Volatility prediction on SPY product

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PLAN

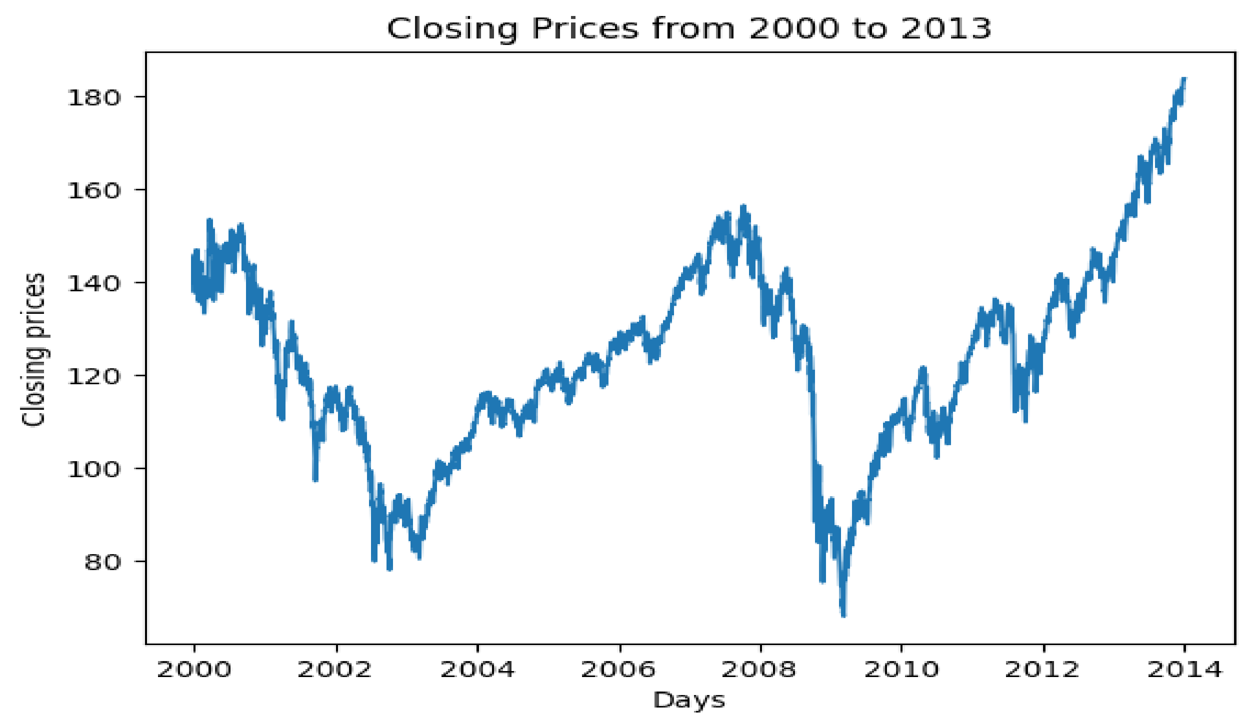
- **Part I:** Volatility estimation*
- **Part II:** Rough volatility models
- **Part III:** Trading Strategy (risk management)

Part I : Volatility estimation

SPY: SPDR S&P 500 ETF Trust

- **Overview**: SPY is an exchange-traded fund (ETF) that tracks the performance of the S&P 500 Index.
- **Composition**: It holds stocks from 500 leading companies across various sectors in the U.S. economy.
- **Purpose**: Provides investors with a cost-effective and convenient way to gain broad market exposure.
- **Benefits**:
  - Diversification: Reduces risk by spreading investments across multiple companies.
  - Liquidity: Highly traded, making it easy to buy and sell.
  - Dividends: Pays dividends based on the underlying stocks.
- **Use Cases**: Suitable for both individual and institutional investors seeking to match the performance of the S&P 500.

