THE EVOLVING DYNAMICS OF PRICE VOLATILITY IN ERCOT: THE ROLE OF WIND, SOLAR, AND BATTERY ENERGY STORAGE SYSTEMS

Amina Talipova, Air Liquide Americas, (832)208-8599, amina.talipova@gmail.com

Overview

The Electricity Reliability Council of Texas (ERCOT) manages the production and flow of electricity to more than 26 million Texas customers - about 90% of the state's total electric demand. Every five minutes, the ERCOT market coordinates the electricity output from more than 1,250 generating resources to satisfy customer demand and manages the resulting flows of power across more than 54,100 miles of transmission lines in the region. Notably, ERCOT is fully deregulated and the only physically isolated electricity market (TSO) in the US.

ERCOT operates one of the most dynamic and unique energy markets in the United States, characterized by high penetration of renewable energy resources and a rapidly evolving infrastructure. In recent years, the increasing integration of wind, solar, and battery energy storage systems (BESS) that accounted for over 35% of total generation has transformed the traditional dynamics of price and volatility in the ERCOT real-time market. This research explores the interplay between renewable energy resources and price volatility, emphasizing the periods of extreme market stress and fluctuations in prices.

Wind and solar resources contribute significantly to ERCOT's energy mix, providing clean and low-cost electricity. However, their inherent intermittency poses challenges to grid stability and price predictability. Simultaneously, battery storage technologies have emerged as a critical component in balancing supply and demand by storing excess energy and discharging during peak demand periods. This study investigates the dual impact of renewable energy resources and BESS on price volatility, focusing on the frequency and magnitude of price spikes and their implications for market participants. By leveraging advanced volatility modelling techniques and extensive datasets, this research aims to provide insights into the evolving dynamics of price volatility in ERCOT, contributing to the understanding of market behaviour under the influence of renewables and energy storage.

Methods

This study deploys a data-driven approach to analyze the influence of wind, solar, and battery energy storage systems on price volatility in the ERCOT market. Data was sourced from ERCOT's real-time market settlement prices, ancillary services, and generation mix reports spanning from 2018 to 2024. These datasets include hourly and sub-hourly (15 minutes) records of energy prices and generation profiles for various fuel types, ensuring a comprehensive view of market dynamics.

To assess price volatility, the research utilizes statistical and econometric techniques, including generalized autoregressive conditional heteroskedasticity (GARCH) models, exponential GARCH (EGARCH) models, and exponentially weighted moving average (EWMA) techniques. Daily average prices and volatility metrics are calculated from sub-hourly data to capture both short-term fluctuations and long-term trends and shocks. Fuel mix data is preprocessed and pivoted to align generation by fuel type with timestamped market prices. The correlation between renewable generation and price volatility is then examined using regression analysis and time-series modeling. To account for the role of BESS, the study evaluates periods of high renewable penetration and assesses the stabilizing effects of storage during periods of market stress.

Model Fitting:

- GARCH(1,1) model to estimate conditional volatility (δ_t^2) based on past squared residuals (ε^2) and past volatility values:

$$\delta_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\delta_{t-1}^2$$

where δ_t^2 - conditional variance (volatility) at time t, ω - long-run variance, α - coefficient for lagged squared residuals, capturing the impact of shocks, β - coefficient for lagged conditional variance, capturing the persistence of volatility, ϵ - residuals (errors)

- EGARCH(1,1) model extends GARCH by allowing for asymmetry, meaning it can capture the impact of negative and positive shocks differently:

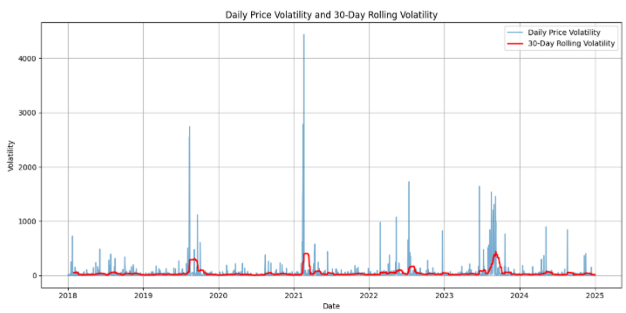
$$ln(\delta_t^2) = \omega + \beta \ln(\delta_{t-1}^2) + \alpha \frac{\varepsilon_{t-1}}{\delta_{t-1}} + \gamma \left(\left|\frac{\varepsilon_{t-1}}{\delta_{t-1}}\right| - \sqrt{\frac{2}{\pi}}\right)$$

