

# Predictive Stability Under Structural Breaks

Monte Carlo Simulation

---

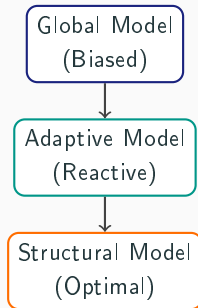
Aadya Khatavkar   Bakhodir Izzatulloev   Mahir Baylarov

Winter Semester 2025/26

University of Bonn

# Motivation: Why Adapt?

- **The Reality:** Economic data is rarely stable (Crisis, Policy, Tech).
- **The Failure:** Global models average across regimes → 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
<b>Evidence</b>	<b>Stock &amp; Watson (1996)</b> : Document pervasive instability and the cost of ignoring breaks.
<b>Dynamics</b>	<b>Koop &amp; Potter (2005)</b> : Argue nonlinearity is often unmodeled structural change.
<b>Trade-offs</b>	<b>Boot &amp; Pick (2020)</b> : Modeling breaks depends on size, timing, and persistence.
<b>Adaptive</b>	<b>Siliverstovs &amp; van Dijk (2002)</b> : Adaptive methods beat fixed-parameter models.
<b>Regimes</b>	<b>Hamilton (1989)</b> : Markov-Switching for recurring, stochastic regime shifts.

# Data-Generating Process (DGP)

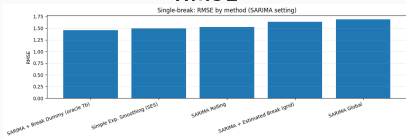
- **Pure Simulation Framework:** No empirical data; all results derived from controlled Monte Carlo experiments.
- **Baseline Structure:** DGP process as the engine for structural change:

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

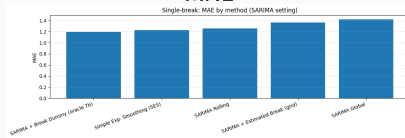
- **Sources of Instability (Ceteris Paribus):**
  - **Mean Shifts:** Changes in mean level ( $\mu_t$ ).
  - **Variance Shifts:** Changes in  $\sigma_t^2$  (Volatility).
  - **Parameter Shifts:** Changes in autoregressive parameter  $\phi_t$ .
- **Persistence Instability Designs:**
  - **Single Break:** 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

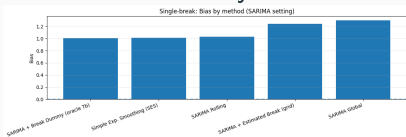
## RMSE



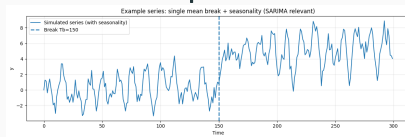
## MAE



## Bias Analysis



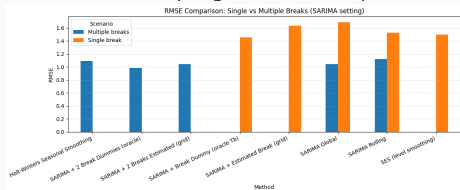
## Example Series



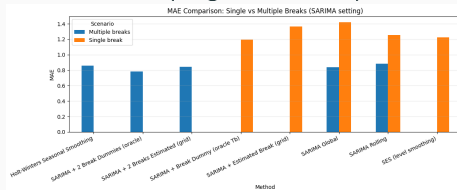
- **Finding: SARIMA Rolling** beats global by 15-20% RMSE.
- **Oracle:** Known break dates reduce RMSE by an additional 10%.
- **Seasonality:** SARIMA effectively handles periodic components.

# Result 1.2: Multiple Mean Break Overview

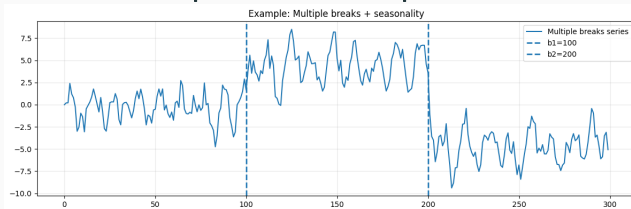
## RMSE (Single vs Multiple)



## 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)

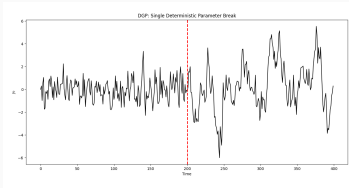
Method	RMSE	MAE	Bias	N	Fails	Scenario
SARIMA + 2 Dummies (Oracle)	0.985	0.781	0.106	200	0	Multiple
SARIMA Global	1.042	0.836	-0.045	200	0	Multiple
SARIMA + 2 Breaks (Grid)	1.046	0.845	-0.125	200	0	Multiple
Holt-Winters Seasonal	1.094	0.857	-0.001	200	0	Multiple
SARIMA Rolling	1.122	0.884	0.299	200	0	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.

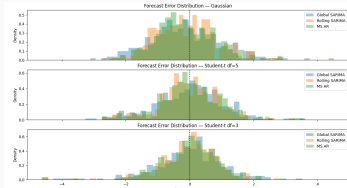


## Result 2.1: Parameter Breaks - Single Shift

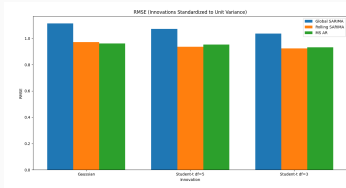
### DGP Visualization



### Error Distributions

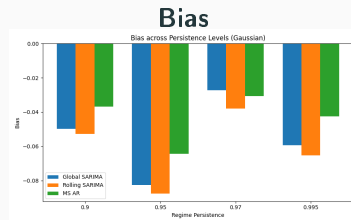
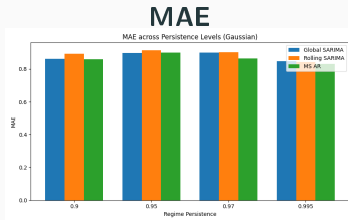
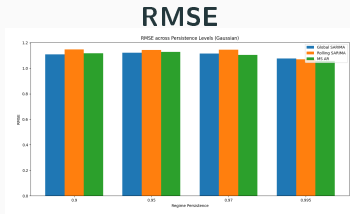