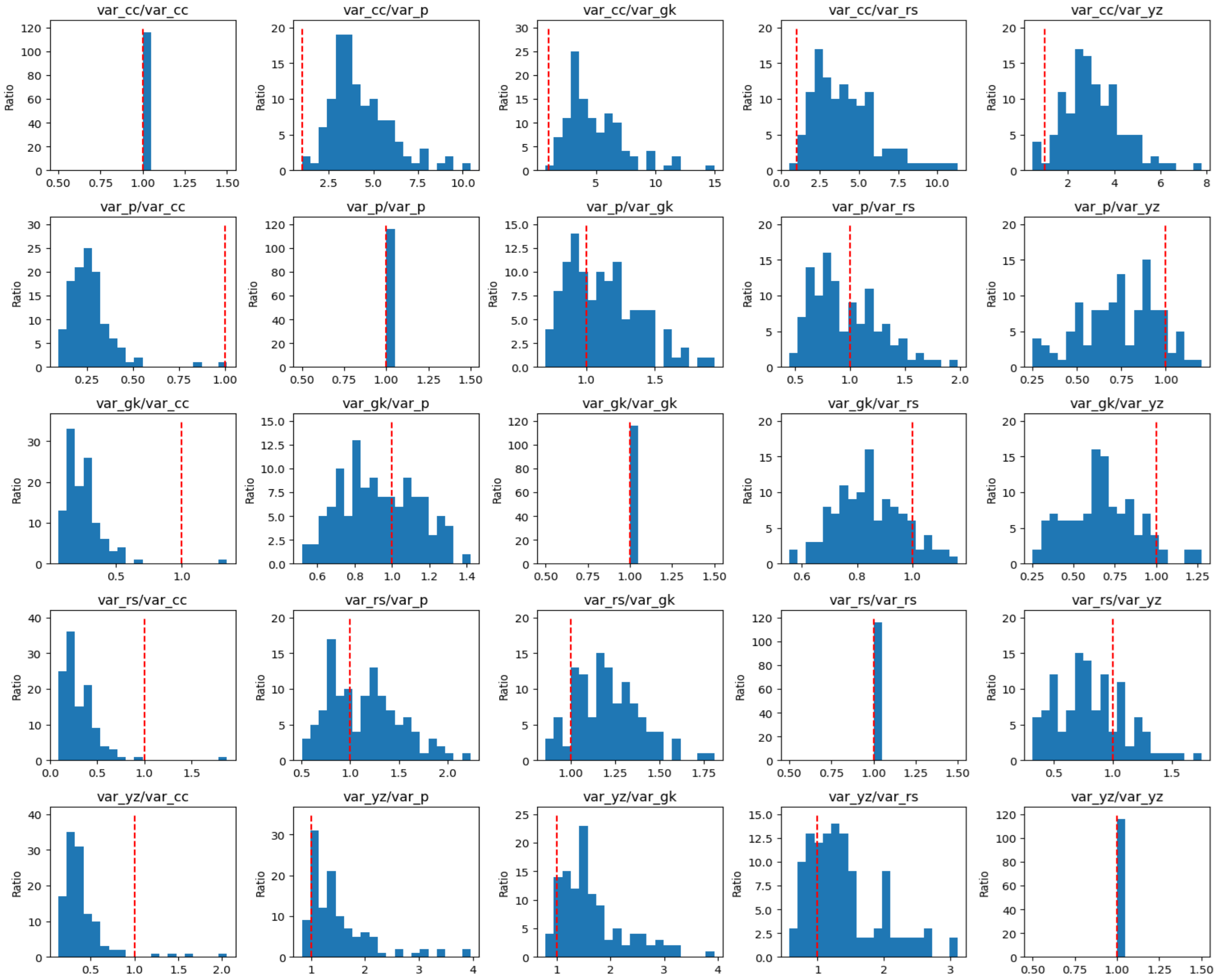
Price development of SPY



Efficiency Comparison Between Estimators

Best: Garman-Klass

Worst: Close-to-Close



Volatility estimators

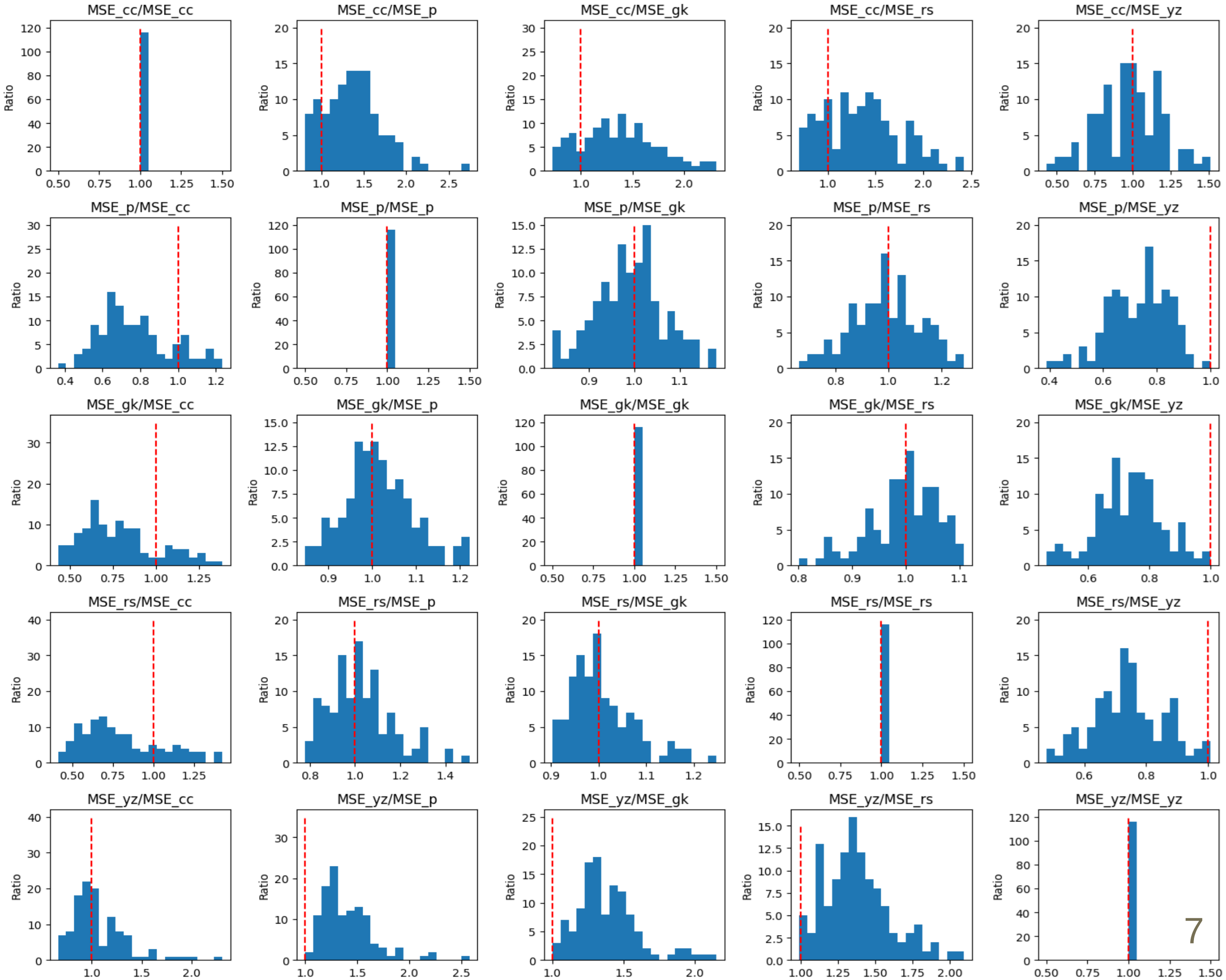
We will be ccompare the following estimators :

- Close-to-close volatility
- Parkinson volatility
- Garman-Klass volatility
- Rogers-Satchell volatility
- Yang-Zhang volatility

