GREEN MIRACLE

DECARBONIZING POWER SYSTEMS: DEMAND, PRICES, AND CHANGING POWER GENERATION MIX

SPAIN'S POWER MARKET

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PROBLEM STATEMENT

1. How much does the electricity price increase when demand rises?
2. How would this impact change in a more decarbonized energy system?

STUDY SCOPE & DATA SOURCES

Time frame: **from 2015 to 2018**

Location: **Spain**

Sources:

- **ENTSO-E** – Electricity consumption and generation data
- **Red Eléctrica de España (REE)** – Day-ahead settlement prices
- **OpenWeather API** – Weather data for Spain’s 5 largest cities

Definitions:

Power generation mix = the proportionate share of various primary energy sources (e.g., coal, natural gas, nuclear, wind, solar, hydro) used to generate electrical power (secondary energy).

1

DESCRIPTIVE ANALYSIS

2

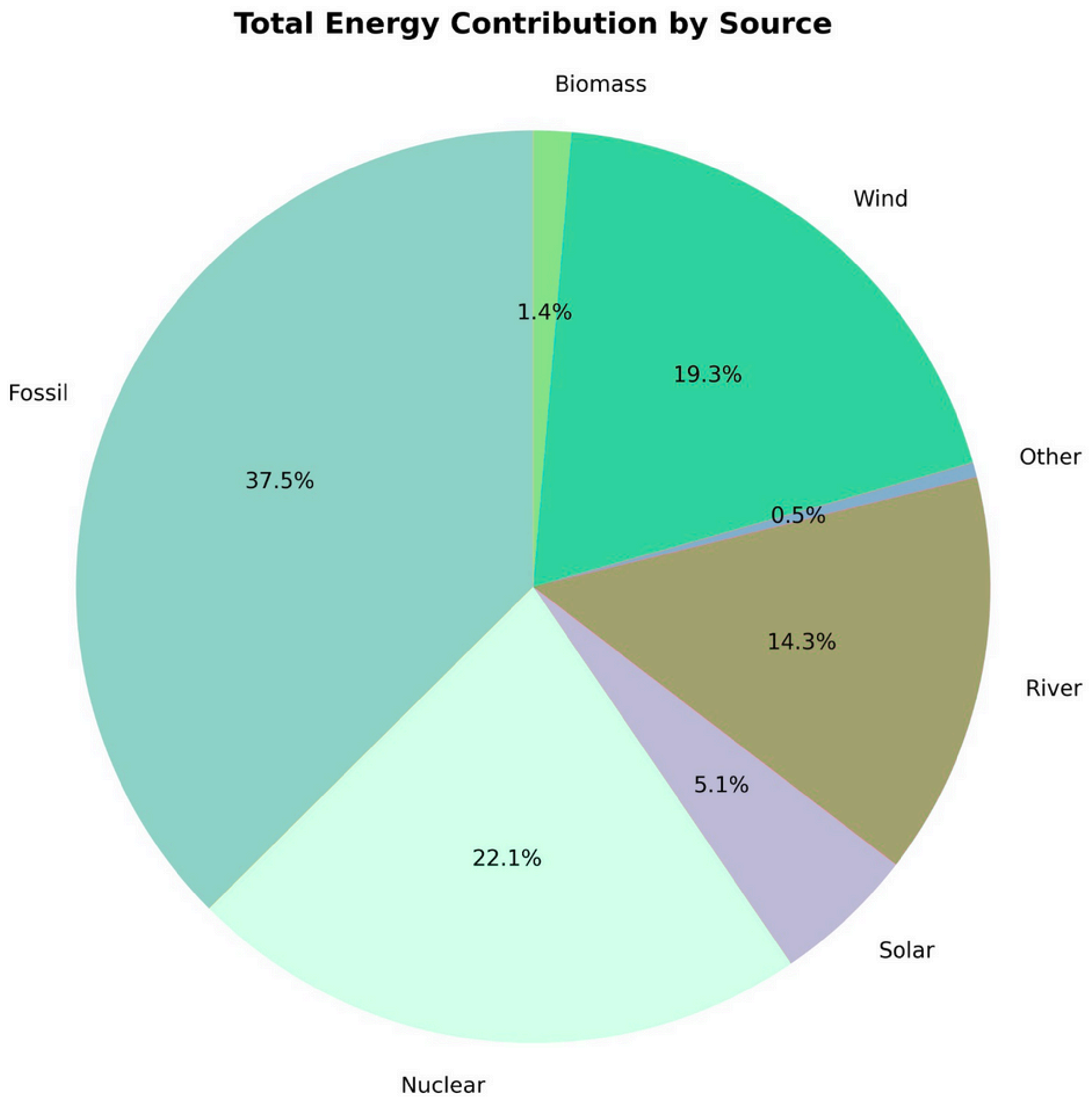
MODELLING DAILY ELECTRICITY PRICE

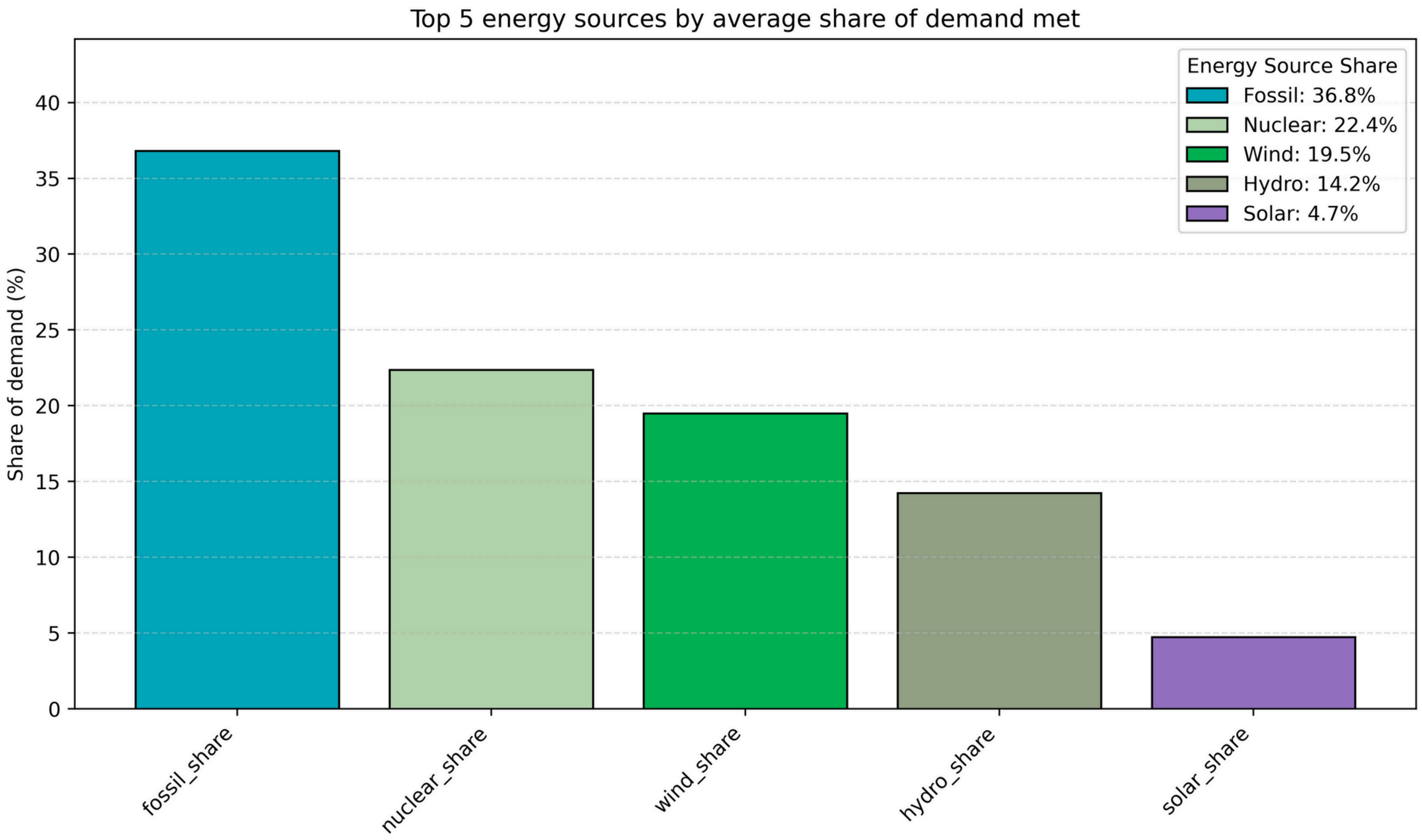
3

MODELLING PRICE IMPACT

DESCRIPTIVE ANALYSIS

1.1. LEADING ENERGY SOURCES BY DEMAND COVERAGE





1.2. PERCENTAGE OF ENERGY DEMAND SATISFIED BY EACH GROUP

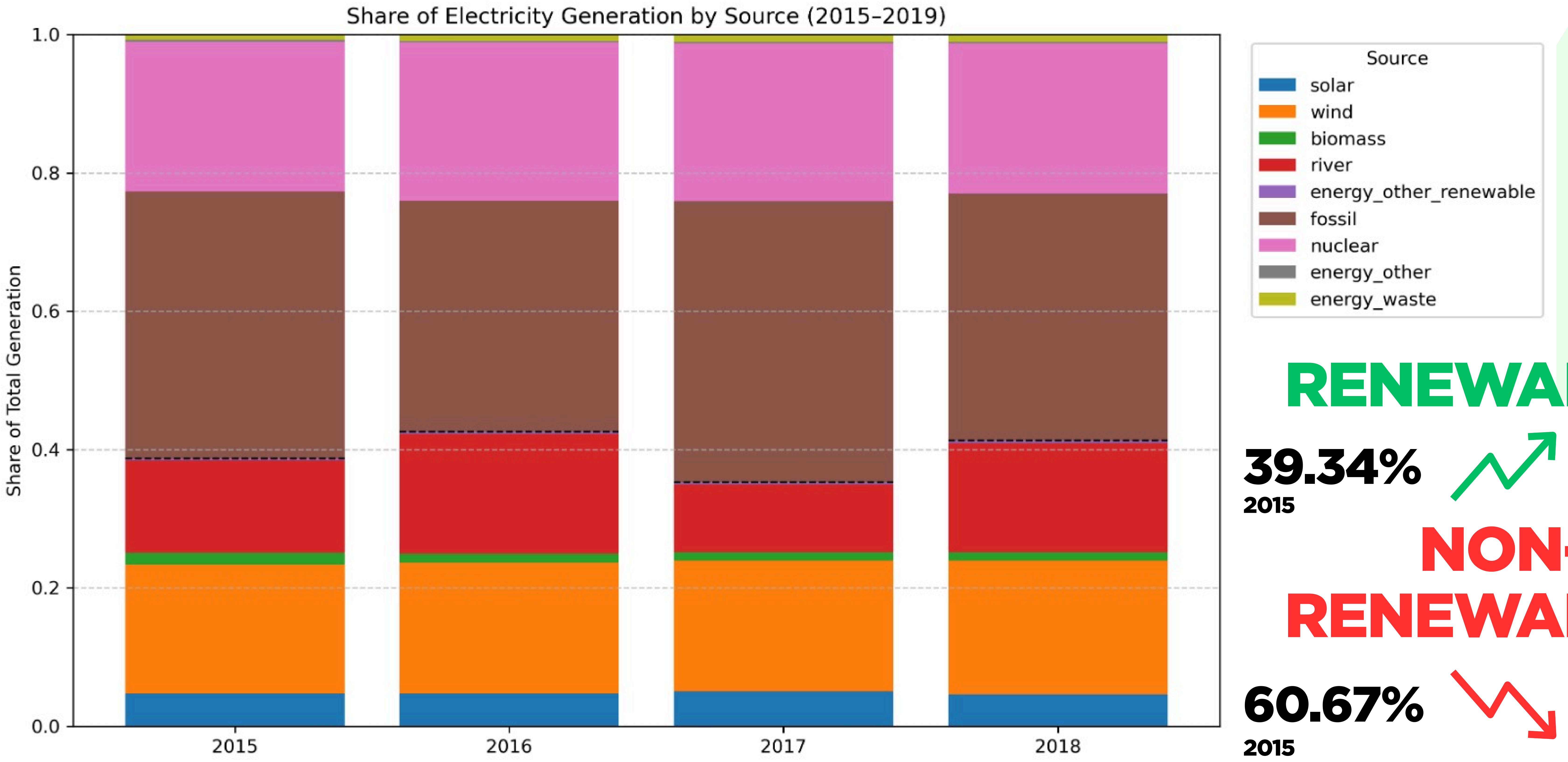
CHECK

	Renewable	Non-Renewable
Overall Average Shares	39.82%	59.19%
Year 2015	40.33%	62.21%
Year 2018	40.87%	56.14%

Shift Toward Renewable Energy (2015-2018)

- Modest increase in renewable energy share: **+0.54%**
- Significant decrease in non-renewable energy share: **-6.07%**
- Indicates reduced reliance on fossil fuels and improved energy efficiency
- **Positive trend toward decarbonization**

1.2. DEMAND COVERAGE THROUGH TIME



RENEWABLES

39.34% 2015 → **42.13%** 2018

NON-RENEWABLES

60.67% 2015 → **57.87%** 2018

1.3. STANDARD DEVIATION ANALYSIS

In **December**, solar has the lowest variability (4.39%) and wind the highest (12.11%), reflecting stable winter solar output and fluctuating wind conditions.

