Time Series Analysis and Forecasting

Chapter 10: Comprehensive Review

Daniel Traian PELE

Bucharest University of Economic Studies
IDA Institute Digital Assets
Blockchain Research Center
AI4EFin Artificial Intelligence for Energy Finance
Romanian Academy, Institute for Economic Forecasting
MSCA Digital Finance

Outline

- Forecasting Methodology
- Case Study 1: Bitcoin Volatility (GARCH)
- Case Study 2: Sunspot Cycles (Fourier)
- Case Study 3: Unemployment (Prophet)
- Case Study 4: Multivariate Analysis (VAR)
- Synthesis and Guidelines

The Scientific Approach to Forecasting

Research Question

How do we **rigorously evaluate** forecast performance while avoiding overfitting?

The Fundamental Problem

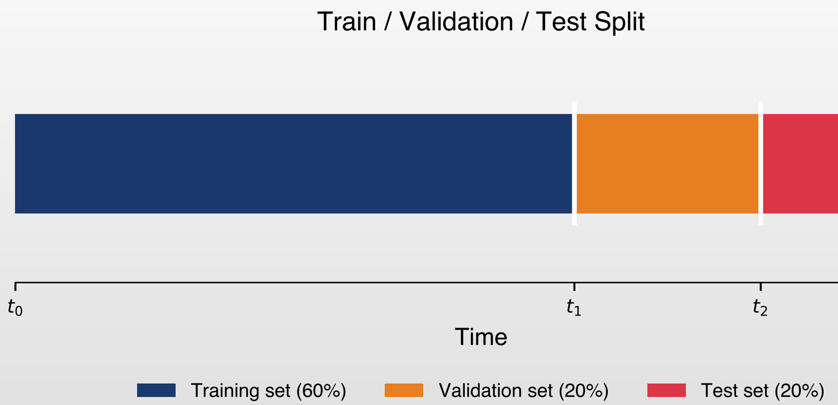
- In-sample fit $\neq$ Out-of-sample performance
- Models can "memorize" training data without learning patterns
- **Solution**:
  - Proper train/validation/test methodology

Key Principle

"The test set must remain **untouched** until final evaluation."

— Standard practice in machine learning and econometrics

Train/Validation/Test Framework



Training Set

- Fit parameters

Validation Set

- Compare models

Test Set

- **Held out**

Evaluation Metrics

Definition 1 (Forecast Error Metrics)

Let y_t be actual, $\hat{y}_t$ forecast:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_t (y_t - \hat{y}_t)^2}, \quad \text{MAE} = \frac{1}{n}\sum_t |y_t - \hat{y}_t|, \quad \text{MAPE} = \frac{100\%}{n}\sum_t \left|\frac{y_t - \hat{y}_t}{y_t}\right|$$

When to Use Each

- **RMSE**: Penalizes large errors
- **MAE**: Robust to outliers
- **MAPE**: Scale-independent (%)

Caution

- MAPE undefined when $y_t = 0$
- Compare on **same** test set
- Report **out-of-sample** metrics

Bitcoin: Problem Statement

Research Question

Can we forecast Bitcoin's **volatility** using GARCH models?

Data Characteristics

- Source: Yahoo Finance (BTC-USD)
- Period: Jan 2019 – Jan 2025
- Frequency: Daily
- Observations: $\approx 2,200$ days

Stylized Facts

- Returns: near-zero mean
- Fat tails (kurtosis > 3)
- Volatility clustering

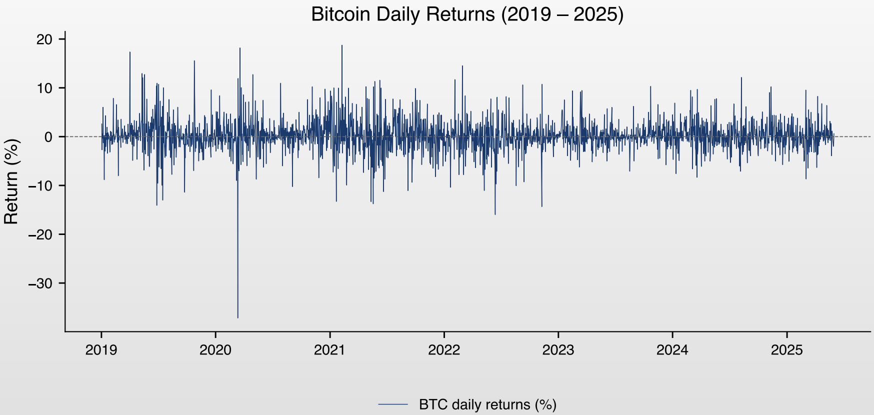
Key Insight

Financial returns are typically:

- **Unpredictable** in mean
- **Predictable** in variance

$\Rightarrow$ Focus on **volatility forecasting**

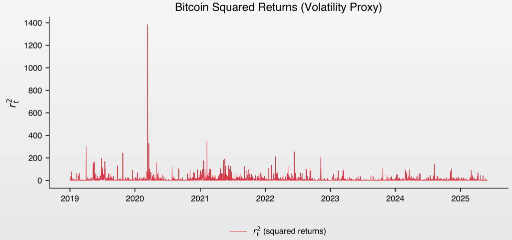
Bitcoin: Volatility Clustering



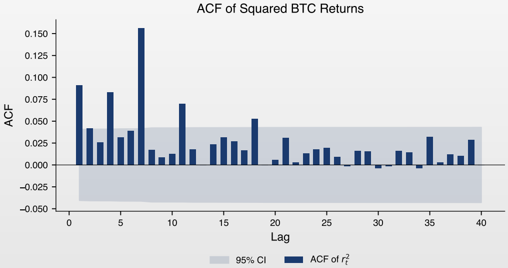
Observation

Large returns follow large returns, small follow small—**volatility clustering**.

Bitcoin: Evidence for GARCH



Squared returns r_t^2 proxy for volatility.



Significant ACF at multiple lags.

Why GARCH?

Significant ACF in r_t^2 means **past volatility predicts future volatility**.

GARCH Model Specification

Definition 2 (GARCH(p,q) Model)

Let r_t denote returns. The GARCH(p,q) model:

$$r_t = \mu + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t, \quad z_t \sim N(0,1)$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

where $\omega > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$, and $\sum \alpha_i + \sum \beta_j < 1$.

Model Variants

- **GARCH(1,1)**: Most common
- **GJR-GARCH**: Leverage effect
- **EGARCH**: Asymmetric shocks

Interpretation

- α: Impact of past shocks
- β: Persistence of volatility
- $\alpha + \beta \approx 1$: High persistence

Bitcoin: Data Split and Stationarity

Data Split

Set	Period	N
Training (70%)	2019-01 to 2023-03	1,543
Validation (20%)	2023-03 to 2024-06	441
Test (10%)	2024-06 to 2025-01	221
Total		**2,205**

Stationarity Tests

Series	ADF	Result
Prices	$p = 0.50$	Non-stationary
Returns	$p < 0.01$	Stationary

$\Rightarrow$ Model **returns**, not prices

Why Stationarity Matters

GARCH requires weakly stationary input. Prices follow random walk; returns are stationary.

Bitcoin: Model Selection on Validation Set

Methodology

Fit each model on **training data**, evaluate on **validation set**.

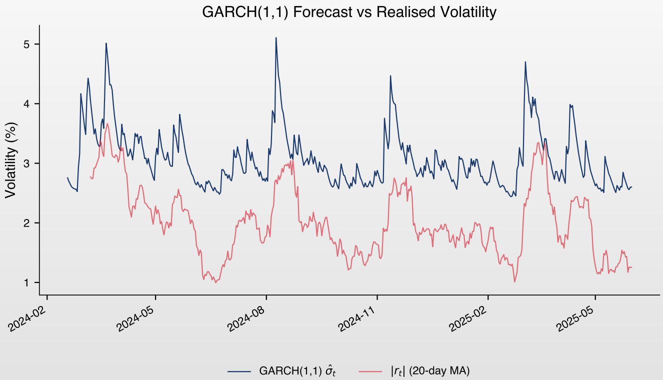
Model	**AIC**	**BIC**	**Val MAE**	**Selection**
GARCH(1,1)	6,994.8	7,020.6	**2.638**	**Best**
GARCH(2,1)	6,993.7	7,024.6	2.640	
GJR-GARCH(1,1)	6,983.7	7,014.6	2.669	
EGARCH(1,1)	—	—	—	Failed*

*Analytic forecasts not available for $h > 1$

Result

GARCH(1,1) selected based on lowest validation MAE for volatility forecasts.

Bitcoin: Final Test Set Evaluation



Parameters

$\omega = 0.87$, $\alpha = 0.09$, $\beta = 0.84$

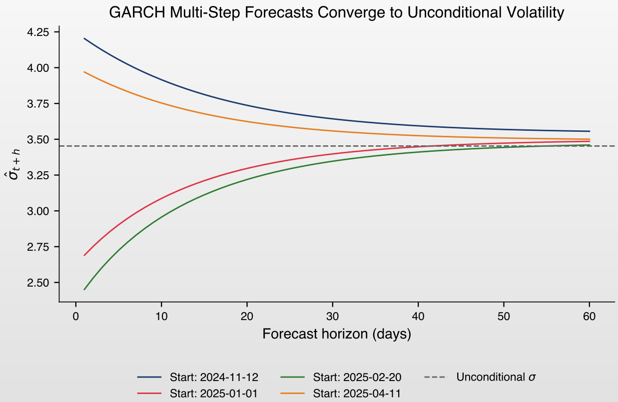
$\alpha + \beta = 0.93$ (high persistence)

Test Performance

MAE = 1.82, RMSE = 2.14

Rolling forecasts track volatility well.