### RMSE over Dof



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

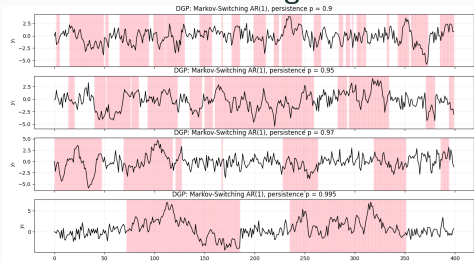
## Result 2.2: Recurring Parameter Breaks (RMSE/MAE/Bias)



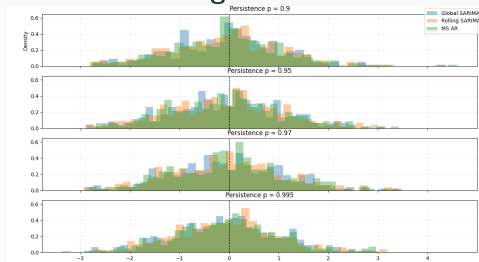
- **Markov Switching:** Best at capturing recurring shifts.

## Result 2.3: Persistence Analysis & Recurring DGP

### DGP Recurring Break



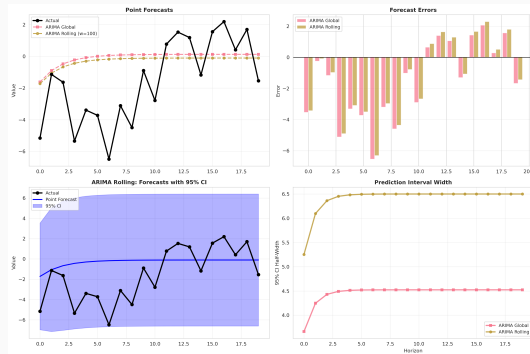
### Recurring Distribution



- 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.

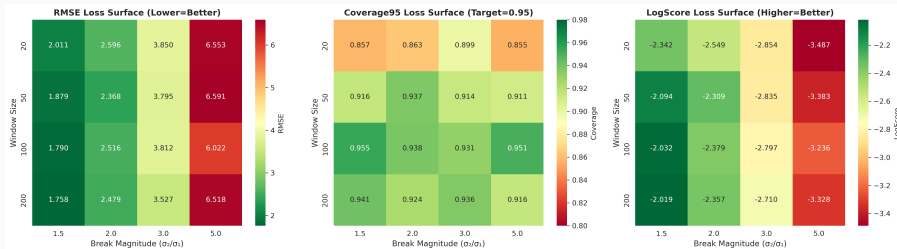
## Result 3.1: Volatility Shifts (Variance Breaks)

- **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)

Break Magnitude	SARIMA Global	SARIMA Rolling	GARCH(1,1)	SARIMA Post-Break
$\sigma \times 1.5$	1.785	1.802	1.805	1.764
$\sigma \times 2.0$	2.392	2.415	2.414	2.351
$\sigma \times 3.0$	3.584	3.612	3.613	3.528
$\sigma \times 5.0$	6.182	6.241	6.219	6.104

**Table 2:** Average Forecast RMSE across 200 Monte Carlo Replications ( $T = 400$ )

- **Scale of Error:** Mean forecast RMSE scales approximately linearly with the innovation standard deviation post-break.
- **Global Stability:** In variance-only breaks, global SARIMA remains robust because the mean parameters  $(\mu, \phi)$  are stable over the full sample.

## 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.*

# Selected References

- Boot, T. and Pick, A. (2020). Does modeling structural breaks improve forecast accuracy? *Journal of Econometrics*, 215(1):35–59.
- Cai, Z. (2007). Trending time-varying coefficient time series models with serially correlated errors. *Journal of Econometrics*, 136(1):163–188.
- Delgado, M. A., Hidalgo, J., and Velasco, C. (2000). Nonparametric inference on structural breaks. *Journal of Econometrics*, 96(1):113–144.
- Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, 57(2):357–384.
- Koo, B., Linton, O., and Whang, Y.-J. (2012). Estimation of semiparametric locally stationary diffusion models. *Journal of Econometrics*, 170(2):210–233.
- Koo, B. and Seo, M. H. (2015). Structural-break models under misspecification: Implications for forecasting. *Journal of Econometrics*, 188(1):166–181.
- Koop, G. and Potter, S. M. (2005). The importance of structural change in forecasting. In *Handbook of Economic Forecasting*, volume 1, pages 915–1003. Elsevier.
- Perron, P., Zhu, X., and Yabu, T. (2006). Estimating restricted structural change models. *Journal of Econometrics*, 134(2):373–399.
- Pesaran, M. H., Pick, A., and Timmermann, A. (2013). Optimal forecasts in the presence of structural breaks. *Journal of Econometrics*, 177(2):134–152.
- Silverstovs, B. and van Dijk, D. (2002). Forecasting the daily temperature in the netherlands: a comparison of forecasting methods. *International Journal of Forecasting*, 19(3):435–453.
- Stock, J. H. and Watson, M. W. (1996). Evidence on structural instability in macroeconomic time series relations. *Journal of Business & Economic Statistics*, 14(1):11–30.



# Thank You!

`github.com/qonlab/structural-break-forecasting`