Analysis of the Volatility of Renewable Sources of Electricity in Romania and the Assessment of Their Capacity to Replace the Conventional Sources

Ioan Cătălin MURĂRAȘU
Bucharest University of Economic Studies, Romania
murarasu.catalin9@gmail.com

Abstract
The current energy crisis in Europe, largely generated by the considerable reduction in Russian natural gas flows, forces the European authorities to accelerate the transition to renewable energy sources, although changing the structure of the energy mix too quickly can generate accentuated imbalances, which translate into major costs of balancing and in higher bills for end consumers. The study involves the analysis of the historical volatility of energy production from renewable sources in Romania (hydropower, wind energy, photovoltaic energy, and that from biomass), by using ARCH/GARCH models through EVIEWS 12 software, and its contribution to national consumption, in the period January 1st, 2020 - September 1st, 2022, using actualized at 10-minutes intervals. The research results highlight the instability of energy production from renewable sources and the need to identify solutions to reduce balancing costs, so that green energy can represent a cost-effective solution for ensuring energy independence and combating pollution, both from a technical and economic point of view.

Keywords: electricity; renewable energy; volatility; pollution;

JEL Classification: F64; K32; P18; Q42;

DOI: http://doi.org/10.24818/ejis.2023.07

1. Introduction

Renewable energy sources are considered by most of the public opinion as the main energy sources of the future; in the view of many they are even the only ones. In the context of an increasingly intense fight against climate change, led by the Western community, green energy production technologies hold the hope that the transition from a non-polluting to a climate-neutral economy is not just a dream, but a desirable, time-bounded, quantifiable, and achievable goal.

However, the policies to combat pollution, especially in the energy sector, are often contested, and their opponents have no shortage of arguments, mainly social and technical. If most of the social disadvantages of the energy transition can be combated through social policies (Hoffman et al., 2021), often consisting of job losses or the deindustrialization of some regions (Arora and Schroeder, 2022), in the case of the technical ones, the solutions are more difficult to identify and, sometimes, even more expensive.

The present work does not dispute the determining role of renewable energy sources for the future of Europe or Romania and does not aim to highlight their disadvantages, but to

Received: 14 February 2023; Revised: 26 April 2023; Accepted: 15 May 2023

identify and analyse the most important of them - the volatility of production, caused by the dependence of production capacity on meteorological factors. Only by discussing the systemic shortcomings of today's technology can it be developed to the point where it would represent a viable solution, both from the environmental and economic point of view.

The dependence of energy production from renewable sources on meteorological factors is the main obstacle on the way of these technologies to obtain a monopoly on the European energy market. The instability of their nominal efficiency caused by numerous natural factors, from reduced wind speed to reduced solar radiation caused by shading, directly causes losses (Maradin, 2021). Under these conditions, the transmission and system operators are forced to introduce the electricity produced from other sources into the network, in order to balance the system. This energy, purchased on the balancing market, through spot transactions by the operator – Transelectrica, in the case of Romania - is subsequently reflected in the bills paid by the final consumers and the price evolution for it does not discount the market evolution, which currently registers the highest values in modern history.

In the current paper, the volatility of energy production from renewable sources will be studied by applying the Autoregressive conditional heteroskedasticity (ARCH), Generalized ARCH (GARCH) and Exponential GARCH (EGARCH) models to the available data (143,429 observations) during the period January 1st, 2020 - September 1st, 2022. The inclusion of all seasons and meteorological events, encountered in this temporary interval, gives a high degree of accuracy to the research, because the storage capacities connected to the national grid are reduced, amounting to approximately 2 MW at an average consumption of 6700 MW.

Although ARCH, GARCH and EGARCH models are usually used in the case of financial time series, the article aims to test the hypothesis that they can also be applied to analyze the volatility of renewable energy production, whose values fluctuate considerably depending on natural external factors. For this variable, events such as lack of sunlight, low winds, sleet, or frost cause values to decrease, while strong sunlight, strong and steady wind, or heavy rains causes values to increase. So, the current research shows that these factors act similarly to positive and negative events on the stock market indices, according to which their returns increase or decrease.

The study contributes to researchers' efforts to estimate and predict the volatility of energy production so that imbalances in national energy systems can be prevented or quickly remedied at low economic cost. The article aims to highlight the usefulness of ARCH models for establishing the percentage that can be covered by renewable sources in the national energy mix, so that the risk of them becoming too unstable can be kept under control, similar to a portfolio of financial assets. Currently, in Romania, renewable energy sources are prioritized in the system, this practice sometimes creating large production fluctuations. In these cases, balancing is achieved through imports from neighbouring countries at high prices or through the use of polluting sources, whose profitability is increasingly lower. This practice reduces the energy security of Romania, which will become more and more dependent on imports, once the conventional production capacities in the European Union are closed. Given that renewable energy sources will almost completely replace the conventional ones in the next two decades, the analysis of their volatility (their main disadvantage) will have to become more and more precise.

