International Journal of Academic Management Science Research (IJAMSR)
ISSN: 2643-900X
Vol. 5 Issue 10, October - 2021, Pages: 89-96

Assessment Relationship Between Components of the World's Leading Stock Indices in Reflection on the World Financial Market Dynamics

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Abstract: *The development of the global economy presupposes the stable functioning of all its constituent parts, institutions, and markets. Among such markets of the global economy, a special place is occupied by the financial market, which is able to redistribute financial resources. However, such redistribution must be protected from various risks, unfavorable development of negative situations. To solve such problems, the concept of stock indices is used, which reflects the dynamics of price changes for different groups of securities. Knowing the dynamics of the values of stock indices, one can analyze and predict the development of the financial market as a whole. It is also necessary to take into account the relationship of stock indices and the relationship between the components of various stock indices. Based on this, the paper examines a qualitative assessment of the relationship between the components of the world's leading stock indices in reflecting the dynamics of the world financial market. It is proposed to consider such a qualitative estimate taking into account the wavelet coherence. To this end, the paper proposes a general approach to considering a qualitative assessment of the relationship between the components of the world's leading stock indices. The paper considers real data in the context of various world stock indices, presents research results, and draws general conclusions.*

Keywords—valuation; risk; stock index; financial market; securities; wavelet analysis.

1. INTRODUCTION

The financial market plays an important role in the development of the world economy, its various sectors, regional economies and the activities of various business entities [1], [2]. The structured nature and scale of the financial market makes it possible to reallocate resources in the most priority areas. Such a redistribution of financial resources can be both long-term and short-term. At the same time, the financial market has tools that allow you to protect financial resources and their redistribution between different directions [3]-[5].

Among the instruments of the financial market, stock indices should be distinguished. Stock indices reflect the value of a certain group of securities that are traded on the market [6], [7]. Thus, the change in the values of stock indices is a reflection of the change in the price of securities traded on the market. Changes in prices occur under the influence of various factors that determine the dynamics of the functioning and development of the financial market [8], [9].

There are also many different groups of securities circulating in the financial market. Some groups form the basis for the formation of stock indices, other groups form hedging instruments to minimize risks. There are also groups of securities that are components of major stock indices. Thus, it is these components that can determine the dynamics of changes in securities prices, the development of the financial market as a whole.

Analysis of the dynamics of individual components of stock indices is an important task. This makes it possible to better analyze the change in the dynamics of prices for securities, to understand the trends in the development of the financial market. At the same time, an important point of such an analysis is a qualitative assessment of the relationship between the components of the world's leading stock indices in reflecting the dynamics of the world financial market. It is these questions that are considered in this study.

2. MATERIALS AND METHODS

2.1 Related Work

There are many works that deal with various aspects of the analysis of the dynamics on securities prices. At the same time, the key point of such consideration is the analysis of the dynamics of the values of stock indices. At the same time, various tools are used for such analysis: methods of statistical analysis, methods of qualitative analysis, theory of chaos and uncertainty, theory of neural networks, and much more.

For example, A. Gajera uses the methodology of comparative analysis to study the dynamics of the values of the main world indices [10]. The author uses a variety of computational, statistical and mathematical tools to conduct relevant comparative analysis. At the same time, such an analysis is performed for different stock indices, for different stock exchanges. This makes it possible to minimize possible computational errors, the influence of the peculiarities of changes in stock indices, taking into account the functioning of different stock exchanges.

S. Siami-Namini, N. Tavakoli and A. S. Namin use such statistical tools to analyze time series of stock index values as ARIMA and LSTM [11]. This allows a detailed analysis of changes in the values of stock indices at different time horizons. At the same time, to analyze the values of stock indices, the authors compare such values with the dynamics of major currencies in relation to the US dollar. This makes it possible to study the mutual dynamics of the values of stock indices, to expand the results of relevant studies.

In the work of the authors Y. Pu and K. Wu, a combined model is considered for predicting changes in stock indices [12]. This model is based on regression analysis and support vector theory. This model allows us to consider in a new way the time series, which are represented by the dynamics of the values of stock indices. As a result, the authors have a reference time series, which is the basis for predicting a specific stock index. In other words, the authors receive the most significant component that influences the formation of a certain stock index.

