Journal of Business Economics and Management
ISSN 1611-1699 / eISSN 2029-4433
2023 Volume 24 Issue 2: 221–244
https://doi.org/10.3846/jbem.2023.19050

UNDERSTANDING ELECTRICITY PRICE EVOLUTION – DAY-AHEAD MARKET COMPETITIVENESS IN ROMANIA

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Received 09 February 2023; accepted 20 April 2023

Abstract. The unexpected pandemic eruption in March 2020, the European efforts to diminish the gas house emissions, prolonged drought, higher inflation and the war in Ukraine clearly have had a strong impact on the electricity price. In this paper, we analyze the electricity prices on the Romanian Day-Ahead Market (DAM) along with other variables (inflation, consumption and traded volume of gas on DAM) over the last three and a half years in an attempt to understand its evolution and future trend in the economic and geopolitical context. Autoregressive Distributed Lag models are proposed to analyze the causality among variables on short- and long-term perspective, whereas Quantile Regression (QR) is proposed to enhance the results of the Ordinary Least Squares (OLS) regression. Furthermore, using market concentration metrics – Herfindahl-Hirschman Index (HHI), C1 and C3 ratio, we analyze the competitiveness on the Romanian DAM and correlate it with the electricity price evolution. The concentration indicators on this market reflect the degree of competition manifested between sellers and buyers respectively, their dynamics being able to influence the price level. The higher concentration on the sellers' side (HHI = 1500) indicates a potential speculative behavior on this market that led to higher prices on DAM.

Keywords: market concentration metrics, day-ahead market, electricity price, causality, autoregressive distributed lag, quantile regression.

JEL Classification: O13, Q43, C52.

Introduction

On a timeline, several events and trends have dominated the last three years and significantly lead to today's energy crisis. The COVID-19 pandemic disease that burst out in March 2020 is not yet eradicated. The consumption flows significantly changed from business and commercial centers to households during the lockdowns, some affairs were closed or drastically diminished their activity. Renewable Energy Sources (RES), especially PV panels, become more attractive for investors and residential consumers and their impact on the electricity

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price is indubitable. The recent prices of the CO_2 emission certificate that have to be acquired by electricity producers have influenced the electricity price. Moreover, two recent aspects, such as the conflict in Ukraine and the entire geopolitical context have impacted the electricity price. Ultimately, it will be reflected in more expensive products and services and fretful inflation. Therefore, the process of understanding the factors that influence the electricity price and its future evolution are tremendously important especially for policy makers to reduce inflation (Raimi et al., 2022); (Fernández-González et al., 2022), modeling the covariances of financial assets (Boloș et al., 2023).

The gradual elimination of restrictions related to the COVID-19 pandemic means a resumption of economic activities at the global level, which also determines an accelerated demand for natural gas consumption. On top of this cause, in Europe there is also the context created by the prolonged winter 2020–2021, which led to the emptying of natural gas deposits. The fall of last year found several European states, including Romania, with reduced natural gas stocks. In addition, the new policy of the European Union to accelerate measures to reduce carbon emissions has led to the increase in the price of carbon dioxide emission certificates, which doubled in 2021 compared to 2020 for fossil fuel producers. The immediate effect was an increase in the price of raw materials, which was then felt in the invoices. The tense situation between Russia and Ukraine also contributes to the current evolution of natural gas and oil prices.

Domestically, the market suffered by the end of last year, on the one hand, due to insufficient natural gas stocks, but also because local production was lower than in 2020. According to data provided by the gas providers, Romania's imports in 2021 have increased by over 300% compared to 2020, during a period when the purchase price on the Russian market increased. For the natural gas price evolution in 2021 and the beginning of 2022, it was interesting to notice whether the liberalization of the market for all consumers, starting on July 1, 2020, contributed to the increase in prices. However, energy specialists argue that liberalization is not the cause of price increases or decreases, it only establishes the conditions for the formation of fair prices. The increase in natural gas prices in the European Union has also affected countries that have a liberalized natural gas market that has been operating for years, not just Romania. However, the accumulation of external and internal factors made the price increase level to be among the highest at the European level.

There are several gaps that motivated us to perform this study. First, no recent studies were performed considering the random events (COVID-19 lingering effects, conflict in Ukraine in the Black Sea region) that took place in the recent years and led to a disruptive economic and geopolitical context. The lack of data sets was also a reason that motivated us to create a relevant data set with economic variables (inflation, interest rates), market prices (for gas, oil, electricity and traded quantities) and understand their relationship. Second, most studies focused on the Western European countries and less on the S-E European region that is near the conflict and equally affected by the inflation and energy market volatility.

Considering these reasons, we built up a data set merging several variables from various sources that can be input data for other studies. The input data is publicly available for open research. The interval of data extracted from web is generous and contains records taken before and after COVID-19 and Russian invasion.

The main contribution of the current study consists of:

- Proposing an Autoregressive Distributed Lag (ARDL) model to check the long-run and the short-run causalities between electricity price on DAM and the independent variables consumption, inflation and traded volume of gas on DAM.
- Revealing a long-run relationship between electricity price on DAM and the three independent variables.
- Using Quantile Regression (QR) to find associations of predictors at 25^{th}, 50^{th} and 75^{th} percentiles of electricity price on DAM.
- Revealing that the effect of consumption and inflation on the electricity price increases for higher quantiles, while the effect of traded volume of gas on the electricity price decreases for higher quantiles.
- Analyzing the market concentration metrics to estimate the competitiveness on the Romanian DAM and understand their relationship with the electricity price.
- Revealing a strong causality between market concentration and the level of prices, as the higher concentration of sellers was followed in July and August 2022 by the higher prices on DAM.

This paper aims to analyze the factors that influence the competitiveness on the DAM, electricity price and its trend. The price set for the Romanian electricity DAM by a uniform price auction is considered. The bidding process takes place 24 hours before delivery. The producers and suppliers bid to sell or buy the electricity that was unsold or unbought on the bilateral market on which bilateral negotiated contracts are signed more in advance. Thus, the DAM is much closer to real-time and covers the fluctuations that usually appear in consumption. Furthermore, for RES generators this market is suitable as their forecast improves closer to the delivery time. The data set spans over three and a half years. We started to collect data from 1^{st} of January 2019, before the COVID-19, to end of August 2022. This generous time span for data collection also covered the first shock waves generated by the Russian aggression towards Ukraine.

The remainder of this paper is structured as follows: in Section 1, a brief literature review is presented, in Section 2, the input data is described emphasizing on the data pre-processing and analytics. Section 3 is dedicated to competitiveness assessment on DAM, Section 4 to methodology, Section 5 to the results, Section 6 includes discussions and the last Section consists in drawing conclusion and providing several implications.

1. Literature review

1.1. Electricity price fluctuations on DAM and Renewable Energy Sources (RES)

RES forecast and demand are significant determinants of electricity prices using enhanced regressive models (K. Wang et al., 2022; Ma et al., 2015; Chaikumbung, 2021). These forecasts are helpful for spot and balancing markets and may result in an increase of revenues (Maciejowska et al., 2021).

