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Carbon Pricing in Current Global Institutional Changes

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Abstract: Global institutional changes (GICs), having influenced energy prices, led to a steady upward trend in carbon prices on the EU ETS. The aim of the article is to assess the changes in the relationship between carbon prices and energy prices under GICs. The Bai–Perron tests for structural breaks identified two dates as the breakpoint, 21 April 2016 and 21 September 2020. We test the hypothesis that powerful external factors (GIC) are changing the trend pattern of the carbon price time series. New pricing rules of the carbon price are being formed after the breakpoint. We use daily observations from 4 January 2010 to 1 September 2022. We use GARCH models with multiple stationary time series to discover a relationship energy price with the carbon price before and after the break points. We found that three models for two breakpoints better describe the relationship between carbon prices and energy prices than two models for one breakpoint, much less one model for the entire period. We find that the carbon price depends on energy prices, especially on the price of oil, in a statistically significant way, but the gas price is not statistically significant after 21 September 2020.

Keywords: ETS; greenhouse gases; carbon price; global institutional changes; breakpoints; econometric analysis

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1. Introduction

According to the UN, the 2015 sustainable development goals and the Paris climate agreement remain at the center of the global political agenda [1]. The emissions trading system (ETS) is now a key feature of carbon regulation worldwide. ETS is an economic mechanism to stimulate businesses to reduce GHG emissions into the atmosphere. There are currently 24 different systems for emissions trading worldwide [2].

The European Union Emissions Trading System (EU ETS) is the largest in volume of transactions, in terms of the number of participants, with rather a long history of operation. It was established in 2005, and nowadays is in the 4th phase of development (2021 to 2030). The EU ETS plays a major role in the decarbonization of Europe. Currently, the EU ETS covers only 19% of global emissions and it is of much importance to ensuring the development of other emissions trading systems worldwide [2].

National ETSs exist only in China, South Korea and New Zealand in the Asia–Pacific Region [3]. Numerous studies have proven that ETS contribute to the reduction of carbon emissions in the industry under certain conditions [4–10]. The achieved success in reducing emissions in China and other countries could be an example for emerging economies. Russia's inclusion in the global sustainable development agenda means that the state faces the task of developing carbon regulation.

The carbon pricing Is important incentive for the greenhouse gas emission reduction. We have noticed that, in the period from 4 January 2010 until 1 September 2022, carbon prices dynamics have changed significantly. After reaching a breaking point in 2020, it is showing a steady rising trend. A sharp and steady increase in CO_2 prices after the breakpoint raises the question of its decisive factors.

Numerous studies have argued that breaking points of carbon pricing are typically associated with structural changes driven by key events. After the breakpoint the EUA pricing model changes. The cost of LNG largely depends on external factors. First of all, these are current global institutional changes (GICs); the COVID-19 and global economic recovery from the pandemic; the climatic anomalies in the EU, Asia and North America; a transition from long-term contracts to spot prices for gas supply by Russian suppliers; etc. The rise in the price of fossil fuels leads to an increase in the price of electricity as a form of GIC [11–15]. Over time, these events and processes change the fundamental characteristics of the system under study.

The paper aims to assess potential structural changes in the relationship between carbon prices and energy prices in a GIC period.

In this article, we explore the impact of GIC on carbon price dynamics. We identify a breaking point, from which the carbon price shows a steady uptrend. We define strong external shocks such as the GIC and disclose the relevant events underlying it. We test the following hypothesis: the trend of the time series of carbon prices is characterized by structural instability in the period under analysis. The samples of carbon price values obtained under different conditions—before and after the breakpoint—are not homogeneous. Powerful externalities (GICs) are altering the trend of the time series of carbon prices. Therefore, several individual models better describe the dynamics of carbon price. New CO_2 pricing rules are emerging in the context of global institutional changes. We check the regression results before and after the breakpoint.

The determinants of carbon prices have been explored by many scholars. But there is no research under the current global institutional changes and regulatory reforms. Using recent data is important, because the relevance of variables changes over time.

The results of this study may be useful to politicians and practitioners in the formation of national carbon regulation.

The rest of the paper is organized as follows. In Section 2, we briefly discuss global institutional changes and their economic implications based on a review of the relevant literature. In Section 3, we describe data used in the empirical analysis and the research methodology. Section 4 summarizes the empirical findings. Section 5 presents the discussion of results.

2. Theoretical Foundations and Literature Review

The economic nature of environmental pollution under the influence of the anthropogenic factor is associated with negative external effects (externalities) of the economic activity of market economy agents. ETS, as a market-based tool for reducing greenhouse gas emissions, operates on a cap-and-trade basis. The key principle of carbon regulation is that the polluter pays. The government sets an upper threshold for the total amount of emissions in one or more sectors of the economy, acceptable for a certain period of time for a given territory. Companies in selected sectors must have a permit for each unit of their emissions above the threshold. Polluters receive such permits free of charge or buy from the state and companies participating in the ETS [16,17].

One of the main conditions for the effective functioning of the ETS is the pricing mechanism for emission permits. The price of emission permits (or "carbon price") is important in the ETS. A low carbon price will not compensate for environmental damage and will not encourage companies to reduce greenhouse gas emissions, e.g., replace high-carbon fuels with low-emission fuels. However, the prohibitive price may reduce the motivation to use ETS.

The identification of carbon pricing factors is important. Economic theory distinguishes two main groups of product pricing factors—supply and demand. Appended to the price of emission permits is the supply of and demand for carbon permits. The offer for carbon emission permits depends on the results of the implementation of carbon sequestration projects and technological change projects and the number of quotas distributed by the state on a free basis or in the form of an auction. Economic entities that emit greenhouse gases (CO_2 and CO_2-equivalent) in the course of their production and economic activities demand for carbon emission permits. A large number of factors affect the level of emissions. The volume and structure of consumption of fuel and energy resources, etc., determine it (Figure 1).