In **June**, nuclear remains the most stable (4.38%), while fossil shows the highest variability (11.36%), likely due to shifting demand or substitution effects. Overall, nuclear is consistently stable, while wind and fossil show seasonal fluctuations.

	Lowest Std Deviation Source	**Highest Std Deviation Source**
December	Solar (4.39%)	Wind (12.11%)
June	Nuclear (4.38%)	Fossil (11.36%)

1.4. DEMAND SATISFIED BY SOLAR ENERGY WITH RESPECT TO TOTAL DEMAND

	Mean Solar Share	Mean Hydroelectric Share
March	0.1147	0.1671
July	0.1378	0.1179
August	0.1383	0.1033
September	0.1374	0.0960

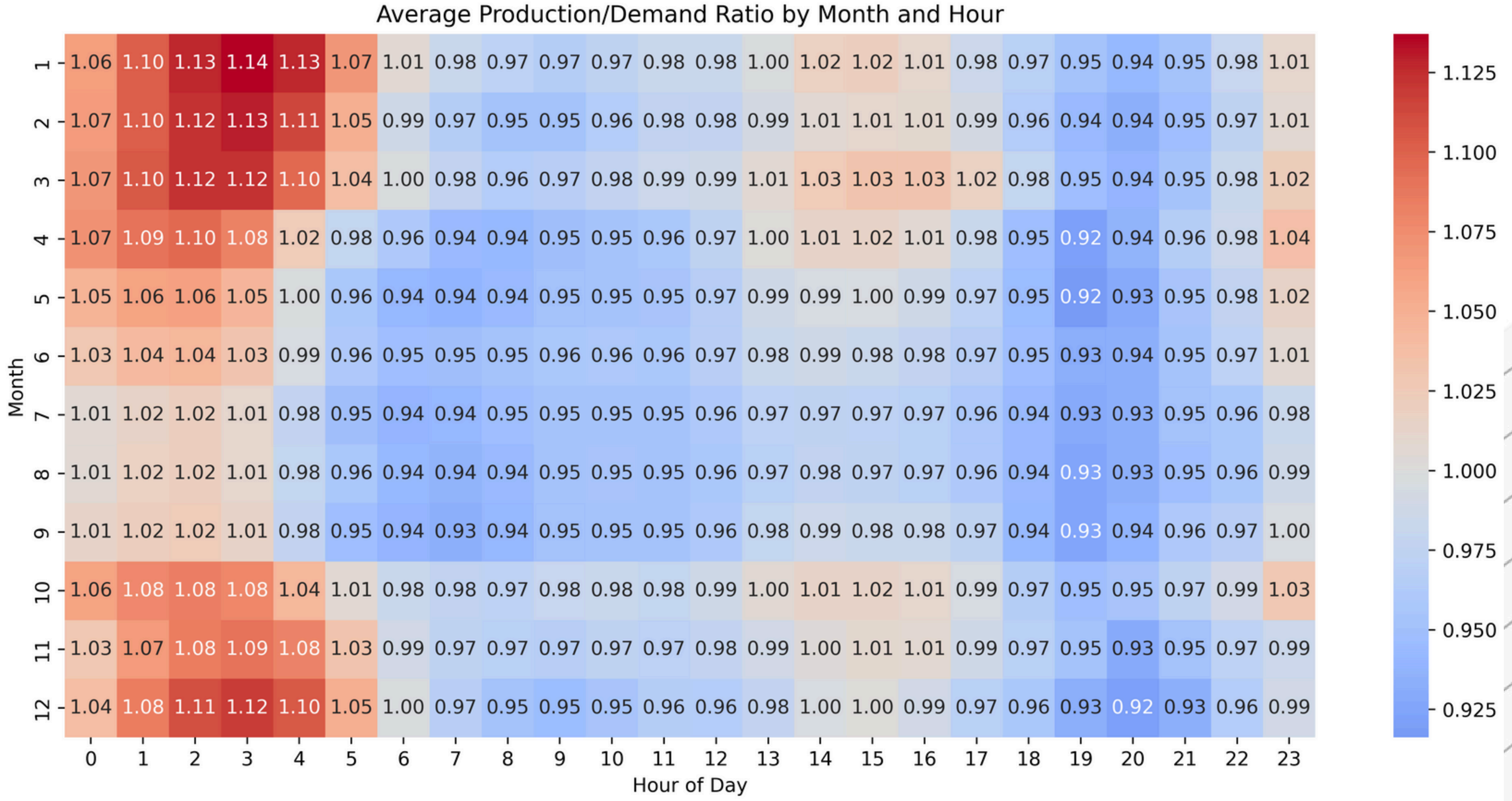
March at 12:00

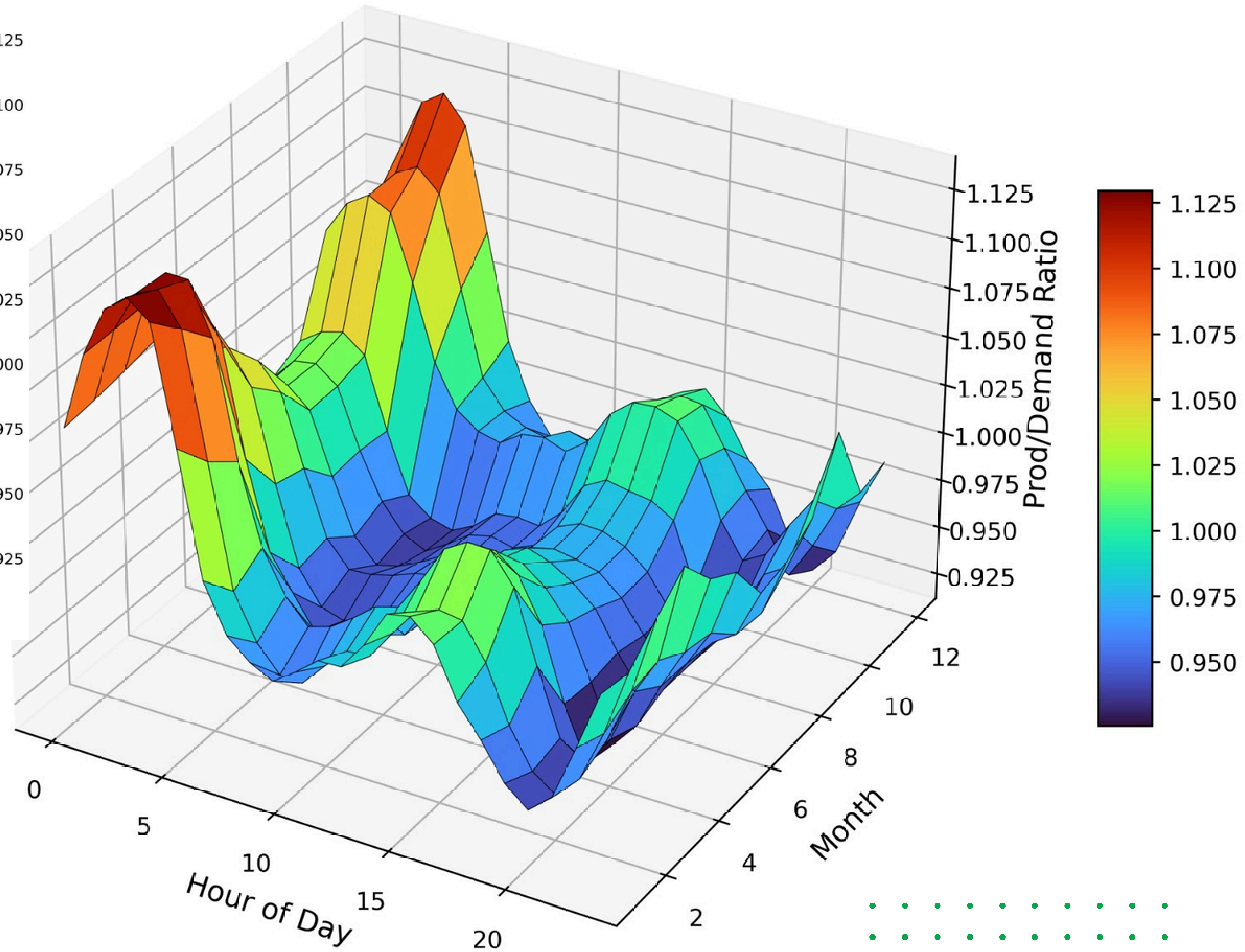
- Solar energy share is lower than hydroelectric.
- Reflects limited springtime solar radiation compared to early-season river flow.

