AN EMPIRICAL EVIDENCE FOR GENERALIZED SHRINKAGE METHODS: APPLICATION OF BAGGING IN DAY-AHEAD ELECTRICITY PRICE FORECASTING AND FACTOR AUGMENTATION

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ABSTRACT

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Fundamental dynamics behind electricity prices are multi-dimensional and elaborate. A popular approach to forecasting electricity price is to utilize large number of predictors. In this study, using the day-ahead electricity price data from commonly studied markets of five major series and GEFCom2014 data, a variant of shrinkage method, **B**ootstrap **Agg**regation (bagging) is proposed to incorporate information from available predictors. Bagging manifests itself as a computationally simpler alternative to commonly used **L**east **A**bsolute **S**hrinkage and **S**election **O**perator (lasso) in multivariate EPF context and even shows superior forecasting ability in some markets. Moreover, considering the significant dependence of intra-day electricity prices, we also propose factor augmentation to exploit this dependence. The inclusion of latent factors, selected via Bayesian Information Criterion, improves ability to forecast in multivariate modeling framework and in some cases even outperform sophisticated shrinkage methods as measured by the Diebold-Mariano test.
Keywords: Bagging, Shrinkage methods, Electricity price forecasting, Factor models

ÖZ

GENELLEŞTİRİLMİŞ SHRINKAGE MODELLERİ İÇİN BİR AMPİRİK BULGU: BAGGİNG YÖNTEMİNİN GÜN ÖNCESİ ELEKTRİK FİYATLARININ TAHMİNİNE UYGULANMASI VE FAKTÖR MODELLERİ İLE DESTEKLENMESİ

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Elektrik fiyatların oluşmasında temel değişkenler çok boyutlu ve kapsamlı. Çok sayıda açıklayıcı değişken ile elektrik fiyatlarının tahmin edilmesi günümüzde yaygın kullanılan yaklaşımlardan biri. Bu çalışmada, literatürde sıklıkla kullanılan ana elektrik piyasalarında beş farklı seri ve GEFCom2014 yarışma verisi kullanılarak, bir shrinkage yöntemi olan Bootstrap Aggregation (bagging) yöntemiyle, mevcut açıklayıcı değişkenlerdeki bilgilerin elde edilmesi önerilmektedir. Bagging yöntemi, multivariate elektrik fiyat tahmini literatüründe yaygın olarak kullanılan bir diğer yöntem olan Least Absolute Shrinkage and Selection Operator (lasso)'e göre çok daha uygulaması basit ve hatta bazı piyasalarda daha iyi tahmin performans göstermesiyle öne çıkmaktadır. İlaveten, gün içerisindeki elektrik fiyatlarının birbiriyle olan yüksek bağımlılığını modellere yansıtmak adına faktör destekli modeller önerilmektedir. Bayesian Kriteri ile seçilen faktörlerin modellere eklenmesi modellerin performanslarını iyileştirdiği gibi, bazı durumlarda gelişmiş shrinkage yöntemlerinden bile daha iyi sonuçlar verdiği Diebold-Mariano testi ile gösterilmiştir.

Anahtar Kelimeler: Bagging, Shrinkage, Elektrik fiyat tahmini, Faktör modelleri

TABLE OF CONTENTS

CHAPTER 1

INTRODUCTION

Forecasts of electricity prices are necessary inputs for number of institutions spanning from power plant operators to market operators and from transmission system planners to power portfolio managers. Over the past decade, sophisticated forecast models are derived for the day-ahead electricity prices. A detailed review is given by Weron (2014). Number of shrinkage methods are used to estimate complex models with explanatory variables of well above 200. Among them, **L**east **A**bsolute **S**hrinkage and **S**election **O**perator (lasso) due to Tibshirani (1996), was applied very elegantly by Ziel et al. (2015) in EPF context outperforming several competitive models and since then literature has a wide consensus on it. Ludwig et al. (2015) focuses on German electricity spot prices with weather data to formally select relevant weather stations via lasso as well as Random Forests. Uniejewski et al. (2016) concentrates on lasso together with stepwise regression and ridge regression. Ziel (2016) considers again lasso to capture the intra-day dependencies of prices. Ziel (2017) estimates a number of regression models via lasso to make inferences on the effect of renewable energy forecasting errors on intra-day electricity spot prices. Lasso is also used to compare the effects of sixteen different variance stabilizing transformations used in the EPF literature by Uniejewski et al. (2018). In an extensive empirical forecasting exercise to judge the performances of univariate vs. multivariate modelling frameworks Ziel and Weron (2018) argues that, lasso is the best model in both modelling frameworks among various other benchmark models including Naive, Expert, AR Meanhow, VAR. Recently, Uniejewski et al. (2019) applies lasso in intra-day electricity forecasting for the first time and concluding that it is superior to two commonly implemented benchmark models denoted by Naive and ARX.

Nonetheless, despite its extensive application in the literature and highly improved forecast accuracy, lasso is not the only available shrinkage method nor does it come without disadvantages. Need for a dedicated numerical optimization procedure and considerable dependency on the regularization parameter are clearly seen when looked at the glass as half full. Indeed, recent research by Stock and Watson (2012) characterizes that some forecasting methods including Pretest and Information Criterion Methods, Normal Bayes Methods, Bayesian Model Average, Empirical Bayes and **B**ootstrap **Agg**regation (bagging) asymptotically all these methods have the same "shrinkage" representation, in which the weight on a predictor is the ordinary least-squares (OLS) estimator times a shrinkage factor that depends on the t-statistic of that coefficient. Given that it is asymptotically a shrinkage forecast (Huang and Lee (2010); Jin et al. (2014)), bagging manifests itself as a computationally simpler alternative to commonly used lasso in the EPF literature to estimate the forecast models which incorporate large set of predictors.

When many predictors are available in a forecasting exercise, selection of appropriate subset of statistically significant explanatory variables is notoriously a long-standing question of econometric forecasting literature. Traditional econometric model selection procedures such as t-statistics or other data dependent methods like Akaike and Bayesian Information Criterions all introduce instability due to the model selection decision rules. As first explained by Breiman (1996a,b), bagging is a natural method to eliminate the side-effects of unstable decision rules and to harvest as much information as possible from available predictors. Theoretical advancements of bagging are well established. See Hall et al. (1995); Bühlmann and Yu (2002); Andrews (2004); Friedman and Hall (2007); Lee et al. (2010) among others. Lee and Yang (2006) extends the application of bagging to time series setting with asymmetric cost functions in a forecasting exercise of predicting signs and quantiles together with different bagging combination weights in addition to baseline version of equal weighting. In a recent research, Jin et al. (2014) elaborates on theoretical framework of time series applications of bagging, in particular, dependent time series data[1].

[1]Bagging was originally developed by Breiman (1996a,b) for independent and identically dis-

Empirical studies on bagging in forecasting macroeconomics variables is also intriguing. See Yu (2011); Bergmeir et al. (2016); Dantas and Cyrino Oliveira (2018) among others. Inoue and Kilian (2008) shows that bagging has similar forecast performance on U.S. Consumer Price Inflation using large number of macroeconomic series as explanatory variables, among many other sophisticated shrinkage methods including Bayesian shrinkage predictor, the ridge regression predictor, the iterated lasso predictor, or the Bayesian model average predictor based on random subsets of extra predictors. Rapach and Strauss (2010) applies bagging elegantly to predicting U.S. Employment Growth data with 30 potential predictors and finds motivating results in name of bagging against various forecast combination methods. Kim and Swanson (2014) carries out a "horse-race" on forecast of macroeconomic variables between number of forecasting models of shrinkage techniques including bagging, diffusion index models, factor models and some combination of different groups of forecast models. Despite its broad application in macroeconomic forecasting literature, to the best of our knowledge, bagging is never discussed in energy economics except a recent research of Zhao et al. (2017), which brings bagging into energy literature in the framework of WTI crude oil price forecasting using 198 economic series as explanatory variables. Considering both theoretical advancements of bagging in the time series analysis and successful empirical applications, bagging manifests itself as a promising tool for energy forecasting area.

Our contribution to electricity price forecasting is in two dimensions. First, we consider that how well the approach of baseline bagging forecast extends to the context of electricity prices in a multivariate setting. Using the day-ahead electricity price data from commonly studied markets of five major series and GEFCom2014 data, our empirical results suggest that, in parallel to the generalized shrinkage theory of Stock and Watson (2012), bagging forecast results are as accurate as lasso and even outperforms it in some markets. One important drawback of the lasso is that its high dependence on regularization parameter. This parameter determines the

tributed datasets. Theory of bagging was later extended to dependent data starting with "moving block bootstrap" and "block-block bootstrap", see Hall et al. (1995) and Andrews (2004).

shrinkage rate of the explanatory variables and even though it can be interpreted in various ways, it has no apparent economical meaning. On the other hand, bagging's forecasting performance relies on simple t-statistics which is the indicator of the statistical significance of the explanatory variable for which it is calculated. In any econometric model, corresponding t-values are used almost unanimously for significance levels of 1%, 5% and 10% and accepted as reasonable values. In this work, we share the forecasting results of bagging for all significance levels mentioned above and continuously find 1% significance level as the best performing model, interpreted as only "highly significant" explanatory variables should be included in electricity price forecasting models to obtain better forecasts. Another drawback of lasso is that it needs rather sophisticated optimization algorithms which may not be readily available to the forecaster. Whereas, bagging is simple to implement in any commonly used software routine [2].

Our second contribution relates the intra-day hourly dependencies of day-ahead electricity prices to latent factors estimated from a panel of day-ahead prices by means of augmenting existing models with that factors. Since factor augmentation captures the intra-day price dependencies as was studied by Maciejowska and Weron (2015, 2016), we augment the traditional models with factors estimated using principle components from the panel of intra-day prices selected via in-sample Bayesian Information Criterion. We find that in half of the markets, factor augmented expert model (fEXPERT) gives comparable results with the shrinkage methods. Expert models employed with factors capture the intra-day price effects (otherwise missing in multivariate modelling framework for expert models) and this in turn results in superior forecast performances. We also apply the factor augmentation exercise to multivariate large scale models with many explanatory variables. Similar results are obtained compared to the simple model (i.e. not factor-augmented version), proving that large scale models with many explanatory variables already contain hourly dependencies (and other information contained in factors) which also sup-

[2]The replication material and the forecasting toolbox in Gauss Aptech Programming language is available upon request by authors.

ports the findings of Ziel (2016). Overall, these findings suggest that parsimonious models, used in EPF context should be augmented with latent factors such that while they are is still abstract and interpretable they also capture the hourly dependency dimension of the electricity prices. Furthermore, factor augmentation is an important alternative to the univariate modeling because one of the most upcoming feature of univariate modeling over its multivariate counterpart is its ability to capture the intra-day hourly dependencies which, at least to some extend, is missing in the multivariate models where now we address this inadequacy through factor augmentation.

Remaining part is organized as follows. In section 2, we discuss the details of our data and data transformation for day-ahead hourly electricity prices. Then, in section 3, we construct econometric models including bagging and factor-augmented models and discuss their properties. In this section we also consider forecast performance evaluation techniques. Section 4 presents forecast performances of models and occurrence of variables. In section 5, we offer concluding thoughts.

CHAPTER 2

DATA

Our full sample is based on hourly data for 6 major electricity day-ahead price series, see Table 1. The GEFCom2014 dataset covers a 3-year period from January 1, 2011 to December 17, 2013, the remaining datasets cover a 6-year and 9-month period from January 1, 2013 to September 19, 2019. Five out of six datasets are from five major markets (hereby Markets) including Nordic Power Exchange Nord Pool for system price (NP.SYS) and for United Kingdom (NP.N2EX), Commonwealth Edison (COMED) zone in the PJM market from United States (PJM.COMED), OTE and OMIE which manage the Czech Republic (OTE.CZ) and Iberian market (OMIE.SP), respectively. Finally, the last series comes from the price track of the Global Energy Forecasting Competition 2014 (GEFCom2014). This series is included for allowing a cross comparison between forecast models utilized in different studies on flourishing literature of electricity price forecasting. The source of the data is not publicized by the organizers of the competition. Reader is referred to Hong et al. (2016) for details of this series. Price series (excluding GEFCom2014) are pre-processed to account for missing values and changes to/from daylight-saving-time as given in Uniejewski et al. (2016). The missing values (including the clock change in March) are set to average of two neighbor hours as well as the doubled hours (including the clock change in October) are averaged and substituted for the corresponding hour.

We consider 1470-day (ca.4-year) and 350-day (ca.1-year) out-of-sample period for the evaluation of day-ahead electricity price forecast for markets and GEFCom2014, respectively. This leaves, as estimation window, 983-day (ca.3-year) and 732-day (ca.2-year) for markets and GEFCom2014. The market's out-of-sample period covers from September 11, 2015 to September 19, 2019 whereas GEFCom2014's is from January 2, 2013 to December 17, 2013. Estimation is realized using a rolling estimation window following the previous literature. Rolling estimation window is also beneficial for Diebold and Mariano (1995) test (abbreviated DM) of predictive ability which is used extensively in the EPF literature to statistically judge the performance of competing forecast models and also utilized in this study. If expanding estimation window is employed, in the case of encompassing forecast models, i.e when the null hypothesis of equal predictive ability is true, since the forecast errors from competing models are equal and perfectly correlated, both numerator and denominator of the DM test converges to zero, as estimation sample grows . Virtue of the rolling window is due to the fact that number of data in estimation period always remains finite as sample size grows which renders the above pathological case invalid even if null of equal predictive ability is true. For further details we refer to Giacomini and White (2006) and Diebold (2015).

Recently, though, various other estimation window selection strategies are investigated as well as, in cooperation with forecast pooling approaches. Marcjasz et al. (2018) underlies that longer windows allow for more precise estimation of forecast models but short windows adapt changes well. They exploit the trade-off between these two approaches and together utilizing the forecast combination methods they propose a $WAW(T)$ approach. Hubicka et al. (2019) further elaborates on this idea and proposes some more specific estimation windows. Application of bagging in different estimation windows could be an interesting forecasting exercise and is left as a subject of future research.

Table 1: Summary of the day-ahead electricity price series

Electricity Market	Acronym	#of Data Points	oos	Source
Nord Pool (system price)	NP.SYS	58872/2453	35280/1470	nordpoolgroup.com
Nord Pool,UK	NP.N2EX	58872/2453	35280/1470	nordpoolgroup.com
PJM,USA	PJM.COMED	58872/2453	35280/1470	dataminer2.pjm.com
OTE price for the Czech Republic	OTE.CZ	58872/2453	35280/1470	ote-cr.cz
OMIE price for Spain	OMIE.SP	58872/2453	35280/1470	m.omie.es
GEFCom2014 competition data	GEFCom2014	25968/1082	8400/350	Hong et al. (2016)

Note: The table reports the summary of the power exchange data set considered. All series are in hourly resolution. Number of Data Points and length out-of-sample (oos) is given for univariate/multivariate setting, respectively. The GEFCom2014 dataset covers a 3-year period from Jan 1, 2011 to Dec 17, 2013, the remaining datasets – a 6-year and 9-month period from Jan 1, 2013 to Sep 19, 2019. NP.N2EX price is in terms of GBP/MWh, PJM.COMED and GEFCom2014 is in terms of USD/MWh and remaning series are in terms of EUR/MWh.

2.1 Data transformation

Electricity hourly price series exhibit severe spikes and their marginal distributions can be quite different from normal distribution. This renders the statistical inference of econometric models estimated using the raw series prone to severe problems and, in turn, results in inferior forecasting performances. In particular, among other forecasting methodologies, bagging estimation relies on simple t-statistics to determine the statistically significant explanatory variables. In this sense, inference process effects the results of bagging forecasts much more compared to other model estimation and forecasting techniques.

There is a vast literature on data transformation in time series literature. Even robust estimation techniques are proposed to be used in raw data which eliminate the need for data transformation (Huber and Ronchetti (2009)). A thorough examination of data transformation techniques utilized in EPF literature comes from Uniejewski et al. (2018). Among the proposed data transformation methods, the logarithmic transform is one of the simpler methods which answers the need of spike elimination and variance stabilization but it's major drawback is that it cannot be applied to the series where some of the prices go down to negative which is an increasingly observed phenomena in electricity markets[3]. Due to the merit order effect of increased renewable sources, some base-load power plants bid negative prices during off-peak times which is more advantageous compared to ramping down to zero output in terms of technical operational constraints. We therefore employ, in our empirical study in Section 4, another method called *area* (or *inverse*) *hyperbolic sine* transformation which was also applied elegantly by Ziel and Weron (2018). Define $Y_{d,h}$ as day-ahead price at day d and hour h and $y_{d,h}$ as *area hyperbolic sine* transformed version of that:

[3]See Uniejewski et al. (2016) for an application of logarithmic transform in EPF.

$$asinh(x) = log(x + \sqrt{x^2 + 1}) \quad (1)$$

$$y_{d,h} = asinh(\frac{Y_{d,h} - a}{b}) \quad (2)$$

where $x = \frac{1}{b}\{Y_{d,h} - a\}$, a and b are called shift and scale parameter, respectively. Following the Ziel and Weron (2018) and Uniejewski et al. (2018) we set the shift parameter equal to median of the estimation sample and the scale parameter equal to the sample median absolute deviation (MAD) around the sample median adjusted by a factor for asymptotically normal consistency to the standard deviation. This factor is $\frac{1}{z_{0.75}} \approx 1.4826$ where $z_{0.75}$ is the 75% quantile of the normal distribution. It is also noted that as $|x| \to \infty$ $asinh(x)$ asymptotically converges to $sign(x)log(2|x|)$.

Models are estimated using the asinh transformed series and forecasts are calculated. Once the forecast values are obtained, we apply inverse transform (*hyperbolic sine transform*) and compute the forecasted prices. Define $\hat{y}_{d,h}$ as the forecast of *area hyperbolic sine* transformed price at day d and hour h and $\hat{Y}_{d,h}$ as the inverse transformed version of that:

$$\hat{Y}_{d,h} = b \cdot sinh(\hat{y}_{d,h}) + a \quad (3)$$

CHAPTER 3

ECONOMETRIC METHODOLOGY

We consider multivariate modeling framework in which each hour of the day $h = 1, ..., 24$ is treated as a separate series and forecast next day's day-ahead price for a given hour h, i.e. the forecast horizon is equal to one. In what follows, denote the complete available sample of T observations and divide it into an in-sample portion of first R observations (estimation window) and out-of-sample period of remaining P observations and form a series, comprised of P observations of rolling window out-of-sample forecasts. We denote this series by $\{\hat{Y}_{d+1,h|d}\}_{d=R}^{T-1}$.

In terms of the exercises we carry out, our value added will be in introduction of bagging estimation method in electricity price forecasting and factor augmentation to exploit the intra-day dependencies of prices. This requires a comprehensive comparison of the results of newly introduced methods with commonly used and best performing methods in existing EPF literature. In below sections we explain them in detail.

3.1 Seasonal dummies

We define two types of dummy variables used in the econometric models. First one is the *day-of-the-week dummy* for l, where l stands for the days of the week from 0 (Sunday) to 6 (Saturday):

$$dow_{d,h}^{l} = \begin{cases} 1, & \text{if } d \text{ is the } l\text{-th day of the week,} \quad (4) \\ 0, & \text{oth.} \quad (5) \end{cases}$$

Next one is the *hour-of-the-week dummy* for l, where l stands for the hours of the week from 1 (Monday, $h = 1$) to 168 (Sunday, $h = 24$):

$$how^{l}_{d,h} = \begin{cases} 1, & \text{if } 24(d-1)+h \text{ is the } l\text{-th hour of the week,} \quad (6) \\ 0, & \text{oth.} \quad (7) \end{cases}$$

3.2 Models

Let us define a simple linear regression model represented in matrix form. Let $\mathcal{Y}_h$ denote an R-vector of observations for a given estimation window of R, $\mathcal{Y}_h = \begin{bmatrix} y_{d,h} & \dots & y_{d+R-1,h} \end{bmatrix}'$, $\mathcal{X}_h$ denote an $R \times k$ matrix that consists of columns of explanatory variables, $\mathcal{X}_h = \begin{bmatrix} \mathbb{X}'_{d,h} & \dots & \mathbb{X}'_{d+R-1,h} \end{bmatrix}'$, where $\mathbb{X}_{d,h}$ is a k-vector of transformed explanatory variables at day d for a given hour h, and $\boldsymbol{u}_h$ denote R-vector with typical element $\epsilon_{d,h}$, $d = 1, 2, \dots, T - R$. Then matrix notation of econometric model used in this study is given below:

$$\mathcal{Y}_h = \mathcal{X}_h \boldsymbol{\beta}_h + \boldsymbol{u}_h \tag{8}$$

where $\boldsymbol{\beta}_h$ is a k-vector of coefficients with typical element β_i, $i = 1, 2, \dots, k$.

We compute forecast of day-ahead electricity prices using the best performing and well-known existing models in the EPF literature, as well as bagging and factor augmented models, introduced in this study. Suppose we are interested in forming a forecast of $Y_{d+1,h}$ at time d. The procedure begins with the estimation of the general model given in Eq.(8) for the initial estimation window of fixed length of 983 for Markets and 732 for GEFCom2014. Using the estimated coefficients we substitute the most up-to-date values of explanatory variables and forecast the hourly price of first day of out-of-sample period for all 24 hours by setting the error term, $\boldsymbol{u}_h$, equal to its expected value of zero. This returns $\hat{y}_{t+1,h|t}$ for $t = R$ and substituting this into Eq. (3) one obtains $\hat{Y}_{t+1,h|t}$. Then, keeping the window lengths same, the window is rolled forward by one day and the second day of out of sample prices are forecasted. This procedure is repeated until the forecasts of last day of out-of-sample period (September 19, 2019 for Markets and January 1,2013 for GEFCom2014) are computed. The procedure applies to all as given in the following sections[4].

3.2.1 Mean$_{\mathbf{how}}$

This is a conventional benchmark model in the EPF literature. In this model, forecast of the day d and hour h is estimated computing the weekly mean of corresponding hour-of-week in the estimation window. **mean$_{\mathbf{how}}$** takes the form:

$$y_{d,h} = \sum_{j=1}^{168} \beta_j how_{d,h}^{j} + \epsilon_{d,h} \tag{9}$$

where $\epsilon_{d,h}$ is an error term. It is also possible to write "*day-of-the-week dummy*" version of this model utilizing Eq.(4) where forecast of the day d and hour h is estimated computing the daily mean of corresponding days for a given hour. In this study we consider first version since it has a superior forecasting performance compared to the latter. More details are given in Ziel and Weron (2018).

3.2.2 Naive

This model is another benchmark model introduced to EPF literature by Nogales et al. (2002) and classified under the similar days approach of Weron (2014). In this model, weekdays are divided into two categories. First, category contains Saturday, Sunday and Monday, whereas the second category contains the rest of the weekdays. Forecasts of first category days are set to previous week's same hour of the corresponding day. Forecasts of the second category days are set to previous day's same hour.We denote this model by **naive**:

$$Y_{d,h} = \begin{cases} Y_{d-7,h}, & \text{if } dow_{d,h}^{l} = 1 \text{ for } l = 0, 1, 6, \quad (10) \\ Y_{d-1,h}, & \text{oth.} \quad (11) \end{cases}$$

[4]Strictly speaking, **naive** model, which is explained in Section 3.2.2 is not represented by the general model given in Eq.(8), thus we exclude it from this definition.

As was discussed in several other studies, it was shown **naive**'s forecasting performance remains superior even compared with some of the advanced models (Uniejewski et al. (2016); Nogales et al. (2002); Conejo et al. (2005)).

3.2.3 Autoregressive model

Last benchmark model is the simple autoregressive model demeaned with $\bar{y}_{how,d,h}$, where $\bar{y}_{how,d,h}$ is the weekly mean of hourly frequency for asinh-transformed prices estimated with ordinary least squares (OLS) using Eq. (6), for each estimation window of 983-day (732-day for GEFCom2014). Let, p_h be the lag length for the AR process for a given hour h, the process can be denoted by AR(p_h):

$$y_{d,h} = \bar{y}_{how,d,h} + \psi_{h,0} + \sum_{i=1}^{p_h} \psi_{h,i}(y_{d-i,h} - \bar{y}_{how,d-i,h}) + \epsilon_{d,h} \qquad (12)$$

Following Ziel and Weron (2018) we set maximum lag length, $p_{h,max} = 8$. Lag length is chosen repeatedly for each estimation window using Akaike Information Criterion (AIC). Detailed explanations of information criterions used throughout the text is given in Appendix A. We estimate the model with OLS. To forecast next day's day-ahead price, we directly substitute corresponding prices without demeaning with respect to their weekly mean. We denote this model by $\mathbf{AR_{how}}$. Later in the text, we extend this model adding estimated factors.

3.2.4 Expert

Expert models manifest themselves being abstract and parsimonious. In this sense, they are very valuable for daily applications. There are various versions of expert models are proposed in the EPF literature after Misiorek et al. (2006)'s first contribution. See (Weron (2006); Weron and Misiorek (2008); Kristiansen (2012); Nowotarski et al. (2014a); Ziel (2016); Maciejowska et al. (2016); Uniejewski et al. (2016); Uniejewski and Weron (2018); Ziel and Weron (2018) among others. Since these models are built upon field knowledge of experts they are denoted as *expert*.

