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# The Nexus between Wholesale Electricity Prices and the Share of Electricity Production from Renewables: An Analysis with and without the Impact of Time of Distress

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**Abstract:** The continuous integration of renewable energy sources into the EU's energy mix is reshaping the electricity market dynamics mainly due to the merit order mechanism affecting wholesale electricity prices (WHEP). This article aims to review the wholesale electricity market mechanism, identify the key factors affecting WHEP, and assess the extent of their contributions under different circumstances. Time series datasets, consisting of monthly observations of commodity prices and energy data regarding 25 EU members over the time horizons January 2015–December 2020 (pre-crisis) and January 2015–August 2023 (co-crisis), are used to support the theory, perform the comparison, and verify the validity of our hypotheses with the use of correlation and multiple linear regression analyses. Our empirical results show that in both cases, a 1% increase in the share of renewable electricity generation (RES) from one period to the next is ceteris paribus associated with an average of approx. 0.96% decrease in WHEP for the same period. However, extreme natural gas prices during times of distress significantly increase WHEP due to the merit order mechanism, from an average of 0.19% to 0.55%. This novel approach provides deeper insights into the interconnectedness of WHEP and the energy and environmental commodity prices and RES during changing economic and geopolitical circumstances, primarily highlighting the influencing factor of RES in WHEP developments.

**Keywords:** wholesale electricity price; electricity market; renewable energy share; correlation analysis; regression model



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## 1. Introduction

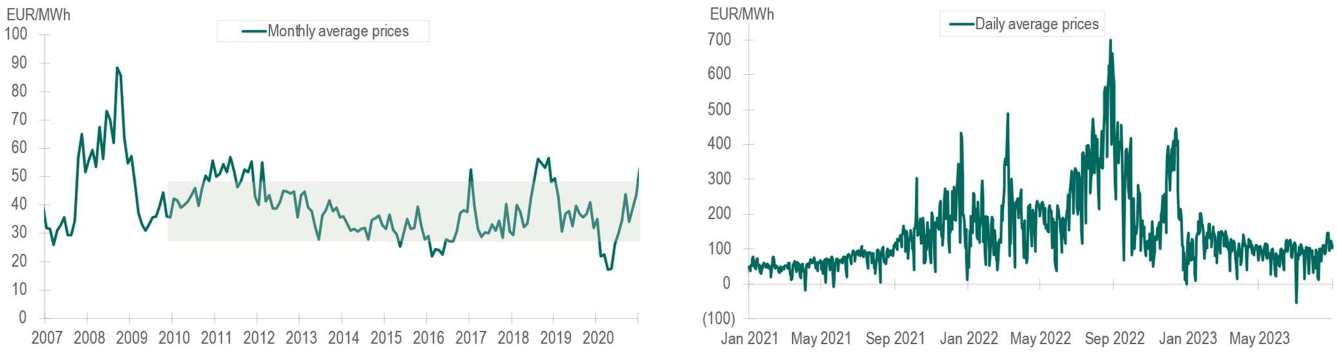
In the first half of the last decade, the European Union (EU) was defined by its recovery from the Great Recession caused by the 2008 housing market crisis and the following Eurozone debt crisis. This recovery was not only measured by common economic indicators (GDP growth, unemployment rates, consumer spending, investment levels, etc.) and by policy responses (structural reforms and fiscal consolidation efforts) that were put in place to restore confidence in EU economies [1,2] but via the context of the energy markets as well.

The energy market in the EU was characterized by a series of complex transformations driven by various economic, regulatory, and technological factors, reflecting the industry's adaptation to new market conditions following the Great Recession and the broader shift toward sustainability and integration. Hence, the EU's energy strategy, built around the energy transition, mainly focuses on sustainability, security, and competitiveness, such as the growing penetration of renewable energy sources, decarbonization efforts, phasing out nuclear and coal, further market liberalization, introducing newer energy efficiency measures, and renewable subsidies [3,4]. The Kyoto Protocol, the introduction of EU Emissions Trading Systems, Renewable Energy Directives, and the Climate and

Energy packages are just a few examples of the EU's efforts toward the shift to sustainable energy [4].

The proportion of RES has increased since the beginning of the 2000s, especially after the end of the first decade as the EU members accepted a mandatory target of 20% final energy consumption from renewable energy sources by 2020, along with 20% reduction in the greenhouse gas emissions and 20% increase in energy efficiency [5]. According to the European Statistical Office (EUROSTAT) [6,7], RES accounted for approximately 527 TWh or 17.6% of gross electricity generation in the EU-27 in 2007. By the end of 2022, RES had more than doubled (1108 TWh), while the percentage had risen to 39.2%, considering the proportion of combustible renewable biomass. With the increasing propensity to green investments, technological advancements, and cost reductions in the manufacturing of green power plants, these commitments multiplied the growth rate of RES [8]. However, due to the characteristics of the electricity market, the energy transition substantially influences the trends and volatility of wholesale electricity prices (WHEP).

As shown in Figure 1a, in the aftermath of the financial crisis, there was a general decline in WHEP primarily due to the reduction in industrial activities and, consequently, in the demand for electricity. However, as the EU's economy started recovering, electricity consumption was also restored. Meanwhile, electricity production from renewable energy sources (RES) was also growing, and even though the output is heavily dependent on weather conditions, it slowly became dominant in electricity generation [9]. Overall, a transition toward more renewable sources, increased market integration, and evolving regulatory landscapes marked the period from 2010 to 2020 in the EU's electricity market. The average monthly WHEP remained relatively stable during the previous decade, ranging between 30 and 50 EUR/MWh on average.




(**a**) (**b**)

**Figure 1.** (**a**) Monthly average EPEX SPOT Germany electricity prices (January 2007–December 2020). (**b**) Daily average EPEX SPOT Germany electricity prices (January 2021–August 2023). Source: created by the authors based on the Energy-Charts database [10].

However, the beginning of the second decade brought a new era with unexpected events affecting the economies and societies and causing the energy commodity prices to surge—especially concerning WHEP, natural gas, and coal prices—and reaching never-before-seen levels for WHEP (Figure 1b). The COVID-19 pandemic, caused by the novel coronavirus SARS-CoV-2, emerged in late 2019 and rapidly evolved into a global pandemic. The virus spread swiftly, prompting global lockdowns, travel restrictions, and a race to develop effective vaccines. At the same time, the economy suffered from disrupted trade and supply chains, business closures, and, due to the initially reduced industrial activities, declined electricity demand, leading to a temporary decrease in WHEP, as seen in Figure 1a. However, sooner than expected, the rapid economic rebound and increased demand, accompanied by unusual weather conditions and below-average level of natural gas storage in the EU, delayed capital expenditures, and maintenance at power plants all increased energy prices, particularly from 2021 [11]. Consequently, the energy crisis emerged from and lived along with the COVID-19 pandemic, and it peaked as a comprehensive global energy crisis following the next geopolitical event, when Russia attacked Ukraine at the beginning of 2022. The Russia–Ukraine war heightened concerns about the EU's energy security and supply stability, as the EU heavily relied on Russia for its natural gas supply. Thus, the growing probability of potential supply disruptions or punitive measures against Russia impacting gas exports led to uncertainty in the market, which all contributed to the spike in natural gas prices during 2022 [12]. As the interconnectedness between the energy commodity prices is relatively high [13–15], high natural gas prices caused the daily average WHEP to soar in the EU, reaching almost 710 EUR/MWH in the Czech Republic at the end of August 2022, while slightly lower level can be observed for the European Power Exchange (EPEX) spot price in Germany in Figure 1b too.

The energy market is particularly affected by such geopolitical and financial crisis events. The demand fluctuations, supply chain disruptions, increasing fuel prices, and geopolitical responses to the evolving circumstances resulted in highly volatile and extremely high WHEP across the EU [16,17]. Meanwhile, the current energy transition also aims to address the energy trilemma by finding a sustainable balance between security, equity, and environmental sustainability, out of which energy security has been given exceptional attention due to the recent geopolitical situations [18]. It has become a top priority for many countries, leading to a reevaluation of energy sources from this aspect [19]. These external circumstances and internal factors determined WHEP development trends and the share of renewable energy sources in the current and future energy mix.

Despite many studies examining the nexus of these variables, this study has a clear rationale and novelty. In light of recent events, the key factors that affect WHEP during a crisis-free period can now be assessed after a sufficient amount of time has elapsed throughout times of distress, particularly focusing on how RES impacts WHEP movements in different circumstances. Furthermore, instead of carrying out a pre-post analysis, we chose to conduct our evaluation by comparing datasets between the pre-event and the entire assessed timeline, thus incorporating the extreme event period into the total observed time series. Consequently, our study significantly contributes to the existing literature with novel time horizon assessment by dividing the analyzed periods into "pre-crisis period" and "co-crisis period", choosing the coverage of EU-25 data, and conducting special sensitivity analyses based on regression focusing on the changes in WHEP in certain circumstances.

In this article, we used qualitative and quantitative research methods to delve into the subject and choose an adequate comparison method. Accordingly, our research questions are two-folded as well:

(1) To review the wholesale electricity market in detail and the key factors affecting WHEP, primarily focusing on the role of RES in it;
(2) To assess whether the selected factors have statistically significant relationships with WHEP, and if so, estimate the extent of the contributions in the different circumstances.

Based on the qualitative assessment, three hypotheses were stated and tested via quantitative analysis, serving as a bridge between the two methodologies. For this purpose, the correlation between the factors will be determined first. Then, a multiple (time series) linear regression statistical model will be constructed based on the January 2015–December 2020 dataset (pre-crisis period). A similar approach will be carried out by incorporating the time of distress period, extending the examined period to January 2015–August 2023 (co-crisis period), and the results will be evaluated.

This paper is organized into the following chapters: Section 2 introduces the wholesale electricity market mechanism and the factors affecting WHEP, followed by an overview of related literature on past research on this subject. We also formulate our hypotheses in this section. Section 3 covers the data and methodology used in our empirical study. Section 4 details the results from the statistical approach. Section 5 discusses the main findings of the comparison. Finally, Section 6 adds the final wording as conclusions for the article.

