WAVELET ANALYSIS OF THE CRISIS EFFECTS IN STOCK INDEX RETURNS

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Abstract. *The article considers local peculiarities of the world stock indices in 2007–first half 2012 and offers a comparative analysis of the indices. The research is based on the time series decomposition of the most liquid European, Asian, USA, and Brazil stock indices. The aim of the research was to localize and describe the crisis effects on index dynamics in time and scope by using wavelet decomposition techniques. This approach allows to identify clusters of stock indices and to study their common and individual features. The window transformation method is used for the investigation of index returns' volatility dynamics. This method allows to investigate the nature and characteristics of the identified critical waves in the stock markets studied. The combined application of wavelet transform, neural networks and SSA is proposed for the prediction purposes. This approach is used for the return forecast of the German index DAX30.*

Key words*: economic crisis, stock index returns, the wavelet transform, neural networks, SSA*

Introduction

After the crisis of 2008, known as the Crash of the 2008, the idea of the economic theory collapse began dominating among many economists. The ambiguous scientists' interpretations of the crisis reasons and its duration remain to be of interest among the academic community. The crisis of economics as a science requires finding new mechanisms explaining the system instability emergence and deployment.

The global character of the world crisis had some local peculiarities at the level of national economies. The research of these features allowed us to evaluate the stability of economic systems against exogenous shocks and their ability to quickly recover after the crisis. The stock market dynamics, which is expressed in substantial non-linearity and non-stationary time series of stock indices, reflects the systematic problems of economics (Sornette, 2004).

The effective modeling of such time series involves the usage of the modern methods of nonlinear dynamics, including the wavelet transformation technique of the signals with a complex structure. The wavelet functions represent a compact wave localized in time; the expansion coefficients of such waves store information about the drift of the approximated parameters of the function.

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The object of the paper was to conduct the stock market analysis of the developed and emerging countries, based on the decomposition of a time series of stock indices in order to localize and describe the crisis effects in time and scope, as well as to forecast stock indices' returns by using the wavelet decomposition techniques, neural networks and SSA method.

The rest of the paper is organized as follows. The next section contains a literature review, and the third section describes the wavelet decomposition, SSA and neural networks methodology. The empirical results are presented in the fourth section which is divided into three parts: analysis of the European stock markets; analysis of the USA, Brazil and Asian stock indices return dynamics; techniques of the forecast of the stock index returns. The final section concludes with a brief summary and directions for future research.

Literature review

Among the most popular scientists who made a significant contribution to the wavelet theory were P. Goupillaud, J. Morlet, I. Daubechies who developed a continuous and discrete wavelet foundation of transformations.

Applications of wavelet analysis in financial markets analysis have been recently performed by E. Capobianco (2004), M. Gallegati (2008), and T. Kravets (2012). E. Capobianco applied wavelet techniques to the multiresolution analysis of the high frequency Nikkei stock index data, showing the use of the wavelet matching pursuit algorithm in uncovering the hidden periodic components. M. Gallegati investigated the relationship between stock market returns and economic activity, applying the maximum overlap discrete wavelet transform to the Dow Jones Industrial Average and the USA industrial production indices. The application of discrete and continuous wavelet techniques for crisis detection by the analysis of the European stock indices is offered in the paper of Kravets and Sytienko (2012). A comparative analysis of the local peculiarities of crisis deployment in Ukraine and Poland has also been performed in the research.

The wavelet application using the macroeconomics indicator aspect is considered in the works of S. Kim (2005), A. Rua, L.C. Nunes (2009), P.M. Crowley (2007), R. Gencay (2001), H. Lee (2004). P.M. Crowley used a wavelet as a tool of the explanatory analysis, time scale decomposition of relationships, and destiny estimation in the US. He also analyzed the frequency components of the European business cycle by the wavelet multiresolutional analysis. R. Gencay investigated the foreign exchange rate scaling properties by the wavelet techniques. H. Lee studied international transmission effects among the US, Japan, Germany and two emerging markets, including Turkey and Egypt. He states that developing markets are strongly affected by developed markets but not vice versa. S. Kim studied the interdependence of the economic and financial time series using the wavelet variance, correlation, and cross-correlation. Rua and Nunes tested changes in the indices' comovements over time, using monthly data from the US, Germany, UK, and Japan. However, most of the mentioned researches were based on the discrete wavelet transform.

A.A. Subbotin (2008) studied the multiscale stock volatility coefficients using wavelet techniques in the portfolio analysis. R.H. Abiyev (2012) used a combination of the wavelet techniques and neural networks for a time series prediction (we proposed the alternative forecasting method in our research).

Methods

The wavelet analysis is widely used in signal processing for the time series decomposition into a series of hierarchical "approximations" and "parts" (multifrequency analysis), as the well as the decomposition of signal variation (energy) on frequencies. Let us consider the theoretical foundations of the wavelet transform and its application to the analysis of a time series.

The input of continuous wavelet transform (CWT) of the input signal *f(t)* is formally written as follows:

$$\gamma(s,\tau) = \int f(t)\overline{\psi}_{s,\tau}(t)dt, \tag{1}$$

where $\psi_{s,\tau}(t)$ is an affiliated wavelet built from the main wavelet $\psi(t)$ using the scaling and shifting operations.

