Bajo-Buenestado, R., 2021. Operating reserve demand curve, scarcity pricing and intermittent generation: Lessons from the Texas ERCOT experience. Energy Policy 149, 112057. https://doi.org/10.1016/j.enpol.2020.112057

In this paper, Bajo-Buenestado uses hourly data to show a significant negative association between increased wind generation and ORDC pricing in ERCOT between January 2015 and February 2019. “This paper’s main contribution is to empirically estimate and quantify how (intermittent) wind generation affects the ORDC price adder.” This empirical analysis is performed with regression. The author finds a link between increased wind generation and reduced ORDC prices, to the point where when wind reaches 9000 MW, the price is zero.

For their analysis, they take into account seasonal and time varying factors that could affect generators such as peak loads at certain times of day or year by using “time-of-day dummies, day-of-week dummies, day-of-month dummies, year dummies, month dummies, and month-year dummies.” This accounts for the fact that some technologies will produce energy on specific hours and days of the week.

Their model for all this is as follows: log(RTORPA)t = α0 + α1 log(Wind)t + α2 log(Wind) 2 t + α3 log(Load)t + α4Θt + εt,

Or, log(Real time price adder $/MWh) = log(total wind in an hour (MW)) + log(total wind in an hour)­2 + log(Ercot load for that time period) + time dummies + error, with the alpha’s as constants.

The deal with logging the RTROPA (which is often 0) by adding 1 to it before processing.

They capture dynamic components by adding a lagged version of the dependant and explanatory variables with an autoregressive distributed-lag (ARDL) model.

Important note: “Before March 2019, in order to capture historical differences at different times and seasons, ERCOT also valued reserves differently according to the time of the day and season of the year. In particular, operating hours were divided into four seasonal and six daily bins –ERCOT (2013) and Levin and Botterud (2015). However, on March 1, 2019, the ORDC was changed to replace the seasonal and time-of-day bins by a blended curve –Potomac Economics (2020).”

Basically, they did [ $$$ ~ Wind + Wind2 + Load ], with some dummy variables and lagging. That’s pretty solid. Biggest R2 with the most dummies, best p values with 5 of 6 dummies.

In their appendix, they looked at adding weather data (Wunderground daily means for cities in TX) to their model. Temp had a correlation with load, and wind generation still had the same association with price.

They also repeated the model with a squared load ([ $$$ ~ Wind + Wind2 + Load +Load2]). “ we find evidence of a **non-linear effect of load on ORDC prices** if **load is relatively low**. This is consistent with the fact that, if load is low and the ORDC price is zero, a further decrease in load does not impact upon the ORDC price, since it cannot be negative. However, **this non-linear effect occurs within a very small range** of the **load parameters**.”

They also dropped hours where the system lambda (The cost of providing one MWh of energy at the reference Electrical Bus) is negative and found the same results again. Sweet.

Shan, R., Abdulla, A., Li, M., 2021. Deleterious effects of strategic, profit-seeking energy storage operation on electric power system costs. Applied Energy 292, 116833. <https://doi.org/10.1016/j.apenergy.2021.116833>

This is another paper focused on the ORDC. They demonstrate that with the new ORDC schema,

Model in 15 minute intervals: (🥧 profits from new generation unit $/MWY) = ((market price of electricicty $/MWh) – (Variable costs $/MWh)) \* (unit online [binary])

Where variable costs for a 15 minute interval are VC = (Heat rate MMBtu/MWh) \* (Gas price on a given day $/MMBtu) + (Per MW variable O&M costs $/MWh)

With all that, they find the cost of a new plant: K. When (🥧 – K) < 0, new plants aren’t profitable.

