Simulation-based Forecasting for Intraday Power Markets

Modelling Fundamental Drivers for Location, Shape and Scale of the Price Distribution

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Essener Energiegespräche - Intraday Trading in Academia and Practice
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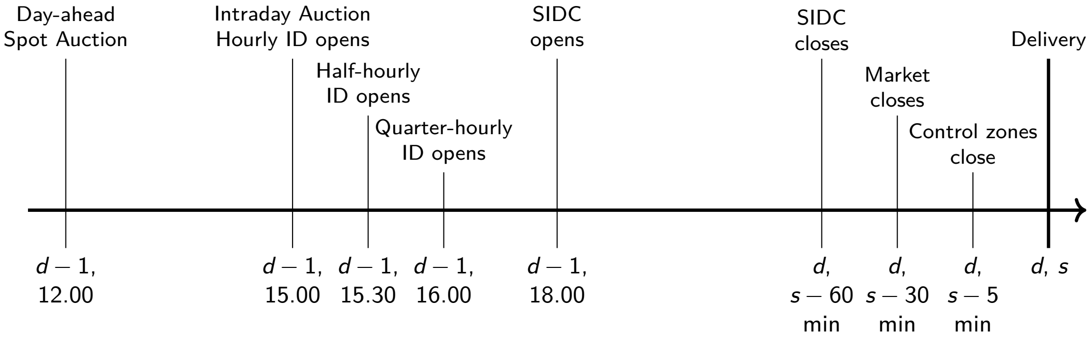
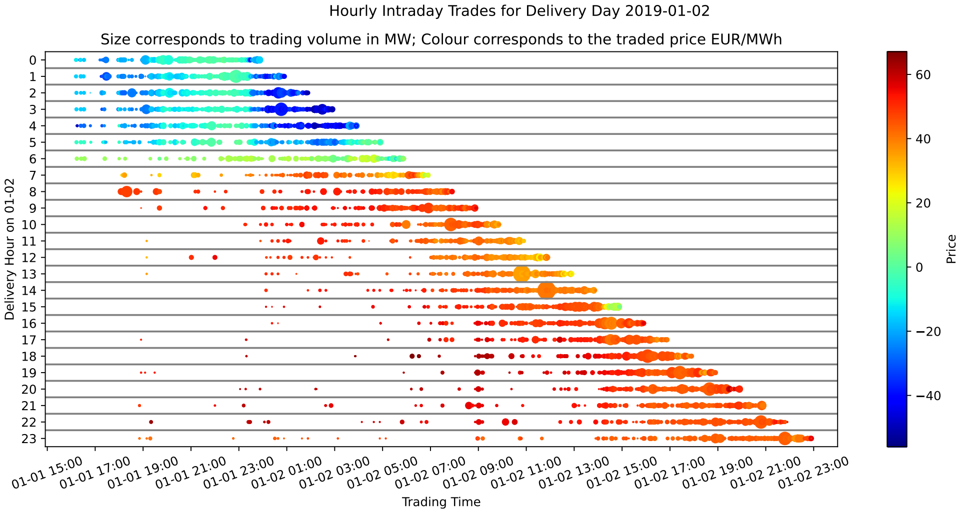
Agenda

Introduction

Short-term markets are structured as discrete auction(s) followed by continuous intraday market with parallel trading for all delivery periods