Efficiency Comparison Between Estimators

Best: GK, P and RS

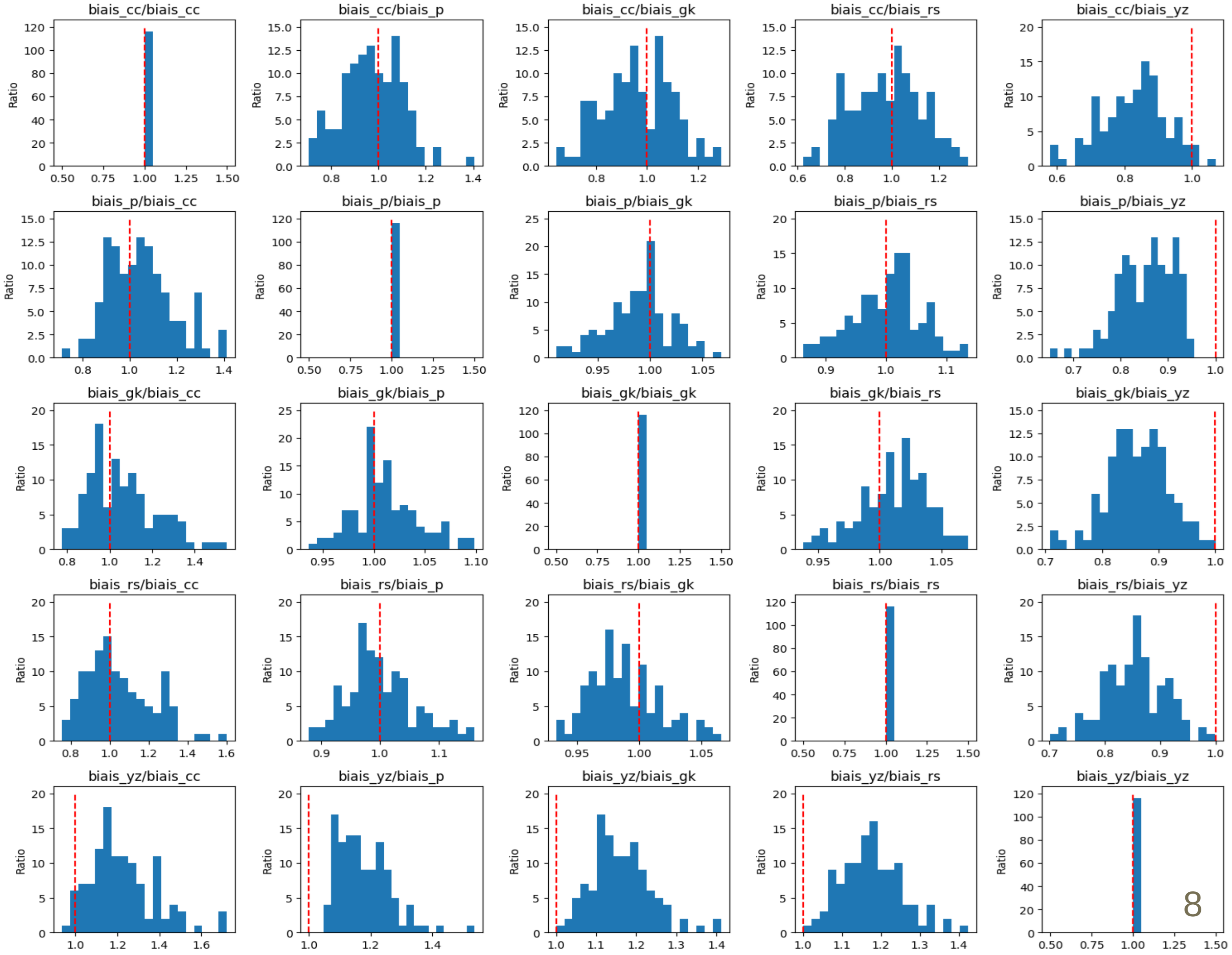
Worst: YZ and CC



Stability Comparison Between Estimators

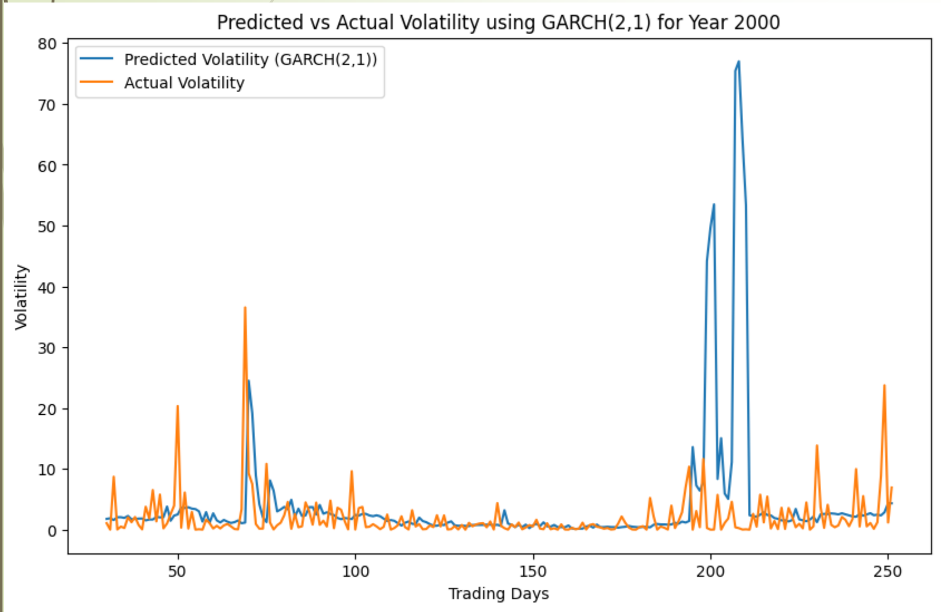
Best: P, CC and RS

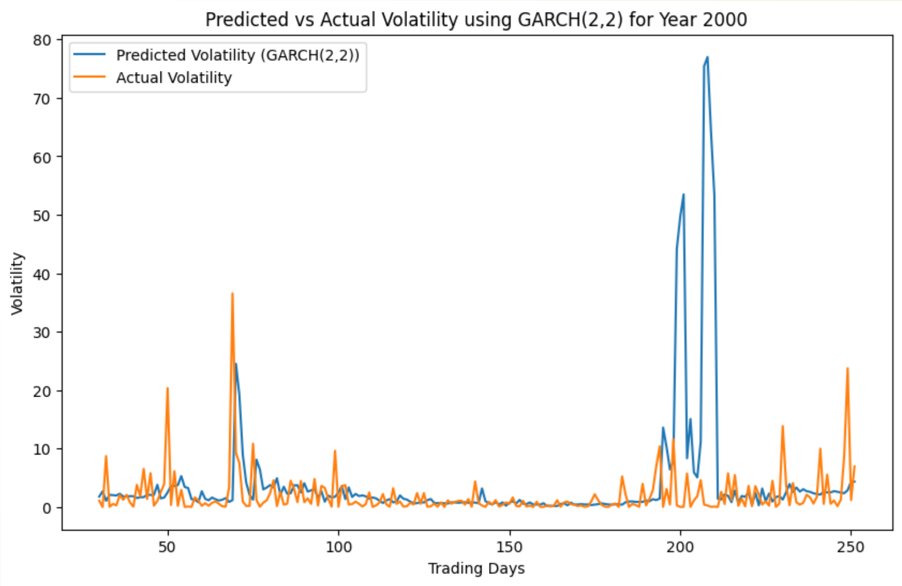
Worst: Yang-Zang



Part I : Volatility estimation

Fitted Garch Models : The two best models regarding AIC and BIC





Part I : Volatility estimation

Fitted Garch Models : The two best models regarding AIC and BIC

Model Comparison: MSE and Bias

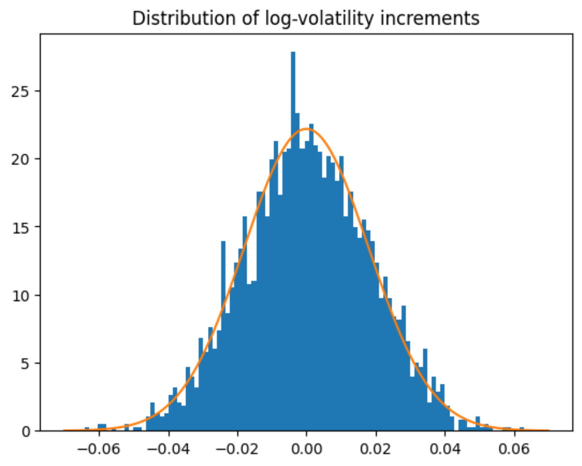