As the ORDC is shifting “right” and the price is increasing for increased available loads, the paper finds that new plants will be more incentivized. They show that if the price has shifted earlier, the plant operators would have made more money. They believe this shift will stave off some retirements in the near future, but the overall growth of renewables means that prices will keep falling, while at the same time, reserve margins will keep shrinking as low prices disincentivize new plants. They believe that this shift to the ORDC will be insufficient to solve the “missing money” problem that is pushing plants to retire as investment returns dwindle. Suggestions for what actually to do are “beyond this paper’s scope, lmao)

Mills, A., Wiser, R., Millstein, D., Carvallo, J.P., Gorman, W., Seel, J., Jeong, S., 2021. The impact of wind, solar, and other factors on the decline in wholesale power prices in the United States. Applied Energy 283, 116266. <https://doi.org/10.1016/j.apenergy.2020.116266>

This paper looks at the whole of the US, to investigate the trend of power prices declining and power plants retiring. “Wholesale prices at major trading hubs declined by $19–64/MWh between 2008 and 2017,” and they think it may be due to more than cheap natural gas. The “‘merit order’ effect—namely, that the addition of VRE with low marginal costs leads to lower market-clearing prices” is called up here, and they are trying to hammer out just how much VRE’s contribute nationwide, alongside a wide array of other price drivers.

They start by reviewing 16 papers that correlate VRE penetration % with decrease in wholesale power price in different markets. These are set up to get a feeling for the average effects of this stuff.

For their model, they construct a “fundamental supply curve model”. They compare modeled annual average prices while changing one variable at a time to the 2008 level. Their model is supposedly simple, but to implement it, they used a boat load of data: “wind and solar deployment, changes in natural gas prices, thermal plant retirements and additions, changes in electricity load, permit prices for pollution emissions, and hydropower water levels.” Hella data.

They validate this model by comparing the output of the model (wholesale prices) with historical pricing, using historical figures for input variables. The model was accurate within 13% for most years tested this way. Their model fails to capture hourly volatility, however, so they say you should only use this model to look at drivers of annual wholesale prices market-wide, and not to look at geographic or temporal variability in the prices.

The ultimate results of this model show natural gas prices as the main driver in falling wholesale prices, but wind and solar are the 2nd place, though at a significantly lower magnitude. “Across all markets, each incremental percentage-point increase in wind or solar penetration since 2008 reduces average wholesale prices in 2017 by approximately $0.14/MWh. In most markets, the total impact on average prices in 2017 is below $1.3/MWh.”

Given increasing projections of VRE growth in the coming years, the authors expect the downward pressure from VREs to increase. That said, they’re still going to be on a different scale form the effect of nat gas prices.

Factors were also found to interact, with individual factors understating the magnitude of wholesale price decrease compared to everything all together.

“The finding that the reduction in natural gas prices was the primary contributor to the fall in wholesale electricity prices since 2008 is consistent with an emerging literature” – nice to see this in print again, haha. They also state that “non-linear interactions between factors place a limit on isolating the effect of changes in individual factors.” Temporal and geographic factors may be more heavily affected by wind and solar, and since those were not accounted for by this model, they may have a more significant affect than these authors determined.

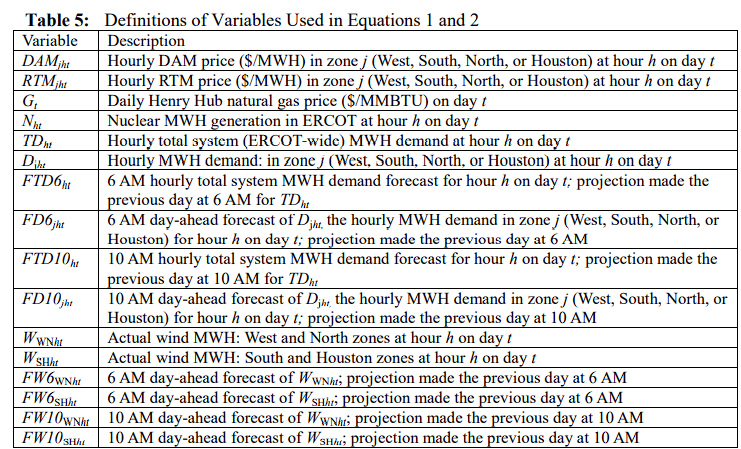
Woo, C.K., Zarnikau, J., Tsai, C.H., Zhu, S., 2020. Cost-effectiveness of a modest expansion of renewable generation capacity in Texas. The Electricity Journal 33, 106696. <https://doi.org/10.1016/j.tej.2019.106696>

