Analyzing Forward Premiums and Energy Sources in ERCOT: A Time Option and Error Correction Model Approach to Forecasting Equilibrium Price

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Motivation:

Energy independence is the key to a prosperous economy and manufacturing industry. Electricity Reliability Council of Texas (ERCOT) market is unique, its independence and scale mean that energy prices can shift quickly, impacting firms that purchase electricity daily. With renewable energy (solar and wind) making up more than half of Texas's supply and dramatic growth in solar capacity in recent years, understanding the factors that drive short-term price changes is more important than ever. Unusual weather events such as the 2021 cold snap that froze wind turbines, demonstrates how renewable capacity and weather interact to affect market prices. The study explores these dynamics to help electricity buyers better forecast and manage costs in an evolving energy market. This study zeroes in on the "time option", the strategic value derived from the ability to choose the optimal timing for electricity transactions between the Day-Ahead and Real-Time markets. For firms purchasing electricity, this timing flexibility can lead to considerable cost savings and enhanced risk management.

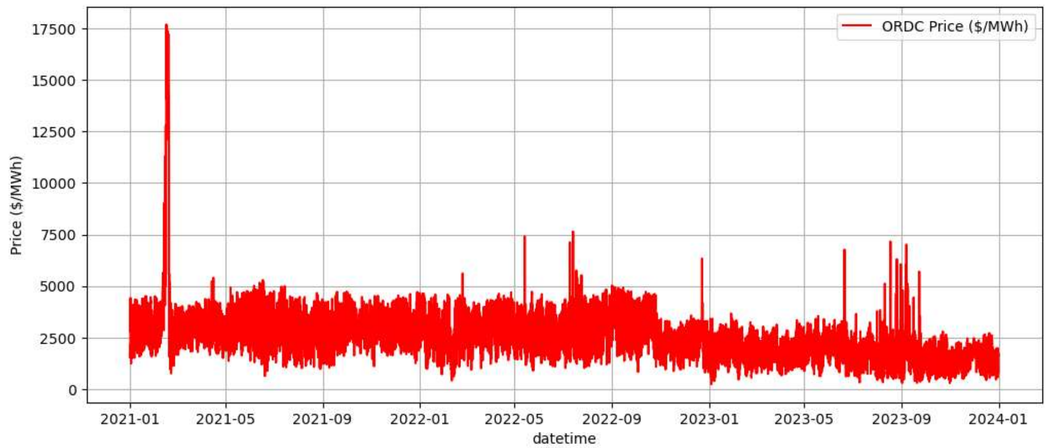
Background:

The ERCOT market equilibrium is well documented and is used by market participants to accurately assess their needs day to day. In **Figure 1**, I show the Operating Reserve Demand Curve, it is the real time market pricing mechanism which reflects tight market conditions, creating a supply response to changes in the energy market. In other words, when reserve margins are low, the ORDC determines a higher price that firms ultimately pay for electricity in the real-time market.

Renewable energy sources affect ORDC price. Windmills constructed in Texas were made without a heating element to make the cost cheaper and under the assumption that they would not freeze in Texas. Unforeseen cold temperatures had a drastic effect on energy prices in 2021 when the windmills were frozen by an unanticipated cold freeze. From 2021-2024 solar installation in Texas increased from 5649 to 21173 MW, around 4 times in three years. Windmills constructed in Texas increased from 31790 to 38610 MW with efficiency growing moderately over the last decade as well. Total solar and wind production account for 52.4% of the current energy supply in Texas.

Given increasing capacity for renewables and the impact of weather conditions, it is necessary to assess how these play a role in hour-to-hour prices paid by firms who purchase electricity day to day. Instead, market timing, specifically the time option emerges as a critical factor. The time option encapsulates the decisions made by market participants to exploit the price differentials between the Day-Ahead and Real-Time markets, serving as a hedge against unexpected volatility.

Figure 1: Operating Reserve Demand Curve



Research Questions:

How does the time option captured by the price differential between Day-Ahead and Real-Time market influence both short-run price adjustments, and the return to long-run equilibrium in the ERCOT electricity market?

- What supply variables influence the Long Run and Short Run price changes?
- How does the time option variable impact price changes in the Long Run and Short Run?

Data and Variables:

This study uses a comprehensive time series hourly dataset from the ERCOT market covering the period from January 2021 through December 2023. **Table 1** presents the data obtained from ERCOT's publicly available market reports and include key variables required to evaluate the time option and its influence on price dynamics. The dataset comprises both Day-Ahead Market (DAM) and Real-Time Market (RTM) prices, which are essential for constructing the time option variable.

