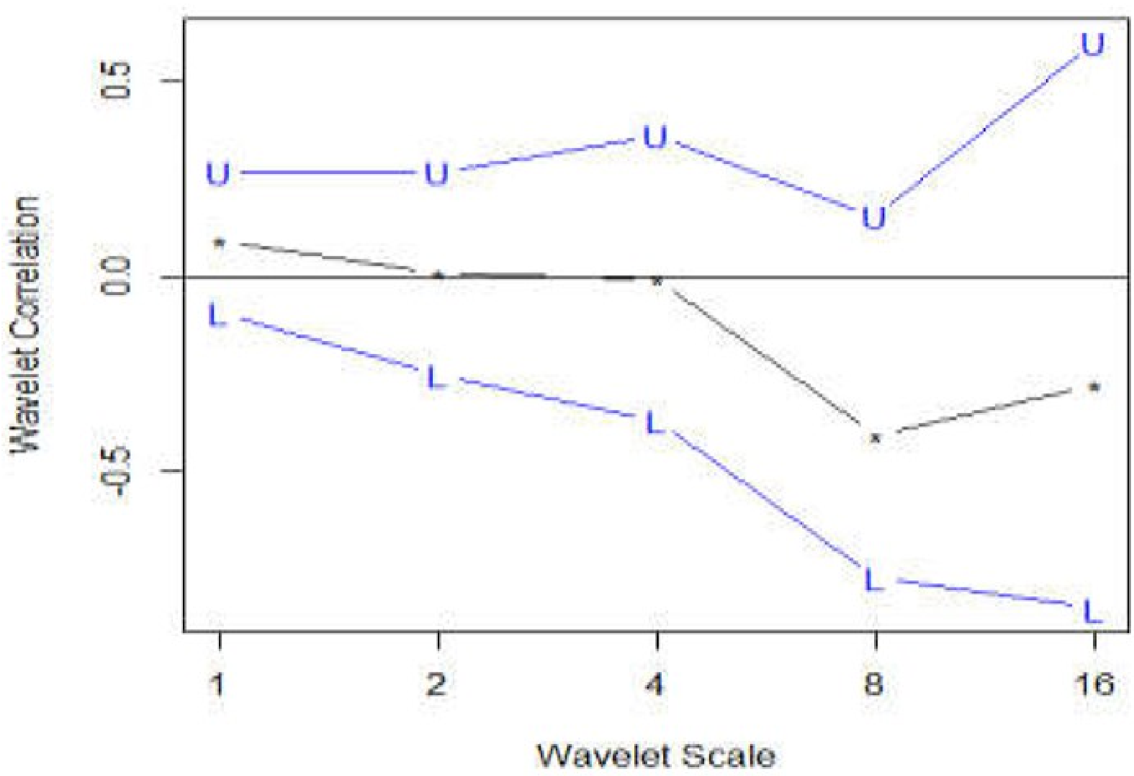

Fig 9. Wavelet correlation between exchange rate fluctuations scales and stock price indicator
Source. Research findings

The point is that the wavelet correlation of D_4 is the same as sixteen months. In other words, the correlation between the fluctuations of the exchange rate scales and the stock price indicator from the period of eight months to thirty-two months (Long-run) is in the opposite direction; it is remarkable.

Table 2
Covariance and correlation between the analyzed series of exchange rate fluctuations scales and stock price index

Analyzed Series [3]	Correlation Coefficient	Covariance
D_1	0.09	0.53
D_2	0.007	0.03
D_3	0.006	0.01
D_4	*-0.41	-0.82
D_5	*-0.27	-0.54

Source. Research findings

[3] The values with the sign (*) have a significant correlation coefficient.

Coherence wavelet transform (WTC)

Although a wavelet correlation, though correlating on different time scales, does not answer which variable has caused the change in another variable. This response is given by the coherence figures and the fuzzy differences in these figures.[4] WTC[5] can be defined by normalizing the wavelet cross-spectrum to the single WPS[6] and WTC.

This section will discuss the continuous WTC results, and fuzzy differences are estimated in figure 10, which show the relationship between the exchange rate fluctuations scale and the stock price indicator. There are three components of these figures: scale, time, and power of wavelet coherence. The scale and time interval on the vertical axis and time on the horizontal axis are shown. The coherence intensity is also shown vertically with the color column along with the diagram. The parts that are surrounded by a bold black line, also red parts are areas where the coherence is statistically significant at a 5% level.

