Network

Rimini Centre for Economic Analysis Working Paper Series

wp 21-20

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Anna Gloria Billé
Angelica Gianfreda
Filippo Del Grosso
Francesco Ravazzolo

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Anna Gloria Billé[a], Angelica Gianfreda[c,d], Filippo Del Grosso[b], Francesco Ravazzolo[b,e,f]

[a]*Department of Statistical Sciences, University of Padua, Italy*
[b]*Faculty of Economics and Management, Free University of Bozen–Bolzano, Italy*
[c]*Department of Economics, University of Modena and Reggio Emilia, Italy*
[d]*Energy Markets Group, London Business School, London, UK*
[e]*BI Norwegian Business School, Norway*
[f]*RCEA, Rimini Center for Economic Analysis, Italy*

Abstract

This paper provides an iterative model selection for forecasting day–ahead hourly electricity prices, while accounting for fundamental drivers. Forecasts of demand, in-feed from renewable energy sources (RES), fossil fuel prices, and physical flows are all included in linear and nonlinear specifications, ranging in the class of ARFIMA–GARCH models hence including parsimonious autoregressive specifications (known as *expert-type* models). Results support the adoption of a simple structure that is able to adapt to market conditions. Indeed, we include forecasted demand, wind and solar power, actual generation from hydro, biomass and waste, weighted imports and traditional fossil fuels. The inclusion of these exogenous regressors, in both the conditional mean and variance equations, outperforms in point and, especially, in density forecasting. Considering the northern Italian prices and using the Model Confidence Set, predictions indicate a strong predictive power of regressors, in particular in an expert model augmented for GARCH-type time-varying volatility. Finally, we find that using professional and more timely predictions of consumption and RES improves the forecast accuracy of electricity prices more than predictions freely available to researchers.

Keywords: Demand, Wind, Solar, Biomass, Waste, Fossil Fuels (coal, natural gas, CO_2), Weighted Inflows, Commercial and Public Forecasts

JEL Classification: C13, C22, C53, Q47

September 20, 2021

1. Introduction

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

Day–ahead electricity prices are determined for each hour of the following day, 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 weather conditions have been taken into account for the demand curve, whereas the predicted intermittent generation by renewable energy sources (RES) has been recently considered a risk source in the supply curve, together with import and export flows and the international movements of fossil fuel prices used in traditional thermal plants; for extensive reviews see Weron (2014), Nowotarski and Weron (2018) and Hong et al. (2020).

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 RES 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).

The increasing RES generation dispatched on the day-ahead (and intra-day) market has a twofold effect. According to the merit order, producing units that pollute less have the priority of dispatch and move the supply curve towards the right as soon as their generation increases. Consequently, equilibrium prices decrease due to the new RES generation. On one hand, all this has the effect of moving thermal conventional technologies out of the day–ahead market, and, on the other hand, it reduces the spreads between maximum and minimum prices which make water pumping units less profitable. They have no more time-arbitrage opportunities in buying electricity in off-peak hours and selling it during peak hours in the day–ahead market. Then, those units allowed to act in real-time sessions can try to recover there their profits. This occurred in

Italy attracting the attention of the energy regulator in 2016, when enormous costs were generated within the system as a consequence of the speculative trading of few thermal units. Gianfreda et al. (2018) studied the auction/bid data for the the northern Italian zone, characterized by a high solar PV and hydro penetration. Considering all market sessions, from the day–ahead to real time and passing through intra-day sessions, they provide empirical evidence that balancing costs increased between two samples associated with low (in years 2006–08) and high (in years 2013–15) RES levels. They studied the up- and down-regulation in the balancing market sessions, which differ across the Italian physical zones because of the location and characteristics of RES capacity. It is intuitive that a geographically balanced portfolio may compensate easily and promptly any variations in demand or in generation (due to the forecast errors of RES output). However, the authors observed that the northern zone appears to be subject to a systematic overestimation of PV generation capacity sold in the day–ahead market, hence requiring up-regulation to restore the system equilibrium at a price which is generally more costly than the one for down-regulation. Considering that the seasonality of solar production reduces the residual demand covered by conventional technologies during hours of irradiation and that it requires a strong increase in programmable and flexible production at sunset, the evening ramp increased from 8250 MW in 2012 to 11,050 MW in 2014; and it was contemporary paired with the dismissal of a number of old thermal units. They observe that some generators, allowed to act on the balancing market, were withholding capacity on the day–ahead market (or closing their net position to zero over day–ahead and intra–day sessions) and selling energy in the real–time sessions, where the pay–as–bid pricing mechanism grants the (higher) price declared in accepted bids. These Italian sessions have a limited number of traders and are dominated by conventional (thermal, hydro and water pumping) technologies with no competition from RES units (indeed they are not allowed to participate into the Italian balancing sessions) and so they can only reduce the day–ahead prices, as an effect of the merit order.

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 thermal conventional as well as water pumping units consider the price spreads among the various sequential sessions; together with the possibility to act over a long–term capacity market. Based on all these arguments 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, therefore, an exceptionally good example for several reasons. First, the zone is well interconnected with foreign countries, from whom electricity can be imported at lower prices. Second, a high share of solar PV generation has been observed in recent years. Third, most of the hydro generation is located in the Alps. Fourth, and more importantly, the demand of electricity in this zone represents almost half of the national demand; hence, variations in demand and supply can boost the strategic use of balancing sessions. Finally, all three thermal conventional, hydro and water pumping technologies act in this zone across all different market sessions. Therefore, the prediction of day–ahead electricity prices observed in Northern Italy can increase the understanding of the main drivers of these prices, and could contribute to the monitoring (hence in controlling) the bidding strategies across market sessions, according to the price levels expected in the day–ahead market. Other studies based on different markets and considering bidding strategies and their associated economic value are presented in Bunn et al. (2018), Lisi and Edoli (2018), Abramova and Bunn (2020) and Kath et al. (2020).

Others attempts to capture the impacts of economic, technical, strategic, and risk factors on intra-day prices are presented in Karakatsani and Bunn (2008). 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 with 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 forecasted production from renewable energy sources, to predict hourly day–ahead electricity prices in several European markets.

According to the literature, few papers have inspected the predictability of day–ahead prices in Northern Italy. The most notable studies are Gianfreda and Grossi (2012), Shah and Lisi (2019) and Bernardi and Lisi (2020). The latter two papers adopt a generalised additive location–scale model with a non-parametric estimation of the conditional mean and variance and a nonparametric functional autoregressive model based on individual bids. Whereas the former one considers the Italian zonal prices during years 2006–2008, when RES had a limited (or none) role in the determination of prices. Indeed, in that contribution, wind, solar, or hydro were not considered.

Accounting for the arguments that strong electricity price autocorrelations and long memory may be induced by the mean–reverting nature of market fundamentals, or by the highly repetitive nature of electricity auctions or also by the increased market integration (Knittel and Roberts, 2005; Haldrup and Nielsen, 2006; Conejo et al., 2005; Koopman et al., 2007 and Jeon and Taylor, 2016), 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 one and to replace negative forecasted prices with null prices (since that negative pricing is not allowed in the Italian market). Additionally, parsimoniuos autoregressive models extended for regressors and time-varying volatility have been included in the analysis; following Ziel (2016) and Ziel and Weron (2018). Therefore, in what follows with refer to these models as those built on some *experts' knowledge*.

It is worth noting that we expand these models by including our set of fundamentals (that is predicted RES values for wind and solar PV, forecasted demand, actual biomass, hydro, waste, and weighted flows together with fossil fuel prices). Then, we explore a total of 58 linear and nonlinear specifications to provide empirical evidence of their forecasting performance, given the mixed results in the literature (see Hong et al., 2014 among others). Specifically, we test several AR(FI)MAX–GARCH and *expert-type* models, and we additionally investigate LASSO variants for the selection of exogenous regressors, dummy variables, and autoregressive terms when the lag ordering is set at high values. Recent literature on LASSO and its applications can be found in Ziel et al. (2015), Ziel and Weron (2018), Uniejewski et al. (2019) and Messner and Pinson (2019); among others.

In addition, our contribution relies on applying both the Diebold–Mariano (DM) (Diebold and

Mariano, 1995) and the Model Confidence Set (MCS) (Hansen et al., 2011) testing procedure to account for the large model uncertainty in evaluation, and a density forecast exercise to guide practitioners in choosing the best model according to different hours.

More importantly, given the issue of data availability, market transparency and economic relevance of accurate predictions as discussed in Kezunovic et al. (2020) and Gonçalves et al. (2021), we include an interesting analysis in which we compare the forecasting performance when professional and more timely forecasts are used in place of public and freely available forecasts.

We confirm that including fundamental factors improves the forecasting ability. In particular, our expert EX_4X model augmented with fundamental drivers gives more accurate point forecasts: none of the other 57 models is statistically superior to it at any hour, despite the large number of specifications found in the model confidence set.

The evidence is different when the loss function is generalized to the density forecasting: all models with GARCH time-varying volatility give the most accurate density forecasts and they are statistically superior to models that exclude it.

When professional forecasts are used, the forecast power further increases, in particular for the early-morning and peak hours.

In details, we find that the inclusion of exogenous regressors reduces both the RMSEs and the CRPSs, especially during peak hours. More specifically, an expert model (our EX_4X) and its GARCH specifications drastically outperform all other models in point forecasts. From practical point of view, this expert model and its GARCH variants are the only ones retained for all hours in the MCS, and especially when hour 19 is considered. In addition, the results on CRPS and DM show that there are substantial improvements when all models are enlarged to include the GARCH time-varying volatility.

In a context characterized by a limited number of regressors with respect to the amount of statistical information available, we find that there are no substantial improvements when LASSO models are considered.

In addition, for the first time to our best knowledge, we provide the empirical evidence that using commercial forecasts improves substantially price forecasts, especially during hours 1-7 and peak hours 8-20. Then, as soon as the forecasting horizon increases, as after hour 21, the benefits of these more timely forecasts disappear. And we emphasize that this evidence is driven by the usage of professional forecasts and not by considering simple or complex models (in both cases, we observe improvements).

Finally, we also assess the coefficients of the exogenous regressors in our best model to investigate their degree of significance through the considered sample. We provide evidence that a model accounting for the dependence of prices over their demeaned prices of the previous 8 days, and including forecasted load, wind, and solar, as well as actual hydro and natural gas prices seems 'expert' enough to explain well and forecast even better the northern Italian day-ahead prices.

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 describes the estimation and Section 4 presents the results. 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. Day–ahead and intraday 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 where only balancing units with the required degree of flexibility are allowed to act. 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 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.

[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).

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 Gianfreda et al. (2016), Gianfreda et al. (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). In 2017, the production in the northern zone was 149,204 GWh over a total of 289,708 GWh, roughly 51%.

The northern area is also characterised by a varied, flexible generation mix, with 26% hydropower, and other renewables such as solar (6%) and biomass (8%); with conventional thermal generation covering the remaining proportion. Yearly details on the evolution of the portfolio generation are reported in Table A.7 in Appendix A, for all zones and across years 2015-2019. At first sight, given the low share of wind, a reader could argue about the choice of selecting Northern Italy to understand the contribution of main drivers to the forecasts of future prices. However, we would like to emphasize that this zone has the highest hydro generation and demand; and more importantly, all three type of thermal, hydro and water pumping units acting in all market sessions. This zone is also connected with four foreign countries, whereas the others have only national connections or limited numbers of foreign connections.

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. Table A.8 in Appendix A summarizes the information related to the local mix, and it reports the technology shares over total installed capacity in neighbouring countries. Furthermore, the inspection of import/export flows presented in Table 1 shows the relevance of imports[2] Hence, cross–border flows are included in this analysis through the construction of an artificial variable to account for prices determined in interconnected countries and in Central North, where local mix differ substantially. In this way, we do account for their generating portfolio when using prices weighted by the quantity imported.

	France		Austria		Switzerland		Slovenia		Malta		Greece	
Years	Imports	Exports	Imports	Exports	Imports	Exports	Imports	Exports	Imports	Exports	Imports	Exports
2015	13335	85	1526	33	25263	47	6179	16	0	926	588	1657
2016	11056	286	1420	55	19846	315	6371	16	0	1522	302	1999
2017	10860	280	1313	108	20490	272	5784	23	33	887	325	1614
2018	13102	79	1391	20	21406	122	6707	11	8	606	1053	621
2019	15134	98	1215	1	21231	121	5140	170	18	654	55	3028

Table 1: Italian *Imports from* and *Exports to* other Neighbouring Countries (in GW). Data: ENTSO-E.

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

To perform our analysis, we use day–ahead electricity prices determined hourly in the northern zone of Italy, and hourly forecasted load, wind and solar generation, actual biomass, waste and

[2] Details on the dynamics of imports from neighbouring countries over months and across hours are omitted but are available on request.

hydropower generated in Northern Italy, together with weighted imports and prices for fossil fuels (coal and natural gas) and CO_2 emissions.

Northern Italian zonal prices (in €/MWh) were collected directly from the website of the Italian system operator (*Gestore dei Mercati Energetici*, GME[3]). Forecasted load, wind and solar were collected from the *European Network of Transmission System Operators for Electricity* (ENTSO-E) and from Refinitiv Thomson Reuters (RTR); and re-scaled from MW to GW.

Then, we use both public and private forecasts to compare the forecasting performances of our models. Specifically, we use public ENTSO-E forecast data[4] from 2015 to 2019; and professional RTR forecasts from 2018 to 2019, since hourly forecasted load, wind and solar were fully available for the northern Italian region only from 2018. In the latter case, we consider the forecasts produced by two weather providers: the *European Centre for Medium-Range Weather Forecast* (ECMWF) and the *Global Forecast System* of the American weather service of the National Centers for Environmental Prediction (GFS). Both providers use two types of weather models - a deterministic one with no involved randomness and a high resolution (the *operational* model), and a probabilistic one with lower resolution but with variations of weather conditions (the ***ens**emble* model) - and different runs (one run for the `op` and between 21 or 51 runs for the `ens`) at specific hours (namely at midnight, at 6 a.m., at 12 a.m. and at 6 p.m.). Then, according to their ending time of updates and publication, we use two different series of forecasts[5]: one for forecasting models running quickly (*fast*, F), and so including more recent information released at 7.40 a.m.; and one for models running less quickly (*less fast*, LF), then including the information released at 6.55 a.m.. These contain the latest information available to market operators to run their forecasting models and formulate their day-ahead bidding strategy of 24 forecasted hourly prices to be submitted (by noon) on the day–ahead market. Hence, in this paper we compare public ENTSO-E with private

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

[4]This information is published per time unit at the latest two hours before the gate closure time of the day-ahead market or at 12:00 (in local time) at the latest when the gate closure time does not apply. This represents the publication deadline for ENTSOE and actually refers to data available to market operators at (the latest) 10 a.m.

[5]The first series for *fast* models uses forecasts obtained considering first the model ECens00 (which ends its updates at 7.40 a.m.) then any missing forecasts are replaced by the ECop00 (since this ends at 6.55 a.m.), and, if necessary, we use the same replacement scheme using respectively GFSen00, GFSop00, ECen18, ECop18, GFSen18, and GFSop18. Whereas, the second series for *less fast* models simply starts with ECop00. Please note that the runs at 18 were available only from 2018.

RTR forecasts to inspect the different forecasting performances.

The relevant information for actual biomass, waste and hydro (generated for all 24 hours) and physical flows are collected from ENTSO-E. However, this information is not available in a timely manner for their inclusion in the forecasting models of all the 24 price series, because the quantities usually displayed before noon refer up to hour 11.[6] Therefore, we consider the lagged actual biomass, waste and hydro generation together with flows for hours from 1 to 10, and their realised values observed at hour 10 for hours 11–24.