After presenting several points of view on the topic of the volatility of renewable energy from the specialized literature (Section 2), the paper presents the theoretical approach of the heteroskedastic ARCH, GARCH and EGARCH models (Section 3). In the practical part of the work (Section 4), the three models are applied to the series of data representing the production of renewable energy in Romania from January 2020 to September 2022. After the interpretation of the results and a discussion based on them in relation to other research (Section 5), the paper presents the conclusions of the study (Section 6), which also include some recommendations for reducing the exposure of the energy system to the volatility of renewable sources.

2. Literature Review and Problem Statement

Rintamaki et al. (2017) demonstrated, using a seasonally adjusted autoregressive moving average (SARMA) model, that solar energy production in Denmark and Germany influences, both statistically and economically, the volatility of the day-ahead price for electricity in the analyzed states. According to the mentioned study, one way to reduce this volatility is to make production more flexible by improving transmission capabilities.

In the context of the decarbonization of the European energy sector, the share of volatile energy sources will continue to increase, the European Union's objective being to achieve the climate neutrality. For the integration of these productive capacities in the energy sector, it is necessary to increase the storage possibilities, but the costs for the implementation of the currently available electricity storage technologies exceed the benefits brought by them (Abrell et al., 2019). Under these conditions, for the energy system to be maintained at normal parameters (frequency of 50Hz in Europe), demand and supply must always match, and only one of the two parameters that can be controlled is the second of them. Thus, each state has at least one system operator that automatically controls the production of electricity that is put into the system. This practice is hampered by some renewable energy sources, such as wind farms, which cannot be fully controlled by operators (Sims et al., 2011).

The national energy mix can be compared to an asset portfolio, the risk of which is determined by the volatility of its components. Its instability increases the balancing costs of national system operators. Zipf and Most (2013) argue that the volatility of production differs from one type of production capacity to another, specifying that some of them would have a positive effect on the portfolio, while others would reduce its return.

Ketterer (2014) argues that the resilience of the electric power system is crucial in the case of European states' intention to increase the contribution of renewable sources to the energy mix. This condition can be met by integrating intermittent production capacities (solar power, tidal power, wave power, etc.). Moreover, a high degree of stability in this economic sector would also increase its attractiveness for investors (Dixit and Pindyck, 1994).

The impact of the volatility of daily electricity production on its price is also revealed by Da Silva and Horta (2019), who showed that greater intraday variations of variable generation sources cause greater price fluctuations for them. Basically, the increase in the degree of destabilization of the energy system causes the transmission operator to invest more in the purchase of energy for balancing, generating an increase in prices on the spot markets. Going even further, Soini (2021) claims that the instability of energy production from renewable sources can even create some non-competitive advantages for dispatchable energy producers, who can calibrate their offers on the balancing market according to the yield given by volatile sources. Thus, if renewable energy production occupies a high percentage of the energy mix, in periods of low efficiency, dispatchable operators can force the system operator to buy energy at overestimated prices.

Impram et al. (2020) argue that the flexibility of national transport systems is in fact the objective to be pursued to solve the problems related to the integration of renewable energy sources. This feature ensures the ability to adapt to the supply-demand ratio in the market and prevents a collapse. Renewable energy sources, being unpredictable and volatile, put pressure on the system, which needs to become more flexible in order to integrate them. However, for the system to be able to adapt, since energy is not storable, it is necessary to increase the forecasting capacity of production in the context of the increasing importance of risky renewable energies (Shen and Ritter, 2015).

The issue of volatility of renewable energy has been addressed more and more often in the specialized literature in the last decade, both from the point of view of production and price. After Brown et al. (1984) used autoregressive models to forecast wind speed and wind power in the Pacific Northwest, more and more applications of these models have been used for many similar forecasts. Autoregressive models have also been used on a smaller scale. ARCH models have been applied by Tastu et al. (2014) for an offshore wind farm in Denmark. Also, Lau and McSharry (2010) used ARIMA and GARCH models to predict wind power production from a few minutes to a few hours before. However, GARCH-class models have been used too rarely in the energy field, even with regard to renewable energy stocks, which may lead to errors in risk assessments for investors (Wang et al., 2022). This is a literature gap that requires more and more diverse studies to be covered.
In the case of Romania, the country where the present research is applied, the percentage of energy from renewable sources in the national mix increased between 2000 and 2016 by 1.6% per year, while in the other states of the European Union it increased by 4.6% per year (Cîrstea et al., 2018). This increase is due to European policies aim to achieve climate neutrality in the community space and put considerable pressure on national power systems (Lund and Kempton, 2008). The Paris Agreement increased the global awareness of climate change and further boosted the advance of European states in renewable energy investments, making them to redistribute percentages of their GDP to achieve climate neutrality goals (Khan et al., 2021).