We consider below model which is also utilized by Ziel and Weron (2018)[5]:

$$
\begin{aligned}
y_{d,h} =& \beta_{h,1} + \underbrace{\beta_{h,2} y_{d-1,h} + \beta_{h,3} y_{d-2,h} + \beta_{h,4} y_{d-7,h}}_{\text{autoregressive effects}} \\
&+ \underbrace{\beta_{h,5} y_{d-1,min} + \beta_{h,6} y_{d-1,max}}_{\text{non-linear effects}} \\
&+ \underbrace{\beta_{h,7} y_{d-1,24}}_{\text{last-hour effect}} + \underbrace{\sum_{i=1}^{6} \beta_{h,7+i} dow_{d,h}^{i}}_{\text{weekday dummies}} \\
&+ \underbrace{\sum_{i=1}^{6} \beta_{h,13+i} dow_{d,h}^{i} y_{d-1,h} + \sum_{i=1}^{6} \beta_{h,19+i} dow_{d,h}^{i} y_{d-1,24}}_{\text{periodic effects}} + \epsilon_{d,h}
\end{aligned}
\tag{13}
$$

where $y_{d-1,min} = \min_{\text{h=1, ..., 24}} \{y_{d-1,h}\}$ and $y_{d-1,max} = \max_{\text{h=1, ..., 24}} \{y_{d-1,h}\}$ are minimum and maximum of previous day's hourly prices and, together, we call these regressors non-linear effects. They contain information about previous day's extreme price levels. $y_{d-1,24}$, on the other hand, represents the price of the last hour of previous day where as recent literature shows price of early morning hours are sensitive to the last-hour effect, as we call it (Maciejowska and Nowotarski (2016)). Day-of-week dummies and periodic effects emphasize the short-term seasonality components of the hourly prices.

For $h = 24$, we drop $y_{d-1,24}$ due to the multicollinearity between $\beta_{h,7}$ and $\beta_{h,2}$, we also drop $dow_{d,h}^{i} y_{d-1,24}$ again due to a multicollinearity between $\beta_{h,13+i}$ and $\beta_{h,19+i}$, for $i = 1, \ldots, 6$. Consequently, we estimate 25 parameters (18 for $h = 24$) using OLS. We denote this model by **EXPERT**. Later in the text, we extend this model adding estimated factors.

[5]This version is the the most generic version of the Expert model employed in the main text of Ziel and Weron (2018), please see Eq. (A.1) in their Appendix. Also see **mAR1hm** and **AR2hm** models of Uniejewski et al. (2016)

3.2.5 Large scale models and shrinkage estimation procedures

A challenging situation in a forecasting exercise is that availability of plenty of other useful predictors to the forecaster. One way of selecting the most informative predictors among them is to rely on expert knowledge and past experiences together with utilizing the commonly accepted results in the literature. One prominent example of this, as we also implement in Section 3.2.4, is the Expert Models. Further forecast improvements, however, can still be gained by harvesting useful information by incorporating many other predictors into forecasting model. But there is a well established literature stating that incorporating many predictors in a model may lead overfitting and hence worse off the forecast performance. On the other hand, selecting only a subset of available predictors may cause loss of information and unstable and unreliable forecasts since some variables may perform better in some periods and deteriorate the results in rest of the time (see e.g. Stock and Watson (2003)). This situation is particularly relevant for the EPF literature. Thus, there is an apparent need for a formal estimation procedure while utilizing all available variables and extracting as much information as possible and also making the models reliable, i.e. purifying them from pathological effects of over estimation and instability arising from predictor selection. This calls shrinkage estimation methods.

In our forecasting exercise with a large scale model, we mainly focus on **B**ootstrap **Agg**regation, i.e. **bagging** procedure of Breiman (1996a,b). Bagging is a natural method to eliminate the side-effects of unstable decision rules and to harvest as much information as possible from available predictors and by definition it is a shrinkage method. The key idea is to resample the original data, i.e. sampling from the empirical distribution of the data, and constructing new datasets. Up to this part, is the bootstrap half of the bagging. Each newly created dataset used one at the time to estimate the models, where each estimated model contains a different information from the imitated dataset, leads to extraction of as much explanatory power from the original dataset as possible. Combining (e.g. simple averaging) forecast results, from the models estimated with imitated datasets, constitutes the remaining half of the bagging which is called aggregation.

Consider the general model given in Eq. (8). We begin by establishing some definitions for bagging estimation procedure. Let $\hat{y}_{d+1,h|d}$ is the forecast of $y_{d+1,h}$ based on the most recent observations available. Let $\hat{\boldsymbol{\beta}}_h$ denote the OLS estimator of $\boldsymbol{\beta}_h$ in Eq. (8). Also let t_i denote the t-statistic for which null of β_i is equal to zero in the model where β_i is equal to i-th element of $\boldsymbol{\beta}_h$, $i = 1, 2, \ldots, k$ [6]. Form a $R \times l$ pretested (PT) predictor matrix by deleting the i-th column of $\mathcal{X}_h$, if $|t_i| < t_c$ and denote it with $\mathcal{X}_h^{PT}$, where $1 \leq l \leq k$ and t_c is the critical value of the t-test [7]. Define its corresponding row as $\mathbb{X}_{d,h}^{PT\prime}$. Using PT predictor matrix, one can estimate below compact model with OLS:

$$\mathcal{Y}_h = \mathcal{X}_h^{PT} \boldsymbol{\eta}_h + \boldsymbol{\zeta}_h \tag{14}$$

where $\boldsymbol{\eta}_h$ is a l-vector of coefficients with typical element η_j, $j = 1, 2, \ldots, l$. Then PT forecast of $y_{d+1,h}$ is denoted by $\hat{y}_{d+1,h|d}^{PT}$ and given by the next equation:

$$\hat{y}_{d+1,h|d}^{PT} = \begin{cases} 0, & if |t_i| < t_c \forall i, \\ \mathbb{X}_{d+1,h}^{PT\,\prime} \hat{\boldsymbol{\eta}}_h, & oth. \end{cases} \tag{15}$$

where $\hat{\boldsymbol{\eta}}_h$ is the OLS estimator of $\boldsymbol{\eta}_h$ in Eq. (14). To compute PT forecast, first, we fit Eq. (8) and calculate the t-statistic for each predictor and conduct a two-sided t-test on each coefficient and discard the insignificant variables and estimate the Eq. (14). After that, we calculate the PT forecast from Eq. (15).

We utilize from PT forecast in constructing bootstrap aggregated forecasts as follows. Construct a $R \times (k+1)$ matrix by combining $\mathcal{Y}_h$ and $\mathcal{X}_h$ as given below:

[6] The t-statistics for the OLS estimates of Eq. (8) are computed using Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors.

[7] In the empirical analysis,unless otherwise stated, we consider as t_c values, 2.58, 1.96, and 1.65 for 1%, 5% and, 10% significance levels, respectively.

$$\begin{bmatrix} y_{d,h} & \mathbb{X}'_{d,h} \\ y_{d+1,h} & \mathbb{X}'_{d+1,h} \\ \vdots & \vdots \\ y_{d+R-1,h} & \mathbb{X}'_{d+R-1,h} \end{bmatrix}$$

After that, generate imitated or psuedo-samples by randomly drawing blocks of (overlapping) size m with replacement from the above matrix and form bootstrap samples [8]:

$$\begin{bmatrix} y^*_{d,h} & \mathbb{X}^{*\prime}_{d,h} \\ y^*_{d+1,h} & \mathbb{X}^{*\prime}_{d+1,h} \\ \vdots & \vdots \\ y^*_{d+R-1,h} & \mathbb{X}^{*\prime}_{d+R-1,h} \end{bmatrix}$$

For each psuedo-sample fit Eq. (8), apply the pretesting procedure as explained above and estimate the Eq. (14). Forecast of each randomly generated sample is given in (16).

$$\hat{y}^{*PT}_{d+1,h|d} = \begin{cases} 0, & if \left|t^*_i\right| < t_c \forall i, \\ \mathbb{X}^{*PT}_{d+1,h}{}' \hat{\boldsymbol{\eta}}^*_h, & oth. \end{cases} \tag{16}$$

where $\hat{y}^{*PT}_{d+1,h|d}$, $\mathbb{X}^{*PT\prime}_{d,h}$, t^*_i, and, $\hat{\boldsymbol{\eta}}^*_h$ are bootstrap analogs of $\hat{y}^{PT}_{d+1,h|d}$, $\mathbb{X}^{PT\prime}_{d,h}$, t_i, and, $\hat{\boldsymbol{\eta}}_h$. Finally, the bagging forecast is the expectation of the bootstrap pretested forecasts across bootstrap samples (Inoue and Kilian (2008))[9]:

$$\hat{y}^{ba}_{d+1,h|d} = \mathbb{E}^* \hat{y}^{*PT}_{d+1,h} \tag{17}$$

[8]In time series application, data dependency is an important phenomena which effects the performance of bagging. To address the possible data dependency problem block bootstrap is proposed instead of regular bootstrap. Given that m is the block length, in time series forecasting applications m is set equal to forecast horizon (Gonçalves and Kilian (2004)). In our empirical analysis, we forecast for the next day's day-ahead price, that is why following Inoue and Kilian (2008) and Rapach and Strauss (2010) we set $m = 1$ implying we are effectively considering regular bootstrap. For a textbook treatment of time series applications of bootstrap we refer Davison and Hinkley (1997) and, Chapter 8 particularly for dependent data applications.

[9]We abbreviate bagging model as "BA" or "ba" in the text.

where $\mathbb{E}^*$ denotes the expectation operator with respect to the bootstrap probability measure. Let B equal to total number of randomly generated psuedo-samples. In theory, $B \to \infty$, but in our empirical study, following the Inoue and Kilian (2008) and Rapach and Strauss (2010), we set $B = 100$. In application, the bootstrap expectation may be estimated by:

$$\hat{y}^{ba}_{d+1,h|d} = \frac{1}{B}\sum_{b=1}^{B} \hat{y}^{*PT}_{d+1,h,b|d} \tag{18}$$

where $\hat{y}^{*PT}_{d+1,h,b|d}$ is the pretested forecast computed using the b-th bootstrap sample. Substituting the $\hat{y}^{ba}_{d+1,h|d}$ into Eq. (3), one can easily solve for $\hat{Y}^{ba}_{d+1,h|d}$. In Eq. (18), i.e. in aggregation part of bagging, we assign equal weight to each bootstrapped forecast. In principle, equal weighting is not a necessity, bagging predictor can be estimated with data-dependent techniques, as well (see e.g. Yu (2011)).

Other shrinkage method that we study in our framework is the **L**east **A**bsolute **S**hrinkage and **S**election **O**perator (lasso) due to Tibshirani (1996). Unlike bagging lasso has been applied in various electricity price forecasting exercises and showed superior forecasting performance compared to other conventional non-shrinkage methods in the EPF literature. One other prominent property of lasso is it's ability to set some variables equal to zero. In this sense lasso is also a variable selection procedure. But from the forecasting performance point of view, shrinkage property does the job (Ziel and Weron (2018)). We standardize the variables in the general forecasting model given in Eq. (8), i.e. set variance equal to one and mean equal to zero. Let $\tilde{\mathcal{Y}}_h$ and $\tilde{\mathcal{X}}_h$ be the columnwise standardized analogs of $\mathcal{Y}_h$ and $\mathcal{X}_h$, respectively. Then lasso estimator can be written in terms of standardized variables as (Hastie et al. (2015)) [10]:

$$\hat{\tilde{\boldsymbol{\beta}}}_{h,\lambda} = \underset{\tilde{\boldsymbol{\beta}}_h}{\operatorname{argmin}}\{\|\tilde{\mathcal{Y}}_h - \tilde{\mathcal{X}}_h\tilde{\boldsymbol{\beta}}_h\|_2^2 + \lambda\|\tilde{\boldsymbol{\beta}}_h\|_1\} \tag{19}$$

[10] $\|.\|_2$ is the usual Euclidean norm and $\|\tilde{\boldsymbol{\beta}}_h\|_1 = \sum_{i=1}^{k} \tilde{\beta}_i$

where λ refers to regularization parameter of lasso. Setting $\lambda = 0$, Eq. (19) turns to be a simple OLS estimation, whereas, as λ grows more and more parameters are set to zero and in the limiting case, i.e. as $\lambda \to \infty$, all parameters are forced to be zero. $\hat{\boldsymbol{\beta}}_{h,\lambda}$ can be obtained from $\hat{\tilde{\boldsymbol{\beta}}}_{h,\lambda}$ through rescaling. As it was mentioned earlier, lasso estimation results highly depend the regularization parameter, λ. We consider two different regularization parameter selection procedure. First one is using the in-sample information criterion, which is denoted by IC, and second one is the ex-post selection procedure denoted by $Post$. In Appendix B, λ selection procedures are given in detail.

We study the ability of bagging to reduce the prediction error. Formally, we are concerned with the usefulness of bagging in forecasting time series of electricity prices from linear multiple regression models in a multivariate setting. Together, various extensions of lasso are also considered. Both bagging and lasso make use of large scale models in the EPF literature in terms of selecting the most relevant variables among many predictors thus one can incorporate all available predictors into a general model and step back and leave the variable selection procedure to the estimation technique used. Having said this, we propose a large scale model, i.e. model with many predictors, which is inspired from Ziel and Weron (2018)[11]. This is called Large Scale pure-price model and defined in the next equation:

$$
\begin{aligned}
y_{d,h} = & \underbrace{\sum_{i=1}^{8}\sum_{j=1}^{24} \mu_{h,i,j,1} y_{d-i,j}}_{\text{price autoregressive effects}} + \underbrace{\sum_{i=1}^{8} \mu_{h,i,1,2} y_{d-i,min} + \sum_{i=1}^{8} \mu_{h,i,1,3} y_{d-i,max}}_{\text{price non-linear effects}} \\
& + \underbrace{\sum_{i=1}^{7} \mu_{h,i,1,4} dow^{i}_{d,h}}_{\text{weekday dummies}} + \underbrace{\sum_{i=1}^{7} \mu_{h,i,1,5} dow^{i}_{d,h} y_{d-1,avg}}_{\text{average price effects}} \\
& + \underbrace{\sum_{i=1}^{6} \mu_{h,i,1,6} dow^{i}_{d,h} y_{d-1,h} + \sum_{i=1}^{6} \mu_{h,i,1,7} dow^{i}_{d,h} y_{d-1,24}}_{\text{price periodic effects}} + \epsilon_{d,h}.
\end{aligned} \tag{20}
$$

[11] See Eq. (13) in their main text.

where, $y_{d,avg}$ is the average hourly day-ahead price at time d. The model contains 234 explanatory variables for $h = 1, \ldots, 23$. For the last hour of the day, we drop the second term in *"price periodic effects"*, since it creates a multicollinearity with the first term, thus we have 228 variables in total. We denote this model by **BA_LS1**, **BA_LS5**, and **BA_LS10** when it is estimated with bagging using the corresponding t_c value for 1%, 5% and, 10% significance levels, respectively. We further denote it by **LASSO_LS$^{\mathbf{IC}}$** and **LASSO_LS$^{\mathbf{Post}}$** when it is estimated with lasso by selecting regularization parameter with information criterion and with ex-post manner, respectively.

3.2.6 Factor-augmented models

One major drawback of multivariate modeling is that it lacks intra-day hourly dependencies. To capture the intra-day dependencies a VAR model can be considered, but this dramatically increases the total number of parameters needed to be estimated which renders the estimation procedure infeasible for the small sample sizes. Another alternative is to utilize univariate modeling. In univariate modeling, contrary to multivariate models, one large model is considered. This helps to capture the intra-day hourly dependencies with a cost of accumulated errors as the error of the previous hour's forecast extends to the next hour's simply because it is used as the most up-to-date price information available. One other disadvantage of univariate modeling is the increased estimation time due 24-times greater sample size and model size compared to multivariate case. Therefore, in order to capture those intra-day dependencies, we propose factor-augmented models. The factor-augmented models are easy and fast to estimate and since the multivariate structure is preserved they are more tractable. In essence, we extend the models explained in previous sections and augment them with the factors computed from the panel of price series, $R \times 24$. In other words, we keep the existing predictors and add computed factors as explanatory variables into the models. As stated above, we propose and motivate this modeling strategy from the fact that multivariate models lack intra-day dependencies and estimated factors capture this dependency because intuitively they represent co-movements of hourly prices in different degrees.

Factor models were previously employed in EPF literature by Maciejowska and Weron (2016) and Ziel (2016) sharing the same motivation as explained here. Our modeling and implementation strategy for factor models, however, differs from existing ones in various dimensions. First, we augment the existing models with factors, whereas current literature directly forecast factors with AR and ARX type models, see e.g. Eq. (15) and (16) in Ziel (2016) or PC_N and $PC_N X$ models, Eq. (9) and (10) in Maciejowska and Weron (2016). Second, we choose the total number of factors out of 24, using an in-sample information criterion, namely BIC, in OLS estimated models. But the current literature does not propose a data-dependent factor selection procedure, instead, fixed number of factors is considered in Maciejowska and Weron (2016) which is equal to first five factors and Ziel (2016) exercises with first two to twelve factors.

We estimate the latent factors for each estimation window using the panel of raw (not transformed) price series. The $\boldsymbol{Y}$ matrix has hour of day in its twenty-four columns with each row corresponding to price of the hour in the estimation window. In other words, The $\boldsymbol{Y}$ is the price matrix for an estimation window of length R with a typical column of $\boldsymbol{Y}_h = \begin{bmatrix} Y_{d,h} & \dots & Y_{d+R-1,h} \end{bmatrix}'$, $\boldsymbol{Y} = \begin{bmatrix} \boldsymbol{Y}_1 & \dots & \boldsymbol{Y}_{24} \end{bmatrix}_{R\times 24}$. The factor structure is:

$$\boldsymbol{Y} = \boldsymbol{F}\boldsymbol{\Lambda} + \boldsymbol{\epsilon} \tag{21}$$

where $\boldsymbol{F}$ is the common latent factors, with the n-th column is equal to $\boldsymbol{F}_n = \begin{bmatrix} F_{d,n} & \dots & F_{d+R-1,n} \end{bmatrix}'$, $\boldsymbol{\Lambda}$ is the 24×24 factor loadings matrix, and $\boldsymbol{\epsilon}$ is the idiosyncratic variation of prices at different hours, $n = 1, \dots, 24$. We also arrange factors according to decreasing values of corresponding eigenvalues. In other words, we set $n = 1$ for the factor with the highest explanatory power and $n = 2$ for the factor with the second highest explanatory power and so on. We estimate the factors-common drivers of price changes-by principal components. Let $\boldsymbol{f}_n = \begin{bmatrix} f_{d,n} & \dots & f_{d+R-1,n} \end{bmatrix}'$, be the $asinh$ transformed version of the original factor $\boldsymbol{F}_n$. In below models, transformed version of the estimated factors are considered.

The latent factors, $\boldsymbol{F}$, do not have clean interpretations or any economic meaning. In order to make them economically interpretable they should be identified by imposing constraints to factor loadings [12]. This process is called factor rotation and is a commonly used technique at event study analysis, see for a very informative and elegant application (Gürkaynak et al., 2004, and references therein).

We apply factor augmentation to $\mathbf{AR_{how}}$, **EXPERT**, $\mathbf{LASSO\_LS^{IC}}$, and **BA_LS1**. We denote factor-augmented $\mathbf{AR_{how}}$ model by $\mathbf{fAR_{how}}$. It forms:

$$y_{d,h} = \bar{y}_{how,d,h} + \psi_{h,0} + \sum_{i=1}^{p_h} \psi_{h,i}(y_{d-i,h} - \bar{y}_{how,d-i,h}) + \sum_{n=1}^{N} \alpha_n f_{d-1,n} + \epsilon_{d,h} \tag{22}$$

We also denote factor-augmented **EXPERT** model by **fEXPERT** and it is given in the next equation:

$$\begin{aligned} y_{d,h} =& \beta_{h,1} + \underbrace{\beta_{h,2}y_{d-1,h} + \beta_{h,3}y_{d-2,h} + \beta_{h,4}y_{d-7,h}}_{\text{autoregressive effects}} + \underbrace{\beta_{h,5}y_{d-1,min} + \beta_{h,6}y_{d-1,max}}_{\text{non-linear effects}} \\ &+ \underbrace{\beta_{h,7}y_{d-1,24}}_{\text{last-hour effect}} + \underbrace{\sum_{i=1}^{6} \beta_{h,7+i} dow^i_{d,h}}_{\text{weekday dummies}} \\ &+ \underbrace{\sum_{i=1}^{6} \beta_{h,13+i} dow^i_{d,h} y_{d-1,h} + \sum_{i=1}^{6} \beta_{h,19+i} dow^i_{d,h} y_{d-1,24}}_{\text{periodic effects}} + \underbrace{\sum_{n=1}^{N} \alpha_n f_{d-1,n}}_{\text{intra-day effects}} + \epsilon_{d,h} \end{aligned} \tag{23}$$

Factor-augmented **BA_LS1**, and $\mathbf{LASSO\_LS^{IC}}$ models are denoted by **fBA_LS1**, and $\mathbf{fLASSO\_LS^{IC}}$. Since the model structure is the same and the only thing that changes is the estimation technique below equation holds for both models:

[12] Maciejowska and Weron (2016) interprets first three factors intuitively.

$$
\begin{aligned}
y_{d,h} = & \underbrace{\sum_{n=1}^{24} \alpha_n f_{d-1,n}}_{\text{intra-day effects}} + \underbrace{\sum_{i=1}^{8}\sum_{j=1}^{24} \mu_{h,i,j,1} y_{d-i,j}}_{\text{price autoregressive effects}} + \underbrace{\sum_{i=1}^{8} \mu_{h,i,1,2} y_{d-i,min} + \sum_{i=1}^{8} \mu_{h,i,1,3} y_{d-i,max}}_{\text{price non-linear effects}} \\
& + \underbrace{\sum_{i=1}^{7} \mu_{h,i,1,4} dow_{d,h}^{i}}_{\text{weekday dummies}} + \underbrace{\sum_{i=1}^{7} \mu_{h,i,1,5} dow_{d,h}^{i} y_{d-1,avg}}_{\text{price average effects}} \\
& + \underbrace{\sum_{i=1}^{6} \mu_{h,i,1,6} dow_{d,h}^{i} y_{d-1,h} + \sum_{i=1}^{6} \mu_{h,i,1,7} dow_{d,h}^{i} y_{d-1,24}}_{\text{price periodic effects}} + \epsilon_{d,h}.
\end{aligned} \tag{24}
$$

Total number of factors, i.e. N, in the $\mathbf{fAR_{how}}$ and **fEXPERT**, models is chosen according to in-sample Bayesian Information Criterion. In the Large Scale pure-price model, we insert all twenty-four factors into the model, thus factor-augmented version of that model contains 258 parameters (252 for $h = 24$).

3.3 Forecast performance evaluation

In empirical analysis, we compare forecast performance of models, given in above sections, in terms of Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean of Weekly-weighted Mean Absolute Error ($\overline{\text{WMAE}}$) [13]:

$$
\text{MAE} = \frac{1}{24P} \sum_{i=1}^{P} \sum_{j=1}^{24} \left| \hat{\epsilon}_{i,j} \right| \tag{25}
$$

$$
\text{RMSE} = \sqrt{\frac{1}{24P} \sum_{i=1}^{P} \sum_{j=1}^{24} (\hat{\epsilon}_{i,j})^2} \tag{26}
$$

[13] Forecast performance evaluation techniques are vast in econometric forecasting literature. Particularly for the EPF literature, we refer reader to Hyndman and Koehler (2006); Nowotarski et al. (2014b); Nowotarski and Weron (2016).

$$\overline{\text{WMAE}} = \frac{1}{P/7}\sum_{k=1}^{P/7}\left(\frac{\sum_{i=7k-6}^{7k}\sum_{j=1}^{24}|\hat{\epsilon}_{i,j}|}{\sum_{i=7k-6}^{7k}\sum_{j=1}^{24}Y_{i,j}}\right) \tag{27}$$

where, P is the number of days in the out-of-sample period, $\hat{\epsilon}_{i,j} = \hat{Y}_{i,j|i-1} - Y_{i,j}$ for the out-of-sample period. Note that it is required that out-of-sample period must be a multiple of seven or a week to calculate the $\overline{\text{WMAE}}$. Thus, while computing the $\overline{\text{WMAE}}$ only full weeks are taken into account. In our empirical analysis, we consider 1470 days for markets (350 days for GEFCom2014) out-of-sample window length which corresponds to 210 weeks (50 weeks) in total. Notice that, RMSE is the optimal loss function for any forecast exercise we consider in this study. Recall from above sections that we are interested in $\hat{Y}_{d+1,h|d}$ which corresponds to forecast of $Y_{d+1,h}$, in other words, from Eq. (8), we want to find $\mathbb{E}(Y_{d+1,h}|\mathbb{X}_{d+1,h})$. When a quadratic loss function is considered, this means one chooses $\hat{Y}_{d+1,h|d}$ such that $\mathbb{E}(Y_{d+1,h} - \hat{Y}_{d+1,h|d})^2$ is minimized. This optimization process sets $\hat{Y}_{d+1,h|d}$ equal to $\mathbb{E}(Y_{d+1,h}|\mathbb{X}_{d+1,h})$, i.e. $\hat{Y}_{d+1,h|d} = \mathbb{E}(Y_{d+1,h}|\mathbb{X}_{d+1,h})$. For a more detailed theoretical exposition we refer to Hamilton (1994). In empirical application, MAE and $\overline{\text{WMAE}}$ are more robust to outliers compared to RMSE (Uniejewski et al. (2019)). In our forecasting exercise, we present results for each loss function, separately.