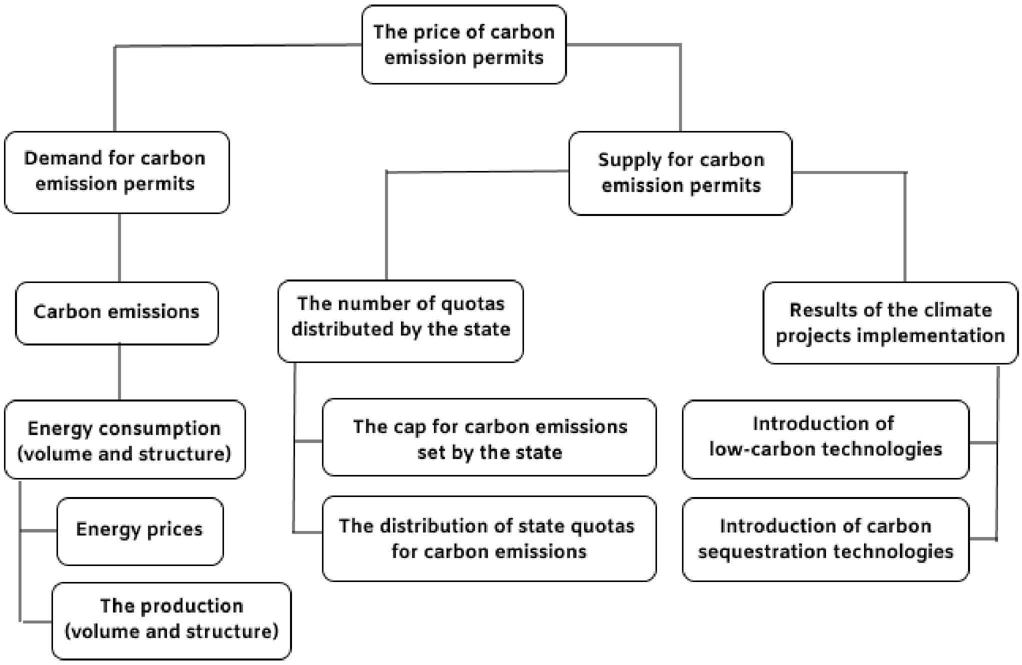

Figure 1. Formation of supply and demand for the carbon price.

For ETS to function effectively, it is essential to identify price factors and assess their impact on carbon price. Since the establishment of the EU ETS, there has been ample scientific literature produced on the factors influencing the price of carbon (the European Union Allowance (EUA) of the European Union emission trading scheme (EU ETS)). Scientific literature analysis on the identification for CO^2 pricing factors allows us to allocate climatic and non-climatic factors. Researchers divide non-climatic factors into energy (prices of fossil fuel sources (oil, gas, coal), switching costs (from coal to gas) and the price of electricity), economic activity, macroeconomic changes (assessed by the yield of stock indices) and others [18,19].

In the first two phases of the EU ETS operation, scientists have laid down fundamental approaches to the analysis of pricing factors and the evaluation of their impact on the price of carbon. Many studies have focused on the impact of energy variables on CO_2 prices [20–26]. Using a variety of econometric methods and techniques, the authors researched different aspects of the influence of carbon pricing factors. The impact of the fossil energy market on the carbon market has been changing over time. At the beginning of the EU ETS operation, the coal market and the natural gas market had the greatest impact on the carbon market. In the second phase of the EU ETS, the impact of the coal market was the most significant and positive. When the EU ETS had entered the third phase, the natural gas market showed shock effect, and the direction of the impact changed from negative to positive [27].

Researchers identify three of the most important factors that determine the price of carbon. The electricity price and the stock index are positive influence, and the coal price has a negative impact on the carbon price. In addition, changes in electricity and stock prices have a short-term impact on carbon prices, whereas coal, oil and gas prices determine the price of carbon in the medium and long term [28]. Options for fuel change have a strong impact on carbon price. The difference between coal and gas prices is likely to remain an important factor in the future until carbon capture and sequestration become widely available [29,30]. Up to 90% (on average 65%) of carbon price fluctuations are explained by fundamental market variables. At the same time, by the end of 2018, the role of economic activity and natural gas prices in the carbon price variation decreased in favor of oil and coal. Researchers also emphasize the importance of speculation in the dynamics of the carbon market [31].

In general, the influence of energy prices on the dynamics of carbon prices is generally recognized. However, the degree of the impact varies over time and depends on the sample under consideration. In addition, structural changes are an important feature of the EUA pricing process. Different causes underlie structural changes. These can be regulatory announcements, changes in expectations, economic reforms and external shocks (COVID-19, etc.). Breakpoints in the EUA price are usually associated with major events. Researchers raised the issue of structural breaks in European carbon prices back in 2008. They found two structural changes related to the disclosure of information on emissions (April 2006) and the distribution of EUAs (October 2006), and also proved that the division into subperiods provides a better idea of institutional and market events that affect the change in EUA prices.

The carbon market is informationally linked to a wide range of other markets. In particular, the authors determined that financial market crises (the US subprime mortgage crisis of 2008, the European sovereign debt crisis of 2011) led to break points of carbon price volatility [32]. The importance of taking into account structural breaks in data when analyzing the relationship between the carbon price and its factors is also justified in the study of ETS pilot projects in China. The authors propose a cointegration model with structural breaks to better explain the actual relationships [33].

Different methods are used to detect structural breaks in carbon price time series. The authors used the Bai–Perron test to diagnose the point of structural change in a series of prices in the carbon market in China and the impulse response function to analyze the interaction between carbon prices and determinant prices (energy prices, stock price indices, utilities indices and similar asset prices). These points of structural change are related to the economic situation. The mechanisms by which factors affect the price of China's carbon market change significantly before and after points of structural change [34,35]. Based on the ICSS algorithm, scientists detected structural breaks in the time series of carbon futures and put forward several hypotheses about the occurrence of breakpoints associated with a period of high carbon emissions or, with the 2008 mortgage crisis and the 2011 European debt crisis [36]. The use of a hybrid prediction model, including a long short-term memory (LSTM) neural network, allows for the acquisition of up to fifteen control points in the price of EUA. Compared to other models, this hybrid model provides the best prediction accuracy [37].

By identifying breakpoints, the authors showed their impact on expected carbon returns and volatility, which confirmed the effectiveness of successive policy adjustments in the carbon market [38]. The basis (an object) of empirical research is not only the carbon market of the European Union, but also the pilot carbon markets in China. The results show many sharp transitions in the carbon price series in these markets that are closely linked to major events [39].

Events that destabilize business, economic activity and consumption are causing breakpoints in carbon prices. The COVID-19 pandemic had a significant impact on the demand for electricity and oil, both directly and indirectly. By sharply reducing economic activity, it has short-term and long-term consequences, including the impact on climate change [40–43]. The COVID-19 pandemic impacted not only energy markets (energy stock indices, energy futures indices, ETFs, and implied volatility indices), but also the behavior of investors in a high-risk environment. Indicators of uncertainty caused by COVID-19 have had a marked impact on the historical volatility of energy markets [44]. The global economy is in a severe recession due to COVID-19. CO_2 emissions are estimated to fall by 3.9–5.6%

in 5 years compared to a non-pandemic baseline scenario. The reduction in emissions associated with the pandemic has had a strong impact on price dynamics in the carbon market [45]. An examination of the factors that influenced carbon price fluctuations in the EU ETS showed that the price of carbon has undergone significant structural changes as a result of COVID-19 and the "Green Recovery Plan". The study confirmed the effectiveness of the EU's "Green Recovery Plan" in stabilizing the carbon market during the COVID-19 pandemic [46]. In general, the COVID-19 pandemic, by sharply reducing economic activity and CO_2 emissions, has led to significant structural changes in the carbon market in the EU.

