FinQuest

Volatility-Driven Trading Strategy Using GARCH Models, Technical Indicators, and Monte Carlo Simulations

Aryan Singh

What is Market Volatility?

Volatility refers to the degree of variation in asset prices over time. It helps traders assess the risk and uncertainty associated with an asset.

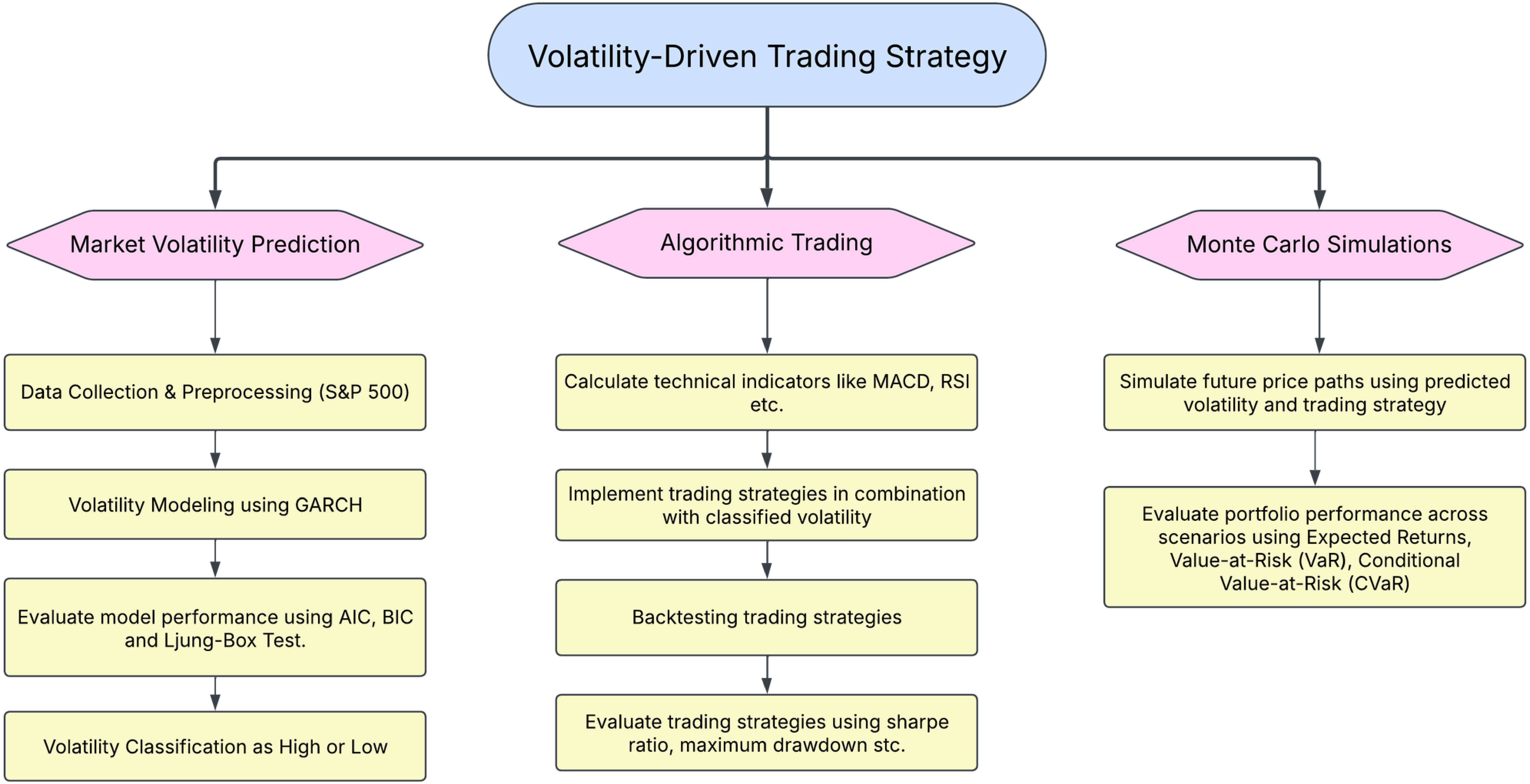
Mathematically, volatility is measured as the standard deviation of returns:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(r_i - \bar{r})^2}$$

where:

- σ = volatility
- r_i = return on day i
- $\bar{r}$ = mean return over N days

Flow of the Project



Data Collection & Preprocessing

Dataset Used

- S&P 500 stock data from Yahoo Finance.
- Time period: Last 10 years (customizable).