Model	MSE	Bias
GARCH(2,1)	134.90926498396993	2.0450884007989525
GARCH(2,2)	135.16597148422528	2.027775158458846
GARCH(1,1)	135.47752829443598	1.9965653527420124
GARCH(1,2)	136.0164371999599	2.0271544478604118

Part II : Rough volatility models

Fractional Ornstein-Uhlenbeck model for the log-volatility Xt

$$dX_t = \nu dW_t^H + \alpha(m - X_t)dt$$

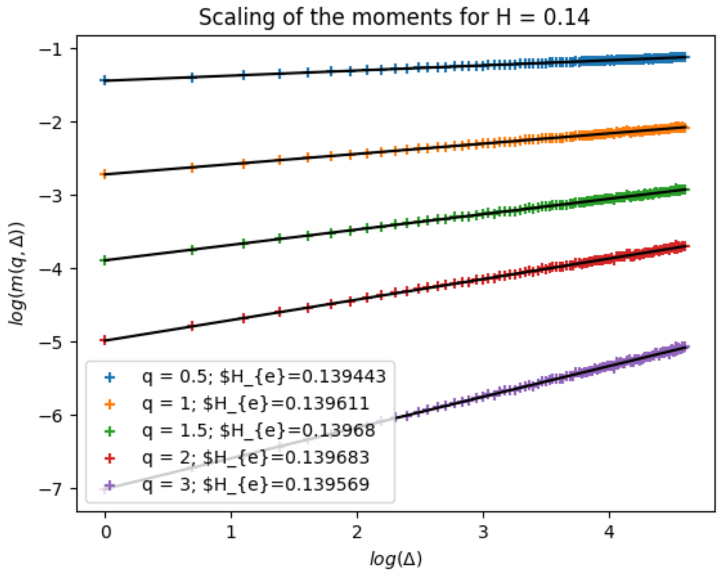
Where W_t^H follows a fractional Brownian motion



Part II : Rough volatility models

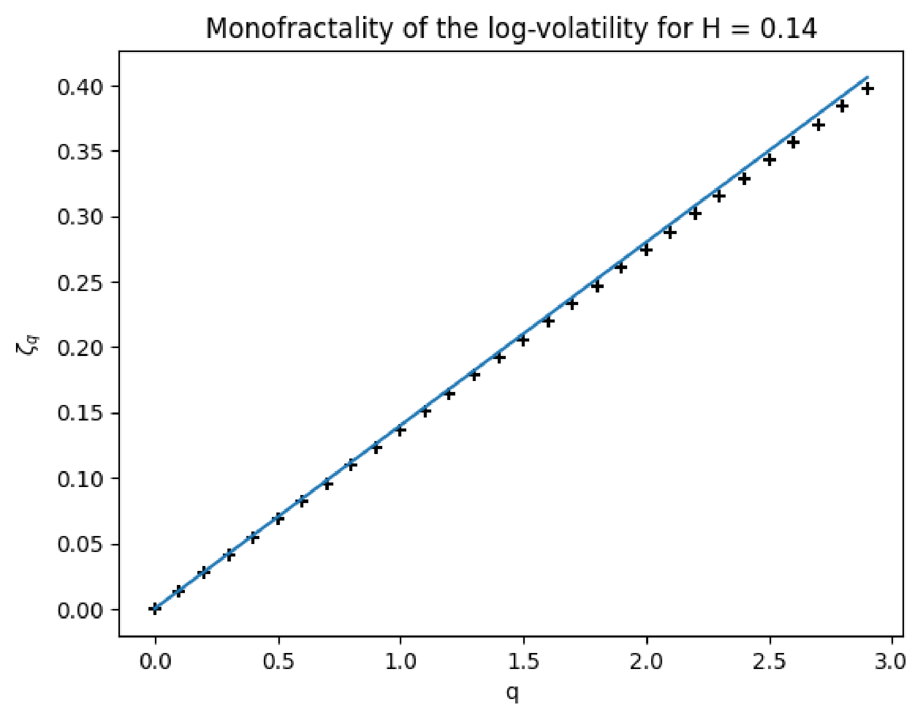
Measure of the regularity of the log-volatility

