

SUMMATIVE ASSESSMENT

2

Time Series Analysis and Modeling

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Overview

DATASET A

GARCH Volatility

SPY Daily Returns (2015-2025), GARCH(1,1) with Student-t distribution

DATASET B

ARIMAX Transfer Function

Sales and Advertising, Prewhitening and CCF Analysis

DATASET C

SARIMAX Intervention

Spanish Electricity Demand, Policy Impact Analysis

DATASET A

GARCH Volatility Modeling

S&P 500 ETF (SPY) Daily Returns

DATA SOURCE

Yahoo Finance

TIME PERIOD

2015 - 2025

OBSERVATIONS

~2,750 daily returns

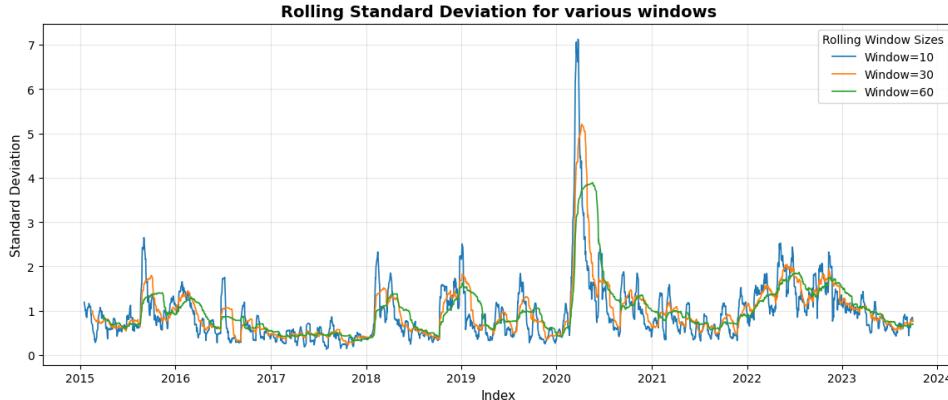
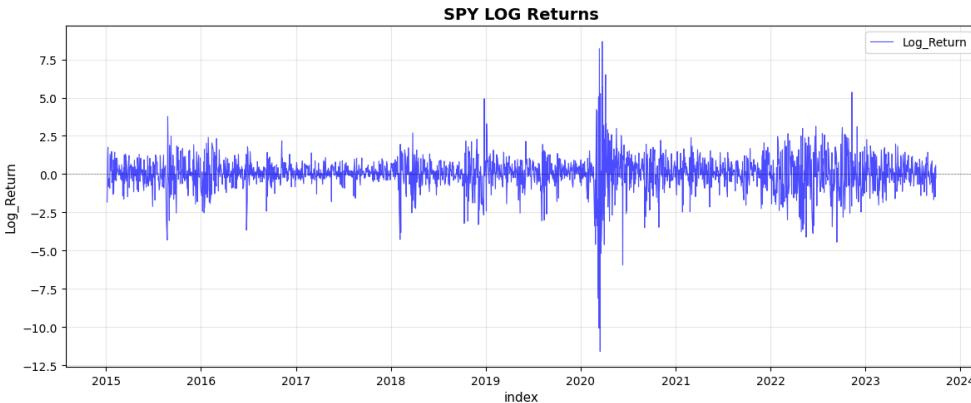
Exploratory Data Analysis

Key Observations

Clear volatility clustering. COVID crash shows -12% drop with +8% rebound. Classic GARCH behavior.

