Forecasting short term electricity prices

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Short-term Electricity Price Forecasting Workshop
April 28, 2014

What do we do?

- We forecast the day ahead electricity spot price
- We show that the intra-day relation between the hourly prices is important
- We show that we can gain from multivariate framework
- We show that a further improvement can be achieved by combining forecasts from different models

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A bit on electricity prices

Electricity Prices Distinct Characteristics:

- Pronounced day of the week and seasonal cycle effects
- Possible negative price
- Extreme price swings, sometimes referred to as "spikes"
- Mean reversion
- Highly volatile

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Data

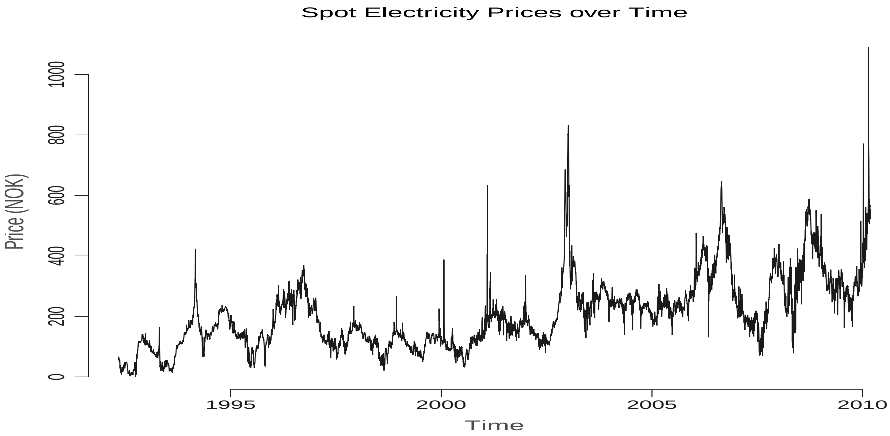
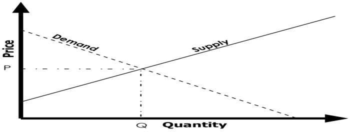


Figure: Spot electricity prices over time

Price formation

- Invisible hand –> visible hand
- "Nord Pool Spot" is an auction based exchange
- The quotes are submitted simultaneously for all hours of the next day
- *Hourly* bids and offers from producers and consumers Price is set such that opposing sides are balanced



- Spot price is the average of these 24 hourly prices

Why do we do it?

- The spot price is used as a reference for derivative pricing, e.g. hourly power options or daily callable options
- Market participants may develop efficient bidding strategies that help to control risk and increase profit

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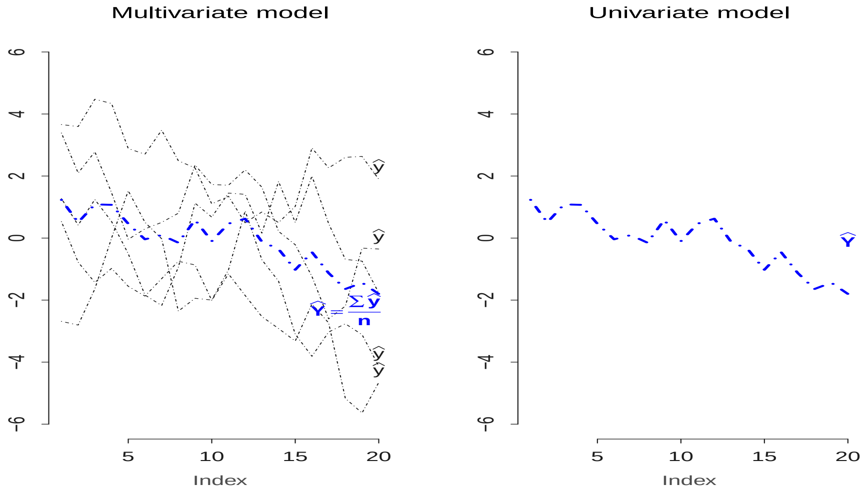
Competing approaches



what do we know?

