UNIVERSITÀ CATTOLICA del Sacro Cuore

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Abstract

This paper examines the impact of extreme weather events on electricity price volatility in Italy, using a novel combination of advanced econometric techniques and a robust variable selection process. A key feature of the study is the application of the Best Path Algorithm (BPA) for variable selection, which identifies the most relevant predictors, with extreme weather events emerging as the primary drivers of price volatility. These selected variables are incorporated into a GARCH-MIDAS model, allowing for the integration of high-frequency electricity price data with low-frequency climate data to capture both short- and long-term volatility components. Additionally, the study incorporates external shocks, such as the Russia-Ukraine war, as exogenous variables to account for their effects on the energy market. The results highlight the significant predictive power of extreme weather events and external factors on returns of electricity prices. This approach provides policymakers and energy stakeholders with improved forecasting tools, emphasizing the need for resilience in energy market planning. Future research may extend this methodology to other regions and incorporate additional variables to enhance predictive accuracy.

Keywords: Weather; Climate change; Electricity prices; GARCH-MIDAS

JEL codes: Q41; Q54; C1; C53

Highlights:

1. **Direct Impact of Extreme Weather:** The study shows that extreme weather events are a very effective predictor of the returns of electricity prices in Italy and Granger-cause these price fluctuations.

2. **Volatility Decomposition:** Using the GARCH-MIDAS model, the study decomposes electricity price volatility into short-term and long-term components, revealing the significant influence of low-frequency extreme weather data on long-term price volatility.

3. **Predictive Accuracy:** Models that incorporate extreme weather events (such as GJRM-X and DAGM-X) show superior predictive power for electricity price volatility, with the GJRM-X model (Student's t-distributed innovations) being the most accurate.

4. **Forecast Improvement:** The inclusion of extreme weather variables in volatility models improve the accuracy of price forecasts, particularly when combined with ARIMA models, enhancing both short- and medium-term forecasting of energy prices.

1 Introduction

The paper examines the impact of extreme weather events on electricity prices in Italy using a combination of graphical models for variable selection and volatility estimation techniques. The forecast of both volatility and average monthly prices of electricity is the main objective of this study. To purse this goal, a novel methodological approach, offering several key contributions to the field, is employed. First, a novel graphical model-based method to variable selection is used to identify and select variables that encapsulate the main factors influencing electricity prices and their volatility. This approach for variable selection shows that extreme weather events are the best predictors of electricity prices compared to other variables. This outcome is not surprising, if one considers that the increasing frequency and severity of extreme weather events due to climate change pose significant challenges for energy markets. These events affect energy prices through multiple interconnected pathways, including changes in demand and supply dynamics, technical challenges, infrastructure vulnerabilities, and broader economic variables. Understanding and forecasting these impacts is crucial for developing effective mitigation and adaptation strategies. The urgency to improve this understanding is further exacerbated by the rise in global electricity demand, which, for Italy alone, is estimated to increase by about 20% by 2030. This increase is driven by the transition to greener technologies across various sectors, from transportation to housing. These trends further underscore the importance of accurately predicting electricity price volatility to ensure stable and reliable energy supplies.

The paper shows that a model relying exclusively on weather-related variables can effectively capture all the necessary information to explain and predict electricity prices without any loss of accuracy. In this study, extreme weather events are first employed to explain the volatility of electricity prices. Subsequently, these events are used as exogenous variables in an ARX-type model for electricity price forecasting, highlighting the significant predictive power of meteorological factors in the energy market.

The issue of differing temporal granularity between day-ahead electricity prices and the time span of the effects of atmospheric exogenous variables is addressed via the use of a Generalized Autoregressive Conditional Heteroskedasticity - Mixed Data Sampling (GARCH-MIDAS) approach. The latter allows the integration of high-frequency price data with lower-frequency weather data, thus capturing the detailed effects of extreme weather on price volatility. To handle data spikes, appearing in the series of electrical prices and in its volatility, a GARCH-Jump with Regime Switching model (GJRM) is employed. To account for the war in Ukraine, the extension of this model, namely the GJRM-X model, is also considered. The results of the GJRM-GJRM-X models are then compared with those of Double Asymmetric GARCH-MIDAS (DAGM) and DAGM-X models, that account for possible asymmetries and significant external events. Eventually, the resulting best model is used to predict the energy price volatility, which is decomposed into a short-and a medium-term component. The estimated volatility is then used to normalize electricity price, thus enhancing the accuracy of predictions obtained through an ARIMA model.

The paper is structured as follows: Section 2 discusses the existing literature on electricity price forecasting and the impacts of extreme weather events. Section 3 describes the methodology used for variable selection and the volatility modeling based on GARCH-MIDAS model. Section 4 presents the data used in the analysis and shows evidences about the occurrence of extreme weather events in Italy, while Section 5 details the empirical results so obtained. A discussion of the implications of the findings and suggestions for future research conclude the paper.

2 Electricity price forecast and extreme weather events

This paper examines the impact of climate changes on electricity prices volatility, highlighting how rising energy demand and the shift to alternative sources increase price volatility amind extreme weather events. The latter are becoming more frequent and severe due to climate change. This increase poses significant challenges across various sectors, especially in energy markets. Extreme weather events influence energy prices through several interconnected pathways. These include changes in demand and supply dynamics, technical challenges, infrastructure vulnerabilities, and broader economic variables. Each of these pathways contributes to the overall volatility and pricing.

One of the most direct impacts of extreme weather on energy prices is through changes in demand. For instance, heatwaves significantly increase the use of air conditioning, leading to higher electricity consumption. Conversely, cold snaps drive up heating needs, which similarly elevates energy demand. For instance, in their review on the climatic impact on energy consumption, which focus on the use and adoption of air conditioning, Auffhammer and Mansur [2014] demonstrated that such weather events can cause substantial spikes in electricity consumption, leading to short-term price surges. During extreme heat, the grid often relies on more expensive peaking power plants fueled by natural gas, increasing the marginal cost of electricity [Stone Jr et al., 2021, Ke et al., 2016]. Similarly, cold spells elevate electricity demand in regions with electric heating, while in areas relying on natural gas, the heightened demand can push up natural gas prices, subsequently raising electricity prices [Kim and Lee, 2019]. A notable contribution to understanding demand under extreme weather conditions is the work by Miller and Nam [2022], who modeled peak electricity demand using a semiparametric approach with weather-driven cross-temperature response functions. Their study underscores how varying temperature extremes influence peak demand patterns, highlighting the intricate relationship between weather variables and energy consumption.

Extreme weather also disrupts the supply side of the energy market. Renewable energy sources such as wind and solar are particularly affected by weather conditions. Storms can increase or decrease wind power production; for instance, while high winds may boost generation, turbines might need to be shut down to prevent damage, reducing supply [Leahy and Foley, 2012]. Solar power is similarly affected, with cloud cover or hurricanes significantly decreasing generation. This reduction in renewable energy supply often necessitates greater reliance on fossil fuels, which are more costly and subject to price volatility.

Additionally, fossil fuel supply chains are directly impacted by extreme weather. Hurricanes, for example, can disrupt oil and natural gas production, especially in regions like the Gulf of Mexico, leading to fuel price spikes that translate into higher electricity prices. Hurricane Harvey in 2017 is a notable example of such disruptions. Power outages resulting from these disruptions can have broader economic impacts as well. Chen et al. [2023] found that power outages can significantly hinder economic growth, further highlighting the importance of maintaining a stable energy supply. Furthermore, Kaufmann and Schroer [2023] discussed how environmental events, such as Hurricane Harvey, can disrupt the relationship between gasoline prices and market fundamentals, emphasizing the cascading effects on related energy markets. Overall, Staffell and Pfenninger [2018] developed a general framework based on high resolution data and showed robust evidence of an increasing impact of whether on electricity supply and demand and surmise that a key challenge is to successfully deal with extremes. The technical challenges posed by extreme weather events to the power grid are numerous. Transmission and distribution networks are particularly vulnerable to damage from high winds, ice, and flooding. When these networks are damaged, power outages occur with consequent reduced supply capacity, and both these events contribute to rising energy prices. Restoration of these networks, being costly and time-consuming, further affects prices. Technical factors also include the efficiency of power plants, which can be compromised by extreme temperatures. High temperatures can reduce the efficiency of thermal power plants, including fossil fuel and nuclear plants, as cooling becomes less effective. This reduction in efficiency means that more fuel is required to produce the same amount of electricity, increasing production costs and, consequently, prices.

Historical case studies illustrate the significant impact of extreme weather on energy prices. Hurricane Katrina in 2005 caused extensive damage to the Gulf Coast's energy infrastructure, leading to substantial spikes in oil, gas, and electricity prices across the United State [Reed et al., 2010]. Similarly, Hurricane Sandy in 2012 disrupted energy supplies in the Northeast, causing price surges and highlighting the vulnerability of coastal energy infrastructure [Meng and Mozumder, 2021]. More recently, the 2021 Texas freeze showcased how extreme cold can disrupt both supply and demand dynamics, leading to unprecedented spikes in electricity prices [Bunker, 2020]. The freeze caused a surge in heating demand, while simultaneously crippling natural gas supply and power generation capacity, resulted in widespread outages and price spikes. Panteli and Mancarella [2015] highlighted how resilience of energy infrastructure is crucial in mitigating the impacts of extreme weather on energy prices. Hurricanes, floods, and wildfires can cause significant damage to energy infrastructure, leading to disruptions in energy supply chains and subsequent price increases. The 2021 Texas freeze highlighted how extreme cold can cripple energy infrastructure, causing widespread outages and skyrocketing electricity prices [Bunker, 2020]. Investments in resilient infrastructure, such as underground power lines and more robust grid systems, are essential but costly, influencing the prices charged to consumers. These investments are necessary to withstand the impacts of extreme weather and ensure stable energy supplies. Thus, extreme weather events also impact broader economic variables and are expected to affect energy prices. Natural disasters can disrupt economic activities, reducing industrial energy demand while recovery and reconstruction efforts can lead to increased demand. The consequence of these contrasting effects is that insurance and financial markets respond to these events by adjusting risk assessments. The latter can result in higher insurance premiums for energy infrastructure, costs that are often passed on to consumers. Additionally, speculative activities in energy markets can exacerbate price volatility. For instance, the anticipation of supply disruptions due to approaching hurricanes might drive up prices through speculative trading even before the actual impact is felt.

Therefore, understanding and accurately forecasting the impact of extreme weather events on electricity price volatility is essential. Thus,the aim of this paper is to forecast both the volatility and the average monthly prices of electricity in Italy. The methodological approach followed for this scope brings to the fore the crucial role played by the meteorological variables as predictors of electrical prices. The paper aligns with that of Weron [2006, 2014], who used six types of theoretical and empirical models for electricity price forecasting (EPF), Also the current study employs different types of models: regression models, autoregressive models with exogenous variables (ARX-type models), and models for conditional heteroskedasticity (GARCH). Additionally, a MIDAS-GARCH is used to deal with the differing temporal granularity between the day-ahead electricity prices, representing the forecast target, which is daily sampled, and the weather exogenous variables, which is sampled on monthly basis. At a first step of the analysis, a selection of the factors that are crucial in explaining electricity price in Italy is operated. These factors are then employed as independent variables in econometric models finalized to explain and forecast electricity volatility. The issue of variable selection has been largely discussed in the literature with a plenty of contributions. The typical approach selects predictors in an ad hoc fashion, sometimes using expert knowledge, seldom based on some formal validation procedures but more recently different approach have been proposed [García-Martos et al., 2012, Maciejowska et al., 2020, Raviv et al., 2015, Uniejewski et al., 2016, Yang et al., 2022] For the purpose of variable selection, the algorithm by Riso et al. [2023], based on graphical models [Jordan et al., 2004, Lauritzen, 1996], is here implemented. This algorithm selects the subset of variables that maximize the information content for explaining and predicting a target variable, tallying with the electricity prices, in the study in exam. The algorithm performs a reduction of the size of the original dataset, by ruling out variables that are not informative and therefore redundant for the explanation of a variable of interest.

When it is applied to a broad series of potential independent variables for the electricity prices, including extreme weather events, the algorithm selects the latter as best predictors. A possible explanation of this result is that, as previously discussed, extreme weather events encapsulate vital information regarding demand mechanisms, supply disruptions, and infrastructure challenges.

The application of this novel machine learning algorithm represents a first contribution of the paper. Since probabilistic graphical models allow the identification of the conditional dependencies between variables within the dataset, a direct dependency between extreme weather events and electricity price returns is established using an information-theoretic approach. Although this relationship is only Granger-causal, the findings are consistent with the work of Mosquera-López et al. [2024], which demonstrated the causal impact of weather extremes upon energy prices through non-linear mechanisms. However, the use of extreme weather events to explain the volatility of the energy price arises the problem of the discrepancy between the sampling frequency of these variables. This issue is addressed by employing mixed data sampling GARCH or GARCH-MIDAS models that combine high-frequency daily electricity price data with lower-frequency monthly weather data, thus capturing the effects of extreme weathers events on price volatility. GARCH-MIDAS models have been applied successfully in energy markets. For instance, Liang et al. [2022] used an extended GARCH-MIDAS model for gas prices, incorporating both extreme and normal weather conditions. Their findings demonstrated that models including weather indicators outperformed those that neglect them. Their work highlighted the effectiveness of GARCH-MIDAS-W-ES models that include temperature or precipitation data. However, unlike the present study, their focus was on general weather conditions, rather than on extreme events. The employment of GARCH-MIDAS models to model energy price volatility in terms of extreme events represents another methodological contribution of this paper.