Trading in the intraday market happens parallel in many products



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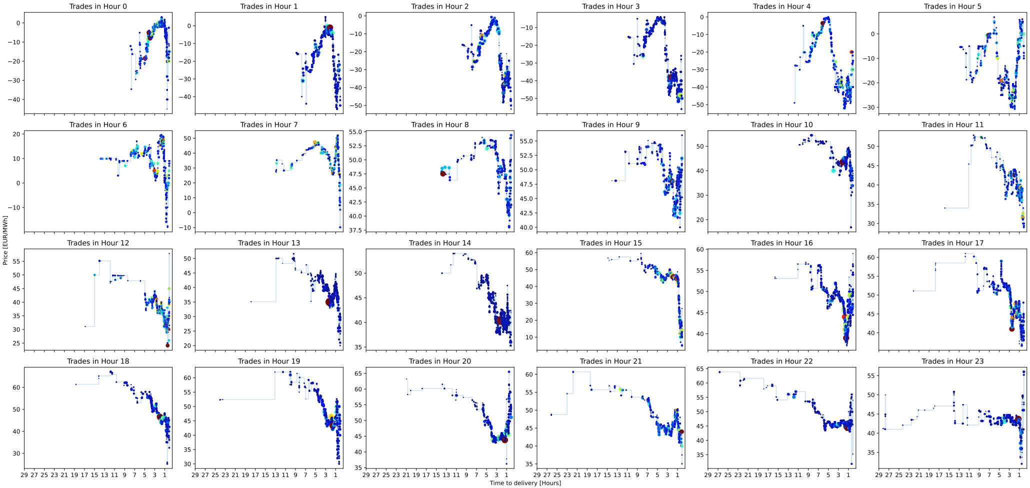
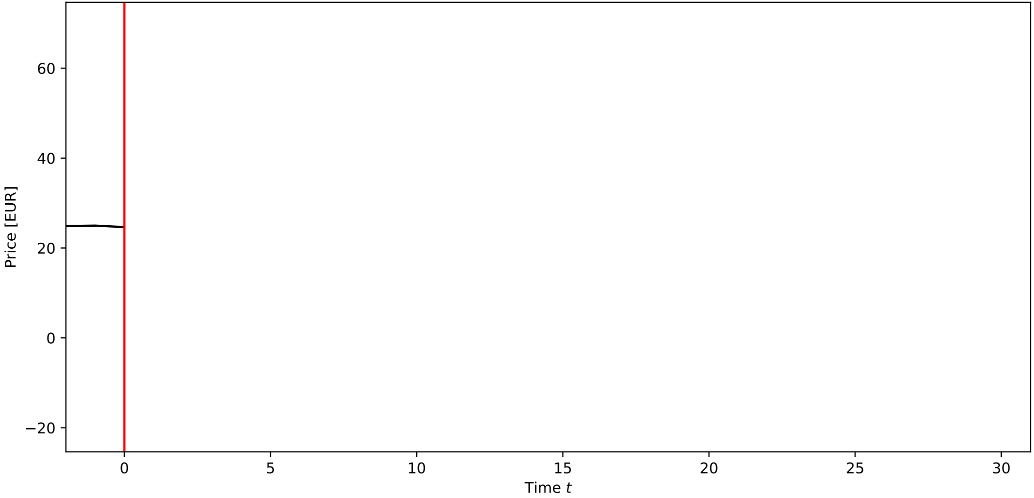
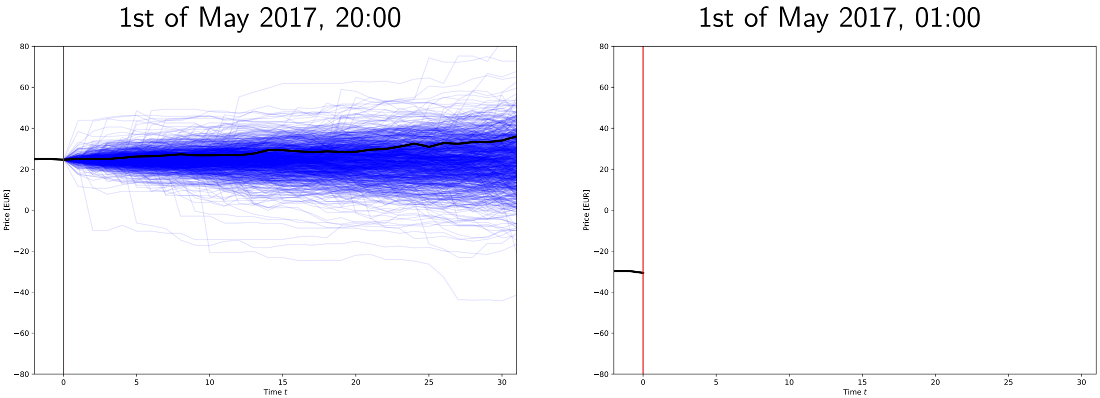


