Renewable Energy Supply, Energy Storage, and the Economics of Forecasting

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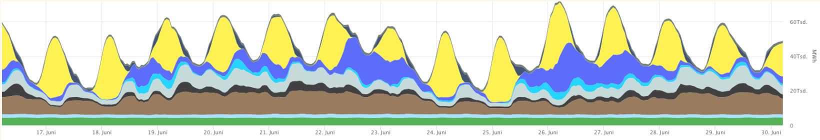

Forecasting in Electricity Markets

- What are the economic benefits of forecasting?
  - better accuracy $\longrightarrow$ larger profits?
  - reduced price volatility $\longrightarrow$ less risk?
  - is forecast benefit asymmetric (w.r.t. sign of forecast error)?
- What is the time horizon for forecasting?
  - Many electricity markets are organized in Day-Ahead Markets (DAM), with offers received 24 hours in advance, and settlement in Real-Time Market (RTM). Market participants need demand & supply forecasts.
  - Also need long-term forecasts for investment decisions!
- Who needs to forecast, and why?
  - Market participants: RE suppliers, storage providers, traders. $\longrightarrow$ bids
  - System operator: system balance. $\longrightarrow$ standby reserves
- Who benefits most from better forecasts? Consumers, Producers, Storage Operators? $\longrightarrow$ who pays for better forecasts? (Forecasts are costly: they require labour and capital.)

Forecasting: Time Horizon Challenges

Purpose	**Prediction & Forecasting**	**Structural Modelling**
Domain	Historic (Observed)	Historic+Future
Validation	in-sample (training) and out-of-sample (validation)	scenarios (sensitivity) (+ future data)
Tools	Machine Learning, Neural Networks, SVM, etc.	Econometric Model & Parameter Estimation

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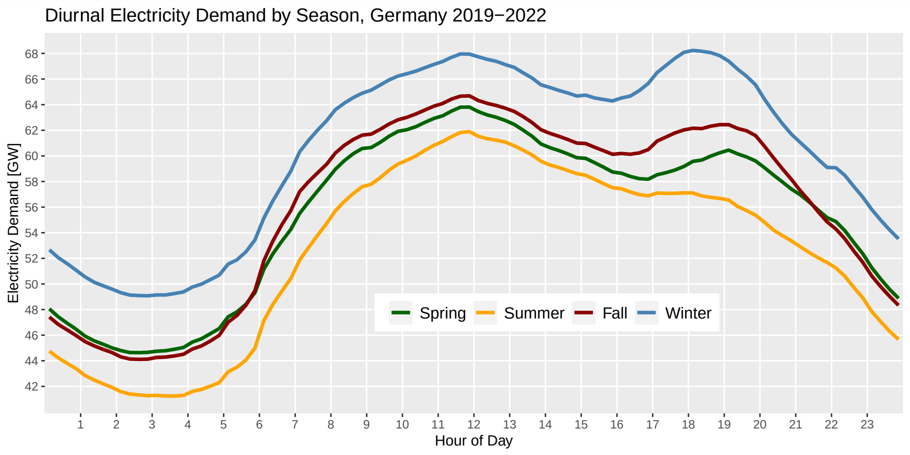
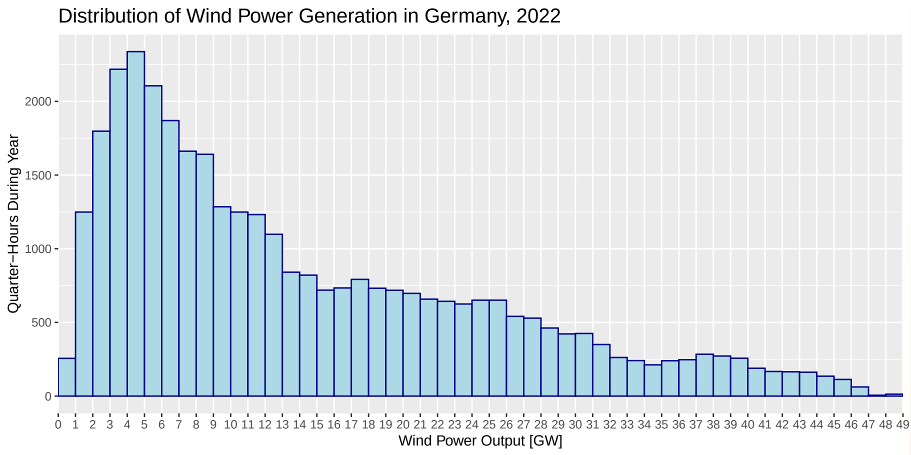
- Forecasting within observed ranges can work well, but what if the range expands due to structural shifts, inducing parameter changes?
- Example 1: price-elasticity of electricity demand — usually very inelastic. 2022 price spike in Europe out of normal range. $\rightarrow$ salience
- Example 2: Climate change shifts electricity demand from winter-peaking to summer-peaking. For a given temperature, future demand $\uparrow$ due to new investment into A/C. $\rightarrow$ endogeneity