We also consider hourly performances of the models in terms of hourly Mean Absolute Error (MAE_h) and hourly Root Mean Squared Error (RMSE_h) for $h = 1, \ldots, 24$:

$$\text{MAE}_h = \frac{1}{P}\sum_{i=1}^{P}|\hat{\epsilon}_{i,h}| \tag{28}$$

$$\text{RMSE}_h = \sqrt{\frac{1}{P}\sum_{i=1}^{P}\hat{\epsilon}_{i,h}^2} \tag{29}$$

We further evaluate forecast models in terms of forecast encompassing test. The virtue of forecast encompassing test comes from its ability to draw formal statistical conclusions between different forecasting models. If, say, Model-A encompasses Model-B, this implies there is no extra information in the latter model beyond that contained in the first one or vice versa. If both models fail to encompass each other this implies both of them contains valuable information absent in either model. This procedure allows us to investigate formally whether one model outperforms other. We consider Diebold and Mariano (1995) test (abbreviated DM) as the forecast encompassing test.

We implement standart DM test for 24 h of the day separately. Consider the loss differential series for Model-A and B:

$$\Delta_{A,B,d,h} = \left|\hat{\epsilon}_{A,d,h}\right| - \left|\hat{\epsilon}_{B,d,h}\right| \tag{30}$$

where, $\hat{\epsilon}_{X,d,h}$ is the prediction error of model X, $X = A, B$ at time d for a given hour h. Assuming that loss differential series are covariance stationary, we pairwise compute p-values of two one-sided tests for each dataset: where null of $H_0 : \mathbb{E}(\Delta_{A,B,d,h}) \leq 0$ implies that Model-A encompasses B, whereas null of $H_0 : \mathbb{E}(\Delta_{A,B,d,h}) \geq 0$ implies Model-B encompasses A for hour h. Rejection of both nulls at the same time means failure of models to encompass each other for hour h.

Following Ziel and Weron (2018), we also consider "*multivariate*" DM test which allows us to derive a single statistic for each forecasting model instead of 24. Loss differential series for multivariate DM test is:

$$\Delta_{A,B,d} = \sum_{i=1}^{24}\left|\hat{\epsilon}_{A,d,i}\right| - \sum_{i=1}^{24}\left|\hat{\epsilon}_{B,d,i}\right|. \tag{31}$$

Again assuming that loss differential series are covariance stationary, we pairwise compute p-values of two one-sided tests for each dataset: where null of $H_0 : \mathbb{E}(\Delta_{A,B,d}) \leq 0$ implies that Model-A encompasses B, whereas null of $H_0 : \mathbb{E}(\Delta_{A,B,d}) \geq 0$ implies Model-B encompasses A considering all 24 h of the day. Rejection of both nulls at the same time means failure of models to encompass each other considering all 24 h of the day.

CHAPTER 4

EMPIRICAL RESULTS

4.1 Forecast results

Table 2 reports the MAE, RMSE, and $\overline{\text{WMAE}}$ results for bagging and other conventional forecasting models together with factor augmented versions as defined in Section 3.2. Results are given for six datesets over the out-of-sample period of 1470-day for markets and 350-day for GEFCom2014. We formally compare predictive accuracy of forecast models with DM test as explained earlier. Figure 1 shows multivariate DM test results for each datasets and Figure 2 presents standard DM test where each cell indicates total number of hours out of 24 for which model on the X-axis encompasses model on the Y-axis at 5% significance level. Since we observe similar patterns for different loss metrics we compute DM test results in terms of Mean Absolute Error.

Table 2 Panel A shows that shrinkage estimation methods (i.e. bagging and lasso) outperform benchmark models (i.e. $\mathbf{mean_{how}}$, **naive**, $\mathbf{AR_{how}}$). This result is also valid in Panel B and C. This is also confirmed by both multivariate and standard DM test results. Benchmark models are always encompassed by the remaining models and this holds for almost all hours of day as given in Figure 2. In sharp contrast to benchmark models, **EXPERT** gives very close results to large scale shrinkage models. Even thought it is encompassed by **BA_LS1** in five of the series according to the DM test results, it is very promising model in terms of forecast loss function.

Before comparing the forecast abilities of bagging and lasso, we discuss the effect of regularization parameter on lasso estimation. The regularization parameter, λ, is the main determinant of the performance of the lasso estimation as explained in above sections. We maximize in sample information criterion to determine the λ in $\mathbf{LASSO\_LS^{IC}}$. But this may result in sub-optimal forecast performances and

Table 2: Forecasting results for bagging and other conventional day-ahead price forecasting models

Panel (A): Mean Absolute Errors (MAE)

Market	mean_{how}	naive	AR_{how}	EXPERT	$\text{LASSO\_LS}^{\text{IC}}$	$\text{LASSO\_LS}^{\text{Post}}$	BA_LS1	BA_LS5	BA_LS10	fAR_{how}	fEXPERT	$\text{fLASSO\_LS}^{\text{IC}}$	fBA_LS1
NP.SYS	8.306	2.991	2.625	2.122	2.104	2.075	**2.042**	2.130	2.228	2.375	2.156	2.166	2.054
NP.N2EX	10.154	5.951	5.055	4.768	4.618	**4.591**	4.620	4.668	4.779	4.917	4.745	4.634	4.653
PJM.COMED	7.811	5.113	4.077	3.594	3.461	3.431	3.325	**3.313**	3.349	4.183	3.462	3.367	3.388
OTE.CZ	9.918	7.466	7.329	5.366	5.306	5.272	**5.246**	5.262	5.413	6.671	5.304	5.354	5.344
OMIE.SP	10.136	5.615	5.103	3.860	3.974	3.958	**3.798**	3.799	3.879	4.381	3.829	3.990	3.826
GEFCom2014	15.065	9.463	8.194	7.348	7.257	7.225	**7.047**	7.068	7.197	8.153	7.357	7.333	7.091

Panel (B): Root Mean Squared Error (RMSE)

Market	mean_{how}	naive	AR_{how}	EXPERT	$\text{LASSO\_LS}^{\text{IC}}$	$\text{LASSO\_LS}^{\text{Post}}$	BA_LS1	BA_LS5	BA_LS10	fAR_{how}	fEXPERT	$\text{fLASSO\_LS}^{\text{IC}}$	fBA_LS1
NP.SYS	11.210	5.667	4.713	4.187	4.215	**3.977**	4.232	5.014	5.807	4.358	4.521	4.808	4.255
NP.N2EX	18.780	18.560	13.902	13.809	13.573	**13.522**	13.576	13.595	13.682	13.819	14.454	13.778	13.663
PJM.COMED	14.105	10.743	8.432	8.192	8.029	7.821	7.351	7.074	**7.017**	25.425	8.475	7.219	7.451
OTE.CZ	13.785	11.287	10.447	8.070	8.004	**7.931**	7.941	7.937	8.144	9.635	8.005	8.077	8.026
OMIE.SP	12.901	8.305	7.141	5.399	5.447	5.412	5.333	**5.307**	5.398	6.162	5.362	5.467	5.358
GEFCom2014	31.220	18.082	16.117	15.387	15.336	15.027	13.813	**13.493**	13.511	17.385	15.597	15.082	14.076

Panel (C): Mean of Weekly-weighted Mean Absolute Error ($\overline{\text{WMAE}}$)

Market	mean_{how}	naive	AR_{how}	EXPERT	$\text{LASSO\_LS}^{\text{IC}}$	$\text{LASSO\_LS}^{\text{Post}}$	BA_LS1	BA_LS5	BA_LS10	fAR_{how}	fEXPERT	$\text{fLASSO\_LS}^{\text{IC}}$	fBA_LS1
NP.SYS	40.495	15.924	13.834	11.032	10.847	10.752	**10.664**	11.106	11.612	12.319	11.058	11.085	10.742
NP.N2EX	36.188	21.570	18.295	17.208	16.699	**16.605**	16.723	16.899	17.308	17.789	17.102	16.753	16.847
PJM.COMED	42.348	26.860	21.230	18.502	17.630	17.486	17.221	**17.210**	17.472	19.824	17.596	17.468	17.446
OTE.CZ	43.707	35.611	34.410	25.146	24.798	**24.659**	24.696	24.784	25.461	31.236	24.813	24.968	25.143
OMIE.SP	38.675	21.231	19.439	14.669	14.966	14.894	14.386	**14.361**	14.622	16.595	14.533	15.002	14.427
GEFCom2014	37.329	26.026	22.275	19.473	19.302	19.222	19.341	19.598	20.094	21.471	19.531	19.616	**19.125**

Note: The table reports the model forecasting results calculated for full out-of-sample period as defined by Eq. (25), (26), *and* (27), *respectively. Best performing model result is indicated with boldface in each dataset.*

may not be the best available lasso estimated model to compare with bagging. That is why, following Uniejewski et al. (2019), we also consider a hypothetical forecast exercise where an ex-post λ selection procedure is taken into account as details are given in Appendix B. Ex-post selection procedure is the limiting case in the sense that it gives one of the best feasible forecast result that can be reached by calibrating the λ. Thus, not surprisingly, $\textbf{LASSO\_LS}^{\textbf{Post}}$ outperforms $\textbf{LASSO\_LS}^{\textbf{IC}}$ in Table 2, in each dataset. This result is also strengthened by DM test where for four of the series ex-post selection procedure encompasses the IC selection procedure and converse is not true and for NP.SYS and GEFCom2014 they have similar predictive ability.

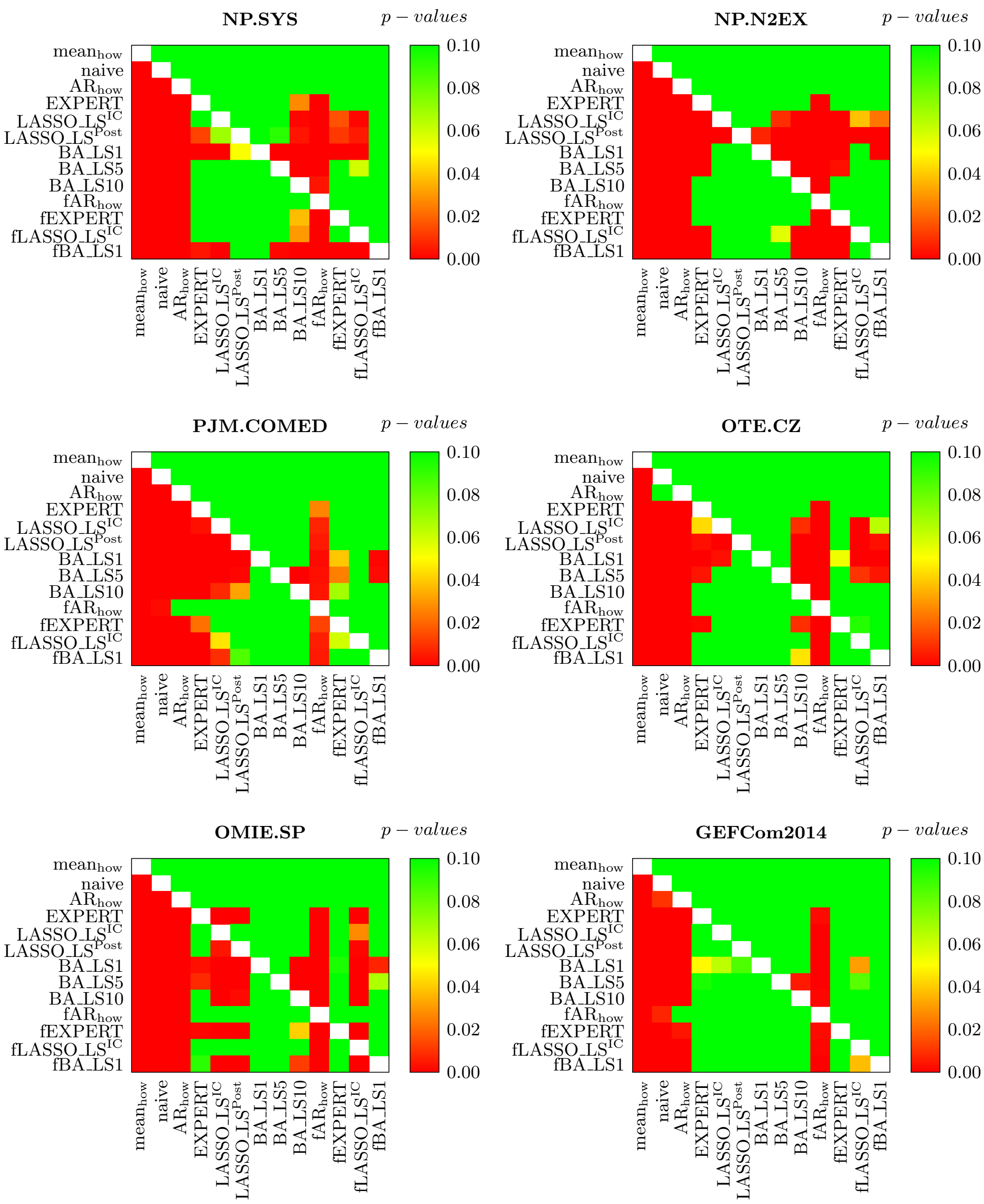

Figure 1: Multivariate DM test results for each dataset as defined by the loss differential series given in Eq. (31). p-values are given for the null hypothesis of $H_0 : \mathbb{E}(\Delta_{X,Y,d}) \leq 0$ which implies that the model on the X-axis encompasses the model on the Y-axis. A heat-map is used to indicate the range of p-values with the corresponding colorbars.

Having said this, we compare the forecast performance of **LASSO_LS$^{\textbf{Post}}$** with bagging. Bagging estimated models are the best performing ones for five series in terms of MAE and **LASSO_LS$^{\textbf{Post}}$** is the best for the remaining one series. A similar pattern is also observed in Panel B and C, where in half of the series bagging

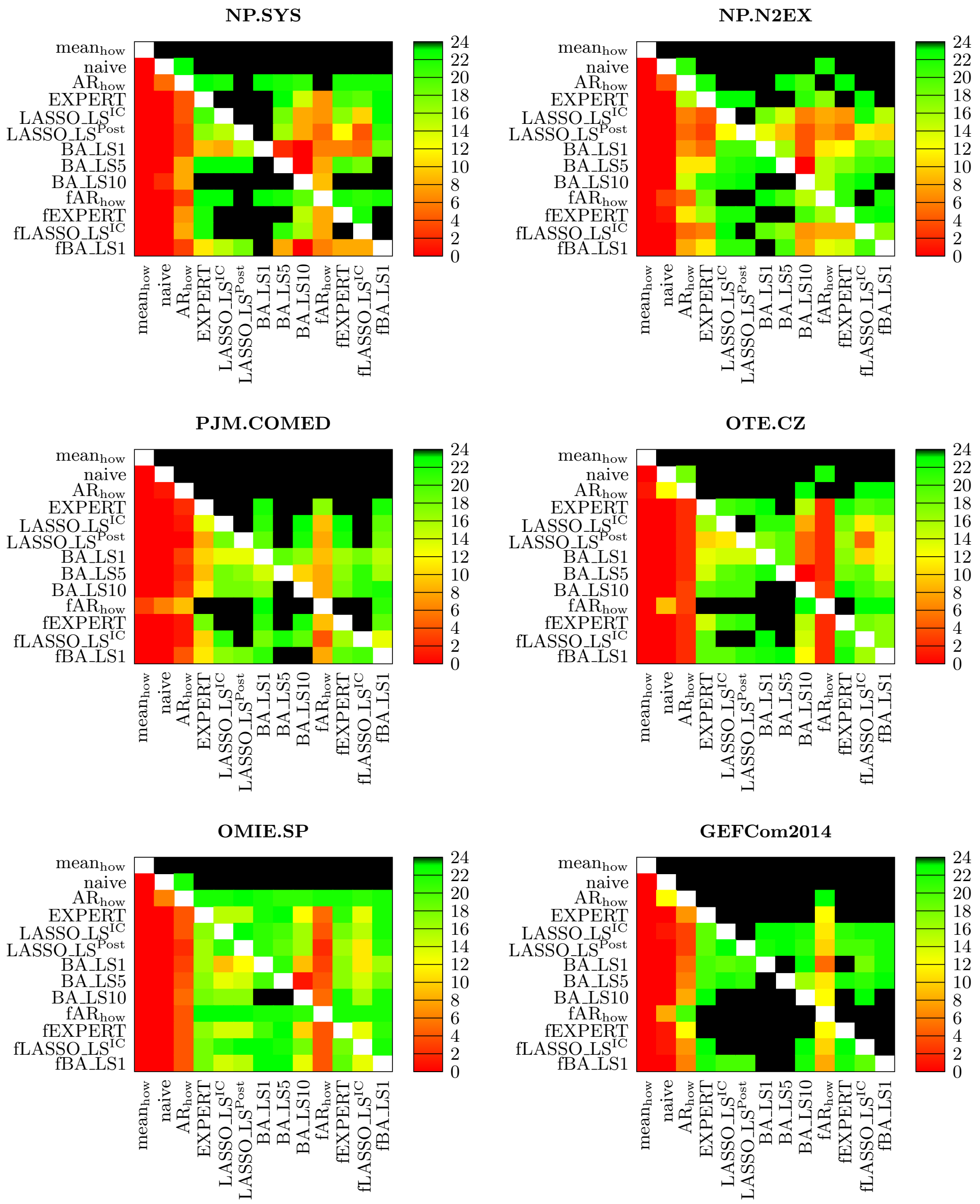

Figure 2: Hourly DM test results for each dataset as defined by the loss differential series given in Eq. (30). Each cell indicates total number of hours out of 24 for which model on the X-axis encompasses model on the Y-axis at 5% significance level. A heat-map is used to indicate the range of hours with the corresponding colorbars.

estimated models outperform the lasso estimated models in terms of loss metrics. Forecasting ability of bagging and lasso estimated models are, however, mixed in terms of DM test results. Null of **BA_LS1** encompasses **LASSO_LS$^{\mathbf{Post}}$** cannot be rejected even at 10% significance level for all datasets and converse is correct for four of the series. This is also confirmed by hourly DM test results in Figure 2, where from twelve to twenty two hours of day both models encompass each other in different series and only in NP.SYS, **BA_LS1** encompasses $\mathbf{LASSO\_LS^{Post}}$ for all hours and converse is correct for only sixteen hours of day. Figure 3 presents forecast performances of shrinkage methods separately for each 24 h of the day. As figure clearly show **BA_LS1**, and $\mathbf{LASSO\_LS^{Post}}$ follow almost the same trace in terms of MAE. Overall, these results imply that bagging is highly competitive among conventional forecast models used so far in the EPF literature. In particular, bagging estimation has very similar forecasting ability with lasso, and, given that these two methods can be categorized under shrinkage estimation, our findings empirically confirm theoretical implications of Stock and Watson (2012).

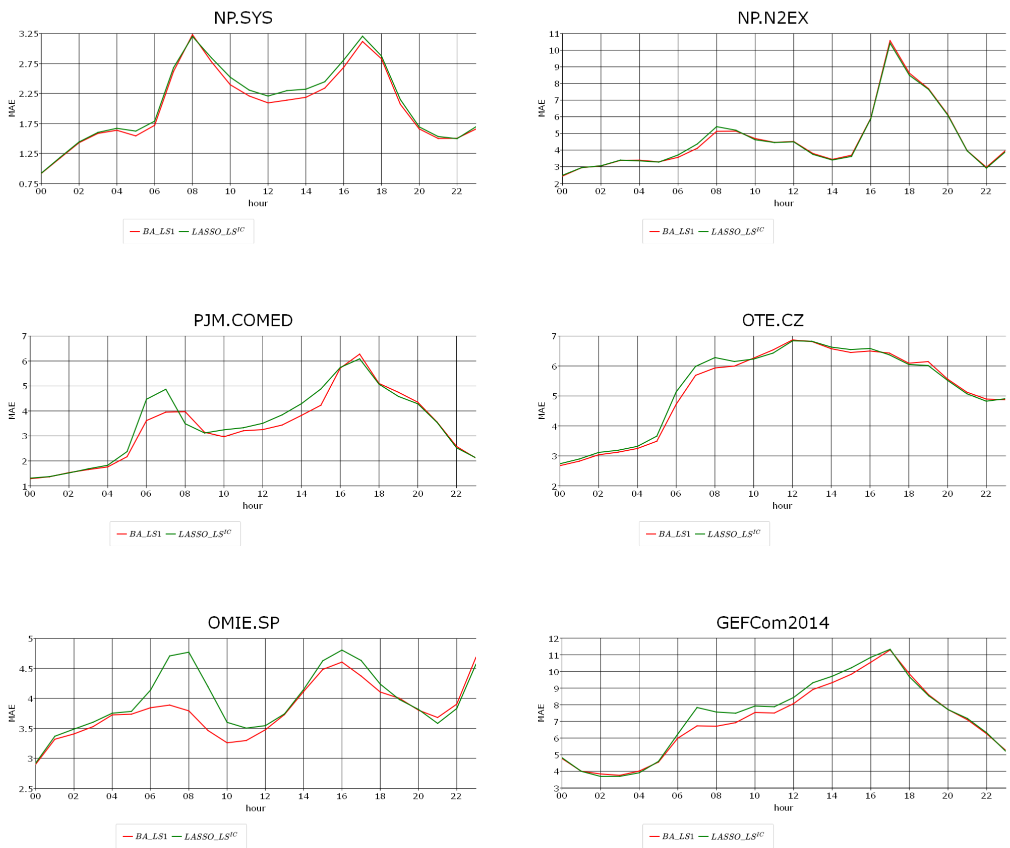

Figure 3: Hourly Mean Absolute Error for $\mathbf{LASSO\_LS^{IC}}$ and **BA_LS1** models as defined in Eq. (28) for full out-of-sample period. Results are given for each dataset in separate panels.

In last four columns of the Table 2, we share the forecast results of factor-augmented models and we also compare them with the corresponding simple versions in Table 3. We implement factor augmentation only for autoregressive model among other benchmark models. Factor-augmented version of autoregressive model outperform the simple version in five of the six series in terms of MAE and in four of the six series in terms of RMSE, and for all series in terms of $\overline{\text{WMAE}}$. **fEXPERT** model also shows a similar pattern. In four of the series factor-augmented version of **EXPERT** model outperforms the simple version in terms of MAE. The same is also true in terms of $\overline{\text{WMAE}}$. Additionally, according to Fig. 1, in three of the series factor-augmented version of the **EXPERT** model encompasses simple version and converse is not true. We also find that **fEXPERT** shows equal predictive ability with **BA_LS1** in three of the series, which is not true for simple version of it. Overall, while keeping it still abstract, factor augmentation helps to approach forecast performance of **EXPERT** closer to that of large-scale shrinkage methods.

While factor-augmented version of **EXPERT** performs quite promisingly, the same cannot be deduced for factor-augmented versions of shrinkage methods. In Table 3, for $\mathbf{LASSO\_LS^{IC}}$, only in one or two series factor augmentation performs better than the simple version, depending on the loss metric. For other shrinkage method, **BA_LS1**, factor-augmented model is inferior for all series in terms of all loss metrics. Factors mostly represents intra-day dependencies of electricity prices which is absent in multivariate modeling framework by construction. Therefore, one can attribute the forecast performance improvements due to this property of the factors in autoregressive benchmark model and in **EXPERT** model. Since factor augmentation results in inferior forecast results, this implies that large scale shrinkage methods already include intra-day dependencies in their simple versions even if they are multivariate models. Increased complexity of univariate modeling pays off with superior forecast performances thanks to its viability to model the intra-day price dependencies. Consequently, our findings imply that univariate large scale shrinkage estimated models may be unnecessarily complex. Furthermore, for the multivariate benchmark and expert models, factor augmentation as proposed in this study, may be a simpler alternative to the univariate modeling framework.

Table 3: Forecasting results for factor-augmented (fa) day-ahead price forecasting models together with corresponding simple version.