Simulation of the Price Path in Continuous Intraday Markets



Volatility and tail behaviour are important



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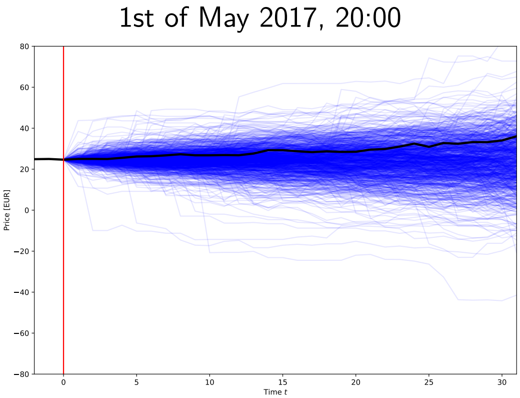

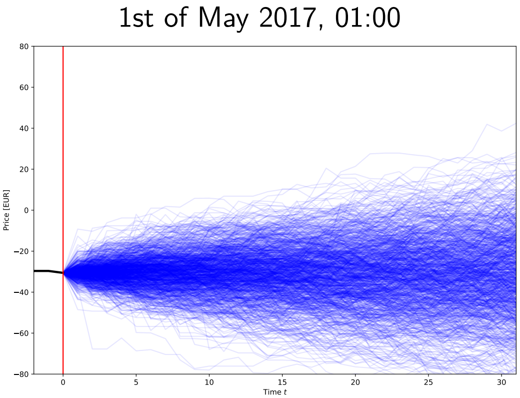

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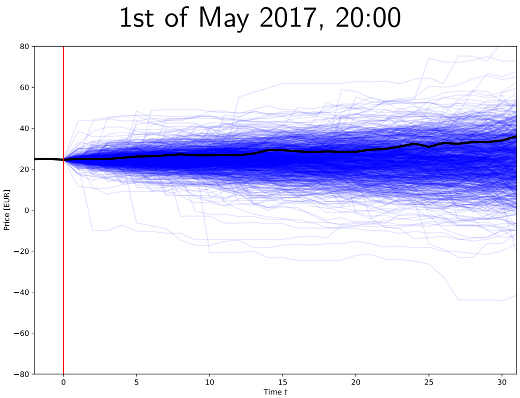
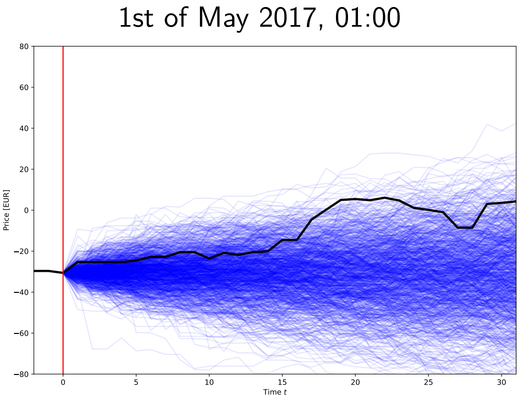




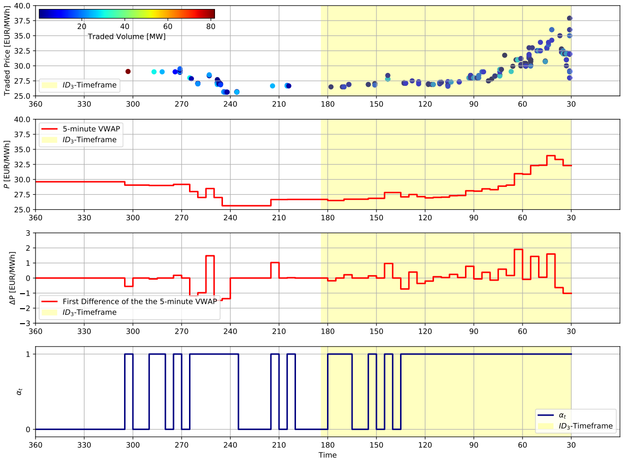
Approach yields significant improvements in modelling the time-varying volatility and tail-behaviour

- Model the price changes in the intraday market and simulate the price changes to derive a (probabilistic) forecast
- Two stage approach:
  1. Model the probability of at least one trade
  2. Model the distribution parameters using fundamental variables

  and simulate the path of the price process (Narajewski and Ziel, 2020)
- Forecasting study with benchmark models: random walk, ARIMA, naive sampling of past trajectories confirms a (statistically significant) improvement in the forecasting performance on a wide range of scoring rules
- Parametric modelling of the distribution parameters allows to analyse the impact of fundamental variables of on expected price changes, volatility and tail behaviour