To construct the *weighted imports*, we use ENTSO-E data for imports and prices of foreign countries. In particular, to consider the effect of imports from foreign countries and from the contiguous zone (Central–Northern Italy), we account for the different prices observed in neighbouring foreign markets and we construct a series of average hourly prices (expressed in €/MWh) *weighted* for the quantity of electricity imported. Specifically, this is calculated as the average of day–ahead hourly prices determined in Austria, France, Switzerland, Slovenia and in Central–Northern Italy, weighted for the actual hourly electricity physical flows, to capture the effects of electricity transits across bordering markets and the neighbouring national zone.

Finally, to account for the marginal costs of conventional thermal generation, we use the Dutch TTF natural gas prices (for delivery over the next month), the ICE API2 Rotterdam Future prices for coal and the EEX-EU CO2 emissions E/EUA prices in euros, all collected from RTR Datastream. These prices are settlement prices, released at the end of the day at approximately 7 p.m.; hence, included with a time lag $t-1$.

Our final database comprises 35,064 hourly observations for each variable, from January 2015 to December 2019; apart from models using RTR forecasted regional data, which cover only 2018 and 2019.

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

[6] The hourly aggregated output are generally published no later than one hour after the operational period, as described by ENTSO-E.

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 2, and their dynamics are depicted in Figures 1 and 2. Prices show a degree of skewness and a high kurtosis (as for solar, wind and weighted imports). 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 the sake of generality, completeness and consistency with the local generation mix, as suggested by Ziel et al. (2015); for the same reason, we included biomass and waste. This general approach can be applied to other zones or markets, since it is reasonable to include all fundamental drivers and to expect limited significance of those with lower generation shares. Moreover, it allows for possible changes in the local generation induced by changes in policy regulation or weather conditions.

Consumption and electricity prices present weekly and calendar seasonality, with consumption levels higher on working days and lower values 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 and solar PV generation fluctuate according to weather conditions, and solar PV generation also fluctuates according to hours of solar radiation. Electricity inflows from the bordering central–northern Italian zone and foreign markets (Austria, France, Switzerland, and Slovenia) also exhibit strong seasonality, especially at the beginning of our sample. To help in understanding the effects of these regressors

	Min	Mean	Max	Std.Dev	Skewness	Kurtosis
Price	1.000	52.345	206.120	16.364	1.107	3.426
Load	7.344	18.624	31.617	4.858	0.164	-1.107
Weighted Import	0.000	43.075	249.340	15.551	0.911	2.883
Coal	4.280	6.961	9.840	1.598	0.143	-1.350
Natural Gas	9.630	17.575	29.330	3.986	0.296	-0.367
CO_2	0.440	1.330	3.316	0.877	0.829	-0.937
Solar	0.000	0.765	5.499	1.153	1.417	0.832
Wind	0.000	0.004	0.035	0.004	1.509	3.623
Hydro	0.550	3.910	10.510	2.029	0.348	-0.772
Biomass	0.044	0.128	0.237	0.036	0.818	-0.013
Waste	0.008	0.037	0.056	0.009	-0.532	0.058

Table 2: Descriptive Statistics of Fundamental Variables computed over the Full Sample. Note that *Std.Dev.* means *standard deviation*.

on prices, their intra-daily dynamics are shown in Figure B.3 in Appendix B.

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), and 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. These results for all hours are omitted but available on request.

3.2. Model Specifications

We use several expert- and AR(FI)MA–GARCH–type models.

The first expert specification (EX_1) simply considers past prices observed on one, two and seven days before with weekdays dummies. Formally, the hourly price y_t (for simplicity we omit the subscript h) is modelled as

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 y_{t-7} + \sum_{k=1}^{6} \gamma_k D_t^k + \varepsilon_t \quad (1)$$

where D_t^1 is equal to one for Mondays, D_t^2 for Tuesdays, and so on up to D_t^6 for Saturdays. We

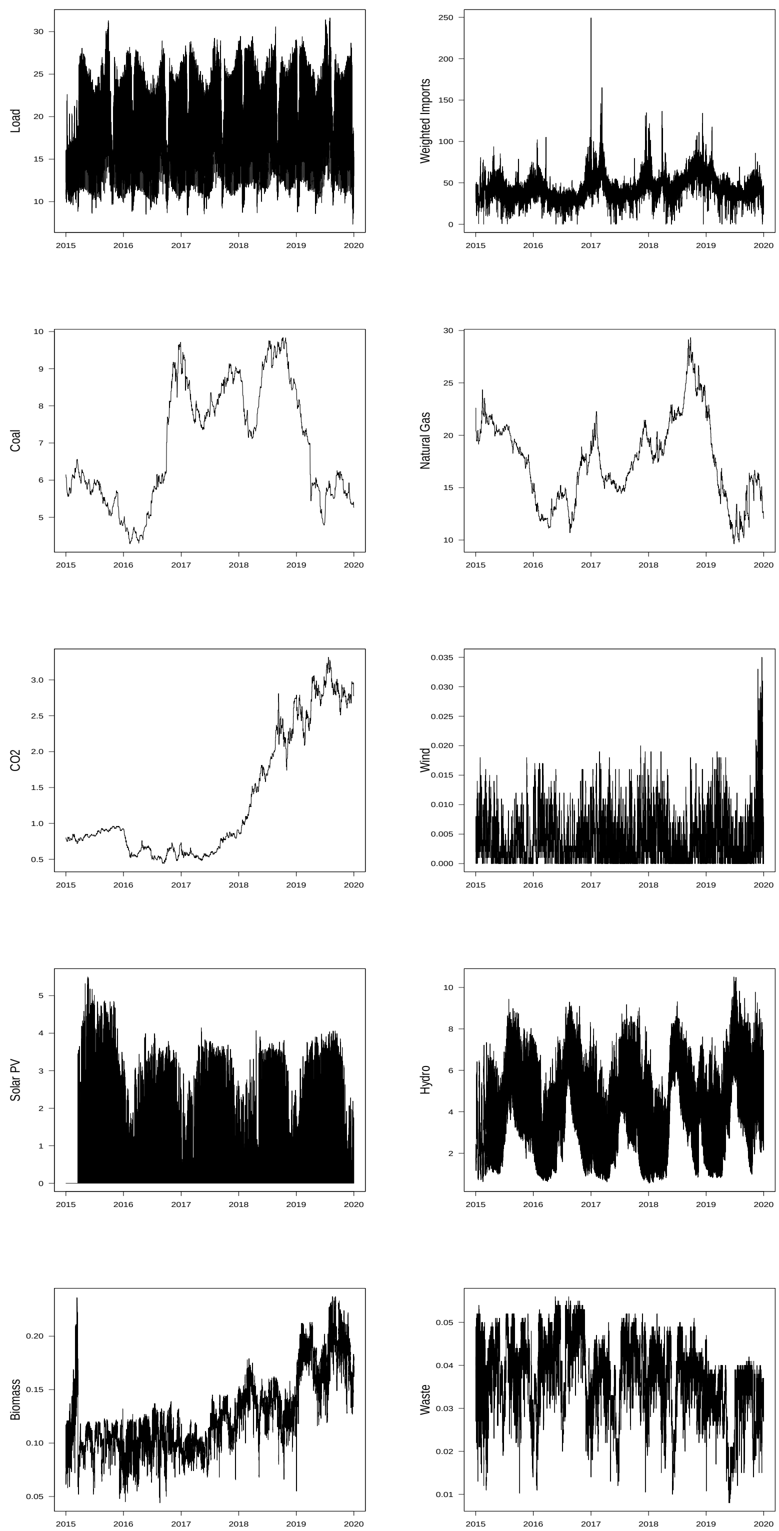

Figure 1: Time Series of all used Exogenous Variables.

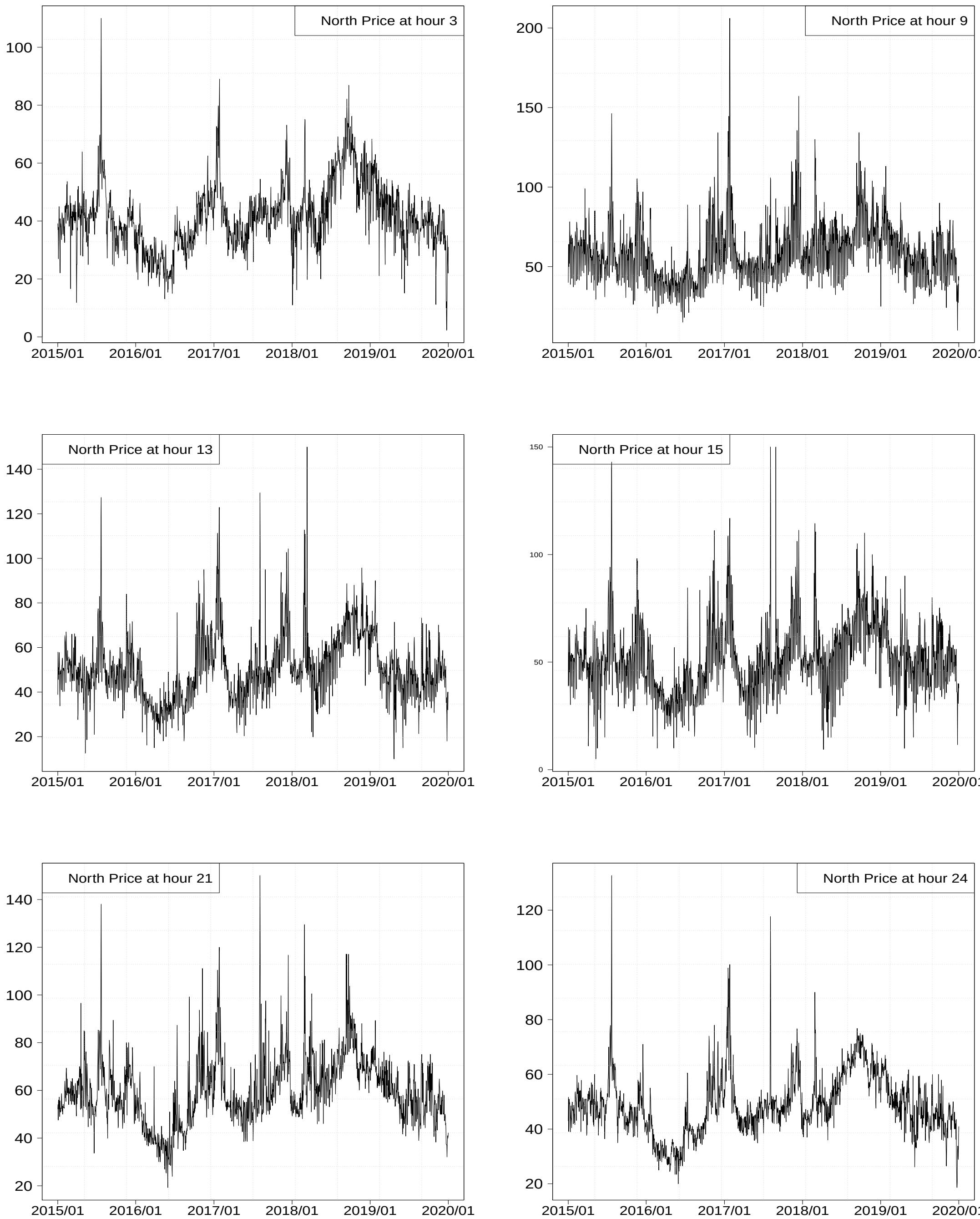

Figure 2: Day–ahead Electricity Prices in Northern Italy at hours 3, 9, 13, 15, 21, and 24.

extend this model with a set of exogenous regressors, having the EX_1X defined as

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 y_{t-7} + \sum_{k=1}^{6} \gamma_k D_t^k + \lambda' \mathbf{x}_t + \kappa' \mathbf{z}_{t-1} + \varepsilon_t \tag{2}$$

where $\mathbf{x}_t$ is the vector at time t of exogenous regressors, which include forecasted load, wind and solar PV generation, whereas $\mathbf{z}_{t-1}$ is a vector for exogenous regressors at time $t-1$ since we use actual hydro, biomass and waste generation, together with weighted imports, natural gas and CO_2 prices.

The second expert model (EX_2) builds upon the EX_1 model including the lowest and the highest hourly prices observed on the previous day, formally

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 y_{t-7} + \beta_4 y_{min,t-1} + \beta_5 y_{max,t-1} + \sum_{k=1}^{6} \gamma_k D_t^k + \varepsilon_t \tag{3}$$

As before the EX_2X includes the exogenous regressors $\mathbf{x}_t$ and $\mathbf{z}_{t-1}$.

The third expert model EX_3 expands the EX_2 by including the price at hour 24 of the previous day (this is omitted when the price at hour 24 is considered)

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 y_{t-7} + \beta_4 y_{min,t-1} + \beta_5 y_{max,t-1} + \beta_6 y_{24,t-1} + \sum_{k=1}^{6} \gamma_k D_t^k + \varepsilon_t \tag{4}$$

and, similarly, we have model EX_3X augmented for regressors.

The last expert model EX_4 takes into account demeaned prices, formally

$$y_t = \alpha_0 + \alpha_1 \bar{y}_t^w + \sum_{k=1}^{8} \beta_k \left(y_{t-k} - \bar{y}_t^w\right) + \varepsilon_t \tag{5}$$

where $\bar{y}_t^w$ is the mean value of the (hourly) price over the week, and a possible dependency over the $k = 8$ past days in considered, as in Ziel and Weron (2018). Its augmented variant EX_4X is expanded by including daily dummies D_t^k (with $k = 1, 2, \ldots, 6$ for Mondays, Tuesdays, and so on to Saturdays) and all exogenous regressors.

Moving to the AR(FI)MA models, the first specification is an AR(7), a simple autoregressive process with 7 lags given by the frequency of our data; and its variant AR(p) with lag length p estimated over a maximum length size of 7. Formally, our AR(p) models are defined as

$$y_t = \alpha + \sum_{k=1}^{4} \beta_s D_t^k + \sum_{j=1}^{11} \gamma_j M_t^j + \sum_{r=1}^{p} \phi_r y_{t-r} + \varepsilon_t \tag{6}$$

with D_t^k, differently from before, being dummies with $k = 1$ for Mondays, $k = 2$ for Saturdays, $k = 3$ for Sundays, and $k = 4$ for Holidays (not occurring on Saturdays or Sundays); M_t^j are dummies for months with $j = 1, 2, \ldots, 11$ for January, February, …, until November, excluding December. Monthly dummy variables are used to model calendar seasonality, whereas the $Monday_t$ dummy captures the impact of a change in consumption among working days and the first day after the weekends. ρ_r with $r = 1, \ldots, p$ are the coefficients for the autoregressive terms, with p varying from 1 to 7. If p is fixed to 7, then we have the AR(7) process; differently, if p is estimated from the data, then we have the AR(p) process (details on the estimations are reported in the following section). We also consider their variants augmented for regressors, that is ARX(7) and ARX(p).

Then, the autoregressive process is generalized to include moving average components and we consider the general ARMA models with p and q orders, fixed or again estimated from the data. The general formulation for an ARMA(p,q) is

$$y_t = \alpha + \sum_{k=1}^{4} \beta_s D_t^k + \sum_{j=1}^{11} \gamma_j M_t^j + \sum_{r=1}^{p} \phi_r y_{t-r} + \sum_{s=1}^{q} \theta_s \varepsilon_{t-s} + \varepsilon_t \tag{7}$$

with D_t^k dummies with $k = 1$ for Mondays, $k = 2$ for Saturdays, $k = 3$ for Sundays, and $k = 4$ for Holidays, θ_s with $s = 1, \ldots, q$ are the coefficients for the moving average terms, with q varying from 1 to 7; and again both are estimated, within a maximum range of 7, that is $p_{max} = 7$ and $q_{max} = 7$. For comparisons, we have also considered several specifications of this general process with fixed values, that is: the ARMA(7,7), with $p = q = 7$, the ARMA(7,1) with $p = 7$ and $q = 1$, and the ARMA(1,7) with $p = 1$ and $q = 7$. As for the other models, we include in our analysis all ARMAs augmented with exogenous regressors, then testing ARMAX(p,q), ARMAX(7,7), ARMAX(7,1) and ARMAX(7,1).

