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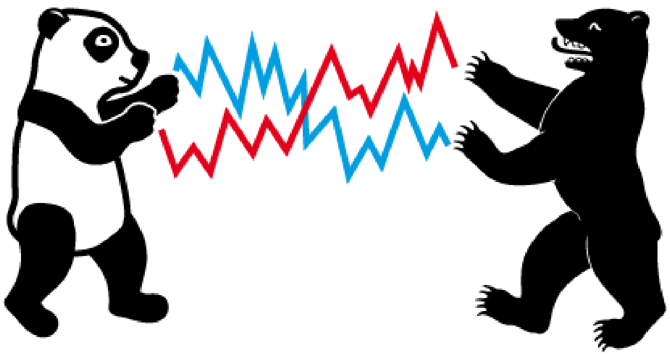

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Deregulated day-ahead electricity markets in Southeast Europe: Price forecasting and comparative structural analysis

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Abstract

Many Southeast European countries are currently undergoing a process of liberalization of electric power markets. The paper analyses day-ahead price dynamics on some of these new markets and in Germany as a benchmark of a completely decentralized Western European market. To that end, several price forecasting methods including autoregressive approaches, multiple linear regression, and neural networks are considered. These methods are tested on hourly day-ahead price data during four two-week periods corresponding to different seasons and varying levels of volatility in all selected markets. The most influential fundamental factors are determined and performance of forecasting techniques is analysed with respect to the age of the market, its degree of liberalization, and the level of volatility. A comparison of Southeast European electricity markets of different age with the older German market is made and clusters of similar Southeast European markets are identified.

Keywords: ARIMA models, energy forecasting, time series models, neural networks

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1. Introduction

In the end of the 20th century, the world's economy witnessed the beginning of decentralization and liberalization of electricity markets. Traditional vertically integrated and government-controlled market structures responsible for electricity generation, transmission, and distribution were gradually replaced by a competitive market environment where these functions are separated from each other. Following the worldwide trend, the European Commission adopted three liberalization directives in the last two decades in order to restructure the energy markets of the European Union member states and to open them up for competition. The new market design incorporated two components: bilateral contracts and the pool, which in turn included the intraday and the day-ahead markets.

European states are at different stages in the market reforming process. Many Western European countries such as Germany, United Kingdom and Netherlands underwent those transformations in the late 1990s – early 2000s (Weron, 2006). Most Southeast European countries are still in the process of implementing the European Commission's directives. Some of the markets such as Slovenia and Greece have been operating for several years. Others including Bulgaria, Croatia, and Serbia just started to operate in 2016.

One of the most essential changes of the new decentralized markets compared to the vertically integrated ones is the price setting mechanism. While the traditionally cost-based electricity pricing was often subject to politically justified directives, the prices on the new markets have become an outcome of competitive market forces. The price on the intraday market is implemented on a pay-as-bid basis. On the day-ahead market, the parties submit their bids and asks for the hours of the next day. The marginal bid at the intersection of the resulting demand and supply curves determines the market-clearing price, which all market participants have to accept.

Forecasting of day-ahead electricity prices has been subject to intensive research in the last two decades with different forecasting methods and different markets in focus. However, until now, no attempts have been made to analyse and forecast the electricity price dynamics on these young markets. This might be caused by their relative youth as well as by the lack of understanding of fundamental factors influencing the price formation and development in these markets. Hence, the paper strives to close this research gap through developing empirical models that forecast the day-ahead electricity prices in a set of Southeast European states.

Time series models have proved to be a suitable tool to forecast electricity prices on other markets. Prior work focusses on either stochastic autoregressive models or artificial intelligence models. As no ultimate winner can be identified, both approaches shall be applied in the paper in the order to compare their performance and to find the most effective models.

Contrary to the prevailing approach in prior work to choose one target market and to identify the best technique for this market, this paper explicitly puts emphasis on the analysis of Southeast

European power markets using an example of several selected countries. However, there are some factors which make analysing this area both challenging and insightful:

1. Though geographically closely located, the energy systems of the Southeast European countries are diverse in terms of the chosen energy mix; consider for example the still very coal-intensive power generation in Bulgaria compared to renewables- and hydro energy-based electricity generation systems in Slovenia and Croatia.
2. Due to different historical preconditions, most Southeast European markets such as Slovenia, Serbia or Croatia had first to define themselves considering their united Yugoslavian past, whereas others had to struggle with the heritage of the partly socialist planned economy (Bulgaria) or of a military regime (Turkey).
3. Despite of these differences, the Southeast European energy markets are closely interconnected which can be seen as a part of the overall European Union strategy but can also be explained by their geographical proximity.

Accordingly, a question to answer in the paper is whether there are structural differences between the investigated countries in respect of the impact of their energy mix on the electricity prices and to estimate the degree of their integration considering their geographical (Southeast Europe) and partly historical (Yugoslavia and nowadays European Union) similarities.

Finally, until now there was no research aiming to compare price dynamics and formation between the highly liberalized markets of Western European countries using the example of Germany and the developing power exchange markets in Southeast Europe. We assume that prices on the “old” markets can be better explained by exogenous variables on the supply and demand sides than prices on newly introduced power exchanges, where price-setting mechanisms are still in the process of their formation and stabilization. A remarkable example is the Turkish day-ahead market where the transmission operator controls the prices by not allowing the market to generate price spikes (International Energy Agency, 2016). On the other side, it is possible that strategic behaviour of market participants, which is more difficult to model, is stronger on the “old” markets, where traders have gained more experience through the years. Amjady and Hemmati (2009) suggest that complexity of power markets increases with time due to increasing market competition after restructuring. This last question of the paper is especially important due to the high speed of power markets’ development and could allow to anticipate some trends on the new Southeast European markets based on the experience of the “old” markets in Western Europe.

The insights expected from the paper have both theoretical and practical relevance. On the one hand, it is a worldwide unique possibility to track the development of rather small or medium-sized day-ahead electricity markets which were opened within a relatively short period of time in a highly interconnected yet very diverse region. It is especially interesting to see how far the integration of the markets has proceeded and which factors are speeding it up – the geographical proximity or the market opening time. On the other hand, day-ahead prices are a key information for energy producers’ and distributors’ decision-making mechanisms because day-ahead markets account for the prevailing part of the total electricity trade. Besides, power generating companies rely on the market-clearing price for the decision which part of the total produced electricity should be sold through bilateral contracts and which part should be traded on the day-ahead market.

Bilateral contracts, in turn, also rely on day-ahead price forecasts. And finally, as Nogales et al. (2002) notice, the information about market-clearing prices is often the only openly available information about the power markets. This factor is of particular importance for Southeast European countries, many of which are still in the process of opening their markets and providing information about them.

The paper is organized as follows. Chapter 2 provides an overview of the existing literature on electricity price forecasting and creates a link to Southeast Europe. In Chapter 3, the experimental design including the dataset and the general setup of the forecasting study is introduced. After an explanatory data analysis in Chapter 4, Chapter 5 presents the models in detail and Chapter 6 discusses the empirical results. Chapter 7 concludes the paper.

2. Literature review and paper contributions

In the last decade, electricity price forecasting has experienced an increasing interest, which was pushed on by theoreticians' need to explore a new forecasting application and practitioners' efforts to operate at a profit on the new power markets. However, forecasting is challenging due to the specifics of electricity as commodity, including no physical storage possibilities of the electrical energy, the requirement of a constant balance between generation and load, an oligopolistic structure at the supplier side, and the inelastic nature of demand, which cause strong unanticipated price spikes (Amjady & Keynia, 2008) and an annualized volatility of day-ahead prices of up to 200 %, that is extremely high compared to other commodities (Singhal & Swarup, 2011).

Though concerned with the same issues inherent in the nature of electricity prices, the empirical research literature on electricity price forecasting is highly diverse. In particular, there is no consistency towards the selection of the models to be applied, the input variables and the accuracy estimation measures (Aggarwal et al., 2009). In this regard, the literature review serves two objectives: i) to sketch the state of the art in the field and ii) to illustrate research gaps and the corresponding necessity of further work including the work carried out here. To that end, we review existing studies along the following dimensions:

1. Market area: most electricity markets are bound to a country. Some exceptions are the Nord Pool market operating in Scandinavian and Baltic countries or the USA, where, in contrary, several markets are operating.
2. Forecasting method: as the whole variety of forecasting methods could be a subject to a separate paper, we consider only the most popular and promising approaches. Due to the distinct autoregressive nature of prices, these include, first of all, several autoregressive models with and without exogenous predictors, which we refer to as AR(IMA) and AR(IMA)X (e.g. dynamic regression and transfer function), but also GARCH specifications. Neural networks are another popular approach.
3. Error measure: as Weron (2014) notices, there are no "industry standards" among many error indicators and even worse, they are named inconsistently in different studies. The literature analysis reveals the most popular error measures: mean absolute error (MAE), root mean squared error (RMSE), mean absolute percentage error (MAPE), per unit sample error e_{sample}, and the sample error variance v_{sample}.

4. Pre-processing procedures including log-transformation and normalization of data, but also treatment of outliers, separate modelling of different hours and using dummy variables for weekdays.
5. Input variables including the focal price time series, but also auxiliary predictors such as system load, fuels, and renewable energy sources (RES) prices.

Table 1 depicts the results of the literature review.

[Table 1 about here]

The analysed sample of studies includes 28 (mainly journal) publications. Table 1 shows that the majority of studies concentrates on a single market, with a strong emphasis on Spain, USA, and the Nord Pool region, which represent some of the oldest and the biggest day-ahead markets. Autoregressive forecasting models are by far most popular among researchers, while the employed error measures vary a lot. Data pre-processing techniques are not applied consistently[3], each of them being in use in 20-40 % of all cases. Besides, almost half of all papers work exclusively with price data, ignoring possible exogenous predictors, the most popular of which is the system load.

The review provides some useful insights for this paper and more generally future research. First, it evidences the need to expand forecasting research and examine other markets. Many markets have received little attention. This is especially true for the Southeast Europe region, which no prior study covers. Second, it becomes clear that there is no unanimous 'leader' among the applied forecasting techniques in spite of the popularity of the classical ARIMA approach. Therefore, it seems valuable to compare several methods in a benchmarking setting. The same holds true for data pre-processing and the choice of the predictors. And finally, as noticed by Aggarwal et al. (2009), there have been no attempts so far to apply one model across a larger number of markets which could help to find out if the price behaviour on different markets could be explained by approximately the same factors.

Against this background, the contribution of the paper is twofold. First, it closes the existing geographical gap by forecasting and analysing prices on the Southeast European day-ahead electricity markets, which have up until now eluded analysis. Second, it represents the first attempt to extend a model to a relatively large set of countries in order to estimate its performance in different contexts and to investigate similarities and differences between them.

3. Data and experimental design

3.1. Market and feature selection

An analysis of day-ahead electricity markets of Southeast Europe requires a representative set of countries. More specifically, in addition to being representative for the geographical region, the sample should also represent the diversity of markets in political sense and, more importantly,

[3] We acknowledge the possibility that a study considers some form technique data preparation without explicating this in the paper. Results of Table 1 are limited to data preparation methods the use of which is clearly articulated in the corresponding paper.

diversity with respect to age and structure of the power markets. With this in mind, we consider the following countries: Serbia, Croatia, Slovenia, Greece, Bulgaria, and Turkey. Serbia and Croatia are typical representatives of the young Balkan markets. While the Bulgarian market is of the same age (cf. Table 2), it has evolved under the influence of the planned socialist economy. Greece and Slovenia opened their day-ahead markets substantially earlier and represent different climatic and economic conditions, with the Slovenian market being fully liberalized and the Greek market being only a transitional solution. Finally, the Turkish market is older than the other markets and evolved in completely disparate circumstances. It is still at least partly under state supervision, which makes this market extremely interesting. Due to these characteristics, the Turkish market is included in the sample although it is not part of Southeast Europe with its whole territory. Given that one of the goals of the paper is to compare relatively young Southeast European markets with the older Western European markets, we also consider the German market as one of the oldest and most interconnected markets in Western Europe.

[Table 2 about here]

The paper focuses on electricity price modelling. Price data has been obtained from the websites of the respective power exchanges and from the ENTSO-E website. For all markets, price data is available on an hourly time scale. However, it is important to note that prices for the next 24 hours are usually settled simultaneously (Raviv et al., 2015). Consequently, it is not possible to use the price of hour *t* on a given day to forecast the price of the hour *t+1* on the same day.

In addition to historical prices, electricity prices are also affected by exogenous factors including, for example, power plant availability, wind infeed, and emission allowances on the supply side and total vertical system, seasonal effects, and the business cycle on the demand side. Erni (2012) proposes a detailed list of possible price drivers. In this study, we focus on publicly available data as proposed by Karakatsani and Bunn (2008) and Weron and Misiorek (2008). We use the day-ahead forecasts of external drivers, as opposed to their actuals, to ensure the practical applicability of the forecasting methods. Table 2 reports the input variables for the study. We chose these variables based on the literature review, an analysis of correlation between power prices and exogenous factors, and the overall intention to guarantee comparability of the participating markets by selecting the same variables for each market. For most countries, variables include total load and wind and solar infeed. Total system load is one of the main drivers of electricity prices, while the influence of wind and solar depends largely on the country under study (Weron and Misiorek, 2008). The exceptions are Slovenia, where wind power does not play a significant role yet (REVE, 2017); Serbia, where the energy generation is still very coal-intensive, while wind and solar energy amounts are negligible (CEE Bankwatch Network, 2013); and Turkey, where solar energy is negligible (Enerji Atlasi, 2017) and wind infeed is not really correlated with the power prices. For Turkey, we include six other predictors based on the analysis of the correlation between electricity prices and exogenous predictors. However, due to the absence of day-ahead forecasts of exogenous predictors such as electricity production from coal and gas it was only possible to include the data from the final daily production program, which is published on the Exist Transparency Platform for the current day. Therefore, they can only be used to explain the prices, but not to forecast them for the future. As long as the practical applicability of the forecasts has to be ensured, total load is the only exogenous predictor among the investigated ones which may be applied in the models for the Turkish market.