## 2. Literature Review

### *2.1. The Wholesale Electricity Market and the Key Factors Affecting the Prices*

WHEP is a unique energy commodity asset. It is determined by a combination of different factors. The most fundamental one is the balance between supply and demand. However, while the basic economic principle of demand and supply applies to the electricity market, it has unique characteristics, resulting in behavior different from other commodity markets [20,21]. Concerning these dynamics, the cost of produced electricity depends on how much and what type of power plant generates such an amount of electricity that meets the demand. This concept is called marginal cost pricing [22,23].

As per [20,21,24,25], in a market-based electricity system, the price at any given time is often set by the marginal cost of the last unit of electricity needed to meet demand. This unit is often referred to as the "marginal unit". The marginal cost can vary depending on the technology and fuel used in electricity generation and the current level of demand. After the power demand for a specific period is forecasted, electricity producers submit bids indicating how much electricity they can supply and at what price, representing the marginal costs. Then, the market operator matches supply with demand, starting with the lowest bids and continuing with more expensive plants as demand increases. This concept is known as the merit order, represented by Figure 2. Finally, the price of the last unit needed to meet the demand sets the electricity clearing price for all power supply during that given period under the bidding zone (bidding zones in the electricity market are defined areas within which WHEP are determined uniformly).

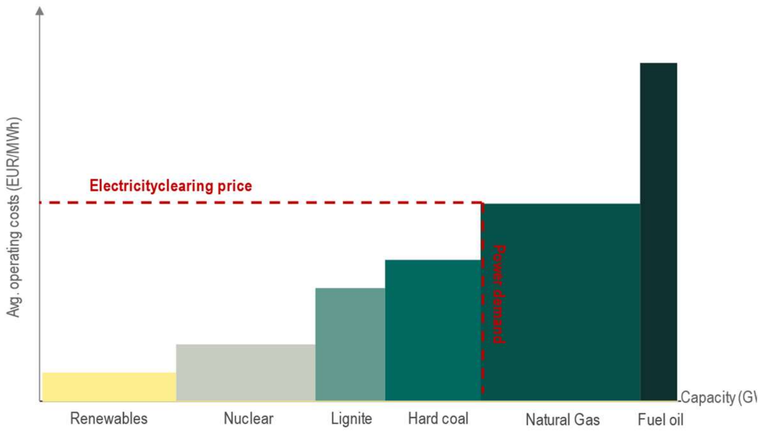
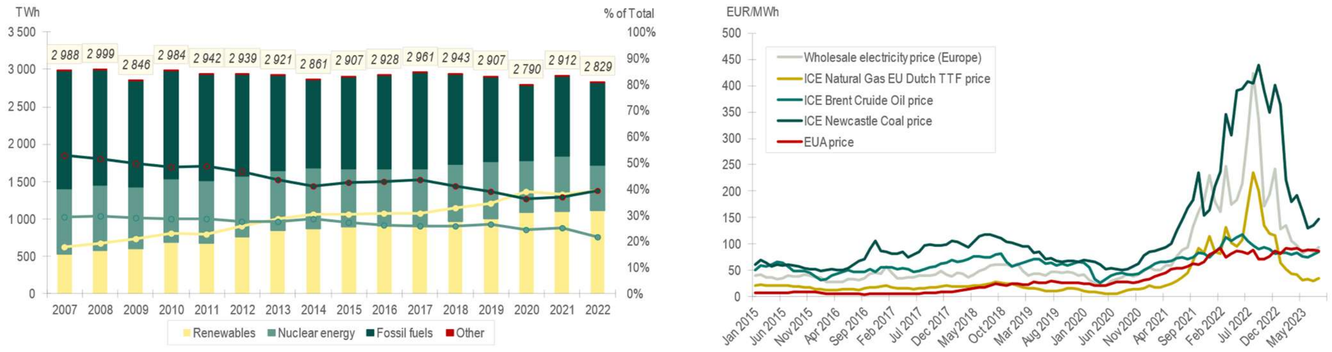



**Figure 2.** Illustrative electricity clearing price due to merit order effect. Source: created by the authors based on [24,26].

This means that plants are ordered from the lowest to the highest marginal cost, and those with lower costs are dispatched first. Marginal costs include operating and maintaining the given power plant but do not include installation costs or future recultivation expenses. Consequently, among renewables, solar and wind energy come first in the ranking as they do not require fuel, only scheduled maintenance, which is relatively low compared to fossil fuel plants. Other renewables also have lower marginal costs than non-renewable sources (hydroelectric, geothermal, and bioenergy) [19,23,27]. As such, the low marginal costs provide renewable energy sources a comparative advantage in electricity markets [28]. This is a positive side-effect of the EU's energy strategy in transforming the energy sector toward using more sustainable and low-carbon sources. Hence, the increasing integration of intermittent renewable energy sources in replacement of fossil fuels—the current energy transition—not only means a pathway to achieve a climate-safe future but also supports the affordability of electricity via the merit order effect and generally lowers the dependency on external energy import that are not available at the given geographical region (assuming that the renewable sources are adequately accessible at the same time to cover the demand). In other words, this matter is the energy trilemma, which refers to the challenge of finding a balance between energy affordability, security, and sustainability [18].

Upon examination of Figure 2, a rise in RES should cause a decrease in the clearing price ceteris paribus, resulting in the exclusion of pricier units from the market. Favorably, the EU is moving in the right direction, even if it is slow-paced. Figure 3a shows the annual gross electricity generation in the EU-27 for the last 16 years. At the time of the financial crisis, RES reached 527 TWh, which, compared to the total generation of 2988 TWh, only represented a 17.6% share. In contrast, fossil fuels reached 53.0% of the total, almost three times the renewable's percentage. However, RES passed behind the fossil proportion for the first time in 2020, too, mainly due to external matters, as it was accelerated by the unique circumstances caused by the COVID-19 pandemic and the economic downturn in that year in parallel with the ongoing energy transition efforts. In 2022, the share of fossils and RES was nearly identical (both rounded to 39.2%).




(**a**) (**b**)

**Figure 3.** (**a**) Gross electricity generation by type of source in EU-27 (2007–2022). (**b**) Monthly average energy commodity and EU ETS carbon prices (January 2015–August 2023). Source: created by the authors based on the EUROSTAT database [6,7] and EMBER [29], Investing.com [30], and Refinitiv [31] databases.

In the last decade, wind and solar power plant installations increased the most. At the same time, the potential in tidal and wave energy was largely unexploited in the EU due to several technical, economic, and geographical factors, while geothermal energy was primarily utilized in heating [32]. Hydropower is a significant renewable energy source, but its potential for expansion is limited as many suitable sites for large-scale hydropower plants in the EU have already been developed. Furthermore, the deployment of such power plants often faces environmental and social concerns, while the impact of climate change significantly affects water availability [27,28]. Hence, the EU's hydropower capacity is relatively mature, and most of the best locations for large dams and reservoirs are already in use. Lastly, bioenergy—which includes biomass, biofuels, and biogas—is a vital part of the EU's renewable energy strategy, but its expansion and development must be balanced with sustainability considerations. Concerns revolve around the impact of biomass production on land use, biodiversity, food security, and carbon emissions, as the carbon neutrality of bioenergy has been questioned [19]. There are ongoing discussions and policy revisions to ensure that bioenergy contributes to the EU's climate goals without adverse environmental impacts [8].

However, the current side-effect of the energy transition is the volatile ratio of RES combined with the day-to-day changing power demand for the economy and society, which requires flexible and adjustable power plants that can start up and ramp up faster. That is why we still need energy sources like natural gas to operate gas power plants partly on a demand basis [33]. Figure 3b visualizes the monthly average WHEP in Europe and selected specific trading contracts from the commodity market between January 2015 and August 2023. To an extent, the interconnectedness of these energy commodity prices is clearly visible. Coal, gas, and oil products are all fuels in power generation, thus influencing WHEP under the merit order principles. These energy sources are standardized for trading purposes, and the prices of these commodities are heavily affected by global supply and demand dynamics and volatility due to factors like strict regulations, geopolitical events, natural disasters, or changes in production levels.

Fossil fuels have lost approximately 13.8% of their share since 2007, primarily because the increasing penetration of RES heavily impacted the need for such fossil fuels. Furthermore, coal and gas products showed significantly changing trends as the energy landscape shifted due to economic reasons, energy transition efforts, and rising energy security concerns. Environmental concerns and international agreements like the Paris Agreement, adopted in 2015, have pressured countries to reduce emissions [8]. Since coal is one of the most carbon-intensive forms of energy, many countries have embraced policies to reduce or phase out their use of coal in favor of cleaner energy sources.

Another consideration of utilizing natural gas rather than coal is the flexibility of its usage. Burning gas is far more flexible than burning coal regarding speed, which is essential to balance the supply volatility of RES [12]. Around the middle of the last decade, a shift from coal to natural gas in the EU's energy mix was observed. Natural gas prices started to fall, and gas products became more competitive than coal due to the characteristics of RES, the impact of carbon prices, and as more liquefied natural gas (LNG) entered the EU market [9,12,34]. The shift lasted until 2020, when this trend was interrupted. Not only did the overall level of fossil fuels used in gross electricity generation increase from 36.3% to 39.2% between the last two years (Figure 3a), but coal products enjoyed a renaissance in tendency over natural gas. Economic and geopolitical factors primarily influenced this renewed preference. As per the natural gas trends, a sharp increase in natural gas prices was driven by the rapid global demand during the recovery from the COVID-19 pandemic. Shortly after, the rising geopolitical tensions and the subsequent war between Russia and Ukraine caused concerns about the reliability of natural gas supplies from Russia, which were further enhanced by the sanctions later. Additionally, many EU countries also chose to conserve their natural gas reserves in anticipation of potential shortages in the winter months. These led EU countries to seek alternative energy sources to ensure the security of supply, and in these circumstances, coal has recently become more economically viable [12,18,20]. This uncertainty made coal—which can be sourced more diversely and is often stockpiled in large quantities—a more secure short-term option for some countries. The surge in demand caused coal prices to rise. It is important to emphasize that this shift toward coal in 2021–2022 was a temporary response to the extraordinary market and geopolitical conditions [34]. The EU's long-term commitment to reducing greenhouse gas emissions and transitioning to renewable energy sources remains a key policy focus, with natural gas often viewed as a "bridge fuel" in this transition [33].

