Analysis of relations and forecast of prices of energy resources with the use of spectral analysis and time series methods

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Abstract. The subject of deliberations discussed in this article was the assessment of the possibilities of using spectral analysis and time series methods for examining relations and forecasting prices of energy resources, i.e. crude oil, coal, and natural gas. Separation of the cyclical component and analysis of cross-correlations and turning points allowed to indicate the leading energy resource in terms of prices, that is, crude oil, and to determine its interrelations with coal and natural gas. On the basis of TRAMO/SEATS and ARIMA methodology, the created models of prices of energy resources allowed to obtain reliable forecasts in the assumed time horizon.

1. Introduction
The insecurity and changeability, which mark the world economy of today, largely make taking decisions and forecasting the future difficult. As Kotler and Caslione write [1], the age we are living in is an age of turbulence which is the effect of progressive globalization and huge technological development. In such conditions of mutual connections and relations, forecasting becomes extremely difficult, especially if the forecast concerns intricate structures such as, e.g. international energy markets. Price fluctuations of energy resources on these markets are no longer only a result of the classic relationship between demand and supply, but also they are an effect of the mechanisms that are perceptible on financial markets. The interest in energy resources and the influence of risk capital on their prices is usually mostly visible when we deal with temporary slump in financial markets. Are we therefore able to create accurate forecasts in conditions of such a great instability and chaos? The answer to this question is not clear. Undoubtedly, there is a great need for searching for information about the future and gaining knowledge about future shaping of economic phenomena and therefore, an observation of the surrounding reality and an attempt to draw conclusions are by all means very needed. There is just the question whether we will use quantitative or qualitative methods for forecasting the future and how long-term forecasts we will create. Mathematical models should materialize to a greater or lesser extent in short prospect, but for long-term forecasts it is better to use expert methods which are based on knowledge, experience, intuition, and opinion. An increase in computational capabilities allowed the use of methods thanks to which scientists are able to build complex mathematical models often concentrating only on numbers and obtained forecasts without searching for additional information that may have an influence on the phenomenon under study. This, exactly, is the problem of contemporary science which was noticed several years ago by David Deutsch, a physicist at the University of Oxford, and which consists in the fact that the main emphasis is put on prediction of phenomena instead of their explanation. Thus, we are prone to accept a forecast that is supported by
complex mathematical calculations as more reliable and legitimate, even if in the end it will turn out to be incorrect, than the one which results from expert opinion. Such a view turns contemporary science back to the principles promoted by logical positivists who based the whole knowledge on empirical data and who rejected everything that did not have support in it. Today, we perfectly know that a theory that was once verified cannot be acknowledged as true for good, but when Karl Popper introduced the concept of falsifiability, not everybody was an enthusiast of his views. Currently, even though we have an access to better and better forecasting tools, there is no perfect method which allows the prediction of the future with 100 percent certainty and the issue of forecasting and predicting economic phenomena is still complex and unresolved.

The subject of forecasting prices of energy resources has been very popular among scientists since many years and recently, a number of publications has been created on this topic. The integration of crude oil, coal, and natural gas markets in the USA was researched by, among others, Lance J. Bachmeier and James M. Griffin [2], and the relationship between crude oil and coal by Zamani [3] with the use of the SVAR model. In Poland, the latest research into the relationships of prices of energy resources was conducted by, among others, Monika Papież, Sławomir Śmiech [4], and Zbigniew Grudziński [5,6]. In their research, the authors used various methods for assessing the phenomenon under study, however, they are different to those presented in this publication.