3.2. Data pre-processing and partitioning

The most popular data pre-processing techniques in price forecasting include a log-transformation of prices and outlier treatment; both are applied in nearly every third paper from the literature review. Logarithmization is normally used in markets where negative prices are forbidden in order to stabilize the variance and to enforce the normality. Outlier treatment is supposed to increase forecasting accuracy, especially with linear parametric models. We consider both procedures. For the German market, where negative prices regularly occur, we first rescale prices through adding the smallest negative price before performing the log-transformation. However, no substantial improvement could be observed in the normality of the price data or in the resulting forecasting accuracy. This goes along with the findings of Keynia (2012), who suggest that in some cases additional nonlinear transformation of raw prices, which are themselves a nonlinear signal, can complicate forecasting.

We implement outlier treatment in two ways. First, we replace obvious errors such as positive solar infeed values during the night hours with reasonable proxies, i.e. zero infeed. For price spikes, we use the damping scheme of Weron (2006) according to which an upper limit T of the prices is calculated as the sum of the mean and three standard deviations. All prices P_t exceeding this limit are truncated and set to $P_t = T + T\log_{10}(P_t / T)$. As the German market is also confronted with negative spikes, we adapt the damping scheme for negative values by replacing all sum signs in the above formulae with differences.

However, through performing some preliminary analysis with the preprocessed values we observed increases in forecast accuracy during calm forecasting periods, whereas accuracy decreased in moderately or highly volatile times. This coincides with results of Weron (2006). As model stability is one of the primary goals of forecasting due to the high volatility and, accordingly, high risks on the electricity markets, we use the unmodified price data for further analysis.

Missing values are another issue to handle in the pre-processing stage. In line with the approach of Ziel et al. (2015), we replace missing values by values from the preceding week (i.e., 168 hours ago). This helps to preserve not only the initial data length, but also its temporal structure and the seasonal dependencies. In exceptional cases, when forecast total load data from the preceding week were missing as well, we use the actual total load as replacement. Given that load forecasts are rather precise and the number of such cases has been negligible, we argue that this procedure does not distort the reliability of our results. Special care was taken of the switch to and from the daylight saving time in order to guarantee that a year always comprises 24*365 or 24*366 hours.

According to the prevailing “standard” testing scheme in the literature, the data includes historical prices and exogenous predictors up to the hour 24 of the previous day and forecasts of exogenous predictors for the analysed day (Weron & Misiorek, 2008). However, it has to be considered that bids for all hours of the next day are to be submitted by midday of the previous day and the day-ahead prices are published shortly after midday. Contrary to the “standard approach”, we use only historical price data that is available by midday of the previous day *t*-1 to forecast prices on day *t* in order to guarantee practical applicability. For exogenous factors, we use forecasts.

To ensure the reliability of the forecasting model, we consider four test periods of two weeks each. The periods correspond to different seasons of the year. They also display varying levels of price volatility as recommended by Singhal and Swarup (2011). More specifically, we use the summer period (04-17.07.2016), the autumn period (3-16.10.2016), the winter period (16-29.01.2017), and the spring period (27.03.-09.04.2017) for forecast model testing.

Concerning the calibration period, two established approaches are considered: the rolling window scheme as applied by Raviv et al. (2015) and the adaptive scheme favoured by Weron and Misiorek (2008). While rolling window means taking a calibration set of a fixed length and shifting it day by day in the future, the calibration set in the adaptive scheme gets longer with every added day and the first day of the calibration period remains the same. The main reason to implement the adaptive scheme is that it allows to test the effect of longer time series compared to shorter ones in order to oppose the older markets to the younger ones.

Fig. 1 illustrates the chosen test periods corresponding to different seasons by using the example of the Serbian market. The summer and the spring periods are characterized by quite stable prices, while the autumn and the winter periods show, respectively, moderate and high price volatility. Similar price behaviour can be observed on other markets; the Turkish market being an exception in that prices are relatively stable across all periods with slightly elevated volatility in summer.

[Fig. 1 about here]

3.3. Error measures

The literature review shows that the community uses multiple error measures for forecasting accuracy estimation. In this paper, we consider two indicators that have been developed based on the weekly errors proposed by Shafie-khan et al. (2011):

- per unit sample error e_{sample}

$$e_{sample} = \frac{1}{336} \sum_{i=1}^{336} \frac{|p_t^{true} - p_t^f|}{\overline{p_{sample}^{true}}} \text{, where} \tag{1}$$

$$\overline{p_{sample}^{true}} = \frac{1}{336} \sum_{i=1}^{336} p_t^{true} \tag{2}$$

- sample error variance v_{sample}.

$$v_{sample} = \frac{1}{336} \sum_{i=1}^{336} \left(\frac{|p_t^{true} - p_t^f|}{\overline{p_{sample}^{true}}} - (e_{sample})\right)^2 \quad , \tag{3}$$

where p_t^{true} is the actual price at time t and p_t^f is the forecast price. Our motivation to choose these indicators is twofold. First, using the average sample price in the quotient helps to avoid the adverse effect of prices close to zero, which is ignored in other error measures, and is a direct measure of model accuracy (Amjady, 2006). Second, the sample error variance evaluates the volatility of the error and, consequently, the model stability.

4. Explanatory data analysis

The section gives a brief overview of characteristics of the price data and how they influence forecast model development. Also, the analysis empirically substantiate the patters of price data mentioned in the previous section (e.g., volatility, seasonality, etc.). In the interest of brevity, we exemplify prevailing patterns using examples of individual markets and report main findings of the explanatory data analysis, which are useful to appreciate empirical results from the forecast model comparison.

The time series under consideration represent hourly prices at the exchanges of the selected countries. The series vary in length depending on the age of the market (cf. Table 2). Fig. 1 illustrates typical price characteristics of pronounced volatility, strong spikes, and superimposed seasonality (Karakatsani & Bunn, 2008) using the example of the Serbian market. These features are inherent in the nature of prices and can be observed in the same manner on the power markets considered here. Modelling volatility and price spikes can represent a challenge to a forecasting model. Seasonality is clearly structured at the daily, weekly, and yearly level and thus easy to capture by a model.

Fig. 2 presents the distribution of prices over a day for one market. It shows that prices during a day (from 7 am till 7 pm) are higher and significantly more volatile than at night. This distribution is typical for the markets under study (box plots for other countries are available in the Appendix). Some distinctive features deserve a mention:

- The box plots for the German and the Slovenian markets look very similar. The reason is the stepwise implementation of the Austrian-Slovenian Market Coupling Project (APG, 2016), which aims to integrate the shared German-Austrian and Slovenian markets;
- Croatian and Serbian markets have similar hourly price distribution. Deliberations of their market coupling is under way but not implemented yet (Zuvela, 2015). The price similarities might be due to the fact that the two countries are neighbours and that the day-ahead markets started to operate with a 1 week difference in 2016;

We also observe some differences in day versus night volatility patterns compared to Fig. 2. Bulgarian prices are extremely volatile by day and show almost no volatility at nighttime. Turkish prices are more volatile by night than by day, and Greek prices are quite stable over the whole day in terms of both volatility and absolute value (see Appendix for details).

[Fig. 2 about here]

Given that power prices are demand-driven, there are also differences between weekdays and weekends due to the weekly volatility (see Fig. 3). While night hours remain quite stable, as there are almost no business activities and domestic demand is nearly the same during the week, the peak load hours on weekdays are more expensive than on the weekend due to the higher industrial and organisations demand. Fig. 3 also demonstrates lows and peaks in the price dynamics during the day. The most distinctive lows are between 2-4 am in the night due to the suspension of all business and domestic activities and at 1 pm due to the lunch break, whereas the peaks are between 7-9 am and 6-7 pm due to the high domestic and transport energy demand. Power prices commonly show such behaviour (Cuaresma et al. 2004).

[Fig. 3 about here]

The yearly seasonality results in higher prices in winter and summer and lower prices in other seasons, but also in the effect of special calendar days, such as Christmas or national holidays. Its effect is not as pronounced as in the case of daily and weekly volatility.

The distribution of prices impacts the accuracy of forecasting models. Therefore, we examine whether market data follows a normal distribution. The histograms of all countries but Turkey show a leptokurtic positively skewed distribution. This is illustrated in Fig. 4a. According to Raviv et al. (2015), this also holds if hours are tested separately. Positive skewness indicates that the price distribution is affected by outliers above the mean rather than below the mean. All markets display this behaviour but the Turkish market where the price distribution is negatively skewed and thus dominated by prices lower than the mean.

[Fig. 4 about here]

As Voronin (2013) notices, high leptokurtosis signals that extremely high or low values are more likely to occur than in the case of a normal distribution. The price pre-processing using the outlier damping scheme described in Chapter 3 brings price data closer to a normal distribution by decreasing the leptokurtosis. This is exemplified in Fig. 4b (note the different scaling between Fig. 4a and 4b). Normality tests such as Jarque-Bera, Komogorov-Smirnov, and Anderson-Darling confirm the visual analysis and reject the hypothesis of the data being normally distributed. Despite the fact that distribution properties of pre-processed prices are more regular, both the literature review and our preliminary tests suggest that forecast models predict more accurately when using the raw data. This can be explained by the fact that price spikes have repeating nature and are easier to forecast when exact values of historical spikes are known.

The autocorrelation function in Fig. 5a is slowly decreasing and exhibits lags according to the daily and weekly seasonality. However, the partial autocorrelation plot in Fig. 5b shows that, out of all lags, lag 1 has the strongest impact on prices, followed by the lags 24, 48, etc. While this implies that knowing the day-ahead price of the hour t facilitates predicting the price of the hour t+1 quite accurately, this knowledge cannot be applied for forecasting because all hours of a day are traded simultaneously.

[Fig. 5 about here]

As time series stationarity is a precondition for many time series models, we test it using the augmented Dickey-Fuller and the Phillips-Perron tests. The null hypothesis of a unit root is rejected for both the raw and the pre-processed data, which coincides with the findings of Karakatsani and Bunn (2008) and Kristiansen (2012) for longer time series. Whereas for artificial intelligence models this issue is not of high importance, data stationarity enables the use of autoregressive models for forecasting as well.

5. Forecasting models

In line with previous studies, we concentrate on point estimates of prices rather than estimating confidence intervals, which also capture uncertainty (Ziel et al., 2015). We motivate this choice as follows: first, confidence intervals do not serve the main goal of the study to compare alternative price forecasting methods in different countries and to identify the impact of exogenous predictors on the prices. Second, we estimate forecast uncertainty via the sample error variance (see Chapter 3) and thus do not require an additional measure of uncertainty.We consider two types of forecasting models: statistical time series models and data-driven machine learning methods. Subsequent chapters sketch these models.

5.1. Naïve model

As Ziel et al. (2015) point out, autoregressive models are the most fundamental models in the electricity prices analysis. This is due to the highly autoregressive nature of electricity prices (see Fig. 5). The most popular naïve model in the literature is based on the similar day approach. For example, a Tuesday is considered to be similar to the Tuesday from the previous week, etc. (Conejo et al., 2005). This approach implies that the naïve model corresponds to the 168^{th} lag in an hourly time series. However, the partial autocorrelation plot shows that the correlation with prices of the preceding day is more pronounced in our data. Therefore, to obtain a stronger benchmark, we implement the naïve model in such a way that it uses the 24^{th} lag of the price to be forecast.

5.2. Autoregressive model with seasonal decomposition

Chapter 4 demonstrates that price time series exhibit superimposed levels of seasonality, i.e. daily, weekly, and yearly. Weron (2014) argues that prior work may not pay sufficient attention to seasonality. With this in mind, we perform a seasonal moving averages based decomposition in its additive form, because the amplitude of seasonal volatility is not constantly increasing or decreasing but remains quite stable in the long term. Hence, providing the three seasonality levels, the decomposition formula is:

$$p_t = t_t + s_{t,d} + s_{t,w} + s_{t,y} + e_t \, , \qquad (4)$$

where p_t is the price, t_t is the trend component, $s_{t,d}$, $s_{t,w}$, and $s_{t,y}$ are, respectively, the daily, weekly, and yearly components, and e_t is the error term. After price time series have been deseasonalized, we fit an autoregressive model to the data based on the Akaike information criterion (AIC). We then use the model to forecast prices for the next 24 hours and add the respective seasonal components to obtain the final forecast. To investigate the impact of individual seasonality levels, we consider three versions of the decomposition, assuming only daily seasonality, daily and weekly levels, and all three levels.

5.3. ARIMA model with and without fundamental factors as input variables

We consider a basic ARIMA model the parameters of which are optimized for every country and test set separately using the AIC. In addition, we test ARIMA models with fundamental regressors to examine exogenous regressors and to identify the most influential regressors, respectively. Literature commonly refers to these model specifications as AR((I)MA)X or ARIMA-E.

Three kinds of exogenous regressors are considered in the paper:

- fundamental predictors such as wind and solar infeed and total system load (recall that predictors differ for Turkey; see Chapter 3),
- dummy variables for weekdays and hours and
- additional lags.

The common approach of using dummy variables for weekdays is to differentiate between Saturday, Sunday, and the rest of the week as a whole, i.e. two dummy variables (and the third alternative is modelled by setting both dummies to zero). Some researchers also differentiate between Mondays, which experience the impact from the preceding weekend, and Fridays, which behave differently than the rest of the week due to the fact that many business and industrial activities are suspended earlier. However, in order to prevent disregarding any information helpful to obtain more precise forecasts, a differentiation between all weekdays is made here. That is, we include six dummy variables.