The inverse wavelet transform which restores the initial signal $f(t)$ is

$$f(t) = \int\int \gamma(s,\tau)\psi_{s,\tau}(t)d\tau ds. \tag{2}$$

The discrete wavelet transform (DWT) is used for the time series processing in real problems:

$$f(t) = \sum_{j,k} \gamma(j,k)\psi_{j,k}(t). \tag{3}$$

The low-pass filter, which is represented as a scaling function $\varphi(t)$ in DWT, is used to decrease the number of wavelets. As the input signal $f(t)$ can be presented with the help of a wavelet to the scale (level) $j - 1$, we can capture it using the scaling function $\varphi(t)$ to the scale of j:

$$f(t) = \sum_{k} \lambda_j(k)\varphi\left(2^j t - k\right). \tag{4}$$

If we change this equation by scaling the level $j - 1$ in order not to lose the detail level, we should add wavelets:

$$f(t) = \sum_{k} \lambda_{j-1}(k)\varphi\left(2^{j-1}t - k\right) + \sum_{k} \gamma_{j-1}(k)\psi\left(2^{j-1}t - k\right). \tag{5}$$

If we continue to decrease the scale by adding wavelets, we can obtain the function development in the wavelet series in the scale i in a simplified form:

$$f(t) = \sum_k \lambda_i(k)\varphi_{i,k}(t) + \sum_k \sum_{j=i}^{\infty} \gamma_j(k)\psi_{j,k}(t), \tag{6}$$

where $\lambda_i(k)$ are the approximation coefficients and $\gamma_j(k)$ are the detail coefficients. The first sum in (6) includes the average function $f(t)$ values on intervals $[k \cdot 2^{-i}, (k+1) \cdot 2^{-i}]$, with the weight functions $\varphi_{i,k}(t)$), and the second one shows fluctuation values in the intervals $[k \cdot 2^{-j}, (k+1) \cdot 2^{-j}]$, $j \geq i$. Therefore, the first sum in (6) gives the smoothed average values of the function at the scaling level i, and the second one adds more small details to the chosen approximation of the signal at the lowest scaling level.

During the research, the SSA and neural networks methods were used for the forecast. Usually, a number of assumptions and simplifications are made during the construction of neural networks. The assumptions include training properties based on training experience, generalization, extraction of significant data from redundant information. Neural networks can change their behaviour depending on the state of their environment. After analyzing the input signals, they adjust by themselves and train to provide the correct response. The trained network can be resistant to some input variation, which allows it to recognize correctly the form that contains a variety of obstacles and distortions (Minu, Lineesh, John, 2010).

The basic version of the SSA method is the transformation of a one-dimensional time series into a multidimensional one using one-parametric procedures of shifting and the research of the obtained multivariate procedure using the principal components method (singular value decomposition) and recovery (approximations) on a number of selected principal components (Golyandina, Nekrutkin, Zhigljavsky, 2001). Thus, the result of the method is the decomposition of a time series into simple components: slow trends, seasonal and other periodic or valuation components, and noise components. The resulting decomposition can serve as a basis for forecasting both the time series and its individual components (Hassani, Soofi, Zhigljavsky, 2010).

Results

The research was conducted by analysing a non-stationary time series of logarithmic returns of Ukrainian (UX), Russian (RTS), Polish (WIG20), German (DAX30), English (FTSE100), French (CAC40), American (Dow Jones), Hong Kong (Hang Seng), Brazilian (Ibovespa), Korean (Kospi), Japanese (Nikkei 225), Shanghai (Shanghai) stock indices for the 08/01/2007–06/31/2012 time period. These indices are most liquid for each region, and their returns are formed by market fluctuations. For the UX index, which emerged only in 2008, data for 2007 were replaced by zeros. The indices' returns were calculated using the latest prices. The wavelets that describe the phase transitions of the studied systems in the best way were defined experimentally for each stock index.

The stock return analysis of the European indices

During the research, the European indices were grouped into two clusters depending on the amplitude of valuation and characteristic features of the obtained components of wavelet decompositions. The first cluster includes the DAX30, FTSE100, CAC40 and WIG20 stock indices.

Figure 1 presents the trend charts of returns of DAX30, FTSE100, CAC40, WIG20 recovered by the approximation coefficients after the decomposition of indices using the DB1 wavelet (Daubechies wavelet with one vanishing moment) with seven decomposition levels. It should be noted that the WIG20 index will be discussed with the second cluster indices in order to compare the crisis behaviour.

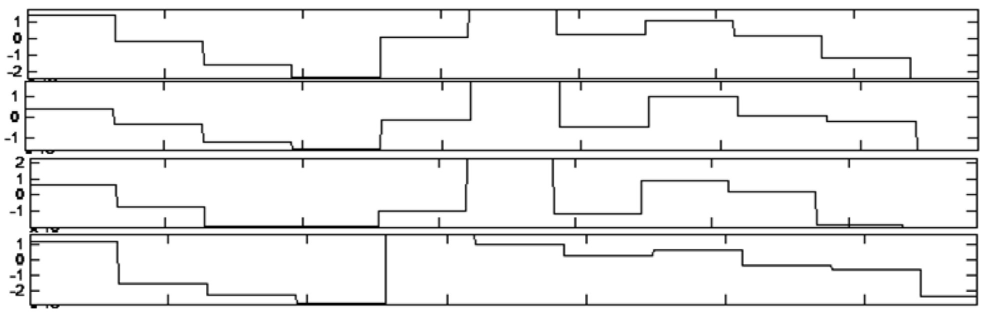

FIG. 1. **Trend charts of DAX30, FTSE100, CAC40, WIG20 returns recovered by the approximation coefficients at the 7th level of decomposition**

Source: authors' calculations.

In Fig. 1, there is a small zone of instability of the indices in late 2007, followed by a sharp decline of returns in mid-2008. Since the late 2008, the indices' dynamics remained very similar, but the DAX30 and FTSE100 indices had more similar trends.

These regularities can be explained by the local characteristics of the above indices. The FTSE100 index is more international than DAX30. Therefore, FTSE100 exceeds the DAX30 during the weak pound sterling, falling interest rates, low levels of economic growth and a decline in global stock markets.

It is well known that DAX30 has shown a greater volatility than FTSE100. Besides, indices repeat each other's tendencies with some minor time-lags, but this feature is hardly evident when analyzing the indices' returns. Usually, DAX30 is more cyclical than FTSE100, since its dynamics strongly depends on German exporters and the European banks' policy. CAC40 is considered to be one of the most international European stock indices (Madaleno, Pinho, 2012).