Preprocessing Steps

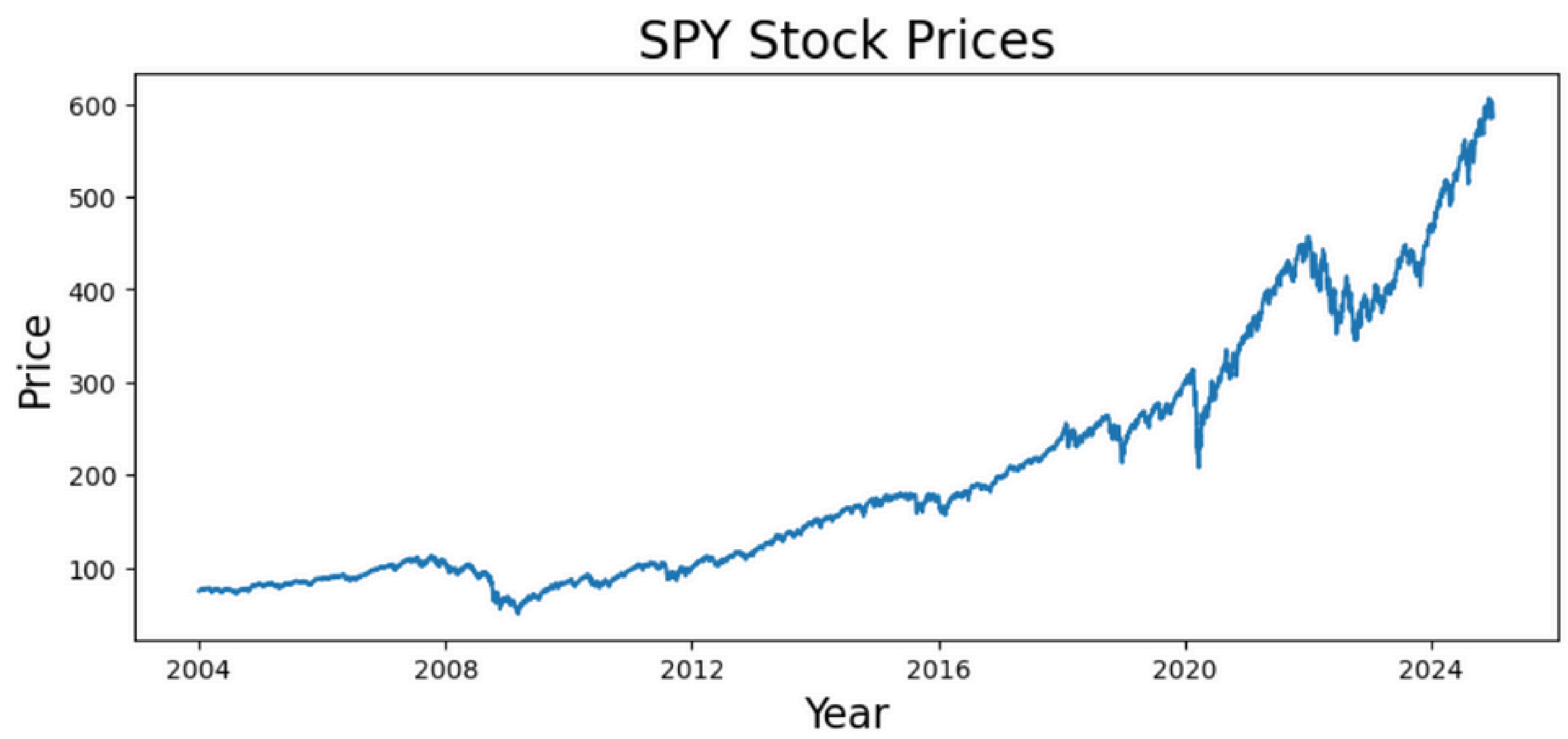
1. Calculate Percentage Returns

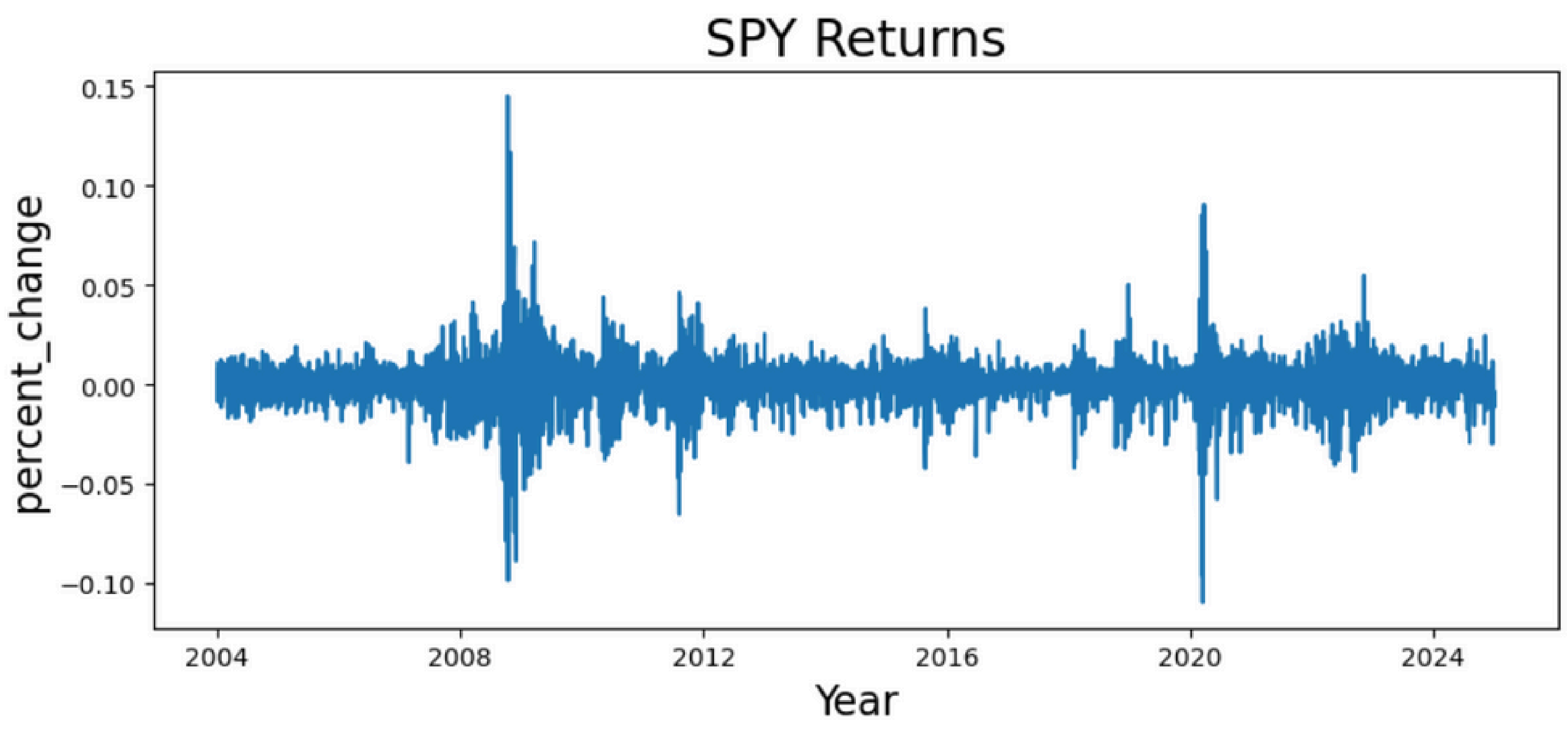
- Since financial time series data is non-stationary, we work with percentage returns instead of raw prices:

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}} \times 100$$

where:

- P_t = closing price at time t
- P_{t-1} = closing price at time t-1





Volatility Modeling Using GARCH

Why GARCH?

- GARCH (Generalized Autoregressive Conditional Heteroskedasticity) captures volatility clustering, meaning high-volatility days follow high-volatility days.
- Unlike simple moving standard deviation, GARCH adapts dynamically.

GARCH Model

The GARCH(p,q) model is defined as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i r_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

where:

- σ^2_t = conditional variance at time t
- r^2_{t-i} = past squared returns (ARCH component)
- σ^2_{t-j} = past variances (GARCH component)
- α_0, α_i, β_j = model coefficients

EGARCH (Exponential GARCH)

EGARCH uses log variance instead of variance, making it better at capturing asymmetric volatility.

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \beta_i \ln(\sigma_{t-i}^2) + \sum_{j=1}^{q} \alpha_j \frac{|r_{t-j}|}{\sigma_{t-j}} + \sum_{j=1}^{q} \gamma_j \frac{r_{t-j}}{\sigma_{t-j}}$$

TGARCH (Threshold GARCH)

TGARCH applies different effects depending on whether past returns were positive or negative.

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

where $d_t = 1$ if $r_t < 0$ (negative shock), otherwise 0.