To account for long memory, we finally consider the *autoregressive, fractionally integrated, moving-average*, or ARFIMA(p,d,q) models, defined as

$$\Phi\left(L\right)\left(1-L\right)^d\left(y_t-\mu_t\right) = \Theta\left(L\right)\varepsilon_t \qquad \text{with } \varepsilon_t \mid \mathcal{F}_{t-1} \sim \mathcal{N}\left(0, \sigma^2\right) \tag{8}$$

where the normal distribution of the errors has a constant variance, $\sigma^2 \forall t$. d is the fractional integration parameter (with $0 < d < 0.5$) and μ_t is defined as

$$\mu_t = \mu + \sum_{k=1}^{4} \beta_s D_t^k + \sum_{j=1}^{11} \gamma_j M_t^j \tag{9}$$

with D_t^k dummies with $k = 1$ for Mondays, $k = 2$ for Saturdays, $k = 3$ for Sundays, and $k = 4$ for Holidays; and monthly dummies, M_t^j. As in the ARMA models, we set the p,d,q to be estimated within a range of $p_{max} = 7$, $d_{max} = 2$, and $q_{max} = 7$. We extend this model with our sets of exogenous regressors, obtaining the the ARFIMAX(p,d,q) model, and we compare it with

ARFIMAX variants with fixed values for p and q, leaving instead d free to change between 0,1 and 2. Specifically, we include in our analysis the ARFIMAX(7,d,7) and the ARFIMAX(7,d,0).

Moreover, 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), Jeon and Taylor (2016) and Laporta et al. (2018). Therefore, we follow consolidated and well-established modelling approaches.

In particular, when the Italian market is considered, Bosco et al. (2007) used an ARMA–GARCH model, whereas Gianfreda and Grossi (2012) used ARFIMAX–GARCHX models.

Hence, we compare the performances of several AR(FI)MA models with their variants including GARCH–type specifications, while allowing for an automatic selection of the length of autoregressive and moving average processes and the switching among models, when necessary. To this aim, the considered GARCH specifications are: the *standard* GARCH (SGARCH), the *exponential* GARCH (EGARCH), the *threshold* GARCH (TGARCH), and finally the GARCH-*in-mean* (GARCH-M); all with Normal distribution.

These models differ according to the type of the GARCH adopted. Thus, the second set of models extends the previous one with time–varying volatility expressed without loss of generality on day t as $\sigma_t^2 = \mathbb{V}\left(\varepsilon_t \mid \mathcal{F}_{t-1}\right) = Var\left(\varepsilon_t \mid \mathcal{F}_{t-1}\right)$. Let us recall them below.

The SGARCH(1,1) can be defined as

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2, \tag{10}$$

while the EGARCH(1,1) is defined as

$$\log\sigma_t^2 = \omega + \tau g\left(Z_{t-1}\right) + \beta\log\sigma_{t-1}^2, \tag{11}$$

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).

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

$$\sigma_t = \omega + \alpha_1^+\varepsilon_{t-1}^+ + \alpha_1^-\varepsilon_{t-1}^- + \beta\sigma_{t-1} \tag{12}$$

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.

Finally, to consider the possibility that price levels may be influenced by their past price variability and by the fact that volatility in electricity prices is generally stronger when prices are high, we include the standard deviation, as obtained from the conditional variance equation, in the conditional mean equation (as in Kyritsis et al., 2017; Gianfreda and Scandolo, 2018). The adopted GARCH(1,1)-in-mean (or simply, GARCH-M) is defined as

$$y_t = \mu + c\sigma_t + \varepsilon_t \text{ with } \sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2. \tag{13}$$

These GARCH specifications are expanded to include the exogenous regressors following evidence in Huurman et al. (2012) that fundamental drivers improve accuracy when the volatility equation is also included.

Finally, we estimate LASSO of further autoregressive models with 28 lags to account for changing market conditions in the last four weeks; their augmented specifications for regressors, that is AR(28)$_{LASSO}$ and ARX(28)$_{LASSO}$; and also the formulation including the time-varying volatility, that is the ARX(28)-GARCHX(1,1)-M$_{LASSO}$.

To summarize, our model set contains 58 models divided in 5 groups: (i) four different *expert* models (EX$_1$, EX$_2$, EX$_3$ and EX$_4$), their extensions with fundamental drivers (EX$_1$X, EX$_2$X, EX$_3$X and EX$_4$X) and the EX$_4$X extended with the time-varying volatility (that is EX$_4$X-SGARCHX, EX$_4$X-EGARCHX, EX$_4$X-TGARCHX and EX$_4$X-GARCHX-M); (ii) autoregressive AR and ARX models with the order p estimated for the AR(p) and ARX(p), or a priori fixed for the AR(7) with the ARX(p) and ARX(7) extended with the time-varying volatility; (iii) ARMA and ARMAX models where AR and MA lags are estimated or fixed (ARMA(p,q), ARMA(7,7), ARMA(1,7), and ARMA(7,1)), their extensions for regressors (ARMAX(p,q), ARMAX(7,7), ARMAX(1,7), and ARMAX(7,1)), and their ARMA(p,q) and ARMA(7,7) with the time-varying volatility; (iv) ARFIMA and ARFIMAX models where the AR and MA lags and the fractional integration order are estimated or fixed (ARFIMA(p,d,q), ARFIMAX(p,d,q), ARFIMAX(7,d,7) and ARFIMAX(7,d,0)), and their extensions with the time-varying volatility; (v) the least absolute shrinkage and selection operator (LASSO) (Tibshirani, 1996) for the AR and ARX models with up to 28 lags and their extension with GARCH-in-mean volatility.

3.3. Estimation Methods and Iterative Optimization Procedures

The iterative procedure adopted for the selection of the model ordering allows to adapt the price structure to the changing market conditions, as the increasing RES shares in generation, or changes in import/export flows due to additional interconnections, or more generally to agent learning, regulatory and market structural changes. However, to account for possible bias in day–ahead predictions induced by the iterative ordering selection, we compare the iterative models with the ones with ex-ante and pre–determined orders. Let us now describe the iterative model selection process while defining also the estimation and optimization procedures.

The iterative model selection is essentially a two–step estimation procedure. In the first step the autoregressive and moving average orders p and q, and (eventually) the fractionally integrated parameter d, are estimated through a grid search process by finding the best model according to the corrected AIC value (AICc), a modification of the original AIC for small sample sizes. The maximum values of the orders are set to 7 in order to consider the 7-day-per-week frequency of our data, so $p_{max} = 7$ and $q_{max} = 7$ respectively, whereas the maximum value of the fractional integration parameter is $d_{max} = 2$.

The second step is then used for the ARFIMAX(p,d,q) and the ARMAX(p,q)–GARCHs models, both with exogenous regressors. In the former cases, the estimated orders $(\hat{p}, \hat{q})$ enter in the ARFIMAX process, and then the fractional integration parameter d is estimated simultaneously with the other parameters of interest. In the latter case, the estimated orders $(\hat{p}, \hat{q})$ enter in the ARMAX(p,q)–GARCHs processes, and the GARCH orders are estimated simultaneously with the other parameters. For both, we found the *nloptr* nonlinear optimization algorithm to be suitable for estimating these type of models. Due to convergence problems in some specific cases and in order to ensure the invertibility of the processes, we changed the numeric tolerance of the solver, or, alternatively, tried a combination of other different solvers. Finally, the model parameters are all estimated by maximum likelihood.

Models with fixed orders are instead estimated without any adaptive scheme, due to the ex-ante pre-determined specified orders. In these situations, the estimation procedure is based on conditional sum of squares to find the starting values and then on the maximum likelihood, with the use of the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm for optimization; see Broyden (1970), Fletcher (1970), Goldfarb (1970), Shanno (1970). As before, if convergence problems occur, the procedure allows to fit the model via maximum likelihood and the optimization via a modification of the Simulated Annealing (SANN) of Bélisle (1992), which always guarantees the convergence even with non–differentiable functions, but it can be relatively slow.

As far as the LASSO is concerned, we proceed in a way that the relevant exogenous regressors $\mathbf{x}_t$

and $\mathbf{z}_{t-1}$, combined with the autoregressive terms up to 28 earlier periods, i.e. $\mathbf{y}_{t-h}$ $h = 1, \ldots, 28$, are selected by considering a simple linear model. In this way, we are able to properly define a potential subgroup of regressors and autoregressive terms selected at each iteration and for each hour. The criterion used for the statistical bias–variance trade–off, which determines the tuning/penalty parameter, is the *standard cross–validation (cv)* that minimizes the average error.

All computations have been executed using the software R and using an AMD EPYC 7542 32-Core 2.90 GHz Processor.

3.4. Assessment of the Forecasting Performance

We compare different model specifications to model and forecast the electricity zonal prices observed over individual hours: each hour is modelled separately by following a daily frequency for prices and drivers. Because all 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 forecasts for the 24 hours of the following day.

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 three years from 1/1/2017 to 31/12/2019, using the ENTSO-E forecasted data. 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 have to complete their runs before 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 fuel prices determined on day $t-1$; the forecasted values for RES and zonal load available on day t; the hydro generation, weighted imports, biomass and waste observed on day $t-1$ for hours 1–10 and their realised values observed at hour 10 on the day t for modelling and forecasting electricity prices of hours 11–24 on day $t+1$. Indeed, Maciejowska and Nowotarski (2016) and Ziel (2016) note and suggest that prices for early morning hours depend more on the latest information than on information contained at the same hour but on the previous day.

To assess the forecasting performance of implemented models, we use both point and density metrics, as the root mean square error (RMSE) and the the continuous ranked probability score (CRPS); see for example Gneiting and Ranjan (2011) and Groen et al. (2013) for early applications in economics, and Gianfreda et al. (2020) for an application to Italian electricity prices. In addition, we implement the Diebold–Mariano (DM) test to judge the superiority among two competing models (see 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 (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. We also consider a comparison in terms of the full density forecasts by applying the DM and MCS tests to the CRPS metrics.

Finally, we compare the forecasting ability of the best performing model when the RTR professional forecasts for consumption, wind and solar replace the ones provided by ENTSO-E. In this latter analysis, the in–sample estimation considers only 365 observations for 2018 and produces forecasts for the whole 2019, because of the reduced size of RTR Italian regional forecasts.

4. Results

To judge the quality of the forecasted prices, RMSEs and CRPSs are computed and presented in Tables 3 and 4, which also include the Superior Set of Models and the DM tests. These results refer to hours 3, 9, 11, 13, 19, and 21, to the average metrics computed over the 24 hours (Avg_{1-24}) and over the peak hours 8–20 (Avg_{8-20}). Results for other hours are omitted but are available on request.

Firstly, we observe that the inclusion of exogenous regressors reduces both the RMSEs and the CRPSs, especially during peak hours. Therefore, we extend the empirical evidence in Gianfreda et al. (2020) on the predictive power of a large set of exogenous regressors to forecast, this time, regional prices; whereas, the *single national prices* were forecasted in the cited reference.

Considering the whole set of 58 models, it can be easily observed that the expert EX_4X model and its GARCH specifications drastically outperform all other models in point forecasts, with the lowest average errors of around 7 and 6 €/MWh over peak and base periods, respectively. These results clearly declare the EX_4X model as the superior specification in point forecasting. The other AR(FI)MA models provide higher and similar errors, even if they differ in their structures.

Notably, the forecasting precision drastically decreases during the ramp–up and ramp–down phases (hours 9 and 19), when the conventional thermal generation is necessary to restore the balance between demand and supply. Across peak hours, the non programmable renewables (especially solar and wind) bid at 0 € /MWh and have priority of dispatch of the produced energy. Therefore, their intermittent, erratic in-feed increases the variability of prices and consequently affects the forecasting errors, especially when demand is at its higher levels (at hours 9 and 19).

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.

There are no substantial improvements when LASSO models are considered. Therefore, based on this evidence and on previous explorations[7], we conclude that the LASSO is not necessary to improve accuracy in our context, characterized by a limited number of regressors with respect to the amount of statistical information available.

Indeed, when all models are simultaneously compared, the computations of the Superior Set of Models[8], in terms of minimum loss function for level forecasts, show that the LASSO models are always discarded. Moreover, all models provide forecasts not statistically different from the EX_4X, considered as benchmark in the DM tests. This model is always retained in the Superior Set of Models and also the DM tests confirm its out-performance in pairwise comparisons. More

[7] In previous analyses on LASSO specifications, we note that on average LASSOs perform better when considering the simultaneous selection of the autoregressive terms with the exogenous regressors, revealing that not all the lagged terms are useful at each iteration. Moreover, including exogenous regressors both in the conditional mean and conditional variance does not improve on average the power predictability of the same model.

[8] 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).

importantly for a practical point of view, this expert model and its GARCH variants are the only ones retained for all hours in the MCS, and especially when hour 19 is considered. Hence, market operators willing to adopt a single model to forecast all hourly prices should consider this relevant and so clearly assessed fact.

For completeness, we extend the analysis to density forecasting and investigate if a more general loss function provide different evidence. Looking at Table 4, results on CRPS show that there are substantial improvements when all models are enlarged to include the GARCH time-varying volatility. Indeed, the average of CRPS over the 24 hours of all the models with time-varying volatility is in the range 0.156-0.160, whereas the same average for models without time-varying volatility is around 0.3. Specifications for only the conditional mean are always excluded from the MCS, apart for the $AR(28)_{LASSO}$, which however does provide forecasts not statistically different from the benchmark EX_4X in the DM tests. The expert models augmented with time-varying volatility are the only (class of) models that is never excluded from the MCS. Moreover, the DM tests show that all GARCHs specifications are statistically superior to the benchmark, confirming the importance of including the time-varying volatility. Therefore, when the loss function is generalized to the full distribution, sophisticated specifications that allow for time-varying volatility are essential to improve the forecast accuracy.

Given the focus on forecasting, we compare the forecasting performance of the EX_4X and EX_4X-SGARCHX models when professional and more timely forecasts are used in place of public and freely available forecasts. The RMSEs and CRPSs for a selection of hours and averages over base and peak hours are presented in Tables 5 and 6. However, to show in full the performance of these models, we have decided to report results for all 24 hours in Tables A.9 and A.10 in Appendix A.

We compare the forecasting performances of EX_4X when ENTSO-E forecasts are considered, with those obtained by the same model when instead RTR forecasts are used. As anticipated, these professional forecasts are released more timely and represent the best updated information available at 6.55 and at 7.40 a.m. when market operators can start running their forecasting models to formulate their day-ahead bidding strategy. Then, we distinguish between models which can run quickly (and their forecasts are labelled with F for *fast*), from those running less quickly (hence labelled with LF for *less fast*). In our case, we compare the forecasting performances of EX_4X-F and EX_4X-LF with EX_4X and the ones from EX_4X-SGARCHX-F and EX_4X-SGARCHX-LF with EX_4X-SGARCHX. Also for this exercise, we have studied other model specifications with professional forecasts and results are qualitative similar. Then, we emphasize that the evidence is not driven by considering simple or complex models, but by the usage of professional forecasts.

