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Quantifying the Impact of Risk on Market Volatility and Price: Evidence from the Wholesale Electricity Market in Portugal

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Abstract: This research aims to identify suitable procedures for determining the size of risks to predict the tendency of electricity prices to return to their historical average or mean over time. The goal is to quantify the sensitivity of electricity prices to different types of shocks to mitigate price volatility risks that affect Portugal's energy market. Hourly data from the beginning of January 2016 to December 2021 were used for the analysis. The symmetric and asymmetric GARCH model volatility, as a function of past information, help to eliminate excessive peaks in data fluctuations. The asymmetric model includes additional parameters to separately obtain the impact of positive and negative shocks on volatility. The MSGARCH model is estimated to be in two states, allowing for transitions between low- and high-volatility states. This approach effectively represents the significant impact of shocks in a high-volatility state, indicating an acknowledgment of the lasting effects of extreme events on financial markets. Furthermore, the MSGARCH model is designed to obtain the persistence of shocks during periods of elevated volatility. Accurate price forecasting aids power producers in anticipating potential price trends and allows them to adjust their operations by considering the overall stability and efficiency of the electricity market.

Keywords: electricity price; symmetric and asymmetric GARCH models; volatility; Markov-switching GARCH model; electricity market

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1. Introduction

The price of electricity is considered one of the most volatile financial assets due to its constant fluctuations in response to supply and demand dynamics. Moreover, electricity prices are interconnected, and significant global events can produce shocks that have a widespread impact on countries' economies and financial systems [1]. Indeed, geopolitical events, natural disasters, and disruptions to production facilities, refineries, or transportation routes can trigger price spikes. These disruptions can result in a temporary supply shortage and a rapid price increase. Increased electricity flow, facilitated by an efficient transmission system, can lead to more stable day-ahead electricity prices, thereby reducing market volatility [2].

Significant price movements in financial markets can have extensive effects. Rapid and extreme price changes can affect the overall stability of a financial system and the economy, making it challenging for investors to buy or sell assets at desired prices. High fluctuation is often associated with higher risk and extreme price variations [3]. A global economic downturn affects various industries and markets. Reduced consumer spending, declining corporate profits, and lower trade volumes can create an adverse economic environment (negative news). Investors often respond by selling assets. This situation can lead to a decline in stock prices and negative price fluctuations. Positive news and a belief in continued economic growth can attract investors to the market, leading to increased buying activity and upward price movements [4].

This research aims to analyze the hourly electricity prices in Portugal from 2016 to 2021 using time series models and the day-ahead electricity market. This approach allows for determining the magnitude of risks associated with electricity prices and investigating the persistence of high or low volatility. This objective also involves assessing price volatility and identifying factors that can provide insights into how market conditions, regulatory measures, or other interventions can be adjusted to promote market stability.

It is important to note that financial markets can experience changes in volatility structure over time. During periods of uncertainty or market stress, volatility can increase significantly. High fluctuation indicates a rapid change in volatility levels and price increases in financial markets. Indeed, quantifying risks is essential for energy traders, investors, and risk managers to make informed decisions and develop effective strategies to mitigate risks. If a model does not account for this increased volatility, it may underestimate the risk and fail to predict significant price swings accurately.

Therefore, this research uses hourly data from 1 January 2016 to 31 December 2021 to create a data model. A generalized autoregressive conditional heteroskedastic (GARCH) model measures the variation in price trends and previous movements to anticipate how factors such as economic indicators and market trends impact the level of unanticipated news and potential losses. This case includes extended perception, leverage effects, and short-term and long-term forecasting of shock effects in financial markets.

This research innovates using Markov-switching models to analyze extended periods of high or low instability in financial markets. Considering the impact of shocks in a high-volatility state that may persist for a significant period, these models provide a more accurate estimation of electricity price fluctuations. The decision to employ two regimes in the model helps to consider the issue of extreme values, tail fatness, and outliers in volatility estimation. As a result, the market becomes more predictable [5].

This study attempts to answer the following triple research question: (i) What is the impact of shocks on the average electricity price? (ii) Which type of event, positive or negative, has the most significant effect on financial market volatility? (iii) Does the electricity price volatility that has occurred in recent years influence market stability today?

This study has implications for understanding the resilience or stability of the system in the face of short-term disturbances. The observation that the effects of shocks become less significant as time follows suggests the system's tendency to return to its long-term trend [6]. In other words, while short-term shocks may cause deviations from the long-term trend, there is a tendency for the system to mitigate the impact of these disturbances. Positive overall trends in both states could be interpreted as a long-term trend of increasing values. This trend could be related to occurrences of volatility clustering. The remainder of the essay is formatted as follows: a literature review is presented in Section 2, the Portuguese electricity system is described in Section 3, the data and methods are reported in Section 4, the empirical outcomes are evaluated in Section 5 and discussed in Section 6, and the conclusions are presented in Section 7.

2. Literature Review

Byström [7] has investigated price spikes using the Peak-Over-Threshold (POT) approach to separate short-term variations from average price changes. Jump-diffusion models are commonly used for electricity pricing and assessing futures and forward contracts because they explain the dynamics of electricity prices. Barlow [8] has examined the potential of spike-diffusion models to represent mean reversion and price spike behavior in the Alberta and California energy markets. Janczura and Weron [9] have proposed models that reflect short-term reactions to fluctuating price spikes, illustrating mean-reverting behavior and "Up" and "Down" trends in price spikes.

Benjamin [10] has examined the once-a-week variations in 24 h electricity prices. He discovered that as nuclear power plants were gradually replaced with renewable energy sources (RES), there was an increase in volatility, particularly at night, and a decrease in volatility during specific daytime hours. According to Zalzar et al. [11], the limited interconnection capacity of the Iberian Peninsula with central European electricity markets may be a factor in the interconnection of electricity prices in the day-ahead and intraday markets. Maciejowska [12] and Rai and Nunn [13] have argued that unpredictable and uncontrollable electricity production intensifies electricity price volatility and causes undesirable variation and uncertainty, affecting market participants' profits.

Given the Portuguese power grid's sensitivity to renewable energy sources (e.g., [14,15]), it is crucial to consider implementing policy measures that encourage investment in stability and backup capacity. These measures could include providing financial incentives for storage and flexible generation operators or establishing a long-term capacity market that rewards generators for delivering reliable and secure electricity.

It is essential to enhance electricity price forecasting to eliminate the vulnerabilities of the Portuguese electricity system. One approach is to use statistical models like GARCH [16], as suggested by Weron and Ziel [17], to better predict the temporal structure of electricity prices and account for the asymmetric nature of these prices. Bollerslev et al. [18] have examined the impact of positive and negative return shocks on financial markets and found evidence of asymmetric volatility in electricity prices. Volatility tends to increase when negative returns occur, while it tends to decrease when positive returns occur. This phenomenon, known as asymmetric volatility, highlights the non-symmetric effects of positive and negative return shocks on market volatility.

However, these models have faced criticism in the literature for not adequately considering power sector dynamics and operations or incorporating regulation changes and market constraints. Furthermore, Lago et al. [19] argue that traditional forecasting methods may not be suitable for volatile and complex electricity markets. As a result, alternative models should be explored that are better suited for price formation in such markets.

Liu and Shi [20] and Xie [21] have evaluated different models for predicting the hourly fluctuations in electricity prices. They found that the ARMA and model-averaging methods were the most effective tools. On the other hand, Kochling et al. [22] showed that Gaussian distributions were the most reliable for the model confidence set, and Naimy and Hayek [23] found that EGARCH was best for predicting Bitcoin volatility.

Zareipour et al. [24] demonstrate how time series data and unpredictability similarity in the growth rates of electricity prices can be accurately modeled by GARCH processes. As a result, the authors can offer helpful insights into the volatility and mean patterns seen in the electricity markets. Furthermore, this study can be used to predict the current price of electricity in the Indian electricity market by using the GARCH model. Finally, Girish [25] evaluated the forecasting performance of autoregressive-GARCH models using the hourly price of the Indian spot electricity market from 1 October 2010 to 15 November 2013, and they concluded that these models' prediction performance is a suitable tool for estimating the average and conditional variance in a day's price.