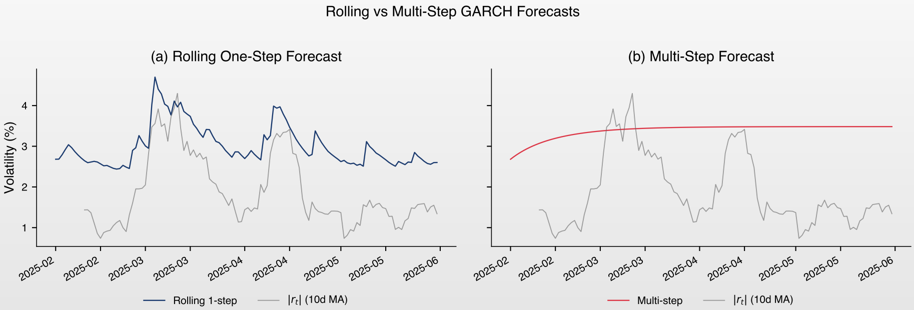
GARCH: Multi-Step Forecasts Converge



Key Insight

Multi-step forecasts converge to $\bar{\sigma}^2 = \frac{\omega}{1-\alpha-\beta}$. Use rolling forecasts.

GARCH: Rolling One-Step-Ahead Solution



Multi-Step (Left)

Converges to $\bar{\sigma}^2$ (flat)

Rolling 1-Step (Right)

Re-estimate at each t (dynamic)

TSA_ch10_rolling_vs_multistep

Bitcoin: Key Findings

Summary

1. **Returns are stationary**; prices are not
2. **GARCH(1,1)** outperforms more complex variants
3. **High persistence** ($\alpha + \beta = 0.93$)
4. Volatility is **predictable** even when returns are not

Limitations

- GARCH assumes **symmetric** shocks
- Does not capture **jumps**
- Normal distribution may be restrictive

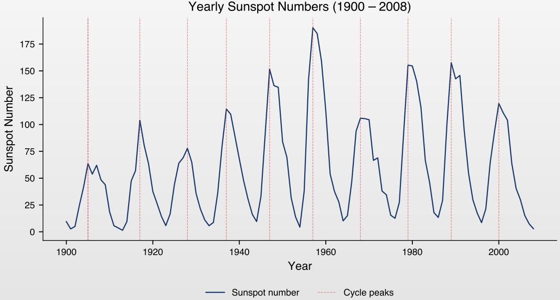
Practical Implications

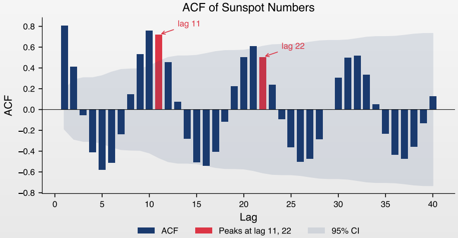
- Risk management: VaR, Expected Shortfall
- Option pricing requires volatility forecasts
- Portfolio optimization with time-varying risk

Extensions

- Student-t innovations
- Realized volatility
- HAR models

Sunspots: The 11-Year Solar Cycle





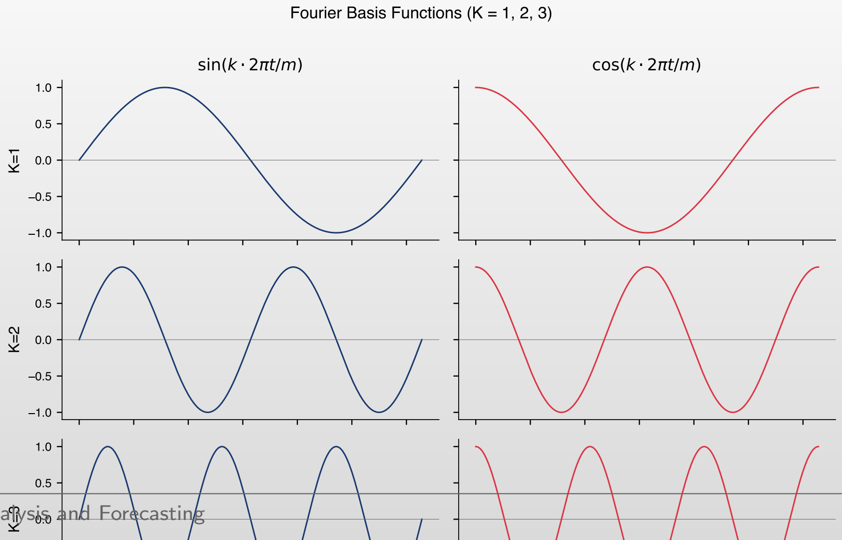
ACF peaks at lag 11, 22.

