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Dynamics of Changes in Commodity Indices for Commodities: Wheat, Corn, Soybeans, Sugar, Cocoa

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Abstract: *Commodity indices determine the weighted price of various groups of goods. At the same time, the dynamics of such indices reflects the dynamics of prices for the corresponding goods. In turn, commodity indices are interconnected with the dynamics of indices, both the securities market and the general world market. An analysis of this relationship helps to understand the dynamics of the functioning and development of individual market segments, the economy as a whole, and various business entities. An important aspect of this analysis is the assessment of relationships, primarily between groups of goods that are placed on the commodity market. Based on this, the paper considers the main aspects of the analysis of the dynamics of commodity indices, presents graphs of commodity indices for individual groups of goods, and considers the main statistical characteristics of such data. To assess the mutual analysis of the dynamics of changes in commodity indices, the wavelet coherence methodology was used. This methodology makes it possible to evaluate the mutual dynamics of commodity indices over different time horizons. We can better understand the dynamics of the relevant relationship, which is important for making investment decisions. Such assessments are also important for making decisions about interaction in different segments of the world market or the stock market. Some results of assessments of such a methodology are presented. The paper presents a lot of factual material, which helps to understand the logic of the study.*

Keywords—analysis; dynamics; price; wheat; corn; soybeans; sugar; cocoa; commodity market; commodity indices; wavelet coherence

1. Introduction

Commodity markets are one of the components of the common world market [1], [2]. In the structure of the world market, commodity markets are defined by the way they trade. At the same time, commodity markets trade goods of the primary sector of the economy, and not industrial goods [3], [4]. In other words, it is commodity trading. Then the sustainable development of the commodity market can be considered as a source of effective functioning of various segments of the world market, the economy as a whole.

Various tools are used to implement the functions of the commodity market. At the same time, futures contracts are a classic way of investing in commodities [5], [6].

Thus, the dynamics of the development of commodity markets can be traced on the basis of the dynamics of prices for the corresponding securities. In this aspect, the commodity market can be considered as a segment of the general securities market. At the same time, we can talk about the interaction of various segments of the securities market, and, consequently, segments of the world market. Such interaction is manifested in the movement of the corresponding financial flows, which are determined by the dynamics of prices for various securities [7]-[9]. Thus, we can talk about the general concept of analysis based on the movement of various financial flows [10]-[16].

An analysis of such dynamics makes it possible to assess the functioning and development of both the commodity market and the securities market, the common world market. The primary data in such an analysis structure is the analysis of commodity market data. In this aspect, an important component of the analysis is the dynamics of prices for individual groups of goods. It is also important to know the trends in the mutual dynamics of such groups of goods.

Various methods and approaches are used to analyze commodity market data. As a rule, classical methods and approaches of statistical analysis can be distinguished among such tools [17]-[19]. You can also use specialized tools and tools that are widely used in other areas of research [20]-[26]. This allows you to better understand the dynamics of the development of the commodity market, its relationship with other segments of the world market.

Therefore, we can note the importance and relevance of the chosen research topic. This is based on the relationship of the commodity market with various segments of the stock market, the world market. The importance of such a study is also associated with the possibility of studying the conditions for the development of the economy, the functioning of various business entities.

Thus, the main purpose of this study is to analyze the dynamics of prices for certain groups of goods in the corresponding segment of the world market.

2. Related Works

As noted earlier, various methods and approaches can be used to analyze the dynamics of prices in the commodity market. This, in particular, is confirmed by the analysis of related works. Such an analysis is presented below.

For example, E. Antwi, E. N. Gyamfi, K. Kyei, R. Gill and A. M. Adam in their work explore the main components of prices for commodity futures using the decomposition method [27]. For these purposes, the authors use various models of time series analysis. At the same time, the authors define the components that justify the market price of commodity futures. The authors also use decomposition methods, empirical mode decomposition (EMD), variational mode decomposition (VMD) [27]. The paper also uses the hierarchical clustering method and the Euclidean distance method for classification. The paper also shows that the prices of commodity futures are influenced by economic development, and not by short-term market fluctuations caused by the usual disequilibrium of supply and demand [27]. This confirms the importance of this study, conducting a new analysis in this direction.

F. Benedetto, G. Giunta and L. Mastroeni consider the possibility and expediency of using the maximum entropy method to assess the predictability of financial and commodity prices [28]. To do this, the authors consider data for analysis in the form of time series. In their work, the authors use the signal processing method to analyze time series of financial and commodity prices to assess the predictability of financial markets [28]. The work also uses the maximum entropy method (MEM), which predicts the entropy of the next future time interval of the time series under study using the least squares minimization approach [28]. This allows you to get more accurate results, additional information for analysis.