2. The cyclicity and analysis of time series
The search for some regularities and cyclicity in economic phenomena aroused the interest of researchers around the world for many years. Before the theories of business cycle were developed, there had been many economic doctrines that very often were a tool of economic policy which attempted to justify the decisions taken before. Protectionism, the first economic doctrine of the early modern period, was formed in the 17th century. It regulated the customs policy and provided foundations for later mercantilism whose glory days fell on the 17th and 18th century. Mercantilism assumed that a favourable balance of trade determines the prosperity of a country. In the second half of the 18th century, especially in France, the arguments of physiocrats, who emphasized the significance of work and agriculture as the main source of prosperity, became more popular. At this point, it is worth mentioning Richard Cantillon, a “mercantile physiocrat”, who was the first, long before Adam Smith and his notion of “the invisible hand”, to occupy himself with researching economic processes. Later, in the second half of the 19th century, John Stuart Mill developed the psychological theory of business cycles according to which expectations concerning further development change in the periods of prosperity as they curb credit granting and lead to a surplus of aggregate supply [7].

The research on the cyclicity of economic phenomena made progress mainly due to great depressions which researchers tried to justify and, above all, predict. Several theories and their creators became part of economics and to this day we speak of the Juglar cycles when we think of classic cycles, Kitchin cycles when we think of short cycles, and Kondratiev waves when we think of long cycles. At this point, it is also worth mentioning Stanley Jevons who opposed Juglar’s views and looked for causes of fluctuation in the environment and natural factors claiming at the same time that the British economy is synchronized with the sunspot cycle and that it moves in a cycle period of 10.5 years. Although he is the creator of the class theory of business cycle, Michał Kalecki was an underestimated researcher of business cycles. The results of his research were published in English after John M. Keynes’ famous work and consequently, they did not win proper renown. However, the biggest contribution was made by an Austrian researcher Joseph Schumpeter who linked Juglar’s, Kitchin’s, and Kondratiev’s theories with innovations and distinguished three cycles the rhythmicity of which was responsible for economic and social crises [7]. Unfortunately, none of the above-mentioned theories was 100% accurate and did not have the power to predict crises. All of them were an answer to the already occurring economic phenomena and aimed at explaining their causes. Nonetheless, each of them changed the approach to research and introduced new aspects which had not been noticed before. Currently, two types of approach to economic cycles are distinguished: a classic and a modern approach. The classic approach
was described in the Burns-Mitchell monograph [8], where the following phases of business cycle were identified [9, 10]:

- an expansion is characterized by increasing rates of production, employment, investments, demand, and prices and by decreasing rate of unemployment;
- a peak marks the end of growth when the above-mentioned rates are at the highest point;
- a contraction (recession) is a phase where unemployment increases while production, employment, investments, demand, and prices decline;
- the trough (depression) is a phase where the slowing ceases and the above-mentioned rates remain at a low level.

Currently, due to increasing globalization, the modern economic cycles are divided only into two phases [10]:

- the expansion phase that is a phase of heightened economic activity;
- the recession phase that is a phase of low economic activity.

Recognizing regular cycles and their individual phases would allow the prediction of periods of economic boom and crises. But in fact, economies, in dynamically changing ambient conditions, are not as harmonious as we would want them to be and cause more and more problems in analysis. However, researching the cyclicity allows to find some relations that are useful in understanding and extrapolating given phenomena. Detection of the cyclical component in discrete random processes when the period of economic cycle is unknown may be accomplished through harmonic or spectral analysis.

3. Empirical analysis and its results
Thanks to the application of spectral methods to energy markets, it is possible to describe the properties of cyclical components of a time series under study and their interrelations. In order to demonstrate the relations between prices of the main energy resources such as coal, crude oil, and natural gas, historical data concerning their changes and current trends were analyzed. Figure 1 presents changes of monthly prices of basic energy resources, i.e. coal, crude oil, and natural gas in the years 2004-2017 (168 observations were analyzed in total). All values represent monthly averages. Coal prices are spot prices (FOB Newcastle) relating to coal with calorific value of 6.300 kcal/kg until 2010 and 6.700 kcal/kg until 2011, sulphur content below 0.8% and 13% ash content. Crude oil prices are average spot prices of Brent, WTI, and Dubai crude oil, while prices of natural gas are average spot prices of import to Europe (data until 2010 does not include prices of British gas). All data was taken from the World Bank website [11]. Several computer programs, MS Excel, Gretl, Statistica, Casis among others, were used in order to check the correctness of calculations.
The procedure of performing spectral analysis requires the following algorithm:

- data selection, selection of appropriate scope of data and its frequency;
- data filtering – testing the compatibility of periodicity of data, detection of outliers, elimination of trend and seasonality, identification of cyclical component, data normalization, checking the degree of integration of cyclical component;
- spectral analysis – identifying the length of dominant cycles and their turning points, distinction and application of weight to the components of aggregate variable, series aggregation;
- characteristics of filtered data – defining dynamic correlations, time shift, intensification, character of relations, and synchronization.

Seasonal components were removed with the use of TRAMO/SEATS method methodology of which is closely based on ARIMA methodology. It was used not only as an auxiliary tool for time series forecast and smoothing, but also as a basic tool for proper decomposition (separation of components). The number of parameters of parts of moving and autoregressive average was chosen on the basis of correlograms (autocorrelograms) and trial method indicated by parameters gravity, autocorrelation of model residuals and mean squared prediction error (MSE). As a result of applying the above-mentioned procedure, the following models were matched to original series:

- ARIMA model (1,1,0) for time series of crude oil prices;
- ARIMA model (1,1,0) for time series of coal prices;
- ARIMA model (3,1,0) for time series of natural gas prices.

Outliers, that is observations which are not in the normal scope of expected values, were located and identified regarding their nature with the use of TRAMO module of TRAMO/SEATS procedure, and then they were replaced by process estimated value in the series of power coal prices – observation of February 2008 – original: 132, revised: 103.7. TRAMO method may also complement missing values of a series, however, adopted data sets were complete and did not require any complementation.

Identification of cyclical fluctuations of a series which requires removing two components, that is a long-term trend and a high-frequency noise, is the next step in process filtering. This process is
performed thanks to band-pass filtering. Out of many available filters, the Christiano-Fitzgerald filter (CF) was chosen and used in the research. Equally as the Hodrick-Prescott filter (HP), it improves stability of estimated cyclicity and gives better operational stability [12]. The popular Baxter-King filter was rejected due to the necessity to lose initial and final observations, that is shortening of the trial.

Because the application of the Christiano-Fitzgerald filter requires determining appropriate CF filter specification (I(1) or I(0) filter), the degree of integration of variables, that were tentatively adjusted for seasonal fluctuations with the use of TRAMO/SEATS method, was measured. The Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests were used for this purpose. The null hypothesis of the ADF test assumes the presence of a unit root, while the null hypothesis of the KPSS test assumes the stationarity of the examined variable. The number of lags in the ADF and KPSS tests was chosen on the basis of William Schwert’s model [13]:

- for the ADF test:
  \[
  \text{int}\left\{4 \left(\frac{T}{100}\right)^{1/4}\right\}
  \]
  (1)

- for the KPSS test:
  \[
  \text{int}\left\{12 \left(\frac{T}{100}\right)^{1/4}\right\}
  \]
  (2)

| Degree of integration | I(0) Test | I(1) Test |
|-----------------------|-----------|-----------|
|                       | ADF       | KPSS \(^{a}\) | ADF       | KPSS \(^{b}\) |
| COAL PRICE            | -2.24     | 0.193     | 0.550     | -5.16     | 0.0001     | 0.062     |
| CRUDE OIL PRICE       | -2.69     | 0.075     | 0.542     | -6.51     | 0.0001     | 0.034     |
| NATURAL GAS PRICE     | -2.49     | 0.118     | 0.538     | -4.43     | 0.0001     | 0.213     |

\(^{a}\) Empirical p-value means the probability of obtaining calculated value of a test statistic assuming that the null hypothesis is true. If the probability is smaller than 0.05, the hypothesis should be rejected.

\(^{b}\) Critical value of the KPSS test statistic amounts to 0.464 for \(\alpha=0.05\)

Table 1. ADF and KPSS test results.

