Recent trends and advances in electricity price forecasting (EPF)

Rafał Weron

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http://www.ioz.pwr.wroc.pl/pracownicy/weron/

Agenda

1. Beyond point forecasts
   ⇒ probabilistic forecasts
2. Combining forecasts
   - Point forecasts
   - Probabilistic forecasts
3. Variable selection and shrinkage
   - LASSO
   - Elastic nets
4. Guidelines for evaluating forecasts

International Journal of Forecasting 30 (2014) 1030–1081
Contents lists available at ScienceDirect
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Review

Electricity price forecasting: A review of the state-of-the-art with a look into the future

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energies
Energies **2016**, *9*, 621; doi:10.3390/en9080621
MDPI

Article

Automated Variable Selection and Shrinkage for Day-Ahead Electricity Price Forecasting

Bartosz Uniejewski, Jakub Nowotarski and Rafał Weron *

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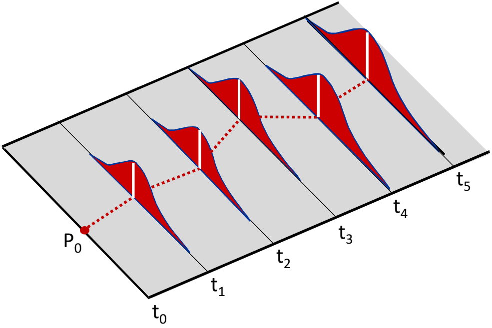
Beyond point forecasts

- Variability of supply and demand has become a challenge to the utility industry in the smart grid era (Hong & Fan, 2016, IJF)
- Resulting extreme variability of electricity prices
  - In the day-ahead market
  - Even more so in the intraday market
- Probabilistic (interval, density) forecasting has a lot to offer (Nowotarski & Weron, 2016, RePEc)
  - Useful in practice for risk management and decision-making
- GEFCom2012 (point) ⇒ GEFCom2014 (probabilistic forecasts)

Probabilistic (interval, density) forecasting

(Gneiting & Katzfuss, 2014, Annu.Rev.Stat.Appl.)

- Improved assessment of future uncertainty
- Ability to plan different strategies for the range of possible outcomes
- Possibility of more thorough forecast comparisons



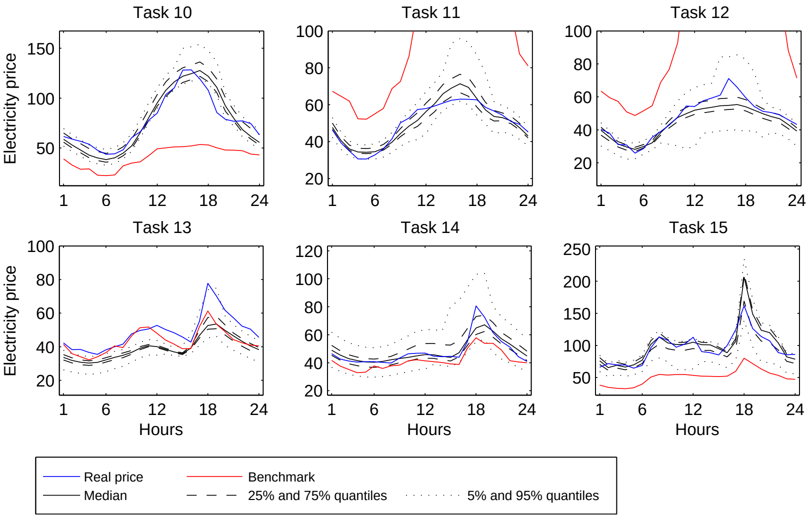
Global Energy Forecasting Competition 2014

(Hong, Pinson, Fan et al., 2016, IJF)

GEFCOM 2014 Load Forecasting | GEFCOM 2014 Price Forecasting | GEFCOM 2014 Wind Forecasting | GEFCOM 2014 Solar Forecasting | IEEE PES Power & Energy Society®

- Incremental data sets released on weekly basis
- Price Track:
  - 287 contestants
  - Submit 99 quantiles for 24h load periods of the next day

Price Track


Task 10
Task 11
Task 12
Task 13
Task 14
Task 15
Electricity price
Hours
Real price
Median
Benchmark
25% and 75% quantiles
5% and 95% quantiles

Price Track: Top winning teams

(1st and) 2nd place for QRA!

1. Pierre Gaillard, Yannig Goude, Raphaël Nedellec (EDF R&D, F)
2. Katarzyna Maciejowska, Jakub Nowotarski (Wrocław UT, PL)
3. Grzegorz Dudek (Częstochowa UT, PL)
4. Zico Kolter, Romain Juban, Henrik Ohlsson, Mehdi Maasoumy (C3 Energy, USA)
5. Frank Lemke (KnowledgeMiner Software, D)

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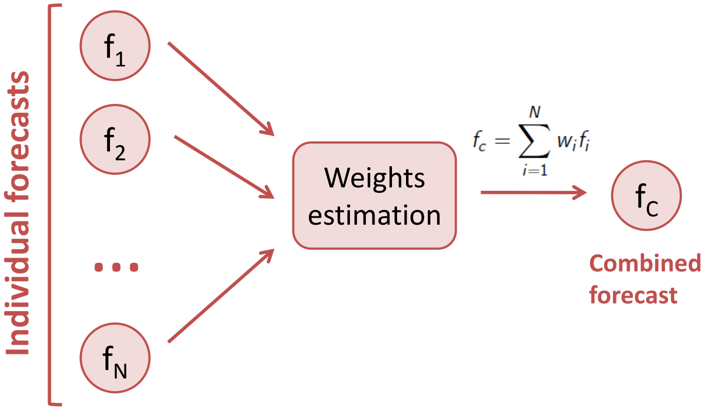
Point forecast averaging: The idea



- Dates back to the 1960s and the works of Bates, Crane, Crotty & Granger
- 'AI world': *committee machines*, *ensemble averaging*, *expert aggregation*

Interval forecast averaging

- For point forecasts: $f_c = \sum_{i=1}^{N} w_i f_i$ (e.g. a linear regression model)
- For interval forecasts the above formula does not hold
- A linear combination of q-th quantiles is **not** the q-th quantile of a linear combination of random variables

$$x_c^q \neq \sum_{i=1}^{N} w_i x_i^q$$

$\Rightarrow$ Need for development of new approaches

Quantile Regression Averaging (QRA) defined

Comput Stat (2015) 30:791–803
DOI 10.1007/s00180-014-0523-0

CrossMark

ORIGINAL PAPER

OPEN ACCESS

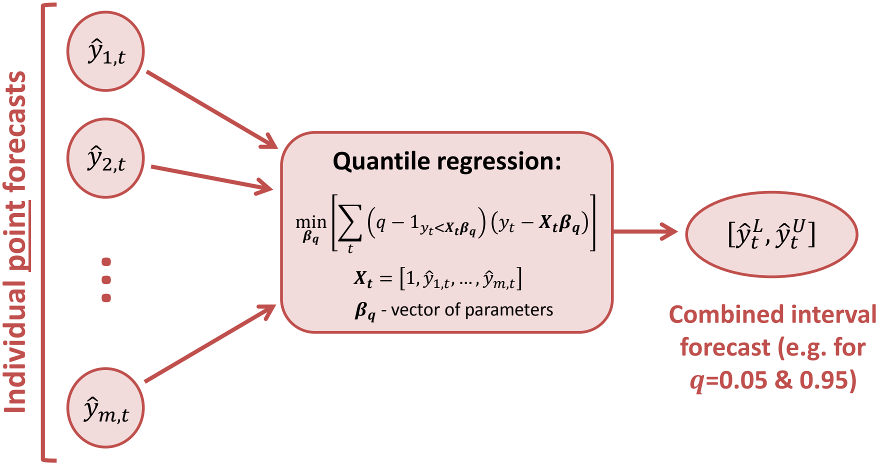
Computing electricity spot price prediction intervals using quantile regression and forecast averaging

Jakub Nowotarski · Rafał Weron

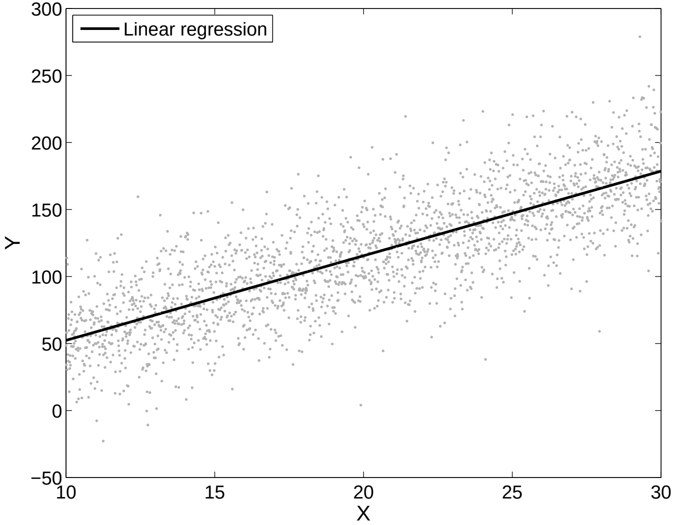
Received: 31 December 2013 / Accepted: 6 August 2014 / Published online: 19 August 2014

Abstract We examine possible accuracy gains from forecast averaging in the context of interval forecasts of electricity spot prices. First, we test whether constructing empirical prediction intervals (PI) from combined electricity spot price forecasts leads to better forecasts than those obtained from individual methods. Next, we propose a new method for constructing PI—Quantile Regression Averaging (QRA)—which utilizes the concept of quantile regression and a pool of point forecasts of individual (i.e. not combined) models. While the empirical PI from combined forecasts do not provide significant gains, the QRA-based PI are found to be more accurate than those of the best individual model—the smoothed nonparametric autoregressive model.

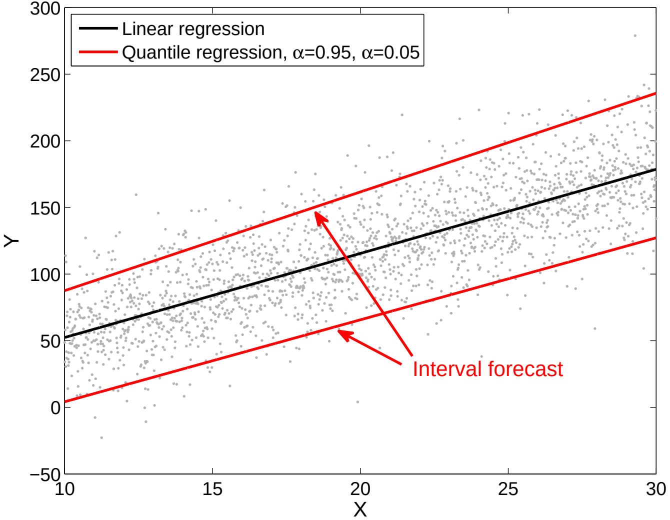
Quantile Regression Averaging: The idea



Quantile regression



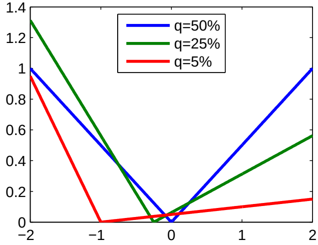
Quantile regression



How does the score function look like?

