Day-ahead Electricity Price Forecasting by Iterative Model Selections

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Abstract

This paper provides iterative model selection for forecasting day–ahead hourly electricity prices, while accounting for fundamental drivers. The iterative procedure is based on the automatisation of the forecasting process, by allowing for switching across several model specifications. Forecasts of demand, infeed from renewable energy sources, traditional fossil fuel prices, and physical flows are all included in linear and nonlinear specifications, ranging in the class of ARFIMA–GARCH models. Results support the adopting a flexible structure that is able to adapt to market conditions. Predictions, made for the northern Italian hourly electricity prices and compared by using the Diebold–Mariano test and the Model Confidence Set, indicate a strong predictive power from forecast demand at any hour and from RES mainly at peak hours, as well as a non–diminishing role of natural gas and CO_2 prices, and a high level of significance of electricity weighted inflows, especially during the morning hours.

Keywords: Day–ahead Hourly Prices, Demand, RES, Fossil Fuels, Weighted Inflows

JEL Classification: C13, C22, C53, Q47

1. Introduction

Forecasting day–ahead electricity prices has always attracted attention from practitioners and scholars because trading decisions are based on strategic and stochastic components such as arbitrage speculations and variability introduced into the system by effects of new regulations and imperfect predictability of fundamental drivers. This paper investigates both aspects.

On one hand, day–ahead electricity prices are determined for each hour of the day, before delivery, by the intersection of the aggregated curves of demand and supply. Therefore, factors that influence both curves have been largely investigated in price modelling. Fundamental variables such as forecasted demand, and often weather conditions, have been taken into account for the demand curve, whereas the predicted intermittent generation by renewable energy sources has been recently considered a risk source in the supply curve, together with import/export flows and the international movements of fossil fuel prices used in traditional thermal plants; for extensive reviews see Weron (2014) and Nowotarski and Weron (2018).

All these variables must be considered in the formulation of ex–ante expectations of day–ahead electricity prices. Furthermore, in recent years, the power generated by renewable energy sources has increased substantially due to incentives and the worldwide goal of reducing carbon emissions. Indeed, as a country in the European Union (EU), Italy is among the top six countries in the world for renewable power capacity (not including hydro), after Germany and together with the United Kingdom. Specifically, Italy is among the top EU countries for wind and solar photovoltaic (PV) capacity addictions in 2017 (REN21, 2018).

On the other hand, it has been recently observed that the organisation of electricity markets allows for strategic bidding and speculations. Some generators can explore the arbitrage opportunities among sequential market sessions and decide to withhold capacity unsold on the day–ahead market if they are allowed to bid on balancing market sessions. These sessions are close to real time, can realise higher profits because of the pay–as–bid pricing mechanisms, and thus obtain the price declared in submitted bids. In Italy, this behaviour attracted the attention of the energy regulator in 2016 because enormous costs were generated within the system as a consequence of speculative trading of few units acting in the balancing sessions. Gianfreda et al. (2018) documented the time evolution of balancing costs in Italy by investigating auction–bid data observed over all market sessions, from the day–ahead to real time, and passing through intraday sessions. Another observation is that units allowed to bid on a balancing market attempted to close their position with zero quantities sold in the day–ahead market to have the capacity to be sold at higher prices in balancing sessions, where there is no competition of traders and renewable energy sources (RES) units. The last ones depress the day–ahead prices as an effect of the merit order: according to this principle, producing units that pollute less have the priority of dispatch and move the supply curve towards the right, decreasing equilibrium prices and consequently reducing profit opportunities for conventional technologies (which generally act on balancing sessions, together with some hydro units).

To overcome these critical issues, some EU countries, including Italy, have started to discuss the possibility of allowing RES units to act also in the balancing markets. However, in the meanwhile, the prediction of prices on the day–ahead market is becoming an increasingly important and essential step in the evaluation of trading strategies since operators (of thermal conventional units) consider the price spreads among the various sequential sessions and the possibility to act over a long–term capacity market. Based on all these considerations and because of the raised issue in 2016, Italy is an excellent case study. Moreover, the zonal structure allows the consideration of the operators' bidding behaviour across different areas and according to the composition of their generation mix.

Northern Italy is an exceptionally good example for the following main reasons: 1) the zone is well interconnected with foreign countries, from whom electricity can be imported at lower prices; 2) a high share of solar PV generation has been observed in recent years; 3) most of the hydro generation is located in the Alps; 4) and more importantly, the zonal demand represents almost half of the national one; hence, variations in demand and supply can boost the strategic use of balancing sessions. Therefore, the prediction of day–ahead electricity prices observed in northern Italy can increase the understanding of the main drivers in modelling these prices, and in monitoring (hence controlling), the bidding strategies across market sessions, according to the day–ahead price levels expected in the day–head market.

According to the literature, few papers have inspected the predictability of day–ahead prices in northern Italy. The limited inspection mainly occurred because this area was observed to have no notable implications. The most notable studies are Gianfreda and Grossi (2012) and Shah and Lisi (2019). The latter adopts a nonparametric functional autoregressive model based on individual bids, whereas the former considered the Italian zonal prices by studying the first years after liberalisation (2006–2008), during which RES had a limited and marginal role in the determination of prices. In that contribution, no quantities from wind, solar, or hydro were considered, and only indicators for marginal units determining the prices, as well as demand, an index to detect market power and zonal congestions, were considered as zonal price drivers. This paper represents an extension of that work by including (predicted) RES values, weighted import flows, and fossil fuel prices in the model specifications for the prediction of northern Italian zonal prices. In addition, our contribution relies on both the Diebold–Mariano (DM) (Diebold and Mariano, 1995) and the Model Confidence Set (MCS) (Hansen et al., 2011) testing procedures to guide practitioners in choosing the best model specification according to different hours.

For other market structures, Karakatsani and Bunn (2008) and others have attempted to capture the impacts of economic, technical, strategic, and risk factors on intraday prices. Oberndorfer (2009) focused on the relationship between energy market developments, external shocks, and pricing of European utility stocks. Hickey et al. (2012) implemented ARMAX–GARCH models trend, dummy variables for seasonality and load for five MISO pricing hubs. Subsequently, Maciejowska and Weron (2016) focused on the increased granularity of data available on the British market (where prices have a half–hour frequency) to test a set of fundamental explanatory variables (i.e. natural gas, coal, and CO_2 emissions). de Marcos et al. (2019) proposed an econometric and fundamental approach to forecast short–term prices in the Iberian market by pairing a neural network with a set of expected and actual fundamental variables. Gianfreda et al. (2020) compared several univariate and multivariate models augmented with fundamental variables, including demand forecasts, and production forecasts from fossil and renewable energy sources, to predict hourly day-ahead electricity prices in several European markets.

Following the extensive literature, we select AR(FI)MA–GARCH–type models and compare their forecasting ability with/without a set of regressors, while adopting a rolling window approach and an adaptive scheme. The former approach recalls the dynamic evolution of fundamentals over time, in line with the time–varying parameter regression model implemented in Karakatsani and Bunn (2008) to adapt continuously price structures to market changes. Furthermore, the latter scheme develops to the estimation strategy implemented in Weron and Misiorek (2008), Chen and Bunn (2014) and Maciejowska and Weron (2016), by extending the selection to both the autoregressive and moving average lag–orders for each calibration window and each model specification, including the options to switch from one model to another in cases of problems of convergence of some model specifications and to replace negative forecasted prices with null prices (since that negative pricing is not allowed in the Italian market). Moreover, we expand the set of fundamentals including RES (wind, solar PV, and hydro) and weighted flows and we explore nonlinear models to provide empirical evidence on their forecasting performance, given the mixed results in the literature and their under-performance assumed in Hong et al., 2014 and explored only in British and German markets.

We tested several AR(FI)MAX–GARCH models and we observed that both the ARFIMAX model with Normal distribution and the ARMAX–EGARCH model with skew Student's t distribution perform quite accurately. These models have the lowest average root mean square errors (RMSEs) in the out–of–sample and highlight different pattern behaviours across the 24 hours. The separate analysis over hours without solar (1–7 and 21–24) suggests the presence of volatility clustering, especially during the 21–24 hours, simultaneously suggesting a combined significant effect between gas and hydro (during 1–7 hours) and the use of GARCH–type specifications (during 21–24 hours), with the relative forecasting accuracy that decreases across the ramp–up and ramp–down hours. We also assess the coefficients of the exogenous regressors to investigate their degree of significance through the considered sample and we provide evidence that fundamental factors can drive zonal electricity prices differently within trading periods. The most notable evidence is that RES (wind, solar, and hydro) and imports from neighbouring countries play a relevant role in price creation. Differently from the empirical results found in UK and Germany, coal is found to be not statistically significant, whereas natural gas confirms its relevance especially at ramp–up and ramp–down hours. Surprisingly, carbon prices can exhibit a significant negative effect which may be understood as a consequence of energy policy of increasing green generation.

The remainder of the paper is structured as follows. Section 2 presents a brief description of the Italian market with a focus on the northern zone, Section 3 provides a detailed description of the data employed and the methodological strategy used to predict hourly electricity prices, Section 4 presents the results, and finally Section 5 concludes.

2. The Italian Market Structure and the Northern Zone

The Italian electricity market is structured into three main segments: the day–ahead, the intraday, and the ancillary services markets. The latter is paired by the balancing market operated in real time on the day of delivery. All segments are open to a variety of national and international operators (producers, consumers, traders), for a total of 258 different market participants in 2017[1]. Market participation is voluntary both in the day–ahead and in the intraday markets, whereas it is compulsory in the ancillary services market sessions. We focus on the day–ahead market, which opens nine days before the day of delivery and closes at noon on the day before delivery.

The Italian electricity market is structured into geographical and foreign virtual zones. The

[1] The spot market is complemented by the forward market (a platform for different types of contracts) and by the bilateral contract platform (where all OTC energy transactions that require flows through the power grid are registered).

geographical zones represent a portion of the national grid delimited by bottlenecks in transmission capacity, and these are northern Italy, central–northern Italy, central–southern Italy, southern Italy, Sicily, and Sardinia. The foreign virtual zones are points of interconnection with neighbouring countries. In this paper we consider northern Italy; thus, the foreign virtual zones in this analysis are France, Switzerland, Austria, and Slovenia.

Each geographical and virtual zone yields an hourly (clearing) price, obtained from an implicit bidding mechanism in which pairs of quantities (in MWh) and prices (in €/MWh) are considered by accounting for the market splitting in case of congestions. Therefore, in the same hour, zonal prices in contiguous market zones can differ depending on transmission bottlenecks. The zonal prices concur to generate the single national price (or *prezzo unico nazionale*, PUN), that is, the average of zonal day–ahead prices weighted for total purchases, net of purchases for pumped–storage units, and purchases by neighbouring zones. Additional details on the Italian market structure and the process of the creation of a system marginal price are found in Bosco et al. (2007), Gianfreda and Grossi (2012), Gianfreda et al. (2016, 2019) and Shah and Lisi (2019).

These researchers have emphasised the differences in the generation mix across regions and how the industrial activities are mainly concentrated in the northern area of the country, which is by far the most relevant in terms of consumption, due to the high concentration of population and industries. The northern consumption is 175,396 GWh over 303,443 GWh at the national level. Energy intensity is consistently higher, with an average of 6,326 kWh per inhabitant versus a national average of 5,024 kWh (Terna, 2018).