ADF and KPSS test results presented in table 1 show that all analyzed time series should be perceived as series integrated in the first degree. That is why the specification I(1) of the CF filter was used in all cases.

Before applying filters, analyzed series were recognized by TRAMO module as multiplicative or additive. Multiplicative series were subjected to logarithmic transformation after which they were treated in the same way as the additive series. Since simultaneous analysis of several series requires normalization because of different units and scales, normalization process was performed, values of standard deviation were calculated on filtered data and a 100 was added to each observation.

Then, after performing filtration with the use of wide-band filters, cycles with a length shorter than 18 months and longer than 96 months were eliminated. The choice of the length of a cycle, which limits the period of fluctuations and determines the cyclical component, is made arbitrarily. 6-96 months, 18-96 months, 18-120 months, and 24-120 months are the most frequently chosen periods in literature. Even though the results obtained by applying other restrictions did not differ in terms of quality, the last period, i.e. 1.5-8 years, was chosen in the end because of the length of series and obtaining courses that are economically easier to interpret.
Then, the degree of integration of obtained cyclical components was measured by the Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests the results of which are presented in table 2.

Table 2. ADF and KPSS tests with a constant for analyzed cyclical components.

| FILTER TEST | CHRISTIANO-FITZGERALD (CF) ADF statistics | p-value\(^a\) | KPSS\(^b\) statistics |
|-------------|------------------------------------------|-------------|---------------------|
| COAL PRICE  | -9.4067                                  | <0.0001     | 0.090848            |
| CRUDE OIL PRICE | -14.8721                                | <0.0001     | 0.157364            |
| NATURAL GAS PRICE | -13.0635                                | <0.0001     | 0.194424            |

\(^a\) Empirical p-value means the probability of obtaining calculated value of a test statistic assuming that the null hypothesis is true. If the probability is smaller than 0.05, the hypothesis should be rejected.

\(^b\) Critical value of the KPSS test statistic amounts to 0.464 for \(\alpha=0.05\).

The ADF and KPSS test results show that obtained cyclical components are stationary, therefore the application of spectral analysis is possible. In order to investigate relations on energy market, sets of cyclical components were compared in order to distinguish reference variables in relation to others.

Prices of energy resources were compared in the first place due to the leading character of crude oil prices which was noticed during graphic analysis of the series.

The leading character of crude oil prices in relation to prices of other energy resources is observed once more in the figure 2. On the basis of periodograms, the length of cyclical fluctuations of prices of energy resources, which are shaped by dominant cycle that lasts for about 3 years, was identified. The comparison of cyclical components in the figures above seems to confirm the influence of crude oil prices on other components, therefore, the series of crude oil prices was accepted as a reference in order to make an identification of turning points and to calculate the characteristics of filtered data.

The identification of turning points was made using a simplified version of the Bry-Boschan algorithm [14]. Bry and Boschan, in order to automatize the procedure of cycle dating used by the
National Bureau of Economic Research, worked out an algorithm intended for data with a monthly frequency, which was later adapted to quarterly data by Harding and Pagan [15]. According to the latter algorithm, the identification of turning points is made on the basis of the following rules (where product dynamics or dynamics of other measures of economic activity are determined):

- in \( T \) period, a business cycle reaches its peak if:
  \[
  t = \{(\Delta y_{t-2}, \Delta y_{t-1}) < \Delta y_t > (\Delta y_{t+1}, \Delta y_{t+2})\} \tag{3}
  \]

- in \( T \) period, a business cycle falls to a trough if:
  \[
  t = \{(\Delta y_{t-2}, \Delta y_{t-1}) > \Delta y_t < (\Delta y_{t+1}, \Delta y_{t+2})\} \tag{4}
  \]