The CAC40 index includes the 40 companies largest by market capitalization, listed on the Euronext Paris. However, despite the fact that the index basket consists almost

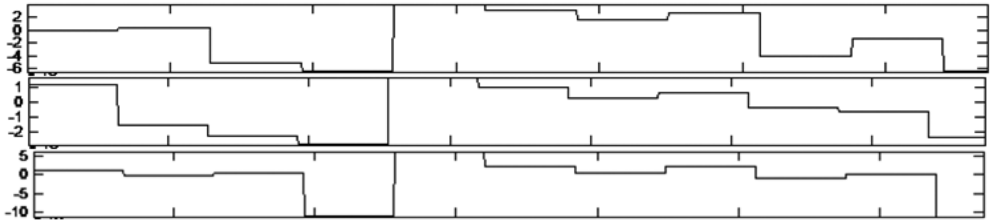

FIG. 2. **Trend charts of UX, WIG20, RTS returns recovered by the approximation coefficients at the 5th level of decomposition**

Source: authors' calculations.

exclusively of French companies, about 45% of the shares included in the list are owned by foreign investors. Such investment attractiveness is easily explained by the fact that French companies have more than 2/3 of their business abroad. So, the CAC40 index is considered to be the most international European index. This high level of dependence on the success of TNC explains some variance of the yield dynamics of the French index from the German and London indices in the aforementioned crisis and recovery period.

The second cluster includes the Ukrainian UX and the Russian RTS. As mentioned above, the Polish WIG20 is analyzed with the second cluster of indices to compare the crisis behaviour in Ukraine and Russia with the EU countries. The choice of WIG20 as an object for comparison can be explained by a stronger similarity of the Polish stock index to the indices of post-Soviet economies. Moreover, during 2006–2007, the Warsaw stock exchange became one of the most popular trading platforms for IPO among the Ukrainian companies.

Similarly to the first cluster, the returns of indices of the second cluster started sharply decreasing in the summer of the 2008 (Fig. 2). Moreover, the decline in RTS return is deeper than the fluctuations of UX returns. This difference was caused by the sharp decline in oil prices as oil is the engine of the Russian economy. In October 2008, a 12-month low of oil prices was achieved. In March 2010, a small decline in both indices returns took place. This decline coincided with the deputies' elections in Russia and the dismissal of Yulia Tymoshenko in Ukraine. Thus, there is some similarity between the UX and the RTS indices. The Ukrainian index repeats the RTS tendencies with a certain time lag.

There was a very similar trend of returns of WIG20 and of the first cluster during 2007 – 1st half of 2008. These trends can be explained by the high popularity of these stock exchanges as an IPO platform (especially at the London and the Warsaw Stock Exchange). After the record for the IPO year 2007, according to the Thomson Reuters, the IPO volume decreased by 71.6% in 2008, it accounted for only 91.7 billion dollars versus 322.9 billion dollars in 2007. The volume of mergers and acquisitions also fell by 31% in 2008. Many companies rejected the IPO due to the global market instability. As a result, in 2008, the London Stock Exchange (LSE) lost its leading position in favour of the New York Stock Exchange.

However, in 2010, the IPO growth in the European market began to recover. It was caused by the fact that private equity funds were coming out from investments in order to fix their profits. This fact explains the similarity of trends in the Polish and Frankfurt exchanges in the above-mentioned period. The difference from FTSE100 and CAC40 is explained by the narrower IPO focus on the Warsaw Stock Exchange (predominantly an agrarian agricultural company) and the more international nature of the English and French markets.

Let us investigate the dynamics of the index return volatility, using the window transformation method (Gencay, Selcuk, 2001). It is based on the calculation of squares smoothed by the centered moving average, detail coefficients of wavelet transform.

$$\tilde{\gamma}_j(k)=\frac{1}{n_j}\sum_{i=-\frac{n_j}{2}}^{\frac{n_j}{2}-1}\gamma_j(k+1)^2,\quad k=\frac{n_j}{2},\quad N_j-\frac{n_j}{2}+1, \tag{7}$$

where N_j is the total quantity of the detail coefficients, and n_j is the window's size at the j-th scaling level.

The application of window transformation at all scaling levels using the discrete wavelet transform allows investigating the nature and characteristics of the identified critical waves in the stock markets studied. Figure 3 presents the dynamics of the volatility of FTSE100, DAX30 and CAC40 returns at the first level of decomposition. The graph clearly defines a wave for all indices, and another zone of instability is more defined for the CAC40 and DAX30, followed by a sharp increase in variance for all indices at the end of the period. A similar picture is observed at the other scaling levels.

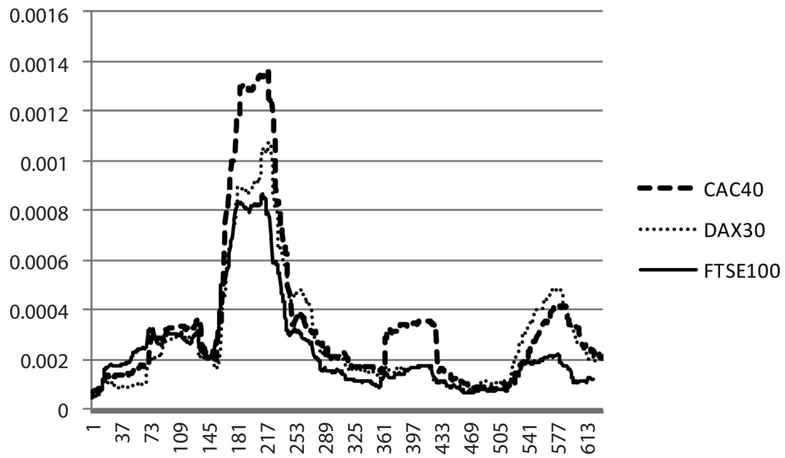

FIG. 3. **Smoothed squares of detail coefficients at the 1st scaling level for CAC40, DAX30, FTSE100 returns**

Source: authors' calculations.