Cycle peaks every 11 years.

Challenge

SARIMA_{11} requires too many parameters. **Solution**: Use Fourier terms.

Fourier Terms for Seasonality



Sunspots: Model Selection

Methodology

Compare $K = 1, 2, 3, 4$ Fourier harmonics on validation set.

Data Split

Set	Period	N
Training (70%)	1900–1975	76
Validation (20%)	1976–1997	22
Test (10%)	1998–2008	11
Total		**109**

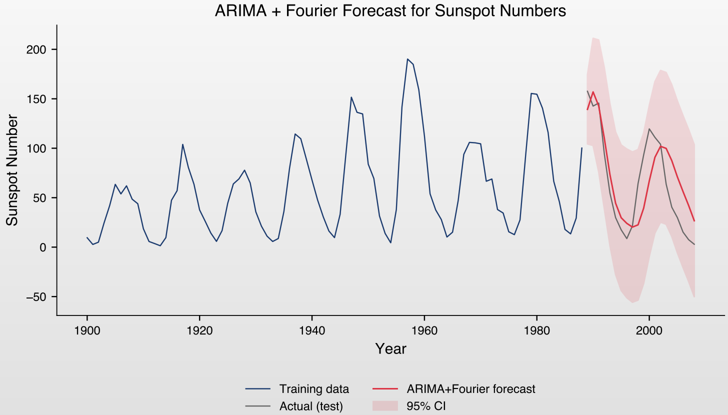
Model Comparison

K	AIC	Val RMSE	
1	665.9	87.15	
2	668.0	86.92	
3	671.8	**86.81**	Best
4	674.5	87.93	

Result

K = 3 Fourier harmonics selected (6 parameters for 11-year cycle).

Sunspots: Forecast Results



Model

ARIMA(2,0,1) + 3 Fourier terms

Test Performance

RMSE = 31.10, MAE = 25.83.

Sunspots: Key Takeaways

When to Use Fourier Terms

- Seasonal period s is **long** (e.g., 11 years, 52 weeks)
- SARIMA would require too many seasonal lags
- Pattern is **smooth and periodic**
- Multiple cycles need to be captured

Fourier vs SARIMA

	Fourier	**SARIMA**
Long seasons	✓	×
Short seasons	OK	✓
Parameters	$2K$	Many
Flexibility	Fixed	Adaptive

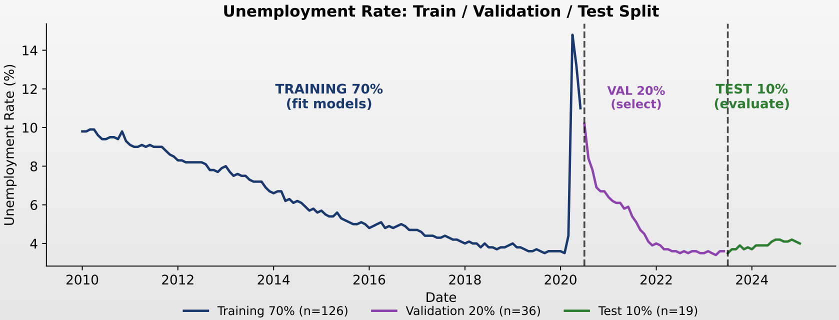
Choosing K

Start with $K = 1$, increase until validation error stops improving. Too high K = overfitting.

Applications

Climate cycles, business cycles, astronomical phenomena

Unemployment: Train / Validation / Test Split

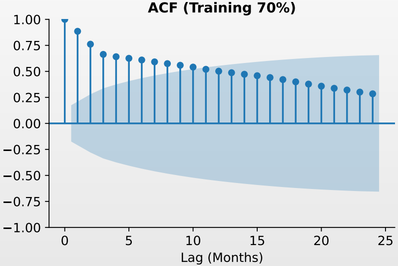


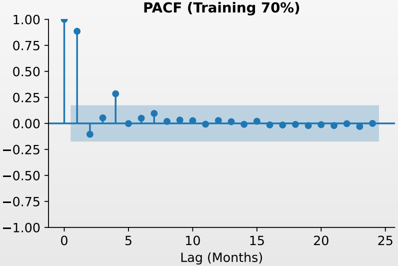
Methodology

Training: Fit models. **Validation**: Select best. **Test**: Final evaluation.