In [13], an extensive literature review is presented on the use of various neural networks for predicting changes in the values of stock indices. Similar methods are also considered as decision support tools. For this analysis, both separate groups of securities and weighted values of stock indices are considered.

I. K. Nti, A. F. Adekoya and B. A Weyori presented in their research a systematic overview of fundamental and technical analysis for predicting the values of various stock indices [14]. The authors consider the respective models in the context of forecasting time horizons and taking into account various forecasting components. The research also focuses on forecasting methods, taking into account the geography of stock exchanges, the peculiarities of their functioning.

P. Yu and H. Yan investigate the features of building predictive models for changes in prices on the stock exchange, taking into account the use of deep neural networks [15]. The authors consider in detail such elements of the forecasting process as: description of price series of stock indices, data analysis, selection of model elements for forecasting, construction of a forecast model. In general, this approach allows you to get a high-quality forecast model, improve the reliability of the forecast.

The paper [16] discusses the issues of forecasting the dynamics of the values of stock indices, taking into account the volatility of prices for securities of a certain group. This makes it possible to improve the accuracy of the forecast, to take into account the variability of the dynamics of the values of stock indices. The authors also take into account the sentiment of potential investors, which affects the price of securities. For this, recurrent neural networks are used.

In the study of such authors as A. K. Tiwari, C. T. Albulescu and S. M. Yoon multifractal analysis is used to assess changes in the dynamics of the values of stock indices [17]. Such an analysis is aimed at studying fluctuations in the efficiency of the financial market, which allows us to talk about the possible directions of its development. The authors also consider the individual components of stock indices. In particular, the work deals with the sectorial indices of the Dow Jones.

Also interesting are the works in which the authors use the ideology of wavelets to analyze various trends on the stock exchange [18], [19]. In these studies, a lot of factual material is presented, interesting results are obtained. This allows us to speak about the expediency of using the ideology of wavelets when considering various issues in the analysis of stock indices. At the same time, it is of interest to consider the ideology of wavelets in the context of research in this work.

2.2 Wavelet Analysis as a Basis for Constructing Qualitative Process Assessments

Wavelet analysis is one of the directions in the study of data, which are presented in the form of a certain sequence. Such a sequence can be a time series or other ordered data set.

Wavelet coherence is distinguished among the methods of wavelet analysis [20]-[23]. The interest in wavelet coherence is due to the fact that this method makes it possible to implement an analogue of multiple correlations. At the same time, we can get such a result, where individual results of multiple correlations are presented in one research window. This allows for joint analysis of data for different time horizons. Such analysis is based on the analysis of cross-references between the data series that are analyzed. For this, the following expression is used [24]-[26]:

$$D^2(a,b) = \frac{\left|\Pi(a^{-1}W_{z1z2}(a,b))\right|^2}{\Pi(a^{-1}\left|W_{z1}(a,b)\right|^2)\Pi(a^{-1}\left|W_{z2}(a,b)\right|^2)},$$

where:

$W(a,b)$ – is a values of cross wavelet spectra;

a, b – is a scale and center of time localization, that determine the scale of the wavelet transform;

$z1,z2$ – is a data series that we explore;

Π – is a smoothing operator;

$D^2(a,b)$ – is a squared wavelet coherency coefficient. $0 \le D^2(a,b) \le 1$. If these values tend to zero, then we have a weak correlation. Otherwise, we have a strong correlation [24], [25], [27].

It should be noted that the result of the wavelet coherence is presented in the form of a color diagram. In this diagram, each value of the coherence wavelet has its own color display. This correspondence between color and the value of the wavelet correlation is ranked as a colored column that is displayed on the right side of the results window.

If we are talking about assessing the relationship of some data series, then we can do this based on the following sequence of steps:

– select the data that we will evaluate. For example, this is some stock index (let it be a time series $g1$);

– consider the components of this stock index (let it be time series $z1$ and $z2$);

– find wavelet coherence for the following pairs ($g1, z1$), ($g1, z2$), ($z1, z2$);

– on the basis of a comparative analysis, we draw conclusions about the estimates between the corresponding components and their influence on the dynamics of the stock market values;

– we do similar procedures for different values of stock indices and their components;

– find wavelet coherence between different values of the series of stock index data and their corresponding components;

– draw conclusions about the assessment of the relationship between the components of different stock indices.