For vector $\boldsymbol{X_t} = [1, \hat{y}_{1,t}, ..., \hat{y}_{m,t}]$ of point forecasts, i.e. explanatory variables, weights $\boldsymbol{\beta_q}$ are estimated by minimizing:

$$\min_{\boldsymbol{\beta_q}} \left[\sum_{\{t:y_t \geqslant \boldsymbol{X_t}\boldsymbol{\beta_q}\}} q|y_t - \boldsymbol{X_t}\boldsymbol{\beta_q}| + \sum_{\{t:y_t < \boldsymbol{X_t}\boldsymbol{\beta_q}\}} (1-q)|y_t - \boldsymbol{X_t}\boldsymbol{\beta_q}| \right]$$



Case study

978-1-4799-6095-8/14/$31.00 ©2014 IEEE

Merging quantile regression with forecast averaging to obtain more accurate interval forecasts of Nord Pool spot prices

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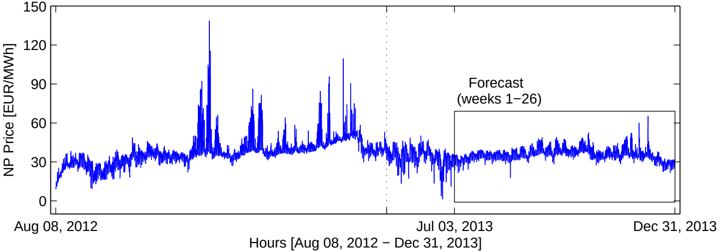
***Abstract*—We evaluate a recently proposed method for constructing prediction intervals, which utilizes the concept of quantile regression (QR) and a pool of point forecasts of different time series models. We find that in terms of interval forecasting of Nord Pool day-ahead prices the new QR-based approach significantly outperforms prediction intervals obtained from standard, as well as, semi-parametric autoregressive time series models.**

tions we are interested in PI, i.e. intervals which contain the true values of future observations with specified probability, not in confidence intervals.

From a practical point of view, PI provide additional information on price forecasts. High volatility and uncertainty of electricity price forecasts may frequently deviate from the true price levels. In fact, possible errors in point predictions

QRA at work



- Nord Pool hourly prices (2012-2013)
  - **Seven** months for calibration of individual models
  - **Four** weeks for calibration of quantile regression
  - **26** weeks for evaluation of interval forecasts
- **Six** individual point forecasting models
  - AR, TAR, SNAR, MRJD, NAR, FM

Evaluation of forecasts

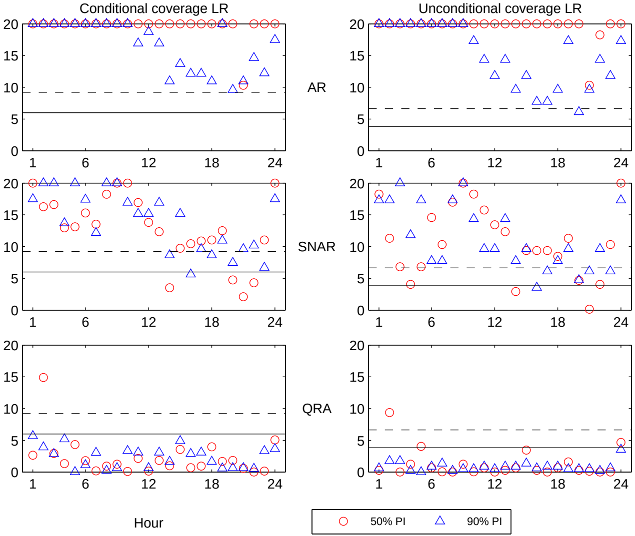
- 50% and 90% two-sided day-ahead prediction intervals
- Two benchmark models: AR and SNAR
- Christoffersen's (1998, IER) test for unconditional and conditional coverage
- The focus on the sequence: $I_t = \begin{cases} 1 & y_t \in [\hat{y}_t^L, \hat{y}_t^U] \\ 0 & y_t \notin [\hat{y}_t^L, \hat{y}_t^U] \end{cases}$
- <u>Conditional Coverage test</u>
  (UC + independece)
  Asymptotically $\chi^2(2)$

  <u>Unconditional Coverage test</u>
  Asymptotically $\chi^2(1)$

Results: Unconditional coverage

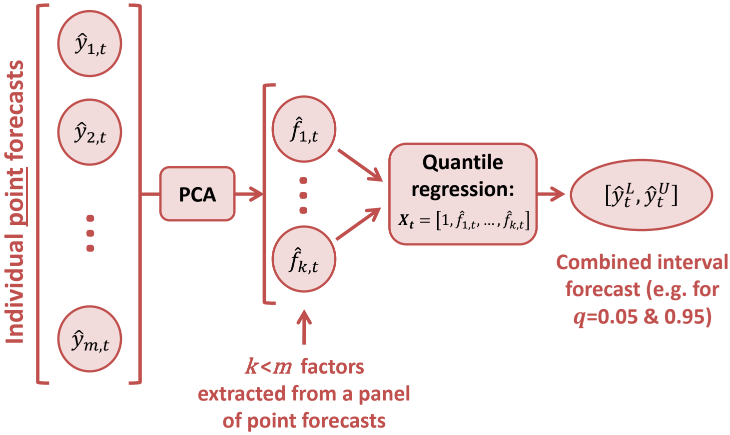
PI	AR	SNAR	**QRA**
	Unconditional coverage		
50%	77.50	61.93	**49.77**
90%	97.53	96.41	**89.33**
	Mean width (STD of interval width)		
50%	4.55 (1.34)	2.76 (0.61)	**2.23 (0.81)**
90%	11.14 (3.31)	9.33 (2.45)	**6.78 (2.20)**

Results: Christoffersen's test



FQRA: When the number of predictors is large

(Maciejowska, Nowotarski & Weron, 2016, IJF)



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Automated variable selection

Consider a general regression:

$$\hat{y}_i = \sum_{j=1}^{p} \beta_j x_{i,j} + \varepsilon_i$$

How to select predictors $x_{i,j}$? How to estimate β_j's?

- Single-step elimination of insignificant predictors
  - In EPF: Gianfreda & Grossi (2012)
- Stepwise regression
  - Forward stepwise selection
  - Backward stepwise elimination
  - In EPF: Karakatsani & Bunn (2008), Misiorek (2008), Bessec et al. (2016), Keles et al. (2016)

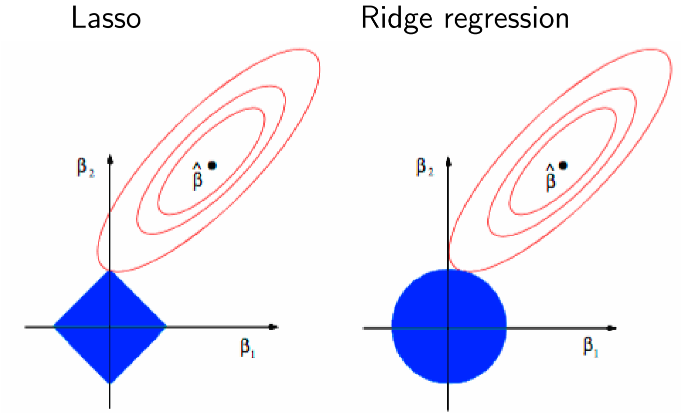
What is shrinkage (regularization)?

- Minimize the residual sum of squares (RSS) + a penalty function of the betas:

$$\hat{\boldsymbol{\beta}} = \underset{\beta_j}{\operatorname{argmin}} \left\{ \underbrace{\sum_{i=1}^{N} \left(y_i - \sum_{j=1}^{p} \beta_j x_{i,j} \right)^2}_{RSS} + \lambda \underbrace{\sum_{j=1}^{n} |\beta_j|^q}_{penalty} \right\}$$

- Ridge regression ($q = 2$)
  - Introduced by: Hoerl & Kennard (1970, Technometrics)
  - In EPF: Barnes & Balda (2013)
- Least Absolute Shrinkage & Selection Operator (LASSO; $q = 1$)
  - Introduced by: Tibshirani (1996, JRSSB)
  - In EPF: Ludwig et al. (2015), Ziel et al. (2015), Gaillard et al. (2016), Ziel (2016), Ziel and Weron (2016)

How does it work?

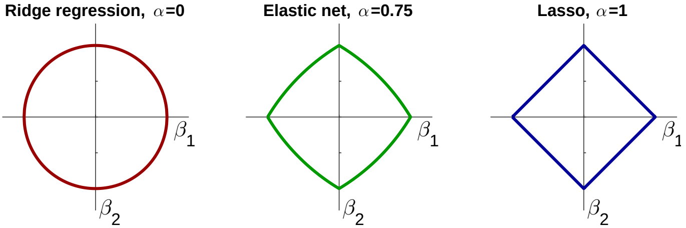


Blue areas – constraint regions, i.e., $|\beta_1| + |\beta_2| \leqslant t$ and $\beta_1^2 + \beta_2^2 \leqslant t$
Red ellipses – contours of the least squares error function

Elastic net

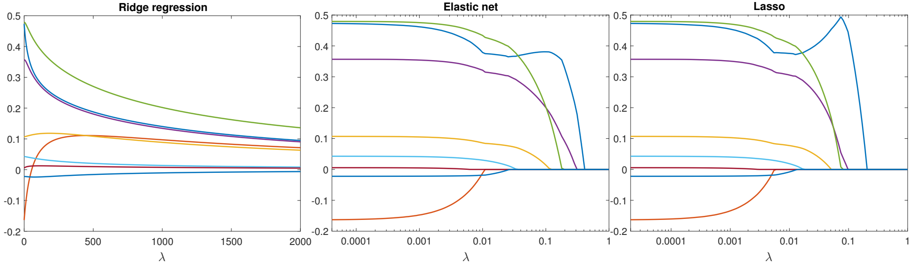
- RSS penalized by a mixed quadratic and linear shrinkage factor

$$\hat{\beta}^{EN} = \underset{\beta_j}{\operatorname{argmin}} \left\{ \text{RSS} + \lambda \left(\frac{1-\alpha}{2} \sum_{j=1}^{n} \beta_j^2 + \alpha \sum_{j=1}^{n} |\beta_j| \right) \right\}$$



- Introduced by: Zou & Hastie (2015, JRSSB)
- In EPF: Uniejewski, Nowotarski & Weron (2016, Energies)

How $\hat{\beta}$'s change when λ increases?



- *Left*: Ridge regression with $\lambda \in (0, 2000)$, linear scale
- *Center*: Elastic net with $\alpha = 0.5$ and $\lambda \in (0, 1)$, log-scale
- *Right*: Lasso with $\lambda \in (0, 1)$, log-scale

Results: WMAE errors

(Uniejewski et al., 2016, Energies)

