NYISO Enhanced Scarcity Pricing Policy: Impacts on Consumer Prices

Ibrahim Zubairi (mz3074) Riya Yingran Guo (yg2837) Lina Li (tl3262) Mitsuyo Murata (mm6334)
Iris Chu (ic2668) Colby Dorcély (cmd2280) Pedro Jose Villa (pjv2122)

ElectriCUTE U

Abstract

New York's Independent System Operator (NYISO) introduced an "Enhanced Scarcity Pricing" policy in 2021 by revamping its Operating Reserve Demand Curve (ORDC). This mechanism dynamically increases day-ahead energy prices during stressed conditions to encourage resource availability. This paper examines the policy's impacts on wholesale electricity prices in East NY (NYISO Zone F) using West NY and New England as control (ISO-NE Internal Hub + NYISO Zone C). Using data from 2019–2025, we apply difference-in-differences and synthetic control methods to estimate how retail prices responded to the policy. We find that the ORDC revamp has led to higher prices during peak and volatile conditions (when reserves are scarce) relative to the counterfactual control.

Github: https://github.com/riyagooo/energy-econ-ordc

1 Introduction

The design of electricity markets involves trade-offs between reliability incentives and consumer costs. Some regions rely on centralized capacity markets with advance commitments; capacity markets secure reliability through forward commitments. ISO-NE's Forward Capacity Market (FCM) holds annual auctions three years in advance, procuring sufficient capacity to meet future demand [4]. Resources receive guaranteed capacity payments if they clear these auctions. ISO-NE also employs Pay-for-Performance (PFP) incentives: resources underperforming during actual scarcity events pay penalties, while overperformers earn bonuses [5]. By contrast, others use scarcity pricing mechanisms that sharply raise prices when reserves are tight. In scarcity-pricing models, unused generation capacity is valued as operating reserves. An Operating Reserve Demand Curve (ORDC) sets a price adder that rises with the probability and cost of supply shortfall.

NYISO has operated a version of scarcity pricing prior to 2022, but the previous design was more static and did not adequately reflect the real-time value of reserves during stressed conditions. Coming into effect from May 2022, NYISO implemented the Enhanced Scarcity Pricing (ESP) policy introducing a steeper and more dynamic curve, which raises reserve prices sharply as the probability of shortage increases. The maximum reserve price ($750/MWh, i.e. VOLL) now applies only when NY reserves drop to 1,965 MW (1.5 x the largest contingency). The remaining 655 MW of the 2,620 MW requirement are covered by a 9-step, downward-sloping curve (versus the prior 4-step curve), with these steps being sized and priced to reflect escalating scarcity. In practice, NYISO now operates a month-ahead Installed Capacity Market (ICAM) along with ESP compliant dynamic reserves to drive generator availability and flexible load response, reducing the risk of reserve shortfalls.

2 Literature Review

Research suggests that scarcity pricing mechanisms, such as NYISO's Enhanced Scarcity Pricing Policy, can significantly impact consumer electricity prices, particularly during peak and volatile periods. Studies indicate that scarcity pricing raises market prices above offer caps during reserve shortages, directly affecting consumer costs by increasing energy prices, especially in real-time markets. Scarcity pricing introduces an elastic demand curve in real-time markets, adding to energy prices (system lambda) and back-propagating to day-ahead markets, which can lead to higher consumer bills during shortages. Different approaches to scarcity pricing across ISOs, such as ex-post price adders or stepwise demand curves, can lead to varying degrees of price increases. NYISO's policy incorporates the Emergency Demand Response Program (EDRP) into pricing, ensuring prices reflect scarcity conditions more accurately, which can result in higher costs for consumers during peak hours.

An industry report from IGS Energy [3] highlights a case in Texas, where scarcity pricing events led to dramatic price spikes, with costs increasing by up to 10,000% higher than typical averages during insufficient reserves, illustrating the potential for significant consumer price impacts. The impact is particularly pronounced during extreme conditions, such as operating reserve shortages or demand curtailments. While real-time hourly price averaging can dilute price signals, reducing the immediate impact on consumers, long-term effects can include higher energy prices for future delivery periods, suggesting that scarcity pricing may expose consumers to higher costs during market stress despite enhancing reliability.