To achieve this level, Monte Carlo simulation methods have been used. The thin black lines shown in the diagram as a cone shape indicate that the values outside the cone should be interpreted and justified with caution, and it seems that it is not easy to comment on these values. Also, there are arrow directions in the form of fuzzy differences. These directional arrows will have a significant contribution to analyzing the results. In general, if the direction of these arrows was to the right, it means that the two variables are in the opposite fuzz from each other. (The two variables have the opposite relationship with each other.) If the arrows' direction is right and down or left and up, the first variable is the agent and causes the second variable. If left to right and up or down, this relationship is reversed.

According to the above explanation and figure 10[7], the following results can be obtained. First, there is an inverse linkage between the two variables between the eight and sixteen months between 2005 and 2009; there is an inverse relationship between them. The stock price index is a leading variable. In this period of fluctuations, the exchange rate is not the fluctuation of the stock price indicator. This relationship is highly coherent between the years 2005 to 2016 in the long run (Sixteen months upwards), and the exchange rate fluctuations are causing fluctuations in the stock price index. Although a factor other than

[4] The calculations in this section of the study were done with the Biwavelet software in R software, written by Torres and Campo.
[5] Wavelet transform coherence
[6] Wavelet Power Spectrum
[7] *Note.* In this figure the date is in Hijri Shamsi

the exchange rate caused a downturn in the stock market in this period, for example, the reasons for market failure in that period can be mentioned.

An increase in bank interest rates and irregularities in the payment of profits of unauthorized institutions, the recession in the interior, the high supply of shares by state-owned enterprises (Privatization), ownership interest in mines, increased petrochemical feed rates, Conversely, the exchange rate, and stock price can be interpreted in such a path that, given that a large part of the country's industry is highly dependent on the exchange rate for the import of raw materials and intermediate goods, then an enhance in the exchange rate would increase the cost Of domestic production significantly and thus increase the stock price of many industrial companies in the stock market and as a result, has had a negative impact on the stock price indicator. In other intervals, as can be seen, there is no coherence or significant relation between the stock price indicator and the exchange rate on short-term horizons to long-term horizons.

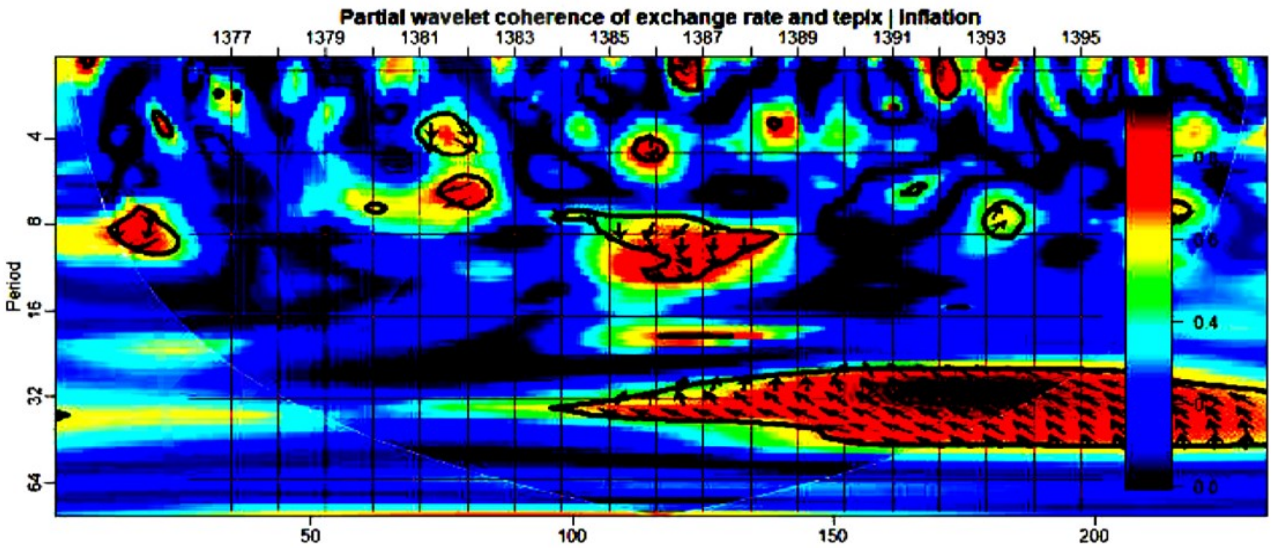

Fig 10. A partial coherence between exchange fluctuations scales rate and stock price index, inflation as a control variable
Source. Research findings

Discussion

In the present study, we tried to analyze the relationship between the two variables (DWT) and (CWT). In this regard, wavelet correlation transforms. The first time series of two variables with discontinued maximum overlap (MODWT) technique was applied to five different time scales of variance-covariance analysis and wavelet correlation transforms. In the variance analysis, the stock price index shows more fluctuations than the variance of exchange rate fluctuations. Also, both variables are more variance in short-term scales and decreased variance on a larger scale.

