



Econometric modelling and forecasting of intraday electricity prices

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Open-Minded

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Motivation and aims

- ▶ Scarce literature regarding the electricity price forecasting (EPF) on intraday markets, i.e. [Monteiro et al., 2016] ; [Andrade et al., 2017]; [Uniejewski et al., 2018a];
- ▶ Better understanding of the market itself and the processes that drive the price formation of both hourly and quarter-hourly Intraday Continuous products;
- ▶ The continuity of the market allows taking advantage of all the information that is available on the market;
- ▶ Very short-term forecasting of the ID₃-Price on German Intraday Continuous Electricity Market.

Market description

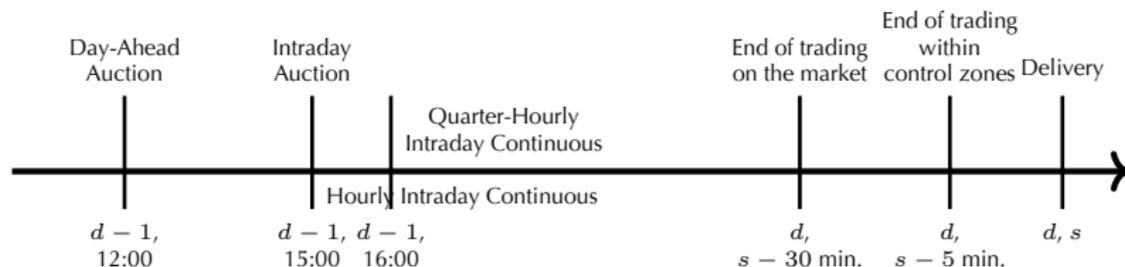
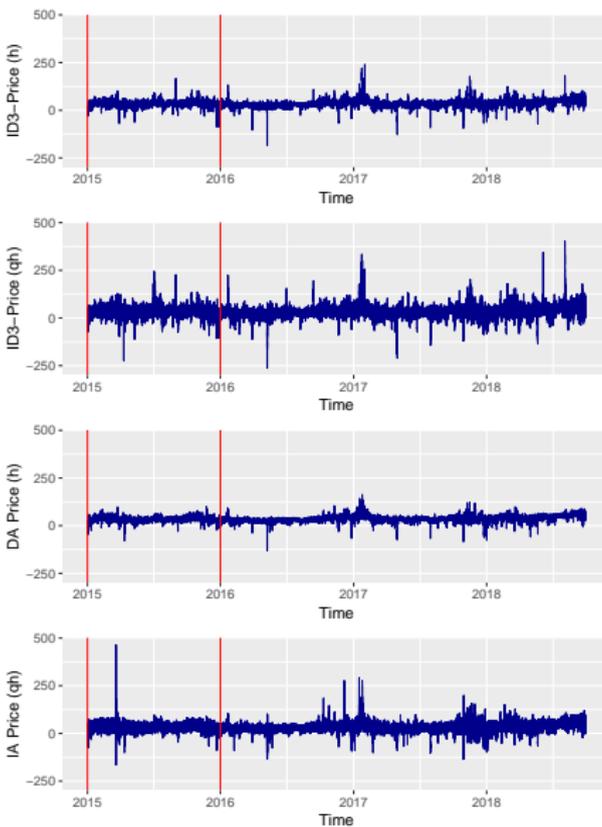


Figure: Daily routine of German Spot Electricity Market. d corresponds to the day of delivery and s corresponds to the hour of delivery.

- ▶ Problem: no clear definition of "Intraday Price".
- ▶ Solution: Price measures introduced by EPEX: Price Index, ID₃-Price and ID₁-Price.

Price over time



x ID $_y$ Price

To measure the intraday price at particular time during the trading period, we define x ID $_y$ function as follows.

$$x\text{ID}_y^{d,s} := \frac{1}{\sum_{k \in \mathbb{T}_{x,y}^{d,s} \cap \mathcal{T}^{d,s}} V_k^{d,s}} \sum_{k \in \mathbb{T}_{x,y}^{d,s} \cap \mathcal{T}^{d,s}} V_k^{d,s} P_k^{d,s},$$

- ▶ where $\mathbb{T}_{x,y}^{d,s} = [b(d,s) - x - y, b(d,s) - x)$, $x \geq 0$ and $y > 0$.
- ▶ Note: EPEX ID $_3 = 0.5$ ID $_{2.5}$ and EPEX ID $_1 = 0.5$ ID $_{0.5}$.

