Predictive Stability Under Structural Breaks

Monte Carlo Simulation

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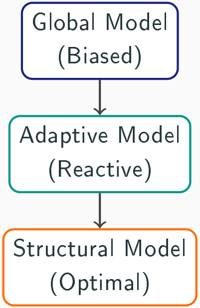
Motivation: Why Adapt?

- **The Reality:** Economic data is rarely stable (Crisis, Policy, Tech).
- **The Failure:** Global models average across regimes $\rightarrow$ Massive Bias.
- **The Goal:** Navigate shifts in **Mean**, **Variance**, and **Parameter**.



Research Question

How do different forecasting strategies react to structural breaks across various simulation scenarios?

Literature Review: Key Authors

Pillar	Foundational Contribution
Evidence	**Stock & Watson (1996)**: Document pervasive instability and the cost of ignoring breaks.
Dynamics	**Koop & Potter (2005)**: Argue nonlinearity is often unmodeled structural change.
Trade-offs	**Boot & Pick (2020)**: Modeling breaks depends on size, timing, and persistence.
Adaptive	**Siliverstovs & van Dijk (2002)**: Adaptive methods beat fixed-parameter models.
Regimes	**Hamilton (1989)**: Markov-Switching for recurring, stochastic regime shifts.

Data-Generating Process (DGP)

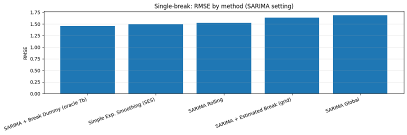
- **Pure Simulation Framework:** No empirical data; all results derived from controlled Monte Carlo experiments.
- **Baseline Structure:** DGP process as the engine for structural change:

$$y_t = \mu_t + \phi_t y_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim \text{Dist}(0, \sigma_t^2)$$

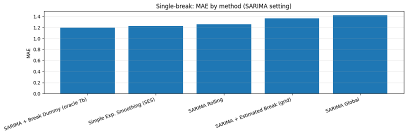
- **Sources of Instability (Ceteris Paribus):**
    - **Mean Shifts:** Changes in mean level (μ_t).
    - **Variance Shifts:** Changes in σ_t^2 (Volatility).
    - **Parameter Shifts:** Changes in autoregressive parameter ϕ_t.
- **Persistence Instability Designs:**
    - **Single Break:** Deterministic shifts at a specific time point.
    - **Recurring Breaks:** Shifts governed by a **finite-state Markov process**.
- **Design Philosophy:** Isolate single sources of instability while holding others fixed to evaluate predictive stability.

Result 1.1: Single Mean Break Overview

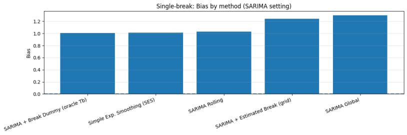
RMSE



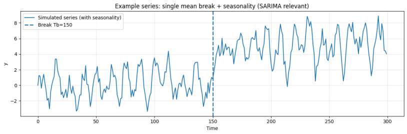
MAE



Bias Analysis



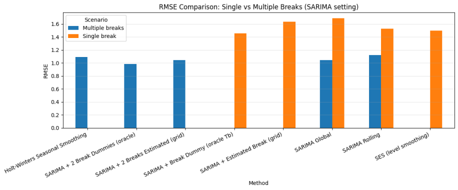
Example Series



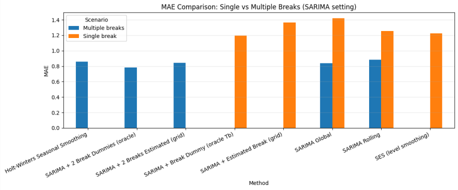
- **Finding: SARIMA Rolling** beats global by 15-20% RMSE.
- **Oracle:** Known break dates reduce RMSE by an additional 10%.
- **Seasonality:** SARIMA effectively handles periodic components.

Result 1.2: Multiple Mean Break Overview

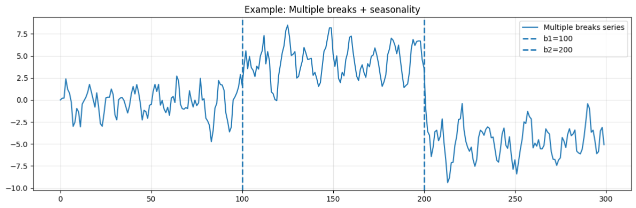
RMSE (Single vs Multiple)



MAE (Single vs Multiple)



Example Series with Multiple Breaks



- **Complexity:** Multiple breaks degrade performance; SARIMA + Dummies remains consistent.