Panel (A): Mean Absolute Errors (MAE)

Markets	AR_{how}		EXPERT		$LASSO\_LS^{IC}$		BA_LS1	
	simple	fa	simple	fa	simple	fa	simple	fa
NP.SYS	2.625	**2.375**	**2.122**	2.156	**2.104**	2.166	**2.042**	2.054
NP.N2EX	5.055	**4.917**	4.768	**4.745**	**4.618**	4.634	**4.620**	4.653
PJM.COMED	**4.077**	4.183	3.594	**3.462**	3.461	**3.367**	**3.325**	3.388
OTE.CZ	7.329	**6.671**	5.366	**5.304**	**5.306**	5.354	**5.246**	5.344
OMIE.SP	5.103	**4.381**	3.860	**3.829**	**3.974**	3.990	**3.798**	3.826
GEFCom2014	8.194	**8.153**	**7.348**	7.357	**7.257**	7.333	**7.047**	7.091

Panel (B): Root Mean Squared Error (RMSE)

Markets	AR_{how}		EXPERT		$LASSO\_LS^{IC}$		BA_LS1	
	simple	fa	simple	fa	simple	fa	simple	fa
NP.SYS	4.713	**4.358**	**4.187**	4.521	**4.215**	4.808	**4.232**	4.255
NP.N2EX	13.902	**13.819**	**13.809**	14.454	**13.573**	13.778	**13.576**	13.663
PJM.COMED	**8.432**	25.425	**8.192**	8.475	8.029	**7.219**	**7.351**	7.451
OTE.CZ	10.447	**9.635**	8.070	**8.005**	**8.004**	8.077	**7.941**	8.026
OMIE.SP	7.141	**6.162**	5.399	**5.362**	**5.447**	5.467	**5.333**	5.358
GEFCom2014	**16.117**	17.385	**15.387**	15.597	15.336	**15.082**	**13.813**	14.076

Panel (C): Mean of Weekly-weighted Mean Absolute Error ($\overline{\text{WMAE}}$)

Markets	AR_{how}		EXPERT		$LASSO\_LS^{IC}$		BA_LS1	
	simple	fa	simple	fa	simple	fa	simple	fa
NP.SYS	13.834	**12.319**	**11.032**	11.058	**10.847**	11.085	**10.664**	10.742
NP.N2EX	18.295	**17.789**	17.208	**17.102**	**16.699**	16.753	**16.723**	16.847
PJM.COMED	21.230	**19.824**	18.502	**17.596**	17.630	**17.468**	**17.221**	17.446
OTE.CZ	34.410	**31.236**	25.146	**24.813**	**24.798**	24.968	**24.696**	25.143
OMIE.SP	19.439	**16.595**	14.669	**14.533**	**14.966**	15.002	**14.386**	14.427
GEFCom2014	22.275	**21.471**	**19.473**	19.531	**19.302**	19.616	**19.341**	19.125

Note: The table reports the model forecasting results calculated for full out-of-sample period as defined by Eq. (25), (26), *and* (27), *respectively. "fa" represents the factor-augmented version of the "simple" model as defined in Section 3.2.6. Results of the simple models and factor-augmented versions, given in Table 2, are reproduced here to compare with each other. Best performing model result is indicated with boldface between simple and factor-augmented versions in each dataset.*

4.2 Occurrence of variables

In this section we present the selected variables by the shrinkage methods. In Appendix C, Table 4 to 8 show the mean occurrences of variables in percentage points across all datasets by $\mathbf{LASSO\_LS^{IC}}$ for full out-of-sample test period. We count the total number of non-zero coefficients assigned by lasso in each out-of-sample point and average over all datasets. We also share the selected variables by bagging estimation from Table 9 to 13. We compute the mean occurrences of variables in bagging estimated model by counting the total number of variables selected by the t test at 1% significance level in each out-of-sample point and average over datasets.

Our results for occurence matrix of lasso estimation are mostly in parallel with the findings of Ziel and Weron (2018) and other studies in the EPF literature. Thus, instead of a detailed explanation of occurrence tables we offer a comparison between bagging and lasso occurrence tables. In terms of autoregressive part of the model, previous day's same hour price (i.e. diagonal part of the day: d-1 in Table 4) is mostly selected by lasso estimation and this pattern is also valid for bagging estimation in Table 9 even if it is not that apparent compared to lasso. A similar but vanishing pattern also exists in for day: d-2 to d-8 in lasso. For bagging however, diagonal selection completely vanishes after day: d-1, in other words diagonal part is selected at most as the other variables selected in the autoregressive part. Another important variable selected by lasso is the last-hour effect which corresponds to last row of day: d-1 in Table 4. This variable is also selected by the bagging as can be seen from the same row of Table 9. However, lasso selected hour 18 to 23 with high percentage, as well, which is not much apparent in bagging. Even thought they are sharper in lasso and sometimes hardly visible in bagging, one can still observe similar patterns for daily minimums, daily maximums, day-of-week-dummies, average prices, and periodics. These findings imply that there is no structural difference between bagging and lasso in terms of variable selection.

We now turn our attention to the selected factors in $\mathbf{fAR_{how}}$ and **fEXPERT** where results are given in Table 14 and Table 15, respectively. Factors are selected by minimizing the Bayesian Information Criterion such that we include factors one by one starting from the $n = 1$, first factor with highest eigenvalue, and include next factor with second highest eigenvalue and continue until all $n = 24$ factors are included to the model. After that, we find the n^* which gives the smallest BIC. We repeat above process in each out-of-sample point and count the total number of factor and average over all datasets. Occurrence tables show that, in both models first three factors are selected almost at all hours of day. Since we know from above results that inclusion of factors improves the forecast performances of $\mathbf{fAR_{how}}$ and **fEXPERT** one may conclude that simple versions of that models are missing some part of the information contained in first three factors if not at all. For first three hours of day, factors up to fourteen are selected in $\mathbf{fAR_{how}}$ but this number decreases to six to ten in **fEXPERT** implying that for first three hours of day, explanatory variables (not including the autoregressive part) in Eq. 23 contain information also exists in those factors. These facts can be utilized in future research in identification of factors through factor rotation techniques.

CHAPTER 5

CONCLUSION

We have introduced a new shrinkage method to the EPF literature, namely bagging, and applied this procedure in five commonly used market datasets and GEFCom2014 data. Our findings show that bagging is a very competitive and promising estimation method for large scale models or models with many explanatory variables. It is much simpler alternative to the widely used shrinkage methods in the electricity price forecasting applications. Forecast performances of bagging and lasso are mixed and they do not strictly dominate each other in terms of both forecast performances and DM test results.

Another contribution of this study is factor augmentation to exploit the dependence of intra-day electricity prices in a multivariate setting. The inclusion of latent factors improves ability to forecast in multivariate modeling framework and for expert model it helps to improve its forecast performance such that, it has comparable results with sophisticated shrinkage methods. Our findings also suggest that large scale models already contain, to some extend, the intra-day dependencies of electricity prices which in turn implies that univariate modeling strategy may be unnecessarily complex for large scale models and for the expert models, those dependencies can be easily incorporated to the model with factor-augmentation without switching to univariate model.

It would be interesting in future research to examine the various extensions of bagging in the EPF literature such as using data dependent weight selection for each pseudo-sample in bagging instead of equal weight and combining forecast results of both shrinkage methods to see whether forecast ensemble further improves the results or not. Moreover, application of bagging to datasets after decomposing them into long term seasonal component and stochastic component can bring further performance gains and validation of this approach is left for future research. Furthermore, for the factor-augmented models, identification of factors, at least for some first 4 to 6 factors, through rotation techniques is left as a future research.

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APPENDICES

A. INFORMATION CRITERIONS

In this study, we utilize different information criterions as a part of our data dependent parameter and variable selection approach. Akaike Information Criterion (**AIC**), Bayesian Information Criterion (**BIC**), and Hannan-Quinn Information Criterion (**HQC**) are used throughout the text.

Let n be the estimation sample size, $\boldsymbol{e}$ be n-vector residuals and k be the total number of parameters in the model (including the intercept when valid). Information Criterions can defined as:

$$AIC = log(\frac{\boldsymbol{e}'\boldsymbol{e}}{n}) + 2\frac{k}{n} \tag{A.32}$$

$$BIC = \boldsymbol{e}'\boldsymbol{e} + log(n)k\frac{\boldsymbol{e}'\boldsymbol{e}}{n-k} \tag{A.33}$$

$$HQC = \boldsymbol{e}'\boldsymbol{e} + 2log(log(n))(k-l)\frac{\boldsymbol{e}'\boldsymbol{e}}{n-(k-l)} \tag{A.34}$$

where, l in **HQC** refers to the number of parameters that set equal to zero in lasso estimation, zero otherwise and log stands for the natural logarithm.

B. REGULARIZATION PARAMETER SELECTION

Lasso estimation results highly depend the regularization parameter, λ. We consider two different λ selection procedure. In the first procedure, following Uniejewski et al. (2019), we construct a grid of values: $\lambda_i = 10^{-\frac{19-i}{6}}$ for $i = 1, \ldots, 10$, and choose the optimal λ among the grid of λ values with the in-sample Hannan-Quinn Information Criterion (**HQC**). Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) can be used to select the regularization parameter, as well. Detailed explanations of information criterions are given in Appendix A. We motivate HQC-based model due to its superior performance at Ziel and Weron (2018) compared to AIC and BIC selection procedures. In this procedure, λ is chosen for each out-of-sample and for each hour.

As the second alternative, we opt to an ex-post λ selection. In this procedure, for each hour of the day, i.e. for each model of twenty-four, we evaluate the forecast results for a grid of ten λ values and choose the one with the best forecast performance in terms of Mean Absolute Error (MAE) metric. In this procedure, only one λ value is considered for whole out-of-sample period. This is an hypothetical forecasting exercise in the sense that, in application forecaster never knows the λ value which gives the best prediction for that hour. That is why it is called ex-post.

C. OCCURRENCE TABLES

Table 4: Mean occurrences of the **LASSO_LS$^{\mathbf{IC}}$** model parameters across all six datasets and full out-of-sample test period in percentage points. A heat-map is used to indicate the range of occurrence values between 0 (→ red) and 100 (→ green). Continued in Table 5.

	h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
day: $d-1$	$\mu_{h,1,1,1}$	57	40	27	37	38	43	42	22	17	22	24	14	21	22	15	8	7	7	12	16	11	19	45	39
	$\mu_{h,1,2,1}$	37	39	14	1	3	25	13	12	8	6	3	3	4	4	4	4	2	0	0	0	5	6	1	12
	$\mu_{h,1,3,1}$	17	43	38	19	6	11	10	11	13	3	8	5	3	2	7	6	4	2	10	7	4	9	5	13
	$\mu_{h,1,4,1}$	25	22	42	48	22	8	2	4	9	7	7	5	3	4	3	2	2	3	1	3	2	1	1	1
	$\mu_{h,1,5,1}$	14	23	32	46	68	31	8	23	8	18	17	7	2	2	1	3	0	2	6	12	3	1	1	2
	$\mu_{h,1,6,1}$	13	24	25	31	51	70	52	31	21	16	10	22	31	31	35	25	21	10	15	17	18	20	22	17
	$\mu_{h,1,7,1}$	27	35	27	22	24	48	84	49	50	27	11	13	16	27	35	40	39	30	9	4	3	6	15	14
	$\mu_{h,1,8,1}$	18	9	5	5	14	13	14	70	59	32	17	14	22	20	23	22	22	23	24	24	22	20	35	28
	$\mu_{h,1,9,1}$	20	16	11	8	13	20	16	13	47	32	7	1	17	19	22	20	23	10	23	14	7	15	9	13
	$\mu_{h,1,10,1}$	5	11	12	11	10	10	11	6	9	28	6	0	0	1	15	16	25	35	10	3	14	14	13	15
	$\mu_{h,1,11,1}$	3	2	8	8	12	12	14	10	9	26	35	9	7	4	8	14	15	15	9	3	5	9	14	8
	$\mu_{h,1,12,1}$	2	11	11	17	20	12	15	21	25	24	39	38	27	12	9	10	19	26	22	7	2	3	10	6
	$\mu_{h,1,13,1}$	0	2	9	12	11	9	4	3	5	13	28	47	41	10	5	4	4	3	14	3	1	2	7	3
	$\mu_{h,1,14,1}$	0	2	1	1	1	1	1	0	3	1	6	36	52	36	8	1	1	5	7	3	0	0	10	4
	$\mu_{h,1,15,1}$	23	14	9	6	6	10	16	23	7	12	18	18	41	51	53	48	10	3	4	4	3	2	9	2
	$\mu_{h,1,16,1}$	28	24	18	19	21	31	27	32	21	23	23	29	51	69	65	68	15	8	11	10	4	0	0	12
	$\mu_{h,1,17,1}$	6	15	17	22	23	19	21	18	23	20	13	35	54	64	78	86	97	18	9	18	12	9	3	11
	$\mu_{h,1,18,1}$	40	38	37	16	15	12	11	18	30	27	41	54	52	56	54	52	76	97	32	12	6	9	15	18
	$\mu_{h,1,19,1}$	53	58	70	69	66	61	51	67	54	46	47	29	18	18	19	32	32	57	95	37	24	24	22	14
	$\mu_{h,1,20,1}$	33	35	42	34	39	56	83	84	82	70	58	45	38	34	36	29	24	16	47	96	27	6	10	10
	$\mu_{h,1,21,1}$	39	52	64	67	77	91	87	90	87	87	89	77	64	62	61	53	48	27	21	56	100	65	23	12
	$\mu_{h,1,22,1}$	18	24	30	43	49	42	53	67	79	82	71	73	67	57	52	50	58	39	35	37	57	100	55	36
	$\mu_{h,1,23,1}$	48	41	48	45	46	56	57	50	38	54	80	85	83	79	79	67	62	61	62	48	52	75	100	92
	$\mu_{h,1,24,1}$	100	100	100	100	98	87	89	74	82	96	95	81	77	75	75	69	68	71	68	67	53	54	88	100
day: $d-2$	$\mu_{h,2,1,1}$	22	10	6	12	20	15	17	13	13	7	7	7	12	22	27	31	20	11	17	17	21	18	24	23
	$\mu_{h,2,2,1}$	2	23	6	1	3	2	14	1	3	6	4	3	3	5	13	6	8	8	7	6	8	5	4	7
	$\mu_{h,2,3,1}$	1	7	34	19	9	11	10	12	7	1	2	1	3	7	6	3	2	0	1	1	0	2	2	1
	$\mu_{h,2,4,1}$	4	10	27	37	29	19	7	5	6	1	2	1	3	3	1	0	1	3	6	6	5	3	3	3
	$\mu_{h,2,5,1}$	9	14	12	19	33	28	15	19	10	9	4	0	1	1	1	7	1	0	1	2	4	5	4	6
	$\mu_{h,2,6,1}$	8	6	4	4	3	19	17	11	11	1	3	6	17	17	14	15	1	1	4	6	1	1	7	3
	$\mu_{h,2,7,1}$	17	4	4	9	6	11	4	10	10	10	3	5	6	12	11	15	12	13	14	22	10	5	10	3
	$\mu_{h,2,8,1}$	8	5	8	5	8	8	5	12	16	16	11	13	21	17	22	25	24	5	14	11	6	9	9	3
	$\mu_{h,2,9,1}$	2	4	6	7	5	9	5	8	13	9	5	2	7	8	10	15	16	18	19	11	11	16	13	17
	$\mu_{h,2,10,1}$	6	4	5	6	4	3	4	11	8	11	8	0	0	1	0	2	3	7	2	1	0	3	0	5
	$\mu_{h,2,11,1}$	4	8	6	9	6	4	8	3	11	18	21	10	8	4	6	7	5	1	3	5	3	12	9	10
	$\mu_{h,2,12,1}$	7	8	4	2	6	5	12	13	9	16	19	24	13	6	6	5	2	1	1	1	3	6	4	7
	$\mu_{h,2,13,1}$	7	12	9	9	11	22	13	2	2	1	5	8	7	1	1	3	0	2	5	0	0	3	12	13
	$\mu_{h,2,14,1}$	9	14	12	5	10	17	11	9	6	4	4	6	20	13	3	2	3	4	1	0	0	7	5	7
	$\mu_{h,2,15,1}$	11	8	6	10	16	16	22	14	4	4	2	0	3	21	28	20	7	25	21	25	2	4	19	11
	$\mu_{h,2,16,1}$	2	4	6	13	13	9	17	29	17	2	4	3	1	2	6	11	5	18	16	7	1	6	16	18
	$\mu_{h,2,17,1}$	10	4	1	6	6	18	11	15	21	25	31	8	11	10	16	24	34	14	8	9	10	9	6	17
	$\mu_{h,2,18,1}$	8	9	9	10	18	18	13	12	11	11	11	12	19	27	34	38	38	44	5	17	5	4	3	4
	$\mu_{h,2,19,1}$	15	7	9	9	22	16	17	16	12	3	3	20	22	21	27	27	24	26	60	28	42	17	9	15
	$\mu_{h,2,20,1}$	29	29	27	20	22	22	26	20	24	13	10	15	15	19	19	18	20	31	6	47	14	33	29	25
	$\mu_{h,2,21,1}$	38	26	22	24	15	25	17	19	16	12	10	5	4	5	11	4	10	21	32	25	53	25	18	19
	$\mu_{h,2,22,1}$	36	41	27	25	26	27	21	15	9	7	7	2	3	4	4	4	5	8	11	34	10	31	7	9
	$\mu_{h,2,23,1}$	30	54	62	61	62	55	32	19	7	19	18	12	11	11	15	2	13	3	10	8	19	8	40	46
	$\mu_{h,2,24,1}$	41	43	54	62	54	51	50	39	26	28	22	30	30	23	28	20	23	14	23	33	21	29	43	44

Note: The table reports the mean occurrences of variables in Eq. (20) *estimated with lasso where regularization parameter is selected through information criterion as explained in Section 3.2.5.*

Table 5: Mean occurrences of the **LASSO_LS$^{\mathbf{IC}}$** model parameters across all six datasets and full out-of-sample test period in percentage points. A heat-map is used to indicate the range of occurrence values between 0 (→ red) and 100 (→ green). Continued in Table 6.

	h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
day: $d-3$	$\mu_{h,3,1,1}$	10	0	2	5	2	4	1	7	13	8	5	5	9	11	15	22	21	17	12	11	11	15	15	17
	$\mu_{h,3,2,1}$	31	32	13	2	3	11	4	1	1	2	16	15	12	10	14	12	11	7	6	16	4	3	4	3
	$\mu_{h,3,3,1}$	8	11	23	13	11	15	13	13	9	1	0	9	8	8	10	9	10	14	15	2	1	4	8	7
	$\mu_{h,3,4,1}$	6	16	31	30	33	27	9	7	3	6	6	4	9	11	7	4	4	0	3	0	5	2	1	3
	$\mu_{h,3,5,1}$	5	6	9	19	29	21	10	4	2	2	3	1	1	4	3	4	2	1	1	1	0	1	1	0
	$\mu_{h,3,6,1}$	4	6	5	9	9	32	24	13	8	3	1	2	2	3	12	10	9	10	9	10	9	8	10	7
	$\mu_{h,3,7,1}$	23	30	27	28	36	39	55	25	25	28	25	11	11	12	14	13	11	6	9	14	6	6	8	10
	$\mu_{h,3,8,1}$	3	6	8	4	8	9	16	29	21	12	8	1	0	0	3	7	7	2	9	7	6	3	2	3
	$\mu_{h,3,9,1}$	4	7	9	10	4	8	11	16	20	11	12	4	3	6	6	5	12	7	5	5	4	8	8	4
	$\mu_{h,3,10,1}$	13	12	8	7	10	5	4	7	12	8	4	0	2	0	5	5	7	2	1	2	7	6	7	8
	$\mu_{h,3,11,1}$	5	9	8	5	3	3	7	8	3	11	27	12	12	9	9	5	3	1	5	4	9	12	3	1
	$\mu_{h,3,12,1}$	13	21	24	17	13	22	6	7	9	8	20	30	18	16	12	16	3	8	10	7	2	8	7	7
	$\mu_{h,3,13,1}$	6	5	2	2	3	3	3	5	3	1	7	8	14	4	2	3	2	2	3	3	2	2	19	7
	$\mu_{h,3,14,1}$	7	1	1	2	5	6	18	17	8	0	2	4	16	18	21	15	13	9	3	11	6	3	5	12
	$\mu_{h,3,15,1}$	3	10	9	9	10	5	2	11	11	7	5	4	5	11	18	2	6	7	6	2	1	5	0	1
	$\mu_{h,3,16,1}$	8	14	11	12	12	12	9	6	5	7	5	10	14	20	9	26	2	3	8	9	3	2	2	2
	$\mu_{h,3,17,1}$	5	4	9	12	6	18	25	10	21	29	23	6	7	11	10	9	18	0	7	4	1	3	5	5
	$\mu_{h,3,18,1}$	6	0	6	1	6	5	9	17	11	8	8	15	16	16	23	25	43	63	5	15	8	9	10	7
	$\mu_{h,3,19,1}$	4	6	12	7	10	20	24	17	10	5	12	7	2	3	4	6	2	2	65	8	4	2	6	2
	$\mu_{h,3,20,1}$	3	2	3	3	7	11	8	7	9	1	2	0	3	2	1	1	2	9	10	68	8	4	2	3
	$\mu_{h,3,21,1}$	10	2	4	8	7	7	3	9	10	7	6	1	0	0	0	1	0	1	6	7	42	6	4	7
	$\mu_{h,3,22,1}$	14	20	25	26	23	15	9	11	21	14	12	6	9	8	8	8	7	4	0	0	8	41	16	11
	$\mu_{h,3,23,1}$	12	17	24	22	22	17	9	7	11	9	7	8	13	16	18	16	11	6	6	5	7	21	48	25
	$\mu_{h,3,24,1}$	17	18	23	19	26	25	25	7	14	11	2	9	11	11	5	8	14	8	7	1	2	8	12	27
day: $d-4$	$\mu_{h,4,1,1}$	24	12	6	5	5	8	1	3	7	3	1	0	0	1	6	11	9	3	1	3	3	8	20	24
	$\mu_{h,4,2,1}$	13	14	12	6	6	6	3	6	5	6	9	2	2	4	8	6	7	17	6	13	12	23	22	32
	$\mu_{h,4,3,1}$	11	16	18	15	16	17	16	14	6	1	0	1	2	1	5	6	6	4	2	1	8	5	3	7
	$\mu_{h,4,4,1}$	5	16	27	38	27	16	13	10	7	7	4	5	7	5	5	6	6	4	5	5	6	4	1	4
	$\mu_{h,4,5,1}$	9	17	20	18	30	19	18	16	10	7	7	4	7	8	6	7	7	3	3	6	4	7	9	4
	$\mu_{h,4,6,1}$	17	28	16	11	17	37	30	18	18	6	4	4	8	4	4	3	7	1	7	3	8	1	7	9
	$\mu_{h,4,7,1}$	9	11	13	13	15	14	20	17	14	12	6	0	4	8	9	10	10	3	9	7	3	3	7	4
	$\mu_{h,4,8,1}$	1	4	5	9	8	8	8	27	19	16	12	5	5	3	3	4	4	0	1	3	4	6	6	5
	$\mu_{h,4,9,1}$	6	8	5	5	4	6	4	8	13	11	10	8	4	8	5	2	9	3	3	9	4	4	6	7
	$\mu_{h,4,10,1}$	12	10	10	8	8	13	10	8	20	22	14	0	0	2	4	7	11	8	8	4	8	15	6	3
	$\mu_{h,4,11,1}$	6	7	5	5	12	8	4	6	6	23	34	12	12	4	4	8	13	14	10	2	10	11	10	7
	$\mu_{h,4,12,1}$	4	15	9	7	9	12	17	15	14	11	16	32	29	18	23	18	12	3	8	5	10	5	13	4
	$\mu_{h,4,13,1}$	6	11	14	12	15	15	11	13	13	0	3	13	13	0	3	5	9	8	11	8	2	0	5	4
	$\mu_{h,4,14,1}$	5	4	2	2	4	7	1	4	3	1	0	1	4	12	13	11	5	9	7	11	1	1	7	3
	$\mu_{h,4,15,1}$	3	8	11	17	14	9	2	7	4	2	3	3	6	13	16	0	0	2	0	4	3	3	13	11
	$\mu_{h,4,16,1}$	12	9	16	13	18	8	8	12	10	8	3	4	6	19	19	11	5	1	5	9	4	1	2	1
	$\mu_{h,4,17,1}$	9	6	7	3	4	6	4	10	5	25	24	14	14	9	11	12	13	9	7	5	9	8	8	6
	$\mu_{h,4,18,1}$	7	8	6	9	10	8	9	5	4	9	19	8	14	15	9	9	6	28	5	13	8	9	11	8
	$\mu_{h,4,19,1}$	15	11	12	14	17	16	7	11	16	8	10	11	8	8	8	5	6	15	44	14	14	13	8	7
	$\mu_{h,4,20,1}$	11	5	4	7	11	17	32	22	24	15	6	2	4	4	2	4	9	14	24	54	17	16	7	3
	$\mu_{h,4,21,1}$	8	14	11	12	7	15	12	14	14	14	5	1	1	2	3	0	0	2	8	5	42	4	5	5
	$\mu_{h,4,22,1}$	9	16	16	23	22	19	14	20	29	24	19	3	5	1	4	3	2	3	6	9	4	38	5	17
	$\mu_{h,4,23,1}$	9	15	18	15	24	22	5	7	5	3	1	1	4	1	5	2	1	0	0	5	6	11	41	20
	$\mu_{h,4,24,1}$	17	22	19	16	16	12	11	7	18	16	12	10	17	11	10	14	22	18	9	10	2	1	18	27

Note: The table reports the mean occurences of variables in Eq. (20) *estimated with lasso where regularization parameter is selected through information criterion as explained in Section 3.2.5.*