$$m(\Delta, q) = \mathbb{E}(|\log(\sigma t + \Delta) - \log(\sigma t)|^q)$$



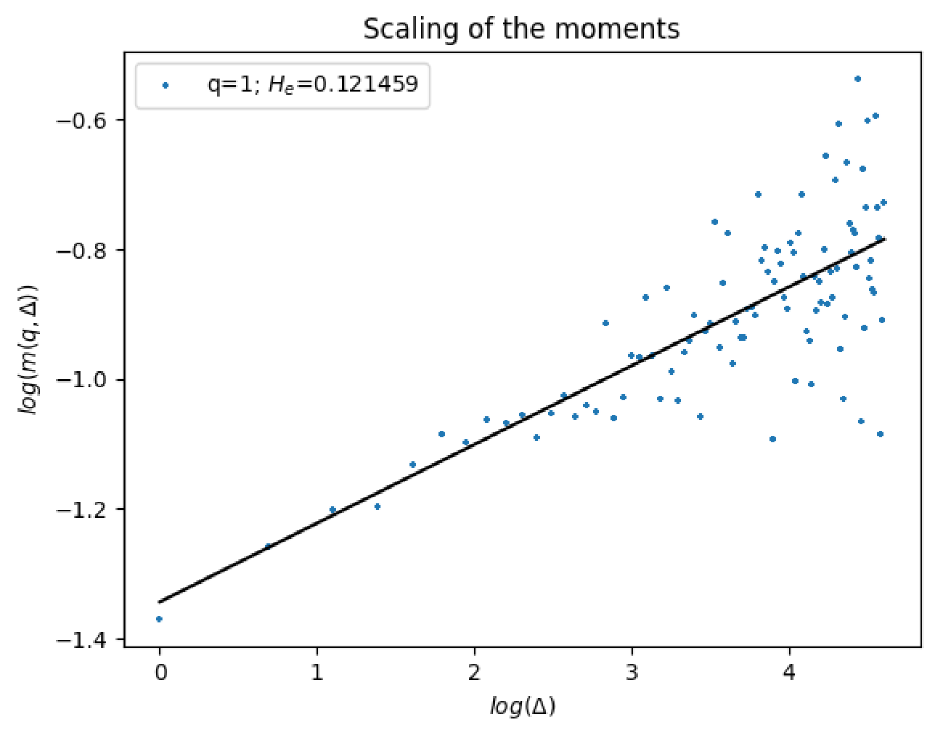
Part II : Rough volatility models

Monofractality of the log-volatility



Part II : Rough volatility models

Tests with real market data



Part II : Rough volatility models

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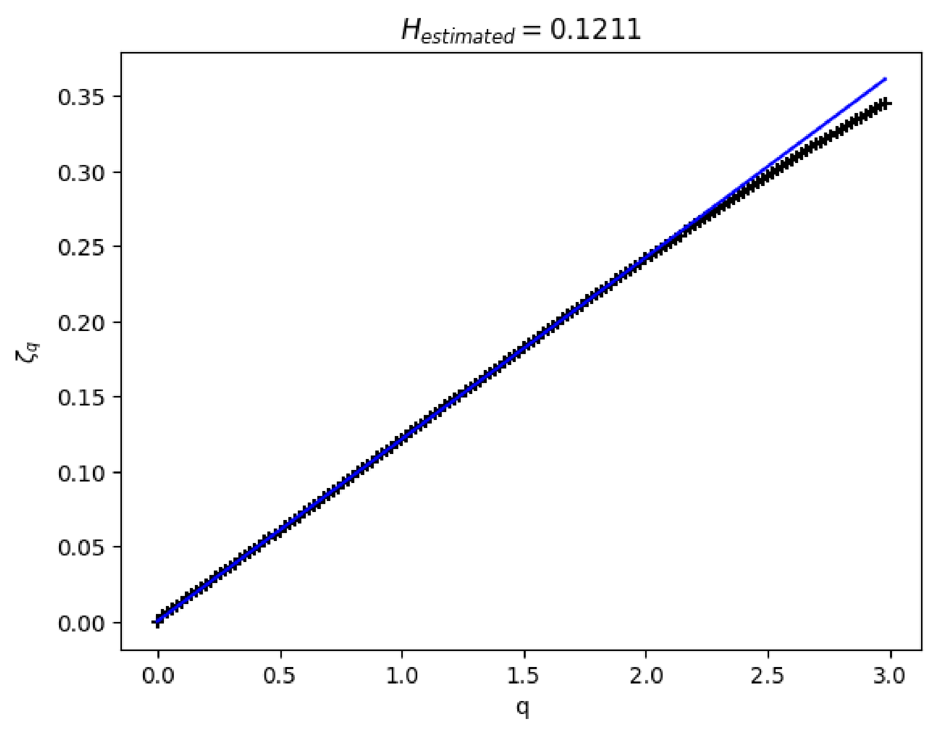
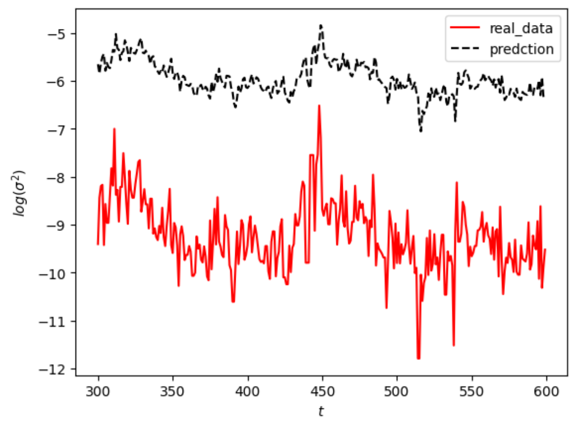
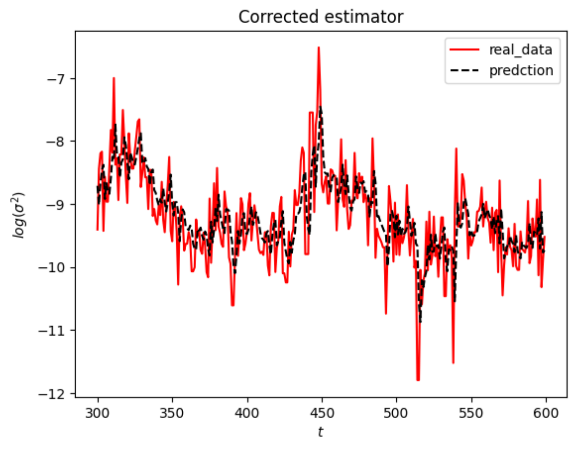