Supplementary information on weather conditions, primarily temperature readings for major Texas cities including Houston, Dallas, Austin, Fort Worth and San Antonio is also incorporated to account for potential influences on market operations, creating a weighted average for temperature based on population size of these cities. Thus giving us Heating and Cooling degree variables which represent when temperature is below and above the critical temperature designated at 67 degrees Fahrenheit. Solar radiance and wind speed data were collected on the regions that contained the majority of ERCOT's solar and wind power. Cooling degree days have a mean of 8.5, meaning that on average, temperatures exceeded 67°F by 8.5°F, pointing to a moderate level of heat stress across the observations. The standard deviation of 9.8 suggests that there is also a wide range in how much temperatures surpass the baseline, and the maximum value of 40.1 highlights that there are instances of very high temperatures. Heating degree days, the mean of 5.4 indicates that, on average, temperatures were 5.4°F below the 67°F baseline used to define heating needs. This suggests that moderate cold conditions are common in the dataset. However, the relatively high standard deviation of 9.1 implies considerable variability some days are much colder than the average, as reflected in the maximum value of 54.5, which indicates that on extreme days, temperatures fell substantially

As done with the temperature we construct a weighted average for solar radiance and wind speed to obtain the hourly average based on their location and the amount in each. Solar Radiance and Wind Speed were tested as exogenous variables impacting the production of Wind and Solar generation. For wind speed, the mean value is 1.3 m/s, indicating that on average, wind conditions are relatively mild. The standard deviation of 1 m/s suggests there is moderate variability around the mean, with wind speeds ranging from a minimum of 0 m/s to a maximum of 6.3 m/s. The interquartile range, with the 25th percentile at 0.5 m/s and the 75th percentile at 1.9 m/s, confirming that most observations fall within a narrow range, while the maximum value points to occasional periods of stronger wind.

For solar radiance, the average is 122.3 W/m^2; The high standard deviation of 197.9 W/m^2 and a maximum value of 901.9 W/m^2 reflect significant variability in solar energy received, typical of diurnal patterns. With the 25th percentile at 0 W/m^2 and the 75th percentile at 188.4 W/m^2, the data captures the contrast between periods of no sunlight and times when solar radiance is high, primarily due to nighttime.

Supply factors in electricity production were included from renewables such as Wind, Solar, Hydro, and Biomass, to more reliable sources such as Gas, Gas CC, and Coal. “Other”, may include oil-fired generation, cogeneration units, waste-to-energy plants, or smaller-scale renewable sources that are less prominent in the overall production mix. The most significant sources of fuel in the long run are Coal, Gas-CC, Nuclear, and Wind with a mean of 7917MW, 17340 MW, 4668 MW, and 11820 MW respectively. These means indicate the typical scale of each fuel source's contribution to electricity production, reflecting their relative importance in meeting long-term demand. Although Gas and Solar have a high maximum and a larger standard deviation relative to some sources, with a Maximum of gas at 19466MW and solar 13930MW, with both their standard deviations being 3849 MW and 3672MW respectively. For gas this suggests that while it typically contributes a moderate amount, there are periods of very high output likely due to its flexible and flexible nature. As well as for solar, it reflects significant fluctuations in solar generation that are primarily driven by weather and daylight conditions.

Table 1: Descriptive Statistics (2021-2023 Hourly Data)

Variable	Count	Mean	STD	Min	25%	50%	75%	Max
Biomass (MW)	26275	54.7	38.8	2.5	20.9	31.8	84.1	134.5
Coal (MW)	26275	7917.4	2212	857.7	6283.6	7875	9654	14197.9
Gas (MW)	26275	3507	3484.8	92.6	1053.7	2174.6	4666.3	19466.6
Gas-CC (MW)	26275	17340	6945	1052.2	11928	17127	22848	31937
Hydro (MW)	26275	45.4	45.9	0	9	28.2	68.9	340.6
Nuclear (MW)	26275	4667.9	646.5	1251.4	4225.1	4977.6	5092.1	7719
Other (MW)	26275	54	77.4	-112.9	5.1	36.5	74.3	1645.8
Solar (MW)	26275	2751.9	3672.3	0	0	150.6	5277.9	13930
Wind (MW)	26275	11820	6244.8	31.1	6469.5	11547	16998	36329
Heating Degrees	26275	5.4	9.1	0	0	0	8.6	54.5
Cooling Degrees	26275	8.5	9.8	0	0	4.9	15.2	40.1
Cosine Day	26275	0	0.6	-1	-0.4	0	0.4	1
Wind Speed (m/s)	26275	1.3	1	0	0.5	1.1	1.9	6.3
Solar Radiance (w/m2)	26275	122.3	197.9	0	0	0	188.4	901.9
Option Value	26275	17.5	164	0	0	0	2.1	5907

Methodology:

The methodological approach centers exclusively on the Error Correction Model to evaluate the influence of the time option on ERCOT's price dynamics. An Error Correction Model is designed to capture both the short-run dynamics and the long-run equilibrium relationship among non-stationary time series. ECM models explains changes in the dependent variable based on changes in the independent variables and includes a lagged error correction term that reflects deviations from the long-run equilibrium, in this case the price. A statistically significant and negative coefficient on this term indicates that the price mechanism reverts to the mean. **Table 2 and 3** presents the regression results for ECM as well as IV 2SlS using solar radiance and wind speed as instrumental variables.