In Iran's exchange fluctuations, scale rate changes are more stable than stock price indices. Long-term stock prices seem to be relatively stable, but they fluctuate over up to eight months. The wavelet correlation coefficient also shows that this coefficient is meaningful from the D_4 time scale, the eight to sixteen-month period. In other words, the correlation between the exchange rate fluctuations scales and the price indicator from the eight months to thirty-two months (Long-term) is in the opposite direction. The results of this part of the research are in line with the follow of research: Clide and Osler, 2016; Iori, et al., 2017.

Such a similar result can be deduced from the partial co-integration between the two variables. It can be concluded that by keeping the effects of the inflation rate first, there is a period up to sixteen months, and between the years 2005 to 2009, there is an inverse relationship between the two variables. In this period of fluctuations, the exchange rate is not the fluctuation of the stock price indicator. This relationship is reversed from 2005 to 2016 in the long run (Sixteen months upwards), and fluctuations in the exchange rate are causing fluctuations in the stock price index. In other words, with the enhance in the exchange rate, the stock price indicator declined (Wolf, 2015).

The negative relationship between the two variables in the long term was the intensification of sanctions against Iran's Islamic Republic. Sanctions against Iran since 2006 were more serious than before and continued to expand widely in 2011, leading to an increase in the exchange rate. With the vast number of sanctions, it was normal for stock prices to increase for most industries (Whether imported or exported).

In this study, the Chaos was analyzed. The performance of various types of *"NN"* models was evaluated using wavelet data analysis to predict TSE's price index and cash returns. The results of this part of the research are in line with the research of Pring (2016) and Clide and Osler (2016).

Considering the importance of capital markets in the economy and especially in each country's development, the fluctuations of capital market indices and their impact on micro and macro variables have attracted economic researchers' attention. Particularly the global financial crisis in 2008 and the debt crisis in Europe, the importance of monitoring and evaluating periods of instability in financial markets, and its potential effects on the economy (Ferrer et al., 2018).

The linkage between exchange rate changes and stock prices has always been a matter for the attention of economic researchers, capital market participants, and foreign exchange and enterprise firms with imported and exported products. In this paper, the multi-dimensional analysis approach and the wavelet transform to the relationship between these two-time series were investigated at different time scales (Cao et al, 2015).

Studies represented in the literature to analyze and predict fluctuations scale rate and stock exchange price index changes dynamics assume that one may collect helpful information to understand the price formation mechanism by looking at the past. The main strategies proposed in the literature, the so-called technical analyses, presume that the price dynamics could be approximated with linear trends and analysed utilizing a standard mathematical or graphical algorithm (Pring, 2016).

This research, like other studies and research, is not without limitations. One of the main limitations of the present study was the complexity of the work process. Therefore, the researcher must integrate scattered information in different fields in a relatively long process for analysis. Another limitation of this study was the irregular and complex process of the Iranian Stock Exchange, which led to their collection and classification within 9 months. Also, values, perceptions, mentalities, perceptions, interests, knowledge and characteristics and knowledge of the researcher and other personal characteristics such as the ability to interact with others, etc. in open source selection, categories, question design, statistical methods and research Communication with others and analysis of the work of this research is not safe from these effects and naturally, the characteristics, knowledge and interests of the researcher have also influenced this research, which should be considered as one of the limitations of the research.

Conclusion

According to the study's results, we can sa that this series predictability, non-martingale, and nonlinearity were confirmed; therefore, this series efficient-market hypothesis is rejected. Also, the series has been a chaotic study, and hence the fractal markets' assumption of a stock return series is confirmed. Based on this result, the predictability level in this study, that is, the number of predictable days equal to the reciprocal of the maximum Lyapunov exponent, was 31 days. On the other hand, using multilevel *"NN"* models and the fuzzy *"NN"* of decomposed and not decomposed data, by wavelet analysis, the stock return index for 31 days as out of sample forecasting, was modeled and predicted.