Major Sources of Variation: Demand



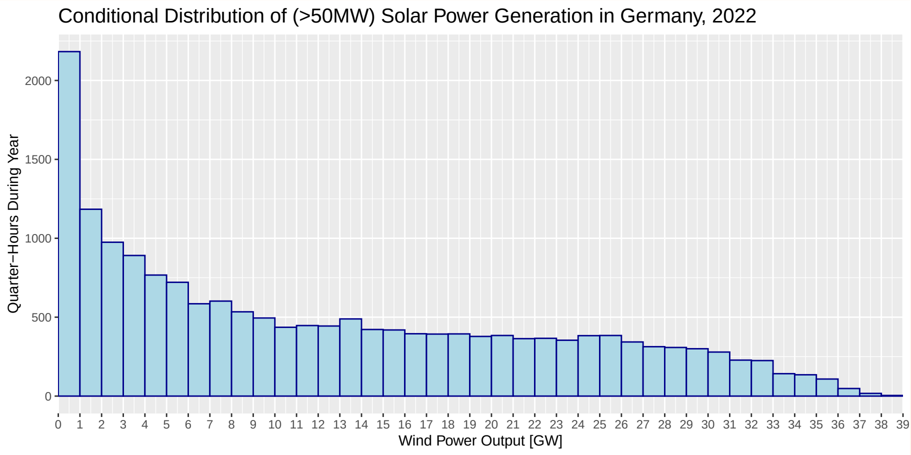
Demand is highly predictable based on seasonal and diurnal patterns, but is also influenced by weather conditions (Heating-Degree Days, HDD, and Cooling-Degree Days, CDD).

Major Sources of Variation: Renewable Energy Supply



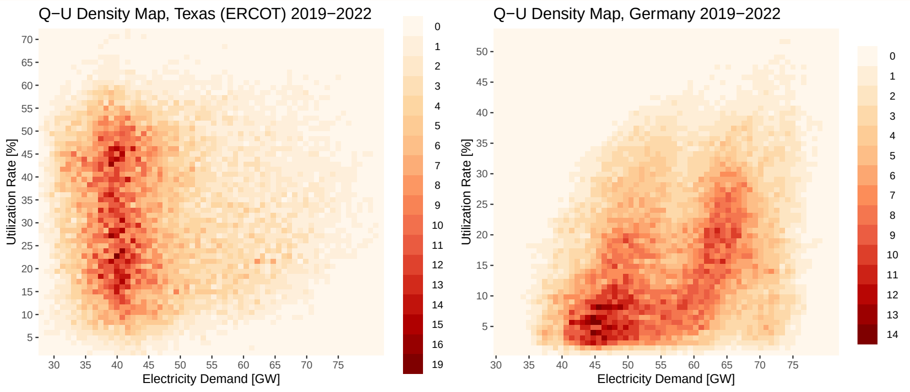
Dealing with the *Kalte Dunkelflaute* (cold dark lull) problem requires conventional back-up, location diversification (transmission), & storage.

Major Sources of Variation: Renewable Energy Supply



Solar power has forecasting issues too, beyond diurnal and seasonal cycles: significant effect of cloudiness. No output during the night, and little output during winter months in Northern latitudes.