M. Kateregga, S. Mataramvura and D. Taylor consider estimates of the parameters of stable distributions using the logarithms of commodity futures returns [29]. First of all, the authors explore the theory of α-stable distributions for estimating parameters from financial asset logs. The authors discuss four-parameter estimation methods, including quantiles, the log-moment method, the maximum likelihood (ML) method, and the empirical characteristic function (ECF) method [29]. This allows you to more accurately assess the profitability of commodity futures.

L. Y. He and S. P. Chen explore an approach to quantifying power-law cross-correlation and its application to commodity markets [30]. The authors consider detrended moving average cross-correlation analysis (DMCA) to detect power-law cross-correlation between two correlated non-stationary time series by combining detrended cross-correlation analysis (DCCA) and detrended moving average (DMA) [30]. This allows you to more accurately explore the data, get additional information to make the necessary decisions. The proposed method was used to analyze real data and made it possible to substantiate some dependencies.

The paper [31] considers the issues of using neural networks to model the dynamics of energy prices. At the same time, the authors emphasize that pricing models and the methods used to estimate price dynamics are becoming increasingly important for data analysis. The authors also carry out a statistical evaluation of the considered forecasting models and prove that some of them provide the first four unconditional moments of the predicted sequences with almost equal moments that are estimated from market data [31]. This allows the proposed method to be compared with other approaches.

M. Pal, P. M. Rao and P. Manimaran in their study use multifractal cross-correlation analysis to analyze gold and crude oil prices [32]. At the same time, the cross-correlation was measured quantitatively by the Hurst scaling exponents and the singularity spectrum [32]. The authors established the presence of a multifractal cross-correlation between all the time series that were analyzed [32]. This highlights the importance of using multifractal analysis for relevant studies.

In the work of the authors F. Wu, W. L. Zhao, Q. Ji and D. Zhang, the issues of studying the dependence of international prices on commodity futures are considered [33]. At the same time, the authors consider a network approach based on various statistical indicators. First, the authors use partial correlations to build a static dependency network for a vector of variables, and then determine intrasystem relationships in a minimum spanning tree (MST) to evaluate the centrality of variables [33]. This allows you to build an easy-to-use method for studying various dependencies.

M. K. Ahmed, G. M. Wajiga, N. V. Blamah and B. Modi consider various problematic aspects of stock market forecasting using the ant colony optimization algorithm [34]. The paper also noted that neural networks have some shortcomings in learning data patterns and that they can work inconsistently, unpredictably due to the complexity of stock market data. Therefore, the authors propose to use a computational intelligence method called Ant Colony Optimization (ACO), which is suitable for solving a distributed control problem, in order to obtain the most optimal solution [34]. The paper presents various statistical data, the results of experiments.

Y. R. Ma, Q. Ji, F. Wu and J. Pan explore various factors that affect price changes in commodity markets [35]. At the same time, first of all, the return dynamics of movement in international commodity markets is considered. For this analysis, the authors use a minimum spanning tree (MST) characterized by the DCC-GARCH specification to depict the joint movement of returns between different commodities [35]. A connectivity network is also being built to study the contribution of both fundamental and non-fundamental factors to the level of joint movement of commodity yield [35]. The paper presents a lot of factual material that helps to understand the logic of the study.

M. Hu, D. Zhang, Q. Ji and L. Wei explore macro factors and volatility in commodity markets [36]. The authors analyze the relationship between macro factors and realized volatility in commodity futures. To do this, the authors consider economic policy uncertainty (EPU), economic surprise index

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Vol. 6 Issue 10, October - 2022, Pages: 74-80

(ESI), default spread (DEF), investor sentiment index (SI), volatility index (VIX) and geopolitical risk index (GPR) [36]. Thus, the authors create a dynamic communication network to conduct the appropriate analysis.

The analysis carried out showed the possibility of using various methods and approaches to analyze the dynamics of prices in commodity markets. At the same time, it should be noted the importance of analyzing the joint dynamics of prices for different goods. In particular, various methods of multifractal cross-correlation analysis are used for this.

3. Statistical Evaluations of Individual Commodity Indices

For analysis in this study, we will consider one of the groups of the commodity market, the so-called group of non-solid goods. This group includes: wheat, corn, soybeans, sugar, and cocoa. Below will be presented graphs of the dynamics of changes in the corresponding commodity indices. All data from the site https://www.investing.com/. The data considered in the period from 01.01.2021 to 12.10.2022. These data are shown in their weekly average for the convenience of mutual analysis.