IV 2SLS is a methodological approach that addresses endogeneity in explanatory variables which are correlated with the error term. By initially regressing these explanatory variables on the Instrumental Variables that do not inherently have correlation to your endogenous variable but do influence your choice variable. Using these predicted values of my explanatory variable(s) input them into your equation replacing the original variable. This two step process allows to mitigate bias caused by omitted variables, simultaneous causality, and measurement errors. In this case we use solar radiance and wind speed as instrumental variables on the endogenous variables Solar and Wind. We suspect that Solar and Wind production may be jointly determined with prices, as market conditions may influence both renewable production and price simultaneously. Therefore, the instruments chosen to isolate the exogenous variation in Solar and Wind when treating them as endogenous.

First, we construct a dummy variable representing the time option by measuring the price differential between the Day-Ahead Market and the Real-Time Market. This variable captures the immediate value that market participants derive from choosing when to transact, Representing Implicit value of flexibility in decision-making, particularly under uncertainty to capture the economic benefit of waiting for more information before committing to an irreversible decision.

We integrate this time option variable into an ECM framework. The model allows us to associate short-run price deviations with long-run market equilibrium. Quantifying the speed and extent to which prices adjust following a shock in the market, providing insights into both the immediate impact of timing decisions and correction toward equilibrium.

While renewable energy data covering solar and wind generation are included in the dataset, the analysis confirms that these variables do not significantly drive short-term price changes. Renewable generation data, covering both solar and wind outputs, are included primarily to control long-term trends and overall market supply but are secondary to the focus on the time option. As a result, the ECM places emphasis on the time option as the key explanatory factor for price dynamics. Through this approach, we aim to deliver clear insights for firms looking to optimize their electricity purchase strategies based on market timing.

Table 2: Coefficient Comparison Table

Variable	OLS (ΔPrice)	IV2SLS (ΔPrice)	ECM (Long-Run)	ECM (Short-Run)
Constant	1212.2412***	960.0901***	4130.0585***	0.0126
	(57.743)	(122.09)	(106.249)	(2.345)
Biomass	-1.8583***	-1.9038***	-0.8959***	-0.6028
	(0.152)	(0.2098)	(0.281)	(0.438)
Coal	-0.0425***	-0.0337***	0.0237***	- 0.02***
	(0.003)	(0.0040)	(0.006)	(0.006)
Gas	0.0146***	0.0199***	0.0330***	0.0162***
	(0.003)	(0.0035)	(0.005)	(0.004)
Gas-CC	-0.0273***	-0.0194***	-0.0739***	0.0076**
	(0.002)	(0.0027)	(0.003)	(0.003)
Hydro	0.8170***	0.8177***	0.1252	-0.0405
	(0.111)	(0.11)	(0.204)	(0.123)
Nuclear	-0.1143***	-0.1063***	-0.1262***	0.0175
	(0.008)	(0.0125)	(0.015)	(0.035)
Other	0.1963***	0.041	-1.4150***	-0.0918*
	(0.076)	(0.0784)	(0.140)	(0.053)
Solar	-0.0315***	-0.0196***	-0.0961***	0.0014
	(0.003)	(0.001)	(0.005)	(0.003)
Wind	-0.0303***	-0.0147***	-0.0745***	0
	(0.002)	(0.001)	(0.004)	(0.003)
Heating Degrees	25.5036***	23.5258***	45.0301***	9.1992***
	(0.800)	(2.0548)	(1.473)	(2.495)

Cooling Degrees	17.2545*** (1.387)	12.6931*** (1.8933)	30.5861*** (2.552)	-4.7190* (2.712)
Cosine Day	-76.0951*** (22.123)	-66.5587*** (23.359)	-263.4130*** (40.707)	-27.6768 (22.222)
Wind Speed	57.9059*** (10.025)	—	210.5824*** (18.446)	18.3833 (15.084)
Solar Radiance	0.0762** (0.046)	—	0.4902*** (0.085)	-0.0552 (0.047)
Option Value	2.0117*** (0.025)	2.0293*** (0.1323)	2.5903*** (0.046)	0.9292*** (0.025)
Lag ECM	—	—	—	- 0.2548*** (0.002)
Time-of-day dummies	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes
Day-of-week dummies	Yes	Yes	Yes	Yes
R2	0.384	0.3822	0.287	0.166

Note: t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Time Dummy Coefficient Comparison