Demand and RES Supply in Texas and Germany



- Texas and Germany show significantly different supply-demand correlation patterns for utilization of renewables and electricity demand. Texas has overall more favourable conditions, and high summer spikes. Germany has two “lobes”.
- Strong differences in diurnal and seasonal patterns.

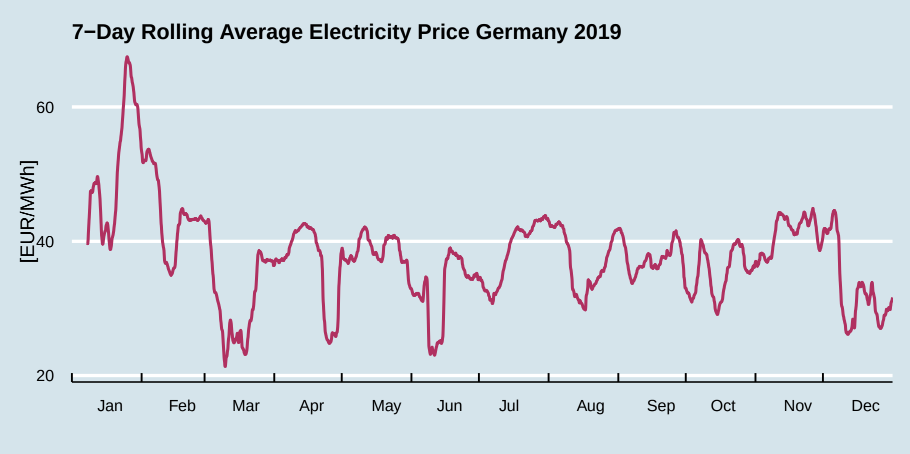
Supply-Demand Correlation Patterns (2019-2022)

Pearson Correlation Coefficients
Q: Demand / V: PhotoVoltaics / W: Wind

	Texas (ERCOT)			Germany		
	Q/V	Q/W	V/W	Q/V	Q/W	V/W
Overall	0.439	−0.157	−0.318	0.275	0.182	−0.213
Diurnal	0.643	−0.616	−0.931	0.742	−0.585	−0.824
Seasonal	0.766	−0.633	−0.176	−0.777	0.812	−0.764

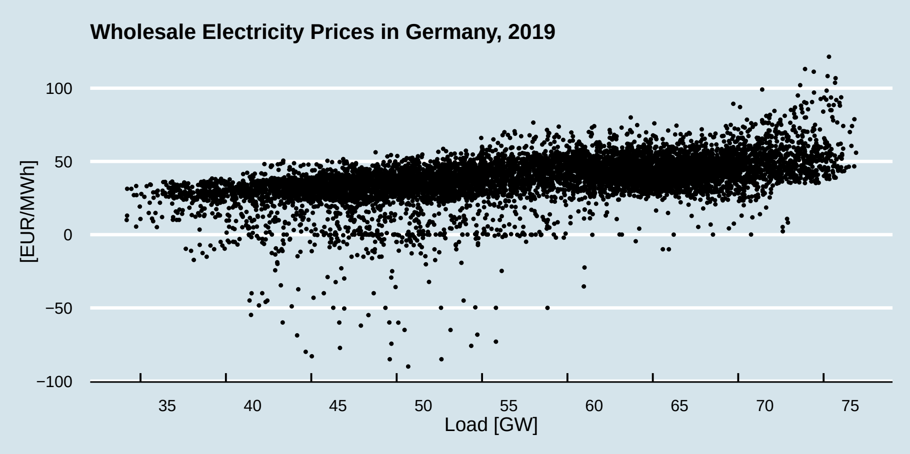
- Overall correlations re based on hourly/quarter-hour raw data.
- Diurnal and seasonal correlations are based on 'filtered' estimates of 24 hours and 24 semi-monthly indicator variables, respectively.
- Solar PV is naturally correlated with demand diurnally, wind negative.
- Solar PV has positive seasonal demand correlation in Texas, but negative correlation in Germany. Opposite effect for wind: negative correlation in Texas, but strong positive correlation in Germany.