July, August, and September at 12:00

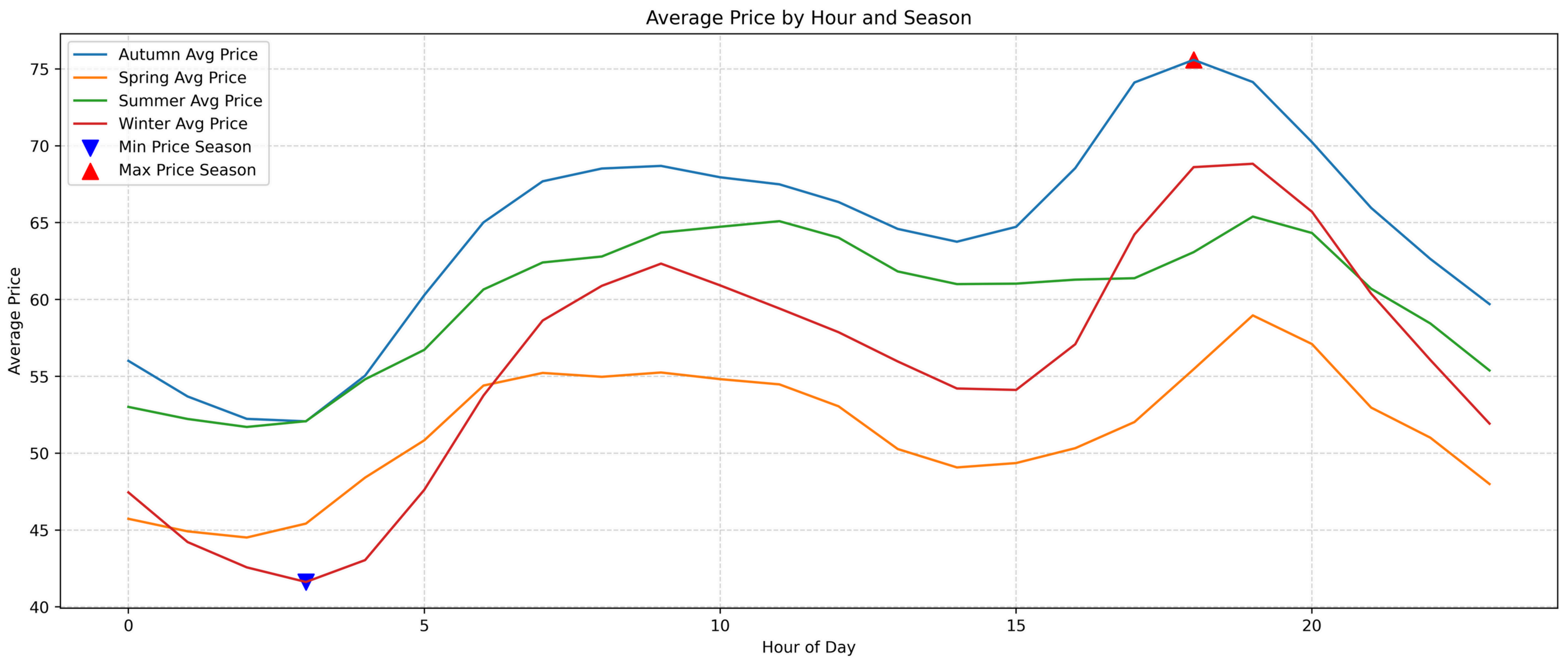
- Solar energy becomes dominant at midday.
- Due to longer days and high solar intensity.
- Hydroelectric contributions may decline.
- Reduced summer rainfall or depleted reservoirs.
- Seasonal contrast confirms solar as the key driver of midday electricity during summer months.