A challenge that arises in using GARCH models is how to handle data spikes due to exogenous shocks. To address this problem, a GARCH-Jump with Regime Switching model (GJRM) incorporating additional exogenous variables (GJRM-X) to account for shocks, such as the war in Ukraine, is implemented. The outcomes of this model are then compared to those of a Double Asymmetric GARCH-MIDAS (DAGM) model, that considers possible asymmetric impacts of specific factors on the volatility of a target variable, and a DAGM-X model including exogenous variables. The innovations of these models have been assumed to be distributed either as a normal or as a Student's t-law. As it is well known, the latter distribution proves to be more suitable for heavy-tailed scenarios, as expected in datasets involving extreme events. The best model among all these mentioned variants is then used to explain both the short-term and the long-term volatility of electricity prices, thus addressing the first research question on whether extreme weather events influence volatility. Eventually, the estimated volatility is used to forecast electricity prices using an ARIMA model. The next section details the methodological approach followed in the paper.

3 Methodology

This section outlines the methodology approach followed to explain and forecast electrical price returns in Italy.

The first step of the analysis is finalized to identify the optimal set of variables for explaining the volatility of national electricity prices in Italy. The detection of the best predictors for the Italian electricity price has been operated via a machine learning algorithm, called the Best Path Algorithm (BPA hereafter) by Riso et al. [2023]. The BPA has been applied to a dataset comprising the Italian electricity price along with various financial variables and the extreme climate events that occurred in Italy from 2009-01 to 2023-12. The application of the algorithm has lead to establish that the Italian electricity prices are more directly influenced by climatic and atmospheric conditions rather than by broader financial factors.

Once the BPA has identified the variables that are most closely associated with electricity prices, the directions of these relationships have been verified via Granger causality tests [Granger, 1969]. Subsequently, the volatility of the electricity prices has been modeled and forecast using different types of GARCH-MIDAS models [Amendola et al., 2021]. These models, allowing the inclusion of variables sampled at different frequencies allow the use of extreme climate events as explanatory factors of the long-run volatility of electricity prices. Several GARCH-MIDAS models have been employed for this scope. The most appropriate one has been selected via the Model Confidence Set procedure [Hansen et al., 2011]. Finally, the volatility from the optimal model has been used to normalize electricity prices for forecasting purposes [Sharpe, 1966].

3.1 Variable Selection via BPA

The BPA first constructs the graphical model [see, among others, Edwards et al., 2010, Riso and Guerzoni, 2022] that depicts the relationships between the variables of the data set under examination. The BP algorithm belongs to the Sequential Forward Search category [Nava et al., 2023], as it starts with an empty set and progressively adds variables that may serve as potential determinants for a variable of interest, say Y, which, for the case in exam, corresponds to the monthly average of the electricity price in Italy.

The optimal set of predictors for Y is then detected by using the concept of mutual information . As it is well known, mutual information between two variables represents the information gained in one variable due to its entropy reduction when it is explained by the other variable. Therefore, the higher the mutual information between two variables, the more significant the explanatory role that one variable can play for the other.

The BPA detects the set of admissible predictors for Y by considering the variables of the graph that belong to different path-steps w_i linking the predictors to Y. A path step is the set of all variables X_j whose distance from Y is equal or lower than k

$$\mathbf{X}_{w_k} = \{X_j : d_{Y,X_i} \leq k\}. \tag{1}$$

where the distance between Y and another variable X_j is meant to be the number of variables lying along the path of the graph connecting Y and X_j.

The best path-step is the one including variables that share the maximal mutual information, I, with Y, that is

$$I(Y, \boldsymbol{X}_{w_i}) \geq I(Y, \boldsymbol{X}_{w_j}), i \neq j, i = 1, \dots, k \tag{2}$$

where $\boldsymbol{X}_{w_i}$, $\boldsymbol{X}_{w_j}$ denote the set of variables belonging to the path-steps w_i and w_j.

The mutual information between Y and the variables belonging to different path-steps is then measured via the Kullback-Leibler Information (KLI) index. The KLI of the distribution $f(Y)$ of Y and that of its conditional expectation given the predictors $\boldsymbol{X}_{w_i}$, say $f(Y|\boldsymbol{X}_{w_i})$, is related to their mutual information, as the latter tallies with the expectation of the KLI between the two densities [Dembo et al., 1991], that is

$$I(Y|\boldsymbol{X}_{w_i}) = \mathbb{E}_{f(Y)}[KL(f(Y), f(Y|\boldsymbol{X}_{w_i})]. \tag{3}$$

The closer the two distributions, the greater the reduction of the entropy of Y when the set of variables X_{w_i} are employed to explain it.

To evaluate the mutual information between Y and $Y|\boldsymbol{X}_{w_i}$, the BPA algorithm employs the entropy coefficient of determination (ECD) [Eshima and Tabata, 2010], given by

$$ECD = \frac{EC}{EC + 1} \tag{4}$$

where EC is the entropy coefficient proposed by Eshima and Tabata [2007]. ECD hinges on the symmetric Kullback-Leibler Information, $KL^{(s)}$ measuring the distance between either $f(Y)$ and $f(Y|\boldsymbol{X}_{w_i}))$ or $f(Y|\boldsymbol{X}_{w_i}))$ and $f(Y)$

$$EC = \frac{\sum_{\boldsymbol{X} \in w_i} KL^{(s)}(f(Y), f(Y|\boldsymbol{X}_{w_i}))}{\{\#\boldsymbol{X} \in w_i\}} \tag{5}$$

which can be read as the proportion of the variation in entropy of Y explained by $\boldsymbol{X}_{w_i}$. ECD can be viewed as a generalization of the coefficient of determination in the class of generalized linear models and, in the special case of linear models, it tallies with the standard coefficient of determination.

Once, the set of best predictors for the variable Y has been detected, the explanatory role of each of them is tested by applying the Kraskov et al. [2004] Mutual Information test of independence between Y and each variable of the optimal pat-step. Indeed, as some variables within w_i may be not relevant for Y, the set of predictors can be further improved by ruling out those of them which turn out to be not statistically significant for Y. This would allow to obtain a more parsimonious set of predictors for Y. The set of predictors, so selected is then employed in GARCH-MIDAS regressions to estimate, now cast and forecast the electricity price for Italy.

3.2 Granger causality

After identifying the most appropriate predictors for electricity prices using the BPA, the Granger causality test has been carried out to determine the direction of the relationships between the selected variable and returns of the electrical prices.

The Granger causality test is finalized to check whether one variable can be usefully employed to predict another one. Introduced by Clive W. J. Granger in 1969, the test assesses whether the past values of one variable contain information that can help to predict the future values of another variable, beyond what is explained by the past values of the latter variable itself [Granger, 1969]. Unlike traditional notions of causality, which imply a direct cause-and-effect relationship, Granger causality identifies predictive causality. It is worth pointing out that variables identified as Granger-causing one another do not necessarily imply direct causation; rather, economic theory should provide the rationale for the dependency between these variables. In this study, the Granger test is employed to verify if the variables selected by the BPA Granger-cause the log returns of electricity prices, so that changes in these variables precede and predict changes in log returns of electricity prices.

3.3 Garch-Midas

The GARCH-MIDAS model proposed by Engle et al. [2013] decomposes volatility into two components: a short-term component driven by a GARCH process for high-frequency data and a long-term volatility component captured by a MIDAS process for low-frequency data. In the study dealt with by this ppaer, the former component is the national electricity price in Italy, the latter the variables selected by the BPA [Riso et al., 2023].

This model can flexibly handle mixed frequency data and it is becoming increasingly popular in analyzing the macroeconomic determinants of financial return volatility [see, among others, Pan and Liu, 2018, Riso and Vacca, 2024, Fang et al., 2020]. It also finds applications in the study of geopolitical risks [Salisu et al., 2022, Yang et al., 2021] and economic policy uncertainty [Liu et al., 2021].

A GARCH-MIDAS model is specified as follows

$$\begin{aligned} &r_{i,t} = \sqrt{\tau_t \times g_{i,t}}\epsilon_{i,t} \quad \forall i = 1, .., N_t \quad t = 1, ..., T \\ &\epsilon_{i,t}|I_{i-1,t} \sim \mathcal{N}(0,1) \end{aligned} \tag{6}$$

where r_{it} is the high-frequency component, with i denoting the high-frequency interval (e.g., day) within the low-frequency interval t (e.g., month); $I_{i-1,t}$ denotes the information set available at day $i-1$ of the period t and N_t is the number of days in month t. In this study, $r_{i,t}$ represent the log return, that is, the first log-difference of the electricity prices for the day i of the month t (with $i = 1, ..., N_t$, where N_t is the number of days for the period t). $g_{i,t}$ and τ_t are the short and long-term volatilities.

The short-term volatility component is assumed to follow a GARCH process ([Bollerslev, 1986]), while the long-term volatility follows a MIDAS regression [Pan and Liu, 2018]. In particular, the extended specification proposed by [Amendola et al., 2021] is considered for the short-term volatility component. The authors suggest extending the short-run equation to include additional volatility determinants observed at the same frequency as $r_{i,t}$. This permits to move beyond the classical (GJR)-GARCH-MIDAS framework [GJRM; Conrad and Kleen, 2018, Wang et al., 2020], which typically includes only macroeconomic variables. Specifically, for the issue under study, this additional volatility determinant is represented by a daily dummy variable $X_{i,t}$ for the Russia-Ukraine conflict, an exogenous event that increased the cost of electricity in Europe [Liadze et al., 2023, Ali et al., 2023]. Accordingly, the short-run component is specified as follows:

$$\begin{aligned} g_{i,t} &= (1-\alpha-\gamma/2-\beta)+(\alpha+\gamma\cdot\mathbb{1}_{(r_{i-1,t}<0)})\frac{(r_{i-1,t})}{\tau_t}+ \\ &+\beta g_{i-1,t}+z\cdot(X_{i-1,t}-\mathbb{E}(X_{i-1,t})) \end{aligned} \tag{7}$$

where $\mathbb{1}_{(\cdot)}$ is an indicator function. As it is customary in a GARCH model, the short-run parameters are subject to: $\alpha>0$, $\beta\geq 0$; $\alpha+\beta+\gamma/2\geq 1$ [Bollerslev, 1986]. Following Amendola et al. [2021]and [Candila, 2020] , it is assumed that $z\geq 0$; $X_{i,t}\geq 0$, $\forall i$ and t

The logarithm of the long-term component τ_t follows a MIDAS regression (see e.g., Pan and Liu [2018])

$$\tau_t = exp\left\{m+\theta\sum_{k=1}^{K}\delta_k(\omega)MV_{t-k}\right\} \tag{8}$$

where m is an intercept, MV is a stationary predetermined variable that plays the role of MIDAS term, being sampled at a lower frequency than τ_t, and $\delta_j(\omega)$ is a chosen weighting function. A GARCH-MIDAS with $g_{i,t}$ and τ_t specified as above is called GJRM, or GJRM-X if an exogenous variable is included in $g_{i,t}$.

In this study also a Double Asymmetric GARCH–MIDAS (DAGM) model ([Amendola et al., 2019a]) is implemented. In a DAGM model the asymmetry in the short-run is captured by a GJR-type reaction to the sign of past returns. This model allows positive and negative variations in the MV values to have different impacts on the long-run, providing an economic interpretation of what drives the average level of volatility. The term τ_t in the DAGM model represents the slow-moving local level of volatility (long-run component) defined as:

$$\tau_t = exp\left\{m+\theta^+\sum_{k=1}^{K}\delta_k(\boldsymbol{\omega}^+)MV_{i-k}\mathbb{1}_{\{MV_{i-k}\geq 0\}}+\theta^-\sum_{k=1}^{K}\delta_k(\boldsymbol{\omega}^-)MV_{t-k}\mathbb{1}_{\{MV_{t-k}<0\}}\right\} \tag{9}$$

where θ^+ and θ^- represent the asymmetric responses to the one-sided filter, and $\delta_k(\omega)^+$ and $\delta_k(\omega)^-$ are suitable functions weighing the past K realizations of the additional stationary predetermined variable labelled MV_t [Amendola et al., 2021]. In this analysis, the parametric function $\delta_k(\boldsymbol{w}^*)$ is assumed to follow a Beta structure [Candila, 2020]:

$$\delta_k(\boldsymbol{\omega}^+)=\frac{(k/K)^{\omega_1^+-1}(1-k/K)^{\omega_2^+-1}}{\sum_{j=1}^{K}(j/K)^{\omega_1^+-1}(1-j/K)^{\omega_2^+-1}},\quad \delta_k(\boldsymbol{\omega}^-)=\frac{(k/K)^{\omega_1^--1}(1-k/K)^{\omega_2^--1}}{\sum_{j=1}^{K}(j/K)^{\omega_1^--1}(1-j/K)^{\omega_2^--1}}$$

which, being a monotonically decreasing weighting scheme, weigh more the most recent observations.
To summarize, when the effect of an exogenous event is considered in the model, the GARCH-MIDAS framework corresponds to either a GJRM-X or a DAGM-X model (if asymmetries of volatility's determinants are accounted for) with either a normal or a Student's t density for the innovations. In the current study, the exogenous event represents the Russia-Ukraine conflict and it is incorporated in the models via a dummy variable (which assumes value equal to 1 in presence of the conflict and 0 otherwise).
When no exogenous shocks are considered, the GARCH-MIDAS model tallies with either a GJRM or a DAGM model (if asymmetric responses of the MIDAS term in the volatility equation are considered).