We select additional lags based on the ACF and PACF analysis and include important lags as separate regressors (Weron, 2014). More specifically, to investigate the influence of individual variables, they are included in the ARIMA analysis sequentially. First, the AIC-based ARIMA is used to identify the appropriate ARIMA specification for a chosen country, taking the maximum of the respective AR and MA terms for the four test periods. The lags 24, 25, 48, 168, and 336 are included as the next step due to high auto-correlation. Then, exogenous predictors are included separately and in different combinations to find the optimal set of variables.

5.4. Multiple linear regression

Whereas ARIMA models are the most popular approach in the electricity price forecasting literature, their applicability in real conditions can be questioned due to the fact that all the hours of the next days are determined simultaneously. As a result, the use of lag 1 is only restricted to the hour 1 of the following day, lag 2 – to hours 1 and 2, etc. The forecasts of later hours have to rely on forecasts of preceding hours, e.g. for the hour 10 of the next day the forecast of the hour 9 should be used instead of the lag 1, which makes the model instable and prone to error propagation. To avoid this, we consider multiple linear regression. It includes all explanatory variables identified in the previous section with the exception of the autoregressive part. Lags 24, 25, 48, 168, and 336 are included as well, because they are known before the forecasts should be made.

5.5. Autoregressive neural network

The last type of model to test in this paper are neural networks. Their main advantage and the reason for their increasing use in the price forecasting literature is the capability to model non-linear behaviour, which linear models are unable to accommodate. In addition, they can handle noise in the input variables space more efficiently than other forecasting methods. We use neural networks in a NARX specification, which allows us to account for the autoregressive part in addition to the exogenous inputs and to pass on the forecast values of earlier hours as inputs for later hours. We consider a three-layer feed-forward specification with no restriction on the number of hidden neurons. In order to ensure comparability with ARIMA and multiple linear regression models, the same sets of exogenous regressors are used.

6. Empirical forecasting results

Empirical results emerge from applying the forecasting methods introduced in the previous chapter to the six Southeast European countries and Germany using four different calibration and test periods (see Chapter 3 for details). The test periods correspond to different seasons and varying levels of volatility. The resulting forecasting errors and their variance for the spring period with moderate volatility and the highly volatile winter period are presented in Tables 3 and 4, respectively. The results for the non-volatile summer and moderately volatile autumn periods coincide with the findings in Tables 3 and 4 to a large extent and can be found in the Appendix. Differences will be pointed out in this chapter.

Tables 3 and 4 report on three types of autoregressive price models and three types of models that also include fundamental factors. The purely autoregressive models are 1) the naïve model; 2) an autoregressive model with a) daily, b) daily and weekly, and c) daily, weekly, and two types of yearly decomposition; and 3) AIC-based ARIMA. Models with exogenous predictors include ARIMA, multiple linear regression (MLR), and autoregressive neural network (NARX). These use the same set of factors including a) lags 24, 25, 48, 168, and 336; b) predictors including solar, wind, and system load; c) lags from a) and only solar infeed; d) lags from a) and only wind infeed; e) lags from a) and only total system load; f) lags from a) and all predictors from b); g) lags from a) and hourly and daily dummies; and h) lags from a), all predictors from b) and all dummies.

[Table 3 and Table 4]

6.1. Naïve model

Forecast accuracy of the naïve model varies substantially across Southeast European countries. With respect to forecast errors, we can distinguish two main patterns:

- Error magnitude: While most naïve model sample errors for Greece, Serbia, and Turkey are below 15 %, the rest of the countries is more difficult to forecast with average errors in all seasons from 24 % in Slovenia and Croatia to above 30 % in Bulgaria. A reason of better predictability might be the partly state-controlled power market of Greece, Serbia, and Turkey, which suppresses price spikes, while electricity markets of other countries except for Bulgaria are significantly more liberalized;

- Error stability: The more predictable markets of Greece, Serbia, and Turkey seem to be more vulnerable under difficult market conditions, cf. the average sample error of 10 % (Greece), 14 % (Serbia), and 14 % (Turkey) in calm periods vs. 25 %, 22 %, and 33 % in volatile periods. As mentioned in Chapter 3.4., Turkey is the only country where the volatile period is the summer and not the winter, possibly due to largely increasing air conditioning in the summer. In contrary, Slovenian, Bulgarian, and Croatian sample errors remain quite stable.

The results of the naïve model also underline the autoregressive nature of electricity prices in that this simple model achieves errors below 30 % in almost all conditions.

6.2. Autoregressive model with seasonal decomposition

The second type of model combines autoregression with a previous deseasonalization of price time series. A daily decomposition improves the results of the naïve model. Adding an additional weekly decomposition provides the best forecast accuracy from the whole model family. Interestingly, the superiority of a daily and weekly decomposition over only a daily decomposition and of the daily decomposition over the naïve model seems to maintain over all test periods and across all countries, though to a varying extent, which emphasizes the potential of using decomposition for forecasting. We observe the strongest (smallest) gain in accuracy in Slovenia and Serbia (Greece and Turkey). Fig. 6 depicts forecast prices in Slovenia against the actual ones. While the model turns out to be able to capture the seasonal price dynamics under stable market conditions quite accurately, it fails in the more volatile ones where other factors than seasonal patterns are of importance.

[Fig. 6 about here]

Yearly decomposition does not yield better forecasts in both tested options, which can be explained by different weather and economic conditions possible on the same day of the year during different years. A remarkable result is that the practice “1 year = 365.25 days”, which is popular in time series analysis, yields the worst results out of all models. This is a reasonable outcome when considering that prices are given on an hourly scale. Applying fractional parts of the day (365.25) enforces the comparison of completely different hours of the day, which cannot work out successfully due to the strong daily pattern of electricity prices.

Table 3 shows the autoregressive model based on the daily and weekly decomposition to produce very good results during calm and moderately volatile periods in all countries except Germany; even compared to more sophisticated models including fundamental variables. Interestingly, this approach is not popular in the electricity price forecasting literature and the whole issue of seasonality is not given proper attention (Weron, 2014). Usually, the seasonal impact is addressed by including hourly and daily dummy variables. Considering the studies of Table 1, this method was preferred in nearly every third paper.

6.3. ARIMA model with and without fundamental factors as input variables

ARIMA models include the AIC-based pure ARIMA and the ARIMAX models with exogenous variables. The pure AIC-based ARIMA performs akin to the naïve model in calm and moderately volatile periods but inferior to the naïve model during highly volatile periods across all countries (recall that for Turkey, the highly volatile period is the summer and not the winter as for the other countries). The reason of this behaviour might be a memory of price spikes (both positive and negative) during volatile periods, which means that price spikes are likely to occur on the same hour of different days, so that the inclusion of lag 24 yields better forecasting accuracy than including more recent lags.

The inclusion of exogenous predictors improves the forecasting accuracy for all countries and test periods substantially, independently from the choice of the predictor set. The improvement is about 3-6 % during calm periods and about 10 % during volatile periods. In the case of the Bulgarian market in the winter period, the per unit sample error even improves by about 25 %. This is a useful finding since highly volatile periods are the most difficult to forecast.

Though fundamental factors lead to a significant improvement of forecast accuracy, the choice of the variables seems to be of secondary importance. More specifically, we observe alternative sets of variables to produce comparable results. For example, most ARIMAX models for Bulgaria yield a per unit sample error of 22-23 % in the spring and 34-37 % in the winter vs. 26 % and 59 % with the AIC-based ARIMA, respectively. Still, it is a good idea to look for the best sets of fundamental factors due to the fact that even small improvements may lead to large financial gains or savings on the market and in order to avoid model specifications that produce unstable results (cf. ARIMA with predictors for Bulgaria in the winter test period in Table 4). With this in mind, we consider a multi-step process to search for the best set of variables. First, it is interesting to compare whether current prices are more influenced by lagged prices or by fundamental factors (wind, solar, total load), or, put differently, how important the own price dynamics are in comparison to exogenous factors. However, we observe no clear behaviour that holds true for all test sets not to mention different countries. An exception are Serbia and Greece, which seem to be more influenced by distant lags than by exogenous regressors during less volatile periods. One unambiguous finding is that including distant lags in the highly volatile period is a necessary step because exogenous regressors alone are not enough to produce reliable forecasts (cf. Bulgaria, Greece, Croatia, and Serbia in winter). Again, the reason is the price spikes memory mentioned above. As this rule seems to hold true only for the aforementioned countries, while Germany, Turkey, and Slovenia are not affected, it seems natural to suppose that young markets are more sensitive to recurring dynamics of price spikes.

Second, the question arises whether dummy variables are able to yield similar forecasting accuracy results as fundamental predictors. The question has its validity if one keeps in mind that both total system load and some of the fundamental predictors (e.g., solar infeed) have a strong dependency on the time of the day and day of the week, so that hourly and weekly dummy variables could be able to capture the effect of exogenous drivers; at least to some extent. Besides, as dummy variables are easy to calculate in advance, whereas precise forecasts of fundamental factors are published several days ahead or not published at all (e.g., Turkey), using dummies would enable earlier forecasts of day-ahead prices. However, comparison of sample errors of ARIMA specifications including lags and predictors vs. lags and dummy variables evidences superiority of fundamental variables over dummies under almost all volatility conditions and for all markets. However, it should be noted that the difference is often not substantial and varies between 0.1 -2 %. Yet, if accuracy it of utmost importance, our analysis shows that fundamental factors cannot be replaced by dummies for the sake of simplicity.

Third, out of the fundamental predictors, gas production volume and total system load seem to be the most influential variables in Turkey and wind infeed in Germany. Greece, Slovenia, and Croatia are most influenced by the total load, whereas for Bulgaria no clear price driver could be identified. To verify these findings, Table 5 shows a correlation matrix, where we exclude Serbia due to the non-availability of data on fundamental factors.

[Table 5 about here]

Table 5 shows that total system load is the main price driver for all countries, closely followed by wind infeed in Germany and gas production in Turkey. It coincides with the results of forecast accuracy analysis. The reason why wind infeed explains more price volatility than total system load in Germany might be the fact that wind infeed itself exhibits a significant level of volatility and is vulnerable to outages and weather conditions, while the total load can be forecast quite precisely and covered by different electricity sources. The inconsistence between the high correlation of prices and the total load in Bulgaria vs. its negligible effect on forecast accuracy remains unclear and might come from the young age of this market.

Another important question is which ARIMA specification out of the whole model family produces the most precise and – what is no less important – the most reliable forecasts. The winner is ARIMA with lags, predictors, and dummies, which is the most comprehensive specification, closely followed by ARIMA with lags and predictors. Although both models are outperformed by more parsimonious models in some cases (e.g. ARIMA with predictors works well for Slovenia and ARIMA with lags and total load for Serbia), they produce the most reliable forecasts under all conditions without heavy outliers among the sample errors.

6.4. Multiple linear regression

As mentioned in Section 5.4., linear regression models are less popular in the forecasting literature due to their inability to capture non-linear price dynamics. Our analysis shows the performance of linear regression models to vary considerably across countries and volatility levels. The sample errors give strong evidence of the superiority of multiple linear regression models during volatile periods in Germany, Greece, and Slovenia. For the Serbian and the hardly predictable Bulgarian markets these models even outperform their ARIMA counterparts under all conditions. The most successful model specification is, as in the ARIMA case, a multiple linear regression with lags, predictors, and dummies. Surprisingly, the specification with lags and dummies, which fails to perform well for ARIMA, ranks second for multiple linear regression. Except for this difference, multiple linear regression models show similar preferences with respect to variable sets as

ARIMA. For example, total system load is the most important variable for most countries, while the inclusion of wind infeed works best for the German market.

Despite the overall success of multiple linear regression, one of the specifications – the one that includes only predictors – missed the actual spot price by a significant amount on the new Croatian, Serbian, and Greek markets even under favourable conditions of small volatility. During highly volatile periods, the difference becomes more substantial (cf. sample error of about 40 % on the above markets during winter time, while most other models produced sample errors of just about 20 %). While the reasons of this pattern are hard to identify, the result supports the previous finding that young markets in Southeast Europe exhibit recurring price spike behaviour, which previous price dynamics (captured by distant lags) can explain better than fundamental factors.

6.5. Autoregressive neural network

We test the same explanatory variables for the autoregressive neural network. Corresponding results agree with the findings from the ARIMA tests, which might come from the autoregressive component of both methods. Model specifications with predictors outperform purely autoregressive specifications. The most influential variable is total system load, and all specifications show substantial improvements compared to the naïve model. The best model specification is again the most comprehensive one with lags, predictors, and dummy variables. Similar to the multiple linear regression case and differently from ARIMA, the model specification with lags and dummies performs well. On the Turkish, Greek, and Serbian markets, it renders some of the best forecasts across all models for three out of four test periods; in Slovenia even for all four periods.

Three things have to be pointed out regarding the neural network performance:

- For almost all countries and almost all climatic conditions, neural networks produce reasonable results compared to their ARIMA and multiple linear regression counterparts;
- During extremely volatile periods, neural networks yield the best forecasts in all countries except for Croatia and Serbia. The German market seems to be especially well captured by neural networks under extreme conditions: neural networks contribute five out of six best performing model specifications;
- Neural networks turn out to be the most stable method as they are able to produce reliable forecasts for all countries and all volatility levels.

Albeit high forecast accuracy, the drawback of neural networks is their computational intensity, which becomes especially burdensome in the case of markets with long price history such as Turkey and Germany. If computation times represent an issue in practical applications, options to tweak neural network models include providing one dummy for all weekdays instead of one dummy for each day, including only total system load instead of all predictors, or limiting the number of hidden nodes. These modifications can help to balance between forecast accuracy and computation time.

6.6. Comparison across all models and markets

Table 6 summarizes the forecasting model evaluation with respect to which models provide the most precise and reliable forecasts for each country.