Zarnikau, J., Woo, C.-K., Zhu, S., 2016. Zonal Merit-Order Effects of Wind Generation Development on Day-Ahead and Real-Time Electricity Market Prices in Texas (SSRN Scholarly Paper No. ID 2867345). Social Science Research Network, Rochester, NY.

* a **regression**-based approach to explore the impact of wind generation development on wholesale electricity prices in the Electric Reliability Council of Texas (ERCOT)
* wind generation development has a greater effect on real-time market (RTM) prices than day-ahead market (DAM) prices (glad I have both). (**Wind ~ RTM**) **>** (**Wind ~ DAM**)
* Higher wind generation **forecast errors** tends to **reduce the RTM prices**, chiefly because unanticipated increases in wind generation reduce the real-time net loads to be served by fossil fuel power plants
* estimated merit-order effects are greatest in the ERCOT zones where the wind generation capacity locally resides (colocation + **geospatial** stuff is real!)

Descriptive stats on RTM and DAM prices… Maybe I should do this on my newer data too? Sorted out by zone etc., v fancy!

Regression variables:



Woo, C.K., Moore, J., Schneiderman, B., Ho, T., Olson, A., Alagappan, L., Chawla, K., Toyama, N., Zarnikau, J., 2016. Merit-order effects of renewable energy and price divergence in California’s day-ahead and real-time electricity markets. Energy Policy 92, 299–312. <https://doi.org/10.1016/j.enpol.2016.02.023>

* Two policy questions:
  + what are the **estimated merit-order effects of renewable energy** in the California Independent System Operator’s (**CAISO’s**) day-ahead market (**DAM**) and real-time market (**RTM**)? and
  + what **causes** the **hourly DAM and RTM prices to systematically diverge**?
* **Regression** on 21,000 **hourly observations of CAISO market prices** and their fundamental **drivers** during 2013–2015, we document statistically significant estimates (p-value≤0.01) for the DAM and RTM merit-order effects
* **RTM-DAM price divergence** partly **depends** on the CASIO’s **day-ahead forecast errors** for **system loads** and **renewable energy**; this means better forecasts could improve trading efficiency
* Lots of plotting DAM vs RTM, forecast vs actual VRE gen & system load, etc…
* Model: **regional** hourly forecasts and actual figures for wind, solar, hydro, nuclear, stuff like gas price, system load… all as explanatory for either region’s DAM or RTM price
* Findings:
  + the marginal DAM merit-order effects of a region’s renewable energy differ from the RTM merit-order effects
  + the RTM prices move with the CAISO’s forecast errors. Hence, the DAM–RTM price divergence is partly attributable to these errors
  + the marginal DAM price effect of a 1-MWh increase in the forecast load increase is offset by that of a 1-MWh increase in the renewable energy forecast
* natural gas price escalation, nuclear plant retirement and economic growth tend to increase the CAISO’s electricity prices

A latent-factor system model to estimate merit-order effects in energy markets Kang Hua Cao1 , Paul Damien2 , and Jay Zarnikau

