Carbon Alignment of Time-of-Use and Critical Peak Pricing: Evidence from Duke Energy's 2023 Tariffs

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May 8, 2025

Abstract: Electricity generation is a major source of CO2 emissions, and aligning residential energy use with low-carbon periods presents an opportunity for emissions reduction. This study examines whether Duke Energy's time-of-use (TOU) and critical peak pricing (CPP) tariffs in North Carolina align with hourly carbon intensity in 2023. Using hourly grid data, matched household demand, and carbon intensity estimates, I assess alignment through regression models, logistic regressions, average marginal effects (AMEs), and a policy misalignment score. Findings reveal that CPP tariffs are more environmentally aligned than TOU tariffs: 65% of CPP peak hours overlap with high-carbon periods, while TOU summer peaks show no significant distinction from off-peak hours. However, neither structure consistently targets clean periods. These misalignments suggest that well-intentioned pricing can inadvertently encourage high-emission consumption. Policy implications include redesigning tariffs using emissions data, implementing carbon labeling, and piloting dynamic, carbon-aware pricing.

Index Terms: carbon intensity

1. Introduction

Climate change and environmental sustainability are pressing global challenges, with the electricity generation sector contributing to approximately 40% of global carbon dioxide emissions from fossil fuels. Carbon intensity, the amount of carbon dioxide emissions per kilowatt-hour (kWh) of electricity consumed, varies throughout the day due to changes in grid mix, demand, and the availability of renewable energy. As the urgency to reduce greenhouse gas emissions grows, there is increasing emphasis on optimizing energy consumption patterns to align with periods of lower carbon intensity, particularly as the grid shifts towards intermittent renewable sources. However, most consumers lack access to real-time environmental signals, limiting their ability to adjust energy use in ways that support climate goals. Understanding the temporal dynamics of carbon intensity in relation to energy pricing structures is essential for designing effective, environmentally informed energy policies.

This study examines whether Duke Energy's time-of-use (TOU) tariffs align with low-carbon periods in North Carolina (NC). TOU tariffs are energy pricing mechanisms designed to shift demand away from peak periods to ensure grid stability, but if misaligned with carbon intensity trends, they may inadvertently incentivize high-emission consumption. Using a year of hourly electricity generation data, this analysis identifies periods of elevated carbon intensity and compares them to peak and off-peak pricing windows. Regression models and descriptive statistics are used to assess the alignment between tariff structures and emissions patterns. The results offer insights into whether existing tariffs effectively balance grid management with emissions reduction, or if adjustments are needed to improve their environmental impact.

This research contributes to the growing literature on climate-informed energy policy by empirically evaluating the relationship between TOU pricing and carbon intensity. While TOU pricing is widely implemented to manage grid demand, few studies assess whether these economic signals also promote emissions reduction. By leveraging hourly electricity generation data, this research provides a novel assessment of how operational tariff windows correspond with periods of high and low carbon intensity. The findings offer actionable insights for utilities, regulators, and policymakers seeking to design tariff structures that advance both grid reliability and environmental sustainability. More broadly, it highlights how temporal misalignments in policy design can yield unintended consequences for both consumer behavior and climate outcomes, informing future integration of emissions-based metrics into energy pricing strategies.

2. Literature Review

Residential energy consumption plays a significant role in global carbon emissions, with the United States contributing approximately 20% of total emissions (EPA, 2022). In response, policymakers and researchers have explored various strategies to influence consumer behavior and reduce emissions. One such strategy is the implementation of time-of-use (TOU) tariffs, which incentivize consumers to shift their energy consumption away from peak periods, thereby stabilizing grid demand. However, these tariffs do not always align with environmental objectives, as they may encourage consumption during periods of high carbon intensity. This misalignment has raised concerns about the environmental efficacy of TOU tariffs, particularly as smart technologies and electric vehicles (EVs) increase electricity demand and grid complexity (Miller et al., 2020; Siddik et al., 2024).

Carbon intensity is a key metric in assessing the sustainability of energy generation (EIA, 2024). It fluctuates based on the energy mix supplying the grid, with coal-fired electricity being significantly more carbon-intensive than solar or wind power (Siddik et al., 2024; Huber et al., 2023). However, real-time carbon intensity data is often inaccessible to consumers, preventing them from aligning their energy consumption with lower-carbon periods (Daneshzand et al., 2023; de Chalendar et al., 2019). This lack of information contributes to suboptimal energy consumption patterns, undermining the potential environmental benefits of TOU pricing.

Despite growing evidence of consumer responsiveness to TOU pricing (Apostolaki-Iosifidou et al., 2020), these mechanisms may fail to achieve climate goals if they incentivize usage during carbon-intensive periods (Zivin et al., 2014; Zohrabian et al., 2023). Studies by Siddik et al. (2024) and Miller et al. (2020) argue that while TOU tariffs balance grid demand, they often neglect carbon intensity, limiting their effectiveness in achieving environmental goals. These findings underscore the need for tariff structures that incorporate carbon intensity data to better align consumer behavior with environmental sustainability (Daneshzand et al., 2023; Miller et al., 2020).