Comparative analyses with capacity markets, such as ISO-NE's FCM, reveal key trade-offs in market design. Studies like Bushnell et al. [1] argue that capacity markets reduce price volatility by socializing capacity costs across all hours, potentially benefiting consumers in the short term by stabilizing prices. However, this stability may come at the cost of efficiency, as forward commitments can lead to over-procurement, increasing overall system costs. In contrast, NYISO's Enhanced Scarcity Pricing Policy is designed to enhance market efficiency by aligning prices with real-time scarcity conditions, but this can result in higher consumer prices during peak and volatile periods. Wolak [6] notes that capacity markets can mitigate price spikes during extreme conditions, benefiting consumers, but may discourage investment in new, flexible generation, highlighting the complexity of choosing between these mechanisms. Hogan [2] advocates for scarcity pricing through operating reserves, arguing it enhances market efficiency by sending accurate price signals, but acknowledges potential consumer cost increases during scarcity events.

3 Methodology

The analysis draws on hourly electricity price data from January 1, 2019, to January 31, 2025, resulting in 160,038 total observations. Given the importance of price dynamics during peak hours, the model restricts attention to the 4–7 PM window, when demand tends to be most acute and ORDC incentives are most binding.

The DiD model is constructed to compare changes in price trajectories across a treatment and control group before and after the ORDC revision. The treatment group corresponds to Zone F in NYISO's West region, where the ORDC structure was reformed in 2022. The control group comprises Zone C in NYISO's West region and the ISO New England internal hub, which did not experience similar market design changes during the study period. The identification strategy assumes that, in the absence of the policy intervention, price trends between these zones would have remained parallel.

To isolate the treatment effect, the model includes interaction terms between treatment assignment, post-policy period, and peak-time indicators. The main coefficient of interest is the triple interaction term, which captures the differential impact of the ORDC policy on peak-hour prices in the treated zone. The regression specification also includes fixed effects for zone and time, along with key control variables to account for external price determinants. These include hourly system load, city-gate natural gas prices (reflecting fuel cost pass-through), and binary indicators for extreme weather events that may affect regional energy supply or demand. Year fixed effects are also included to control for unobserved temporal shocks.

In parallel, a synthetic control is constructed to generate a counterfactual trajectory for Zone F's prices in the absence of ORDC changes. The donor pool includes multiple subzones from ISO New England: Maine, New Hampshire, Vermont, Connecticut, Rhode Island, Southeast Massachusetts, Western Massachusetts, and the NEMA/Boston hub. Using a weighted linear combination of these zones, the synthetic control approximates the pre-treatment behavior of Zone F. Post-2022 deviations between actual and synthetic trajectories are then interpreted as the causal effect of the ORDC revision.

3.1 Control Variables and Data Sources

Table 1: Control Variables

Variable	Units	Type	Data Source
Extreme Weather (Storm, Flood, Cold)	N/A	Dummy	Weather.gov, PBS News, etc.
Load Data	MWh	Continuous	NYISO, ISO-NE (interpolated for 82 missing data points, very small portion)
Natural Gas Price	\$/Mcf	Continuous	U.S. Energy Information Administration

3.2 Peak Hour Analysis: Empirical Strategy

3.2.1 Synthetic Control for Peak Hour Analysis

We apply synthetic control to estimate a counterfactual price path for NYISO Zone F during peak hours. This method constructs a weighted average of control zones to match NYISO Zone F's pre-2022 price history. The control group was generated with the following zonal information: Internal Hub, ME (Maine), NH (New Hampshire), VT (Vermont), CT (Connecticut), RI (Rhode Island), SE-MA (Southeast MA), WC-MA (Western MA), NEMA/Boston, NY Zone C. The synthetic control then projects what Zone F's prices would have been without the ORDC change.

3.2.2 Difference-in-Differences with Peak Hour Interaction

We implement a fixed-effects difference-in-differences (DiD) regression with triple interaction to evaluate price effects during peak hours. The specification compares price trends before and after the policy for Zone F (treated) versus the ISO-NE hub (control), with additional interaction terms for peak hours. Key regressors include: a treatment indicator (1 for Zone F), a post indicator (1 after ORDC implementation), a peak hour indicator (1 for hours 4-7 PM), and their interactions. The triple interaction term captures the differential impact of the policy during peak hours specifically.