Part II : Rough volatility models

RFSV prediction

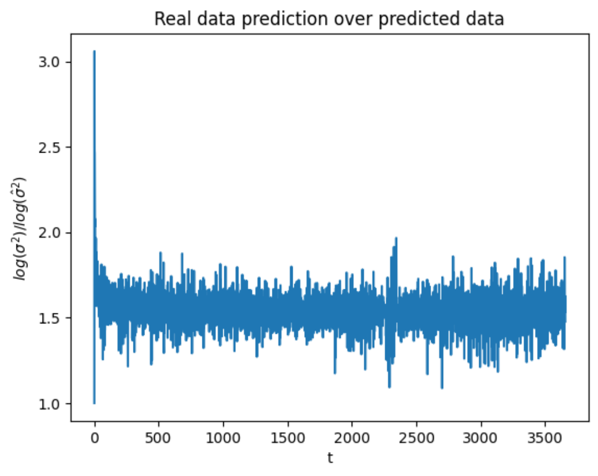
$$\mathbb{E}\left[\log \sigma^2_{t+\Delta} \mid \mathcal{F}_t\right] = \frac{\cos(H\pi)}{\pi} \Delta^{H+1/2} \sum_{k=0}^{N} \frac{\log \sigma^2_{t-k}}{(k+\Delta+1/2)(k+1/2)^{H+1/2}}$$

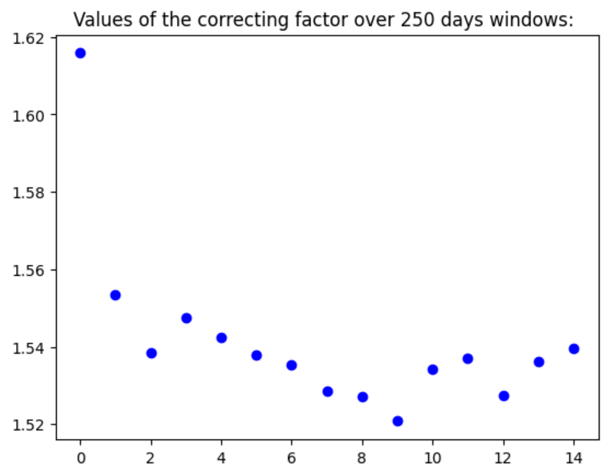




Part II : Rough volatility models

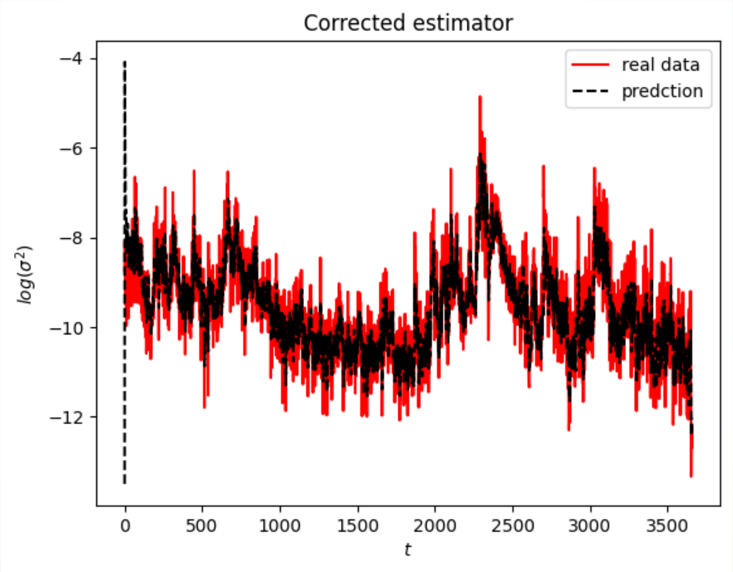
RFSV prediction : determination of the correction factor