As per the emissions, the impact of fossil fuels on air quality and public health contributed to the stricter regulations on emissions, particularly regarding coal-fired power plants. The pressure was further enhanced by introducing the European Union Emission Trading System (EU ETS) carbon prices. The mechanism aims to force market players to gradually reduce their emissions in line with a timetable set by the Kyoto Protocol and the Paris Agreement. In order to lower greenhouse gas emissions, the EU ETS releases a limited number of tradable allowances (EUA) on the market, which will decrease each year [24]. Since coal emits more $CO_2$ per unit of energy produced than natural gas, coal power plants require more allowances [24]. The cost of EUAs adds to the operational expenses of fossil fuel-based power plants. The higher the EUA prices, the more costly it is to emit $CO_2$. Hence, WHEP typically reflects these additional costs. The EUA prices can be volatile and prone to change due to policy changes and economic conditions, contributing to the fluctuations in WHEP.

In summary, Figure 3a,b present the key factors affecting WHEP. As the wholesale electricity market is an integrated system, prices are highly dynamic, influenced by factors beyond and via the general demand–supply curve, including the increasing penetration of RES in the energy mix via the merit order mechanism. The current system needs increasing amounts of flexible generation as we shift to more renewables on standby to meet the electricity demand, as many of these sources are weather-dependent. Renewable power plants could not respond to volatile demands (peak loads) with sufficient flexibility, although advances in battery technology and smart grid management could improve the situation. Furthermore, based on the merit order principle, the prices of energy commodities such as coal, gas, or oil used as fuels in producing electricity and the linked environmental commodities (carbon credits) also affect the clearing price of the wholesale electricity supply. Since the energy crisis, these commodities have shown high volatility and all-time high prices in some instances. However, in areas with higher penetration of RES, the impact of the high volatility of fossil fuel prices on WHEP might be less noticeable if the greater instability it can cause in the electricity forecast is disregarded [22].

Overall, we can conclude that there is a theoretical association between the development of WHEP and the behavior of certain energy and environmental commodity prices, electricity demand, and RES. Therefore, the following hypotheses were stated:

**H1**. *A strong and negative significant relationship exists between RES and WHEP in both periods;*

**H2**. *The relationship between natural gas prices and WHEP during the co-crisis period is stronger than during the pre-crisis period;*

**H3**. *WHEP is expected to decrease less during the co-crisis period when RES increases by one unit ceteris paribus compared to the pre-crisis period, while the opposite is true in the case of natural gas*.

### *2.2. State of the Art*

Previous research and studies in energy commodities primarily focused on the relationship between fossil fuel prices and WHEP. Asche et al. [35] conducted a co-integration analysis to examine variations in the correlation between prices and time intervals, using monthly wholesale prices of crude oil, natural gas, and electricity. They found that besides fluctuations in fuel costs that can impact electricity prices, an interconnected market was discovered between January 1995 and June 1998, before the physical connection of the UK gas market with the European continental market. Bencivenga et al. [14] investigated the relationship between crude oil, natural gas, and electricity prices via an unconditional correlation analysis for short-term and co-integration approaches for long-run relationship assessment. Their result confirmed an integrated market between these energy commodities. Mohammadi [36] also examined the connection of the three common fossil fuel prices to electricity prices in long- and short-run relations using annual data for 1960–2007 in the USA. He found no unified energy market consisting of electricity, coal, natural gas, and crude oil, as fuel prices are not the primary factors of electricity prices in the USA based on the analysis. Emery et al. [37] also found co-integration between the electricity futures prices and the natural gas futures prices in their study. Mjelde et al. [38] applied a multivariate time series method to weekly price data, showing that US electricity prices affect natural gas prices during peak times, while the latter also influences crude oil prices. Moutinho et al. [13] investigated the long-term and short-term relationship among commodity prices and between electricity prices and commodity prices. According to the result, the price of electricity is explained by the development of natural gas. Due to the recent geopolitical turbulences, Zhou et al. [39] examined the linkage between gas and electricity prices. Their results revealed the co-integration relationship of long-term gas and electricity price stability. Last, Uribe et al. [40] investigated the direct impact of natural gas shocks on electricity prices for 21 European markets between January 2015 and March 2022. Their quantile regression analysis found that the effect depends on the market integration level and that vulnerability emerges during market distress scenarios for countries with a relatively small share of natural gas in their energy mixes.

Studies are also concerned with the determinants of WHEP, including RES perspectives. Hirth [26] modeled the electricity market in Germany and Sweden between 2008 and 2015 to determine which factors, such as energy prices, renewable energy, electricity demand, net import, etc., contributed the most to the changes in day-ahead prices. He found that the expansion of renewable energy had the most significant impact on prices in both countries. Cevik et al. [22] used a panel quantile regression approach to assess the impact of renewable energy (wind and solar) on the level and volatility of wholesale electricity prices across 24 EU members over the period 2014–2021. They observed that a 1% increase in the use of renewable energy leads to a 0.6% decrease in wholesale electricity prices. Ballester et al. [41] focused on the Spanish electricity market, assessing the relationship between renewable production share and day-ahead electricity prices and finding a statistically significant and negative relationship between these variables based on the analyzed dataset. Moving from Spain to Germany, Cludius et al. [42] used a time series regression analysis with wind, solar, and electricity load as independent variables to estimate the merit order effect of wind and solar electricity generation in Germany for 2008–2012. The model showed that the average decrease in the spot market price is between 0.8 and 2.3 EUR/MWh per additional renewable energy unit, ceteris paribus. Rathmann [43] also investigated the electricity prices in Germany from the perspective of the EU Emission Trading Scheme and renewable energy support schemes. Moreno et al. [44] developed an econometric panel model based on a dataset covering EU-27 countries from 1998 to 2009 to explore the relationship between household electricity prices and renewable energy generation in total gross electricity production, among other variables. They found that household electricity prices increase with the deployment of renewable energy generation as it is mainly driven by public renewable support schemes (feed-in-tariffs, quota obligations, investment grants, etc.), usually paid by the end customer. Sorokin et al. [45] also explored the relationship between crude oil prices and renewable energy production, among other variables. Their various statistical approaches concluded that when crude oil production continues to be constant, evidence supports the estimation that an upsurge in energy generation from renewable sources leads to a rise in oil prices. Halkos et al. [46] focused on the key drivers of household electricity prices instead of wholesale electricity prices in 26 EU countries for a time horizon of 2003–2019. Based on their panel econometric method, the overall effect of renewable energy share is found to be negative and significant; precisely, a relationship of quadratic form between the two variables was observed.

Our empirical study makes a significant contribution to this literature. Our framework enables us to offer compelling evidence regarding the changes in the relationship between the determinants of WHEP in the light of transforming market conditions. Hence, our study brings a new perspective and deepens our insights into the interconnectedness of the energy and environmental commodities and RES in the electricity market with its methodological toolkit during different economic and geopolitical circumstances.

## 3. Data and Methods

### *3.1. Data Description*

Following the overview of the key factors influencing WHEP, Table 1 summarizes the selected variables, their units, the data sources, and the expected relationship between the independent and dependent variables.

WHEP figures, as the response variable, are obtained from the EMBER database, which gathers, curates, and analyzes data on the power sector. Based on their description, WHEP denotes wholesale day-ahead electricity prices for European countries, sourced from the European Network of Transmission System Operators for Electricity (ENTSO-E) database. These are the daily prices paid to electricity generators, which we have converted to monthly averages.

The net electricity generation (NEG) and RES are monthly electricity data collected from the International Energy Agency (IEA) database. The other variables are commodity (TTF, BRENT, and NEWC) and EU ETS (EUA) futures prices, gathered from Investing.com and the Refinitiv Eikon database daily and converted into monthly averages manually. These commodity prices were selected as major EU benchmark coal, natural gas, and oil prices.

**Table 1.** Details of variables used in the research and their expected relationships. Source: compiled by the authors.

| Variables | Description | Unit | Source | Expected Relationship * |
|---|---|---|---|---|
| WHEP | Wholesale electricity price | EUR/MWh | EMBER [29] | |
| NEG | Net electricity generation | TWh | IEA [47] | +1 |
| RES | Renewable energy shares of gross electricity generation | % | IEA [47] | −3 |
| TTF | ICE Natural Gas EU Dutch TTF price | EUR/MWh | Invensting.com [30] | +3 |
| BRENT | ICE Brent Crude Oil price | USD/bbl | Refinitiv Eikon [31] | +1 |
| NEWC | ICE Newcastle Coal price | USD/t | Invensting.com [30] | +2 |
| EUA | EU ETS carbon price | EUR/t | Invensting.com [30] | +2 |

* Positive and negative signs refer to the direction, while the values on a scale of 1–3 refer to weak (1), moderate (2), and strong (3) relationship expectations.

As per the data availability across the EU members, electricity data are limited for bidding zones that have not introduced a power exchange, which is the case for Malta and Cyprus. Therefore, no WHEP from these island countries was available to incorporate into our dataset. As a result, the monthly average WHEP was calculated across 25 EU members. In line with this, the electricity production datasets (RES and NEG) do not contain Malta- and Cyprus-specific figures.

Based on the wholesale electricity market and the reviewed main factors influencing WHEP detailed in the previous chapter, we expect that the relationship between the dependent variable and each explanatory variable will be positive, except for the RES, due to the merit order mechanism. Increased production from renewable energy sources should push the theoretical curve to the right on average in Figure 2; however, the sudden disappearance of significant renewables capacity from the merit order caused by, e.g., weather changes would cause the opposite effect to the prices as the dropout has to be balanced out with activating alternative power plants. Nevertheless, on a long-term basis, RES shall decrease WHEP on average. All the other variables should have a positive relationship with the response variable. As per their strength, we assume that RES and TTF should have the strongest, while EUA and NEWC should have moderate relationship strength with the dependent variable. Furthermore, neither NEG nor BRENT should significantly impact WHEP as the former does not show any definite tendency on a year-on-year basis. At the same time, we understood that the commodity behind the BRENT, in general terms, was only responsible for approximately 2.3% on average of the gross electricity output during 2007–2022.

All of these (monthly) data were collected and calculated for the period January 2015 to December 2020, totaling 72 observations for the pre-crisis period, while for the co-crisis period (time of distress), the dataset contains 104 observations for the time horizon of January 2015 to August 2023. We note that the co-crisis period in our analysis lasted until August 2023 because that was the latest month for which reliable and comprehensive data were available.