2.3 Selected Stock Indices and Their Components as Data for Analysis

Among the world stock indices, the most famous and significant are: Dow Jones Industrial Average (DJI), S&P 500 (SPX), Nasdaq 100 (NDX), DAX (GDAXI), FTSE 100 (FTSE) and Nikkei 225 (N225) [28], [29]. Each of these indices has a number of related components, among which are: futures, ETFs, indices.

In particular (according to the website investing.com),

2 futures, more than 20 ETFs and 7 indices are linked to the DJI;

2 futures, more than 40 ETFs and 21 indices are associated with the SPX index;

2 futures, more than 40 ETFs and 12 indices are linked to the NDX index;

2 futures, more than 40 ETFs and 13 indices are associated with the GDAXI index;

1 future, over 30 ETFs and 5 indices are associated with the FTSE;

4 futures, more than 20 ETFs and 5 indices are associated with the N225 index.

We see that the dynamics of changes in the values of each stock index is determined by many components. Therefore, a qualitative analysis of such relationships is a difficult but important task that can be solved using wavelet analysis.

Below in fig.1 - fig. 5 shows the dynamics of some accompanying components of individual stock indices. As such components, we consider accompanying indices, since in our study we are talking specifically about indices. These data will be used below for an appropriate estimate of the wavelet coherence. The data presented in fig. 1 - fig. 5 covers the period from 05.01.2020 to 23.10.2021 and is presented in averaged weekly values.

In fig. 1 shows the dynamics of the values of the major stock indices DJI and N225.

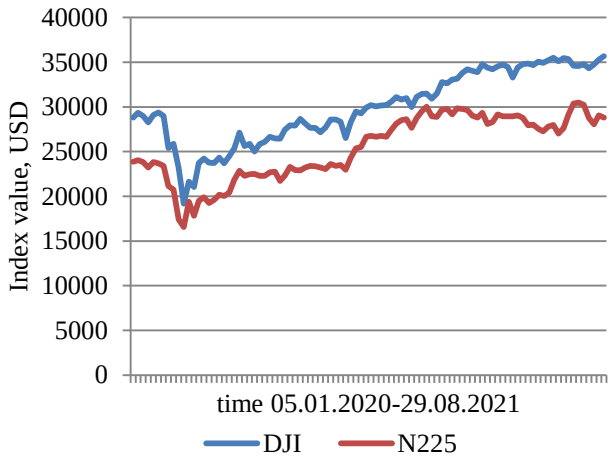

Figure 1. Dynamics of the values of the major stock indices DJI and N225

In fig. 2 shows the dynamics of the values stock index Dow Jones US.

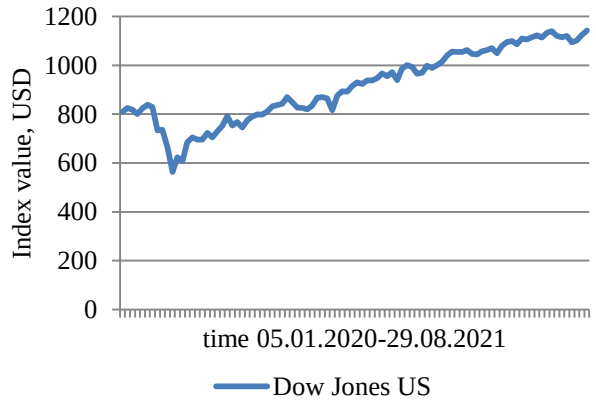

Figure 2. Dynamics of the values stock index Dow Jones US

In fig. 3 shows the dynamics of the values stock index Dow Jones 30.