As the urgency to mitigate climate change grows, understanding the relationship between residential energy consumption and carbon intensity becomes critical. Research has shown that consumers respond to electricity price signals imposed in TOU tariffs. While this approach is designed to prevent electric grid overload and blackouts (Apostolaki-Iosifidou et al., 2020), TOU tariffs do not always align with environmental objectives, which can inadvertently increase emissions if those off-peak periods rely on fossil fuels (Zivin et al., 2014; Zohrabian et al., 2023). While Siddik et al. (2024) argue that TOU tariffs are beneficial in terms of balancing grid demand, the failure to account for the carbon intensity of energy during different periods limits their effectiveness in achieving environmental goals. This misalignment underscores the need for tariff structures that incorporate carbon intensity considerations, particularly as smart technologies and EVs increase electricity demand (Miller et al., 2020; Siddik et al., 2024). Daneshzand et al. (2023) and Miller et al. (2020) argue that TOU tariffs must evolve to integrate carbon intensity data to avoid incentivizing energy consumption at times that are detrimental to the environment and provide consumers with better information on how their consumption patterns align with the environmental impact of energy use.

Several studies have highlighted the importance of dynamic pricing models that incorporate carbon intensity considerations. Miller et al. (2020) and Dixon et al. (2020) analyzed household- and neighborhood-level emissions data, finding that carbon intensity fluctuates significantly throughout the day and across regions. Similarly, Li et al. (2023) and Huber et al. (2021) emphasized how changes in grid mix influence emissions, reinforcing the need to align energy pricing with the availability of low-carbon energy. The policy implications of these findings are significant: integrating carbon intensity-based dynamic pricing could help utilities optimize grid management while reducing emissions (Kucuksari & Erdogan, 2021).

Although international research has assessed the environmental implications of tariff-driven energy use (Daneshzand et al., 2023; Li, 2023), few studies have focused on U.S. utilities, particularly Duke Energy, a major provider in the southeastern United States. This study addresses this gap by evaluating Duke Energy's TOU pricing structure in relation to hourly carbon intensity trends. By analyzing whether TOU pricing signals align with low-emission periods, the study provides insight into the unintended environmental consequences of current rate designs. While TOU tariffs are widely favored for demand management, their effectiveness in reducing emissions hinges on whether pricing windows correspond with clean energy availability. Without this alignment, well-meaning policies may inadvertently increase emissions, potentially undermining trust in utilities and public sustainability initiatives. The findings of this study aim to inform utility design and policy revisions that better align economic incentives with environmental goals.

3. Hypotheses

- Tariff Structure and Carbon Intensity
  - H_0: There is no significant association between tariff structures and carbon intensity.
  - H_1: Tariff structures are significantly associated with carbon intensity.
- Seasonality and Carbon Intensity
  - H_0: Carbon intensity does not vary seasonally.
  - H_1: Carbon intensity varies by season due to differences in grid mix and renewable generation.
- Temporal Variation in Carbon Intensity
  - H_0: Time of day has no significant effect on carbon intensity.
  - H_1: Carbon intensity varies significantly by hour due to changes in grid mix and demand.

4. Data

This analysis draws on multiple datasets to examine the relationship between tariff structures and carbon intensity in residential energy consumption for the year 2023. The primary data sources include the U.S. Energy Information Administration (EIA), Duke Energy, and carbon intensity estimates based on emission factors from Huber et al. (2021). Hourly data on electricity generation by fuel type for the Duke Energy grid mix was obtained from the EIA. This dataset captures the megawatts (MW) generated by various energy sources, including natural gas, coal, nuclear, solar, hydro, and other sources, for every hour except the houring ending 2:00 am March 12th in 2023.

Total emissions per hour were calculated by multiplying the MW generated by each energy source by its corresponding carbon intensity factor, as reported by Huber et al. (2021). The emission factors used are shown in Table 1. The sum of these emissions was then divided by the total generation for that hour to obtain a measure of hourly carbon intensity in grams of CO2 per kilowatt-hour (gCO2/kWh):

$$\text{Hourly Carbon Intensity} = \frac{\text{Hourly Total Emissions}}{\text{Hourly Total Generation}}$$

Tariff data were collected from Duke Energy's 2023 consumer reports for both the Duke Energy Progress (DEP) and Duke Energy Carolinas (DEC) service territories. These reports include details on standard rates, time-of-use (TOU) pricing, and critical peak pricing (CPP). Table 2 summarizes key tariff periods under each program, which vary by season and region. A sample of 40 residential customers was selected from the DEP and DEC territories. Each customer was enrolled in one of the subsequent rate plans. Their hourly energy consumption in 2023 was matched with the applicable tariff to determine their price exposure at each hour. This allows for an analysis of how tariff structures influence energy usage behavior and, subsequently, household-level carbon intensity.

TABLE I
TABLE 1: CARBON INTENSITY BY ENERGY SOURCE

Energy Source	Carbon Intensity (gCO_2/kWh)
Coal	832
Gas	410
Other	971
Nuclear	0
Solar	0
Hydro	0

TABLE II
NORTH CAROLINA TIME-OF-USE (TOU) FRAMEWORK

Period	Days	RTOU (DEP)
Peak Summer	Mon–Fri (excl. Holidays)	1–6 PM
Peak Winter	Mon–Fri (excl. Holidays)	6–9 AM
Shoulder Summer	All Days	11 AM–1 PM, 6–8 PM
Shoulder Winter	All Days	9 AM–12 PM, 5–8 PM
Off-Peak Summer	All Days	All hours not Peak or Shoulder

Note: Holidays include New Year's Day, Good Friday, Memorial Day, Independence Day, Labor Day, Thanksgiving Day, Day after Thanksgiving, and Christmas Day. Observed on Friday if on Saturday, Monday if on Sunday.