The higher volatility levels of the French and German indices indicate a cumulative effect of instability of some economies on the basic economies of France and Germany.

In Fig. 3, the coincidence of the first crisis wave, which became evident in March 2008, is considered for all the countries of the cluster. The French index has the highest peak at this level of decomposition in comparison with the other indices of the cluster. At the same time, the peak of the FTSE100 fluctuations is the lowest. This situation is explained by the higher stability of the UK economy.

We should pay attention to the surge of CAC40 at the referencing points 360–440 (Fig. 3), which corresponds to the time-bound period from December 2009 to August 2010. This surge appears at both levels of decomposition. Thus, we see an instability period for the 2nd largest economy in the Eurozone in the mentioned period.

This situation was a consequence of the market crisis of the Greece government bonds in the autumn of 2009. In 2010, the lending crisis spread to almost all Eurozone countries. In the late 2009, the public debt of France was 80% of its GDP; the budget deficit and unemployment also reached their critical values.

Such instability of the French index is explained by the fact that French banks are among the biggest holders of the Greek debt (15 billion euros). In spring 2010, a plan aimed at reducing the size of the budget deficit and public debt was designed. The banking system rescue was the top priority like in other countries, and then the loans were aimed to support the companies. The return dynamics stabilized as a result of the taken measures.

However, since March 2011 we see a notable surge in volatility for all three mentioned indices, although the amplitude of CAC40 and DAX30 fluctuations is considerably larger than of the FTSE100. Considering the fact that Britain is not part of the Eurozone and does not carry currency risks associated with the euro, unlike France and Germany, such difference in volatility becomes clear.

The surge of volatility during this period was due to the cumulative effect of the problems of the European Union, the decreasing confidence in its financial situation and the single European currency. The euro crisis changed the governments of Ireland, Portugal, Greece, Italy, Spain and sharpened the relations between Britain and the continent.

Let us perform a similar analysis for the second cluster. Figure 4 shows the volatility dynamics of returns of the UX, RTS and WIG20 indices at the first level of decomposition.

Figure 4 shows that neither Poland nor Russia clearly marked the second wave of the crisis. This fact is explained by the successful economic reforms in the Polish case, and the absence of significant instability in the Russian market is a result of a strong economy dependence on market conditions and commodity prices (namely oil and gas). The second wave of the crisis in Ukraine started in mid-September 2010 when Ukraine, according to the government officials' statements, finally survived from the global

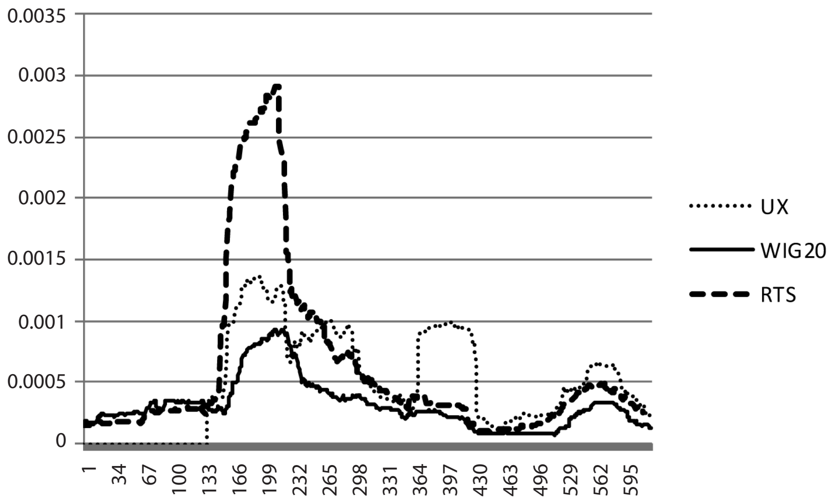

FIG. 4. **Smoothed squares of detail coefficients at the 1st scaling level for UX, WIG20, RTS indices**

Source: authors' calculations.

financial crisis, but the country still experienced the consequences of the crisis through the rising commodity prices and the high indebtedness of the economy.

Nowadays, the transnational corporations (TNCs) have gained such power that sometimes it seems that business and not politics rules the world. In a research conducted by scientists for the Swiss Federal Institute of Technology in Zurich and the European Union (Vitali, Glattfelder, Battiston, 2011), it was determined that among 43 thousands of multinational corporations there is more than 1 million connections at the level of ownership. Moreover, 1300 (3.2%) of them account for 20% of the total operating income of TNCs; they control 60% of the global operating income.

Scientists have gone further and identified that only 147 TNC have the greatest influence. Such TNC concentrate about 40% of control over all global multinational corporations. Researchers believe that this structure has emerged naturally as a result of simple mechanisms of the market economy. Interestingly, the nationality of the companies is mainly Anglo-Saxon, and ¾ of all participants are financial brokers.

Therefore, it is unclear to what extent the fundamental factors and political events affect the global stock index quotes and what impact the close TNCs connections have on these indicators.

The analysis of dynamics of the USA, Brazil and Asian countries' stock indices

A similar analysis for Asia, the U.S., and Brazil was conducted. We cannot clearly identify distinct clusters as in the case of the European indices. At the beginning, the index returns often comply with the same trends and then enter the antiphase.

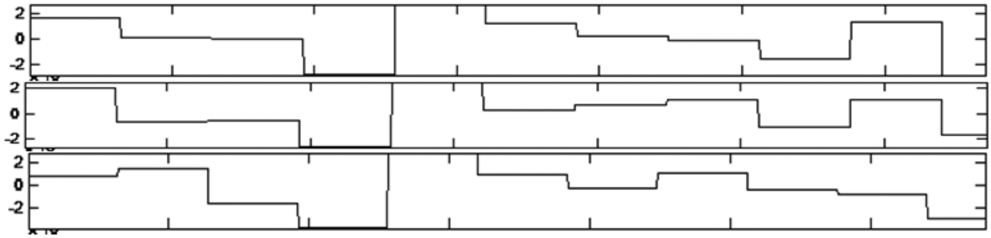

FIG.5. **Trend charts of the Ibovespa, Kospi and HangSeng returns recovered by the approximation coefficients at the 7th level of decomposition using the Db1 wavelet**

Source: authors' calculations.