We are considering the transition of a number of EU countries from long-term contracts to spot prices for gas supplies by a Russian supplier as an element (as an integral part) of GIC. This issue is also the focus of attention of researchers. Continental European gas markets are moving inexorably from oil-linked pricing on long-term contracts to hub-based pricing, accompanied by major changes in the energy markets and, as a result, in the carbon market [47]. The authors examined the economic risks associated with the dominance of the Russian seller in the European gas market and analyzed possible EU responses in relation to the reality of the perceived risks of gas dependence [48]. The benefits of a single Russian gas price are exaggerated for Russia and Europe, a single gas price reduces the security of gas supplies to the EU [49,50]. Natural gas is the main driver of electricity prices in Europe. Since natural gas is mainly imported to Europe, electricity prices are subject to geopolitical risks associated with gas supplies, as well as economic risks associated with currency exchange and natural gas price volatility [51,52].

Thus, a review of the relevant literature shows the key role of energy variables in the behavior of the carbon price, as well as the importance of taking into account structural changes caused by major events. COVID-19, the recovery of the economy after the pandemic, the transition of the Russian gas supplier to spot prices, and other events determine the GIC in the period up to September 01, 2022, taking into account the inertia of the economic system. They have a multidirectional and, at the moment, completely unexplored influence of energy determinants on the dynamics of carbon prices in the context of structural breaks. Using the latest data is important because the relevance of variables changes over time, reflecting important external events. We have focused our attention on studies conducted in recent years on the influence of energy factors and structural changes caused by GIC on the dynamics of carbon prices for EU ETS. All of the abovementioned confirms the relevance and novelty of our study, and its practical significance.

Thus, a breakpoint in EU ETS could influence the pricing of European Union CO_2 allowances (EUA) and, hence, the optimization of EUA management. Therefore, it is very important to identify breakpoints in the carbon price for further research the evolution of EUA prices. In addition, examining the reasons behind the breakpoints is essential to formulating a coherent market reform policy (public policy response measures).

3. Materials and Methods

We used several econometric models with multiple stationary time series to discover the relationship between the fundamentals, such as electricity prices, gas, oil and coal prices, and prices of EUA in the conditions of the GIC.

The stationarity of time series is an important condition for their analysis. We test time series for stationarity using the Dickey–Fuller test [53]. The series of levels turned out to be nonstationary. We switched to stationary series using the Hodrick–Prescott filter [54,55]. We examined the correlation between variables (the price of emission permits, the price of coal, the price of oil, the price of gas, and the price of electricity). Then, we began our econometric analysis using classical least squares regression model.

The general linear regression model has the following form:

$$Y = b_0 + b_{1\times 1} + b_2X_2 + \ldots + b_nX_n + \mathcal{E}, \tag{1}$$

where $X_1, X_2, \ldots, X_\mathrm{n}$ are several independent variables (regressors); Y denotes the dependent variable, i.e., the carbon price in the case under consideration; b_0 is a constant; b_1, b_2,

. . . , b_n are the coefficients of the model and $\mathcal{E}$ is a random component (model error).This makes it possible to analyze the influence of independent variables (energy prices) on the dependent variable, i.e., the price of emission permits.

The absence of autocorrelation of the residuals and their homoscedasticity are the conditions for the adequacy of the linear regression model. The Breusch–Godfrey test and the Breusch–Pagan test indicated the presence of autocorrelation and heteroscedasticity of the residuals. We also tested the residuals on ARCH processes and found them. Application of the GARCH model is adequate under these conditions [56]. The GARCH model has had great success in empirical research on finance in recent decades. GARCH (p, q) is a model for the general autoregressive conditional heteroscedasticity, where q is the order of the autoregressive term and p stands for the moving average.

The models used in the analysis are in general of the form:

$$y_t = b_0 + \sum_{i=1}^{n} b_i X_i + \sum_{i=1}^{m} a_i y_{t-i} \tag{2}$$

where y_t is the value of the price of carbon emissions for the t-th observation, a_i are the coefficients of the model for the lag y_t for i periods;

$$h_t = c + \sum_{i=1}^{q} c_i e_i^2 + \sum_{i=1}^{p} d_i h_{t-i} \tag{3}$$

where h_t is conditional variance of the series, c is a constant, q is the order of the ARCH terms e^2 and p is the order of the GARCH terms h.

We tested the adequacy of the model specification using the Ramsey test (the RESET test).

We applied the Bai–Perron test to identify the break point [57–59]. We then built some separate GARCH models describing the carbon price dynamics before and after the breakpoint using the econometric analysis logic above.

Several metrics are used to evaluate the quality of the model in this study. We use the standard error of regression (SE), the adjusted R-square and the Akaike and Schwartz information criterions. SE allows for the comparison of models of the same type with a different number of observations and variables. The quality of the generated models is better if the standard error is lower, and the adjusted R-square is higher [60]. Information criteria, which are to be minimized, allow for choosing the best model from a variety of models.

For regression analysis, we used daily observations from 4 January 2010 to 1 September 2022. We used historical futures prices for European Union Allowance (EUA) on the European Energy Exchange (EEX), which is the largest organized carbon market in the world. Independent variables are represented by energy variables (future prices for Brent oil, natural gas, coal, electricity). Based on the research hypothesis, only energy prices that have undergone significant changes in dynamics were taken into account. Other factors affecting the carbon price were excluded from the analysis. Data were collected from the financial platform Investing.com [61], from which the daily closing prices of futures contracts for emissions permits (Carbon Emissions Futures—CFI), Brent oil (Brent Oil Futures—LCO), natural gas (Natural Gas Futures—NGX), coal (Rotterdam Coal Futures—ATW) and electricity (German Power Base load Calendar Month Futures—DBE) were loaded. The entire dataset, after recovering the missing data, contained a total of 3167 daily values. The gaps in the price data were restored by repeating the previous values.

4. Results

There are two main tasks in time series analysis: identification and forecasting. Solving the identification problem involves answering the question, what are the parameters of the system that generated this time series.

The analytical part of the article begins with the study of descriptive statistics. The descriptive statistics of data series in levels are presented in Table 1.

Table 1. Descriptive statistics for data of level series.

	Number	Minimum	Maximum	Mean	Median	Standard Deviation
Carbon emissions	3167	2.700	98.430	19.870	12.760	20.590
Brent oil	3167	17.799	117.460	63.181	60.337	18.343
Natural gas	3167	1.321	9.701	2.824	2.596	1.077
Coal	3167	35.021	402.650	78.498	65.886	56.361
Electricity	3167	15.520	465.180	53.438	38.760	55.037

Correlation analysis of the carbon price and energy prices based on a matrix of paired correlation coefficients revealed the relationship of variables (Table 2).