3. Portuguese Electricity System

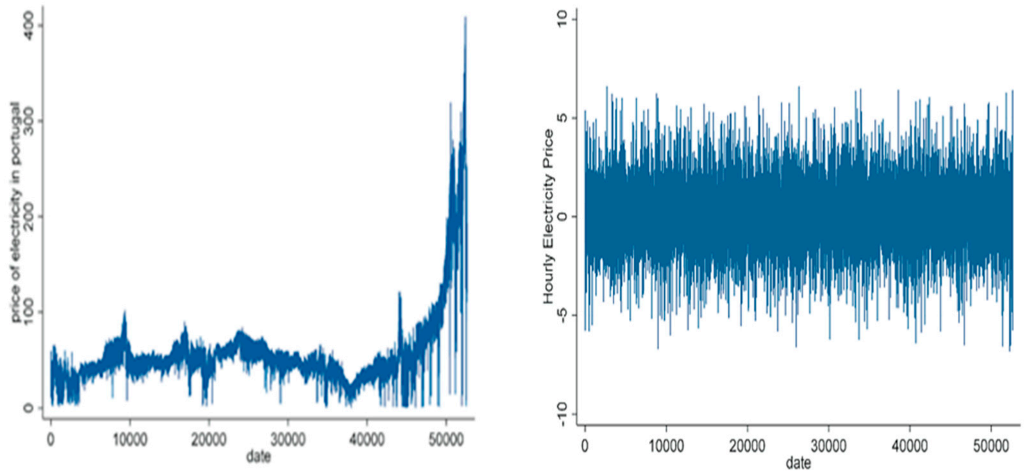
The Portuguese and Spanish electricity markets were combined in 2007 to establish the Iberian Market (MIBEL), an integrated electricity market. The MIBEL has an Iberian Market Operator (OMI) consisting of two distinct systems: the OMIP and the OMIE. The OMIE, also known as the Spanish Centre, organizes the day-ahead bidders and sets wholesale energy costs. On the other hand, the OMIP, or the Portuguese Centre, is responsible for managing the day and intraday markets and controlling the exchange of power-variant instruments such as futures, transfers, and forward contracts. Depending on the level of interaction between the two countries, the price may vary from country to country. Loureiro et al. [26] have noted that the Portuguese and Spanish governments should consider increasing their power capacity. The MIBEL encourages competition and comprehensive policy and procedure integration. However, this market is not very large due to its limited interconnectivity capacity.

To help reduce the risk of electricity supply disruptions, improve the efficiency of energy markets, and minimize price volatility, the implementation of a portfolio of policy instruments, as suggested by Macedo et al. [27], may promote the integration of renewable energy sources (RES) into the Iberian Electricity Market (MIBEL). Power Purchase Agreements (PPAs) and Constitutional Balance Maintenance Expenses are examples of long-term statewide agreements used to manage the power system in Portugal (CMEC). However, these schemes could make electrical grids less dynamic. Therefore, examining the influence of importing or exporting power on energy prices and their unpredictability in Portugal is crucial to preserving the stability of the MIBEL system and minimizing the effect of increased residential consumption on the electrical market.

4. Data and Method

4.1. Data

This study used high-frequency hourly data from the Portuguese electricity system (average of 24 h data) published for Portugal from 1 January 2016 to 30 December 2021. In the two samples shown in Figure 1, the hourly electricity prices are not initially stationary, meaning they do not have a constant mean or variance over time. This lack of stationarity can be attributed to various factors, such as changes in demand, weather conditions, and market dynamics. By taking the second-order difference variable, we can remove any trend or seasonality in the data, resulting in a stationary price log. The mention of "second-order difference" suggests that some form of mathematical transformation has been applied to the data. In this case, the kurtosis may decrease by this transformation, reducing the impact of extreme events. Figure 1 also exhibits that price movements are non-random, and that unexpected events or shocks can lead to sudden spikes in volatility. These shocks often have a lasting impact, causing volatility to remain elevated for an extended period as the market adjusts to new information. Investors typically prefer stability for long-term investment strategies as it reduces the uncertainty and potential for significant losses. The market stability indicated by the second-order difference may make it more appealing for investors seeking safer investment options.



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

Figure 1. (**a**) Non-logarithmic (not stationary). (**b**) Logarithmic (stationary) hourly electricity prices (1 January 2016–30 December 2021).

4.2. Value-at-Risk Example

Skewness suggests there may be outliers or extreme values in the dataset, leading to an asymmetric distribution. These outliers can heavily influence the mean and skew the distribution. It is crucial to consider the presence of outliers when interpreting skewness values, as they can significantly impact the overall shape of the distribution. Removing outliers may help reduce skewness and provide a more accurate data representation. Table 1 displays hourly stats; the highest skewed value in price is 3.463, indicating a significant price variation. The second-order difference of 0.328 further suggests that the price change rate is not constant, potentially indicating fluctuations in the market. The presence of non-zero rates of return indicates that the price fluctuations are not random. Kurtosis is a statistical measure that describes the tails of a distribution. A high kurtosis indicates heavy tails, meaning the distribution has more extreme values than a normal distribution. In the context of financial markets, there is a higher probability of extreme events. The different rates of returns are 18.39 and 10.814. It seems that taking the second difference has helped decrease the kurtosis. This transformation can help make the distribution more normal-like. Reducing the likelihood of price movements makes the market environment more stable and predictable.

Table 1. Portfolio data mean.

Variables	Mean	Std. Dev.	Min.	Max.	Sum of Wgt	Variance	Skewness	Kurtosis
$r = (\log p_t/p_{t-1})^2$	0.158	1.279	−4.605	4.578	52.600	1.636	−0.467	3.652
Price	57.265	41.402	1.018	409	52.541	1714.126	3.463	18.391

Notes: Std. Dev., Min., Max., and Perc. denote standard deviation, minimum, maximum, and percentile, respectively.

Standard deviation measures the dispersion of data points from the mean. A lower standard deviation of the second-order difference price (0.896) indicates less variability or risk than the initial price variable (41.402). Lower variability or risk implies greater stability in the market. Therefore, the market represented by the second-order difference is considered more stable than the one represented by the initial price variable.

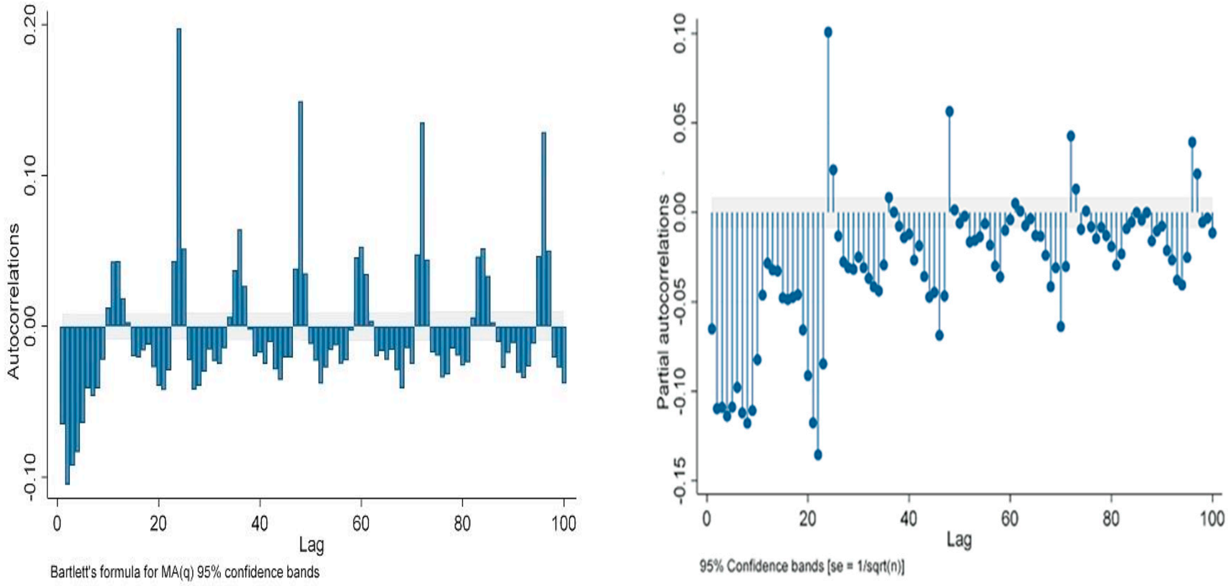
A mean value of 57.262 for the initial data indicates that, on average, the data points cluster around this central tendency. However, a mean value of 0 for the second-order difference does not imply minimal variation between the data points. Variance is a measure of the spread of values in a data set. In this case, the initial price variable initially had a variance of 1714.126, indicating a high degree of variability in the data points. However, after applying the second difference, the variance decreased substantially to 1.636. The data points, as is the mean, are now much closer to each other, indicating a more stable and consistent trend in the variable's values. The initial price variable likely has associated weights, and the sum of these weights reflects their total contribution to the calculation. The increase from 52.541 to 52.600 indicates only a minor shift in the overall weight calculation and may not significantly impact the analysis or interpretation of the data.