Part II : Rough volatility models

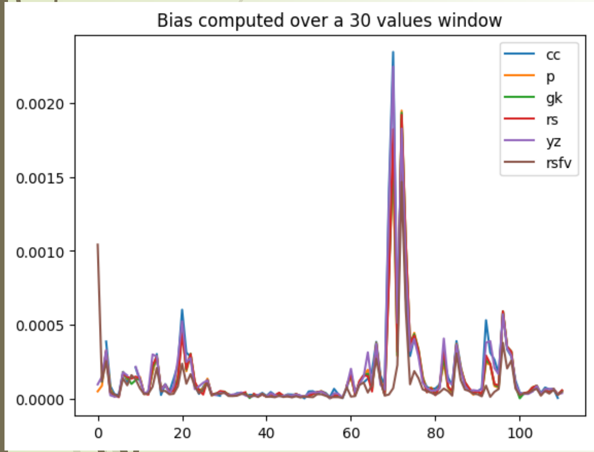
RFSV prediction : Mean Square Error

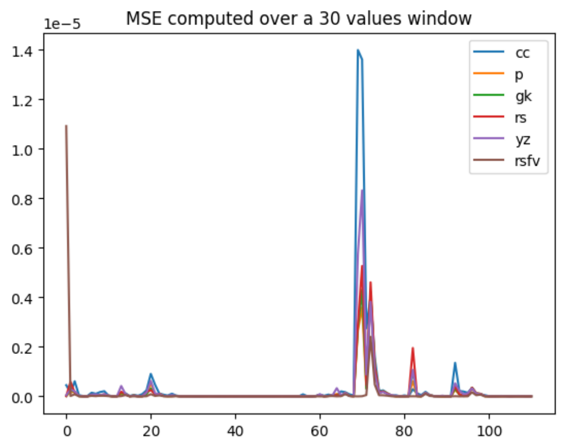


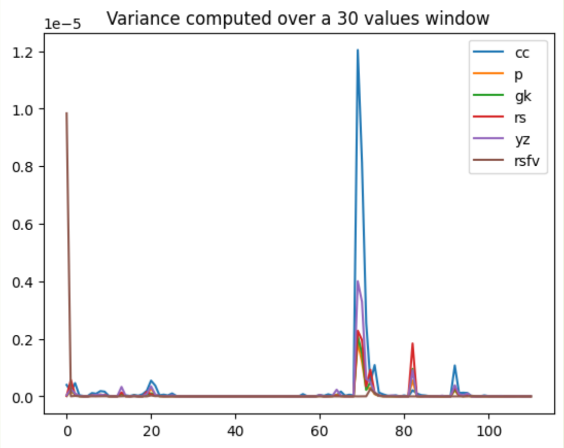
MSE = 1.35 x 10e-7

Part II : Rough volatility models

RFSV prediction : Comparison with other predictors

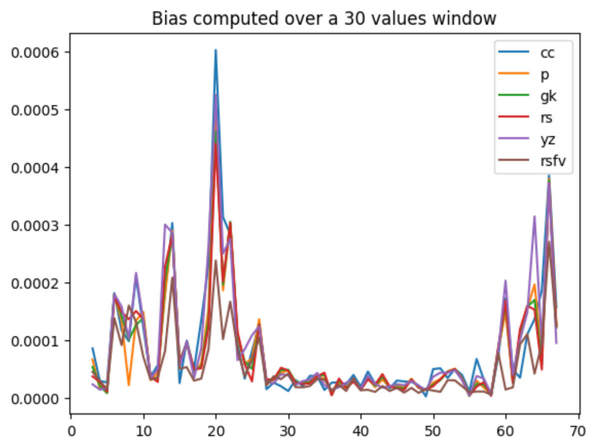


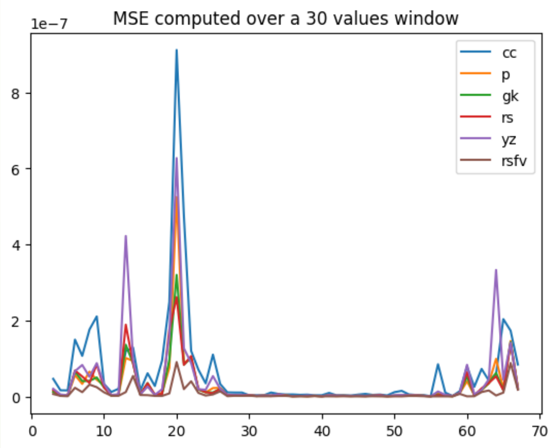


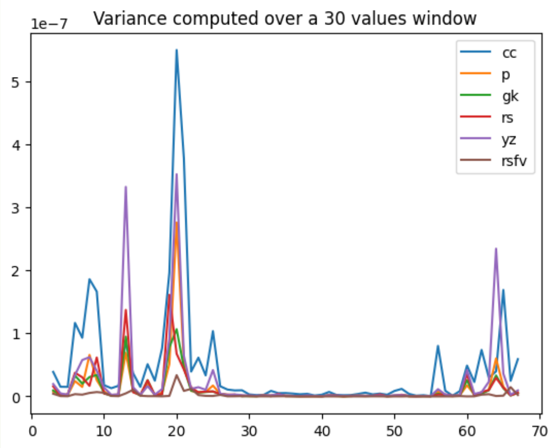


Part II : Rough volatility models

RFSV prediction : Comparison with other predictors

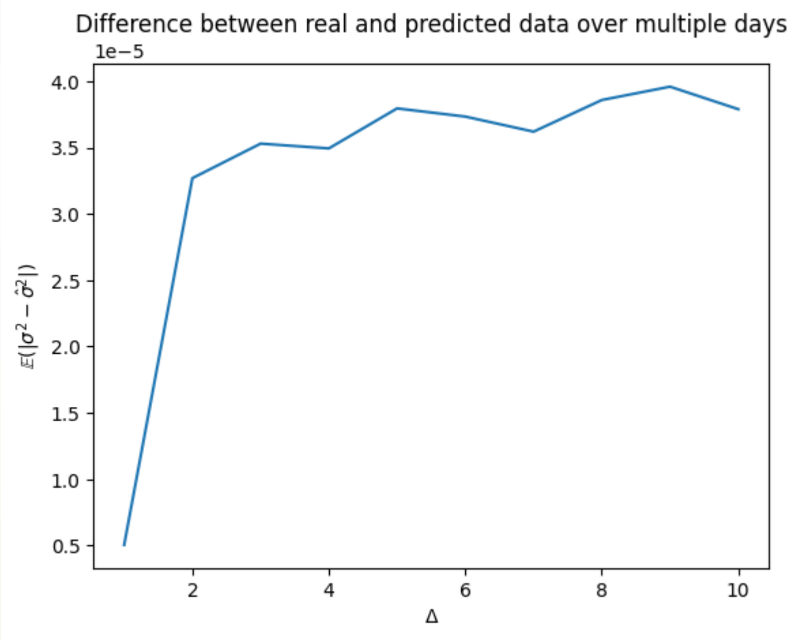






Part II : Rough volatility models

RFSV prediction : Prediction over multiple days



Part III : Trading Strategy (risk management)

The idea is to be able to predict the intraday volatility for the next year and based on that, trade the SPY only during low volatility periods