Full model: fARX, fAR

$$\widehat{p_{d,h}} = \underbrace{\sum_{i=1}^{24}\left(\beta_{h,i}p_{d-1,i} + \beta_{h,i+24}p_{d-2,i} + \beta_{h,i+48}p_{d-3,i}\right)}_{\text{72 hourly prices from the three previous days}} + \underbrace{\beta_{h,73}p_{d-7,h}}_{\text{week before}}$$

$$+ \underbrace{\sum_{j=1}^{3}\left(\beta_{h,j+73}p^{min}_{d-j} + \beta_{h,j+76}p^{max}_{d-j} + \beta_{h,j+79}p^{avg}_{d-j}\right)}_{\text{minimum, maximum \& average price of the three previous days}}$$

$$+ \underbrace{\beta_{h,83}z_{d,h} + \beta_{h,84}z_{d-1,h} + \beta_{h,85}z_{d-7,h} + \beta_{h,86}y_{d,h}}_{\text{exogenous variables}}$$

$$+ \underbrace{\sum_{k=1}^{7}\beta_{h,86+k}D_k + \sum_{k=1}^{7}\beta_{h,93+k}D_k z_{d,h} + \sum_{k=1}^{7}\beta_{h,100+k}D_k p_{d-1,h}}_{\text{weekly seasonality}}$$

$$+ \varepsilon_{d,h}$$

	ARX-type			AR-type		AR - ARX
	GEFCom	Nord Pool		GEFCom	N2EX (UK)	GEFCom
Naive	14.708 (0.975)	11.141 (0.778)	**Naive**	14.708 (0.975)	9.767 (0.310)	0.000
Expert benchmarks						
ARX1	11.069 (0.639)	9.739 (0.614)	**AR1**	11.183 (0.701)	8.384 (0.253)	0.114
ARX1h	11.072 (0.639)	9.693 (0.616)	**AR1h**	11.181 (0.704)	8.389 (0.253)	0.109
ARX1hm	10.976 (0.617)	8.673 (0.516)	**AR1hm**	11.062 (0.657)	8.229 (0.247)	0.086
mARX1	11.102 (0.621)	9.482 (0.601)	**mAR1**	11.320 (0.696)	8.258 (0.253)	0.218
mARX1h	11.105 (0.622)	9.461 (0.602)	**mAR1h**	11.322 (0.699)	8.270 (0.254)	0.218
mARX1hm	10.974 (0.598)	8.461 (0.518)	**mAR1hm**	11.168 (0.644)	**8.098** (0.246)	0.195
ARX2	10.742 (0.575)	8.878 (0.546)	**AR2**	11.331 (0.700)	8.290 (0.253)	0.589
ARX2h	10.739 (0.575)	8.826 (0.546)	**AR2h**	11.333 (0.704)	8.288 (0.253)	0.594
ARX2hm	10.625 (0.565)	8.206 (0.485)	**AR2hm**	11.070 (0.656)	8.237 (0.249)	0.444
Full ARX model						
fARX	10.911 (0.507)	10.131 (0.708)	**fAR**	12.279 (0.602)	9.724 (0.334)	1.368
Selection and shrinkage methods						
ssARX	10.669 (0.577)	8.861 (0.537)	**ssAR**	12.061 (0.644)	9.344 (0.270)	1.393
ssARX1	9.894 (0.548)	8.409 (0.507)	**ssAR1**	11.343 (0.641)	8.395 (0.261)	1.449
fsARX	9.876 (0.502)	8.130 (0.502)	**fsAR**	11.193 (0.592)	8.563 (0.272)	1.317
bsARX	10.449 (0.502)	9.421 (0.599)	**bsAR**	11.968 (0.582)	9.252 (0.301)	1.519
RidgeX	9.777 (0.544)	8.972 (0.479)	**Ridge**	10.775 (0.653)	8.237 (0.260)	0.998
LassoX	9.476 (0.516)	8.419 (0.503)	**Lasso**	10.722 (0.609)	8.125 (0.253)	1.246
EN75X	9.475 (0.517)	**8.056** (0.489)	**EN75**	10.708 (0.610)	8.124 (0.253)	1.233
EN50X	**9.473** (0.518)	8.287 (0.496)	**EN50**	10.688 (0.611)	8.121 (0.253)	1.215
EN25X	9.474 (0.522)	8.529 (0.503)	**EN25**	**10.650** (0.613)	8.113 (0.253)	1.176

Variable significance across hours

(Ziel & Weron, 2016, RePEc)