Rolling Volatility

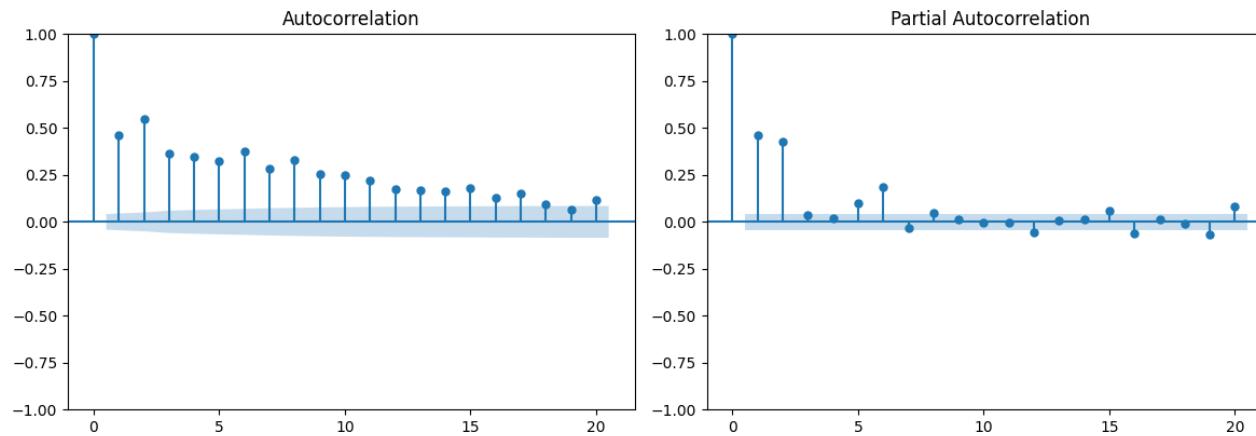
Spikes during COVID (~7%). Elevated in Aug 2015, late 2018, and 2022.



SPY LOG Returns Plot

ACF/PACF of Squared Returns

Autocorrelation and Partial Autocorrelation Functions of Squared (LOG_RETURN)



ACF Analysis

Slow decay from ~ -0.47 at lag 1 through lag 20. GARCH term needed.

PACF Analysis

Sharp cutoff after lags 1-2. ARCH(1) sufficient.

Recommendation

Start with GARCH(1,1) - parsimonious specification

Model Selection: Grid Search

Grid search: p,q in {1,2,3}, distributions: Normal, Student-t

	AIC	BIC	LogLik
GARCH(1,1)_t	5564.679176	5593.160239	-2777.339588
GARCH(2,1)_t	5566.354130	5600.531406	-2777.177065
GARCH(1,2)_t	5566.679176	5600.856451	-2777.339588
GARCH(2,2)_t	5567.207559	5607.081047	-2776.603779
GARCH(3,1)_t	5568.354130	5608.227618	-2777.177065
GARCH(1,3)_t	5568.644663	5608.518152	-2777.322332
GARCH(2,3)_t	5569.156788	5614.726489	-2776.578394
GARCH(3,2)_t	5569.207559	5614.777260	-2776.603779
GARCH(3,3)_t	5571.555018	5622.820932	-2776.777509
GARCH(1,1)_normal	5704.150342	5726.935193	-2848.075171
GARCH(1,2)_normal	5706.141558	5734.622621	-2848.070779
GARCH(2,1)_normal	5706.150342	5734.631406	-2848.075171
GARCH(2,2)_normal	5707.628401	5741.805677	-2847.814200
GARCH(3,1)_normal	5708.084622	5742.261898	-2848.042311
GARCH(1,3)_normal	5708.141557	5742.318833	-2848.070778
GARCH(2,3)_normal	5709.114862	5748.988350	-2847.557431
GARCH(3,2)_normal	5710.051802	5749.925290	-2848.025901
GARCH(3,3)_normal	5710.524075	5756.093776	-2847.262037