To interpret the regression coefficients as elasticities, we applied the natural logarithm transformation to the datasets and used the transformed variables in our calculations. Using the logarithm base 10, a one-unit increase on the logarithmic scale is equivalent to multiplying the original value by ten on the linear scale. Applying the mathematical transformation of the natural logarithm to time series data is a common technique used in time series analysis, not only to interpret with elasticities but also for stabilizing the variance of a series, reducing skewness, and linearizing the relationship, therefore enhancing the overall accuracy of the model [48–53]. However, it is important to note that logarithmic transformation does not guarantee stationarity, which will therefore be tested separately.

### 3.2. Methodological Framework

Before carrying out our analysis, it is therefore necessary to perform a stationarity check. For this purpose, we employ stationarity and unit root tests, namely Augmented Dickey–Fuller (ADF) tests, Phillips–Perron (PP) tests, or Kwiatkowski–Phillips–Schmidt–Shin (KPSS). The presence of a unit root suggests that the time series may exhibit properties like a random walk or trend. Each variable is tested on the level and first difference to determine whether the null hypothesis of stationarity can be rejected. Once we conclude that all variables are stationary after first differencing by necessity, we may proceed with the empirical analysis.

First, various correlation analyses will be conducted, as they can provide a quick and straightforward way to assess the linear relationship between pairs of variables. This relationship can be examined in different ways, such as by conducting bivariate, partial, or multivariate correlation [48,49,51]. Bivariate correlation is a valuable analysis in measuring the strength and the direction of the linear relationship between the independent and a given dependent variable, but without taking away the effect of the other dependent variables on that particular relationship. Partial correlation analysis shall be used for this assessment, as it measures the degree of association between two variables while controlling for the effect of one or more other variables. In terms of multiple correlation coefficients, correlation involves analyzing the relationships among more than two variables simultaneously in a multiple regression context. Consequently, this will be discussed via the regression model.

Correlation analysis serves as a pre-modeling diagnostic tool. By identifying variables that are strongly correlated with the dependent variable, one can make more informed decisions about which variables to include in the regression model. In other words, this method could confirm the theory behind selecting the potential regressors for the model.

After the proper selection of variables, the next step is to build statistically significant regression models. Regression analysis investigates the relationship between a specific variable of interest (the dependent variable) and one or more explanatory (independent) variables, assuming a linear link between them. These independent variables are exogenous, explanatory, non-random, and measurable and are used to explain the variability in the dependent variable. When there is more than one independent variable, it is called a multiple regression model [48–50,53–55].

There are several types of regression models, each suited to different kinds of data. In this paper, we are using linear regression. The model assumes a linear connection but has an error factor for randomness, as the observations would not lie on a straight line but are scattered around it. Accordingly, each of these observations consists of the systematic or explained part of the model and the random error. However, conducting multiple linear regression on time series data can be challenging due to the unique characteristics of the data. In our model, all variables are measured as a time series; hence, the general regression model equation is modified to highlight the continuous measurement of values over a period of time, as per below:

$$\hat{y}_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \cdots + \beta_n x_{nt} + \varepsilon_t \quad (1)$$

where $\hat{y}_t$ is the variable to be predicted, $x_{nt}$ presents the independent variables at time $t$, $\beta_0$ is the $y$-intercept (constant), $\beta_n$ represents the regression parameters of the model, and $\varepsilon_t$ is the random error term at time $t$.

Standard linear regression has several assumptions that need to be verified during model evaluation, such as linearity, multicollinearity, independence, homoscedasticity, and normality, which could be validated in a graphical (e.g., scatterplots and histogram) or analytical (e.g., calculating Durbin–Watson statistic and variance inflation factors) way. Furthermore, the chosen sample must be representative of the population. Yet, as we have time series data, we shall have many observations of the same variables over time instead of a random sample from the population. Harrel [54] indicated that as a general rule of thumb, 10–20 observations per independent variable should be used in the analysis, while according to Hair et al. [56], at least five observations for each independent variable incorporated in the model should be collected.

As our regression model implies that the prediction would not be perfectly correct due to the existence of random errors, the aim should be to find the line that fits the data "best"; thus, the random errors are minimalized. Based on the assumptions mentioned, the most popular method for finding the "best fitting line" and estimating the parameters is the ordinary least squares (OLS) method, which minimizes the sum of the squared random errors between the observed and predicted values. Nevertheless, in a time series regression, the independence condition might fail as the random errors in the model are often positively correlated over time, meaning that each error is much more likely to resemble the previous error rather than being independent of each other. This phenomenon is known as autocorrelation (or serial correlation). If autocorrelation occurs, an autoregression (AR) model and the Cochrane–Orcutt (CO) procedure can address this issue (among other transformation methods) in different contexts. The CO procedure is a correction method applied to linear regression models that are not initially designed to handle autocorrelated residuals. It is crucial that after performing the CO adjustment, the coefficient of the intercept needs to be modified. The correct estimate of the intercept for the original model is calculated as follows:

$$\beta_0 = \hat{\beta}_0 / (1 - \hat{\rho}) \tag{2}$$

where $\hat{\beta}_0$ is the intercept obtained from the adjusted regression, and $\hat{\rho}$ presents the estimated lag 1 autocorrelation in the residuals from the regression.

None of the other parameters (slopes) need to be recalculated, i.e., those are taken directly from the regression with the adjusted variable. However, it is crucial to incorporate the modeled error structure into the equation when calculating predictions for regression with autoregressive errors.

All things considered, an ordinary regression analysis involves model formulation, estimation, evaluation, and usage. However, evaluation should be carried out before, during, and after the regression analysis to verify the assumptions and the model results.

## 4. Results

The IBM SPSS version 27 program with its R extension was used for data analysis. Before conducting correlation and regression analysis, various stationarity tests were first performed on the natural logarithm of the original dataset to verify the stationarity assumption of the time series data. We prefer natural logs as the coefficients on the natural-log scale are directly interpretable as approximate proportional differences. However, we have also performed such tests on the original dataset. Furthermore, the tests were only conducted based on the pre-crisis dataset (January 2015–December 2020) as we assume that the result from the co-crisis period—which only extends the pre-crisis period with approximately two and a half years—would not result in significantly different conclusions.

Appendix A (Table A1) shows the results of the ADF, PP, and KPSS tests performed at Level I (0) and First Difference I (1), including the *p*-values from the test results. In the case of ADF and PP tests, if *p*-values are below our chosen significance level of 5%, we can reject the null hypothesis and define the series as stationary. As per the KPSS test, if we fail to reject the null hypothesis then the test may provide evidence that the series is stationary.

In line with our expectation, all the natural logarithms of energy and environmental commodity prices are non-stationary at Level I (0). Hence, further transformation will definitely be needed in these cases. However, NEG and RES variables already presented stationary results. To stabilize the statistical properties, differencing is required. As the logarithmic transformation has already been carried out, we have performed the differencing, which involves subtracting the previous observation from the current observation in a given series. For the sake of unified interpretation, we have performed the transformation for all cases, which gave the same result except in two cases. Regarding NEWC and EUA, there is a contradiction between the results as per ADF; the series is still not stationary, but both the

PP and KPSS tests show stationarity. Afriyie et al. [57] highlight that the performance of the ADF test is weaker on observation sizes less than 100 in contrast to the PP test. As a result, we conclude that all the series are stationary when first-order integrated.

### *4.1. Analyzing the Pre-Crisis Period (January 2015–December 2020)*

Via the pre-crisis period analysis, WHEP (dependent variable) is modeled with the selected independent variables in the timeframe of January 2015 to December 2020. Figure 4 visualizes the historical monthly average WHEP and the band between which the daily average values ranged, as well as the monthly average RES ratio, while Appendix A (Table A2) contains additional descriptive statistics for the variables.

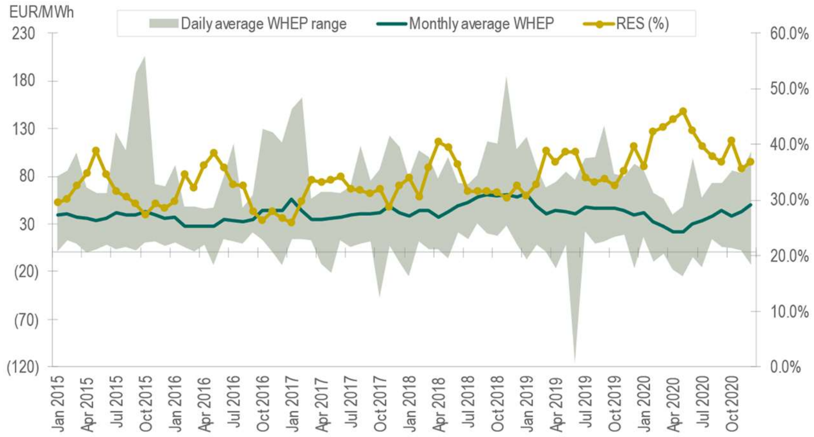



**Figure 4.** Monthly average wholesale electricity prices and RES (%) trends in EU-25 (January 2015–December 2020). Source: created by the authors based on EMBER [29] and IEA [47] databases.

The monthly average WHEP during this period ranged between 21.55 EUR/MWh and 61.44 EUR/MWh, with a mean of 40.97 EUR/MWh and a standard deviation of 8.73 EUR/MWh. Also, looking at RES, the monthly averages across the EU-25 were moving between 25.9% and 46.0%, with an average of 34.0% during the examined period, which aligns with the annual averages discussed in Figure 3a. To understand the dispersion of the datasets, the coefficient of variations (CV) is a normalized measure that expresses variability relative to the mean. Based on the results, EUA had the highest ratio (62.7%), but this is because EUA prices significantly increased after the beginning of the new phase (i.e., after the decrease in available quotas) discussed previously (the monthly average carbon price was 6.42 EUR/t during 2015–2017, while 22.99 EUR/t in 2018–2020).

To statistically assess the relationship between the variables, we first conducted a Pearson correlation coefficient test (Table 2). The zero-order correlation test and all of the following analyses were based on the log-differenced series dataset started in February 2015 due to the data loss caused by the differentiation process.