* novel methodology to model the merit-order effect, **namely the tendency for greater non-dispatchable renewable energy generation** (VRE) or baseload generation to **lower wholesale market prices** by shifting supply curves
* using a **system-wide latent factor model** for prices in Texas, we **quantify** the **merit-order effects** on **wholesale prices**
* Findings:
  + (a) **latent causes** are **highly significant** throughout ERCOT
  + (b) the estimated **latent factor series strongly and positively correlates to system-wide prices** during peak and off-peak hours
  + (c) the **merit-order effect of wind significantly dampens prices**, **regardless** of **region** and **time of day** throughout ERCOT
  + (d) the **nuclear baseload generation** also **significantly lowers prices** during a 24-hour period in the entire system
  + (e) **solar generation** needs to **grow faster in order to be a significant** renewable resource.
* Summary stats for prices at different times of day vs different locations. Just using HOU, AES, and WEST
* **Exogenous** variables: **wind, nuclear** and **solar generation**, where the last one appears only in the sunlight hours; the **Henry Hub gas price**; and a **dummy variable for real-time prices exceeding $500**, which will not appear in the night and early morning hours since prices do not rise to very high levels at these times

Morthost, P.E., Ray, S., Munksgaard, J., Sinner, A.F., 2010. Wind energy and electricity prices. Exploring the “merit order effect.”

* About the **effect of wind energy on the electricity price** in the power market. As the report will discuss, **adding wind into the power mix has a significant influence** on the resulting price of electricity, the so called **merit order effect (MOE)**
* **increased penetration** of **wind** power **reduces** wholesale spot **prices**
* **Wind** **replaces CO2-intensive** production technologies
* **Wind can replace part of the base load**
* **Consumers pay lower prices**
* Lit review of a bunch of papers that led to the findings above… Kinda old and smells a little biased but good stuff regardless.
* The literature shows consistently that wind drives prices in European countries down as it increases in gen
* Two papers showing link between wind and lower consumer prices
* Yad a yada

Merit-order effects in the Texas energy market via quantile regression

Mary Rudolph1 , Paul Damien2 and Jay Zarnikau3 – Draft

* […] how **the merit-order effect**, namely the tendency for greater non-dispatchable renewable energy generation or baseload generation to lower wholesale market prices by shifting bid stacks or supply curves, **varies with the level of wholesale prices**
* At **night**, price dampening **diminishes at higher price levels**
* in the **morning** and **afternoon** (the hours ending 11 am and 4 pm), **the price-dampening effects** of increased nuclear, wind, and solar generation **tends to increase at higher price levels**
* impacts **vary by region**
* **Data:**
  + 2015-2018; 2019 the “shift” happened and prices were greatly impacted
  + Dependent: 8 zones of 15-minute SCED price values
  + Explanatory:
    - demand for electricity
    - natural gas prices (Henry Hub only)
    - generation from baseload power plants (nuclear, in this case)
    - non-dispatchable intermittent renewable energy sources
* **Model:**
  + We use **quantile multivariate regression** to estimate the direction and magnitude of the associations between **price distributions** and several exogenous factors that could affect them
    - Quantiles: 0.10, 0.25, 0.50, 0.75 and 0.90
      * To capture the impact of the covariates at various positions along the entire distribution of prices in each region
* When **quantifying** these **merit order effects**, it is important to recognize that **these impacts are likely differ** in **different times of the day**, in **different zones** within a market, and at **different levels overall levels of wholesale prices**.

Zarnikau, J., Woo, C.K., Zhu, S., Tsai, C.H., 2019. Market price behavior of wholesale electricity products: Texas. Energy Policy 125, 418–428. <https://doi.org/10.1016/j.enpol.2018.10.043>

* regression-based approach to a newly developed sample of over 60,000 **hourly** observations for **2011**–**2017**
* Trying to **determine factors** that move **RTM** and **DAM** in **ERCOT**
* Main findings:
  + the **DAM energy price increases** with the **day-ahead forecasts of natural gas price**, **system load** and **AS requirements** but **declines** with **nuclear** and **wind generation's forecasts**
  + **AS prices increase** with the **DAM energy price** and the **AS procurement forecasts** but **decline** with the **AS offer forecasts**
  + **RTM energy price increases** with the **DAM energy price** but **diverges** from **the DAM energy price** due to **forecasting errors** related to the **DAM energy price's fundamental drivers**
* **Model**
  + all data series are found to be stationary at the 1% level based on the Phillip-Perron unit-root test
  + DAM energy price ($/MWh) ~ (day ahead) gas price + nuke gen + system load + wind gen + RRS req + NSRS req + REGUP + REGDN
  + They do a similar thing to predict RRS, NSRS, REGUP, REGDN, and RTM prices