The northern area is also characterised by a varied, flexible generation mix, with 26% hydropower, and other renewables such as solar (6%) and biomasses (8%); conventional thermal generation covers the remaining portion. In 2017, the production in the northern zone was 149,204 GWh over a total of 289,708 GWh, roughly 51%.

Moreover, Italy has arranged market–coupling agreements with Slovenia since 2011, and with France and Austria since 2015, which represent completion steps to the creation of a single internal electricity market in Europe. Market coupling allows for the simultaneous calculation of electricity prices and cross–border flows across coupled regions, and the main benefits are both an optimised and more efficient utilisation of cross–border capacity and a better price alignment among different countries. Because of the relevant interconnection capacity between foreign countries and northern Italy, it is possible to import electricity at a lower price. For instance, in 2018, Italy imported

47,170 GWh of electricity (approximately equivalent to 15% of total consumption) from French, Swiss, and Slovenian borders. Hence, cross–border flows are included in this analysis.

3. Data and Methodology

This section provides a detailed overview of the available data and then explains the methodological strategy to predict hourly electricity prices. In particular, subsection 3.1 describes both the endogenous and the exogenous variables used in our model specifications, while subsection 3.2 shows all the model specifications and the forecast procedure.

3.1. Data and Preliminary Analysis

To perform our analysis, we use day–ahead electricity prices determined hourly in the northern zone of Italy. We directly retrieve these prices (in €/MWh) from the website of the Italian system operator (*Gestore dei Mercati Energetici*, GME[2]) and collect from ENTSO–E the forecasted day–ahead load (quoted in MW) for the same zone. Load is used as a proxy for predictions of local electricity demand. From the same platform, we download hourly actual hydro generation for northern Italy and forecasts of renewable solar PV and wind generation (all quoted in MW). Forecasted load and RES quantities were re–scaled from MW to GW, as in Chen and Bunn (2010) among many others.

In addition, we include flows with foreign countries and with the contiguous zone, i.e. the central–northern Italy. To account for different prices and quantities observed in neighbouring foreign markets, we construct a series of average hourly prices (expressed in €/MWh) *weighted* for imports of electricity into the northern zone. Specifically, this is calculated as the average of day–ahead hourly prices observed in Austria, France, Switzerland, Slovenia, and in central–northern Italy, weighted for actual hourly electricity physical flows, to capture the effects of electricity transits across bordering markets and the connected national zone.

Finally, we consider commodity prices to account for the marginal costs of conventional thermal generation, such as Dutch TTF natural gas prices (for delivery over the next month) and CO_2 emissions prices[3]. We collect these variables from Datastream, whose misure units are converted

[2]http://www.mercatoelettrico.org

[3]We also considered the ICE API2 Rotterdam Future prices for coal, but coefficients were not significant and thus we excluded it from the analysis. Results are available upon request. However, we would like to emphasize

to €/MWh when necessary. Our final database comprises 35,064 hourly observations for each variable, from January 2015 to December 2018.

Following Bunn (2000), Cuaresma et al. (2004) and subsequent references, we adopt a variable segmentation approach. The modelling and forecasting process considers hourly time series per time, i.e. we model and forecast each of the hourly prices individually. Moreover, the model specification strategy replaces missing or incomplete hourly actual data (when they are unavailable because they have not yet been published) with the corresponding information observed for the same hour on the day before.

Differently from Weron (2007) and Afanasyev and Fedorova (2019), we maintain the outliers in all the variable series and we do not decompose the effects of seasonality. We claim that outliers represent peculiar characteristics of the Italian market since they incorporate notable market information in terms of sample variance and arbitrage opportunity from a day–ahead trading perspective. In addition and in contrast to Conejo et al. (2005), Garcia et al. (2005), Weron and Misiorek (2008), Bordignon et al. (2013) among others, we do not apply logarithms to prices to improve normality and stabilize variance, since this transformation could mask the statistical price properties and volatility dynamics that we want to capture and model, see Karakatsani and Bunn (2010) and Paraschiv et al. (2014) for a similar choice to our paper.

The descriptive statistics of the selected variables are reported in Table 1, and their dynamics are depicted in Figure 1. Even if the hourly electricity prices range between 5 and 206.12€/MWh, Italian power prices have a floor of 0€/MWh and a cap of 3,000€/MWh. Notably, even if wind generation in northern Italy exhibits low values (a range between 0 and 20 MW), we include this variable for completeness and consistency with the zonal generation mix.

Electricity prices time series present a weekly seasonality, with consumption behaviour peaking on central working days, and a more relaxed load pattern during the weekends. These features are more evident in Figure 2, where time series are presented for a sample of hours within peak and off–peak periods (i.e. hours 3, 9, 13, 15, 21, and 24). Consistently, a monthly seasonality is characterised by a consumption peak in winter months (January and February) and a peak in summer months, because of the widespread use of cooling systems and heat pumps. Wind

that, in case of a further reduction of coal prices and/or a sudden increase of emission prices, electricity prices will be expected to react differently to what observed in this sample.

and solar PV generation fluctuate according to weather conditions, and solar PV generation also fluctuates according to hours of solar radiation. Electricity inflows from bordering zones (central–northern Italy) and foreign markets (Austria, France, Switzerland, and Slovenia) also exhibit strong seasonality, especially in the beginning of our sample.

We consider the Jarque–Bera (JB) test to check for normality of error terms (Jarque and Bera, 1987), and both the augmented Dickey–Fuller (ADF) (Dickey and Fuller, 1979; Said and Dickey, 1984), and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests for the stationarity (Kwiatkowski et al., 1992). Since we observed non–normality according to JB test, stationarity according to the ADF test and both level and trend non–stationarity according to the KPSS test, we opted to account for alternative distributions of the error terms and consider the ARFIMA model specifications.

	Min	Mean	Max	Std.Dev	Skew.	Ex. Kurt.
Price	5.00	52.62	206.12	17.11	1.16	3.36
Load	8.41	18.54	31.30	4.82	0.17	-1.12
Weighted Import	0.00	43.55	248.98	16.20	0.92	2.74
Natural Gas	10.70	18.31	29.33	3.83	0.24	-0.28
CO_2	3.91	8.70	25.20	4.90	1.60	1.51
Solar	0.00	0.77	5.50	1.16	1.42	0.89
Wind	0.00	0.00	0.02	0.01	1.02	0.36
Hydro	0.55	3.81	9.44	1.99	0.34	-0.83

Table 1: Descriptive Statistics of Fundamental Variables computed over the Full Sample. Note that *Std.Dev.*, *Skew.*, *Ex. Kurt.* mean *standard deviation*, *skewness* and *excess of kurtosis* respectively.

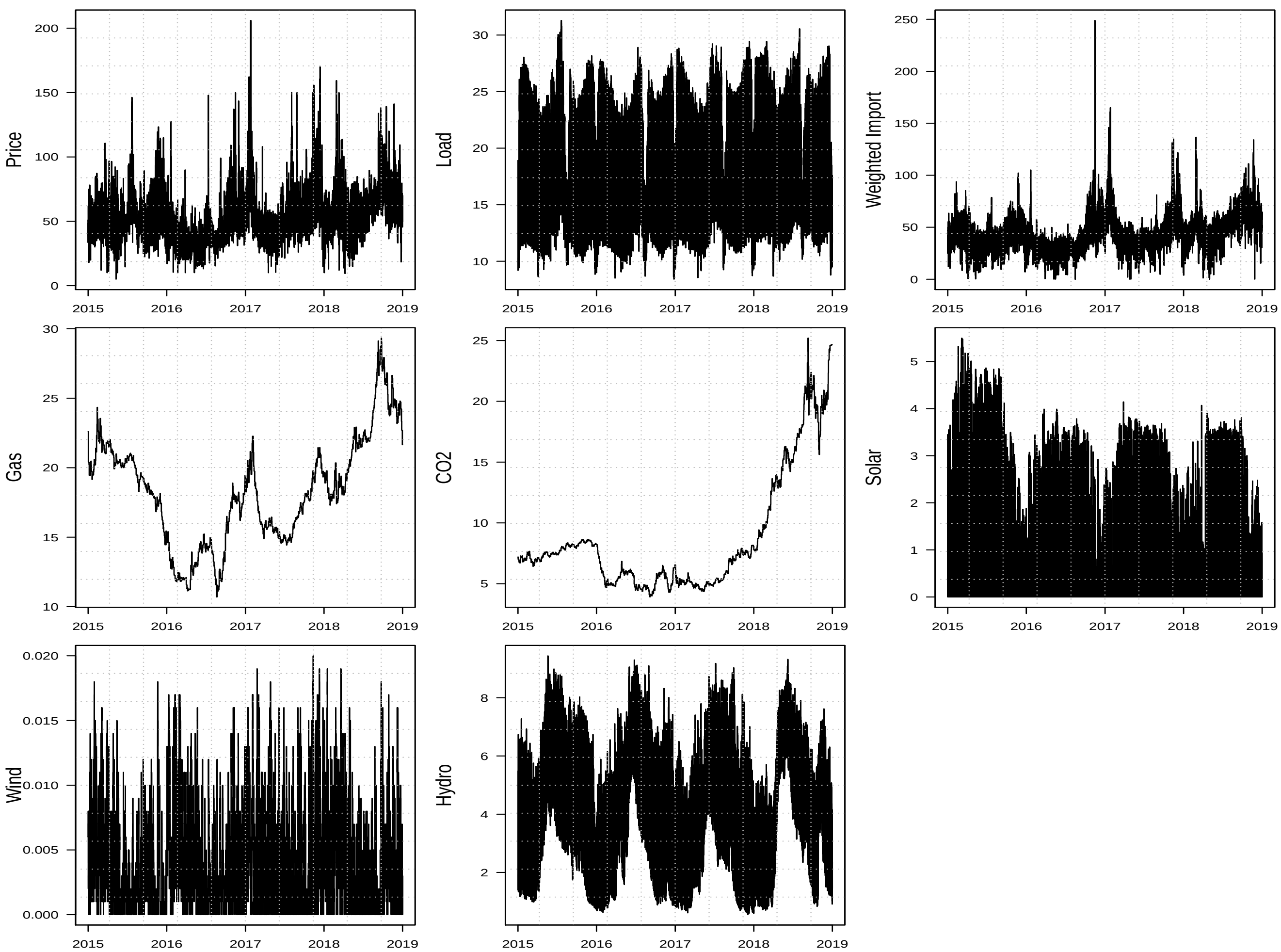

Figure 1: Time Series of all used Endogenous and Exogenous Variables.