1.5 HEATMAP PRODUCTION/DEMAND RATIO BY MONTH AND HOUR

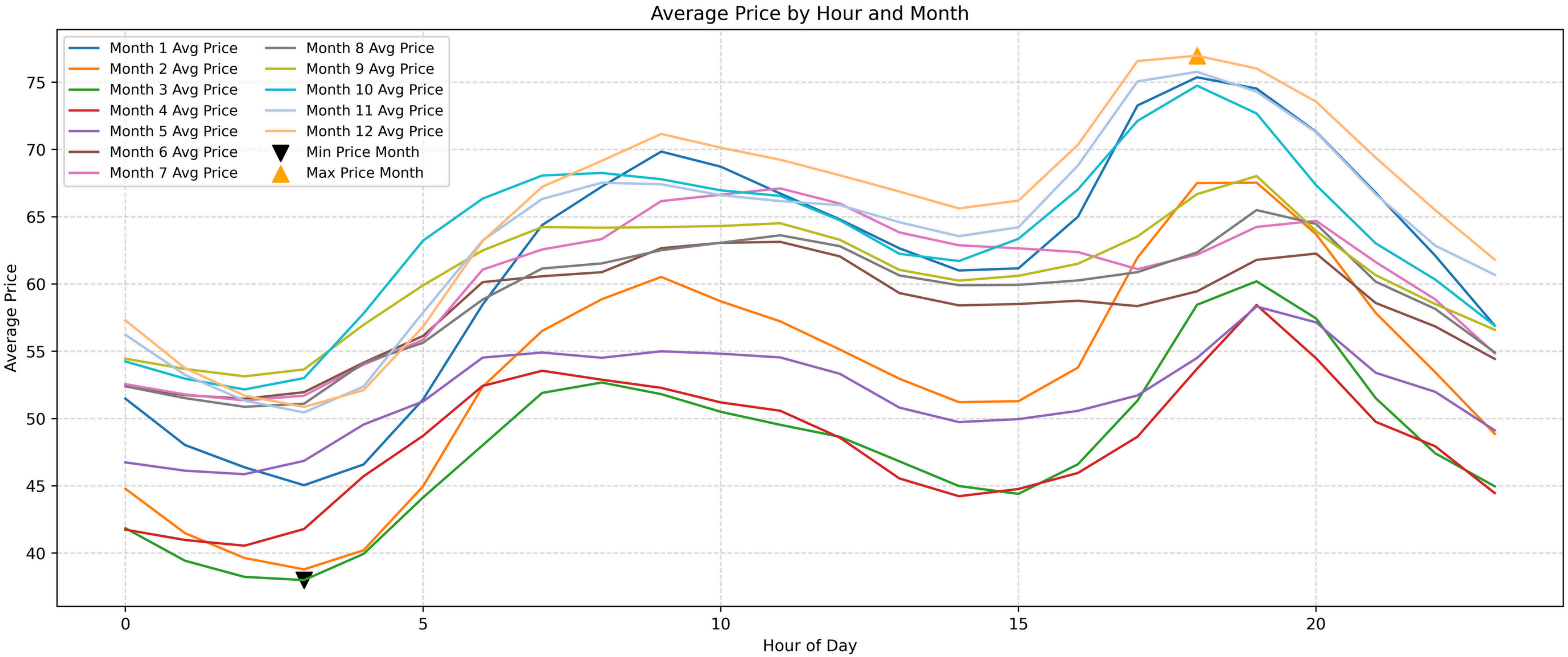




AVERAGE PRICE BY HOUR AND SEASON

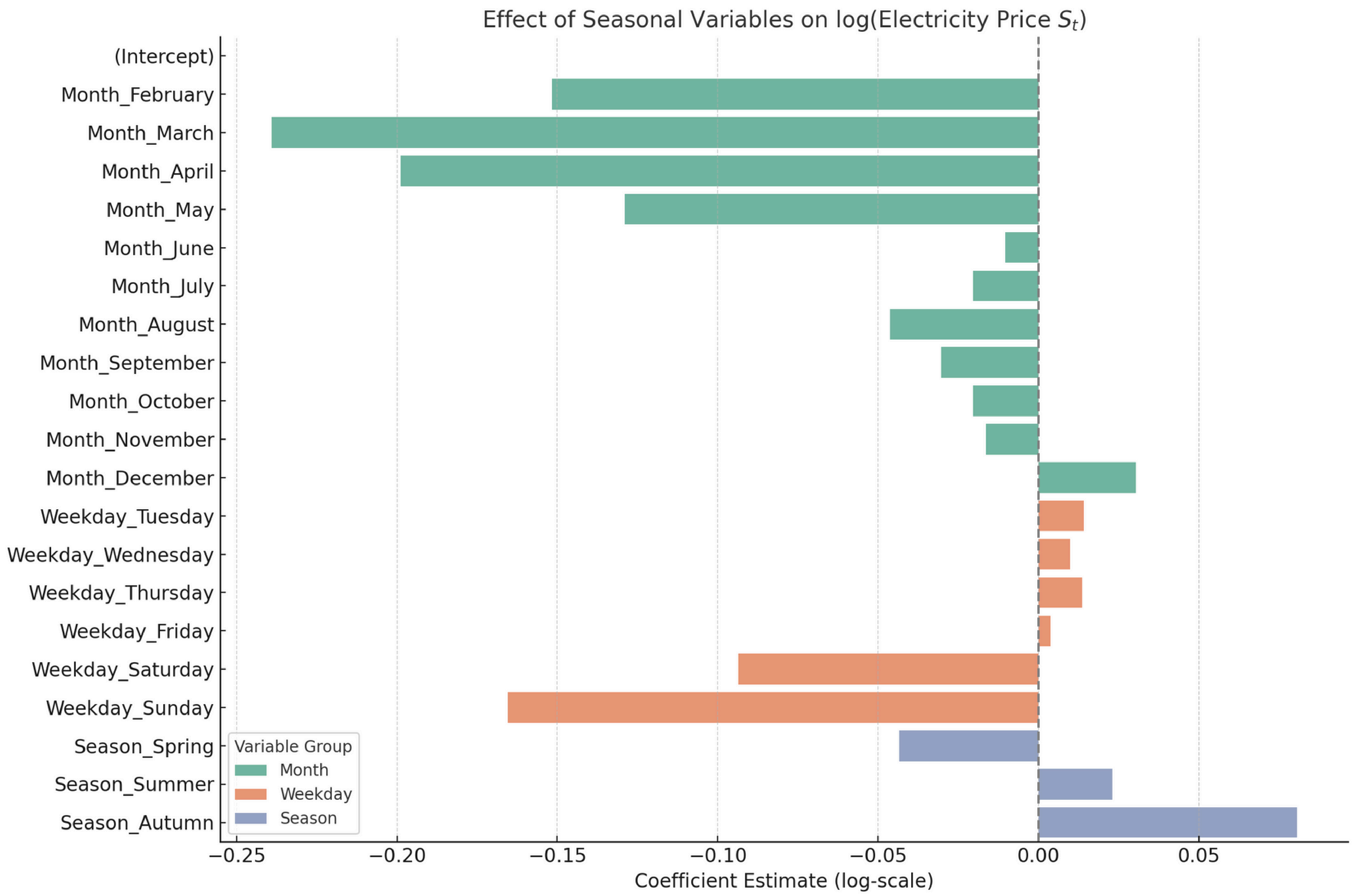


AVERAGE PRICE BY HOUR AND MONTH

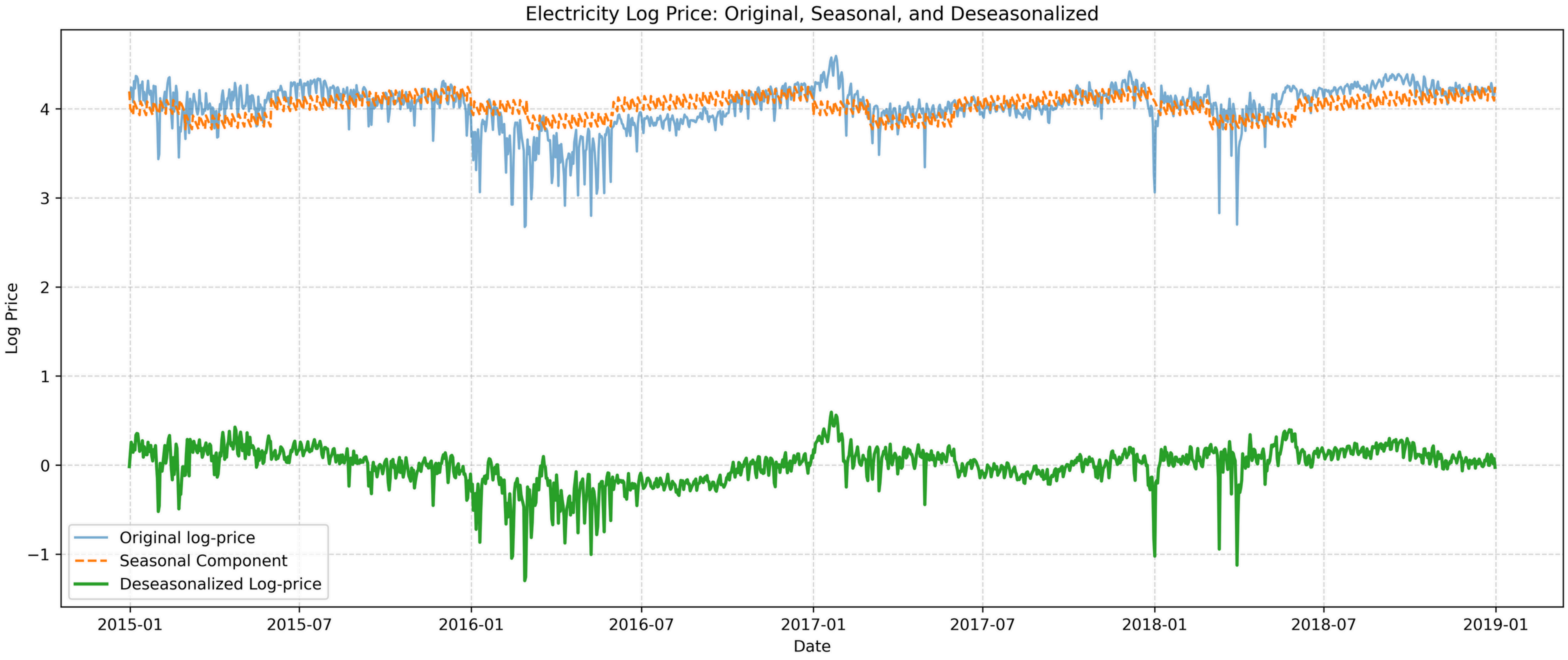


MODELLING DAILY ELECTRICITY PRICE

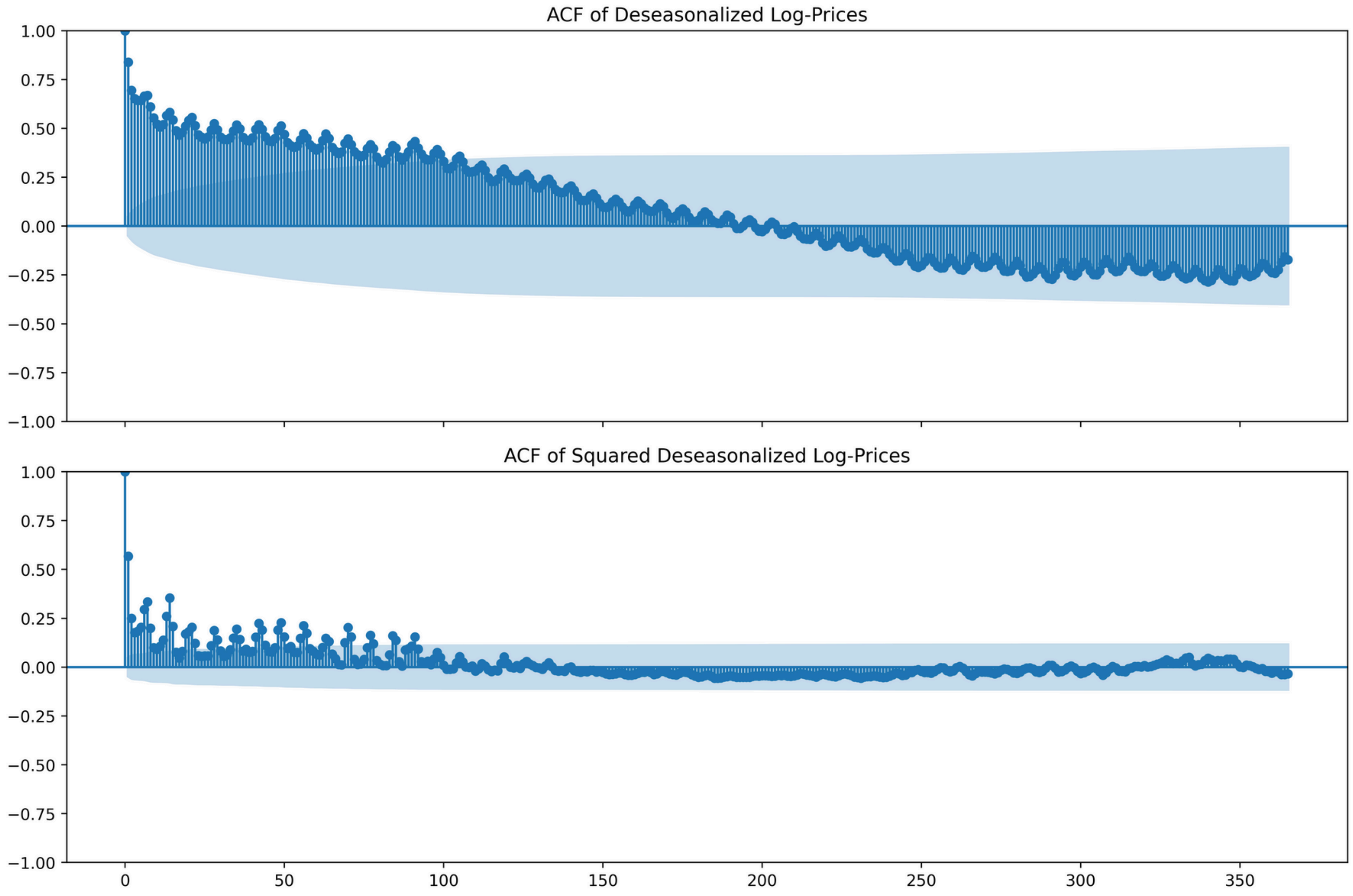
2.1 (A) ESTIMATING SEASONAL EFFECTS ON DAILY LOG ELECTRICITY PRICES USING LINEAR REGRESSION



2.1 (B) LOG PRICE DECOMPOSITION



2.1 (C) AUTOCORRELATION FUNCTION FOR THE DESEASONALIZED LOG-PRICES



- Strong autocorrelation in mean and variance
- Skewed to the left

2.2. TESTING THE AR(1) MODEL

- We first run an ADF test to check the stationnary of the series.
- The test statistic being more negative than the critical value, we reject the null hypothesis, the series is stationary!

statistic
-5.151

- We now run an AR(1) to estimate the series:

$$\tilde{S}_t = \phi \tilde{S}_{t-1} + \varepsilon_t$$

term	estimate	std.error	statistic	p.value
ϕ	0.8429	0.01408	59.86	0

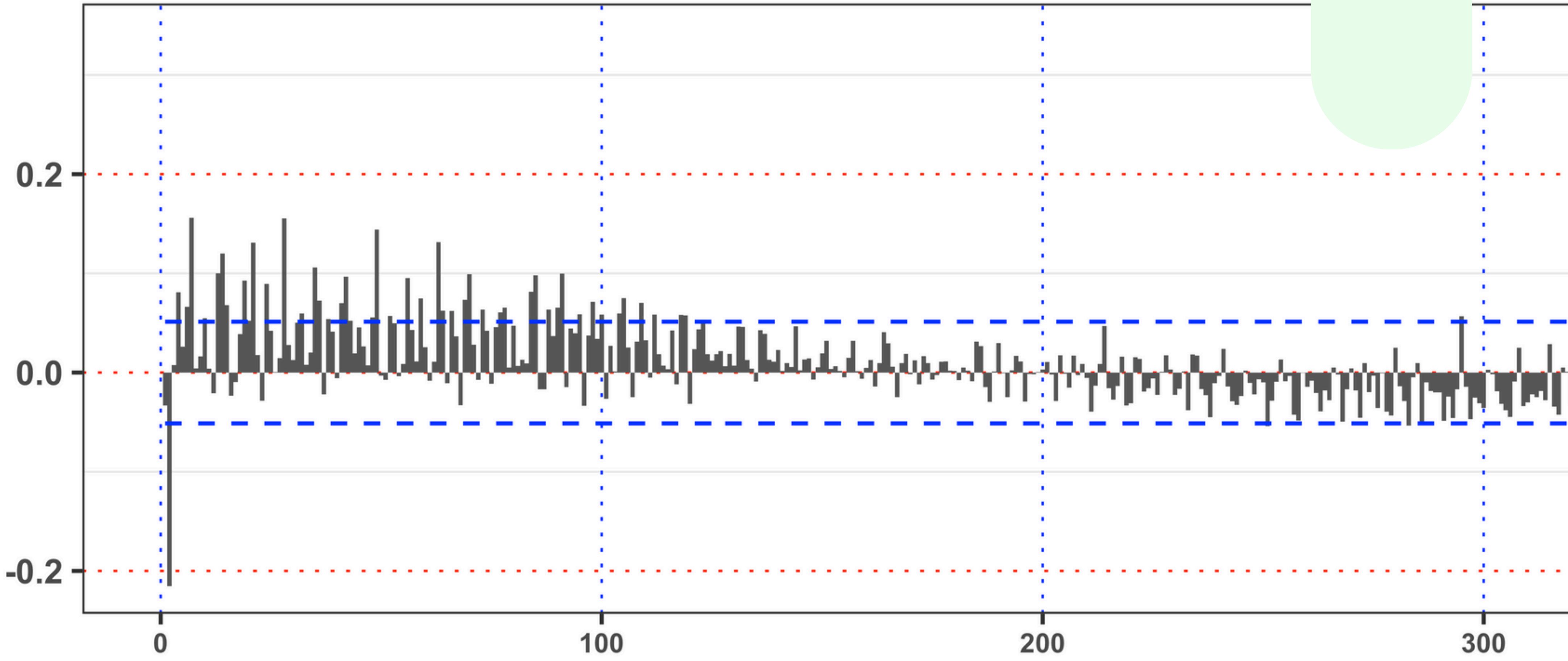
Note that, since ϕ= 0.843 is less than 1 in absolute value, then the AR(1) model is stationary

CHECKING THE RESIDUALS

- The plot shows the residuals present a significant autocorrelation in mean

- A regression on the residuals show a model AR(7) is globally significant, confirming the autocorrelation

- The AR(1) model applied to our variable is not able to capture this autocorrelation



TESTING THE ARMA(2,2) MODEL

$$\tilde{S}_t = \phi_1 \tilde{S}_{t-1} + \phi_2 \tilde{S}_{t-2} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \varepsilon_t;$$

term	estimate	std.error
ϕ_1	1.1792	0.0801
ϕ_2	-0.1916	0.0765
θ_1	-0.4497	0.0770
θ_2	-0.3180	0.0378

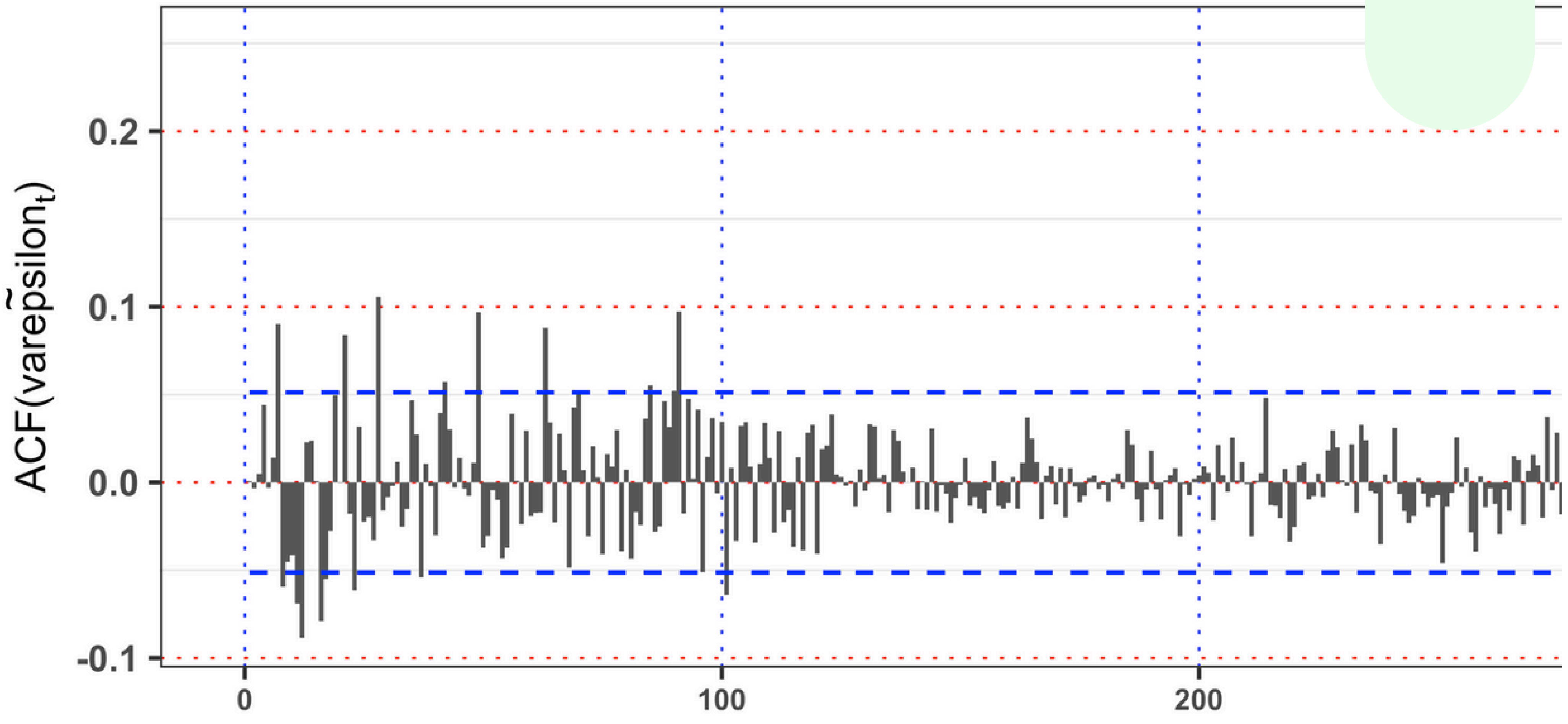
- the estimates are significant, with minimal error.