The general specification for our DiD model with peak hour interaction is as follows:

$$\begin{aligned} Price_{ijt} = \alpha &+ \beta_1 Treat_j + \beta_2 Post_t + \beta_3 Peak_t \\ &+ \beta_4 (Treat_j \times Post_t) + \beta_5 (Treat_j \times Peak_t) + \beta_6 (Post_t \times Peak_t) \\ &+ \delta (Treat_j \times Post_t \times Peak_t) + \gamma X_{ijt} + \lambda_j + \theta_t + \epsilon_{ijt} \end{aligned} \tag{1}$$

where $Price_{ijt}$ is the wholesale electricity price in zone j at hour t of day i, $Treat_j$ is a dummy variable equal to 1 for the treatment zone (Zone F), $Post_t$ is a dummy variable equal to 1 for the post-intervention period (after May 2022), $Peak_t$ is a dummy variable equal to 1 for peak hours (4-7 PM), X_{ijt} is a vector of control variables (load, natural gas price, extreme weather), λ_j and θ_t are zone and time fixed effects, and ϵ_{ijt} is the error term. The parameter of interest is δ, which represents the causal impact of the ORDC policy on peak-hour prices.

Under this quasi-experimental design, the DiD estimator with the treated#post#peak interaction captures the causal impact of ORDC on peak-hour prices.

3.3 Volatile Market Conditions: Empirical Strategy

3.3.1 Difference-in-Differences with Volatility Interaction

We employ a fixed-effects difference-in-differences (DiD) model with triple interaction to assess price effects during volatile market conditions. The specification compares price trajectories before and after the May 2022 policy implementation for Zone F (treated) versus Zones C and NE (controls). Key regressors include: a treatment indicator (1 for Zone F), a post-implementation indicator (1 after May 1, 2022), their interaction (treated#post), and a volatility indicator identifying price spikes. To isolate heterogeneous effects during volatile periods, we incorporate a triple interaction between treatment status, post-implementation period, and market volatility.

The specification for our DiD model with volatility interaction is as follows:

$$\begin{aligned} Price_{it} &= \alpha_i + \gamma_t + \beta_1 Treated_i + \beta_2 Post_t + \beta_3 Volatile_{it} \\ &+ \beta_4 (Treated_i \times Post_t) + \beta_5 (Treated_i \times Volatile_{it}) \\ &+ \beta_6 (Post_t \times Volatile_{it}) + \beta_7 (Treated_i \times Post_t \times Volatile_{it}) \\ &+ \delta_1 Load_{it} + \delta_2 Gas_{it} + \delta_3 Weather_{it} + \gamma_{year} + \epsilon_{it} \end{aligned} \tag{2}$$

where $Price_{it}$ is the wholesale electricity price for observation i at time t, $Treated_i$ indicates treatment assignment (Zone F), $Post_t$ indicates the post-policy period (after May 2022), $Volatile_{it}$ is a binary indicator for volatile market conditions, $Load_{it}$, Gas_{it}, and $Weather_{it}$ are control variables, γ_{year} represents year fixed effects, and ϵ_{it} is the error term. The parameter of interest is β_7, which captures the differential impact of the ORDC policy during volatile periods in the treated zone.

We define volatile days as those with prices exceeding two standard deviations from the long-term mean, representing significant market stress. The model includes zone fixed effects to control for time-invariant differences between zones and year fixed effects to account for common temporal trends.

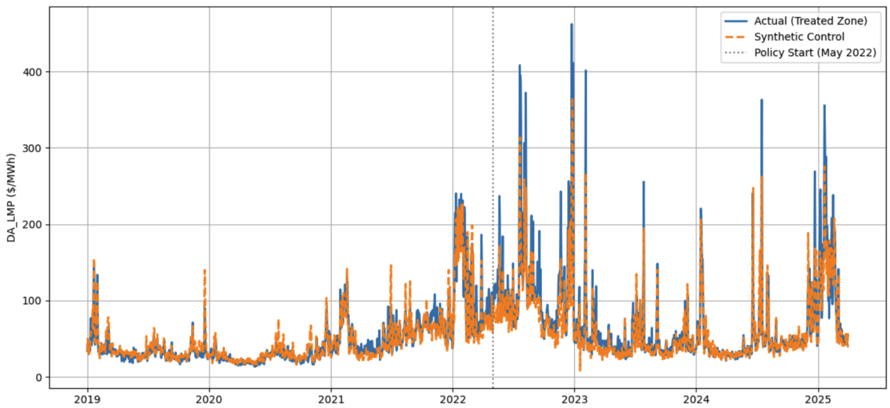
Additionally, we estimated a log-transformed DiD model on the subset of volatile days to measure the percentage impact of the policy. This approach allows us to interpret the treatment effect in relative rather than absolute terms.