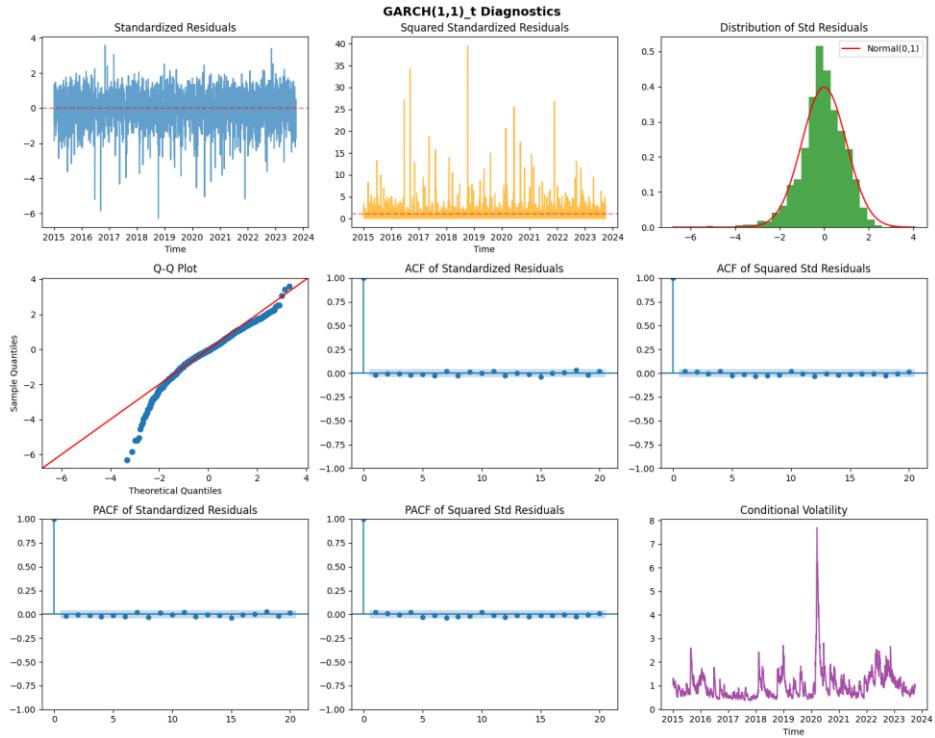
Best Model: GARCH(1,1)_t

Lowest BIC, parsimonious. Student-t handles fat tails.

Key Findings

Student-t models outperform Normal by ~140 BIC. Higher-order models offer minimal improvement.

Model Diagnostics



Ljung-Box (Residuals): $p > 0.67$ - No serial correlation

Ljung-Box (Squared): $p > 0.37$ - No ARCH effects

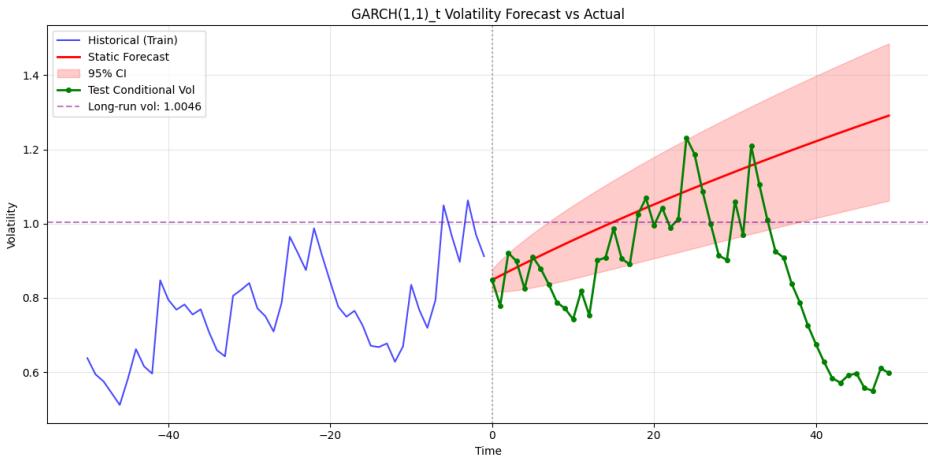
ARCH-LM: $p = 0.55$ - Volatility captured

Normality: JB $p = 0$ - Non-normal (expected with t-dist)

Conclusion

GARCH(1,1)_t well-specified. Suitable for forecasting.