Table 6: Mean occurrences of the **LASSO_LS$^{\mathbf{IC}}$** model parameters across all six datasets and full out-of-sample test period in percentage points. A heat-map is used to indicate the range of occurrence values between 0 (→ red) and 100 (→ green). Continued in Table 7.

	h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
day: $d-5$	$\mu_{h,5,1,1}$	26	17	12	8	7	10	5	6	4	0	0	1	0	2	0	0	0	0	0	0	2	2	10	25
	$\mu_{h,5,2,1}$	22	19	14	9	8	9	10	6	5	0	0	3	0	1	1	0	0	1	1	1	1	1	3	4
	$\mu_{h,5,3,1}$	4	6	15	10	2	1	3	6	10	5	1	1	2	3	5	3	5	4	2	4	2	2	10	12
	$\mu_{h,5,4,1}$	4	21	34	43	19	8	7	6	5	10	12	7	5	10	7	8	12	6	1	0	2	2	3	3
	$\mu_{h,5,5,1}$	3	3	8	12	28	17	6	1	3	0	1	0	1	3	4	8	3	0	1	2	1	2	1	0
	$\mu_{h,5,6,1}$	15	10	7	4	16	34	27	12	13	4	5	1	1	0	3	6	4	3	10	15	13	10	6	9
	$\mu_{h,5,7,1}$	15	10	11	17	22	19	27	9	7	6	2	1	4	7	5	3	2	6	25	25	15	0	0	1
	$\mu_{h,5,8,1}$	9	10	10	11	16	11	9	10	5	4	4	0	2	7	7	9	13	7	13	9	3	2	2	2
	$\mu_{h,5,9,1}$	11	10	11	12	10	6	11	10	7	12	13	9	9	9	11	9	2	7	7	9	8	9	4	3
	$\mu_{h,5,10,1}$	15	18	5	3	8	12	18	24	24	16	12	5	5	5	6	11	20	19	14	4	9	11	3	1
	$\mu_{h,5,11,1}$	13	4	0	1	3	5	0	1	6	6	9	7	5	8	8	11	6	7	5	5	3	2	6	2
	$\mu_{h,5,12,1}$	7	7	8	4	7	6	4	2	2	1	15	18	15	11	3	3	10	1	3	1	0	0	0	1
	$\mu_{h,5,13,1}$	2	2	4	6	13	15	14	9	6	1	7	8	11	7	4	4	3	0	1	1	4	3	2	0
	$\mu_{h,5,14,1}$	0	1	2	0	1	1	4	4	2	0	0	2	9	7	4	2	0	0	1	1	6	3	4	1
	$\mu_{h,5,15,1}$	10	4	18	19	16	6	6	13	7	3	1	1	6	10	9	4	0	1	1	4	2	2	1	1
	$\mu_{h,5,16,1}$	4	3	3	6	9	9	7	19	6	7	3	1	0	14	17	18	3	9	9	1	2	1	1	3
	$\mu_{h,5,17,1}$	3	1	3	7	10	21	18	14	22	27	12	2	1	7	18	21	39	6	3	7	2	0	1	7
	$\mu_{h,5,18,1}$	15	11	6	2	4	7	10	7	5	6	4	3	3	4	7	7	4	33	8	7	6	8	10	9
	$\mu_{h,5,19,1}$	26	27	29	31	31	28	27	20	19	13	11	4	8	9	11	17	12	25	69	19	5	6	4	3
	$\mu_{h,5,20,1}$	5	11	5	5	4	13	18	6	5	9	7	4	4	8	6	3	3	4	14	56	16	0	2	4
	$\mu_{h,5,21,1}$	2	2	5	10	7	11	2	2	6	1	2	1	1	2	2	2	3	9	12	5	40	9	4	0
	$\mu_{h,5,22,1}$	6	9	12	10	13	16	10	8	11	3	5	15	2	6	5	7	5	4	3	1	1	43	8	8
	$\mu_{h,5,23,1}$	10	8	13	14	18	21	14	14	11	2	2	1	1	7	6	2	2	1	4	2	0	7	40	16
	$\mu_{h,5,24,1}$	22	27	21	21	26	17	16	17	9	2	6	8	20	16	13	17	21	9	14	7	0	1	7	13
day: $d-6$	$\mu_{h,6,1,1}$	27	6	4	3	6	9	8	11	13	7	11	7	3	2	1	2	1	0	1	2	2	0	0	10
	$\mu_{h,6,2,1}$	23	27	19	9	8	2	1	2	2	0	0	1	0	1	1	3	3	4	4	3	5	4	1	3
	$\mu_{h,6,3,1}$	1	5	21	15	10	2	3	3	5	1	0	1	3	6	6	4	6	9	5	4	1	0	1	4
	$\mu_{h,6,4,1}$	0	10	6	6	2	0	0	2	3	1	2	1	2	6	12	4	3	13	8	11	8	4	4	0
	$\mu_{h,6,5,1}$	5	13	25	30	38	24	10	2	1	7	7	6	8	7	12	7	8	9	5	7	2	0	5	1
	$\mu_{h,6,6,1}$	21	13	9	9	22	63	14	8	6	1	2	4	4	4	2	2	1	1	1	4	3	0	1	6
	$\mu_{h,6,7,1}$	1	5	10	11	12	51	77	43	31	23	5	5	6	17	22	22	15	8	14	21	13	9	8	14
	$\mu_{h,6,8,1}$	5	7	10	9	4	10	26	49	20	17	11	6	3	6	13	10	4	4	10	12	20	12	3	7
	$\mu_{h,6,9,1}$	10	6	12	13	2	4	3	6	30	3	1	3	7	14	16	20	22	9	6	6	12	11	14	5
	$\mu_{h,6,10,1}$	8	11	4	4	4	7	9	22	32	29	17	7	8	7	8	7	12	7	2	3	6	3	3	3
	$\mu_{h,6,11,1}$	3	10	10	5	6	8	8	8	11	21	34	11	4	4	1	2	3	9	13	9	5	3	1	5
	$\mu_{h,6,12,1}$	10	5	13	4	1	5	7	1	6	0	13	26	25	8	5	3	3	5	2	1	5	1	1	2
	$\mu_{h,6,13,1}$	9	14	19	17	14	11	5	5	5	3	2	6	11	3	2	1	1	1	1	0	0	3	2	2
	$\mu_{h,6,14,1}$	18	17	11	15	10	10	3	15	16	8	3	5	21	28	20	4	2	0	0	1	9	13	15	8
	$\mu_{h,6,15,1}$	8	17	22	24	21	2	9	4	2	6	6	7	11	27	25	11	7	17	6	7	2	5	4	4
	$\mu_{h,6,16,1}$	4	2	0	1	2	2	1	4	4	2	2	3	7	12	28	42	20	1	3	10	11	12	4	11
	$\mu_{h,6,17,1}$	3	5	8	10	8	3	6	12	9	7	8	14	20	27	24	42	59	12	1	1	2	1	3	6
	$\mu_{h,6,18,1}$	9	4	5	10	19	18	19	25	21	12	17	10	14	19	26	18	31	81	18	3	5	2	11	8
	$\mu_{h,6,19,1}$	7	6	8	10	9	16	14	18	11	3	2	0	1	2	4	5	11	12	75	28	9	3	7	8
	$\mu_{h,6,20,1}$	16	8	10	14	19	17	12	8	6	3	4	1	1	0	1	1	1	1	1	64	17	2	6	1
	$\mu_{h,6,21,1}$	8	1	4	5	7	5	5	9	7	6	2	0	3	2	6	8	11	5	2	17	42	14	2	0
	$\mu_{h,6,22,1}$	14	15	25	19	22	19	13	9	10	12	1	1	1	2	6	8	8	9	3	3	2	46	16	14
	$\mu_{h,6,23,1}$	11	20	24	28	30	28	21	13	12	4	6	1	3	1	1	2	3	3	2	3	3	8	38	16
	$\mu_{h,6,24,1}$	20	17	7	17	19	30	29	23	28	21	14	13	11	11	13	14	22	20	23	23	7	2	4	25

Note: The table reports the mean occurences of variables in Eq. (20) *estimated with lasso where regularization parameter is selected through information criterion as explained in Section 3.2.5.*

Table 7: Mean occurrences of the **LASSO_LS$^{\mathbf{IC}}$** model parameters across all six datasets and full out-of-sample test period in percentage points. A heat-map is used to indicate the range of occurrence values between 0 (→ red) and 100 (→ green). Continued in Table 8.

	h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
day: $d-7$	$\mu_{h,7,1,1}$	37	8	16	12	5	10	32	36	20	10	6	6	5	4	4	3	4	4	2	2	7	3	25	17
	$\mu_{h,7,2,1}$	12	27	19	8	9	7	9	5	12	7	6	2	1	1	0	3	3	0	3	1	2	2	0	2
	$\mu_{h,7,3,1}$	8	13	22	11	6	10	14	12	10	7	1	1	1	0	0	0	2	7	0	1	0	0	0	2
	$\mu_{h,7,4,1}$	10	21	18	20	5	4	10	7	11	11	12	9	7	8	10	6	8	8	8	4	2	1	0	0
	$\mu_{h,7,5,1}$	14	11	18	29	33	4	1	3	9	4	5	6	6	8	10	4	1	0	2	3	1	1	2	1
	$\mu_{h,7,6,1}$	10	6	10	10	38	71	10	5	8	4	8	5	6	6	5	7	5	2	2	6	2	0	1	6
	$\mu_{h,7,7,1}$	9	19	14	13	31	65	99	49	38	17	15	11	13	15	19	32	17	12	17	23	26	22	13	20
	$\mu_{h,7,8,1}$	20	10	5	2	8	26	52	95	70	39	19	10	12	10	21	22	4	23	17	18	12	6	6	3
	$\mu_{h,7,9,1}$	6	7	5	1	6	8	6	18	62	67	32	18	14	6	9	12	11	6	9	6	4	6	14	9
	$\mu_{h,7,10,1}$	1	2	3	1	6	3	2	3	4	30	42	18	10	9	6	7	8	9	6	10	14	9	7	20
	$\mu_{h,7,11,1}$	8	4	4	5	10	13	11	13	6	10	46	21	0	0	2	1	4	1	1	2	5	2	4	2
	$\mu_{h,7,12,1}$	2	8	8	1	2	3	9	13	12	4	9	36	10	9	7	8	8	5	1	2	1	5	3	2
	$\mu_{h,7,13,1}$	11	19	13	5	6	10	6	12	11	1	4	13	28	16	7	5	1	1	1	2	1	6	3	3
	$\mu_{h,7,14,1}$	3	5	4	2	4	6	3	4	4	1	7	25	37	41	30	7	3	5	2	3	2	10	9	7
	$\mu_{h,7,15,1}$	2	3	7	19	8	5	4	2	3	3	4	12	19	21	30	16	7	1	3	2	8	2	3	4
	$\mu_{h,7,16,1}$	5	3	1	1	3	4	6	6	11	5	8	14	41	51	52	66	37	10	6	9	6	4	5	3
	$\mu_{h,7,17,1}$	2	7	1	3	2	10	4	5	8	15	19	14	16	16	15	34	48	22	10	4	1	4	3	2
	$\mu_{h,7,18,1}$	17	26	20	12	18	14	5	11	8	19	30	23	39	46	55	42	20	64	11	7	10	11	0	1
	$\mu_{h,7,19,1}$	7	11	17	25	30	30	18	20	14	4	4	1	4	4	19	11	6	10	64	22	9	2	0	1
	$\mu_{h,7,20,1}$	5	15	8	14	17	30	15	13	10	16	10	6	8	13	18	18	17	12	9	50	25	2	6	2
	$\mu_{h,7,21,1}$	3	5	2	1	2	3	7	17	13	6	2	1	1	2	9	5	9	11	6	9	37	14	9	8
	$\mu_{h,7,22,1}$	17	14	10	5	16	19	18	11	8	3	3	0	0	1	4	3	4	6	4	2	4	41	23	12
	$\mu_{h,7,23,1}$	7	22	22	24	27	32	27	13	9	9	14	6	8	7	7	9	18	16	14	9	0	2	48	19
	$\mu_{h,7,24,1}$	10	12	17	26	35	27	39	28	22	17	13	12	12	12	16	15	18	20	26	24	4	10	16	16
day: $d-8$	$\mu_{h,8,1,1}$	10	12	23	33	31	24	19	17	14	10	7	2	6	6	7	8	7	8	10	11	15	10	29	15
	$\mu_{h,8,2,1}$	8	7	6	6	3	9	12	10	12	4	5	3	4	15	13	4	0	1	2	5	6	9	8	1
	$\mu_{h,8,3,1}$	2	13	14	11	3	5	0	0	1	1	1	2	1	0	0	0	1	0	2	1	1	4	6	5
	$\mu_{h,8,4,1}$	23	20	11	19	11	7	2	5	11	2	2	0	4	5	6	6	9	5	5	16	20	17	12	18
	$\mu_{h,8,5,1}$	10	16	11	19	32	18	10	12	12	8	7	11	9	8	6	5	3	1	4	2	1	2	1	4
	$\mu_{h,8,6,1}$	12	13	15	19	20	25	7	10	8	2	1	3	5	5	4	3	4	2	0	1	0	0	1	3
	$\mu_{h,8,7,1}$	13	10	11	13	18	15	17	15	8	15	14	8	19	26	25	25	25	16	7	9	10	7	9	7
	$\mu_{h,8,8,1}$	8	10	8	10	9	10	4	10	11	7	4	0	0	0	0	0	1	0	1	2	1	0	7	1
	$\mu_{h,8,9,1}$	3	8	6	3	3	7	1	1	3	2	1	1	3	3	2	4	10	11	13	12	3	4	19	12
	$\mu_{h,8,10,1}$	3	2	3	7	10	12	15	15	18	5	1	2	1	4	4	5	9	9	7	4	1	11	9	5
	$\mu_{h,8,11,1}$	9	10	9	12	7	10	20	25	18	8	2	1	0	0	0	0	5	6	10	7	5	5	6	1
	$\mu_{h,8,12,1}$	7	20	9	6	4	7	4	6	6	2	6	16	14	9	1	1	2	7	6	3	1	1	2	8
	$\mu_{h,8,13,1}$	9	7	9	9	6	2	2	2	3	4	8	9	3	2	3	4	7	10	4	5	6	1	4	0
	$\mu_{h,8,14,1}$	3	4	4	2	5	12	14	4	2	3	5	4	6	8	5	3	2	0	1	1	0	0	1	0
	$\mu_{h,8,15,1}$	7	6	7	6	6	11	14	7	6	1	0	2	5	8	16	15	10	5	1	1	1	1	2	5
	$\mu_{h,8,16,1}$	5	2	5	9	9	9	10	19	21	8	7	17	18	23	25	23	5	0	1	2	0	1	1	1
	$\mu_{h,8,17,1}$	5	7	6	7	7	4	6	9	5	3	8	13	14	14	16	23	39	13	14	28	14	22	22	17
	$\mu_{h,8,18,1}$	9	9	1	3	5	16	12	9	5	8	11	7	15	14	8	8	12	52	12	2	19	10	8	2
	$\mu_{h,8,19,1}$	5	10	10	18	20	17	22	24	11	1	1	7	11	10	7	5	8	6	37	18	3	2	3	7
	$\mu_{h,8,20,1}$	10	7	8	13	16	21	16	13	22	9	4	6	2	3	9	6	6	7	7	21	6	5	0	2
	$\mu_{h,8,21,1}$	14	7	9	8	8	19	7	22	16	12	7	5	4	6	9	10	9	6	9	6	6	0	1	3
	$\mu_{h,8,22,1}$	17	9	4	7	13	16	18	13	9	2	1	1	1	0	1	1	2	1	5	1	2	30	5	1
	$\mu_{h,8,23,1}$	13	29	35	35	34	36	30	21	17	16	12	4	10	11	5	6	8	9	9	8	1	1	28	20
	$\mu_{h,8,24,1}$	13	37	36	28	31	35	34	19	11	6	1	1	7	9	7	9	6	6	6	13	3	4	19	24

Note: The table reports the mean occurences of variables in Eq. (20) *estimated with lasso where regularization parameter is selected through information criterion as explained in Section 3.2.5.*

Table 8: Mean occurrences of the **LASSO_LS$^{\mathbf{IC}}$** model parameters across all six datasets and full out-of-sample test period in percentage points. A heat-map is used to indicate the range of occurrence values between 0 (→ red) and 100 (→ green).

	h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Daily Minimums	$\mu_{h,1,1,2}$	58	74	87	86	82	59	35	25	22	16	1	0	1	3	7	6	12	5	8	6	6	5	3	1
	$\mu_{h,2,1,2}$	2	2	7	16	22	20	8	10	4	2	7	3	0	0	2	1	2	9	7	3	2	1	5	2
	$\mu_{h,3,1,2}$	12	29	31	34	28	31	8	8	9	10	4	3	2	3	5	6	2	1	3	1	3	9	10	9
	$\mu_{h,4,1,2}$	13	18	21	30	26	15	18	17	14	10	6	11	10	9	15	12	22	20	12	10	9	5	17	9
	$\mu_{h,5,1,2}$	18	23	26	27	29	33	15	9	6	7	1	5	7	7	8	11	10	3	6	7	3	5	5	8
	$\mu_{h,6,1,2}$	9	26	25	34	39	14	18	25	19	12	5	3	10	11	21	20	12	5	10	16	14	5	18	15
	$\mu_{h,7,1,2}$	7	12	12	15	17	6	9	25	16	5	0	0	1	2	3	3	2	3	1	1	6	4	9	5
	$\mu_{h,8,1,2}$	15	7	9	7	17	19	7	22	23	14	18	11	7	7	9	8	12	13	16	13	9	14	11	11
Daily Maximums	$\mu_{h,1,1,3}$	11	10	8	16	17	18	20	38	40	43	29	20	18	11	8	15	3	9	34	30	21	24	17	14
	$\mu_{h,2,1,3}$	32	35	46	48	52	44	33	32	36	35	36	41	38	29	30	27	20	3	3	23	20	20	23	3
	$\mu_{h,3,1,3}$	7	10	18	16	13	21	20	22	15	14	21	11	13	5	3	4	9	9	16	25	14	25	24	20
	$\mu_{h,4,1,3}$	23	24	20	19	26	24	15	23	15	5	13	5	6	7	15	6	17	16	17	6	11	8	12	6
	$\mu_{h,5,1,3}$	23	23	20	11	13	29	22	17	11	24	28	26	22	13	14	5	4	6	12	18	14	5	5	6
	$\mu_{h,6,1,3}$	17	18	13	16	14	14	7	15	26	19	10	6	9	10	8	6	7	4	12	13	4	9	10	16
	$\mu_{h,7,1,3}$	15	12	16	16	16	40	32	13	12	12	16	14	20	15	22	18	13	4	4	7	4	9	7	11
	$\mu_{h,8,1,3}$	9	17	6	6	6	18	25	21	24	20	7	3	7	8	7	8	11	6	9	12	3	5	7	7
dow Dummies	$\mu_{h,1,1,4}$	80	72	70	70	95	98	87	98	99	100	99	84	100	90	83	93	97	84	77	54	51	52	27	38
	$\mu_{h,2,1,4}$	46	45	52	44	39	77	91	77	72	71	75	75	78	75	86	84	84	85	85	87	73	72	66	46
	$\mu_{h,3,1,4}$	29	33	40	40	45	33	39	43	41	39	43	50	32	25	29	28	37	41	33	31	22	22	18	27
	$\mu_{h,4,1,4}$	33	32	33	23	25	26	24	31	25	20	18	18	19	21	25	26	30	45	47	47	19	13	9	11
	$\mu_{h,5,1,4}$	24	20	15	22	25	41	25	24	24	28	26	32	28	28	28	34	34	25	31	49	44	38	32	18
	$\mu_{h,6,1,4}$	42	44	40	35	33	34	23	23	44	44	44	40	31	35	40	45	65	58	78	93	91	86	50	42
	$\mu_{h,7,1,4}$	79	81	78	69	69	100	100	100	100	84	100	97	99	100	100	100	100	86	88	86	83	67	72	74
average price	$\mu_{h,1,1,5}$	14	23	34	33	52	41	29	28	15	4	4	5	8	8	9	14	11	12	17	5	21	33	24	21
	$\mu_{h,2,1,5}$	43	39	31	24	20	25	37	35	31	18	11	6	4	3	5	8	13	17	26	21	11	12	11	16
	$\mu_{h,3,1,5}$	35	37	39	20	21	29	21	21	26	17	13	4	7	8	8	5	11	5	11	12	9	18	21	15
	$\mu_{h,4,1,5}$	16	17	15	9	18	15	15	16	23	6	12	6	12	19	13	11	15	12	7	18	9	6	8	5
	$\mu_{h,5,1,5}$	23	24	25	27	36	32	24	23	17	4	3	1	3	2	1	3	2	5	13	7	13	14	11	7
	$\mu_{h,6,1,5}$	22	28	29	25	29	24	23	17	21	10	16	13	18	20	27	28	25	19	21	27	29	41	29	22
	$\mu_{h,7,1,5}$	37	49	78	65	57	60	36	52	40	38	37	35	41	39	32	26	37	57	56	53	41	45	46	37
Per. on $y_{*,h}$	$\mu_{h,1,1,6}$	60	50	42	36	37	56	30	23	30	22	28	24	20	22	21	15	33	28	44	43	32	31	6	30
	$\mu_{h,2,1,6}$	27	24	25	41	39	29	42	28	28	13	21	23	30	36	35	42	51	38	44	59	34	31	25	32
	$\mu_{h,3,1,6}$	42	43	41	49	49	37	40	59	57	46	39	32	35	36	48	47	52	60	45	36	29	13	21	29
	$\mu_{h,4,1,6}$	23	24	30	31	33	46	68	72	63	58	45	45	45	37	44	51	46	54	44	36	21	16	25	26
	$\mu_{h,5,1,6}$	36	29	31	34	27	40	68	74	82	75	70	67	71	59	58	59	57	43	45	49	57	42	41	39
	$\mu_{h,6,1,6}$	10	24	33	36	37	47	68	67	51	37	22	19	26	20	33	35	31	20	26	34	29	4	1	16
Per. on $y_{*,24}$	$\mu_{h,1,1,7}$	62	58	44	46	28	40	35	29	19	26	13	13	16	19	23	25	20	27	23	15	19	28	19	.
	$\mu_{h,2,1,7}$	36	35	49	54	47	65	43	41	39	48	47	42	46	39	38	32	45	53	67	56	45	40	31	.
	$\mu_{h,3,1,7}$	20	22	28	27	27	36	50	32	34	34	33	29	25	18	17	24	24	19	21	22	21	15	20	.
	$\mu_{h,4,1,7}$	50	36	34	32	26	27	27	30	26	22	27	24	34	35	35	29	33	29	30	23	13	14	25	.
	$\mu_{h,5,1,7}$	30	32	25	30	27	29	38	38	34	20	25	24	25	24	26	26	31	39	35	36	13	11	11	.
	$\mu_{h,6,1,7}$	47	29	26	35	33	31	22	26	39	36	17	18	14	17	31	17	32	23	21	35	32	28	17	.