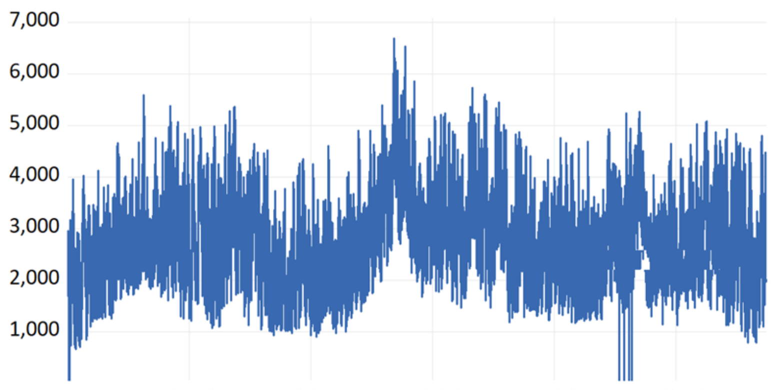
The social pressure for the implementation of renewable energy projects has increased considerably and the local social acceptance is one of the most important factors that impacts the green energy projects (Segreto et al., 2020), so European authorities will face more and more requests to connect these new sources to the national power system.

3. Research Methodology

The ARCH model was first introduced by Robert Engle in 1982 and is most often used to model the volatility of time series in the financial field. This model is very attractive to financial analysts, who can use it to forecast the future variations of some indices based on their evolution in previous periods. ARCH (q) model supposes that the conditional forecast variance depends on past data. Specifically, the conditional variance is determined by the squared past values of q (Engle, 1982). Later, the equation introduced by Engle (1982) was developed, and several methods were created to estimate the volatility of time series. One of them is the Generalized autoregressive conditional heteroskedasticity model, GARCH (p.q), introduced by Bollerslev in 1986, much more efficient than its predecessor. In its case, p shows that the dispersion is influenced by residual terms from the past, and q shows that the current dispersion is influenced by the previous one (Bollerslev, 1986). One of the models built on the basis of GARCH is the so-called Exponential Generalized Autoregressive conditional heteroscedastic model, EGARCH (p.q), introduced by Daniel Nelson in 1991. The main advantage of this variant is that it does not impose any restriction on the parameters, due to the fact that in the equation is introduced the logarithmic variation instead of the simple one, its positivity being guaranteed. Usually, the model is faster to apply and more reliable than ARCH and GARCH (Nelson, 1991).

To analyse the volatility of renewable energy sources, public data provided by Transelectrica (Romanian transmission system operator) was collected for electricity consumption from 01.01.2020 to 01.09.2022 and renewable energy production, calculated as the sum of wind, photovoltaic, hydropower and biomass energy production. Using the EVIEWS 12 software, the graph (***Figure 1***) was created for the production of electricity from renewable sources during the analysed period, marked by RE_P.

Figure 1. RE_P Graphic (MW)



Source: author's research based on Transelectrica's data.

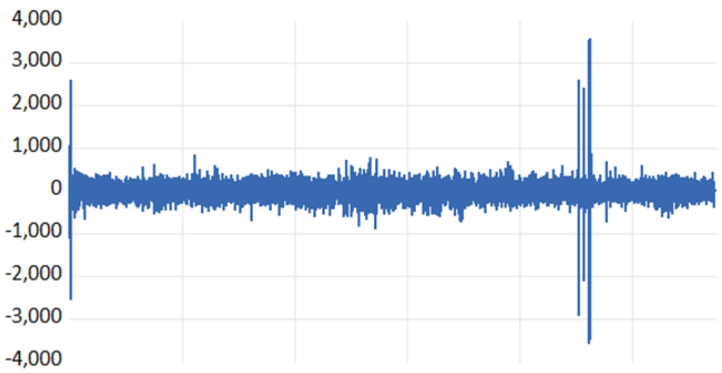
Considering the large number of terms, in order to eliminate the possibility of the existence of trends that determine the non-stationarity of the series, the D_RE_P series was generated. It represents the first difference (the change in value from one point in the series to the next point) of the RE_P series, calculated according to the formula:

$$y_t = y_t - y_{t-1}$$

where y_t and y_{t-1} represent the consecutive terms of the RE_P series.