Results clearly show that using professional forecasts improves substantially price forecasts, especially during hours 1-7, and peak hours 8-20. Then, as soon as the forecasting horizon increases, as after hour 21, the benefits of using professional forecasts disappear. Moreover, in the very short-horizon up to hour 18, there is no difference between the two forecasting models running with the latest information: indeed *fast* and *less fast* models perform equivalently. They diverge when the fast model shows better (but small) gains at hour 19, before losing any forecasting power as soon as the forecasting horizon further increases to hours 21-24. Therefore, these results emphasize the importance of implementing forecasting models with accurate and professionally computed forecasts; and, if possible, traders should wait for the latest published forecasts to take longer benefits of the forecasting gain. Even in this case, GARCH specifications do not substantially improve the point forecasts, whereas the opposite occurs for the density forecasts. And the take home messages are that traders and market operators are encouraged to use models accounting for higher moments of the distributions, as suggested in Gianfreda and Bunn (2018), while considering professional forecasts.

Finally, in what follows, we discuss the estimated coefficients (with confidence intervals at 90%) of the EX_4X model. Results generally refer to hours 3, 9, 15, and 21 in the out–of–sample period. However, some additional hours are considered with respect to the intra-daily profiles of drivers, and 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 as shown in Figure B.4 in Appendix B. However, for hour 3, we document an increasing influence in 2018, then decreasing in 2019. Hours 9 and 15 show different dynamics with an almost constant influence until the end of 2018 but a substantial lower and progressively decreasing influencing power over the whole 2019, which may reflect the *negative demand* effect played by solar PV generation according to its generation and new addictions. Whereas, hour 21 exhibits a decreasing influence already from July 2017, probably for more conventional power available to cover demand (and so being less at the margin).

The estimated coefficients for solar PV forecasts are depicted in Figure B.5, and it shows that it is statistically significant at hours 13 and 15 with a negative sign, implying the reduction of the mean level of zonal prices. At hour 9 or 11 when sun starts to shine, it turns from significant to non significant from the last part of 2017 or middle 2018 and through all the other years. Notwithstanding the limited generation in northern Italy, forecasted wind is found to have a significant negative effect at hour 3, whereas its effect turns from significant to non significant from roughly the beginning of 2018 at hours 9 and 21. Instead, it is found almost never significant at hour 15; see Figure B.6.

Looking at hydro and its intra-daily profile, we were expecting significant (negative) effects at hours 9 and 21 when its generation is at its maximum. Whereas, the estimated coefficients for actual hydropower generation is not found statistically significant at these hours. Figure B.7 shows that it is found statistically significant only at hour 3, when it does not suffer the competition of solar PV (and wind to less extent).

As far as weighted imports are considered, they are not found to be significant (as reported at hours 3, 9, 15 and 21), see Figure B.10. Therefore, foreign prices and imported quantities seem not to affect northern Italian electricity price via scheduled capacity on interconnectors. The same conclusion is drawn for biomass and waste. Coal is instead found to be significant only at hour 15 and up to the beginning of 2018, then it turned out to be misplaced by the progressive penetration of RES. Figure B.12 shows that natural gas confirms its attitude to increase electricity prices at hour 3. This finding is surprising considering the relevant share of electricity generation covered by combined cycle gas turbine plants in northern Italy. Similarly, also CO_2 emission prices exhibit an almost never significant effect, see Figure B.13.

However, it must be noted that these conclusions on the dynamics of coefficients for exogenous regressors are based on a model accounting for the dependence of prices over the previous 8 demeaned prices. Then, the model seems 'expert' enough with the inclusion of past essential information together with the contribution of load, wind, solar, hydro and natural gas.

Models	3	9	11	13	19	21	Avg_{8-20}	Avg_{1-24}
EX_1	6.468	12.501	10.822	9.834	11.836	8.911	10.973	9.150
EX_2	6.437	12.162	10.533	9.636	11.748	8.809	10.760	9.016
EX_3	5.984	11.960	10.309	9.411	11.804	8.756	10.616	8.824
EX_4	5.204	9.469	8.284	7.998	8.365	6.643	8.516	7.074
EX_1X	6.151	11.691	10.196	9.144	11.169	8.614	10.303	8.644
EX_2X	6.113	11.563	10.062	9.062	11.175	8.636	10.237	8.602
EX_3X	5.814	11.378	9.864	8.895	11.237	8.756	10.131	8.499
EX_4X	4.860	8.691	7.708	7.318	8.106	6.466	7.871	6.615
EX_4X-SGARCHX	4.861	8.834	7.712	7.274	8.284	6.449	7.919	6.628
EX_4X-EGARCHX	4.912	8.790	7.805	7.230	8.207	6.473	7.907	6.626
EX_4X-TGARCHX	4.894	8.835	7.791	7.286	8.401	6.595	7.992	6.689
EX_4X-GARCHX-M	4.925	8.846	7.788	7.313	8.264	6.420	7.976	6.662
AR(7)	5.577	11.500	9.867	9.228	10.272	8.122	10.130	8.327
AR(p)	5.529	11.977	10.170	9.545	10.521	8.223	10.582	8.596
ARX(7)	5.489	10.706	9.162	8.521	9.932	7.837	9.412	7.847
ARX(p)	5.449	11.000	9.428	8.739	10.135	7.871	9.703	8.024
ARX(7)-SGARCHX	5.462	10.722	9.177	8.337	9.739	7.689	9.367	7.795
ARX(7)-EGARCHX	5.462	10.873	9.225	8.455	9.712	7.786	9.395	7.826
ARX(7)-TGARCHX	5.506	10.596	9.208	8.489	10.048	7.745	9.472	7.871
ARX(7)-GARCHX-M	5.470	10.692	9.184	8.348	9.804	7.689	9.405	7.843
ARX(p)-SGARCHX	5.436	10.924	9.404	8.591	10.088	7.777	9.736	8.034
ARX(p)-EGARCHX	5.446	11.074	9.536	8.618	10.021	7.899	9.720	8.030
ARX(p)-TGARCHX	5.498	11.001	9.484	8.979	10.309	7.837	9.932	8.164
ARX(p)-GARCHX-M	5.468	11.025	9.571	8.603	10.091	7.813	9.824	8.114
ARMA(7,7)	5.717	13.542	10.430	9.402	10.629	9.974	10.615	8.934
ARMA(1,7)	5.589	11.808	9.942	9.362	10.449	8.192	10.309	8.447
ARMA(7,1)	5.584	11.483	9.821	9.191	10.310	8.105	10.091	8.300
ARMA(p,q)	5.561	11.805	10.066	9.429	10.520	8.160	10.450	8.516
ARMAX(7,7)	5.533	10.418	9.197	8.493	9.950	7.685	9.339	7.824
ARMAX(1,7)	5.518	10.770	9.176	8.571	10.003	7.819	9.444	7.873
ARMAX(7,1)	5.494	10.710	9.136	8.498	9.968	7.832	9.394	7.836
ARMAX(p,q)	5.467	10.959	9.353	8.660	10.129	7.827	9.630	7.975
ARMAX(7,7)-SGARCHX	5.693	10.562	10.574	8.461	9.831	7.893	9.708	8.044
ARMAX(7,7)-EGARCHX	5.578	12.429	9.732	8.662	9.827	8.050	9.702	8.045
ARMAX(7,7)-TGARCHX	5.624	10.768	9.261	8.762	10.003	7.752	9.495	7.910
ARMAX(7,7)-GARCHX-M	5.689	10.746	9.228	8.530	9.959	7.719	9.519	8.135
ARMAX(p,q)-SGARCHX	5.453	10.867	9.314	8.649	10.060	7.737	9.625	7.959
ARMAX(p,q)-EGARCHX	5.456	10.875	9.376	8.522	10.138	7.779	9.626	8.009
ARMAX(p,q)-TGARCHX	5.507	10.959	9.248	8.638	10.303	7.822	9.781	8.060
ARMAX(p,q)-GARCHX-M	5.501	11.157	9.526	8.766	10.112	7.756	9.991	8.195
ARFIMA(p,d,q)	5.572	11.261	9.827	9.267	10.054	8.223	10.063	8.289
ARFIMAX(p,d,q)	5.467	10.959	9.353	8.661	10.121	7.827	9.630	7.975
ARFIMAX(p,d,q)-SGARCHX	5.459	10.847	9.303	8.620	10.044	7.762	9.617	7.947
ARFIMAX(7,d,7)-SGARCHX	5.604	10.782	9.134	8.462	10.064	7.799	9.513	7.923
ARFIMAX(7,d,0)-SGARCHX	5.455	10.806	9.143	8.317	9.895	7.698	9.385	7.804
ARFIMAX(p,d,q)-EGARCHX	5.468	10.807	9.482	8.678	10.132	7.745	9.653	7.975
ARFIMAX(7,d,7)-EGARCHX	5.763	10.655	9.828	10.534	10.007	8.823	9.703	8.110
ARFIMAX(7,d,0)-EGARCHX	5.458	10.727	9.064	8.473	9.775	7.749	9.354	7.796
ARFIMAX(p,d,q)-TGARCHX	5.480	11.010	9.247	8.543	10.213	7.782	9.702	8.007
ARFIMAX(7,d,7)-TGARCHX	5.588	10.447	9.217	8.664	9.895	7.780	9.424	7.884
ARFIMAX(7,d,0)-TGARCHX	5.506	10.671	9.110	8.383	10.009	7.689	9.400	7.833
ARFIMAX(p,d,q)-GARCHX-M	5.480	10.999	9.424	8.671	10.178	7.839	10.068	8.262
ARFIMAX(7,d,7)-GARCHX-M	6.586	10.883	9.334	8.595	10.209	7.962	9.913	8.402
ARFIMAX(7,d,0)-GARCHX-M	5.480	10.782	9.084	8.289	10.021	7.714	9.436	7.852
AR(28)_{LASSO}	6.415	12.395	10.802	9.960	11.462	9.007	10.914	9.117
ARX(28)_{LASSO}	6.197	11.736	10.094	9.210	11.051	8.649	10.259	8.636
$\text{AR(28)-GARCH-M}_{LASSO}$	6.394	12.614	10.845	10.045	11.859	9.171	11.143	9.275
$\text{ARX(28)-GARCHX-M}_{LASSO}$	6.295	11.577	10.258	9.195	11.060	8.678	10.361	8.721

Table 3: RMSEs of all selected models and for a section of hours. The average over the 24 hours and the average over peak hours 8-20 are also included. Grey cells refer to specifications excluded from the Superior Set of Models selected according to the Hansen-Luden-Nason MCS procedure at $\alpha = 0.15$. ***, **, * and . are the 0.1%, 1%, 5%, 10% significant levels according to the DM test statistic when the EX_4X model is used as benchmark.

Models	3	9	11	13	19	21	Avg_{8-20}	Avg_{1-24}
EX_1	0.255	0.332	0.317	0.298	0.323	0.313	0.317	0.298
EX_2	0.254	0.332	0.318	0.299	0.323	0.313	0.317	0.298
EX_3	0.253	0.333	0.318	0.300	0.324	0.313	0.318	0.298
EX_4	0.252	0.323	0.309	0.291	0.314	0.309	0.309	0.292
EX_1X	0.254	0.327	0.312	0.294	0.319	0.314	0.312	0.295
EX_2X	0.253	0.327	0.312	0.294	0.319	0.314	0.312	0.295
EX_3X	0.253	0.327	0.312	0.294	0.320	0.313	0.313	0.295
EX_4X	0.251	0.320	0.307	0.289	0.313	0.308	0.307	0.290
EX_4X-SGARCHX	0.125***	0.199***	0.174***	0.156***	0.178***	0.166***	0.178	0.158
EX_4X-EGARCHX	0.125***	0.198***	0.173***	0.155***	0.180***	0.164***	0.178	0.158
EX_4X-TGARCHX	0.124***	0.199***	0.174***	0.155***	0.178***	0.167***	0.179	0.158
EX_4X-GARCHX-M	0.125***	0.201***	0.173***	0.155***	0.178***	0.164***	0.179	0.158
AR(7)	0.254	0.326	0.312	0.294	0.317	0.312	0.312	0.295
AR(p)	0.252	0.324	0.310	0.292	0.314	0.309	0.310	0.292
ARX(7)	0.252	0.323	0.309	0.292	0.315	0.310	0.309	0.292
ARX(p)	0.252	0.324	0.310	0.292	0.314	0.310	0.310	0.293
ARX(7)-SGARCHX	0.124***	0.201***	0.176***	0.158***	0.177***	0.163***	0.179	0.158
ARX(7)-EGARCHX	0.124***	0.205***	0.179***	0.159***	0.177***	0.166***	0.181	0.159
ARX(7)-TGARCHX	0.124***	0.200***	0.175***	0.154***	0.179***	0.162***	0.178	0.158
ARX(7)-GARCHX-M	0.124***	0.201***	0.175***	0.158***	0.177***	0.163***	0.179	0.158
ARX(p)-SGARCHX	0.124***	0.200***	0.174***	0.153***	0.176***	0.163***	0.177	0.157
ARX(p)-EGARCHX	0.124***	0.208***	0.179***	0.156***	0.177***	0.166***	0.181	0.160
ARX(p)-TGARCHX	0.124***	0.201***	0.173***	0.149***	0.177***	0.161***	0.176	0.156
ARX(p)-GARCHX-M	0.124***	0.201***	0.175***	0.154***	0.176***	0.163***	0.178	0.158
ARMA(7,7)	0.264	0.341	0.326	0.308	0.328	0.324	0.326	0.307
ARMA(1,7)	0.264	0.338	0.324	0.307	0.328	0.322	0.324	0.306
ARMA(7,1)	0.264	0.338	0.324	0.307	0.328	0.322	0.324	0.306
ARMA(p,q)	0.262	0.337	0.323	0.305	0.327	0.320	0.323	0.304
ARMAX(7,7)	0.252	0.323	0.310	0.292	0.315	0.310	0.310	0.292
ARMAX(1,7)	0.261	0.335	0.321	0.303	0.326	0.319	0.321	0.303
ARMAX(7,1)	0.252	0.323	0.309	0.292	0.315	0.310	0.309	0.292
ARMAX(p,q)	0.261	0.335	0.321	0.303	0.326	0.319	0.321	0.303
ARMAX(7,7)-SGARCHX	0.125***	0.202***	0.179***	0.157***	0.180***	0.165***	0.180	0.159
ARMAX(7,7)-EGARCHX	0.126***	0.203***	0.183***	0.159***	0.179***	0.166***	0.182	0.160
ARMAX(7,7)-TGARCHX	0.125***	0.201***	0.178***	0.156***	0.180***	0.163***	0.180	0.159
ARMAX(7,7)-GARCHX-M	0.125***	0.202***	0.177***	0.158***	0.178***	0.164***	0.181	0.159
ARMAX(p,q)-SGARCHX	0.124***	0.202***	0.176***	0.157***	0.178***	0.163***	0.179	0.158
ARMAX(p,q)-EGARCHX	0.124***	0.206***	0.179***	0.157***	0.177***	0.166***	0.181	0.159
ARMAX(p,q)-TGARCHX	0.124***	0.201***	0.175***	0.152***	0.179***	0.161***	0.178	0.157
ARMAX(p,q)-GARCHX-M	0.124***	0.202***	0.176***	0.158***	0.177***	0.163***	0.179	0.158
ARFIMA(p,d,q)	0.263	0.339	0.325	0.307	0.328	0.321	0.325	0.306
ARFIMAX(p,d,q)	0.261	0.335	0.321	0.303	0.326	0.319	0.321	0.303
ARFIMAX(p,d,q)-SGARCHX	0.124***	0.201***	0.175***	0.157***	0.178***	0.164***	0.178	0.158
ARFIMAX(7,d,7)-SGARCHX	0.125***	0.202***	0.178***	0.158***	0.179***	0.164***	0.181	0.160
ARFIMAX(7,d,0)-SGARCHX	0.125***	0.201***	0.176***	0.158***	0.177***	0.163***	0.179	0.158
ARFIMAX(p,d,q)-EGARCHX	0.125***	0.206***	0.179***	0.158***	0.177***	0.166***	0.181	0.160
ARFIMAX(7,d,7)-EGARCHX	0.126***	0.204***	0.182***	0.161***	0.179***	0.167***	0.183	0.161
ARFIMAX(7,d,0)-EGARCHX	0.125***	0.205***	0.179***	0.159***	0.178***	0.167***	0.181	0.160
ARFIMAX(p,d,q)-TGARCHX	0.124***	0.200***	0.176***	0.152***	0.179***	0.162***	0.178	0.157
ARFIMAX(7,d,7)-TGARCHX	0.125***	0.200***	0.178***	0.157***	0.179***	0.164***	0.180	0.159
ARFIMAX(7,d,0)-TGARCHX	0.124***	0.200***	0.176***	0.154***	0.179***	0.162***	0.178	0.158
ARFIMAX(p,d,q)-GARCHX-M	0.124***	0.202***	0.175***	0.157***	0.177***	0.163***	0.178	0.158
ARFIMAX(7,d,7)-GARCHX-M	0.126***	0.203***	0.177***	0.158***	0.178***	0.165***	0.180	0.160
ARFIMAX(7,d,0)-GARCHX-M	0.124***	0.201***	0.176***	0.158***	0.177***	0.164***	0.179	0.158
AR(28)_{LASSO}	0.254	0.327	0.313	0.294	0.317	0.312	0.312	0.295
ARX(28)_{LASSO}	0.256	0.327	0.311	0.294	0.318	0.313	0.312	0.295
$\text{AR(28)-GARCH-M}_{LASSO}$	0.124***	0.201***	0.176***	0.158***	0.181***	0.163***	0.179	0.158
$\text{ARX(28)-GARCHX-M}_{LASSO}$	0.125***	0.200***	0.173***	0.153***	0.179***	0.166***	0.178	0.158