International Journal of Academic Management Science Research (IJAMSR)
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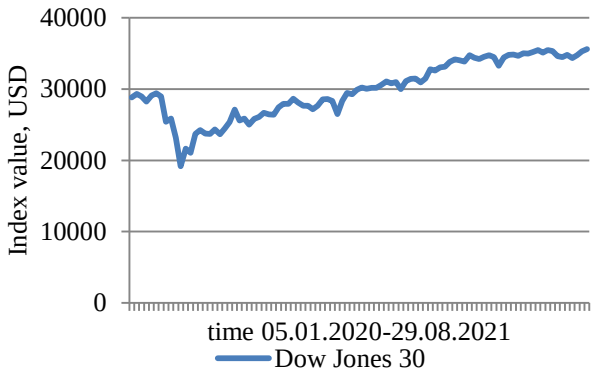

Figure 3. Dynamics of the values stock index Dow Jones 30

In fig. 4 shows the dynamics of the values stock index Nikkei 225 Leveraged.

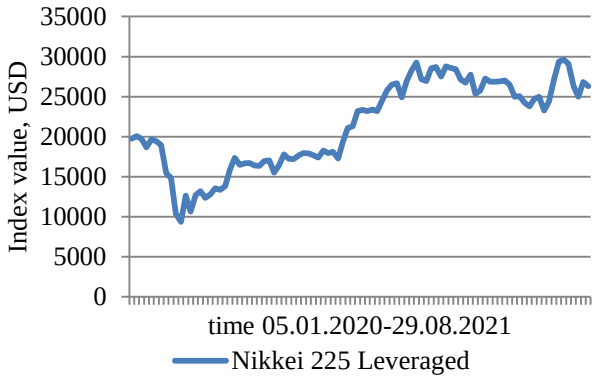

Figure 4. Dynamics of the values stock index Nikkei 225 Leveraged

In fig. 5 shows the dynamics of the values stock index Nikkei 225 Inverse.

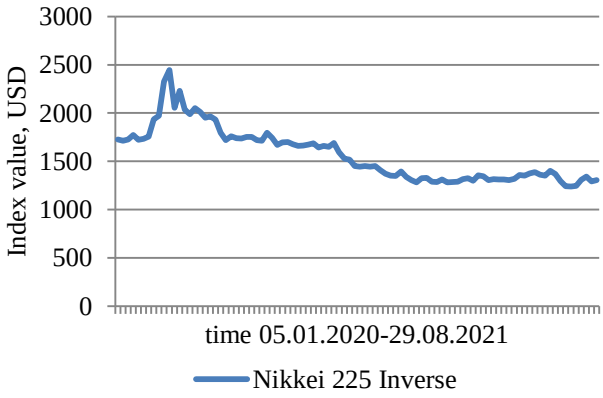

Figure 5. Dynamics of the values stock index Nikkei 225 Inverse

We can see that the dynamics of the indices that we analyze are different. Therefore, there is a natural interest in assessing the relationship between the data presented. Next, we will consider such a relationship based on the application of wavelet coherence.

3. Some Estimates of the Relationship Between the Values of Stock Indices and Their Accompanying Components

In accordance with the approach proposed above, consider the estimates of the wavelet coherence for the DJI stock index and its accompanying components: stock index Dow Jones US and stock index Dow Jones 30.

In fig. 6 shows the values of the wavelet coherence between the values of DJI and Dow Jones US.

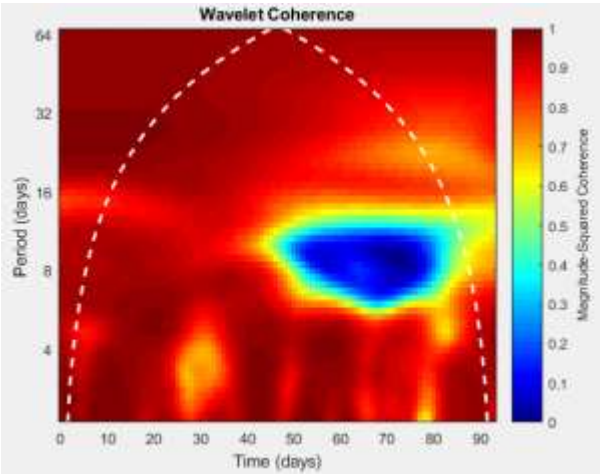

Figure 6. Values of the wavelet coherence between the values of DJI and Dow Jones US

In fig. 7 shows the values of the wavelet coherence between the values of DJI and Dow Jones 30.