On Fig. 1 shows a graph of the dynamics of the commodity index wheat.

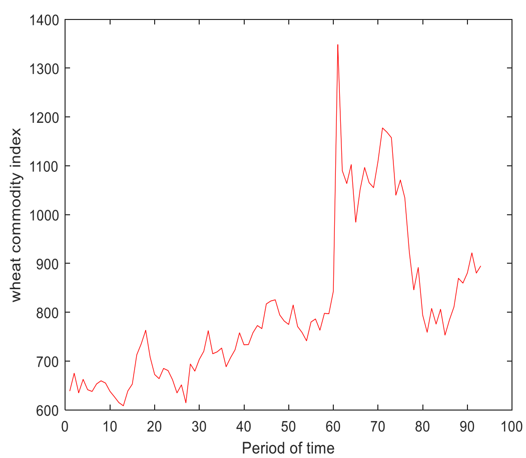

Figure 1: Graph of the dynamics of the commodity index wheat

We can observe a significant surge in the values of the wheat commodity index at the end of the second third of the study period. Then there is a decrease in the values of the wheat commodity index, followed by its growth. At the end of the study period, there is also an increase in the values of the wheat commodity index.

The dynamics of the wheat commodity index values is described by the following statistical data: mean – 803.5005; median – 763.25; mode – 757.9; standard deviation – 158.3832; kurtosis – 0.916004; skewness – 1.202607 (all calculations were made at a confidence level of 95.0%).

On Fig. 2 shows a graph of the dynamics of the commodity index corn.

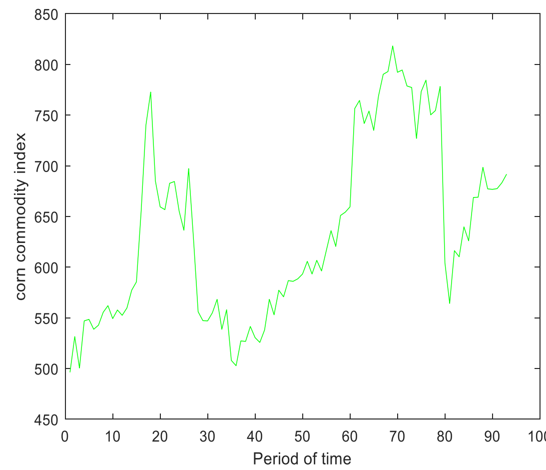

Figure 2: Graph of the dynamics of the commodity index corn

On Fig. 3 shows a graph of the dynamics of the commodity index soybeans.

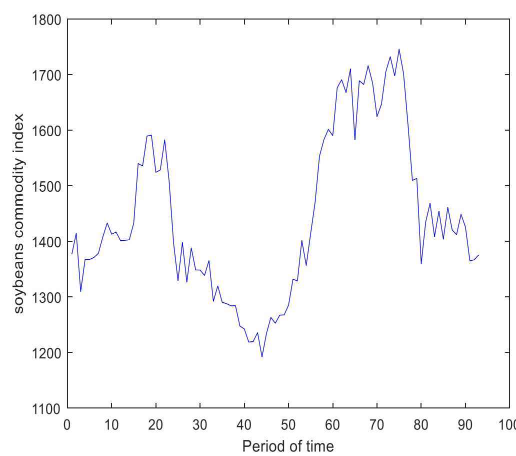

Figure 3: Graph of the dynamics of the commodity index soybeans

We can see several spikes in the corn commodity index. Such bursts are characterized by their decrease upon reaching the maximum values. It should also be noted that in Fig. 2 also has several minimum values for the commodity index corn. In general, the dynamics of the values of the commodity index corn is variable.

The dynamics of the values of the commodity index corn is described by the following statistical data: mean – 634.733871; median – 616.25; mode – 547.01; standard deviation – 88.94891064; kurtosis – -1.044354051; skewness – 0.423560577 (all calculations were made at a confidence level of 95.0%).

The dynamics of the values of the commodity index soybeans (see Fig. 3) is similar to the dynamics of the values of the commodity index corn (see Fig. 2). For the values of the soybeans commodity index, we can also observe several spikes and the same drops in the index values in the future.

The dynamics of the soybeans commodity index values is described by the following statistical data: mean – 1443.515054; median – 1408.75; standard deviation – 146.5984029; kurtosis – -0.800801571; skewness – 0.465160343 (all calculations were made at a confidence level of 95.0%).

On Fig. 4 shows a graph of the dynamics of the commodity index sugar.