Time Variables	ECM (Long-Run)	ECM (Short-Run
4-7 AM	17.8607	-17.1174
8-11 AM	191.368***	-24.3527**
12- 3 PM	243.7983***	-8.8524
4- 7 PM	182.8762***	-11.9869
8-11 PM	128.9415***	6.426
Monday	-64.6943***	-80.8798***
Tuesday	-18.9035	-49.6631**
Thursday	-49.5925**	-24.642
Friday	-35.627	-25.8189
Saturday	-152.871***	-39.5653
Sunday	-127.081***	-81.1672***
January	-54.3713	62.2141
February	164.504***	-49.994
April	175.1111***	557.5844***
May	496.8017***	455.6955**
June	707.8247***	262.4359
July	833.3823***	520.9927
August	972.9085***	566.8471
September	1180.251***	621.5176
October	754.3162***	569.3731
November	7.5502	342.7885
December	336.6011***	63.3112

Table 4: Variable Definition

Variable	Definition	Symbol
Real Time Market	Current Price	RTM
Day Ahead Market	Tomorrow's Price	DAM
Operating Reserve Demand Curve	Equilibrium Pricing Mechanism	ORDC
Heating Degrees	Temperature readings for major Texas cities including Houston, Dallas, Austin, Fort Worth and San Antonio is also incorporated to account for potential influences on market operations, creating a weighted average for temperature based on population size of these cities. If temperature is below 67°F, heating degrees are calculated as the difference between 67°F and the actual temperature.	HD
Cooling Degrees	Temperature readings for major Texas cities including Houston, Dallas, Austin, Fort Worth and San Antonio is also incorporated to account for potential influences on market operations, creating a weighted average for temperature based on population size of these cities. If temperature is above 67°F, cooling degrees are calculated as the difference between the actual temperature and 67°F	CD
Cosine Day Length	Mathematical transformation used to model seasonal variations in daylight hours, based on the idea that day length follows a sinusoidal pattern throughout the year, with longer days in summer and shorter days in winter	CDL
Option Value	Implicit value of flexibility in decision-making, particularly under uncertainty to capture the economic benefit of waiting for more information before committing to an irreversible decision. Where S1 is RTM and S2 is DAM Volatility: σ= std(ln(S1/S2)) Computing D1 and D2: $d1=(\ln(S1/S2)+((\sigma^2+r)/2)T)/ \sigma*T^{.5}$ $d2=d1-\sigma*T^{.5}$ Where the option value = $S1\cdot\Phi(d1)-S2\cdot\Phi(d2)$	OV
Wind Speed	Wind speed measures the velocity of air movement, with higher wind speeds typically increase wind turbine output	WS
Solar Irradiance	Solar irradiance measures the amount of solar energy received per unit area, directly influencing the output of solar photovoltaic (PV) systems	SI

Discussion:

In the ECM estimation, the option value variable exhibits a robust and statistically significant positive coefficient of 0.9292. Specifically, a one-unit increase in the option value variable is associated with a 0.93 percentage point rise in short-run price changes, underscoring the importance of timing decisions between the DAM and RTM. This result indicates that increases in the option value often interpreted as the market's valuation of future uncertainty and pricing flexibility are associated with higher short-run adjustments in ORDC prices. In other words, when market participants perceive greater optionality, potentially due to volatility in supply or demand expectations, firms tend to face higher short-run price changes on the ORDC curve. This finding aligns with expectations that in environments with significant uncertainty, the value of having the option to defer or accelerate investment decisions becomes critical, exerting upward pressure on market prices. **Figure 2** represents the key instrument of this study "option value", accounting for 31.1% of the variation of predictive power in price change.

Energy source variables display mixed effects. This analysis of energy dynamics indicates that the fuel mix contributes significantly to market behavior. Natural gas, coal, and gas combined-cycle generation all exhibit statistically significant, though varied, impacts on short-run price adjustments, reflecting the complex interplay of operational flexibility and efficiency within the energy system. The results show that a one-unit increase of MW power in natural gas input is associated with a 0.0162 unit rise in short-run prices, indicating that even small increments in natural gas supply can nudge prices upward.

On the other hand, a one-unit increase in coal power generation in MW causes a decrease of 0.0196 price, suggesting that greater coal-based generation exerts a negative effect on price changes. Similarly, each MW increase in gas combined-cycle generation contributes approximately 0.0076 dollars to price adjustments, while increases in "Other" generation sources are associated with a notable reduction of 0.0918 dollars per MW, although the amount produced by these "Other" sources are minimal. The negative impact suggests that, in the short run, any contribution from these "Other" sources tends to exert a downward pressure on prices, potentially due to their higher marginal costs and/or their role in diversifying supply and mitigating price spikes during peak demand periods. **Figure 6 and 7** represent the impact that these non renewables have on short run prices in terms of managing electricity cost, it is important to keep in mind that specific sources take more time to bring online and are more costly compared to other energy sources. In contrast, renewable energy sources such as solar, wind, biomass, nuclear, and Hydro do not show statistically significant effects on short run price, suggesting that their incremental variations may be absorbed by the broader market dynamics or their influence manifests more in the long-run equilibrium. In interpretation, renewable sources of energy are the baseline supply and their impact is more prominent in long-term market trends, whereas nonrenewable sources are used to mitigate short run price fluctuations.