CHECKING THE RESIDUALS

- The plot shows the residuals present a non significant autocorrelation in mean

- A regression on the residuals show a model AR(7) is globally not significant

- With the ARMA(2,2) model we do not have anymore autocorrelation in mean that the AR(1) was not able to completely remove.

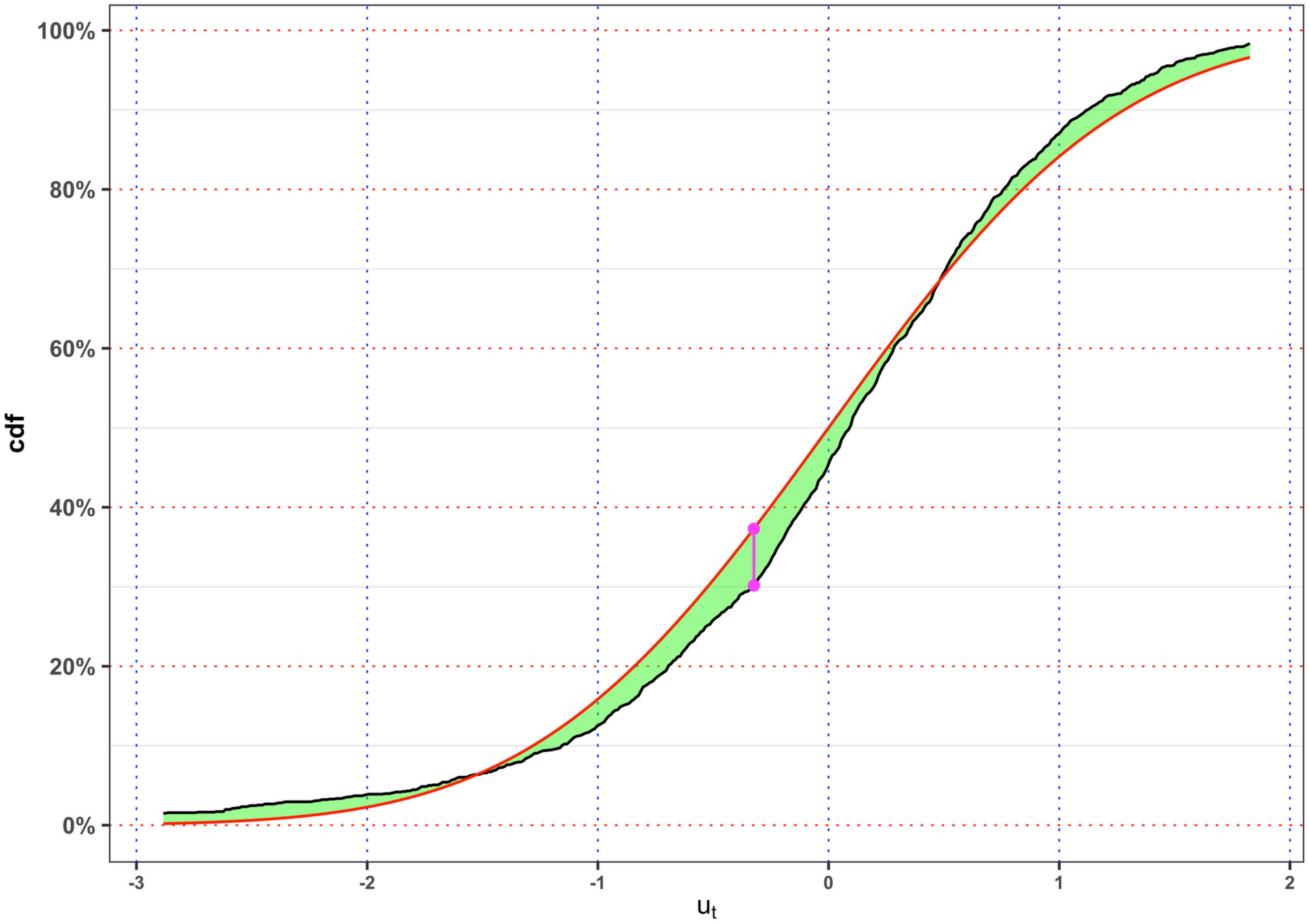


2.3. MODELING CONDITIONAL VARIANCE WITH GARCH

- Modelling with a simple GARCH(1,1) model
- Targeting the long term variance
- Stationarity: $\alpha + \beta < 1$
- KS-Test → not Normal Distributed

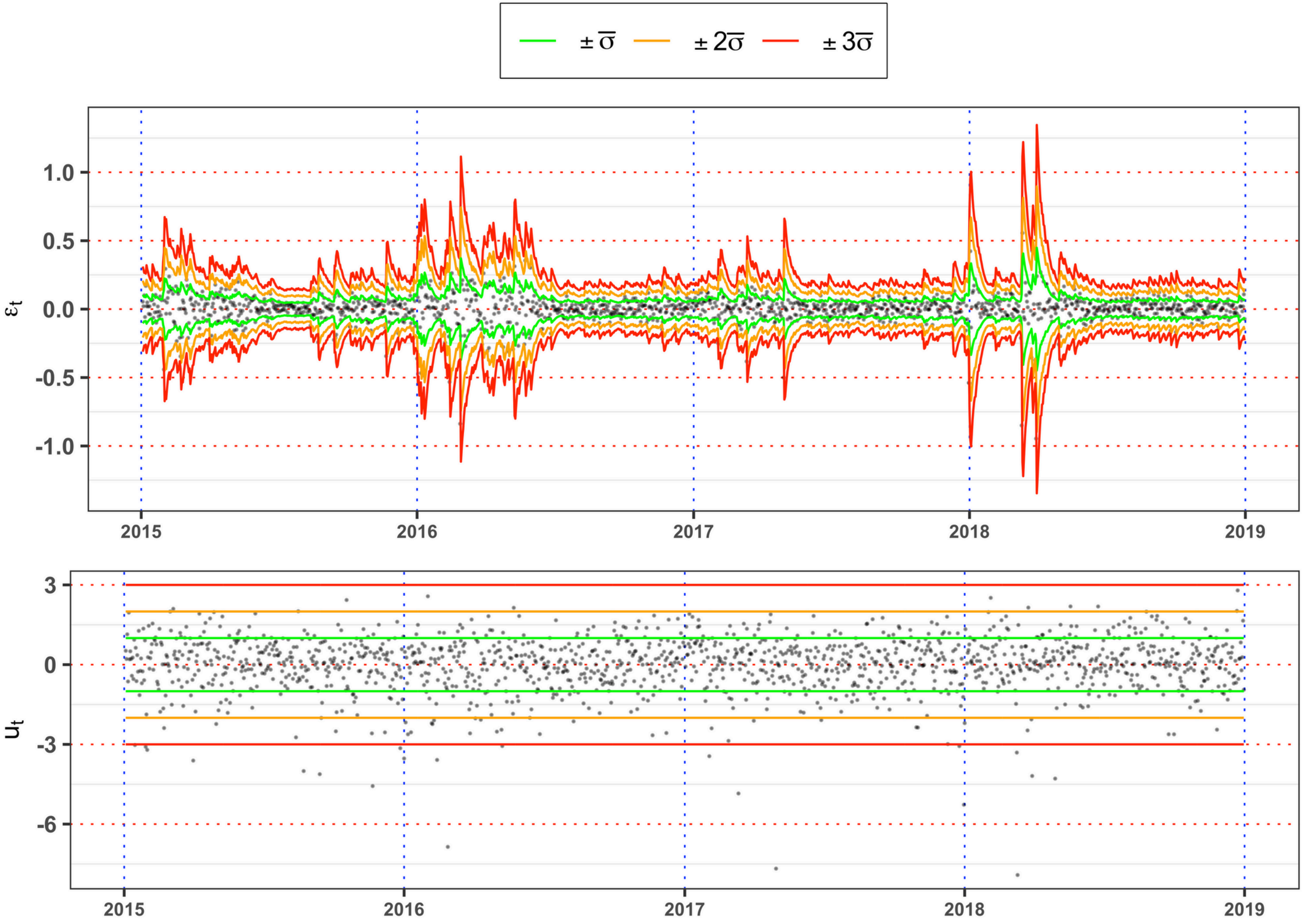
params	estimates	se.coef
ω	0.1793855	0.01242
α	0.7892810	0.01486
β	0.0003374	NA
σ^2_∞	0.0107691	NA

GARCH KS-TEST FOR NORMALITY



GARCH - VARIANCE

- Volatility clusters captured by GARCH
- Residuals not normal and not symmetrically distributed
- Skewed to the left