Volatility Forecasting



Forecast Accuracy

MSE: 0.1109, MAE: 0.2339

95% CI Coverage: 48.0%

Limitation

Static forecasts converge to unconditional mean. Use rolling re-estimation for better performance.

Long-run Volatility

1.0046

DATASET B

ARIMAX Transfer Function

Sales and Advertising Analysis

METHODOLOGY

Prewhitening, CCF, Transfer Function

FREQUENCY

Weekly (52 periods/year)

VARIABLES

Sales (output), Advertising (input)

Baseline: Auto ARIMA

Stationarity

ADF Test $p < 0.01$ - Series is stationary

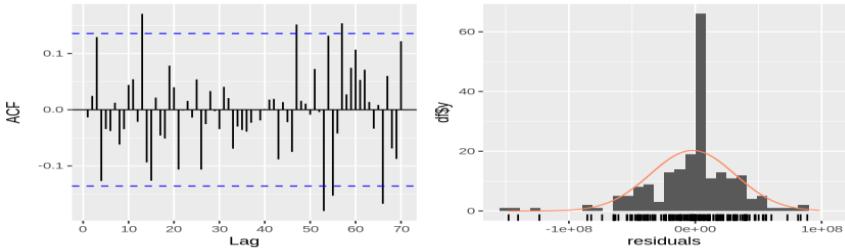
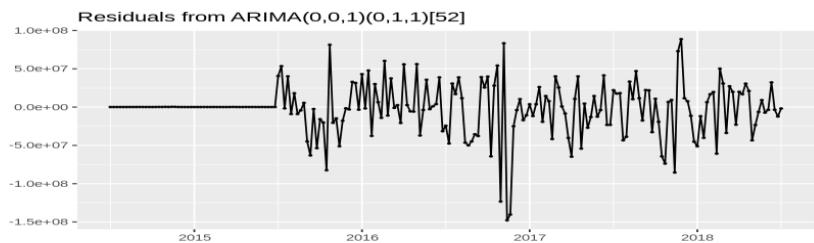
Auto ARIMA Selection

ARIMA(0,0,1)(0,1,1)[52]