Normal Wholesale Electricity Prices in Germany, 2019



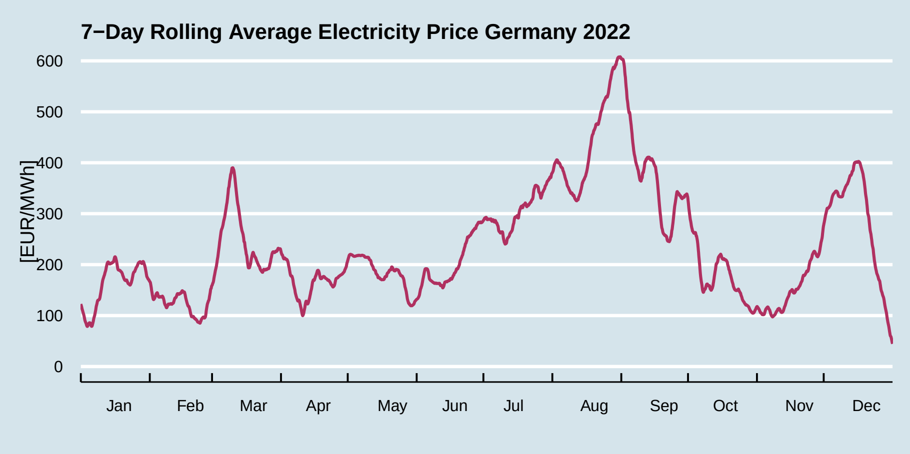
Prices mostly reflect generation cost at different times of day as lower-cost base load and higher-cost peak load alternate, and on a weekly basis persistent favourable RES conditions.

Normal Wholesale Electricity Prices in Germany, 2019



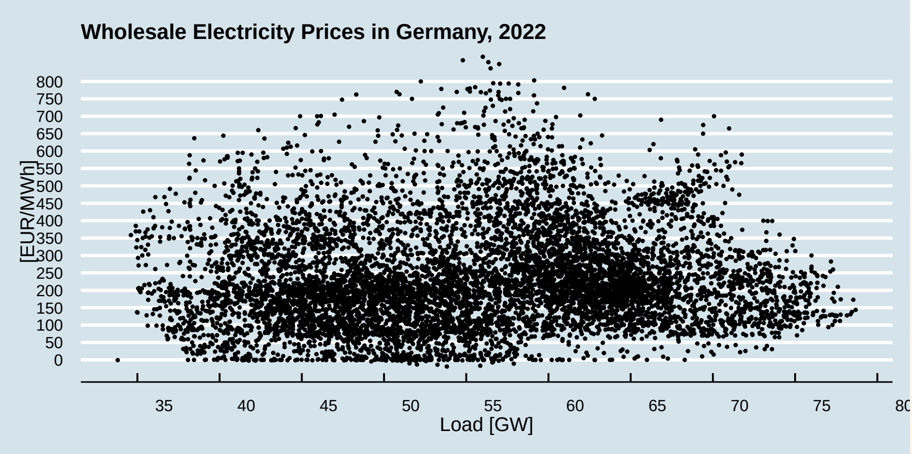
Significant price variation, but roughly following a linear load-price relationship. Prevalence of negative(!) prices due to RES oversupply and ramping constraints.

Abnormal Wholesale Electricity Prices in Germany, 2022



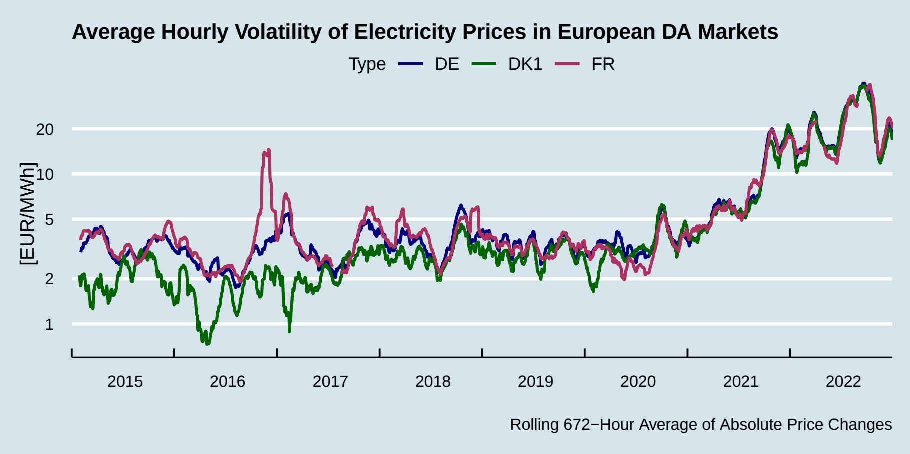
Forecasting can be completely off the mark when geopolitical events conspire to create a perfect storm. $\Longrightarrow$ Model error v. forecast error.