[Table 6 about here]

Overall, we observe the best forecasts for two neural networks and two multiple linear regression specifications. The strength of neural network models is their ability to capture price dynamics even through highly volatile time periods, which is in line with insights from the price forecasting literature (Weron, 2014). However, due to their computational intensity, a replacement by ARIMA and multiple linear regression models is reasonable in many cases. While neural networks perform well for almost all markets and volatility levels, the choice of other models is more country-specific. Young Southeast European markets seem to be captured well by multiple linear regression models, whereas for the older German and Turkish markets, multiple linear regression beats its autoregressive counterparts. Finally, under moderately volatile conditions on the Croatian and Serbian markets, the simple autoregressive model combined with daily and weekly decomposition performs appealing.

At this point, it is worth reiterating the special characteristics of the Turkish market. That is, whereas for all other markets all models can be directly used for price forecasting under real market conditions, the models involving fundamental factors in Turkey can be only applied to recover the electricity price dynamics, but not to forecast them. This issue is due to the day-to-day publication of the respective data. At the same time, as Table 6 shows, the neural network model involving lags and dummies is able to produce good forecasts without requiring those data, so that Turkish prices can be forecast with a significant degree of success as well.

6.7. Modelling of separate hours

A popular approach in the day-ahead price forecasting literature in recent years is to model separate hours. This involves developing individual forecast models for individual hours in a day. Hence, a forecaster adopting this paradigm develops 24 different models – one for each hour - to predict one day into the future. This practice has been considered in nearly one third of papers in the literature review. Bessec et al. (2016) and Mazengia (2008) attribute the success of this approach to its ability to replicate the unique hourly patterns of electricity prices shown in Fig. 3. On the other hand, the above analysis encompasses hourly dummy variables and it seems plausible that hourly dummies capture hourly price patterns. To test the potential of a further separation of hours, we perform a residual analysis of hourly errors using the example of the Serbian market in the moderately volatile spring period. We choose ARIMA with lags, dummies, and predictors for this purpose because this model produces less accurate forecasts for the Serbian market compared to neural networks and multiple linear regression (cf. 11.31 % vs. 9.93 % and 10.51 %, respectively). Fig. 7 shows the resulting hourly errors over the two spring weeks.

[Fig. 7 about here]

Despite the inclusion of hourly dummy variables, Fig. 7 demonstrates clear similarity with Fig. 3, which displays hourly price dynamics. Whereas night hours can be forecast quite accurately, daily errors are high, which is typical of many forecasting models due to the higher volatility and, hence, unpredictability of daily hours (Ziel et al., 2015).

To check if modelling separate hours is able to improve forecasting accuracy, we choose one representative of each model family based on two criteria: a) its previous forecasting performance and b) computational speed. For ARIMA and multiple linear regression, the specification with lags, predictors, and weekday dummies is tested. For neural networks, the inclusion of weekday dummies combined with separate hourly modelling would lead to a vast increase of model complexity and number of parameters to be estimated. Therefore, we consider the simpler specification with only lags and predictors. As Raviv et al. (2015) point out, the increasing complexity is a typical problem of separate hours modelling and could result in overfitting and increased variability of forecast errors. The results of separate hours modelling are presented in Tables 7 and 8 for spring and winter periods. The hourly errors on the summer and autumn sets are available in the Appendix.

[Table 7 and Table 8 about here]

Tables 7 and 8 reveal mixed results for the three tested methods combined with separate hours modelling. While the results for ARIMA show some improvements across countries and test periods, the error of multiple linear regression increases notably. The performance of neural networks shows no consistent pattern. For Croatia and Serbia, ARIMA-based hourly modelling provides the best forecasts out of all tested models in three and four out of four test periods, respectively, which is a remarkable result. At this point, it might be insightful to conduct a residual analysis for the new sample errors. Fig. 8 visualises forecasting errors for both approaches to enable a direct comparison. For most of the hours, especially 0-4 and 7-16, the sample errors have decreased, contributing to the model stability and improved forecasting accuracy. Thus, in the example of Serbia the individual models produce better forecasts than the inclusion of dummy variables. The same reasoning applies to other markets as well.

[Fig. 8 about here]

6.8. A peculiarity of electricity price forecasting in Southeast Europe

In previous sections, we have shown that appropriate forecasting methods can identify electricity price drivers and explain price development. However, in some cases, additional background information on the underlying conditions is inevitable to understand untypical price movements. Such underlying conditions include recent issues on fuels and renewable energy sources markets, power plant outages, legislation concerning electricity production and generation, and other factors that are difficult or even impossible to forecast. We demonstrate the importance of such background information using the example of the Bulgarian day-ahead market.

As discussed in Chapter 3, Fig. 1 visualises a price development that is typical of the investigated markets except Turkey. A thorough inspection of Bulgarian prices dynamics in Fig. 9a shows that most of the time the prices follow the common pattern also observed in other Southeast European markets, i.e. stable prices until October 2016, moderate volatility in October-December 2016 and February 2017, and, again, stable prices from March 2017. At the same time, while in the Serbian market shown in Fig. 1 as well as other Southeast European markets prices in January increase substantially, this is not the case in Bulgaria. Fig. 9b shows the unusual Bulgarian day-ahead price dynamics from December 2016 to February 2017.

[Fig. 9 about here]

As shown in Fig. 9b, after day-ahead prices initially started to rise as on other markets, they unexpectedly fell several days later and the whole January 2017 was characterized by strong volatility without any obvious trend. In our analysis, the traditional autoregressive models with sample errors of about 35 % are clearly unable to recover this type of price behaviour. Only neural networks manage to provide results with an accuracy of about 19 %.

While the reason for the increasing winter trend in other countries is clearly the rising electricity demand caused by colder outside temperatures, it does not explain why prices fell shortly afterwards in Bulgaria. To understand this, it is necessary to note the specifics of the Bulgarian day-ahead electricity market, which was introduced in 2016 and is still subject to execution of state power in extraordinary cases. According to Spassov (2017), one of such situations happened in January 2017. In order to balance the increased electricity demand and the decreased supply due to the untypically cold weather and to avoid further price spikes, the Bulgarian Minister of Energy temporarily suspended all power exports from Bulgaria. This, in turn, led to substantial surpluses in electricity generation capacities, which resulted in decreasing prices and huge losses for electricity exporters. Any connection between the suspension of exports and decreased auction prices was denied by the Minister upon request of the European Commission.

The case of Bulgaria evidences that even on Southeast European markets with a high degree of liberalization, the supply side is still experiencing some state control, which makes the price behaviour on average less predictable. Besides, as Zuvela (2016) notices, the Bulgarian market has a very high level of liquidity compared to other Balcan countries. This can lead to less predictable price dynamics due to sophisticated interactions of a large number of market actors. While such issues can hardly be accounted for during the modelling process, it is important to employ models of different types, which are able not only to replicate the autoregressive nature of prices, but also to cope with unanticipated effects.

7. Conclusion

Whereas the worldwide liberalization and decentralization of electricity exchanges have motivated intensive research in the field of day-ahead price forecasting, the recently introduced Southeast European power markets have been beyond the scope of this research so far. However, the complexity and diversity of this region provide a unique opportunity for a comparative analysis of several interconnected markets that have emerged under different climatic and political conditions.

This paper provides such analysis by developing price forecasting models for these markets and examining their structural differences.

Unlike prior work in the field, which typically focuses on one target market and its specific requirements, the paper adopts a standardized approach to examine forecast performance across the markets of Bulgaria, Greece, Slovenia, Serbia, Croatia, Turkey, and Germany (for comparison). Empirical results observed across several different market conditions, types of forecasting models, and input variables evidence the relevance of fundamental factors for forecasting and hint at both structural differences and similarities across markets. In general, we find models using the most comprehensive set of input variables (distant lags, fundamental factors, and hourly and weekday dummy variables) to produce the best forecasts on average. We also observe the best model specifications to vary considerably across countries and levels of volatility. For example, ARIMA models with exogenous predictors perform best for the older German and Turkish markets, whereas multiple linear regression shows good results for the relatively young markets of Greece, Slovenia, and Serbia. Both types of models display equally good results for the Croatian market but fail to forecast the Bulgarian market satisfactory. In most cases, the computationally most intensive neural networks predict energy prices most accurately and show higher robustness than alternative models.

Surprisingly, a simple autoregressive model combined with a seasonal decomposition also produces good results for the new markets of Croatia and Serbia. Out of all investigated countries, these two exhibit the most similarities, which might be due to their geographical proximity and ongoing coupling work.

With respect to the best performing input variables set, total system load turns out to be the most important driver of power prices, followed by wind infeed in Germany. Besides, the analysis shows that including distant lags such as 24, 48, and 168 hours ago is of considerable significance for a risk mitigating strategy especially on the young markets of Bulgaria, Croatia, and Serbia, which might be due to their sensibility to recurring dynamics of price spikes.

Finally, we find separate hours models, an approach that recently gained popularity in the day-ahead price forecasting literature, to deliver superior performance when combined with ARIMA models. This result holds true for all countries and for Croatia and Serbia in particular.

In summary, we conclude that, on average, forecasting prices in relatively liberalized markets of Germany, Croatia, and Slovenia requires more comprehensive modelling and yields less precise results compared to Greece, Serbia, and Turkey, which are still experiencing more state control. An exception is Bulgaria, which is difficult to forecast and state-controlled. The sophisticated price dynamics on fully liberalized markets might be caused by intensive interactions of the participating market players, which are difficult to replicate with traditional stochastic models. Including elements of game theory might be a way forward. On the contrary, the age of the market does not seem to exert significant influence on the forecasting success, cf. the older but more predictable Greek and the younger but less predictable Slovenian markets. As market liberalization in Southeast Europe is an ongoing process, this view is best re-appraised by future research.

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Table 1. Analysis of literature on electricity price forecasting.

Evaluation criterion / Research paper	Market										Method					Error measure						Pre-processing						Input variable				
	Spain	UK	France	Germany	Austria	Nord Pool	USA	Canada	Australia	Southeast Eur.	AR(IMA)	GARCH	AR(IMA)X	Neural network	other	MAE	RMSE	MAPE	e_{week}	v_{week}	other	Logarithms	Normalization	Outliers	Hourly models	Daily dummies	other	Price	System load	Fuels prices	RES prices	other
Amjady, 26	x						x							x				x	x	x	x							x				
Amjady & Keynia, 28							x							x	x			x	x		x		x				x	x	x			x
Amjady & Hemmati, 29	x													x		x		x	x	x								x				
Bessec et al., 2x6			x								x				x	x	x	x				x		x	x	x	x	x	x	x		x
Christensen et al., 2x2									x						x	x	x				x							x	x			x
Conejo et al., 25	x										x		x	x	x		x		x	x	x	x					x	x	x			
Cuaresma et al., 24				x							x					x	x					x		x	x			x				
Diongue et al., 29				x								x					x				x	x						x				
Erni, 2x2				x							x	x	x		x	x		x			x			x	x	x		x	x	x	x	
Franco et al., 2x5	x										x		x			x	x	x										x	x		x	
Garcia et al., 25	x						x				x	x					x	x				x			x			x				
Gareta et al., 26														x							x		x			x		x				
Guirguis & Felder, 24							x				x	x	x		x	x	x				x			x		x	x	x		x		
Guthrie & Videbeck, 27							x				x										x					x		x				
Heering, 29				x							x				x	x	x				x		x		x			x				x
Karakatsani & Bunn, 28		x									x				x	x	x	x			x		x		x	x	x	x	x			x
Keynia, 2x2	x						x							x	x			x	x	x	x		x				x	x	x			
Kristiansen, 2x2						x					x		x					x	x		x	x				x		x	x		x	
Mazengia, 28						x		x			x	x	x	x	x			x							x		x	x				
Nogales et al., 22	x						x						x		x	x	x				x	x						x	x			
Raviv et al., 2x5						x					x					x	x	x			x				x	x		x				
Shafie-khah et al., 2xx	x										x			x	x				x	x								x				
Singhal & Swarup, 2xx							x							x		x	x							x				x	x			x
Vilar et al, 2x2	x														x	x								x		x	x	x	x			
Voronin & Partanen, 2x3						x					x			x	x				x		x			x			x	x	x			x
Voronin, 2x3						x					x	x	x	x	x		x	x	x		x	x		x				x	x			
Weron & Misiorek, 28						x	x				x		x		x				x			x	x	x	x	x	x	x	x			
Ziel et al., 2x5					x						x										x						x	x				
TOTAL SUM	**9**	**1**	**1**	**4**	**1**	**6**	**9**	**1**	**1**		**18**	**6**	**9**	**11**	**16**	**13**	**14**	**13**	**10**	**5**	**18**	**9**	**6**	**9**	**9**	**10**	**11**	**28**	**15**	**3**	**3**	**7**
This paper				*x*						*x*	*x*		*x*	*x*	*x*				*x*	*x*				*x*	*x*	*x*		*x*	*x*	*x*	*x*	

Table 2: Key information and data availability on selected Southeast European electricity markets.

Market	Germany	Bulgaria	Greece	Slovenia	Croatia	Serbia	Turkey
Market opening year	2000	2016	2005	2001	2016	2016	2009
Price data available from	01.01.2010	20.01.2016	01.01.2015	01.01.2015	11.02.2016	18.02.2016	01.07.2009
All data available from	01.01.2015	20.01.2016	01.01.2015	01.01.2015	19.05.2016	18.02.2016	01.12.2011
Input factors	Load	Load, wind, solar	Load, wind, solar	Load, solar	Load, wind, solar	Load	Load, gas, lignite, black coal, imported coal, hydro, river
Liberalization	Mostly completed	In progress; market partly state-controlled	In progress; market partly state-controlled	Mostly completed	In progress	Mostly completed	In progress; market partly state-controlled

Table 3: Per unit sample error and sample error variance of day-ahead price forecasts in the moderately volatile spring period 27.03.-09.04.2017 in Southeast Europe. Best results are underlined, the next best results are marked bold.