	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 $(d-1)$	$\phi_{h,1,1,0}$	21.42	10.61	9.04	21.81	21.58	11.41	12.62	13.04	12.07	8.86	8.89	8.62	7.10	8.43	6.13	5.93	3.17	0.92	1.63	3.26	4.87	9.18	13.31	19.85
	$\phi_{h,1,2,0}$	41.75	24.36	11.67	4.86	5.44	11.05	16.98	9.80	7.99	6.77	10.67	7.19	6.35	10.08	11.18	10.70	8.47	4.43	4.91	3.58	6.20	5.52	9.19	27.72
	$\phi_{h,1,3,0}$	31.88	39.68	34.41	16.96	9.72	11.60	7.48	2.46	1.29	1.62	1.82	0.64	1.10	2.06	2.39	2.40	4.34	5.21	9.95	10.41	8.36	10.53	10.91	21.31
	$\phi_{h,1,4,0}$	21.50	29.19	39.28	58.20	40.34	11.96	3.39	3.25	4.58	4.36	3.61	2.66	3.26	0.75	0.67	0.25	0.42	1.02	3.02	3.37	2.65	3.66	1.14	9.88
	$\phi_{h,1,5,0}$	32.53	28.35	35.31	51.97	63.97	45.06	13.95	13.64	16.55	15.18	15.80	10.09	11.89	7.81	5.01	3.56	4.77	1.17	1.04	0.74	5.41	7.99	3.39	6.69
	$\phi_{h,1,6,0}$	39.64	41.88	41.60	44.22	54.20	72.06	42.67	20.43	12.95	12.71	6.73	6.12	7.24	4.20	5.07	3.16	2.35	1.75	2.59	2.39	4.03	4.41	1.55	4.67
	$\phi_{h,1,7,0}$	14.67	17.46	10.22	9.48	12.07	19.85	59.92	24.92	14.61	10.70	3.68	7.14	10.71	11.75	10.44	10.80	7.79	7.74	6.96	5.86	6.98	3.43	0.37	0.27
	$\phi_{h,1,8,0}$	10.51	16.08	15.98	16.44	18.32	17.81	19.94	50.14	43.98	15.24	5.71	5.87	6.80	6.71	6.25	7.10	7.60	2.82	2.14	8.68	10.28	4.71	4.77	1.70
	$\phi_{h,1,9,0}$	4.55	3.23	3.04	3.29	3.26	4.73	3.44	10.45	29.03	16.02	6.90	5.66	13.84	13.96	15.17	13.27	20.25	19.73	12.12	7.87	6.27	3.52	3.95	2.94
	$\phi_{h,1,10,0}$	1.06	0.67	1.70	3.14	2.71	4.41	2.55	0.85	6.53	12.52	10.24	4.29	3.46	7.52	10.73	17.44	28.05	29.79	14.38	10.66	5.65	7.72	4.44	3.46
	$\phi_{h,1,11,0}$	9.82	0.19	4.06	3.58	4.56	4.58	1.80	2.58	11.75	19.77	8.90	2.99	0.31	0.00	0.00	0.17	2.62	4.57	3.84	0.54	0.07	0.12	0.41	0.02
	$\phi_{h,1,12,0}$	3.18	0.54	3.59	5.93	12.65	8.56	6.02	2.27	5.97	27.63	33.81	23.73	7.70	1.39	0.61	2.69	6.35	8.62	8.90	6.10	4.08	2.32	2.24	0.15
	$\phi_{h,1,13,0}$	2.61	2.15	2.05	10.61	10.86	5.85	5.27	3.58	4.75	6.53	13.51	25.40	26.51	10.94	3.80	1.42	0.82	3.80	3.62	1.76	1.72	2.51	3.43	2.72
	$\phi_{h,1,14,0}$	8.11	3.18	5.33	6.03	7.05	5.39	6.29	8.75	6.23	16.75	32.36	48.57	55.45	46.23	27.45	8.23	4.38	1.85	2.65	1.00	0.90	2.04	1.39	1.05
	$\phi_{h,1,15,0}$	5.69	5.40	1.01	1.24	1.20	1.04	0.09	5.44	6.44	22.26	30.49	28.40	36.55	43.33	40.31	21.81	4.59	1.32	0.80	0.74	0.61	2.13	1.68	2.46
	$\phi_{h,1,16,0}$	8.71	9.36	5.90	5.94	4.72	14.99	11.28	17.03	23.49	22.16	25.10	30.27	41.13	37.42	45.01	46.93	19.64	6.17	4.26	6.80	4.30	1.24	0.85	5.83
	$\phi_{h,1,17,0}$	15.47	17.07	7.86	5.12	5.31	10.53	10.93	4.56	7.90	8.56	14.35	28.22	35.94	46.70	61.90	69.02	71.11	21.76	5.54	3.82	1.66	1.06	2.20	2.52
	$\phi_{h,1,18,0}$	45.87	38.17	34.61	36.67	38.24	35.07	30.71	26.87	20.60	27.90	36.43	44.84	53.83	60.77	67.40	76.67	96.86	98.27	46.23	11.23	2.72	5.66	6.31	11.48
	$\phi_{h,1,19,0}$	40.18	54.28	61.40	53.42	46.69	49.64	22.85	43.51	39.30	42.98	46.41	32.88	29.82	32.84	25.37	28.45	27.92	67.46	93.92	28.63	4.60	5.87	8.42	19.06
	$\phi_{h,1,20,0}$	26.83	36.61	33.45	23.02	25.11	49.99	63.97	61.77	42.97	41.38	36.44	27.63	28.21	22.75	19.95	19.69	18.18	10.17	43.88	94.59	46.29	7.63	3.84	9.61
	$\phi_{h,1,21,0}$	35.19	31.57	23.84	23.38	23.04	45.30	77.22	69.11	67.79	67.09	63.11	59.66	43.68	42.45	41.45	38.86	35.14	25.28	26.83	51.94	92.74	48.93	11.74	16.59
	$\phi_{h,1,22,0}$	43.63	38.34	39.88	45.70	47.89	50.66	70.33	61.18	68.10	60.56	63.11	64.87	52.10	48.25	47.32	47.90	42.08	27.31	25.42	28.63	75.75	99.17	60.31	32.36
	$\phi_{h,1,23,0}$	30.38	22.55	18.56	18.73	22.85	17.96	25.37	30.99	41.82	50.92	62.93	70.34	65.37	61.04	57.70	56.01	51.60	46.40	38.14	37.16	32.31	63.60	95.44	68.07
	$\phi_{h,1,24,0}$	100	100	100	100	100	100	99.99	96.41	94.71	93.01	91.30	90.15	92.68	93.25	95.27	95.59	91.48	90.29	87.18	77.23	77.69	81.20	90.89	100
Day $(d-2)$	$\phi_{h,2,1,0}$	15.84	1.79	4.21	5.25	5.34	3.34	3.83	5.68	6.57	8.00	10.54	10.66	8.02	11.72	11.28	11.46	14.86	11.63	9.81	6.47	7.57	17.03	12.15	32.15
	$\phi_{h,2,2,0}$	11.33	11.67	7.23	5.03	4.41	6.66	12.34	6.97	4.28	5.55	4.67	5.33	8.32	8.02	7.12	5.63	4.00	6.00	5.11	3.81	3.23	3.82	2.50	10.75
	$\phi_{h,2,3,0}$	6.16	19.18	16.01	5.20	3.99	12.08	14.63	12.38	13.78	9.46	5.96	5.47	6.82	7.90	7.75	9.05	9.76	8.52	7.94	4.85	5.64	3.63	1.80	5.23
	$\phi_{h,2,4,0}$	7.46	7.07	17.57	28.57	20.01	20.24	15.02	14.12	10.38	4.21	4.35	2.68	2.03	7.60	9.97	8.58	5.64	5.61	5.57	2.74	2.69	2.10	0.26	1.05
	$\phi_{h,2,5,0}$	28.03	22.72	22.68	31.32	44.40	26.97	23.42	20.64	17.51	13.66	7.71	3.55	6.29	5.84	8.70	8.59	6.37	5.43	6.28	1.62	0.25	2.31	4.53	6.02
	$\phi_{h,2,6,0}$	5.56	12.60	6.95	7.92	8.61	17.33	19.61	14.77	8.82	7.02	8.17	8.44	9.15	8.67	5.67	5.31	5.11	4.59	6.25	5.51	5.62	4.47	3.62	2.76
	$\phi_{h,2,7,0}$	7.69	7.04	6.93	9.31	7.69	5.55	13.85	10.65	5.23	1.83	2.63	2.86	6.14	8.08	5.06	3.25	3.08	0.70	0.50	2.54	0.89	0.49	1.06	3.11
	$\phi_{h,2,8,0}$	3.06	4.69	9.56	8.40	10.46	14.53	7.63	6.42	3.82	3.07	3.20	6.65	11.17	10.39	11.62	12.43	12.32	10.38	4.77	4.20	2.95	5.24	3.71	2.50
	$\phi_{h,2,9,0}$	4.38	4.91	6.96	7.16	4.28	6.49	0.88	0.83	2.22	0.50	0.13	0.22	0.25	2.50	5.54	9.77	16.26	18.22	13.66	14.32	6.20	3.02	6.17	8.61
	$\phi_{h,2,10,0}$	0.58	3.38	9.78	12.23	8.61	8.68	2.64	4.91	6.27	8.20	1.41	0.90	0.71	1.51	1.19	3.80	6.17	8.54	5.95	4.83	2.51	1.85	0.35	0.29
	$\phi_{h,2,11,0}$	4.12	5.40	6.54	8.88	5.96	7.08	0.78	2.43	4.39	8.52	7.44	2.22	0.91	0.92	0.83	2.70	4.55	6.91	10.88	9.55	4.27	0.87	1.10	1.12
	$\phi_{h,2,12,0}$	2.87	7.99	10.28	16.54	15.03	8.20	2.49	3.39	2.09	5.72	10.04	4.87	0.77	0.07	0.14	0.03	0.08	1.01	2.95	2.84	4.55	1.37	2.40	2.96
	$\phi_{h,2,13,0}$	1.60	2.15	7.18	9.78	9.10	8.91	9.30	4.47	2.52	3.00	9.57	16.71	20.59	10.52	8.47	5.60	2.31	4.66	10.47	7.13	2.42	0.82	4.37	2.99
	$\phi_{h,2,14,0}$	0.34	3.70	4.58	5.43	7.52	6.51	2.43	2.35	1.31	1.12	2.02	3.82	5.66	5.38	3.44	0.63	0.21	3.03	3.84	5.05	3.62	0.74	0.01	0.40
	$\phi_{h,2,15,0}$	0.53	2.00	7.82	8.78	11.00	8.52	15.17	12.04	5.29	1.82	2.79	8.16	9.21	7.86	5.62	0.28	0.42	6.18	2.34	6.29	1.78	2.78	0.22	2.90
	$\phi_{h,2,16,0}$	2.25	3.88	5.04	6.00	7.62	7.56	1.89	4.49	2.91	2.73	1.85	4.04	4.37	5.83	5.29	8.06	5.37	12.93	12.28	6.63	1.72	3.06	2.85	12.53
	$\phi_{h,2,17,0}$	1.87	2.68	8.77	10.66	15.49	9.29	1.75	4.29	7.67	8.33	1.10	1.99	6.61	8.02	14.35	19.60	22.91	10.93	5.91	1.53	0.50	0.47	0.96	3.47
	$\phi_{h,2,18,0}$	0.45	5.17	7.79	6.99	7.79	6.17	6.30	6.01	1.53	1.50	2.35	4.88	14.11	16.96	23.02	35.14	55.58	71.47	19.41	2.91	0.60	1.75	3.62	6.15
	$\phi_{h,2,19,0}$	1.13	0.78	1.21	0.59	0.90	0.24	0.59	2.20	1.07	0.86	1.85	8.21	9.90	11.38	11.78	15.90	20.69	22.86	65.00	7.55	10.46	2.90	3.92	4.87
	$\phi_{h,2,20,0}$	8.56	3.10	4.47	4.71	6.34	2.30	8.83	8.58	4.52	3.57	3.77	9.78	13.00	14.00	13.53	15.40	13.24	13.86	15.47	78.76	18.60	12.22	15.66	16.72
	$\phi_{h,2,21,0}$	10.20	15.79	20.62	28.96	26.19	13.22	9.92	18.27	3.90	9.20	9.18	7.61	8.50	15.20	15.75	13.42	10.50	9.22	8.66	20.05	70.64	18.09	11.22	8.16
	$\phi_{h,2,22,0}$	17.33	31.56	25.33	22.22	18.10	15.44	7.23	8.50	1.41	0.87	2.39	6.00	2.21	1.54	5.28	6.41	5.99	3.83	1.45	6.88	6.76	57.21	24.05	5.87
	$\phi_{h,2,23,0}$	21.07	25.48	36.76	34.48	41.17	42.37	25.07	18.53	14.87	11.26	14.30	13.81	9.53	9.50	7.35	7.67	12.92	6.47	5.57	6.29	9.65	13.14	49.49	30.34
	$\phi_{h,2,24,0}$	14.67	14.58	24.65	33.56	34.54	25.40	16.97	16.40	12.55	10.68	10.74	11.94	22.76	19.63	15.06	14.10	9.93	2.97	7.17	12.21	14.60	27.42	38.10	54.77
Day $(d-3)$	$\phi_{h,3,1,0}$	6.76	4.68	5.62	8.37	9.62	6.95	12.04	4.02	5.48	5.87	3.20	4.20	4.75	6.05	5.69	7.44	6.69	3.50	5.22	4.71	4.83	6.12	6.56	21.20
	$\phi_{h,3,2,0}$	6.71	6.10	4.81	1.07	0.17	3.75	4.57	9.02	8.90	6.80	8.74	9.71	8.63	12.30	9.25	10.05	11.82	8.93	9.36	2.98	5.10	8.73	10.69	16.67
	$\phi_{h,3,3,0}$	9.07	16.58	10.43	3.99	1.45	2.82	2.76	2.82	2.61	1.22	0.74	2.87	3.20	2.54	2.06	1.33	2.04	0.61	0.79	0.79	1.29	0.12	4.29	1.71
	$\phi_{h,3,4,0}$	11.31	16.38	24.62	25.34	29.17	24.38	9.08	7.18	1.13	3.04	2.11	2.52	4.20	4.14	5.01	2.93	5.00	2.91	2.68	0.34	2.51	0.53	1.22	1.86
	$\phi_{h,3,5,0}$	4.55	7.51	5.18	11.50	13.86	10.25	4.71	4.42	2.25	3.15	3.46	6.39	6.50	2.19	4.91	4.63	6.75	5.63	6.11	3.54	1.71	0.69	0.52	1.79
	$\phi_{h,3,6,0}$	13.44	5.62	5.04	10.06	11.01	24.92	7.88	3.92	5.14	5.53	3.90	5.35	4.41	3.86	3.85	5.16	7.73	10.25	6.99	3.58	3.67	4.78	3.50	2.63
	$\phi_{h,3,7,0}$	14.88	15.06	22.54	21.76	17.35	15.99	24.22	20.67	17.07	14.44	11.17	9.17	3.54	3.58	5.84	4.86	4.48	10.15	9.30	16.67	4.84	2.52	0.84	1.69
	$\phi_{h,3,8,0}$	2.08	5.13	6.03	8.81	3.08	1.13	4.88	9.29	3.95	2.66	1.28	0.58	0.11	2.14	2.79	3.34	1.53	3.32	2.19	2.29	1.57	[illegible]	3.82	1.81
	$\phi_{h,3,9,0}$	2.95	3.12	1.51	5.82	4.95	2.60	1.45	8.35	11.09	5.59	2.15	1.59	0.71	0.49	1.80	3.25	5.84	8.81	7.98	7.24	6.00	5.61	4.56	4.46
	$\phi_{h,3,10,0}$	4.74	7.72	2.39	2.12	0.76	0.61	0.82	5.03	9.25	8.54	5.29	1.84	0.76	0.38	2.64	3.20	2.93	4.66	3.88	3.67	5.40	3.38	3.78	7.51
	$\phi_{h,3,11,0}$	2.71	0.50	1.67	2.93	3.18	3.77	7.27	12.10	4.69	6.89	6.04	2.51	0.08	2.90	3.18	1.04	0.91	2.49	1.58	1.63	0.49	0.31	0.49	1.09
	$\phi_{h,3,12,0}$	0.95	2.48	2.33	2.80	3.99	7.35	2.23	0.57	1.34	3.40	6.99	12.17	7.93	3.26	2.52	3.32	2.12	3.54	3.67	3.69	1.50	0.61	0.92	3.07
	$\phi_{h,3,13,0}$	1.51	0.77	1.83	3.64	4.05	2.26	2.06	1.21	1.35	5.31	8.46	17.77	25.33	16.77	8.93	6.91	5.25	0.92	0.06	2.53	1.20	0.49	2.56	4.59
	$\phi_{h,3,14,0}$	2.09	1.48	2.70	4.38	6.91	6.25	5.37	3.13	3.46	0.21	0.31	4.82	7.43	6.88	5.60	3.29	2.32	2.27	0.58	1.29	2.96	0.93	2.35	5.52
	$\phi_{h,3,15,0}$	0.18	1.83	1.13	2.36	3.11	3.55	4.05	3.76	5.32	0.71	0.34	0.13	0.29	4.58	9.83	12.53	5.95	6.97	8.04	3.82	2.68	2.76	3.18	6.47
	$\phi_{h,3,16,0}$	3.33	3.45	5.66	7.45	12.35	5.57	2.80	2.70	3.26	1.92	0.62	0.55	0.44	2.18	7.96	7.10	0.25	0.57	4.34	5.17	2.96	5.56	4.21	2.19
	$\phi_{h,3,17,0}$	0.55	0.65	6.17	8.98	11.99	12.71	15.72	12.11	15.58	15.59	7.68	4.72	5.74	9.33	9.37	7.54	18.29	7.02	6.31	7.39	3.89	2.39	2.46	0.59
	$\phi_{h,3,18,0}$	4.20	1.31	3.42	3.02	3.20	1.92	0.53	1.33	0.87	2.22	8.35	4.44	9.65	9.77	13.13	16.15	26.09	43.75	11.98	0.84	1.38	4.57	3.18	1.88
	$\phi_{h,3,19,0}$	3.68	3.48	4.53	3.18	3.07	4.96	4.24	0.47	0.07	2.25	5.67	5.29	5.11	2.04	1.43	1.25	3.92	11.59	46.20	7.92	1.84	4.00	3.25	3.54
	$\phi_{h,3,20,0}$	3.02	1.09	0.79	2.69	2.05	3.38	7.04	2.56	1.78	4.24	6.14	0.61	2.79	0.74	1.12	1.42	2.56	1.53	1.87	46.83	11.70	0.65	0.82	1.66
	$\phi_{h,3,21,0}$	5.73	3.04	4.21	7.49	7.74	2.76	18.60	11.10	6.76	2.87	1.35	2.77	3.19	1.88	4.40	2.58	5.53	3.78	2.71	8.09	34.61	6.37	2.49	1.03
	$\phi_{h,3,22,0}$	3.90	8.02	5.68	7.28	9.30	1.82	2.31	4.21	5.82	3.29	0.87	2.37	2.75	5.79	7.44	5.71	8.61	12.19	14.01	2.47	4.59	21.98	3.95	3.08
	$\phi_{h,3,23,0}$	5.57	14.75	16.49	16.00	12.54	8.54	4.50	2.11	3.83	4.15	7.82	4.86	4.80	3.53	3.24	5.44	4.35	4.63	7.63	8.56	4.66	11.53	29.60	12.28
	$\phi_{h,3,24,0}$	2.56	4.32	10.43	13.79	11.89	7.55	4.66	9.26	3.64	3.13	6.52	11.26	11.33	8.73	7.67	6.34	8.65	5.25	3.51	2.12	4.19	9.10	17.41	41.48