Normal Wholesale Electricity Prices in Germany, 2022



A forecasting model tuned on 2019 data would have failed miserably in 2022! What is a forecasting model's out of sample performance? Past performance is no reliable indicator of future performance.

Heteroskedasticity of Prices

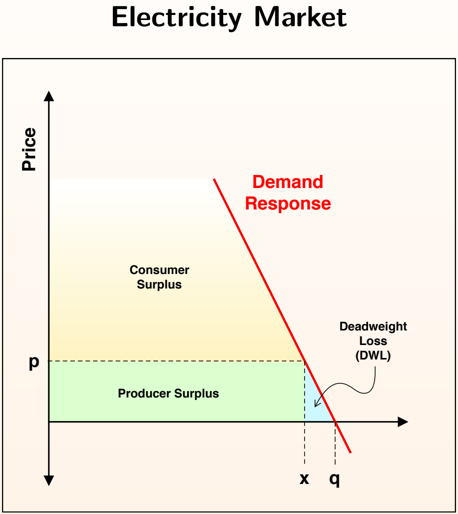


Market volatility influenced by persitent events. (Note the logarithmic scale of the vertical axis.) Forecasting is more difficult in a 'noisier' environment, but it is also more valuable. → regime-switching models

The Economic Forecasting Space

- **Demand**
  - Strong diurnal, weekly, and seasonal patterns predict >80% variation.
  - Weather captured by heating-degree/cooling-degree days (HDD, CDD)
  - Long-term changes: climate change
- **Supply**
  - RES forecasts (wind, sun)
  - Probabilistic outages of conventional generators
  - Long-term changes: climate change
- **Day-Ahead Prices** $\rightarrow$ short-term planning
  - Dispatch Model $\rightarrow$ non-linear effects, location (transmission) effects
  - More difficult to forecast than supply or demand
- **Long-Term Prices** $\rightarrow$ long-term planning (investment)
  - Models of innovation: Levelized Cost of Electricity (LCOE)
  - Integrated market models
  - Climate change effects on supply and demand

Forecasting and Electricity Prices



- Consumer have latent demand (q) at price zero.
- Supply (x) must equal realized demand.
- Market price p induces demand response
- Price-inelastic linear demand $p = \theta(q - x)$
- Deadweight Loss (DWL) $\mathrm{DWL} = \theta(q - x)^2/2$ or $\mathrm{DWL} = p^2/(2\theta)$ captures efficiency loss.
- What does that imply for forecasting errors for whom?

Potential Asymmetric Forecasting Cost

- High prices reshuffle consumer surplus (CS) to producer surplus.
- High prices also induce disproportionately higher deadweight losses (DWL) than low prices.
- Look at effect of a forecasting error $\delta \equiv |\hat{x} - x|$ on DWL:
  - Overestimating supply by δ: $\mathrm{DWL}_o = \theta(q - (x + \delta))^2/2$
  - Underestimating supply by δ: $\mathrm{DWL}_u = \theta(q - (x - \delta))^2/2$
  - $\mathrm{DWL}_o - \mathrm{DWL}_u = -2\delta\theta(q - x) < 0$
    Underestimating supply has a larger DWL effect.
- **Asymmetric Forecasting Cost**
  - Welfare-maximizing social planner cares about DWL.
  - Power producers cares mostly about a higher p because inelastic demand puts more weight on price response than output change.