Note: The table reports the mean occurences of variables in Eq. (20) *estimated with lasso where regularization parameter is selected through information criterion as explained in Section 3.2.5.*

Table 9: Mean occurrences of the **BA_LS1** model parameters across all six datasets and full out-of-sample test period in percentage points. A heat-map is used to indicate the range of occurrence values between 0 (→ red) and 100 (→ green). Continued in Table 10.

	h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
day: $d-1$	$\mu_{h,1,1,1}$	40	33	27	27	23	21	21	19	22	22	24	27	28	29	28	24	20	17	22	25	23	24	30	27
	$\mu_{h,1,2,1}$	10	12	10	12	11	11	12	11	10	12	13	16	18	19	21	18	14	12	11	10	10	13	15	11
	$\mu_{h,1,3,1}$	10	13	14	15	16	16	17	18	17	17	15	16	15	16	17	16	15	11	13	13	13	12	14	13
	$\mu_{h,1,4,1}$	13	15	17	16	15	15	16	15	13	14	15	13	12	11	12	12	15	13	12	11	11	13	14	11
	$\mu_{h,1,5,1}$	16	14	15	17	26	15	14	10	10	10	12	9	9	8	8	7	8	10	11	11	10	8	9	9
	$\mu_{h,1,6,1}$	14	15	13	15	20	36	21	22	16	13	11	12	14	15	16	14	13	13	13	14	19	16	18	15
	$\mu_{h,1,7,1}$	14	17	15	14	13	16	32	18	15	14	15	12	12	11	12	11	12	15	12	14	14	15	15	20
	$\mu_{h,1,8,1}$	15	16	19	18	16	14	17	18	19	12	11	11	14	15	14	14	11	12	11	14	16	13	16	13
	$\mu_{h,1,9,1}$	15	15	16	15	15	18	20	19	27	21	12	10	9	9	9	11	11	9	11	10	11	11	11	10
	$\mu_{h,1,10,1}$	13	15	16	14	14	13	17	21	22	18	21	17	16	17	17	17	17	14	12	12	19	17	17	14
	$\mu_{h,1,11,1}$	19	16	15	15	17	14	17	21	17	17	14	19	15	18	17	17	19	17	18	19	19	19	20	18
	$\mu_{h,1,12,1}$	12	15	12	14	15	12	14	17	17	18	16	20	13	17	17	16	20	23	21	22	16	17	15	14
	$\mu_{h,1,13,1}$	12	15	11	11	11	14	19	18	17	17	14	16	14	12	14	16	19	21	23	21	20	17	17	12
	$\mu_{h,1,14,1}$	14	12	11	11	10	10	13	12	12	10	9	10	9	9	13	12	12	13	12	15	15	12	13	15
	$\mu_{h,1,15,1}$	13	11	13	13	11	11	12	17	15	13	12	13	12	13	12	18	15	11	12	14	15	16	14	16
	$\mu_{h,1,16,1}$	15	18	15	16	14	19	16	16	16	21	17	16	15	16	17	16	19	17	16	17	18	16	13	19
	$\mu_{h,1,17,1}$	15	14	14	15	19	18	18	18	16	14	13	15	19	23	26	34	44	33	24	23	23	23	16	21
	$\mu_{h,1,18,1}$	16	13	15	15	16	14	15	21	22	26	24	25	25	25	27	24	35	47	19	13	18	14	13	12
	$\mu_{h,1,19,1}$	19	18	21	21	23	27	29	27	24	19	21	14	14	15	14	15	17	24	46	18	20	18	13	12
	$\mu_{h,1,20,1}$	11	11	11	11	12	14	16	27	23	21	22	21	20	20	20	18	19	15	20	35	15	17	16	16
	$\mu_{h,1,21,1}$	14	23	24	25	29	28	29	27	36	36	38	31	28	29	28	29	24	23	17	19	47	25	17	16
	$\mu_{h,1,22,1}$	12	15	14	15	17	13	17	22	26	26	22	23	23	24	23	25	27	26	29	25	25	31	26	26
	$\mu_{h,1,23,1}$	32	33	35	35	38	45	37	35	29	24	27	25	24	23	26	24	21	20	22	21	24	27	20	27
	$\mu_{h,1,24,1}$	97	98	94	88	82	81	80	69	65	61	50	43	37	33	33	30	28	25	32	29	28	28	36	56
day: $d-2$	$\mu_{h,2,1,1}$	19	13	13	16	17	14	17	16	16	16	15	16	19	19	19	20	15	13	16	13	12	14	17	14
	$\mu_{h,2,2,1}$	9	12	10	8	10	9	11	11	14	15	13	15	16	15	13	15	12	12	13	14	15	11	11	10
	$\mu_{h,2,3,1}$	12	16	20	15	16	14	10	11	12	13	12	15	16	15	13	15	17	12	13	15	12	11	14	11
	$\mu_{h,2,4,1}$	15	15	11	14	15	15	13	8	11	15	17	18	18	16	14	15	13	13	14	14	9	11	14	14
	$\mu_{h,2,5,1}$	11	10	11	12	13	11	12	10	11	14	14	16	17	15	13	11	11	12	14	11	10	10	12	11
	$\mu_{h,2,6,1}$	10	10	11	11	10	8	11	11	10	11	12	12	14	15	14	14	11	11	10	11	12	12	16	12
	$\mu_{h,2,7,1}$	12	10	10	11	11	11	11	14	12	14	16	16	15	15	14	14	16	17	14	13	12	15	16	14
	$\mu_{h,2,8,1}$	13	13	13	12	12	12	17	15	13	14	15	14	13	14	13	13	14	13	11	11	10	11	10	11
	$\mu_{h,2,9,1}$	14	13	15	17	14	12	13	11	13	14	13	12	10	10	11	11	11	11	11	13	16	14	17	14
	$\mu_{h,2,10,1}$	12	14	12	17	14	13	11	15	16	17	17	19	19	15	15	14	14	18	16	16	16	18	17	13
	$\mu_{h,2,11,1}$	7	10	12	14	13	13	13	13	12	11	11	12	12	12	11	10	10	11	13	15	11	12	10	11
	$\mu_{h,2,12,1}$	12	10	13	13	13	12	13	18	12	12	12	12	13	13	15	11	10	15	13	10	10	10	9	8
	$\mu_{h,2,13,1}$	9	8	6	8	8	7	8	9	8	8	7	8	9	8	11	11	11	13	9	10	9	9	9	10
	$\mu_{h,2,14,1}$	11	10	10	10	9	10	11	8	9	9	8	8	9	8	9	8	10	11	9	8	9	10	11	10
	$\mu_{h,2,15,1}$	14	16	15	15	15	13	15	15	15	17	16	16	16	20	26	22	20	20	19	22	19	15	17	15
	$\mu_{h,2,16,1}$	13	16	14	13	12	13	14	12	11	12	11	13	10	9	12	11	11	13	14	14	15	13	12	13
	$\mu_{h,2,17,1}$	10	10	9	9	10	10	11	9	11	12	11	14	12	11	12	11	12	12	10	10	11	10	9	9
	$\mu_{h,2,18,1}$	16	16	13	12	14	14	16	16	13	15	11	9	10	9	9	9	10	13	11	12	11	11	12	11
	$\mu_{h,2,19,1}$	14	15	13	14	15	14	13	14	14	17	12	11	14	14	16	13	16	15	15	18	10	11	12	16
	$\mu_{h,2,20,1}$	12	11	12	11	10	14	16	14	13	13	11	12	12	14	13	13	11	16	13	17	11	9	10	11
	$\mu_{h,2,21,1}$	10	7	6	8	8	7	9	11	12	12	12	11	10	9	8	8	8	9	8	10	22	12	10	10
	$\mu_{h,2,22,1}$	8	10	10	11	11	15	14	13	11	11	11	9	9	10	10	10	11	10	10	17	15	13	14	14
	$\mu_{h,2,23,1}$	15	19	19	20	20	18	18	15	13	16	12	14	13	15	18	16	16	12	10	12	13	13	12	15
	$\mu_{h,2,24,1}$	36	33	29	22	19	22	31	30	27	25	22	19	18	20	22	21	19	16	17	20	18	21	28	21

Note: The table reports the mean occurences of variables in Eq. (20) *estimated with bagging for 1% significance level as explained in Section 3.2.5.*

Table 10: Mean occurrences of the **BA_LS1** model parameters across all six datasets and full out-of-sample test period in percentage points. A heat-map is used to indicate the range of occurrence values between 0 (→ red) and 100 (→ green). Continued in Table 11.

	h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
day: $d-3$	$\mu_{h,3,1,1}$	12	12	10	11	10	10	11	11	12	10	9	9	11	12	11	12	12	13	14	12	10	10	11	8
	$\mu_{h,3,2,1}$	15	16	14	15	15	14	14	11	13	10	10	11	9	11	10	10	10	10	10	11	10	9	12	12
	$\mu_{h,3,3,1}$	10	14	18	16	15	12	13	9	10	7	6	10	11	12	12	13	13	16	16	14	13	15	17	14
	$\mu_{h,3,4,1}$	13	14	16	17	15	11	14	14	14	18	16	13	16	13	14	16	16	14	13	12	12	13	14	11
	$\mu_{h,3,5,1}$	13	11	10	11	13	8	14	15	18	20	22	18	19	18	17	18	17	12	12	12	11	12	13	9
	$\mu_{h,3,6,1}$	14	14	13	13	11	12	13	13	12	10	11	12	13	14	14	13	16	18	15	19	18	22	18	17
	$\mu_{h,3,7,1}$	13	14	10	10	11	15	20	14	13	13	15	14	13	14	14	14	14	14	16	13	11	12	9	11
	$\mu_{h,3,8,1}$	10	10	12	12	13	11	10	17	18	14	14	12	12	13	10	12	9	10	10	10	11	13	9	8
	$\mu_{h,3,9,1}$	13	16	18	19	18	18	12	19	20	16	16	13	14	13	15	17	14	10	11	12	11	11	11	9
	$\mu_{h,3,10,1}$	14	14	13	14	11	13	11	12	15	14	14	11	11	11	15	16	14	13	12	12	13	13	12	14
	$\mu_{h,3,11,1}$	11	14	12	10	9	12	13	14	12	10	10	10	9	9	9	10	11	12	12	9	11	9	9	11
	$\mu_{h,3,12,1}$	16	16	14	12	11	11	13	17	15	13	10	10	11	9	10	10	9	9	10	10	10	10	10	9
	$\mu_{h,3,13,1}$	15	17	18	19	17	17	14	14	16	19	16	21	21	21	22	21	21	15	14	15	15	15	21	17
	$\mu_{h,3,14,1}$	17	19	17	18	20	21	17	17	19	18	15	19	17	16	15	15	14	12	10	11	13	13	15	17
	$\mu_{h,3,15,1}$	13	11	10	11	13	11	12	13	14	15	12	9	10	11	12	13	13	12	11	11	14	13	12	14
	$\mu_{h,3,16,1}$	15	17	13	15	13	13	15	15	13	13	15	12	13	14	13	16	13	14	13	14	18	13	13	15
	$\mu_{h,3,17,1}$	15	14	14	15	13	13	17	12	8	12	11	9	9	9	11	10	12	9	9	8	12	12	11	9
	$\mu_{h,3,18,1}$	9	14	14	13	13	12	11	11	11	8	10	13	13	15	19	19	20	19	12	12	11	12	10	11
	$\mu_{h,3,19,1}$	13	14	12	14	14	14	12	10	10	9	10	11	10	11	12	12	13	11	14	11	12	11	11	11
	$\mu_{h,3,20,1}$	13	13	16	15	13	11	10	9	12	13	13	14	12	14	13	15	16	15	16	23	17	14	16	18
	$\mu_{h,3,21,1}$	13	13	15	15	13	11	11	12	13	12	13	13	13	15	16	16	13	11	14	16	14	12	13	13
	$\mu_{h,3,22,1}$	15	13	13	13	16	13	13	12	12	9	10	9	11	15	15	16	16	13	9	11	11	15	17	16
	$\mu_{h,3,23,1}$	8	8	8	8	10	10	10	13	12	12	12	13	12	15	14	14	14	17	16	20	18	19	24	22
	$\mu_{h,3,24,1}$	13	14	13	12	15	15	13	14	17	12	9	11	11	12	12	11	13	12	12	14	15	14	16	20
day: $d-4$	$\mu_{h,4,1,1}$	14	15	16	16	16	15	12	13	13	13	13	12	14	13	15	14	12	11	14	13	15	14	17	13
	$\mu_{h,4,2,1}$	9	9	11	11	11	12	10	11	11	8	9	9	9	10	10	10	8	9	9	9	8	9	12	9
	$\mu_{h,4,3,1}$	12	13	11	11	11	10	10	9	11	11	13	12	13	13	13	14	13	14	10	14	13	11	12	11
	$\mu_{h,4,4,1}$	16	13	13	15	16	11	12	12	11	11	12	10	11	12	12	15	13	12	12	12	11	10	10	11
	$\mu_{h,4,5,1}$	9	9	11	10	10	10	12	9	10	10	9	10	9	11	12	13	13	13	9	10	10	10	13	12
	$\mu_{h,4,6,1}$	15	17	18	14	15	18	16	13	14	11	11	11	13	14	15	15	14	11	9	8	10	11	15	14
	$\mu_{h,4,7,1}$	12	11	12	11	10	10	14	14	11	10	12	10	11	16	14	14	11	11	8	8	9	10	11	10
	$\mu_{h,4,8,1}$	12	8	8	8	8	8	11	15	12	12	11	9	11	12	10	10	10	12	12	10	10	13	7	7
	$\mu_{h,4,9,1}$	10	10	11	11	10	10	14	16	16	13	12	9	11	12	10	10	10	12	12	11	14	13	11	11
	$\mu_{h,4,10,1}$	10	9	15	13	13	10	11	11	12	11	12	11	10	10	10	9	9	9	12	13	10	10	10	9
	$\mu_{h,4,11,1}$	10	11	12	12	12	10	9	10	12	14	14	13	14	13	14	12	13	13	12	9	12	11	10	15
	$\mu_{h,4,12,1}$	12	12	15	15	13	13	14	14	15	13	10	10	14	16	18	15	15	13	12	11	14	12	9	10
	$\mu_{h,4,13,1}$	8	12	13	14	13	14	10	9	12	10	7	10	9	10	13	11	11	13	11	11	12	12	13	12
	$\mu_{h,4,14,1}$	10	9	11	13	13	11	10	13	16	14	11	10	9	9	10	11	12	13	11	14	11	15	12	9
	$\mu_{h,4,15,1}$	9	11	12	12	12	11	10	13	12	13	10	10	11	11	12	10	10	9	8	8	9	13	12	11
	$\mu_{h,4,16,1}$	9	10	9	11	10	11	12	15	14	12	16	13	18	18	18	16	16	11	12	13	12	14	14	14
	$\mu_{h,4,17,1}$	11	10	12	12	14	11	9	14	11	10	10	9	9	8	8	10	10	10	11	12	10	15	15	17
	$\mu_{h,4,18,1}$	13	10	15	14	12	11	11	13	10	10	12	14	14	11	11	12	12	12	10	10	9	10	10	8
	$\mu_{h,4,19,1}$	10	10	11	12	13	10	15	12	17	15	15	14	17	16	15	17	20	19	16	16	14	10	12	10
	$\mu_{h,4,20,1}$	16	15	14	14	15	11	22	15	18	22	17	14	17	18	20	22	18	15	20	17	12	13	13	13
	$\mu_{h,4,21,1}$	15	18	21	20	20	15	18	14	16	18	13	12	11	11	15	11	9	10	9	9	8	9	8	9
	$\mu_{h,4,22,1}$	17	18	17	17	18	13	14	21	21	23	22	18	19	18	15	16	16	20	18	19	15	19	15	19
	$\mu_{h,4,23,1}$	12	12	13	14	14	11	14	11	11	10	12	11	12	12	13	14	13	11	11	9	12	11	16	11
	$\mu_{h,4,24,1}$	13	11	12	12	13	14	14	11	9	13	13	14	14	14	13	14	14	15	17	13	11	14	15	16

Note: The table reports the mean occurences of variables in Eq. (20) *estimated with bagging for 1% significance level as explained in Section 3.2.5.*

Table 11: Mean occurrences of the**BA_LS1** model parameters across all six datasets and full out-of-sample test period in percentage points. A heat-map is used to indicate the range of occurrence values between 0 (→ red) and 100 (→ green). Continued in Table 12.

	h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
day: $d-5$	$\mu_{h,5,1,1}$	15	15	14	14	17	11	15	13	11	13	13	13	11	9	9	9	10	10	10	10	11	14	12	14
	$\mu_{h,5,2,1}$	10	13	17	15	15	14	15	11	9	13	13	14	10	10	10	10	8	11	10	10	12	12	10	12
	$\mu_{h,5,3,1}$	8	9	12	11	11	9	8	7	6	8	10	10	11	12	14	14	16	16	12	11	13	10	14	13
	$\mu_{h,5,4,1}$	10	11	13	15	12	11	10	12	12	12	14	14	16	12	10	11	11	12	8	10	11	10	11	12
	$\mu_{h,5,5,1}$	10	12	9	12	14	15	15	14	17	18	15	14	12	11	11	12	12	13	14	14	17	14	14	16
	$\mu_{h,5,6,1}$	15	15	19	15	13	14	15	12	12	13	14	12	15	13	12	12	12	11	16	20	15	14	16	17
	$\mu_{h,5,7,1}$	12	9	9	11	10	11	12	11	9	10	10	10	11	12	10	10	9	9	8	12	9	11	11	10
	$\mu_{h,5,8,1}$	8	10	9	11	10	11	10	8	9	11	11	11	11	14	15	11	10	10	10	9	11	14	15	10
	$\mu_{h,5,9,1}$	9	11	13	12	11	10	10	10	10	12	13	12	12	11	11	12	11	10	10	12	10	11	14	13
	$\mu_{h,5,10,1}$	7	9	9	10	11	10	11	13	12	13	12	11	10	10	9	12	14	13	12	12	13	14	9	9
	$\mu_{h,5,11,1}$	10	12	11	11	13	11	12	11	8	12	10	13	13	15	15	17	16	16	13	11	15	12	11	11
	$\mu_{h,5,12,1}$	10	10	11	9	10	11	12	9	8	9	11	15	14	15	16	17	21	14	13	12	12	11	9	10
	$\mu_{h,5,13,1}$	15	17	15	12	11	11	14	13	13	11	10	11	10	9	10	11	9	8	8	9	10	9	10	10
	$\mu_{h,5,14,1}$	10	10	11	8	9	11	13	11	12	11	11	12	14	13	15	15	13	12	11	14	15	15	12	11
	$\mu_{h,5,15,1}$	10	13	11	11	10	11	14	12	12	12	11	10	12	11	11	10	11	13	11	13	11	13	9	7
	$\mu_{h,5,16,1}$	12	9	9	12	12	14	20	16	12	10	9	11	12	14	16	16	14	11	12	11	11	11	9	9
	$\mu_{h,5,17,1}$	11	10	10	11	12	14	15	9	10	10	9	11	12	13	14	15	12	11	13	12	11	12	10	11
	$\mu_{h,5,18,1}$	12	11	13	13	14	12	15	10	14	14	11	11	12	11	10	11	12	13	15	12	11	10	10	15
	$\mu_{h,5,19,1}$	9	13	15	15	15	13	19	11	12	17	13	11	14	13	15	14	12	15	17	14	10	9	9	17
	$\mu_{h,5,20,1}$	12	11	12	12	12	14	21	13	11	15	13	13	14	13	14	16	16	17	15	16	12	11	13	11
	$\mu_{h,5,21,1}$	10	7	8	7	8	10	15	11	9	8	10	10	8	11	10	8	8	10	10	11	18	10	10	8
	$\mu_{h,5,22,1}$	13	10	10	10	10	12	11	13	16	14	15	14	12	15	14	15	14	15	12	11	12	15	9	13
	$\mu_{h,5,23,1}$	13	9	11	11	11	12	10	12	13	12	10	10	12	15	15	16	16	16	18	17	15	17	16	14
	$\mu_{h,5,24,1}$	19	20	17	15	13	9	10	11	10	10	10	12	11	13	14	14	14	15	13	13	13	12	13	12
day: $d-6$	$\mu_{h,6,1,1}$	11	9	10	11	10	11	9	9	9	10	13	12	10	10	9	10	10	11	13	12	14	11	11	14
	$\mu_{h,6,2,1}$	10	14	13	13	12	9	10	10	11	14	11	11	13	12	12	10	12	13	14	14	17	15	16	15
	$\mu_{h,6,3,1}$	12	14	18	17	14	13	12	13	11	15	12	12	12	12	10	10	9	11	10	8	11	14	14	15
	$\mu_{h,6,4,1}$	10	12	15	13	13	15	13	13	12	11	12	14	17	16	17	18	16	17	14	12	13	14	16	16
	$\mu_{h,6,5,1}$	9	13	13	14	13	14	15	12	14	13	13	14	17	16	16	17	17	17	16	13	13	12	12	11
	$\mu_{h,6,6,1}$	14	11	11	10	11	11	11	12	10	11	9	8	9	11	10	9	9	13	12	10	9	9	8	11
	$\mu_{h,6,7,1}$	11	11	12	11	14	16	18	13	13	14	11	10	10	12	15	12	13	13	17	13	13	15	13	17
	$\mu_{h,6,8,1}$	11	10	9	11	9	9	14	17	12	15	15	14	13	12	10	10	16	18	16	11	13	13	13	19
	$\mu_{h,6,9,1}$	9	8	10	13	10	13	11	9	9	15	18	19	13	13	10	11	15	15	15	14	14	12	14	15
	$\mu_{h,6,10,1}$	9	8	9	9	10	12	11	16	19	15	14	14	11	11	9	9	9	9	9	9	10	11	11	12
	$\mu_{h,6,11,1}$	11	10	11	9	9	11	10	15	16	15	14	10	10	10	10	10	9	8	9	8	7	8	9	11
	$\mu_{h,6,12,1}$	10	11	13	12	10	9	11	11	9	9	7	9	10	9	9	9	10	10	9	8	8	10	7	8
	$\mu_{h,6,13,1}$	7	11	9	9	9	7	8	9	9	9	8	8	8	8	11	8	10	10	10	7	7	7	7	6
	$\mu_{h,6,14,1}$	10	13	11	10	10	11	12	13	14	14	12	12	11	10	14	11	11	10	10	13	15	15	14	14
	$\mu_{h,6,15,1}$	12	13	11	10	9	12	9	10	9	9	9	11	15	19	19	17	18	16	14	16	14	18	17	23
	$\mu_{h,6,16,1}$	13	11	9	9	9	12	14	14	13	10	10	10	11	14	14	15	13	15	20	19	17	20	16	20
	$\mu_{h,6,17,1}$	11	10	11	13	12	11	9	11	10	10	13	11	12	11	13	13	16	11	11	16	18	15	9	17
	$\mu_{h,6,18,1}$	12	12	14	14	16	13	12	14	17	13	14	14	13	15	14	15	14	18	14	12	11	14	12	17
	$\mu_{h,6,19,1}$	8	11	12	12	12	10	11	12	14	15	12	11	11	10	10	11	11	12	12	14	13	15	14	15
	$\mu_{h,6,20,1}$	14	13	15	15	14	12	17	14	15	18	14	12	14	13	12	11	13	15	12	13	9	9	15	9
	$\mu_{h,6,21,1}$	13	9	10	11	11	10	12	11	10	11	11	9	10	11	11	10	10	12	14	15	13	10	10	9
	$\mu_{h,6,22,1}$	13	12	11	10	10	10	13	7	6	10	10	10	13	14	15	14	13	13	13	8	8	15	11	12
	$\mu_{h,6,23,1}$	9	9	9	12	9	8	10	9	8	9	8	7	7	7	6	6	7	7	9	10	10	10	11	9
	$\mu_{h,6,24,1}$	17	17	12	11	10	11	11	12	9	10	12	12	12	15	14	13	13	13	15	16	12	15	14	13

Note: The table reports the mean occurences of variables in Eq. (20) *estimated with bagging for 1% significance level as explained in Section 3.2.5.*

Table 12: Mean occurrences of the **BA_LS1** model parameters across all six datasets and full out-of-sample test period in percentage points. A heat-map is used to indicate the range of occurrence values between 0 (→ red) and 100 (→ green). Continued in Table 13.