- Hendry and Hubrich (2006)
- Multivariate framework is more complex

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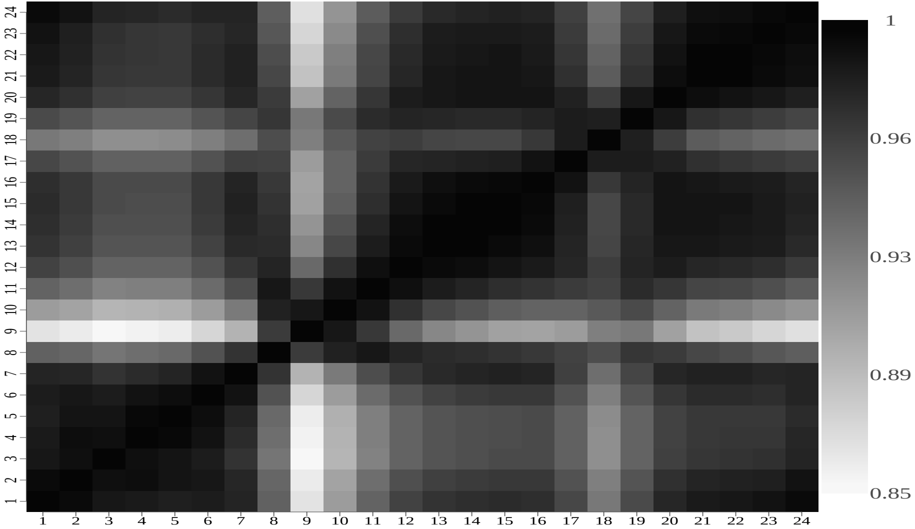
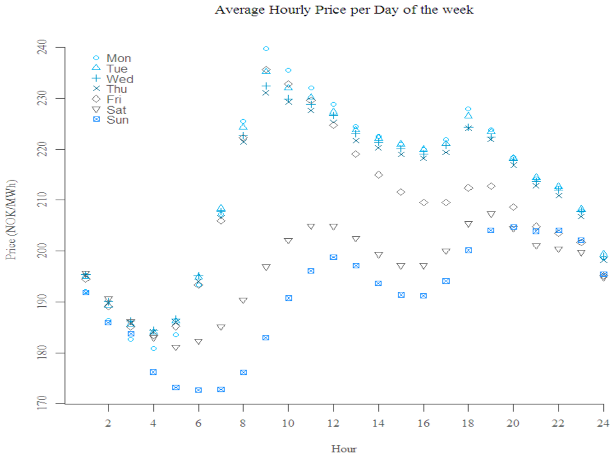
Related work

- Weron and Misiorek (2008)
- Cuaresma et al. (2004)

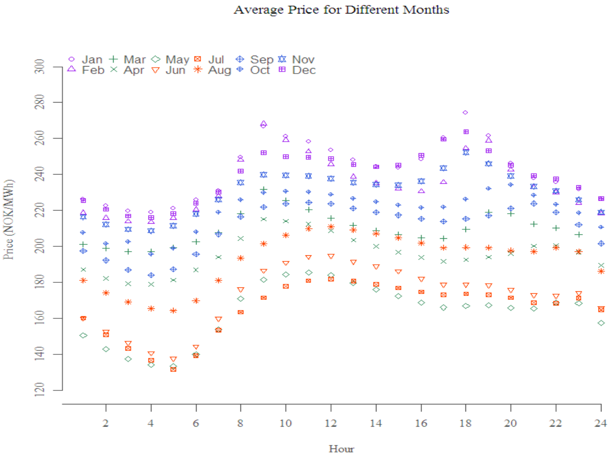
Data


1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
1
0.96
0.93
0.89
0.85

Data


Average Hourly Price per Day of the week
Mon
Tue
Wed
Thu
Fri
Sat
Sun
Price (NOK/MWh)
170
180
190
200
210
220
230
240
2
4
6
8
10
12
14
16
18
20
22
24
Hour

Data


Average Price for Different Months
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Price (NOK/MWh)
120 140 160 180 200 220 240 260 280 300
Hour
2 4 6 8 10 12 14 16 18 20 22 24

Estimation

- Levels
- Five years rolling window
- Dummy variables
- Lags 1, 2, 7

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Univariate models

- Benchmark model: Dynamic ARX model

$$\bar{y}_t = \varphi_0 + \sum_{i=1}^{P} \varphi_i \bar{y}_{t-i} + \sum_{k=1}^{K} \psi_k d_{t,k} + \varepsilon_t$$

- HAR:

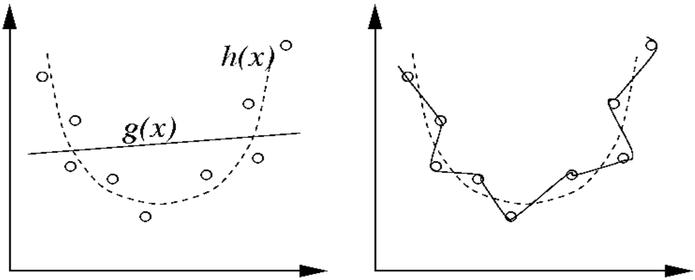
$$\bar{y}_t = \alpha_0 + \alpha_1 \bar{y}_{t-1} + \alpha_2 \bar{y}_{t-1,Week} + \alpha_3 \bar{y}_{t-1,Month} + \sum_{k=1}^{K} \psi_k d_{t,k} + \varepsilon_t$$

Multivariate models

- VAR models, unrestricted (UVAR) and restricted (DVAR)

$$Y_t = \Phi X_t + e_t, \qquad e_t \sim i.i.N(0, \Sigma)$$

- Potential overfitting.