	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 $(d-4)$	$\phi_{h,4,1,0}$	7.04	3.46	4.05	3.88	5.11	6.11	5.25	3.59	5.40	5.71	6.34	5.70	7.68	5.49	5.49	3.00	3.37	3.27	3.79	0.36	3.20	6.37	9.02	21.62
	$\phi_{h,4,2,0}$	8.20	15.72	11.92	4.16	2.60	4.17	2.98	1.45	2.82	0.91	1.37	1.23	0.31	2.52	5.12	4.38	6.57	2.74	3.53	0.31	0.41	8.85	8.46	13.46
	$\phi_{h,4,3,0}$	7.60	6.20	4.56	3.19	1.22	3.25	4.85	5.82	3.79	3.73	2.39	3.37	1.13	0.58	2.68	3.88	4.26	3.64	4.47	0.79	0.67	0.94	1.00	4.21
	$\phi_{h,4,4,0}$	1.99	3.84	10.93	15.62	12.19	10.30	7.11	4.39	0.46	0.97	1.29	3.15	3.75	6.44	7.23	6.97	8.54	8.32	3.79	1.85	1.94	1.57	2.58	1.07
	$\phi_{h,4,5,0}$	7.24	7.20	15.26	26.49	33.18	21.68	13.41	6.91	2.44	2.79	2.41	4.25	7.33	8.80	7.24	6.98	5.73	9.79	8.92	4.72	1.20	1.20	0.35	3.90
	$\phi_{h,4,6,0}$	8.60	9.12	13.70	19.93	21.98	28.30	17.11	10.89	9.51	9.10	7.20	5.67	8.27	1.86	2.43	5.36	6.86	4.66	4.92	3.97	11.37	4.68	1.30	4.69
	$\phi_{h,4,7,0}$	6.53	4.18	4.12	3.12	1.56	2.02	13.36	3.47	5.23	4.67	3.11	4.24	7.67	4.78	4.32	3.60	2.57	1.54	1.77	1.83	3.12	2.23	2.02	0.25
	$\phi_{h,4,8,0}$	6.37	3.23	6.63	9.56	5.71	6.61	6.92	11.66	8.34	5.94	3.04	2.69	2.31	2.47	6.52	6.70	6.05	4.74	4.68	3.11	2.13	3.11	2.52	2.48
	$\phi_{h,4,9,0}$	2.19	5.16	5.11	3.44	2.11	1.82	0.10	2.04	4.71	3.86	2.23	1.20	1.15	3.39	1.01	1.43	4.93	8.86	6.79	5.63	1.58	0.89	0.21	0.51
	$\phi_{h,4,10,0}$	5.65	1.77	3.37	4.71	4.72	2.24	2.09	5.20	5.35	3.27	1.61	2.83	1.20	3.22	5.04	4.06	5.29	4.26	4.77	4.08	0.84	0.59	0.14	0.47
	$\phi_{h,4,11,0}$	0.99	2.42	4.48	3.44	3.47	1.65	6.13	10.38	8.40	9.64	13.62	2.76	1.83	0.97	0.64	1.08	1.78	4.47	1.44	1.10	4.81	5.05	0.78	3.64
	$\phi_{h,4,12,0}$	0.66	2.38	3.08	3.14	6.12	5.19	4.81	5.00	3.48	5.08	9.48	11.13	10.18	6.02	5.46	3.52	1.63	2.22	2.74	4.24	1.74	0.93	0.27	2.04
	$\phi_{h,4,13,0}$	0.42	0.83	1.65	3.72	4.18	7.29	4.06	4.41	2.23	3.58	10.56	17.34	23.28	11.29	5.15	3.66	2.12	0.94	0.63	0.44	0.38	0.01	0.01	2.78
	$\phi_{h,4,14,0}$	1.07	6.83	3.53	0.55	0.72	1.42	2.14	1.47	0.51	1.02	0.41	1.85	5.26	4.28	2.64	1.34	0.20	1.16	5.85	5.98	2.83	0.99	0.31	1.35
	$\phi_{h,4,15,0}$	2.75	7.44	9.80	6.51	6.40	1.18	1.45	0.50	3.94	2.23	1.53	6.74	6.86	11.60	12.82	4.81	0.90	1.48	0.71	0.89	3.48	1.35	0.26	1.20
	$\phi_{h,4,16,0}$	2.62	2.86	2.08	2.56	2.37	2.35	2.23	3.69	3.70	3.86	3.44	1.96	0.71	1.34	2.91	6.08	2.78	2.24	4.86	7.15	5.71	6.05	3.56	2.65
	$\phi_{h,4,17,0}$	0.78	2.15	8.98	8.08	12.57	8.70	10.31	7.68	7.01	4.23	5.08	3.64	10.39	8.34	13.09	19.38	22.70	9.37	4.22	3.34	1.75	10.93	12.37	8.81
	$\phi_{h,4,18,0}$	5.85	4.99	1.86	2.51	3.84	3.76	2.74	1.79	1.99	4.03	6.41	7.13	17.60	17.29	13.86	15.90	21.60	47.44	13.53	0.55	0.11	2.18	3.71	2.56
	$\phi_{h,4,19,0}$	1.27	2.58	2.52	3.86	8.66	12.19	10.85	9.85	3.45	3.56	3.17	1.59	5.71	4.91	4.75	3.08	1.76	14.59	43.77	6.43	0.74	2.36	1.72	3.07
	$\phi_{h,4,20,0}$	1.90	0.67	1.98	4.73	3.50	4.67	8.68	8.91	4.33	3.71	3.03	2.75	1.59	0.80	1.90	2.65	3.60	3.10	9.78	54.95	4.03	0.36	0.78	3.35
	$\phi_{h,4,21,0}$	1.09	1.05	2.87	5.47	4.55	4.55	8.88	4.56	3.03	5.31	5.70	4.63	2.17	0.99	0.82	1.05	0.24	0.97	1.55	16.10	44.70	5.74	4.17	4.62
	$\phi_{h,4,22,0}$	2.90	9.04	10.37	13.75	13.66	4.42	1.82	0.52	2.07	2.70	2.61	3.67	4.31	1.91	1.92	1.43	1.45	4.95	3.42	2.36	13.60	40.77	6.25	3.55
	$\phi_{h,4,23,0}$	3.24	11.00	13.53	15.06	17.27	15.62	13.03	14.55	11.77	5.61	3.30	5.78	7.34	4.23	5.17	3.73	3.20	3.43	5.15	7.66	5.90	21.55	45.20	26.62
	$\phi_{h,4,24,0}$	3.74	3.62	9.13	11.97	11.38	8.35	6.89	4.17	4.11	5.61	2.45	2.10	3.99	5.51	5.80	3.15	2.30	0.96	1.63	3.11	6.56	12.47	15.58	23.28
Day $(d-5)$	$\phi_{h,5,1,0}$	6.95	2.11	3.09	2.65	3.35	2.83	7.92	11.50	6.36	5.40	2.57	3.39	3.68	2.73	2.29	3.96	2.99	4.19	4.19	2.92	5.87	9.97	17.58	23.10
	$\phi_{h,5,2,0}$	1.97	6.10	3.33	1.44	1.45	4.34	4.36	2.11	1.32	1.73	2.12	1.37	1.22	1.05	1.30	1.30	0.66	3.34	3.25	3.40	4.34	3.59	2.45	7.86
	$\phi_{h,5,3,0}$	5.76	13.50	11.56	4.88	3.22	6.80	6.27	2.04	0.71	0.47	0.36	1.15	0.60	0.62	0.79	0.13	0.39	0.87	2.08	0.89	0.46	0.98	1.72	2.71
	$\phi_{h,5,4,0}$	2.04	7.59	16.96	21.56	18.29	9.84	4.93	0.15	1.34	0.29	2.00	2.20	1.14	3.24	1.94	0.61	1.60	1.69	0.13	0.05	0.83	0.69	1.09	0.17
	$\phi_{h,5,5,0}$	3.98	6.64	9.87	15.86	25.14	13.39	5.33	3.23	3.34	3.13	1.06	1.23	2.57	3.30	4.35	3.97	1.46	1.31	2.04	0.88	0.81	2.20	0.99	4.10
	$\phi_{h,5,6,0}$	8.33	9.08	12.27	12.98	10.10	17.17	11.12	5.28	2.08	0.17	0.36	0.38	0.55	1.26	1.92	6.23	9.17	8.40	10.04	11.95	9.61	16.67	4.59	6.93
	$\phi_{h,5,7,0}$	2.97	1.35	5.11	3.83	3.58	8.62	12.56	14.47	12.34	7.89	1.09	1.33	3.17	2.60	2.11	1.51	2.91	8.08	8.51	18.40	19.27	4.35	1.67	0.67
	$\phi_{h,5,8,0}$	1.50	0.53	3.92	5.47	4.97	2.90	4.75	8.73	4.76	1.59	1.31	0.92	0.67	1.34	1.47	0.50	4.25	0.73	2.56	7.45	6.07	0.70	0.35	0.18
	$\phi_{h,5,9,0}$	0.32	1.99	2.08	3.78	4.21	2.18	4.36	2.89	4.03	1.80	2.36	1.60	1.84	3.05	3.87	3.22	2.49	1.99	4.76	5.83	3.80	2.75	0.72	0.05
	$\phi_{h,5,10,0}$	7.34	3.03	3.35	2.02	1.72	2.05	1.18	4.46	11.03	12.29	6.85	2.95	1.13	1.08	1.64	1.91	1.91	2.31	2.20	3.98	4.26	1.60	1.21	0.16
	$\phi_{h,5,11,0}$	2.40	1.33	1.03	0.67	0.35	1.77	0.32	0.59	2.70	2.89	4.95	4.51	2.68	0.87	1.07	0.86	0.90	0.26	0.06	1.38	1.93	1.13	4.30	1.15
	$\phi_{h,5,12,0}$	0.37	1.34	1.06	1.93	3.23	4.28	1.72	1.75	0.56	3.74	4.03	4.64	1.79	1.50	1.51	2.03	1.14	1.33	0.75	0.66	0.46	0.09	0.38	0.87