Table 4: CRPSs of all selected models and for a section of hours. The average over the 24 hours and the average over peak hours 8-20 are also included. Grey cells refer to specifications excluded from the Superior Set of Models selected according to the Hansen-Luden-Nason MCS procedure at $\alpha = 0.15$. ***, **, * and . are the 0.1%, 1%, 5%, 10% significant levels according to the DM test statistic when the EX_4X model is used as benchmark.

	3	9	11	13	19	21	Avg_{1-24}	Avg_{8-20}
EX_4X	5.082	9.782	7.515	6.888	6.719	5.105	6.605	7.814
EX_4X-F	4.629	6.562	6.325	5.681	5.354	4.668	5.264	5.938
EX_4X-LF	4.624	6.553	6.329	5.694	5.357	4.673	5.266	5.941
EX_4X-SGARCHX	5.090	9.939	7.663	7.074	6.739	5.269	6.745	8.031
EX_4X-SGARCHX-F	4.592	6.573	6.273	5.525	5.400	4.645	5.302	5.932
EX_4X-SGARCHX-LF	4.580	6.593	6.307	5.597	5.362	4.647	5.303	5.937

Table 5: RMSEs of the best performing model with ENTSO-E forecasts (EX_4X and EX_4X-SGARCHX-norm) and with ETR forecasts for *fast* (EX_4X-F and EX_4X-SGARCHX-norm-F) and *less fast* (EX_4X-LF and EX_4X-SGARCHX-norm-LF) models, over 365 forecasts computed for the whole 2019 for a selection of hours.

	3	9	11	13	19	21	Avg_{1-24}	Avg_{8-20}
EX_4X	0.239	0.310	0.301	0.280	0.293	0.295	0.278	0.296
EX_4X-F	0.269	0.297	0.295	0.307	0.313	0.301	0.285	0.299
EX_4X-LF	0.269	0.297	0.295	0.307	0.313	0.301	0.285	0.299
EX_4X-SGARCHX	0.103	0.179	0.164	0.140	0.144	0.134	0.135	0.159
EX_4X-SGARCHX-F	0.098	0.128	0.113	0.117	0.141	0.121	0.112	0.125
EX_4X-SGARCHX-LF	0.099	0.126	0.112	0.117	0.144	0.122	0.112	0.125

Table 6: CRPSs of the best performing model with ENTSO-E forecasts (EX_4X and EX_4X-SGARCHX-norm) and with ETR forecasts for *fast* (EX_4X-F and EX_4X-SGARCHX-norm-F) and *less fast* (EX_4X-LF and EX_4X-SGARCHX-norm-LF) models, over 365 forecasts computed for the whole 2019 for a selection of hours.

5. Conclusions

Forecasting day–ahead electricity prices has become extremely important for generation planning, given the imperfect predictability of weather conditions that affects 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 comparison of expert and AR(FI)MA models with GARCH specifications with fixed or estimated structures through a flexible model selection by an iterative and adaptive procedure. Results show that the best performing model is an expert one augmented for exogenous regressors and time-varying volatility, especially if density forecasting has to be assessed. The importance of producing good and timely predictions of hourly day–ahead prices for northern Italy is also tested against the usage of commercial forecasts, since monitoring the bidding strategies for detecting strategic behaviours across market sessions is becoming crucial to avoid market speculations and consequent increasing costs for final customers.

Using a set of drivers, including forecasted demand, forecasted wind and solar PV generation, fossil fuels, and hydro, biomass and waste generations together with price–weighted flows, northern Italian electricity prices are forecasted through linear and nonlinear models, some of them with a flexible structure iteratively selected at both the autoregressive and moving average orders over each calibration window, including the possibility to switch from one model to another one. Our results clearly show that if point forecasts are of concern a simple expert model overcomes all other specifications, and that adopting a flexible structures changing with time–varying market conditions and avoiding over-parametrisation in an ex–ante ordering selection performs equally well, although is not recommended for all hours.

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. However, when studying the density forecasting, only nonlinear models that allow for time-varying volatility and second-moment dynamics provide more accurate results. Finally, we find that using professional and more timely consumption and RES predictions improves the forecast accuracy of electricity prices more than using predictions freely available to researchers.

Acknowledgements

We thank the editor, the associate editor and two anonymous reviewers for useful comments and suggestions which led us to improve the paper. Authors also thank seminars and conference participants at 39th International Symposium on Forecasting in Thessaloniki. Special acknowledgements go to Giorgio Battisti and Diego Ganz for useful discussions and suggestions. Alperia Energy S.p.A. is acknowledged for funding this research project. In addition, Angelica Gianfreda wishes to acknowledge the RTDcall2017 support for the FoMoPM project on *Forecasting and Monitoring electricity Prices, volumes and market Mechanisms* and RTDcall2018 support for the ERMUn project on *Energy Risk Modelling Under uncertainties*, funded by the Free University of Bozen–Bolzano.

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Appendix A. Tables

Years	Gas	Oil	Coal	Other	Hydro	Wind	Solar	Geothermal	Biomass	Waste
North										
2015	0.608	0.000	0.000	0.665	0.807	0.012	0.371		0.359	0.867
2016	0.568	0.000	0.000	0.710	0.811	0.004	0.357		0.373	0.879
2017	0.625	0.000	0.220	0.716	0.816	0.004	0.357		0.327	0.941
2018	0.626	0.091	0.336	0.760	0.799	0.003	0.358		0.343	0.962
2019	0.608	0.054	0.172	0.713	0.818	0.004	0.370		0.316	0.792
Central North										
2015	0.130	0.000	0.003	0.020	0.056	0.014	0.118	1.000	0.090	
2016	0.137	0.002	0.001	0.020	0.068	0.013	0.114	1.000	0.067	
2017	0.126	0.003	0.001	0.036	0.062	0.014	0.124	1.000	0.027	
2018	0.109	0.004	0.000	0.032	0.066	0.014	0.123	1.000	0.022	
2019	0.075	0.005	0.000	0.051	0.054	0.016	0.124	1.000	0.042	
Central South										
2015	0.085	0.001	0.752	0.142	0.081	0.175	0.153		0.039	0.101
2016	0.140	0.001	0.635	0.134	0.073	0.188	0.169		0.011	0.087
2017	0.138	0.002	0.476	0.116	0.072	0.182	0.168		0.019	0.000
2018	0.160	0.001	0.396	0.066	0.082	0.172	0.183		0.031	0.000
2019	0.123	0.001	0.200	0.104	0.071	0.178	0.173		0.119	0.000
South										
2015	0.000	0.000	0.000	0.047	0.044	0.504	0.234		0.329	0.032
2016	0.000	0.000	0.000	0.048	0.039	0.497	0.234		0.371	0.034
2017	0.001	0.000	0.000	0.049	0.038	0.536	0.232		0.470	0.059
2018	0.003	0.000	0.000	0.049	0.040	0.522	0.226		0.477	0.038
2019	0.129	0.000	0.189	0.089	0.039	0.531	0.224		0.420	0.208
Sicily										
2015	0.177	0.971	0.039	0.040	0.006	0.185	0.082		0.054	
2016	0.155	0.997	0.157	0.013	0.003	0.188	0.083		0.053	
2017	0.111	0.994	0.085	0.014	0.003	0.166	0.080		0.042	
2018	0.102	0.717	0.075	0.014	0.002	0.190	0.076		0.037	
2019	0.065	0.763	0.065	0.029	0.009	0.168	0.077		0.023	
Sardinia										
2015	0.000	0.028	0.205	0.086	0.006	0.110	0.042		0.130	
2016	0.000	0.001	0.207	0.076	0.006	0.111	0.042		0.126	
2017	0.000	0.002	0.218	0.070	0.009	0.099	0.039		0.114	
2018	0.000	0.187	0.193	0.079	0.011	0.100	0.033		0.089	
2019	0.000	0.176	0.374	0.014	0.009	0.103	0.033		0.081	

Table A.7: Generation Shares across Zones and Years, as proportion of total national yearly production by source according to the classification for technologies adopted by ENTSO-E. Note that Italy does not generate electricity using nuclear, marine, peat and shale oil. Data: ENTSO-E from 2015-2019.

	Italy					France					Austria					Slovenia				
	2015	2016	2017	2018	2019	2015	2016	2017	2018	2019	2015	2016	2017	2018	2019	2015	2016	2017	2018	2019
Nuclear						0.522	0.569	0.512	0.478	0.483						0.176	0.190	0.187	0.186	0.186
Gas	0.203	0.306	0.426	0.417	0.491	0.051	0.055	0.054	0.090	0.091	0.217	0.215	0.207	0.203	0.210	0.124	0.134	0.132	0.131	0.131
Coal	0.017	0.073	0.094	0.086	0.071	0.040	0.026	0.024	0.030	0.030	0.057	0.037	0.028	0.027	0.028	0.310	0.251	0.248	0.247	0.247
Oil	0.049	0.090	0.053	0.026	0.015	0.055	0.060	0.043	0.047	0.025	0.009	0.009	0.008	0.008	0.008	0.000	0.000	0.016	0.016	0.016
Other	0.369	0.142	0.018	0.062	0.011	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001					
Marine						0.002	0.002	0.002	0.002	0.002										
Hydro	0.213	0.223	0.234	0.235	0.234	0.194	0.212	0.191	0.188	0.186	0.555	0.553	0.553	0.545	0.522	0.311	0.337	0.331	0.330	0.330
Wind	0.082	0.089	0.096	0.099	0.102	0.085	0.013	0.110	0.095	0.104	0.102	0.120	0.125	0.131	0.142	0.001	0.001	0.001	0.001	0.001
Solar	0.049	0.049	0.050	0.050	0.050	0.051	0.061	0.062	0.054	0.063	0.028	0.035	0.048	0.054	0.056	0.066	0.072	0.071	0.074	0.074
Geother	0.008	0.009	0.009	0.009	0.009						0.000	0.000	0.000	0.000	0.000					
Biomass	0.009	0.016	0.017	0.014	0.016	0.000	0.002	0.001	0.014	0.015	0.022	0.023	0.022	0.022	0.023	0.004	0.005	0.005	0.005	0.005
Waste	0.001	0.003	0.003	0.002	0.001						0.007	0.007	0.007	0.007	0.007	0.009	0.011	0.011	0.011	0.011
other RES	0.000	0.000	0.000	0.000	0.000						0.001	0.002	0.002	0.002	0.002	0.000	0.000	0.000	0.000	0.000

	Switzerland				
	2015	2016	2017	2018	2019
Nuclear	0.274	0.269	0.230	0.212	0.210
Hydro	0.726	0.731	0.770	0.788	0.790

Table A.8: Technology Shares over Total Installed Capacity. Data: ENTSO-E.

	1	2	3	4	5	6	7	8	9
EX$_4$X	4.790	4.964	5.082	5.138	4.876	6.236	8.137	9.412	9.782
EX$_4$X-F	4.170	4.345	4.629	4.644	4.640	5.498	5.482	6.042	6.562
EX$_4$X-LF	4.170	4.343	4.624	4.652	4.646	5.496	5.480	6.042	6.553
EX$_4$X-SGARCHX	4.811	4.984	5.090	5.153	4.961	6.235	8.159	9.382	9.939
EX$_4$X-SGARCHX-F	4.170	4.351	4.592	4.558	4.597	5.452	5.438	6.099	6.573
EX$_4$X-SGARCHX-LF	4.172	4.342	4.580	4.536	4.585	5.459	5.434	6.068	6.593

	10	11	12	13	14	15	16	17	18
EX$_4$X	8.341	7.515	6.409	6.888	8.459	8.565	8.546	7.628	7.391
EX$_4$X-F	6.442	6.325	5.433	5.681	6.728	6.531	6.330	5.263	5.205
EX$_4$X-LF	6.437	6.329	5.445	5.694	6.738	6.529	6.344	5.271	5.207
EX$_4$X-SGARCHX	8.501	7.663	6.612	7.074	8.626	9.006	9.116	8.105	7.558
EX$_4$X-SGARCHX-F	6.481	6.273	5.368	5.525	6.632	6.550	6.469	5.356	5.242
EX$_4$X-SGARCHX-LF	6.460	6.307	5.353	5.597	6.635	6.551	6.453	5.351	5.278

	19	20	21	22	23	24	Avg_{1-24}	Avg_{8-20}
EX$_4$X	6.719	5.934	5.105	4.457	3.732	4.423	6.605	7.814
EX$_4$X-F	5.354	5.295	4.668	4.033	3.142	3.892	5.264	5.938
EX$_4$X-LF	5.357	5.282	4.673	4.036	3.149	3.895	5.266	5.941
EX$_4$X-SGARCHX	6.739	6.080	5.269	4.487	3.749	4.580	6.745	8.031
EX$_4$X-SGARCHX-F	5.400	5.152	4.645	4.030	3.161	5.137	5.302	5.932
EX$_4$X-SGARCHX-LF	5.362	5.178	4.647	4.032	3.158	5.137	5.303	5.937

Table A.9: RMSEs of the best performing model with ENTSO-E forecasts (EX$_4$X and EX$_4$X-SGARCHX) and with ETR forecasts for *fast* (EX$_4$X-F and EX$_4$X-SGARCHX-F) and *less fast* (EX$_4$X-LF and EX$_4$X-SGARCHX-LF) models, over 365 forecasts computed for the whole 2019.