Woo, C.K., Moore, J., Schneiderman, B., Olson, A., Jones, R., Ho, T., Toyama, N., Wang, J., Zarnikau, J., 2015. Merit-Order Effects of Day-Ahead Wind Generation Forecast in the Hydro-Rich Pacific Northwest. The Electricity Journal 28, 52–62. <https://doi.org/10.1016/j.tej.2015.10.001>

* assessment of the **performance** of the **day-ahead wind generation forecast** published by Bonneville Power Administration in the hydro-rich Pacific Northwest region finds BPA's **daytime forecast unbiased**, but **not** the **nighttime forecast**
* **market-price regressions** to estimate the **day-ahead merit-order effects** of BPA's forecast finds that the **merit-order effect estimates** do **not** materially **depend** on **whether** the **forecast or actual** MW are **used**
* **merit-order effect** estimates are **small**
* Views **market reforms** and **new wind technology** as **transformative** early 21st century **events**
* estimates **a day-ahead wind generation forecast's merit-order effects**, thereby complementing the regression analyses of another study
* BPA’s **daytime wind forecast** was **better** than **nighttime**
* Model:
  + Dependent: **daytime price** P1t ($/MWH) on day t = **2012**–**2015**
  + Regression on these independent variables:
    - Day & Night Hub Price of electricity
    - Henry Hub nat gas price
    - Daily MW available at Columbia generating station
    - Daily hydro index
    - Dalles Dam’s daily avg discharge
    - System load (daily average of hourly figures)
    - Daily daytime average of hourly actual wind MW
    - Daily daytime average of hourly forecast wind MW
    - Lagged daily daytime mean error
    - Lagged daily daytime mean absolute error
    - Lagged daily daytime mean absolute percentage error
    - Lagged daily nighttime mean absolute percentage error
    - Lagged daily nighttime root-mean-squared-error (RMSE)

Brown, D.P., Zarnikau, J., Woo, C.-K., 2020. Does locational marginal pricing impact generation investment location decisions? An analysis of Texas’s wholesale electricity market. J Regul Econ 58, 99–140. <https://doi.org/10.1007/s11149-020-09413-0>

* Texas Market data, the relationship between **nodal prices** and **investment location decisions** of **utility-scale generation**.
* **some** evidence that **new investment arises** in areas with **recently elevated nodal prices**
  + **However**, we also find the **lowest two price quartiles have more new capacity than the highest two price quartiles**
* **no** evidence that **new generation** resources receive a **nodal price premium post-entry**
  + **large capacity additions suppress post-entry LMPs**
* the probability of **natural gas-fred generation investments** tends to **increase** with **expected nodal prices in peak hours**
  + **statistically and economically weak** and sensitive to model specifcation.
* **other factors are more important drivers** than **nodal prices of location**
  + a generation investment’s location is a **complex long-run decision shaped by** additional factors such as **site availability, transmission access, interconnection costs, fuel availability or renewable resource** **potential**, **etc**
* **Data**
  + 5-min **RTM price data** act the resource node level
    - Aggregate LMP nodal data up to the 15-min interval by taking the time-weighted average of the 5-min LMPs
    - 160 of the current 252 resource nodes that existed in January 2011.
  + **market-level data** made available by ERCOT that include information on **market demand** and **observed generation by technology**
  + **Henry hub**
  + **Location data of nodes** to map distance from new gen
  + **NREL’s** National Solar Radiation Database (**NSRD**) that includes realized **solar irradiation measures** and **wind speeds** at the 30-min interval
  + **EIA** data on **generation units in ERCOT**
    - all **existing power plants** with nameplate **capacities** that are **1 MW or greater**
    - **Planned Generation Unit Addition data** from the EIA’s Electric Power Monthly dataset to gather **information on planned capacity additions**
* **Methodology**
  + measures of **price dispersion**, including the differencebetween the 75th and 25th percentile LMPs, variance, the coefficient of variation, and a Gini coefficient.
  + decompose **generation capacity investments** into various **price-tiers based on lagged LMPs**
    - descriptive evidence of **whether LMPs send signals for investment location decisions**
  + **descriptive statistics** to investigate if **newly** constructed power **plants** **receive an LMP premium post-entry**
  + a **binary logit regression analysis** to investigate if **firms locate at a specific node based on the expectation of higher operating profits** due to higher expected LMPs
    - illustrative two-period model of investment location decisions