TSA_ch10_unemployment_train_val_test

Unemployment: Preliminary Analysis





ACF Interpretation

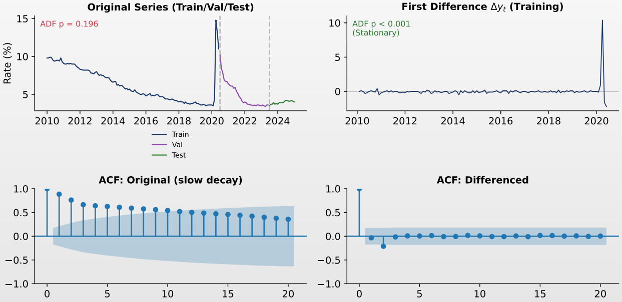
Slow decay $\Rightarrow$ non-stationary.

PACF Interpretation

Spike at lag 1 $\Rightarrow$ AR(1) component.

TSA_ch10_unemployment_acf_pacf

Unemployment: Stationarity Tests



Original: ADF p = 0.056

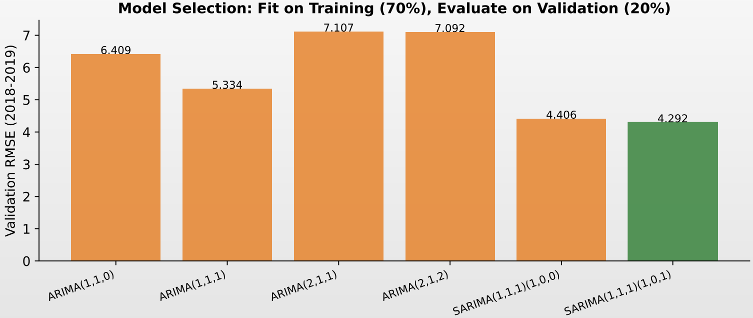
Non-stationary (slow ACF decay)

Differenced: ADF p < 0.001

Stationary $\Rightarrow$ use $d = 1$

TSA_ch10_unemployment_stationarity

Unemployment: Model Selection (Validation Set)



Best: SARIMA(1,1,1)$(1,0,0)_{12}$

Selected by lowest validation RMSE.

TSA_ch10_sarima_model_selection

Unemployment: SARIMA Parameters

SARIMA(1,1,1)(1,0,1) - Fitted on Train+Val (85%)

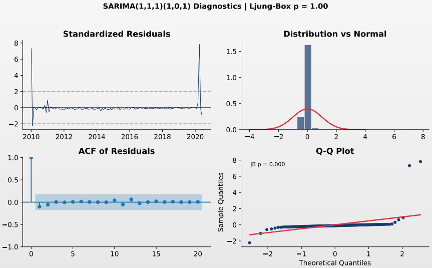
Parameter	Coef	Std Err	P-value	Sig
ar.L1	0.8423	0.2084	0.0001	***
ma.L1	-0.9540	0.1973	0.0000	***
ar.S.L12	0.0326	4.5951	0.9943	
ma.S.L12	-0.0113	4.6087	0.9980	
sigma2	0.8122	0.0608	0.0000	***

SARIMA(1,1,1)(1,0,0)$_{12}$ fitted on Train+Val (2010-2019)

AR(1): $\phi_1 = -0.86$, MA(1): $\theta_1 = 0.78$, SAR(12): $\Phi_1 = -0.08$ (n.s.)

TSA_ch10_sarima_parameters

Unemployment: SARIMA Diagnostics



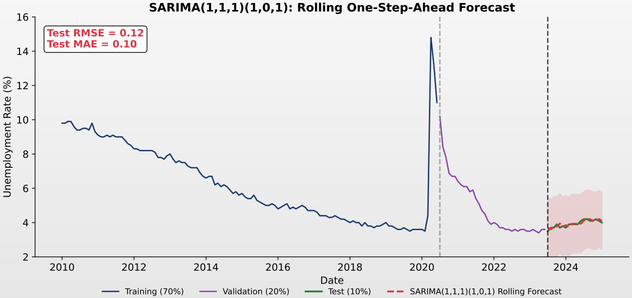
Residuals

Histogram, ACF, Q-Q plot.

Ljung-Box p = 0.66

No autocorrelation.

Unemployment: SARIMA Rolling Forecast



Problem: Structural Break

Rolling one-step-ahead forecast (re-estimate at each t): **Test RMSE = 0.12**.