Using the software program EVIEWS 12, the graph for D_RE_P was made (***Figure 2***).

Figure 2. D_RE_P Graphic



Source: author's research based on Transelectrica's data.

To confirm that the D_RE_P series is stationary, so that the ARCH and GARCH models could be applied, there was used the Augmented Dickey-Fuller test and the Phillips-Perron test to identify the existence of possible unit roots.

In the case of the Augmented Dickey-Fuller test, the null hypothesis is tested, according to which α=1, where α is the coefficient of the first lag in the equation:

$$y_t = c + \beta t + \alpha y_{t-1} + \varphi \Delta Y_{t-1} + e_t$$

where y_{t-1} is the first term of the time series, and ΔY_{t-1} it is the first difference of the time series t-1.

For a higher degree of accuracy, it was also applied the Phillips-Perron test, whose null hypothesis is that p=1 in the equation:

$$\Delta y_t = (p-1) y_{t-1} + y_t,$$

where Δy_t is the first difference operator.

The Phillips-Perron test could invalidate the Augmented Dickey-Fuller test, if the process generating data for y_t had a higher degree of autocorrelation than is allowed in the above equation, making y_{t-1} endogenous.

The concept of ARCH refers to stationary time series with volatility that changes over time conditioned by past lags. Specifically, in the case of ARCH models, the variation depends on past squared innovations.

The formula for the ARCH (1) is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \gamma_{t-1}^2 ,$$

where $\alpha_0 > 0$ $și$ $\alpha_1 \geq 0$.

In the case of the ARCH test, the null hypothesis (H_0) assumes that $\alpha_1=0$ and the alternative one (H_1) that $\alpha_1 \neq 0$.

The GARCH models were first introduced by Bolleslev (1986) and is much more generalized than ARCH. These models are conditionally heteroskedastic, but they benefit from a constant unconditional variance (Baybogan, 2013). Engle (2001) claims that the use of GARCH (Generalized ARCH) models are more efficient than ARCH models for large series of numbers. In the case of the GARCH (1.1) model, the variance is a function consisting of an intercept, a prior shock, and the variance from the last period. The conditions to be fulfilled by the GARCH model are that the coefficients of the variation equation are positive, and their sum is less than 1.

The formula of the GARCH model (1.1) is:

$$\sigma_t^2 = \omega + \alpha_1 y_{t-1}^2 + \beta_1 \sigma_{t-1}^2 ,$$

where $\omega > 0$, $\alpha_1 \geq 0$ and $\beta_1 \geq 0$.

In order to identify the most suitable model for the analysed series, we also applied the EGARCH model, introduced by Nelson (1991), which specifies the conditional variation in logarithmic form, without the need to impose constraints to avoid the negative variant. The representative formula for the EGARCH model is:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right]$$

4. Results

Applying the Augmented Dickey-Fuller test (***Table 1***), it is observed that the absolute value of the t-Statistic (65.58606) is greater than all critical levels (1%, 5% and 10%), and the probability that the null hypothesis (RE_P has a unit root test) to be true is well below the 0.05 threshold. In this context, it can be assumed that the series is stationary.

Table 1. Stationarity tests

Test used		**Augmented Dickey-Fuller**		**Phillips-Perron**	
		t-Statistic	**Probability**	**Adjusted t-statistic**	**Probability**
		-65.58606	0.0001	-359.3985	0.0001
Test critical values	**1% level**	-3.430227		-3.430227	
	5% level	-2.861370		-2.861370	
	10% level	-2.566720		-2.566720	

Source: Author's own research.

Applying the Phillips-Perron test (***Table 1***) it is observed that the absolute value of the adjusted t-Stat (359.3985) is higher than the critical thresholds, and the probability of the null hypothesis is 0.0001, as in the case of the previous test. Thus, it can be concluded that D_RE_P is stationary.

Table 2. Heteroskedasticity Test: ARCH

	D_RE_P
F-statistic	43096.56
Obs. R-squared	33139.39
Probability F (1,143425)	0
Probability Chi-Square	0

Source: Author's own research.

By testing for ARCH effects (***Table 2***) it emerged that the F-statistic is significant, prob. F being 0. Under these conditions, we can reject the null hypothesis (H_0), according to which there are no first level ARCH effects, so there can be proceeded to estimate ARCH/GARCH models.