Extensions to basic structural models are often performed including the solar and wind power or CO_2-emissions as in Carmona et al. (2013), Hildmann et al. (2015). Scientists underlined that electricity prices show typical characteristics regardless of where the electricity is traded. The results of Forbes and Zampelli (2014) offered evidence of a significant relationship between the DAM electricity price, natural gas price and hourly load. This correlation allowed a better prediction with ARMA than the Californian Independent System Operator. Several factors are considered to predict the spikes of the electricity price using classification and decision tree (Fragkioudaki et al., 2015).

Electricity price fluctuations on DAM are interesting for optimization and storage purposes and the electricity price forecast plays an important role. Ziel and Steinert (2016) emphasized on the five types of electricity price models: fundamental (based on market fundamentals), multi-agent (based on supply and demand), statistical, reduced form and computational intelligence. Except the first two types, they are based on the price, renewable energy and/or electricity demand. They propose a model (known as X-model) using real auction data considering both bids and asks, or sale and purchase curves, and identifying the extreme price or spikes. One of the proposed models is based on a recent novel X-model that captures price spikes. An adjustment to the X-model to handle data from the Great Britain market is proposed. This approach could be translated to the local energy markets that require probabilistic price forecasting models to show the price uncertainty and future trends (Haben et al., 2021).

A methodology using the Artificial NN (ANN) is proposed to predict the electricity prices (Keles et al., 2016). Load, fuel prices, RES generation and available capacity are considered as fundamental factors. The selection and preparation of fundamental data that have a noticeable impact on electricity prices gained focus. This was performed using cluster algorithms, but also by comparing the results.

1.2. Electricity price fluctuations on DAM and Analytical Models

Numerous visions regarding electricity price forecast exposed the complexity of the concept (Lago et al., 2021). Contradiction among supporters of statistical and Machine Learning (ML) methods, small size data sets that are not relevant for this type of analysis, lack of replicability and publicly available data sets and various software implementation are only a few aspects that make the comparison of these methods very difficult. Statistical methods, such as linear regression, Least Absolute Shrinkage and Selection Operator (LASSO), elastic net, Lasso Estimated Autoregression, ensemble methods, including clustering analysis, Generalized Autoregressive Conditional Heteroskedastic (GARCH), ARIMA, ML (Multi-Layer Perceptron – MLP, Support Vector Regressor – SVM), deep learning (Convolutional Neural Networks – CNN, Long Short-Term Memory – LSTM) as well as hybrid methods were identified in the context of the electricity price forecast.

A framework architecture with numerous statistical and ML models (especially automatic ML – H2O AutoML and TPOT), exogenous features, several time series decomposition methods and time series analysis methods were applied to the Spanish wholesale market, proving good accuracy on mean absolute error and mean absolute scaled error (Beltrán et al., 2022). Romero et al. (2019) analyzed the electric market in Spain to understand prices and market participants that can make prices vary. They noticed the close relationship between the objective variable and the electric demand. A normalization of the price variable due to a strong seasonal component and usage of several models of ML, such as: ridge regression, k-nearest neighbors, support vector machines, Neural Networks (NN) and random forest were proposed, identifying random forest as providing the best results without normalizing the objective.

1.3. Electricity price fluctuations on DAM and Geopolitical Overview

The disruptive economic and geopolitical context dramatically influenced the electricity markets. As resulted from data analytics, inflation, interest rates and other resources prices (such as oil and gas) increased in the last two years influencing the electricity prices in the European Union countries. This also affected forecast accuracy that recorded higher errors due to higher market volatility and RES share. The prices for CO_2 emissions and prolonged drought in the European countries additionally increased electricity prices. Therefore, the most recent studies in the electricity price forecast field also showed a lower accuracy that is provoked by the unstable geopolitical context. Several similar studies were performed before and after the random events that influenced the electricity markets.

The weather parameters influence on the DAM in Italy is considered in Bigerna (2018). The data set of hourly market variables and temperature variables was considered. A new econometric estimation showed some evidence of different effects of temperature and provided a more accurate estimation of the hourly prices. The results offered welfare-improvement and policy implications to handle extreme weather conditions. NN are investigated to forecast day-ahead electricity spikes in prices in the electricity market of Ontario, Canada Sandhu et al. (2016). They were trained using a data set consisting of similar price days. The spikes were identified using a spike classification method showing improvements in terms of accuracy.

The Singular Spectrum Analysis (SSA) is a technique in time series analysis and forecasting having capabilities in extracting the main structure of the broad classes of the time series. Using SSA, the original electricity price series was decomposed into components: trend, periodic and noisy. The processed price series was considered as input for predicting the day-ahead electricity prices, proving performant for the Australian and Spanish electricity markets (Miranian et al., 2013). In Spain, real-time energy-related data can be extracted to develop algorithms for price forecasting and understand how price vary. For the prediction, a Quantile Regression (QR) model based on Gradient Boosted Regression Trees was proposed in Díaz et al. (2019), improving the accuracy over regression models. Furthermore, it is simpler than ML approaches, providing low prediction errors when using the median as point prediction method. A method of Bootstrap Aggregation (bagging) was proposed in Özen and Yıldırım (2021) to facilitating the traceability of the predictors selection.

However, according to B. Wang et al. (2021), the impact of the electricity prices on residential electricity consumption is not that significant. Habits influence households' electricity consumption. Thus, it is important to create policies to diminish electricity consumption considering the perspective of households' habits rather than electricity prices (B. Wang et al., 2021).

2. Input data and data analyses

For analyzing the electricity price on the DAM in Romania, the following data sets were collected for interval 1st of January 2019 – 31st of August 2022: from various websites such as:

- OPCOM[1] – the Romanian Electricity Market Operator from where the DAM data – hourly prices and quantities were extracted using web scraping.
- Curs BNR[2] from where interest rate (ROBOR 3M) was extracted.
- Bursa Romana de Marfuri[3] from where the DAM gas price and quantity were extracted.
- Institutul National de Statistica[4] from where the consumption prices indices are extracted and the inflation index in Romania is calculated. Web scraping was used to obtain the prices for food, non-food products and services.
- Rate inflation[5] in European Union from where inflation rate was extracted.
- Macrotrends[6] from where the oil price was extracted.
- Danube level[7] from where water level was measured in Turnu Magurele, Braila and Tulcea using web scraping.

A data sample from OPCOM is presented in Table 1. The data was extracted using *BeautifulSoup* and *Selenium* libraries in Python.

Table 1. Data sample for DAM prices and traded volumes from OPCOM website

Trading area	Hour	ROPEX_DAM_H Price [lei/MWh]	Volume [MWh]
Romania	1	326.62	2418.2
Romania	2	288.92	2525.9
Romania	3	259.02	2569.6

Most data sets are time series with two columns (date and value) and they are open source data that can be found visiting the links below. After the data was extracted, as in Figure 1, the pre-processing stage was required as the time granulation was various (hourly, daily, monthly, trimester). From OPCOM, for instance multiple files were extracted using web scraping. 44 files, one for each month, was obtained. To concatenate and map the data into one single data set, pre-defined Pandas methods were used (*concat* and *map*). Then, the *Date* column of each time series was converted to date and time to prepare the data sets for merging. Numerous missing values were encountered due to different recordings, thus backfill and forward fill were necessary. The code for data extraction can be found on github[8].