4 Results

4.1 Peak Hour Effects

4.1.1 Synthetic Control Results for Peak Hours

Figure 1: Synthetic Control Results: Peak Hour Price Effects



The parallel trend assumption pre-treatment appears to hold pre-2022, and there appears to be a noticeable difference between the magnitude of peak prices relative to the synthetic counterfactual. The difference between the actual post-2022 prices and this synthetic counterfactual yields an estimated Average Treatment Effect on the Treated (ATT) of +8.86 \$/MWh (p=0.091). Synthetic control suggested an increase in retail electricity prices by about \$9/MWh during peak hours, which was significant at the 90% level, but not at the 95% confidence level. Given that no control variables were included, and the lack of statistical power at the 95% level suggests possible confounders dampening the statistical power.

4.1.2 Difference-in-Differences Results for Peak Hours

Table 2: Difference-in-Differences Results: Peak Hour Effects

Variable	Coefficient	Robust Std. Err.	t	P>|t|	95% Conf. Interval
1.treated	0 (omitted)				
1.post	−5.648	4.298	−1.31	0.319	[−24.139, 12.843]
treated#post	−1.049	0.851	−1.23	0.343	[−4.732, 2.613]
1.peaktime	4.195	4.680	0.90	0.465	[−15.944, 24.333]
treated#peaktime	−3.534	4.654	−0.76	0.527	[−23.560, 16.491]
post#peaktime	5.246	0.584	8.99	0.012	[2.735, 7.757]
treated#post#peaktime	**7.235**	**0.568**	**12.75**	**0.006**	**[4.793, 9.678]**
load_interp	0.046	0.008	5.85	0.021	[0.017, 0.075]
natural_gas_price	−3.597	0.583	−6.04	0.045	[−3.858, 1.958]
extreme_weather	16.784	7.885	2.13	0.167	[−17.142, 50.709]
Year fixed effects					
2020	−6.432	1.913	−3.36	0.078	[−14.667, 1.798]
2021	14.345	2.839	5.04	0.037	[2.091, 26.600]
2022	59.228	12.284	4.82	0.040	[6.376, 112.080]
2023	15.380	3.569	4.32	0.050	[0.059, 30.782]
2024	19.532	3.636	5.37	0.033	[3.808, 35.174]
2025	94.054	13.657	6.89	0.020	[35.321, 152.788]
_cons	−19.219	6.288	−3.06	0.092	[−46.274, 7.836]

Note: The coefficient of interest (treated#post#peaktime) is highlighted in bold.
$\sigma_u = 49.283$, $\sigma_e = 24.438$, $\rho = 0.803$ (fraction of variance due to u_i)

The basic difference-in-differences effect (treatment#post) outside peak hours is both small and statistically insignificant (-1.05 $/MWh, p=0.343). We can confidently interpret that outside peak hours, there was no significant effect on wholesale electricity prices in Zone F relative to control. However, when focusing on peak hours, the triple-interaction term (treated#post#peak) is +7.24 $/MWh (t=12.75, p=0.006) and highly significant even at the 99% confidence interval relative to control. In other words, during the peak daily demand window, prices in Zone F rose by about $7/MWh more than they would have without the policy.

Additionally, all Year-on-Year coefficients were significant. From 2021-2025, all effects are consistently positive YoY effects, with statistically significant p-values ($p \leq 0.05$). The overall positive trend may indicate factors driving prices up, such as regional capacity retirements in NY over the period. Major retirements of note are Indian Point Nuclear Plant's Unit 3 in April 2021 (1,051 MWe) and Somerset Coal Plant (675 MWe).

4.2 Volatile Market Condition Effects

4.2.1 Difference-in-Differences Results for Volatile Days

The baseline difference-in-differences effect (treated#post) during normal market conditions is both small and statistically insignificant (0.98 $/MWh, p=0.201). We can confidently interpret that during standard operations, there was no significant effect on wholesale electricity prices in Zone F relative to control. However, the triple interaction term (treated#post#is_volatile) reveals a substantial and statistically significant price increase of 23.68 $/MWh (t=2.41, p=0.016) during volatile periods. This finding is corroborated by our supplementary models, where restricting analysis to only volatile days yields a significant treatment effect of 22.14 $/MWh (p=0.008). In other words, during periods of market stress, prices in Zone F rose by about $24/MWh more than they would have without the policy.