For a more convenient presentation, we grouped the indices into two clusters depending on the amplitude component obtained by wavelet decomposition. The first cluster includes Hang Seng, Ibovespa, and Kospi indices and the second the Nikkei 225, Shanghai composite (SSE), Dow Jones indices.

Figure 5 illustrates that the returns of the Kospi and Ibovespa indices have very similar trends. In general, it is believed that the behaviour of the Kospi index is closer to the behaviour of the U.S. indexes; it is not characterized by a strong trend component. The Hong Kong index has a similar trend with the above two indices since the summer of 2008.

Let us have a detailed look at the dynamics of the first cluster indices' returns. We will start with the Brazilian Ibovespa and the characteristics of the crisis deployment in the country. It is known that the financial crisis had almost no impact on Brazil. Let us verify this claim. The global financial crisis has caused the devaluation of the real to the U.S. dollar (from 1.6 real per dollar in August 2008 to 2.3 in April 2009) and the euro. However, this fact had no crushing impact on the economy.

Brazil almost did not import foreign products due to the extremely high import duties. Besides, the national currency depreciation increased the competitiveness of Brazilian products. Brazil had a sharp increase of its exports and significantly improved its external account. The domestic inflation increased the internal prices of food, but they remained reasonable for the population.

Since Brazil was providing food not only to itself but also to a significant part of the world population, the positive dynamics of its index returns becomes clear. Besides, the so-called "accelerated development program", which was aimed to attract investments in the country and was preceded by the economic crisis, played a significant role in the stability of the Brazilian economy. Thus, the Brazilian economy was in the upraising stage at the early deployment of the financial crisis and had some margin of strength.

The economic crisis of 2008–2010 strongly affected the South Korean economy. In 2008, the industrial production in the country decreased by 26% together with increased unemployment and the won's devaluation against the dollar. During 2009, the economy gradually recovered, aided by the anti-crisis government program evolved during 2008.

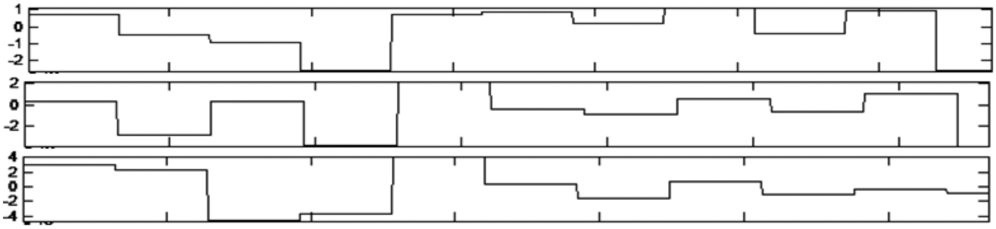

FIG.6. **Trend charts of returns of the Dow Jones, Nikkei 225, Shanghai composite indices recovered by the approximation coefficients at the 7th level of decomposition**

Source: authors' calculations.

This has created favorable conditions for Korean exporters. The growth accelerated in 2010, after the beginning of the world markets recovery which stimulated the demand for the South Korean goods. Particularly, in the first quarter of 2010, the annual GDP growth rate reached 5.2%, and unemployment fell from 4.4% to 3.8% (Smith, 2009).

Figure 6 presents the trends of the returns of Dow Jones, Nikkei 225, Shanghai composite indices recovered by approximating coefficients at the 7th decomposition level using Db1.

Figure 6 demonstrates the similar behaviour of returns of the Nikkei 225 and Shanghai Composite indices in the post-crisis period, although the volatilities of returns occur at different amplitudes. The dynamics of Dow Jones returns during 2007 – the first half of 2008 resembles the dynamics of returns of the first cluster of the European indices, but it inherited a greater stability, taking into consideration the oscillation amplitude.

If we consider the impact of the financial crisis on the U.S. economy, we can see a more or less stable tendency of the Dow Jones returns dynamics. This was a result of the program of quantitative easing and unconventional macroeconomic policies which stimulate the economy during the crisis. Due to the exhaustion of quantitative easing programs in August 2011, the U.S. faced the problem of approaching the actual percentage of the public debt to the GDP to its critical point, which preceded the default state of the country. However, the increase in the indicator's level had a positive effect on the index returns dynamics.

Figure 6 presents very different trends of returns of the Japanese and Chinese indices. First, let us characterize the dynamics of returns of the Japanese index Nikkei 225.

Despite the fact that Japan is the second largest world economy after the U.S. and has a high-tech industry and a stable economy, its economy was still affected by the global financial crisis. The main reason for this effect was the high level of country's export dependency. Japan exports most of the products to the West. However, during the 2008–2009 global financial crisis, the demand for high-tech products began to decline sharply; this fact weakened the Japanese economic situation. Only in 2008 the volume of Japanese exports fell by 35%. The greatest losses were suffered by the automobile and electronic industries.

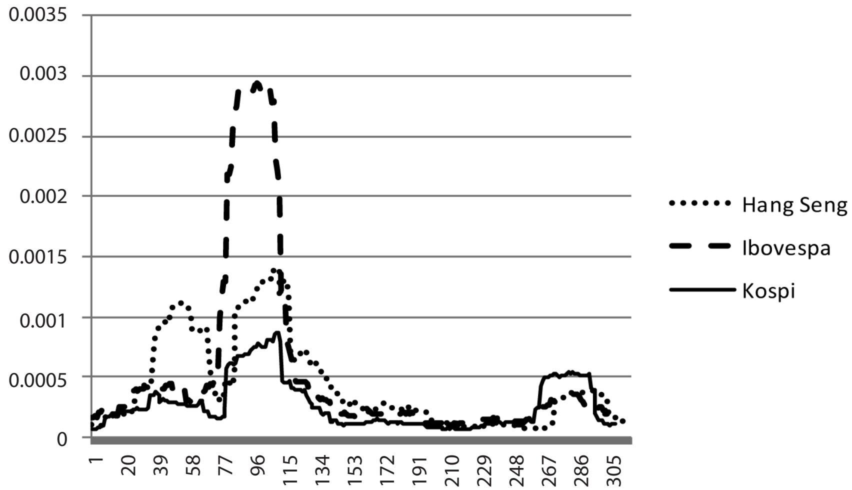

FIG.7. Smoothed squares of detail coefficients at the 2nd scaling level for Hang Seng, Ibovespa and Kospi indices

Source: authors' calculations.