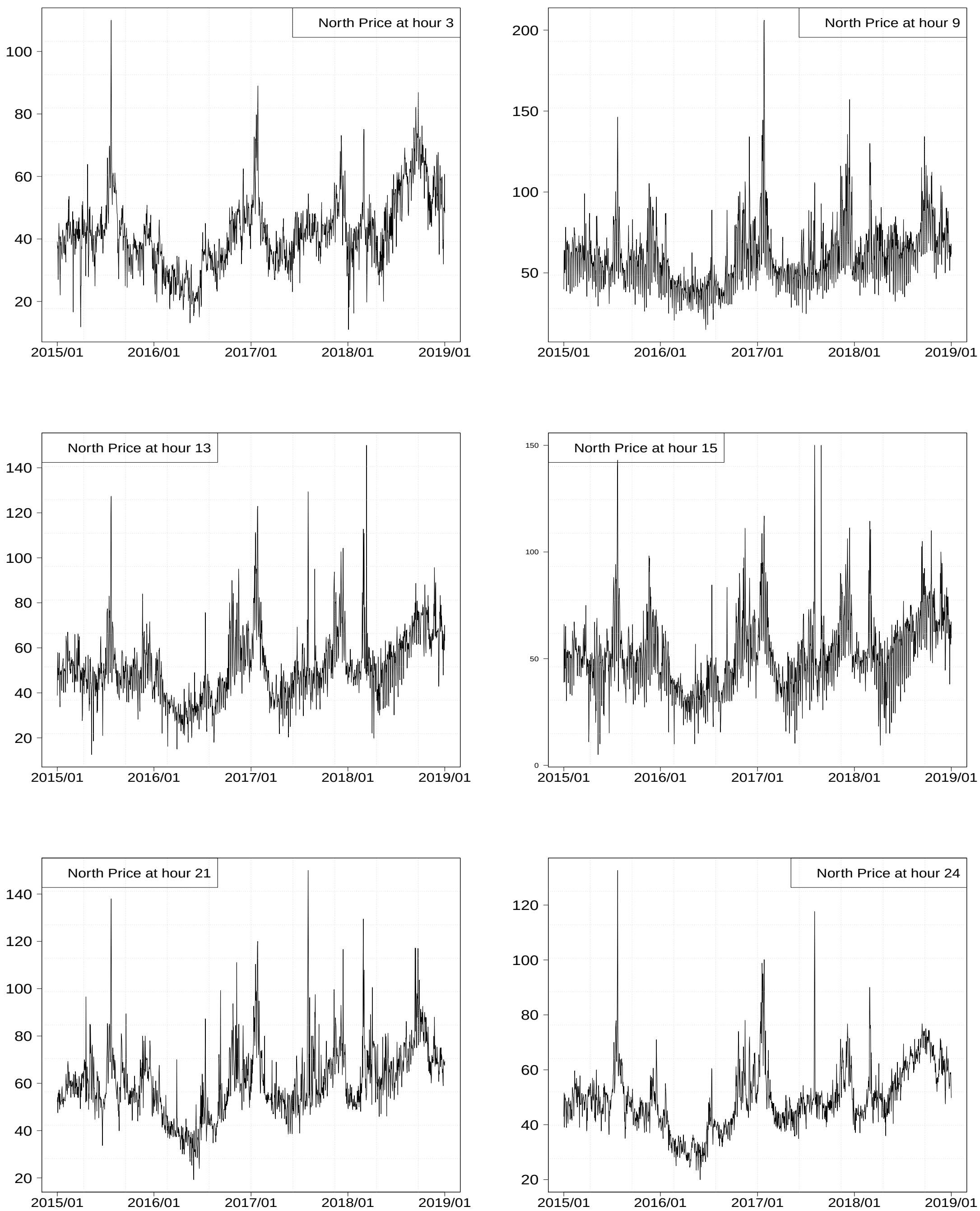

Figure 2: Day–ahead Electricity Prices in Northern Italy at hours 3, 9, 13, 15, 21, and 24.

3.2. Model Specifications

Based on the preliminary analysis and common practice, we propose and compare different specifications to model the electricity zonal prices observed over individual hours: each hour is modelled separately by following a daily frequency for prices and drivers. Because all the information is available or reconstructed at approximately 11 a.m. (i.e. before the market closure when traders must submit their offers), we are able to model all the 24 hours and forecast them for the next day by a simple prediction process that produces a set of 24 price predictions for the 24 hours of the following day.

Our initial set of models contains six specifications: (i) an ARMAX(p,q) model with only dummy variables (the benchmark model); (ii) an ARMAX(p,q) model with dummies and all the exogenous regressors previously described; (iii) an ARMAX(7,7), as in the previous formulation but with fixed parameters $p = 7$ and $q = 7$; (iv) an ARIMAX(7,1,7) that contains a fractionally integrated parameter $d = 1$ in addition to $p = 7$, $q = 7$, dummies and all the regressors; (v) an ARFIMAX(p,d,q), with dummies, all the regressors, and a Normal distribution for the error terms; and (vi) an ARFIMAX(p,d,q) specified as before but with a skew Student's t distribution. In both the ARMAX(p,q) and ARFIMAX(p,d,q) model specifications, the procedure automatically suggests the orders of the autoregressive and moving average polynomials, and the inclusion of the fractionally integrated coefficient d. In other words, following an adaptive scheme for selection and estimation, the values of p and q are selected at each iteration within a range of 1–7 for both the orders, and d is estimated over the rolling window, when included; then, price forecasts are obtained according to these iteratively selected coefficients.

Let consider first the benchmark ARMA(p,q) process, i.e.

$$\Phi(L)(y_t - \mu_t) = \Theta(L)\varepsilon_t \qquad \varepsilon_t \mid \mathcal{F}_{t-1} \sim \mathcal{D}\left(0, \sigma_\cdot^2\right) \qquad t = 1, ..., T \tag{1}$$

where y_t is the hourly electricity price observed on day t and L is the lag operator defined as $L^l y_t = y_{t-l}$. The polynomials $\Phi(L) = 1 - \sum_{i=1}^{p} \phi_i L^i$ and $\Theta(L) = 1 + \sum_{j=1}^{q} \theta_j L^j$ represent the autoregressive and moving average components with p and q orders, respectively. $\mathcal{F}_{t-1}$ is the information up to time $t-1$, while the conditional expected value of the dependent variable on day t, i.e. $\mu_t = \mathbb{E}(y_t \mid \mathcal{F}_{t-1})$, is equal to

$$\mu_t = \mu + \psi_1 D_t^1 + \cdots + \psi_{11} D_t^{11} + \gamma Weekend_t + \xi Monday_t \tag{2}$$

where D_t^j for $j = 1, \dots, 11$ are dummies for months, $Weekend_t$ is a dummy for weekends and holidays, $Monday_t$ is a dummy for Mondays, and ψ_j, ξ and γ are their coefficients, respectively. In particular, D_t^1 is the dummy for January, D_t^2 is the dummy for February, ..., D_t^{11} is the dummy for November, excluding December. Monthly dummy variables are used to model calendar seasonality, and $Monday_t$ captures the impact of a change in consumptions among working days and the first day after the weekends.

Based on the aforementioned considerations regarding the fundamental drivers of Italian electricity prices, we extend the benchmark model with a set of regressors $\mathbf{x}_t$; then, the mean equation is specified as follows

$$\mu_t = \mu + \psi_1 D_t^1 + \cdots + \psi_{11} D_t^{11} + \gamma Weekend_t + \xi Monday_t + \lambda' \mathbf{x}_t \tag{3}$$

where $\mathbf{x}_t$ is the vector at time t of exogenous regressors, which include forecasted load, wind and solar PV generation, weighted imports, natural gas, CO_2 prices, and actual hydro generation.

The ARFIMAX model specifications are defined as in the following

$$\Phi(L)(1-L)^d (y_t - \mu_t) = \Theta(L)\varepsilon_t \tag{4}$$

where d is the fractional integration parameter and μ_t is defined in equation (3). For both the specifications in equations (1) and (4), the variance of the errors is assumed to be constant; hence, $\sigma_t^2 = \sigma^2 \; \forall t$.

To account for possible time–varying volatility patterns, asymmetries and shocks induced by fundamental drivers, we expand our models by including GARCH–type specifications. A similar approach has been used by, for example, Koopman et al. (2007), Huurman et al. (2012), Paraschiv et al. (2014), Ketterer (2014) and Laporta et al. (2018). For the Italian market, Bosco et al. (2007) used an ARMA–GARCH model, whereas Gianfreda and Grossi (2012) used ARFIMAX–GARCHX models with Student's t distributions and several exogenous factors to address congestion, market power, traded volumes, and marginal technologies.

Hence, we compare several GARCH–type models: standard GARCH (SGARCH); exponential GARCH (EGARCH); and threshold GARCH (TGARCH) with Normal, Student's t, skew Student's t, generalised error, and skew generalised error distributions. These models differ according to the type of GARCH adopted and the distribution of the error terms. Thus, the second set of models extends the previous one with time–varying volatility expressed w.l.o.g. on day t as $\sigma_t^2 = \mathbb{V}(\varepsilon_t \mid \mathcal{F}_{t-1})$.

The SGARCH(1,1) can be defined as

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2, \tag{5}$$

while for the EGARCH(1,1) we have

$$\log \sigma_t^2 = \omega + \tau g\left(Z_{t-1}\right) + \beta \log \sigma_{t-1}^2, \tag{6}$$

where $g\left(Z_{t-1}\right) = \kappa Z_{t-1} + \eta\left(\left|Z_{t-1}\right| - \mathbb{E}\left(Z_{t-1}\right)\right)$, and it allows the conditional variance process to respond asymmetrically to rises and falls in electricity prices (Nelson, 1991). Finally, to account for asymmetries in volatility, making it a function of positive and negative values of the innovations, we consider the TGARCH(1,1) process (Zakoian, 1994), defined as follows

$$\sigma_t = \omega + \alpha_1^+ \varepsilon_{t-1}^+ + \alpha_1^- \varepsilon_{t-1}^- + \beta \sigma_{t-1} \tag{7}$$

where $\varepsilon_{t-1}^+ = \varepsilon_{t-1}$ if $\varepsilon_{t-1} > 0$ and 0 otherwise, $\varepsilon_{t-1}^- = \varepsilon_{t-1}$ if $\varepsilon_{t-1} \leq 0$ and 0 otherwise. We expand the proposed GARCH specifications to also include the vector of exogenous regressors, $\mathbf{x}_t$. Furthermore, we consider the model by Ziel and Weron (2018) as an alternative benchmark.

As anticipated, we use a rolling window approach to compare models with an ex–ante fixed structure and those in which the orders of p, d and q are automatically selected at each iteration according to the Akaike Information Criterion (AIC). To achieve this objective, we use the first 730 days of our dataset (i.e. from 1/1/2015 to 31/12/2016) for the in–sample estimation, and then the first out–of–sample prediction is obtained for 1/1/2017; thereafter, the window is rolled one step–ahead with further estimation and forecasts obtained for 2/1/2017, and so forth, until the last observation in the sample. Therefore, we produce forecasts over two years from 1/1/2017 to 31/12/2018.

We recall that the modelling and forecasting process is undertaken on day t to provide a set of 24 hourly prices forecasted for the next day $t+1$. These forecasts must be submitted before the closure of the market, i.e. before noon on day t (thus, we assume that these models must be started no later than 11 a.m. and have completed their runs by noon). To predict the day–ahead hourly price on day $t+1$, we use the information referred to that specific hour as follows: we assume that market operators submit their bids by noon on day t, based on predicted prices for day $t+1$, obtained by considering commodity prices and hydropower generation determined on day $t-1$ (and, in this case, as in Conejo et al. (2005) we use a two–step–ahead random walk prediction); the weighted import prices for the hours before 11 a.m. and the realised values on day t (in this case, we use a 1–step–ahead random walk prediction); and finally, the forecasted values for RES and zonal load available for day $t+1$. Further details on timing of the relevant variables are reported in Appendix 5.