1 https://www.opcom.ro/pp/grafice_ip/raportPIPsiVolumTranzactionat.php?lang=ro

2 https://www.cursbnr.ro/robor

3 https://www.brm.ro/piata-spot-gn/

4 http://statistici.insse.ro/shop/?page=ipc1

5 https://www.rateinflation.com/inflation-rate/euro-area-historical-inflation-rate/

6 https://www.macrotrends.net/2480/brent-crude-oil-prices-10-year-daily-chart

7 https://www.cotele-dunarii.ro/

8 https://github.com/simonavoprea/opcom_pzu_data/blob/main/data_extraction

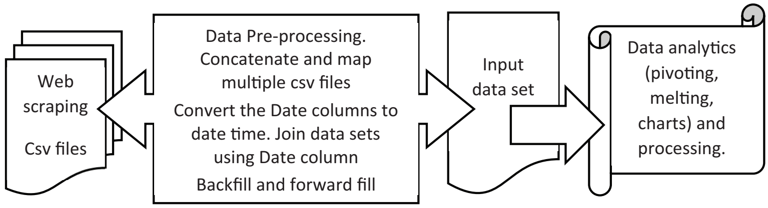


Figure 1. Data processing and analytics flow

The electricity price varied from 0.01 to 4698.99 RON/MWh, whereas the quantity of electricity traded on the DAM was up to 5052.9 MW. Most of the prices vary between 0 and 1150 RON/MWh. The traded electricity on DAM varies between 1250 and 4500 MW that is an important share of the load in Romania.

Very interesting insights can be found in Figure 2 that consists in the hourly electricity price average variation on DAM during the analyzed interval. The data based on which the graphical representations in Figures 2 and 3 are shown was extracted from OPCOM website. Two important aspects are identified: the tremendous increase of the price (more than 5 times) from 2020 to 2022 and the price curve shape that is changing from an almost flat curve in 2019 and 2020 to two-humped curve in 2021 and 2022. The standard deviation of the electricity price on the DAM sharply increased from 85.7 in 2020 to 707.9 in 2022. Additionally, we can notice that the electricity was cheaper in 2020 during lockdowns due to COVID-19 pandemic times.

Also, interesting insights can be obtained from Figure 3 that depicts the hourly variation on average of the traded electricity on the DAM. The data for Figure 3 is based on the OPCOM website. The request for electricity traded on DAM also increase but this increase is not that impressive and is somehow expected due to the fact that the business activities were restored gradually in 2021 and 2022 after lockdowns (Dobrowolski et al., 2022).

In Figure 4, the Pearson correlation indices between the dependent variable (electricity price on DAM) and the other variables are represented.

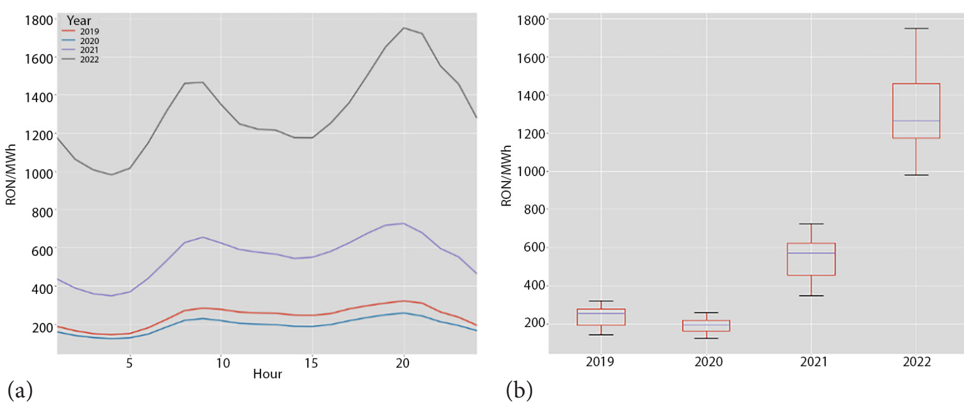
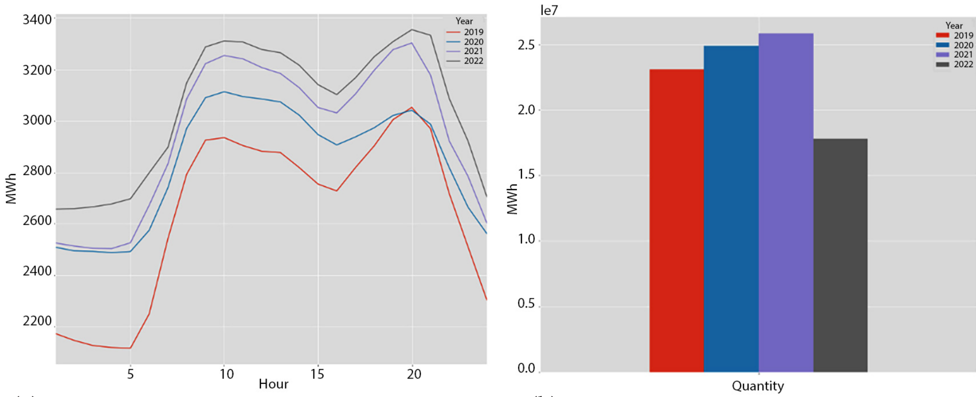


Figure 2. Average hourly electricity price curves (a) and price variation (b)



(a) (b)

Figure 3. Average hourly electricity load curves (a) and total traded electricity (b) on DAM between Jan. 2019 – Aug. 2022

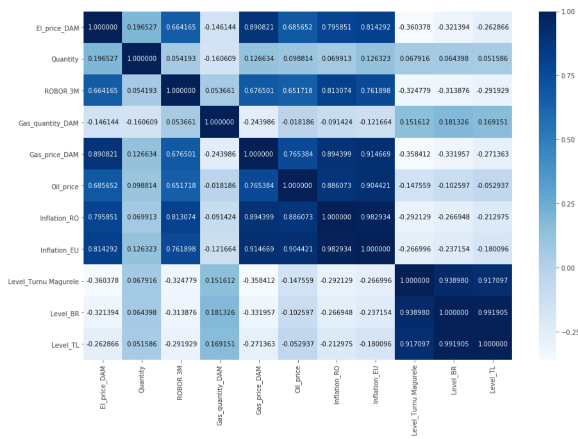


Figure 4. Correlation between electricity price on DAM and other variables

Very strong direct correlations are noticed between the electricity price and gas price (0.89), inflation rate in EU (0.81) and in Romania (0.79), oil price (0.68) and ROBOR 3M (0.66). This correlation suggests that variables are highly dependent. The higher the gas price and oil prices, the higher the electricity price on DAM. Furthermore, the inflation in Romania followed the trend of the inflation in EU and it impacted the interest rate as well.

Moderate inverse correlations are identified between the electricity price and the Danube water levels (–0.36). Very relevant is that in 2022, the dependency between the electricity price and Danube water levels is increasing to –0.6 showing a strong inverse correlation, that is the more drought, the higher prices. The prolonged drought led to less hydro energy. Therefore, more conventional sources (gas and oil) were consumed to generate electricity and it has influenced the DAM.