Table 3. ARCH (1), GARCH (1.1) and EGARCH (1.1) Variance Equations

Variable	**Coefficient**	**Std. error**	**z-Statistic**	**Prob.**
ARCH (1)				
C	4522.229	2.269145	1992.922	0.0000
RESID(-1)^2	0.181022	0.001336	135.4900	0.0000
GARCH (1.1)				
C	727.8047	2.867958	253.7711	0.0000
RESID(-1)^2	0.122119	0.000727	168.0586	0.0000
GARCH(-1)	0.756695	0.000939	806.1704	0.0000
EGARCH (1.1)				
C(3)	0.930297	0.004590	202.6943	0.0000
C(4)	0.230113	0.000902	255.2092	0.0000
C(5)	-0.024928	0.000445	-56.04840	0.0000
C(6)	0.872485	0.000587	1487.087	0.0000

Source: Author's own research.

The result of the ARCH (1) model shows that the value of RESID(-1)^2, which represents γ_{t-1}^2 in the ARCH (1) equation is 0.181022, indicating quite a small variation considering that it can take values from 0 to 1. On the other hand, RESID(-1)^2 is positive and the p-value is 0, so the model may be correctly estimated.

Using EViews 12 to estimate the volatility of the D_RE_P series (***Table 3***), it turned out that the term RESID(-1)^2 (y_{t-1}^2) has the value 0.122119, and the term σ_{t-1}^2 has the value 0.756695, both being positive. Also, both ARCH and GARCH parameters are highly significant (p-value = 0). The sum of the two terms is 0.878814, a value very close to 1, which means that shocks to the conditional variance are very persistent.

Applying EGARCH (1.1) model it must be specified that C(3) is a constant (ω), C(4) is the ARCH term (the last term of the equation), C(5) represents the leverage effect (the third term of equation) and C(6) is the GARCH term (the second term of the equation). The result of applying the EGARCH (1,1) model can show us how negative or positive events (the so-called bad news or good news) affect the evolution of the D_RE_P series.

The ARCH term, C(4), is significant (p-value = 0), so the size of the shock has a significant impact on the volatility of the renewable energy production. Moreover, C(4) is positive, so the relation between the past variance and the current variance in absolute value is positive. Under these circumstances, bigger shocks to the variance determine a higher volatility. While C(5) is negative (-0.024928), the bad events (so named bad news), like dryness, low winds or cloudy days, have a bigger impact on the volatility than the good events (constant strong wind, heavy rains, etc.). Also, the C(6) term shows a very high persistence of past volatility and its p-value is also 0, so we can predict the future volatility based on the past volatility.

To validate the models, the Nyblom Parameter Stability Test (***Table 4***) was performed, which indicates that the parameters are stable (above 0.05) for all the asymptotic Critical Values (1%, 5% and 10%). Subsequently, the Engle-Ng Sign-Bias Test was applied. Its null hypothesis is that the models are correctly specified. The test results indicated probabilities well above the 0.05 threshold for Sign-Bias, Negative-Bias, Positive-Bias, and Joint-Bias for all three models. To check whether the residuals of the series still have ARCH effects after the estimation of the models, the ARCH LM Test was performed. From it resulted that the residuals no longer present ARCH effects, so the models were correctly estimated.

Table 4. Testing the results

		ARCH (1)	GARCH (1.1)	EGARCH (1.1)
Nyblom Parameter Stability Test	**1% Crit.**	0.748	0.748	0.748
	5% Crit.	0.470	0.470	0.470
	10% Crit.	0.353	0.353	0.353
Engle-Ng Sign-Bias Test	**Sign-Bias**	0.2685	0.4540	0.7041
	Negative-Bias	0.4362	0.2109	0.5528
	Positive-Bias	0.4252	0.5248	0.4169
	Joint-Bias	0.0725	0.0925	0.7716
ARCH LM Test	**p-value**	0.6472	0.3610	0.8441