Result 1.3: Single Mean Break Performance (Numerical)

Method	RMSE	MAE	Bias	N	Fails
SARIMA + Break Dummy (Oracle)	1.455	1.194	1.006	200	0
Simple Exp. Smoothing (SES)	1.496	1.225	1.015	200	0
SARIMA Rolling	1.525	1.257	1.029	200	0
SARIMA + Estimated Break	1.635	1.368	1.243	200	0
SARIMA Global	1.692	1.423	1.302	200	0

Table 1: Mean metrics across 200 replications ($T = 300$)

- **Best Performer:** Oracle dummy model (benchmarking the theoretical limit).
- **Observation:** Even simple SES outperforms global SARIMA by discarding history.

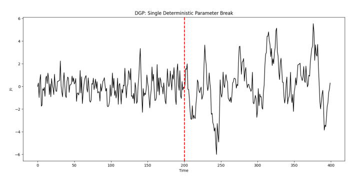
Result 1.4: Mean Break Comparison (Numerical)

Method	RMSE	MAE	Bias	N	Fails	Scenario
SARIMA + 2 Dummies (Oracle)	0.985	0.781	0.106	200	0	Multiple
SARIMA Global	1.042	0.836	-0.045	200	0	Multiple
SARIMA + 2 Breaks (Grid)	1.046	0.845	-0.125	200	0	Multiple
Holt–Winters Seasonal	1.094	0.857	-0.001	200	0	Multiple
SARIMA Rolling	1.122	0.884	0.299	200	0	Multiple
SARIMA + Dummy (Oracle)	1.455	1.194	1.006	200	0	Single
SES (level smoothing)	1.496	1.225	1.015	200	0	Single
SARIMA Rolling	1.525	1.257	1.029	200	0	Single
SARIMA + Break (Grid)	1.635	1.368	1.243	200	0	Single
SARIMA Global	1.692	1.423	1.302	200	0	Single

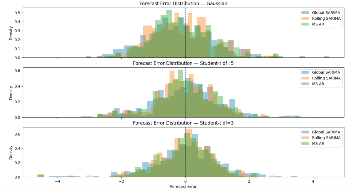
- **Multiple Breaks:** Paradoxically lower RMSE for Global models due to variance.
- **Single Break:** Clear dominance of adaptive (Rolling/Oracle) methods.

Result 2.1: Parameter Breaks - Single Shift

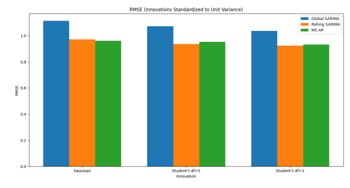
DGP Visualization



Error Distributions



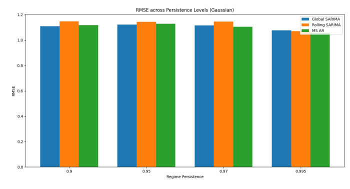
RMSE over Dof



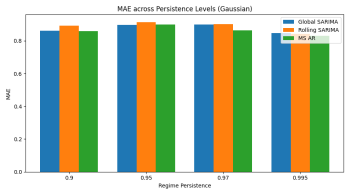
- **Scenario:** Shift in persistence $\phi_1 \to \phi_2$.
- **Impact:** Leads to systematic under/over-estimation of memory.

Result 2.2: Recurring Parameter Breaks (RMSE/MAE/Bias)

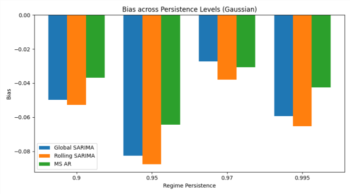
RMSE



MAE



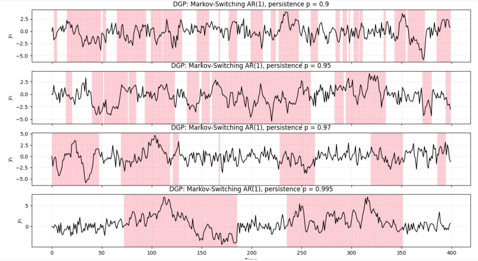
Bias



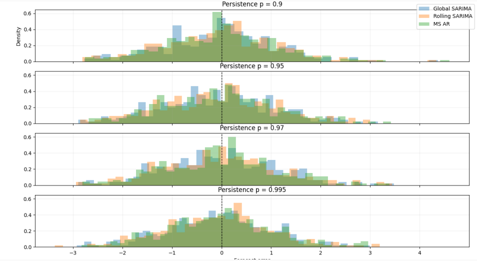
- **Markov Switching:** Best at capturing recurring shifts.