	27.03.-09.04.2017	Germany	Bulgaria	Greece	Slovenia	Croatia	Serbia	Turkey***
Naïve: Lag(24)		15.96 % (2.15 %)	29.86 % (7.05 %)	11.71 % (0.95 %)	19.59 % (2.94 %)	23.14 % (2.60 %)	14.78 % (1.14 %)	14.07 % (1.62 %)
AR	+day	13.02 % (1.22 %)	23.98 % (4.29 %)	8.67 % (0.78 %)	16.99 % (1.66 %)	19.31 % (2.02 %)	14.12 % (0.84 %)	11.93 % (1.04 %)
	+day+week	12.30 % (0.95 %)	**20.72 % (2.84 %)**	**7.95 % (0.61 %)**	<u>**11.54 % (0.73 %)**</u>	**16.28 % (1.63 %)**	**10.91 % (0.63 %)**	12.04 % (1.03 %)
	+day+week+y1*	13.45 % (1.15 %)	---	14.13 % (1.78 %)	17.92 % (2.55 %)	---	---	12.53 % (1.20 %)
	+day+week+y2*	37.54 % (5.26 %)	---	16.98 % (2.21 %)	28.28 % (4.04 %)	---	---	19.09 % (2.21 %)
ARIMA(AIC)		16.11 % (1.68 %)	26.46 % (4.40 %)	12.50 % (1.03 %)	22.19 % (2.10 %)	22.08 % (2.42 %)	17.49 % (1.55 %)	14.98 % (1.32 %)
ARIMA	+lags	**10.02 % (0.83 %)**	23.11 % (3.43 %)	8.21 % (0.62 %)	14.31 % (1.11 %)	18.06 % (1.61 %)	11.61 % (0.63 %)	**10.83 % (0.82 %)**
	+predictors	11.11 % (0.78 %)	23.53 % (3.80 %)	<u>**6.79 % (0.53 %)**</u>	**11.51 % (0.81 %)**	**16.29 % (1.40 %)**	13.70 % (1.00 %)	15.10 % (1.24 %)
	+lags+solar	**10.66 % (0.83 %)**	23.41 % (3.34 %)	8.07 % (0.61 %)	14.23 % (1.11 %)	18.04 % (1.62 %)	---	**10.46 % (0.70 %)**
	+lags+wind	11.59 % (0.86 %)	23.08 % (3.38 %)	8.01 % (0.64 %)	---	17.53 % (1.56 %)	---	**10.89 % (0.84 %)**
	+lags+load	**10.80 % (0.74 %)**	22.71 % (3.52 %)	**7.72 % (0.61 %)**	12.16 % (0.72 %)	17.73 % (1.52 %)	11.76 % (0.67 %)	**10.89 % (0.75 %)**
	+lags+predictors	<u>**8.77 % (0.40 %)**</u>	22.90 % (3.26 %)	<u>**6.72 % (0.47 %)**</u>	**11.48 % (0.70 %)**	**16.99 % (1.47 %)**	11.76 % (0.67 %)	**10.71 % (0.70 %)**
	+lags+dummies	<u>**9.53 % (0.72 %)**</u>	22.86 % (2.92 %)	**7.64 % (0.57 %)**	13.64 % (0.97 %)	18.64 % (1.74 %)	11.45 % (0.58 %)	**10.83 % (0.76 %)**
	+lags+d.+pr.**	<u>**9.24 % (0.53 %)**</u>	21.78 % (3.16 %)	<u>**6.29 % (0.40 %)**</u>	<u>**10.91 % (0.69 %)**</u>	**16.19 % (1.27 %)**	11.31 % (0.54%)	**10.10 % (0.63 %)**
MLR	+lags	10.99 % (1.07 %)	21.53 % (3.12 %)	**7.80 % (0.64 %)**	13.30 % (1.04 %)	17.85 % (1.52 %)	**10.60 % (0.53 %)**	**10.34 % (0.77 %)**
	+predictors	13.24 % (0.71 %)	22.48 % (4.04 %)	**7.01 % (0.52 %)**	13.60 % (0.90 %)	20.33 % (2.26 %)	15.87 % (1.49 %)	11.60 % (1.03 %)
	+lags+solar	11.04 % (1.06 %)	21.52 % (3.12 %)	**7.73 % (0.63 %)**	13.40 % (1.04 %)	17.82 % (1.53 %)	---	<u>**9.63 % (0.64 %)**</u>
	+lags+wind	**10.48 % (0.85 %)**	21.48 % (3.05 %)	**7.55 % (0.59 %)**	---	**16.85 % (1.47 %)**	---	**10.31 % (0.78 %)**
	+lags+load	12.26 % (1.00 %)	**20.90 % (3.25 %)**	**7.60 % (0.59 %)**	12.84 % (0.84 %)	18.33 % (1.35 %)	**10.62 % (0.57 %)**	<u>**9.92 % (0.72 %)**</u>
	+lags+predictors	**10.10 % (0.55 %)**	**20.99 % (3.06 %)**	**7.15 % (0.49 %)**	12.64 % (0.85 %)	17.03 % (1.40 %)	**10.62 % (0.57 %)**	<u>**9.60 % (0.64 %)**</u>
	+lags+dummies	11.37 % (1.06 %)	**20.76 % (3.14 %)**	**7.84 % (0.62 %)**	12.34 % (0.84 %)	**16.98 % (1.57 %)**	**10.47 % (0.54 %)**	**10.69 % (0.78 %)**
	+lags+d.+pr.	11.21 % (0.69 %)	**20.15 % (3.12 %)**	**7.22 % (0.44 %)**	**11.67 % (0.81 %)**	**16.63 % (1.46 %)**	**10.51 % (0.51 %)**	<u>**9.68 % (0.67 %)**</u>
NARX	+lags	**10.92 % (1.01 %)**	24.03 % (3.17 %)	**7.97 % (0.55 %)**	12.91 % (0.90 %)	**16.68 % (1.46 %)**	**10.84 % (0.57 %)**	**10.94 % (0.87 %)**
	+predictors	**10.53 % (0.86 %)**	22.88 % (3.68 %)	8.93 % (0.55 %)	13.53 % (1.19 %)	**16.56 % (1.47 %)**	13.66 % (0.84 %)	12.01 % (1.05 %)
	+lags+solar	11.53 % (1.09 %)	22.83 % (2.92 %)	8.00 % (0.55 %)	13.48 % (0.98 %)	**16.63 % (1.53 %)**	---	11.12 % (0.80 %)
	+lags+wind	**10.98 % (0.96 %)**	23.82 % (3.15 %)	**7.83 % (0.58 %)**	---	<u>**15.17 % (1.33 %)**</u>	---	11.06 % (0.89 %)
	+lags+load	**10.59 % (0.91 %)**	23.08 % (3.13 %)	**7.46 % (0.50 %)**	12.67 % (0.89 %)	**16.91 % (1.38 %)**	11.13 % (0.63 %)	**10.41 % (0.82 %)**
	+lags+predictors	**10.13 % (0.69 %)**	22.09 % (2.93 %)	**7.42 % (0.49 %)**	13.02 % (0.90 %)	<u>**15.75 % (1.31 %)**</u>	11.13 % (0.63 %)	**10.89 % (0.79 %)**
	+lags+dummies	<u>**9.23 % (0.61 %)**</u>	22.55 % (3.32 %)	**7.56 % (4.67 %)**	**11.68 % (0.72 %)**	18.00 % (2.29 %)	<u>**9.79 % (0.51 %)**</u>	<u>**9.99 % (0.66 %)**</u>
	+lags+d.+pr.	<u>**9.46 % (0.53 %)**</u>	<u>**19.92 % (2.70 %)**</u>	<u>**6.78 % (0.38 %)**</u>	**11.08 % (0.71 %)**	**16.51 % (1.70 %)**	<u>**9.93 % (0.54 %)**</u>	**10.49 % (0.73 %)**

Table 4: Per unit sample error and sample error variance of day-ahead price forecasts in the extremely volatile winter period 16.-29.01.2017 in Southeast Europe. Best results are underlined, the next best results are marked bold.

16.-29.01.2017		Germany	Bulgaria	Greece	Slovenia	Croatia	Serbia	Turkey***
Naïve: Lag(24)		28.95 % (10.06%)	35.81 %(25.64%)	24.90 % (7.76 %)	27.26 % (6.13 %)	21.88 % (3.07 %)	22.47 % (5.82 %)	13.09 % (1.77 %)
	+day	25.18 % (8.76 %)	40.96 %(17.87%)	26.24 % (5.34 %)	28.03 % (3.57 %)	23.39 % (2.71 %)	25.27 % (5.76 %)	12.01 % (0.83 %)
A	+day+week	23.00 % (6.70 %)	36.42 %(14.14%)	25.60 % (4.87 %)	23.88 % (2.79 %)	20.46 % (2.32 %)	22.02 % (5.04 %)	10.37 % (0.73 %)
R	+day+week+y1*	23.50 % (6.97 %)	---	27.14 % (4.98 %)	26.25 % (3.00 %)	---	---	11.28 % (0.89 %)
	+day+week+y2*	34.82 % (10.28%)	---	28.30 % (5.89 %)	29.09 % (4.83 %)	---	---	16.14 % (1.36 %)
ARIMA(AIC)		34.17 % (9.76 %)	59.39 %(42.70%)	34.06 % (5.15 %)	32.40 % (3.80 %)	26.63 % (2.68 %)	27.34 % (5.95 %)	15.74 % (1.55 %)
	+lags	23.77 % (7.37 %)	34.48 % (7.99 %)	24.60 % (4.09 %)	23.04 % (2.32 %)	**17.74 % (1.71 %)**	22.74 % (6.99 %)	**9.75 % (0.75 %)**
A	+predictors	24.64 % (5.62 %)	51.53 %(10.52%)	29.13 % (4.21 %)	24.06 % (2.44 %)	31.27 % (6.09 %)	31.44 % (4.54 %)	13.74 % (1.19 %)
R	+lags+solar	23.72 % (7.08 %)	34.84 % (7.99 %)	24.65 % (4.08 %)	22.97 % (2.29 %)	**17.83 % (1.73 %)**	---	11.41 % (0.96 %)
I	+lags+wind	22.46 % (5.15 %)	34.89 % (8.06 %)	24.61 % (3.85 %)	---	**17.83 % (1.72 %)**	---	**9.52 % (0.72 %)**
M	+lags+load	24.11 % (6.99 %)	36.66 % (7.09 %)	24.04 % (4.11 %)	**21.74 % (2.07 %)**	**17.75 % (1.83 %)**	22.84 % (6.73 %)	**9.68 % (0.74 %)**
A	+lags+predictors	23.09 % (5.02 %)	37.37 % (7.21 %)	24.04 % (3.83 %	**21.79 % (2.07 %)**	**17.97 % (1.89 %)**	22.84 % (6.73 %)	10.86 % (0.88 %)
	+lags+dummies	24.59 % (7.17 %)	37.56 % (7.65 %)	24.69 % (3.90 %)	23.62 % (2.34 %)	**17.63 % (1.77 %)**	22.81 % (0.67 %)	**9.98 % (0.74 %)**
	+lags+d.+pr.**	22.50 % (5.00 %)	37.58 % (6.72 %)	23.51 % (3.51 %)	22.11 % (2.08 %)	**17.58 % (1.88 %)**	22.85 % (6.45 %)	11.04 % (0.94 %)
	+lags	23.52 % (6.45 %)	**24.83 % (7.07 %)**	**21.57 % (5.23 %)**	**21.84 % (2.36 %)**	**18.59 % (2.01 %)**	**19.58 % (3.48 %)**	11.19 % (0.83 %)
	+predictors	29.52 % (11.26%)	54.86 % (8.71 %)	38.14 %(12.19%)	39.42 % (7.33 %)	41.32 % (5.70 %)	40.38 % (6.85 %)	16.50 % (1.97 %)
M	+lags+solar	23.36 % (6.45 %)	**24.83 % (7.07 %)**	**21.56 % (5.22 %)**	**21.87 % (2.38 %)**	**18.60 % (2.02 %)**	**---**	13.21 % (1.05 %)
L	+lags+wind	22.43 % (5.71 %)	**25.00 % (7.07 %)**	**21.83 % (5.33 %)**	---	**18.61 % (2.01 %)**	**---**	11.03 % (0.82 %)
R	+lags+load	24.27 % (6.95 %)	28.95 % (5.86 %)	**21.70 % (5.19 %)**	**21.77 % (2.51 %)**	**18.80 % (1.80 %)**	**19.08 % (3.42 %)**	10.63 % (0.84 %)
	+lags+pred.	22.54 % (6.73 %)	29.38 % (5.87 %)	**22.09 % (5.30 %)**	**21.73 % (2.50 %)**	**18.88 % (1.83 %)**	**19.08 % (3.42 %)**	11.64 % (1.00 %)
	+lags+dummies	22.99 % (6.69 %)	**25.76 % (7.17 %)**	**21.50 % (5.09 %)**	**21.71 % (2.40 %)**	**18.31 % (1.82 %)**	**17.88 % (3.44 %)**	11.33 % (0.86 %)
	+lags+d.+pr.	**20.93 % (6.00 %)**	28.54 % (6.20 %)	**21.35 % (4.96 %)**	**20.58 % (2.08 %)**	**18.18 % (1.76 %)**	**17.57 % (3.35 %)**	11.21 % (0.94 %)
	+lags	22.88 % (7.34 %)	**25.75 % (8.94 %)**	25.92 % (5.77 %)	24.16 % (3.38 %)	22.35 % (8.12 %)	24.93 % (6.48 %)	**9.58 % (0.67 %)**
	+predictors	**19.85 % (6.02 %)**	35.39 %(10.95%)	24.53 % (6.47 %)	**21.57 % (3.29 %)**	24.79 % (6.24 %)	23.45 % (5.62 %)	10.01 % (0.78 %)
N	+lags+solar	23.43 % (7.46 %)	**25.83 % (9.53 %)**	27.75 % (6.09 %)	24.07 % (3.46 %)	23.04 % (6.66 %)	---	10.63 % (0.71 %)
A	+lags+wind	**21.46 % (5.68 %)**	28.54 %(13.47%)	27.96 % (6.80 %)	---	21.55 % (7.32 %)	---	**9.13 % (0.66 %)**
R	+lags+load	**21.41 % (6.44 %)**	**25.88 % (7.37 %)**	**22.09 % (5.07 %)**	22.30 % (2.85 %)	23.14 % (6.91 %)	26.74 % (5.77 %)	**8.66 % (0.70 %)**
X	+lags+pred.	**17.68 % (4.20 %)**	28.41 % (895 %)	23.02 % (5.10 %)	20.52 % (2.64 %)	23.67 % (5.99 %)	26.74 % (5.77 %)	**9.41 % (0.70 %)**
	+lags+dummies	24.78 % (9.75 %)	**18.28 % (6.25 %)**	**21.42 % (5.60 %)**	19.04 % (1.97 %)	19.05 % (1.80 %)	20.00% (4.01 %)	**8.68 % (0.65 %)**
	+lags+d.+pr.	**21.22 % (6.74 %)**	**19.90 % (5.22 %)**	**21.65 % (4.99 %)**	19.47 % (2.08 %)	20.34 % (2.86 %)	21.25 % (4.28 %)	**8.95 % (0.66 %)**

*y1 corresponds to the decomposition formula year = 52 weeks; y2 – to the formula year = 365.25 days.
**lags+dummies+predictors. ***For Turkey, gas and lignite were used instead of solar and wind, respectively.