Additionally, weather-related factors also play a significant role; for each additional heating degree day, short-run prices increase by 9.67 dollars, and each additional cooling degree day contributes roughly 4.5 dollars to price adjustments. This effect suggests that even modest changes in weather conditions expected to become more frequent with ongoing climate change can significantly influence electricity prices. Such insights are crucial for market participants, as they highlight the need to integrate advanced weather forecasting into risk management frameworks. **Figure 5** represents the impact of both cooling and heating degrees, with the significance being shown in its trend line, where heating degrees play a more significant role in determining price increases than cooling degrees, most likely due to the geography and weather of Texas leaning more towards hotter days.

Seasonal and time effects further increase the model's insights. The April dummy with a coefficient of 557.5844 suggests a notable price increase during the month of 557.584 dollars, as well as the May dummy with a coefficient of 455.6955 suggesting a price increase of 455.696 dollars. The April dummy suggests that, in the short run, there is an upward shift in prices during April likely due to seasonal factors such as increased demand, supply constraints, or even weather-related effects that drive up the cost firms pay on the ORDC curve. Similarly, the May dummy indicates a strong positive price effect in May, reinforcing the idea that these spring months experience higher short-run price changes, possibly due to transitions in energy demand or changes in generation patterns as the weather warms.

While the only significant hourly dummy was 8-11 AM, with a coefficient of –24.357, suggesting lower prices during 8-11 AM by 24.357 dollars potentially reflecting shifts in demand or generation patterns during this four hour period. Weekday effects are also evident, with several day-of-week dummies exhibiting statistically significant negative coefficients that suggest systematic intra-week variations in price changes. These dummy variables are Sunday, Monday, and Tuesday with coefficients -81.1672, -80.8798, -49.6631 respectively. Overall, these significant negative coefficients indicate that firms on the ORDC curve experience a systematic reduction in short-run price changes in dollars during these days, which likely reflects both lower overall demand and specific market or operational dynamics that influence pricing at the start of the week.

The Long Run adjustments finds all variables included besides Hydro at the 1% significance level. Wind speed and Solar Radiance do have an effect in adjusting the price level long term, with a positive coefficient of 210.58 suggesting that for every additional increase in 1 unit increase in wind speed there is an increase in long run price by 210.58 dollars. Solar radiance also has a positive coefficient of .49 suggesting that for every one increase in DHI units that there is an equal increase in price of 0.49 dollars in the long run. You would expect that an increase in these exogenous variables on Wind and Solar generation would decrease in price as it should increase supply.

However, in the long run, if renewable generation is correlated with increased demand or if market structures prevent efficient price reductions, prices may increase instead. For the coefficient on the time option is has a positive impact of 2.59 on price in dollars for every additional increase in its calculation, so as the option to buy increases due to a higher change in price differential then the long run prices increase due to this demand. Although in the short run CDL was insignificant in the long run it is, having a negative coefficient of -263.41 suggesting as seasons change from Hot to Cold or longer to shorter days there is a decrease in price of 263.41 dollars due to demand changes.

Coal and gas both exhibit positive coefficients of 0.0237 and 0.033 respectively, suggesting that for every one unit increase in MW, these increase prices in the long run as they are more costly substitutes for energy sources. Gas CC on the other hand has a negative coefficient of 0.0739 suggesting combined cycled turbines are more cost effective, so for every one unit increase in MW power produced there is a 0.0739 price decline in the long run. Biomass had the second largest value of all energy sources in absolute value terms, holding a coefficient of -0.896, suggesting that Biomass is one of the cheapest of all sources and has one of the greatest impacts on price reduction per unit of MW produced.

"Other" came out on top for being the biggest price reducer has a coefficient of -1.45, so for every MW produced by these various sources it has a decrease in price of 1.45 dollars, suggesting that it is the most cost-effective way to lower prices. Nuclear power had the third largest impact on reducing prices with a negative coefficient of -0.1262, so for every one MW produced there is a reduction in price by 0.1262, which makes sense as one of the most powerful energy sources in modern times. Solar and wind had negative coefficients of -0.096 and -.075 respectively, so for every one MW increase produced by these sources there is an equivalent price drop of 0.096 and 0.075 dollars. These two renewable sources account for half the energy produced in Texas and are the baseline to maintain market equilibrium suggesting that although their impacts are minimal to the other sources of energy, the mass production make up for this difference.