Full information model

We construct for each product a linear model

$$\begin{aligned}
 \text{ID}_3^{d,s} = & \sum_{j \in \{-1,0,1\}} \sum_{s=1}^{24} \sum_{x \in \mathcal{I}_H(j,s)} \beta_{j,s,x}^{(1)} \text{ID}_{0.25}^{d-j,s} + \sum_{j=2}^{14} \sum_{s=1}^{24} \beta_{j,s}^{(2)} \text{ID}_3^{d-j,s} \\
 & + \sum_{j \in \{-1,0,1\}} \sum_{s=1}^{96} \sum_{x \in \mathcal{I}_{QH}(j,s)} \beta_{j,s,x}^{(3)} \text{ID}_{0.25}^{d-j,s} + \sum_{j=2}^{14} \sum_{s=1}^{96} \beta_{j,s}^{(4)} \text{ID}_3^{d-j,s} \\
 & + \sum_{j=-1}^{14} \sum_{s=1}^{24} \beta_{j,s}^{(5)} \text{DA}^{d-j,s} + \sum_{j=-1}^{14} \sum_{s=1}^{96} \beta_{j,s}^{(6)} \text{IA}^{d-j,s} + \sum_{j=1}^7 \beta_j^{(7)} \text{DoW}_j^d + \varepsilon^{d,s},
 \end{aligned}$$

► where

- $\mathcal{I}_i(j, s) = \{0, 0.25, 0.5, \dots, b(d-j, s) - c_i(d-j) - 0.25, b(d-j, s) - c_i(d-j)\}$ for $i \in \{H, QH\}$,
- $c_i(d)$ stands for the beginning of trading of a product type i on day d .

Remarks on the model

- ▶ Due to a very large number of regressors we utilize the lasso and elastic net estimation methods.
- ▶ The most recent price of corresponding product s , i.e. ${}_{3.25}ID_{0.25}^{d,s}$ is expected to be the most informative for the model. Therefore we perform model estimation in three ways:
 - we do not penalize the model for size of the corresponding coefficient,
 - we fix the corresponding coefficient to 1,
 - we do not interfere in the coefficient estimation.
- ▶ We take two approaches to the backward transformation.

This results in total in 12 versions of the model.

Benchmark models

► Naive.DA

$$\widehat{\text{ID}}_3^{d,s} = \text{DA}^{d,s} \text{ or } \widehat{\text{ID}}_3^{d,s} = \text{IA}^{d,s}$$

► Naive.MR1

$$\widehat{\text{ID}}_3^{d,s} = 3.25 \text{ID}_{0.25}^{d,s}$$

► Naive.MR2

$$\widehat{\text{ID}}_3^{d,s} = 3.25 \text{ID}_{2.5}^{d,s}$$

► ARX – inspired with **expert_{DoW,nl}** model of [Ziel and Weron, 2018]

$$\begin{aligned} \text{ID}_3^{d,s} = & \beta_1 \text{ID}_3^{d-1(s \leq 4), (s-4) \bmod S+1} + \beta_2 \text{ID}_3^{d-1,s} + \beta_3 \text{ID}_3^{d-2,s} + \beta_4 \text{ID}_3^{d-7,s} \\ & + \beta_5 3.25 \text{ID}_{0.25}^{d,s} + \beta_6 \text{DA}^{d,s} + \sum_{j=1}^7 \beta_{6+j} \text{DoW}_j^d + \varepsilon^{d,s} \end{aligned}$$