3.4 Model Conficence Set

Choosing the most effective GARCH-MIDAS model for explaining the relationship between extreme climate events and electricity prices is particularly challenging when the set of competing models is large. In many applications, no single model significantly outperforms all others because the data may not be sufficiently informative to provide a clear answer [Hansen et al., 2011], especially in the context of price volatility [Poon and Granger, 2003]. Nonetheless, it is possible to reduce the set of models to a smaller subset that contains the best model with a given level of confidence via a testing procedure called Model Confidence Set (MCS).

The MCS, proposed by Hansen et al. [2011], can be implemented to identify the best model, according to a user-specified criterion, from a collection of models.
An MCS is constructed starting from a set of competing models, $\mathcal{M}_0$, by using a criterion for empirically evaluating their performance[1]. The MCS procedure relies on an equivalence test, $\delta_{\mathcal{M}}$, and an elimination rule, $e_{\mathcal{M}}$.
If the equivalence test, when applied to the set $\mathcal{M}$, rejects the null, then there is evidence that models in $\mathcal{M}$ are not equally 'good' as those in $\mathcal{M}_0$. Then, the elimination rule $e_{\mathcal{M}}$ removes the model with the poorest performance form the set [Hansen et al., 2011] $\mathcal{M}$.
This procedure is repeated until $\delta_{\mathcal{M}}$ is accepted', and the MCS is now defined by the set of 'surviving' models.
Typically, two statistics are used to implement the MCS procedure: $Tmax$, which compares the models of the set and allows the identification of the model with the worst performance, and TR, that ranks models according to their performance. Specifically, the $Tmax$ statistic is calculated at each step of the MCS procedure to identify the model that shows the greatest difference from the best one in terms of a given loss function (e.g., mean squared error or absolute error). TR, instead of focusing exclusively on the worst-performing model, as $Tmax$ does, provides a ranking among all models, depending on a specific loss function [Bernardi and Catania, 2018]. This statistic is particularly useful when one seeks to determine not only the worst model but also the relative performance of each model in comparison to those of the others [Bernardi and Catania, 2018].
In the present study, the MCS procedure is used to select the best GARCH-MIDAS model on the basis of a comparison between the estimates of the volatility obtained from these models with the realized volatility (RV) of electricity price returns. The loss functions used for this scope are the Square Error and Absolute Error
As it is well known, RV is a non-parametric measure of the total variability of a time series over a fixed time interval, typically calculated using high-frequency data. Unlike model-based processes such as GARCH, which rely on certain assumptions about the distribution of returns, RV is computed directly from observed data, providing a data-driven assessment of market risk.
For the study in exam, the realized volatility for a day i has been computed as follows:

$$RV_i = \sum_{i=1}^{H} R_{i,h}^2 \tag{10}$$

where $R_{i,h}$ represents the intraday returns at time h on day i and H denotes the number of intraday intervals. The use of high-frequency data enhances the accuracy of volatility estimation by capturing a greater portion of the price dynamics occurring within a trading day. This approach allows RV to account for both continuous price fluctuations and potential price jumps, which may result from news releases or other market events [Andersen et al., 2001].

3.5 Forecasting

The MCS procedure enables to select the most appropriate GARCH-MIDAS model, which integrates the long-run with the short-run volatility of the electrical prices. The former is explained by the MIDAS component, sampled at low-frequency data, that corresponds to the variable selected by the BPA, the latter, is modeled by a GARCH process for high-frequency data. The global volatility of the returns of electricity prices, accounting for both the short and the long-run components of the estimated optimal GARCH-MIDAS model, is then used to standardize the energy prices as follows:

$$n_i = \frac{R_i}{\hat{r}_i} \tag{11}$$

Here R_i represents the returns of electricity prices, $\hat{r}_i$ denotes the estimated global volatility via the GARCH-MIDAS model, and n_i is the normalized value of the returns of electricity prices.
The use of prices adjusted for risk facilitates their forecast as the latter turns out to be based on normalized prices. Normalizing prices by dividing them by their volatility, which is estimated from a GARCH model, produces risk-adjusted measures, making easier the comparisons between assets with different levels of volatility. This approach is valuable not only for the comparative analysis of asset performance but also for enhancing risk management and investment decision-making [Alexander, 2008]. Indeed, the use of normalized prices permits the derivation of indicators that, being less influenced by short-term price

[1]The criterion can coincide with either the Mean Squared Error or the Mean Absolute Error [Catania et al., 2015]

fluctuations, provide more robust evaluations of the assets' risk-adjusted performance.
Finally, a predictive ARMA model, accounting for the leverage effect, is built to forecast the normalized electricity prices. The model is specified as follows

$$n_{i+h} = \sum_{j=1}^{p} \phi_j n_{i-j} + \beta_2 \mathrm{Lev}_i + \epsilon_i + \sum_{j=1}^{q} \theta_j \epsilon_{i-j} \tag{12}$$

Here the variable $\mathrm{Lev}_i = D_i\, R_i$, where y_i is the return of the electricity prices, and D_i is a dummy variable that takes the value of one if $R_i < 0$, and zero otherwise, is used as proxy of the leverage (Lev) effect.

4 Data

4.1 Extreme climate events in Italy: an overview

Climate-related hazards are expected to increase in both frequency and intensity across Europe, particularly those associated with heat waves, droughts, and heavy precipitation events [Noto et al., 2023]. By 2100, climate-related disasters could impact approximately two-thirds of the European population annually, thus involving an Expected Annual Number of People Exposed (EAPE) of 351 million, in contrast to 5% of the population (25 million EAPE on average) between 1981 and 2010 [Masselot et al., 2023]. Similarly, the number of fatalities attributable to these events could rise from an average of 3,000 per year (1981–2010) to 152,000 per year by 2100, predominantly due to an increase in the frequency of heatwaves, with southern Europe being the most affected [Masselot et al., 2023, Noto et al., 2023]. However, the modest advancements in combating climate changes highlight how many European cities continue to struggle with achieving the targets set forth in the Paris Agreement. Therefore, there is a pressing need for increased efforts to mitigate the most severe impacts [Salvia et al., 2021, VijayaVenkataRaman et al., 2012].
Italy is not exempt from this culpable delay, having been severely affected by climate change in recent decades [Amendola et al., 2019b, Iannuccilli et al., 2021]. From this perspective, analyses and studies on extreme climatic events, such as extreme precipitation, and their trends at regional and local scales strongly encourage the identification and the use of more optimal strategies for adaptation and mitigation. Studies on extreme climatic event trends at the local scale are particularly crucial in the Mediterranean area, both for the complexity of the Mediterranean climate and for the lack of specific studies in this region [Iannuccilli et al., 2021].
Giorgi [2006] analyzed several model projections based on the IPCC Special Report scenarios [Hoegh Guldberg et al., 2018], describing the complexity of the Mediterranean area as "one of the most responsive regions to global change." Stronger signals of this trend can be identified in the decrease in mean precipitation and in the increase of precipitation variability during the dry (warm) season. The climatic complexity of the Mediterranean area is further intensified in the Italian peninsula due to its unique geographical location, complex topography, and orography. Italy, a long and narrow peninsula situated in the middle of the Mediterranean Sea, spans from North Africa to continental European latitudes (between 36° and 47°N) [Iannuccilli et al., 2021]. This places it in a transition area between a very hot and dry climate in the south and a temperate and rainy climate in the north [Bartolini et al., 2012]. According to Kottek et al. [2006], Italy exhibits a variety of climate types, ranging from humid subtropical (typical of the Adriatic coastal areas and the Po Valley) to cold continental and tundra (found in the alpine region and high mountainous areas). Due to this climatic complexity, analyzing the Italian climate is challenging, particularly in studies focused on identifying precipitation trends. It is not surprising that many studies conducted over the past few decades, aimed at analyzing and reporting precipitation trends and extremes, have produced discordant conclusions or chaotic and nonlinear tendencies [Iannuccilli et al., 2021]. The dataset proposed by Legambiente, known as *Città Clima* [2], has been employed in this study to analyze the hypothesis of an increase in the frequency and intensity of extreme rainfall events in a warming climate. *Città Clima* is an observatory by Legambiente, supported by UnipolSai Assicurazioni, that monitors the impacts of climate change on the Italian territory, with a particular focus on urban areas. This project aims to increase and broaden awareness of phenomena that are increasingly changing in both magnitude and frequency. The climate risk map helps to understand what is happening in the Italian territory by collecting and processing information on the impacts of climate events on urban areas, infrastructure, and historical assets. The map considers episodes since 2009 that have caused damage to begin creating an initial chart of the risk geography of our country. The objective of the map is

[2]Source: Legambiente

to understand where and how these phenomena occur with greater frequency as well as to analyze the impacts they cause, also comparing them with what occurred in the past. This aims to highlight, where possible, the relationship between the acceleration of climate processes and issues related to settlement or infrastructural factors in the Italian territory. The *Città Clima* dataset presents ten possible extreme climate events due to climate change, classified as follows:

- Flooding from intense rainfall [Beniston, 2007, Agarwal et al., 2024];
- Damage to historical heritage from intense rainfall [O'Neill et al., 2022, Sesana et al., 2021];
- Damage to infrastructure from intense rainfall [Garg et al., 2015, Cohen et al., 2018];
- Hail damage [Hohl et al., 2002, Muehleisen et al., 2018];
- Damage from prolonged drought [Byers et al., 2020, Jääskeläinen et al., 2018];
- Tornado damage [Unnikrishnan and van de Lindt, 2016, Paudel, 2022];
- River flooding [Venus et al., 2020, Kataria, 2009];
- Landslides from intense rainfall [Lebourg et al., 2010, Roccati et al., 2019];
- Storm surges [Lewis et al., 2017, Boggess et al., 2014];
- Extreme temperatures in urban areas [Santágata et al., 2017, Waite et al., 2017].

Using this dataset, a preliminary analysis of the extreme climate events that occurred in Italy from 2009 to 2023 has been conducted. Figure 1, that shows the frequencies of different extreme climate events in Italy from 2009 to 2023, confirms that these phenomena have increased during the last decade [Iannuccilli et al., 2021, Moonen et al., 2002]. Looking at the the damage frequencies caused by extreme events, it emerges that the appearance of some climatic events that were previously absent, such as prolonged droughts, storms, and tornadoes as well as the intensification of others, such as intense rainfall and extreme temperature in urban areas. Table 8 in Appendix A provides detailed frequencies of extreme climate events.

Figure 2 shows the frequencies of deaths caused by extreme climate events in Italy in the same period. The frequencies are not stable over the time span considered in the analysis, what changes over time is the type of extreme events that are responsible for deaths. If flooding and intense rainfalls are, more or less, always responsible of deaths in the last 15 years (through damages to infrastructure [3], in the first part of the period, rather than through river flooding or landslides, in the last part), the prolonged drought caused deaths in 2022 when it affected large parts of the country and was the worst in some areas since 1976. It was part of wider European drought, believed to be the worst on the continent in 500 years. Finally, the treats of tornadoes, often underestimated, is evident from the report of deaths that this atmospheric event has caused, in almost all Italian regions. Figures 12 and 13 in Appendix A show the details of fatalities resulting from extreme climate events. It is evident that the years with the highest number of deaths due to these events are 2009, 2018, and 2022. It is equally apparent, that the extreme climate events causing the most fatalities are river flooding, flooding from intense rainfall, followed by infrastructure damage due to intense rainfall, and tornado damage.

Figure 3 depicts a map highlighting the Italian provinces that were more hit by extreme climate events that occurred in the considered time span, the intensification of the red color indicates a greater presence of extreme climate events occurring in that year. The map clearly highlights how climatic events have intensified over time, gradually affecting all provinces of the country. In the early years, the provinces hardest hit by extreme climate events were Milan and those in the North-West of Italy. Gradually, the province of Rome assumed the unenviable position of being the most affected by extreme climate events. From 2016 to 2023, it stood out as the Italian province experiencing the highest number of such events within its territory.