Obviously, the crisis in Japan was completely a result of the world financial crisis; there were no serious internal structural problems in the Japanese economy. The other reason was the dramatic increase of the yen against the euro and the dollar, which significantly reduced the competitiveness of the Japanese products. Another significant factor was the decline in domestic demand in the country as a consequence of the crisis.

Figure 7 presents the smoothed squares of detail coefficients at the second decomposition level for the Hang Seng, Ibovespa, and Nikkei 225 indices. The figure illustrates the relatively similar tendencies of volatility of these indices. However, the volatility differs at different decomposition levels.

The volatility dynamics of the Brazil Ibovespa is very similar to the volatility of the European indexes shown in Fig. 3. In turn, the volatility of the Korean index is the lowest and demonstrates the internal stability and resistance to the crisis of South Korea. The Hong Kong index has a double peak of the crisis, which was marked also at other levels of decomposition. This feature is explained as a reflection of the both internal Hong Kong instability and the world crisis, as the listing of the index includes stocks of numerous international companies.

If we examine the second cluster (Fig. 8), we can see almost identical volatility trends of the Dow Jones and Nikkei 225 indices. The volatility of the Shanghai index has a wider peak as compared with the other indices examined in the research.

The volatility surge of the Hang Seng index in the first half of 2012 was caused by the Chinese public policy aimed to slow the economic growth in order to enhance economic development and promote the implementation of reforms. Besides, the stock indices' instability was enhanced by the political disorder in the mainland, the first signs of which

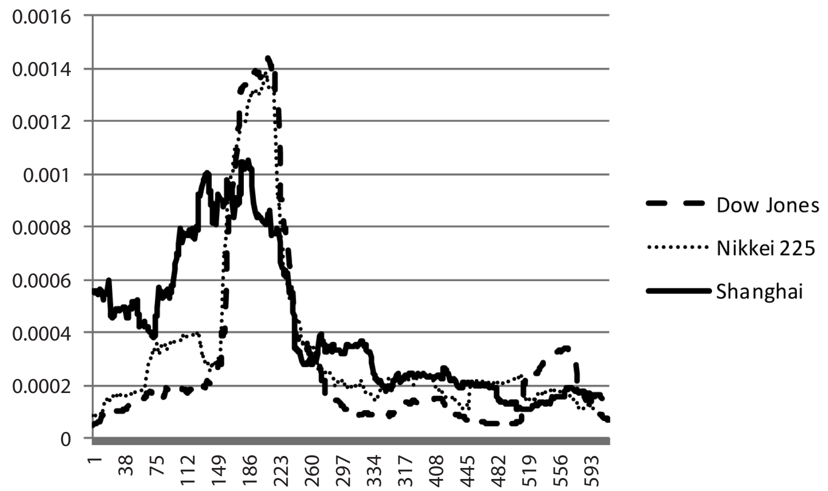

FIG.8. **Smoothed squares of detail coefficients at the 1st scaling level for the Dow Jones, Nikkei 225 and Shanghai composite indices**

Source: authors' calculations.

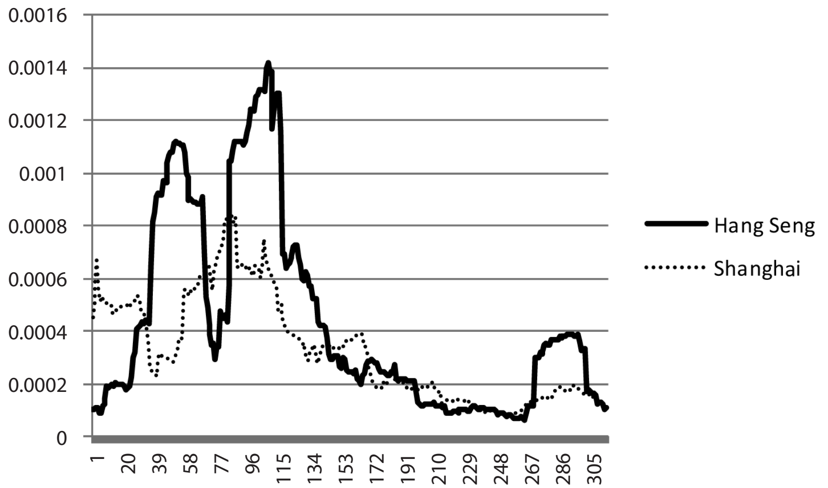

FIG. 9. **Smoothed squares of detail coefficients at the 2nd scaling level for the Hang Seng and Shanghai composite indices**

Source: authors' calculations.

were evident in April 2012. It should be noted that two Chinese stock indices – Shanghai composite and Hang Seng – have a different crisis deployment (Fig. 9).

The point is that the Shanghai composite index is calculated based on the daily prices of all stocks traded in the quotation lists A and B of the Shanghai Stock Exchange, while the Hang Seng index takes into account changes in the quotations of the largest 34 Hong Kong companies.

Given the rapid development of more dynamic Chinese companies in the recent years and one of the famous Asian tigers, on the other hand, we observe the dynamics of absolutely different indices. The Shanghai composite index demonstrates the development only of the Chinese companies and the country as a whole, while the Hong Kong index reflects the local development of the Asian tiger. The dynamics of these two indices differs because of their historically separated development. However, recently there has been a slow smoothing of the dynamics of the Hang Seng index and the Shanghai Stock Exchange index.