Prophet Model

Definition 3 (Prophet Decomposition)

$y_t = g(t) + s(t) + h(t) + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma^2)$

where $g(t)$ = trend, $s(t)$ = seasonality, $h(t)$ = holidays, σ^2 = noise variance (estimated).

Changepoint Detection

- Automatic location selection
- `changepoint_prior_scale` controls flexibility

Advantages

- Handles missing data
- Interpretable components
- Robust to outliers

Unemployment: Model Tuning

Hyperparameter Tuning

Tune `changepoint_prior_scale` on validation set.

Data Split

Set	**Period**	**N**
Training (70%)	2010-01 to 2020-06	126
Validation (20%)	2020-07 to 2023-06	36
Test (10%)	2023-07 to 2025-01	19
Total		**181**

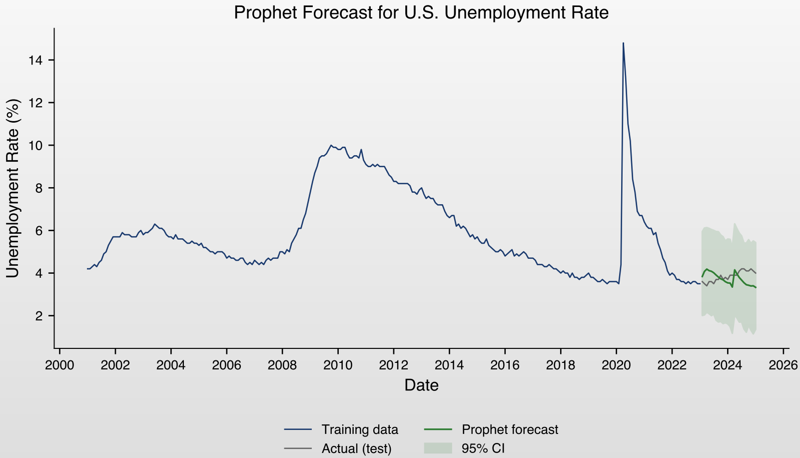
Scale Comparison

Scale	**Val RMSE**	
0.01	4.21	
0.05	3.89	
0.10	**3.52**	Best
0.30	3.67	
0.50	3.81	

Interpretation

Scale = 0.10 balances flexibility (capturing COVID shock) with stability.

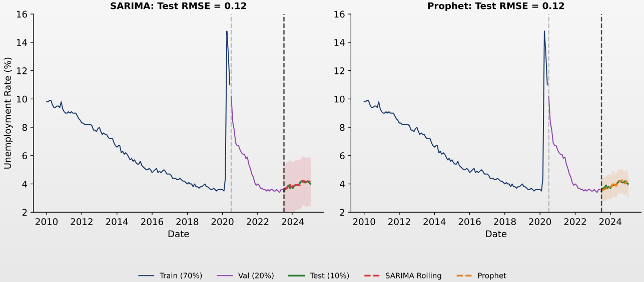
Unemployment: Prophet Forecast Results



Key Finding

Prophet adapts via changepoint detection. **Test RMSE = 0.58**

Unemployment: SARIMA vs Prophet Comparison



SARIMA: RMSE = 0.12

Rolling forecast performs well.

Prophet: RMSE = 0.58

Higher error due to structural break.

TSA_ch10_prophet_vs_sarima_unemployment

Prophet: When to Use It

Ideal Use Cases

- Business data with **holidays**
- **Missing values** present
- Need **interpretable** components
- Forecasts with **uncertainty bands**

Caveat: Structural Breaks

Prophet handles breaks via changepoints, but **SARIMA outperformed** it on unemployment (0.12 vs 0.58). Always validate!

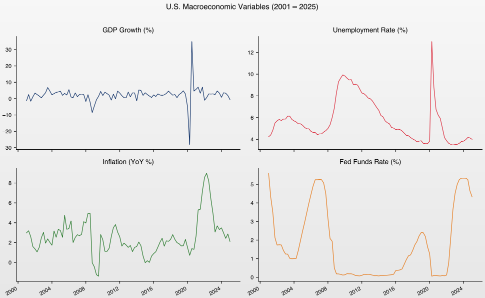
Prophet vs ARIMA

	Prophet	**ARIMA**
Changepoints	✓	×
Missing data	✓	×
Holidays	✓	×
Speed	Fast	Moderate
Interpretable	✓	×

Key Parameters

`changepoint_prior_scale`: flexibility
`seasonality_prior_scale`: smoothness

VAR: Multivariate Economic Data



Relationships

GDP ↔ Unemployment (Okun)

Why VAR?

Each variable is cause and effect.