Model Selection Criteria

- Akaike Information Criterion (AIC):

$$AIC = 2k - 2\ln(L)$$

- Bayesian Information Criterion (BIC):

$$BIC = k\ln(n) - 2\ln(L)$$

- Ljung-Box Test for autocorrelation in residuals:

$$Q = n(n+2)\sum_{k=1}^{m} \frac{\hat{r}_k^2}{n-k}$$

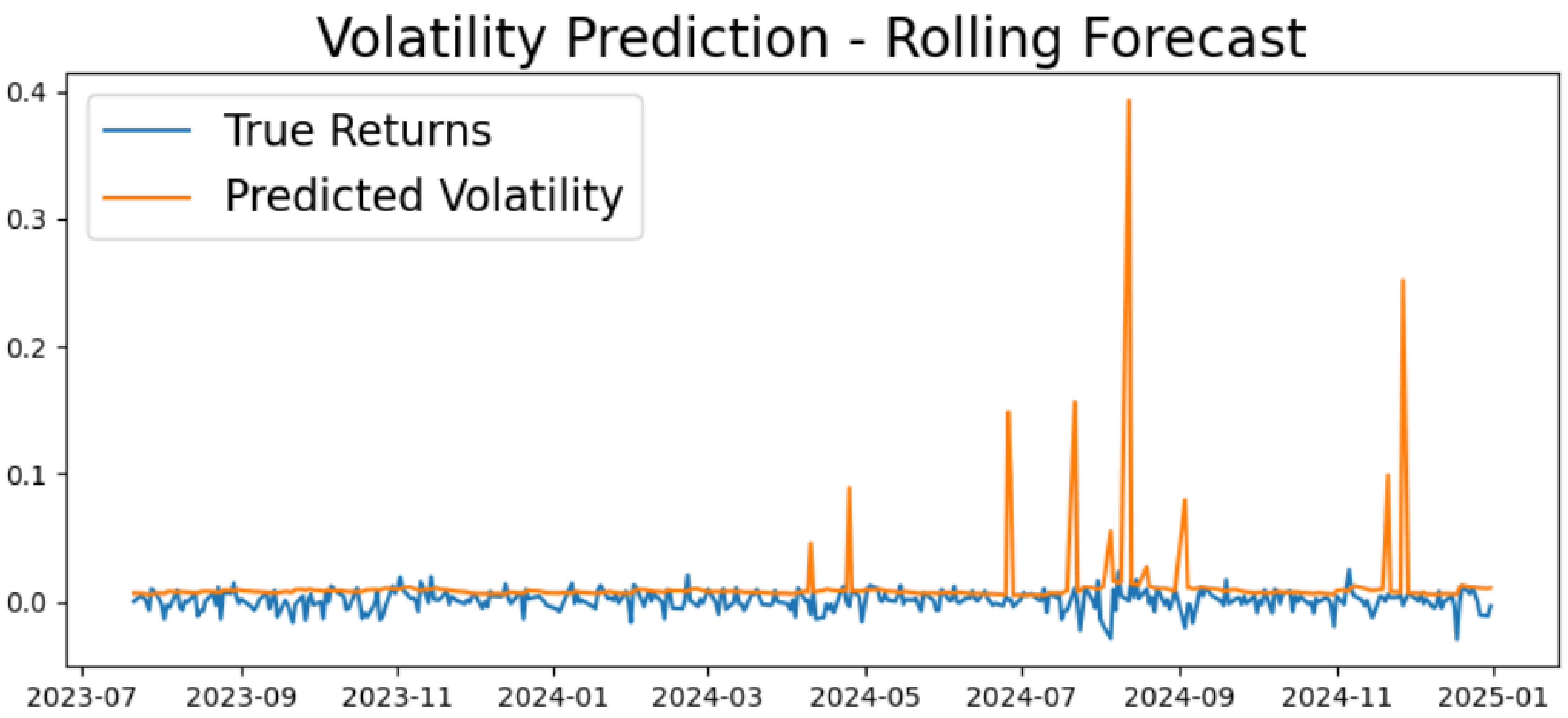
where Q follows a chi-square distribution.

	Model	p	q	AIC	BIC	Ljung-Box p-value
0	GARCH	1	1	-34768.976013	-34742.686258	1.921200e-17
1	GARCH	1	2	-34749.174240	-34716.312047	1.921200e-17
2	GARCH	2	1	14796.193416	14829.055610	1.921200e-17
3	GARCH	2	2	-34799.446704	-34760.012072	1.921200e-17
4	EGARCH	1	1	-34758.755513	-34732.465758	1.921200e-17
5	EGARCH	1	2	-34756.755513	-34723.893320	1.921200e-17
6	EGARCH	2	1	-34760.031026	-34727.168833	1.921200e-17
7	EGARCH	2	2	-34768.831977	-34729.397345	1.921200e-17
8	TGARCH	1	1	-34773.262097	-34746.972342	1.921200e-17
9	TGARCH	1	2	-34771.262097	-34738.399904	1.921200e-17
10	TGARCH	2	1	-34562.085208	-34529.223014	1.921200e-17
11	TGARCH	2	2	-34783.754802	-34744.320170	1.921200e-17

GARCH(2,2) has the lowest AIC and BIC values. So we will use this model to predict volatility.