Table 2. Correlation matrix of energy variables and carbon emissions prices of level series.

	Carbon Emissions	Brent Oil	Natural Gas	Coal	Electricity
Carbon emissions	1				
Brent oil	0.26	1			
Natural gas	0.61	0.52	1		
Coal	0.75	0.54	0.85	1	
Electricity	0.81	0.45	0.79	0.91	1

An analysis of the matrix of paired correlation coefficients shows the greatest correlation between carbon emissions price and electricity, coal and natural gas prices (0.81, 0.75 and 0.61, respectively). The change in electricity prices is strongly associated with changes in coal and natural gas prices, 0.91 and 0.79, respectively. The prices of coal and natural gas as alternative energy sources also show a strong correlation.

For correct modeling, it is necessary to ensure the stationarity of time series. The Dickey—Fuller test for unit root showed the non-stationarity of the level price data (Table 3).

Table 3. Augmented Dickey–Fuller test for daily prices.

	Carbon Emissions	Brent Oil	Natural Gas	Coal	Electricity
p-value with a constant	0.9962	0.5327	0.9997	1.000	1.000
p-value with constant and trend	0.9925	0.8606	1.000	1.000	1.000

Therefore, we transformed the price data using the Hodrick—Prescott filter and obtained stationary price series as shown in Figures 2 and 3.

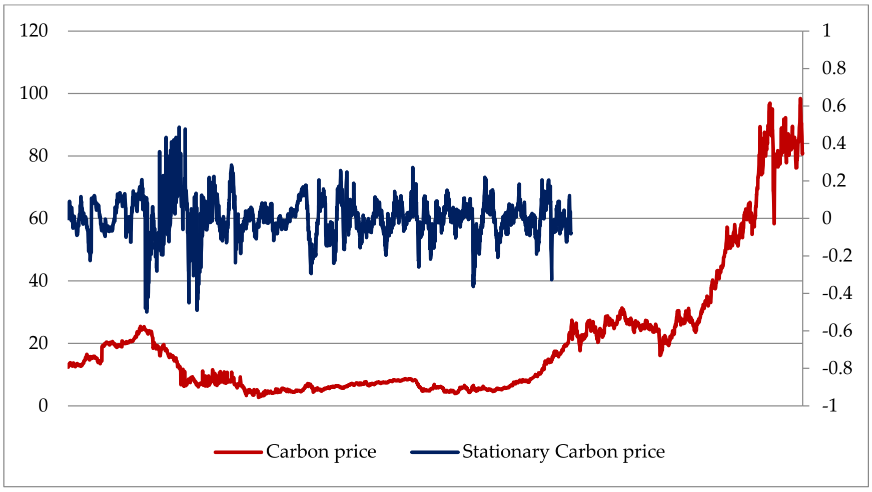

Figure 2. Data series in levels and stationary data series for carbon prices.

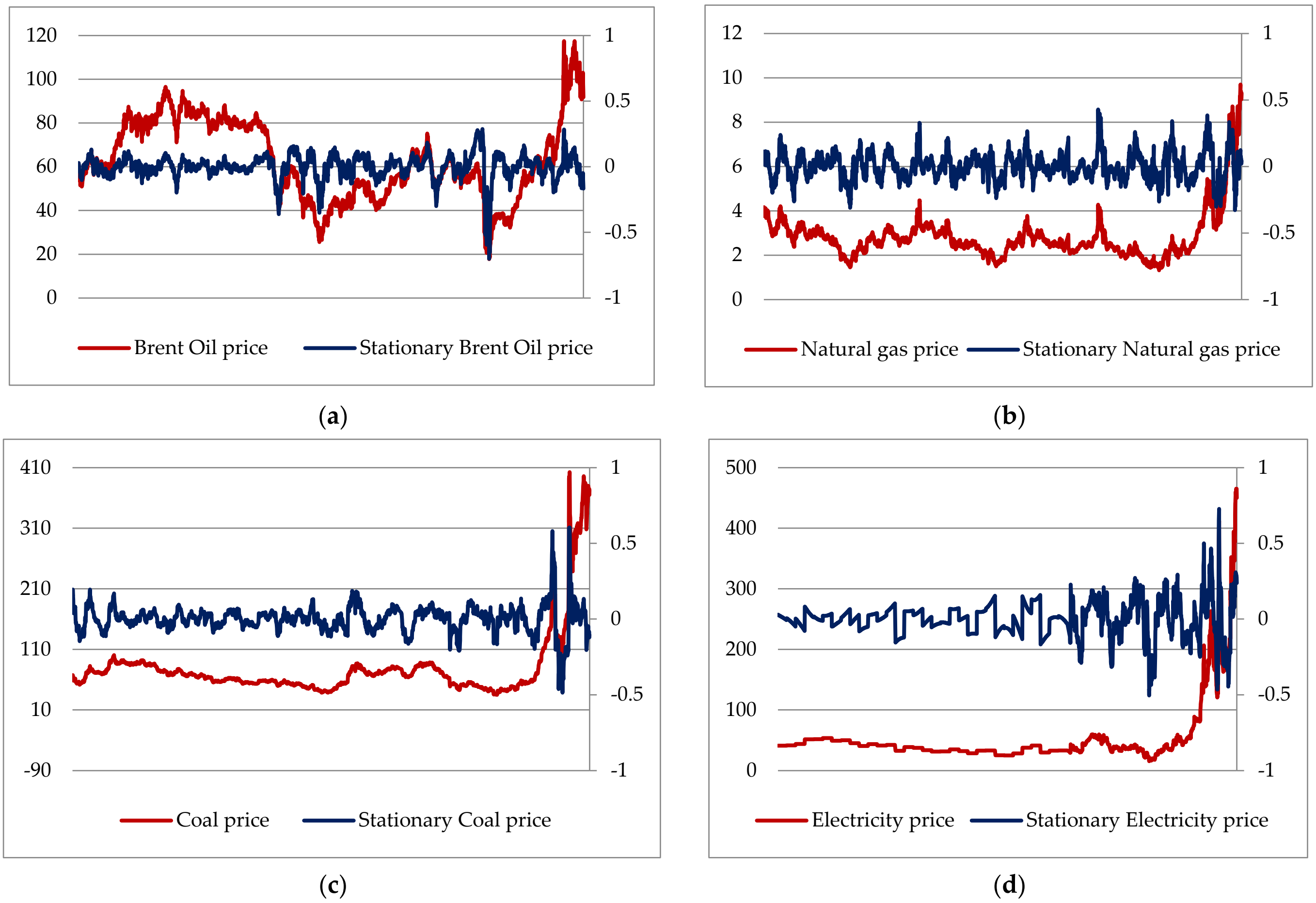

Figure 3. Data series in levels and stationary data series for energy prices. (**a**) Brent oil; (**b**) Natural gas; (**c**) Coal; (**d**) Electricity.