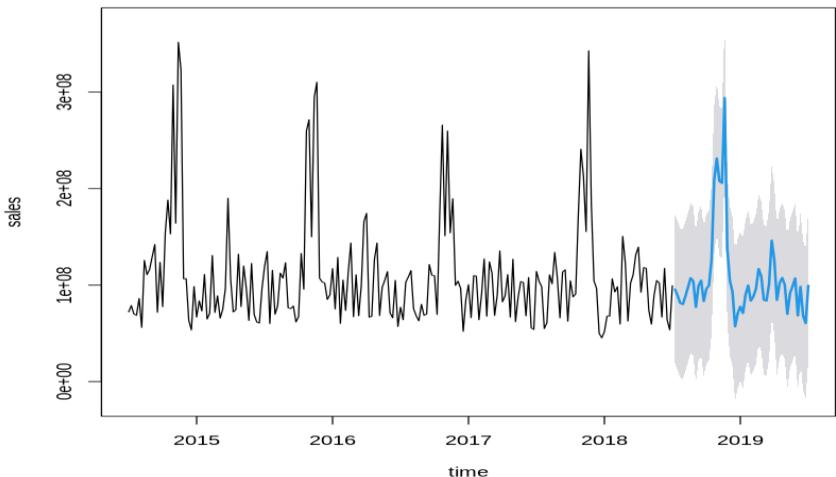
Model Fit

AIC: 5958.77, BIC: 5967.94, MAPE: 22.07%

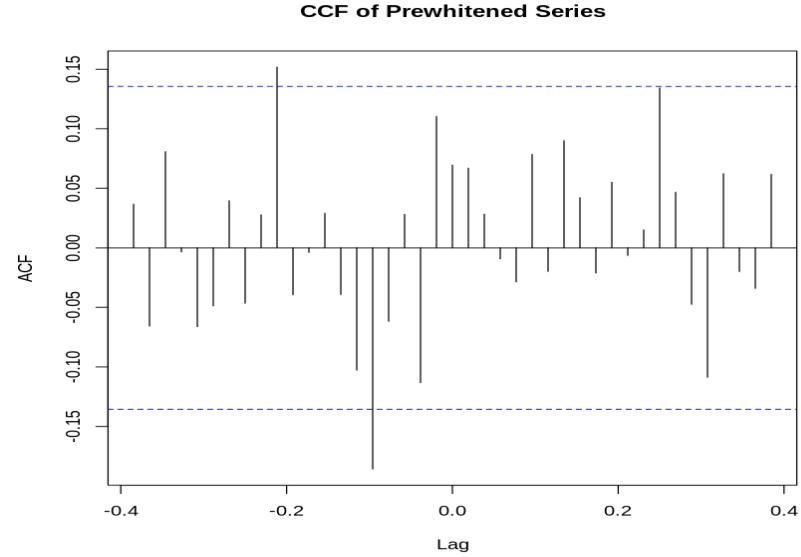
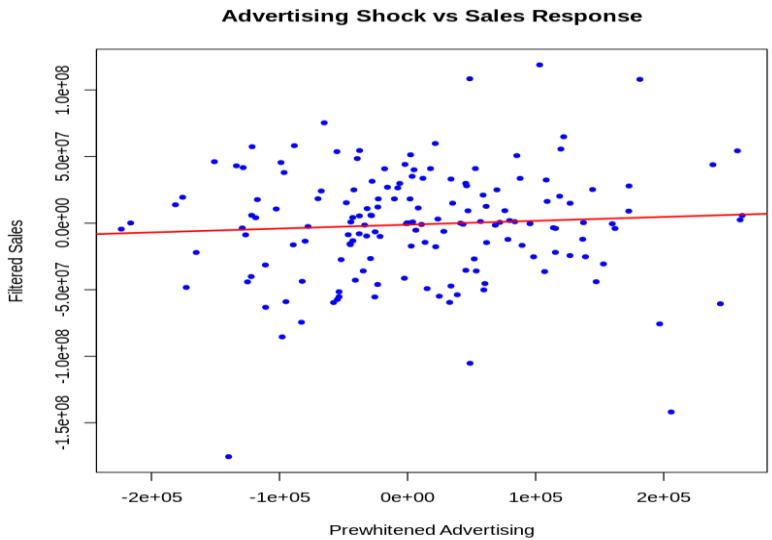
Ljung-Box: $p = 0.69$ - Residuals uncorrelated



Baseline Forecast for Auto ARIMA Model



Prewhitenning and CCF Analysis



Prewhitenning

ARIMA(0,1,2)(1,1,0)[52] filter applied to both series

CCF Findings

Only 2 significant lags (10 and 16). Weak relationship overall.

