[*MID-TERM ELECTRICITY PRICE FORECASTING: THE ROLE OF FUNDAMENTAL DRIVERS*]

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Overview

Electricity markets were traditionally designed for delivering electricity; however, nowadays they play numerous important roles in society. For instance, sustainable development of energy supply, energy security, environmental protection, climate change mitigation, employment opportunities, and economic efficiency are some of their policy targets (Kyritsis et al., 2017). Therefore, an accurate electricity price forecasting is an essential task for all market participants as well as for policy makers. In this regard, the mid-term electricity price forecasting is crucial for maintenance scheduling, planning, resources reallocation and budgeting, and bilateral contracting (Yan and Chowdhury, 2015). There are several methods available for short-term forecasting of day-ahead electricity price (e.g., Shi et al., 2021; Yang et al., 2022). However, there are very few methods available in mid-term forecasting of the day-ahead electricity price (e.g., Steinert and Ziel, 2018; Lehna et al., 2022), and they are mainly forecasting the price up to one-month ahead. The main goal of this study is to extend the day-ahead electricity price forecasting literature by comparing several models and methods accounting for fundamental drivers. Our case study is the Northern region of Italy electricity market, where the day-ahead price is determined based on production and consumption. We forecast day-ahead electricity price from one-day to six-months ahead. For our empirical analysis, we apply daily data from 1 January 2016 to 31 December 2019 to forecast price for the years 2018-2019, within a rolling window process.

Methods

We implement our forecasting on Northern Italy daily electricity price, traded on Italian Power Exchange (IPEX) day-ahead market (in levels). We downloaded day-ahead price data from the Gestore Mercati Energetici (GME), quoted in euros per Megawatt hour (€/MWh). We consider both the demand and the supply sides effects as the main drivers of price. We proxy demand by daily electricity actual load, downloaded from the European Network of Transmission System Operators for Electricity (ENTSO-E) in MWh. Further, we downloaded daily temperature data from the University of Dayton weather archive (University of Dayton). As far as supply is concerned, we consider the fossil fuels prices to account the marginal cost of conventional thermal generation, and renewables generation. To account for fossil fuels prices, we downloaded coal prices (ICE, API2 cost, insurance and freight Amsterdam, Rotterdam, and Antwerp, with ticker LMCC.01-EURO), natural gas prices (ICE UK, with ticker LNQC.01-EURO), Brent crude oil prices (ICE UK, with ticket LCC-01-EURO), and CO2 emissions prices (EEX-EU CO2 emissions E/EUA, with ticker EEXEUAS) from the Refitiv Datastream database. All fuels prices are daily settlements quoted in €/MWh. Further, we consider the actual renewables generation from onshore wind, solar PVs, hydro-pumped-storage, hydro-run-of-river and poundage, and hydro-water-reservoir. We downloaded values for renewables generation, measured in MWh, from the ENTSO-E. Therefore, we focus on four groups of variables that we expect them to increase day-ahead electricity price forecast accuracy in the mid-term, i.e., consumption proxied by actual load (L), fossil fuels prices (FP), carbon cost (CC), and renewables generation (RES).

First, we evaluate the role of each group of fundamental variables on forecast performance. Therefore, we estimate several models: model 1 is the benchmark accounting for all explanatory variables (includes L, FP, CC, RES), model 2 inspects the importance of RES (includes L, FP, CC), model 3 examines the importance of carbon cost (includes L, FP, RES), model 4 tests the significance of fossil fuels prices (includes L, RES, CC), and model 5 explores the effect of consumption (includes FP, CC, RES) on one-day to six-months ahead electricity price forecasting performance. In all models, we control for weekly and monthly seasonality, national holidays, and the day before and after national holidays. We compare the accuracy of models 2-5 against model 1 to test whether including each group of fundamental variables develop forecasting performance of price models.

We know that load as a determinant factor of price mainly depends on the outside meteorological condition. In the summer, the use of electricity is primarily for air conditioning and in the winter is for heating, and this increases demand during periods of sufficiently high or low temperature (Borovkova and Schmeck, 2017). Changes in weather condition strongly affect load (De-Felice et al., 2015) and consequently price. Therefore, air temperature might directly explain electricity price. In the second step of our analysis, we assess whether modelling electricity price with having temperature into the models outperforms the load-based models. Therefore, we estimate models 1-5 with considering the daily air temperature rather than actual load.

Results

We estimate our models using conventional parametric and nonparametric techniques. We compare the forecasting performance of our models at different time horizons from one-day until seven-days ahead; and from one-month to six-months ahead. We use the years 2016-2017 for initial estimation in a rolling basis, while forecasting the years 2018-2019. We estimate all models using a one-year rolling window. All models use previous predictions as inputs for any forecast horizon longer than one-day, running a recursive multi-step ahead forecasts.

We perform both ex-post and ex-ante forecasts of price. The ex-post forecasts use actual information of the explanatory variables and is not genuine, but it is useful for investigating the fitness of forecasting models (Hyndman and Athanasopoulos, 2018). Further, we perform the ex-ante forecasts, using forecasted explanatory variables for the forecasting period of price. Therefore, we need the forecasted values of the explanatory variables. We adopt several models and methods to forecast our fundamental variables to be used in price forecasting models.

We measure the forecast performances of price models by using the root mean square error (RMSE). Further, we apply the Diebold and Mariano (1995) test to compare the forecast performances of models 2-5 against model 1. The outperformance of model 1 against any of the next models indicates the effectiveness of the lacking variables in the relevant model on electricity price forecasting.

Some of our important findings indicate that, first, methods that account for nonlinearity of relationships show better forecasts. We explain this by the non-linear nature of the relationship between some of our outcome and fundamental variables. Second, for all forecast horizons, model 5 including all fundamental variables, outperforms to other models, indicating the effectiveness of all fundamental variables on price forecasting. Third, price forecasting performance decreases when applying forecasted fundamental variables rather than the actual data, therefore in the ex-ante mid-term forecasts, having reliable forecasted explanatory variables, i.e., load, temperature, fuels and carbon prices and renewables generation is as important as forecasting electricity price. Fourth, load-based models outperform temperature-based models.

Conclusions

We conclude that from mid-term electricity price perspective, it is important to account for both demand and supply side effects, by means of load/temperature, renewables generation, and fossil fuels and carbon prices. Further, the non-linear regression models seem to have interesting advantages over linear regressions.

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