**Table 2.** Pearson correlation coefficients (February 2015–December 2020). Source: created by the authors with the use of IBM SPSS Statistics 27 software.

| | DIFF_LN _WHEP | DIFF_LN _NEG | DIFF_LN _RES | DIFF_LN _TTF | DIFF_LN _BRENT | DIFF_LN _NEWC | DIFF_LN _EUA |
|---|---|---|---|---|---|---|---|
| DIFF_LN_WHEP | 1 | | | | | | |
| DIFF_LN_NEG | 0.351 *** | 1 | | | | | |
| DIFF_LN_RES | −0.724 *** | −0.261 ** | 1 | | | | |
| DIFF_LN_TTF | 0.493 *** | 0.189 | −0.254 ** | 1 | | | |
| DIFF_LN_BRENT | 0.316 *** | 0.003 | −0.038 | 0.250 ** | 1 | | |
| DIFF_LN_NEWC | 0.247 ** | 0.209 * | −0.121 | 0.342 *** | 0.151 | 1 | |
| DIFF_LN_EUA | 0.410 *** | −0.030 | −0.069 | 0.182 | 0.359 *** | 0.181 | 1 |

Note: correlation is significant at the 0.01 level (***), at the 0.05 level (**), and at the 0.1 level (*) (2-tailed).

As per the result, all the potential variables for the regression model are statistically significant, at least on a 5% level with WHEP. Furthermore, only the RES presents a negative correlation with the dependent variable, which is in line with our expectation that as RES increases, WHEP shall decline. Regarding the strength of the relationship, only RES is in the top third (0.724), while BRENT and NEWC show the weakest links (0.316 and 0.247, respectively). Overall, no other independent variable correlates strongly with WHEP or with each other than RES has with WHEP. We note that other independent variables show significant correlations with each other on different significant levels in certain cases, which might offer some insights into multicollinearity, but this will be assessed more precisely via the regression model's variance inflation factor (VIF) values.

Bivariate correlation does not adjust for the influence of other variables on the examined pair of variables, which could lead to misleading conclusions (spurious correlations). However, partial correlations are controlling for the effect of one or more additional variables. Table 3 contains the result from the partial correlations analyses, where WHEP was always one of the paired variables.

**Table 3.** Partial correlation coefficients (February 2015–December 2020). Source: created by the authors with the use of IBM SPSS Statistics 27 software.

| Dependent Variable: DIFF_LN_WHEP | | | | | |
|---|---|---|---|---|---|
| DIFF_LN_NEG | Correlation<br>Sign. (2-tailed) | 0.297<br>0.015 | DIFF_LN_BRENT | Correlation<br>Sign. (2-tailed) | 0.243<br>0.049 |
| DIFF_LN_RES | Correlation<br>Sign. (2-tailed) | −0.756<br>0.000 | DIFF_LN_NEWC | Correlation<br>Sign. (2-tailed) | −0.016<br>0.897 |
| DIFF_LN_TTF | Correlation<br>Sign. (2-tailed) | 0.382<br>0.002 | DIFF_LN_EUA | Correlation<br>Sign. (2-tailed) | 0.471<br>0.000 |

Partial correlation coefficients show slightly different results from the bivariate correlation. RES remains the most highly correlated element (0.756), while the correlation between WHEP and NEWC turned out to be insignificant in this assessment (as $p > \alpha$), meaning that NEWC shows near nil linear relationship with WHEP after accounting for all the other controlled variables. Furthermore, BRENT was also on the edge of not rejecting the null hypothesis on a 5% significance level and showing a weak correlation with WHEP (0.243), just like NEG (0.297).

Determining partial correlation coefficients is crucial for building a multiple regression model as it supports isolating the unique contribution of each potential predictor variable while controlling for the influence of other variables, which aids in creating a more reliable and effective regression model. Hence, multiple linear regression coefficients and partial correlation coefficients are directly linked and have the same significance ($p$-value) if all the potential variables in the initial regression model are included. However, if we select the significant variables as input for the model then due to the excluded variables, the partial correlation coefficients will be recalculated again in the changed circumstances. The following independent variables were selected for the regression analysis based on the partial correlation assessments: NEG, RES, TTF, BRENT, and EUA.

After building the initial regression model with these regressors, we tested the general time series regression model assumptions. Out of those assumptions, the stationarity of the variables is given as we were using transformed variables for the model, verified by the stationarity tests. Next, the independence assumption that the residuals do not show autocorrelation has to be verified. For this purpose, the Durbin–Watson (DW) statistic is calculated, which ranges from 0 to 4; a value around 2 suggests no autocorrelation, while values considerably greater or lower than 2 indicate positive or negative autocorrelation, accordingly. Based on our pre-crisis regression model, the DW statistic shows a 2.377, meaning there is some sort of autocorrelation in the residuals. We might accept it, but it can be adjusted further via statistical techniques like the CO method, which estimates the first-order autocorrelation coefficient (Rho) of the residuals. As it is an iterative method, it refines the estimation of the Rho several times until the process converges to a stable solution. This is similar to the ρ in an AR(1) model, which measures the relationship between consecutive observations. Then, this coefficient is used to adjust the regression model. The output of the adjusted regression model is summarized in Table 4.

**Table 4.** Summary of the CO estimated regression model output (February 2015–December 2020). Source: created by the authors with the use of IBM SPSS Statistics 27 software.

| **Iterations** | **Rho (AR1) Value** | | **Rho (AR1) Std. Error** | | **DW Stat** | | **Mean sqr. Errors** | |
|---|---|---|---|---|---|---|---|---|
| 0 | −0.194 | | 0.123 | | 2.135 | | 0.004 | |
| 3 | −0.221 | | 0.122 | | 2.101 | | 0.004 | |
| | | | | | 90.0% Conf. Interval for B | | 95.0% Conf. Interval for B | |
| | Coefficient | Std. Error | t-stat | $p$-value | Lower Bound | Upper Bound | Lower Bound | Upper Bound |
| Intercept (constant) | −0.001 | 0.006 | −0.088 | 0.930 | | | | |
| DIFF_LN_NEG | 0.267 | 0.125 | 2.138 | 0.036 | 0.059 | 0.476 | 0.018 | 0.517 |
| DIFF_LN_RES | −0.956 | 0.101 | −9.478 | 0.000 | −1.124 | −0.787 | −1.157 | −0.754 |
| DIFF_LN_TTF | 0.195 | 0.058 | 3.355 | 0.001 | 0.098 | 0.292 | 0.079 | 0.312 |
| DIFF_LN_BRENT | 0.180 | 0.071 | 2.543 | 0.013 | 0.062 | 0.298 | 0.039 | 0.321 |
| DIFF_LN_EUA | 0.343 | 0.079 | 4.328 | 0.000 | 0.211 | 0.475 | 0.185 | 0.501 |
| R | | 0.889 | F-stat | | 48.000 | | | |
| R square | | 0.790 | $p$-value (F-stat) | | 0.000 | | | |
| Adjusted R square | | 0.770 | Durbin–Watson stat | | 2.101 | | | |
| Std. error of estimate | | 0.064 | N | | 71 | | | |

Dependent variable: log-differentiated wholesale electricity price.

The adjusted regression model shows improvement in the global F test and overall goodness-of-fit, and the DW stat decreased from the original 2.377 value to 2.101 in the adjusted model.

Further assumptions of the variables were linearity and no multicollinearity among them. The former can be assessed via the goodness-of-fit statistics (R, $R^2$) and visually via, e.g., partial regression plots. Neither of these scatterplots shows non-linearity. As per multicollinearity, VIF provides information about the presence and severity of multicollinearity, which occurs when independent variables in the regression model are highly correlated. A VIF value of 1 indicates no correlation between a given independent variable and any other independent variables in the model, while values between 1 and 5 suggest moderate correlation in general, but they are often not a cause for concern. As the VIF values from our model are around 1, we can conclude that no significant multicollinearity shall occur between the variables in the model.

The remaining assumptions are about the residual's behavior, namely normality and homoscedasticity. These properties can be tested primarily in a graphical way. The normal P-P (probability–probability) plot of the regression standardized residual can serve as an assessment of normality for the regression model's residuals, as it compares the cumulative distribution of a set of data to the cumulative distribution of a theoretical normal distribution. The P-P plot closely followed a straight diagonal line, indicating that the data are normally distributed. Then, a scatterplot is a crucial diagnostic tool to assess homoscedasticity, which means that the residuals have constant variance across the range of predicted values. As per the scatterplot based on our model, the residuals do not fan out or form a funnel shape as they move along the axis of expected values. Therefore, there is no sign of heteroscedasticity.

The multiple correlation coefficient (R) measures the strength—the maximum degree of the linear relationship—of the relationship between the single dependent and the set of independent variables, and it can be viewed as the correlation between the observed and the predicted values of the dependent variable. The 0.889 indicates a strong linear relationship. Furthermore, the 79.0% coefficient of multiple determination ($R^2$), which expresses the proportion of the variance of the outcome variable explained by the regressors together, also seems relatively high. The larger the percentage, the better the fit of the model. However, when comparing different models, which is our aim, the adjusted $R^2$ indicator could serve as a better basis as it adjusts for the different numbers or regressors in the models, if any. Furthermore, the standard error of the model (0.064) shows the average error made when using the values estimated by the model instead of the original values.

The analysis of variance (ANOVA) for the regression model provides a way to test the overall significance of the model. The F-test produces an F-statistics and a *p*-value, where the null hypothesis is that all regression coefficients are equal to zero (meaning that the predictors do not explain variability in the dependent variable) against the alternative hypothesis that at least one coefficient is different from zero. A small *p*-value ($p \leq 0.05$) indicates that the model provides a better fit to the data than a model with no predictors; thus, the model as a whole is statistically significant, which is the case for our model ($p = 0.000$). However, it does not yield which specific regressors are significant. For that, the partial regressions coefficients serve as an explanation. In line with our selection of the independent variables, all the included predictors are statistically significant on a 5% significance level.