The Dickey—Fuller test showed the stationarity of these data series (Table 4).

Table 4. Augmented Dickey–Fuller test for stationary data series.

	Carbon Emissions	Brent Oil	Natural Gas	Coal	Electricity
p-value with a constant	0.0000	0.0000	0.0000	0.0000	0.0000
p-value with constant and trend	0.0000	0.0000	0.0000	0.0000	0.0000

The descriptive statistics of stationary data series are presented in Table 5.

Table 5. Descriptive statistics for stationary data series.

	Number	Minimum	Maximum	Mean	Median	Standard Deviation
Carbon emissions	3167	−0.4990	0.4880	0.0000	0.0007	0.1060
Brent oil	3167	−0.7000	0.2880	0.0000	0.0053	0.0923
Natural gas	3167	−0.3280	0.4290	0.0000	0.0032	0.1030
Coal	3167	−0.4860	0.6050	0.0000	0.0033	0.0908
Electricity	3167	−0.5030	0.7270	0.0000	0.0072	0.1160

The transformation of price data into a stationary price series changed the paired correlation coefficients (Table 6).

Table 6. Correlation matrix for stationary series of energy variables and carbon emissions prices and their 5% bilateral significance (correlation coefficient/*p*-value).

	Carbon Emissions	Brent Oil	Natural Gas	Coal	Electricity
Carbon emissions	1				
Brent oil	0.16/0.00	1			
Natural gas	−0.02/0.18	0.06/0.00	1		
Coal	−0.08/0.00	0.24/0.00	0.38/0.00	1	
Electricity	0.17/0.00	0.15/0.00	0.02/0.28	0.27/0.00	1

An analysis of the matrix of paired correlation coefficients shows that the carbon emissions price is positively related to the Brent oil price and the electricity price. The relationship between the coal price and the natural gas price with the carbon price becomes weakly negative. The correlation between the coal price and the natural gas price on stationary price series remains.

We use the ordinary least squares method and designed the carbon price model (Table 7).

Table 7. The carbon price model Y.

Variable	Coefficient	Prob.
Constant	0.000	1.000
Brent oil	0.201	0.000
Natural gas	0.032	0.097
Coal	−0.212	0.000
Electricity	0.179	0.000

The significance of the multiple regression coefficients is tested using Student's *t*-test. Regression coefficients are statistically significant at the level of 1%, with the exception of the constant, the natural gas price coefficient is significant at the level of 10%.

We tested the errors of the Y model for the presence of autocorrelation (Breusch–Godfrey test), heteroskedasticity (Breusch–Pagan test) and ARCH processes. The results are shown in Table 8.

Table 8. Results of testing model Y errors.

	Breusch–Godfrey Test	Breusch–Pagan Test	ARCH Processes
test statistic	186.782	55.702	1713.910
p-value	0.000	0.000	0.000

Autocorrelation, heteroscedasticity and ARCH processes are present in the errors of the Y model. To eliminate autocorrelation, we add the first lag of the dependent variable—AR(1)—and the first error lag—(moving average) MA(1)—to the mean equation. To eliminate ARCH processes, we conducted ARCH modeling. We tested different GARCH models to fit the data and decided on the GARCH(1,1) model (model Y_1)). The parameters of this model are shown in Table 9.

An analysis of the residual correlogram shows that one lag in the mean equation is sufficient to eliminate autocorrelation. The number of lags of squared residuals and variance was chosen in such a way as to eliminate the presence of ARCH processes. The Broich–Pagan–Godfrey test shows the absence of heteroscedasticity. The Ramsey test shows the correctness of the selected specification.

The quality characteristics of the model Y_1 are presented in Table 10.

The Y_1 model approximates carbon pricing more accurately. The standard error of the Y_1 model is 0.050. The coefficient of determination shows that the model explains 77.7% of the changes in the dependent variable. In the Y_1 model, all coefficients before energy variables are significant, with the exception of the coefficient before natural gas.

The dynamics of the actual carbon prices and model carbon prices are shown in Figure 4.

Table 9. The carbon price model Y_1.

Variable	Coefficient	*p*-Value
Constant	0.013	0.281
Brent oil	0.139	0.000
Natural gas	0.002	0.867
Coal	0.057	0.003
Electricity	0.051	0.000
AR(1)	0.971	0.000
MA(1)	−0.063	0.000
RESID(−1)^2	0.146	0.000
GARCH(−1)	0.846	0.000

Table 10. Quality of the carbon price model Y_1.

Indicator	Y_1
S.E. of regression	0.050
R-squared	0.777
Adjusted R-squared	0.777
Schwarz criterion	−4.270
Akaike info criterion	−4.291

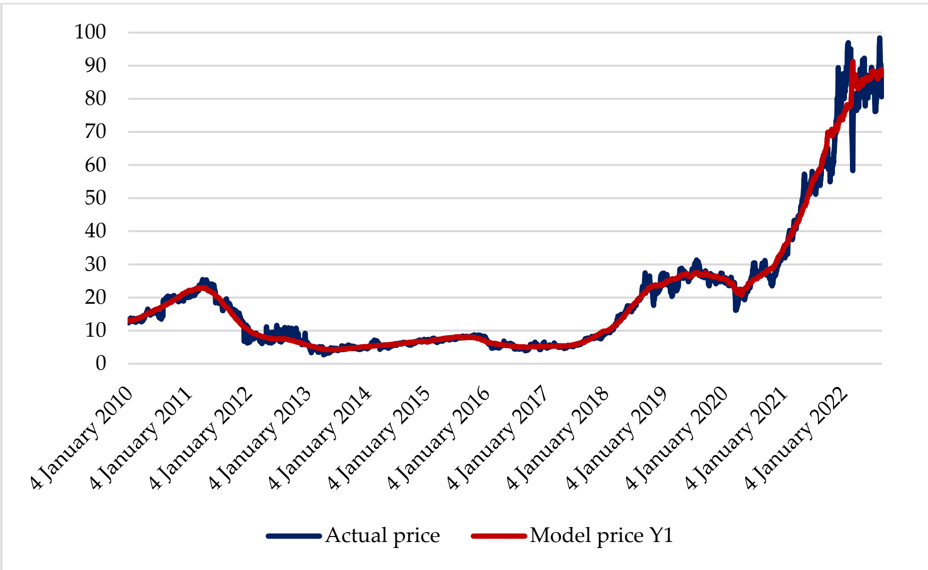

Figure 4. Actual and model carbon prices (model Y_1).

We drew attention to the change in the dynamics of carbon prices, which has been showing a steady upward trend since some time. This may be due to the GIC according to our hypothesis.

We used different Bai–Perron approaches to testing multiple break points. The results of the sequential Bai–Perron test at the significance level of 5% are shown in Table 11.