[3]The Messina floods and mudslides of 2009 were the most fatal extreme climate events in Italy in the last 15 years [Lombardo et al., 2014]

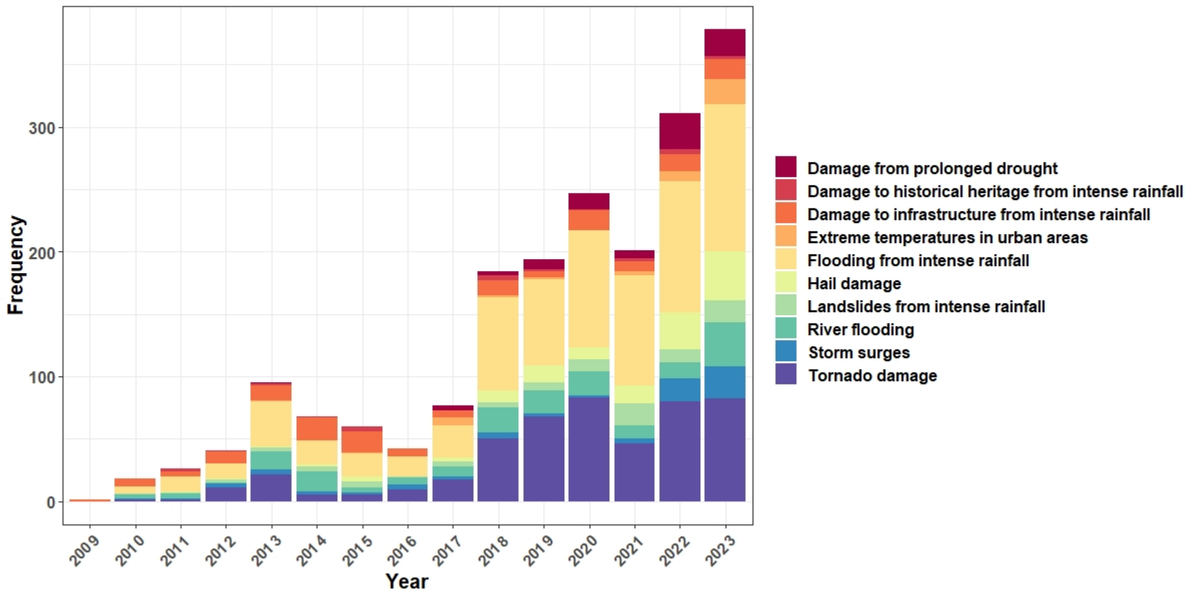


Figure 1: Frequencies of extreme climate events by type in Italy from 2009 to 2023

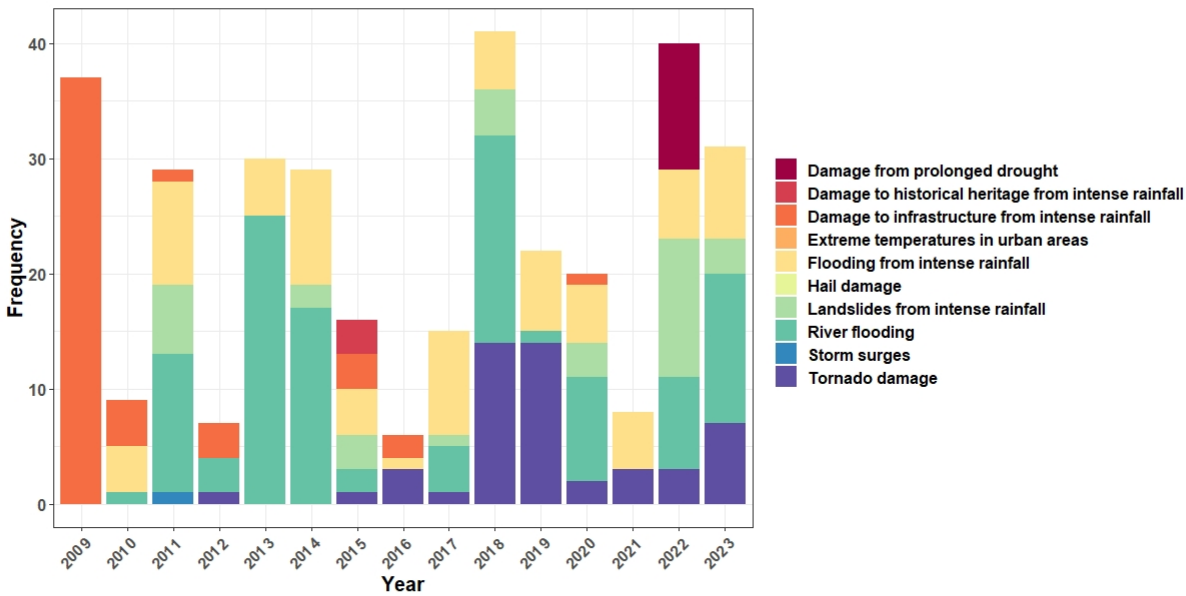
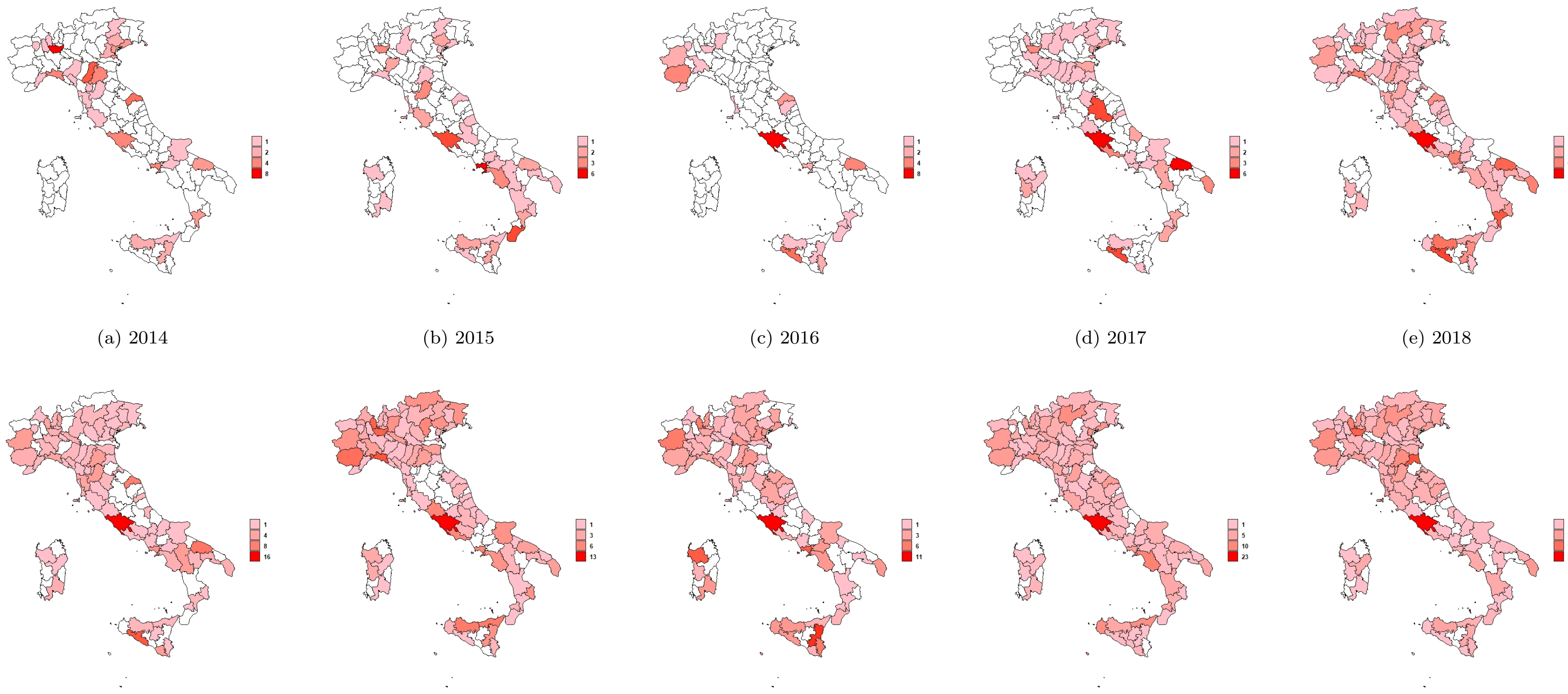


Figure 2: Frequencies of deaths due to extreme climate events in Italy from 2009 to 2023



(a) 2014 (b) 2015 (c) 2016 (d) 2017 (e) 2018

(f) 2019 (g) 2020 (h) 2021 (i) 2022 (j) 2023

Figure 3: Maps illustrating extreme climatic events that occurred across Italian provinces from 2014 to 2023.

4.2 Electricity Price

The electricity data is provided by the Gestore dei Mercati Energetici (GME) [4]. GME was established by the Gestore dei Servizi Energetici (GSE S.p.A.), a company wholly owned by the Italian Ministry of Economy and Finance. GME conducts its activities in accordance with the guidelines set by the Ministry of Environment and Energy Security (MASE) and the regulatory provisions issued by the Regulatory Authority for Energy, Networks, and Environment (ARERA). GME operates the electricity, gas, and environmental markets. As part of the electricity sector liberalization process, the Gestore dei Mercati Energetici S.p.A. (GME) was initially tasked with the organization and economic management of the wholesale Power Market under principles of neutrality, transparency, objectivity, and competition. On the power market platform managed by GME (also known as the Italian Power Exchange, IPEX), producers and purchasers trade wholesale electricity. Regarding electricity, GME operates a physical forward market (MTE), a market for trading daily products (MPEG) with continuous trading, a day-ahead auction market (MGP), and an intraday market (MI) consisting of three auction sessions (MI-A) and one continuous trading session (MI-XBID).
Figure 4 depicts the series of the hourly Single National Price (SNP) in Italy from December 2009 to December 2023, corresponding to the period when data collection on extreme climatic events in Italy began. As it can be seen, the electricity price for average household consumers in Italy peaked at 66 euro cents per kilowatt hour in the fourth quarter of 2022. This figure set an all-time electricity price record for Italy. Since 2021, electricity prices for domestic consumption kept increasing in Italy, driven by the growth of coal and natural gas prices. The main factors contributing to the European electricity price spike were the economic recovery after the COVID-19 pandemic in 2021 and the interruption of Russian imports following the Russian invasion of Ukraine in 2022.

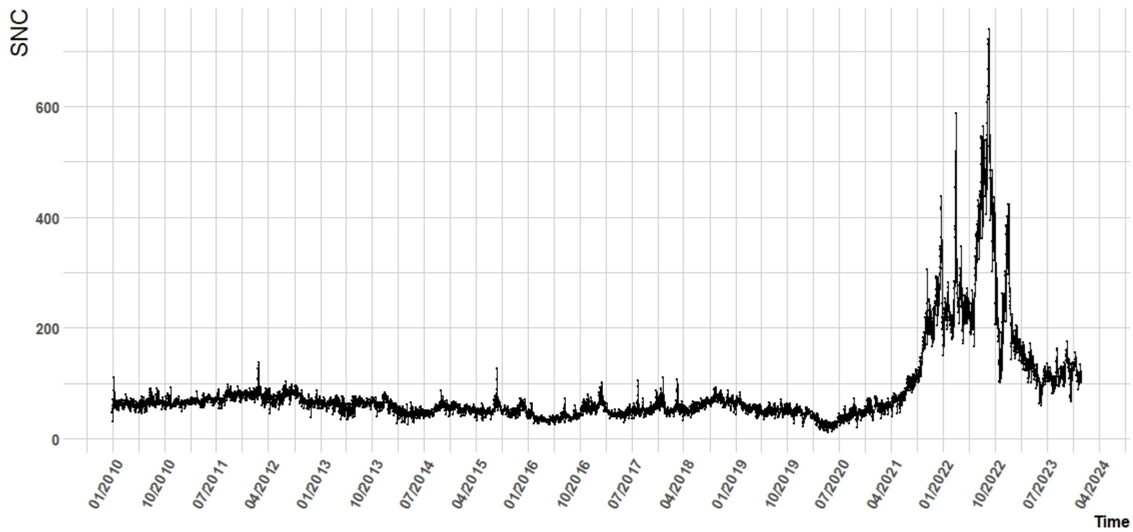


Figure 4: Time series of electricity prices in Italy from December 30, 2009, to December 31, 2023.

Figure 5 represents the returns of the SNP, obtained by computing the first-order differences of the logarithmic prices [Pan and Liu, 2018] defined in the following way:

$$R_t = log(SNP_t) - log(SNP_{t-1})$$

where SNP_t represents the price of the electricity at time t.