	$\phi_{h,5,13,0}$	2.06	0.23	2.52	1.82	3.90	5.86	1.39	1.29	3.42	2.67	5.83	9.15	14.99	9.30	6.09	2.68	0.38	0.53	0.56	0.17	2.32	5.07	2.28	0.02
	$\phi_{h,5,14,0}$	0.86	1.94	1.38	0.16	1.37	1.12	5.36	1.11	0.63	0.15	0.62	0.94	4.50	7.21	5.39	3.08	1.39	0.29	0.58	0.84	0.73	3.14	2.18	0.71
	$\phi_{h,5,15,0}$	0.03	0.49	4.55	8.39	8.29	5.32	3.83	4.09	0.85	1.17	0.28	0.04	1.91	3.90	6.09	4.60	2.68	2.45	0.49	0.05	0.03	0.29	0.49	1.88
	$\phi_{h,5,16,0}$	1.31	1.09	3.01	4.49	5.40	3.54	0.89	4.86	1.19	1.96	0.42	0.19	1.07	2.98	4.02	2.50	1.69	1.30	1.19	1.52	1.37	0.91	3.21	1.09
	$\phi_{h,5,17,0}$	0.50	2.64	2.78	3.97	6.24	15.39	11.83	8.38	10.38	9.67	1.94	0.19	0.25	3.06	7.24	10.56	13.65	3.86	1.62	0.74	0.85	2.32	2.76	2.82
	$\phi_{h,5,18,0}$	0.81	1.60	4.35	4.44	6.84	5.47	5.71	3.91	6.97	4.03	4.44	4.69	5.45	11.93	16.43	26.55	40.35	47.62	15.31	2.38	1.84	0.79	2.78	4.76
	$\phi_{h,5,19,0}$	0.31	0.91	1.12	2.08	5.43	2.26	2.95	1.49	0.71	2.15	3.96	4.09	4.89	3.80	2.34	1.84	2.95	5.76	40.46	13.01	2.04	1.19	2.28	2.07
	$\phi_{h,5,20,0}$	2.74	5.37	9.53	13.28	12.34	9.54	9.59	8.58	1.47	2.78	3.61	3.08	5.29	5.60	5.68	3.40	2.90	2.95	6.47	34.74	11.14	1.48	7.43	6.57
	$\phi_{h,5,21,0}$	4.95	7.25	8.84	11.95	9.28	8.30	14.43	8.81	7.71	7.20	3.59	5.96	2.59	0.78	2.11	2.86	3.28	3.13	2.35	11.68	34.88	12.99	4.81	0.74
	$\phi_{h,5,22,0}$	7.25	8.59	6.79	16.52	20.78	17.47	10.90	5.90	2.50	1.21	1.66	2.75	3.75	4.61	4.65	3.49	4.91	9.80	5.92	2.24	8.16	35.97	5.75	0.99
	$\phi_{h,5,23,0}$	14.06	13.11	18.99	19.36	23.16	22.93	12.49	14.44	7.86	3.39	3.99	2.36	3.00	5.47	4.62	4.06	4.55	13.72	11.26	6.21	5.18	8.48	30.28	6.61
	$\phi_{h,5,24,0}$	1.96	7.34	12.52	21.73	28.14	21.71	12.55	6.12	6.31	5.15	3.18	4.68	6.27	7.55	6.80	9.47	10.12	11.60	7.92	14.24	6.49	6.39	19.49	31.33
Day $(d-6)$	$\phi_{h,6,1,0}$	14.59	11.22	5.16	5.24	6.15	5.00	4.96	5.26	4.78	1.82	1.13	3.34	5.44	4.62	6.31	6.91	9.46	10.75	9.47	17.59	15.18	5.08	4.44	9.21
	$\phi_{h,6,2,0}$	8.46	17.63	10.12	7.40	1.63	7.72	9.82	6.54	4.29	0.86	2.92	4.60	2.73	2.26	2.51	4.31	5.18	8.10	7.89	5.76	7.75	5.58	1.45	0.87
	$\phi_{h,6,3,0}$	2.58	6.07	9.06	8.89	7.39	6.70	6.40	2.78	3.41	2.72	2.04	1.37	0.91	1.11	2.79	5.19	7.75	10.50	9.46	5.51	3.25	2.39	1.67	0.62
	$\phi_{h,6,4,0}$	1.62	8.72	20.28	29.32	24.29	10.40	7.63	4.67	1.91	4.00	5.24	5.48	8.90	7.07	7.89	7.39	11.54	13.39	10.66	9.71	8.08	3.14	2.96	2.89
	$\phi_{h,6,5,0}$	3.75	10.68	21.70	35.28	35.50	26.09	8.17	3.64	0.61	2.79	4.11	5.52	10.15	6.74	7.16	9.61	6.72	12.66	7.51	6.84	3.57	1.02	1.14	2.04
	$\phi_{h,6,6,0}$	6.85	6.32	12.12	16.75	24.77	48.61	15.46	2.71	1.95	1.17	2.66	3.63	4.51	5.16	3.02	1.33	0.45	1.13	0.06	0.35	0.12	1.45	0.52	6.03
	$\phi_{h,6,7,0}$	6.12	6.75	13.94	11.31	16.66	36.09	68.94	30.73	19.46	15.33	7.86	6.92	9.52	9.18	8.44	9.19	8.78	6.14	4.54	7.37	13.65	18.28	7.99	17.83
	$\phi_{h,6,8,0}$	4.55	5.00	5.11	3.31	7.04	8.49	12.97	40.52	31.86	16.08	9.02	7.80	3.02	4.22	8.31	6.83	5.69	5.56	9.40	23.87	27.40	17.03	6.91	1.47
	$\phi_{h,6,9,0}$	0.18	1.67	2.94	3.07	2.41	9.02	7.96	25.07	32.56	18.82	7.77	4.30	4.16	4.52	4.11	4.75	2.52	1.90	2.98	4.87	7.70	12.22	5.98	3.87
	$\phi_{h,6,10,0}$	0.87	0.42	0.85	2.03	1.81	1.09	4.05	10.49	22.96	34.41	19.48	12.12	6.32	5.58	4.68	3.76	2.64	1.92	3.31	6.76	13.13	13.27	11.14	4.67
	$\phi_{h,6,11,0}$	2.64	2.06	0.61	1.62	1.86	2.77	3.67	5.07	7.22	20.94	27.53	15.41	9.16	7.49	5.24	3.53	2.70	2.99	5.57	3.45	2.78	2.87	3.36	4.99
	$\phi_{h,6,12,0}$	1.82	1.66	4.42	2.22	2.12	2.74	1.19	2.58	2.36	7.98	18.74	24.60	14.90	9.98	8.32	5.43	1.15	0.75	1.08	0.71	4.39	3.98	8.53	5.00
	$\phi_{h,6,13,0}$	4.28	4.69	2.79	7.33	4.61	5.95	4.32	0.81	0.85	4.15	8.24	17.85	24.02	18.14	7.62	4.96	2.67	4.19	10.45	12.26	8.53	4.41	6.43	7.11
	$\phi_{h,6,14,0}$	3.29	2.24	3.27	4.73	5.20	6.03	1.64	1.23	2.38	1.24	5.08	8.20	15.71	21.44	14.19	9.31	5.01	1.88	4.55	7.00	5.84	8.46	6.55	9.11
	$\phi_{h,6,15,0}$	0.29	0.63	3.48	7.54	7.17	1.30	3.06	2.47	0.07	1.28	2.07	6.84	9.71	21.96	31.09	25.24	13.46	4.31	4.03	5.54	12.33	11.69	14.79	15.32
	$\phi_{h,6,16,0}$	0.46	0.54	0.53	4.94	2.73	0.69	1.90	4.51	1.95	1.28	1.90	3.17	1.76	10.17	17.28	19.50	12.10	1.99	4.87	4.60	5.66	7.27	3.83	2.59
	$\phi_{h,6,17,0}$	1.60	2.99	1.13	6.83	2.16	1.31	1.50	0.57	1.98	2.24	2.24	6.32	9.83	12.50	13.15	21.49	31.71	3.74	0.55	0.90	0.89	3.71	0.98	1.34
	$\phi_{h,6,18,0}$	1.04	1.81	2.95	4.29	1.76	4.43	3.23	7.22	4.87	12.09	18.86	18.74	22.84	30.15	33.29	42.53	55.96	77.30	27.60	2.87	3.59	9.59	4.60	5.27
	$\phi_{h,6,19,0}$	0.90	3.23	3.38	5.44	7.73	13.06	18.17	12.52	5.56	6.79	3.99	2.10	3.49	4.78	1.67	2.37	4.78	24.90	71.83	40.92	7.75	2.27	5.28	3.39
	$\phi_{h,6,20,0}$	0.62	2.15	2.92	4.81	4.11	4.85	7.53	10.17	6.34	5.29	3.43	3.54	4.35	1.66	1.25	1.01	2.02	3.07	10.66	64.34	26.57	2.86	6.62	8.84
	$\phi_{h,6,21,0}$	3.00	6.98	4.81	9.69	6.43	6.20	9.46	8.31	7.09	8.27	7.49	4.58	3.38	5.33	3.88	2.92	1.26	2.50	1.36	14.39	74.66	36.65	7.21	1.13
	$\phi_{h,6,22,0}$	7.35	15.35	17.51	19.41	19.14	11.42	5.20	2.69	4.20	2.68	5.28	4.70	3.28	3.98	3.87	1.53	3.40	6.74	6.60	2.67	5.90	51.75	17.63	5.85
	$\phi_{h,6,23,0}$	1.79	3.87	4.81	11.01	18.62	16.98	9.54	9.24	6.04	1.64	0.96	1.54	1.88	3.00	1.72	1.63	4.55	7.50	12.61	5.93	3.67	7.68	45.68	12.29
	$\phi_{h,6,24,0}$	8.70	4.29	7.86	14.24	16.17	16.02	10.97	9.35	6.12	3.01	2.04	2.72	4.15	2.68	1.88	1.67	1.72	3.19	3.15	4.35	4.97	3.34	15.87	27.41