Multivariate models - dealing with over fitting

Bayesian VAR (BVAR)

- Minnesota prior - posterior is obtained analytically
- Shrinkage towards random walk

$$\Phi_{ij}^{prior} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbf{V}_{h,ii} = \begin{cases} \frac{\lambda_1}{l^2} & \text{for coefficients on own lags for lag } l = 1, \ldots, p \\ \frac{\lambda_2}{l^2}\frac{\sigma_i}{\sigma_h} & \text{for coefficients on cross lags of } y_{it} \text{ for lag } l = 1, \ldots, p \\ \lambda_3 \sigma_h & \text{for coefficients on exogenous dummy variables} \end{cases}$$

- We follow standard literature when choosing hyper parameters. (e.g. Koop and Korobilis 2010)

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Multivariate models - dealing with over fitting

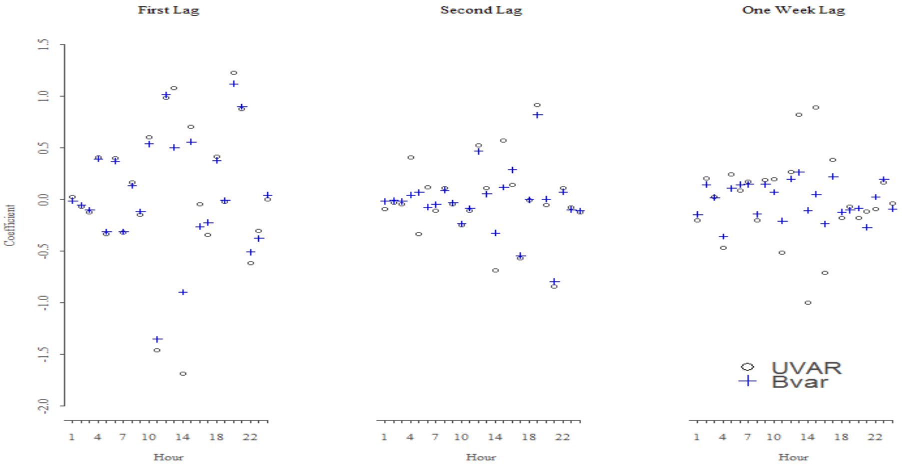
Convenient close form:

$$\alpha \mid \mathbf{y} \sim N(\alpha^{post}, \mathbf{V}^{post}),$$

with

$$\mathbf{V}^{post} = \{(\mathbf{V}^{prior})^{-1} + \widehat{\Sigma}^{-1} \otimes (\mathbf{X}'\mathbf{X})\}^{-1},$$
$$\alpha^{post} = \mathbf{V}^{post}\{(\mathbf{V}^{prior})^{-1}\alpha^{prior} + (\widehat{\Sigma}^{-1} \otimes \mathbf{X})'\mathbf{y}\}.$$

Illustration



Multivariate models - dimension reduction

Another way to reduce the complexity is via dimension reduction.

- VAR - Principal Component Regression

$$\begin{aligned} \widehat{F}_{t+1} &= \widehat{\Delta_1}\widehat{F}_t + \widehat{\Delta_2}\widehat{F}_{t-1} + \widehat{\Delta_3}\widehat{F}_{t-6} \\ \widehat{Y}_{t+1} &= \widehat{\Theta}\widehat{F}_{t+1} + \widehat{\Gamma}D_t \end{aligned}$$

- Reduced Rank Regression, closely related, but with the forecast in mind

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Combination

We can combine the two approaches:

- Reduced Rank Bayesian VAR
- Forecast combination from all models

- How to combine the forecasts? i.e. what are the weights?

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Combination (cont'd)

- Simple average
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Evaluation

Evaluation metrics:

$$RMSE = \sqrt{\frac{1}{(T-h)} \sum_{t=h+1}^{T} (\widehat{y}_t - y_t)^2}$$

$$MAE = \frac{1}{(T-h)} \sum_{t=h+1}^{T} |\widehat{y}_t - y_t|$$

$$MPE = \frac{1}{(T-h)} \sum_{t=h+1}^{T} \frac{|\widehat{y}_t - y_t|}{|y_t|}$$

Evaluation (cont'd)

Apart from the spot price, we look at the individual hourly forecast. We add another "overall" fit measure:

$$WRMSE = RMSE'Q$$

with

$$Q_j = \left(\frac{var(y_j)}{\sum_{j=1}^{24} var(y_j)}\right)^{-1}, \qquad j = 1, ..., 24$$