This study compares the performance of symmetric and asymmetric GARCH (p, q) models. Therefore, the difference price log variable $r = (\log p_t/p_{t-1})^2$ helps reveal the magnitude of the percentage change in the logarithm of prices over time. Including the initial price variable in the MSGARCH $(1, 1)$ model indicates a consideration for the starting values of the time series.

Min and Max values may represent the minimum and maximum electricity generation levels. Inflexible power generation refers to systems that cannot easily adjust their output levels in response to changing demand or production conditions. Grid instability can manifest as voltage fluctuations, frequency deviations, or even blackouts, especially during periods of high demand or sudden changes in generation. It may arise from a lack of capacity to store extra electricity and manage fluctuations in supply and demand. When supply exceeds demand, prices may drop; in extreme cases, they can even turn negative. Energy storage helps balance supply and demand, preventing negative prices and fluctuations [28].

4.3. Autocorrelation and Partial Autocorrelation Properties

Figure 2 displays the autocorrelation function (ACF), a statistical tool used for second-order difference variable log of price $r = \log (p_t/p_{t-1})^2$ to measure the correlation between a time series at different lags. A slowly decreasing ACF indicates that long-term dependence on the data means that past observations substantially affect future observations. In other words, the influence of past values extends across a wide range of periods. The slow decrease in ACF suggests that trends in the time series tend to persist over time. This occurrence could be due to various factors, such as seasonality, trends, or other underlying structures in the data.



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

Figure 2. Correlation chart for hourly electricity prices. (**a**) Autocorrelation function (ACF); (**b**) Partial autocorrelation function (PACF) hourly electricity prices (1 January 2016–30 December 2021).

The PACF plot helps identify the direct influence of each lag on the current observation. Significant spikes in the PACF at certain lags (lag 2) suggest that observations at those specific lags directly impact the current observation. This occurrence indicates short-term dependencies between observations at those lags, and it helps capture the immediate effects of past observations on future values. Incorporating appropriate lagged terms in the model based on the PACF analysis is essential for improving the forecasting accuracy.

4.4. Stability Check of Variables

Elliott et al. [29] have introduced the DF-GLS test as an improvement over the traditional ADF test, making it more reliable and robust in certain situations. This test statistic is compared to critical values from a distribution to determine whether to reject the null hypothesis of a unit root.

Engle's [30] Lagrange multiplier ARCH-LM test validates the existence of ARCH effects in the residuals by calculating an alternative ordinary least squares regression for the difference price log variable. Therefore, the GARCH technique is the best-suited model that matches conditional volatility.

4.4.1. Unit Root Test

The optimal number of lags was set at two based on the PACF (Figure 2). The Dickey–Fuller (GLS) test was used in the price return series. The findings prove that the series' t-statistics are far less than the critical values at the 1% significance level. The unit root null hypothesis was rejected after using a second-order difference variable price log. This result indicates that hourly electricity prices are stationary (see Table 2).

Table 2. Dickey–Fuller GLS test for unit root.

Test	Dickey–Fuller GLS for $\log(p_t/p_{t-1})^2$			
[lags]	DF-GLS	1% Critical	5% Critical	10% Critical
2	−81.225	−2.580	−1.950	−1.620
Min SIC = 0.0367399 at lag2 with RMSE 1.018224				

Notes: MacKinnon's approximate p-value for Z(t) = 0.0000; null hypothesis: hourly price time series has a unit root; exogenous: constant.

4.4.2. ARCH-LM Test

The first step is to select suitable ARCH (p,q) model p and q values obtained through autocorrelation and partial autocorrelation. The values of p = 0 and q = 2 indicate that the squared standardized residuals are best modeled with a moving average component in the of order two and no autoregressive. The ARCH test was used to detect autoregressive conditional heteroskedasticity in the residuals of a time series model up to two lags (see Table 3).

Table 3. LM Test for autoregressive conditional heteroskedasticity (ARCH).

ARCH-LM	chi^2	df	Prob > Chi^2
$price_{t-2}$	1227.954	2	0.000

Notes: H0: no ARCH (p) effects; H1: ARCH (p) effects.

4.5. Method

This study analyses wholesale power price features like mean reversion, unexpected spikes, seasonality, and volatility clustering. It uses symmetric and asymmetric models to model electricity price fluctuations. Comparing the MS-GARCH model with other models helps to identify the most effective approach for accurately capturing and predicting price fluctuations in Portuguese wholesale electricity prices.

4.5.1. AR–ARCH Model Specification

The autoregressive conditional heteroskedastic (ARCH) model, introduced by Engle [30], is specifically intended to represent the methodology that volatility in financial markets fluctuates over time. By integrating lagged squared errors into the model, the occurrence of periods of high and low volatility can be better explained by ARCH models, providing a more nuanced understanding of market dynamics. These models have been demonstrated to outperform traditional volatility measures, such as GARCH models, in forecasting accuracy and risk management strategies, making them a valuable tool for researchers and practitioners seeking to enhance their analysis of price movements. The model calculates the inflation means and variances, indicating that the current volatility depends on past observations. The key idea is that the variance in the error term in a financial return equation is not constant but varies over time. Equations (1) and (2) describe the model:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_q\varepsilon_{t-q} = \alpha_0 + \Sigma_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2 \tag{1}$$

Baillie and Bollerslev [31] have explained that the variation in error terms has been changed from the constant to a random sequence.

$$\varepsilon_t = \nu_t\sqrt{\alpha_0 + \sum_{i=1}^{p}\alpha_i\varepsilon_{t-i}^2} \tag{2}$$

Regression residuals, ε_t, and standardized residuals, ν_t, are independent and uniformly distributed (iid) random variables with zero mean and conditional variance. The distributional assumption is crucial in determining the best parameters for observed data, assessing the statistical significance of estimated coefficients, and validly inferring variable relationships.

The mean equation captures the time series' mean-reverting behavior, while the conditional variance equation describes the volatility clustering behavior of the time series. These initial ARCH models were developed to analyze and predict financial data volatility, which was crucial for predicting future profits. However, as research progressed, more advanced versions of the ARCH models were introduced to account for additional complexities and improve forecasting accuracy.

The ARCH term ε_{t-i}^2 assumes that positive and negative shocks have the same impact on conditional volatility. This case means it does not account for asymmetric effects in financial time series data, where positive and negative shocks may have different magnitudes or durations. Generalized autoregressive conditional heteroskedastic (GARCH) models were introduced to overcome this limitation. These models can generally be divided into symmetric and asymmetric GARCH models.

4.5.2. Generalized-ARCH Symmetric Model (GARCH)

Bollerslev [32] has modified the original ARCH into the GARCH model, the symmetric generalized autoregressive conditional heteroskedasticity (GARCH), providing precise knowledge of the structure of turbulence through modeling the volatility of financial returns using historical observations. Specifically, the GARCH models are concerned with managing the time-varying aspect of volatility, which is crucial for understanding and forecasting market movements. The general structure of GARCH (p, q) can be written as revealed by Equations (3)–(5).

$$Y_t = c + \delta X_t + \varepsilon_t \tag{3}$$

$$\varepsilon_t = \sigma_t^* z_t \tag{4}$$

$$\sigma_t^2 = \alpha_0 + \Sigma_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \Sigma_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{5}$$

where Y_t is the aggregate amount of the price of electricity; σ_t^2 denotes the conditional variance in Y_t; c and α_0 are constants; α_i and β_j denote the estimated coefficients; X_t, is the explanatory variables; ε_t is the error term; p and q denote the orders for GARCH and ARCH parameters, respectively; and z_t is a sequence of iid random variables with zero (0) mean and variance one (1).

Thus, in the general case, the conditional variance is described by Equation (5), where c denotes the constant term and the random error term of the previous period is ε_{t-i}^2. (i.e., ARCH term). The prediction variance in the previous period is σ_{t-j}^2 (i.e., GARCH item). α_i and β_j are the coefficients ε_{t-i}^2 of and σ_{t-j}^2, respectively. The weighted average of invariant variance α_0, the predicted value of variance in the previous period σ_{t-j}^2, and the residual square of the previous period are crucial for predicting the variance in the current period.