ARIMAX Transfer Function Model

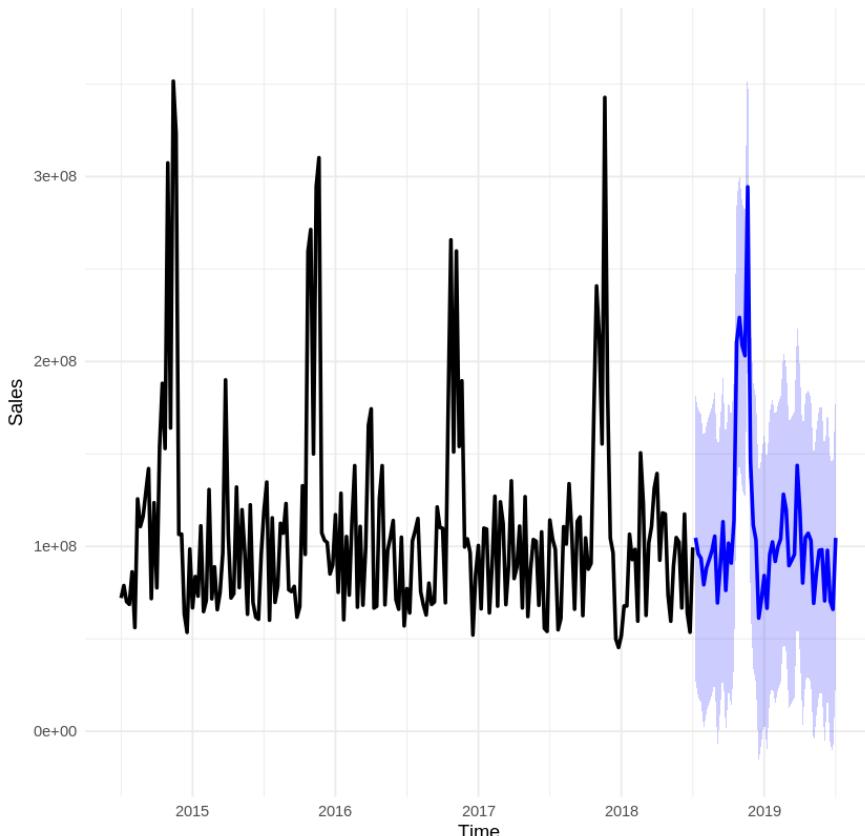
Model

ARIMA(0,0,1)(0,1,1)[52] + lags

Advertising lags NOT significant. Sales driven by own history.

AIC: 325.32 (much lower than baseline)

ARIMAX Forecast with 95% CI



DATASET C

SARIMAX Interventi on

Spanish Electricity Demand

DATA SOURCE

Kaggle Energy Dataset

TIME PERIOD

2015 - 2019 (Daily)

INTERVENTION

January 1, 2017

Exploratory Data Analysis



Intervention Model Design

Intervention Variables

PULSE DUMMY

= 1 on intervention day only (Jan 1, 2017)

STEP DUMMY

= 1 from intervention day onwards

Best Model (AIC Selection)

SARIMAX(0,1,1)x(1,0,1)7

Model Selection

Grid search over p,q and P,Q

Best AIC: -2610.88

Train/Test Split

Train: Dec 2014 - Jun 2018

Test: Jul 2018 - Dec 2018

Intervention Effects

Ljung-Box test:

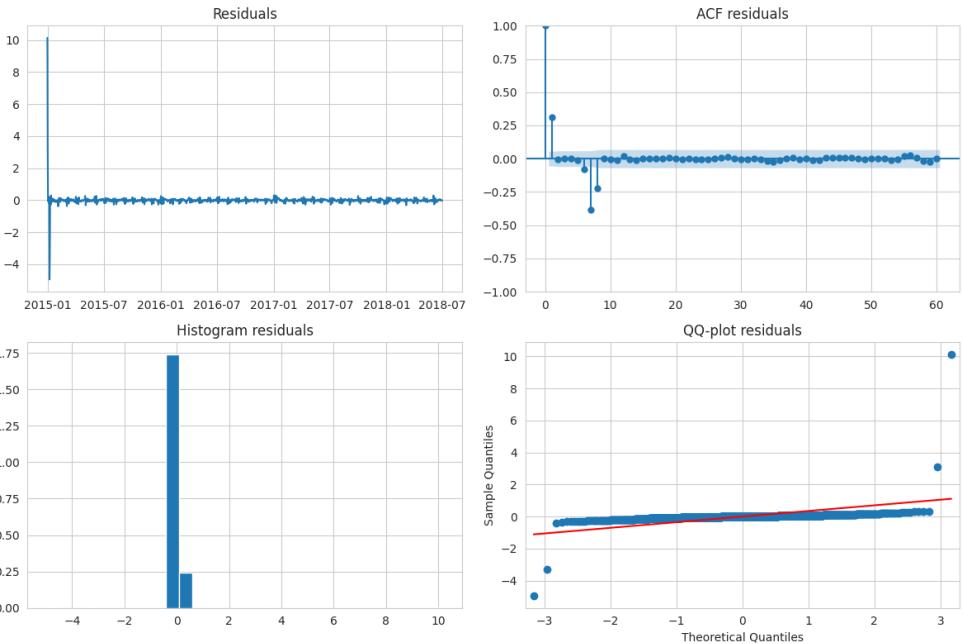
	lb_stat	lb_pvalue
10	384.824035	1.593365e-76
20	385.732855	1.850808e-69
30	386.329629	1.601987e-63