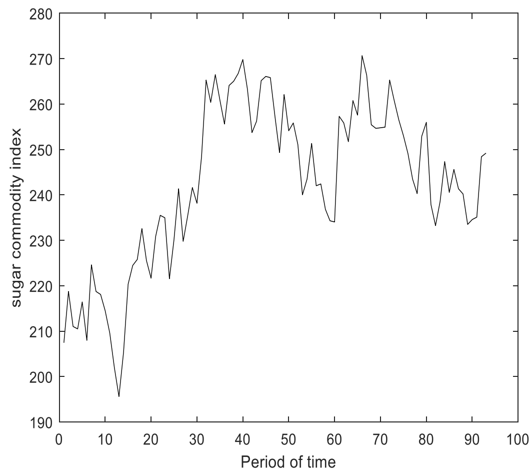

Figure 4: Graph of the dynamics of the commodity index sugar

It should be noted that the overall dynamics of the sugar commodity index is positive. However, against the background of the growth of the values of the sugar commodity index, its correction towards a decrease in the corresponding values is also observed.

The dynamics of the sugar commodity index values is described by the following statistical data: mean – 242.3753151; median – 243.484; mode – 218.75; standard deviation – 18.09378697; kurtosis – -0.504890256; skewness – -0.538870211 (all calculations were made at a confidence level of 95.0%).

On Fig. 5 shows a graph of the dynamics of the commodity index cocoa.

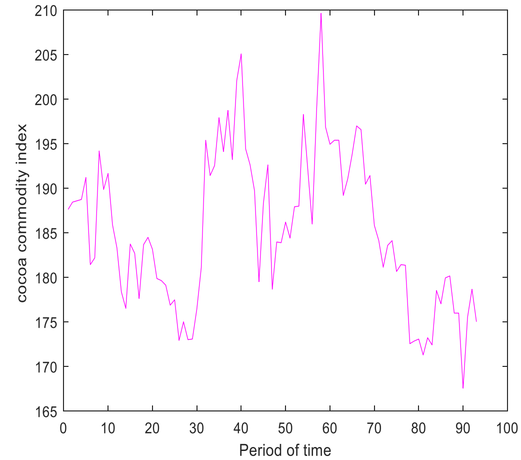

Figure 5: Graph of the dynamics of the commodity index cocoa

The dynamics of the values of the cocoa commodity index has the highest values in the middle of the time period that we are studying. At the same time, further we can observe a general decrease in the values of the cocoa commodity index. This is observed in the last third of the time period that we are examining. This trend is also typical for the values of the wheat commodity index.

The dynamics of the cocoa commodity index values is described by the following statistical data: mean –185.243871; median – 184.12; mode – 195.38; standard deviation – 8.605050594; kurtosis – -0.420848953; skewness – 0.305052144 (all calculations were made at a confidence level of 95.0%).

Thus, in general, we see different dynamics of the values of the commodity indices that we have analyzed. At the same time, we can also note some similar trends for individual time intervals. This allows us to speak about the expediency of considering the mutual dynamics of the values of commodity indices.

4. Wavelet Coherence as a Tool for Analyzing the Mutual Dynamics of Commodity Indices

The analysis of mutual dynamics is one of the central aspects in the study of various data [37], [38]. Moreover, such data can be presented in the form of a time series. Then we study the mutual dependence of the dynamics of different time series. The simplest tool for studying such dependence is correlation analysis [39]. In a graphical aspect, this can be the construction of mutual diagrams [40], [41]. A more complex but more adequate tool for analyzing the mutual dynamics of different time series is the wavelet methodology. Among the methods of such a methodology, one can single out wavelet coherence, which has found wide application in economic research [42]-[46]. Wavelet coherence makes it possible to obtain mutual influence estimates for different pairs of time

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Vol. 6 Issue 10, October - 2022, Pages: 74-80

series for different time intervals from the period under study [47]-[49]. This allows qualitatively and quantitatively to study the mutual dependence of the dynamics of different time series.

Let's consider some estimates for the data that were described above, which are time series for the respective trade indices. First of all, we will consider wavelet coherence estimates for those data pairs that had some similarity in their dynamics (see the data in Fig. 1 – Fig. 5).

On Fig. 6 shows wavelet coherence between corn and soybeans commodity indices. As noted earlier, the dynamics of these indices has some similarities.