	1	2	3	4	5	6	7	8	9
EX_4X	0.261	0.247	0.239	0.232	0.232	0.240	0.263	0.290	0.310
EX_4X-F	0.285	0.284	0.269	0.246	0.241	0.232	0.250	0.282	0.297
EX_4X-LF	0.284	0.284	0.269	0.246	0.241	0.232	0.249	0.282	0.297
EX_4X-SGARCHX	0.109	0.104	0.103	0.099	0.098	0.098	0.111	0.142	0.179
EX_4X-SGARCHX-F	0.113	0.120	0.098	0.078	0.078	0.077	0.089	0.094	0.128
EX_4X-SGARCHX-LF	0.110	0.125	0.099	0.078	0.079	0.075	0.085	0.095	0.126
	10	11	12	13	14	15	16	17	18
EX_4X	0.306	0.301	0.298	0.280	0.284	0.296	0.300	0.300	0.291
EX_4X-F	0.296	0.295	0.301	0.307	0.286	0.279	0.300	0.307	0.319
EX_4X-LF	0.296	0.295	0.302	0.307	0.287	0.279	0.300	0.307	0.319
EX_4X-SGARCHX	0.173	0.164	0.164	0.140	0.153	0.173	0.175	0.166	0.146
EX_4X-SGARCHX-F	0.125	0.113	0.121	0.117	0.108	0.118	0.125	0.129	0.171
EX_4X-SGARCHX-LF	0.126	0.112	0.119	0.117	0.106	0.118	0.125	0.132	0.169
	19	20	21	22	23	24	Avg_1-24	Avg_8-20	
EX_4X	0.293	0.296	0.295	0.285	0.273	0.248	0.278	0.296	
EX_4X-F	0.313	0.309	0.301	0.296	0.289	0.245	0.285	0.299	
EX_4X-LF	0.313	0.309	0.301	0.296	0.289	0.245	0.285	0.299	
EX_4X-SGARCHX	0.144	0.143	0.134	0.116	0.107	0.107	0.135	0.159	
EX_4X-SGARCHX-F	0.141	0.131	0.121	0.110	0.105	0.084	0.112	0.125	
EX_4X-SGARCHX-LF	0.144	0.131	0.122	0.109	0.107	0.084	0.112	0.125	

Table A.10: CRPSs of the best performing model with ENTSO-E forecasts (EX_4X and EX_4X-SGARCHX) and with ETR forecasts for *fast* (EX_4X-F and EX_4X-SGARCHX-F) and *less fast* (EX_4X-LF and EX_4X-SGARCHX-LF) models, over 365 forecasts computed for the whole 2019.

Appendix B. Figures

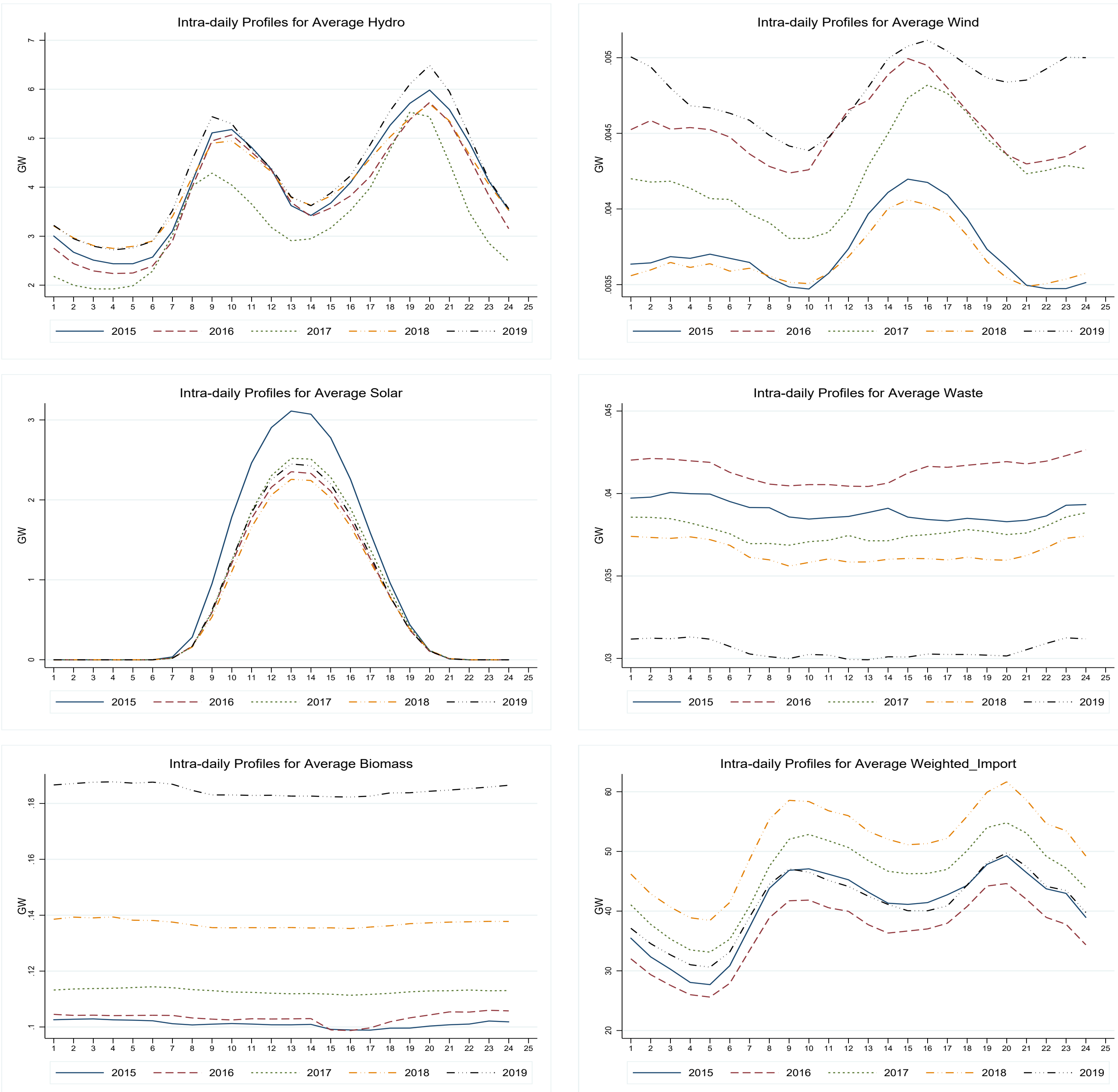

Figure B.3: Intra-daily Profiles of some Exogenous Regressors from 2015 to 2019. Data: ENTSO-E.

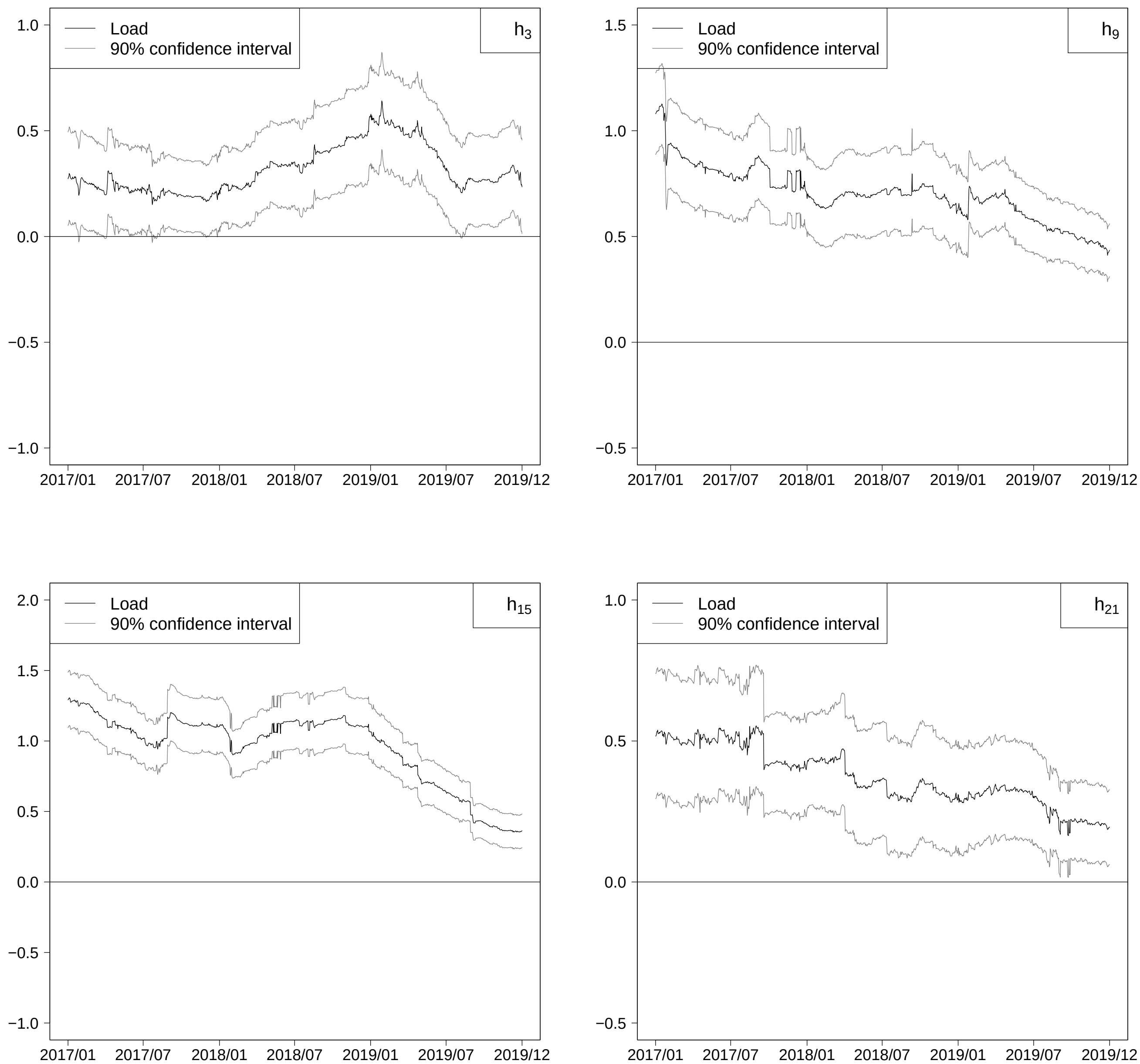

Figure B.4: Estimated coefficients for ENTSO-E Forecasted Load by using the EX_4X model at hours 3, 9, 15, and 21. Robust Confidence Intervals at 90% are also reported over the out–of–sample period from 2017/01/01 to 2019/12/31.

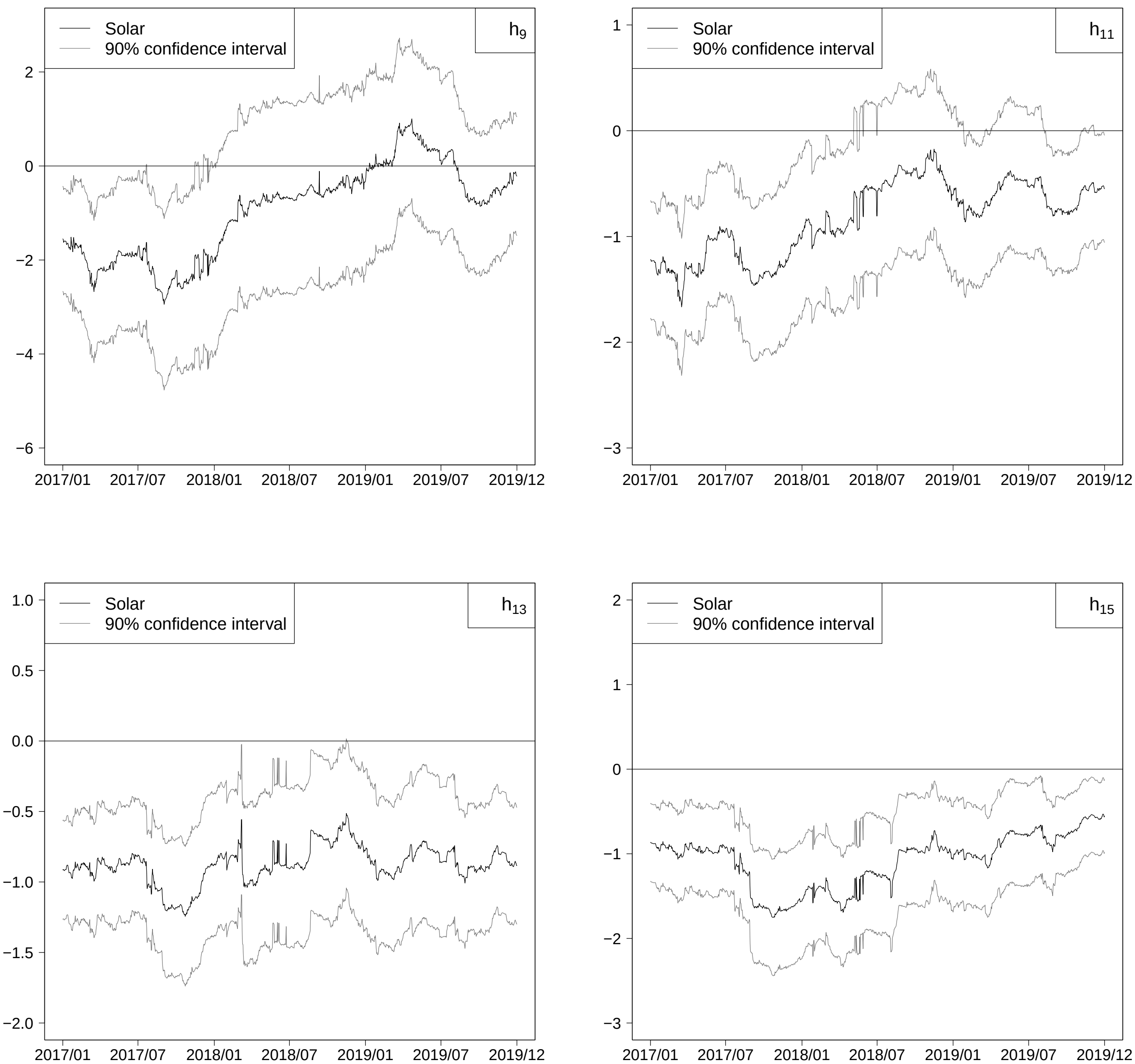

Figure B.5: Estimated coefficients for ENTSO-E Forecasted Solar PV Power using the EX_4X model at hours 9, 11, 13 and 15. Robust Confidence Intervals at 90% are also reported over the out–of–sample period from 2017/01/01 to 2019/12/31.