Rolling Window Forecasting:

- Used a 365-day rolling window to predict one-day-ahead volatility.
- Ensures predictions use the most recent data while adapting to market changes
- At each step:
  - Trained GARCH(2,2) on the past 365 days of data.
  - Forecasted volatility for the next day.
  - Shifted the window forward by one day and repeated the process.



Technical Indicators for Algorithmic Trading

MACD (Moving Average Convergence Divergence)

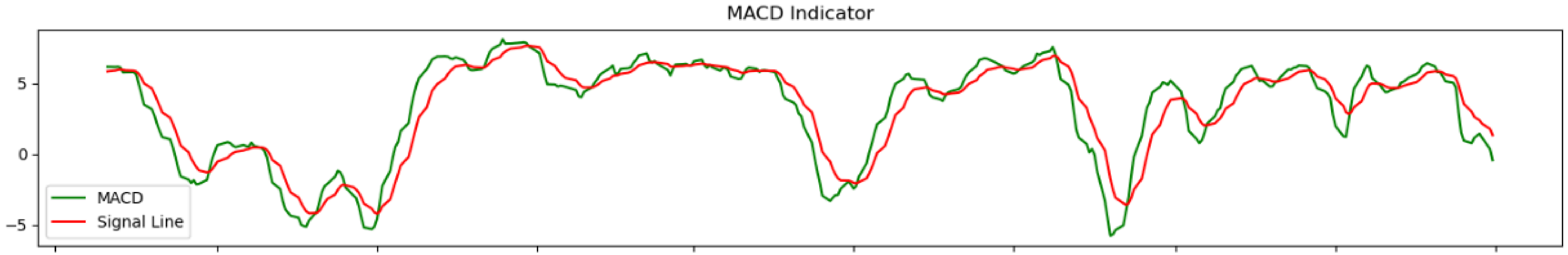
- Exponential Moving Average (EMA):

$$EMA_t = \alpha P_t + (1 - \alpha) EMA_{t-1}, \quad \alpha = \frac{2}{N+1}$$

- MACD Line:

$$MACD = EMA_{12} - EMA_{26}$$

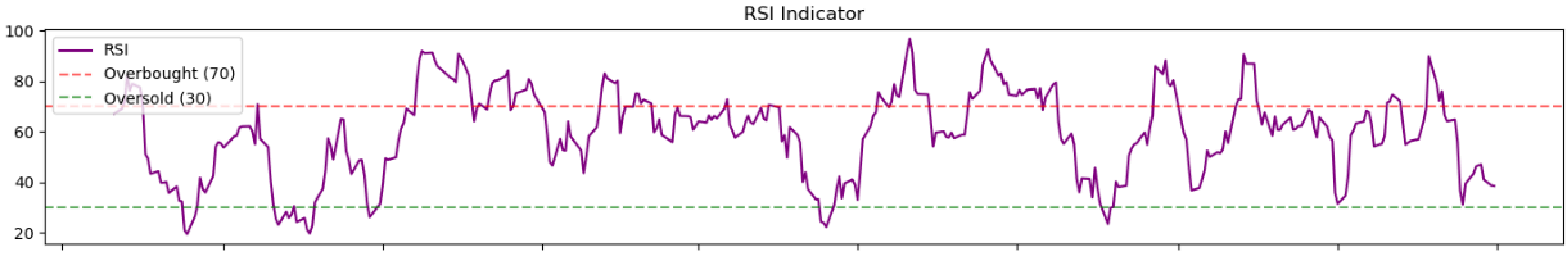
- Signal Line: 9-day EMA of MACD.



RSI (Relative Strength Index)

The Relative Strength Index (RSI) is a momentum oscillator that measures the speed and change of price movements to identify overbought and oversold conditions in a market.

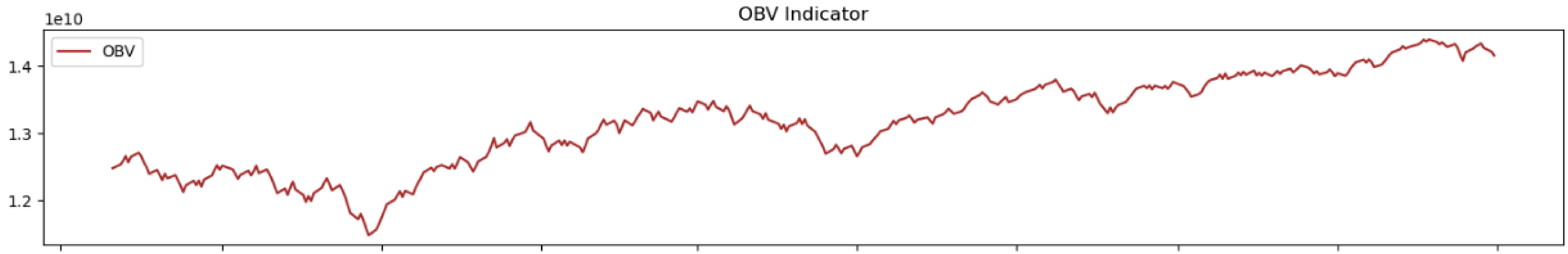
$$RSI = 100 - \frac{100}{1 + RS} \quad \text{where} \quad RS = \frac{\text{Avg. Gain (14 days)}}{\text{Avg. Loss (14 days)}}$$



On-Balance Volume (OBV)

OBV is a momentum-based technical indicator that uses volume flow to predict price movements.