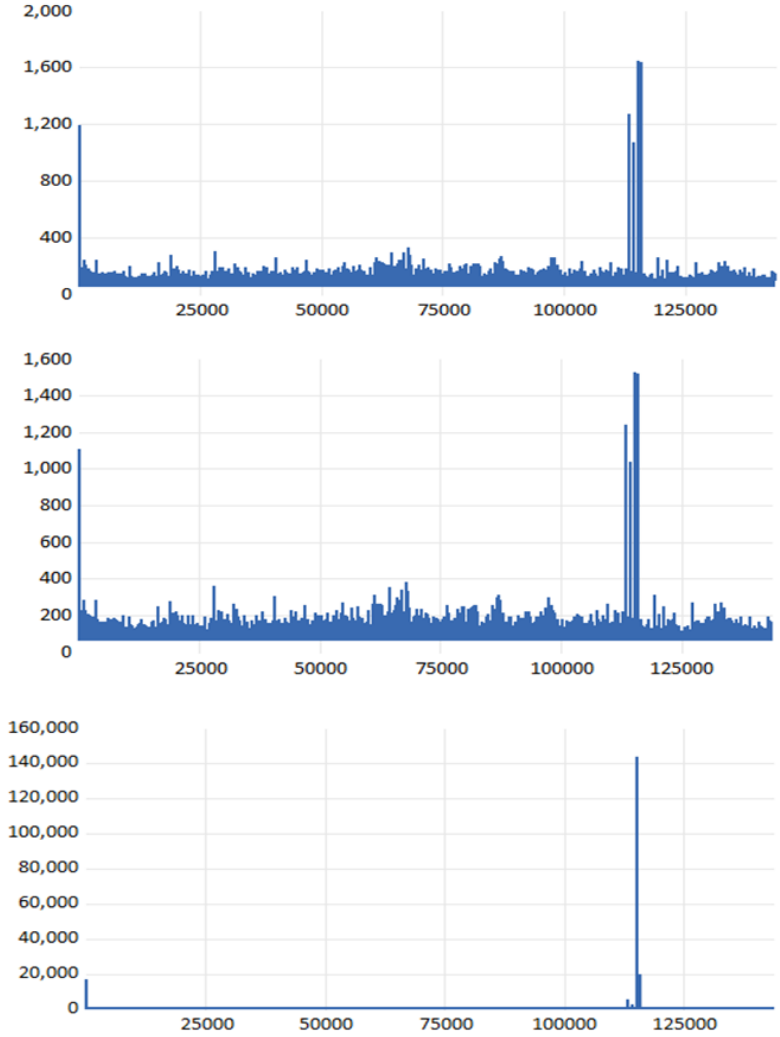
Source: Author's own research.

Figure 3. Conditional standard deviation for D_RE_P using ARCH (1), GARCH (1.1) and EGARCH (1.1)

ARCH (1)

GARCH (1.1)

EGARCH (1.1)



Source: author's own research.

The higher the standard deviation, the higher the volatility of the data series. So, an increase in standard deviation means that there is an increase in risk associated with the analyzed data. In ***Figure 3***, which illustrates the results obtained by applying the autoregressive models, we can observe the volatility clusters and the high instability of the analyzed series.

Table 5. Regression Statistics of Return

	ARCH (1)	**GARCH (1.1)**	**EGARCH (1.1)**
R-squared	-0.000179	-0.000423	-0.001009
Adjusted R-squared	-0.000179	-0.000423	-0.001016
S.E. of regression	75.06294	75.07211	75.09460
Sum squared resid	8.08E+08	8.08E+08	8.09E+08
Log likelihood	-816957.9	-814856.0	-813424.0
Durbin-Watson stat	1.897634	1.897170	2.136741
Mean dependent var	-0.002649	-0.002649	-0.002656
S.D. dependent var	75.05622	75.05622	75.05649
Akaike info criterion	11.39193	11.36263	11.34277
Schwarz criterion	11.39214	11.36291	11.34319
Hannan-Quinn criterion	11.39199	11.36272	11.34290

Source: Author's own research

The comparison of the three applied models, having as analysis criteria Log likelihood, Akaike info criterion, Schwarz criterion and Hannan-Quinn criterion, shows that the most effective model in the case of the D_RE_P series was the EGARCH, which recorded the highest value of Log likelihood and the lowest values for the other criteria.

5. Discussion

The research results confirm the effectiveness of autoregressive models for measuring the volatility of renewable energy production in Romania, where unstable sources, such as wind farms, occupy significant percentages (sometimes over 30%) of the national mix. Tastu et al. (2014) highlight the increased volatility of the production of onshore wind farms compared to that of offshore turbines, where the wind is more constant. In the case of Romania, such capacities have not yet been developed and they could be a solution to reduce the instability of green energy.

The efficiency of ARIMA-GARCH models is also revealed by Lau and McSharry (2010), who used them to forecast wind energy production from 64 onshore and offshore perimeters in Ireland. These exceeded the accuracy of all other methods used in their study. Autoregressive models can be similarly used in Romania to increase the adaptability of the power system by scheduling production from renewable sources, not by increasing imports from neighbouring countries, as is the current case.