Asymmetric Forecasting Cost

- Forecast errors are associated with a potentially asymmetric cost to a decision maker. Decision maker cares about the net present value:

$$\mathcal{C}_t = \sum_{i=0}^{T} \frac{C^+(\max\{0, \hat{x}_{t+i} - x_{t+i})\}}{(1+r)^i} + \sum_{i=0}^{T} \frac{C^-(\max\{0, x_{t+i} - \hat{x}_{t+i})\}}{(1+r)^i}$$

  with $C(0) = 0$, $C(\cdot) \geq 0$, $C^+(\cdot) \neq C^-(\cdot)$, and T the commitment period for which forecast $\hat{x}_{t+i}$ is locked into an agent's decision and cannot be undone or corrected without incurring some positive cost.

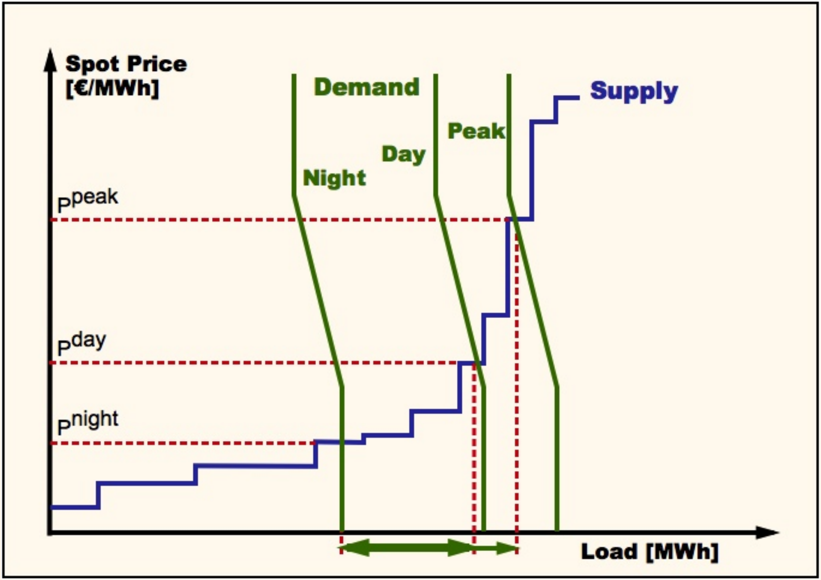
- Implications for insuring risk: asymmetric hedging.
  (Practiced widely in futures markets, using call/put options.)
- The metric for evaluating forecast accuracy goes beyond root mean squared error (RMSE) and other statistical measures;
  forecast accuracy is about minimizing forecasting error cost $\mathcal{C}_t$

Source of Non-Linearities for Price Forecasting

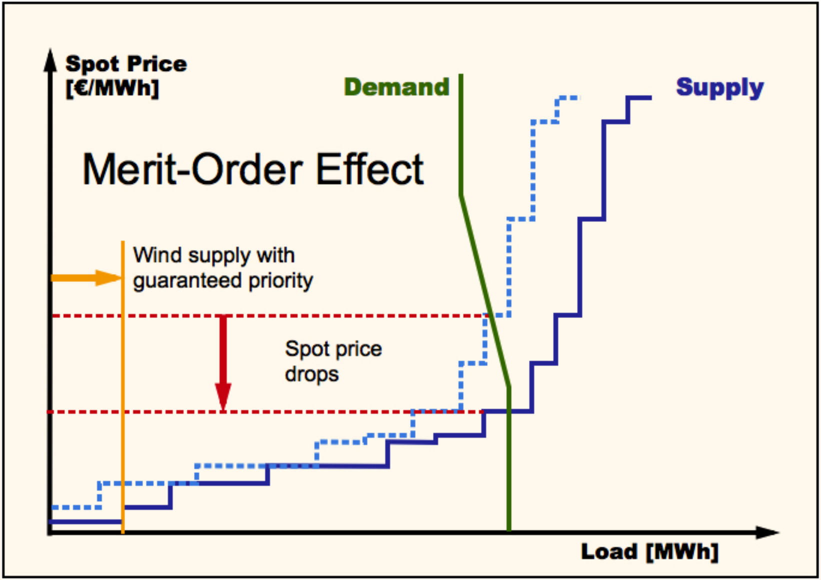
- Objective function: DWL?
- Inflexible generators with ramping constraints: time/cost needed for powering up/down
- Transmission constraints: power line ratings and interconnections
- Market (Merit) Order: prioritization of generators
- Market Structure: market power of market participants

$\Longrightarrow$ Price can vary hugely for given level of demand, can even be negative!