Jarque-Bera test:

JB stat: 18138920.002995897
p-value: 0.0
Skew: 16.517018780609153
Kurtosis: 585.7055411816755

ARCH LM test:

LM stat: 84.54284441631629
p-value: 6.423641835234612e-14

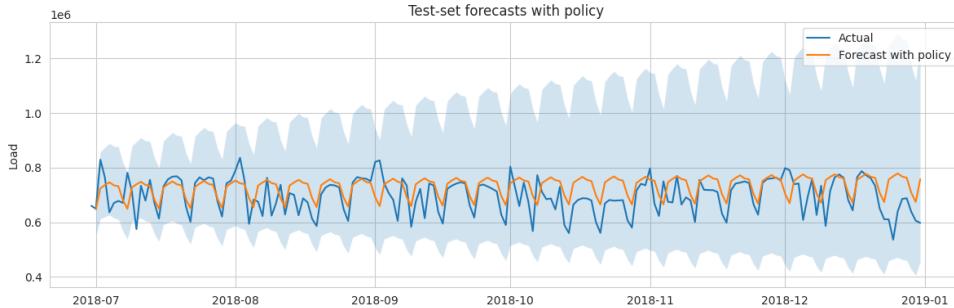


Interpretation (Original Scale)

Step: -19.1% permanent reduction

Pulse: +5.7% one-day spike (not significant)

Policy Impact Analysis



Average actual load: 696802.9162162162

Average forecast with policy: 730417.8625492862

Average forecast without policy: 903172.1269084964

Estimated average reduction (%): 19.12750174770534

Forecast Accuracy

RMSE: 76,067 MWh

MAPE: 8.7%

Counterfactual Comparison

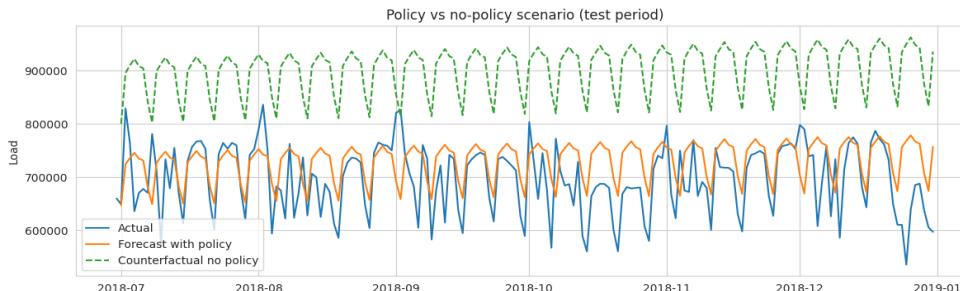
With Policy: 730,418 MWh/day

Without Policy: 903,172 MWh/day

Estimated Reduction

19.1%

Significant demand reduction from policy intervention



Key Takeaways

Summative Assessment 2 Findings

Dataset A

GARCH(1,1) with Student-t

Captures volatility clustering in SPY returns. Persistence near 1.0. No residual ARCH effects.

Dataset B

ARIMAX Transfer Function

Advertising has limited delayed impact on sales.
Seasonal component essential.

Dataset C

SARIMAX Intervention

Policy intervention reduced demand by 19%. Step effect dominates long-run impact.