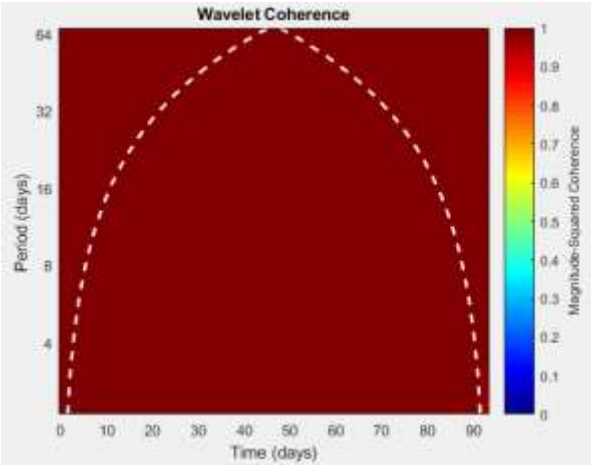

Figure 7. Values of the wavelet coherence between the values of DJI and Dow Jones 30

We see that the estimate of the values of the wavelet coherence of the DJI stock index with its accompanying

components (Dow Jones US and Dow Jones 30) is high and significant. At the same time, the estimate of the values of the wavelet coherence between DJI and Dow Jones 30 is identical. Then we can say that it is the dynamics of the Dow Jones 30 values that determines the trend in the values of the DJI stock index. It is important to take this into account when considering the directions of development of the financial market as a whole, building appropriate forecast models.

This fact is confirmed by the data in fig. 8, which shows the values of the wavelet coherence between the values of the Dow Jones US and Dow Jones 30.

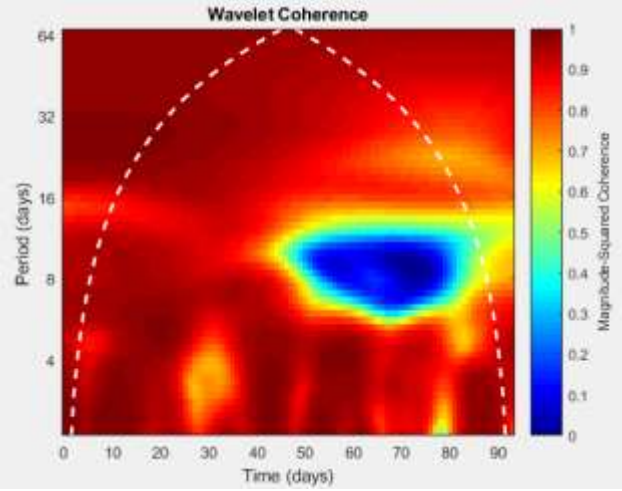

Figure 8. Values of the wavelet coherence between the values of Dow Jones US and Dow Jones 30

In fig. 9 shows the values of the wavelet coherence between the values of N225 and Nikkei 225 Leveraged.

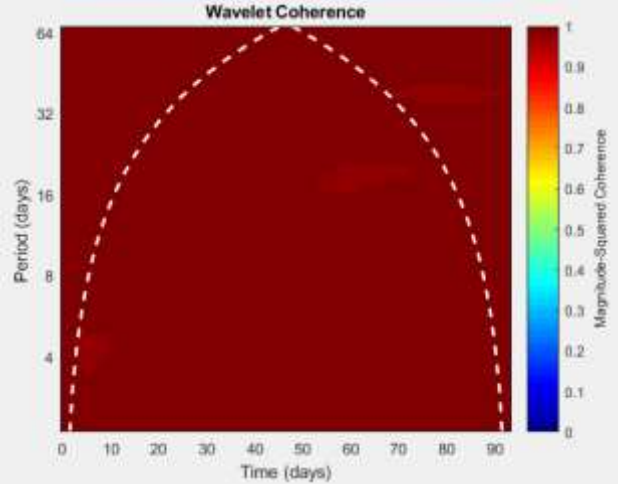

Figure 9. Values of the wavelet coherence between the values of N225 and Nikkei 225 Leveraged

In fig. 10 shows the values of the wavelet coherence between the values of N225 and Nikkei 225 Inverse.