GARCH models have been successfully used in this field by Shen and Ritter (2015), who show that the Markov regime-switching (MRS) GARCH model was the most suitable for estimating the volatility of wind energy production in a German park. Satisfactory results were also recorded in that case by the EGARCH model, which had the best fit in the present study. Thus, it can be observed that in different cases, several types of autoregressive models fit better, but not always the same one is the most suitable. In these conditions, it is recommended to use several of them in order to be able to choose the most effective one.

In the case of renewable energy, high volatility translates into high balancing costs, a fact specified by Abrell et al. (2019), who claim that the solution would be to increase storage capacities but admits that the technical solutions are currently uncertain and the costs are very high. The present study reinforces the idea that green energy sources affect the stability of the system and increase the amount of energy needed to balance it, thus making it even more expensive.

Not all the producers can participate at the balancing power market and renewable energy operators are rarely found, with the exception of hydropower producers. As Soini (2021) states, they must be very flexible, with the ability to supply the network a few minutes after notification, so they use conventional and more polluting power. The high volatility of renewable sources increases the energy requirement for the balancing market, a context in which the abandonment of polluting energy can only be done by increasing the forecasting time of consumption and production, so that the system operator knows long in advance how much energy it needs.

6. Conclusion

The contribution to the national energy mix of renewable energy sources fluctuates strongly depending on weather and climate conditions. These natural factors affect the production of renewable energy similar to how positive or negative news impact the stock market indices. In this context, balancing the national energy system, where the share of renewable sources often exceeds 20%, becomes difficult, expensive, and dependent on conventional production capacities.

The result of applying the EGARCH model, the one that best fitted the analyzed time series, shows that the stronger the shocks, the more they generate a stronger volatility. In conclusion, the greater the decline in production, the more difficult and long its return to normal. Furthermore, the analysis shows that after production declines recovery is more difficult than in the case of production increases, indicating that balancing the system requires the use of conventional sources or imports for long periods of time.

If in the case of portfolios of financial assets, the risk generated by volatility can be reduced by diversifying the components, in the case of the energy mix this strategy is not valid, since the technology has not evolved enough to allow the production of energy from countless sources. Currently, the renewable sources that produce enough energy to make their operation cost-effective are hydropower plants, solar panels, wind turbines and biomass processing plants. Other technologies, such as inertial sea wave energy converters, have been developed in recent decades, but they have not evolved enough to be used on a large scale. Thus, the options for the production segment are still limited.

Currently, to balance energy systems in periods of low productivity from renewable sources, conventional production capacities (natural gas or coal power plants or nuclear plants) are used, whose production is always constant, but polluting and increasingly expensive as a result of the European Union's policies to discourage investment in them. In this context, aggravated by the current energy crisis, the balancing activity is expensive for the system operator and, above all, for the final consumer.

However, there are alternatives, in the medium and long term, to reduce the risks and the most effective is to increase the transport and interconnection capacities of the national energy systems, so that they have the technical capacity to integrate as many renewable sources as possible from as many geographical areas as possible. In this way, in situations where a region is affected by a production deficit, energy can be delivered from an area with a surplus and vice versa, without the need to use polluting sources.

The larger the interconnected area and the larger and more varied the installed production capacities, the lower the impact of production volatility, making it possible to balance the system through imports of green energy, not conventional, as is often the case today. This method requires considerable investment in transport infrastructure and a harmonization of national legislation at the European level, as well as an assumption of increased technological costs, as a result of transporting energy over longer distances, but it could be the only way for successful implementation of the European Union's policies to achieve climate neutrality by 2050.

The main limitation of the study is the fact that the models were applied to the total production of renewable energy from January 2020 to September 2022 and not separately, for each type of source. Although all these production capacities are unstable, the degree of volatility differs from one to another. For example, wind energy production is much more volatile and harder to predict than that from photovoltaic panels. However, the objective of the research was to analyze the entire green energy sector and to show the usefulness of autoregressive models. Another limitation of the study is represented by the large amount of hydropower available in Romania, which, although it is part of the renewable category, is one with a constant efficiency. Excluding it, as would happen in periods of drought, the volatility of green energy production could be much higher.

For further researchers, it would be useful to separately analyze the volatility of green energy sources and simulate a low-risk and profitable portfolio for producers, which would provide energy as constantly as possible for their customers.

References:

Abrell, J., Rausch, S., & Streitberger, C. (2019). Buffering volatility: Storage investments and technology-specific renewable energy support, *Energy Economics*, 84(1), 104463.

Arora, A., Schroder, B. (2022). How to avoid unjust energy transitions: insights from the Ruhr region. *Energy. Sustainability and Society*, 12, 19.