TABLE III
NORTH CAROLINA CRITICAL PEAK PRICING (CPP) FRAMEWORKS BY REGION

Period	Days	RSTCP (ALL)	RSTC (DEP)	RETC (DEC)
Peak Summer	Mon–Fri (excl. Holidays)	6–9 PM	6–9 PM	6–9 PM
Peak Winter	Mon–Fri (excl. Holidays)	6–9 AM	6–9 AM	6–9 AM
Discount Summer	All Days	1–6 AM	1–6 AM	1–6 AM
Discount Winter	All Days	1–6 AM, 11 AM–4 PM	1–3 AM, 11 AM–4 PM	1–3 AM, 11 AM–4 PM
Off-Peak	All Days	Other Hours	Other Hours	Other Hours

Note: Holidays include New Year's Day, Good Friday, Memorial Day, Independence Day, Labor Day, Thanksgiving Day, Day after Thanksgiving, and Christmas Day. Observed on Friday if on Saturday, Monday if on Sunday.

5. Methodology

This study investigates how residential energy demand interacts with dynamic carbon intensity patterns and tariff structures. I utilize a directed acyclic graph (DAG) to map causal relationships between these variables, revealing whether tariffs can reshape demand patterns, or if factors like grid mix and inflexible consumption habits ultimately dictate carbon outcomes. The DAG explicitly models how tariff structures alter demand and carbon intensity, testing the hypothesis that such interventions significantly alter carbon intensity (H1). It also captures seasonal dynamics, probing whether observed variations in carbon intensity stem from grid mix changes or inflexible demand patterns (H2). Finally, the study explores temporal variation in carbon intensity, investigating whether time of day significantly affects carbon intensity due to changes in grid mix and demand (H3). By analyzing Duke Energy's hourly demand and carbon intensity data through a DAG, this study investigates whether certain tariff structures reduce carbon intensity by shifting energy use to cleaner periods, or if seasonal variations in carbon intensity play a more decisive role.

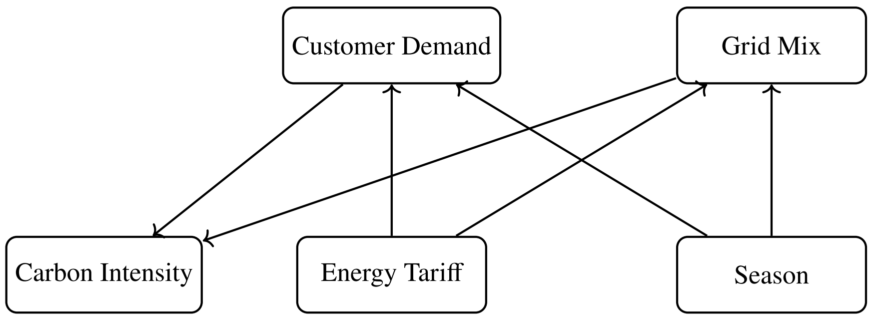

Fig. 1. Directed Acyclic Graph (DAG) illustrating hypothesized relationships.

To investigate these relationships, the study integrates multiple regression models, mixed-effects models, and diagnostic tests to identify the key drivers of carbon intensity in relation to tariff types and consumer behavior. The primary dataset includes detailed information on energy generation, emissions, energy tariffs, and time. The first step in the analysis involves creating several derived variables to capture the temporal and tariff-related aspects of energy consumption and carbon intensity. For example, binary variables are introduced to identify whether data points correspond to summer rate periods. Summer rates are defined as being applicable from April to September for TOU tariff plans and from May to September for CPP tariff plans.

5.1. Multiple Linear Regression

To estimate the effects of tariff structures, seasonality, and electricity consumption on carbon intensity, a stepwise multiple linear regression model is employed. To test the relationships between tariff structures, seasonal effects, time of day, and carbon intensity, a stepwise modeling strategy is employed for clarity, first specifying a baseline model and progressively incorporating additional variables to observe changes in explanatory power and coefficients. The full model is specified as:

$$\text{Carbon Intensity}_{it} = \beta_0 + \beta_1 \cdot \text{TariffStatus}_{jt} + \beta_2 \cdot \text{Season}_t + \beta_3 \cdot \text{kWh}_{it} + \beta_4 \cdot \text{Hour}_t + \epsilon_{it} \tag{1}$$

Where tariff factor represents the categorical variable for different pricing schemes j at time t, including TOU and CPP peak and off-peak windows, season is a binary indicator for summer rate applicability, kWh represents electricity consumption of individual i at time t, hour represents the hour of the day at time t, and epsilon is the error term for individual i at time t.

To ensure that multicollinearity did not skew the results, the Variance Inflation Factor (VIF) for each independent variable was calculated. No VIF value exceeded a threshold of 4, indicating that multicollinearity was not a significant concern in the model. To account for serial correlation and heteroskedasticity in the data, we conducted diagnostic tests. The Durbin–Watson test revealed strong evidence of positive autocorrelation ($DW = 0.074,\ p < 0.001$), while the Studentized Breusch–Pagan test indicated significant heteroskedasticity ($BP = 12251,\ df = 32,\ p < 0.001$). To ensure valid inference, we report robust standard errors using Heteroskedasticity- and Autocorrelation-Consistent (HAC) estimators.