Furthermore, for the entire interval, relevant is the rather weak correlation between electricity price and quantity or demand (0.19). In 2020, this correlation was higher (0.31), but decreased in 2020 to 0.16. The demand did not follow the price trend, it remained in its usual trend characterized by a small annual increase (up to 5%).

3. Competitiveness assessment on DAM

In this section, we aim to assess the competitiveness evolution on the DAM from January 2019 to August 2022. The Sherman Antitrust Act in 1880–1890 was a reaction to monopolist or anti-competitive behavior. Since then, the antitrust agencies relied on the market concentration metrics to estimate the competitiveness on markets. They are essential in determining market power in controlling prices and quantities. In accordance with economic theory, the following market indices are calculated:

- HHI Herfindahl – Hirschman Index is the sum of the squared market shares. Interpretation of HHI is: HHI < 1000 low concentration; 1000 < HHI < 1800 moderate concentration; HHI > 1800 high concentration.
- C1 ratio is the market share of the biggest market participant (%). Interpretation of C1 is: C1 > 20% warning concentration; C1 > 40% probable dominant position; C1 > 50% dominant position.
- C3 ratio is the sum of market shares of the biggest three market participants (%). The interpretation of C3 is as following: 40% < C3 < 70% moderate concentration; C3 > 70% high concentration.

These indicators can be calculated for the entire market (electricity, ancillary services) or for its components, on which competition is directly manifested, including DAM. The concentration indicators on this market reflect the degree of competition manifested between sellers and buyers respectively, their dynamics being able to influence the price level. For buyers, HHI indicates a low-moderate (by mid-2022) concentration. Less concentration on the buyers' side would improve the electricity market competitiveness.

For sellers, HHI indicates a low concentration until May–July 2022, when HHI increases to the limit of high concentration. This concentration on the sellers' side disturbed the electricity market competitiveness. The almost high concentration on the sellers' side indicates a potential speculative behavior on this market that led to higher prices on DAM. The sum of market shares of the biggest three market participants indicated the same trend of low competitiveness. The higher concentration increases the likelihood of collusion between dominant sellers, resulting in higher electricity pricing on DAM. Therefore, there is a causality between market concentration and the level of prices.

4. Methodology

4.1. ARDL model

In economy, changes in one variable cause changes in another variable reflected over time. Over time various cointegration methods have been proposed, among which one can distinguish (Engle & Granger, 1987), in which the residuals came from the static regression (Phillips & Hansen, 1990), based on fully modified least squares regression (FMOLS) and (Johansen, 1988; Johansen & Juselius, 1990) based on maximum likelihood estimation. Johansen test and Phillips and Ouliaris (1990) overcame the limitations of the Engle-Granger method. Johansen test (1998) checked the cointegration between several time series simultaneously and is applied to large samples, while Philip–Ouliaris (1990) worked under the assumption of asymptotic distributions of residual unit root tests. The most appropriate technique used to model the causality relation is Autoregressive Distributed Lag (ARDL) cointegration technique developed by Pesaran and Shin (1999) and Pesaran et al. (2001). Narayan and Smyth (2005) remarked that the older cointegration methods were not adequate for small samples. They are among the first who applied ARDL in the energy modelling. ARDL was successfully applied when the time series dataset is affected by regime shifts and shocks (Menegaki, 2019). ARDL is applied when the variables have different orders of integration, I(0) and I(1). The form of the ARDL model is:

$$Y_t = \alpha_i + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{i=0}^{q} \gamma_i X_{t-i} + \varepsilon_{it}, \tag{1}$$

where Y_t is the dependent variable, X_t is the vector of the independent variables, α is the constant, β, γ are coefficients, p, q are the optimal lag numbers for the dependent and independent variables and ε_{it} are the uncorrelated and independent errors. t denotes the time.

From the results of the bounds test, we can decide if the variables are cointegrated. If the variables are cointegrated, one should specify the short-run ARDL model and the long-run Vector Error Correction Model (VECM). If the variables are not cointegrated, one should specify only the short-run ARDL model.

4.2. Quartile regression

Standard linear regression models the average relationship between the independent variables x and the conditional mean of the dependent variable y, $E(y|x)$. This approach may be sometimes incomplete. Therefore, a more complex view of the relationship between x and y at any point of the conditional distribution of y is given by the Quantile Regression (QR). It was introduced by Koenker and Bassett (1978), generating many extensions (Koenker & Hallock, 2001; Koenker, 2004). QR models the relation between the independent variable x and the conditional quantiles of y. QR estimations are more efficient when the normality condition is not fulfilled, or the distribution has a long tail. QR does not assume any hypothesis on the distribution of the residuals. Variyam et al. (2002) and Fávero and Belfiore (2019) observed that QR is more efficient to capture group differences represented by various group of quantiles, rather than Ordinary Least Squares (OLS) which estimates mean regression models.

Considering the linear model:

$$y_t = x_t^{'}\beta + \varepsilon_t, \tag{2}$$

where y is the dependent variable, x is the vector of the independent variables, ε are the errors.

Standard regression minimizes the sum of squares of the residuals, while QR minimizes the weighted sum of the absolute values of the residuals (Fávero & Belfiore, 2019). The solution of the following minimization problem:

$$\min_{b \in R^k} \left(\sum_{t \in \{t | y_t \geq x_t^{'}\beta\}} q \left| y_t - x_t^{'}\beta_q \right| + \sum_{t \in \{t | y_t < x_t^{'}\beta\}} (1-q) \left| y_t - x_t^{'}\beta_q \right| \right) \tag{3}$$

is the estimator of the q^{th} quantile denoted by $\hat{\beta}_q$, where $q \in (0,1)$.

The optimal value of the objective function from the optimization problem (3) becomes symmetric when q = 0.5 and asymmetrical when q is near 0 or 1. The standard conditional quantile is linear:

$$Q_q(y_t \mid x_t) = x_t' b_q. \tag{4}$$

For the j^{th} regressor, the coefficient for the q^{th} quartile gives the marginal effect:

$$\frac{\partial Q_q(y \mid x)}{\partial x_j} = \beta_{qj}, \tag{5}$$

where β_{qj} represents the change in quartile q of y at a one-unit change in regressor x_j.

QR coefficients, if statistically significant, have a different effect than OLS coefficients.

5. Results

5.1. ARDL results

In this section, we apply ARDL model to study the long-run and the short-run causality between *El_price_DAM* and the regressors *Consumption*, *Inflation_EU* and *Gas_quantity_DAM* for each year between 2019–2022, period January–March. The ARDL causality has been analyzed by means of EVIEWS 12. First, we check the unit root tests. The null hypothesis of the unit root tests is that the time series is not stationary (there is a unit root) versus the alternate hypothesis that the time series is stationary. If the *p-value* is less than a certain significant level (say 0.05), then we accept the null hypothesis and infer that the time series is stationary.

Table 2 shows that the variables are integrated either I(0) and I(1), by Augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1979) and Phillips and Perron (PP) (Phillips & Perron, 1988) unit root tests. Due to the mixed orders of integration I(0) and I(1), we will apply the ARDL bounds test of cointegration to examine the long run and the short run causality among the variables.