To complement our absolute price effect findings, we also estimated a log-transformed DiD model restricted to volatile days. This analysis revealed that the policy led to an 11.6% increase in prices during volatile market conditions (p=0.046). This relative effect underscores the substantial economic impact of the Enhanced Scarcity Pricing policy during periods of market stress.

Table 3: Difference-in-Differences Results: Volatile Day Effects

Variable	Coefficient	Robust Std. Err.	t	P>|t|	95% Conf. Interval
1.treat	11.135	0.397	28.063	0.000	[10.357, 11.912]
1.post	4.231	1.578	2.681	0.007	[1.138, 7.323]
treat#post	0.977	0.764	1.277	0.201	[−0.522, 2.475]
1.is_volatile	97.873	7.556	12.953	0.000	[83.064, 112.683]
treat#is_volatile	12.435	9.027	1.378	0.168	[−5.258, 30.129]
post#is_volatile	−4.947	13.066	−0.379	0.705	[−30.555, 20.661]
treat#post#is_volatile	**23.678**	**9.808**	**2.414**	**0.016**	**[4.454, 42.901]**
load_interp	0.053	0.007	7.571	0.000	[0.039, 0.067]
natural_gas_price	12.368	1.489	8.305	0.000	[9.450, 15.287]
extreme_weather	27.546	4.784	5.758	0.000	[18.169, 36.922]
Year fixed effects					
2020	−6.282	0.666	−9.436	0.000	[−7.587, −4.977]
2021	12.818	2.647	4.843	0.000	[7.630, 18.006]
2022	31.305	7.856	3.985	0.000	[15.907, 46.703]
2023	0.969	2.103	0.461	0.645	[−3.153, 5.091]
2024	3.566	0.901	3.958	0.000	[1.800, 5.332]
2025	26.409	2.466	10.710	0.000	[21.576, 31.242]
_cons	18.760	1.520	12.345	0.000	[15.782, 21.738]

Note: The coefficient of interest (treat#post#is_volatile) is highlighted in bold.
R^2: 0.718 Method: Least Squares N: 164,520

5 Conclusions

The results indicate that ISO-NE consumers were exposed to lower prices and reduced volatility during peak hours compared to NYISO Zone F, with a consistent positive effect across Synthetic Control (+8.86 \$/MWh, p = 0.091), DiD with peak hour interaction (+7.24 \$/MWh, p=0.006), and DiD with volatility interaction (+23.68 \$/MWh, p=0.016). The findings reinforce that there is not only a trade-off between efficiency vs. volatility in market design. Additionally, the overall increasing YoY effect in the DiD analysis suggests that NYISO's ESP programme has resulted in both a strong and a significant upwards trend in wholesale prices during peak hours. In the long run, this is additional evidence that ORDC mechanisms are well suited to signal and incentivize new generation to meet capacity requirements in a more efficient manner. In contrast, capacity markets tend to socialize the capacity costs more evenly across all hours instead of concentrating costs during scarcity events, which is inefficient but results in less volatility and lower peak pricing for consumers in the immediate-to-short term. However, these findings cannot be interpreted to reflect a change in consumer surplus, as the overall consumer surplus changes are difficult to interpret from scarcity price exposure alone, given the data limitations to individual behavior and household consumption data.

References

[1] Bushnell, J., Flagg, M., & Mansur, E. (2017). *Capacity markets at a crossroads.* Energy Institute at Haas Working Paper 278.

[2] Hogan, W. W. (2013). *Electricity scarcity pricing through operating reserves.* Economics of Energy & Environmental Policy, 2(2), 65-86.

[3] IGS Energy. (2023). *Understanding scarcity pricing and its impact.* IGS Energy Resource Center.

[4] ISO New England. (n.d.). *Forward Capacity Market (FCM).* ISO-NE.

[5] ISO New England. (2017). *Pay-for-Performance in the FCM.* ISO-NE.

[6] Wolak, F. A. (2019). *The role of capacity markets in facilitating renewable energy development in the Western United States.* Economics of Energy & Environmental Policy, 8(2), 29-52.