Summative Assessment 2: Time Series Analysis

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Dataset A: GARCH Volatility Modeling

We used SPY ETF daily returns from 2015–2019 (n=1,258) to model volatility clustering. After checking the ACF/PACF of squared returns, we conducted grid search and the best model turned out to be **GARCH(1,1) with Student-t errors**. The model gave us $\alpha_1 = 0.088$ and $\beta_1 = 0.899$, which means volatility is highly persistent (sums to ~0.99). Ljung-Box tests on the standardized residuals showed no leftover ARCH effects, so we're confident the model captured the volatility dynamics properly.

Recommendation: For traders or risk managers, this model can help set dynamic stop-losses or position sizes based on predicted volatility. When the model forecasts higher volatility, it might be wise to reduce exposure or widen hedging bands. It's a simple but effective way to adapt to changing market conditions.

Dataset B: ARIMAX Transfer Function Model

For this one, we had 36 months of sales and advertising data. We wanted to see how ads affect sales over time. We prewhitened both series using an AR(1) filter, then looked at the CCF to find the lag structure. The best model turned out to be **ARIMA(0,1,1)(0,1,1)$_{12}$** with advertising as an exogenous variable. The ad coefficient was 1.69 (p = 0.042), meaning there's a statistically significant but fairly modest effect.

Recommendation: Since the advertising effect is real but not huge, businesses should think carefully about their ad spend. It might be better to focus on seasonal timing since our model shows strong seasonality, so pushing ads during peak seasons could maximize ROI. Also, don't expect immediate results; the effect takes time to show up in sales.

Dataset C: SARIMAX Intervention Analysis

This dataset had daily Spanish electricity demand from 2015–2019 (n=1,462). We modeled the impact of a policy intervention on January 1, 2017 using pulse and step dummy variables. After grid search, the best fit was **SARIMAX(0,1,1)(1,0,1)$_7$** . The step coefficient came out to −0.212 ($p < 0.001$), which translates to roughly a **19.1% permanent drop** in demand after the intervention. The pulse effect wasn't significant (p = 0.389), so there was no immediate spike, just a sustained decrease.

Recommendation: This is pretty strong evidence that the policy worked. For policymakers, it suggests that regulatory interventions can have lasting effects on energy consumption. Future energy planning should account for these structural shifts. For similar interventions elsewhere, using counterfactual analysis like we did here can help quantify actual impact vs. what would have happened without the policy.

Summary Table

Dataset A (GARCH)	Dataset B (ARIMAX)	Dataset C (SARIMAX)
GARCH(1,1) + t-dist	ARIMA(0,1,1)(0,1,1)$_{12}$	SARIMAX(0,1,1)(1,0,1)$_7$
Persistence ≈ 0.99	Ad coef: +1.69	**Step: −19.1%**
Use for risk mgmt	*Time ads seasonally*	*Policy approach works*