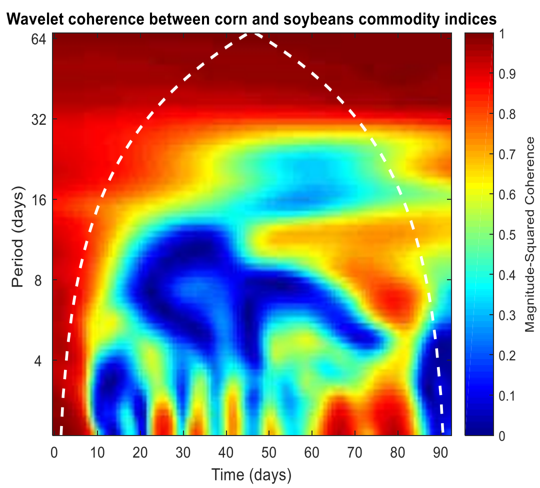

Figure 6: Evaluation of wavelet coherence between corn and soybeans commodity indices

It should be noted that there is indeed some reciprocity between the values of the trade indices corn and soybeans. This consistency is most pronounced at the end of the time period that we are analyzing. Such consistency is characterized by the greatest depth of mutual influences. It should also be noted that there is consistency between the values of the trade indices corn and soybeans in the second third of the study period. However, the depth of mutual influences is smaller compared to previous data. This can be used in the development of investment strategies for entering the relevant segments of the commodity market.

On Fig. 7 shows an estimate of the wavelet coherence between sugar and cocoa commodity indices.

On Fig. 8 shows an estimate of the wavelet coherence between wheat and cocoa commodity indices.

We can see different trends in the wavelet coherence estimates between the data under study.

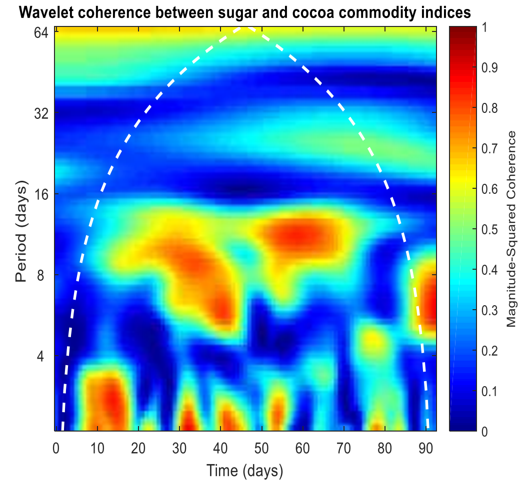

Figure 7: Evaluation of wavelet coherence between sugar and cocoa commodity indices

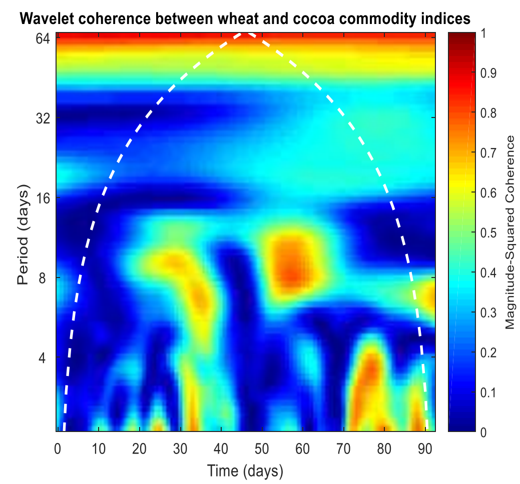

Figure 8: Evaluation of wavelet coherence between wheat and cocoa commodity indices

The wavelet coherence estimate between sugar and cocoa commodity indices has stable values over the entire time interval that we are studying. The depth of such estimates is also more significant and uniform in comparison with the estimates between corn and soybeans commodity indices. This indicates a stronger relationship between commodities such as sugar and cocoa (compared to other commodity groups).

The wavelet coherence estimates between wheat and cocoa commodity indices are not as large as for the previous data. At the same time, such estimates are significant for the end of the first third of the period under study and the end of the time period that we are studying. However, this is consistent with the dynamics of the data presented in Fig. 1 and Fig. 5.

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In general, it should be noted that wavelet coherence estimates provide additional data for making appropriate investment decisions.

5. CONCLUSION

The paper considers the dynamics of changes in one of the segments of the commodity market. We consider the dynamics of changes in commodity indices for the so-called group of non-solid goods. Among such products we consider wheat, corn, soybeans, sugar, cocoa.

First, we consider the descriptive statistics of the commodity indices of the respective products. We also present a visualization of the dynamics of commodity indices in the form of graphs.

We also provide estimates of the wavelet coherence between the corresponding commodity indices. These estimates provide additional information and help make the necessary investment decisions.

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