Variable significance across hours cont.

(Ziel & Weron, 2016, RePEc)

	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 $(d-7)$	$\phi_{h,7,1,0}$	7.63	5.08	3.28	11.69	8.09	8.32	18.94	20.24	12.53	6.10	5.94	8.06	6.96	7.17	12.78	10.98	11.13	7.86	5.03	11.65	13.40	6.63	10.35	10.54
	$\phi_{h,7,2,0}$	16.14	11.99	4.62	3.70	2.92	3.55	5.05	4.44	11.14	7.41	6.32	5.74	3.29	2.73	3.46	2.97	4.23	2.38	1.77	2.54	1.32	1.49	4.26	2.13
	$\phi_{h,7,3,0}$	1.65	10.53	14.62	6.82	4.46	3.43	4.02	1.83	2.20	3.16	0.97	0.41	0.17	1.26	1.88	3.93	3.42	6.11	6.35	2.36	1.01	0.73	5.93	7.78
	$\phi_{h,7,4,0}$	7.89	14.45	28.85	32.46	18.52	4.86	10.64	5.65	6.67	6.48	7.67	9.94	17.36	13.55	16.59	12.07	11.26	11.73	12.06	8.80	6.65	2.24	0.98	1.79
	$\phi_{h,7,5,0}$	5.21	5.88	11.13	17.71	28.45	9.01	6.09	1.43	1.56	4.23	8.84	11.41	11.21	12.19	10.50	7.18	5.89	6.53	5.90	2.28	6.20	3.85	1.63	0.83
	$\phi_{h,7,6,0}$	5.00	2.84	7.63	6.19	15.50	43.53	12.10	4.73	11.38	10.83	7.28	6.44	5.37	4.96	2.35	3.12	2.86	2.23	4.12	6.06	5.88	2.55	1.37	8.15
	$\phi_{h,7,7,0}$	5.99	4.39	2.83	4.79	9.45	37.85	74.12	34.04	18.63	11.32	5.94	5.88	8.05	7.11	8.02	7.40	7.43	10.37	16.85	21.78	28.56	32.35	12.63	21.31
	$\phi_{h,7,8,0}$	3.20	5.40	6.25	6.09	9.49	16.02	41.35	63.65	47.78	27.13	14.78	8.92	5.73	7.79	7.44	7.63	8.76	6.76	17.32	17.44	20.32	17.89	11.19	16.41
	$\phi_{h,7,9,0}$	6.76	7.22	9.06	7.16	7.29	5.64	6.15	18.23	48.89	45.78	23.62	16.16	9.05	6.86	5.43	4.41	5.85	3.72	11.26	5.79	4.48	6.48	12.23	10.53
	$\phi_{h,7,10,0}$	8.02	7.89	8.82	10.34	7.53	4.73	2.92	8.38	19.97	40.90	26.43	16.12	13.11	8.84	3.83	3.81	3.67	2.81	2.40	6.92	7.19	5.73	3.92	3.51
	$\phi_{h,7,11,0}$	3.70	5.69	4.66	2.22	2.50	3.87	0.26	0.22	3.90	11.45	23.37	14.97	5.28	4.83	2.64	1.93	0.30	0.92	3.55	4.95	6.20	5.69	2.54	4.18
	$\phi_{h,7,12,0}$	0.35	1.04	2.75	4.93	6.16	3.89	0.33	0.80	4.52	11.54	23.58	25.99	14.21	10.18	7.84	4.39	4.77	3.79	5.97	8.33	9.88	10.76	9.23	5.54
	$\phi_{h,7,13,0}$	8.67	14.66	10.44	6.65	1.95	4.12	2.00	1.31	1.45	3.44	13.25	20.35	23.09	17.65	9.94	3.94	4.42	10.78	14.03	14.69	18.83	13.79	16.34	7.68
	$\phi_{h,7,14,0}$	0.98	3.28	4.48	3.80	4.68	3.14	0.46	3.28	5.48	16.18	24.23	31.74	40.15	39.80	33.42	25.45	11.10	10.58	11.57	11.17	9.28	9.85	10.78	11.24
	$\phi_{h,7,15,0}$	2.51	2.48	1.88	3.55	4.23	3.67	2.36	5.51	5.07	8.20	8.46	19.33	29.07	33.27	31.92	20.39	11.72	11.09	2.91	2.50	1.75	4.80	10.69	9.05
	$\phi_{h,7,16,0}$	1.71	1.37	2.61	1.23	1.56	1.18	2.96	8.90	6.31	7.56	7.45	9.05	18.90	30.08	40.75	43.55	26.06	13.35	15.82	11.09	7.72	8.80	12.07	9.67
	$\phi_{h,7,17,0}$	1.15	0.10	1.22	3.24	0.78	1.68	1.66	5.41	3.00	11.73	19.36	23.54	23.14	32.93	43.37	50.99	74.85	44.31	14.12	8.74	5.34	7.43	8.15	12.32
	$\phi_{h,7,18,0}$	5.17	4.04	3.54	3.47	5.08	5.51	1.80	5.13	5.29	9.02	14.89	16.87	31.49	36.37	31.46	25.29	33.01	64.05	38.59	4.06	3.80	1.07	3.03	3.31
	$\phi_{h,7,19,0}$	2.28	8.38	7.88	8.89	11.79	11.65	13.45	19.51	14.12	10.86	14.54	12.97	9.90	13.94	8.90	14.39	13.80	31.28	64.06	39.26	8.67	8.23	8.92	10.24
	$\phi_{h,7,20,0}$	6.90	3.15	8.81	13.58	17.73	17.47	14.03	4.51	6.36	7.14	4.36	4.77	5.70	5.99	4.44	5.98	6.36	1.02	4.20	64.78	35.84	13.33	7.72	0.41
	$\phi_{h,7,21,0}$	1.94	5.95	11.41	15.17	15.01	19.16	16.86	9.81	9.61	4.19	1.90	3.44	3.92	5.08	6.38	6.69	12.72	6.25	1.92	2.44	21.43	10.86	4.80	4.89
	$\phi_{h,7,22,0}$	1.92	9.97	12.42	13.71	9.17	10.11	8.71	4.24	6.52	5.05	3.55	0.83	1.59	3.79	9.39	8.51	9.19	14.18	15.43	4.14	0.58	20.74	9.44	2.53
	$\phi_{h,7,23,0}$	3.06	14.16	25.30	28.82	30.17	36.45	28.01	20.00	10.29	10.65	5.89	2.38	3.73	8.66	17.44	22.40	27.80	38.14	33.85	23.71	10.64	2.35	11.74	5.47
	$\phi_{h,7,24,0}$	1.48	4.50	4.36	10.01	13.63	18.41	17.36	15.93	12.52	8.19	6.52	7.43	10.97	12.09	18.52	18.73	22.12	22.65	23.41	22.86	10.06	2.78	3.32	14.86
Day $(d-8)$	$\phi_{h,8,1,0}$	5.88	6.91	15.66	20.37	22.41	20.24	17.72	18.14	15.94	11.14	4.26	5.04	5.84	7.88	7.94	10.02	11.18	10.41	14.16	12.92	10.13	7.03	4.33	3.76
	$\phi_{h,8,2,0}$	17.69	3.78	5.43	2.55	2.91	4.06	5.59	4.12	4.61	1.64	3.43	5.17	3.76	3.67	4.53	3.10	6.29	3.89	2.39	2.70	8.73	6.11	5.93	4.30
	$\phi_{h,8,3,0}$	4.15	4.83	6.61	6.46	6.49	6.69	4.27	5.57	3.95	1.49	3.93	3.87	3.02	5.50	4.56	6.86	5.40	4.91	5.71	4.19	4.89	7.03	5.49	4.02
	$\phi_{h,8,4,0}$	11.20	8.46	7.18	11.54	15.78	17.29	6.24	4.83	8.18	3.87	5.82	2.19	4.28	5.65	7.90	11.29	15.53	14.31	12.58	16.80	14.51	10.53	2.80	10.74
	$\phi_{h,8,5,0}$	0.27	2.15	4.47	9.21	9.26	5.91	5.03	7.37	6.97	5.64	5.57	8.18	11.15	9.40	7.90	6.55	8.36	4.05	2.59	3.64	2.17	0.45	1.25	1.94
	$\phi_{h,8,6,0}$	10.72	7.53	8.52	12.95	12.53	17.23	5.86	1.19	2.07	0.63	2.47	4.03	3.34	4.59	2.97	2.88	2.73	3.43	4.77	4.01	1.97	0.54	0.39	1.05
	$\phi_{h,8,7,0}$	8.81	7.72	10.22	9.29	6.51	5.46	9.04	2.10	2.04	3.52	5.26	5.87	13.78	17.31	16.14	13.55	11.60	7.62	5.67	7.67	5.84	3.44	3.21	0.65
	$\phi_{h,8,8,0}$	4.66	3.17	4.08	6.15	6.49	3.50	2.51	4.39	2.98	1.84	1.42	2.29	2.39	1.83	2.56	3.74	4.18	3.26	4.79	5.99	7.79	5.16	2.82	2.47
	$\phi_{h,8,9,0}$	3.13	1.67	3.79	3.18	3.40	4.29	4.10	0.76	0.43	0.81	0.59	0.43	0.55	0.87	2.50	2.12	13.36	7.87	6.47	3.09	4.44	4.18	3.86	0.62
	$\phi_{h,8,10,0}$	5.83	2.25	0.88	1.13	2.08	6.66	6.47	1.08	0.29	1.60	2.49	4.73	5.84	7.38	6.11	6.97	10.43	12.64	11.80	9.22	4.73	1.13	1.56	2.26
	$\phi_{h,8,11,0}$	8.79	3.54	5.52	1.91	6.17	3.53	6.37	3.69	2.83	1.62	1.41	0.46	0.09	0.09	0.43	1.43	1.11	1.84	3.16	2.85	1.77	0.93	3.06	0.35
	$\phi_{h,8,12,0}$	3.27	3.30	5.23	4.42	5.16	8.83	4.32	2.98	1.76	2.16	1.53	1.83	0.54	0.09	0.29	0.46	0.63	2.31	4.66	1.62	1.34	0.46	0.15	1.10
	$\phi_{h,8,13,0}$	0.36	0.19	1.05	1.50	2.84	3.01	6.30	2.61	2.82	1.32	3.46	4.78	2.72	1.62	2.72	2.98	2.98	2.29	0.66	0.07	0.39	0.16	0.00	1.77
	$\phi_{h,8,14,0}$	0.46	3.25	4.82	5.10	4.88	8.39	3.63	4.69	3.54	1.21	1.37	2.59	5.73	3.88	2.55	1.60	0.50	1.63	0.54	0.51	2.19	1.20	1.58	1.50
	$\phi_{h,8,15,0}$	2.19	0.73	0.43	3.11	6.34	0.54	3.39	5.84	6.03	1.99	0.66	1.17	1.79	2.17	2.68	2.88	5.60	5.23	1.91	0.15	0.21	0.18	0.82	1.15
	$\phi_{h,8,16,0}$	1.44	0.17	0.51	0.39	1.39	0.99	0.47	0.81	1.09	1.86	2.07	6.94	9.02	8.58	8.83	9.69	2.49	0.68	0.53	0.35	0.22	0.81	2.34	2.54
	$\phi_{h,8,17,0}$	2.40	0.85	0.89	2.46	5.15	6.12	6.21	1.46	3.99	1.03	0.12	3.53	2.27	5.12	3.19	8.51	17.71	12.80	4.82	6.57	6.28	9.64	8.58	8.68
	$\phi_{h,8,18,0}$	2.52	1.07	0.80	0.94	4.46	3.60	6.07	2.51	6.72	4.24	3.01	1.92	3.06	4.27	4.58	6.70	12.62	33.95	14.70	1.75	1.91	9.46	6.98	2.66
	$\phi_{h,8,19,0}$	7.50	3.67	3.57	7.86	9.93	6.87	2.20	6.61	12.92	7.01	2.59	3.42	3.50	5.13	5.20	2.38	0.79	3.05	23.49	11.22	0.78	7.32	5.08	1.11
	$\phi_{h,8,20,0}$	4.16	2.46	8.50	11.45	13.97	12.30	9.71	15.00	6.37	5.97	6.68	5.25	5.85	4.23	4.84	5.81	4.88	3.70	3.47	20.80	7.43	2.55	5.23	1.74
	$\phi_{h,8,21,0}$	7.25	12.75	16.64	17.77	16.35	7.40	3.42	15.39	7.08	8.85	6.45	9.65	6.87	5.48	12.20	9.48	10.70	9.66	6.38	5.55	14.34	1.82	4.11	5.72
	$\phi_{h,8,22,0}$	4.33	8.93	10.04	16.30	12.54	7.28	4.64	4.91	3.29	0.34	1.96	1.72	1.56	1.07	2.47	1.92	3.46	6.31	6.93	1.18	8.10	26.47	8.96	4.88
	$\phi_{h,8,23,0}$	4.56	15.33	26.87	30.59	31.56	20.93	21.06	9.42	6.06	3.55	2.21	3.01	5.48	5.35	5.33	5.20	7.48	11.30	12.26	9.60	3.58	5.07	23.33	7.84
	$\phi_{h,8,24,0}$	7.34	7.58	11.25	12.36	13.77	17.66	13.78	13.75	11.42	10.62	10.16	6.56	7.43	8.48	10.14	10.85	8.36	9.18	5.80	4.67	3.00	3.83	9.83	11.31