Table 5: Price correlation with fundamental factors on electricity markets in Germany and Southeast Europe.

Market	Germany	Bulgaria	Greece	Slovenia	Croatia	Turkey*
Solar infeed	-9,01 %	14,59 %	7,64 %	2,94 %	-0,78 %	53,34 %
Wind infeed	-38,49 %	4,89 %	10,50 %	-	7,24 %	30,80 %
Total system load	59,09 %	53,25 %	46,03 %	65,28 %	66,69 %	63,17 %

**For Turkey, gas and lignite were used instead of solar and wind, respectively.*

Table 6: Best forecasting models for day-ahead markets in Southeast Europe and Germany. X stands for good performance during non-volatile and moderately volatile periods, XX – during highly volatile periods, and XXX – under any conditions.

	Germany	Bulgaria	Greece	Slovenia	Croatia	Serbia	Turkey
AR + day + week					X	X	
ARIMA lags + predictors	XXX						
ARIMA lags + predictors + dummies	XXX				XXX		XXX
MLR lags + dummies		X	XX	XXX		XXX	
MLR lags + predictors + dummies			XX		XXX	XXX	
NN lags + dummies			XXX	XXX			XXX
NN lags + predictors + dummies	XX	XXX	XXX	XXX		X	XXX

Table 7: Per unit sample error and sample error variance of hourly modelled day-ahead price forecasts in the moderately volatile spring period 27.03.-09.04.2017 in Southeast Europe. Best results are underlined, the next best results are marked bold, and results that show an improvement through the hourly modelling have a star mark.

27.03.-09.04.2017	**Germany**	**Bulgaria**	**Greece**	**Slovenia**	**Croatia**	**Serbia**	**Turkey**
ARIMA+dummies+ lags+predictors	11.40 % (0.64 %)	**<u>19.15 % (2.80 %)</u>** *	**<u>6.33 % (0.43 %)</u>**	**11.57 % (0.83 %)**	**<u>15.57 % (1.57 %)</u>** *	**<u>9.50 % (0.58 %)</u>** *	**<u>9.44 % (0.67 %)</u>** *
MLR+dummies+ lags+predictors	13.10 % (0.96 %)	19.64 % (2.97 %) *	**7.74 % (0.53 %)**	12.75 % (0.91 %)	22.89 % (2.58 %)	14.30 % (0.84 %)	11.89 % (0.99 %)
NN+lags+predictors	11.59 % (0.78 %)	24.45 % (3.76 %)	8.50 % (0.64 %)	14.13 % (1.36 %)	21.73 % (2.86 %)	12.47 % (0.84 %)	**<u>9.69 % (0.57 %)</u>** *

Table 8: Per unit sample error and sample error variance of <u>hourly modelled</u> day-ahead price forecasts in the extremely volatile winter period 16.-29.01.2017 in Southeast Europe. Best results are underlined, the next best results are marked bold, and results that show an improvement through the hourly modelling have a star mark.

16.-29.01.2017	**Germany**	**Bulgaria**	**Greece**	**Slovenia**	**Croatia**	**Serbia**	**Turkey**
ARIMA+dummies+ lags+predictors	**20.88 % (4.69 %)** *	32.54 % (7.37 %)	**<u>21.81 % (5.33 %)</u>** *	**21.16 % (2.35 %)** *	**<u>15.56 % (1.43 %)</u>** *	**<u>16.56 % (4.12 %)</u>** *	11.04 % (1.01 %)
MLR+dummies+ lags+predictors	30.76 % (10.18%)	40.71 % (9.05 %)	36.66% (10.56%)	40.21 % (6.85 %)	37.34 % (4.76 %)	40.06 % (4.35 %)	16.67 % (2.70 %)
NN+lags+predictors	30.11 % (8.28 %)	33.37 % (7.91 %)	23.83 % (5.97 %)	22.75 % (3.05 %)	21.88 % (2.74 %) *	25.33 % (4.32 %) *	11.30 % (1.00 %)

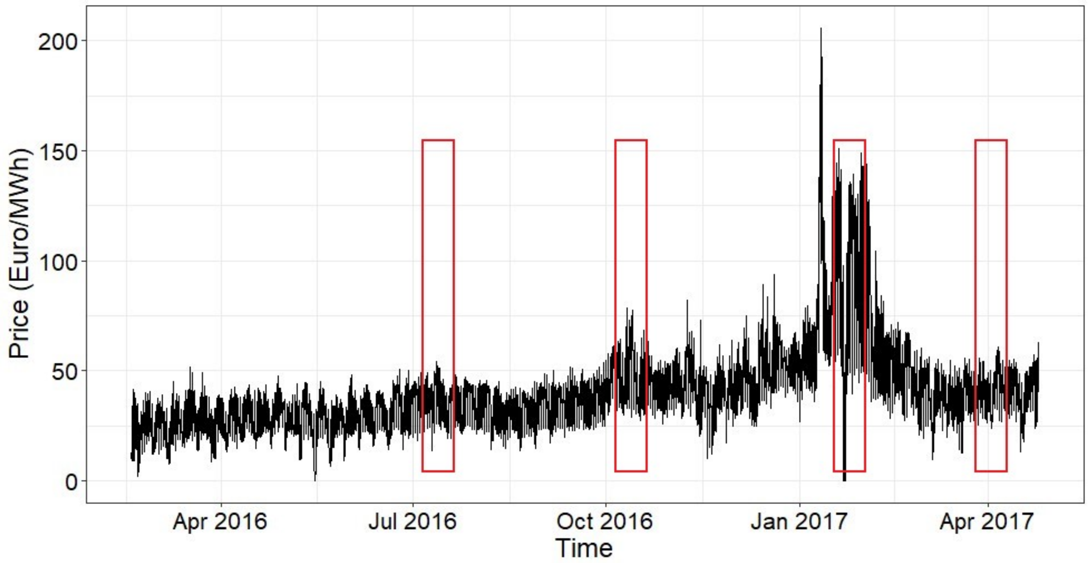


Fig. 1: Day-ahead prices on the Serbian electricity market for the period 18.02.2016-24.04.2017. The four test periods are mar-ked by rectangles.

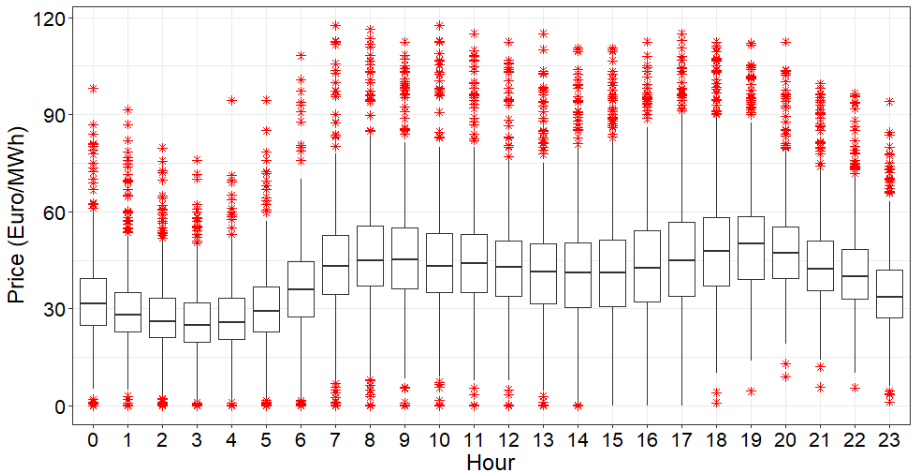


Fig. 2: Box plot of day-ahead prices per hour on the Slovenian electricity market.

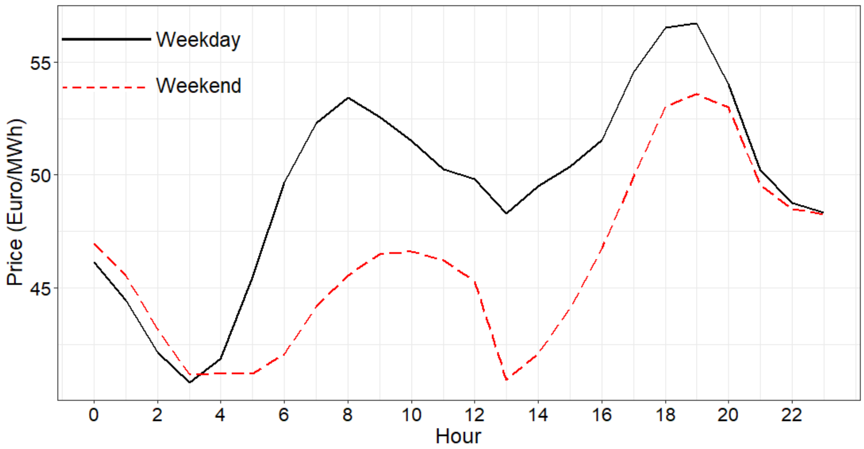
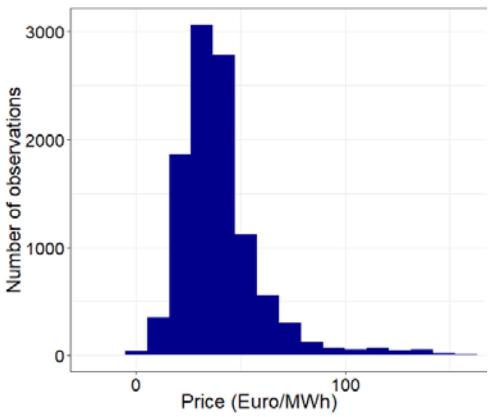
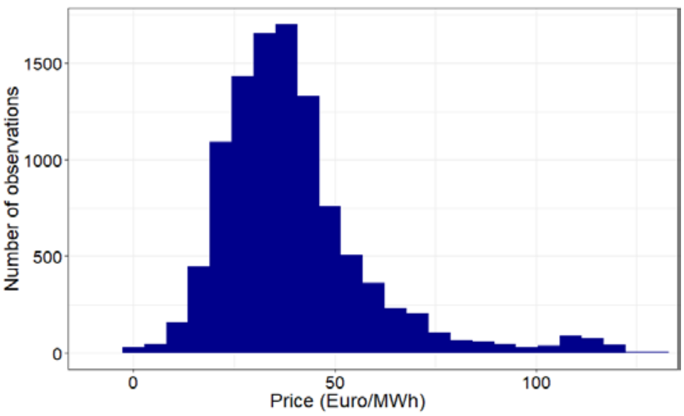


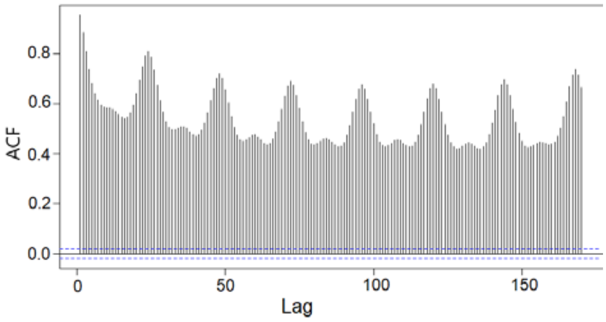
Fig. 3: Hourly prices on weekdays vs. weekends on the Greek electricity market. Based on (Cuaresma, 2004).

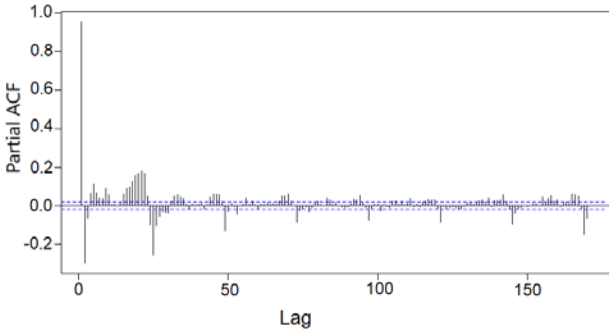




a) original data *b) pre-processed data*

Fig. 4: Histogram of prices on the Croatian electricity market.





a) ACF *b) PACF*

Fig. 5: Autocorrelation analysis of prices on the Croatian electricity market.