This notation indicates that there was a cycle reversal in a given cycle if the dynamics of a given variable in it was higher (lower) than it had been maximally two quarters earlier and two quarters later. This approach is compatible with the universally used definition according to which recession (or expansion) occurs when the economic activity decreases (increases) for two quarters. In the case of monthly data, local maxima and minima are found analogously – the dynamics in a given period is compared with five previous and later months. Furthermore, the algorithm imposes additional censoring procedures in the scope of minimal duration of each phase (two quarters in the Harding-Pagan procedure and six months in the Bry-Boschan algorithm) and of the whole cycle (five quarters and fifteen months respectively), it also assumes the commutativity of occurrence of peaks and troughs. Local maxima and minima are found in the cyclical part of a series keeping at the same time the minimal phase duration and the minimal cycle duration in conditions that guarantee the commutativity of peaks and troughs. The identification of turning points is a crucial criterion in determining a leading series.

Basic relations between cyclical components of the analyzed series, i.e. the force of correlation, character or relations, and relative variation were assessed using the Pearson correlation coefficient, dynamic correlations, and cross-correlations. Analysis of cross-correlations is performed between at least two series one of which constitutes a referential series in relation to others. Locating peaks of cross-correlation functions is a good indicator of average time of leads/lags between two series. The value of the indicator of peak correlation measures how well the profiles of cyclical fluctuations match each other. On the basis of average and peak values of cyclical fluctuations in relation to the referential series, variables may be classified as:

- leading – when a given series leads the referential series;
- convergent – when a given series is convergent with the referential series;
- lagged – when a given series lags behind the referential series.

Dynamic correlations represent the linear correlation coefficient as the frequency function which allows to test the force and sign of correlation of the analyzed variables for various periods of cyclical fluctuations. Table 3. shows a summary of identification of turning points with the analysis of cross-correlations. A series of crude oil prices was the referential series.

**Table 3.** ADF and KPSS tests with a constant for analyzed cyclical components.

| BATCH NAME          | RELATION CHARACTER | CORRELATION COEFFICIENT (MAX) |
|---------------------|--------------------|-------------------------------|
| CRUDE OIL PRICES    | 0                  | 1                             |
| NATURAL GAS PRICES  | -6                 | 0,925                         |
| COAL PRICES         | -1                 | 0,657                         |

* a positive/negative sign indicates a lead/lag regarding the referential series
The figure 3 below shows dynamic correlations of the most important relations for which a three-year window was chosen since fluctuations that last for about 35 months turned out to be dominant for the analyzed variables. At the same time, shifts of the series by the values indicated by the analysis of turning points and cross-correlations were taken into account. A commentary on the figure below is included in the descriptions of individual relations.

The highest concurrence of the courses was obtained in the case of comparison between crude oil prices and natural gas prices – the correlation coefficient reached the maximum value next to a six-month lag of a series of natural gas. The figures below (3 and 4) show identified turning points and a chart of courses including the lag.

![Figure 3. Turning points – natural gas prices in relation to crude oil prices.](image)

Such a concurrence of courses and a six-month lag result from the fact that gas prices are estimated on the basis of half-yearly prices of crude oil and oil derivatives. What is more, the analysis of dynamic correlations indicates that this relation is time-constant and very high.

In the case of relations between coal prices and crude oil prices, the analysis of cross-correlation and turning points indicated that coal prices are lagged by one month in relation to crude oil prices. On the basis of the graphical analysis, it can be noticed that the dependence of coal prices on crude oil prices is not time-constant, there are periods of large and little concurrence of courses. Large concurrence of courses was particularly visible between 2007 and 2011, i.e. in the period of a financial crisis. This fact is also confirmed by the analysis of dynamic correlations – in the years 2004-2006, the correlation between crude oil and coal prices was negative, but with shifting the scope of trial it was successively increasing reaching high, positive level in those years.
Figure 4. Turning points – coal prices in relation to crude oil prices.

Large concurrence of courses was particularly visible since 2007, that is since the beginning of financial crisis. This fact is also confirmed by the analysis of dynamic correlations – in the years 2004-2006, the correlation between crude oil and coal prices was negative, but with shifting the scope of trial it has been successively increasing reaching high, positive level in recent years.