This is a result of the growing influence of mainland China on its island part. Recently, the Chinese government has announced its intention to take measures to stimulate the Hong Kong economy, such as to develop the cross-border infrastructure projects. The deeper integration of Hong Kong with mainland China is anticipated in the near future.

Also, depending on the decomposition level, the indices demonstrate common or opposite dynamics; this greatly complicates the comparative analysis. Among the reasons for this seemingly strange asymmetry, the following items should be mentioned. First, the securities on the Hong Kong stock exchange, unlike the Shanghai's securities, may be sold without coverage. Second, the securities on the Hong Kong Stock Exchange can be bought by both residents and non-residents of the country. Shares listed on the Shanghai Stock Exchange are available only to domestic investors. At the Shanghai Stock Exchange, the system of Internet payments is rather complicated. However, as mentioned earlier, the biggest difference between these two indices is that the listing of the Hong Kong Stock Exchange includes a number of shares of foreign companies, while the Shanghai Stock Exchange listing includes only the shares of domestic producers.

Since the Chinese and Hong Kong markets are rather different, their direct comparison is inappropriate.

Returns forecast

Let us conduct a forecast of stock indices returns, based on the wavelet decomposition, SSA and artificial neural networks methods' synthesis. Calculations were performed using the Matlab package, the Alyuda NeuroIntelligence 2.2 (577) neural networks' analysis package, and the Caterpillar SSA 3.3statistical package**.**

The German index DAX30 was chosen for the demonstration purposes of the proposed forecasting method. It was experimentally found that wavelet Sym2 with two decomposition levels copes with the German index returns in the best way.

In the first version, initially the signal was denoised using a selected wavelet (we used the automatic mechanism of noise removal, programmed in the Matlab statistical package). Then, the denoised signal was processed by the SSA method, and the forecasted values were calculated.

In the second variant, at first we chose the coefficients of the wavelet signal decomposition, significant for the forecast. Then, we selected the optimal neural network from the predicting possibility point of view and performed the forecast. Let us describe the proposed approach in detail.

Let us choose the maximum extent of the series history, which affects the forecasted value. In this case, we limited ourselves to 64 trading days. We conducted a scaling wavelet analysis, calculating the discrete wavelet transform for a sliding 64 length window.

As a result, we obtained a 37-component vector of coefficients for each forecasted day (original series consisted of 1378 samples, and 1378 – 64 = 1314 observations remained for the prediction purposes). All the data constituted an observation matrix with the number of dimension 1314 * 37. The estimated value Y formed the vector of 1314 components. The target of the prediction was to build an effective display $Y = Y(X)$.

Let us select the vector components of wavelet coefficients which have the greatest impact on the predicted values. Thereto, we will use the absolute value of a corresponding coefficient of linear correlation. The calculation results are presented in Fig. 10.

The 12 largest values can be left for the prediction purpose, setting the threshold at the level 0.05. We used the neural network to construct the mapping $Y = Y(X)$. We obtained a list of architectures for multilayer perceptron and the corresponding figures of the training process of the network (see Fig. 11).

The neural network of number 1 is chosen as an optimal one, as it shows the best performance of the training process and the tested parameters of the trained perceptron (Fig. 12). The underlying network's architecture includes 12 input neurons, 12 hidden neurons, and 1 output neuron. Accordingly, the vectors of the most significant wavelet coefficients will be submitted to the input, and the output will have a forecast signal.

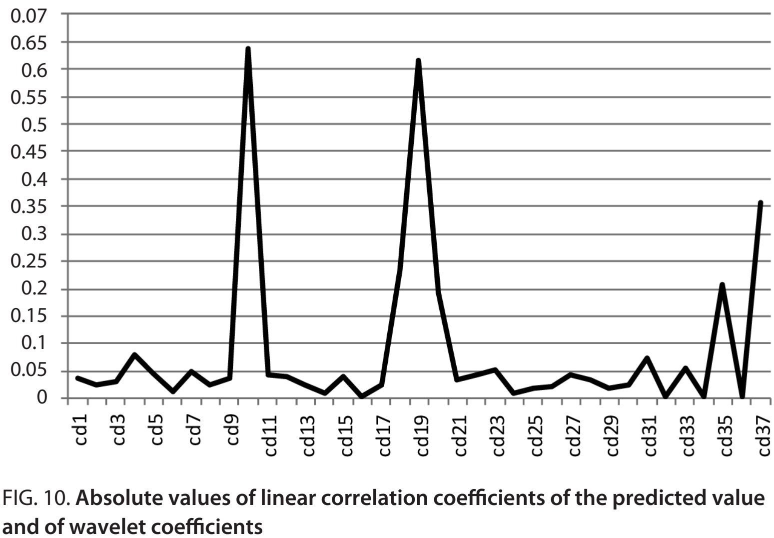

FIG. 10. **Absolute values of linear correlation coefficients of the predicted value and of wavelet coefficients**

Source: authors' calculations.

Architecture	# of Weights	Fitness	Train Error	Validation Error	Test Error	AIC	Correlation	R-Squared
[12-12-1]	**169**	**414,911012**	**0,002204**	**0,002088**	**0,00241**	**-10152,273122**	**0,869181**	**0,755395**
[12-8-1]	113	412,508944	0,002211	0,002099	0,002424	-10261,723985	0,869584	0,756169
[12-16-1]	225	413,544721	0,002208	0,002097	0,002418	-10038,990926	0,869668	0,756316
[12-14-1]	197	412,830189	0,002201	0,002101	0,002422	-10097,242364	0,869552	0,756063
[12-10-1]	141	414,430128	0,002197	0,002093	0,002413	-10210,768446	0,869494	0,755941
[12-13-1]	183	413,051567	0,002213	0,002098	0,002421	-10120,820153	0,869521	0,756062
[12-11-1]	155	414,116746	0,002204	0,00209	0,002415	-10180,474021	0,869279	0,755559

FIG. 11. **Indicators of the network training process**
Source: authors' calculations.