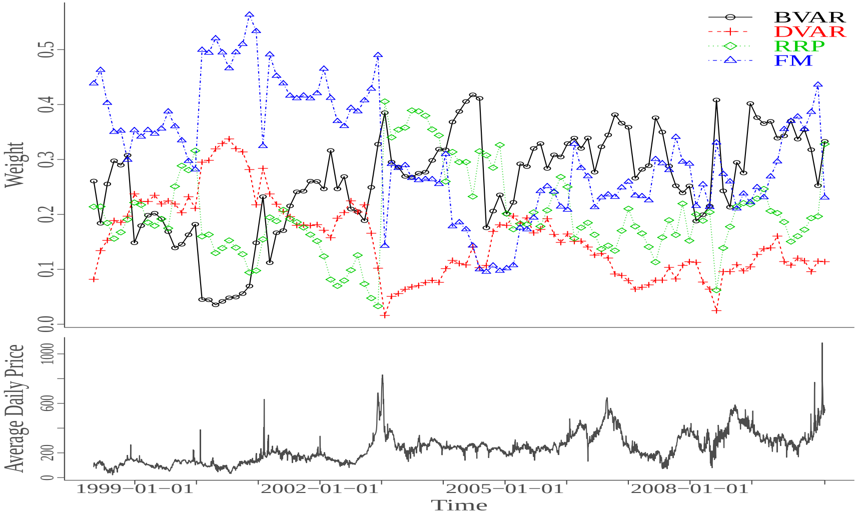
Results

MODEL	*RMSE*	*MAE*	*MPE*
ARX(p)	23.41	11.93	0.054
RRR(5)	0.98	0.85	0.896
FM(5)	0.90	0.88	0.891
DVAR	1.007	1.03	1.026
UVAR	0.94	0.85	0.899
BVAR	0.89	0.83	0.841
RRP(5)	0.91	0.90	0.955
AVE	0.88	0.82	0.834
CLS	**0.84**	**0.80**	**0.819**

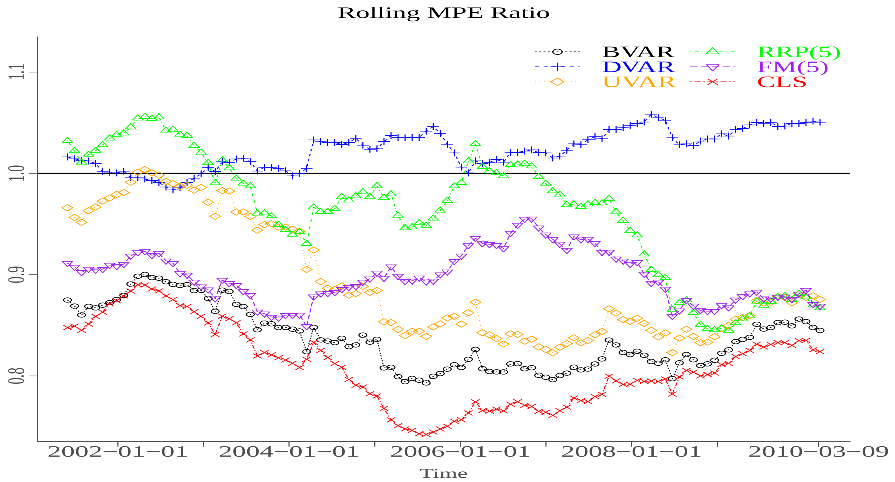
Results (cont'd)

MODEL	*WRMSE*	*RMSE*	*MAE*	*MPE*
RRR(5)	27.44	29.81	12.73	0.062
FM(5)	26.80	28.73	12.94	0.062
DVAR	28.45	30.62	14.03	0.067
UVAR	27.17	29.56	12.47	0.061
BVAR	26.36	28.59	12.30	0.058
RRP(5)	26.94	29.18	13.73	0.066
AVE	27.83	29.83	13.16	0.065
CLS	**25.29**	**27.31**	**11.97**	**0.057**

Results (cont'd)

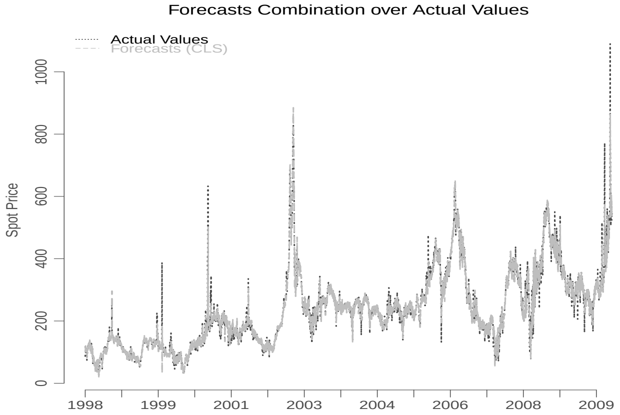


Results - stability



Conclusion

- We forecast the day ahead electricity spot price.



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