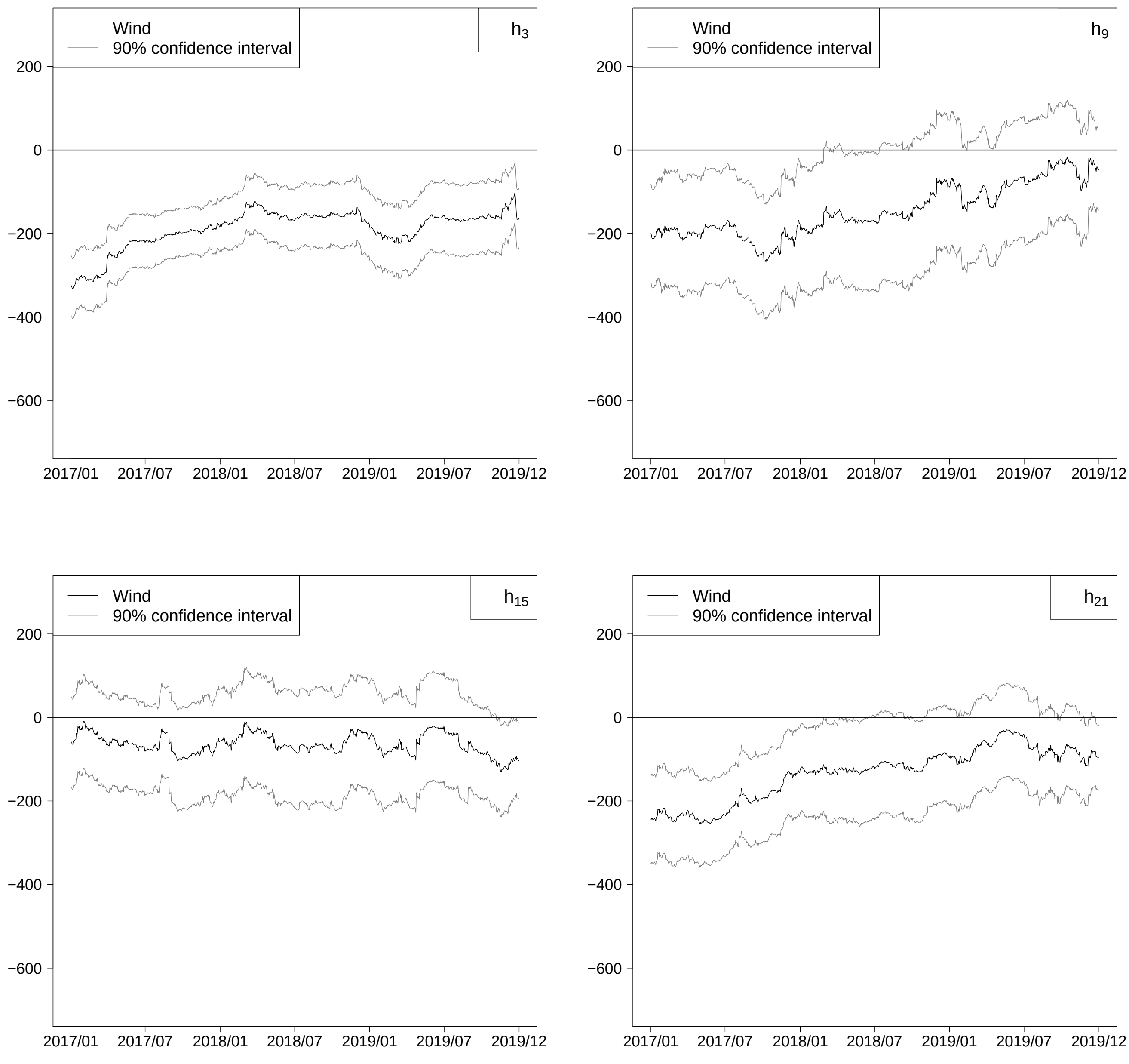

Figure B.6: Estimated coefficients for ENTSO-E Forecasted Wind using the EX_4X model at hours 3, 9, 15, and 21. Robust Confidence Intervals at 90% are also reported over the out–of–sample period from 2017/01/01 to 2019/12/31.

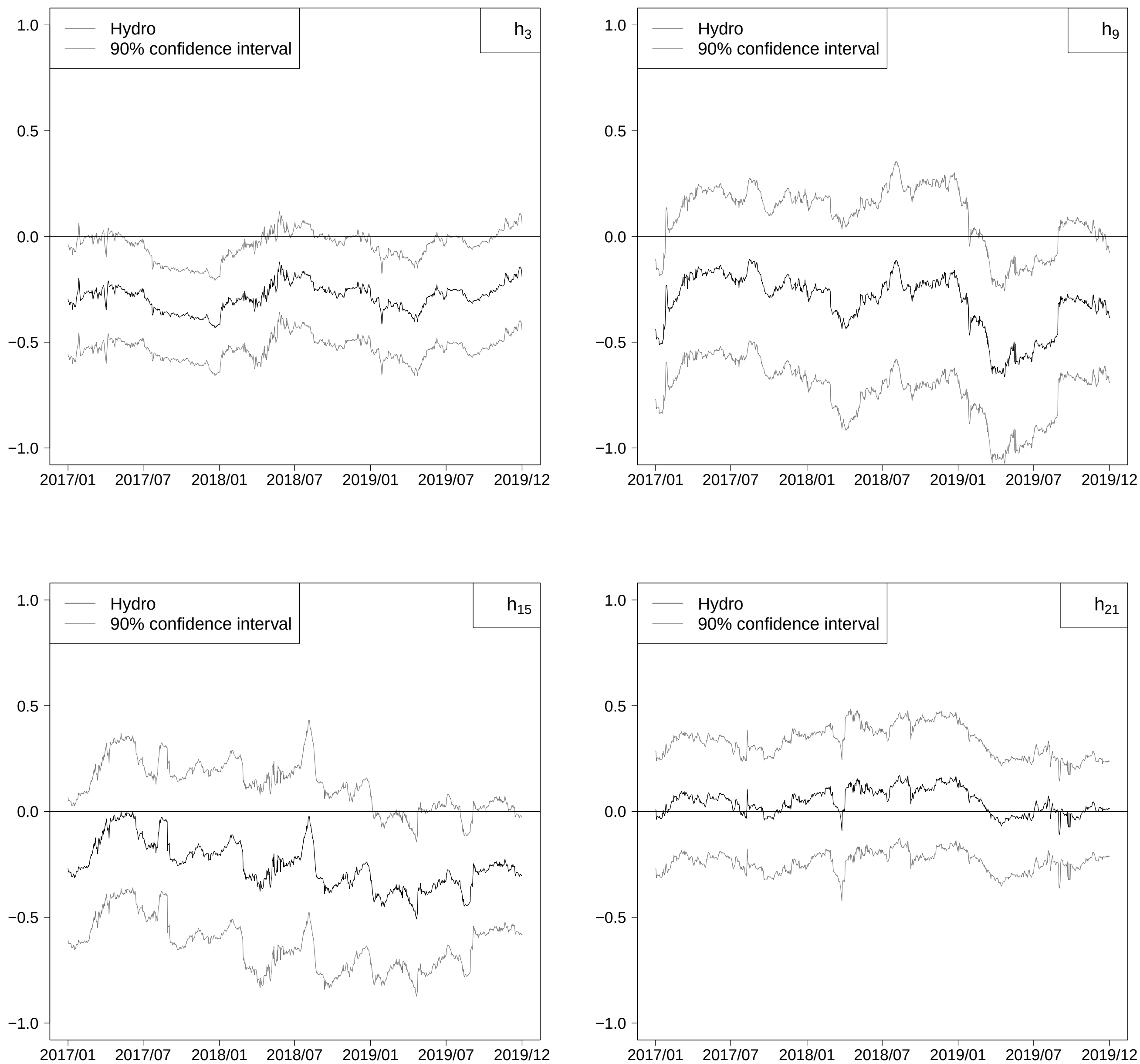

Figure B.7: Estimated coefficients for Hydro using the EX$_4$X model at hours 3, 9, 15, and 21. Robust Confidence Intervals at 90% are also reported over the out–of–sample period from 2017/01/01 to 2019/12/31.

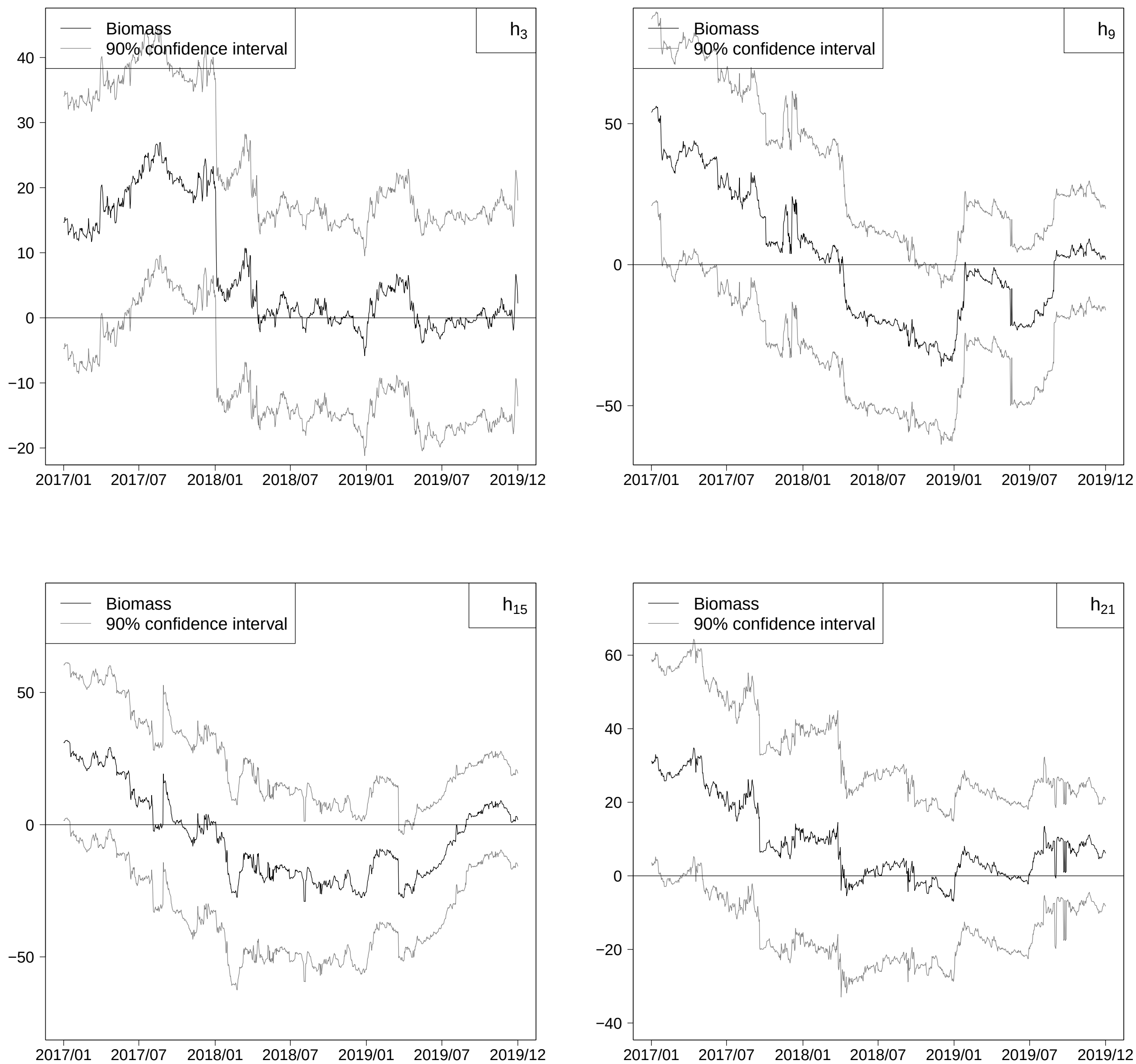

Figure B.8: Estimated coefficients for Biomass using the EX_4X model at hours 3, 9, 15, and 21. Robust Confidence Intervals at 90% are also reported over the out–of–sample period from 2017/01/01 to 2019/12/31.

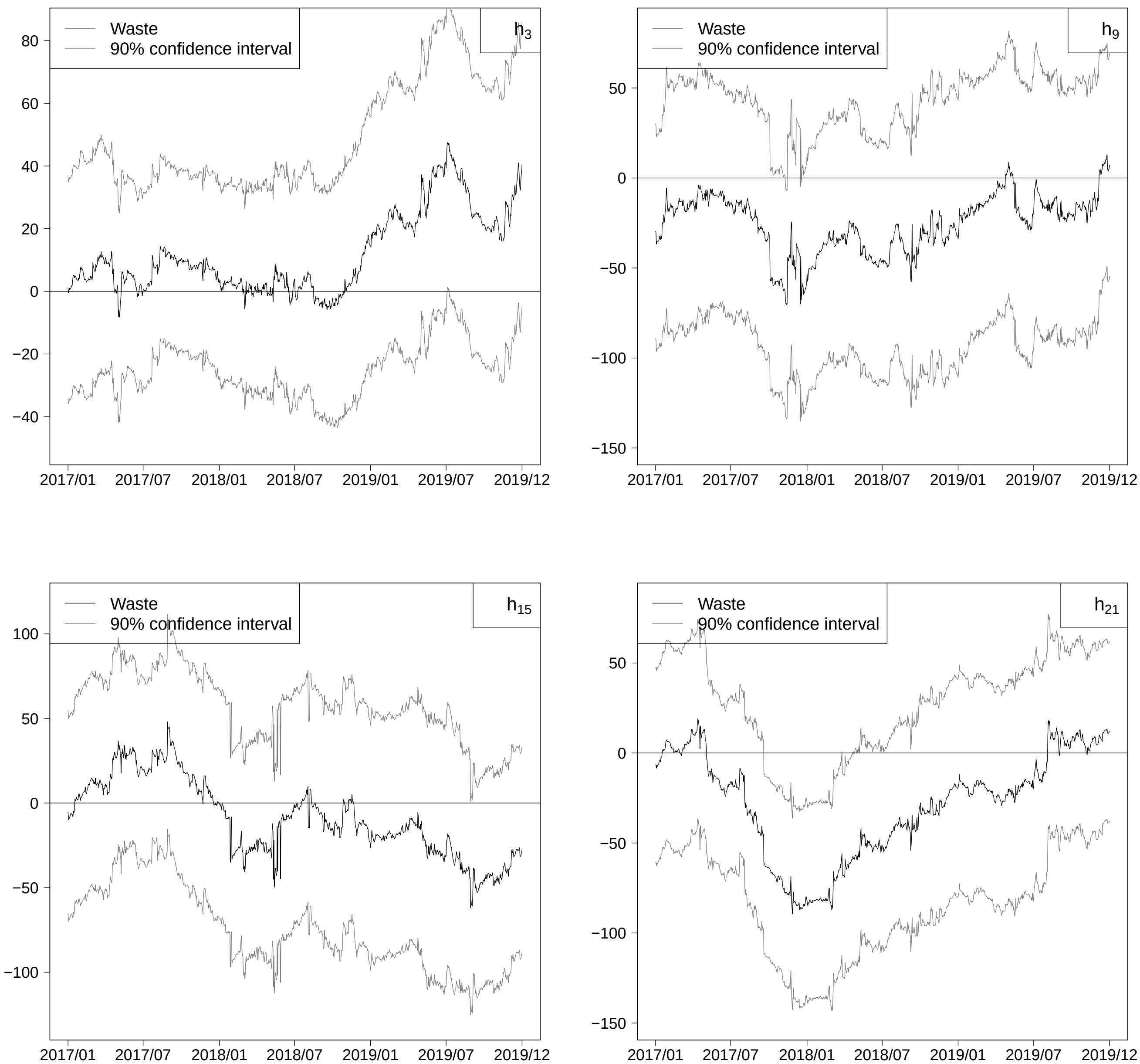

Figure B.9: Estimated coefficients for Waste using the EX_4X model at hours 3, 9, 15, and 21. Robust Confidence Intervals at 90% are also reported over the out–of–sample period from 2017/01/01 to 2019/12/31.