In other words, in both cases, the use of decomposed data and not decomposed data, the performance of the multi-pronged model compared with the fuzzy *"NN"* model was better and more significant. It shall be mentioned that this issue has been a potential issue due to the turbulence of a series of stock returns; Because in the chaotic series, the creating fuzzy models causes the fractal dimension to be lost in the data, and thus the results of modifications and predictions will be affected. Therefore, the comparison of the model mentioned above, one of the most remarkable achievements of this study, is the excellence of neural network "Defuzzification" networks, fuzzy modeling, and forecasting series Chaotic, including financial markets used to Investors and analysts are very important.

Reference

Ausloos, M. (2017). Statistical physics in foreign exchange currency and stock markets. *Physica A: statistical mechanics and its applications, 285*(1-2), 48-65. DOI:[10.1016/S0378-4371(00)00271-5](10.1016/S0378-4371(00)00271-5)

Banfi, A. (2016). *I mercati e gli strumenti finanziari. Disciplina e organizzazione della borsa*. Torino, Italy: ISEDI.

Barnett, W. A., Geweke, J., and Shell, K. (Eds.) (2015). Economic complexity: Chaos, sunspots, bubbles and nonlinearity. New York, USA: Cambridge University Press.

Brock, W. A., & Cars, H. H. (2016), Heterogeneous beliefs and routes to chaos in a simple asset pricing model. *Journal of Economic Dynamics and Control*, *22*, 1235-1274. https://mpra.ub.uni-muenchen.de/4296/

Brock, W., Dechert, W., & Scheinkman, J. (2016). *A test for independence-based correlation dimension*. University of Wisconsin working paper, Madison. https://econpapers.repec.org/paper/attwimass/9520.htm

Brock, W. A., Hsieh, D. A., & LeBaron, B. (2016), *Nonlinear Dynamics, Chaos, and instability: statistical theory and economic evidence*, New York, USA: MIT Press.

Brooks, C. (2018). Introductory Econometrics for Finance. *Cambridge University Press.* [http://prof.iauba.ac.ir/images/Uploaded_files/3%20Brooks_Introductory%20Econometrics%20for%20Finance%20(2nd%20edition)[2591271].PDF](http://prof.iauba.ac.ir/images/Uploaded_files/3%20Brooks_Introductory%20Econometrics%20for%20Finance%20(2nd%20edition)[2591271].PDF)

Broze, L., Gourieroux, C., & Szafarz, A. (2016). *Reduced Forms of Rational Expectations Models.* London: Routledge.

Cao, Q., Leggio, B., & Schniederjans, J. (2015). A Comparison between Fama and French's Model and Artificial Neural Network in Predicting the Chinese Stock Market, *Computers & Operational Research*, *32*, 2499-2512. http://amfa.iau-arak.ac.ir/article_678748_25a1ec81f28536629319b3143d45917c.pdf

Cass, D., & Shell, K. (2017). Do sunspots matters? *Journal of Political Economy*, *91*, pp. 193-207. https://mpra.ub.uni-muenchen.de/4296/1/MPRA_paper_4296.pdf

Clide, W. C., & Osler, C. L. (2016). Charting: chaos theory in disguise? *Journal of future markets*, *17*, 489-514. https://econpapers.repec.org/article/wlyjfutmk/v_3a17_3ay_3a1997_3ai_3a5_3ap_3a489-514.htm

Dajcman, S. (2015). Interdependence between some major European stock markets. A wavelet lead/lag analysis. *Prague Econ, 22*, 28–49. https://ideas.repec.org/a/prg/jnlpep/v2013y2013i1id439p28-49.html

Davis, M. H. A., & Norman, A. R. (2016). Portfolio selection with transaction costs. *Mathematics of Operation Research*, *15*, 676-713. https://econpapers.repec.org/article/inmormoor/v_3a15_3ay_3a1990_3ai_3a4_3ap_3a676-713.htm

Deneckere, R., & Pelikan, S. (2015). Competitive Chaos. *Journal of Economic Theory*, *30*, 13-25. DOI:10.1016/0022-0531(86)90004-9.