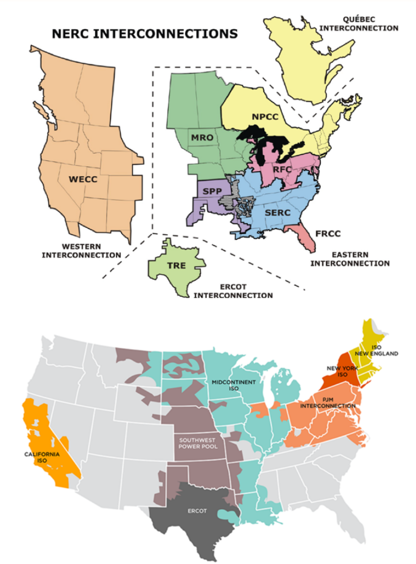
Sources of Non-Linearities: The Merit Order



The (Adverse) Merit Order Effect of Renewable Energy



Sources of Non-Linearities: Interconnections & Markets



United States and Canada are divided into Western, Eastern, ERCOT, and Quebec Interconnections. Few connections in between.

Regional Transmission Organizations (RTOs) and Independent System Operators (ISOs) operate in states/provinces with wholesale electricity markets: PJM, SPP, ISO-NE and ERCOT; in Canada AESO & IESO.

Most RTOs/ISOs operate a day-ahead market (DAM) and a real-time market (RTM), as well as and ancillary services market (ASM) for reliability support. Some RTOs/ISOs also use 3-year ahead capacity markets.

Locational marginal prices account for transmission and congestion constraints.

The Economic Forecast Horizon

Time Horizon	**Short-Term** Hours	**Long-Term** Years
Action	Dispatch	Investment
Focus	Energy (MWh)	Capacity (MW)
Markets	Day-Ahead, Real-Time	Equipment, Construction
Forecast Error	corrigible	persistent
Forecast Cost	high	low
Forecast Benefit	medium	high

- What is the net present value (benefits minus costs) of a forecast?
- Who pays for the forecast?
  - public information (e.g., system operator)
  - private information (e.g., independent power producer)
- Does better forecasting create a competitive advantage for producers?
- Does better forecasting lower retail electricity cost for consumers?

Electricity Storage: Modelling Prices and Price Forecasts

- Electricity Storage System Operator (ESSO) charges a battery of capacity Z (in MW) and storage S (in MWh), with state variable $x_t \in [-1, 0]$ for charging and $x_t \in [0, 1]$ for discharging, and maximizes profits subject to the storage constraint (with loss δ):

$$\max_{x_t} \left[\sum_{t=0}^{T} \hat{p}_t x_t - c \right] Z \quad \text{s.t.} \quad s_t = (1-\delta)s_{t-1} - x_t \in [0, S]$$

- Need to know price forecasts $\hat{p}_t$. DO NOT USE HISTORIC PRICES for modelling price-taker storage system because this introduces hindsight bias. Need a proper forecasting model! Buy low, sell high.
- Price taker models a *marginal* ESSO. Price forecasts matter. Terminal T problem $\longrightarrow$ Appropriate forecast horizon?
- Electricity markets change fundamentally when ESSOs become *price makers* (i.e., have significant market share). Price forecasts do NOT matter much anymore because storage arbitrages away price gaps.

Conclusions

- Intermittency of supply (solar PV, wind) increases volatility of electricity supply. Different correlation structures across markets!
- Climate change and electrification of mobility are contributing to transforming diurnal and seasonal demand patterns.
- In the short term, there is need for more forecasting to plan dispatch decisions in day-ahead markets. Price forecasts are also needed for price-take electricity storage systems.
- In the long term, large-scale deployment of grid-scale electricity storage reduces price variation through arbitrage, reducing the value of forecasting as electricity system becomes more resilient.
- Forecasting may eventually shift from supporting short-term (intra-day) operational dispatch decisions to developing long-term predictions and supporting capacity & investment decisions.

THANK YOU