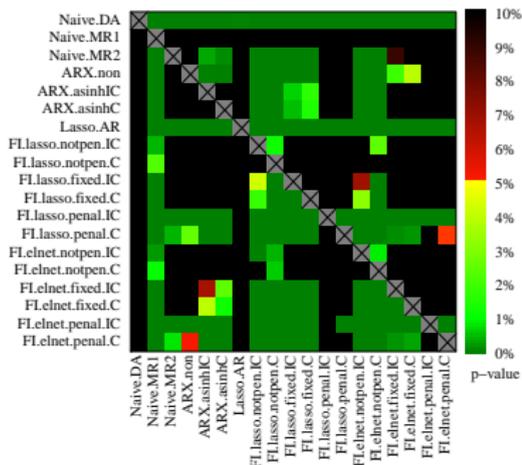
► Lasso.AR – adjusted model of [Uniejewski et al., 2018a]

$$\begin{aligned} \text{ID}_3^{d,s} = & \sum_{i,j=d-7,s}^{d,s-4} \beta_{i,j}^{(1)} \text{HID}_3^{i,j} + \sum_{i,j=d-7,s}^{d,s+8} \beta_{i,j}^{(2)} \text{DA}^{i,j} + \sum_{j=1}^7 \beta_j^{(3)} \text{DoW}_j^d \\ & + \sum_{i,j=d-7,s}^{d,s-13} \beta_{i,j}^{(4)} \text{QHID}_3^{i,j} + \sum_{i,j=d-7,s}^{d,s+32} \beta_{i,j}^{(5)} \text{IA}^{i,j} + \varepsilon^{d,s}. \end{aligned}$$

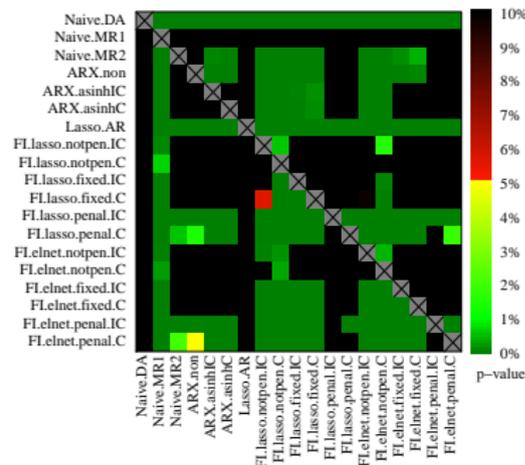
Forecasting evaluation – MAE and RMSE

	MAE_H	$RMSE_H$	MAE_{QH}	$RMSE_{QH}$
Naive.DA	5.004	7.965	7.643	11.701
Naive.MR1	3.334	5.278	7.706	11.714
Naive.MR2	3.501	5.588	7.51	11.434
ARX.non	3.503	5.442	6.977	10.529
ARX.asinhIC	3.442	5.493	6.858	10.627
ARX.asinhC	3.436	5.422	6.896	10.462
Lasso.AR	4.695	7.289	7.76	11.715
Fl.lasso.notpen.IC	3.372	5.415	6.992	10.859
Fl.lasso.notpen.C	3.353	5.319	6.871	10.513
Fl.lasso.fixed.IC	3.387	5.333	7.599	11.566
Fl.lasso.fixed.C	3.393	5.334	7.579	11.533
Fl.lasso.penal.IC	3.728	6.249	7.025	11.224
Fl.lasso.penal.C	3.575	5.983	6.718	10.685
Fl.elnet.notpen.IC	3.376	5.42	7.346	11.364
Fl.elnet.notpen.C	3.356	5.324	7.234	11.019
Fl.elnet.fixed.IC	3.447	5.391	7.731	11.722
Fl.elnet.fixed.C	3.453	5.392	7.723	11.704
Fl.elnet.penal.IC	3.663	6.052	7.044	11.143
Fl.elnet.penal.C	3.547	5.832	6.81	10.7

Forecasting evaluation – DM test (hourly products)



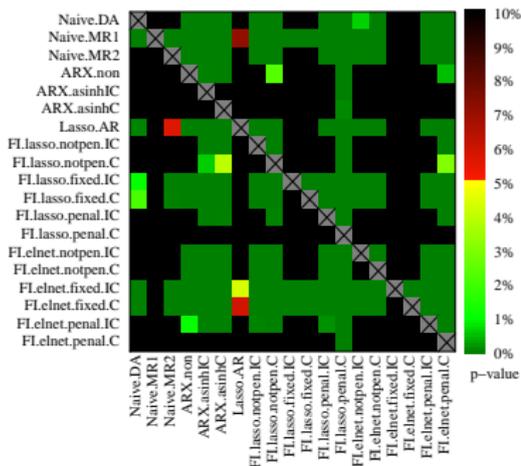
(a)