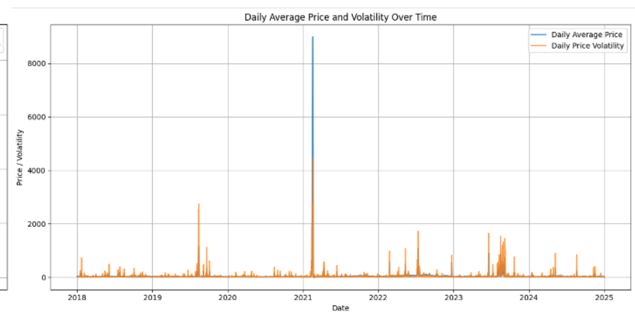
Results

The ERCOT market's volatility and price changed behavior in 2023 and were strongly influenced by the introduction of the ERCOT Contingency Reserve Service (ECRS) in June 2023. Using advanced volatility modeling techniques such as GARCH and EGARCH, our analysis confirms that price volatility during the latter half of 2023 exhibited anomalous spikes, corresponding ***to artificial shortage pricing***. This phenomenon occurred despite sufficient supply in the system, resulting in a significant doubling of average energy prices between June and December 2023.

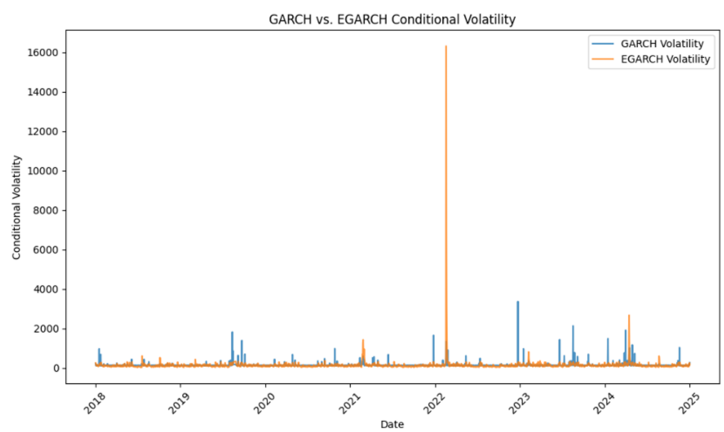
The analysis demonstrates that while real-time and day-ahead energy prices historically showed good price convergence, the introduction of ECRS disrupted this pattern between June and August 2023 ***leading to decoupling***. The results suggest that the availability of ECRS to the energy market and the target quantities procured contributed to these inefficiencies. Specifically, the models captured the increase in real-time price volatility, correlating with frequent artificial shortages.

Our findings also highlight broader market dynamics in 2023, including record-breaking load levels during summer. Despite decreases in energy and fuel prices, average ancillary service costs increased to $4.21 per MWh in 2023 from $3.29 per MWh in 2022. Average real-time prices, however, fell to approximately $65/MWh for the year. These insights align with observed trends in price volatility, which show heightened fluctuations during periods of high system demand and ECRS implementation.






```
GARCH Model Summary:
                     Constant Mean - GARCH Model Results
==============================================================================
Dep. Variable:            DailyReturn   R-squared:                       0.000
Mean Model:             Constant Mean   Adj. R-squared:                  0.000
Vol Model:                      GARCH   Log-Likelihood:               -16371.3
Distribution:                  Normal   AIC:                           32750.7
Method:            Maximum Likelihood   BIC:                           32774.1
                                        No. Observations:                 2547
Date:                Thu, Jan 16 2025   Df Residuals:                     2546
Time:                        02:05:15   Df Model:                            1
                                 Mean Model
========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
------------------------------------------------------------------------
mu            47.6061     11.134      4.276  1.904e-05 [ 25.784, 69.428]
                              Volatility Model
=============================================================================
                 coef    std err          t      P>|t|       95.0% Conf. Int.
-----------------------------------------------------------------------------
omega      1.4334e+04   7562.674      1.895  5.805e-02 [-4.888e+02,2.916e+04]
alpha[1]       1.0000      0.919      1.088      0.277      [ -0.802,  2.802]
beta[1]        0.0000  1.302e-02      0.000      1.000 [-2.552e-02,2.552e-02]
=============================================================================
...
beta[1]        0.8782  8.738e-02     10.051  9.133e-24    [  0.707,  1.049]
===========================================================================
```



Conclusions

The results reveal distinct spikes in conditional volatility measures from GARCH and EGARCH models. These spikes coincide with key periods of market stress, emphasizing the impact of policy changes on price dynamics. Rolling volatility metrics further demonstrate a sustained rise in volatility following ECRS implementation, contrasting with relatively stable periods before mid-2023.

These findings underscore the need for careful evaluation of ancillary market products like ECRS to ensure they do not inadvertently contribute to inefficiencies or artificial pricing behaviors in competitive energy markets.

References

Bollerslev, T. (1986). "Generalized Autoregressive Conditional Heteroskedasticity." *Journal of Econometrics, 31(3), 307–327.*

Nelson, D. B. (1991). "Conditional Heteroskedasticity in Asset Returns: A New Approach." *Econometrica, 59(2), 347–370.*