A GARCH (p, q) model is verified as stationary when $(z) = 1 - \beta_j z^i \ \alpha(z) = 1 + \alpha_i z^j$, lying outside the unit circle, and $\alpha_i + \beta_j < 1$ with $\alpha_i, \beta_j > 0$ to ensure that the unconditional volatility will always be positive. These parameters are crucial for understanding the dynamics of financial markets and predicting future volatility. By measuring the persistence of volatility, economists can assess the extent to which shocks or disturbances affect market stability over time. By considering these factors, GARCH models can more effectively capture the complex and dynamic nature of price fluctuations in financial markets. As a result, the precision of forecasting and risk management techniques improve, making them valuable tools for researchers and practitioners seeking to enhance their analysis of price movements. Studying the rate of convergence of conditional volatility to the long-term average level helps us to understand how quickly markets return to their equilibrium state after experiencing fluctuations.

If $\alpha_i + \beta_j \cong 1$, the series exhibits a strong tendency to gradually return to its previous levels after a spike or shock and has a high resilience to volatility. However, $\alpha_i + \beta_j < 1$ indicates that the series is highly unpredictable and does not exhibit long-term trends. The rapid decay of shocks suggests that any sudden changes in the series will have a short-lived impact, making it difficult to forecast future movements accurately. If $\alpha_i + \beta_j = 1$, it indicates non-stationarity and refers to a time series that does not exhibit a constant mean or variance over time. This lack of stability in the model's parameters can lead to unreliable forecasts and make it difficult to draw meaningful conclusions from the data.

4.5.3. Asymmetric Threshold GARCH (*p*,*q*) Model

The threshold GARCH (or TGARCH) model developed by Glosten et al. [33] and Zakoian [34] considers that previous positive or negative shocks may have an unbalanced impact on volatility. By analyzing the long-term dynamics of volatility shocks, these models may contribute perspective about the persistence of volatility over time. They can highlight how shocks today may impact volatility forecasts for extended periods. The general form of the TGARCH model is as follows:

$$\sigma_t^2 = c + \alpha_i \varepsilon_{t-i}^2 + \gamma_i \varepsilon_{t-i}^2 I_{t-i} + \beta_j \sigma_{t-j} \quad (6)$$

where α_i, β_j are the parameters measuring different volatility behaviors under varying market conditions. Indeed, by capturing these shifts, they provide a more nuanced understanding of how volatility changes in response to different triggers or thresholds, i.e., how volatility responds differently to negative shocks or positive shocks. This case implies that entities might react differently to positive or negative events, resulting in unpredictable responses. σ_{t-j} is the past conditional variance and γ_i, represents the asymmetric effect of negative shocks on volatility. Thresholds in GARCH models help capture non-linearities in mean and variance equations, allowing for a more flexible and accurate representation of volatility dynamics. This flexibility enables the model to adapt more effectively to market conditions and behaviors.

4.5.4. Asymmetric Exponential GARCH (*p*,*q*) Model

The EGARCH model introduced by Nelson [35] extends the traditional GARCH model and can interpret the coefficients to understand the impact of past shocks on current volatility. The following section outlines the methodology of the EGARCH model. Compared to traditional symmetric models, asymmetric GARCH models introduce the capability to model leverage effects, where downward movements in the market lead to greater volatility than upward movements of the same magnitude. This asymmetry is essential for capturing the complex behavior of financial assets and improving forecasting accuracy. Models like Threshold GARCH (TGARCH), Exponential GARCH (EGARCH), and Power GARCH (PARCH) have been developed to address these asymmetries and enhance the modeling of volatility dynamics.

Furthermore, asymmetric GARCH models can offer new insights by better reflecting the actual behavior of financial markets, where volatility is not constant and can vary significantly based on market conditions. By considering leverage effects, where stock price changes are negatively correlated with changes in volatility, they provide a more nuanced understanding of how volatility dynamics interact with market movements. Asymmetries in volatility responses provide a more realistic representation of price movements and improve risk management strategies by accounting for the impact of different market shocks on asset prices.

In summary, asymmetric GARCH models enhance the accuracy of capturing price volatility by incorporating asymmetries in market behavior, providing a more comprehensive understanding of financial markets than traditional symmetric models. Their ability to model leverage effects and different responses to positive and negative shocks offers valuable insights for researchers and practitioners seeking to improve their analysis of price movements and enhance risk management strategies.

$$\log\left(\sigma_t^2\right) = c + \Sigma_{i=1}^{p} g(z_{t-i}) + \Sigma_{j=1}^{q} \beta_j \log \sigma_{t-j}^2 \quad (7)$$

where $g(z_{t-i}) = \gamma_i z_{t-i} + \alpha_i[|z_{t-i}| - E|z_{t-i}|]$; $g(z_t) = \ln[z_{t-i}]$ for some b > 0. $\gamma[|z_{t-i}| - G|z_{t-i}|]$ helps to obtain the asymmetric response of volatility to positive and negative shocks in financial markets. Pantula and Geweke [36] first suggested this particular type of ARCH model.

Defining $z_{t-i} = \frac{\varepsilon_{t-i}}{\sigma_{t-i}}$, and taking the natural logarithms of the conditional variance, Equation (7) can be written as Equation (8):

$$\log\left(\sigma_t^2\right) = c + \Sigma_{j=1}^{q}\beta_j \log\sigma_{t-j}^2 + \Sigma_{i=1}^{p}\alpha_i\left(\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| - E\left(\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right|\right) + \Sigma_{i=1}^{p}\gamma_i\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right. \tag{8}$$

If $\gamma_i < 0$, negative shocks, such as economic downturns or unexpected events, usually have a more substantial and immediate impact on market volatility. On the other hand, positive shocks, such as encouraging economic data or positive news, have a relatively minor impact on market volatility. If $\gamma_i > 0$, the inverse leverage effect confirms the positive shocks' impact; if $\gamma_i = 0$, it implies that positive information can have just as much impact as negative information. The risk premium's magnitude may vary based on the specific context or individual preferences.

4.5.5. Markov-Switching GARCH (1,1)

The Markov-switching model introduced by Hamilton [37] is a statistical framework used to preserve state variations in financial time series data. The states are often associated with different levels of volatility. Market conditions and volatility patterns can change over time due to various factors.

$$z_t = \begin{Bmatrix} \alpha_0 + \beta z_{t-1} + \varepsilon_t,\ s_t = 0 \\ \alpha_0 + \alpha_1 + \beta z_{t-1} + \varepsilon_t,\ s_t = 1 \end{Bmatrix} \tag{9}$$

In Equation (9), $|\beta| < 1$ and ε_t are i.i.d. random variables with mean zero and variance σ_t^2. This case is a stationary AR(1) process with mean $\alpha_0/(1-\beta)$ when $s_t = 0$, and it changes to a different stationary AR(1) process with mean $(\alpha_0 + \alpha_1)/(1-\beta)$ when $s_t = 1$. Markov chains can provide valuable information about the probability of transitioning from one state to another. This information is crucial for predicting future states, and it reduces the limitations of relying solely on a single definition.

$$P = \begin{bmatrix} IP(s_t = 0|s_{t-1} = 0) & IP(s_t = 1|s_{t-1} = 0) \\ IP(s_t = 0|s_{t-1} = 1) & IP(s_t = 1|s_{t-1} = 1) \end{bmatrix} \tag{10}$$

In Equation (10), P_{ij} (i, j = 0, 1) denote the transition probabilities of s_t = j given that s_{t-i} = i. The transition probabilities satisfy $P_{i0} + P_{i1} = 1$. Only two parameters (P_{00} and P_{11}) exist in the transition matrix. These mechanisms help stabilize and prevent any extreme or unpredictable fluctuations in the behavior of the state variable. By examining the swings and instabilities of the GARCH models, as shown in Equation (11), this adjustment makes it easier to compare the magnitudes of different shocks, and heteroscedasticity in the data can be efficiently managed by using conditional standard deviations instead of conditional variances.