The coefficients, presented in Table 4, can also be substituted into Equation (1). With the $-0.001$ $\hat{\beta}_0$ and the $-0.221$ $\hat{\rho}$, the correct estimate for the $\beta_0$ shall be $-0.0005$. None of the other parameters (slopes) need to be recalculated, i.e., those are taken directly from the regression with the adjusted variable. Hence, the substituted regression equation is as follows:

$$\begin{aligned} \Delta lnWHEP_t = -0.0005 + 0.267\Delta lnNEG_t - 0.956\Delta lnRES_t + 0.195\Delta lnTTF_t \\ +0.180\Delta lnBRENT_t + 0.343\Delta lnEUA_t - 0.221\varepsilon_{t-1} + \omega_t \end{aligned} \tag{3}$$

Equation (3) is ready to be interpreted with careful consideration due to the log-differenced nature of the variables. As such, the inverse operation of taking a logarithm is required, which is the use of exponential function *e*.

A 1% increase in RES from one period to the next is ceteris paribus associated with an average of 0.95% decrease in WHEP for the same period. In simpler terms, this relationship suggests that an increase in the gross generation of electricity from renewable sources between two consecutive periods tends to lower wholesale electricity prices in the same period, where a percentage increase in RES is associated with a percentage decrease in approximately the same magnitude in WHEP. As per the confidence intervals, the model estimates with a 95% confidence level that the true coefficient is likely to fall between $-1.124$ and $-0.79$. In other words, a 1% increase in RES from one period to the next with a 95% confidence level is associated with an average of at least 1.11% and, at most, a 0.78% decrease in WHEP for the same period, ceteris paribus. This interval becomes wider if the confidence level decreases to 90% ($-1.157$ and $-0.754$, respectively).

Meanwhile, all the other predictors show a positive contribution to the change in WHEP, e.g., the coefficient of 0.195 for TTF means that a 1% increase in TTF from one period to the next is associated with an average increase of approximately 0.19% in WHEP, holding other factors constant in the same period.

Overall, based on the adjusted model, the coefficient of RES indicates that changes in RES from one period to the next contribute the most to the changes in WHEP in the same period, while the other regressors suggest a mostly weak contribution in this context.

### *4.2. Assessing the Co-Crisis Period (January 2015–August 2023)*

Similarly to the pre-crisis period analysis, WHEP is analyzed with the selected independent variables during January 2015–August 2023 for the co-crisis period. Figure 5 extends Figure 4 timespan with the additional 32 months of observations, while Appendix A (Table A3) contains further statistics.

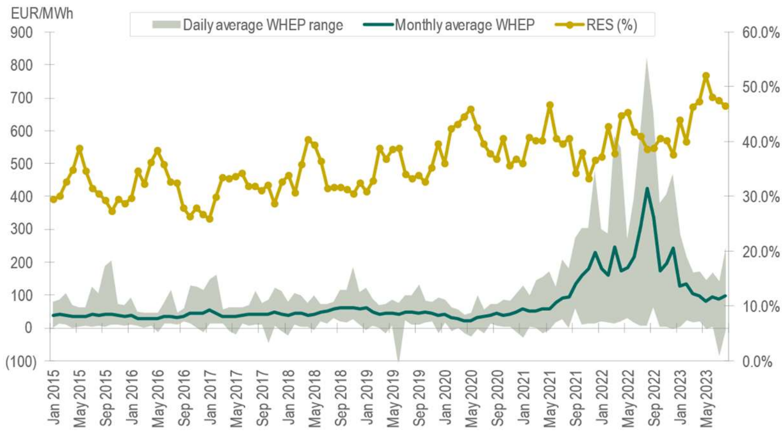



**Figure 5.** Monthly average wholesale electricity prices and RES (%) trends in EU-25 (January 2015–August 2023). Source: created by the authors based on EMBER [29] and IEA [47] databases.

Based on the daily average price ranges, the increasing volatility ramp-up from the beginning of 2021 and at least four spikes of all-time high daily average WHEP emerged during the time of distress period. The highest monthly average WHEP was spotted in August 2022 (425.20 EUR/MWh) in the EU-25. In that month, the average daily price maximum of 823.29 EUR/MWh was experienced on 17 August 2022 in Lithuania and Latvia, while Estonia also accounted for 681.36 EUR/MWh as a result of a combination of different factors [58,59].

In the meantime, the mean of WHEP almost doubled, and monthly average figures spread in a ten times wider range than its pre-crisis values. Furthermore, the coefficient of variation also significantly increased from a pre-crisis value of 0.21 to a co-crisis value of 0.95, meaning WHEP shows more significant fluctuations around the mean value over the co-crisis period. At the same time, the greater relative volatility conclusion is also valid for other energy and environmental commodity prices. Time of distress impact can also be confirmed by looking at the kurtosis for the dataset; those indicate that the distributions of WHEP, TTF, BRENT, and NEWC have heavier tails as there are more extreme values than would be expected in a normal distribution.

Figure 5 clearly shows a break in the previous trends regarding the WHEP development, but this is true for the other energy commodity prices presented in Figure 3b earlier. Meanwhile, monthly RES reached higher maximum percentages compared to the pre-crisis period, exceeding the 50% monthly average in May 2023. A slightly higher mean (36.29% compared to the pre-crisis share of 34.01%) indicates that either there are fewer smaller percentages than the pre-crisis average during the extended period or higher proportions were reached in January 2021–August 2023. Based on the comparison of statistics, RES reached higher maximum average values in the co-crisis period.

Moving to the statistical assessment of the relationship between the variables, Table 5 contains the Pearson correlation coefficients for the co-crisis period. Based on the analysis, all the selected variables are significant, with WHEP on a 5% significance level except BRENT. Furthermore, TTF had the strongest positive correlation with WHEP (0.739), while the second in line was RES with its negative correlation of 0.650.

Pearson correlation coefficients might indicate that BRENT would not be included in the co-crisis regression model. This decision is based on the result of the partial correlation coefficient analyses (Table 6). According to the calculations, only RES, TTF, and EUA appear significant. Among them, TTF has the highest correlation value (0.704) then RES (−0.662) and EUA with its 0.374 value. Hence, all three variables show a moderate to strong correlation with WHEP for the co-crisis period, and these variables are appropriate for building the second regression model.

**Table 5.** Pearson correlation coefficients (February 2015–August 2023). Source: created by the authors with the use of IBM SPSS Statistics 27 software.

| | **DIFF_LN _WHEP** | **DIFF_LN _NEG** | **DIFF_LN _RES** | **DIFF_LN _TTF** | **DIFF_LN _BRENT** | **DIFF_LN _NEWC** | **DIFF_LN _EUA** |
|---|---|---|---|---|---|---|---|
| DIFF_LN_WHEP | 1 | | | | | | |
| DIFF_LN_NEG | 0.251 ** | 1 | | | | | |
| DIFF_LN_RES | −0.650 *** | −0.236 ** | 1 | | | | |
| DIFF_LN_TTF | 0.739 *** | 0.165 * | −0.322 *** | 1 | | | |
| DIFF_LN_BRENT | 0.172 * | −0.020 | −0.044 | 0.167 * | 1 | | |
| DIFF_LN_NEWC | 0.286 *** | 0.160 | −0.061 | 0.432 *** | 0.242 ** | 1 | |
| DIFF_LN_EUA | 0.272 *** | −0.064 * | −0.024 | 0.117 | 0.258 *** | −0.016 | 1 |

Note: correlation is significant at the 0.01 level (***), at the 0.05 level (**), and at the 0.1 level (*) (2-tailed).

**Table 6.** Partial correlation coefficients (February 2015–August 2023). Source: created by the authors with the use of IBM SPSS Statistics 27 software.

| **Dependent Variable: DIFF_LN_WHEP** | | | | | |
|---|---|---|---|---|---|
| DIFF_LN_NEG | Correlation<br>Sign. (2-tailed) | 0.129<br>0.206 | DIFF_LN_BRENT | Correlation<br>Sign. (2-tailed) | 0.015<br>0.883 |
| DIFF_LN_RES | Correlation<br>Sign. (2-tailed) | −0.662<br>0.000 | DIFF_LN_NEWC | Correlation<br>Sign. (2-tailed) | 0.019<br>0.851 |
| DIFF_LN_TTF | Correlation<br>Sign. (2-tailed) | 0.704<br>0.000 | DIFF_LN_EUA | Correlation<br>Sign. (2-tailed) | 0.374<br>0.000 |

For the co-crisis regression analysis, the following independent variables were selected based on the partial correlation assessments: RES, TTF, and EUA. Assessing again first the base assumptions of this multiple linear time series regression model, we have reached the conclusion that all necessary assumptions are verified in this model as well. Regarding the independence criterium, the DW stat is 2.158, which means that negative autocorrelation is barely examined, not indicating a major concern with autocorrelation in this model. However, we have also performed the CO estimation on this regression model to further increase the accuracy and reliability of the model and be comparable with the pre-crisis model. The output of the adjusted regression model is summarized in Table 7.

**Table 7.** Summary of the CO estimated regression model output (February 2015–August 2023). Source: created by the authors with the use of IBM SPSS Statistics 27 software.

| **Iterations** | **Rho (AR1) Value** | **Rho (AR1) Std. Error** | **DW Stat** | **Mean sqr. Errors** |
|---|---|---|---|---|
| 0 | −0.080 | 0.101 | 2.044 | 0.007 |
| 2 | −0.086 | 0.101 | 2.034 | 0.007 |

| | | | | | 90.0% Conf. Interval for B | | 95.0% Conf. Interval for B | |
|---|---|---|---|---|---|---|---|---|
| | Coefficient | Std. Error | t-stat | $p$-value | Lower Bound | Upper Bound | Lower Bound | Upper Bound |
| Intercept (constant) | 0.001 | 0.008 | 0.172 | 0.864 | | | | |
| DIFF_LN_RES | −0.973 | 0.109 | −8.960 | 0.000 | −1.153 | −0.792 | −1.188 | −0.757 |
| DIFF_LN_TTF | 0.549 | 0.049 | 11.132 | 0.000 | 0.467 | 0.631 | 0.451 | 0.647 |
| DIFF_LN_EUA | 0.364 | 0.090 | 4.065 | 0.000 | 0.215 | 0.513 | 0.186 | 0.542 |
| R | | 0.882 | F-stat | | 113.236 | | | |
| R square | | 0.778 | $p$-value (F-stat) | | 0.000 | | | |
| Adjusted R square | | 0.769 | Durbin–Watson stat | | 2.034 | | | |
| Std. error of estimate | | 0.086 | N | | 103 | | | |

Dependent variable: log-differentiated wholesale electricity price.