	Target	Output	AE	ARE
Mean:	0,000316	-0,000081	0,002952	2,529182
Std Dev:	0,007122	0,004805	0,002733	27,185281
Min:	-0,029643	-0,019916	0,000007	0,003743
Max:	0,028949	0,020602	0,02362	748,38697

Correlation: 0,844193

FIG. 12. Tested parameters of trained perceptron
Source: authors' calculations.

To verify the effectiveness of the resulting display, we will add 21 observations to the original time series. Let's make preliminary calculations: go to the representation of the log-differential series and continue the scaling wavelet analysis for the chosen window length. The forecasted values are built on the basis of the obtained matrix of the coefficients of the most significant dimension 21*12.

Figure 13 presents the graphs of the real and denoised dynamics of DAX30 returns and the forecasted values obtained using the neural networks and SSA methods. This figure demonstrates that the forecasted index returns become the overtaking indicator for the real values, as their sharp rise or fall precede similar changes in the real signal. A striking example of the latter is the last forecasted value in which both real and denoised signal values continued growing.

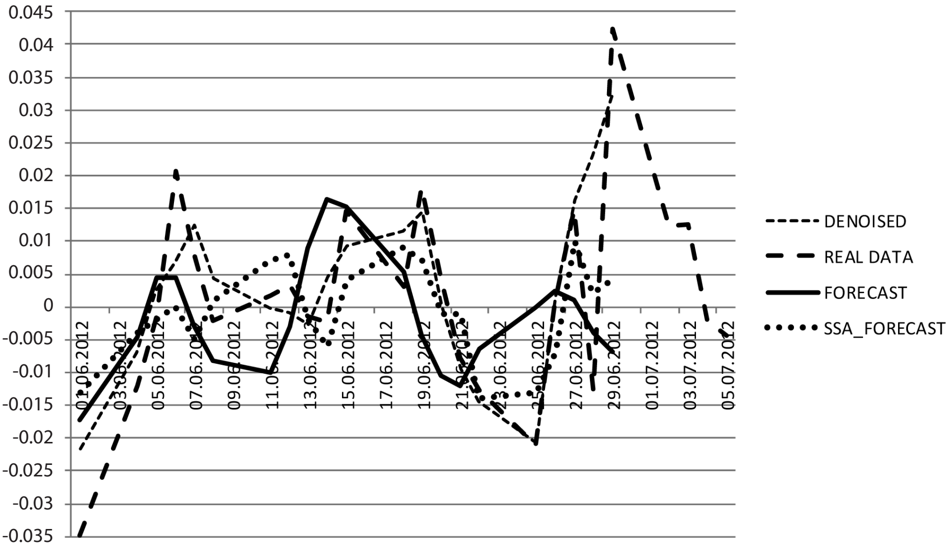

FIG. 13. **DAX30 returns dynamics and its forecasted values**
Source: authors' calculations.

For illustration purposes, the graph shows the signal value dated July 2, 2012, which corresponds to a sharp drop in the values of the signal. Note that the forecast value began to decline at the previous step. In contrast, the estimated values, constructed using the SSA method, match the real signal more accurately, but they should not be used as overtaking indicators.

Thus, the forecast based on a synthesis of the wavelet analysis and the neural networks method is an auxiliary indicator to determine the change in the dynamics of the return signal. This helps a trader to determine the moment of signing the agreement or exiting from it. It should be noted that the above method can be applied to the analysis of returns of other research objects such as currencies, oil, gold, and others.

Conclusions

We live in a non-paradigmatic era when the astronomical amount of speculative money circulates in the world market according to a not fundamental but technical analysis which has been almost not influenced by general macroeconomic indicators. Therefore, fluctuations of stock indices (including their returns) ceased to be reliable indicators of macroeconomic realities. Today, they give us only a rough idea of what is actually happening at the moment.

In the early 2012, the world economy has entered a dangerous phase. Europe has entered a deep recession, and the growth of the major developing countries such as Brazil, India, Russia, South Africa, and Turkey has appreciably slowed down, mostly because of the tightening of their economic policies. Emerging countries are now in a more vulnerable position than at the beginning of the last crisis. Rich countries already have no previous resources; thus, developing countries will have to reduce public expenditures. Therefore, the new global risk could slow down not only the external demand, but also the consumers' one.

The question of the second wave of the global financial crisis is very important, because the situation in the financial sector of the world economy does not improve, but even continues to worsen in some areas. It can be a result of the futility and insufficiency of the announced reforms. Moreover, there is a desire to fix the economic foundations without implementing drastic policies.

During the research, we have observed radically different pictures of the stock returns behaviour during the crisis and relaxation periods around the world. The use of wavelet analysis gave the possibility to detect the time series peculiarities and their volatility. Two clusters – DAX30, CAC40, FTSE100 and UX, WIG20, RTS – were delivered for the European stock markets based on the dynamics and similarity of their returns; and two clusters were developed for Asian countries, Brazil, and the United States (Hang Seng, Ibovespa, Kospi and Dow Jones, Nikkei 225, Shanghai composite). Interestingly, two Chinese indices refer to two different clusters. It should be also noted that, despite the close relationship between the studied indices, the local peculiarities of each of them were highly remarkable.

The research considered a combined application of wavelet transform and neural networks to the problem of forecasting the returns of stock market indices. We have found that the best results are obtained by using the forecasting possibilities of the neural networks, the input of which is the wavelet coefficients of a decomposed time series. Interesting results can be obtained by a combined use of wavelet transform and the SSA method. The obtained results allow forecasting the returns of stock indices in a short term with a fairly high degree of accuracy.

The future research should include a study of the dynamics of the stock market indices using the continuous wavelet transform, determination of coherence indicators of the time series, and an improved forecast employing the newly obtained results.

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