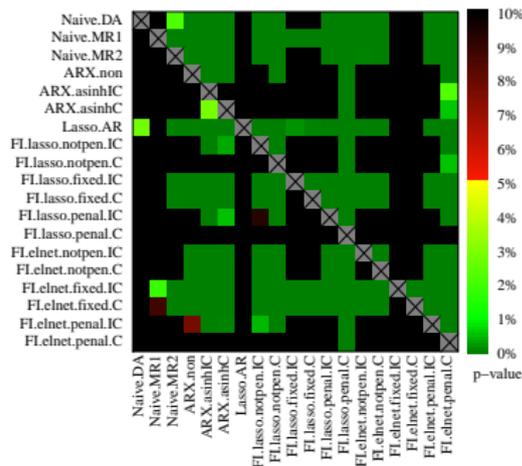
(b)

Figure: Results of the Diebold-Mariano test for hourly products. (a) presents the p -values for $\|\cdot\|_2$ norm, (b) the values for $\|\cdot\|_1$ norm. The figures use a heat map to indicate the range of the p -values. The closer they are to zero (\rightarrow dark green), the more significant is the difference between forecasts of X-axis model (better) and forecasts of the Y-axis model (worse).

Forecasting evaluation – DM test (quarter-hourly products)



(a)



(b)

Figure: Results of the Diebold-Mariano test for quarter-hourly products. (a) presents the p -values for $\|\cdot\|_2$ norm, (b) the values for $\|\cdot\|_1$ norm. The figures use a heat map to indicate the range of the p -values. The closer they are to zero (\rightarrow dark green), the more significant is the difference between forecasts of X-axis model (better) and forecasts of the Y-axis model (worse).