5.2. Logitistic Regression

To evaluate the likelihood that a given hour falls into the top quartile of carbon intensity, logistic regression models were employed. The binary dependent variable high carbon was coded as 1 for hours in the highest-carbon quartile and 0 otherwise. Independent variables included time-of-use (TOU) or critical peak pricing (CPP) tariff status, hourly energy consumption (kWh), and a binary indicator for summer season (summer_rate). Separate logistic regression models were estimated for TOU and CPP structures. The models take the general form:

$$
\begin{aligned}
&\big(P(\text{HighCarbon}_i = 1)\big) = \beta_0 + \beta_1 \cdot \text{TariffStatus}_i + \beta_2 \cdot \text{Hour}_i + \beta_3 \cdot (\text{TariffStatus}_i \times \text{Hour}_i) \\
&+\beta_4 \cdot \text{kWh}_i + \beta_5 \cdot \text{Season}_i
\end{aligned}
$$

Where (P(HighCarbon=1) is the probability that the hour is high carbon, TarrifStatus refers to TOU or CPP categorical indicators, Hour is hour of the day, kWh is hourly household energy consumption, and summer rate is an indicator for the summer season. The baseline category for TOU periods was TOU Off-Peak, while the baseline for CPP periods was CPP Discount Winter, allowing all other tariff effects to be interpreted relative to these reference conditions. Both models were estimated using the generalized linear model (GLM) framework with a binomial family and a logit link function. Model fit was assessed using residual deviance and Akaike Information Criterion (AIC).

5.3. Average Marginal Effects (AMEs)

To enhance interpretability of the logistic models, Average Marginal Effects (AMEs) were computed for each predictor. AMEs represent the average change in the predicted probability of a high-carbon hour associated with a one-unit change in each independent variable, holding all other variables constant.

5.4. Policy Metric Misalignment Score

To evaluate the alignment of time-based electricity pricing structures with environmental objectives, I developed a tariff misalignment score. This metric quantifies the extent to which peak and discount pricing periods overlap with cleaner electricity availability. Specifically, the top 25% of hours by carbon intensity were classified as "high-carbon" periods. For each tariff category, the misalignment score is calculated as:

$$\text{Misalignment} = 1 - \frac{\text{Clean Hours}}{\text{Total Hours}}$$

This formula captures the proportion of peak hours that occur during high-carbon periods, where a higher score indicates poorer environmental targeting. Conversely, a lower misalignment score implies better alignment between pricing signals and carbon intensity, thereby representing a more environmentally conscious design. The metric was applied separately to CPP and TOU structures to compare their relative effectiveness in discouraging energy consumption during high-emission periods.

6. Results

6.1. Descriptive Results

The analysis reveals a consistent trend of higher median carbon intensity during the summer months compared to the winter months. The increased demand for cooling during the summer, coupled with a potential greater reliance on carbon-intensive energy sources during peak times, contributes to this trend. These findings suggest that both higher energy demand, and a shift toward more carbon-intensive generation methods to meet such demand, in the summer are key drivers of the elevated carbon intensity observed in these months.

Figure 2 illustrates a heatmap visualizing the average hourly carbon intensity (measured in gCO/kWh) for the year 2023 highlights seasonal variations in energy demand and carbon intensity. The x-axis represents the hours of the day (from 0 to 23), while the y-axis lists the months of the year (from January to December). The color intensity of the heatmap reflects carbon intensity values, with lighter colors representing higher carbon intensity and darker colors indicating lower carbon intensity. The heatmap clearly demonstrates distinct patterns of carbon intensity across the year. Higher carbon intensity is evident during the summer months, particularly in July and August, when electricity demand for cooling is at its peak. Conversely, lower carbon intensity is observed in the spring months, such as April and May, when milder temperatures reduce the need for heating or cooling. Similarly, winter months show reduced carbon intensity, possibly due to a combination of cleaner energy sources and lower overall energy consumption during this period.