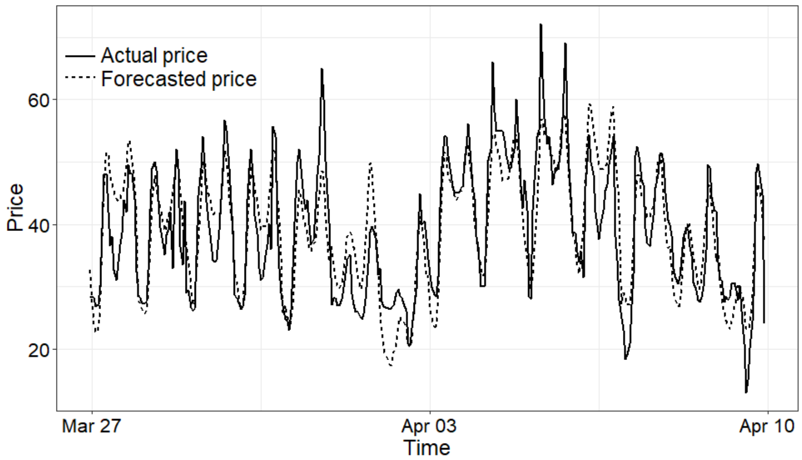


Fig. 6: Forecast vs. actual prices on the Slovenian market for the period 27.03.-09.04.2017

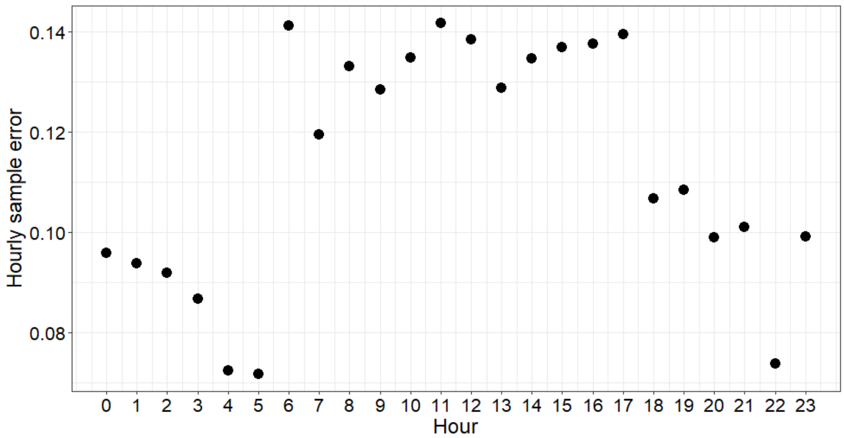


Fig. 7: Hourly sample errors for the Serbian electricity market, ARIMA with lags, predictors, and dummies, 27.03.-09.04.2017.

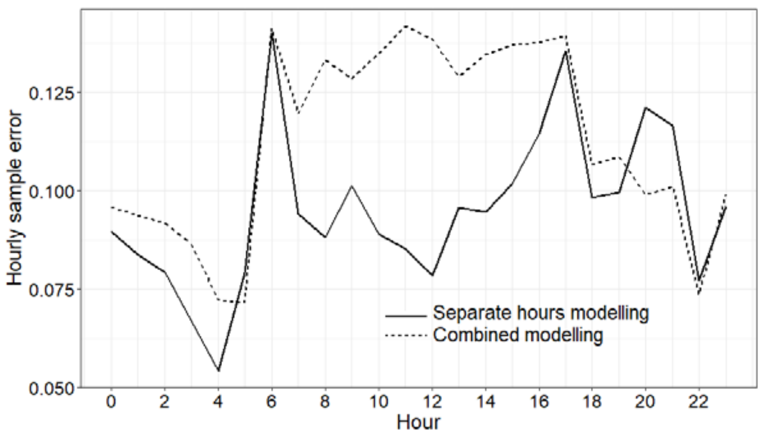
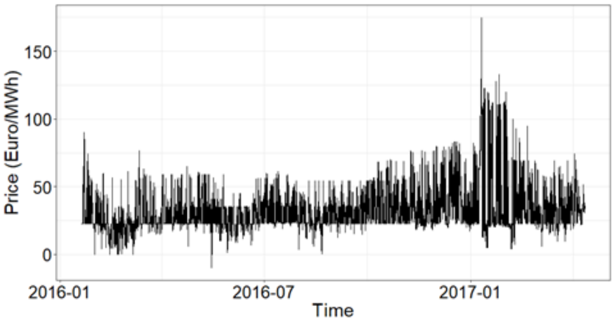
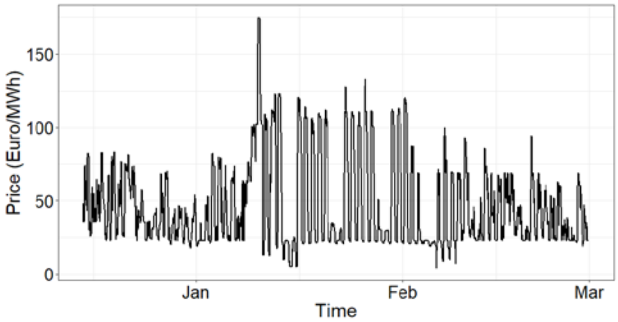


Fig. 8: Hourly sample errors for the Serbian electricity market, separate hours modelling vs. combined forecasts, ARIMA with lags, predictors, and dummies, 27.03.-09.04.2017.



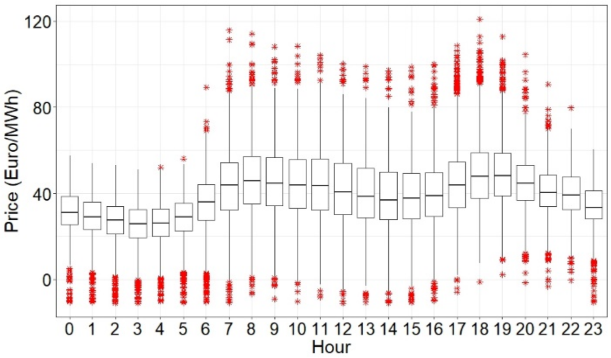
a) for the period 20.01.2016-12.04.2017



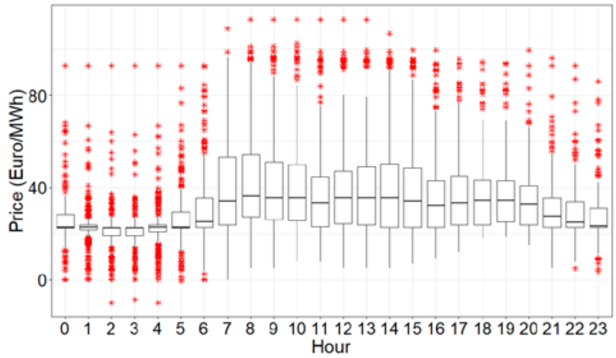
b) for the period 15.12.2016-28.02.2017

Fig. 9: Day-ahead prices on the Bulgarian electricity market.

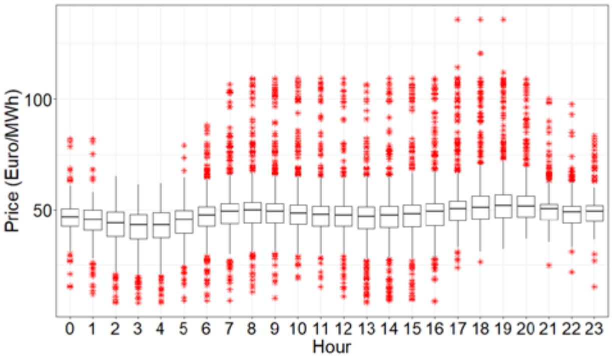
Appendix



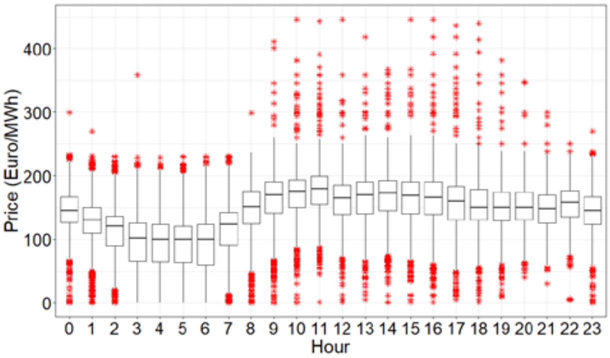
a) Germany



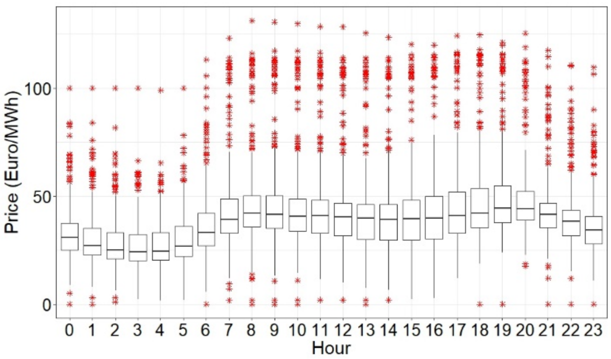
b) Bulgaria



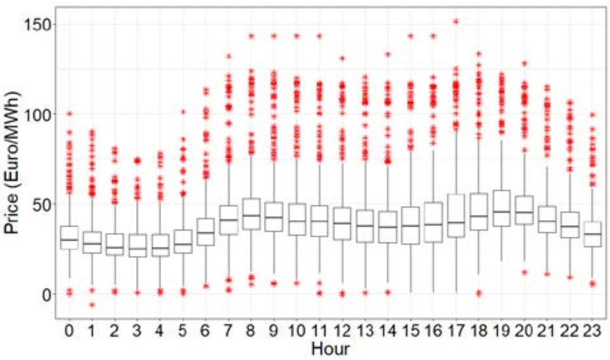
c) Greece



d) Turkey



e) Serbia



f) Croatia

Fig. 10: Box plot of day-ahead prices per hour on Southeast European electricity markets

Table 9: Per unit sample error and sample error variance of day-ahead price forecasts in the non-volatile summer period 04.-17.07.2016 in Southeast Europe. Best results are underlined, the next best results are marked bold.