Table 2. Unit root test results

a) January–March 2019

Variables	At level		At first difference	
	ADF	PP	ADF	PP
El_price_DAM	–2.73 (0.06)	–7.97 (0.00)	–10.80 (0.00)	–44.90 (0.00)
Consumption	–5.48 (0.00)	–5.90 (0.00)	–7.21 (0.00)	–21.04 (0.00)
Inflation_EU	–1.46 (0.54)	–42.93 (0.00)	–1.47 (0.5481)	–42.93 (0.00)
Gas_quantity_DAM	–3.14 (0.02)	–4.18 (0.00)	–12.37 (0.00)	–42.93 (0.00)

b) January–March 2020

Variables	At level		At first difference	
	ADF	PP	ADF	PP
El_price_DAM	–3.44 (0.00)	–9.42 (0.00)	–9.75 (0.00)	–74.49 (0.00)
Consumption	–5.82 (0.00)	–6.29 (0.00)	–6.73 (0.00)	–14.45 (0.00)
Inflation_EU	–0.91 (0.78)	–0.91 (0.78)	–42.96 (0.00)	–42.96 (0.00)
Gas_quantity_DAM	–2.60 (0.09)	–2.64 (0.08)	–42.93 (0.00)	–42.93 (0.00)

End of Table 2

c) January–March 2021

Variables	At level		At first difference	
	ADF	PP	ADF	PP
El_price_DAM	−2.64 (0.00)	−8.28 (0.00)	−10.33 (0.00)	−55.47 (0.00)
Consumption	−7.56 (0.00)	−5.18 (0.00)	−6.81 (0.00)	−24.54 (0.00)
Inflation_EU	−0.80 (0.81)	−0.80 (0.81)	−42.67 (0.00)	−42.67 (0.00)
Gas_quantity_DAM	−3.89 (0.00)	−3.98 (0.00)	−42.65 (0.00)	−42.65 (0.00)

d) January–March 2022

Variables	At level		At first difference	
	ADF	PP	ADF	PP
El_price_DAM	−2.56 (0.10)	−13.03 (0.00)	−10.96 (0.00)	−45.89 (0.00)
Consumption	−6.46 (0.00)	−6.38 (0.00)	−6.87 (0.00)	−15.46 (0.00)
Inflation_EU	−0.98 (0.76)	−0.98 (0.7616)	−42.69 (0.00)	−42.69 (0.00)
Gas_quantity_DAM	−2.17 (0.21)	−2.19 (0.00)	−42.65 (0.00)	−42.65 (0.00)

After finding that all the variables are stationary after the first difference, we apply the first differenced variables for the ARDL models. The results of cointegration bounds tests are reported in Table 3.

Table 3. Results of cointegration bounds test

Test statistic	Value	K (number of regressors)
F-statistic (2019)	109.50	3
F-statistic (2020)	109.84	3
F-statistic (2021)	125.28	3
F-statistic (2022)	138.17	3
Critical value bounds		
Significance	I(0)	I(1)
10%	2.37	3.2
5%	2.79	3.67
1%	3.65	4.66

Since F-calculated is greater than the critical upper bound denoted by I(1) in all periods, we consider that there is evidence of cointegration among variables, therefore long-run causality exists. Since cointegration exists, the estimated long-run coefficients of the corresponding ARDL model are shown in Table 4.

From Table 4, one can see that each year electricity *Consumption* has a positive and statistically significant influence on *El_price_DAM* at 5% level of significance. A 1% increase in *Consumption* exerted each year an increase in *El_price_DAM*. The highest increase in *El_price_DAM* occurred in 2022, when a 1% percent increase in *Consumption* led to 0.18% increase in *El_price_DAM*. The demand for electricity describes the consumption of electric-

Table 4. The long-run estimated coefficients

(2019) ARDL(4,4,0,0)

Variables	Coefficient	T-Statistics	Prob.
Consumption	0.07	25.40	0.00
Inflation_EU	–171.09	–0.45	0.34
Gas_quantity_DAM	8.54E-07	0.25	0.72
C	0.0193	0.03	0.97

EC = D(EL_PRICE_DAM) – (0.0751*D(CONSUMPTION) – 171.0999*
D(INFLATION_EU) + 0.0000*D(GAS_QUANTITY_DAM) + 0.0193)
ARDL(4,4,0,0)

Variables	Coefficient	T-Statistics	Prob.
Consumption	0.0481	22.83	0.00
Inflation_EU	–8.7818	–0.25	0.79
Gas_quantity_DAM	–0.0011	–2.71	0.00
C	–0.00488	–0.11	0.90

EC = D(EL_PRICE_DAM) – (0.0481*D(CONSUMPTION) – 8.7878*
D(INFLATION_EU) – 0.0011*D(GAS_QUANTITY_DAM) – 0.00488)
ARDL(3,2,0,0)

Variables	Coefficient	T-Statistics	Prob.
Consumption	0.0537	25.12	0.00
Inflation_EU	–15.7725	–0.25	0.79
Gas_quantity_DAM	0.0005	1.34	0.17
C	0.0069	0.01	0.99

EC = D(EL_PRICE_DAM) – (0.0537*D(CONSUMPTION) – 15.7725*
D(INFLATION_EU) + 0.0005*D(GAS_QUANTITY_DAM) + 0.0069)
ARDL(4,2,0,0)

Variables	Coefficient	T-Statistics	Prob.
Consumption	0.1817	15.29	0.00
Inflation_EU	162.2979	7.79	0.00
Gas_quantity_DAM	0.0044	1.84	0.06
C	0.5243	0.17	0.85

EC = D(EL_PRICE_DAM) – (0.7*D(CONSUMPTION) + 162.2979*
D(INFLATION_EU) + 0.0044*D(GAS_QUANTITY_DAM) + 0.5243)

ity by human activity. The demand for electricity is one of the most important factors which determines the electricity price. Since the population increases and economies develop, the demand for electricity increases and the price of electricity is higher.

Inflation_EU has a negative and statistically insignificant influence on *El_price_DAM* in 2019, 2020, 2021. In 2022 *Inflation_EU* has a positive and statistically significant influence on *El_price_DAM*. A 1% increase in *Inflation_EU* has a 162% increase in *El_price_DAM*. One reason for this significant influence is that in 2019 the EU inflation rate was 1.63%, in 2020 0.50%, in 2021 2.55%, while in January–March 2022 it doubled.

In 2020 and 2022, *Gas_quantity_DAM* exerted a statistically significant influence on *El_price_DAM*. The influence was negative in 2020 and positive in 2022. In 2020, one percent increase in *Gas_quantity_DAM* decreased *El_price_DAM* by 0.0011%, while in 2022 enhanced *El_price_DAM* by 0.0044%. The results of ARDL-Error Correction Model (ECM) are captured in Table 5.