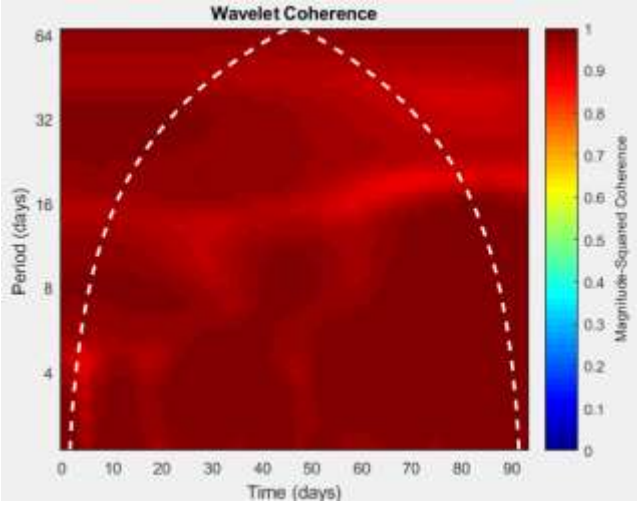

Figure 10. Values of the wavelet coherence between the values of N225 and Nikkei 225 Inverse

For the values of the N225 stock index, it can be seen that its accompanying components under consideration (Nikkei 225 Leveraged and Nikkei 225 Inverse) have the same impact assessment. At the same time, the mutual assessment between Nikkei 225 Leveraged and Nikkei 225 Inverse is also very high (fig. 11).

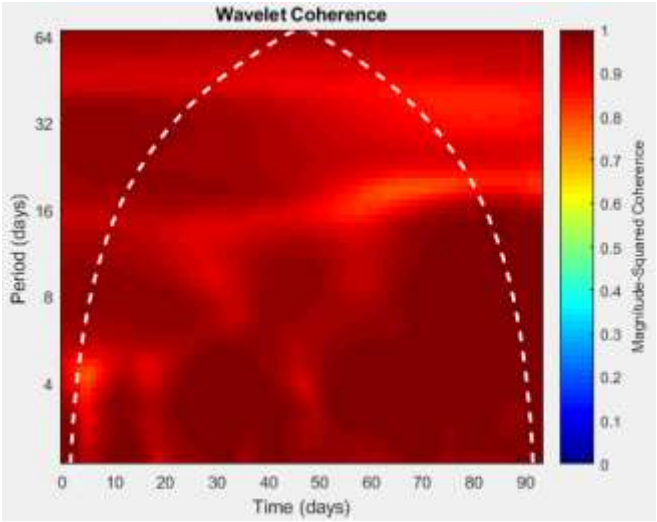

Figure 11. Values of the wavelet coherence between the values of Nikkei 225 Leveraged and Nikkei 225 Inverse

Below we also provide data on the assessment of wavelet coherence between some of the accompanying components of the values of the DJI and N225 stock indices.

International Journal of Academic Management Science Research (IJAMSR)
ISSN: 2643-900X
Vol. 5 Issue 10, October - 2021, Pages: 89-96

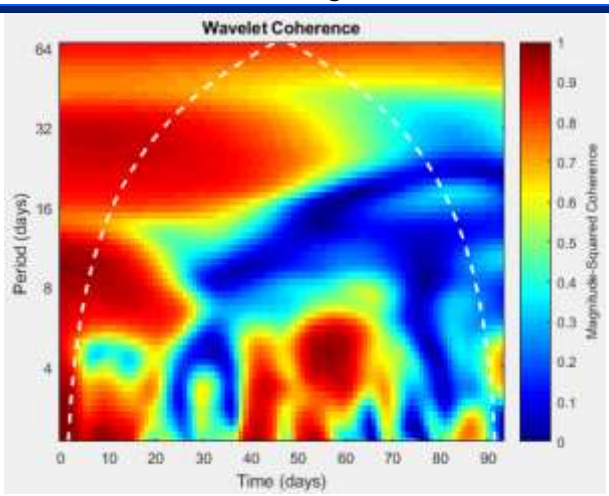

Figure 12. Values of the wavelet coherence between the values of Dow Jones US and Nikkei 225 Leveraged