Result 2.3: Persistence Analysis & Recurring DGP

DGP Recurring Break



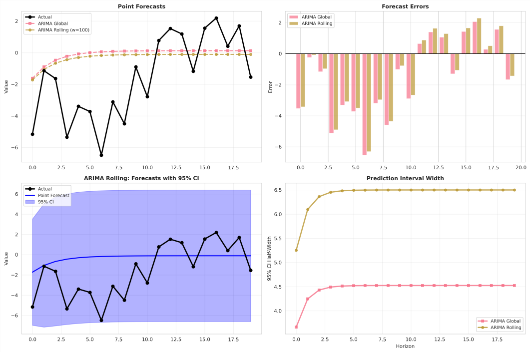
Recurring Distribution



- As persistence increases, regime durations lengthen and the series exhibits extended periods of distinct dynamics. In the high-persistence case, regime switches are rare and regime spells become long but remain stochastic, illustrating near-permanent yet non-degenerate parameter regimes.

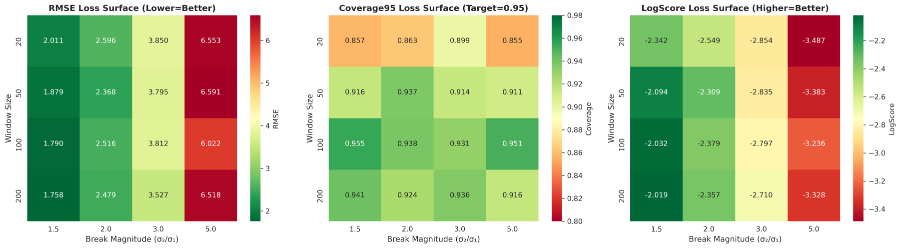
Result 3.1: Volatility Shifts (Variance Breaks)

- **Winner: GARCH(1,1)** adapts fastest to variance shifts.
- **Insight:** Rolling windows must be small ($w < 50$) to capture sudden volatility jumps.
- **Loss Surface:** Clear U-shape showing window size trade-off.



Result 3.2: Variance Robustness: Loss Surfaces

- **Parameter Sensitivity:** Heatmap showing RMSE across varying window sizes and break magnitudes.
- **Optimal Region:** Clear visualization of the stable regions for rolling window adaptation.
- **Insight:** Demonstrates the bias-variance tradeoff as the "U-shape" loss across scenarios.



Result 3.3: Variance Performance (Numerical)

Scenario	ARIMA Global	ARIMA Rolling	GARCH(1,1)	Post-Break
Variance 1.5x	1.807	1.831	1.805	1.848
Variance 2.0x	2.417	2.448	2.414	2.472
Variance 3.0x	3.620	3.677	3.613	3.688
Variance 5.0x	6.231	6.306	6.219	6.341

Table 2: RMSE across 200 Monte Carlo replications ($T = 400$)

- **Observation:** GARCH consistently achieves the lowest RMSE across all magnitudes.
- **Adaptation:** Global ARIMA suffers from persistent bias after the shock.
- **Windowing:** Rolling window performance is sensitive to the $0.6\sqrt{T}$ rule.

Future Research Directions

- **Complex Breaks:** Simultaneous shifts in mean, variance, and parameters.
- **Empirical Tests:** Validating simulation results on GDP and stock returns.
- **Probabilistic Forecasting:** Density scores and improved uncertainty quantification.
- **Multivariate Systems:** Extending breaks to high-dimensional VAR systems.
- **Hybrid Modeling:** Integrating machine learning with classical structural models.

Moving from controlled simulations to real-world complexity.

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Thank You!

github.com/qonlab/structural-break-forecasting