Table 5. Short-run ARDL approach

(2019) ARDL(4,4,0,0)

Variable	Coefficient	T-statistics	Prob.
D(El_price_DAM(-1))	0.1466	3.95	0.00
D(El_price_DAM(-2))	0.1271	4.11	0.00
D(El_price_DAM(-3))	0.0347	1.89	0.05
D(Consumption)	0.0552	22.12	0.00
D(Consumption(-1))	0.0017	0.47	0.63
D(Consumption(-2))	–0.0061	–1.84	0.06
D(Consumption(-3))	–0.0137	–4.73	0.00
CointEq(-1)	–1.0093	–23.42	0.00
R-squared	0.52		
Adjusted R-squared	0.52		
Durbin-Watson statistic	1.99		

(2020) ARDL(4,4,0,0)

Variable	Coefficient	T-statistics	Prob.
D(El_price_DAM(-1))	0.1393	3.84	0.00
D(El_price_DAM(-2))	0.1370	0.00	0.00
D(El_price_DAM(-3))	0.0795	3.41	0.00
D(Consumption)	0.0386	21.56	0.00
D(Consumption(-1))	0.0022	0.88	0.37
D(Consumption(-2))	–0.0032	–1.39	0.16
D(Consumption(-3))	–0.0064	–3.13	0.00
CointEq(-1)	–0.9711	–23.46	0.00
R-squared	0.51		
Adjusted R-squared	0.51		
Durbin-Watson statistic	2.00		

(2021) ARDL(3,2,0,0)

Variable	Coefficient	T-statistics	Prob.
D(El_price_DAM(-1))	0.0654	2.39	0.01

End of Table 5

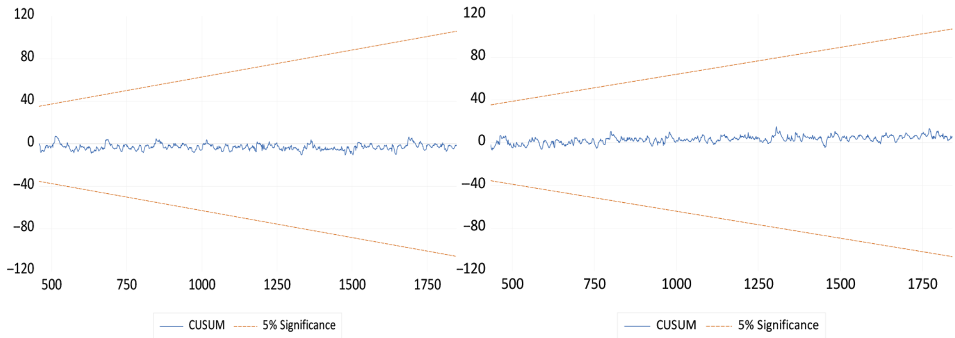
Variable	Coefficient	T-statistics	Prob.
D(El_price_DAM(-2))	0.0450	2.24	0.02
D(Consumption_	0.046	23.27	0.00
D(Consumption(-1))	0.0233	7.87	0.00
CointEq(-1)	–0.8576	–25.05	0.00
R-squared	0.53		
Adjusted R-squared	0.53		
Durbin-Watson statistic	1.99		

(2022) ARDL(4,2,0,0)

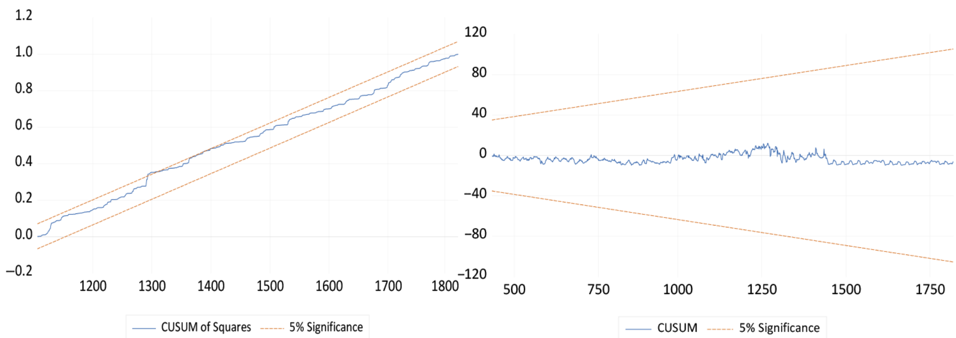
Variable	Coefficient	T-statistics	Prob.
D(El_price_DAM(-1))	0.1484	4.64	0.00
D(El_price_DAM(-2))	0.2030	7.62	0.00
D(El_price_DAM(-3))	0.0911	4.37	0.00
D(Consumption)	0.0595	13.43	0.00
D(Consumption(-1))	0.1682	4.14	0.00
CointEq(-1)	–0.9981	–26.31	0.00
R-squared	0.49		
Adjusted R-squared	0.48		
Durbin-Watson statistic	2.00		

The Error Correction Term (ECT) represents for any shocks the speed of adjustment from short-run disequilibrium to long-run equilibrium. ECT is in all 4 years negative, larger than –2 and statistically significant at 5% level of significance, showing that there is evidence of long-run cointegration. The speed of adjustment to long run equilibrium after a deviation has occurred in the short run was 100% in 2019, 97% in 2020, 85% in 2021 and 99% in 2022. The adjustment coefficients indicate how the deviation from the long-term equilibrium is corrected. In 2019, ECT is between –1 and –2, causing dampening oscillations. This means that the error correction process varied in 2019 around the long-run value in a dampening manner, rather than uniformly converging to equilibrium. Coefficients of the first differenced variables are interpreted as the short-run elasticities. The short-run association between the first lag of *Consumption* and *El_price_DAM* is positive and statistically significant at 5% significance level. As the number of lags of *Consumption* increases, this correlation tends to become negative. Each year the variables jointly explain around 50% of the total variation in *El_price_DAM* as shown by Adjusted R-squared. The Durbin Watson statistic being around 2 indicates no autocorrelation in the residuals. The stability of the model is tested using the CUSUM test (Tanizaki, 1995). The red lines in Figure 5a–d represent the critical bounds at 5% threshold of significance. Since the blue line is situated within the critical bounds, it follows that the parameters are stable each year.

It follows that ARDL-ECM has a good fit and the results are reliable for making inferences and policy recommendations.



a) CUSUM test for January–March 2019 b) CUSUM test for January–March 2020



c) CUSUM test for January–March 2021 d) CUSUM test for January–March 2022

Figure 5. Plots of CUSUM for coefficients' stability of ARDL model at 5% level of significance

5.2. Quartile regression results

The second model that we use is the QR model. The following linear model will be estimated in STATA, following the same steps as Fávero and Belfiore (2019):

$$El\_price\_DAM_t = b_0 + b_1 Consumption_t + b_2 Inflation\_EU_t + b_3 Gas\_quantity\_DAM_t + \varepsilon_t. \tag{6}$$

The specific QR equation is:

$$Quantile(El\_price\_DAM_t \,|\, Consumption_t, Inflation\_EU_t, Inflation\_EU_t, Gas\_quantity\_DAM_t) = b_0 + b_1 Consumption_t + b_2 Inflation\_EU_t + b_3 Gas\_quantity\_DAM_t + \varepsilon_t. \tag{7}$$

The histogram of the dependent variable *El_price_DAM* is shown in Figure 6. The Q-Q plot of the dependent variable *El_price_DAM* is shown in Figure 7.