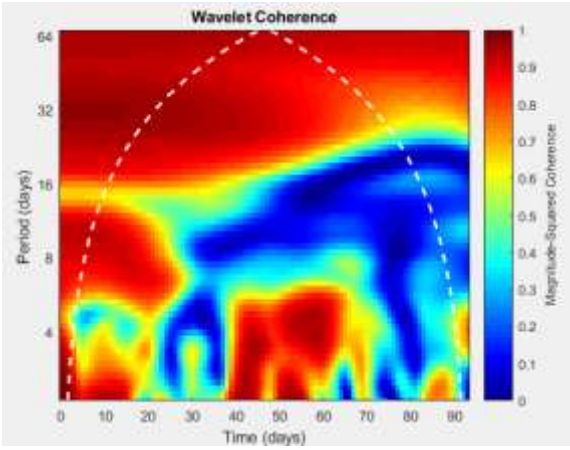

Figure 13. Values of the wavelet coherence between the values of Dow Jones US and Nikkei 225 Inverse

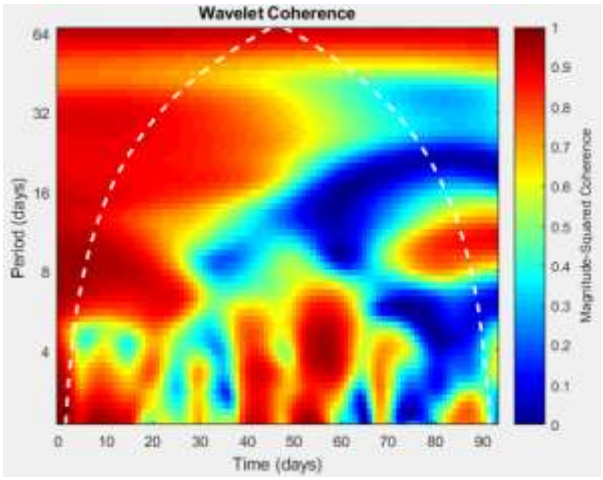

Figure 14. Values of the wavelet coherence between the values of Dow Jones 30 and Nikkei 225 Leveraged

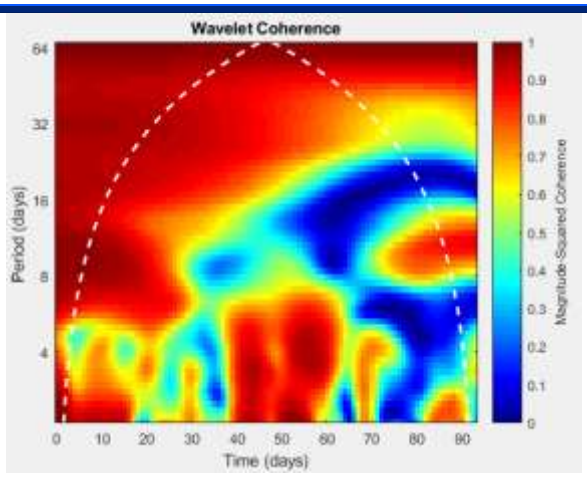

Figure 15. Values of the wavelet coherence between the values of Dow Jones 30 and Nikkei 225 Inverse

We see some identity in the estimates of wavelet coherence between the companion components of the underlying DJI and N225 stock indices. Thus, to build a generalized forecasting model for the development of the financial market, build generalized estimates of the relationship between the main stock indices, it is necessary:

– choose their most significant accompanying components;

– among the set of all accompanying constituent components of different stock indices, limit the choice to those that are not identical. This will provide a simpler but more accurate predictive model.

4. CONCLUSION

The use of various methods of analysis to obtain estimates of the development of the financial market as a whole, the dynamics of changes in the values of stock indices is an urgent and important task. Based on this, the article discusses the possibility and feasibility of using wavelet coherence to obtain estimates of the relationship between the values of various stock indices. Such assessments help to expand understanding of the development of the financial market as a whole.

The article also examines the assessment of the relationship between the accompanying components of various stock indices. It is shown that the evaluation of the wavelet coherence makes it possible to single out the key components of stock indices. This makes it possible to simplify the process of building predictive models, to select the most significant parameters. The paper presents various estimates of the relationship between the components of stock indices, which are obtained on the basis of the real values of such indices.

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