$$h_t = \alpha_{0s_i} + \alpha_{1s_i}\varepsilon_{t-1}^2 \tag{11}$$

In Equation (11), s_i indicates regimes that are volatile in either direction. Considering the impact of the previous and current regimes, this method thoroughly examines the correlation between the variables. Through expanding on the standard GARCH model, Grey and Klaassen [38,39] have suggested a two-regime Markov-switching (MS) GARCH. The Gray [39] type MS-GARCH $(1,1)$ model that we use has the following definition:

$$h_t = [\alpha_0]\varepsilon_{t-1}^2 + \beta_{1(s_t)}h_{t-1}\Big]|s_t = 0\ \Big[\alpha_0 + \alpha_{1(s_t)}\Big]\varepsilon_{t-1}^2 + \beta_{1(s_t)}h_{t-1}\Big]|s_t = 1 \tag{12}$$

In Equation (12), $s_t = 0$ denotes the less volatile market sector, while s_t = 1 shows the mean is higher than the previous state $\left[\alpha_0 + \alpha_{1(s_t)}\right]$, indicating a severe volatility regime. When $p = q = 1$, we have the GARCH $(1, 1)$ model.

$$h_t = c + \alpha_1 z_{t-1}^2 + \beta_i . h_{t-1} \tag{13}$$

Markov-switching GARCH models are flexible and adaptable to various market scenarios due to their ability to model different functional forms across regimes. This flexibility enables the model to adjust more effectively to changing market conditions and behaviors. The model can provide more realistic sensitivity forecasts by considering the impact of regime changes on conditional variance dynamics. The t-distribution is used when the sample size is small, as shown in Equation (13), which provides greater flexibility in modeling extreme events. This case is crucial in financial markets, where extreme events can significantly affect asset prices.

5. Empirical Results

A total of 52,614 observations collected over six years were used to estimate the number of GARCH (p, q) models. It should be emphasized that the reason for the negative electricity prices is a period of high costs and low profits, and outliers, often caused by unexpected shocks, provide valuable information about the market dynamics and help to refine the model's predictions.

5.1. Results of Symmetric GARCH Model

The results of estimating the symmetric ARCH (α_{t-2}), GARCH (β_{t-2}), and asymmetry terms specifications TGARCH (γ_{t-2}), EARCH $\left(\alpha\gamma_{t-2}\right)$, EGARCH $(\beta\gamma_{t-2})$, considering p = 0 and q = 2, stand for the number of lags of variances to be included in the models, which are reported in Tables 4 and 5. The GARCH error parameter, also known as the error terms of the ARCH component, measures the persistence and volatility of the shocks in the time series. Since the probability of its coefficient (except the constant) is less than 0.05, the error term has a normal distribution. This case means that the estimated parameters significantly affect the model's outcome. Significant coefficients indicate a strong relationship between past shocks and the level of volatility observed in today's market. In this case, the GARCH model captures the tendency of high- or low-volatility periods to persist over time and their potential impact on future volatility levels. When the coefficient is less than one, it implies that shocks have a lasting impact on the volatility of the financial time series. The market does not quickly revert to the initial level. Thus, shocks have a sustained effect on the conditional variance.

Table 4. Symmetric Model Regression.

$r = \log(p_t/p_{t-1})^2$	**Coef.**	**St. Err.**	**t-Value**	***p*-Value**	**[95% Conf**	**Interval]**	**Sig**
$price_{t-2}$	−0.111	0.005	−20.295	0	−0.126	−0.0998	***
C	0.019	0.003	5.848	0	0.013	0.0252	***
α_{t-2}	0.219	0.005	46.956	0	0.216	0.228	***
C	0.665	0.002	284.647	0	0.661	0.673	***
Mean dependent var		0.000	SD dependent var				0.896
Number of obs		52,597	Chi-square				411.710
Prob > chi^2		0.000	Akaike crit. (AIC)				136,053.441
$r = \log(p_t/p_{t-1})^2$	**Coef.**	**St. Err.**	**t-value**	***p*-value**	**[95% Conf**	**Interval]**	**Sig**
C	0.017	0.004	4.885	0	0.016	0.025	***
α_{t-2}	0.291	0.007	41.603	0	0.278	0.305	***
γ_{t-2}	−0.093	0.009	−10.576	0	−0.118	−0.075	***
β_{t-2}	−0.037	0.002	−21.834	0	−0.041	−0.034	***
C	0.692	0.003	223.437	0	0.686	0.698	***
Mean dependent variable		0.000	SD dependent variable				0.896
Number of obs		52,599	Chi-square				
Prob > chi^2			Akaike crit. (AIC)				136,380.531

Notes: The table reports the symmetric GARCH and TGARCH models *** $p < 0.01$.

Table 5. Asymmetric Model Regression.

$r = \log(p_t/p_{t-1})^2$	**Coef.**	**St. Err.**	**t-Value**	***p*-Value**	**[95% Conf**	**Interval]**	**Sig**
C	0.024	0.003	7.046	0	0.017	0.032	***
$\alpha\gamma_{t-2}$	−0.026	0.005	−5.519	0	−0.035	−0.017	***
$\alpha\gamma_{t-2} - A$	0.415	0.006	73.553	0	0.404	0.426	***
$\beta\gamma_{t-2}$	−0.048	0.008	−5.809	0	−0.064	−0.032	***
C	−0.195	0.004	−44.384	0	−0.204	−0.186	***
Mean dependent variable		0.000	SD dependent variable				0.896
Number of obs.		52,599					
Prob > chi^2		0.000	Akaike crit. (AIC)				135,481.006
$r = \log(p_t/p_{t-1})^2$	**Coef.**	**St. Err.**	**t-Value**	***p*-Value**	**[95% Conf**	**Interval]**	**Sig**
C	0.096	0.008	11.71	0	0.086	0.112	***
σ^2	−0.104	0.015	−10.93	0	−0.123	−0.085	***
α_{t-2}	0.221	0.004	49.50	0	0.212	0.236	***
β_{t-2}	−0.046	0.003	−16.79	0	−0.051	−0.042	***
C	0.707	0.004	195.11	0	0.735	0.714	***
Mean dependent variable		0.000	SD dependent variable				0.896
Number of obs.		52,599	Chi-square				119.381
Prob > chi^2		0.000	Akaike crit. (AIC)				136,348.364

Notes: The table reports the asymmetric ARCH and EGARCH models. AIC and SIC denote the Akaike information criterion and Bayesian information criterion. *** $p < 0.01$.

The electricity market in Portugal is particularly vulnerable to external shocks, such as changes in energy prices or supply disruptions, which may have a long-term effect on the conditional variance in electricity markets. The impact of energy shocks on financial stability can lead to sharp rises in electricity prices and increased volatility, affecting energy companies, financial agents, and central banks involved in safeguarding Portugal's electricity market's financial stability and pricing dynamics. High volatility can introduce uncertainty for market participants, including consumers, producers, and policymakers, and may impact investment decisions and long-term planning. Diversifying energy sources and enhancing energy security are crucial strategies to mitigating the impact of external shocks on market stability.

Market participants react more strongly to minor shocks during periods of high persistence. This situation suggests that the market is more sensitive to even minor disturbances. However, when the parameter is greater than one, this indicates that as the parameter increases, the impact of past shocks on future volatility decreases, leading to a quicker return to the average level of volatility.

5.2. Results of the Asymmetric GARCH Model

In contrast to traditional ARCH models, the GARCH model recognizes that the effects of shocks do not immediately disappear but persist over time, considering the impact of past shocks on future volatility. The EGARCH model's empirical results often contribute to a more accurate representation of market dynamics.

Positive developments, such as strong economic indicators, successful corporate earnings reports, or favorable policy announcements, often instill confidence in investors and market participants. When we have lower volatility, positive developments reassure investors and market participants the following day, increasing confidence in the overall economic outlook. On the other hand, negative news appears to have the opposite effect, causing an increase in volatility the next day.

The EGARCH $(\beta\gamma_{t-2})$ variance equation indicates that the impact of positive shocks on volatility differs from negative shocks. The estimated coefficient $\alpha\gamma_{t-2}$ is -0.026, and it implies that, on average, for each unit increase in the lagged standardized residual (ε_{t-1}) the log conditional variance $\ln\sigma_t^2$ decreases by 0.026 units. A negative γ_{t-2} coefficient suggests an asymmetric response to shocks. In EGARCH models, this implies that the impact of negative shocks on volatility is greater than that of positive shocks. In other words, negative shocks have a more pronounced effect on increasing volatility than positive shocks.