Variable selection — hourly products

	Importance: 1	Importance: 2	Importance: 3	Importance: 4
00:00	$H ID_{0,25}^{d,00:00}$ (96.8)	$H ID_{0,25}^{d-1,22:00}$ (0.7)	$H ID_{0,25}^{d-1,21:00}$ (0.4)	$H ID_{0,25}^{d-1,23:00}$ (0.3)
01:00	$H ID_{0,25}^{d,01:00}$ (98.5)	$QH ID_{0,25}^{d-1,22:15}$ (0.4)	$QH ID_{0,25}^{d-1,21:15}$ (0.2)	$IA^{d-2,08:00}$ (0.2)
02:00	$H ID_{0,25}^{d,02:00}$ (99.9)	$IA^{d-3,23:15}$ (0)	$DA^{d-13,06:00}$ (0)	$QH ID_{0,25}^{d-1,06:45}$ (0)
03:00	$H ID_{0,25}^{d,03:00}$ (99.9)	$QH ID_{0,25}^{d-1,19:30}$ (0.1)	$QH ID_{0,25}^{d-1,07:00}$ (0)	$QH ID_{0,25}^{d,04:15}$ (0)
04:00	$H ID_{0,25}^{d,04:00}$ (99.9)	$QH ID_{0,25}^{d-1,18:45}$ (0)	$QH ID_{0,25}^{d-1,18:45}$ (0)	$QH ID_{0,25}^{d-4,07:30}$ (0)
05:00	$H ID_{0,25}^{d,05:00}$ (100)	$QH ID_{0,25}^{d-7,21:00}$ (0)	Sun (0)	
06:00	$H ID_{0,25}^{d,06:00}$ (99.9)	$QH ID_{0,25}^{d-1,23:15}$ (0)	$QH ID_{0,25}^{d-10,19:30}$ (0)	$QH ID_{0,25}^{d-1,23:15}$ (0)
07:00	$H ID_{0,25}^{d,07:00}$ (100)	$QH ID_{0,25}^{d-9,19:00}$ (0)	$QH ID_{0,25}^{d,02:30}$ (0)	$QH ID_{0,25}^{d-9,05:15}$ (0)
08:00	$H ID_{0,25}^{d,08:00}$ (99.6)	$QH ID_{0,25}^{d,02:15}$ (0.3)	$QH ID_{0,25}^{d,20:30}$ (0)	$QH ID_{0,25}^{d-5,08:00}$ (0)
09:00	$H ID_{0,25}^{d,09:00}$ (99.7)	$QH ID_{0,25}^{d-6,21:30}$ (0.2)	$QH ID_{0,25}^{d-3,22:15}$ (0.1)	$QH ID_{0,25}^{d,22:45}$ (0)
10:00	$H ID_{0,25}^{d,10:00}$ (99.9)	$QH ID_{0,25}^{d-10,11:15}$ (0)	$DA^{d-2,12:00}$ (0)	$QH ID_{0,25}^{d-10,21:30}$ (0)
11:00	$H ID_{0,25}^{d,11:00}$ (99.8)	$QH ID_{0,25}^{d,00:00}$ (0.1)	$QH ID_{0,25}^{d-1,13:15}$ (0)	$IA^{d-8,17:00}$ (0)
12:00	$H ID_{0,25}^{d,12:00}$ (100)	$QH ID_{0,25}^{d-9,00:15}$ (0)	$QH ID_{0,25}^{d-1,21:30}$ (0)	$QH ID_{0,25}^{d-1,23:45}$ (0)
13:00	$H ID_{0,25}^{d,13:00}$ (99.9)	$QH ID_{0,25}^{d-9,09:30}$ (0)	$QH ID_{0,25}^{d-9,07:45}$ (0)	$QH ID_{0,25}^{d-9,09:45}$ (0)
14:00	$H ID_{0,25}^{d,14:00}$ (100)	$QH ID_{0,25}^{d-1,21:15}$ (0)	$QH ID_{0,25}^{d-9,07:15}$ (0)	$QH ID_{0,25}^{d-2,06:45}$ (0)
15:00	$H ID_{0,25}^{d,15:00}$ (99.7)	$IA^{d-9,06:00}$ (0.1)	$IA^{d-9,05:15}$ (0.1)	$QH ID_{0,25}^{d-10,20:45}$ (0)
16:00	$H ID_{0,25}^{d,16:00}$ (99.9)	$IA^{d-4,18:00}$ (0.1)	$IA^{d-9,00:45}$ (0)	$QH ID_{0,25}^{d-4,13:45}$ (0)
17:00	$H ID_{0,25}^{d,17:00}$ (99.8)	$QH ID_{0,25}^{d,06:15}$ (0.2)	$QH ID_{0,25}^{d-1,15:15}$ (0)	$IA^{d-8,04:45}$ (0)
18:00	$H ID_{0,25}^{d,18:00}$ (99.9)	$QH ID_{0,25}^{d-1,16:45}$ (0)	$QH ID_{0,25}^{d,00:15}$ (0)	$QH ID_{0,25}^{d-1,15:30}$ (0)
19:00	$H ID_{0,25}^{d,19:00}$ (99.9)	$QH ID_{0,25}^{d-1,14:00}$ (0.1)	$QH ID_{0,25}^{d,00:15}$ (0)	$QH ID_{0,25}^{d,18:00}$ (0)
20:00	$H ID_{0,25}^{d,20:00}$ (100)	$QH ID_{0,25}^{d-3,16:45}$ (0)	$IA^{d-5,18:00}$ (0)	$IA^{d-8,23:00}$ (0)

Table: Most relevant coefficients in model **FI.lasso.notpen.C** for selected hourly products