[4]Source: Gestore Mercati Energetici

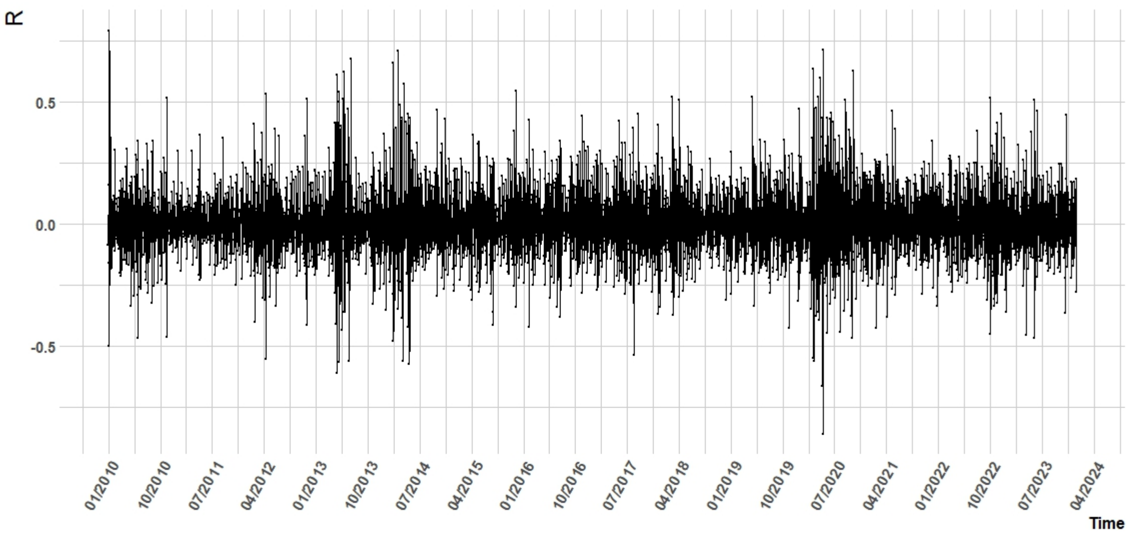


Figure 5: Returns of SNP

5 Results

This section describes in detail the results of the empirical analysis. As explained before, the BPA has been employed to identify the most appropriate set of regressors for the variable of interest: the returns of electricity prices in Italy [5]. The set of variables considered for this scope are: financial data, specifically monthly returns of various stock indexes, including exchange rates (such as "Euro-Dollar", "Euro-Yen", "Euro-GBP", and "Euro-CHF"), the "FTSE MIB index" (representing the Milan Stock Exchange), safe-haven assets (including gold indexes and stock prices of selected mining companies such as "Newmont Corporation", "Agnico Eagle Mines", and "Franco-Nevada Corporation"), stock prices of the U.S. tech companies ("Alphabet [Google]", "Amazon", "Apple", and "Microsoft"), and the most actively traded Italian stocks (such as "ENI", "Ferrari", "Intesa Sanpaolo", "Stellantis", "Leonardo", "Poste Italiane", and "Assicurazioni Generali"), as well as the frequencies of extreme climate events. The period under study spans from January 2009 to December 2023. In this initial step of the analysis, all data are sampled at the same frequency (monthly). A complete list of the variables included in the dataset is provided in Table 9 reported in appendix B.

Figure 6 shows the tree resulting from the minimal BIC tree [Edwards et al., 2010], which represents the starting point for the application of the BPA [Riso et al., 2023]. It is worth noting the particular structure of the minimal BIC tree depicted in Figure 6 that consists of a large component formed by a cluster of refuge assets (yellow nodes) and a cluster of exchange rates (dark green nodes). These two clusters are connected by node 3 (the "Euro-Dollar exchange rate") and node 32 ("Wheaton Precious Metals Corp. Index"). Notably, node 26 ("Pricing Culture Rolex Index"), although classified as a refuge asset, is connected only to node 3 ("the Euro-Dollar exchange rate"). Furthermore, most of the actively traded Italian stocks (green nodes) are directly connected to node 2, which represents the "FTSE MIB Index" (blue node). Finally, the stock prices of U.S. tech companies (pink nodes) are clustered together and are connected to the FTSE MIB Index through node 33 ("Microsoft Corporation Index").
As for the primary focus of this study, the returns of electricity prices, which is represented by node 1 (brown node), turns out to be directly connected to nodes 37 (orange node) and 36. The former identifies the frequencies of extreme climate events, the latter the "Amazon stock index", which is indirectly connected to all other nodes.

[5] In this part of the analysis, electricity price returns are aggregated on a monthly basis to align their frequency with that of other variables in the variable selection process.

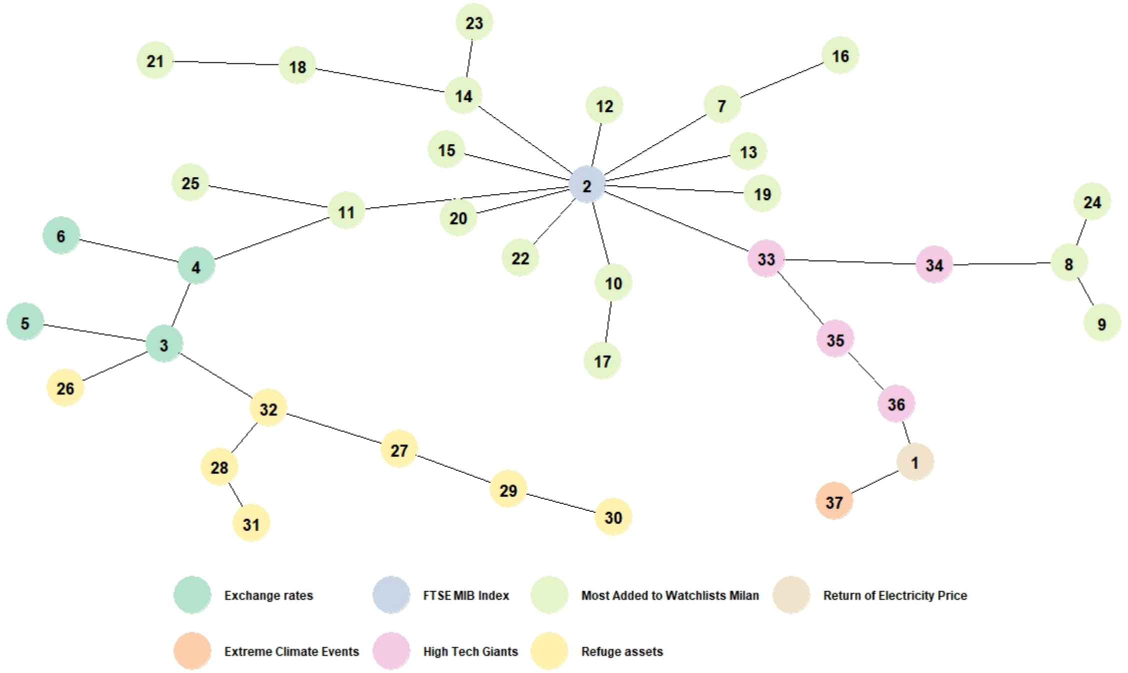


Figure 6: The minimal BIC tree (period 2009-2023)

By computing distances and path steps starting from the return of electricity price R (node 1), it emerges that there are 11 potential subsets of variables to consider for feature selection. According to Table 1, which shows the EC (see formula in Eq. (5)) for each of these path steps, w_1 is identified as the best path, as it exhibits the highest EC and includes the variable extreme climate events (ECE) and the variable "Amazon Index" (AI)

Table 1: Path-steps EC for "Return of Electricity Price"

path-steps w_i	EC
w_1	**0.0133**
w_2	0.0119
w_3	0.1001
w_4	0.0074
w_5	0.0033
w_6	0.0032
w_7	0.0029
w_8	0.0028
w_9	0.0028
w_{10}	0.0027
w_{11}	0.0026

The relevance of the variables, ECE and AI, has been tested via the Kraskov's test [Kraskov et al., 2004]. It results that only ECE is actually the best regressor for the return of electricity price (R). While this result may seem intuitive, it actually suggests that the returns of electricity prices are not influenced by the general trends of various financial stocks. This finding supports the hypothesis put forward in several studies [see, among others, Stone Jr et al., 2021, Ke et al., 2016] that climate patterns can cause substantial spikes in electricity consumption, leading to short-term price increases.

Table 2: Kraskov's mutual information test of independence between the variable EP and X_{w_1}

Variables at w_1	**p-value**
Amazon Index	1.00
Extreme climate events	0.01

Granger causality test have been then carried out to test the significance of the causal relationship between ECE and EP. The null hypothesis that ECE does not Granger-cause the returns of electricity prices is not rejected if no lagged values of the latter variable are retained in the regression. Looking at the result of the test, it emerges that the occurrence of extreme events Granger causes the energy price.

Table 3: Granger Causality (GC) tests between ECE and R, and vice versa. Columns represent the GC direction, the F-test results (columns 2 to 5) and the Wald χ^2 test results (columns 6 to 8). Boldface values denote significant at 1% level or less.

Direction	F	df_1	df_2	p-value(F)	χ^2	df	p-value(χ^2)
$R \Leftarrow$ ECE	3.08	10	138	**0.001****	30.83	10	<**0.001*****
ECE $\Leftarrow R$	1.14	10	138	0.334	11.44	10	0.334

Sample Period: 2009-01-01/2023-12-31

Having proved via the Granger causality test that extreme climate events indeed affect the returns of electricity prices, GARCH-MIDAS models, involving extreme climate events in their long-run component, have been implemented. More precisely, the short-term component of these models is driven by a GARCH process explaining the volatility of high-frequency data (returns of electricity prices sampled at daily frequencies), while the long-term component is a mixed data sampled process which includes a low-frequency component (extreme climate events sampled at monthly frequencies) to explain the long-run volatility of electricity prices.

GJRM and DAGM models have been estimated both with and without the inclusion of the exogenous variable (the Ukraine-Russia war) in the short-term volatility component $g_{i,t}$. The monthly frequencies of extreme climate events have been incorporated as MIDAS terms in the long-term volatility component τ_t. In all models, the innovations have been assumed to have either a Gaussian distribution or a Student's t-distribution. The estimation results for the GARCH-MIDAS models are presented in Table 4 for the GJRM and GJRM-X models, and in Table 5 for the DAGM and DAGM-X models. Focusing on Table 4, looking at the result from the GJRM-X model with Student's t-distributed innovations (Model 1), it emerges, that the Ukraine-Russia war (represented by the coefficient z) is statistically significant, with a positive effect on the volatility of electricity price returns. In contrast, the war variable is not significant in the GJRM-X model with normally distributed innovations (Model 3). For all GJRM and GJRM-X models, the intercept of the long-term component (the component of volatility driven by the frequency of extreme events), m, is statistically significant. The parameter θ, which is statistically significant across all models in Table 4, except for Model 4 (GJRM with normally distributed innovations), reflects the overall sensitivity of long-term volatility to the low-frequency explanatory variable. A positive value of θ suggests that increases in extreme climate events lead to higher long-term volatility in electricity price returns. Similarly, for the DAGM models presented in Table 5, Model 5 (the DAGM-X model with Student's t-distributed innovations) shows that all parameters are significant, including θ^+ and θ^-, which represent the asymmetric responses of long-term volatility to extreme climate events. In Model 7 (the DAGM-X model with normally distributed innovations), as in Model 3 (the GJRM-X model with normally distributed innovations) in Table 4, the parameter z (representing the Ukraine-Russia war) is not significant. Finally, the parameters ω_2^+ and ω_2^-, which are the weighting functions for the past K realizations associated with θ^+ and θ^-, are significant in all DAGM models, except for ω_2^+ in Model 8 (the DAGM model with normally distributed innovations).

Table 4: GJRM models results

	Model 1	Model 2	Model 3	Model 4
	Student-t innovations		**Normal innovations**	
	GJRM-X	GJRM	GJRM-X	GJRM
Best lag	10	11	10	11
α	0.026*	0.025*	0.025**	0.024*
	(0.014)	(0.014)	(0.013)	(0.012)
γ	0.865***	0.863***	0.425***	0.423***
	(0.068)	(0.061)	(0.120)	(0.118)
β	0.259***	0.261***	0.631***	0.634***
	(0.033)	(0.032)	(0.144)	(0.140)
z	0.078**		0.023	
	(0.037)		(0.026)	
m	-3.853***	-3.804***	-3.973***	-3.916***
	(0.128)	(0.104)	(0.131)	(0.104)
θ	0.017***	0.012***	0.013*	0.006
	(0.006)	(0.004)	(0.007)	(0.005)
ω_2	1.003***	1.001***	1.256***	1.009
	(0.297)	(0.147)	(0.174)	(6.540)
ν	5.275***	5.274***		
	(0.482)	(0.174)		
AIC	-2.53	-2.53	-1.33	-1.33
BIC	-2.52	-2.52	-1.32	-1.32
$MSE(\%)$	0.16	0.16	0.15	0.15

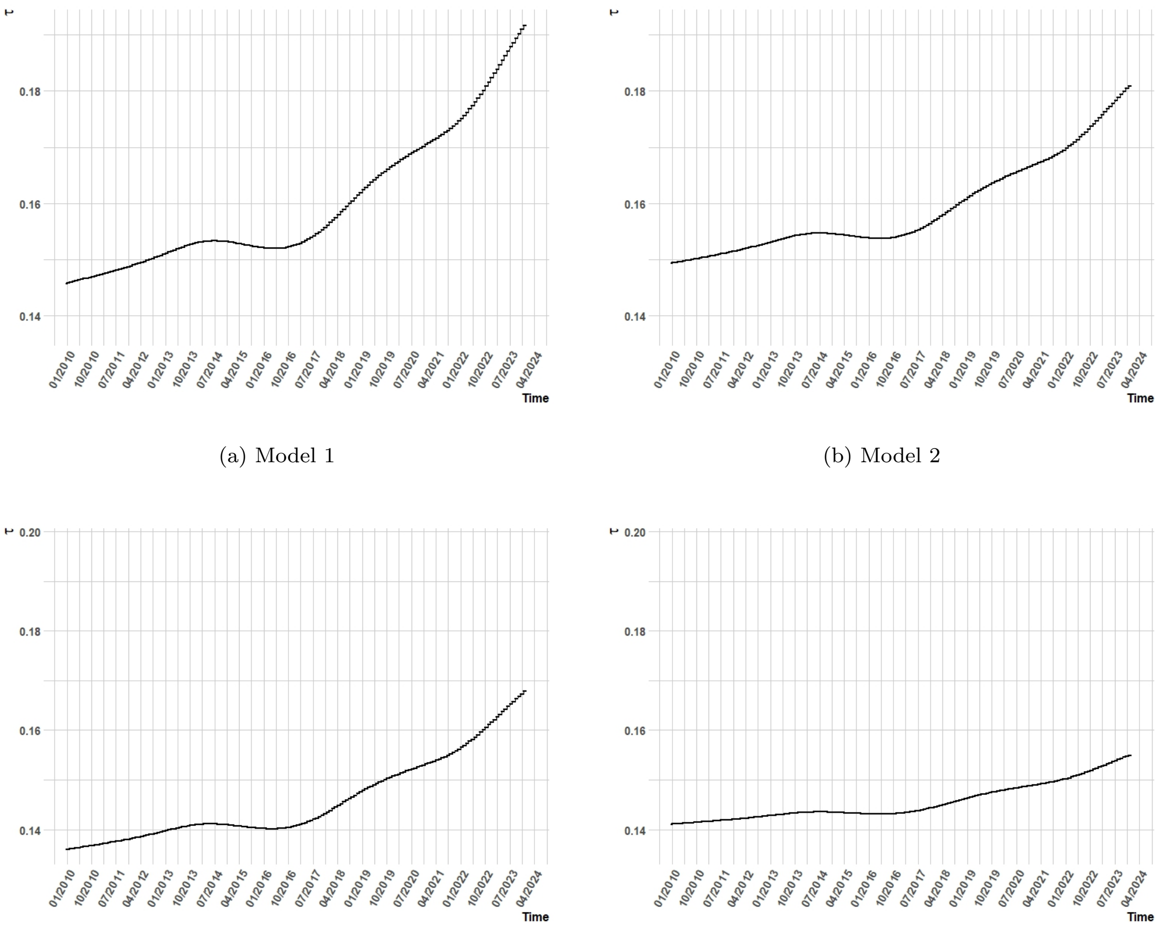
Sample Period: 2009-12-29/2023-12-31
(*) : $p < 0.1$; (**) : $p < 0.05$; (***) : $p < 0.01$.