	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	$\phi_{h,1,\min,0}$	57.99	66.16	80.84	87.56	81.33	54.23	26.01	25.68	20.48	12.72	6.94	5.83	5.42	4.45	7.03	5.54	7.51	5.76	3.28	1.68	5.52	2.91	3.02	7.03
	$\phi_{h,2,\min,0}$	1.01	8.69	13.20	16.20	14.91	12.35	7.52	5.59	3.04	0.15	0.80	1.04	0.95	2.96	3.39	2.68	2.46	1.30	3.75	2.50	1.61	2.15	1.31	3.23
	$\phi_{h,3,\min,0}$	14.29	22.78	22.77	27.55	24.29	18.38	7.56	4.16	4.36	1.51	1.15	1.67	2.45	1.71	1.26	0.97	2.66	1.23	1.70	2.63	5.09	4.54	2.83	3.50
	$\phi_{h,4,\min,0}$	7.84	8.01	11.65	18.02	16.59	12.95	10.40	6.07	1.03	1.34	1.55	2.70	4.06	3.14	5.44	4.67	9.50	15.95	13.49	7.01	6.25	2.85	2.45	3.22
	$\phi_{h,5,\min,0}$	11.53	11.88	21.48	24.25	24.12	13.21	4.08	3.53	0.79	1.89	3.01	4.72	5.50	4.94	4.06	6.11	7.26	3.43	4.33	1.60	2.67	3.86	2.25	1.44
	$\phi_{h,6,\min,0}$	5.37	13.53	23.47	21.92	27.64	25.79	5.19	1.04	3.11	2.32	1.92	2.08	4.27	2.84	2.87	6.69	5.96	3.65	1.56	1.22	1.75	0.50	1.60	2.70
	$\phi_{h,7,\min,0}$	6.48	8.76	13.14	13.48	13.01	5.66	1.90	2.00	0.86	0.26	0.60	1.44	3.69	1.77	1.67	3.56	3.01	3.91	4.35	5.00	5.07	4.00	3.01	1.14
	$\phi_{h,8,\min,0}$	2.46	2.39	6.19	8.26	13.44	7.23	6.97	8.70	6.67	8.64	9.21	10.91	13.49	14.41	13.37	13.08	8.00	7.85	5.49	4.43	3.72	3.80	5.30	6.04
Daily maximums	$\phi_{h,1,\max,0}$	24.53	13.83	21.30	26.21	27.31	21.85	21.41	55.76	62.53	47.56	31.51	25.43	14.92	9.67	6.72	4.31	7.13	7.79	10.33	15.28	7.53	4.03	3.48	3.90
	$\phi_{h,2,\max,0}$	18.14	22.28	25.77	22.57	24.48	16.80	29.67	28.34	24.89	19.93	17.27	14.70	13.86	12.42	6.20	5.94	7.78	2.30	2.96	5.66	8.43	12.15	10.50	7.15
	$\phi_{h,3,\max,0}$	4.96	2.13	7.05	6.47	9.85	10.09	17.09	17.45	15.70	18.45	12.69	8.36	5.49	4.18	0.85	2.04	1.72	0.57	3.99	8.18	15.13	5.33	6.29	4.23
	$\phi_{h,4,\max,0}$	8.31	6.60	5.04	6.54	9.67	6.31	11.52	12.08	10.09	7.87	12.16	8.80	5.78	4.59	4.28	1.30	1.23	1.66	1.87	1.64	3.80	3.60	5.17	11.70
	$\phi_{h,5,\max,0}$	4.73	0.99	4.84	6.88	6.73	3.34	12.91	12.73	11.82	10.93	15.06	15.22	13.08	12.24	11.68	11.31	7.51	8.38	9.51	9.74	4.63	1.08	0.49	0.87
	$\phi_{h,6,\max,0}$	4.04	4.79	4.34	2.91	1.65	1.12	9.46	30.53	30.04	22.47	6.36	2.66	2.35	4.07	4.14	4.70	5.36	6.53	7.78	11.33	9.90	5.09	5.95	2.27
	$\phi_{h,7,\max,0}$	5.20	6.41	13.87	12.78	7.82	14.09	11.58	12.96	15.77	9.49	8.63	8.26	7.30	8.10	7.71	8.68	3.50	3.59	2.66	1.86	2.93	0.89	1.13	3.55
	$\phi_{h,8,\max,0}$	3.87	3.78	2.41	2.89	4.93	5.86	4.38	2.19	2.95	4.50	2.98	2.97	2.02	1.81	2.10	2.56	2.91	2.43	6.39	7.43	6.87	7.05	9.85	9.80
DoW dummies	$\phi_{h,0,0,1}$	22.61	22.29	27.32	25.24	22.66	60.04	88.09	85.89	93.59	97.73	95.53	94.01	95.86	97.22	99.46	99.71	99.94	99.97	99.73	96.70	93.83	87.32	73.40	53.01
	$\phi_{h,0,0,2}$	27.80	46.46	42.87	42.67	45.42	40.12	36.81	43.44	37.81	34.31	30.82	38.15	31.30	37.60	46.98	51.57	52.96	53.39	40.40	28.78	32.96	40.62	33.46	24.70
	$\phi_{h,0,0,3}$	20.98	13.92	15.17	16.09	8.92	14.69	14.61	14.43	14.14	16.02	13.59	15.13	9.03	15.42	19.23	16.85	13.52	17.48	18.64	17.04	19.64	14.92	7.36	3.24
	$\phi_{h,0,0,4}$	23.87	14.91	21.66	21.47	18.69	18.97	20.21	19.36	13.52	14.35	10.08	10.34	14.68	12.45	12.84	14.37	16.01	15.17	23.05	17.48	12.33	7.32	13.14	7.89
	$\phi_{h,0,0,5}$	9.69	12.23	10.71	9.38	10.49	6.86	7.96	5.14	9.29	6.80	7.45	6.65	5.25	6.49	21.41	35.71	26.50	13.57	24.00	38.13	32.87	45.01	29.89	7.29
	$\phi_{h,0,0,6}$	74.08	60.13	55.84	50.60	30.44	92.69	93.32	97.92	99.54	98.71	98.26	93.64	95.58	99.32	99.88	99.84	99.45	97.65	95.34	94.63	97.24	90.99	74.01	64.73
	$\phi_{h,0,0,7}$	52.63	76.93	78.50	78.29	87.97	90.70	89.07	100	100	100	100	100	100	100	100	100	100	98.57	90.35	82.90	73.49	66.47	34.57	50.06
Periodic on $Y_{*,h}$	$\phi_{h,1,h,1}$	18.71	12.25	13.46	14.93	20.98	19.94	20.08	26.92	16.09	22.81	25.79	24.16	22.43	22.62	21.48	23.51	34.66	33.15	34.28	41.74	43.25	34.87	20.82	17.60
	$\phi_{h,1,h,2}$	21.02	16.13	20.15	15.90	13.89	15.38	32.89	33.32	31.00	27.40	31.94	25.89	19.21	24.91	33.36	37.56	44.95	43.46	39.35	32.49	33.03	27.80	30.85	9.19
	$\phi_{h,1,h,3}$	13.65	15.59	26.42	25.76	27.98	31.84	68.69	70.35	72.61	51.85	45.71	48.85	51.43	60.35	67.56	72.94	65.23	58.87	55.16	48.27	33.88	31.34	25.93	15.86
	$\phi_{h,1,h,4}$	35.22	29.29	28.70	35.39	32.62	34.95	63.99	58.20	40.96	31.24	30.25	36.67	42.75	50.46	64.26	66.44	56.31	42.92	38.92	45.47	50.13	49.53	32.71	27.66
	$\phi_{h,1,h,5}$	14.19	28.57	37.94	46.53	36.81	33.22	69.44	76.08	58.60	50.74	47.77	33.40	29.93	19.74	12.16	18.72	26.38	21.65	49.85	32.55	29.84	22.96	15.27	15.82
	$\phi_{h,1,h,6}$	14.39	20.29	19.67	21.81	24.78	44.99	33.90	59.18	48.95	41.35	33.06	33.66	34.78	33.12	31.68	27.99	28.23	13.78	16.30	31.64	19.69	18.37	7.03	27.03
	$\phi_{h,1,h,7}$	29.57	28.45	26.33	28.86	34.16	40.50	24.74	14.12	17.23	13.60	19.40	39.36	41.85	51.45	55.81	54.55	47.65	45.33	36.21	22.29	32.53	33.50	20.88	45.95
Periodic on $Y_{*,24}$	$\phi_{h,1,24,1}$	26.28	24.95	33.33	45.40	41.39	40.10	35.49	25.15	35.69	28.84	26.79	24.19	23.58	14.07	13.97	16.84	18.89	24.81	28.17	26.45	20.64	17.31	14.14	
	$\phi_{h,1,24,2}$	19.80	32.47	45.61	46.47	53.83	57.98	44.03	41.65	33.04	30.98	28.06	27.04	29.38	28.67	30.53	30.74	31.22	32.76	28.73	27.22	19.48	18.88	5.30	
	$\phi_{h,1,24,3}$	18.96	32.24	34.27	42.07	36.84	40.72	31.93	45.29	34.20	29.24	23.01	23.69	22.46	17.62	16.92	15.80	19.28	22.54	18.85	13.86	19.55	11.35	15.59	
	$\phi_{h,1,24,4}$	12.84	27.89	35.46	31.46	40.28	46.01	41.86	44.74	49.17	36.89	27.92	25.85	24.19	18.63	21.74	25.02	30.40	31.96	33.81	27.32	16.69	11.51	12.94	
	$\phi_{h,1,24,5}$	9.65	13.64	19.73	29.84	30.10	23.46	27.57	27.44	30.70	23.16	16.36	16.51	15.68	21.26	29.18	27.49	25.98	25.70	18.82	18.04	23.68	20.49	19.56	
	$\phi_{h,1,24,6}$	35.57	37.69	52.08	52.65	37.73	31.88	41.40	51.12	55.28	49.51	49.57	51.32	51.22	43.32	39.75	32.02	33.27	41.09	40.48	42.39	44.14	35.53	30.17	
	$\phi_{h,1,24,7}$	45.76	40.57	40.44	41.43	35.29	25.55	30.70	35.73	42.99	44.31	43.30	43.39	43.64	24.10	20.25	21.58	28.77	39.88	41.91	46.51	38.83	30.33	33.96	

Agenda

1. Beyond point forecasts
   ⇒ probabilistic forecasts
2. Combining forecasts
   - Point forecasts
   - Probabilistic forecasts
3. Variable selection and shrinkage
   - LASSO
   - Elastic nets
4. Guidelines for evaluating forecasts

International Journal of Forecasting 30 (2014) 1030–1081
Contents lists available at ScienceDirect
International Journal of Forecasting
journal homepage: www.elsevier.com/locate/ijforecast

Review

Electricity price forecasting: A review of the state-of-the-art with a look into the future

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1 2 4

ARTICLE INFO

Keywords:
Electricity price forecasting
Day-ahead market
Seasonality
Autoregression

ABSTRACT

A variety of methods and ideas have been tried for *electricity price forecasting* (EPF) over the last 15 years, with varying degrees of success. This review article aims to explain the complexity of available solutions, their strengths and weaknesses, and the opportunities and threats that the forecasting tools offer or that may be encountered. The paper also ... e next decade ... dies involving ... (iii) statistical

energies
Energies **2016**, *9*, 621; doi:10.3390/en9080621
MDPI

Article

Automated Variable Selection and Shrinkage for Day-Ahead Electricity Price Forecasting

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Academic Editor: Javier Contreras
Received: 5 July 2016; Accepted: 29 July 2016; Published: 5 August 2016

Abstract: In day-ahead electricity price forecasting (EPF) variable selection is a crucial issue. Conducting an empirical study involving state-of-the-art parsimonious expert models as benchmarks, datasets from three major power markets and five classes of automated selection and shrinkage procedures (single-step elimination, stepwise regression, ridge regression, lasso and elastic nets), we show that using the latter two classes can bring significant accuracy gains compared to commonly-used EPF models. In particular, one of the elastic nets, a class that has not been considered in EPF before, stands out as the best performing model overall.

Maximizing *sharpness* subject to *reliability*

(Gneiting & Katzfuss, 2014; Nowotarski & Weron, 2016)

- *Reliability* refers to statistical consistency (x% PI covers x% of obs.)
- *Sharpness* refers to how tightly the PI covers the observations

Interval forecasts **Statistics**	**Tests**	**Density forecasts** **Statistics**	**Tests**
Reliability / calibration / unbiasedness			
Unconditional coverage [46, 74]	Kupiec [74]	Probability Integral Transform (PIT) [14, 75]	Visual 'tests' [14, 16] *Tests for uniformity* [76, 77]
Conditional coverage [46] (CC = UC + Independence)	Christoffersen [46] (*Lagged* [78]) *Ljung-Box Christoffersen* [79] *Duration-based tests* [80, 81] *Dynamic Quantile (DQ)* [82] *VQR* [83]	Berkowitz CC statistic [48]	Berkowitz [48]
Sharpness (and reliability)			
Pinball loss [84, 85] Winkler (interval) score [86]	Diebold-Mariano [87, 88] *Model confidence set* [89] *Forecast encompassing* [90]	Continuous Ranked Probability Score (CRPS) [15, 91] *Logarithmic score* [92]	Diebold-Mariano [87, 88] *Model confidence set* [89] *Forecast encompassing* [90]

Take-home messages

1. Beyond point forecasts
   ⇒ probabilistic forecasts
2. Combining forecasts
   - Point forecasts
   - Probabilistic forecasts
3. Variable selection and shrinkage
   - LASSO
   - Elastic nets
4. Guidelines for evaluating forecasts

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Contents lists available at ScienceDirect

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Electricity price forecasting: A review of the state-of-the-art with a look into the future

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Automated Variable Selection and Shrinkage for Day-Ahead Electricity Price Forecasting

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