Market Regime Anticipation Based on Long Memory

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1 Introduction

This rulebook defines principles, steps, and operational rules for implementing a systematic trading strategy aiming to anticipate market regimes by leveraging long memory properties in various financial time series. The analysis will focus on interest rates, prices, volatilities, and volumes.

The goal is to detect and exploit persistent dynamics and regime shifts to adjust positions accordingly. Long memory, characterized by slowly decaying autocorrelations, can help identify persistent trends. For instance, during periods where strong persistence is detected, we may favor trend-following strategies.

2 Data and Preprocessing

2.1 Data Types

- **Interest Rates**: Bond yields, yield curves, spreads across different maturities.
- **Asset Prices**: Equity indices, liquid stocks, commodities, major currency pairs.
- **Volatilities**: Realized (historical) volatility, volatility indices (e.g., VIX), implied volatility from options, volatility estimated from FIGARCH models.
- **Volumes and Flows**: Trading volumes, open interest, fund flows.

Stationarity: Rules and Procedures

Objective: Ensure that the analyzed time series is (or can be rendered) stationary. Stationarity is a prerequisite for many long-memory models (e.g., ARFIMA) and helps prevent spurious inference and unstable parameter estimates.

Definition of Stationarity

A time series (X_t) is *weakly (or covariance) stationary* if:

$$\mathbb{E}[X_t] = \mu \quad \text{(constant)}, \quad \text{and} \quad \mathrm{Cov}(X_t, X_{t+k}) = \gamma_k \text{ depends only on } k,$$

for all t and k, with no dependence of μ or γ_k on time t.

Testing for Stationarity

Apply at least one standard statistical test for stationarity:

(i) **Augmented Dickey-Fuller (ADF) Test:** The null hypothesis H_0 is that the series has a unit root (i.e., is non-stationary). The test equation typically is:

$$\Delta X_t = \alpha + \beta t + \phi X_{t-1} + \sum_{i=1}^{p} \theta_i \Delta X_{t-i} + \varepsilon_t,$$

where $\Delta X_t = X_t - X_{t-1}$. Rejecting H_0 at a chosen significance level (e.g., $\alpha = 0.05$) suggests stationarity (or trend-stationarity depending on the model variant).

You can access the document `code_test` directly via the following hyperlink: Click here to open template code for adFuller test.

Testing for Stationarity

The decision rule is as follows: if p-value $\leq \alpha$ (e.g., $\alpha = 0.05$) or if the ADF statistic $\mathrm{ADF}_{\mathrm{stat}}$ satisfies $\mathrm{ADF}_{\mathrm{stat}} \leq \text{Critical Value}_\alpha$ for a given significance level ($\alpha \in \{0.01, 0.05, 0.10\}$), then we reject H_0 and conclude that the series is stationary. Otherwise, H_0 is not rejected, and the series is considered non-stationary:

$$\text{Reject } H_0 \iff (\text{p-value} \leq \alpha) \vee (\mathrm{ADF}_{\mathrm{stat}} \leq \text{Critical Value}_\alpha).$$

Dealing with Non-Stationarity

If the series is non-stationary, it must be transformed to achieve stationarity while preserving long-memory features.

Fractional Differencing

Standard differencing ($\Delta X_t = X_t - X_{t-1}$) often destroys long-memory characteristics. Instead, use fractional differencing, defined by the operator $(1-L)^d$, where L is the lag operator and $d \in \mathbb{R}$:

$$(1-L)^d X_t = X_t - \binom{d}{1} X_{t-1} + \binom{d}{2} X_{t-2} - \binom{d}{3} X_{t-3} + \cdots,$$

with

$$\binom{d}{k} = \frac{d(d-1)(d-2)\cdots(d-k+1)}{k!}.$$

For $0 < d < 0.5$, fractional differencing can render the series stationary without removing its long-range dependence.

Rule:

(i) Estimate d using methods such as the Geweke–Porter-Hudak (GPH) estimator or log-periodogram regression.