To assess the forecasting performance of the implemented models, we use root mean square errors (RMSEs). In addition, we implement the Diebold–Mariano (DM) test to judge the superiority among two competing models (see Diebold and Mariano, 2002, Diebold and Mariano, 1995 and also West, 1996), and the Hansen–Luden–Nason procedure of Model Confidence Set (MCS) to verify the statistical significance in terms of differences in forecasting performances among the selected models (see Hansen et al., 2011). The DM test compares the forecast residuals of only two competing models, and the MCS procedure is a sequence of statistical tests in which the null hypothesis is built on the equal predictive ability (EPA) of several model specifications. Given that the EPA statistical tests can be calculated for different loss functions (depending on the aim of the comparison), we consider a *loss function for level* forecasts because of our interest in a comparison of the predictability power in the mean between our models.

4. Results

In this section, we first show the results of the predictability power of the selected models; next, the time evolution of the estimated orders of AR(FI)MA models are shown together with those for the estimated coefficients of the preferred models. To judge the quality of the forecasted prices, the RMSEs over all the 24 hours, and the Average RMSE over the 24 hours (Avg_{1-24}) and over the peak hours 8–20 (Avg_{8-20}) are computed and presented in Table 2.

First, we observe that the inclusion of all the selected exogenous regressors drastically reduces the RMSE over the 24 hours, especially during peak hours, for all the considered models with respect to the ARMA *benchmark* model. Therefore, we extend evidence in Gianfreda et al. (2020) on the predictive power of a large set of exogenous regressors to forecast regional prices. Results show that the ARFIMAX(p,d,q) with Normal (Norm) distribution and the ARMAX(p,q)–EGARCH(1,1) with skew Student's t (SkewStd) distribution have the lowest Average RMSE over the 24 hours: 7.820 and 7.821 (approximately 7.80 €/MWh), respectively. However, the ARFIMAX(p,d,q)–Norm model performs better during midday, when solar power is produced. Additionally, the Average RMSE computed over hours 8–20 (i.e. Avg_{8-20}) equals 9.390, which is slightly lower than 9.424, namely, the same average computed for the ARMAX(p,q)–EGARCH(1,1)–SkewStd specification. Second, the ARMAX(p,q)–EGARCH(1,1)–SkewStd model predicts very well during hours 21–24, suggesting volatility clustering in those hours, and showing its ability to capture intraday realised volatility. Therefore, these two models are the best candidates to forecast performance: they provide on average more accurate results, even if with different performances across hours.

In Figure 3, we compare the performances of the benchmark model with those of the ARMAX and ARFIMAX models (on the left), and the best ARFIMAX with the ARMAX–GARCH specifications (on the right). Notably, forecasting precision drastically decreases during the ramp–up (hours 7–9) and ramp–down (hours 19–21) phases, when the conventional thermal generation is necessary to restore the balance between demand and supply. Across peak hours, the non programmable renewables (solar and wind) bid at 0€/MWh and have priority of dispatch of the produced energy. Therefore, their intermittent, erratic feed–in increases the variability of prices and consequently affects the forecasting errors, especially at 9 and 19 when demand is at its higher levels. The first comparison shows that the benchmark model poorly performs at all hours and in addition that ARIMAXs and ARFIMAXs perform almost equally, with a slightly superior performance exhibited by the ARFIMAX(p,d,q)–Norm especially at hours 9–12 & 17–20. More interestingly, it seems that the inclusion of nonlinear specifications to account for time–varying conditional volatility does not improve the forecasting performance. The ARFIMAX(p,d,q)–Norm is found again to outperform all the ARMAX–GARCH specifications, in line with the findings in Karakatsani and Bunn (2010), Hong et al. (2014) and Paraschiv et al. (2014); hence, adopting a model which properly includes fundamental drivers may be sufficient to eliminate the ARCH effects.

To check the effective superiority of the ARFIMAX model over the ARMAX one, the dynamics of the estimated fractionally integrated parameter d in the ARFIMAX(p,d,q)–Norm model is inspected and its evolution at hour 13 is depicted in Figure 4. The estimated coefficient is lower than 0.5 over the full out–of–sample period, suggesting that the model tends to be more an ARMAX(p,q) than an ARIMAX(p,1,q). This reason is probably why there is no a substantial difference in the predictability power between the ARFIMAX(p,d,q) and the ARMAX(p,q) specifications. However, a drastic change in the evolution can be observed over the last part of the sample: during 2017, the estimated value of the term d fluctuates approximately around

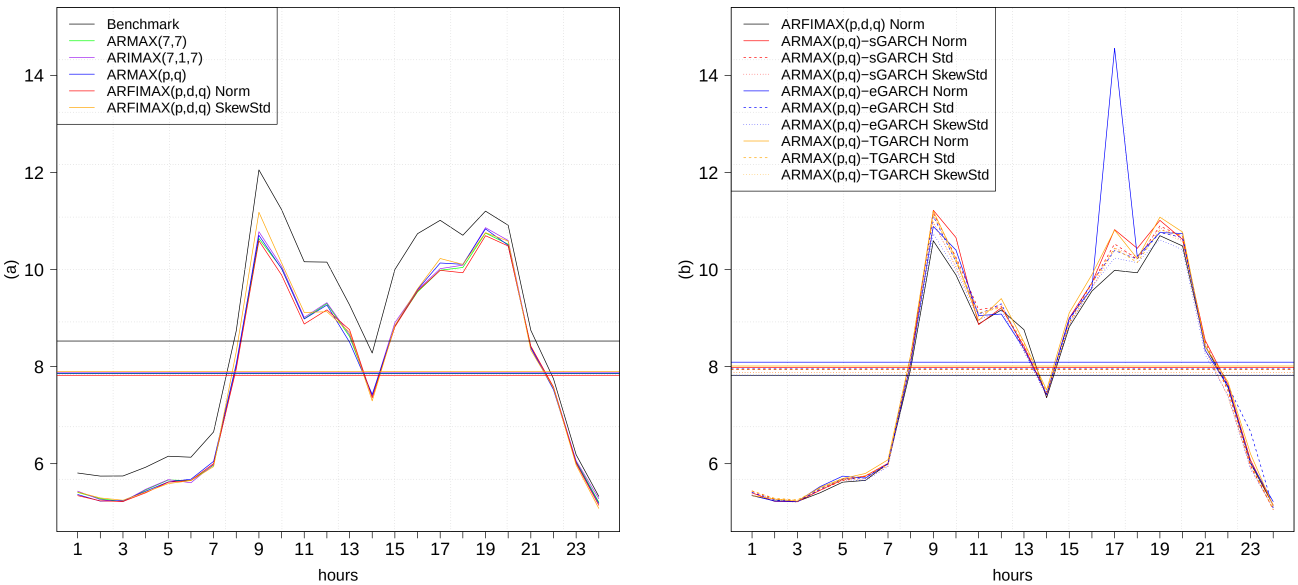

Figure 3: RMSE for different model specifications over the 24 hours: (a) RMSE of the Benchmark model (black line), ARMAX(7,7) model (green line), ARIMAX(7,1,7) model (purple line), ARMAX(p,q) model (blue line), ARFIMAX(p,d,q) model with Normal distribution (red line), ARFIMAX(p,d,q) model with skew Student's t distribution (orange line); (b) RMSE of the ARFIMAX(p,d,q) with Normal distribution (black line), ARMAX(p,q)–SGARCH with Normal distribution (red line), with Student's t distribution (red dashed line), with skew Student's t distribution (dotted red line), ARMAX(p,q)–EGARCH with Normal distribution (blue line), with Student's t distribution (blue dashed line), with skew Student's t distribution (dotted blue line), ARMAX(p,q)–TGARCH with Normal distribution (orange line), with Student's t distribution (orange dashed line), and with skew Student's t distribution (dotted orange line).

0.4, and the series varies between zero and 0.3 during 2018. In addition, the evolutions of the p and q estimated parameters for both the ARMAX(p,q) and ARFIMAX(p,d,q)–Norm models are shown in Figures 5 and 6 for a sample of hours. They clearly show the importance of considering an iterative adaptive scheme.

Regarding the comparisons of forecasting ability, the results of both the DM test and the MCS procedure are also presented in Table 2. The pairwise comparisons between the benchmark model and each alternative specification performed with the DM tests show that the majority of the selected model specifications has significant lower RMSE values with respect to the benchmark model, especially during hours 1–7. In the middle of the day, that is, during the peak hours, the predictability power of some models decreases and loses its significance, especially during the

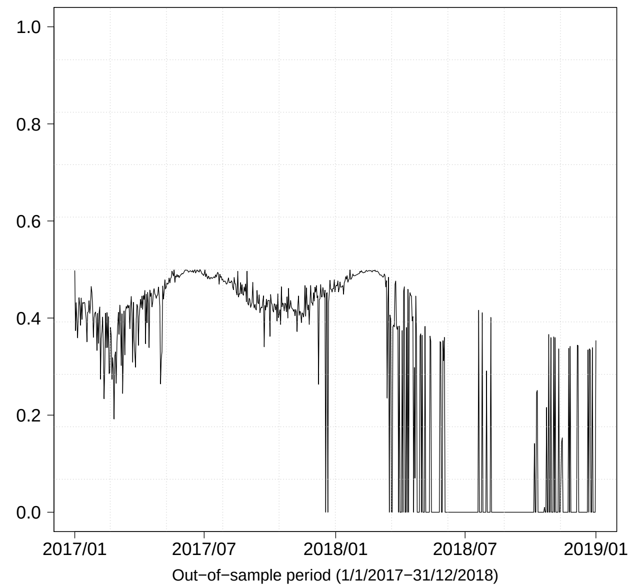

Figure 4: Estimated fractionally integrated parameter d in the ARFIMAX(p,d,q)–Norm model used for electricity prices observed at hour 13.