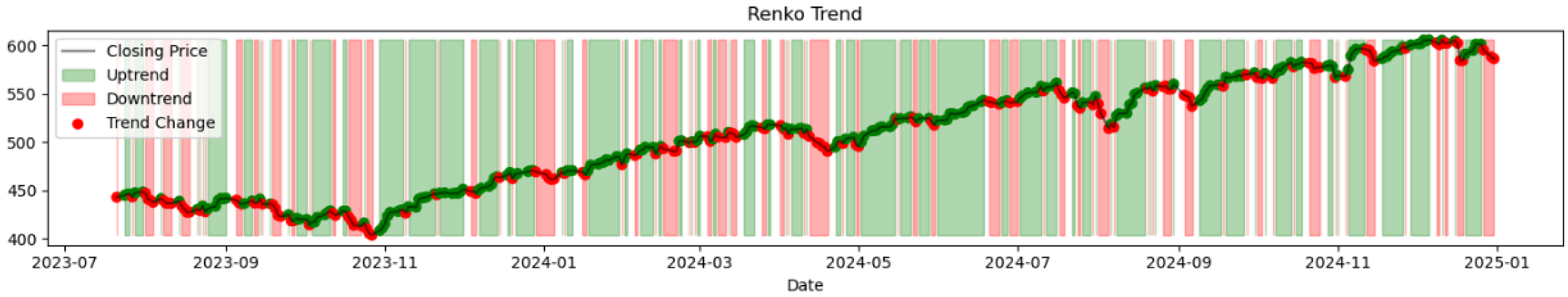
$$OBV_t = OBV_{t-1} + \begin{cases} \text{Volume}_t, & \text{if } P_t > P_{t-1} \text{ (Price Up)} \\ 0, & \text{if } P_t = P_{t-1} \text{ (No Change)} \\ -\text{Volume}_t, & \text{if } P_t < P_{t-1} \text{ (Price Down)} \end{cases}$$



Renko Trend

Construct bricks based on price movements:

$$B_t = P_t - P_{t-1} \quad \text{(Brick size determined dynamically)}$$

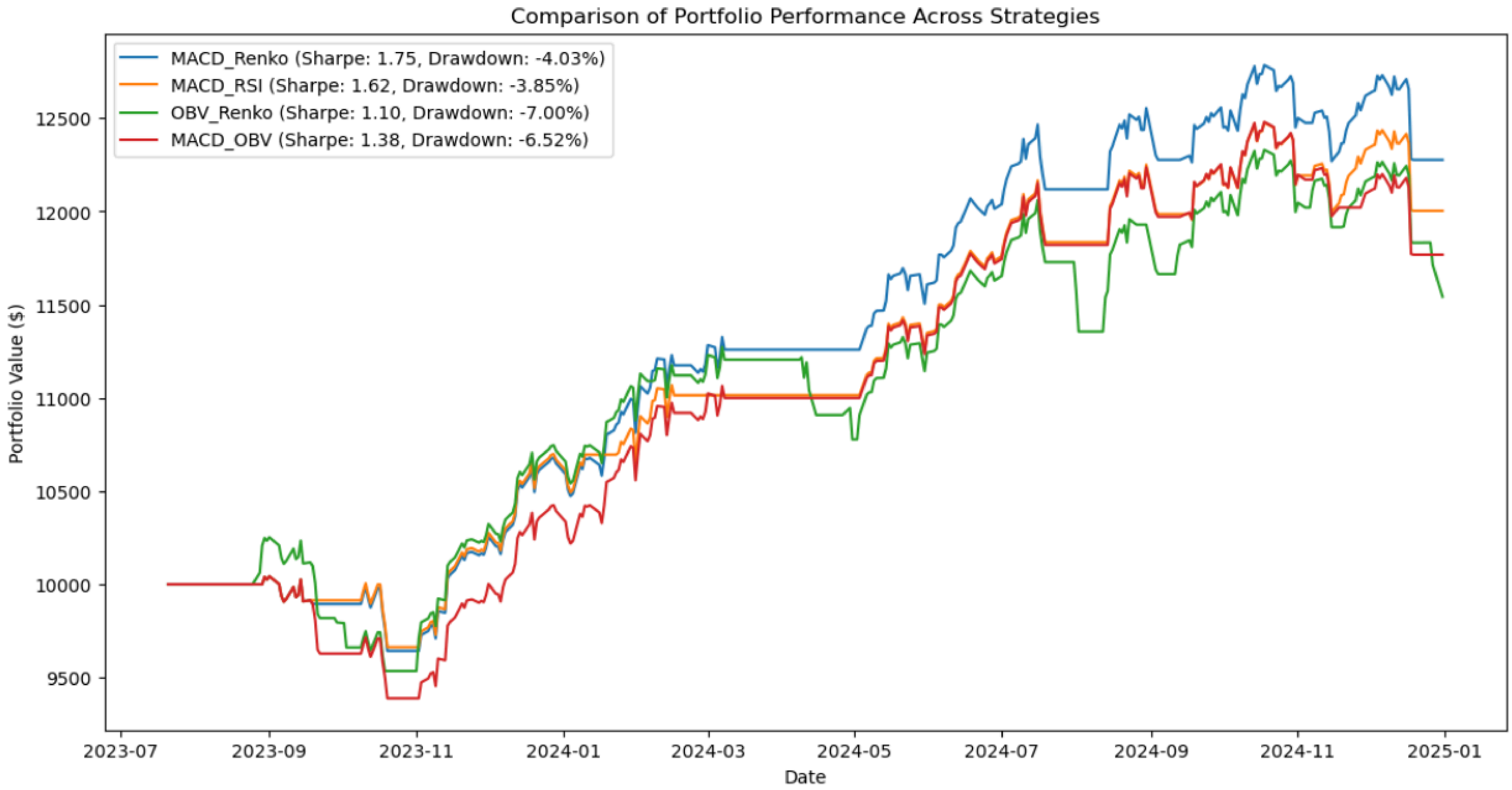


Trading Strategy Buy & Sell Signals

Strategy	Buy Signal	Sell Signal
MACD_Renko	MACD > Signal (Bullish Crossover) & Renko Trend = 1	MACD < Signal (Bearish Crossover) & Renko Trend = -1
MACD_RSI	MACD > Signal & RSI Rising > 30 (Oversold Recovery)	MACD < Signal & RSI Falling < 70 (Overbought Reversal)
OBV_Renko	OBV Rising (More Buying Pressure) & Renko Trend = 1	OBV Falling (More Selling Pressure) & Renko Trend = -1
MACD_OBV	MACD > Signal & OBV Rising (Volume Confirms Trend)	MACD < Signal & OBV Falling (Volume Confirms Decline)
Resistance_Breakout	Price Breaks Above Resistance & Volume > 1.5x Avg	Price Falls Below Support (99% Level)

All signals are executed only in high volatility conditions .

Backtesting Trading Strategies



Evaluation Metrics

- Sharpe Ratio:

$$S = \frac{R_p - R_f}{\sigma_p}$$

- Max Drawdown (MDD):

$$MDD = \frac{\max(P_t) - P_t}{\max(P_t)}$$

- Win Ratio:

$$\text{Win Ratio} = \frac{\text{Total Winning Trades}}{\text{Total Trades}}$$

	Strategy	Sharpe Ratio	Max Drawdown (%)	Portfolio Return (%)	Win Ratio (%)	Executed Trades	Final Portfolio Value ($)
0	MACD_Renko	1.750115	-4.033755	22.763532	31.250000	16	12276.353210
1	MACD_RSI	1.620949	-3.848240	20.035641	31.250000	16	12003.564056
2	OBV_Renko	1.101194	-6.997001	15.432217	18.750000	32	11543.221741
3	MACD_OBV	1.376042	-6.523000	17.679194	27.777778	18	11767.919403

MACD_Renko strategy has the best performance metrics. So we use this strategy to simulate future prices.

Monte Carlo Simulations for Trading & Portfolio Calculation

Simulating Future Price Paths

We generate 10,000 simulated price paths using the formula:

$$S_{t+1} = S_t e^{(\mu_t - \frac{1}{2}\sigma_t^2)\Delta t + \sigma_t \sqrt{\Delta t} Z}$$

where:

- μ_t is dynamically adjusted based on MACD_Renko signals:
  - BUY signal → Increase μ_t
  - SELL signal → Decrease μ_t
- σ_t is the predicted volatility from GARCH, but capped at 5%:

$$\sigma_t = \min(\hat{\sigma}_t, 5\%)$$

- Z N(0,1) is a standard normal random variable.

Trading Strategy Implementation

- Trading signals are generated using simulated price paths.
- However, actual market prices are used for executing trades to verify if the simulated signals align with real-world conditions.
- The strategy follows these rules:
  - BUY if the simulated price suggests an upward trend.
  - SELL if the simulated price suggests a downward trend.