Table 5: DAGM models results

	Model 5	Model 6	Model 7	Model 8
	Student-t innovations		**Normal innovations**	
	DAGM-X	DAGM	DAGM-X	DAGM
Best lag	8	11	7	11
α	0.026*	0.025*	0.025**	0.024***
	(0.014)	(0.014)	(0.013)	(0.001)
γ	0.864***	0.866***	0.426***	0.423***
	(0.063)	(0.053)	(0.025)	(0.117)
β	0.259***	0.261***	0.630***	0.634***
	(0.032)	(0.032)	(0.064)	(0.141)
z	0.078**		0.023	
	(0.034)		(0.022)	
m	-3.853***	-3.795***	-3.973***	-3.919***
	(0.106)	(0.086)	(0.156)	(0.112)
θ^+	0.020***	0.012***	0.014**	0.006
	(0.006)	(0.003)	(0.006)	(0.004)
ω_2^+	1.005***	1.003	1.640***	1.024
	(0.033)	(3.107)	(0.026)	(6.607)
θ^-	6.123***	9.021***	2.221***	9.501
	(0.285)	(0.098)	(0.101)	(269.051)
ω_2^-	4.957***	3.992***	6.050***	5.625***
	(0.201)	(0.037)	(0.008)	(0.012)
ν	5.276***	5.268***		
	(0.307)	(0.378)		
AIC	-2.53	-2.53	-1.33	-1.33
BIC	-2.52	-2.52	-1.32	-1.32
$MSE(\%)$	0.16	0.16	0.15	0.15

Sample Period: 2009-12-29/2023-12-31
(*) : $p < 0.1$; (**) : $p < 0.05$; (***) : $p < 0.01$.

The estimated long volatility τ_t estimated via GJRM-X and DAGM-X models is plotted in Figures 7 and 8, while the global volatility is display in Figures 9 and 10



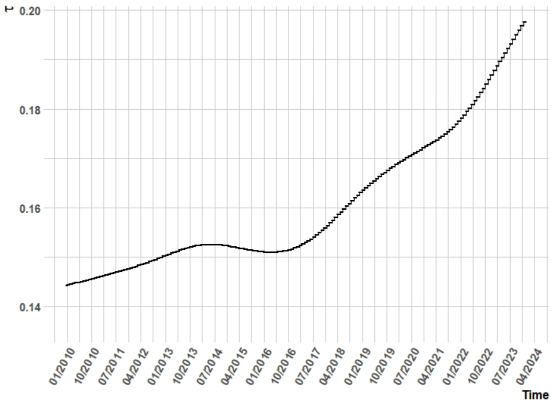
(a) Model 1

(b) Model 2

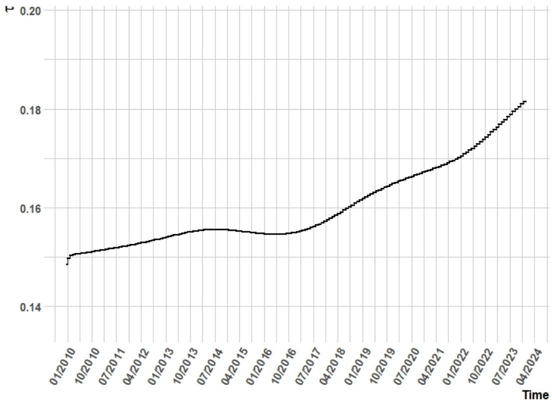
(c) Model 3

(d) Model 4

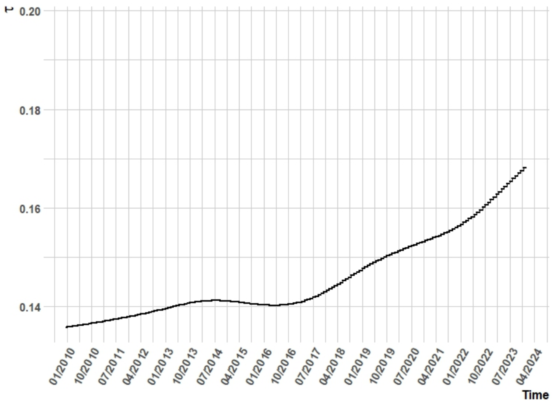
Figure 7: Estimated long run-volatility $\hat{\tau}_i$ for GJRM models. Sample period: 2009-12-29/2023-12-31



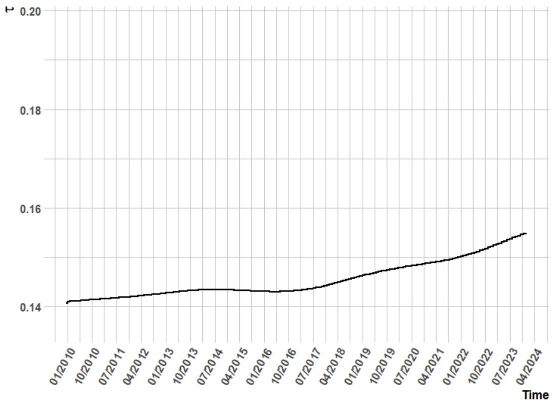
(a) Model 5



(b) Model 6

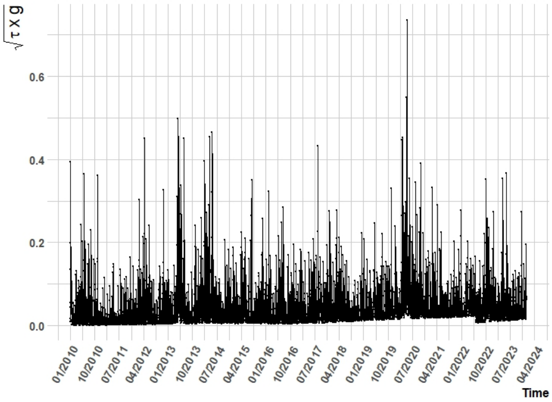


(c) Model 7

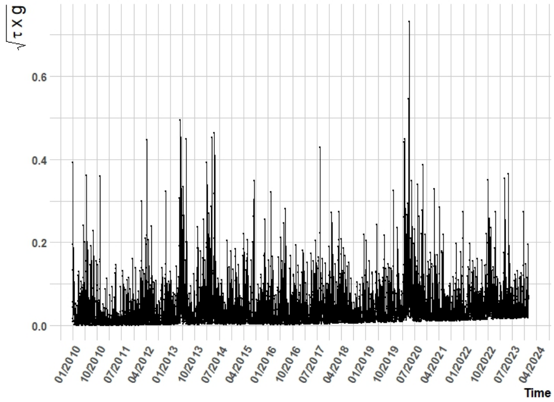


(d) Model 8

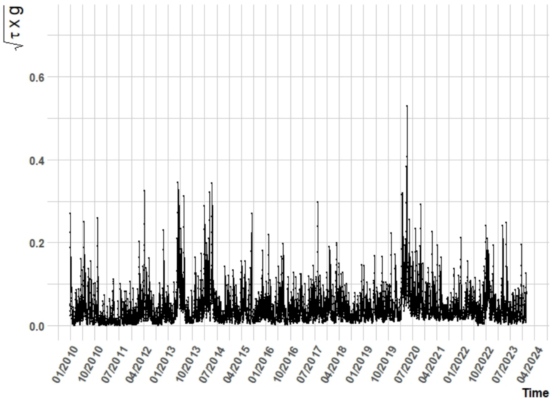
Figure 8: Estimated long run-volatility $\hat{\tau}_i$ for DAGM models. Sample period: 2009-12-29/2023-12-31



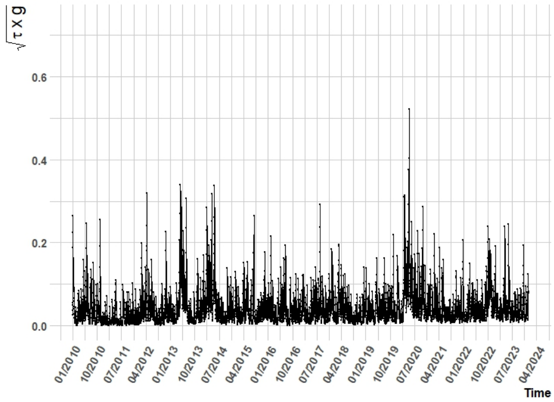
(a) Model 1



(b) Model 2

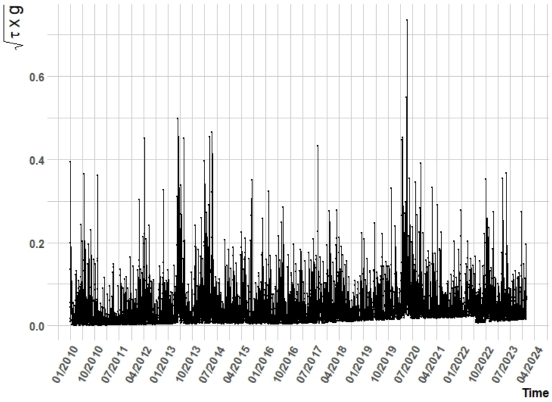


(c) Model 3

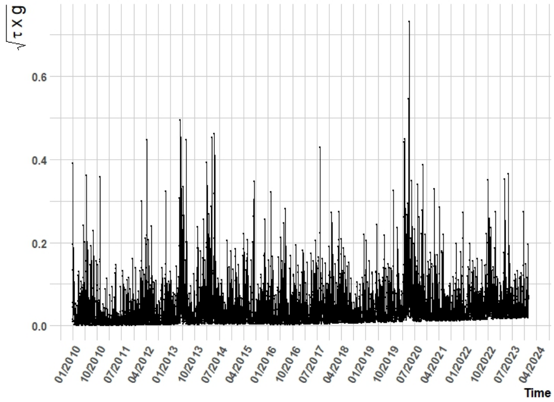


(d) Model 4

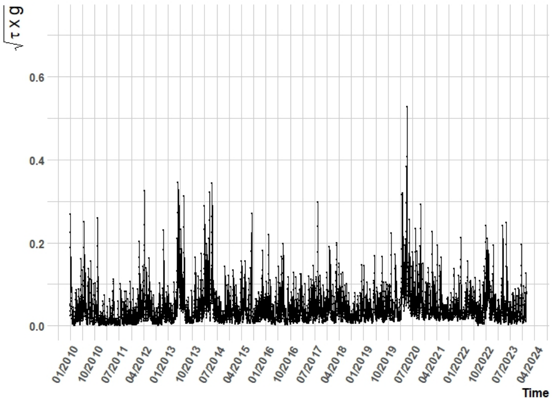
Figure 9: Estimated global volatility $\hat{\tau}_i \times \hat{g}_{it}$ for GJRM models. Sample period: 2009-12-29/2023-12-31



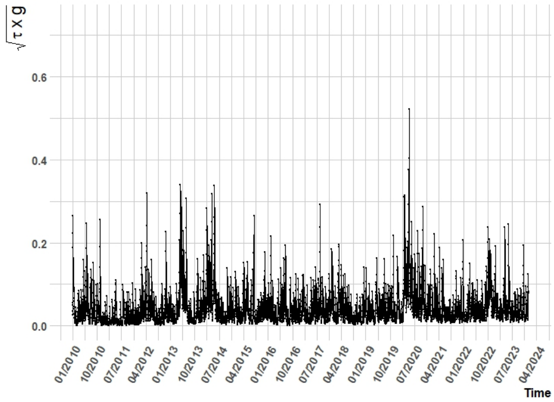
(a) Model 5



(b) Model 6



(c) Model 7



(d) Model 8

Figure 10: Estimated global volatility $\hat{\tau}_i \times \hat{g}_{it}$ for DAGM models. Sample period: 2009-12-29/2023-12-31