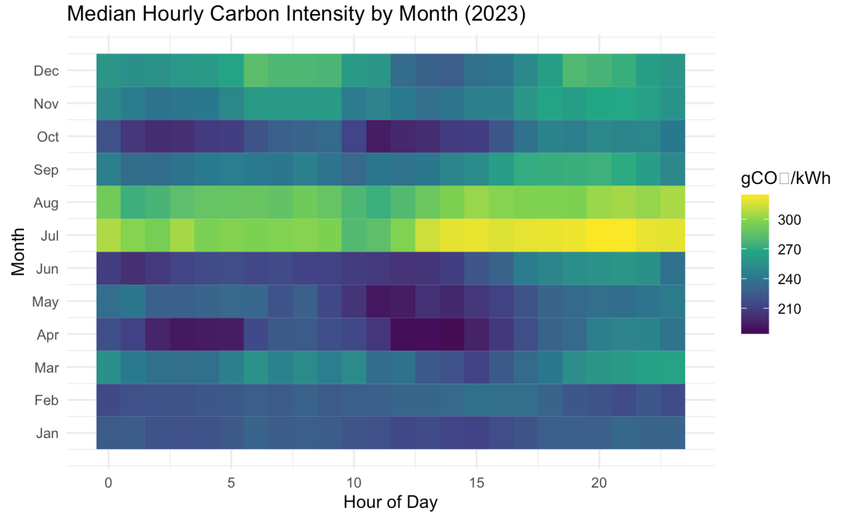

Fig. 2. Median Hourly Carbon Intensity by Month

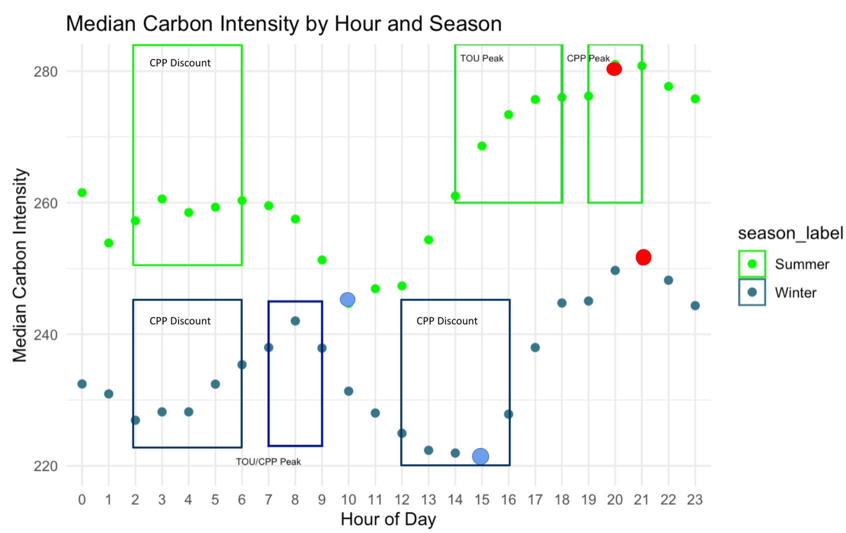

Fig. 3. Median Hourly Carbon Intensity by Hour and Season

Hourly patterns of carbon intensity differ notably between summer and winter, with distinct peak and trough periods in each season. In summer, CPP peak windows effectively capture the highest-carbon hour (20:00), however, CPP discount periods in summer do not align with the cleaner afternoon hours, suggesting missed opportunities for promoting low-carbon consumption. In winter, CPP discount periods coincide with the lowest-carbon afternoon hours, however, CPP and TOU peak windows capture the morning peak in carbon intensity (07:00-09:00) but do not capture the evening peak (21:00), leaving substantial emissions reductions potential unrealized during nighttime hours. Similarly, TOU peak periods in summer avoid the highest-carbon evening hours but similarly fail to target the cleanest periods for shifting demand, which allow TOU off-peak periods to also capture high carbon intensity periods, signifying a large misalignment. Analysis of tariff period alignment revealed mixed performance in targeting low- versus high-carbon periods. Time-of-Use (TOU) peak hours exhibited moderate alignment with high-carbon periods, with 62.8% of TOU peak hours falling outside the dirtiest 25% of carbon intensity hours. In contrast, Critical Peak Pricing (CPP) peak hours demonstrated weaker environmental alignment: only 35% of CPP peak hours fell outside high-carbon periods, suggesting that CPP peak penalties often coincided with the grid's dirtiest periods. However, CPP discount hours performed more favorably, with 79.4% of discount hours aligning with cleaner periods. Thus, while discount windows were relatively well-timed to low-carbon conditions, the alignment of penalty periods—particularly under CPP structures—was suboptimal from an environmental perspective.

6.2. Regression Analysis of Carbon Intensity Determinants

To assess the determinants of hourly carbon intensity, multiple linear regression models with robust standard errors were estimated. Table 3 presents the results from four OLS regression models estimating the relationship between carbon intensity and various predictors of interest. All models are estimated with heteroskedasticity-robust standard errors (HC3), and the dependent variable is hourly carbon intensity (gCO2/kWh). The modeling strategy proceeds in a stepwise fashion, beginning with tariff structure variables and sequentially adding controls. Model 1 includes only tariff structure indicators. Several tariff types are significantly associated with changes in carbon intensity. For example, CPP Summer Peak hours are associated with a 29.36 gCO2/kWh increase in carbon intensity, while CPP Winter Discount hours are associated with a 16.56 gCO2/kWh decrease. Winter peaks also show misalignment with negative and statistically significant coefficients. Summer discount periods also reveal a significant and positive relationship with carbon intensity, which is a counterintuitive result given that these periods are intended to encourage consumption. Although tariff structures are significantly associated with carbon intensity, their explanatory power is modest (R^2 = 0.038), suggesting that current pricing schemes are not explicitly aligned with real-time emissions.

Model 2 isolates the effect of hourly electricity consumption (kWh) on carbon intensity, revealing a strong and positive relationship ($\beta = 2.67$, $p < 0.001$), with a modest model fit ($R^2 = 0.057$). This specification confirms that higher consumption aligns with higher carbon intensity, but a small sample of residential demand is not the key driver. Model 3 uses seasonal and temporal controls, with the summer season showing a significant relationship with carbon intensity ($\beta = 23.08$, $p < 0.001$). Model 3 provides a better model fit ($R^2 = 0.064$), suggesting that season has a stronger relationship with carbon intensity than residential demand or tariffs.

Model 4 presents the fully specified model, combining tariff structure, consumption, and temporal controls. While TOU peak hours in the summer are significantly associated with high-carbon periods, the CPP/TOU winter peak hours show a negative or statistically insignificant association relative to off-peak and discount hours, suggesting a seasonal misalignment between tariff structures and carbon intensity.This model yields (R^2 = 0.62), which reflects the lack of intentional design linking tariff structures to real-time grid carbon intensity. This gap underscores the potential for improvement through more carbon-aware pricing mechanisms or consumer-facing information. Summer peak periods remain positively associated with carbon intensity, even after adjustment. However, winter peaks and the summer discount period show carbon misalignment with tariff structures.