Fama, E. F., & French, K. R. (2015). A Five-Factor Asset Pricing Model. Fama-Miller working paper, *University of Chicago, Dartmouth College, and NBER*. https://repository.tcu.edu/bitstream/handle/116099117/10353/Austin_Hughey_Final_Draft.pdf?sequence=1&isAllowed=y

Famer, J. D., & Joshi, S. (2016). The price dynamics of common trading strategies, *Journal of Economic Behaviour and Organization*, *49*, 149-171. https://econpapers.repec.org/article/eeejeborg/v_3a49_3ay_3a2002_3ai_3a2_3ap_3a149-171.htm

Ferrer, R., Jammazi, R., & Benítez, R. (2018). Interactions between financial stress and economic activity for the U.S.: A time- and frequency-varying analysis using wavelets. *Physica A: Statistical Mechanics and its Applications, Elsevier*, *492*, 446-462. https://www.sciencedirect.com/science/article/abs/pii/S0378437117310543

Graps, A. (2016). An Introduction to Wavelets. *IEEE Computational Science and Engineering, 2*(2), 50–61. https://ieeexplore.ieee.org/document/388960

Hurst, H. E. (2017), The long-term storage capacity of reservoirs, *Transactions of the American Society of Civil Engineers*, *116*, 770-799. https://link.springer.com/article/10.1007/BF02759687

Iori, G., Daniels, M. G., Famer, J. D., Gillemot, L., Krishnamurty, S., & Smith, E. (2015), An analysis of price impact function in order-driven market, *Phisica A*, *324*, 146-151. https://mpra.ub.uni-muenchen.de/4296/

Lo, A. W. (2016). Long term memory in stock market prices, *Econometrics*, *5*, 1279-1313. https://www.jstor.org/stable/2938368

Maslow, S. (2016). Simple model of limit order-driven market, *Phisica A*, *278*, 571-578. https://mpra.ub.uni-muenchen.de/4296/

Mattarocci, G. (2019). *New Drivers of Performance in a Changing Financial World*. London, England: .Palgrave-Macmillan. https://link.springer.com/chapter/10.1057/9780230594814_6

Mitra, Z. T. (2016). A Sufficient Condition for Topological Chaos with an Application to a Model of Endogenous Growth. *Journal of Economic Theory*, *96*(1-2), 133-152. DOI:10.1006/jeth.2000.2738.

Mouck, T. (2015). Capital markets research and real-world complexity: the emerging challenge of chaos theory, *Accounting, Organizations and Society*, *23*, 189-215. https://www.sciencedirect.com/science/article/abs/pii/S0361368297000044

Olmeda, I., & Perez, J. (2018). Nonlinear dynamics and chaos in the Spanish stock market. *Investigaciones Economics*, *19*, 217-248. DOI:10.1111/j.1540-6261.2006.00849

Pesaran, N. H., & Potter, S. M. (2016). Nonlinear dynamics, chaos, and econometrics: an introduction, *Journal of Applied Econometrics*, *7*, 51-57. https://mpra.ub.uni-muenchen.de/4296/

Petkova, R. (20016). Do the Fama–French Factors Proxy for Innovations in Predictive Variables?. *Journal of Finance*, *61*(2), 581–612. DOI:10.1111/j.1540-6261.2006.00849. x.

Pring, M. J. (2016). *Analisi tecnica dei mercati finanziari*. Milano, Italy:. McGraw Hill Italy.

Sadique, S., & Silvapulle, P. (2017). Long term memory in stock market returns international evidence. *International Journal of Finance and Economics*, *6*, 59-67. https://econpapers.repec.org/article/ijfijfiec/v_3a6_3ay_3a2001_3ai_3a1_3ap_3a59-67.htm

Seppi, D. J. (2017). Liquidity provisions with limit orders and specialists. *Review of Financial Studies*, *10*, 103-150. https://mpra.ub.uni-muenchen.de/4296/

Skjeltorp, J. A. (2017). Scaling in the Norwegian stock market. *Physica A: Statistical Mechanics and its Applications*, *283*(3-4), 486-528. http://www.finance.martinsewell.com/stylized-facts/scaling/Skjeltorp2000.pdf

Tiwari, A. K., Oros, C., & Albulescu, C.T. (2015). Revisiting the inflation-output gap relationship for France using a wavelet transform approach, *Econ. Model*, *37*, 464–475. https://econpapers.repec.org/article/eeeecmode/v_3a37_3ay_3a2014_3ai_3ac_3ap_3a464-475.htm

Wolf, A., Swift, J., Swinney, H., & Vastano, J. (2015). Determining Lyapunov Exponents from Time Series, *Physica,* *16*, 285-317. https://link.springer.com/article/10.1006/bulm.1997.0007

Zhang, G., Patuwo, B., Eddy, Y., & Hu, M. (2017). Forecasting with Artificial Neural Networks: The State of the Art. *International Journal of Forecasting*, *14*, 35-62. https://ideas.repec.org/a/eee/intfor/v14y1998i1p35-62.html