Table 11. Bai–Perron sequential test results.

Break Test	Scaled F-Statistic	Critical Value *	Break Date
0 vs. 1	57.78885	18.23	21 April 2016
1 vs. 2	28.17955	19.91	21 September 2020
2 vs. 3	20.85078	20.99	-

* Bai–Perron (*Econometric Journal*, 2003) critical values.

The sequential Bai–Perron test reveals two breakpoints: 21 April 2016 and 21 September 2020. The break dates obtained following the repartition procedure do not change.

The two-break global optimizers are the same as those obtained in the sequential testing example. As we expected, the GIC caused structural change in the relationship between carbon prices and energy prices.

Descriptive statistics of data series in levels and stationary data series for two periods are presented in Tables 12 and 13.

Table 12. Descriptive statistics of data series in levels (before/after 21 September 2020).

	Number	Minimum	Maximum	Mean	Median	Standard Deviation
Carbon emissions	2678/489	2.70/ 23.50	31.30/ 98.40	12.50/60.30	8.00/59.10	8.02/ 21.40
Brent oil	2678/489	17.80/ 32.20	96.50/117.00	62.10/69.40	59.60/63.40	17.1/ 23.00
Natural gas	2678/489	1.32/ 1.56	4.48/ 9.70	2.60/4.05	2.57/3.43	0.55/ 2.01
Coal	2678/489	35.00/ 42.80	101.00/403.00	64.20/157.00	63.80/122.00	14.5/ 111.00
Electricity	2678/489	15.50/ 33.30	59.80/465.00	37.90/139.00	37.50/121.00	8.44/ 103.00

Table 13. Descriptive statistics for stationary price data series (before/after 21 September 2020).

	Number	Minimum	Maximum	Mean	Median	Standard Deviation
Carbon emissions	2678/489	−0.4990/−0.3272	0.4880/0.2059	0.0009/−0.0051	0.0037/−0.0081	0.1100/0.0777
Brent oil	2678/489	−0.7000/−0.4855	0.2880/0.6045	0.0000/0.0003	0.0056/0.0036	0.0950/0.0755
Natural gas	2678/489	−0.3100/−0.3277	0.4290/0.3847	−0.0013/0.0070	−0.0040/0.0065	0.0927/0.1469
Coal	2678/489	−0.2100/−0.4855	0.1950/0.6045	−0.0002/0.0011	0.0022/0.0168	0.0626/0.1789
Electricity	2678/489	−0.5030/−0.4651	0.2710/0.7275	−0.0004/0.0020	0.0075/0.0029	0.0941/0.1973

After the breakpoint, descriptive statistics change significantly for data series in levels and stationary data series.

Correlation matrices of data series in levels and stationary data series for two periods are presented in Tables 14 and 15.

Table 14. Correlation matrix of energy variables and carbon emissions prices of level series (before/after 21 September 2020).

	Carbon Emissions	Brent Oil	Natural Gas	Coal	Electricity
Carbon emissions	1/1				
Brent oil	−0.13/0.88	1/1			
Natural gas	−0.17/0.76	0.34/0.86	1/1		
Coal	0.07/0.78	0.49/0.94	0.42/0.91	1/1	
Electricity	0.37/0.79	0.54/0.79	0.36/0.81	0.78/0.87	1/1

Table 15. Correlation matrix for stationary price series of energy variables and carbon emission prices (before/after 21 September 2020).

	Carbon Emissions	Brent Oil	Natural Gas	Coal	Electricity
Carbon emissions	1/1				
Brent oil	0.19/−0.13	1/1			
Natural gas	0.07/−0.50	0.05/0.08	1/1		
Coal	0.08/−0.55	0.21/0.45	0.36/0.44	1/1	
Electricity	0.29/−0.18	0.28/−0.22	0.08/−0.09	0.38/0.18	1/1

After the breakpoint, the relationship between the variables and the carbon emissions price changes significantly for data series in levels and stationary data series.

After the breakpoint, the correlation coefficients of the energy variables and the carbon price change from positive to negative. The strength of the relationship between the carbon price and variables is increasing, with the exception of Brent oil and Electricity.

Using the above econometric analysis logic, we designed two carbon price models before 21 September 2020 (Y2) and after 21 September 2020 (Y3). A comparative analysis of the models shows changes in the relationship of energy variables and carbon price (Table 16).

Table 16. The carbon prices models Y_2 and Y_3.

Variable	Coefficient Y_2	*p*-Value Y_2	Coefficient Y_3	*p*-Value Y_3
Constant	0.006	0.640	0.030	0.286
Brent oil	0.146	0.000	0.101	0.037
Natural gas	0.013	0.362	−0.035	0.149
Coal	0.044	0.104	0.044	0.099
Electricity	0.048	0.003	0.060	0.006
AR(1)	0.972	0.000	0.962	0.000
MA(1)	−0.058	0.002	−0.097	0.055
$RESID(-1)^2$	0.151	0.000	0.138	0.003
GARCH(−1)	0.849	0.000	0.720	0.000

Comparative analysis shows that the main factor in the formation of the carbon price remains the oil price, although its influence and significance have decreased. The impact of the natural gas price has changed direction from positive to negative, while remaining statistically insignificant. The impact of the coal price remained unchanged, while the significance increased to the level of 10%. The impact of electricity prices increased with a decrease in statistical significance.

The correlograms of the residuals of these models show the absence of autocorrelation. The correlograms of the squares of the residuals show the absence of ARCH processes. The Broich–Pagan–Godfrey test shows the absence of heteroscedasticity. The Ramsey test shows the correctness of the selected specification.

A comparative analysis shows that the Y3 model is of the highest quality (with a small error of 0.030, a large determination coefficient of 0.849 and minimized information criteria) (Table 17).

Table 17. Quality of the carbon price models Y_2 and Y_3.

Indicator	Y_2	Y_3
S.E. of regression	0.053	0.030
R-squared	0.770	0.849
Adjusted R-squared	0.770	0.847
Schwarz criterion	−4.249	−4.283
Akaike info criterion	−4.273	−4.386

To study the two breakpoints, we designed two more models: until 21 April 2016 (Y_5) and from 21 April 2016 to 21 September 2020 (Y_4). Descriptive statistics of data series in levels and stationary data series for three periods (Y_5, Y_4, Y_3) are presented in Tables 18 and 19.

After the breakpoints, descriptive statistics change significantly for data series in levels and stationary data series.

Correlation matrices of data series in levels and stationary data series for three periods are presented in Tables 20 and 21.

Table 18. Descriptive statistics of data series in levels for three periods (before 21 April 2016/from 21 April 2016 to 21 September 2020/after 21 September 2020).