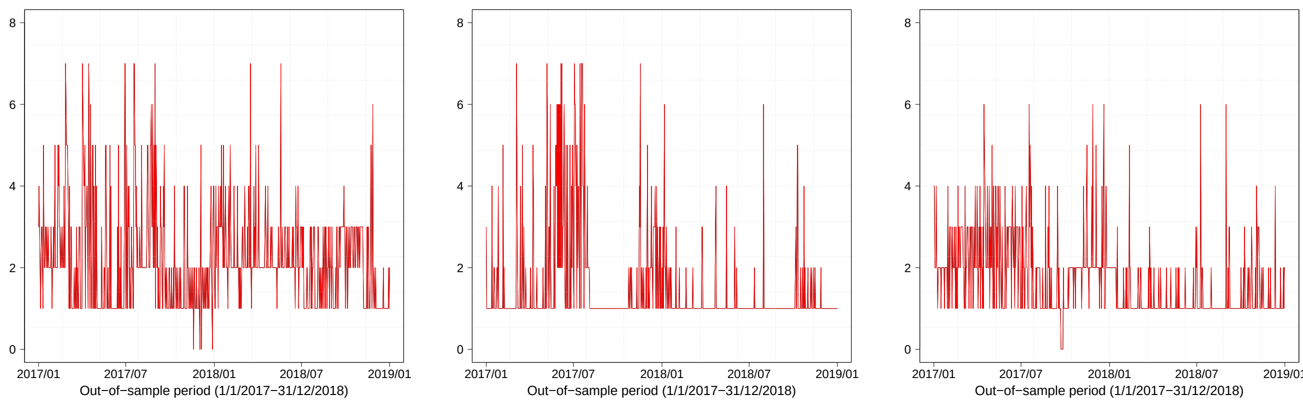

Figure 5: Estimated p parameter for the ARMAX(p,q) (in red) and ARFIMAX(p,d,q)–Norm (in black) models used for electricity prices observed at hours 3, 13 and 21, respectively.

evening. In general, the worst performances are those of the ARMAX(p,q)–GARCH models with generalised error and skew generalised error distributions. Furthermore, we consider the model proposed by Ziel and Weron (2018) as an alternative benchmark. However, the RMSEs for this additional model are higher than the RMSEs of our models for all 24 hours, probably because of the peculiarities of the Italian market structure; thus, we omit these results, but they are available upon request.

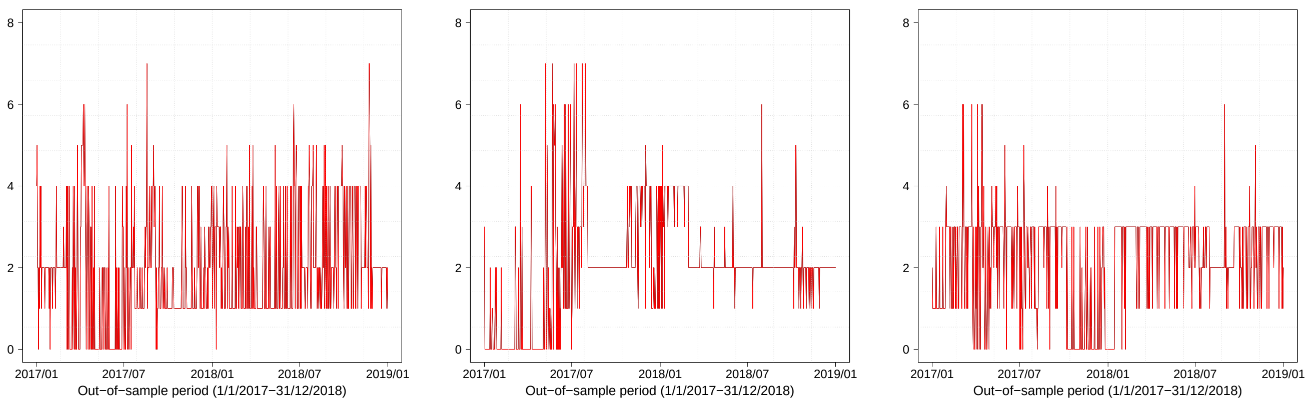

Figure 6: Estimated q parameter for the ARMAX(p,q) (in red) and ARFIMAX(p,d,q)–Norm (in black) models used for electricity prices observed at hours 3, 13 and 21, respectively.

When all the models are simultaneously compared, the computations of the Superior Set of Models (SSM)[4], in terms of minimum loss function for level forecasts, show that several models are not statistically different from each other in predictability power, but differences exist among the 24 hours and especially over the off–peak hours.

The final preferred model is on average the ARFIMAX(p,d,q)–Norm model because of its forecasting ability, especially during peak hours, and its parsimonious specification. However, the combined ARMAX(p,q)–EGARCH–SkewStd model might be useful when forecasting hours 21–24 to account for potential volatility clustering. Furthermore, the predictability power of fundamental variables decreases during the evening hours because the forecast horizons are longer than those for the morning hours. This argument is particularly notable for RES because the accuracy of weather predictions decreases substantially with the length of forecasting horizons.

Regarding the regressors, following the exercise in Paraschiv et al. (2014) their information power is explored by comparing a set of models in which fossil fuels (natural gas and CO_2) and RES (wind, solar, and hydro) are first all included and in a second specification where all regressors are all excluded (the latter one is labelled "No RES & FOSSIL") in the models ARFIMAX(p,d,q)–Norm and ARMAX(p,q)–EGARCH-SkewStd. Figure 7 also shows the RMSEs of the ARMAX(p,q)–EGARCH-SkewStd that comprises all regressors in both the conditional mean

[4]We implement the MCS procedure with the $T_{max,\mathcal{M}}$ test (Hansen et al., 2011, p. 465) at the $\alpha = 0.15$ significance level by using the `R` function `MCSprocedure` within the package `MCS` written by Bernardi and Catania (2018).

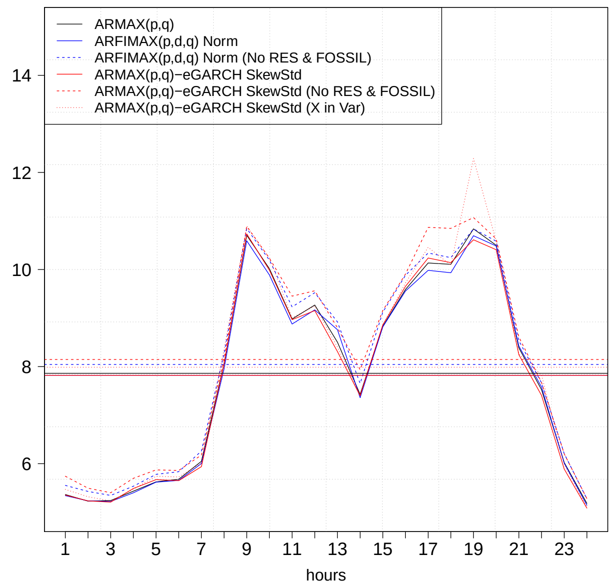

Figure 7: RMSEs for a Selection of Models with and without Fundamental Regressors (Fossil Fuels and RES).

and conditional variance, i.e. ARMAX(p,q)–EGARCH–SkewStd with "X in Var".

First, the intradaily dynamics of the RMSEs shows that the latter specification of ARMAX(p,q)–EGARCH–SkewStd with regressors in both the equations does not improve on average the power predictability of the same model with regressors contained only in the conditional mean equation. This comparison (ARMAX(p,q)–EGARCH–SkewStd with *X in Var* versus the simpler ARMAX(p,q)–EGARCH–SkewStd, using the names in the label) leads us to conclude that a more parsimonious model has to be preferred because fossil fuels and RES have no impact in explaining the conditional variance and in improving the forecasting performance. This finding is particularly evident at hours 17 and 19, and it is in line with Karakatsani and Bunn (2010) and Paraschiv et al. (2014). Given that the forecast performance did not improve in the GARCH specifications with *X in Var*, we omit numerical results to save space.

Second, although we observe no difference on average between the ARFIMAX(p,d,q)–Norm and ARMAX(p,q)–EGARCH–SkewStd, differences emerge when fossil fuels and RES are excluded, with the former model outperforming the latter one. This finding further supports the importance of their inclusion. In detail, the ARFIMAX(p,d,q)–Norm (without these variables) performs better than the GARCH specification, suggesting that the fractional integrated coefficient d plays a greater role than the accounting for time–varying volatility. Notably, this issue is particularly evident during hours 21–24, when only slight differences are observed with respect to the same model with all the regressors included. For hours 1–7, RMSEs vary across different models: we observed a combining and significant effect between gas and hydro that was useful to reduce the RMSE values.

As expected, the inclusion of fundamental variables in the conditional mean equation substantially improves the forecasting performances. Next, we report the estimated coefficients (with confidence intervals at 80%) of the ARFIMAX(p,d,q)–Norm model at hours 3, 9, 15, and 21 in the out–of–sample period. Results for the remaining hours are omitted but are available upon request.

Consistently with the literature, forecasted load is statistically significant with a positive effect on day–ahead price, meaning that prices do respond to load with an increasing influence through the years at hour 3 and a decreasing influence at hours 9 and 21; whereas a flat influence at hour 15, which may reflect the *negative demand* effect of solar PV generation, see Figure 8.

Solar PV forecasts are statistically significant at hour 15 with a negative sign, implying their reduction of the mean level of zonal prices, and it turns non significant in the last year of the sample at hour 9, see Figure 9. Unsurprisingly, the influence of wind power is negative and significant only at hour 3, given its limited generation in northern Italy; these results are omitted for lack of space. Also actual hydropower generation is statistically significant and negative only at hour 3. The dynamics of its estimated coefficient are reported in Figure 10. This finding may be consistent with the findings in Gianfreda et al. (2018), who argued that hydro units mainly abandon the day–ahead market to explore higher profit opportunities in balancing market sessions. Notably, the variable Hydro at hour 10 is significant in the early afternoon.

Weighted imports are significant and positive at hours 3 and 9, especially in the morning, see Figure 12. The Weighted Import and the Weighted Import at hour 10 variables are both positive and significant most of the time with an average range impact of $[0.1, 0.4]$, while the information coming from the Lagged Weighted Import is not statistically different from 0 during the entire period. Therefore, foreign prices and demand affect Italian electricity price via scheduled capacity on interconnectors and shared power exchange algorithms via market coupling. The relevance of the 10–th hour regressor suggests an underlying persistence of short memory in trading decisions.

Figure 14 shows that natural gas confirms its attitude to increase electricity prices across all selected hours, but with a particularly pronounced increasing trend at hours 9 and 15, paired with higher volatility. This finding is consistent with the relevant share of electricity generation covered by combined cycle gas turbine plants in northern Italy.

On the contrary, the CO_2 emission prices in Figure 15 exhibit a significant negative effect only in the last year of the sample and for hours 9 and 15, which may suggest that the increment of CO_2 prices does not affect day–ahead prices because of RES.

5. Conclusions

Forecasting day–ahead electricity prices has become extremely important for generation planning, given the imperfect predictability of weather conditions that affect both demand and RES generation, and for trading decisions influenced by the exploitation of possible arbitrage opportunities that can occur in subsequent market sessions. Hence, this paper provides a new, flexible model selection through an iterative and adaptive procedure which produces good and timely predictions of hourly day–ahead prices for northern Italy, where monitoring the bidding strategies for detecting strategic behaviours across market sessions is becoming critical to avoid market speculations and consequent increasing costs for final customers.

Using a set of drivers, comprising forecasted demand, forecasted wind and solar PV generation fossil fuels and expanded to include hydro generation and price–weighted flows, northern Italian electricity prices are forecasted through linear and nonlinear models with a flexible structure iteratively selected at both the autoregressive and moving average orders over each calibration window and each model, including the possibility to switch from one model to another. Our results clearly show the importance of adopting a flexible structure that adapts to time–varying market conditions and of avoiding overparametrisation in an ex–ante ordering selection.

We provide evidence that fundamental factors can drive zonal electricity prices differently within trading periods and that their simultaneous inclusion (fuels, imports and RES as well) substantially improves the forecast accuracy.