From the histogram and the Q-Q plot of the dependent variable (Figures 6 and 7), we can see that *El_price_DAM* is not normally distributed. We check the existence of skewness in the dependent variable *El_price_DAM*.

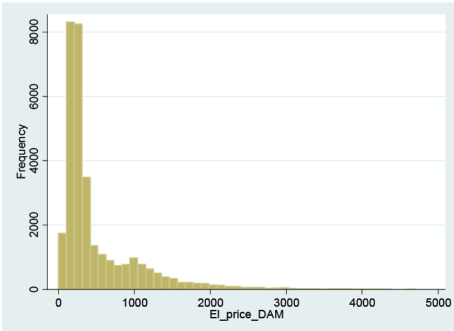


Figure 6. Histogram of the dependent variable El_price_DAM

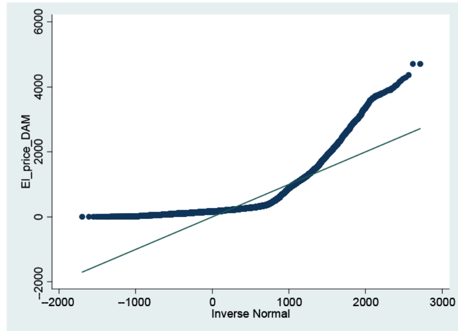


Figure 7. Q-Q plot of the dependent variable El_price_DAM

Table 6. Skewness/Kurtosis tests for normality

Variable	Pr(Skewness)	Pr(Kurtosis)
El_price_DAM	0.00	0.00

Since the *p-value* is less than 0.05 as shown in Table 6, we will reject the null hypothesis which asserts that the distribution of the dependent variable is normally distributed. Together with the Q-Q plot in Figure 7, this points to the estimation of a QR model. First, we examine the standard linear regression in Table 7 and notice that all the regressors are statistically significant.

Table 7. Standard linear regression

El_price-DAM	Coef.	Std. Error	t	P>|t|	[95% Conf. Interval]	
Consumption	0.078	0.00	46.89	0.00	0.07	0.08
Inflation_EU	165.76	0.63	259.71	0.00	164.5	167.01
Gas_quantity_DAM	−0.0000153	1.03e-06	−14.79	0.00	−0.0000173	−0.0000132
Constant	−424.46	11.66	−36.39	0.00	−447.33	−401.60

We analyze the results of the QR model for $q = 25$, $q = 50$ and $q = 75$ (as in Tables 8–10).

Table 8. 0.25 Quantile regression

El_price-DAM	Coef.	Std. Error	t	P>|t|	[95% Conf. Interval]	
Consumption	0.037	0.00	33.22	0.00	0.03	0.04
Inflation_EU	105.85	0.43	242.23	0.00	104.99	106.7
Gas_quantity_DAM	−0.0000105	7.06e-07	−14.89	0.00	−0.0000119	−9.13e-06
Constant	−170.10	7.98	−21.3	0.00	−185.75	−154.44

Table 9. 0.5 Quantile regression

El_price-DAM	Coef.	Std. Error	t	P>|t|	[95% Conf. Interval]	
Consumption	0.042	0.00	29.24	0.00	0.040	0.045
Inflation_EU	136.48	0.56	243.12	0.00	135.37	137.58
Gas_quantity_DAM	–0.0000148	9.08e-07	–16.3	0.00	–0.000016	–0.000013
Constant	–165.13	10.25	–16.10	0.00	–185.23	–145.02

Table 10. 0.75 Quantile regression

El_price-DAM	Coef.	Std. Error	t	P>|t|	[95% Conf. Interval]	
Consumption	0.066	0.00	30.38	0.00	0.06	0.07
Inflation_EU	177.82	0.83	212.45	0.00	176.17	179.46
Gas_quantity_DAM	–0.0000213	1.35e-06	–15.70	0.00	–0.0000239	–0.0000186
Constant	–252.23	15.29	–16.49	0.00	–282.21	–222.25

We notice that in all three cases of QR model, all coefficients are statistically significant. Summarizing the above results, there are discrepancies between the parameters estimated by OLS and the ones obtained by the QR models (as in Table 11).

Table 11. Parameters estimated in each model and their standard errors

Variable	OLS	QREG25	QREG50	QREG75
Consumption	0.078	0.037	0.042	0.066
Standard error	0.00	0.00	0.00	0.00
Inflation_EU	165.76	105.85	136.48	177.81
Standard error	0.63	0.43	0.56	0.83
Gas_quantity_DAM	–0.00001526	–0.00001052	–0.00001479	–0.00002125
Standard error	1.03e-06	7.06e-07	4.07e-07	1.35e-06
Constant	–424.46	–170.1	–165.13	–252.23
Standard error	11.66	7.98	10.25	15.29

The standard errors of the parameters are lower for the 25^{th} percentile QR model, which indicates that the 25^{th} percentile QR model has a greater precision of the estimation. 1% increase in *Consumption* has a lower positive impact (0.037%) on *El_price_DAM* at the 25^{th} percentile than at the 50^{th} percentile, and 75^{th} percentile by 0.042%, respectively 0.066%. 1% increase in *Inflation_EU* at the 50^{th}, 75^{th} percentile has a greater positive impact on *El_price_DAM* by 136.48%, respectively 177.81% than at the 25^{th} percentile, by 105.85%. 1% increase in *Gas_quantity_DAM* at the 50^{th}, 75^{th} percentile has a lower negative impact on *El_price_DAM* by –0.000014%, respectively –0.000021% than at the 25^{th} percentile, by –0.000010%.

In Figure 8, the paneled charts show the difference between the estimators obtained by QR and those obtained by OLS, along with OLS confidence intervals. We also see that the sign of the regressors is the same in all 4 estimation models from Table 11.

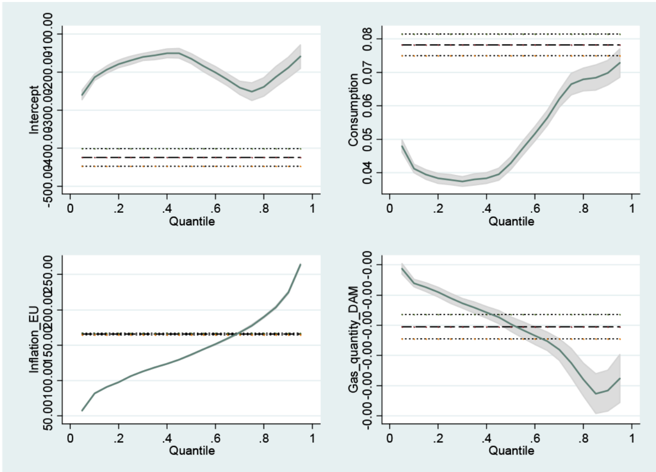


Figure 8. Parameters estimated for QR models and by OLS, with their confidence intervals

In Figure 8, the quantiles of the regressors are represented on the horizontal axis, while the magnitude of the coefficients is represented on the vertical axis. The coefficient obtained by linear regression is represented on the horizontal line, while the dashed lines delimit the confidence intervals of this coefficient. As Fávero and Belfiore (2019) remarked, the parameters obtained by standard regression and their confidence intervals do not vary with the percentiles. This remark motivates the choice of QR models over OLS models. If the percentile coefficient lies outside the OLS confidence interval, then there are significant differences between the quantile and OLS coefficients. From that we conclude that the percentile coefficients for all regressors are significantly different from the OLS coefficients. The effect of *Consumption* and *Inflation_EU* on *El_price_DAM* increases for higher quantiles, while the effect of *Gas_quantity_DAM* on *El_price_DAM* decreases for higher quantiles, as it was implied from Table 11.