The relationship between negative news and increased volatility is a common trend observed across different markets and can serve as a valuable indicator for understanding how adverse information influences market dynamics. Acknowledging the relationship between negative news and volatility is essential for investors to navigate uncertain market environments successfully. By being informed of the latest developments and observing how the market responds to adverse news, investors can better navigate volatile conditions and potentially capitalize on opportunities.

Figures 3–6 illustrate the ARIMA and GARCH models. This model can eliminate excessive peaks in data fluctuations and provide a more accurate representation of the different levels of volatility experienced in the data. The graphs demonstrate that the market is sensitive to unforeseen events because unexpected news can significantly affect the stability of the price variable and lead to rapid and sometimes substantial price changes. This case suggests that although these models can provide valuable predictions, many factors can influence market dynamics, and that the models may not capture all of these complexities. Erdogdu [40] finds that unexpected events, such as political instability, natural disasters, or market changes, are the leading cause of increased volatility in financial markets, which causes rapid and often unpredictable price changes. These fluctuations can be positive or negative. For example, positive fluctuations may occur in response to favorable economic initiatives that stimulate consumer spending. This situation can lead to increased demand and a price rise.

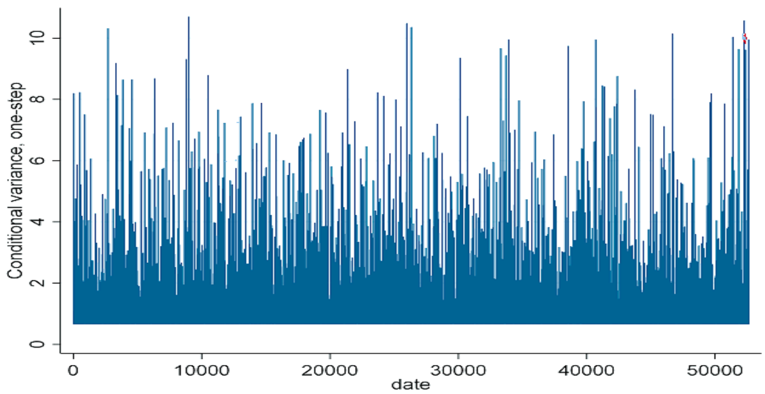


Figure 3. Fluctuation in electricity price and capturing the temporal dependencies and trends in data by ARIMA model estimation.

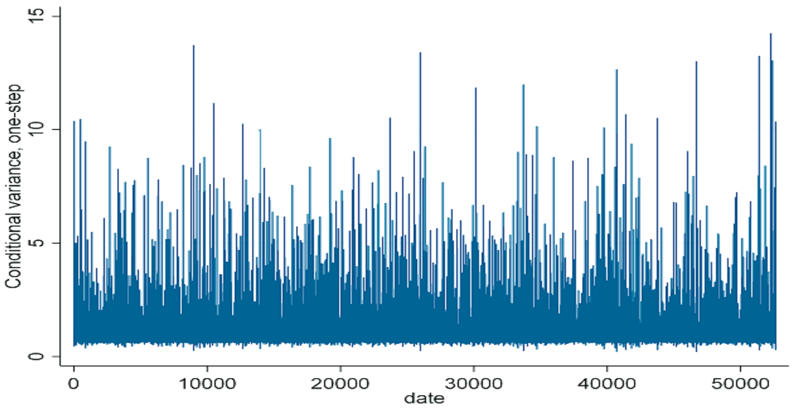


Figure 4. Volatility responds differently to positive and negative shocks in TGARCH.

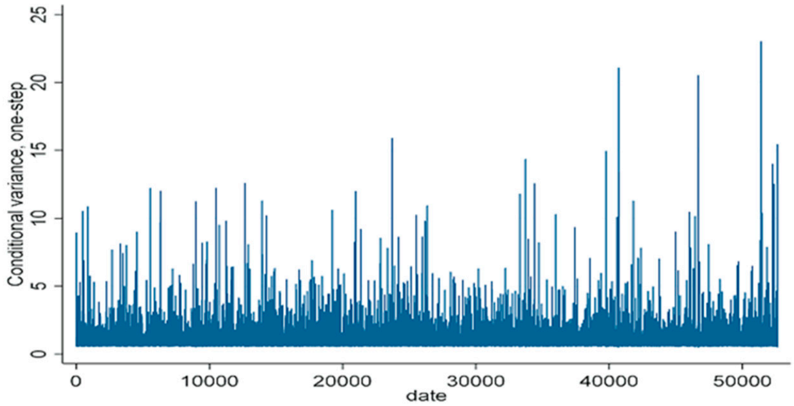


Figure 5. Rapid elimination of shocks to variance ensures the stability of the process over time, by asymmetric EGARCH estimation, making it suitable for the magnitude of fluctuations for long-term forecasting and risk management purposes.

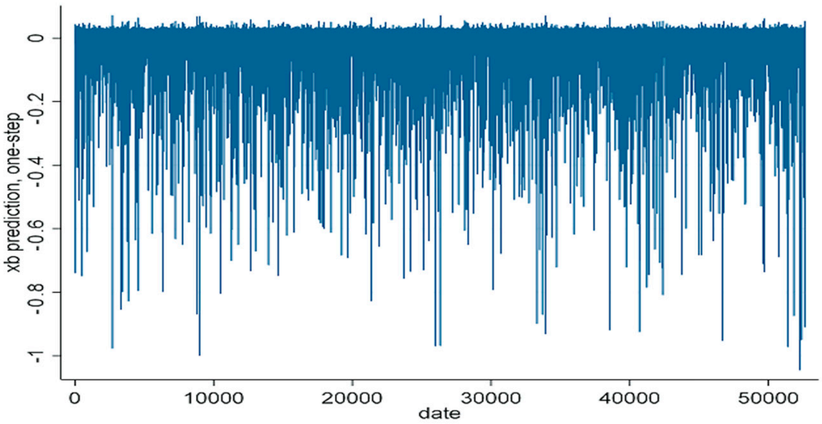


Figure 6. The negative impacts of risk volatility when employing GARCHM. Negative fluctuations can result from sudden decreases in business investment, global economic downturns, or market uncertainty. Such events can trigger a rapid price decline as investors respond to increased risks and uncertainties [41].

5.3. Results of Markov-Switching Model

Markov-switching models are statistical tools used to analyze time series data where a process is used to transition between states. The model separately estimates each state's parameters (such as mean and variance). The duration of each state is considered, representing how long the time series stays within a specific regime before transitioning to another. Transition probabilities indicate the possibility of moving from one state to another, and regime changes help to understand how different factors or events influence the behavior of the time series. The breaking points in the time series data represent the moments when the regime switches occur. Identifying these breaking points is crucial for understanding market conditions or changes in the economic environment.

Table 6 presents the results for each state's mean and the constant error variance. The notation $p_{st,st+1}$ refers to the possibility of transitioning from one state (st) to another $(st+1)$ in a single step. The constant coefficient (C) for each state provides insight into the mean or average price value within that state. State 1 is represented by p11, which is the predicted probability of remaining in State 1 throughout future periods. It averages 3.255%, while the actual value is 0.603. This case indicates that the model predicts a relatively high likelihood of remaining in State 1. State 2 is represented by p12, which indicates the predicted probability of transitioning from State 1 to State 2 in the next period. It is calculated as 0.603 − 0.381 = 0.22. In this case, State 2 has a higher mean value than State 1, with a mean value of 4.232%. The statement indicates that the probability of remaining in State 1 is higher than that of transitioning to State 2. When there is a higher probability of staying in State 1, the system is less likely to move to State 2 in the next step. If State 1 represents a stable condition where supply and demand are balanced, it is more likely to persist. Supply and demand dynamics, weather conditions, and market regulations or changes in the supply and demand for electricity could influence average prices, and a less stable economy might lead to a transition to higher average prices (State 2).

Table 6. Markov-switching dynamic regression.