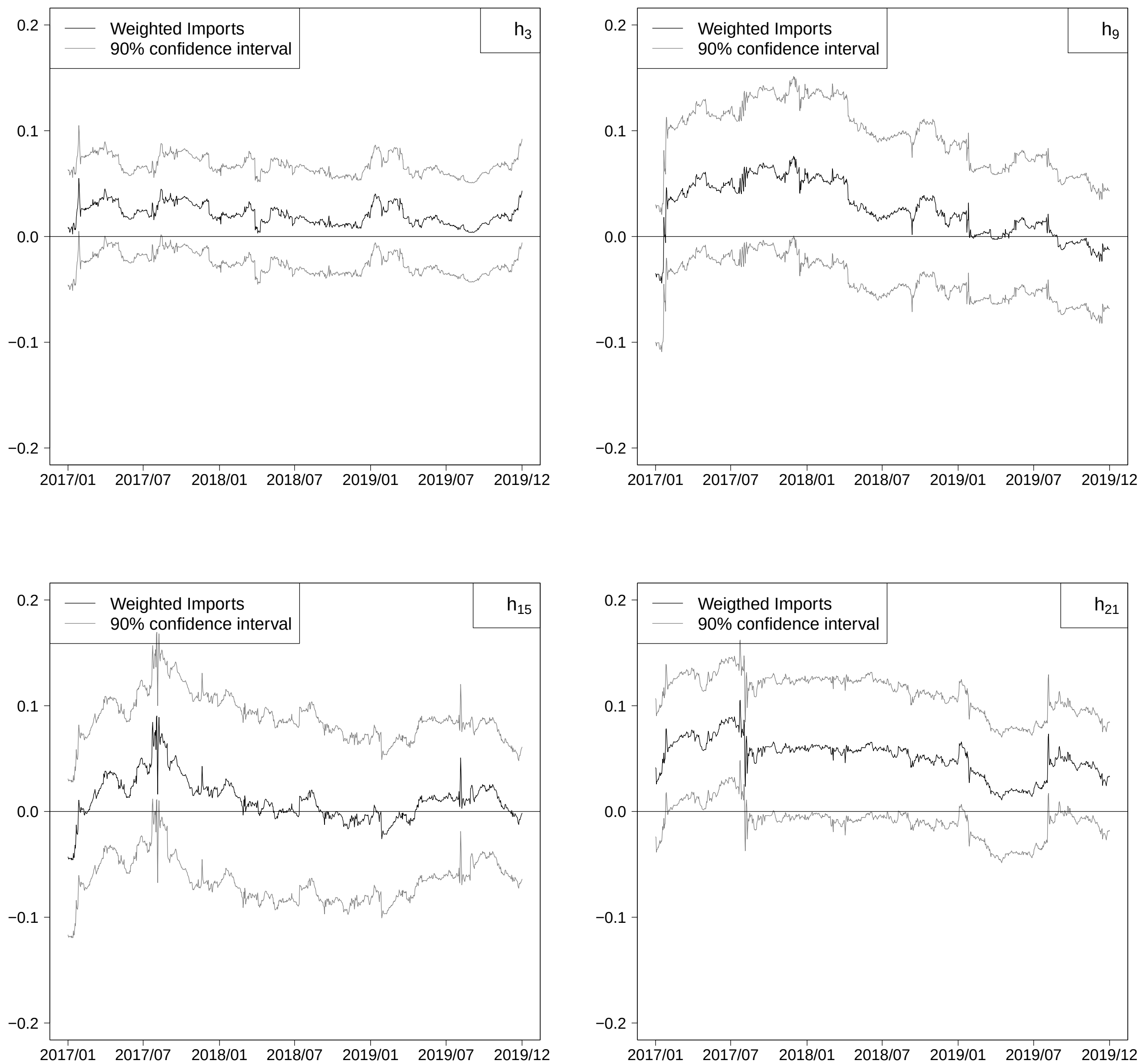

Figure B.10: Estimated coefficients for Weighted Imports using the $\mathrm{EX}_4\mathrm{X}$ model at hours 3, 9, 15, and 21. Robust Confidence Intervals at 90% are also reported over the out–of–sample period from 2017/01/01 to 2019/12/31.

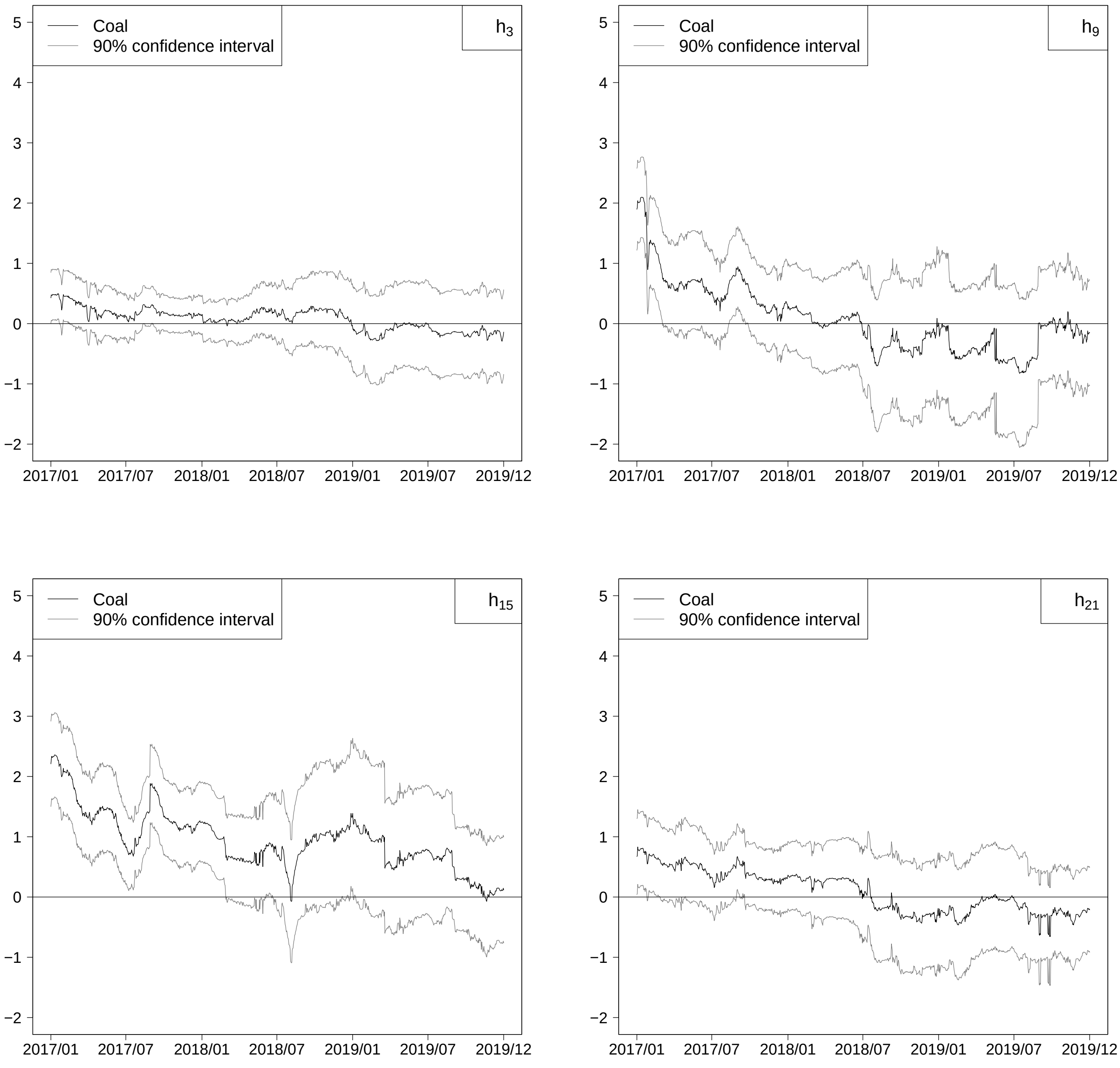

Figure B.11: Estimated coefficients for Coal using the EX_4X model at hours 3, 9, 15, and 21. Robust Confidence Intervals at 90% are also reported over the out–of–sample period from 2017/01/01 to 2019/12/31.

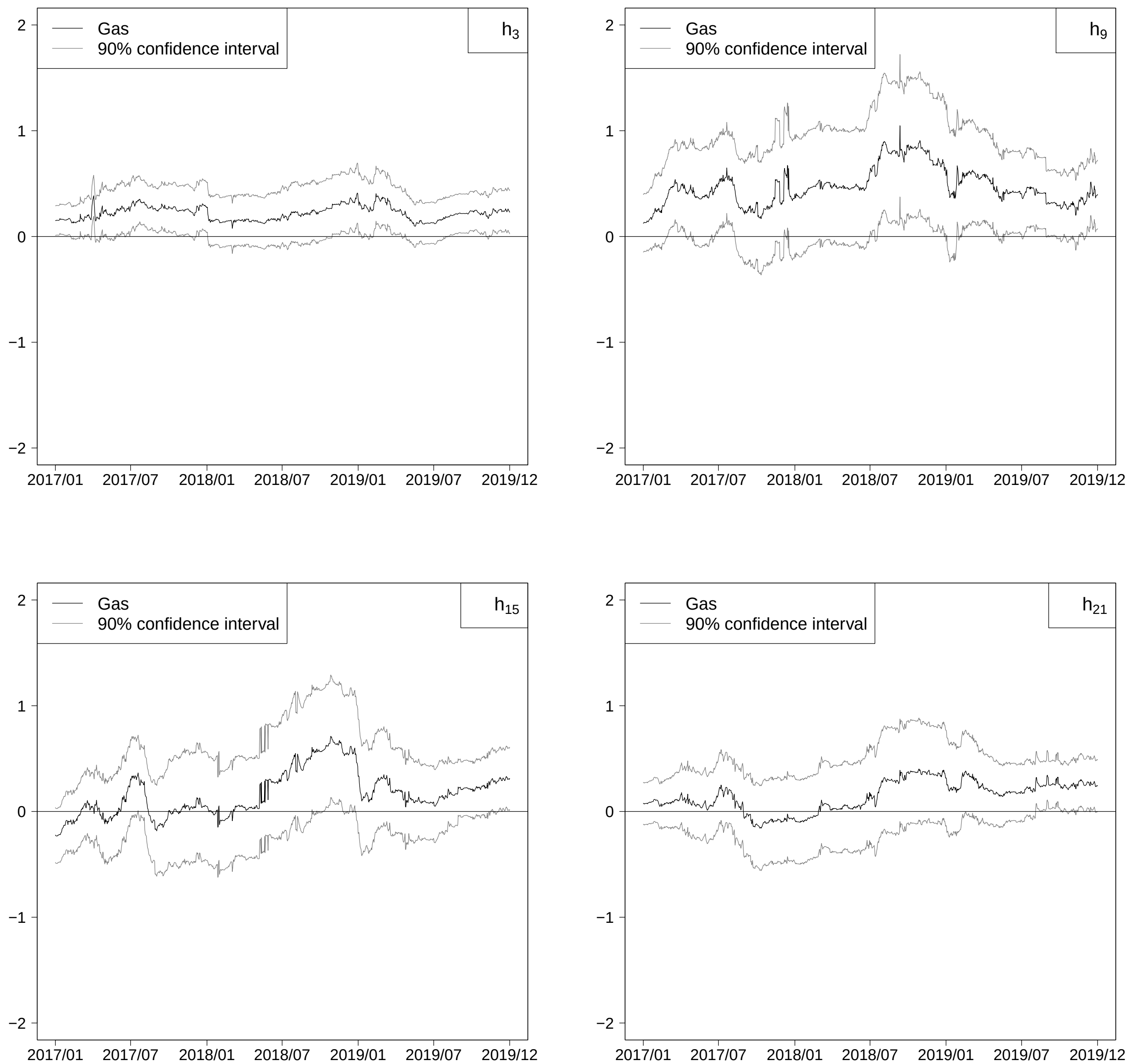

Figure B.12: Estimated coefficients for Natural Gas using the EX_4X model at hours 3, 9, 15, and 21. Robust Confidence Intervals at 90% are also reported over the out–of–sample period from 2017/01/01 to 2019/12/31.

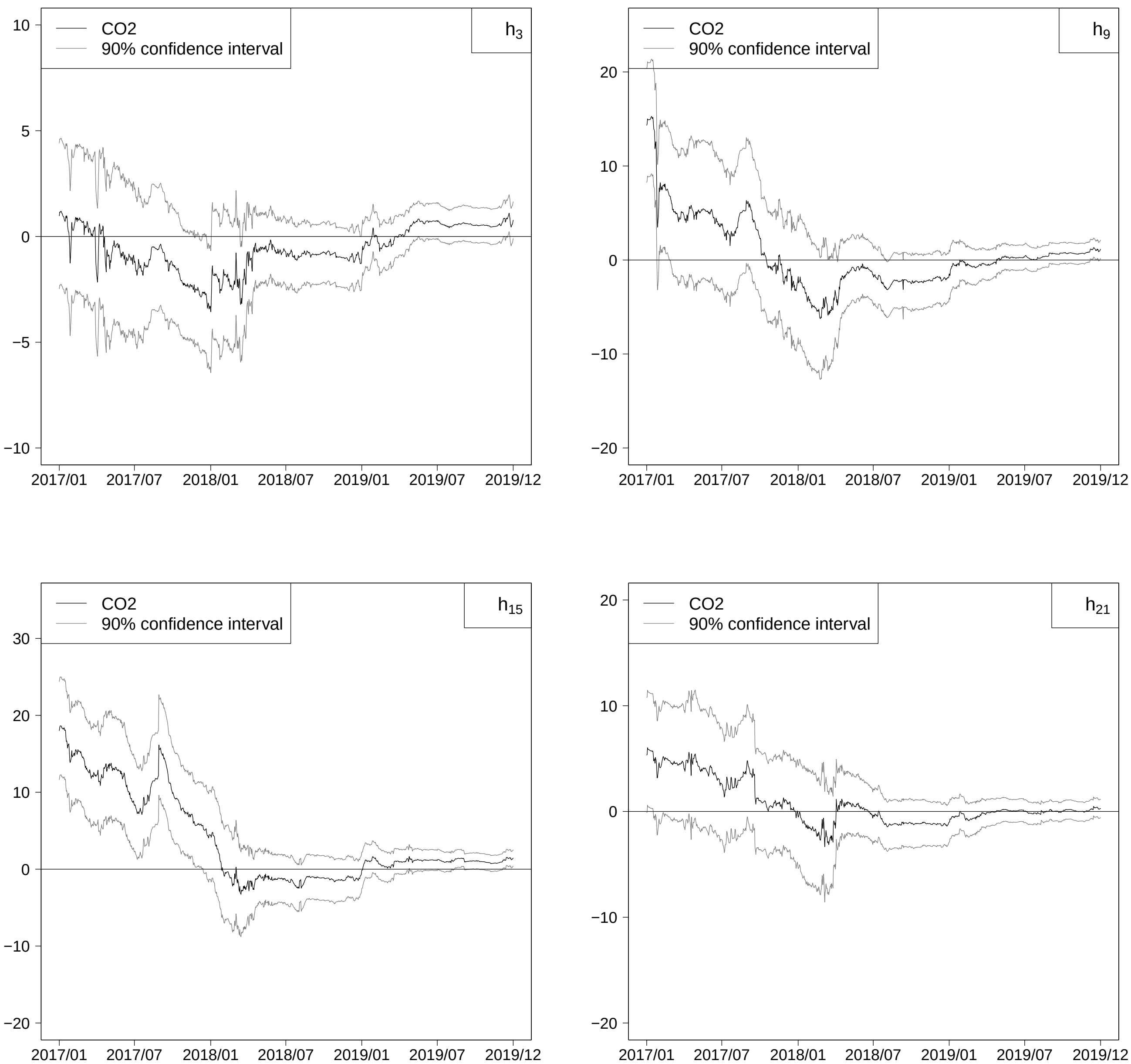

Figure B.13: Estimated coefficients for CO_2 using the EX_4X model at hours 3, 9, 15, and 21. Robust Confidence Intervals at 90% are also reported over the out–of–sample period from 2017/01/01 to 2019/12/31.