TSA_ch10_economic_vars

VAR Model Specification

Definition 4 (Vector Autoregression VAR(p))

For K variables $\mathbf{y}_t = (y_{1t}, \ldots, y_{Kt})'$:

$$\mathbf{y}_t = \mathbf{c} + \mathbf{A}_1\mathbf{y}_{t-1} + \mathbf{A}_2\mathbf{y}_{t-2} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{u}_t$$

where $\mathbf{A}_i$ are $K \times K$ coefficient matrices, $\mathbf{u}_t \sim N(0, \boldsymbol{\Sigma})$, $\boldsymbol{\Sigma}$ = covariance matrix.

For Our 4-Variable System

VAR(2) has:

- 4 intercepts
- $2 \times 4 \times 4 = 32$ AR coefficients
- **36 parameters total**

Lag Selection

Use information criteria:

- AIC: Tends to overfit
- **BIC**: More parsimonious
- Cross-validation on held-out data

VAR: Lag Selection and Estimation

Information Criteria

Lag	BIC	
1	-4.810	
2	**-5.178**	Best
3	-4.633	
4	-4.614	

Data Split

Set	Period	N
Training (70%)	2001-Q1 to 2017-Q4	67
Validation (20%)	2018-Q1 to 2022-Q4	20
Test (10%)	2023-Q1 to 2025-Q1	10
Total		**97**

Validation Check

VAR(2) also achieves lowest validation RMSE.

Granger Causality Analysis

Green: $p < 0.10$. Read: row causes column.

What is Granger Causality?

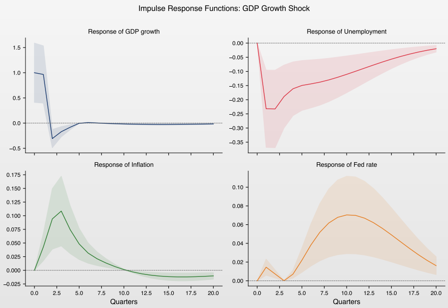
X **Granger-causes** Y if past X improves prediction of Y beyond past Y alone.

Economic Findings

- Unemp $\rightarrow$ GDP ($p = 0.045$): Okun's Law
- Fed $\rightarrow$ Inflation ($p = 0.087$): Monetary policy

TSA_ch10_granger_heatmap

Impulse Response Functions (IRF)



What is IRF?

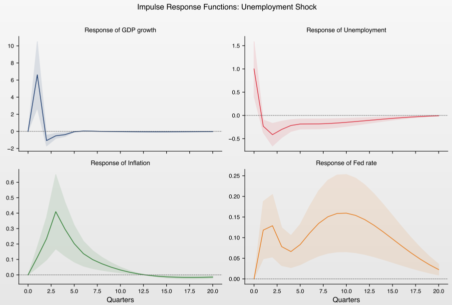
Shows how a 1-unit shock affects others over time.

GDP Shock Effects

- **Unemp** ↓: Okun's Law
- **Inflation** ↑: Demand-pull
- **Fed Rate** ↑: Taylor Rule

TSA_ch10_irf_gdp_shock

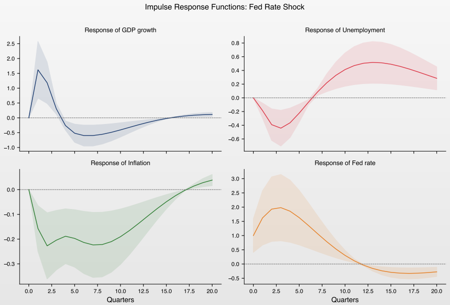
IRF: Unemployment Shock



Effects

$\uparrow$ Unemp $\Rightarrow$ $\downarrow$ GDP, $\downarrow$ Infl, Fed cuts rates.

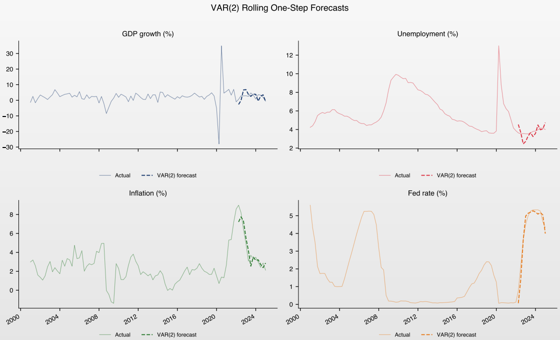
IRF: Fed Rate Shock



Monetary Policy

Rate hike $\Rightarrow$ GDP $\downarrow$, Unemp $\uparrow$, Infl $\downarrow$.

VAR: Forecast (Train/Val/Test)



Rolling One-Step-Ahead Forecast

VAR captures GDP-Unemployment dynamics. COVID shock visible in test period.