Intraday Market Empirics

Trades on the continuous intraday market are aggregated on a 5-minute grid and returns are calculated as first differences

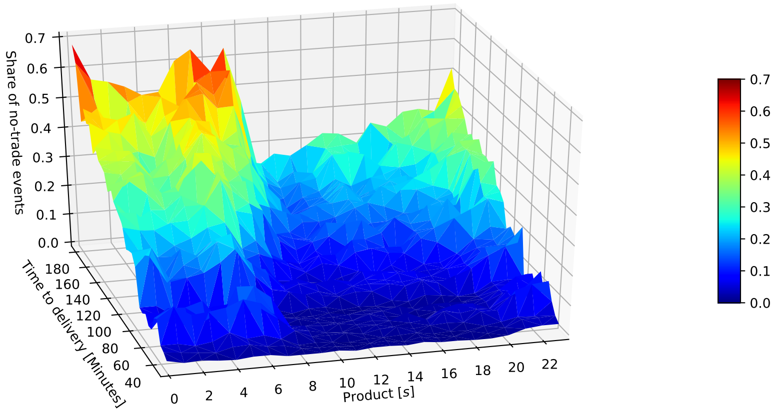


Aggregation procedure

1. Raw trade data
2. Aggregated on 5-minute grid by taking volume-weighted average prices: $P^{d,s}_{\text{ID},t}$
3. First differences: $\Delta P^{d,s}_{\text{ID},t}$
4. Boolean variable for periods with at least one trade: $\alpha^{d,s}_t$

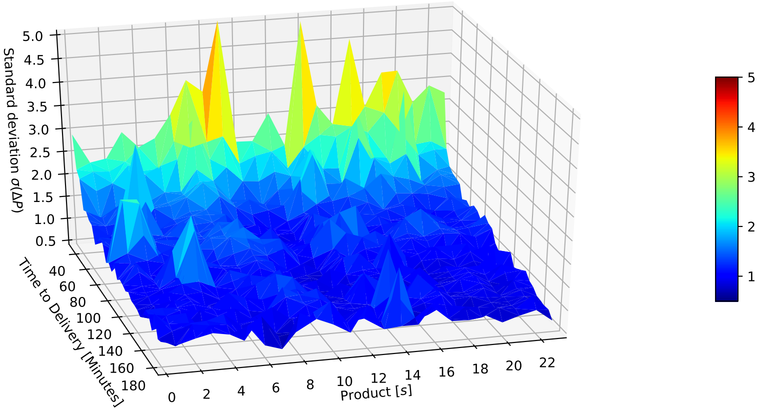
d, s denote day and delivery hour

Trading happens mostly close to delivery



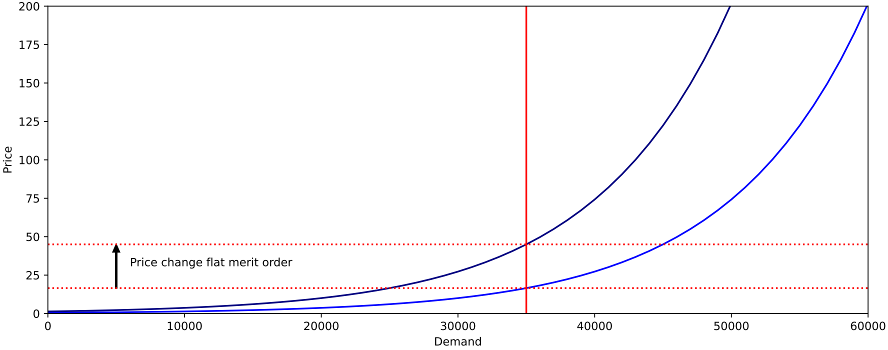
Share of periods where $\alpha_t^{d,s} = 0$ by product and time to delivery

Volatility rises towards gate closure and during peak products



Standard deviation of $\Delta P^{d,s}_{\text{ID, t}}$ by product and time to delivery

