Electricity Price Forecasting: Evaluating Time Series Models

Analysis of U.S. Electricity Prices (2001–2024)

Author: Yihan Wang, Ngoc Vo, Kevin Liu

Why Forecast Electricity Prices?

Significance:

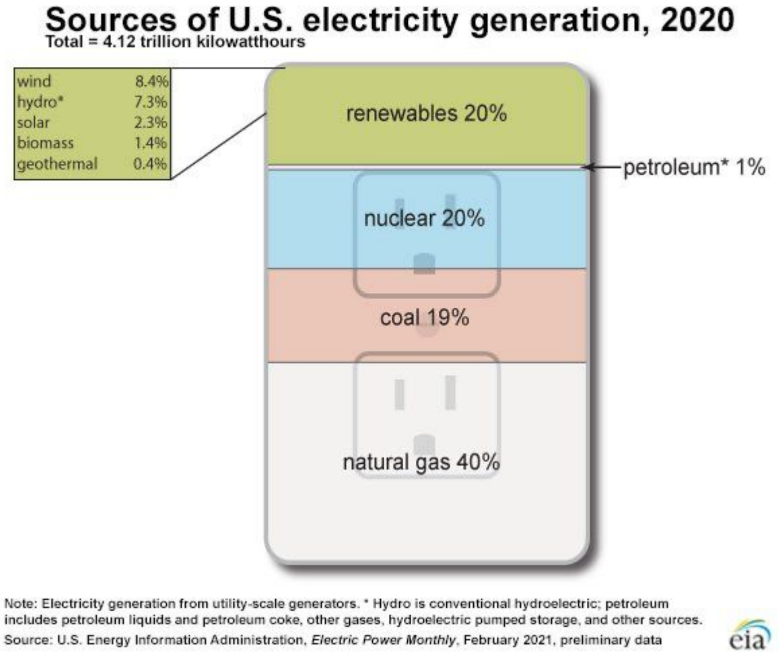
- Crucial for navigating competitive, deregulated energy markets.
- Supports informed decision-making in a volatile environment.

Key Factors Influencing Prices:

- Weather patterns, energy policies, renewable energy growth, and competition.

Challenges:

- Electricity price forecasting remains complex.
- Opportunities to enhance model accuracy and predictive power.



Literature Review

Key Approaches in Literature:

- **Time Series Models**: Commonly used, especially for day-ahead forecasts.
- **Simulation-Based Models**: Less frequent but relevant.

Challenges:

- High price variability complicates accurate forecasting.

Research Focus:

- Comparative analysis of time series, deep learning, and hybrid models.
- Application to U.S. electricity market to enhance forecasting accuracy.
- Targeting price dynamics, volatility, seasonality, and trends.

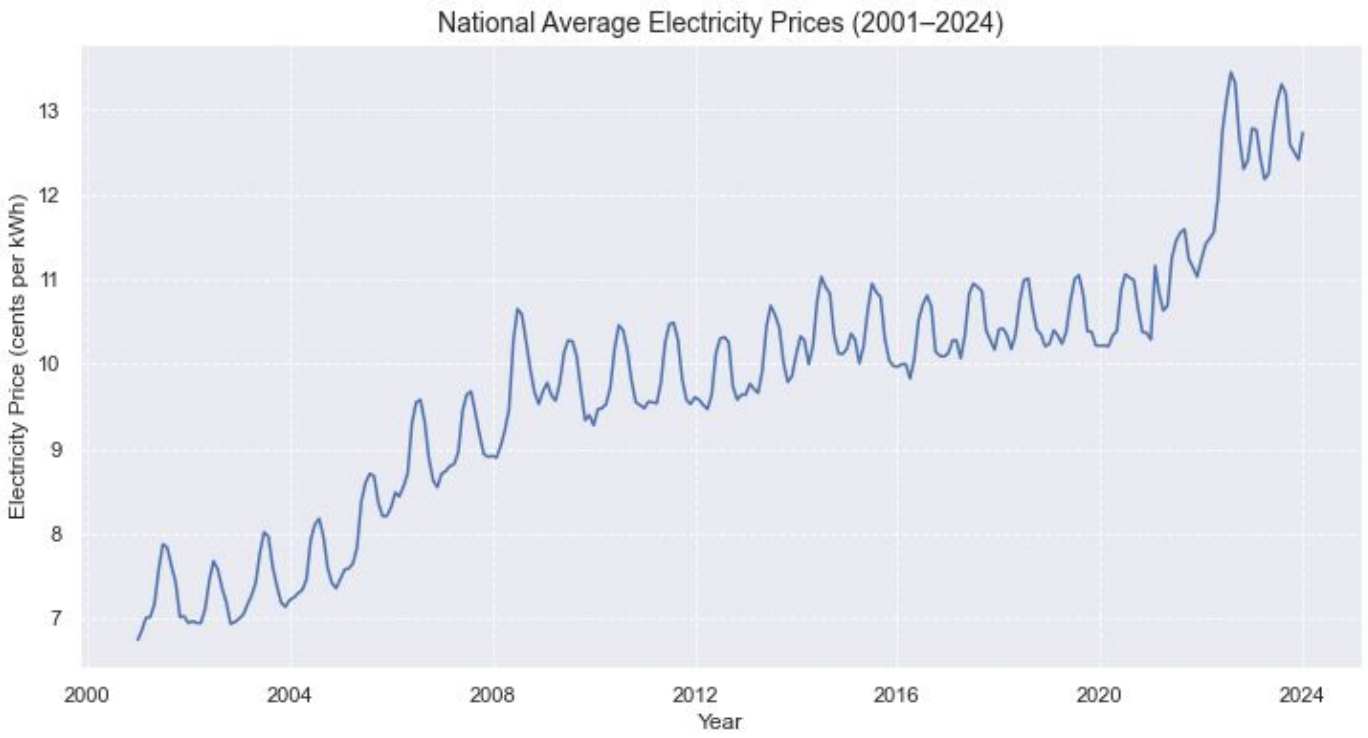
Notable Studies:

- **Wang et al.**: SARIMAX model with exogenous variables (e.g., fuel and carbon prices).
- **Lehna et al.**: German market analysis comparing SARIMAX, LSTM, CNN, VAR, and hybrid models.
  - **Findings**:
    - LSTM: Best single model overall.
    - VAR: Excels in short-term predictions.
    - Hybrid models outperform single approaches.
- **Wagner et al.**: Seasonal layers in neural networks improve accuracy, outperforming LSTM in some cases.

Data

Category	Description
Data Source	Kaggle dataset, compiled from the U.S. Energy Information Administration (EIA).
Time period	2001 to 2024
Resolution	Monthly electricity prices across all U.S. states and sectors.
Features	Date, US State, Sector, Price (¢/kWh)

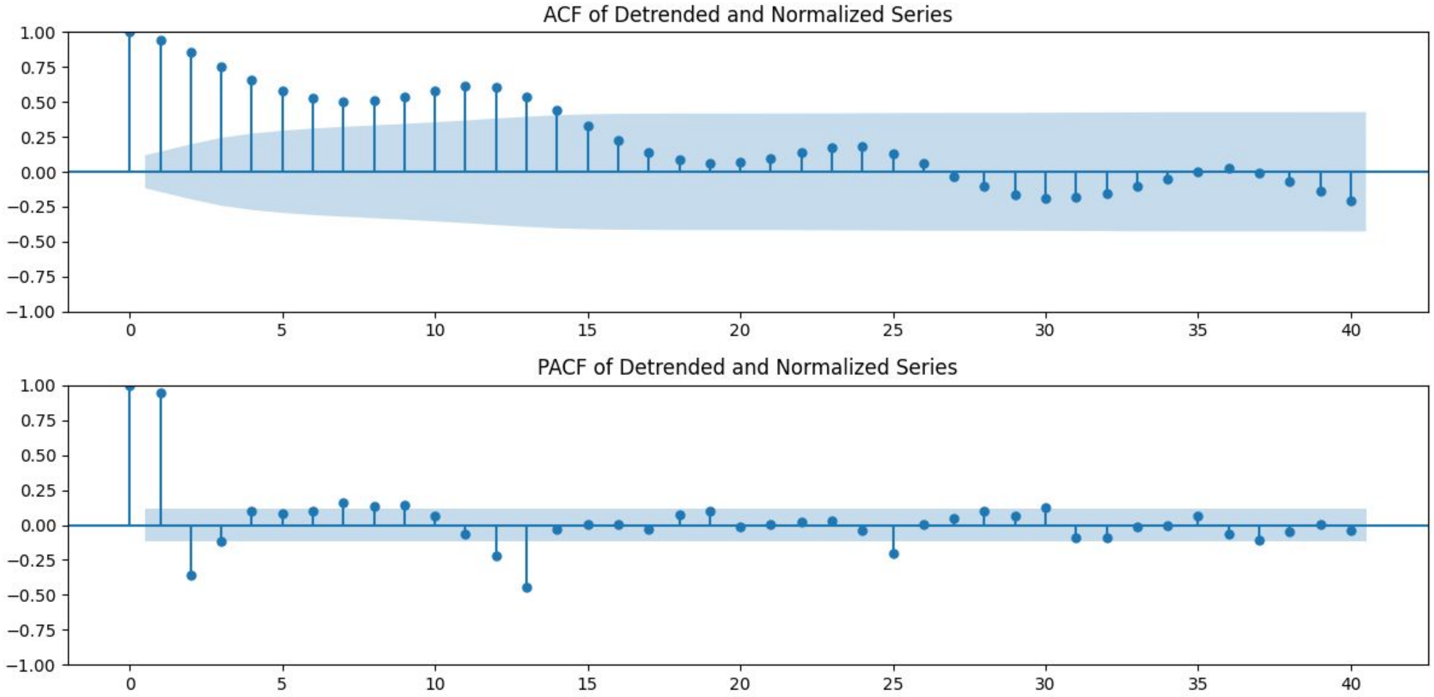
Data


National Average Electricity Prices (2001–2024)
Electricity Price (cents per kWh)
7
8
9
10
11
12
13
2000
2004
2008
2012
2016
2020
2024
Year