Sample: 1–52,614				No. of obs = 52,614		
Number of states = 2				AIC = 2.0668		
Unconditional probabilities: Transition				HQIC = 2.0670		
				SBIC = 2.0676		
Log likelihood = −54,364.995						
Price 1	**Coef.**	**Std. Err.**	**z**	***p* > z**	**[95% Conf.**	**Interval]**
State 1						
C	3.255	0.006	526.420	0.000	3.243	3.267
State 2						
C	4.232	0.006	683.300	0.000	4.220	4.244
σ1	0.492	0.003			0.486	0.499
p11	0.603	0.007			0.590	0.616
p21	0.383	0.007			0.369	0.396
State 1						
AR (L1)	0.224	0.009	23.49	0.000	0.205	0.242
AR (L2)	0.283	0.009	28.14	0.000	0.261	0.300
C	3.236	0.005	554.69	0.000	3.224	3.247
State 2						
AR (L1)	0.223	0.009	23.98	0.000	0.204	0.241
AR (L2)	0.297	0.009	29.93	0.000	0.278	0.317
C	4.246	0.005	737.60	0.000	0.435	0.443
σ2	0.439	0.002			0.435	0.443
p11	0.478	0.005			0.467	0.489
p21	0.499	0.005			0.488	0.510

AIC, SBIC, and HQIC are Akaike's, Schwarz Bayesian's, and Hannan–Quinn's information criteria, respectively.

The Schwarz Bayesian information criteria (SBIC) only applies to stationary models; they cannot be used to evaluate the serial correlation variable in this case. It is essential to consider alternative criteria, such as the Akaike information criterion (AIC) or the Hannan–Quinn information criterion (HQIC), for assessing the serial correlation in nonstationary models. Therefore, the nonstationary model excludes the incorporation of the 2.06 SBIC. The Akaike information criterion (AIC) is commonly used to evaluate the quality of a model by balancing the goodness of fit with the complexity of the model. A value of 2.06 indicates a relatively small amount of missed information in the model, making it a reliable tool for analysis or prediction tasks.

The Hannan–Quinn information criterion (HQIC) is an alternative to the Akaike information criterion (AIC) that balances bias and variance in model selection. Burnham and Anderson [41] found that HQIC was not asymptotically efficient. This situation means that while HQC may perform well in certain situations, it may not always be the most accurate or reliable method for model selection. It is crucial to consider the strengths and limitations of each criterion.

They analyze AR parameters and volatility regimes in a Markov-switching model. In this case, State 2 is characterized by higher volatility (0.297%) compared to State 1 (0.223%), making it more sensitive to recent shocks. The AR coefficients for States 1 and 2 indicate that the shocks' impact will slowly disappear. This finding means that even small changes in the market can potentially have more pronounced effects on asset prices. As a result, disturbances experienced in State 1 will have a lasting impact on the system. The value of sigma (σ) is an important parameter as it assesses the impact of the volatility or standard deviation of the data within each state on the overall model accuracy. A higher sigma value indicates a larger fluctuation in the data, while a lower sigma value is associated with smaller fluctuation patterns in the long term. The sigma value in State 2 is lower (0.439) than in State 1 (0.492), implying that short-term shocks may have a significant impact when the system is in State 1. However, when the system transitions to State 2, these shocks tend to have a smaller and more manageable impact over the long term.

Figure 7 illustrates specific pricing patterns that could characterize two distinct states during specific periods when electricity prices remain constant. An extensive innovation during a low-volatility period will cause an earlier transition to the high-volatility regime. These distinct states are not short-lived but persist for a considerable duration, suggesting that once a trend or significant volatility is established in electricity markets, it tends to continue before transitioning to a different regime and affecting the transition. Markets may experience periods of stability (low volatility) compared to periods of turbulence and uncertainty (high volatility). These transitions are often associated with changes in market dynamics, economic conditions, or external events.

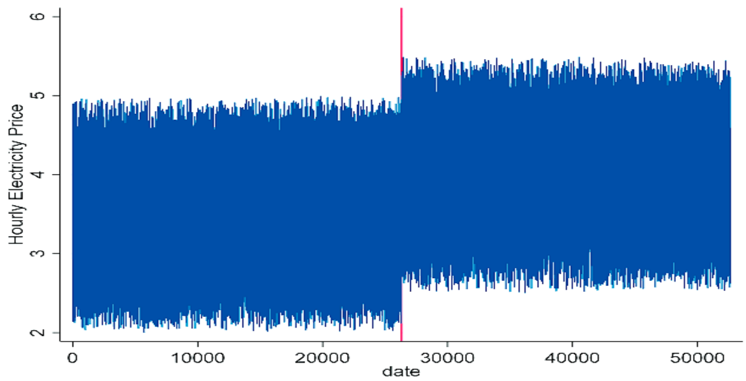


Figure 7. Markov switch GARCH estimation.

In Figure 8, the plot of filtered probabilities is used to identify crisis periods that affect market indices. This analysis provides information about the timing and duration of these crises and helps determine specific points when regime switching occurs, particularly in periods of market instability. Being in State 1 may lead to financial losses during fluctuating times due to unpredictable market fluctuations. Remaining in State 1 could result in missed opportunities for growth, as other states may offer more favorable conditions. State 2 provides enhanced protection and stability, reducing the risk of potential damage during uncertain periods.

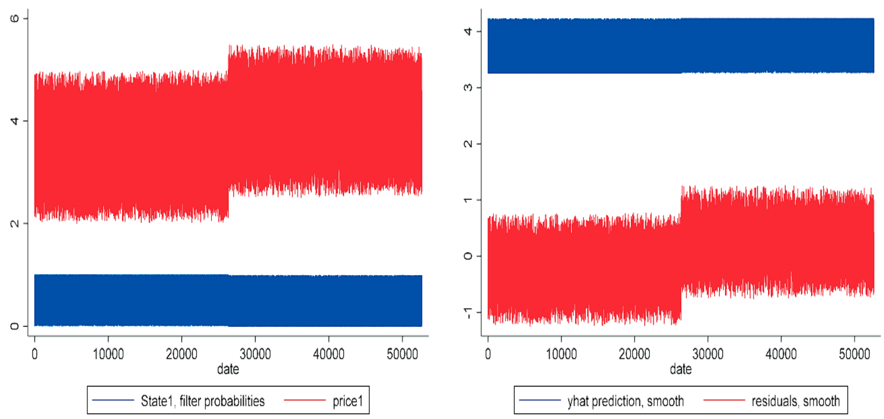


Figure 8. Predicted probability of being in a given state.

The model's predictive performance is evaluated by comparing the fitted price values (predicted values) and residual values (the differences between predicted and actual values) with the actual data. The filtered probabilities can capture trends in the data. This approach enhances the precision of estimating the target variable compared to relying on limited or incomplete information. Figure 9 represents that although there is a GARCH influence on prices, the statement was not sustained in the long run. As prices return to normal levels, it is essential to consider other factors that may contribute to price fluctuations in the long run.

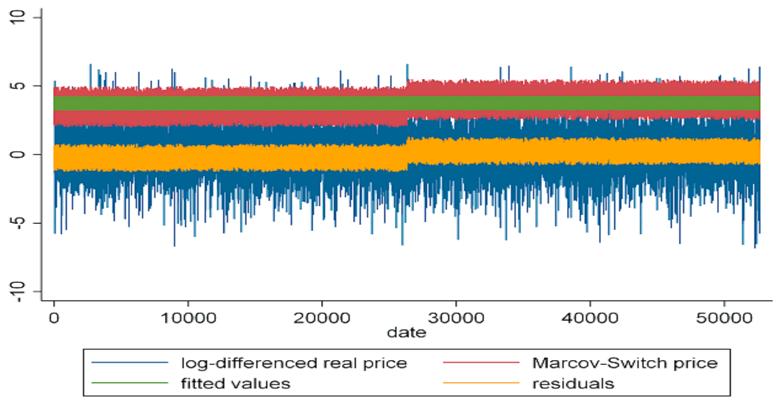


Figure 9. Account of GARCH influence on price variation.

Figure 10 examines the residuals and the differences between the observed and predicted values. Plotting the residuals can help assess whether outliers or influential data points disproportionately affect the model. If the spread of residuals is not constant across all levels of the predictor variable, it may exhibit a pattern that influences the occurrence of price spikes in different directions. Skewness impacts statistical measures, and some observations are related to positive and negative price spikes. Skewness measures the asymmetry of a distribution, with positive skewness indicating a longer right tail and negative skewness indicating a longer left tail. The mention of positive price spikes being associated with high demand or limited supply, and of negative price spikes with oversupply or decreased demand, suggests that there are distinct patterns in the behavior of the data.