Merit-order regime impacts the size of price changes in the intraday market



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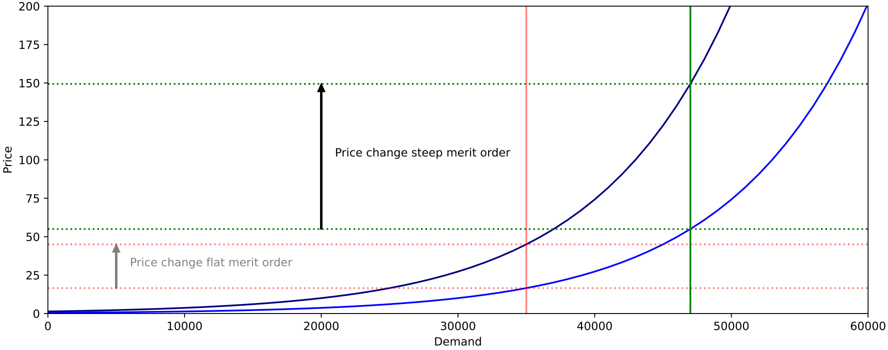
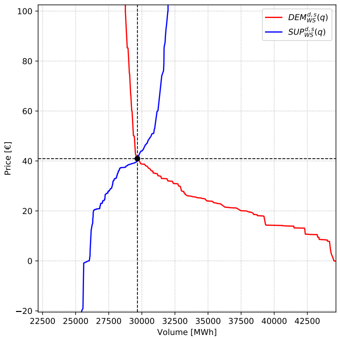


- Kremer et al. (2020, 2021), Narajewski and Ziel (2019) expected price change
- We argue the effect is actually driving *volatility* and *tail* instead of expected value

Use transformed EPEX spot auction curves as merit-order approximation

Original



Core Idea for the transformation of the spot auction curves

A buy order of 100 MW for 50 EUR/MWh is the same as buying 100 MW at any price (i.e. up to 3000 EUR/MWh) and placing a sell order for 100 MW at 50.1 EUR/MWh.

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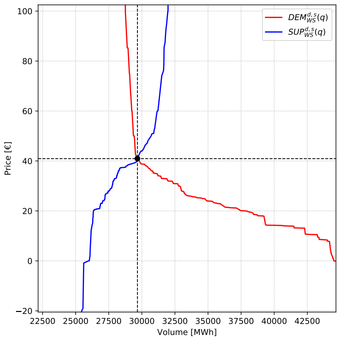
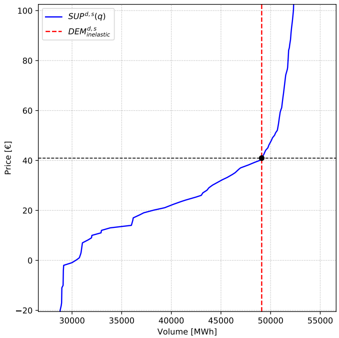


Transformed



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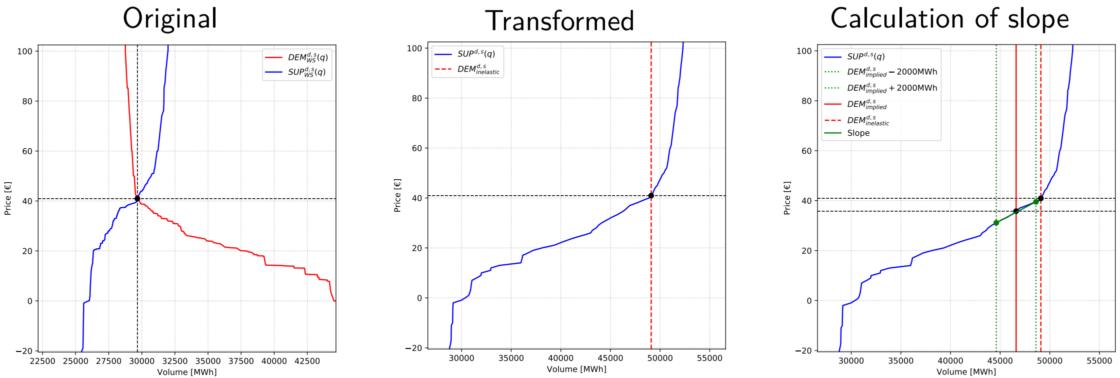