On the basis of previous analyses, forecasts for coal, crude oil, and gas prices were prepared for the years 2018-2019. Data from the period from January 2004 to December 2017 (168 observations in total) was used for making models. Observations from mid-2018 were cut off as a trial set in order to evaluate the forecast accuracy.

Forecasts made for prices of energy resources are shown in figures 5, 6, and 7.

The forecast accuracy was determined using the relative error (percentage) of ex post forecast:

\[ \psi_t = \frac{y_t - y_t^*}{y_t} \]

where:
\( y_t \) – actual value of variable forecasted in momentum \( t \),
\( y_t^* \) – variable forecast for momentum \( t \).
Figure 5. Changes of crude oil prices and a forecast for the years 2018-2019.

Figure 6. Changes of coal prices and a forecast for the years 2018-2019.
Figure 7. Changes of gas prices and a forecast for the years 2018-2019.

The comparison of forecast errors is presented in table 4.

Table 4. Comparison of actual data and obtained forecasts – forecast errors.

|                  | CRUDE OIL PRICE | COAL PRICE | NATURAL GAS PRICE |
|------------------|-----------------|------------|--------------------|
|                  | forecast relative error [%] | forecast relative error [%] | forecast relative error [%] |
| JANUARY 2018     | -1,56%          | 4,33%      | 5,61%              |
| FEBRUARY 2018    | 4,70%           | 9,47%      | 15,90%             |
| MARCH 2018       | -0,13%          | 8,46%      | 7,01%              |
| APRIL 2018       | 0,68%           | 0,35%      | 7,97%              |
| MAY 2018         | 7,24%           | -3,38%     | 16,42%             |
| JUNE 2018        | 13,05%          | 9,31%      | 8,82%              |

Source: own calculations

As it can be noticed in the table above, forecast errors for crude oil prices are acceptable at the level of confidence assumed for the first five months; in the case of natural gas, error above 10% was obtained only in two observations. The model of coal prices worked quite well since it predicted their changeability best and at the acceptable margin of error that does not exceed 10%.

ARIMA models, which were worked out in this study, described well the phenomenon under study within the scope of adopted trial; outside the trial, the price was stabilized at a relatively constant level. The cyclical component brings a much better prognostic view since it shows what trend may be expected and when.

Even though they were characterized by good statistical properties, the obtained models based on ARIMA methodology did not allow to obtain accurate forecasts. Only the model estimated for coal prices can be used in taking decisions concerning an increase/decrease for a short time. Great loss of
information as a result of the necessity to differentiate the input data should be indicated among the causes that underlie the low accuracy of forecasts that are based on time series models.

4. Summary and conclusions

The use of spectral analysis method allowed a thorough and precise study of price relations of energy resources and ascertaining whether we are able to determine the leading energy resource in terms of price on the basis of historical courses. Performed analyses and created models indicate that crude oil, especially in periods of high changeability in the market, determines the increasing and decreasing trends of other energy resources. Strong and time-constant correlation between crude oil and natural gas prices confirms that natural gas prices depend largely on long-term contracts, the prices of which are determined on the basis of prices of basic oil derivatives from the last 6-9 months. The correlation between crude oil and coal prices is not clear, however, on the basis of data of the years 2004-2017, it can be noticed that there were periods of larger concurrence of courses, especially in times of financial crisis, since the dynamic increase in crude oil prices, especially in the years 2007-2008, was not dictated by the fundamental macroeconomic factors, but it was mainly caused by an inflow of speculative capital.

Thanks to such an insightful analysis, created price models of energy resources allow to obtain the most reliable forecasts in the assumed time horizon, which is extremely important in examining prospects for energy market in Poland that is dominated by coal and dependent on the import of natural gas and crude oil. Conducting research in the scope of prices of energy resources is also of great significance in terms of energy security since the prices of energy resources underlie all the elements that determine energy security.

5. References

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