Portfolio Calculation

The portfolio value is updated daily using actual trade executions:

$$V_t = V_{t-1} \times (1 + r_t)$$

where r_t is the actual return for the day based on executed trades.

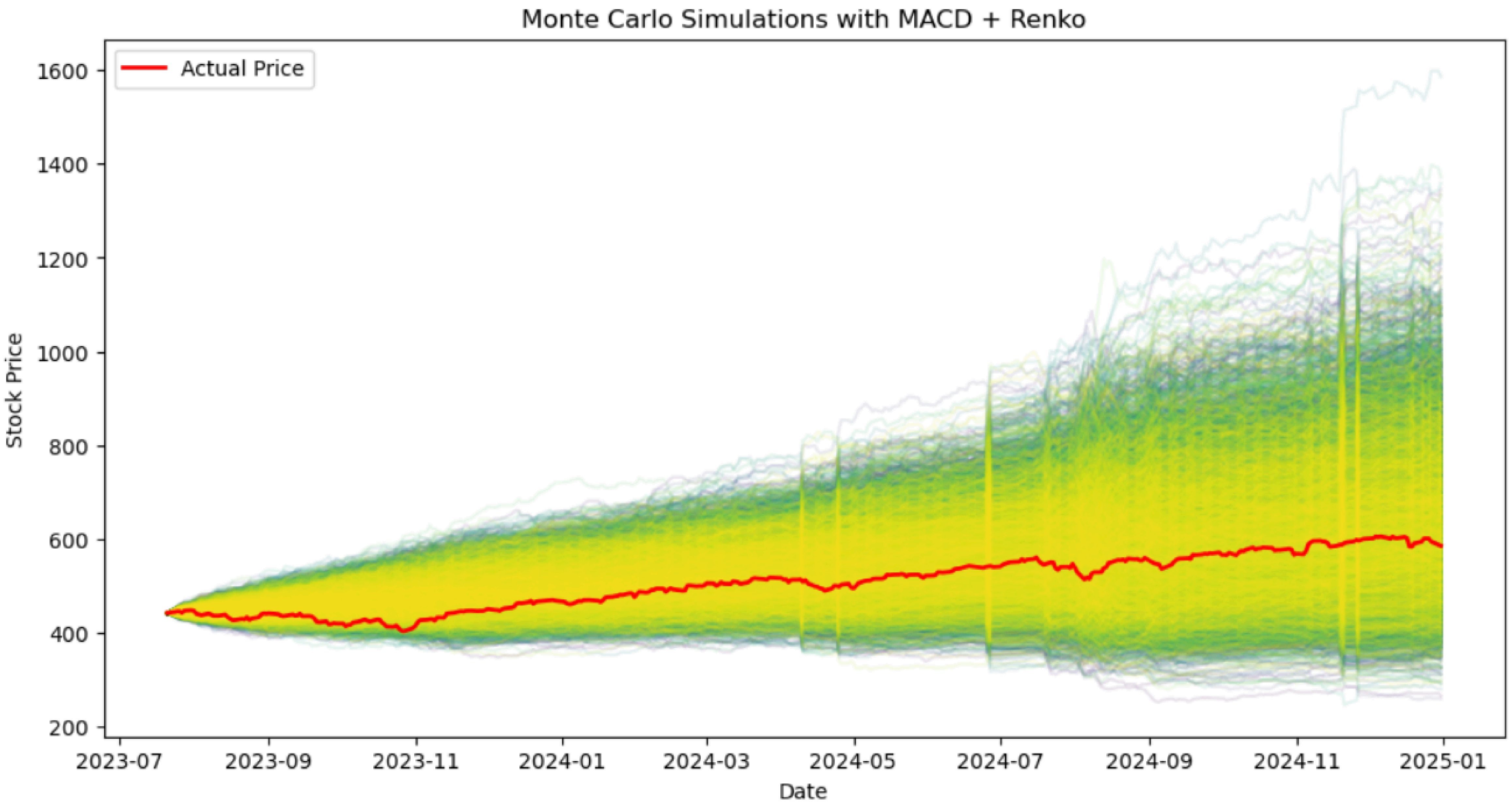
Risk Metrics Calculation

- Value-at-Risk (VaR) at confidence level α:

$$VaR_\alpha = \mu - Z_\alpha \sigma$$

- Conditional VaR (CVaR) aka Expected Shortfall:

$$CVaR_\alpha = E[X \mid X < VaR_\alpha]$$

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Expected Portfolio Value: $12723.25
Expected Return: 27.23%
Average Win Ratio: 34.13%
Value at Risk (VaR 95%): $9618.66
Conditional Value at Risk (CVaR 95%): $9003.12
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THANK YOU