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Models

Two-stage approach by modelling the probability of $\alpha_t^{d,s} = 1$ as binomial variable and the distribution of $\Delta P_{\text{ID, t}}^{d,s}$ as four parameter distribution

1. Estimate the probability of $\alpha_t^{d,s} = 1$ using a logistic regression model
2. Estimate the distribution parameters for

$$\Delta P_{\text{ID, t}}^{d,s} \mid \alpha_t^{d,s} = 1 \sim F$$

   conditional on our explanatory variables using the GAMLSS framework

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- Skew-t distribution and Johnson's S_U distribution for the price
- Regularized estimation using LASSO
- Fundamental variables (wind, solar, demand), lagged prices and trading activity, merit-order slope, time-derived variables

We estimate the probability of $\alpha_t^{d,s} = 1$ using a regularized logistic regression model using a kitchen-sink approach

$$
\log\left(\frac{\pi_t^{d,s}}{1-\pi_t^{d,s}}\right) = \beta_0 + \underbrace{\sum_{j=1}^{3}\beta_j \Delta P_{\text{ID},t-j}^{d,s} + \sum_{j=1}^{6}\beta_{3+j}|\Delta P_{\text{ID},t-j}^{d,s}| + \beta_{10}\sum_{j=7}^{12}|\Delta P_{\text{ID},t-j}^{d,s}|}_{\text{Price differences}}
$$

$$
+ \underbrace{\beta_{11}\text{MON}(d) + \beta_{12}\text{SAT}(d) + \beta_{13}\text{SUN}(d) + \sum_{j=1}^{31}\beta_{13+j}\text{TTD}(t)}_{\text{Time dummies}} + \underbrace{\beta_{47}\hat{D}_{\text{DA}}^{d,s} + \beta_{48}\hat{W}_{\text{DA}}^{d,s} + \beta_{49}\hat{S}_{\text{DA}}^{d,s} + O_{\text{DA}}^{d,s}}_{\text{Day-ahead fundamental variables}}
$$

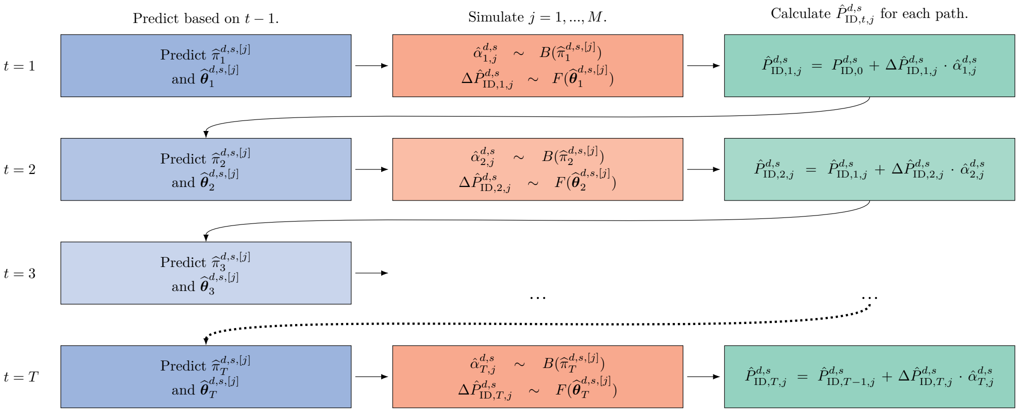
$$
+ \underbrace{\beta_{51}\Delta\hat{W}_{\text{DA,ID}}^{d,s,+} + \Delta\hat{W}_{\text{DA,ID}}^{d,s,-} + \beta_{53}\Delta\hat{S}_{\text{DA,ID}}^{d,s,+} + \beta_{54}\Delta\hat{S}_{\text{DA,ID}}^{d,s,-}}_{\text{Day-ahed to intraday forecast updates}} + \underbrace{\beta_{55}\sigma_{\text{DA,ID}}^{d,s}(\Delta\hat{W}) + \beta_{56}\sigma_{\text{DA,ID}}^{d,s}(\Delta\hat{S})}_{\text{Standard deviation of forecast updates}}
$$