	h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
day: $d-7$	$\mu_{h,7,1,1}$	15	11	11	11	10	12	14	14	11	10	10	13	12	10	10	11	14	11	12	14	16	10	12	10
	$\mu_{h,7,2,1}$	14	10	10	10	10	10	16	12	9	9	10	13	14	12	12	12	13	9	13	12	11	12	10	12
	$\mu_{h,7,3,1}$	9	10	9	8	8	8	12	10	9	9	9	10	10	12	11	10	11	13	12	13	12	12	11	13
	$\mu_{h,7,4,1}$	11	9	10	12	10	13	10	7	7	10	13	10	10	11	12	14	17	15	16	12	11	12	11	11
	$\mu_{h,7,5,1}$	14	11	13	15	14	13	9	9	8	13	13	10	10	12	12	12	14	11	12	10	11	11	13	12
	$\mu_{h,7,6,1}$	17	13	11	13	13	18	17	13	15	16	15	15	16	17	15	17	21	18	16	15	13	15	12	16
	$\mu_{h,7,7,1}$	10	11	10	10	10	10	18	14	12	11	15	17	17	18	18	16	16	14	14	16	12	12	12	13
	$\mu_{h,7,8,1}$	9	13	12	11	10	11	10	10	8	10	10	8	9	10	10	10	12	13	13	14	15	17	12	11
	$\mu_{h,7,9,1}$	8	10	11	10	10	8	9	14	12	14	9	9	10	10	10	9	9	9	12	12	11	9	8	10
	$\mu_{h,7,10,1}$	10	9	8	9	8	8	11	12	10	13	14	11	12	13	12	11	9	11	12	14	14	15	10	11
	$\mu_{h,7,11,1}$	12	12	12	14	17	14	14	13	13	14	16	13	12	16	17	15	14	14	13	17	14	15	11	9
	$\mu_{h,7,12,1}$	12	12	10	8	8	9	12	15	13	12	13	12	12	13	16	15	16	16	13	10	11	10	12	10
	$\mu_{h,7,13,1}$	21	28	23	18	20	18	18	16	16	17	18	18	18	19	20	19	15	19	20	20	17	17	18	17
	$\mu_{h,7,14,1}$	12	14	14	12	13	11	11	15	14	10	12	15	17	18	19	18	13	13	18	19	18	21	22	19
	$\mu_{h,7,15,1}$	10	15	13	12	14	12	15	16	17	15	11	11	13	12	11	12	9	9	11	11	11	9	9	10
	$\mu_{h,7,16,1}$	11	17	15	15	16	13	12	15	14	13	11	13	13	15	13	12	9	10	11	13	14	13	12	11
	$\mu_{h,7,17,1}$	14	13	13	16	14	14	11	9	13	14	10	15	13	15	16	13	15	18	16	18	15	14	16	17
	$\mu_{h,7,18,1}$	21	17	12	13	12	12	9	13	10	10	11	13	14	15	15	12	14	15	15	16	18	18	14	11
	$\mu_{h,7,19,1}$	12	10	8	8	11	12	14	14	12	11	10	11	12	12	11	12	11	15	18	15	13	16	12	13
	$\mu_{h,7,20,1}$	9	9	11	14	11	9	10	8	9	10	10	10	13	13	13	15	17	18	14	11	9	12	14	14
	$\mu_{h,7,21,1}$	9	10	10	12	13	10	8	12	13	13	10	10	10	12	15	14	13	11	9	10	13	12	17	14
	$\mu_{h,7,22,1}$	10	9	11	10	10	11	20	13	13	14	11	11	15	14	13	11	12	12	12	12	14	15	9	9
	$\mu_{h,7,23,1}$	11	12	11	10	12	17	17	14	10	13	11	10	10	9	8	8	12	11	10	12	10	12	14	13
	$\mu_{h,7,24,1}$	11	12	12	12	12	12	13	9	9	9	10	10	9	11	11	9	9	10	7	8	7	13	11	10
day: $d-8$	$\mu_{h,8,1,1}$	10	14	14	12	15	14	12	10	10	12	12	10	10	13	14	11	12	13	12	11	12	11	10	9
	$\mu_{h,8,2,1}$	12	13	12	12	13	13	15	13	13	14	12	10	10	12	14	11	9	11	8	10	13	10	8	8
	$\mu_{h,8,3,1}$	15	14	12	15	14	19	14	10	10	9	8	7	8	9	11	15	11	11	8	8	10	9	8	9
	$\mu_{h,8,4,1}$	12	11	10	10	9	11	10	10	8	9	13	12	11	11	9	9	10	13	15	10	10	10	13	10
	$\mu_{h,8,5,1}$	10	13	14	15	13	10	11	13	12	12	10	12	8	9	8	9	9	8	9	9	9	10	8	7
	$\mu_{h,8,6,1}$	12	14	15	17	15	18	14	13	12	10	10	11	11	12	10	9	10	10	10	10	12	10	9	9
	$\mu_{h,8,7,1}$	10	13	12	11	11	11	13	12	11	11	12	12	12	13	11	16	15	15	13	11	15	14	10	9
	$\mu_{h,8,8,1}$	14	13	9	9	9	11	13	18	14	13	12	9	9	11	10	11	12	12	10	9	11	15	13	11
	$\mu_{h,8,9,1}$	11	13	11	11	13	12	13	12	12	14	14	14	15	14	13	12	12	11	10	11	11	11	13	11
	$\mu_{h,8,10,1}$	15	13	14	17	18	17	14	13	11	11	12	12	15	16	14	12	9	9	11	16	10	11	11	10
	$\mu_{h,8,11,1}$	12	11	11	11	13	12	10	9	9	9	9	11	12	10	11	10	12	11	14	12	10	11	13	12
	$\mu_{h,8,12,1}$	11	12	8	8	8	8	10	12	10	10	11	10	11	11	10	9	18	15	14	12	11	10	10	11
	$\mu_{h,8,13,1}$	10	11	7	7	7	8	9	12	14	11	10	11	13	15	15	16	18	13	12	17	15	13	15	14
	$\mu_{h,8,14,1}$	12	13	10	11	10	14	14	11	12	10	11	11	11	14	15	14	14	13	13	15	14	17	13	12
	$\mu_{h,8,15,1}$	10	10	9	11	11	15	14	13	13	12	9	8	9	11	11	11	15	14	13	14	16	16	12	11
	$\mu_{h,8,16,1}$	11	11	12	12	13	11	11	13	13	13	11	9	9	10	10	10	11	12	13	12	15	14	14	12
	$\mu_{h,8,17,1}$	20	19	16	14	13	11	14	13	16	16	19	21	18	19	16	24	25	20	15	15	17	16	15	15
	$\mu_{h,8,18,1}$	16	18	14	14	12	12	10	10	11	15	15	14	17	20	17	17	19	16	14	13	15	12	13	10
	$\mu_{h,8,19,1}$	8	9	11	12	10	11	12	13	14	12	13	15	17	18	16	16	20	24	17	19	17	14	12	14
	$\mu_{h,8,20,1}$	9	8	8	8	9	9	10	11	10	9	10	10	10	12	10	10	11	12	10	14	15	15	12	13
	$\mu_{h,8,21,1}$	12	12	12	10	11	13	14	12	8	9	11	11	10	10	10	10	11	10	12	15	15	13	13	13
	$\mu_{h,8,22,1}$	12	10	9	10	9	9	18	13	12	12	11	10	10	10	9	9	9	11	10	11	9	13	11	11
	$\mu_{h,8,23,1}$	12	10	7	7	8	13	13	11	14	14	14	15	11	12	12	11	10	9	11	11	11	12	13	16
	$\mu_{h,8,24,1}$	9	12	10	8	11	12	11	12	12	13	14	16	14	16	13	14	11	10	10	15	16	14	15	14

Note: The table reports the mean occurences of variables in Eq. (20) *estimated with bagging for 1% significance level as explained in Section 3.2.5.*

Table 13: Mean occurrences of the **BA_LS1** model parameters across all six datasets and full out-of-sample test period in percentage points. A heat-map is used to indicate the range of occurrence values between 0 (→ red) and 100 (→ green).

	h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Daily Minimums	$\mu_{h,1,1,2}$	28	33	39	45	45	37	32	30	24	21	17	12	11	13	13	14	19	15	15	13	16	15	17	14
	$\mu_{h,2,1,2}$	15	13	14	13	14	15	14	10	10	9	9	11	12	11	8	9	7	13	13	13	14	13	19	16
	$\mu_{h,3,1,2}$	13	16	13	19	15	12	13	9	13	11	9	7	8	9	10	9	8	8	9	10	11	14	17	16
	$\mu_{h,4,1,2}$	11	11	9	8	9	11	17	15	13	12	14	14	16	15	16	17	18	19	15	14	16	17	16	14
	$\mu_{h,5,1,2}$	18	17	14	16	15	16	17	11	13	13	12	11	13	14	13	11	12	14	12	10	11	11	11	12
	$\mu_{h,6,1,2}$	15	18	16	18	18	18	18	17	14	13	11	12	17	16	15	15	14	13	13	14	12	13	15	12
	$\mu_{h,7,1,2}$	17	18	16	18	12	12	17	15	14	10	8	7	9	9	9	9	9	9	10	8	8	11	14	12
	$\mu_{h,8,1,2}$	17	16	17	17	17	17	16	20	15	19	18	16	16	16	15	14	11	13	15	15	16	21	20	20
Daily Maximums	$\mu_{h,1,1,3}$	11	11	11	12	12	14	20	27	20	15	14	15	15	12	14	14	18	21	21	16	10	13	15	11
	$\mu_{h,2,1,3}$	17	19	19	17	19	14	9	11	11	13	13	14	15	18	17	16	13	13	12	13	16	13	14	13
	$\mu_{h,3,1,3}$	12	11	12	13	14	15	13	15	11	12	11	12	13	12	12	14	14	12	11	12	13	10	12	10
	$\mu_{h,4,1,3}$	10	11	10	9	12	11	12	13	17	15	14	15	18	18	15	13	18	22	16	18	15	12	13	15
	$\mu_{h,5,1,3}$	9	11	14	16	16	18	18	17	14	14	14	13	14	13	14	14	16	15	10	12	11	11	11	11
	$\mu_{h,6,1,3}$	10	12	12	13	11	10	10	11	14	14	15	18	17	16	15	15	14	16	16	15	15	13	12	12
	$\mu_{h,7,1,3}$	13	16	16	16	16	17	19	16	14	15	15	13	16	15	14	16	12	10	8	7	7	7	10	9
	$\mu_{h,8,1,3}$	11	14	13	13	13	12	12	13	12	12	11	10	10	11	10	10	13	12	10	8	10	10	11	11
dow Dummies	$\mu_{h,1,1,4}$	22	25	24	23	36	68	78	79	77	81	81	63	68	58	55	56	49	41	35	24	25	16	10	18
	$\mu_{h,2,1,4}$	20	28	29	26	23	29	49	42	40	43	49	46	48	46	52	51	50	48	41	40	28	26	21	19
	$\mu_{h,3,1,4}$	12	13	15	15	15	15	32	46	39	28	27	24	23	21	20	21	25	20	19	18	18	15	11	16
	$\mu_{h,4,1,4}$	13	10	10	8	9	16	30	46	41	27	22	18	16	17	20	21	21	17	17	16	16	15	15	12
	$\mu_{h,5,1,4}$	12	12	12	12	15	24	32	38	35	26	24	27	27	22	19	20	17	11	12	13	17	15	12	14
	$\mu_{h,6,1,4}$	16	16	13	12	11	22	42	38	45	39	32	27	24	23	24	28	29	27	27	29	26	22	17	24
	$\mu_{h,7,1,4}$	33	30	30	23	22	51	86	91	82	55	58	53	49	56	58	57	57	52	52	46	37	33	29	28
average price	$\mu_{h,1,1,5}$	20	21	20	23	23	26	29	32	25	22	21	17	18	23	24	21	20	24	30	21	25	26	23	16
	$\mu_{h,2,1,5}$	16	17	21	25	27	28	34	41	39	33	28	26	24	27	27	29	30	35	38	38	35	31	29	24
	$\mu_{h,3,1,5}$	26	25	22	23	24	27	34	34	32	31	28	21	27	30	29	23	25	29	30	30	31	24	23	17
	$\mu_{h,4,1,5}$	28	25	23	23	23	24	32	37	32	31	29	26	26	29	30	28	29	34	35	34	32	28	29	22
	$\mu_{h,5,1,5}$	28	23	22	22	23	28	36	38	33	31	27	28	34	33	30	27	26	28	35	31	33	29	24	20
	$\mu_{h,6,1,5}$	23	22	22	22	24	30	38	42	39	31	26	24	25	25	30	28	26	25	31	26	29	31	27	22
	$\mu_{h,7,1,5}$	27	25	22	24	26	29	33	36	36	35	31	27	24	28	29	27	27	27	29	28	32	29	26	19
Per. on $y_{*,h}$	$\mu_{h,1,1,6}$	16	18	19	23	20	20	27	26	19	13	20	19	12	14	16	17	17	23	33	14	11	11	10	14
	$\mu_{h,2,1,6}$	20	18	20	24	20	17	27	30	25	16	21	25	18	19	18	20	18	32	25	24	17	15	18	12
	$\mu_{h,3,1,6}$	23	16	15	19	18	17	24	24	26	30	32	21	17	14	17	17	21	19	15	16	14	13	12	19
	$\mu_{h,4,1,6}$	15	11	16	16	15	14	40	36	35	31	30	21	17	15	15	19	20	27	21	17	10	12	14	18
	$\mu_{h,5,1,6}$	14	12	14	15	17	18	31	23	26	26	24	26	32	27	23	22	18	22	28	16	14	17	18	14
	$\mu_{h,6,1,6}$	11	9	13	11	13	13	41	42	37	17	15	14	13	13	14	20	15	16	17	13	23	15	14	12
Per. on $y_{*,24}$	$\mu_{h,1,1,7}$	20	22	22	19	20	22	28	26	31	32	27	28	23	19	16	15	13	17	24	24	16	18	16	.
	$\mu_{h,2,1,7}$	20	23	21	18	18	15	22	23	22	22	18	15	17	17	15	17	12	11	12	16	13	13	17	.
	$\mu_{h,3,1,7}$	22	24	19	16	16	15	21	17	17	21	20	23	18	15	16	17	16	10	19	19	15	14	17	.
	$\mu_{h,4,1,7}$	17	22	23	17	13	16	22	18	19	20	16	20	23	22	24	23	23	17	19	23	17	15	14	.
	$\mu_{h,5,1,7}$	15	21	21	17	14	15	25	25	21	22	22	15	14	15	15	14	16	12	14	13	18	18	17	.
	$\mu_{h,6,1,7}$	15	20	18	18	17	14	20	19	18	19	18	13	12	11	10	10	8	10	13	12	13	13	11	.

Note: The table reports the mean occurences of variables in Eq. (20) estimated with bagging for 1% significance level as explained in Section 3.2.5.

Table 14: Mean occurrences of factors at the $\mathbf{fAR_{how}}$ model across all six datasets and full out-of-sample test period in percentage points. A heat-map is used to indicate the range of occurrence values between 0 (→ red) and 100 (→ green).

h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
α_1	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
α_2	100	100	100	100	100	95	87	96	99	99	91	91	96	86	84	83	88	82	74	67	59	40	56	40
α_3	100	100	100	100	100	95	87	94	97	96	91	88	92	86	84	83	88	81	74	59	50	34	42	34
α_4	100	100	100	100	100	95	79	92	89	90	86	81	90	84	78	75	58	33	38	28	26	13	23	18
α_5	100	94	96	96	98	95	76	77	73	76	68	63	74	75	75	70	51	31	26	20	17	3	19	14
α_6	100	87	91	87	87	82	67	59	63	52	46	50	60	61	56	49	39	25	17	10	12	1	6	2
α_7	100	83	88	87	86	78	58	46	41	30	25	23	32	33	30	28	24	21	13	1	7	0	1	1
α_8	100	83	88	86	86	77	49	38	38	26	20	15	21	20	16	21	17	16	11	1	0	0	0	0
α_9	100	83	88	86	86	77	44	36	32	15	8	2	2	4	6	15	12	12	7	1	0	0	0	0
α_{10}	99	81	84	76	75	69	42	29	24	8	2	1	1	2	4	9	4	6	3	1	0	0	0	0
α_{11}	93	79	80	69	63	59	36	23	15	5	2	1	1	1	3	7	3	3	2	1	0	0	0	0
α_{12}	70	76	74	59	55	51	35	19	12	3	1	0	0	0	3	5	2	3	1	1	0	0	0	0
α_{13}	63	67	61	52	48	41	28	17	10	1	0	0	0	0	2	5	1	3	1	0	0	0	0	0
α_{14}	59	58	47	47	46	38	23	13	8	1	0	0	0	0	0	3	1	3	1	0	0	0	0	0
α_{15}	46	37	32	38	37	31	12	8	6	1	0	0	0	0	0	0	0	3	1	0	0	0	0	0
α_{16}	41	33	29	36	36	30	10	8	3	1	0	0	0	0	0	0	0	3	1	0	0	0	0	0
α_{17}	35	29	25	29	29	21	8	6	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α_{18}	27	28	21	25	23	15	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α_{19}	15	17	11	15	17	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α_{20}	5	12	8	4	7	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α_{21}	3	9	2	1	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α_{22}	3	5	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α_{23}	0	2	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α_{24}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Note: The table reports the mean occurences of factors in Eq. (22). Factors are selected with Bayesian Information Criterion as explained in Section 3.2.6.

Table 15: Mean occurrences of factors at the **fEXPERT** model across all six datasets and full out-of-sample test period in percentage points. A heat-map is used to indicate the range of occurrence values between 0 (→ red) and 100 (→ green).

h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
α_1	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
α_2	82	96	100	100	100	100	86	100	99	90	81	85	88	89	83	77	81	62	53	62	49	51	62	55
α_3	78	95	100	100	96	97	83	90	87	84	75	77	83	84	80	76	81	59	48	54	43	47	48	43
α_4	65	84	94	100	96	97	74	76	75	67	58	64	73	70	67	63	62	35	31	26	21	24	25	27
α_5	47	68	84	95	87	90	65	70	62	64	53	47	58	58	60	57	51	35	21	23	17	18	21	21
α_6	23	37	64	77	74	62	60	53	55	43	27	15	35	42	30	29	26	7	2	5	6	6	0	7
α_7	13	26	54	68	64	48	47	48	39	36	24	11	23	24	26	23	17	7	2	5	5	1	0	7
α_8	10	24	50	60	56	43	27	31	35	27	17	9	17	18	20	21	15	5	2	5	5	0	0	2
α_9	10	21	47	59	55	36	20	26	32	20	11	7	11	12	13	18	15	3	2	4	5	0	0	2
α_{10}	10	20	44	57	53	33	16	24	23	11	6	5	8	10	13	17	10	2	1	4	5	0	0	1
α_{11}	7	11	29	50	48	27	15	19	12	7	5	4	7	9	12	16	8	0	1	4	5	0	0	1
α_{12}	6	11	22	42	39	24	15	19	12	6	4	3	7	7	11	16	8	0	0	4	1	0	0	1
α_{13}	6	8	17	35	35	20	14	11	6	1	1	2	3	4	10	15	6	0	0	1	1	0	0	1
α_{14}	6	8	15	31	33	20	14	10	5	1	1	1	0	0	4	12	3	0	0	0	1	0	0	0
α_{15}	6	6	14	31	29	17	6	2	2	1	1	1	0	0	4	7	3	0	0	0	0	0	0	0
α_{16}	4	5	10	30	28	14	4	1	1	1	1	1	0	0	4	6	2	0	0	0	0	0	0	0
α_{17}	1	2	4	12	14	5	0	0	1	1	0	1	0	0	4	6	2	0	0	0	0	0	0	0
α_{18}	1	1	3	7	7	1	0	0	0	0	0	1	0	0	2	3	2	0	0	0	0	0	0	0
α_{19}	1	1	3	5	7	1	0	0	0	0	0	1	0	0	2	0	0	0	0	0	0	0	0	0
α_{20}	0	0	0	1	3	0	0	0	0	0	0	1	0	0	2	0	0	0	0	0	0	0	0	0
α_{21}	0	0	0	1	2	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0
α_{22}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0
α_{23}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0
α_{24}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Note: The table reports the mean occurences of factors in Eq. (23). Factors are selected with Bayesian Information Criterion as explained in Section 3.2.6.

D. TURKISH SUMMARY / TÜRKÇE ÖZET

Elektrik fiyatı tahminleri (EFT) elektrik santrali operatörlerinden elektrik piyasası işletmecilerine, iletim sistemi planlama çalışmalarından portföy yöneticilerine kadar vazgeçilmez bir girdidir. Son on yılda gün-öncesi elektrik fiyatlarının tahmin edilmesi için yüksek kabiliyetli modeller geliştirilmiştir. Bu modellerin ve kullanılan yöntemlerin genel bir incelemesi Weron (2014) tarafından verilmektedir. İkiyüz ve daha üzeri açıklayıcı değişkenin yer aldığı karmaşık modellerin tahmin edilebilmesi için son dönemde shrinkage yöntemleri ön plana çıkmaktadır. Bunların arasından Tibshirani (1996) tarafından geliştirilen, **L**east **A**bsolute **S**hrinkage and **S**election **O**perator (lasso), Ziel et al. (2015) tarafından EFT literatüründe uygulanmış ve birçok başarılı modelden daha iyi sonuçlar verdiği gösterilmiştir. İlgili makalenin yayımlanmasından sonra lasso'nun başarılı bir şekilde EFT için uygunlanması hususunda literatürde geniş bir kabul oluşmuştur.

Bu kapsamda, Ludwig et al. (2015) elektrik fiyat tahmininde uygun meteoroloji tahmin istasyonlarını seçmek için Random Forests yönteminin yanında lasso'dan da faydalanmaktadır. Uniejewski et al. (2016) de aynı şekilde stepwise regression ve ridge regression yanında lasso'yu da incelemektedir. Ziel (2016) güniçi fiyat bağımlılıklarının incelemek için lasso'yu kullanmaktadır. Ziel (2017) yenilenebilir enerji üretim tahminlerinin güniçi elektrik spot fiyat tahmin sapmalarıyla ilgili çıkarımlar yapmak için lasso ile tahmin edilmiş modelleri kullanmaktadır. Lasso aynı zamanda EFT yazınında onaltı adet farklı varyans stabilize edici yöntemin arasından en iyi sonuç verenlerin seçilmesinde Uniejewski et al. (2018) tarafından kullanılmıştır. Univariate ve multivariate modelleme metdolojisinin birbiriyle kıyaslanması için yapılan geniş kapsamlı bir ampirik çalışmada lasso her iki modelleme yönteminde de diğer kıyaslanan Naive, Expert, AR ve VAR modellerine göre daha iyi sonuçlar ürettiği Ziel and Weron (2018) tarafından gösterilmiştir. Yakın zamanda yapılan bir başka çalışma ise (Uniejewski et al. (2019)), lasso'yu güniçi elektrik fiyatlarının tahmin edilmesi kapsamında ilk defa uygulamış ve literatürde yaygın olarak kullanılan Naive ve ARX modellerine göre daha başarılı sonuçlar elde edildiğini bildirilmiştir.

Bununla beraber, EFT yazınındaki yaygın kullanımı ve ispatlanmış yüksek kestirim kaabiliyetine rağmen lasso bilinen tek shrinkage yöntemi olmadığı gibi bir takım eksik yönlerinin olmadığı da söylenemez. Lasso metodolojisinin hayata geçirilebilmesi için kendine has nümerik bir optimizasyon algoritması gerekliliği ve lasso ile tahmin edilen model performanslarının regülarizasyon parametresinin değerine yüksek derecede bağımlı olması bardağın boş tarafı olarak görülebilir. Esasen, son yıllardaki bir başka araştırmaya göre, Stock and Watson (2012) Pretest ve Information Criterion metodları, Normal Bayes metodu, Bayesian Model Average, Empirical Bayes and **B**ootstrap **Agg**regation (bagging) yöntemlerinin hepsinin asimtotik olarak shrinkage yöntemi olduğu ispatlamıştır. Bu araştırmanın sonuçları dikkate alındığında ordinary least-squares (OLS) yöntemiyle tahmin edilen açıklayıcı değişkenlerin katsayılarının aynı açıklayıcı değişkenin t-istatistiği değeri ile orantılı olan bir shrinkage parametresiyle çarpılması sonucu hesaplanabileceği ortaya çıkmaktadır. Buradan hareketle ve de bir shrinkage yöntemi olduğu göz önüne alındığında (Huang and Lee (2010); Jin et al. (2014)) bagging yönteminin lasso'ya göre daha basit bir hesaplama yöntemine sahip olması açısından EFT yazınında çok fazla sayıda açıklayıcı değişken içeren modellerin tahmin edilmesinde ön plana çıktığı görülmektedir.

Ekonometrik tahmin yazınında, birçok açıklayıcı değişkenin kullanılabilir olduğu durumlarda bu değişkenler arasında uygun bir alt kümenin seçilmesi, uzun zamanlardır üzerinde araştırmalar yapılan ve her araştırmacı tarafından bilinmekte olan bir konudur. Klasik ekonometri teorisinde bilinen açıklayıcı değişken seçim yöntemleri olan t-istatistiği ve diğer Akaike ve Bayesian Bilgi kriteri gibi yöntemlerin tamamı stabil olmayan model seçimine sebebiyet verdiği bilinmektedir. İstatistik ve ekonometri yazınında ilk defa Breiman (1996a,b) tarafından gösterilen bagging yöntemi stabil parametre seçim yöntemlerinin yarattığı yan etkileri ortadan kaldıran ve mevcut kullanıma hazır bütün açıklayıcı değişkenlerdeki bilgiden en üst düzeyde yararlanılmasını sağlayan doğal bir metod olarak görülmektedir. Yazında bagging yönteminin teorik altyapısı oldukça kuvvetlidir. Bunun için diğer pek çok yayın arasından Hall et al. (1995); Bühlmann and Yu (2002); Andrews (2004); Friedman and Hall (2007); Lee et al. (2010) örnek olarak gösterilebilir. Lee and Yang (2006), klasik eşit ağırlıklı katsayı yönteminin yanında farklı ağırlıklı bagging kombinasyonlarını da kullanarak asimetrik kayıp fonksiyonlarıyla oluşturulan bir tahmin çalışmasında, bagging'i zaman serileri literatürüne uygulamıştır. Yakın zamandaki bir başka araştırma olan Jin et al. (2014), bagging yönteminin teorik altyapısının yüksek bağımlılıklı zaman serilerinin teorisine o uygulanması üzerine yoğunlaşmaktadır. Bagging ilk olarak bağımsız ve aynı dağılıma sahip datasetleri için geliştirilmiştir. Daha sonradan bagging teorisi "moving block bootstrap" ve "block-block bootstrap" yöntemleri bağımlı datasetlerine genişletilmiştir. Daha detaylı bir incelem için ayrıca bkz. Hall et al. (1995) ve Andrews (2004).