**Energy trading efficiency in the US Midcontinent electricity markets**

K.H. Caoa, H.S. Qib, C.H. Tsaic, C.K. Wood, J. Zarnikaue,\* - in review

* Analyze energy trading efficiency by estimating three newly developed sets of energy price ***difference*** regressions interconnected by their common root of energy price ***level*** regressions
* Findings:
  + MISO’s **zonal energy markets** are **integrated across space** (zone *j* vs. zone *k* for *j* ≠ *k*) **and time** (day-ahead market vs. real-time market)
    - these markets exhibit inter-day energy **prices differences** that **move** with the **fundamental drivers** (e.g. Day ahead hhub & windgen) of DAM
  + **enhancing inter-day trading efficiency** requires **accuracy improvements** in
    - (a) **day-ahead forecasts** for natural **gas price**, zonal **load levels**, and zonal **wind generation**
    - (b**) day-ahead scheduling** of zonal **nuclear** and **must-run generation**
  + improving **inter-zonal trading efficiency** requires **mitigating inter-zonal transmission congestion** via transmission **capacity expansion**, generation **investment** **and demand reduction** in a load pocket, and virtual **bidding**

**A latent-factor system model to estimate merit-order effects in energy markets**

**Kang Hua Cao, Paul Damien, and Jay Zarnikau – in review**

* **novel methodology** to model the merit-order effect. random, observed prices are influenced by some combination of latent causes – e.g. power outages, erroneous short-term weather forecasts, unanticipated transmission bottlenecks, etc.
* a **system-wide latent factor model for prices** in Texas, we **quantify the merit-order effects** on wholesale prices
* Findings:
  + **Latent causes** are **highly significant**
  + **estimated latent factor** series **strongly and positively correlates** to system-wide **prices during peak and off-peak hours**
  + merit-order effect of **wind** **significantly** **dampens prices**, **regardless** of **region and time** of day throughout ERCOT
  + **nuclear baseload** generation also **significantly lowers prices** during a 24-hour period in the entire system
  + **solar generation** needs to **grow faster** in order **to be a significant** renewable **resource**
* Data
  + Scope:
    - 4 main zones, N W S & Hou, 85% of total market
    - 1/1/2015 – 12/31/2018
    - Dependent variables: ln(price)zone ­n for n=8 zones at 4 AM, noon, and 4 PM
    - Independent/exogenous vars:
      * Observation eq. exogenous variables: (all nat log except dummy)
        + Wind generation
        + nuclear generation
        + solar generation
        + the Henry Hub gas price
        + a dummy variable for spikes in prices that exceed $500 MWH

The solar generation variable and the dummy variable do not appear in the 4am equations

* + - * Latent Factor eq. exogenous variables: (nat log)
        + System-wide load (MWH)

In a sense endogenous to the obs equation via latent factor

* + - * + lagged weighted price ($/MWH)

both across all eight zones

* + - * + first-order autoregressive process for the latent factor is used

used to “capture the lingering effects of hidden variables over time”