04.-17.07.2016		Germany	Bulgaria	Greece	Slovenia	Croatia	Serbia	Turkey***
Naïve: Lag(24)		30,56 % (6,72 %)	26,40 % (8,41 %)	9,31 % (0,67 %)	26,68 % (6,02 %)	23,94 % (3,38 %)	14,38 % (1,78 %)	32,85 % (11,74%)
AR	+day	23,23 % (4,30 %)	23,60 % (3,87 %)	8,12 % (0,51 %)	21,80 % (3,48 %)	**18,77 % (2,99 %)**	15,53 % (1,29 %)	26,96 % (6,05 %)
	+day+week	17,60 % (2,51 %)	**22,16 % (3,83 %)**	7,99 % (0,46 %)	**19,03 % (3,21 %)**	**16,60 % (2,32 %)**	**9,17 % (0,55 %)**	26,13 % (5,95 %)
	+day+week+y1*	16,71 % (2,05 %)	---	---	---	---	---	27,62 % (5,93 %)
	+day+week+y2*	39,72 % (6,32 %)	---	---	---	---	---	33,03 % (6,44 %)
ARIMA(AIC)		26,89 % (3,67 %)	26,15 % (4,71 %)	8,50 % (0,27 %)	23,49 % (4,20 %)	24,92 % (4,39 %)	17,31 % (1,74 %)	39,67 % (8,04 %)
ARIMA	+lags	18,75 % (2,24 %)	**22,25 % (4,02 %)**	**7,25 % (0,24 %)**	20,27 % (3,38 %)	20,36 % (2,83 %)	**10,65 % (0,71 %)**	29,20 % (6,35 %)
	+predictors	**10,79 % (0,68 %)**	**22,61 % (3,36 %)**	8,31 % (0,37 %)	20,15 % (3,39 %)	**18,28 % (1,91 %)**	13,73 % (1,08 %)	28,76 % (5,24 %)
	+lags+solar	18,98 % (2,13 %)	**22,21 % (3,82 %)**	**7,44 % (0,24 %)**	20,27 % (3,35 %)	20,43 % (2,92 %)	---	**22,94 % (4,20 %)**
	+lags+wind	14,63 % (1,41 %)	**22,13 % (4,04 %)**	**7,45 % (0,34 %)**	---	20,16 % (2,83 %)	---	29,24 % (6,28 %)
	+lags+load	18,44 % (2,65 %)	**22,39 % (3,60 %)**	**6,57 % (0,32 %)**	**19,43 % (3,37 %)**	**19,48 % (2,31 %)**	**10,39 % (0,70 %)**	24,81 % (4,75 %)
	+lags+predictors	**9,74 % (0,54 %)**	**22,38 % (3,37 %)**	**7,19 % (0,35 %)**	**19,28 % (3,42 %)**	**19,36 % (2,29 %)**	**10,39 % (0,70 %)**	**22,64 % (4,14 %)**
	+lags+dummies	17,86 % (2,32 %)	**22,30 % (3,27 %)**	**6,94 % (0,26 %)**	20,67 % (3,73 %)	20,93 % (2,69 %)	**10,57 % (0,68 %)**	28,94 % (6,09 %)
	+lags+d.+pr.**	**9,64 % (0,55 %)**	**21,77 % (3,25 %)**	**7,16 % (0,28 %)**	**19,77 % (3,55 %)**	**19,69 % (2,04 %)**	**10,37 % (0,64 %)**	**22,05 % (4,00 %)**
MLR	+lags	21,12 % (2,82 %)	**22,57 % (4,11 %)**	**6,91 % (0,30 %)**	**19,76 % (3,05 %)**	20,80 % (3,21 %)	**9,63 % (0,57 %)**	28,68 % (6,19 %)
	+predictors	**9,55 % (0,52 %)**	**22,06 % (4,80 %)**	25,13 % (1,00 %)	20,19 % (2,81 %)	**19,87 % (1,97 %)**	29,04 % (3,39 %)	27,80 % (5,71 %)
	+lags+solar	21,07 % (2,77 %)	**22,18 % (4,08 %)**	**7,01 % (0,29 %)**	**19,74 % (2,98 %)**	20,93 % (3,38 %)	---	24,98 % (4,30 %)
	+lags+wind	13,42 % (1,12 %)	**22,94 % (3,88 %)**	**7,04 % (0,33 %)**	---	20,12 % (3,53 %)	---	28,75 % (6,13 %)
	+lags+load	21,15 % (2,86 %)	**21,67 % (4,25 %)**	**7,66 % (0,47 %)**	**19,55 % (2,87 %)**	**19,61 % (2,52 %)**	**9,64 % (0,57 %)**	24,12 % (5,36 %)
	+lags+predictors	**10,13 % (0,53 %)**	**21,50 % (3,98 %)**	8,98 % (0,50 %)	**19,56 % (2,86 %)**	20,51 % (2,83 %)	**9,64 % (0,57 %)**	**22,58 % (4,14 %)**
	+lags+dummies	21,02 % (2,70 %)	**21,92 % (3,63 %)**	**6,77 % (0,30 %)**	**18,49 % (2,87 %)**	20,18 % (2,70 %)	**8,50 % (0,40 %)**	27,94 % (5,78 %)
	+lags+d.+pr.	**10,87 % (0,56 %)**	**22,04 % (3,41 %)**	8,69 % (0,46 %)	**18,26 % (2,69 %)**	**19,97 % (2,54 %)**	**8,50 % (0,40 %)**	**22,08 % (4,11 %)**
NARX	+lags	16,79 % (2,02 %)	23,08 % (3,99 %)	**7,79 % (0,25 %)**	**19,55 % (3,27 %)**	23,59 % (3,97 %)	**10,82 % (0,77 %)**	31,12 % (6,66 %)
	+predictors	**11,86 % (0,98 %)**	**22,85 % (4,40 %)**	8,54 % (0,30 %)	21,48 % (3,95 %)	**18,75 % (2,24 %)**	12,06 % (1,29 %)	**22,52 % (4,95 %)**
	+lags+solar	16,54 % (2,04 %)	23,97 % (4,22 %)	8,25 % (0,26 %)	20,22 % (3,43 %)	21,38 % (3,12 %)	---	26,19 % (4,37 %)
	+lags+wind	12,74 % (1,03 %)	**22,63 % (4,43 %)**	**7,84 % (0,32 %)**	---	**19,20 % (2,70 %)**	---	31,92 % (6,76 %)
	+lags+load	16,14 % (1,80 %)	**22,61 % (4,20 %)**	**6,32 % (0,23 %)**	20,06 % (3,19 %)	21,17 % (3,32 %)	**10,91 % (0,78 %)**	26,30 % (5,33 %)
	+lags+predictors	**11,76 % (0,83 %)**	23,05 % (4,24 %)	**6,92 % (0,26 %)**	20,48 % (3,34 %)	**17,85 % (1,82 %)**	**10,91 % (0,78 %)**	**21,84 % (3,83 %)**
	+lags+dummies	15,26 % (1,82 %)	24,33 % (4,66 %)	**6,92 % (0,21 %)**	**17,96 % (2,81 %)**	21,77 % (3,88 %)	**9,63 % (0,48 %)**	27,93 % (6,66 %)
	+lags+d.+pr.	**11,66 % (0,88 %)**	24,10 % (4,25 %)	**7,00 % (0,22 %)**	20,21 % (3,06 %)	21,49 % (4,57 %)	**9,18 % (0,56 %)**	**22,49 % (4,78 %)**

Table 10: Per unit sample error and sample error variance of day-ahead price forecasts in the moderately volatile autumn period 03.-16.10.2016 in Southeast Europe. Best results are underlined, the next best results are marked bold.

03.-16.10.2016		Germany	Bulgaria	Greece	Slovenia	Croatia	Serbia	Turkey***
Naïve: Lag(24)		21,02 % (4,73 %)	33,53 % (7,16 %)	8,38 % (1,46 %)	23,37 % (3,43 %)	27,36 % (5,07 %)	15,20 % (1,62 %)	16,10 % (2,51 %)
	+day	15,96 % (2,19 %)	28,31 % (3,59 %)	7,26 % (0,90 %)	21,29% (2,59 %)	27,22 % (4,18 %)	14,18 % (1,72 %)	13,22 % (1,54 %)
A	+day+week	18,83 % (1,91 %)	**25,87 % (3,50 %)**	7,21 % (0,87 %)	18,22 % (2,00 %)	23,94 % (3,19 %)	9,90 % (0,85 %)	**10,59 % (1,12 %)**
R	+day+week+y1*	19,09 % (2,12 %)	---	---	---	---	---	11,92 % (1,20 %)
	+day+week+y2*	31,47 % (3,99 %)	---	---	---	---	---	20,18 % (2,29 %)
ARIMA(AIC)		19,89 % (3,37 %)	32,14 % (4,72 %)	8,55 % (1,10 %)	24,60 % (3,14 %)	29,74 % (3,89 %)	18,17 % (1,52 %)	18,74 % (2,07 %)
	+lags	14,37 % (2,59 %)	28,26 % (2,97 %)	**6,72 % (0,88 %)**	20,79 % (2,48 %)	25,56 % (2,94 %)	12,25 % (0,81 %)	11,01 % (0,90 %)
A	+predictors	**13,11 % (1,07 %)**	**25,66 % (2,33 %)**	**6,57 % (0,70 %)**	**17,12 % (1,94 %)**	23,12 % (2,92 %)	14,11 % (1,26 %)	**10,09 % (0,94 %)**
R	+lags+solar	14,39 % (2,59 %)	28,26 % (2,97 %)	**6,80 % (0,89 %)**	20,83 % (2,36 %)	25,59 % (2,98 %)	---	**9,48 % (0,66 %)**
I	+lags+wind	14,16 % (2,11 %)	27,84 % (2,84 %)	**6,47 % (0,79 %)**	---	25,58 % (2,97 %)	---	**10,95 % (0,90 %)**
M	+lags+load	14,98 % (2,00 %)	26,50 % (2,73 %)	**6,79 % (0,80 %)**	**17,48 % (1,99 %)**	24,36 % (2,64 %)	**11,82 % (0,74 %)**	**10,26 % (0,78 %)**
A	+lags+predictors	**11,40 % (1,07 %)**	26,07 % (2,55 %)	**6,33 % (0,69 %)**	**17,52 % (1,98 %)**	23,79 % (2,63 %)	**11,82 % (0,74 %)**	**9,61 % (0,67 %)**
	+lags+dummies	14,16 % (2,48 %)	27,26 % (2,83 %)	**6,71 % (0,79 %)**	20,61 % (2,25 %)	26,24 % (2,95 %)	12,25 % (0,88 %)	11,06 % (0,87 %)
	+lags+d.+pr.**	**11,73 % (1,05 %)**	**25,64 % (2,65 %)**	**6,29 % (0,69 %)**	**17,56 % (1,95 %)**	**22,65 % (2,10 %)**	**11,43 % (0,77 %)**	**8,95 % (0,63 %)**
	+lags	15,77 % (2,65 %)	28,92 % (2,96 %)	**6,32 % (0,78 %)**	19,85 % (2,48 %)	23,76 % (3,18 %)	12,64 % (1,14 %)	11,51 % (0,95 %)
	+predictors	15,87 % (1,64 %)	32,34 % (6,16 %)	7,69 % (0,74 %)	20,06 % (2,49 %)	26,28 % (5,15 %)	33,36 % (4,48 %)	12,49 % (0,92 %)
M	+lags+solar	15,76 % (2,64 %)	29,05 % (3,04 % (	**6,30 % (0,78 %)**	19,96 % (2,50 %)	23,81 % (3,18 %)	---	**10,74 % (0,86 %)**
L	+lags+wind	15,38 % (2,24 %)	28,33 % (2,88 %)	**5,91 % (0,72 %)**	---	23,58 % (3,29 %)	---	11,40 % (0,94 %)
R	+lags+load	15,99 % (2,40 %)	28,76 % (2,92 %)	**6,45 % (0,72 %)**	18,29 % (2,08 %)	23,33 % (3,75 %)	12,59 % (1,13 %)	**10,93 % (0,86 %)**
	+lags+predictors	**13,02 % (1,38 %)**	28,28 % (2,89 %)	**5,77 % (0,62 %)**	18,31 % (2,09 %)	**22,88 % (3,61 %)**	12,59 % (1,13 %)	**10,34 % (0,76 %)**
	+lags+dummies	17,52 % (2,37 %)	28,02 % (3,55 %)	**6,18 % (0,76 %)**	**17,45 % (2,21 %)**	**22,91 % (3,25 %)**	**10,77 % (0,78 %)**	11,20 % (0,86 %)
	+lags+d.+pr.	**12,90 % (1,25 %)**	27,61 % (3,48 %)	**5,76 % (0,62 %)**	**16,47 % (2,05 %)**	**20,71 % (2,56 %)**	**10,73 % (0,73 %)**	**10,28 % (0,73 %)**
	+lags	15,08 % (2,30 %)	27,84 % (4,31 %)	7,21 % (0,87 %)	19,82 % (2,27 %)	26,44 % (3,98 %)	14,23 % (1,02 %)	11,48 % (1,00 %)
	+predictors	14,97 % (1,92 %)	**24,99 % (3,67 %)**	8,16 % (0,80 %)	19,49 % (2,01 %)	25,27 % (4,09 %)	13,02 % (0,94 %)	11,74 % (1,01 %)
N	+lags+solar	14,87 % (2,20 %)	27,26 % (3,70 %)	**6,86 % (0,86 %)**	19,72 % (2,14 %)	27,35 % (4,08 %)	---	11,56 % (0,95 %)
A	+lags+wind	15,98 % (2,06 %)	26,77 % (3,66 %)	**6,67 % (0,77 %)**	---	25,90 % (4,33 %)	---	11,72 % (0,97 %)
R	+lags+load	15,18 % (2,04 %)	27,19 % (3,92 %)	8,60 % (0,86 %)	**17,59 % (2,20 %)**	25,22 % (4,08 %)	13,91 % (0,84 %)	11,04 % (0,92 %)
X	+lags+predictors	**13,27 % (1,38 %)**	**25,89 % (3,91 %)**	7,61 % (0,74 %)	**17,91 % (2,14 %)**	24,58 % (3,97 %)	13,91 % (0,84 %)	11,40 % (0,84 %)
	+lags+dummies	14,06 % (1,70 %)	**25,50 % (3,14 %)**	7,27 % (0,85 %)	**17,56 % (1,93 %)**	24,13 % (3,35 %)	**11,74 % (0,80 %)**	**9,92 % (0,62 %)**
	+lags+d.+pr.	**12,22 % (1,11 %)**	**24,91 % (3,48 %)**	**6,89 % (0,80 %)**	**17,62 % (2,17 %)**	23,35 % (2,85 %)	**11,42 % (0,64 %)**	**10,09 % (0,60 %)**

**y1 corresponds to the decomposition formula year = 52 weeks; y2 – to the formula year = 365,25 days.*
***lags+dummies+predictors. ***For Turkey, gas and lignite were used instead of solar and wind, respectively.*

Table 11: Per unit sample error and sample error variance of hourly modelled day-ahead price forecasts in the non-volatile summer period 04.-17.07.2016 in Southeast Europe. Best results are underlined, the next best results are marked bold, and results that show an improvement through the hourly modelling have a star mark.

04.-17.07.2016	Germany	Bulgaria	Greece	Slovenia	Croatia	Serbia	Turkey
ARIMA+dummies+ lags+predictors	**9.90 % (0.48 %)**	24.45 % (4.31 %)	**7.44 % (0.26 %)**	**18.98 % (3.12 %)** *	**18.74 % (2.42 %)** *	**7.60 % (0.31 %)** *	**18.06 % (3.33 %)** *
MLR+dummies+ lags+predictors	**10.30 % (0.67 %)** *	**22.47 % (4.06 %)** *	20.94 % (0.80 %)	**19.59 % (2.97 %)**	**18.14 % (2.31 %)** *	19.88 % (1.66 %)	24.76 % (4.48 %)
NN+lags+predictors	12.07 % (0.94 %)	25.57 % (4.74 %)	8.77 % (0.48 %)	24.58 % (4.80 %)	27.43 % (8.56 %)	11.12 % (0.78 %)	**22.07 % (4.18 %)**

Table 12: Per unit sample error and sample error variance of hourly modelled day-ahead price forecasts in the moderately volatile autumn period 03.-16.10.2016 in Southeast Europe. Best results are underlined, the next best results are marked bold, and results that show an improvement through the hourly modelling have a star mark.

03.-16.10.2016	Germany	Bulgaria	Greece	Slovenia	Croatia	Serbia	Turkey
ARIMA+dummies+ lags+predictors	**10.47 % (0.94 %)** *	**23.78 % (2.26 %)** *	**6.47 % (0.51 %)**	**16.19 % (1.67 %)** *	**19.78 % (2.21 %)** *	**9.98 % (0.54 %)** *	**9.65 % (0.69 %)**
MLR+dummies+ lags+predictors	15.57 % (1.37 %)	30.67 % (4.80 %)	9.75 % (0.81 %)	22.02 % (2.43 %)	**22.36 % (3.62 %)**	37.33 % (2.27 %)	11.45 % (0.67 %)
NN+lags+predictors	**13.00 % (1.31 %)** *	27.62 % (3.41 %)	7.78 % (0.79 %)	18.94 % (2.23 %)	22.89 % (3.32 %) *	13.05 % (1.12 %) *	11.09 % (1.09 %) *

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