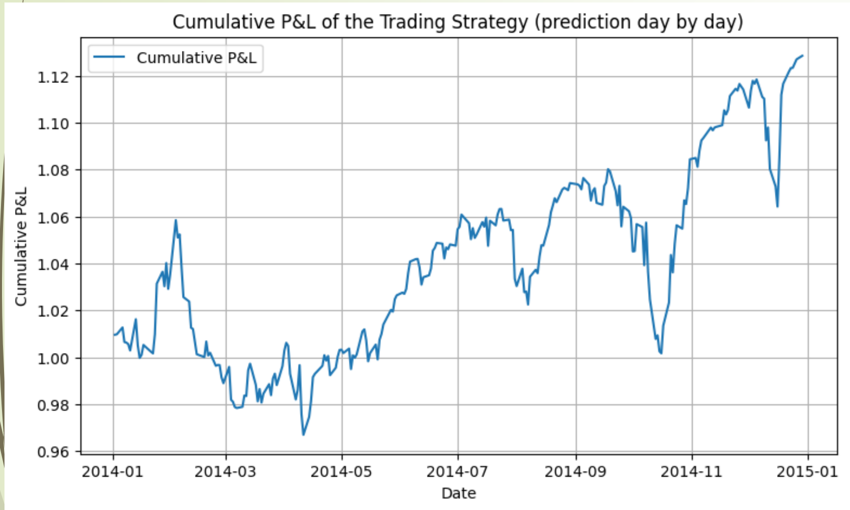
1. Estimate next day the volatility with “Rough Volatility” predictor with a sliding window of 3 years

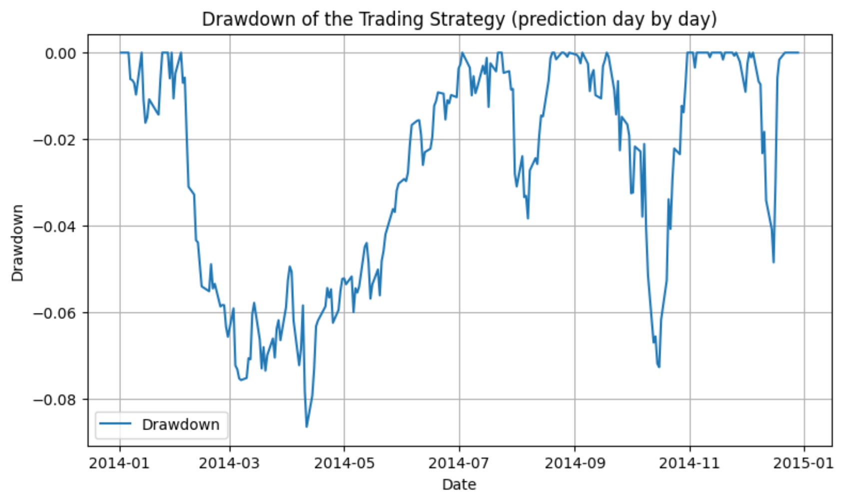
2. Based on the predicted volatility we give the trading signal

   1: Buy if the volatility of the next day is predicted to be lower than the the mean of the last year

   -1: Sell if the volatility of the next day is predicted to be higher than the the mean of the last year

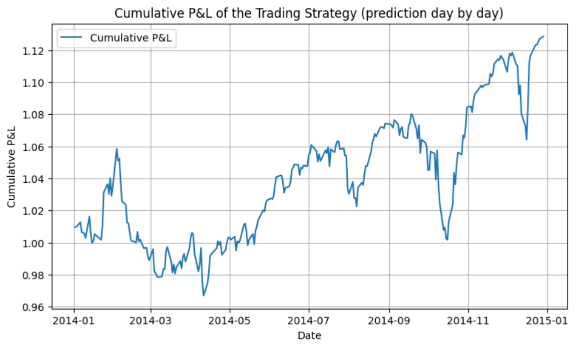
Part III : Trading Strategy (results)

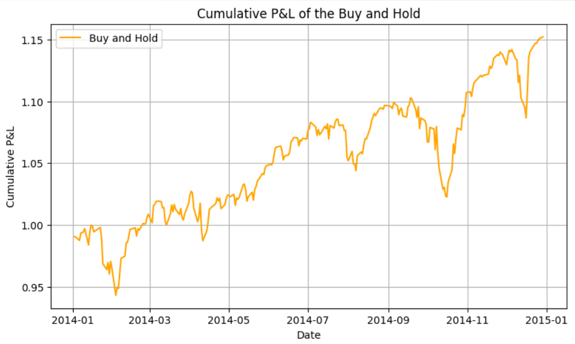


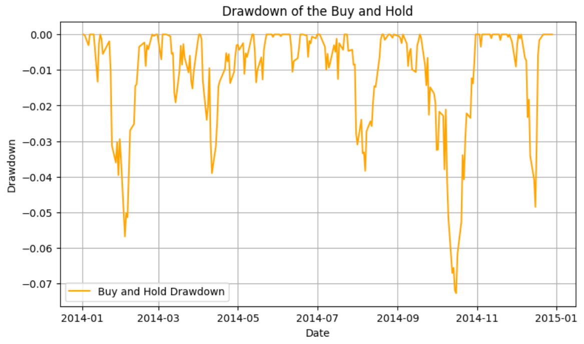


Sharpe Ratio	Max Drawdown	Standard Deviation of Returns	Value-at-Risk (VaR) at 95.0% confidence level	Conditional Value-at-Risk (CVaR)
1.14	-0.086	0.007	-0.011	-0.0158

Part III : Trading Strategy (results comparison)







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Sharpe Ratio	Max Drawdown	Standard Deviation of Returns	Value-at-Risk (VaR) at 95.0% confidence level	Conditional Value-at-Risk (CVaR)
1.328	-0.072	0.007	-0.011	-0.0171

Conclusion

- Comparing the volatility estimators
- GARCH(2,1) or (2,2) results in a big peak of volatility compared to the actual values (not efficient)
- Rough volatility approach outperform the other estimators, especially when it comes to modelize peaks

Possible improvements

1) Improve by estimating next day volatility taking into account the last trade-day and last 3 years and give the trading signal for the next day.
2) Compare the same strategy with the buy and hold on different periods.

Thank you for your attention!!