After estimating the global volatility for each GARCH-MIDAS model, the MCS procedure has been implemented to select the best model based on the quality of its volatility estimates, compared to the realized volatility (RV, calculated as in Eq. 10) of electricity price returns.
Figures 14 and 15, in Appedix C, compare RV with the estimated global volatility of the GJRM and DAGM models, while Table 6 provides the results of the MCS procedure using as the Mean Square Error (MSE) [6] as loss function to evaluate the discrepancies between RV and estimated global volatility of each GARCH-MIDAS model at each time point . The outputs of the loss function, are stored in a loss matrix with dimensions corresponding to the number of models (8) and the days of the evaluation period (from 2009-12-29 to 2023-12-31) Bernardi and Catania [2018]. The MCS procedure produces a Superior Set of Models, shown in Table 6, which ranks the models analyzed in this study. Specifically, the columns "$Rank_M$" and "$Rank_R$" indicate the position of the models based on the statistics $Tmax$ and TR respectively. The values in the columns "v_M" and "V_R"indicate the uncertainty associated with each model according to the statistics $Tmax$ and TR. In particular, the values "v_M" indicate the variability in model performance according to "$Tmax$", with higher variance suggesting greater uncertainty in the model's performance. Similarly, the values "V_R" capture the variability in performance based on the ranking statistic, where higher variance denotes greater uncertainty in rank-based performance. Models are accepted or excluded from the MCS based on each test statistic. The columns "MCS_M" and "MCS_R" indicate inclusion of the model in the MCS, with a value of 1 indicating the model's acceptance when ranked by either $Tmax$ or TR, and a value of 0 indicating its rejection. Finally, the "$Loss$" column measures each model's performance in terms of the loss function that is employed.

[6]The same results are obtained using the MCS procedure with the Absolute Error method

Table 6: Superior Set of Models.

Model	*Rank*$_M$	v_M	MCS_M	*Rank*$_R$	V_r	MCS_R	*Loss*
Model 1	**1**	-1.34	1.00	**1**	-0.28	1.00	0.0757
Model 2	8	1.15	0.33	8	13.29	0.00	0.0764
Model 3	4	-0.82	1.00	3	1.45	0.53	0.0759
Model 4	6	1.00	0.40	6	5.53	0.00	0.0764
Model 5	2	-1.25	1.00	7	7.78	0.00	0.0758
Model 6	7	1.06	0.37	4	5.05	0.00	0.0764
Model 7	3	-0.83	1.00	2	0.28	1.00	0.0759
Model 8	5	0.99	0.40	5	5.49	0.00	0.0764

The results show in Table 6 lead to the conclusion that the best GARCH-MIDAS model in this analysis is Model 1, the GJRM-X model with Student's t-distributed innovations.

Table 7: Optimal ARIMA model for Normalized price of electricity n

	Dependent variable: Normalized price of electricity n.
θ_1	0.106***
	(0.014)
β_0	-0.485^{***}
	(0.012)
Lev	8.613***
	(0.110)
Note:	*p<0.1; **p<0.05; ***p<0.01

After selecting the most appropriate GARCH-MIDAS model through the MCS procedure, the returns of electricity prices (n_i) as in Eq. 11 are normalized by using the global volatility estimate of this optimal model.

Finally, an ARMA model is constructed for predictive purposes using the estimated n_i, with the leverage effect (Lev) as a predictor, as shown in Eq. 11. The optimal ARMA model is selected based on its out-of-sample predictive performance. Specifically, after estimating the model over the period from January 2009 to December 2022, the same is used to forecast the normalized returns of electricity prices from January 2023 to December 2023. The accuracy of these forecasts is evaluated using the out-of-sample RMSE. Figure 16 in Appendix C presents the out-of-sample prediction of normalized electricity price returns for the best model (i.e., the one with the lowest RMSE). The estimates for the best ARMA model are provided in Table 7. Lastly, the forecast for the (unobserved) normalized returns of electricity prices for 2024 is shown in Figure 11.

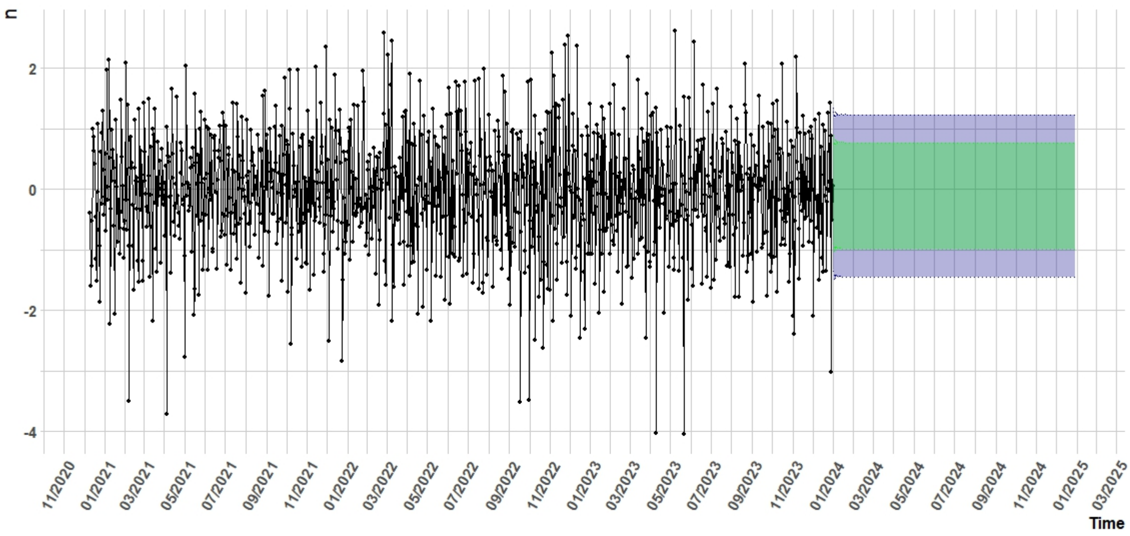


Figure 11: Forecast of normalized electricity price (n). The blue-shaded area represents the 95% forecast interval, while the green-shaded area represents the 80% forecast interval for the year 2024.

6 Conclusion

This study examined the impact of extreme weather events on electricity prices volatility in Italy, utilizing an innovative methodological approach that combines graphical models for variable selection with advanced volatility estimation techniques. The application of an innovative variable selection algorithm, the Best Path Algorithm (BPA), led to identify extreme climate events as the best predictors of returns of electricity prices, highlighting how these atmospheric factors play a predominant role compared to traditional financial variables.

The data used in this research include a detailed historical series of daily electricity prices in Italy, provided by the Gestore dei Mercati Energetici (GME), and a comprehensive dataset on extreme climate events collected by Legambiente through the *Città Clima* project. Integrating these two data sets, with different temporal granularities, posed a methodological challenge that we addressed using GARCH-MIDAS models. This methodology allows for the effective integration of high-frequency data (daily electricity price returns) with low-frequency data (monthly climate events), thereby capturing the detailed effects of extreme weather events on energy price volatility.

To manage anomalies and spikes in the data due to exogenous shocks, such as the Russia-Ukraine war,

GARCH-Jump with Regime Switching (GJRM) and its variant GJRM-X, which incorporates exogenous variables, were used . Different types of GARCH-models, including the Double Asymmetric GARCH-MIDAS (DAGM) and their extended versions, were compared using the Model Confidence Set (MCS) procedure. The latter allowed the identification of the most suitable model for forecasting the volatility of electricity prices.

The results confirm the significant influence of extreme weather events on the volatility of electricity prices in Italy. The selected model demonstrated superior predictive capability, enabling a decomposition of volatility into short- and medium-term components. Furthermore, using the estimated volatility to normalize electricity prices improved the accuracy of forecasts obtained through the ARIMA model.

The originality of this work lies in the integrated approach that combines machine learning techniques for variable selection with advanced econometric models for volatility estimation and forecasting. The adoption of the BPA to identify key predictors and the application of GARCH-MIDAS models to handle data with different frequencies represent significant contributions to the existing literature.

In conclusion, the study underscores the importance of considering extreme weather events in the modeling and forecasting of electricity prices. These findings have relevant implications for policymakers and energy market operators, highlighting the need to develop mitigation and adaptation strategies that account for the increasing frequency and intensity of extreme weather events due to climate change.

Future research could deepen the analysis by extending the approach to other countries or regions, or by including additional climatic and financial variables. Additionally, expanding the set of variables considered during the variable selection phase could further validate the significance of extreme weather events as key predictors or reveal other important factors influencing electricity prices. Moreover, integrating more sophisticated predictive models and employing deep learning techniques could further enhance the understanding of the dynamics between extreme weather events and energy markets.

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A Summary of Extreme climate events

Table 8: Frequencies of extreme climate events by type in Italy from 2009 to 2023

Extreme Climate Events	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Damage from prolonged drought	0	0	0	0	1	0	0	0	4	3	8	13	6	29	21
Damage to historical heritage from intense rainfall	0	0	2	1	1	1	4	0	0	4	2	1	3	4	3
Damage to infrastructure from intense rainfall	1	6	4	10	12	18	17	6	6	12	5	16	8	14	16
Extreme temperatures in urban areas	0	0	0	0	1	0	1	0	6	2	1	0	3	8	20
Flooding from intense rainfall	0	6	12	12	36	20	18	16	26	74	69	94	88	105	118
Hail damage	0	0	1	1	1	1	4	0	3	10	14	9	15	29	39
Landslides from intense rainfall	0	1	1	2	3	4	5	1	4	4	6	10	17	11	18
River flooding	0	3	4	1	15	16	4	6	8	20	19	19	11	13	35
Storm surges	0	1	1	3	4	3	2	4	3	5	2	2	4	18	26
Tornado damage	0	1	1	11	21	5	5	9	17	50	68	83	46	80	82

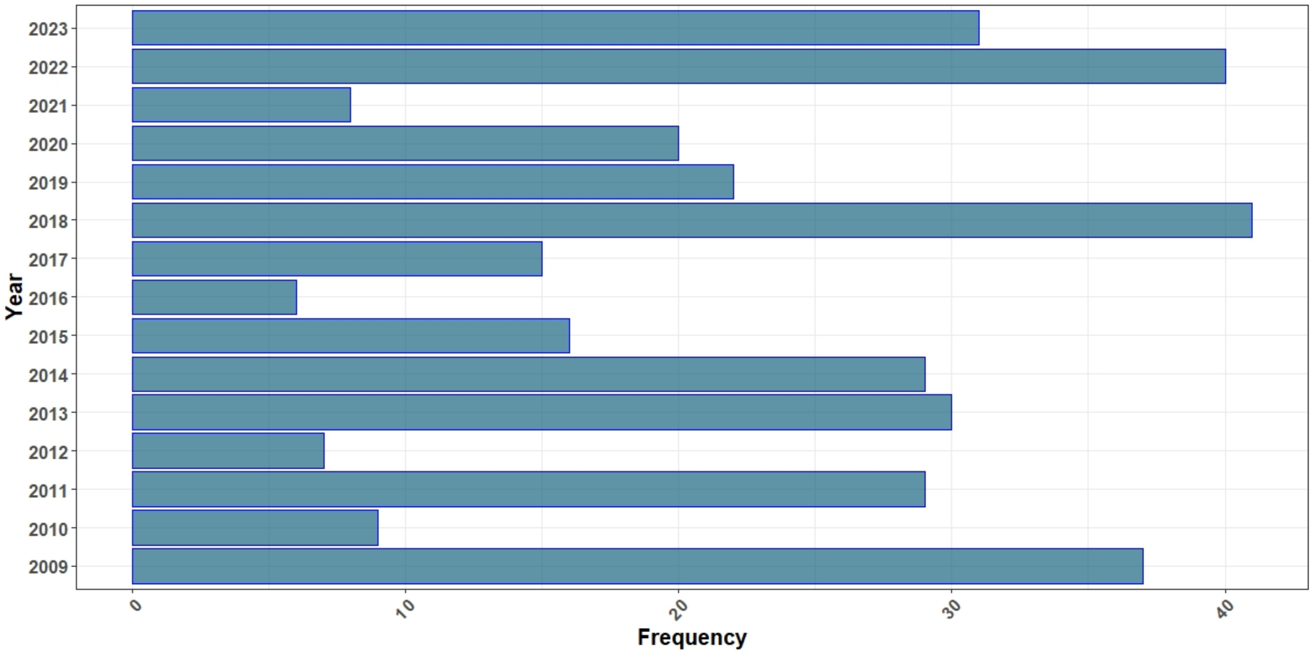


Figure 12: Frequencies of deaths due to extreme climate events in Italy from 2009 to 2023