6.3. Predicting High-Carbon Periods

Logistic regression models were estimated to predict the probability that an hour would fall into the highest-carbon quartile. Results show that TOU summer peak hours are less likely to coincide with high-carbon periods compared to CPP summer peaks, suggesting weaker alignment. However, in winter, TOU and CPP peak hours exhibit similar likelihoods of capturing high-carbon periods. Additionally, summer discount periods are more likely to overlap with high-carbon hours than their winter counterparts. These results also align with the broader pattern that summertime and elevated energy use are both significantly and positively associated with high-carbon intensity periods.

The Average Marginal Effects (AMEs) in Table VI further quantified these associations. A TOU Peak Summer period increased the probability of a high-carbon hour by 5.7%, while a TOU Peak Winter period increased the probability by 13.8% relative to off-peak hours. Under CPP structures, the CPP Peak Summer

TABLE IV
Model Comparison with Robust Standard Errors

	(1: Tariff)	(2: kWh)	(3: Seasonality)	(4: Combined)
Dependent variable:		*Carbon Intensity*		
TOU Peak Summer	10.030***			9.745***
	(0.931)			(0.905)
TOU Peak Winter	-3.822***			-0.734
	(0.889)			(0.881)
TOU Off-Peak	-8.866***			-8.560***
	(0.187)			(0.184)
CPP Summer Peak	29.356***			27.178***
	(0.465)			(0.456)
CPP Winter Peak	-4.470***			-3.166***
	(0.375)			(0.370)
CPP Summer Discount	15.249***			16.195***
	(0.356)			(0.355)
CPP Winter Discount	-16.561***			-14.953***
	(0.255)			(0.255)
kWh		2.668***		2.842***
		(0.033)		(0.032)
Summer Rate			23.082***	
			(0.152)	
Constant	253.145***	240.428***	236.199***	246.797***
	(0.167)	(0.369)	(0.091)	(0.178)
Observations	350,400	350,400	350,400	350,400
R^2	0.038	0.057	0.064	0.062
Adjusted R^2	0.038	0.057	0.064	0.062
Residual Std. Error	44.461 (df = 350392)	44.016 (df = 350375)	43.844 (df = 350398)	43.897 (df = 350391)
F Statistic	1,953.926*** (df = 7; 350392)	878.902*** (df = 24; 350375)	23,995.610*** (df = 1; 350398)	2,887.713*** (df = 8; 350391)

Note: *p¡0.05; **p¡0.01; ***p¡0.001

period raised the probability by 16.2%, and the CPP Peak Winter period by 13.3% compared to the CPP Discount Winter period. CPP Discount Summer periods were also associated with a 5.7% increase in the probability of a high-carbon hour compared to the winter discount period, suggesting an imperfect targeting of cleaner periods in summer.

6.4. Misalignment Scores

The misalignment analysis reveals that CPP structures show stronger alignment with carbon intensity patterns compared to TOU rates. Among CPP peak hours, 65% overlapped with high-carbon periods, resulting in an alignment score of 35%. This indicates that CPP peak pricing effectively targets periods of high emissions, thereby incentivizing demand reduction when it is most environmentally beneficial. Furthermore, 79.4% of CPP discount hours occurred during cleaner periods, reinforcing the structure's effectiveness in encouraging consumption during lower-carbon windows.

In contrast, TOU peak hours exhibited a less targeted alignment, with 62.8% falling outside of high-carbon

TABLE V
LOGIT MODEL COEFFICIENTS

	(1: TOU)	(2: CPP)
Dependent variable:	*High Carbon Outcome*	
TOU Peak Summer	0.314***	
	(0.036)	
TOU Peak Winter	0.718***	
	(0.054)	
CPP Summer Discount		0.349***
		(0.026)
CPP Peak Summer		0.895***
		(0.030)
CPP Peak Winter		0.752***
		(0.029)
CPP Off Peak		0.263***
		(0.019)
kWh	0.114***	0.113***
	(0.001)	(0.002)
Summer Rate	1.262***	1.211***
	(0.008)	(0.009)
Constant	-2.027***	-2.275***
	(0.007)	(0.018)
Observations	350,400	350,400
Log Likelihood	-181,061.000	-180,449.800
Akaike Inf. Crit.	362,132.000	360,913.500

Note: *p¡0.05; **p¡0.01; ***p¡0.001

TABLE VI
AVERAGE MARGINAL EFFECTS (AMES) FOR TOU AND CPP MODELS

Model	**Factor**	**AME**	**SE**	**z**	**p**	**Lower**	**Upper**
TOU Model	kWh	0.019	0.000	78.241	0	0.019	0.020
TOU Model	summer_rate	0.215	0.001	164.968	0	0.212	0.217
TOU Model	TOU_StatusTOU_Peak_Summer	0.057	0.007	8.195	0	0.043	0.070
TOU Model	TOU_StatusTOU_Peak_Winter	0.138	0.011	12.041	0	0.116	0.161
CPP Model	CPP_StatusCPP_Discount_Summer	0.057	0.004	13.621	0	0.049	0.065
CPP Model	CPP_StatusCPP_Peak_Summer	0.162	0.006	29.080	0	0.151	0.173
CPP Model	CPP_StatusCPP_Peak_Winter	0.133	0.005	25.157	0	0.123	0.143
CPP Model	CPP_StatusOther	0.042	0.003	14.266	0	0.036	0.048
CPP Model	kWh	0.019	0.000	76.734	0	0.019	0.020
CPP Model	summer_rate	0.205	0.001	138.976	0	0.202	0.208

periods. While this suggests some effort to avoid peak pricing during high-emission hours, the lower alignment relative to CPP implies reduced environmental impact. Overall, these findings demonstrate that CPP tariffs are more carbon-conscious than TOU structures, better aligning price signals with emissions intensity and supporting their potential as tools for carbon reduction in electricity demand management.