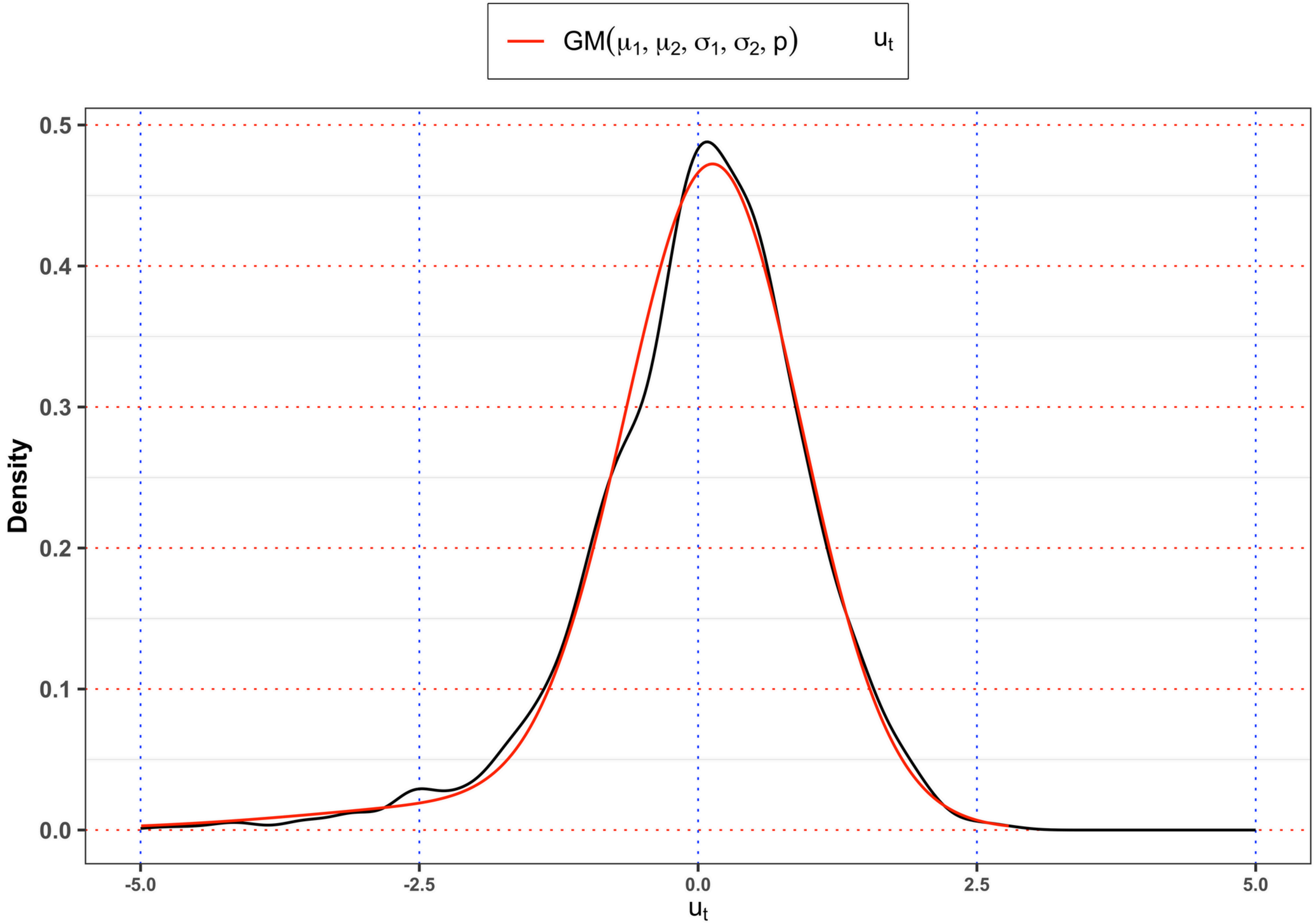
2.4. GARCH WITH GAUSSIAN MIXTURE DISTR. FOR RESIDUALS

- Addresses the non symmetrical error distribution
- Combined and mixes two normal distributions
- Accounts for the negative shocks and approximates the Residuals Distribution

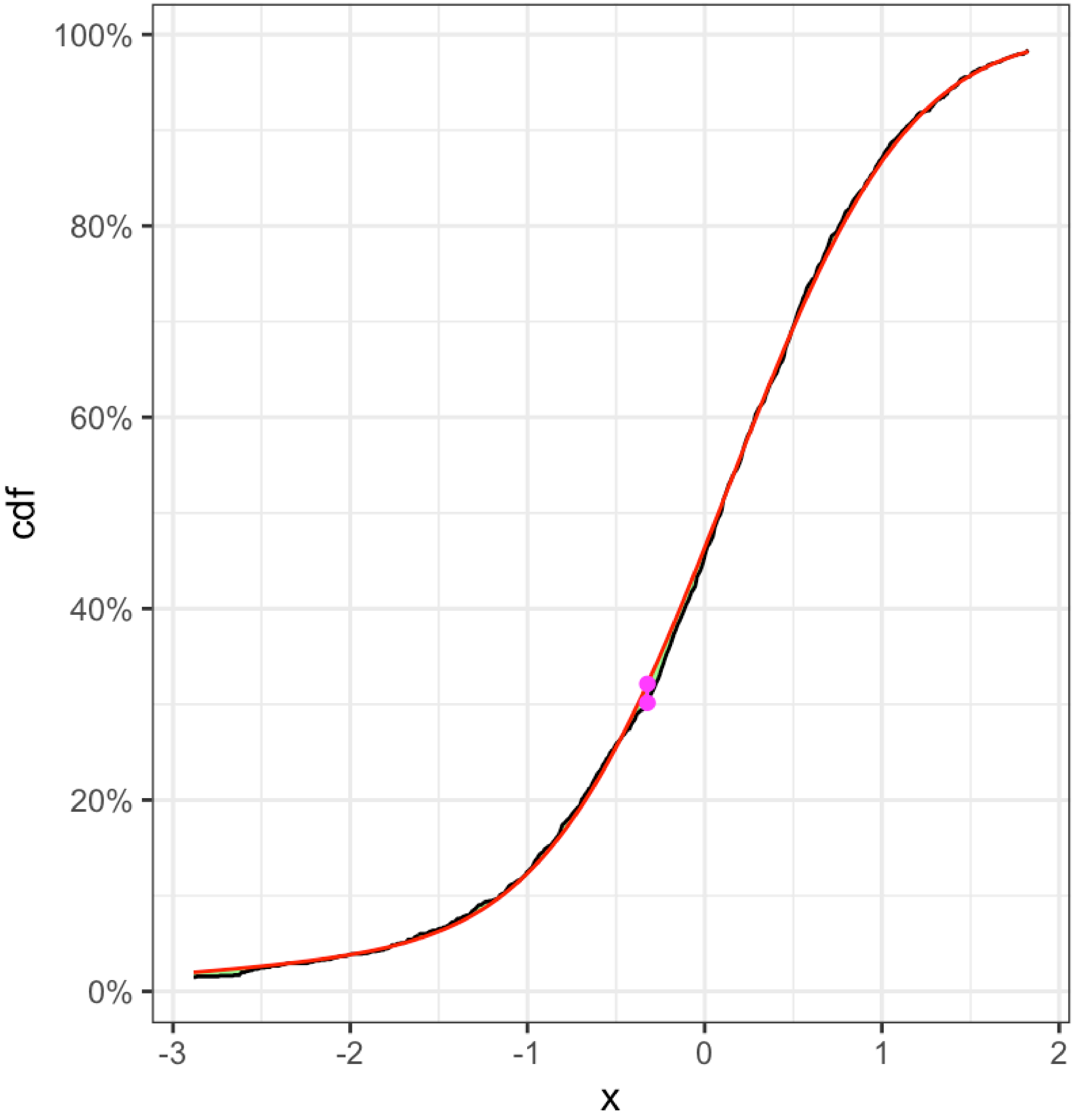
$$u_t \sim B \cdot (\mu_1 + \sigma_1 Z_1) + (1 - B) \cdot (\mu_2 + \sigma_2 Z_2)$$

μ_1	μ_2	σ_1	σ_2	p_1	$1 - p_1$	**log-lik**	$\mathbb{E}\{u_t\}$	$\mathbb{S}d\{u_t\}$
-1.475	0.1389	1.79	0.7897	0.09202	0.908	-1992	-0.009603	1.039

RESIDUAL DISTRIBUTION



GARCH KS-TEST FOR NORMALITY



Model	Conclusions
AR(P)	The series is stationary (AR coefficient < 1), but residuals still show autocorrelation
AR(P) on Residuals	Residuals are not i.i.d. and autocorrelation remains, so AR(1) is insufficient.
ARMA(P,Q)	ARMA(2,2) removes autocorrelation in mean better than AR(1), but volatility clustering persists.
GARCH(R,S) GARCH-GM	Model is stationary, captures conditional heteroskedasticity, and explains volatility dynamics.

MODELLING PRICE IMPACT

3.1. UNDERSTANDING DEMAND SHOCKS

Definition: **Demand shocks** refer to sudden changes in the demand for electricity, which can significantly impact energy prices.

=> Analyze how different energy sources respond to these demand shocks and their subsequent impact on prices.

MODEL

$$S_t = \beta_0 + \beta_1 d_t + \gamma_1 d_t T_t + \sum \gamma_* \cdot [d_t \cdot s_{*,t}] + \text{controls} + \varepsilon_t$$

$$\partial_{d_t} S_t = \beta_1 + \gamma_1 T_t + \sum_* \gamma_* s_{*,t}$$

3.1. SUMMARY OF THE MODEL

R.squared	Adj.R.squared	σ	F-statistic	P.value
0.4471	0.4463	0.2163	577.7977	0

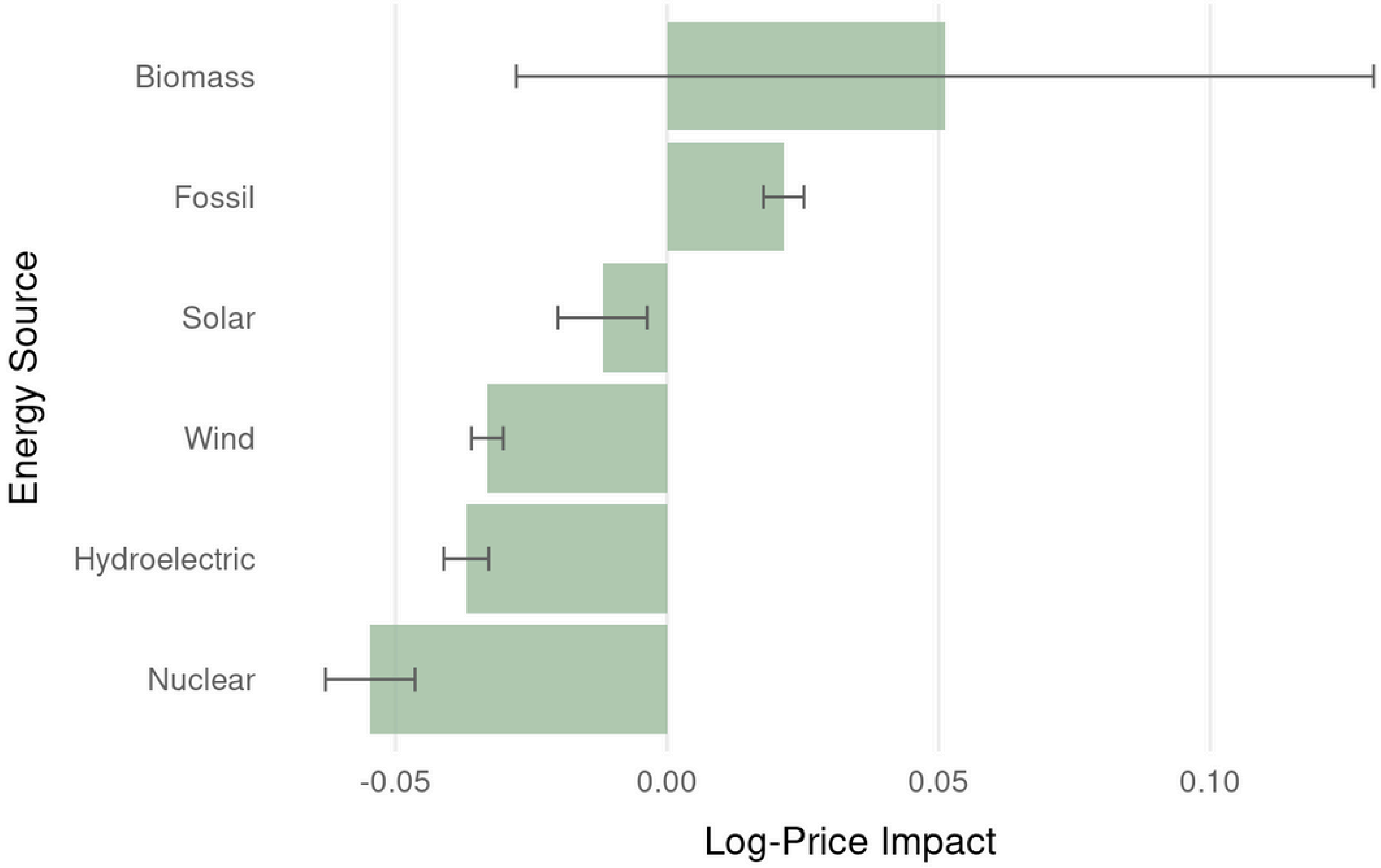
- About 44.71% of the variability in the dependent variable is explained by the model => **moderate level of explanatory power**
- Adjusted R-squared ≈ R-squared value, which indicates that the model **does not contain unnecessary predictors**.
- Low std => **good fit**
- P.value and F-statistic both indicates the **model is statistically significant**