Variable selection — quarter-hourly products

	Importance: 1	Importance: 2	Importance: 3	Importance: 4
00:00	IA ^{d,00:00} (40.1)	QH ID ^{d,00:00} (13.9)	QH ID ^{d-1,21:15} (8.9)	H ID ^{d-1,22:00} (5.4)
00:15	H ID ^{d-1,22:00} (11.8)	3.25 ID ^{d,00:00} (11.7)	0.5 ID ^{d,00:00} (11.3)	1.25 ID ^{d-1,23:00} (10.8)
00:30	2.75 ID ^{d,00:00} (14.3)	H ID ^{d,01:00} (12.9)	IA ^{d,00:15} (11.3)	H ID ^{d,01:00} (7.5)
00:45	IA ^{d,00:45} (39.6)	4 ID ^{d,00:00} (11.6)	1.75 ID ^{d-1,23:00} (9.8)	3.75 ID ^{d,00:45} (6.2)
01:00	IA ^{d,01:00} (25.1)	2.5 ID ^{d,00:00} (11.3)	QH ID ^{d,01:00} (10.3)	QH ID ^{d,01:00} (4.4)
01:15	2.25 ID ^{d,00:00} (42.7)	H ID ^{d,00:00} (13.2)	3.25 ID ^{d,01:00} (7.3)	0.75 ID ^{d,00:00} (6.6)
01:30	H ID ^{d,01:00} (25.7)	3 ID ^{d,00:00} (10.1)	3.25 ID ^{d,00:00} (7.2)	H ID ^{d,01:00} (4.3)
01:45	2.5 ID ^{d,01:00} (32.8)	2.25 ID ^{d,00:00} (31.9)	1.75 ID ^{d,02:45} (3.4)	3 ID ^{d,00:00} (3.2)
02:00	H ID ^{d,00:00} (17.9)	IA ^{d,02:00} (17.2)	4.25 ID ^{d,01:00} (9.1)	QH ID ^{d,02:00} (4.7)
02:15	1.25 ID ^{d,00:00} (19.5)	H ID ^{d,01:00} (18.2)	2.25 ID ^{d,02:00} (13.1)	9.75 ID ^{d,02:15} (5)
02:30	H ID ^{d,01:00} (26.9)	H ID ^{d,05:00} (7.2)	3 ID ^{d,02:00} (6.6)	IA ^{d,02:30} (5.8)
02:45	IA ^{d,02:45} (13.6)	6 ID ^{d,00:45} (12)	2.75 ID ^{d,02:00} (9.4)	QH ID ^{d,02:45} (8.5)
03:00	IA ^{d,03:00} (21.9)	1.25 ID ^{d,01:00} (12.9)	2.5 ID ^{d,00:15} (7.6)	QH ID ^{d,03:00} (6.4)
03:15	H ID ^{d,01:00} (32.4)	H ID ^{d,01:00} (12.5)	0.5 ID ^{d,01:00} (7.6)	3.25 ID ^{d,03:00} (7.1)
03:30	2.75 ID ^{d,03:00} (26.7)	5 ID ^{d,05:00} (7.5)	2 ID ^{d,05:00} (5.6)	H ID ^{d,04:00} (5.5)
03:45	IA ^{d,03:45} (15.2)	QH ID ^{d,02:45} (9.3)	4.75 ID ^{d,03:45} (9.2)	H ID ^{d,05:00} (8.3)
04:00	IA ^{d,04:00} (40.1)	2.25 ID ^{d,04:00} (10.9)	3.25 ID ^{d,03:00} (8.3)	H ID ^{d,02:00} (4.2)
04:15	H ID ^{d,03:00} (24.8)	3.25 ID ^{d,04:00} (10)	2.75 ID ^{d,02:00} (9.6)	H ID ^{d,03:00} (7)
04:30	2.75 ID ^{d,04:00} (22.3)	H ID ^{d,05:00} (9.7)	H ID ^{d,04:00} (8.9)	QH ID ^{d,04:30} (7.8)
04:45	IA ^{d,04:45} (17.1)	4.25 ID ^{d,04:45} (12.2)	3 ID ^{d,05:00} (8.6)	3.25 ID ^{d,03:45} (4.1)
		QH ID ^{d,02:25} (12.2)	3.5 ID ^{d,02:25} (8.6)	2.25 ID ^{d,02:25} (4.1)

Table: Most relevant coefficients in model **FI.lasso.penal.C** for selected quarter-hourly products

Conclusion

- ▶ The results for hourly products suggest that there is no more information that we can get from the transactions data, despite the most recent price, which means that here we deal with an efficient market.
- ▶ The results for quarter-hourly products have shown, that there is some space for improvement. Here the full information model estimated using lasso with standard penalty and correctly back-transformed performed the best.
- ▶ Future research can go in different directions, e.g.:
 - model estimation improvement,
 - incorporation of fundamental regressors,
 - probabilistic forecasting.



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