	Number	Minimum	Maximum	Mean	Median	Standard Deviation
Carbon emissions	1576/1102/489	2.70/3.93/23.50	25.43/31.33/98.40	9.97/16.09/60.30	7.42/17.34/59.10	5.85/9.24/21.40
Brent oil	1576/1102/489	25.60/17.80/32.20	96.48/75.18/117.00	69.96/50.74/69.40	77.69/52.47/63.40	16.53/10.22/23.00
Natural gas	1576/1102/489	1.45/1.32/1.56	4.48/4.28/9.70	2.75/2.39/4.05	2.77/2.41/3.43	0.55/0.48/2.01
Coal	1576/1102/489	38.50/35.02/42.80	100.51/88.56/403.00	65.06/63.08/157.00	62.12/66.19/122.00	13.77/15.39/111.00
Electricity	1576/1102/489	24.79/15.52/33.30	53.61/59.75/465.00	39.28/35.86/139.00	40.39/33.93/121.00	7.80/8.92/103.00

Table 19. Descriptive statistics for stationary price data series (before 21 April 2016/from 21 April 2016 to 21 September 2020/after 21 September 2020).

	Number	Minimum	Maximum	Mean	Median	Standard Deviation
Carbon emissions	1576/1102/489	−0.50/−0.36/−0.33	0.49/0.27/0.21	0.00/0.00/−0.01	0.00/0.01/−0.01	0.12/0.09/0.08
Brent oil	1576/1102/489	−0.31/−0.70/−0.49	0.16/0.29/0.60	0.00/0.00/0.00	0.00/0.02/0.00	0.07/0.12/0.08
Natural gas	1576/1102/489	−0.31/−0.26/−0.33	0.32/0.38/0.43	0.00/0.01/0.00	0.00/−0.01/0.01	0.09/0.09/0.15
Coal	1576/1102/489	−0.15/−0.21/−0.49	0.20/0.19/0.60	0.00/0.00/0.00	0.00/0.01/0.02	0.05/0.08/0.18
Electricity	1576/1102/489	−0.15/−0.50/0.47	0.15/0.27/0.73	0.00/0.00/0.00	0.00/0.01/0.00	0.06/0.13/0.20

Table 20. Correlation matrix of energy variables and carbon emissions prices of level series (before 21 April 2016/from 21 April 2016 to 21 September 2020/after 21 September 2020).

	Carbon Emissions	Brent Oil	Natural Gas	Coal	Electricity
Carbon emissions	1/1/1				
Brent oil	0.01/0.26/0.88	1/1/1			
Natural gas	0.30/−0.41/0.76	0.16/0.34/0.86	1/1/1		
Coal	0.70/−0.39/0.78	0.59/0.51/0.94	0.22/0.73/0.91	1/1/1	

Table 20. *Cont.*

	Carbon Emissions	Brent Oil	Natural Gas	Coal	Electricity
Electricity	0.77/ 0.27/ 0.79	0.49/ 0.68/ 0.79	0.19/ 0.51/ 0.81	0.91/0.63/0.87	1/1/1

Table 21. Correlation matrix for stationary price series of energy variables and carbon emission prices (before 21 April 2016/from 21 April 2016 to 21 September 2020/after 21 September 2020).

	Carbon Emissions	Brent Oil	Natural Gas	Coal	Electricity
Carbon emissions	1/1/1				
Brent oil	0.03/ 0.41/ −0.13	1/1/1			
Natural gas	0.17/ −0.10/ −0.50	0.00/ 0.10/ 0.08	1/1/1		
Coal	0.01/ 0.17/ −0.55	0.26/ 0.18/ 0.45	0.43/ 0.30/ 0.44	1/1/1	
Electricity	0.29/ 0.38/ −0.18	0.08/ 0.36/ −0.22	−0.03/ 0.16/ −0.09	0.20/ 0.47/ 0.18	1/1/1

After the breaking points, the relationship between the variables and the carbon emissions price changes significantly for data series in levels and stationary data series.

A comparative analysis of the models shows changes in the relationship of energy variables and carbon price (Table 22).

Table 22. The carbon prices models Y_5, Y_4 and Y_3 (coefficient (p-value)).

Variable	Y_5	Y_4	Y_3
Constant	0.013 (0.562)	0.007 (0.581)	0.030 (0.286)
Brent oil	0.114 (0.000)	0.199 (0.000)	0.101 (0.037)
Natural gas	0.015 (0.340)	0.058 (0.018)	−0.035 (0.149)
Coal	−0.064 (0.060)	0.167 (0.000)	0.044 (0.099)
Electricity	0.046 (0.192)	0.022 (0.243)	0.060 (0.006)
AR(1)	0.983 (0.000)	0.938 (0.000)	0.962 (0.000)
MA(1)	−0.094 (0.000)	-	−0.097 (0.055)
RESID(-1)^2	0.261 (0.000)	0.100 (0.000)	0.138 (0.003)
GARCH(-1)	0.812 (0.000)	0.857 (0.000)	0.720 (0.000)

A comparative analysis shows that the Y_4 model is of the highest quality (with the smallest error 0.029, the largest coefficient of determination 0.899 and minimized information criteria) (Table 23). The Y_3 model is also of high quality (error 0.030, determination coefficient 0.849 and minimized information criteria).

Table 23. Quality of the carbon price models Y_5, Y_4 and Y_3.

Indicator	Y_5	Y_4	Y_3
S.E. of regression	0.064	0.029	0.030
R-squared	0.723	0.899	0.849
Adjusted R-squared	0.722	0.899	0.847
Schwarz criterion	−4.196	−4.292	−4.283
Akaike info criterion	−4.233	−4.333	−4.386

The dynamics of the actual carbon prices and model carbon prices with two breakpoints are shown in Figure 5.