Diagnostics

Stationarity → Detrended Data

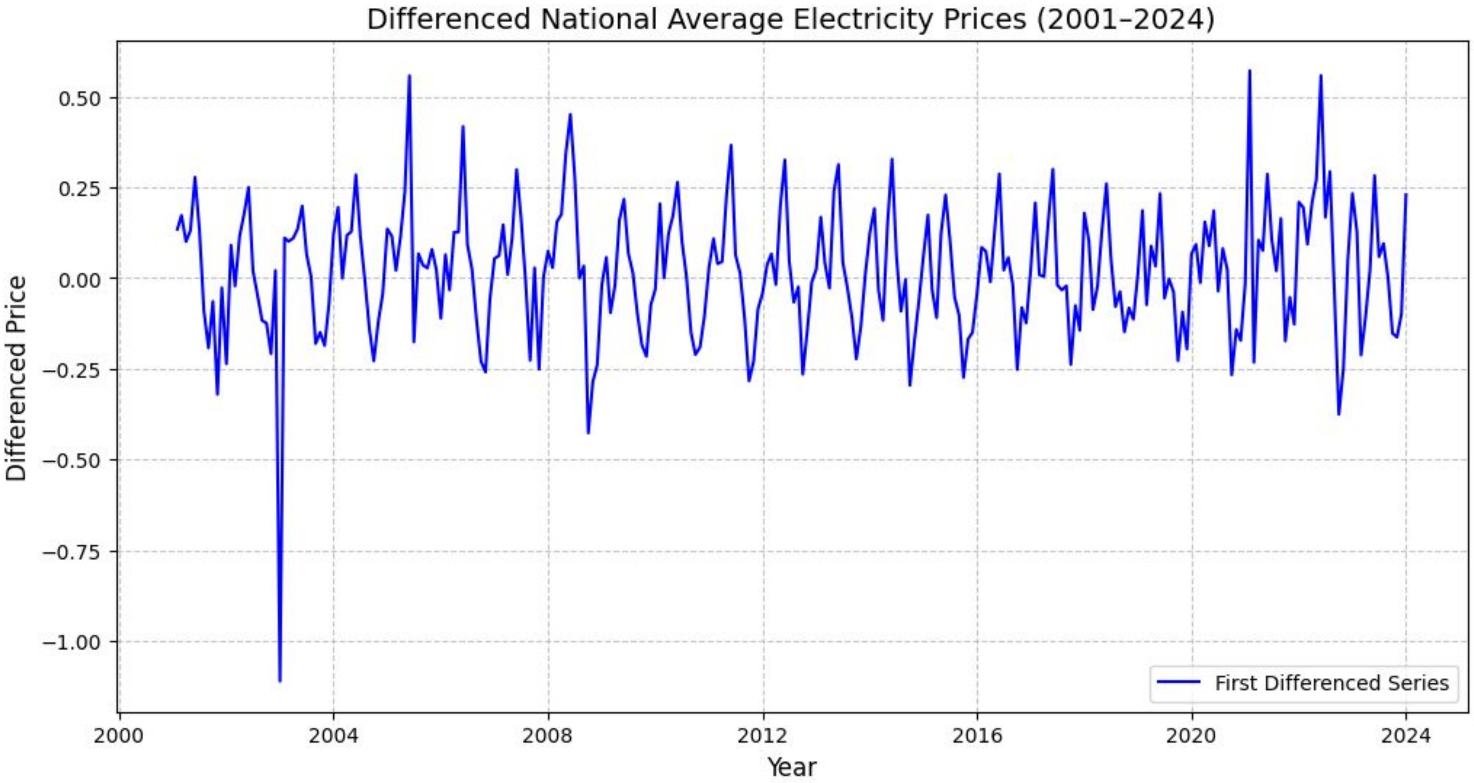