7. Discussion

This study evaluates the alignment between Duke Energy's time-based pricing structures and the carbon intensity of electricity generation, offering both empirical insights and policy-relevant conclusions. The findings reveal significant temporal mismatches between tariff windows and periods of lower carbon intensity, raising questions about the environmental effectiveness of current TOU and CPP designs. Such findings underscore the potential for demand-side interventions to help mitigate grid carbon intensity.

Interestingly, TOU tariffs appear to penalize afternoon energy usage, which, upon closer examination, reveals a misalignment between low-carbon hours and tariff incentives. Rather than incentivizing low-carbon periods, TOU seems to disproportionately incentivize hours after 6:00 pm, a time when carbon intensity tends to be higher. This issue is somewhat alleviated in the winter months, as more carbon-intensive periods coincide with morning hours. However, CPP rates do a better job of penalizing usage during the evening hours when carbon intensity is at its peak, which aligns well with the objective of reducing emissions. However, summer CPP rates fail to incorporate afternoon hours, which are generally lower in carbon intensity, leading to higher overall carbon intensity compared to winter rates. This, combined with typical seasonal adjustments, results in summer tariffs contributing to a greater environmental impact.

The logistic regression results further provide evidence that tariff structures are poorly designed to disincentivize high-carbon hours. While CPP peak periods tend to capture high-carbon hours, TOU peak summer periods show no significant difference from off-peak hours, highlighting a pronounced misalignment. This suggests that while CPP structures penalize usage during carbon-intensive hours, TOU structures may inadvertently fail to discourage, and even enable, consumption during high-emission periods, particularly in summer.

The Average Marginal Effects (AMEs) further emphasize these alignments and disparities. For instance, being in a CPP Peak Summer window increases the probability of a high-carbon hour by 16.2%, while the CPP Peak Winter period raises it by 13.3%, relative to the cleanest reference period CPP Discount Winter, which suggests it does penalize for high carbon periods. By contrast, TOU Peak Summer only increases high-carbon likelihood by 5.7%, indicating weaker environmental targeting. Notably, CPP Summer Discount periods are associated with a smaller but still positive increase in high-carbon probability (5.7%), which suggests that even discount windows are not perfectly timed to clean periods.

Lastly, to quantify environmental alignment more directly, a Tariff Misalignment Score was developed, revealing that CPP peak hours overlapped with high-carbon periods 65% of the time, indicating strong alignment with high carbon periods. CPP discount hours also overlapped with clean periods 79.4% of the time, indicating strong alignment with low-carbon availability. In contrast, TOU peak hours fell outside high-carbon periods 62.8% of the time, suggesting poor alignment with environmental goals. These results imply that CPP is better structured than TOU for carbon-conscious demand management, as its penalty windows align more consistently with emissions peaks. However, no current structure achieves optimal alignment, and even discount windows, designed to encourage consumption, can still occur during periods of elevated carbon intensity.

8. Limitations

This study has several limitations that should be acknowledged when interpreting its findings. First, the estimation of hourly carbon intensity is based on emission factors reported by Huber et al. (2021), which assume average fuel mix characteristics and generation efficiencies across the year. While this provides a practical and widely used approach to estimating carbon intensity, it does not reflect the marginal emissions associated with incremental changes in load. As such, the analysis may understate or overstate the emissions impact of consumption at specific hours, particularly during periods of rapid generation ramping or supply constraints. Similarly, the use of hourly average emissions data may miss real-time grid fluctuations, limiting the granularity of environmental insights.

Second, the analysis is geographically and temporally bounded, focusing on North Carolina's electricity grid in the year 2023. This context reflects particular weather patterns, grid dynamics, and policy conditions relevant to Duke Energy during that period. While the findings offer a valuable snapshot of how tariff structures relate to carbon intensity in this setting, they may not generalize to future years or to regions with different generation portfolios, regulatory environments, or demand-side characteristics.

Third, although this study evaluates the temporal alignment between utility-defined rate periods and grid emissions, it does not directly assess whether these tariff structures influence consumer behavior or reduce actual carbon emissions. The analysis is descriptive and structural rather than causal—it identifies whether tariffs could incentivize low-carbon consumption based on timing, not whether they do in practice. While household-level demand data is used, the behaviors observed reflect existing tariff structures, and no quasi-experimental variation or behavioral interventions were tested. As such, the study does not evaluate demand elasticity or simulate how consumers might respond under alternative pricing or carbon-labeling scenarios.