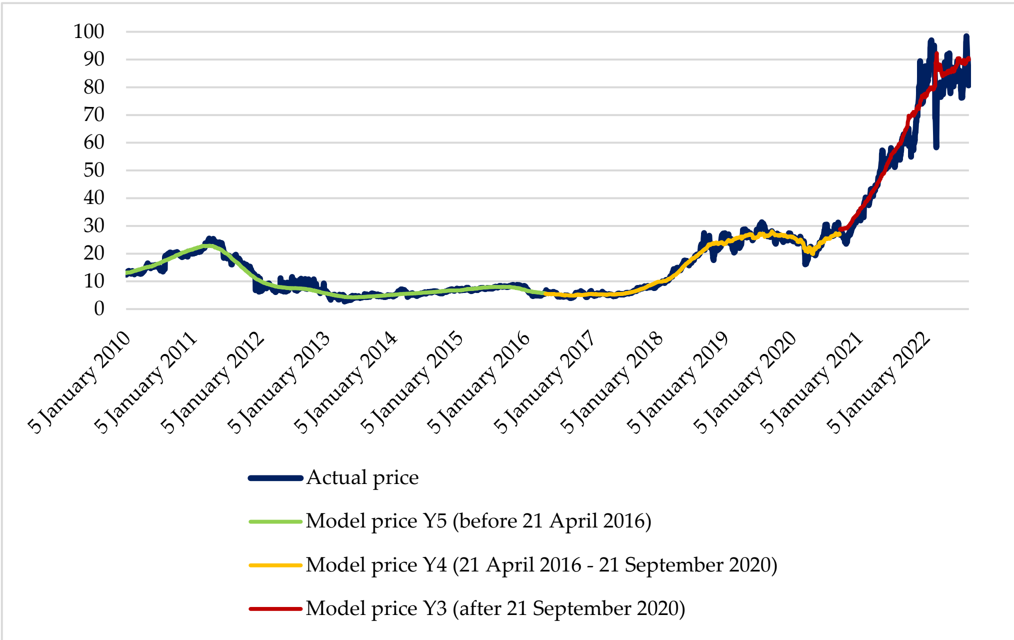

Figure 5. Actual and model carbon prices with two breakpoints.

Several separate models better describe the dynamics of the carbon price. New carbon pricing rules are being formed in the context of global institutional changes. The results of the study are relevant for the development of climate policies.

5. Discussion

In many articles, the authors explore various aspects of the relationship and influence between the prices of energy variables and the price of carbon in the UE ETS at different periods of its operation and, therefore, in different conditions. Our article explores this issue in the conditions of global institutional changes.

Economic and econometric studies to identify changes in the relationship between the price of emission permits and the main energy variables are carried out in the article. We tested the hypothesis that the GIC influences on the price of emission allowances. In the conditions of the global institutional changes new CO_2 pricing rules are being formed.

We assessed how the structural changes driven by the GIC affect the relationship between carbon prices and energy prices. We define GIC as a combination of strong external shocks (key events): the growth in the cost of liquefied natural gas in the countries of the Asia–Pacific region; COVID-19 and the recovery of the global economy after the pandemic; climate anomalies in the EU, Asia and North America; the transition of a number of EU countries from long-term contracts to spot prices for gas supplies by a Russian supplier; etc. These events, considered in aggregate, affected the prices of energy factors and led to a change in the dynamics of the carbon price—the emergence of a stable upward trend, starting from a certain point in time. The Bai–Perron test results revealed two structural breaks in the relationship between emission allowance prices and energy prices over the period 2010–2022. 21 September 2020–a breakpoint, after which a steady increase in carbon prices began. Another structural change in this relationship took place on 21 April 2016.

The GARCH model for the entire analyzed period did not show a statistically significant impact of gas prices on carbon prices. All other energy variables have a statistically significant positive effect on CO_2 prices, with the regression coefficient of the oil price being the highest. Samples of carbon price values obtained under different conditions—before and after the breakpoint—are not homogeneous in the regression sense. Therefore, several separate models better describe the dynamics of the carbon price. We built GARCH models describing the carbon price dynamics before 21 September 2020 and after this date, as well as GARCH models for two breakpoints on 21 April 2016 and 21 September 2020.

Looking at one breakpoint on 21 September 2020 shows that the GIC has made a difference. From January 2010 to 21 September 2020, apart from gas, the price of coal was statistically insignificant (*p*-value 0.1038). The price of oil has the greatest statistically significant positive impact on CO_2 prices. After the breakpoint, the gas price remains statistically insignificant, but the p-value is more than halved. At the same time, the sign of the regression coefficient of the gas price became negative. Among other energy variables, the price of oil has the greatest statistically significant positive effect. The quality of the GARCH model improved after the break point on 21 September 2020.

The situation changed more significantly when considering two breakpoints on 21 April 2016 and 21 September 2020. In the period from January 2010 to 21 April 2016, prices for gas (*p*-value 0.34) and electricity (*p*-value 0.19) behaved statistically insignificantly. The price of oil had the greatest statistically significant positive effect, while the price of coal had a statistically significant negative effect on CO_2 prices (at the level of 10%, *p*-value 0.06). In the period from 21 April 2016 to 21 September 2020, the picture changed. Only the price of electricity remained statistically insignificant (*p*-value 0.24). Among other energy variables, gas prices (5% significance level) and oil prices (1% significance level) had a positive effect on CO_2 prices, with the price of oil having the largest impact. After oil, the price of coal was the most influential, while its influence became positive. A comparison of the model between the period from 21 April 2016 to 21 September 2020 and the model after 21 September 2020 shows that the changes are associated with the following energy variables: gas had a negative statistically insignificant effect on CO_2 prices, the price of electricity shows the second most influential statistically significant positive result, oil price retained its leading positions of influence, but already at a significance level of 5%.

The quality of the model for the period from 21 April 2016 to 21 September 2020 increased compared to the model for the entire period, i.e., the model for the period from 2010 to 21 September 2020 and the model from 2010 to 21 April 2016. At the same time, the quality of this model is similar to the quality indicators of the model after 21 September 2020. In general, the quality of models for two breakpoints is better than for models built for one breakpoint.

Because our sample size and data set are different from those of earlier works, we can only make an indirect comparison of the effects of energy variables on carbon prices under GIC conditions. The researchers substantiated that in general, the COVID-19 pandemic is an integral element of the GIC, and by sharply reducing economic activity and CO_2 emissions, it has led to significant structural changes in the carbon market in the EU. The transition of continental European gas markets from oil-linked pricing on long-term contracts to hub-based pricing (also considered by us as an integral part of the GIC) is accompanied by major changes in energy markets and, as a result, in the carbon market.

We confirmed that in the current post-GIC environment, energy factors are the main determinants of the price of CO_2, as argued in earlier studies. The impact of the fossil energy market on the carbon market changes over time. After September 2020, the role of natural gas prices in the carbon price variation decreased in favor of oil. In addition, structural changes are an important feature of the EUA pricing process. Breakpoints in the EUA price are usually associated with major events. Breaking down into subperiods provides a better representation of the institutional and market events that affect EUA prices. The mechanisms by which factors affect the price of the carbon market change before and after points of structural change are significant. This confirms the effectiveness of successive policy adjustments in the carbon market.

Thus, GIC, taking into account the inertia of the economic system, led to structural changes in the relationship between the price of CO_2 and the prices of energy variables. Therefore, several separate models better describe the dynamics of carbon price. New CO_2 pricing rules are being formed in the context of global institutional changes. It is worth noting that further studies conducted for longer time series covering the period after 21 September 2020 are appropriate and may provide different results. We have empirically shown the impact of global institutional changes on CO_2 price behavior. Examining the reasons behind these breakpoints is important for evaluating the effectiveness of climate policy. Policymakers can draw conclusions about how reliable and predictable climate policy is. Analysis of the causes and consequences of GIC is the subject of future research.

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