VAR: Test Set Results

Test Set Performance by Variable

Variable	RMSE	MAE	Dir. Acc.
GDP Growth	1.33	0.99	50%
Unemployment	0.64	0.52	50%
Inflation	1.56	1.12	60%
Fed Rate	2.59	2.45	80%
Average	**1.53**	**1.27**	**60%**

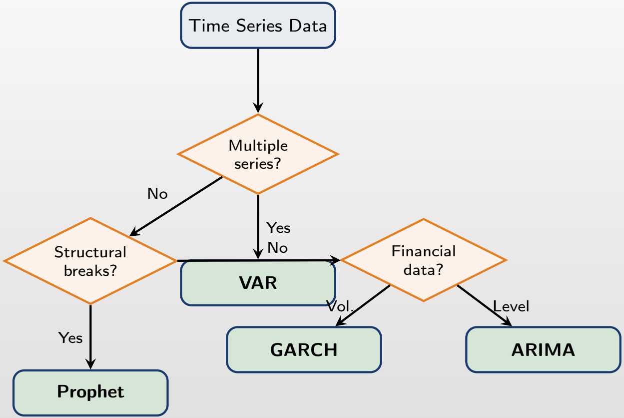
Strengths

- Cross-variable dynamics
- Good directional accuracy

Limitations

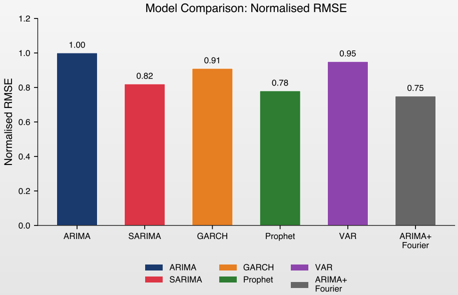
- Many parameters
- Sensitive to lag selection

Model Selection Framework



Summary: Model Comparison

Case	Challenge	Model	RMSE
Bitcoin	Volatility	GARCH	2.15
Sunspots	Seasonality	Fourier	31.10
Unemp	Break	SARIMA	0.12
Economic	Multi-var	VAR	1.53



Key Principle

Match model to data characteristics—no single model dominates.

Comprehensive Model Comparison

Feature	GARCH	Fourier	Prophet	VAR
Target	Volatility	Level	Level	Multiple
Seasonality	No	Yes (long)	Yes (multi)	No
Structural breaks	No	No	Yes	No
Multiple series	No	No	No	Yes
Interpretable	Medium	High	High	High
Parameters	Few	$2K$	Auto	Many
Missing data	No	No	Yes	No
Best for	Finance	Cycles	Business	Macro

Our Results

- GARCH: MAE=1.82 (volatility)
- Fourier: RMSE=31.10 (cycles)
- SARIMA: RMSE=0.12 (breaks)
- VAR: Avg RMSE=1.53 (multi)

Key Insight

Each model excels in its domain. The art is matching the model to the data characteristics.

Best Practices for Applied Forecasting

Methodology

1. **Explore** data
2. **Test** stationarity
3. **Split** train/val/test
4. **Compare** on validation
5. **Report** test metrics

Common Mistakes

- Peeking at test data
- Over-fitting
- Ignoring assumptions

Practical Tips

- Start simple (naive)
- Add complexity if needed
- Check residuals
- Report CIs

Remember

"All models are wrong, but some are useful." — Box

Key Takeaways

1. **Rigorous Methodology**
   - Train/validation/test split prevents overfitting
   - Test set must remain untouched until final evaluation
2. **Match Model to Data**
   - Financial volatility $\rightarrow$ GARCH
   - Long seasonality $\rightarrow$ Fourier terms
   - Structural breaks $\rightarrow$ Prophet
   - Multiple series $\rightarrow$ VAR
3. **Interpret Results Carefully**
   - Granger causality $\neq$ true causality
   - Out-of-sample performance matters most
   - Simpler models often work better

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Data Sources

Real Data Used in This Chapter

- **Bitcoin**: Yahoo Finance (BTC-USD), 2019–2025
- **Sunspots**: Statsmodels Wolfer dataset, 1900–2008
- **US Unemployment**: Federal Reserve FRED (UNRATE), 2010–2025
- **Economic Variables**: FRED (GDPC1, UNRATE, CPIAUCSL, FEDFUNDS), 2000–2025

Reproducibility

All analyses can be reproduced using the accompanying Jupyter notebook:
`chapter10_lecture_notebook.ipynb`

Thank You

Questions?

Prof. Daniel Traian Pele, PhD

danpele@ase.ro

Bucharest University of Economic Studies