3.2. IMPACT OF DEMAND SHOCKS ON ENERGY PRICES

Coefficient Analysis

- Biomass: Highest increase in price but not statistically significant
- Fossil: **Moderate increase** in price.
- Solar: **Slight increase** in price.
- Wind: **Minimal impact** on price.
- Hydroelectric: **Slight decrease** in price.
- Nuclear: **Decrease** in price
- Other: not in graph because out of scale but reflect marginal or rare expensive sources (eg. imports)

Impact on price when demand increases by 1% and is satisfied by a specific energy source



3.2. PRICE RESPONSE TO 1% DEMAND INCREASE BY SOURCE

- Demand shocks are NOT equally expensive : conversion of expected log-price increase in percentage

$$\Delta S_t = \partial_{d_t} S_t \cdot \log(1+r) \implies \%\Delta P_t = (e^{\Delta S_t} - 1) \cdot 100.$$

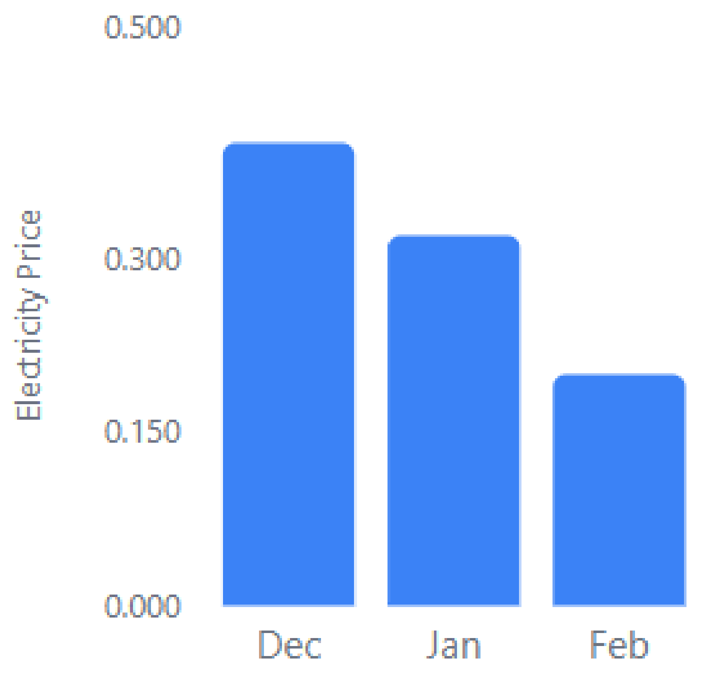
- Cost of meeting additional demand varies significantly by energy source:
  => most when met by **fossil fuels**
  => least when met by **nuclear power**

Energy Source	Price Impact (%)
Fossil	**+0.370**
Solar	**+0.337**
Wind	**+0.316**
Hydroelectric	**+0.312**
Nuclear	**+0.294**

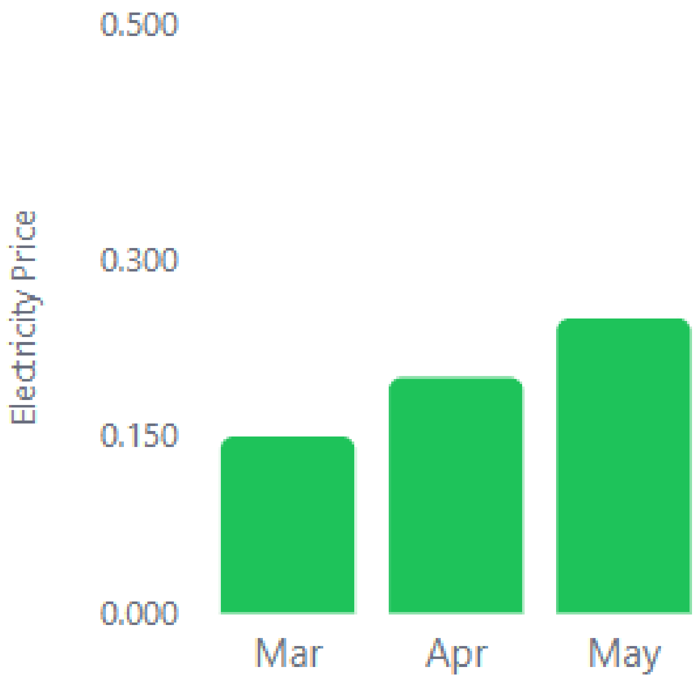
3.2 SEASONALITY

TUESDAY

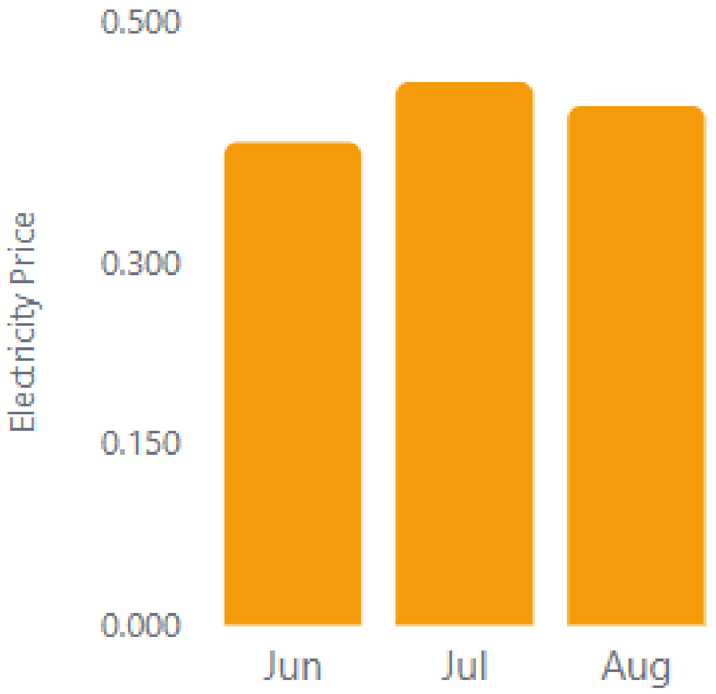
Winter Seasonal Analysis - Tuesday 12:00 PM



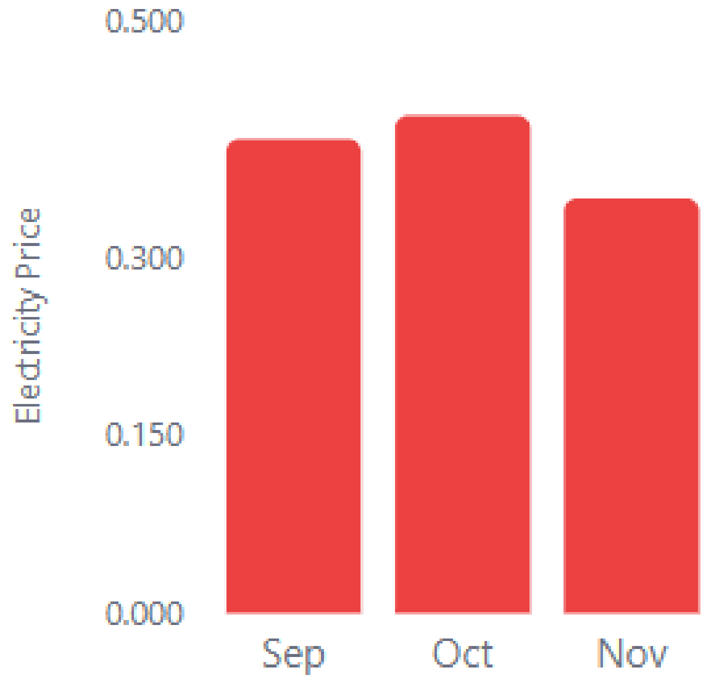
Spring Seasonal Analysis - Tuesday 12:00 PM



Summer Seasonal Analysis - Tuesday 12:00 PM

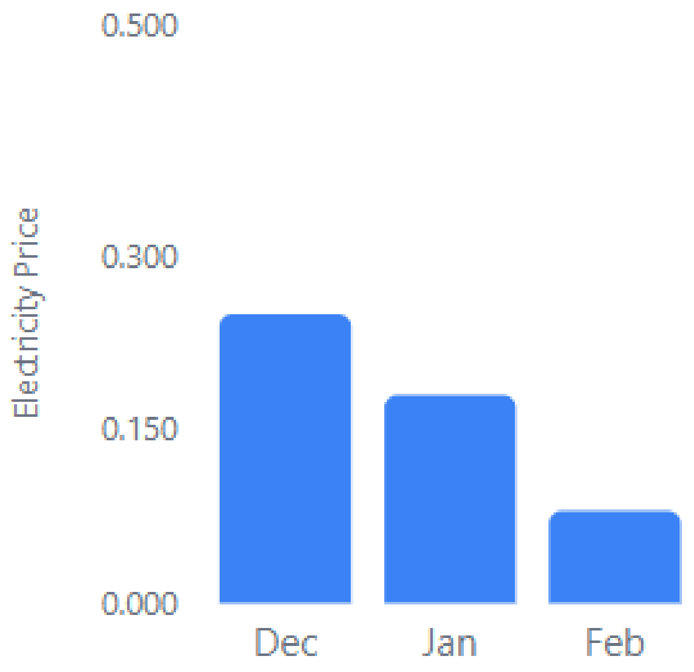


Autumn Seasonal Analysis - Tuesday 12:00 PM

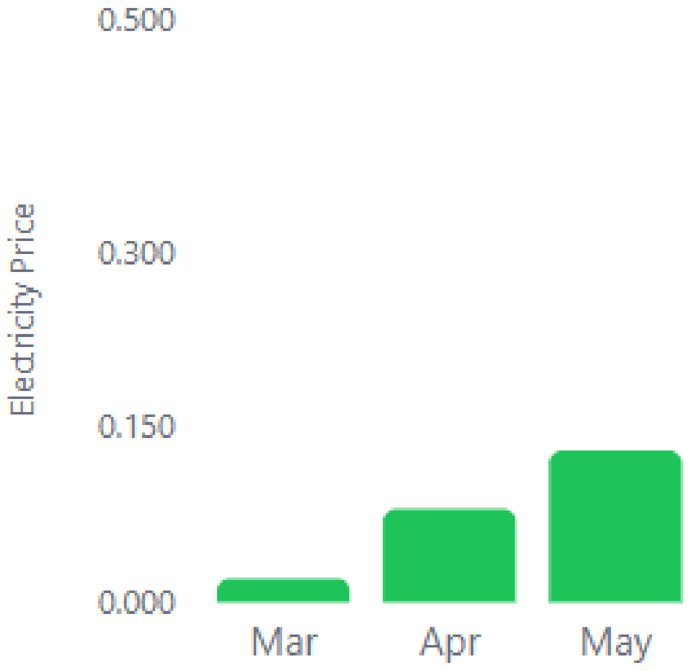


SUNDAY

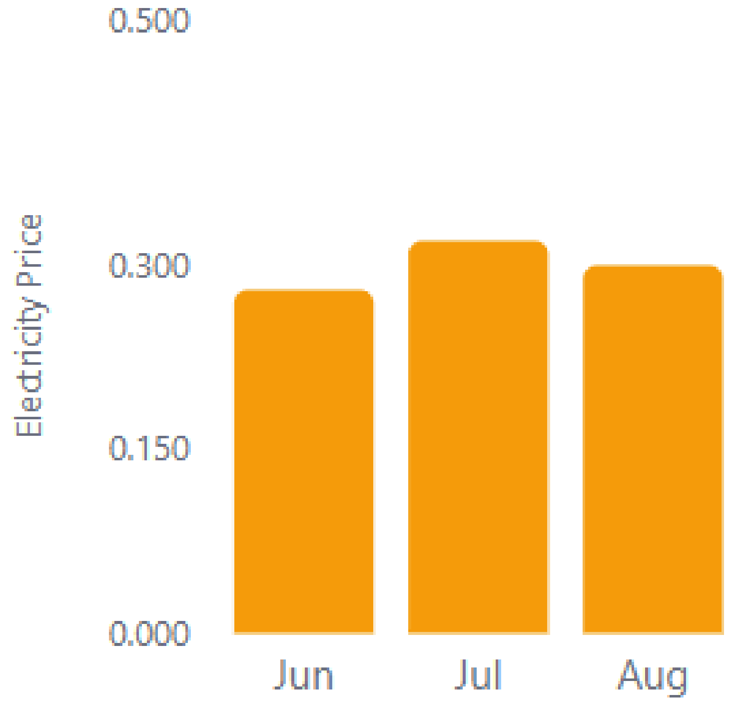
Winter Seasonal Analysis - Sunday 12:00 PM