Figure 3 and 4 represent the forecasted price change and its error in prediction from the last 6 months of 2023 respectively. Central to the ECM is the lagged error correction term – 0.0581, which is highly significant and indicates that approximately 25.8% of deviations from the long-run equilibrium are corrected each period, the models forecast RMSE of about 269.55 indicates moderate predictive performance, offering a perspective by linking short-term dynamics with long-run equilibrium adjustments. The IV 2SLS was comparable with a RMSE of 335.35, although with solar radiance and wind speed as instruments primarily addresses simultaneous endogeneity without capturing the inherent adjustment dynamics between the short-run and long-run relationships.

The Error Correction Model provides a dynamic framework by integrating short-run differences with a lagged error correction term. The estimation for the first difference of ORDC yields an R-squared of 16.6%, indicating that the model explains a relatively modest portion of the variation in short-run adjustments, highlighting modest short-run explanatory power while capturing key market adjustments.

Figure 2: Impact of Option Value on Change in ORDC Price

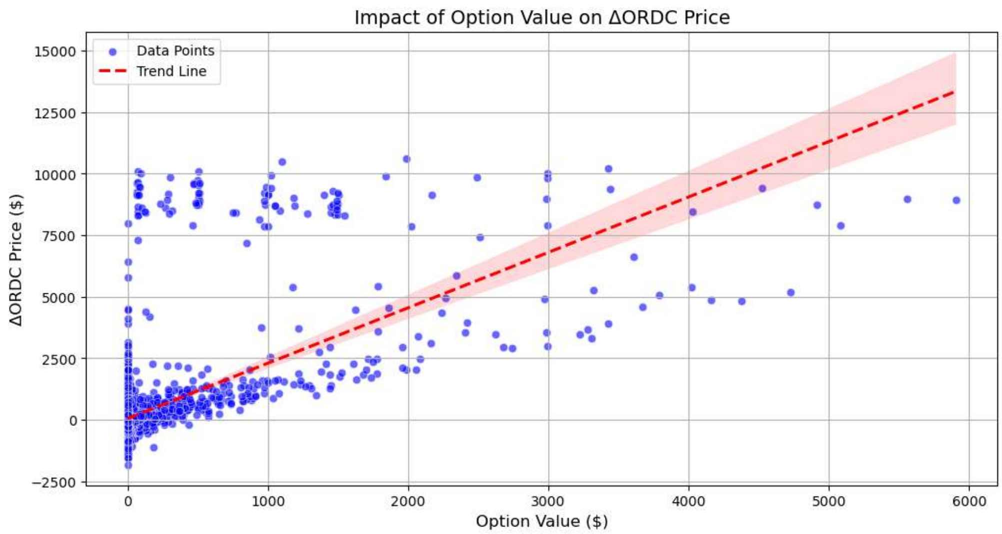


Figure 3: Actual Vs. Forecast

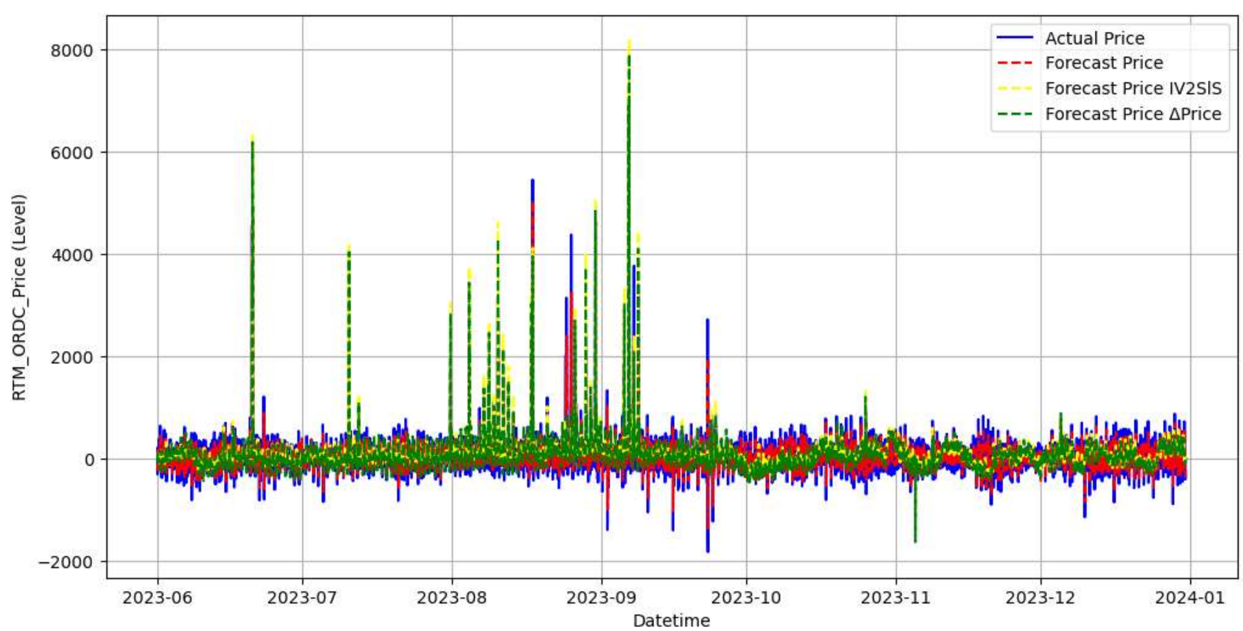


Figure 4: Forecast Errors

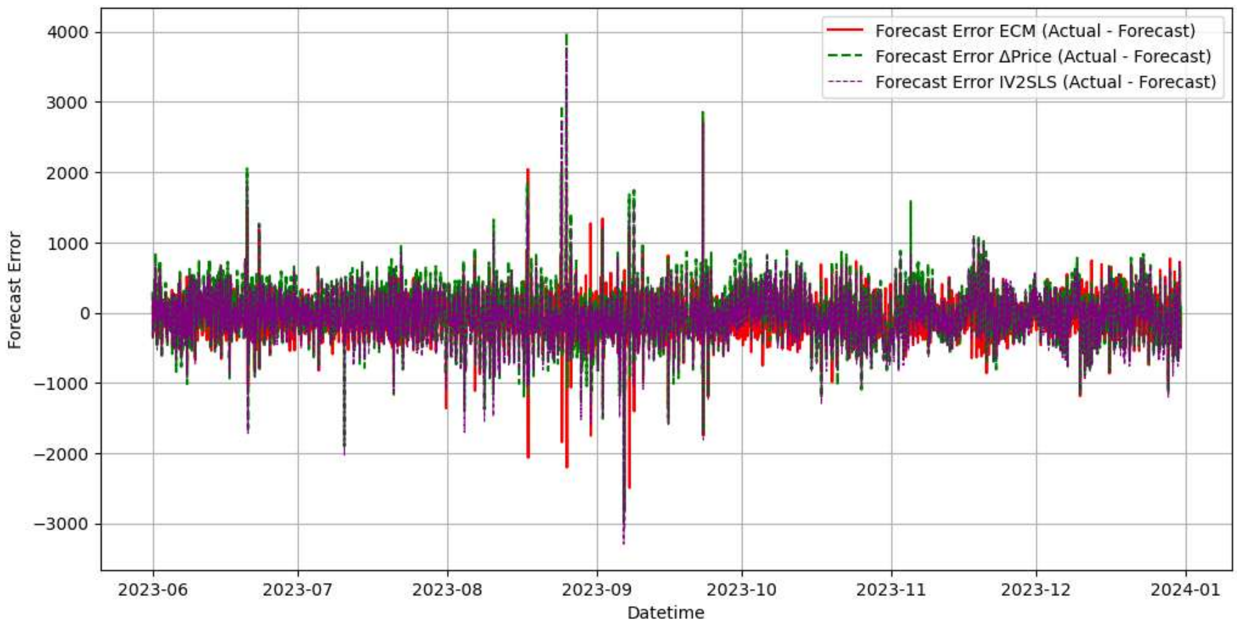


Figure 5: Heating and Cooling Degrees Vs ORDC Price

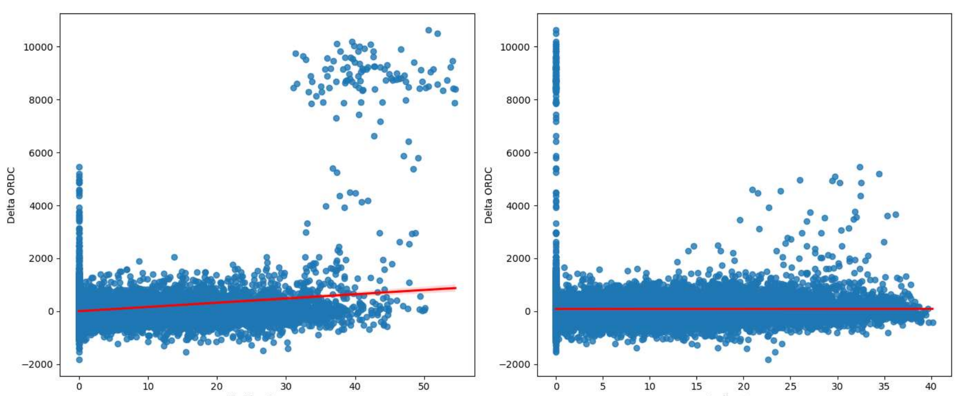


Figure 6: Gas CC and Gas Vs ORDC Price

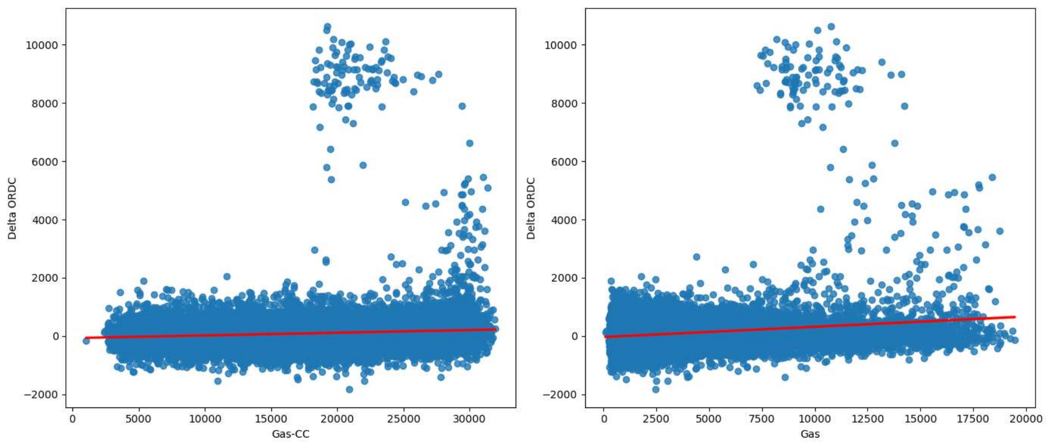
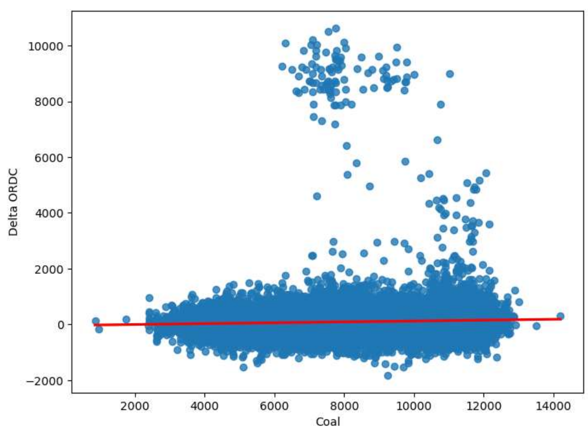


Figure 7: Coal Vs ORDC Price



Policy and Implications:

While this ECM analysis offers valuable insights into the short-run dynamics of electricity prices highlighting the significant roles of fuel mix, weather conditions, and seasonal patterns it is important to recognize that these relationships are subject to change over time. The model captures historical patterns in how these factors influence prices, but market conditions, regulatory shifts, and technological advancements can alter these dynamics. Consequently, firms should view the ECM results as one of several tools in a broader decision-making framework.

For firms purchasing electricity daily, the takeaway is to remain proactive in monitoring the variables that have been identified as significant drivers of price changes. A higher option value indicates that the market expects greater price volatility, signaling that locking in lower DAM prices can mitigate risks associated with sudden price spikes in the RTM. This insight allows you to adjust purchase strategies by increasing your forward purchases or employing hedging instruments, you can lock in favorable rates and reduce exposure to unexpected short-run price surges. Essentially, monitoring the option value can serve as an early warning system, enabling more informed decision-making regarding the timing and scale of electricity purchases to ultimately save money for your company.

Regarding weather-related factors, such as forecasted increases in heating days, the analysis shows that each additional heating degree day tends to drive short-run prices higher by about $9.67. In anticipation of a colder period, it is advisable to wait for the market to adjust due to its decrease in price of $4.72, although. In other words, if a colder period is forecast, the short-run market reaction could drive DAM prices downward, allowing the firm to purchase electricity at a lower cost once the price adjustment takes effect.