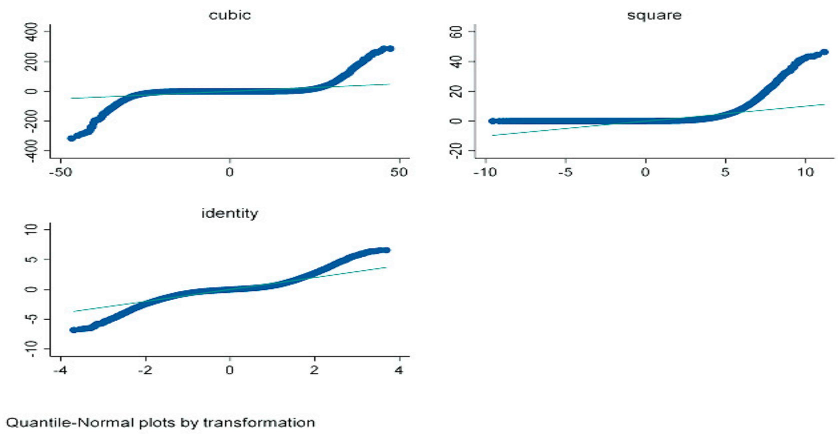


Figure 10. Quantile–Quantile plot models for logarithmic and non-logarithmic electricity prices.

Regarding Quantile–Quantile (QQ) graphs, they help assess the normality of a dataset. Extreme values in high-frequency data might result in spikes or outliers in a QQ plot. It is crucial to consider the context and purpose of the analysis to determine whether these extreme values significantly impact the overall interpretation of the data. The QQ plot in Figure 10 supports the non-normality assumption, indicating heteroscedasticity in electricity prices.

Figure 11 identifies peaks representing significant seasonal frequencies in the price time series. Koopman et al. [42] propose an approach to improve efficiency in modeling seasonal variance. Incorporating these hourly dummy variables allows for more accurate predictions of seasonal patterns and better resource allocation optimization. This method can be advantageous in industries where demand fluctuates significantly throughout the day, such as transportation or hospitality. This approach improves efficiency, accuracy, and reliability by simplifying the model and reducing the risk of overfitting.

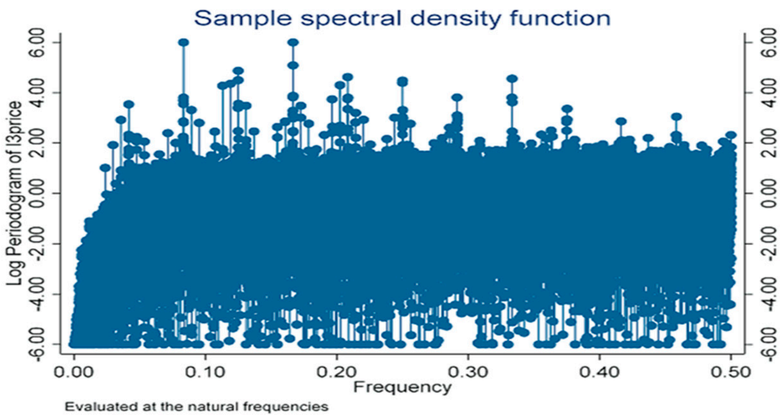


Figure 11. Hourly power price periodogram.

6. Discussion

The summary of the results of the GARCH models also indicates that fluctuations in power prices and upward shocks are attributed to positive economic news. Positive economic indicators may be associated with increased demand for energy, leading to higher prices. After experiencing temporary shocks or deviations, the pricing dynamics tend to revert to an average or equilibrium. This description precisely captures the fundamental properties of electricity price swings, including price movement, spikes, and volatility clustering.

Kočenda and Černý [43] consider the ARCH model to be particularly useful in capturing this clustering phenomenon, as it allows for the variance in the errors to change over time. The time-varying nature of data implies that the volatility is not constant over time. This case contrasts models that assume a constant level of volatility. The ARCH model does not provide insights into the source or underlying causes of variations in financial time series. It is a statistical tool that characterizes how variance changes over time but does not offer information about the fundamental factors driving those changes. Therefore, it does not provide insights into the specific economic or market events causing those changes ([44,45]).

The GARCH models, including EGARCH, are often used for short-term and long-term financial market forecasting. The leverage effect considers that financial markets often react differently to positive and negative shocks [46]. This study revealed that positive and negative returns significantly influenced fluctuations in Portugal's electricity pricing, affecting the electricity market dynamics and leading to price variations.

This study introduces a modification or extension of the MSGARCH (Markov-Switching GARCH) model and incorporates the idea that non-linear behavior is observed during extreme volatility or significant market events. Non-linear models, such as those involving regime switching, are better suited to identifying the complexities and sudden changes in market dynamics that linear models may not adequately represent. Also, it is crucial to efficiently transfer electricity prices between states to maintain energy market stability. This balance is necessary to ensure that energy markets can handle sudden price spikes or drops and avoid extreme fluctuations that could impact producers and consumers. Regarding the persistence of effects, Markov-switching models encourage decision makers to consider the long-term implications of extreme events when making decisions.

However, positive overall trends in both states indicate a general upward movement in the variable over time, which could align with price increases. The model obtains both the short-term dynamics of volatility and the long-term positive trends, leading to the anticipation that the effects of shocks become less significant as time progresses. This finding suggests a tendency for the system to return to its long-term trend, mitigating the impact of short-term shocks over the long term. The statement reveals that employing a Markov-switching approach enhances the predictive performance of volatility models. It also implies that the selection of probability distribution is a critical factor in forecasting volatility.

Table 7 provides the average duration of volatility periods in different states, which can be valuable for various aspects of financial analysis. For instance, the table indicates how long periods of high volatility are expected to persist. Longer average durations (State 1 is 0.917 and State 2 is 2.003) may indicate a more sustained period of uncertainty and risk, influencing investment decisions.

Table 7. Expected duration.

Number of Obs.	52.612	Std. Err	[95% Conf.	Interval]
State1	0.917	0.021	1.878	1.959
State2	2.003	0.022	1.960	2.048

Notes: States' average duration of volatility.

7. Conclusions and Policy Implications

This study presents valid and effective GARCH models to analyze and forecast conditional variance, representing the asymmetric relationship between volatility and previous returns. In traditional GARCH models, volatility is assumed to be constant over time or follow a specific pattern. However, in financial markets, volatility often exhibits regime changes, switching between different states with varying levels of persistence. A regime-switching GARCH model is a more flexible approach that acknowledges and models the changing nature of volatility in financial markets through different regimes, such as low-volatility and high-volatility periods, protecting the time-varying and unpredictable volatility features.

Policy Implications

By identifying extreme positive and negative variations in financial markets, accurate price forecasting that considers hourly differentiation helps power producers to balance unpredictable demand and supply from different locations, potentially reducing the unpredictability of energy prices. The integration of renewable energy sources has a direct impact on electricity pricing dynamics. Insights into how positive and negative returns affect electricity pricing provide valuable information for enhancing market efficiency. Policymakers can use this knowledge to design mechanisms that incentivize efficient energy production and consumption practices, ultimately leading to a more competitive and effective electricity market. Customers more sensitive to price fluctuations can adjust their energy usage to align with lower-cost periods. Researchers can refine their understanding of how past information influences current volatility and how various models represent these processes.

8. Limitations and Future Research

8.1. Study Limitations

Prices in the power sector are described as more volatile and complex compared to regulated markets. Various unpredictable factors may influence the market, making it difficult for market participants to forecast high-precision prices [19]. Regarding methodology, symmetric GARCH models assume that positive and negative shocks have the same impact on volatility, which may not reflect the actual behavior of financial markets where negative shocks often lead to larger volatility changes. Interpreting the impact of asymmetry on volatility dynamics can be complex due to its various forms and potential effects (e.g., leverage affects news impact). Including regime shifts in Markov-switching GARCH models adds complexity to interpreting the results and understanding the underlying dynamics driving volatility changes.

8.2. Future Research

Developing more flexible and robust asymmetric GARCH models is an essential subject for further investigation in financial econometrics. Asymmetric effects, such as leverage effects and news, are standard features observed in financial data, and accurately capturing them can lead to more effective risk management and forecasting. Indeed, estimating complex models such as Markov-switching GARCH (MS-GARCH) models can be computationally complicated, especially when interacting with large databases. Iterative methods like the expectation-maximization (EM) algorithm and Bayesian approaches like Markov chain Monte Carlo (MCMC) can assist in dealing with these issues. More investigation might explore using these models in risk management practices, such as portfolio optimization, value-at-risk estimation, and hedging strategies.

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