Exploring the forecasting performance of linear and nonlinear models when a set of drivers are all included or excluded, we provide important empirical evidence contributing to the mixed results already presented in the literature. Indeed, adding GARCH residuals slightly improves forecast accuracy only in the ARMAX(p,q)–EGARCH(1,1)–SkewStd specification, and we can conclude that the previous documented time–varying volatility is captured by the intermittent behaviour of renewable energy sources. This confirms that adopting a model which properly includes fundamental drivers is sufficient to eliminate the ARCH effects, or that they are a *surrogate for omitted factors* (Karakatsani and Bunn, 2010).

Implementing the DM test and the MCS to gain insights into the best performing models, we find a strong predictive power from forecast demand at any hour and from RES mainly at peak hours. Notably, we also observe that electricity inflows weighted by prices determined in bordering countries and connected zones also have a significant impact on prices. As far as fuels are concerned and contrarily to empirical results found in UK and Germany, coal is found to be non statistically significant in the price formation of zonal prices in northern Italy, at least for the sample considered. Instead, natural gas confirms its importance especially at ramp–up and ramp–down hours. Surprisingly, carbon prices exhibit a significant negative effect only in the last year of the sample and for hours 9 and 15, due to the increase in the PV infeed. This can be a practical consequence of the energy policy of increasing green generation: the increment of CO_2 prices did not affect day–ahead prices because of the substitution effect of RES generation with traditional fuels in the supply curve.

However, it would be interesting to monitor the effects of fuels in the future, especially carbon prices. On one hand, the conversion of power plants into gas–fired units will induce coal prices to further decrease and, in contrast, gas prices to increase. On the other hand, there is an enormous pressure to increase substantially carbon emission prices, since they are considered too low to be effective in reducing emissions. As argued, they are considered inadequate to reflect actual climate costs, then governments and policy makers are demanded for raising them faster to meet their commitments on cutting emissions. This would certainly change their influence on fossil fuel prices and, consequently, on electricity prices.

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Tables

Model/Hour	1	2	3	4	5	6	7	8	9	10	11	12	13
Benchmark	5.808	5.744	5.747	5.927	6.154	6.133	6.655	8.739	12.052	11.234	10.159	10.152	9.270
ARMAX(7,7)	5.410***	5.277***	5.220***	5.460***	5.664***	5.652***	5.969***	8.024***	10.637***	10.026***	8.985***	9.298**	8.619*
ARIMAX(7,1,7)	5.434***	5.259***	5.216***	5.472***	5.670***	5.607***	5.986***	7.993***	10.778***	10.067***	9.013***	9.317**	8.657*
ARMAX(p,q)	5.365***	5.228***	5.241***	5.434***	5.625***	5.680***	6.048***	8.058**	10.704***	10.016***	8.980***	9.268***	8.503**
ARFIMAX(p,d,q) Norm	5.342***	5.234***	5.222***	5.400***	5.620***	5.655***	6.004***	7.952**	10.591***	9.887***	8.876***	9.169***	8.760***
ARFIMAX(p,d,q) SkewStd	5.416***	5.294***	5.247***	5.416***	5.590***	5.652***	5.941***	8.309	11.178*	10.137***	9.115***	9.131**	8.708*
ARMAX(p,q)-SGARCH Norm	5.401***	5.222***	5.215***	5.452***	5.676***	5.748***	6.007***	8.088*	11.221**	10.657·	8.864***	9.211**	8.423*
ARMAX(p,q)-SGARCH Std	5.438***	5.272***	5.233***	5.454***	5.655***	5.736***	5.984***	8.225·	11.162**	10.253***	9.174***	9.239**	8.386*
ARMAX(p,q)-SGARCH SkewStd	5.391***	5.264***	5.225***	5.449***	5.652***	5.687***	5.958***	8.057*	10.980**	10.039***	9.030***	9.294*	8.323*
ARMAX(p,q)-SGARCH Ged	5.446***	5.263***	5.209***	5.510***	5.732***	5.797**	6.220*	9.618	12.424	11.081	9.472*	9.284**	8.907
ARMAX(p,q)-SGARCH SkewGed	8.502	6.753	6.702	6.578	6.575	8.430	7.657	14.280	17.149	15.080	9.132***	9.225**	10.622
ARMAX(p,q)-EGARCH Norm	5.351***	5.228***	5.223***	5.527***	5.744***	5.704***	6.001***	8.067*	10.887***	10.399***	9.051***	9.082***	8.369*
ARMAX(p,q)-EGARCH Std	5.409***	5.254***	5.218***	5.475***	5.686***	5.708***	5.993***	8.218·	11.098***	10.160***	9.078***	9.293**	8.358*
ARMAX(p,q)-EGARCH SkewStd	5.354***	5.234***	5.208***	5.489***	5.672***	5.651***	5.939***	8.055*	10.734***	9.986***	8.967***	9.154**	8.309*
ARMAX(p,q)-EGARCH Ged	12.069	8.446	7.546	7.565	7.494	6.431	12.162	21.713	27.189	13.686	9.229**	9.222**	14.535
ARMAX(p,q)-EGARCH SkewGed	14.257	12.562	13.529	8.417	9.404	10.135	15.701	19.984	32.976	19.478	9.203***	9.162**	12.654
ARMAX(p,q)-TGARCH Norm	5.343***	5.271***	5.229***	5.511***	5.694***	5.798**	6.081***	8.242	11.207**	10.214***	8.948***	9.401**	8.506*
ARMAX(p,q)-TGARCH Std	5.440***	5.287***	5.255***	5.491***	5.674***	5.753***	5.983***	8.236·	11.135**	10.160***	9.107***	9.212**	8.487*
ARMAX(p,q)-TGARCH SkewStd	5.423***	5.274***	5.249***	5.487***	5.663***	5.735***	5.954***	8.079*	10.979***	10.065***	9.094***	9.236**	8.351*
ARMAX(p,q)-TGARCH Ged	5.922	5.328***	5.271***	5.664*	5.723***	6.130	6.397	9.285	12.114	10.945	9.145***	9.383*	9.113
ARMAX(p,q)-TGARCH SkewGed	11.137	6.938	7.048	8.856	6.072	7.319	11.391	10.939	15.967	17.209	10.613	9.240**	10.491

Model/Hour	14	15	16	17	18	19	20	21	22	23	24	Avg_{1-24}	Avg_{8-20}
Benchmark	8.279	9.999	10.738	11.014	10.706	11.203	10.912	8.748	7.750	6.185	5.327	8.526	10.343
ARMAX(7,7)	7.397***	8.841***	9.537***	9.984***	10.042***	10.751**	10.521*	8.414*	7.566·	6.045	5.208	7.856	9.436
ARIMAX(7,1,7)	7.403***	8.903***	9.577***	10.017***	10.090***	10.862*	10.598*	8.397**	7.575*	6.062	5.279	7.885	9.483
ARMAX(p,q)	7.428***	8.828***	9.589***	10.134***	10.107**	10.837*	10.499**	8.385**	7.524*	6.024	5.181·	7.862	9.458
ARFIMAX(p,d,q) Norm	7.359***	8.818***	9.556***	9.983***	9.933***	10.696**	10.485**	8.422**	7.580·	6.011·	5.143*	7.821	9.390
ARFIMAX(p,d,q) SkewStd	7.293***	8.848***	9.603***	10.227***	10.105*	10.759·	10.586	8.338*	7.560	5.972	5.079*	7.896	9.538
ARMAX(p,q)-SGARCH Norm	7.416***	9.001***	9.726***	10.822	10.435	11.013	10.619	8.540·	7.634	6.074	5.143*	7.984	9.654
ARMAX(p,q)-SGARCH Std	7.474***	8.918***	9.716***	10.527*	10.212*	10.896	10.675	8.509	7.503	5.961	5.052*	7.944	9.604
ARMAX(p,q)-SGARCH SkewStd	7.378***	8.882***	9.634***	10.440*	10.260·	10.857	10.595·	8.335*	7.403*	5.923	5.068*	7.880	9.521
ARMAX(p,q)-SGARCH Ged	7.484***	9.304*	10.022*	11.169	12.270	11.067	11.127	8.547	7.831	6.782	5.833	8.392	10.248
ARMAX(p,q)-SGARCH SkewGed	8.243	12.840	11.180	15.503	13.729	17.129	13.909	15.347	13.234	10.214	7.876	11.079	12.925
ARMAX(p,q)-EGARCH Norm	7.431***	8.995***	9.617***	14.557	10.270*	10.761*	10.742	8.338**	7.595·	6.025·	5.219	8.091	9.864
ARMAX(p,q)-EGARCH Std	7.419***	8.948***	9.740***	10.392**	10.214*	10.764*	10.658·	8.435·	7.610	6.661	5.091*	7.953	9.565
ARMAX(p,q)-EGARCH SkewStd	7.399***	8.859***	9.653***	10.237***	10.142**	10.612**	10.408**	8.245***	7.406**	5.889**	5.084*	7.820	9.424
ARMAX(p,q)-EGARCH Ged	11.137	14.707	16.993	20.579	17.917	21.359	17.633	16.243	17.028	11.580	8.994	13.811	16.608
ARMAX(p,q)-EGARCH SkewGed	12.796	13.737	18.689	18.456	21.851	23.768	22.865	20.495	17.700	15.366	13.936	16.130	18.124
ARMAX(p,q)-TGARCH Norm	7.521***	9.108***	9.895**	10.812	10.225*	11.078	10.771	8.414*	7.691	6.200	5.128*	8.012	9.687
ARMAX(p,q)-TGARCH Std	7.466***	8.908***	9.718***	10.440**	10.145**	10.818·	10.703	8.488·	7.536	6.005·	5.062*	7.938	9.579
ARMAX(p,q)-TGARCH SkewStd	7.412***	8.862***	9.596***	10.399**	10.206*	10.802*	10.568*	8.366*	7.371*	5.943*	5.069**	7.883	9.511
ARMAX(p,q)-TGARCH Ged	7.425***	9.364*	12.075	11.356	11.892	11.188	13.356	11.266	10.373	7.761	5.725	8.842	10.511
ARMAX(p,q)-TGARCH SkewGed	8.022	11.417	14.474	14.991	17.612	17.339	18.643	14.572	16.444	10.066	8.290	11.879	13.612

Table 2: RMSEs of all the selected models for 24 hours. The average over the 24 hours and the average over the hours 8–20 are also included. The benchmark refers to an ARMAX(p,q) with only dummies. ***, **, *, . , are the 0.1%, 1%, 5%, 10% significant levels according to the DM test statistic. Grey cells refer to the superior set of models selected according to the Hansen–Luden–Nason MCS procedure at $\alpha = 0.15$.