Time dummy variables capture changes in electricity prices over different periods, allowing us to identify patterns that occur within the day, across days of the week, and between months. For instance, these results indicate that certain time intervals such as the 8–11 AM period and specific days, like Monday, Tuesday, and Sunday, consistently show statistically significant lower prices compared to baseline periods. Similarly, monthly dummies for April and May show significant positive effects, reflecting seasonal price peaks likely driven by increased demand or supply constraints during those months.

Incorporating time dummy variables into this analysis provides insights for optimizing forecasting strategies. Managers can leverage these temporal patterns to strategically time electricity purchases during periods with historically lower prices such as early mornings or less volatile days to achieve cost savings.

On a policy level, the long-run results reveal that even variables like wind speed and solar radiance, which in theory should lower prices by increasing renewable supply, are instead associated with higher equilibrium prices. This suggests that structural issues such as grid limitations, transmission constraints, and demand surges are influencing market dynamics. Policymakers should consider investing in grid enhancements and storage solutions while reexamining market rules to ensure that the full benefits of renewable generation are realized and that the flexibility premium captured by the option value does not unduly inflate long-run prices.

By doing so, companies can adjust their forecasting strategies such as timing purchases more strategically, diversifying their supply contracts, or employing hedging strategies to mitigate price volatility. This approach will help firms navigate the inherent uncertainty of the market, ensuring that they remain responsive to evolving conditions and better positioned to manage risk effectively

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