$$
+ \underbrace{\beta_{57}\Delta O_{\text{DA,ID}}^{d,s,\text{planned}} + \beta_{58}\Delta O_{\text{DA,ID}}^{d,s,\text{unplanned}}}_{\text{Intraday changes in planned and unplanned outages}} + \underbrace{\beta_{59}\mid P_{\text{DA}}^{d,s} - P_{\text{ID},t-1}^{d,s}\mid}_{\text{Day-ahead to } t-1 \text{ price spread}} + \underbrace{\sum_{j=1}^{3}\beta_{59+j}MO_j^{d,s}}_{\text{Slope of the merit-order}} + \underbrace{\sum_{j=1}^{12}\beta_{62+j}\bar{\alpha}_{t-j}^{d,s}}_{\text{Regression on } \bar{\alpha}_t^{d,s}},
$$

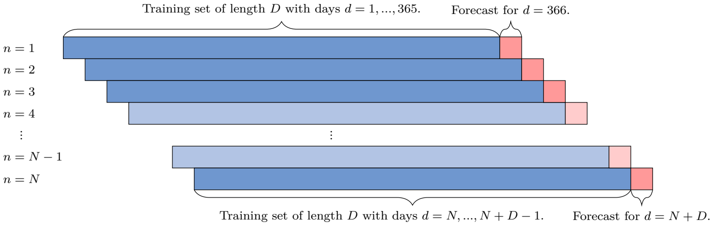
We estimate the location, scale and shape parameters based on the same set of explanatory variables and use the LASSO to avoid overfitting

$$
\begin{aligned}
g_k(\theta^{d,s,k}) = {} & \beta_{k\mathbb{1}(k\geq 2),0} + \underbrace{\sum_{j=1}^{3} \beta_{k,j} \Delta P^{d,s}_{\text{ID},t-j}}_{\text{Price differences}} + \underbrace{\sum_{j=1}^{6} \beta_{k,3+j} \mid \Delta P^{d,s}_{\text{ID},t-j} \mid + \beta_{10} \sum_{j=7}^{12} \mid \Delta P^{d,s}_{\text{ID},t-j} \mid}_{\text{Absolute price differences}} + \underbrace{\beta_{k,11}\text{MON}(d) + \beta_{k,12}\text{SAT}(d) + \beta_{k,13}\text{SUN}(d)}_{\text{Time dummies}} \\
& + \underbrace{\beta_{k,14}\hat{L}^{d,s}_{\text{DA}} + \beta_{k,15}\hat{W}^{d,s}_{\text{DA}} + \beta_{k,17}\hat{S}^{d,s}_{\text{DA}} + \beta_{k,18}O^{d,s}_{\text{DA}}}_{\text{Day-ahead fundamental variables}} + \underbrace{\beta_{k,19}\Delta\hat{W}^{d,s,+}_{\text{DA,ID}} + \beta_{k,20}\Delta\hat{W}^{d,s,-}_{\text{DA,ID}} + \beta_{k,21}\Delta\hat{S}^{d,s,+}_{\text{DA,ID}} + \beta_{k,22}\Delta\hat{S}^{d,s,-}_{\text{DA,ID}}}_{\text{Day-ahed to intraday forecast updates}} \\
& + \underbrace{\beta_{k,23}\sigma^{d,s}_{\text{DA,ID}}(\Delta\hat{W}) + \beta_{k,24}\sigma^{d,s}_{\text{DA,ID}}(\Delta\hat{S})}_{\text{Standard deviation of forecast updates}} + \underbrace{\beta_{k,25}\Delta O^{d,s,\text{planned}}_{\text{DA,ID}} + \beta_{k,26}\Delta O^{d,s,\text{unplanned}}_{\text{DA,ID}}}_{\text{Intraday changes in planned and unplanned outages}} + \underbrace{\beta_{k,27}\alpha^{d,s}_{t-1} + \beta_{k,28}\alpha^{d,s}_{t-2}}_{\text{Lagged } \alpha^{d,s}_{t}} \\
& + \underbrace{\beta_{k,29} \mid P^{d,s}_{\text{DA}} - P^{d,s}_{\text{ID},t-1} \mid}_{\text{Day-ahead to } t-1 \text{ price spread}} + \underbrace{\sum_{j=1}^{3} \beta_{k,29+j} MO^{d,s}_{j}}_{\text{Slope of the merit-order}} + \underbrace{\beta_{k,32} f_{\text{TTD}}(t) + \beta_{k,33}\text{SIDC}(d,t)}_{\text{Time to delivery and SIDC closing}}
\end{aligned}
$$