Stationarity → Detrended Data



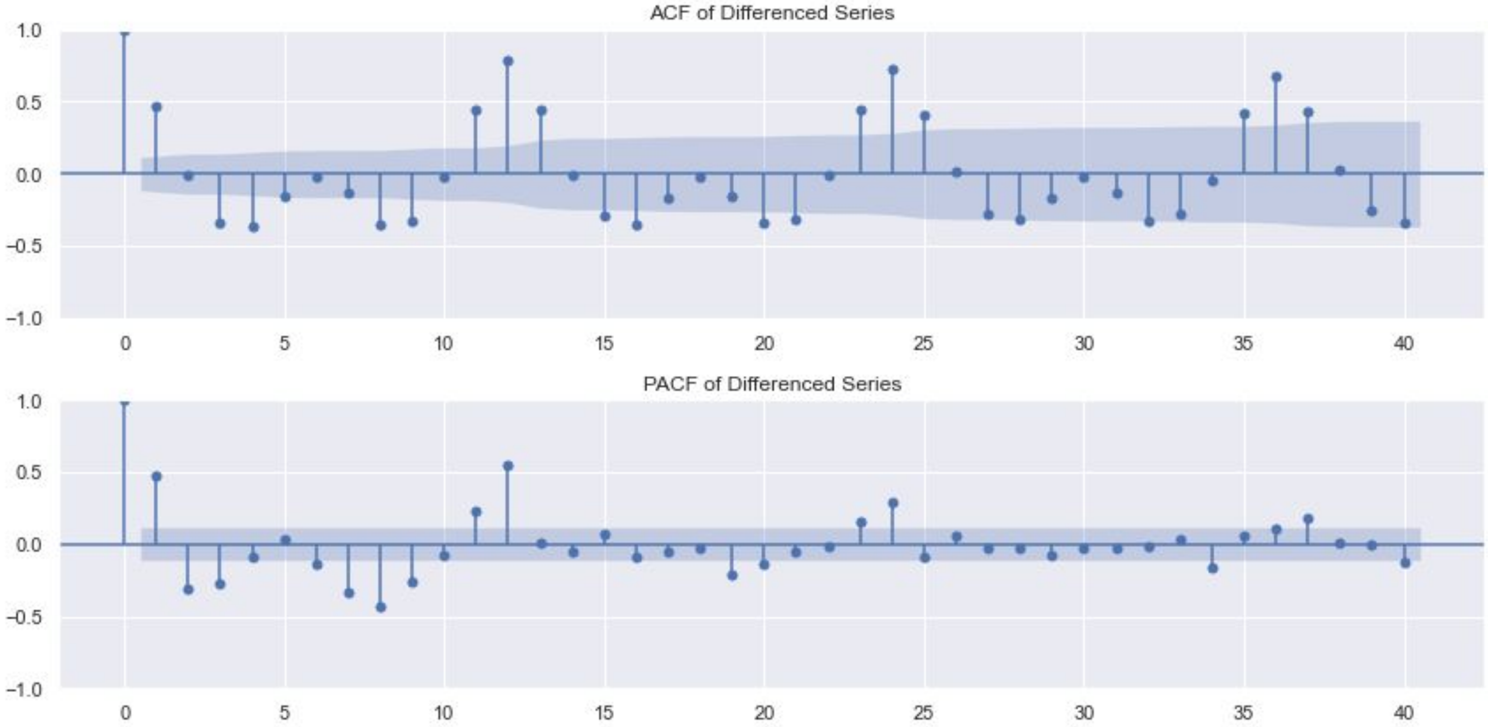
Augmented Dickey-Fuller Test:

P-value = 0.016

Stationarity → Differenced Data



Stationarity → Differenced Data



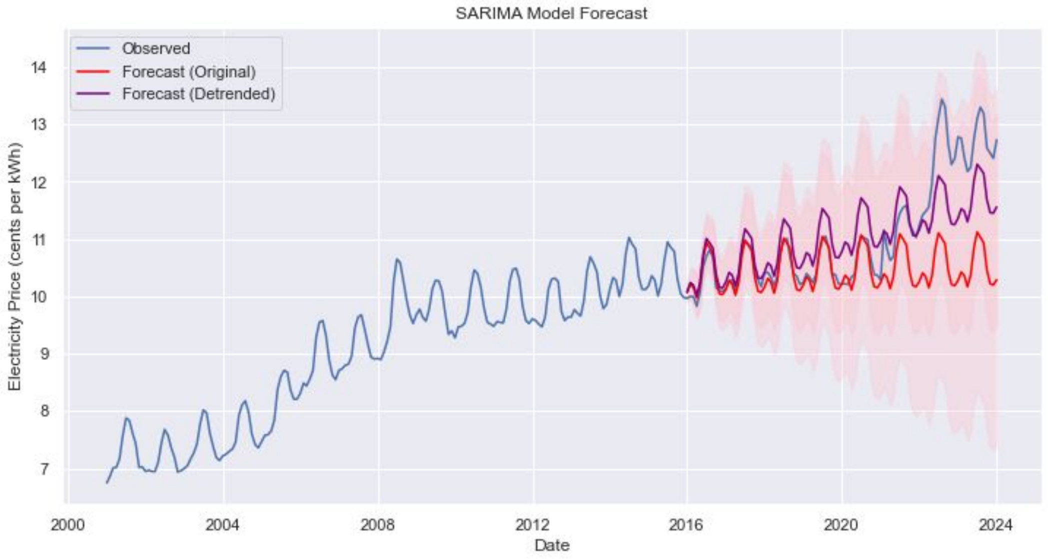
Augmented Dickey-Fuller Test:

P-value = 0.024

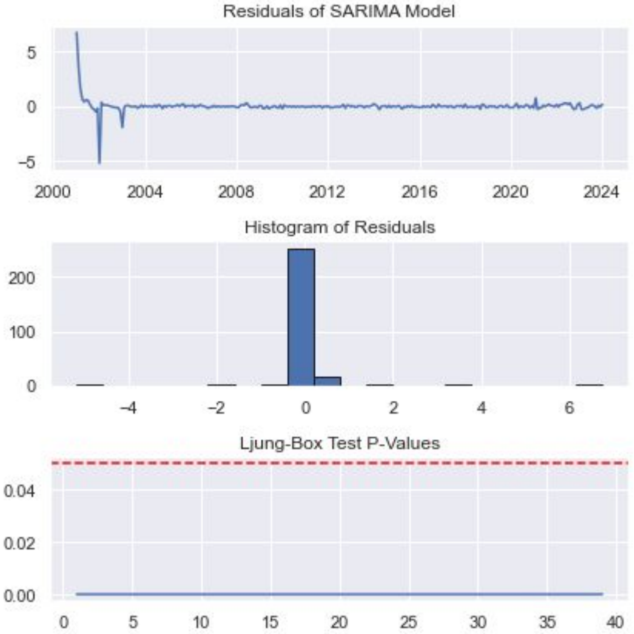
Models

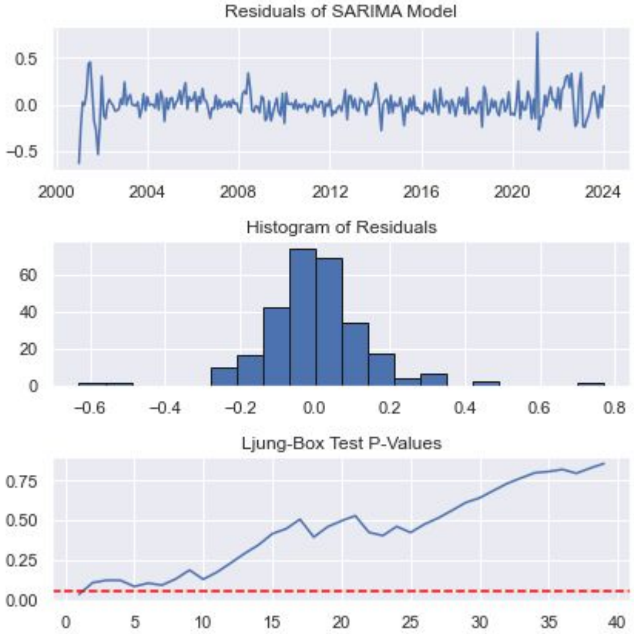
SARIMA

Model	Original	Detrended
Assume trend?	No	Yes (linear)
5-fold CV RMSE	0.666	1.217
AIC	-318.83	-320.31
Ljung-Box result	Reject null	Fail to reject null



SARIMA: Ljung-Box

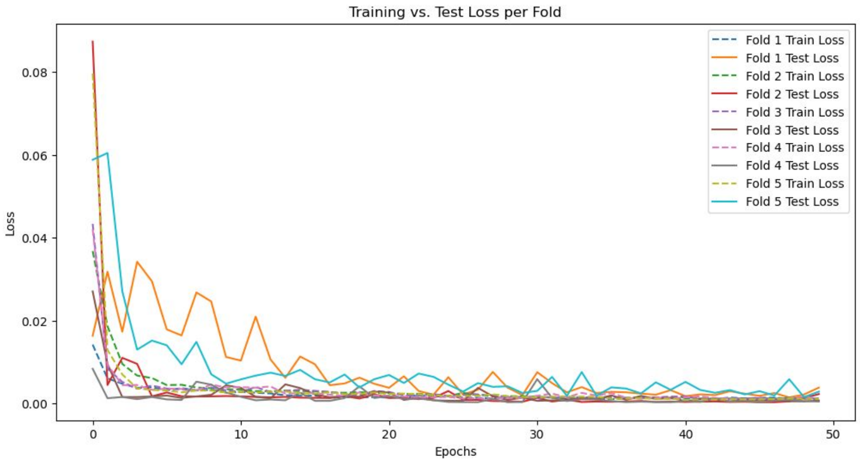


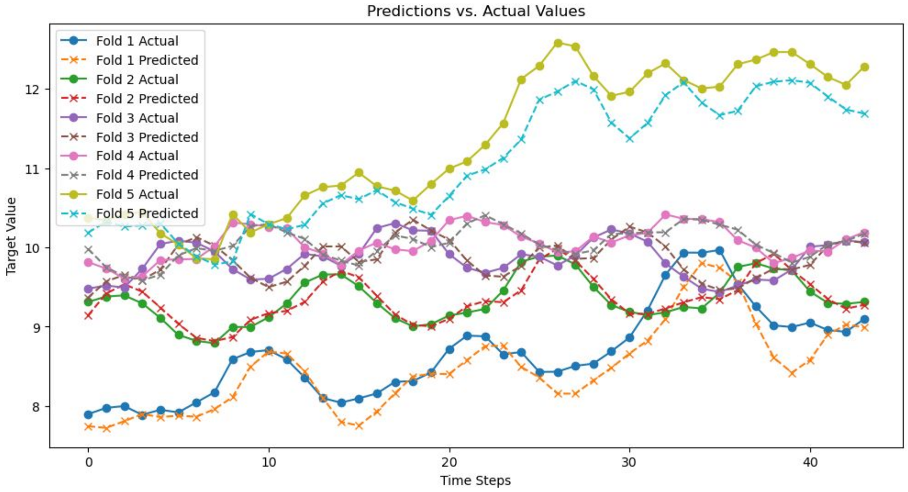


Left: Original model

Right: Detrended model

LSTM





Average RMSE = 0.1949

Hyperparameters: Units = 64, Dropout Rate = 0.1, Learning Rate = 0.01, Batch Size = 16, Epoch = 50

Evaluation Results

Model	Average RMSE from 5-fold CV
SARIMA (Original)	0.666
SARIMA (Detrended)	1.218
LSTM	0.1949

Conclusion

- Nature of data: Seasonal, with upward trend (not perfectly linear)
- Model 1: SARIMA (Original vs. Detrended)
  - Original model has higher predictive power but may not be robust
- Model 2: LSTM
  - Highest RMSE → High predictive power
- Next steps: Incorporate more data and/or explore new models
  - Ex: Look at prices across different states/sectors and consider a vector autoregressive (VAR) model

Thank you!!!