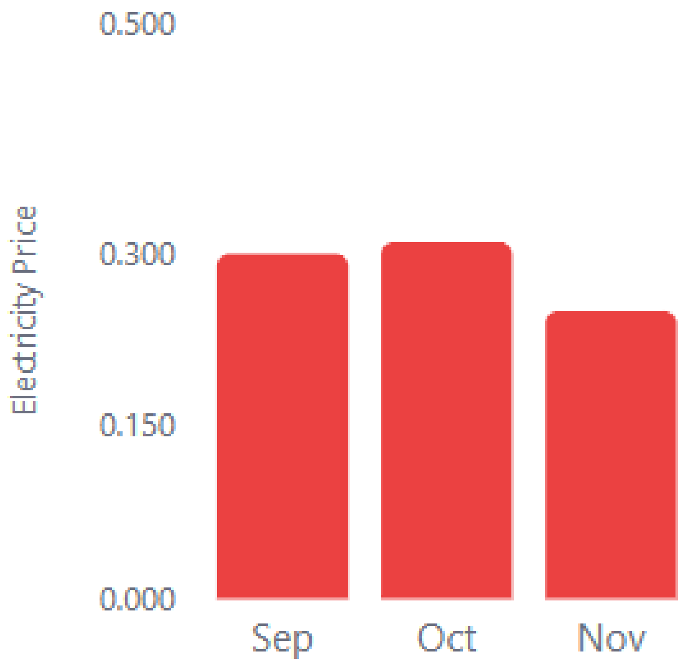
Spring Seasonal Analysis - Sunday 12:00 PM



Summer Seasonal Analysis - Sunday 12:00 PM

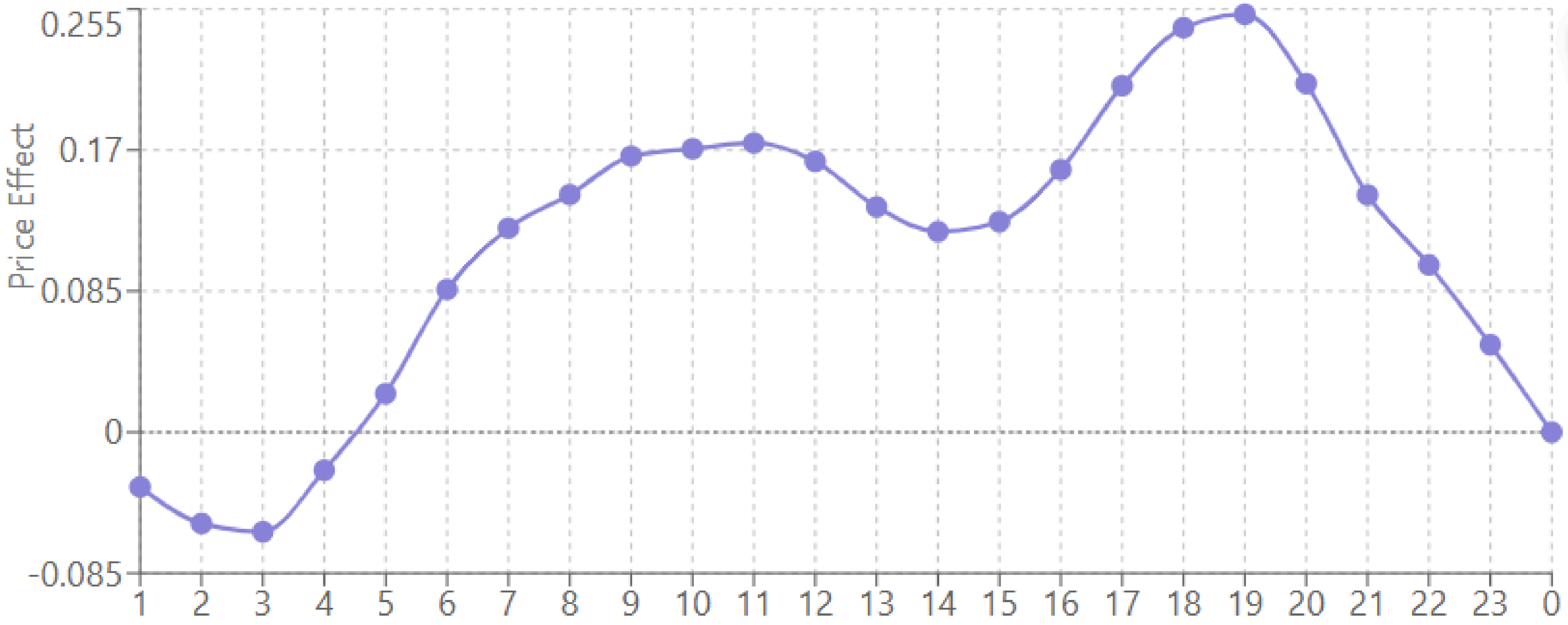


Autumn Seasonal Analysis - Sunday 12:00 PM



3.2 HOURLY PRICE PATTERN

- **Peak price** effects occur during **evening** hours (17-19) with maximum impact around **0.25**
- **Lowest** price effects during **early morning.**
- Clear diurnal pattern reflecting typical **electricity demand cycles**



3.3 IMPACT OF A 5% DEMAND SHOCK ON PRICES

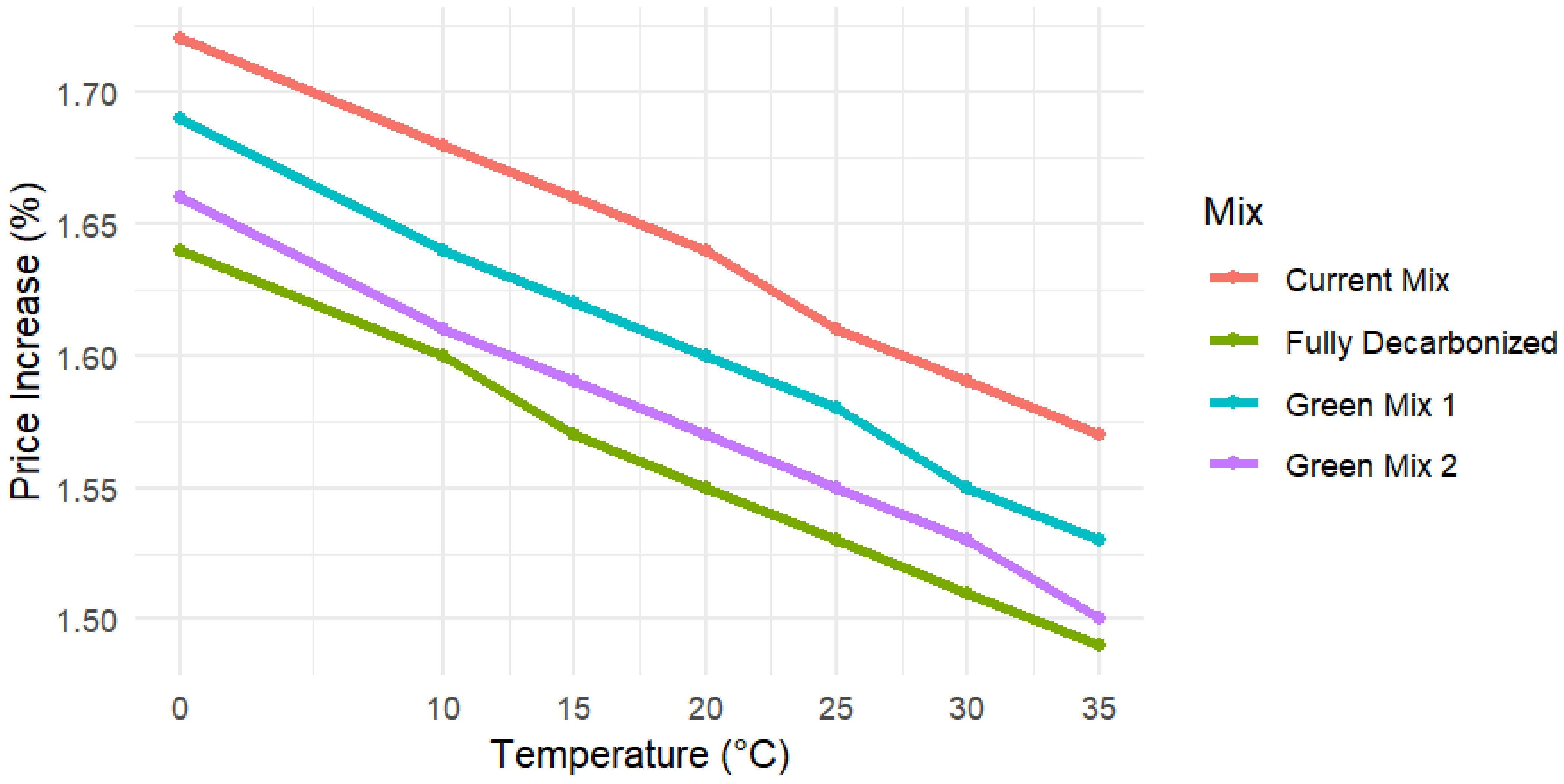
MIXES

- **Current mix**: 37% fossil, 23% nuclear, 20% wind, 15% hydroelettric, 5% solar.
- **Green mix 1**: 20% fossil, 25% nuclear, 25% wind, 15% hydroelettric, 15% solar.
- **Green mix 2:** 10% fossil, 30% nuclear, 20% wind, 20% hydroelettric, 20% solar.
- **Fully decarbonized mix**: 0% fossil, 25% nuclear, 25% wind, 25% hydroelettric, 25% solar.

TEMPERATURE LEVELS

0°, 10°, 15°, 20°, 25°, 30°, 35°.

3.3 RESULTS AND POLICY TAKEAWAYS



- As temperatures increase, the price impact of a 5% demand rise tends to decrease
- Mixes with greater share of renewables result in smaller price increases
- A green energy transition is not justificated , due to the high shift costs
- ''**Green mix 2**'' is the best option, representing a practical balance

FINAL CONCLUSION

- Weather deeply influences hourly supply-demand dynamics, especially through variable renewables.
- The market sees price depressions during renewable overproduction and spikes during fossil-dependent scarcity.
- A transition to a low-carbon system smoothes these swings—reducing extreme prices and strengthening grid independence from fossil sources.
- However, a sharp increase in renewables must be paired with flexible and stable backup systems to maintain grid balance and reliability and avoid high price volatility.

THANK YOU!