Figures

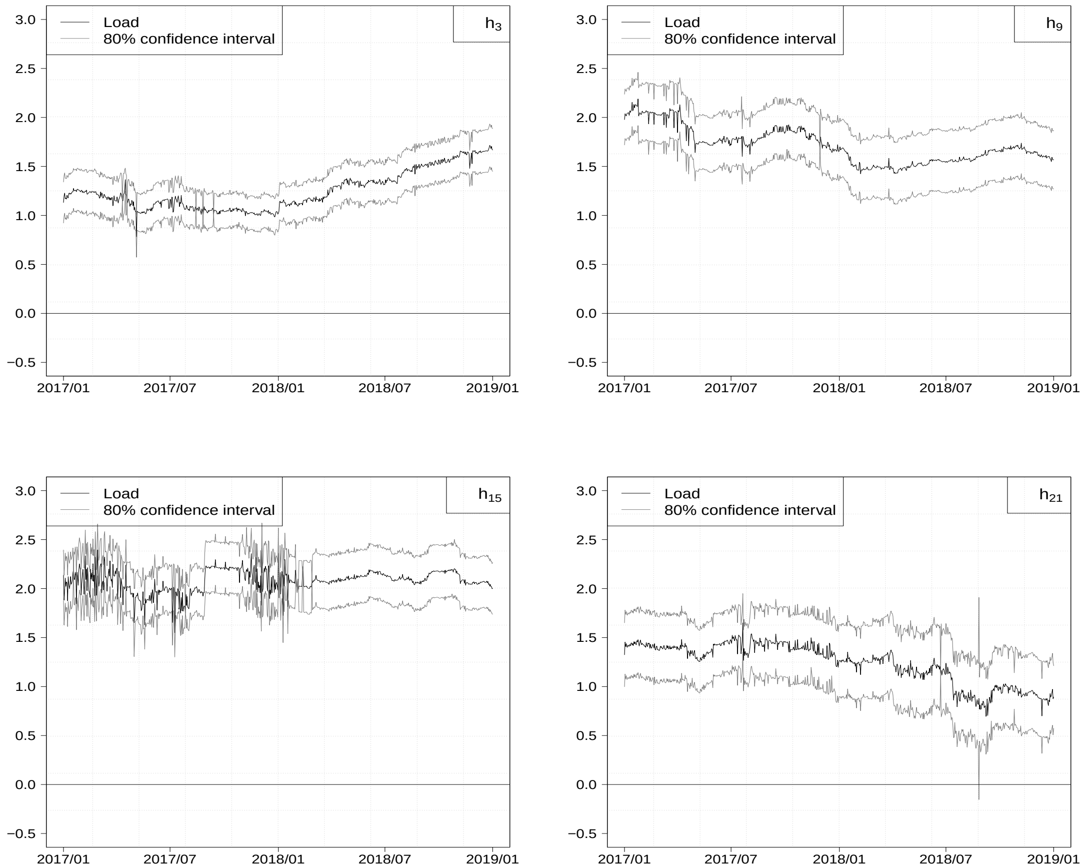

Figure 8: Estimated coefficients for forecasted load by using the ARFIMAX(p,d,q) model with Normal distribution at hours 3, 9, 15, and 21. Robust Confidence Intervals at 80% are also reported over the out–of–sample period from 2017/01/01 to 2018/12/31.

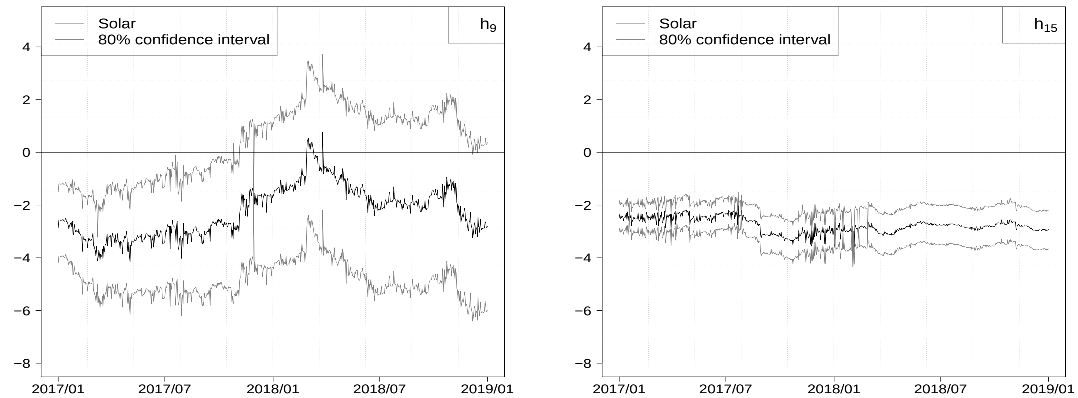

Figure 9: Estimated coefficients for Forecasted Solar PV Power using the ARFIMAX(p,d,q) model with Normal distribution at hours 9 and 15. Robust Confidence Intervals at 80% are also reported over the out–of–sample period from 2017/01/01 to 2018/12/31.

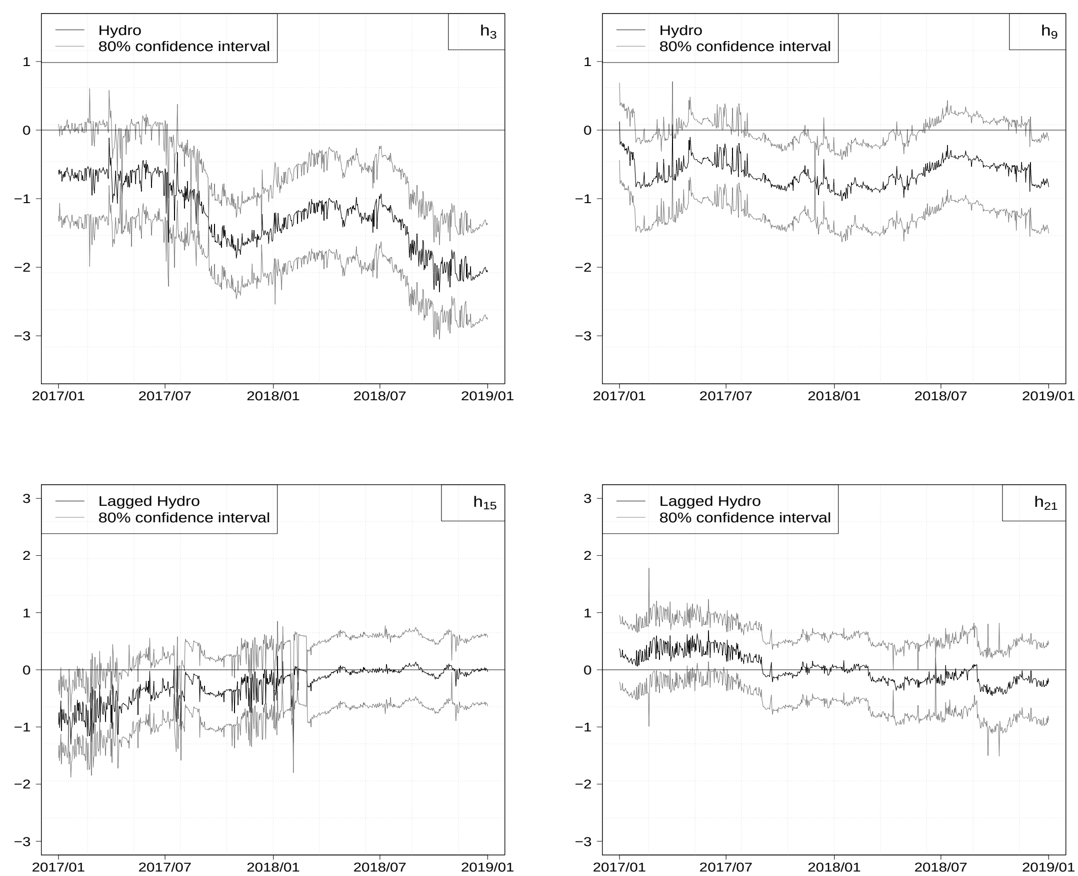

Figure 10: Estimated coefficients for Hydro using the ARFIMAX(p,d,q) model with Normal distribution at hours 3, 9, 15, and 21. Robust Confidence Intervals at 80% are also reported over the out–of–sample period from 2017/01/01 to 2018/12/31. Notably, lagged values are used at hours 15 and 21.

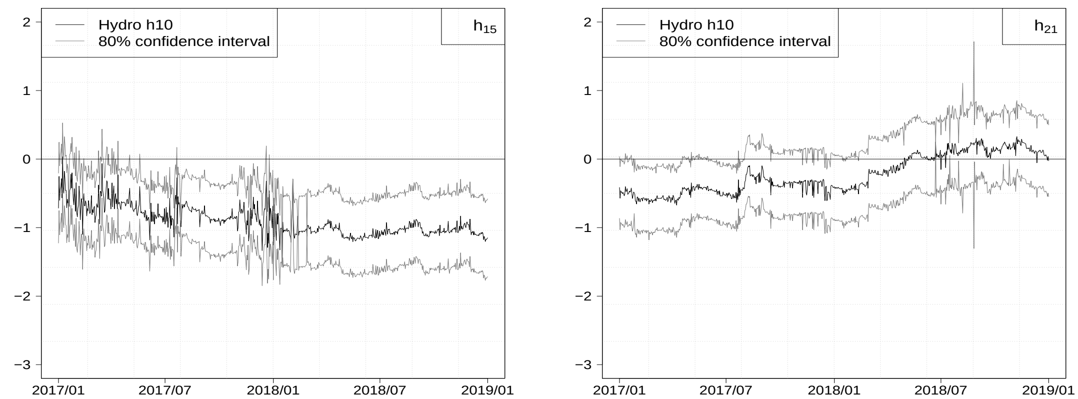

Figure 11: Estimated coefficients for Hydro at hour 10 using the ARFIMAX(p,d,q) model with Normal distribution at hours 15 and 21. Robust Confidence Intervals at 80% are also reported over the out–of–sample period from 2017/01/01 to 2018/12/31.

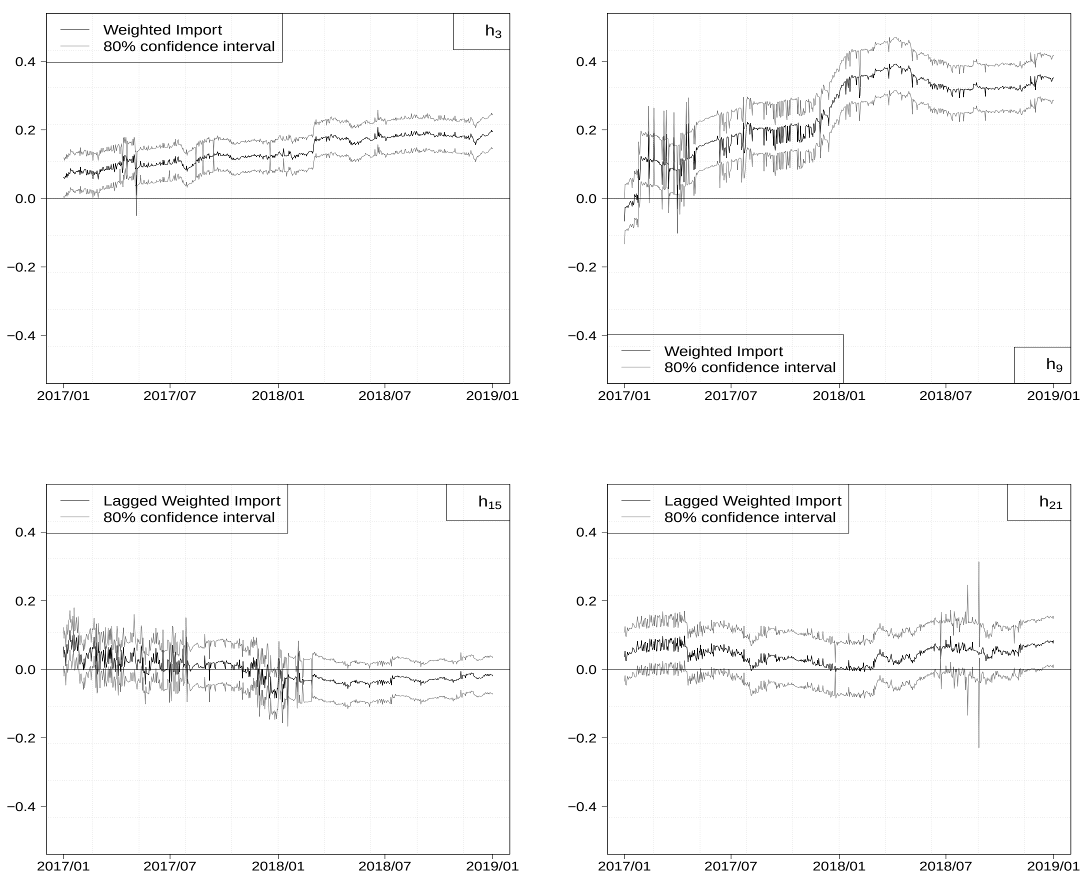

Figure 12: Estimated coefficients for Weighted Imports using the ARFIMAX(p,d,q) model with Normal distribution at hours 3, 9, 15, and 21. Robust Confidence Intervals at 80% are also reported over the out–of–sample period from 2017/01/01 to 2018/12/31. Notably, lagged values are used at hours 15 and 21.