Recursive scheme for the simulation of the price differences



Rolling window forecasting study with various benchmark models



- Benchmark models: Naive sampling of past trajectories, Auto.ARIMA, Random-Walk Type models
- Point and probabilistic scoring rules:
  - Mean absolute error (MAE), root mean squared error (RMSE)
  - Continuously ranked probability score (CRPS) and energy score (ES)

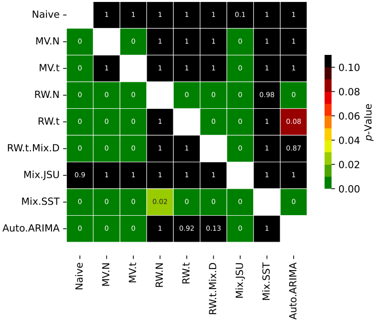
Results

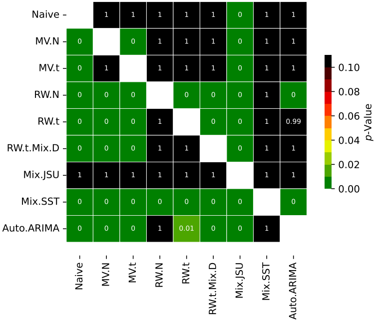
Error metrics show strong performance of the GAMLSS-model using Johnson's S_U and the Naive benchmark model

- Naive benchmark model shows strong performance across all metrics
- Auto.ARIMA surprisingly bad in terms of RMSE and MAE
- GAMLSS-Johnson's S_U model best in terms of CRPS and ES
- GAMLSS-skew-*t* very bad - investigation shows that this is due to outliers

	MAE	RMSE	CRPS	ES
Naive	**3.178**	**6.564**	1.222	17.271
Auto.ARIMA	3.295	7.240	1.313	18.623
MV.N	3.193	6.570	1.275	18.009
MV.t	3.191	6.570	1.240	17.495
RW.N	3.209	6.577	1.472	20.030
RW.t	3.195	6.686	1.323	18.393
RW.t.Mix.D	3.192	6.616	1.304	18.171
Mix.JSU	3.182	6.571	**1.218**	**17.127**
Mix.SST	4.509	109.661	1.748	28.247

Diebold-Mariano-Test shows that improvements in forecasting accuracy are statistically significant for the GAMLSS-Johnson's S_U model





Small p-values imply that the model on the column (or x-axis) has statistically significant better forecasts than the model on the row (or y-axis). CRPS left, ES right.

Estimates show that fundamental variables have little predictive power for the expected value, but explain volatility and tail behaviour

- First lag of $\Delta P^{d,s}_{\mathrm{ID},t}$ has some explanatory power for the price change, while wind and solar forecast (updates) have no explanatory power. This information seems to priced in already, indicating (weak-form) market efficiency.
- Volatility rises with steeper merit-order, closer to delivery and with the closure of the cross-border order books (SIDC).
- None of our explanatory variable seems to explain the kurtosis
- Tails of the distribution is heavier for little trading activity, further away from delivery and steeper merit-order

Conclusion

Proposed approach yields significantly improved forecasting performance while allowing for fundamental insights of the price process

- Simulation based modelling can yield improved forecasting performance if some care is taken for choosing appropriate distributions. Alternatively, simulated paths can be plugged in Monte Carlo-based optimization methods
- Market efficiency: Fundamental variables don't improve forecasting of the next price change
- Fundamental variables (wind, demand , solar, outages) have little influence on the higher moments
- Volatility of the return distribution is driven by the merit order slope: Steep merit order regime leads to higher volatility
- Tails of the return distribution are driven by trading activity and the time to delivery
- Further research possible in multiple directions: cross product effects, the evolution of trading volume, liquidity and volatility and improved modelling of the merit-order for intraday markets

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