(ii) Choose d so that $(1-L)^d X_t$ passes stationarity tests.

(iii) If the series remains non-stationary after applying fractional differencing, adjust d or consider alternative modeling approaches.

Verification After Transformation

After fractional differencing:

(i) Re-apply ADF and/or KPSS tests to $(1-L)^d X_t$.

(ii) Confirm that the transformed series is now stationary.

Rule: Proceed to ARFIMA or other long-memory modeling steps only once stationarity is verified.

Practical Considerations

- **Significance Level:** Use a consistent significance level (e.g., $\alpha = 0.05$) for stationarity tests.
- **Model Specification:** If fractional differencing is employed, ensure subsequent models (ARFIMA, FIGARCH) are fit to the fractionally differenced data.
- **Periodic Re-testing:** Markets evolve. Re-test stationarity periodically (e.g., monthly or quarterly) and adjust d as needed.

3 Characterizing Long Memory

3.1 Measuring Long Memory

- **Hurst Exponent (H)**: Estimate H. If $H > 0.5$, the series exhibits persistence; if $H < 0.5$, anti-persistence; and if $H = 0.5$, it resembles a random walk.
- **ARFIMA Models**: Fit an ARFIMA(p, d, q) model, where the fractional parameter d captures long memory. Validate via the Whittle estimator or Maximum Likelihood methods.

3.2 Selecting High Long Memory Series

- Identify which variables (rates, prices, vol, volumes) show significant long memory.
- Prioritize these series for regime anticipation.

4 Regime Detection and Anticipation

4.1 Market Regimes

A market regime is defined as a state of the market characterized by a certain degree of trend, volatility level, and inter-asset correlation structure. Long memory can help predict the persistence of a current regime.

4.2 Detection Approach

1. **Trend Analysis**: Use the estimated H or the fractional parameter from ARFIMA to identify periods of strong trend persistence.

2. **Regime Indices**: Construct synthetic indicators (e.g., a composite score based on H across different series: prices, volatility, rates). High H in prices might indicate a trending regime, whereas long memory in volatility may indicate a persistent high-risk environment.

4.3 Strategy Based on Long Memory

- **Persistent Regime** ($H > 0.5$ on prices): Implement trend-following strategies; take positions aligned with the established trend.

- **Neutral Regime** ($H \approx 0.5$): Stay neutral or reduce exposure, as the market behaves more like white noise.

- **Anti-Persistent Regime** ($H < 0.5$): Adopt contrarian strategies, betting on mean reversion or trend breaks.

5 Backtesting and Validation

5.1 Historical Backtest

1. Apply the strategy to historical data sets.

2. Evaluate performance: return, Sharpe ratio, drawdown, win/loss ratio.

5.2 Cross-Validation and Walk-Forward Analysis

- Use walk-forward optimization, regularly re-estimating ARFIMA parameters on rolling windows.

- Mitigate overfitting by testing robustness across multiple data samples.

6 Risk Management and Allocation

6.1 Position Sizing and Stops

- Adjust position sizes based on expected volatility.
- Implement stop-loss orders to contain losses.

6.2 Diversification

- Apply the strategy to multiple asset classes.
- Avoid concentration risk in a single market.

7 Operational Implementation

7.1 Technical Infrastructure

- Use quantitative tools (R, Python, MATLAB) to estimate H and fit ARFIMA models.
- Deploy an algorithmic trading platform to automate order execution.

7.2 Continuous Monitoring

- Update long memory estimates on a regular basis.
- Adjust the strategy as new diagnostics and market conditions emerge.

8 Rulebook Updates

This rulebook should be reviewed periodically as new methods or market insights become available, or if the long memory dynamics evolve.

9 Conclusion

This document provides a structured framework for anticipating market regimes through long memory analysis without employing SDEs. By leveraging long memory properties, we aim to adapt positions to persistent market configurations, enhancing our ability to follow established trends and avoid pitfalls associated with undetected regime changes.