Baybogan, B. (2013). Empirical Investigation of MGARCH Models. *Journal of Statistical and Econometric Methods*. 2(3), 75-93.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307-327.

Brown, B., Katz, R., Murphy, A., (1984). Time Series Models to Stimulate and Forecast Wind Speed and Power. *Journal of Climatology & Applied Meteorology*. 23(8), 1184–1195.

Cîrstea, Ș., Martiș, C.S., Cîrstea, A., Constantinescu-Dobra, A., Fulop, M.T. (2018). Current Situation and Future Perspectives of the Romanian Renewable Energy. *Energies*, 11(12), 3289.

Da Silva P., Horta P. (2019). The effect of variable renewable energy sources on electricity price volatility: the case of the Iberian market, *International Journal of Sustainable Energy*, 38(8), 794-813.

Dixit, A., & Pindyck, R. (1994). *Investment under uncertainty*. Princeton University Press, Princeton.

Engle, R. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of Variance of United Kingdom Inflation. *Econometrica*, 50(4), 987-1007.

Engle, R. (2001). GARCH 101: An Introduction to the Use of ARCH/GARCH models in Applied Econometrics. *Journal of Econometrics*, 15(4), 175-168.

Hoffman, J., Davies, M., Bauwens, T., Spath, P., Hajer, A. M., Arifi, B., Bazaz, A., Swilling, M. (2021). Working to align energy transitions and social equity: An integrative framework linking institutional work, imaginaries and energy justice. *Energy Research & Social Science*, 82, 102317.

Impram, S., Nese, S.V., Oral, B. (2020). Challenges of renewable energy penetration on power system flexibility: A survey. *Energy Strategy Reviews*, 31, 100539.

Ketterer, J. C. (2014). The impact of wind power generation on the electricity price in Germany. *Energy Economics*, 44, 270-280.

Khan, A., M., Kwiatkowski, J. K., Osinska, M., Blazejowski, M. (2021). Factors of Renewable Energy Consumption in the European Countries – The Bayesian Averaging Classical Estimates Approach. *Energies*, 14(22), 7526.

Lau, A., McSharry, P. (2010). Approaches for multi-step density forecasts with application to aggregated wind power. *Annals of Applied Statistics*, 4(3), 1311-1341.

Lund, H., Kempton, W. (2008). Integration of Renewable energy into the transport and electricity sectors through V2G. *Energy Policy*. 36(9), 3578-3587.

Maradin, D. (2021). Advantages and Disadvantages of Renewable Energy Sources Utilization. *International Journal of Energy Economics and Policy*, 11(3), 176-183.

Nelson, D.B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, 59, 347-370.

Rintamaki, T., Siddiqui, A.S., Salo, A. (2017). Does Renewable Energy Generation Decrease the Volatility of Electricity Prices? An Analysis of Denmark and Germany. *Energy Economics*, 62, 270-282.

Shen, Z., Ritter, M. (2015). Forecasting volatility of wind power production. Discussion Paper 2015-026. *Economic Risk*. Berlin. https://d-nb.info/1204920923/34.

Segreto, M., Principe, L., Desormeaux, A., Torre, M., Tomassetti, L., Tratzi, P., Paolini, V., Petracchini, F. (2020). Trends in social acceptance of renewable energy across Europe – A literature review. *International Journal of Environmental Research and Public Health*, 17(24), 9161.

Sims, R., Mercado, P., Krewitt, W., Bhuyan, G., Flynn, D., Holttinen, H., Jannuzzi, G., Khennas, S., Liu, Y., O'Malley, M., Nilsson, L.J., Ogden, J, Ogimoto, K., Outhred, H., Ulleberg, Ø., van Hulle, F. (2011). Integration of Renewable Energy into Present and Future Energy Systems. IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Soini, V. (2021). Wind power intermittency and the balancing power market: Evidence from Denmark. *Energy Economics*, 100, 105381.

Tastu, J., Pinson, P., Trombe, P. J., Madsen, H. (2014). Probabilistic forecasts of wind power generation accounting for geographically dispersed information. IEEE Transactions on Smart Grid, no. 5, 480-489.

Wang, L., Wu, J., Cao, Y., Hong, Y. (2022). Forecasting renewable energy stock volatility using short and long-term Markov switching GARCH-MIDAS models: Either, neither or both?. *Energy Economics*, 111, 106056.

Zipf, M., & Most, D. (2013). Impacts of volatile and uncertain renewable energy sources on the German electricity system. 10th International Conference on the European Energy Market (EEM), Stockholm. https://ieeexplore.ieee.org/document/6607397.