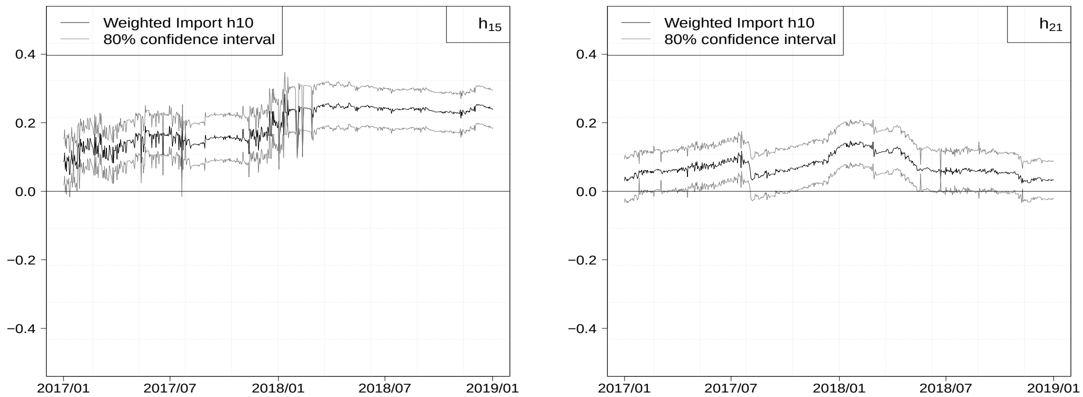

Figure 13: Estimated coefficients for Weighted Imports at hour 10 using the ARFIMAX(p,d,q) model with Normal distribution at hours 15 and 21. Robust Confidence Intervals at 80% are also reported over the out–of–sample period from 2017/01/01 to 2018/12/31.

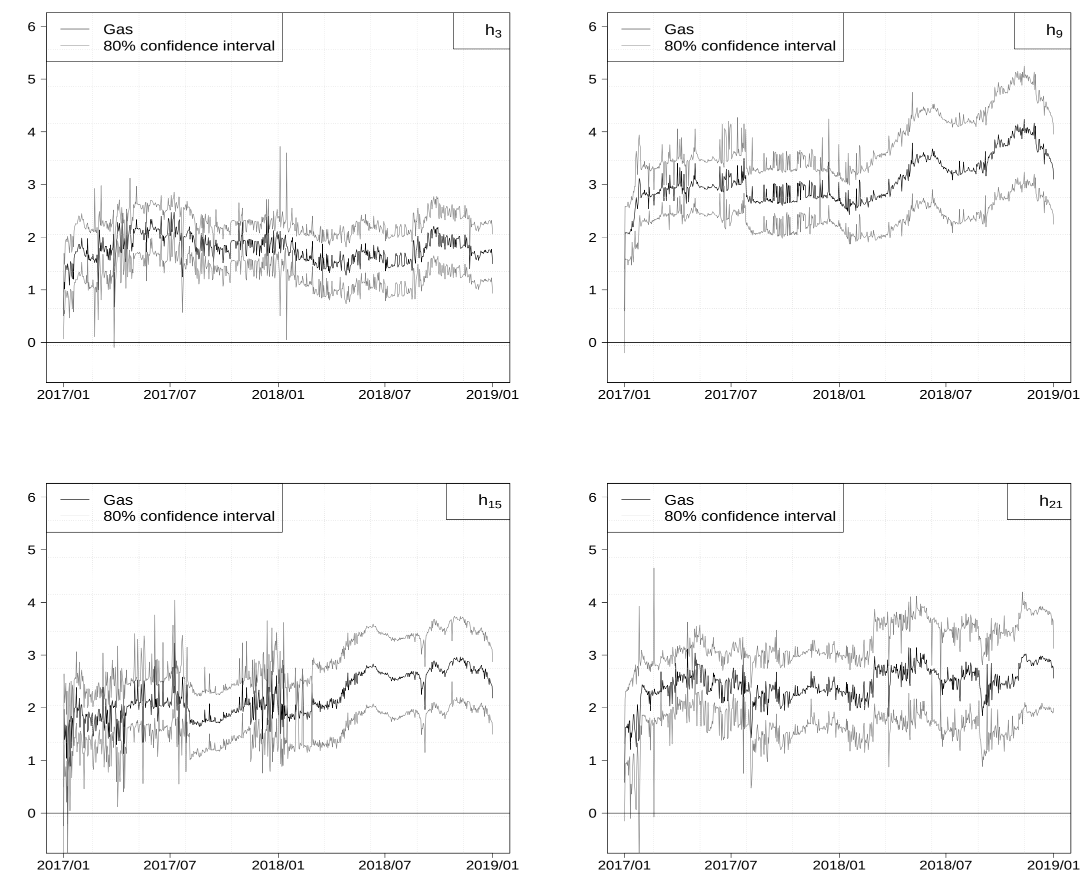

Figure 14: Estimated coefficients for Natural Gas using the ARFIMAX(p,d,q) model with Normal distribution at hours 3, 9, 15, and 21. Robust Confidence Intervals at 80% are also reported over the out–of–sample period from 2017/01/01 to 2018/12/31.

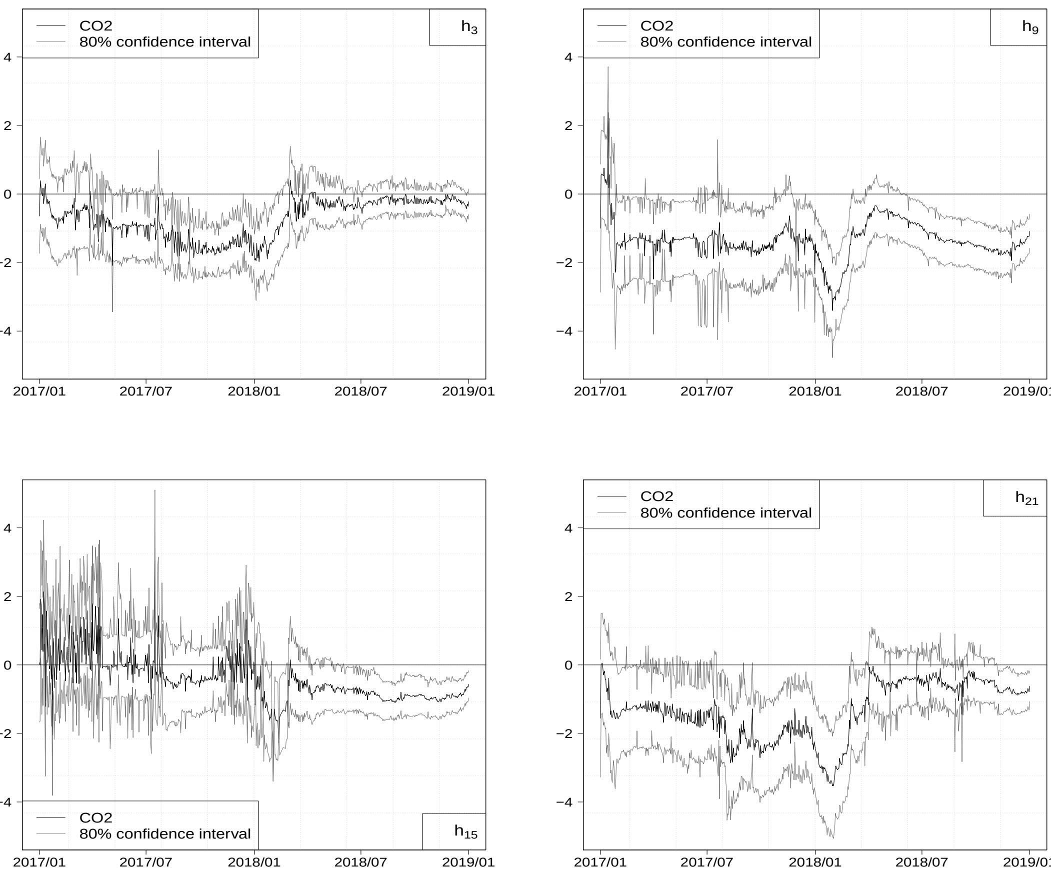

Figure 15: Estimated coefficients for CO_2 using the ARFIMAX(p,d,q) model with Normal distribution at hours 3, 9, 15, and 21. Robust Confidence Intervals at 80% are also reported over the out–of–sample period from 2017/01/01 to 2018/12/31.

Appendix: Data management of hydropower and weighted imports

The regressors included in our models are the values of load, wind, and solar PV power generation forecasted for the next day $t+1$; the fossil fuel prices determined on the day before $t-1$ (given that the settlement prices are released at the end of the day at approximately 19.00 or 7 p.m.); and two additional variables, actual hydropower generated in northern Italy and the weighted imports. The hourly aggregated hydro output and the physical flows are published no later than one hour after the operational period, as described by ENTSO–E.

We emphasise that all the relevant information (i.e. actual hydro generated for all 24 hours and flows) is not available in a timely manner for their inclusion in the forecasting models of all the 24 price series (because the quantities displayed before noon refer up to hour 11). Therefore, we consider the actual hydro generation and flows observed on day t available for early morning hours (i.e. hours 1–10 of the same day), as well as their values observed on the day before; the latter is used for the remaining hours for which actual values are not published before the closure of the day-ahead bidding (i.e. H_{t-1} and W_{t-1} are used for the past hydro and weighted imports included in the modelling and the forecasting process of hours 11–24, respectively). In addition, the values for hour 10 observed on the day t are included in the process of modelling and forecasting electricity prices at hours 11–24 (these variables are named H_t^{10} and W_t^{10}).