In this case, the goodness-of-fit tests (R, (adjusted) $R^2$), the ANOVA test (F-test), and the $p$-values of the partial correlation coefficients all indicate that the model is valid and sufficiently reliable. The model explains a large portion (77.8%) of the variance in the dependent variable.

Substituting the regression coefficients from the adjusted model—with the recalculation of the intercept for the original model—would result in the following equation:

$$\Delta lnWHEP_t = 0.001 - 0.973\Delta lnRES_t + 0.549\Delta lnTTF_t + 0.364\Delta lnEUA_t - 0.086\varepsilon_{t-1} + \omega_t \tag{4}$$

According to the final, adjusted, and substituted co-crisis regression model, the RES variable again has the strongest magnitude as it adds the most to the explanation of the changes in the dependent variable between two consecutive periods. To be precise, the co-crisis model estimates that a 1% increase in RES from one period to the next is ceteris paribus associated with an average of 0.96% decrease in WHEP for the same period. As per the confidence intervals, the model estimates with a 95% confidence level that the true coefficient is likely to fall between −1.153 and −0.792. In other words, a 1% increase in RES from one period to the next with a 95% confidence level is associated with an average of at least 1.14% and, at most, a 0.79% decrease in WHEP for the same period, ceteris paribus. This interval becomes wider when the confidence level is reduced to 90% (−1.188 and −0.757, respectively).

Furthermore, the coefficient for TTF and EUA means that a 1% increase in TTF and EUA from one period to the next is associated with an average increase of approximately 0.55% (TTF) and 0.36% (EUA) in WHEP, holding other factors constant in the same period.

Similarly to the pre-crisis period model, the coefficient of RES indicates that changes in RES from one period to the next contribute the most to the changes in WHEP in the same period, ceteris paribus, based on the adjusted model.

## 5. Discussion

Based on the reviewed primary mechanism of the electricity market, this paper established a theoretical framework for selecting key variables for the empirical analysis of WHEP developments and relationships with its determinants during time horizons with and without time of distress. For the quantitative analysis, we have conducted various correlation and regression analyses as per the pre-crisis (January 2015–December 2020) and co-crisis (January 2015–August 2023) periods.

The bivariate correlation coefficients indicated that all the selected variables are significantly correlated on a 5% significance level with WHEP regardless of the underlying period, with the exception of BRENT for the co-crisis period. RES and TTF had the strongest correlations in both analyses, although their ranking is reversed based on the time horizon. Additionally, partial correlation analyses revealed the unique relationship between WHEP and a given independent variable while controlling for the other variables in the set. The changes in the partial correlation coefficients between the periods, individually seen in Tables 3 and 6, are illustrated in Figure 6.

As per Table 1, we preliminarily expected the direction and strength of each association with WHEP; for example, RES and natural gas prices would have the strongest correlation, even though they are in opposite directions. Starting with RES, our expectation was confirmed, but for TTF, the pre-crisis period only indicated a moderate level of relationship. As per NEG and BRENT, we assumed that the association would be positive and weak, which is verified. Lastly, NEWC and EUA were expected to have a positive and moderate relationship with WHEP, which was confirmed for EUA, but NEWC showed a weak and negative correlation in the pre-crisis period and a positive correlation in the co-crisis period.

When comparing the two periods, NEG, RES, BRENT, and EUA had lower partial correlation strengths based on the co-crisis dataset, while TTF considerably increased, and EUA almost retained its previous value under the same period. It is visible that the correlation magnitude of RES did not decline to a great extent when extending the examined period with the time of distress era. Still, TTF prices are associated more with

WHEP in the overall period due to the merit order mechanism. For further information, Appendix A (Table A4) contains side-by-side the partial correlation results.

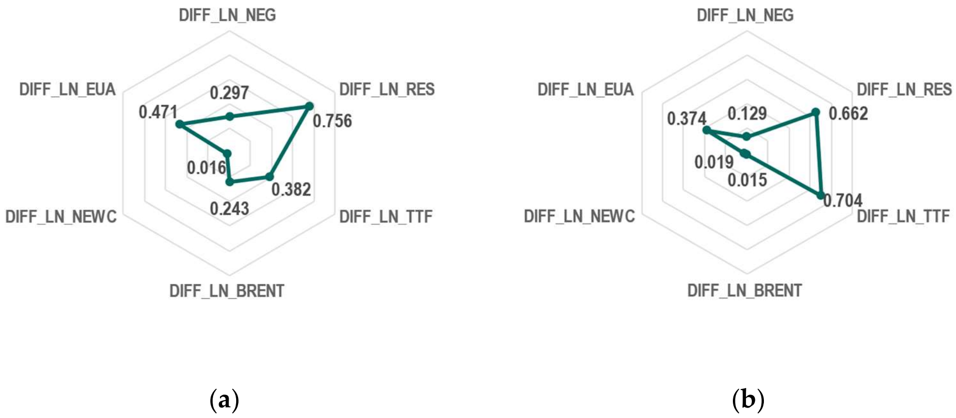



**Figure 6.** Comparison of partial correlation strengths in absolute values between (**a**) pre-crisis and (**b**) co-crisis periods. Dependent variable: log-differentiated wholesale electricity price. Source: created by the authors.

After the evaluation of the comparison of the partial correlations, the first two of our hypotheses can be assessed. In H1, it was stated that a strong and negative significant relationship exists between RES and WHEP in both periods. Based on our analysis, RES had a −0.756 partial regression coefficient within the pre-crisis series, while it was slightly lower, −0.662 within the co-crisis series, and significant in both cases. Consequently, the H2 hypothesis could be positively verified. Furthermore, in H2, we claimed that the relationship between natural gas prices and WHEP during the co-crisis period was stronger than during the pre-crisis period. As described previously, the strength of the correlation between TTF and WHEP nearly doubled, from 0.382 to 0.704, in favor of the co-crisis period. This could be supported by the theory that when RES cannot cover the total electricity demand, following the merit order mechanism, the last power plant in line to settle the demand is usually a gas-powered plant, which has a higher operating cost. As a result, the clearing price of electricity is also driven up. As the fuel for such power plants is mainly natural gas, extreme gas prices during times of distress would significantly increase WHEP. Therefore, the H2 hypothesis could also be positively verified.

Moving toward the regression analysis, selecting the final variable inputs for the regression models was also based on the evaluation of the partial correlations, as only significant correlations were included in the models. Hence, NEWC was not included in either of the regression models, while NEG and BRENT were also excluded from the co-crisis regression model. The substantial properties of each regression model, detailed in Tables 4 and 7, are summarized in Appendix A (Table A5).

Under both periods, the CO-adjusted multiple linear regression models are more accurate and reliable. Furthermore, all the base model assumptions were verified during the analysis, either graphically or analytically. The maximum VIF value across the regressors and the models is around 1, while the DW statistics, after performing the CO estimate, assume little to no autocorrelation in both cases. The adjusted $R^2$ is basically identical between the models, meaning that both models explain the variance in WHEP equally. However, the standard error estimate is slightly lower in the pre-crisis model, which indicates that the first model has a higher predictive accuracy.

Regarding the regression coefficients, only three variables were included in both models: RES, TTF, and EUA, out of which the RES coefficients indicate that changes in RES from one period to the next contribute the most to the changes in WHEP in the same period, ceteris paribus based on the adjusted model. Furthermore, the coefficient value is slightly increased in the co-crisis model, but this can be partly explained by the fewer regressors in the second model as well. Additionally, the entire confidence interval is negative, strengthening the conclusion that the association between RES and WHEP is negative.

In connection with the TTF development, the pre-crisis model estimates that a 1% increase in TTF from one period to the next is associated with an average increase of approximately 0.19% in WHEP, holding other factors constant in the same period. This contribution has increased to 0.55% in the co-crisis model, which means that adding the TTF-WHEP correlation under the time of distress period to the original model resulted in a greater contribution to changes in WHEP by the unit increase in TTF ceteris paribus, between two consecutive periods.

Therefore, the assessment for our third and last hypothesis, which was about the extent of WHEP changes in case RES and TTF increase by one unit ceteris paribus under each modeled period, indicates mixed results. According to the comparison in Appendix A (Table A5), WHEP tends to decrease more during the co-crisis period (−0.973) when RES increases by one unit ceteris paribus compared to the pre-crisis period (−0.956) and not less as estimated. Although, the other part of H3 is verified as WHEP is expected to increase more during the co-crisis period (0.549) when TTF increases by one unit ceteris paribus compared to the pre-crisis period (0.195). Consequently, H3 could only partially be verified.

## 6. Conclusions

The beginning of the second decade in the 21st century, encompassing pandemic and warfare, could be referred to as a time of distress. In such a period, the impact on energy markets can be profound. The recent crisis highlighted the fragility and interconnectedness of global energy systems and the vulnerabilities in the EU's energy regime, especially regarding dependency on natural gas imports. Price volatility has become a significant concern, as energy crisis events caused energy prices to surge and reach never-before-seen levels, especially for electricity prices, while the continuous integration of renewable energy sources into the EU's energy mix is reshaping the electricity market dynamics.

Our empirical study makes a significant contribution to the existing literature. It does not only broaden the currently limited availability of qualitative and quantitative assessments of the impact of extreme events on the development of WHEP but also considers the extent of contribution of various key factors over time horizons with entirely different characteristics, providing valuable novel insights into understanding the interconnectedness of electricity prices and the energy and environmental commodities and RES during changing economic and geopolitical circumstances. Our methodology toolkit and framework enable us to offer compelling evidence regarding the changes in the relationship between the determinants of WHEP in light of transforming market conditions.

Moreover, this article focuses primarily on the nexus between the share of renewable energy in gross electricity production and wholesale electricity price developments. From this perspective, our study brings a new perspective and deepens our insights into the interconnectedness of RES in the electricity market.

The first assessment provided a theoretical framework to find empirical evidence using statistical analysis of whether RES, NEG, TTF, BRENT, NEWC, or EUA has the strongest association with WHEP during different time horizons. The significance and novelty of our approach lie in the time horizon assessment by dividing the analyzed periods into "pre-crisis period" and "co-crisis period", the choice of utilizing the coverage of EU-25 data, and the establishment of a sensitivity analysis based on regression, which could quantify how sensitive the WHEP changes to the increase by one unit of each of the regressors ceteris paribus in either time period.