Fourth, the analytical approach relies on multiple regression and logistic regression techniques, which, while suitable for modeling associations, are constrained by the limitations of observational data. Unobserved confounders, such as weather conditions, localized outages, or real-time market prices, may influence both consumption and carbon intensity but are not fully captured in the model. Additionally, the models assume linear and additive relationships between predictors and outcomes, which may oversimplify the complexity of electricity demand, grid dispatch, and emissions generation. While diagnostic tests and robustness checks were conducted to address issues such as multicollinearity and heteroskedasticity, the results should be interpreted as associational rather than causal.

Finally, the study assumes that existing TOU and CPP tariffs are the relevant baseline for analysis, but it does not simulate or compare alternative tariff structures that might better align with emissions patterns. Nor does it account for socioeconomic or demographic heterogeneity that may affect the ability of households to respond to time- or emissions-based pricing. Without this behavioral segmentation, the findings cannot speak to the equity implications of emissions-aligned pricing or carbon labeling. Addressing these limitations in future research—particularly through experimental designs, marginal emissions modeling, and simulations of dynamic tariffs—would strengthen the evidence base for climate-informed utility pricing and policy design.

9. Policy Implications

These findings have direct implications for utility rate design and climate policy. First, the misalignment between TOU windows and carbon intensity suggests a missed opportunity for emissions mitigation through pricing signals. TOU tariffs are popular for managing grid reliability, but unless they are designed with environmental indicators in mind, they may incentivize demand shifting that is neutral or even harmful from a carbon standpoint. Utilities and regulators could benefit from:

- Redesigning TOU and CPP windows using historical and forecasted carbon intensity data, ensuring peak pricing overlaps with high-emission periods and discount pricing targets low-carbon windows.
- Incorporating real-time carbon labeling into consumer energy interfaces to support more informed behavioral shifts.
- Piloting carbon-informed dynamic pricing schemes, where consumers are exposed to variable rates based on both grid stress and emissions intensity.

This study illustrates how well-intentioned policies can yield unintended consequences when designed without integrating environmental dynamics. From a regulatory perspective, these findings suggest a need to update tariff frameworks to incorporate environmental objectives explicitly. As jurisdictions set increasingly ambitious climate targets, regulators should consider whether rate structures are facilitating or hindering emissions reductions. As utilities integrate more intermittent renewables, the temporal variability in carbon intensity will only increase, heightening the importance of designing pricing strategies that are flexible, responsive, and environmentally coherent. Carbon-aligned pricing models could serve as a valuable policy lever.

10. Future Research

While this study provides a robust foundation for understanding the misalignment between energy tariffs and carbon intensity, several avenues for future research are essential to advancing more climate-conscious energy systems. First, behavioral approaches must continue to explore how consumers respond to pollution information in decision-making contexts. Structural equation modeling (SEM) grounded in the Theory of Planned Behavior (Ajzen, 1991; Yadav & Pathak, 2016) offers a powerful framework for understanding the intention to shift electricity usage based on carbon labeling. Future work should expand upon this framework to evaluate how attitudes, perceived behavioral control, environmental concern, and trust in utilities shape responsiveness to carbon signals. By integrating SEM with survey and usage data, researchers can assess the psychological drivers of energy behavior and identify which consumer segments are most likely to respond to carbon-labeled pricing.

Second, more work is needed to design and simulate alternative tariff schedules that explicitly align with low-emission periods. Rather than relying on static peak/off-peak windows, future studies could use historical grid data to identify optimal consumption windows based on hourly carbon intensity and renewable availability. Simulations of carbon-informed tariffs should evaluate not only potential emissions reductions, but also trade-offs across competing objectives—namely load management, equity, and consumer cost. Scenario-based modeling could help utilities and regulators balance these priorities under different policy constraints or technological adoption rates, including the growing integration of electric vehicles and distributed energy resources.

Third, future research should move beyond average carbon intensity calculations and adopt marginal emissions metrics that more accurately reflect the emissions impact of incremental electricity use. Marginal emissions, when paired with local marginal price (LMP) carbon signals, offer a dynamic and granular view of the grid's environmental profile. Incorporating real-time or forecasted carbon signals into pricing models could enable more responsive and environmentally effective demand response strategies. For example, pricing structures that shift in near-real-time based on marginal emissions could better target high-impact reduction periods while maintaining grid reliability. This shift would also support the development of carbon-aware automation tools for smart appliances and electric vehicle charging systems.

Together, these future directions underscore the importance of interdisciplinary research that bridges behavioral science, engineering, and policy design. By combining dynamic pricing innovations, robust consumer modeling, and emissions-sensitive metrics, future studies can support the creation of energy systems that are not only efficient and equitable but also aligned with climate mitigation goals. This work is essential as utilities and policymakers seek to transition from demand-side management rooted in grid economics to strategies that also advance environmental sustainability.

11. Conclusion

This study provides a timely assessment of how well Duke Energy's time-based electricity tariffs align with hourly carbon intensity patterns in North Carolina. By integrating regression analysis, logistic modeling, average marginal effects, and a novel misalignment score, the findings reveal substantial temporal mismatches that undermine the environmental effectiveness of current pricing schemes. In contrast, CPP tariffs show stronger alignment with high-emission periods, suggesting greater potential for emissions reduction. These results underscore the importance of incorporating environmental metrics into tariff design and highlight the need for more dynamic, behaviorally informed, and emissions-aware pricing models as the grid transitions.

12. Acknowledgements

The author gratefully acknowledges Dr. Radford in advance for their thoughtful feedback and valuable suggestions.

13. References

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