Bagging'in ampirik uygulamaları da ekonometri yazınında oldukça geniş yer kaplamaktadır. Diğerleri arasında Yu (2011); Bergmeir et al. (2016); Dantas and Cyrino Oliveira (2018) çalışmaları iyi birer ampirik uygulama örnekleri olarak sıralanabilir. Inoue and Kilian (2008), Birleşik Devletler tüketici fiyat enflasyonu (CPI) serisi için çok sayıda makroekonomik değişkeni kullanarak gerçekleştirdiği tahmin çalışmasında Bayesian shrinkage predictor, the ridge regression predictor, the iterated lasso predictor (veya the Bayesian model average) predictor based on random subsets of extra predictors modelleri arasında bagging'in benzer performansa sahip olduğunu göstermiştir. Rapach and Strauss (2010) bagging'i otuz farklı prediktör kullanarak Birleşik Devletler İşgücü Büyüme verisine uygulamış ve birçok farklı tahmin kombinasyonu yöntemlerine göre daha sonuçlar bulduğunu rapor etmiştir. Kim and Swanson (2014) makroekonomik değişkenlerin tahmin edilmesi üzerine gerçekleştirdiği bir yarışmada diffusion index models, factor models ve bazı tahmin kombinasyon yöntemleri gibi çok sayıda tahmin modelinin yanında bagging'i de ele almaktadır. Bagging'in makroekonomi yazınında uzun yıllardır yaygın olarak uygulanıyor olması ve başarılı sonuçlar alınmış olmasına rağmen, geniş araştırmalarımız ve bilgimiz dahilinde bu yöntem henüz enerji ekonomisi alanında Zhao et al. (2017) tarafından gerçekleştirilen ve yüzdoksansekiz açıklayıcı değişken kullanarak WTI ham petrol fiyatlarının tahmin edilmesi çalışması dışında bilinen bir uygulaması bulunmamaktadır. Bagging'in zaman serileri yazınına uygulanmasıyla ilgili teorik gelişmeler göz önüne alındığında ve birçok başarılı ampirik uygulama dikkate alındığında, bagging kendini enerji ekonomisi ve özellikle de elektrik fiyatlarının tahmin edilmesinde güvenilir bir tahmin yöntemi olarak ön plana çıkarmaktadır.

Elektrik fiyat tahmini yazınına katkımız iki boyutludur. Birincisi, klasik bagging tahmin yönteminin multivariate modelleme metodolojisi altında kullanılarak elektrik fiyatlarının tahmini için model geliştirilmesidir. Bu kapsamda literatürde sıklıkla kullanılan ana elektrik piyasalarında beş farklı seri ve GEFCom2014 yarışma verisi kullanılarak gün öncesi elektrik fiyatları tahmin edilmiştir. Ampirik bulgularımıza göre, Stock and Watson (2012) genelleştirilmiş shrinkage teorisinin bulgularına paralel olarak, bagging yöntemiyle elde edilen tahmin sonuçları en az lasso kadar isabetli sonuçlar verdiği gibi birçok markette lasso'dan daha iyi sonuçlar elde edilmiştir. Lasso'nun en önemli engeli tahmin performansının yüksek oranda regülarizasyon parametresine bağlı olmasıdır. Bu parametre açıklayıcı değişkenler üzerindeki shrinkage etkisini belirlemekte ve her ne kadar birçok farklı anlamda yorumlanabilse de açık bir iktisadi anlam taşımamaktadır. Diğer yandan bagging'in performansı istatistiki modellerde açıklayıcı değişkenlerin istatistiksel anlamlılığını belirleyen basit t-istatistiği değerine bağlıdır. Herhangi bir ekonometrik modelde ilgili t-istatistiği değeri neredeyse tamamında significance levels of 1%, 5% ve 10% anlamlılık değerleri dikkate alınmakta ve uygulamalı ekonometri yazını tarafından makul değerler olarak kabul edilmektedir. Bu çalışmamızda yukarıda anılan anlamlılık değerlerinin her biri için sonuçlar ayrı ayrı sunulmuştur ve düzenli olarak 1% anlamlılık değerinde en iyi sonucun elde edildiği tespit edilmiştir. Bu durum ekonometrik modelleme düzleminde, daha iyi tahminler gerçekleştirebilmek için sadece çok yüksek anlamlılığa sahip açıklayıcı değişkenlerin yapılan modelde bulundurulmasının önemine işaret etmektedir. Diğer yandan lasso'nun bir başka görece zorluğu ise gelişmiş optimazyon algoritmalarına ihtiyaç duyuyor olmasıdır. Bu algoritma ve yazılımlar tahmini gerçekleştiren araştırmacı için her zaman kolay ulaşılabilir veya ulaşılsa bile kolaylıkla kendi şartlarına adapte edilebilir olmamaktadır. Oysa ki bagging oldukça basit algoritmadan oluşmakta herhangi bir yazılımda özel bir ekstra koda ihtiyaç duyulmadan uygulanabilmektedir.

Yazına ikinci katkımız ise güniçi elektrik fiyatlarının birbirleriyle olan bağımlılıkları üzerinedir. Güniçi elektrik fiyatları birbirlerine yüksek oranda bağımlılık göstermektedirMaciejowska and Weron (2015, 2016). Multivariate modelleme yönteminin en büyük eksikliği, tanımı gereği, güniçi elektrik fiyatları arasındaki bağımlılığı içermemesidir. Güniçin elektrik fiyatlarındaki bağımlılığı modelleyebilmek için VAR modelleri ele alınabilir fakat bu tahmin edilmesi gereken toplam parametre sayısını dramatik olarak arttıracağından düşük veri sayısına sahip veri setlerinde modelin tahmin edilmesini oldukça zorlaştırmaktadır. Diğer bir alternatif ise univariate modelleme yönteminden yararlanmaktır. Ancak bu yönteme göre günün bütün saatlerini içeren tek bir büyük model göz önüne alınmaktadır, öngörüleme hatasının birikimli olarak artmasına ve özellikle günün son saatleri için yapılan tahminlerin kötüleşmesine sebep olmaktadır. Univariate modellemenin diğer bir sorunlu tarafı ise multivariate modellemeye göre 24 kat fazla veri sayısı kullanılarak tahmin ve öngörüleme yapılmak zorunda olduğunda artan bilgisayar hesaplama yüküdür. Bu sebepler, bu çalışmada güniçi elektrik fiyatlarının birbirleriyle ilişkisini modelleyebilmek adına faktörlerle desteklenmiş modeller önerilmektedir. Bu çalışmada önerilen faktörlerle desteklenmiş modeller aynı zamanda multivariate modelleme yapısının korunuyor olmasından dolayı hem tahmin edilmesi hızlı ve kolay hem de takip edilebilirdir. Bu kapsamda EFT yazınında kullanılan klasik modellerin faktörlerle desteklenmesi değerlendirilmektedir. Diğer bir deyişle mevcut modellerdeki açıklayıcı değişkenlere ilave olarak modellere açıklayıcı değişken olarak faktörler eklenmektedir. Yukarıda da açıklandığı üzere, bu modelleme yönteminin kullanılmasındaki motivasyon faktörlerin güniçi elektrik fiyatı değişimlerini temsil ediyor olmasıdır.

Faktör modelleri daha önce EFT yazınında aynı motivasyonla Maciejowska and Weron (2016) and Ziel (2016) tarafından da ele alınmıştır. Bu çalışmadaki faktörleri değerlendirme yöntemimiz ve modelleme şeklimiz çeşitli yönlerden mevcut literatürle farklılıklar göstermektedir. İlk olarak, bu çalışmada faktörler açıklayıcı değişken olarak doğrudan modellerde yer verilmektedir, öte yandan mevcut literatur AR ve ARX tipi modeller kullanarak faktörleri öngörülemektedir (Bunun için Ziel (2016) Denklem (15) ve (16) veya Maciejowska and Weron (2016) Denklem (9) and (10) PC_N ve PC_NX modelleri örnek olarak verilebilir.) İkinci olarak bu çalışmada kullanılacak faktör sayısı toplam faktör sayısı olan 24 faktör içerisinde Bayesian Bilgi Kriteri kullanılarak seçilmiştir. Bugüne kadarki çalışmalar önceden belirlenmiş sayıda faktör kullanılmıştır, örneğin Maciejowska and Weron (2016) ilk beş faktörü dikkate alırken, Ziel (2016) ikiden onikiye kadar değişen sayıda faktörü dikkate almaktadır. Bu çalışmada ise veriye bağlı bir seçim yöntemi kullanılarak faktör sayısı tespit edilmiştir.

Faktör modelleri için her bir saat için toplam 24 saatten oluşan gün öncesi elektrik fiyatları panel verisi kullanılarak principle component yöntemiyle gizli faktörler hesaplanmış ve faktörler modelere yeni açıklayıcı değişkenler olarak eklendikten sonra modeller tekrardan tahmin edilmiştir. Modellere eklenen yeni faktörler Bayesian Information Criterion yöntemi kullanılarak tespit edilmiştir. Çalışılan elektrik marketlerinin yarısında faktörlerle desteklenmiş Exper model (fEXPERT) diğer shrinkage yöntemleri ile kıyaslanabilir sonuçlar verdiği görülmektedir. Faktörlerle desteklenmiş Expert modeller güniçi elektrik fiyatları bağımlılığını içerdiği değerlendirilebilir, bu sayede normal Expert modele göre daha iyi sonuçlar elde edilmektedir (multivariate modelleme yönteminde bu bağımlıkları yakalamak modelleme yapısı gereği her bir gün saati için ayrı bir model olarak değerlendirildiği ve tahmin edildiğinden mümkün olamamaktadır). Aynı zamanda fazla sayıda değişkenli modellere de ilgili faktörler uygulanmış ve tahmin sonuçlarında kayda değer değişimler gözlenmemiştir. Bu durum çok değişkenli modellerin güniçi fiyat bağımlılıklarını (ve faktörlerin içerdiği diğer bilgileri) zaten büyük bir ölçüde içerdiğini kanıtlamaktadır. Bu durumda Ziel (2016) çalışmasındaki bulgularla örtüşmektedir. Bütün bu bulgular birlikte değerlendirildiğinde EFT literatüründe kullanılan sade modellerin faktörler ile desteklenmesi o modelleri hem sade ve yorumlanabili kalmasını sağlarken aynı zamanda güniçi fiyat bağımlılıklarınıa içermesinin önünü açtığında bu modelleri klasik versiyonlarına göre daha başarılı kılmaktadır. Dahası, faktörlerle desteklenmiş çok değişkenli modelleme yöntemi tek değişkenli modelleme yöntemine göre daha tercih edilebilir olarak öne çıktığı değerlendirilmektedir. Bunun en önemli sebebi tek değişkenli modelleme yönteminin en önemli faydasının güniçi fiyat bağımlılıklarını içeriyor olmasıdır. Oysaki çokdeğişkenli yöntem kullanılan modellerde faktörler eklendiği zaman bu bilgi yakalanabilmektedir. Bu sayede çokdeğişkenli modelleme yöntemindeki önemli bir eksiklik de, en azından belli bir oranda, giderilmektedir.

Bu çalışmada önerdiğimiz yeni modeller ve tahmin yöntemlerini ampirik olarak test etmek için altı farklı elektrik piyasasından saatlik gün-öncesi fiyatları kullanılmaktadır.

Bu veriler arasından GEFCom2014 verisi 1 Ocak 2011'den 17 Aralık 2013'e kadar yaklaşık üç yıllık bir zaman dilimini kapsamaktadır. Diğer beş veri seti ise 1 Ocak 2013'den 19 Eylül 2019'a kadar yaklaşık altı yıl dokuz aylık dönemi kapsamaktadır. Bu seriler beş adet büyük elektrik piyasasının verileridir. Bu piyasalar "Nordic Power Exchange" Nord Pool sistem fiyatı (NP.SYS)", Birleşik Krallık (NP.N2EX), ABD Commonwealth Edison Bölgesi (PJM.COMED), Çek Cumhuriyeti Elektrik Piyasası (OTE.CZ), İspanyol Elektrik Piyasası (OMIE.SP). "Global Energy Forecasting Competition 2014 (GEFCom2014)" serisi ise Hong et al. (2016) tarafından düzenlenen uluslararası öngörüleme yarışmasında kullanılan fiyat serisini içermektedir. Bu fiyat serisinin hangi ülkeden alındığı yarışmayı düzenleyen kurul tarafından açıklanmamakla beraber literatürde ABD Elektrik Piyasalarından elde edildiğine yönelik yaygın bir kanı vardır. Bu verinin detayları için okuyucular Hong et al. (2016)'dan yararlanabilirler. Öte yandan fiyat serileri (GEFCom2014 serisi hariç) Mart ayındaki saat değişiminden kaynaklı eksik veri için komşu iki saatin verisinin ortalaması alınarak ve Ekim ayındaki saat değişiminden kaynaklanan birbirini tekrarlayan iki saatin ortalaması ilgil saat yerine konularak düzeltilmiştir. Bu yöntemin detayları için Bkz. Uniejewski et al. (2016).

Marketler ve GEFCom2014 verileri için modellerin öngörüleme performanslarının ölçülmesi amacıyla sırasıyla 1470-gün (yaklaşık 4 yıl) ve 350-gün (yaklaşık 1 yıl) öngörüleme dönemi bırakılmıştır. Elektrik marketlerinin öngörüleme dönemi 11 Eylül 2015'den 19 Eylül 2019'a kadardır. Öte yandan GEFCom2014 için ise 2 Ocak 2013'den 17 Aralık 2013'e kadardır. Modeller mevcut literatürdeki konvensiyon dikkate alınarak kayan-pencere yöntemiyle tahmin edilmiştir. Kayan pencere yöntemi aynı zamanda literatürde geniş olarak yer verilen ve ve farklı tahmin metodlarının öngörüleme yeteneğinin test edilmesinde kullanılan Diebold and Mariano (1995) testinin (DM testi) sağlıklı sonuçlar vermesi için de faydalıdır. Eğer genişleyen-pencere yöntemiyle modeller tahmin edilirse, birbirinin kapsayan öngörüleme modelleri oluşması durumunda, bir başka ifadeyle eşit öngörüleme performansı boş hipotezi doğru ise bu durumda kıyaslanan modellerin öngörüleme hataları eşit ve korele olacağından DM testin pay ve paydası tahmin penceresi genişledikçe sıfıra gidecektir. Buna karşılık kayan-pencere yönteminin faydası tahmin periyodunun sürekli sonlu kalmasını sağlaması ve yukarıda bahsedilen sorunlu durumun ortaya çıkmasını engellemesidir. Bu konuyla ilgili daha fazla bilgi ve diğer detayları için okuyucu Giacomini and White (2006) ve Diebold (2015)'a yönlendirilmektedir.

Elektrik fiyat tahminlemesinde önemli bir diğer konu ise veri dönüşümüdür. Bu konuyla ilgili yazında en uygun transformasyon yöntemlerinin araştırıldığı bilgilendirici makaleler yer almaktadır. Hatta veri dönüşümüne gerek kalmayacak şekilde robust tahmin teknikleri bile geliştirilmiştir (Huber and Ronchetti (2009)). Veri dönüşüm yöntemlerinin detaylı bir incelemesi için okuyucu Uniejewski et al. (2018)'a yönlendirilmektedir. Önerilen dönüşüm yöntemleri arasında en basit ve kullanışlı olanı logaritmik dönüşüm yöntemidir. Bu yöntem, elektrik fiyat serilerinin en bilinen özelliklerinden olan ani ve geçici aşırı fiyatların dönüştürülmesinde ve varyansın stabilize edilmesinde etkilidir. Ancak bu yöntem çoğu zaman eksi elektrik fiyatları için kullanılabilir değildir. Öte yandan eksi elektrik fiyatları son yıllarda özellikle yenilenebilir enerji santrallerinin sistemdeki oranının artmasıyla sıklıkla karşılaşılan bir olaydır. Bazı saatlerde yenilenebilir enerji santrallerinin enerji üretimi arttıkça merit-order etkisinden dolayı baz yük santralleri aşılması yüksek maliyetlere sebep olabilecek teknik kısıtlardan dolayı üretimlerinin belli bir seviyenin altına indirmemek için piyasaya eksi fiyat teklifi verebilmektedirler. Bu çalışmada kullanılan serilerde de oldukça yaygın olarak eksi fiyatlar yer alabilmektedir. Bu sebeple *area* (or *inverse*) *hyperbolic sine* dönüşüm olarak adlandırılan ve Ziel and Weron (2018) tarafından da başarıyla kullanılan yöntem dikkate alınmaktadır.

Bu çalışmanın ön plana çıkan yönü yüksek sayıda açıklayıcı değişken içeren modelleri kullanarak öngörüleme yapılmasıdır. Yüksek sayıda açıklayıcı değişkenin kullanılması aynı zamanda bu açıklayıcı değişkenler arasından en yüksek bilgiyi içeren ve modelin öngörüleme kaabiliyetini bozmayan değişkenlerin oluşturduğu bir alt kümenin oluşturumasını gerektirmektedir. Böyle bir alt kümenin seçilmesi bir yolu tecrübeye dayalı uzman bilgilerine göre en etkili açıklayıcı değişkenlere modellerde yer verilmesidir. Bu modeller EFT yazınında Expert modelleri olarak anılmaktadır. Fakat öngörülemenin iyileştirilmesi için diğer açıklayıcı değişkenlerdeki bilgiler kullanılarak daha iyi sonuçlar elde edilebilir. Fakat diğer yandan da geniş bir yazın modellere fazla sayıda ve düşük açıklayıcı kaabiliyette değişkenlerin konulmasının modelin toplam performansını düşürdüğünü ifade etmektedir. Oysa bu açıklayıcı değişkenlerdeki bilginin kullanılması öngörüleme performansı açısından önemlidir zira belli bir alt kümede yer alan açıklayıcı değişkenlerin sürekli kullanılması bazı dönemler iyi sonuçlar üretirken bazı dönemler modelin öngörüleme performansını çok düşürücü sonuçlara sebep olabilir (Stock and Watson (2003)). Sonuç olarak hem bütün açıklayıcı değişkenlerdeki bilginin kullanılması hem de modelleri güvenilir kılacak formal bir tahmin yöntemine ihtiyaç olduğu açıktır. Bu durumda shrinkage yöntemlerinin kullanılmasını önerilmektedir.

Bu öngörüleme çalışmasında kullanılan yüksek sayıda açıklayıcı değişkenin tahmin edilmesi için Breiman (1996a,b) tarafından geliştirilen **B**ootstrap **Agg**regation (**bagging**) yöntemi önerilmektedir. Bagging açıklayıcı değişkenlerin seçilmesi için kullanılan ve stabil olmayan seçim yöntemlerinin oluşturduğu yan etkileri gidermekle beraber aynı zamanda mevcut açıklayıcı değişkenler arasından en yüksek oranda bilgiyi modele katabilme kaabiliyetine sahiptir. Bagging yöntemindeki en önemli fikir mevcut verinin ampirik dağılımı kullanılarak yeni veri setlerinin tekrardan yapay olarak üretilmesidir. Bu veri setlerinin her biri yeni bir bilgi içermektedir. Bu noktaya kadar olan kısım bagging'in bootstrap kısmını teşkil etmektedir. Yapay olarak üretilen her bir veri seti kullanılarak modellerin tahmin edilmekte ve bu modelle öngörüler hesaplanmaktadır. Ardından, her bir yapay set için üretilen öngörüler birleştirilerek veya diğer bir ifadeyle ortalaması alınarak final öngörü hesaplanmaktadır. Bu kısmı ise baggingin "aggregation" kısmını oluşturmaktadır.

Bu çalışmada yüksek sayıda açıklayıcı değişkenin tahmin edilmesi için kullanılan bir diğer yöntem ise, EFT yazınında yoğun olarak kullanılan ve şuana kadarki bilinen en iyi tahmin ve öngörüleme yöntemi olan ve Tibshirani (1996) tarafından geliştirilen **L**east **A**bsolute **S**hrinkage and **S**election **O**perator (lasso) yöntemidir. Bagging'in aksine lasso EFT yazınında birçok kere kullanılmış ve diğer mevcut non-shrinkage yöntemlerine göre üstün öngörüleme yeteneğine sahip olduğu gösterilmiştir. Lasso'nun bir diğer öne çıkan yanı ise bazı açıklayıcı değişkenlerin katsayısını sıfıra eşitlemesidir. Bu bakış açısından lasso aynı zamanda parametre seçim yöntemi olarak düşünülebilir. Fakat öngörüleme tekniği açısından asıl işi yapan lasso'nun shrinkage özelliğidir (Ziel and Weron (2018)).

Lasso yönteminin performansını belirleyen en önemli parametre regülarizasyon parametresidir, λ. Bu parametrenin doğru bir şekilde seçilmesi öngörüleme performansını doğrudan etkilemektedir. Bu çalışma kapsamında iki farklı λ seçim yöntemi önerilmektedir. İlk seçim prosedüründe Uniejewski et al. (2019)'nin kullandığı yöntem dikkate alınmıştır. Bu kapsamda bir λ grid'i önerilmektedir: $\lambda_i = 10^{-\frac{19-i}{6}}$, $i = 1, \ldots, 10$ ve buradan optimum λ değeri Hannan-Quinn Bilgi Kriteri (**HQC**) kullanılarak seçilmektedir. Burada tabi ki Akaike ve Bayesian bilgi kriterleri de bu seçim kapsamında kullanılabilir. **HQC** yöntemini kullanmaktaki motivasyonumuz Ziel and Weron (2018) tarafından önerilen ve lasso'nun daha iyi öngörüleme yapmasını sağlıyor olmasıdır. Bu yöntemde her saat için ve her öngörüleme periyodu için ayrı ayrı seçilmektedir. İkinci bir alternatif olarak ex-post λ seçim yöntemi önerilmektedir. Bu yöntemde yirmidört modelin her biri için ayrı ayrı on tane λ değerinden oluşan grid değeri içerisinden en düşük MAE değerini verenler seçilmektedir. Bu prosedürde bütün öngörüleme periyodu için tek bir λ değeri dikkate alınmaktadır. Uygulamada en iyi sonucu veren λ değerini önceden hesaplamak mümkün olmadığı için bu yöntem tamamen regülarizasyon parametresinin teorik sınırlarını görebilmek için önerilmiş infizıbıl bir yöntemdir. Bu sebeple ex-post olarak anılmaktadır.

Bu çalışmada EFT yazını için yeni bir shrinkage yöntemi olan bagging yöntemi tanıtıldı ve altı farklı elektrik fiyat serisinde bu yöntemin başarılı sonuçlar ürettiği gösterildi. Bulgularımıza göre bagging yöntemi EFT için yüksek sayıda açıklayıcı değişken içeren modellerin tahmini ve öngörüleme yapılması için güvenilir sonuçlar ürettiği tespit edildi. Bagging EFT yazınında yoğun olarak kullanılan bir başka shrinkage yöntemi olan lasso'ya göre daha kolay hesaplama yapılabilmesini sağlayan oldukça basit bir öngörüleme yöntemi olarak tanıtılabilir. Bagging ve lasso'nun öngörüleme performansları birbirine benzer sonuçlar üretmekle beraber, bazı marketlerde bagging'in daha iyi sonuçlar ürettiği tespit edilmiştir. DM testi sonuçları açısından bu iki yöntem birbirlerine net bir üstünlük kuramamaktadır.

Bu çalışmadaki bir diğer katkımız ise multiivariate modelleme çerçevesi içerisinde gün içi elektrik fiyatlarının birbirleriyle olan ilişkilerini modellere yansıtılabilmesini sağlayan faktörlerle desteklenmiş modellerin geliştirilmesidir. Faktörlerin modellere dahil edilmesi basit modellerin öngörüleme performansını iyileştirdiği gibi aynı zamanda bazı marketlerde çok sayıda değişkenli modeller kullanılarak shrinkage yöntemleri ile tahmin edilen modellerin performansına benzer sonuçlar verebilmektedir. Aynı zamanda faktörlerin eklendiği shrinkage yöntemiyle tahmin edilen çok sayıda açıklayıcı değişken içeren yöntemlerin bu faktörlerin eklenmesiyle öngörüleme performansında dikkate değer bir artış olmadığı gibi çoğunda kötüleşme olduğu da görülmektedir. Bu durum faktörlerde yer alana bilgilerin halihazırda bu modellerde yer aldığı ve buradan hareketle faktörlerdeki en önemli bilgi olan güniçin fiyat bağıntılarının halihazırda bu tip modellerde yer aldığını göstermektedir. Yine bu noktadan hareketle univariate modellerin güniçin elektrik fiyatlarındaki bağımlılıkları temsil etmesi amacıyla tercih edilmesi özellikle shrinkage yöntemleriyle tahmin edilen yüksek sayıda değişken içeren modeller için hesaplama yükünü ve kompleksliği arttırıcı bir yük getirdiği değerlendirilebilir, zira güniçi elektrik fiyatlarının bağımlılığı bu modellerde multivariate setting içerisinde zaten yer aldığı gösterilmiştir.

İlerideki araştırmalar kapsamında bagging birçok farklı uzantısının EFT yazınında değerlendirilmesi söz konusudur. Bunların arasında her bir yapa veri setine eşit ağırlık vermek yerine veriye dayalı ağırlıklandırma, baggign ile lasso nun üretiiği öngörülerin birleştirilerek yeni öngörülerin oluşturulması gibi konular sayılabilir. Dahası bagging'in uzun dönemli trend ile stokastik bileşenin birbirinden ayrıldığı veri setlerinde sadece stokastik bileşene uygulanması yöntemi ile daha başarılı sonuçlar elde edilebileceği değerlendirilmektedir. Öte yandan faktör modelleri için burada elde edilen bulgular kullanılarak faktör döndürme yöntemleri ile identify edilmesi ve anlamlandırılması da gelecekte gerçekleştirilmesi planlanan çalışmalar arasındadır.

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AN EMPIRICAL EVIDENCE FOR GENERALIZED SHRINKAGE METHODS: APPLICATION OF BAGGING IN DAY-AHEAD ELECTRICITY PRICE FORECASTING AND FACTOR AUGMENTATION

<u>TEZİN TÜRÜ</u> / <u>DEGREE:</u> **Yüksek Lisans** / Master ■ **Doktora** / PhD ☐

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