Our empirical results show that not all the variables contribute significantly to the change in WHEP depending on whether the time of distress period is considered. Nevertheless, in both cases, a 1% increase in RES from one period to the next is ceteris paribus associated with an average of approx. 0.96% decrease in WHEP for the same period. This highlights the influencing factor of RES in WHEP developments regardless of the transforming market conditions. However, extreme natural gas prices during times of distress significantly increase WHEP due to the merit order mechanism, from an average of 0.19% to 0.55%.

Our empirical study brings novelty to the existing literature. However, given the complexity and the importance of this subject, further research is suggested in the field of renewable energy share impact on WHEP, but with other major factors in focus as well. A wide range of statistical methods commonly used in time series analysis can vary based on the research aims. For instance, co-integration and causality testing for further investigation on the relationship between the key factors or utilizing an autoregressive model such as autoregressive integrated moving average (ARIMA) model for forecasting the level of a time series or autoregressive conditional heteroskedasticity (ARCH) and generalized autoregressive conditional heteroskedasticity (GARCH) models to predict the volatility of data over time, modeling the variance commodities are useful in understanding deeper the interconnectedness of wholesale electricity market.

In conclusion, the EU's energy transition, while essential for environmental sustainability, introduces complexities in market dynamics, especially concerning WHEP and the general stability of the energy market. The challenges posed by the energy trilemma, particularly during times of distress, require careful navigation. Policymakers must strive to create a resilient energy system that can withstand volatility while ensuring a smooth transition to renewable energy. Balancing the trilemma requires innovative policies, technological advancements, and a collaborative approach among all stakeholders. Although the road to a sustainable energy future might be complex and challenging, it is an essential path for the well-being of our planet and future generations.

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**Conflicts of Interest:** The authors declare no conflicts of interest.

## Appendix A

**Table A1.** Stationarity tests of the studied variables (January 2015–December 2020). Source: created by the authors with the use of SPSS software.

| Variable | Transformation | ADF Test | PP Test | KPSS Test | Conclusion |
|---|---|---|---|---|---|
| WHEP | Original | 0.22 | 0.26 | 0.02 | The series is non-stationary |
| | Natural logarithm | 0.27 | 0.23 | 0.03 | The series is non-stationary |
| | Log-differentiated | <0.01 | <0.01 | >0.10 | The series is stationary |
| NEG | Original | <0.01 | <0.01 | >0.10 | The series is stationary |
| | Natural logarithm | <0.01 | <0.01 | >0.10 | The series is stationary |
| | Log-differentiated | <0.01 | <0.01 | >0.10 | The series is stationary |
| RES | Original | <0.01 | 0.02 | >0.10 | The series is stationary |
| | Natural logarithm | <0.01 | <0.01 | >0.10 | The series is stationary |
| | Log-differentiated | <0.01 | <0.01 | >0.10 | The series is stationary |
| TTF | Original | 0.27 | 0.56 | 0.02 | The series is non-stationary |
| | Natural logarithm | 0.29 | 0.47 | 0.02 | The series is non-stationary |
| | Log-differentiated | <0.01 | <0.01 | >0.10 | The series is stationary |
| BRENT | Original | 0.61 | 0.59 | <0.01 | The series is non-stationary |
| | Natural logarithm | 0.57 | 0.50 | <0.01 | The series is non-stationary |
| | Log-differentiated | <0.01 | <0.01 | >0.10 | The series is stationary |

**Table A1.** *Cont.*

| Variable | Transformation | ADF Test | PP Test | KPSS Test | Conclusion |
|---|---|---|---|---|---|
| NEWC | Original | 0.71 | 0.84 | <0.01 | The series is non-stationary |
| | Natural logarithm | 0.61 | 0.83 | <0.01 | The series is non-stationary |
| | Log-differentiated | 0.42 | <0.01 | >0.10 | The series is trend stationary |
| EUA | Original | 0.63 | 0.80 | <0.01 | The series is non-stationary |
| | Natural logarithm | 0.59 | 0.85 | <0.01 | The series is non-stationary |
| | Log-differentiated | 0.29 | <0.01 | >0.10 | The series is trend stationary |

**Table A2.** Statistical characteristics of the original variables (January 2015–December 2020). Source: created by the authors with the use of SPSS software.

| | WHEP | NEG | RES | TTF | BRENT | NEWC | EUA |
|---|---|---|---|---|---|---|---|
| Mean | 40.97 | 230.08 | 0.34 | 16.32 | 55.41 | 76.37 | 14.70 |
| Minimum | 21.55 | 194.31 | 0.26 | 4.94 | 26.63 | 49.40 | 4.31 |
| Maximum | 61.44 | 273.26 | 0.46 | 27.95 | 80.63 | 117.78 | 31.39 |
| Range | 39.89 | 78.95 | 0.20 | 23.01 | 54.00 | 68.37 | 27.08 |
| Std. dev. | 8.73 | 19.18 | 0.04 | 4.93 | 12.13 | 20.42 | 9.22 |
| Coeff. var. | 0.21 | 0.08 | 0.13 | 0.30 | 0.22 | 0.27 | 0.63 |
| Skewness | 0.36 | 0.41 | 0.54 | −0.22 | −0.08 | 0.41 | 0.34 |
| Kurtosis | 0.39 | −0.70 | −0.09 | −0.04 | −0.43 | −1.10 | −1.65 |
| Observations | 72 | 72 | 72 | 72 | 72 | 72 | 72 |

**Table A3.** Statistical characteristics of the original variables (January 2015–August 2023). Source: created by the authors with the use of SPSS software.

| | WHEP | NEG | RES | TTF | BRENT | NEWC | EUA |
|---|---|---|---|---|---|---|---|
| Mean | 75.56 | 228.58 | 0.36 | 35.15 | 64.15 | 124.40 | 32.51 |
| Minimum | 21.55 | 194.31 | 0.26 | 4.94 | 26.63 | 49.40 | 4.31 |
| Maximum | 425.20 | 273.26 | 0.52 | 235.96 | 117.50 | 439.43 | 92.61 |
| Range | 403.65 | 78.95 | 0.26 | 231.02 | 90.87 | 390.02 | 88.29 |
| Std. dev. | 71.92 | 19.09 | 0.06 | 41.84 | 18.55 | 98.51 | 29.51 |
| Coeff. var. | 0.95 | 0.08 | 0.15 | 1.19 | 0.29 | 0.79 | 0.91 |
| Skewness | 2.51 | 0.47 | 0.41 | 2.66 | 0.60 | 1.96 | 0.91 |
| Kurtosis | 6.92 | −0.71 | −0.35 | 7.55 | 0.32 | 2.84 | −0.67 |
| Observations | 104 | 104 | 104 | 104 | 104 | 104 | 104 |

**Table A4.** Comparison of partial correlation coefficients between the examined periods. Source: compiled by the authors.

| | | February 2015–December 2020 | Δ * | February 2015–August 2023 | Expected Relationship ** |
|---|---|---|---|---|---|
| DIFF_LN_NEG | Correlation<br>Sign. (2-tailed) | 0.297<br>0.015 | ↓ | 0.129<br>0.206 | +1 |
| DIFF_LN_RES | Correlation<br>Sign. (2-tailed) | −0.756<br>0.000 | ↓ | −0.662<br>0.000 | −3 |
| DIFF_LN_TTF | Correlation<br>Sign. (2-tailed) | 0.382<br>0.002 | ↑ | 0.704<br>0.000 | +3 |
| DIFF_LN_BRENT | Correlation<br>Sign. (2-tailed) | 0.243<br>0.049 | ↓ | 0.015<br>0.883 | +1 |

**Table A4.** *Cont.*

| | | February 2015–December 2020 | Δ * | February 2015–August 2023 | Expected Relationship ** |
|---|---|---|---|---|---|
| DIFF_LN_NEWC | Correlation<br>Sign. (2-tailed) | −0.016<br>0.897 | ↑ | 0.019<br>0.851 | +2 |
| DIFF_LN_EUA | Correlation<br>Sign. (2-tailed) | 0.471<br>0.000 | ↓ | 0.374<br>0.000 | +2 |

Dependent variable: log-differentiated wholesale electricity price. * ↑ refers to increase, while ↓ refers to decrease. ** Positive and negative signs refer to the direction, while the values on a scale of 1–3 refer to weak (1), moderate (2), and strong (3) relationship expectations.

**Table A5.** Comparison of the result of the multiple linear regression analyses. Source: compiled by the authors.

| Coefficients | February 2015–December 2020 | | | | February 2015–August 2023 | | | |
|---|---|---|---|---|---|---|---|---|
| | MLR | CO adj. MLR | Lower Bound * | Upper Bound * | MLR | CO adj. MLR | Lower Bound * | Upper Bound * |
| DIFF_LN_NEG | 0.308 | 0.267 | 0.018 | 0.517 | | | | |
| DIFF_LN_RES | −0.935 | −0.956 | −1.157 | −0.754 | −0.972 | −0.973 | −1.188 | −0.757 |
| DIFF_LN_TTF | 0.216 | 0.195 | 0.079 | 0.312 | 0.560 | 0.549 | 0.451 | 0.647 |
| DIFF_LN_BRENT | 0.154 | 0.180 | 0.039 | 0.321 | | | | |
| DIFF_LN_NEWC | | | | | | | | |
| DIFF_LN_EUA | 0.368 | 0.343 | 0.185 | 0.501 | 0.368 | 0.364 | 0.186 | 0.542 |
| R | 0.872 | 0.889 | | | 0.880 | 0.882 | | |
| R square | 0.760 | 0.790 | | | 0.774 | 0.778 | | |
| Adjusted R square | 0.742 | 0.770 | | | 0.767 | 0.769 | | |
| Std. error of estimate | 0.064 | 0.064 | | | 0.086 | 0.086 | | |
| F-stat | 41.234 | 48.000 | | | 112.971 | 113.236 | | |
| *p*-value (F-stat) | 0.000 | 0.000 | | | 0.000 | 0.000 | | |
| Durbin–Watson stat | 2.377 | 2.101 | | | 2.158 | 2.034 | | |
| $VIF_{max}$ | 1.199 | | | | 1.130 | | | |
| N | 71 | 71 | | | 103 | 103 | | |

Dependent variable: log-differentiated wholesale electricity price. * Lower and upper bounds are related to the CO-adjusted MLR models.

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