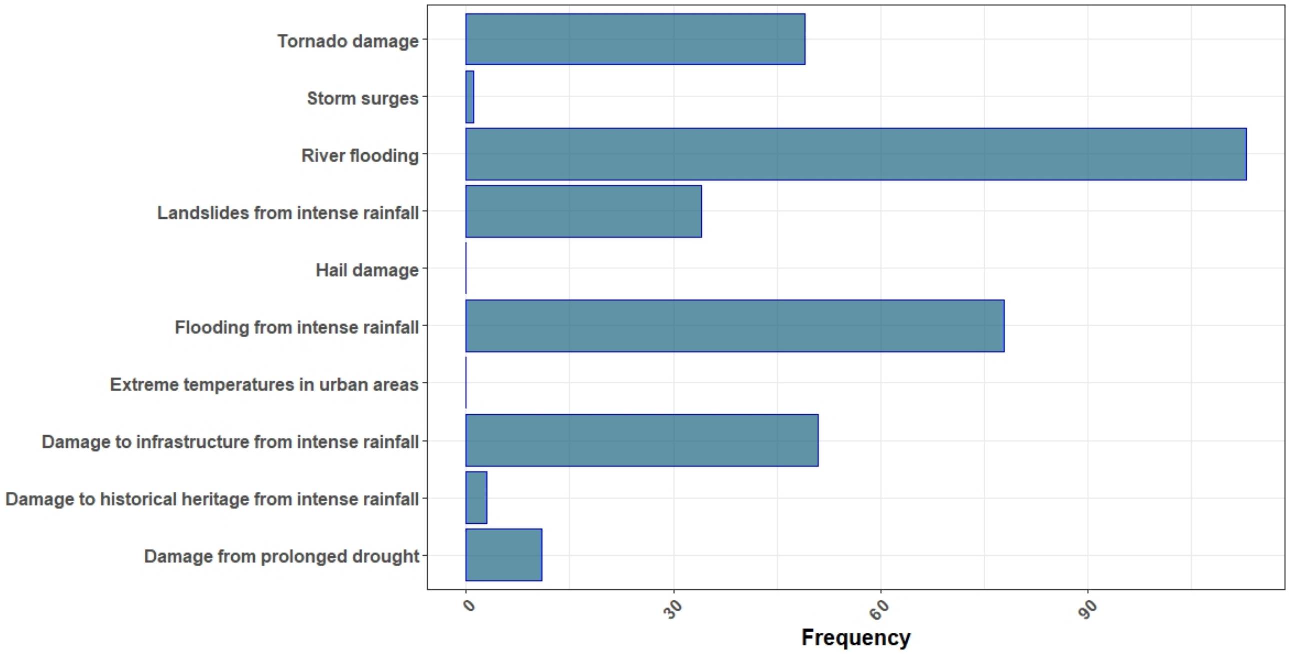


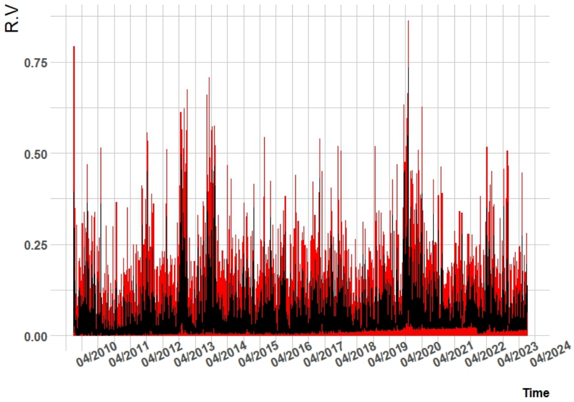
Figure 13: Frequencies of deaths due to extreme climate events by type in Italy from 2009 to 2023

B Data

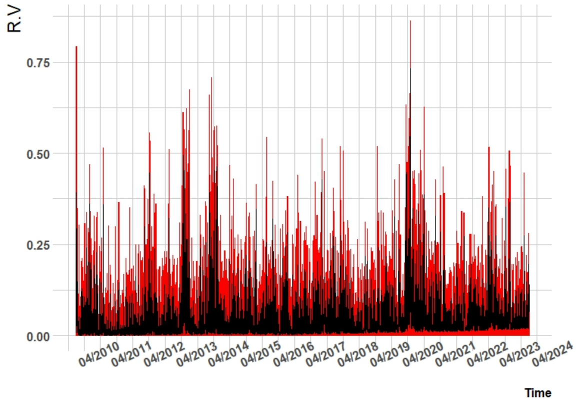
Table 9: Name of the considered variables together with the related identification code of used in label nodes

Label node	**Variable Name**
1	*Return of Electricity Price*
2	*FTSE MIB Index*
3	*Exchange Euro-Dollar*
4	*Exchange Euro-Yen*
5	*Exchange Euro-GBP*
6	*Exchange Euro-CHF*
7	*ENI index*
8	*Ferrari N.V. (RACE) Index*
9	*Moncler S.p.A. Index*
10	*Intesa Sanpaolo S.p.A. Index*
11	*UniCredit S.p.A. Index*
12	*Stellantis N.V. Index*
13	*STMicroelectronics N.V. Index*
14	*Enel Index*
15	*Assicurazioni Generali S.p.A. Index*
16	*Tenaris S.A. Index*
17	*Poste Italiane S.p.A. Index*
18	*Snam S.p.A. Index*
19	*Prysmian S.p.A. Index*
20	*Leonardo S.p.a. Index*
21	*Davide Campari-Milano N.V. Index*
22	*Mediobanca Banca di Credito Finanziario S.p.A. Index*
23	*Recordati Industria Chimica e Farmaceutica S.p.A. Index*
24	*Infrastrutture Wireless Italiane S.p.A. Index*
25	*Banco BPM S.p.A. Index*
26	*Pricing Culture CLONE X - X TAKASHI MURAKAMI Floor Index*
27	*Gold Jun 24 Index*
28	*Franco-Nevada Corporation Index*
29	*Newmont Corporation Index*
30	*Agnico Eagle Mines Limited Index*
31	*B2Gold Corp. Index*
32	*Wheaton Precious Metals Corp. Index*
33	*Microsoft Corporation Index*
34	*Apple Inc. Index*
35	*Alphabet Inc. Index*
36	*Amazon Index*
37	*Extreme Climate Events*

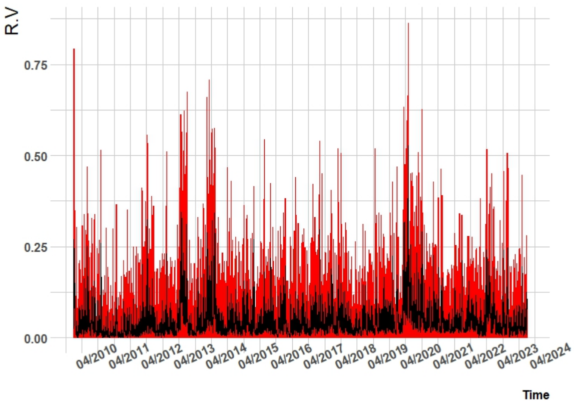
C Realized Volatility and Forecasting in sample



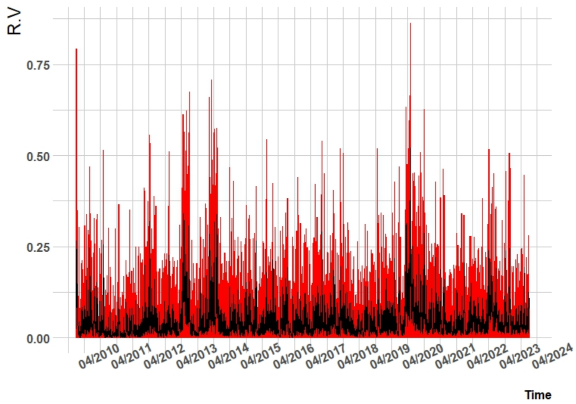
(a) Model 1



(b) Model 2

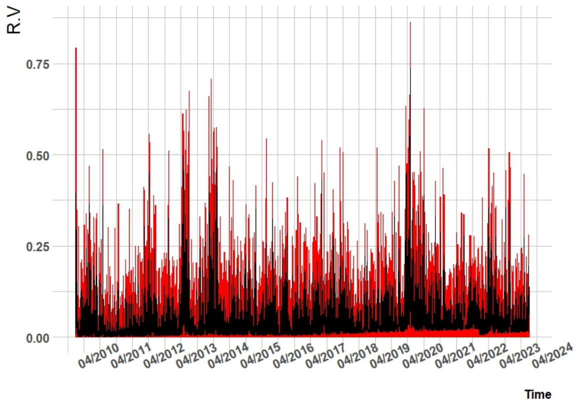


(c) Model 3

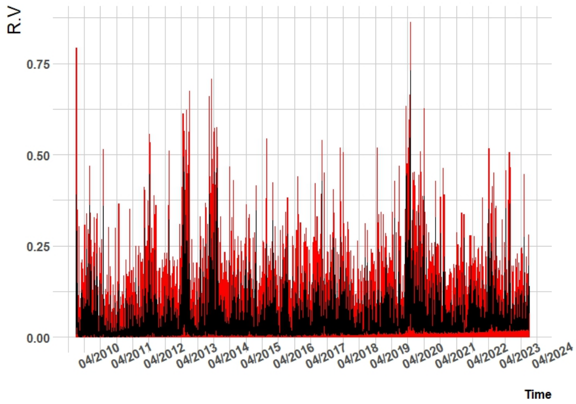


(d) Model 4

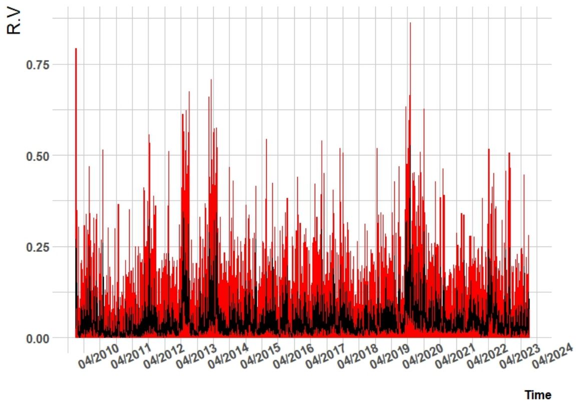
Figure 14: Comparison of RV (histogram in red) with the total volatility computed with the GJRM models (line in black)



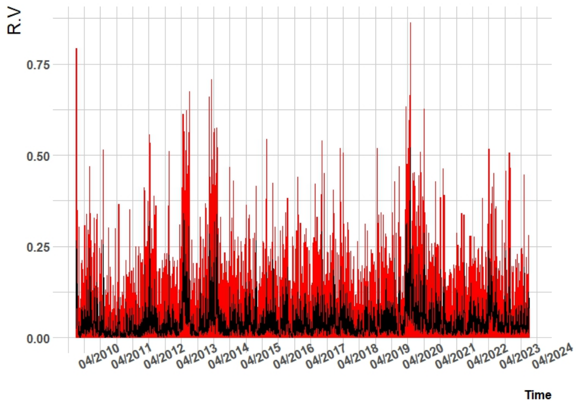
(a) Model 5



(b) Model 6



(c) Model 7



(d) Model 8

Figure 15: Comparison of RV (histogram in red) with the total volatility computed with the DAGM models (line in black)

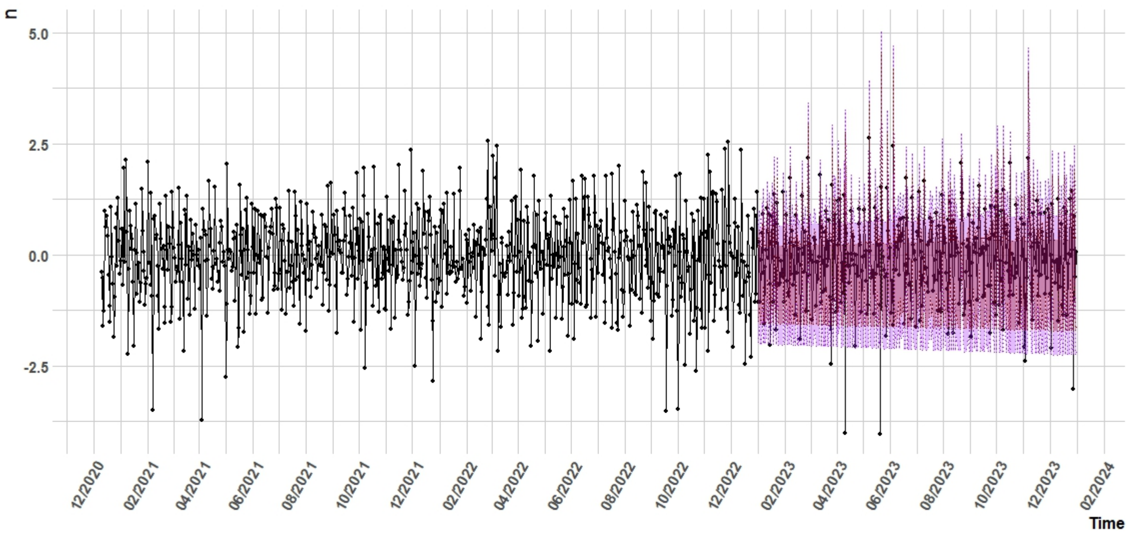


Figure 16: Out-of-sample prediction performed by the optimal ARIMA model for normalized electricity price (n). The red shaded area represents the 95% prediction interval, while the purple shaded area represents the 80% prediction interval.

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