6. Discussions

This paper proposed an ARDL model to check the long-run and the short-run causalities between *El_price_DAM* and the independent variables *Consumption*, *Inflation_EU* and *Gas_quantity_DAM* during January–March 2019–2022. The ARDL bounds test revealed a long-run relationship between *El_price_DAM* and the three independent variables. From this analysis it follows that *Consumption*, *Inflation_EU* and *Gas_quantity_DAM* are important determinants of *El_price_DAM*. The correlations between *El_price_DAM* and its determinants are in accordance with economic theory. Most coefficients of lagged dependent variables are significant at 5% level of significance, meaning that short-term causality also exists.

Then, we used QR to find associations of predictors at 25th, 50th and 75th percentiles of *El_price_DAM*. QR is an effective tool to study how *Consumption*, *Inflation_EU* and *Gas_quantity_DAM* affect the distribution of *El_price_DAM*. Our results reveal that the effect of *Consumption* and *Inflation_EU* on *El_price_DAM* increases for higher quantiles, while the effect of *Gas_quantity_DAM* on *El_price_DAM* decreases for higher quantiles.

The two approaches used in this paper can be enriched with the application of the novel dynamic ARDL (DYNARDL) proposed by Jordan and Philips (2018), Philips (2018). The advantage of DYNARDL is that based on the simulations of the parameters of a multivariate normal distribution, it can check the long and short-run causality in level and in difference.

At present, 60.2% of the total European energy is low carbon, the primary source being nuclear. The Low-Carbon Energy Observatory (LCEO) has been set up to investigate the innovative measures and policies for low-carbon technologies. Streimikiene et al. (2021) connected low carbon energy transition and poverty energy issues. The policies for climate change mitigation in households regarded according to Streimikiene et al. (2021): Greenhouse Gas (GHG) emissions reduction; energy poverty reduction; the increase of energy efficiency and the expansion of renewable energy share in the total energy consumption.

Energy poverty has recently become a multi-parametric issue, having four dimensions in the literature: economic, geographic, in-field and human (Streimikiene & Kyriakopoulos, 2023). The economic dimension refers to energy poverty in different European countries. The in-field dimension takes into account the regional level of analysis, while the human dimension focuses on the population which does not have access to electricity services. The conclusion of this paper is that the heterogeneity of energy and its implications should be analyzed. Streimikiene et al. (2020) developed an integrated framework concerning the measures to reduce energy poverty and increase energy efficiency in energy poor households in the EU. Moreover, the Eastern Europe faces the problem of poor households who suffer from energy poverty. The improvement of energy efficiency in households may be done by means of decarbonization of energy systems and by resorting to renewable energy sources.

Energy consumption is on an increasing trend, therefore renewable energy sources diversification and production intensification should be targeted. Solar photovoltaic (PV) energy has become the third source of renewable energy, behind hydroelectric power and wind. In 2021, solar energy represented 3.6% of total electricity generation. Mišnić et al. (2022) made a financial analysis of a project involving the economic viability of a 5MV solar power plant in Montenegro. The electricity price was predicted by ARIMA and neural networks.

In the first decade of the 2000s, Romania made a significant progress on the electricity market by de-monopolization and its liberalization (Budulan et al., 2003). Clodnițchi and Chinie (2015) recalled that the European Commission established support systems to be implemented by each EU member state, such as to promote renewable energy. Among these support systems (Clodnițchi & Chinie, 2015) recalled: feed-in-tariffs, premium feed-in-tariffs, contracts for differences, quota obligations and renewable energy certificates, capacity procurement auctions, tax incentives, and hybrid instruments. In Romania quota obligations and renewable energy certificates were implemented with the purpose of stimulating energy production from renewable sources.

Conclusions

In this paper, we analyzed the market concentration metrics to estimate the competitiveness on the Romanian DAM and understand their relationship with the electricity price. HHI, C1 and C3 are significant in assessing market power in controlling prices and quantities on the DAM. For sellers, HHI indicates a low concentration until May–July 2022, when HHI has started to increase to the limit of high concentration. This higher concentration on the sellers' side negatively influences the electricity market competitiveness, indicating a potential speculative behavior on this market that ultimately led to higher prices on DAM. The sum of market shares of the biggest three market participants (C3) indicated the same trend of low competitiveness. This higher concentration also increases the likelihood of collusion between dominant sellers, resulting in higher electricity pricing on DAM. Therefore, there is a strong causality between market concentration and the level of prices, as the higher concentration of sellers was followed in July and August 2022 by the higher prices on DAM. However, this trend with higher prices took place in all European countries DAM and it was influenced mainly by the economic and the geopolitical context.

To satisfy the demand for electricity, it must be invested in the development of the power system and diversity of energy resources. Policies should be adopted to fulfill electricity supply by hydroelectric and nuclear sources. In 2021, in Romania the electricity was provided by hydroelectric power plants by 29% of the total generated electricity, followed by the two nuclear power units (by 18.9%). The government should also attract investments into the electricity sector and create the environment for an efficient and competitive market. Energy policies should be directed towards sustainable development, integrating more RES and electricity storage.

The advantage of the ARDL model consists in its suitability for modeling the price fluctuations on the electricity market, characterized by seasonality, volatility and changing dynamics. Possible future directions of this research could be Markov regime switching approach or smooth transition logistic regression model which capture the sensitivity of prices on DAM.

As a limitation, bias-corrected bootstrap method may provide better estimations. Thus, the ARDL model could be continued with the bias-corrected bootstrap model, which provides more robust estimates for the long-run coefficients. The most important limitation of QR is that it leads to global effects. An issue to be studied is how the distribution of the dependent variable is affected if the population characteristics change. Future research will be conducted to extend the data set and extract new insights from the economic and geopolitical context that significantly influences electricity prices and markets.

Acknowledgements

This work was supported by a grant of the Ministry of Research, Innovation and Digitization, CNCS- UEFISCDI, project number PN-III-P4-PCE-2021-0334, within PNCDI III.

Funding

This work was supported by a grant of the Ministry of Research, Innovation and Digitization, CNCS- UEFISCDI, project number PN-III-P4-PCE-2021-0334, within PNCDI III.

Author contributions

Adela Bâra: Conceptualization, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing – Original Draft, Writing – Review and Editing, Visualization, Supervision. Simona-Vasilica Oprea: Conceptualization, Validation, Formal analysis, Investigation, Writing – Original Draft, Writing – Review and Editing, Visualization, Project administration. Irina Alexandra Georgescu: Methodology, Writing – Original Draft, Writing – Review and Editing, Visualization.

Disclosure statement

Authors declare that there is no competing financial, professional, or personal interests from other parties.

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