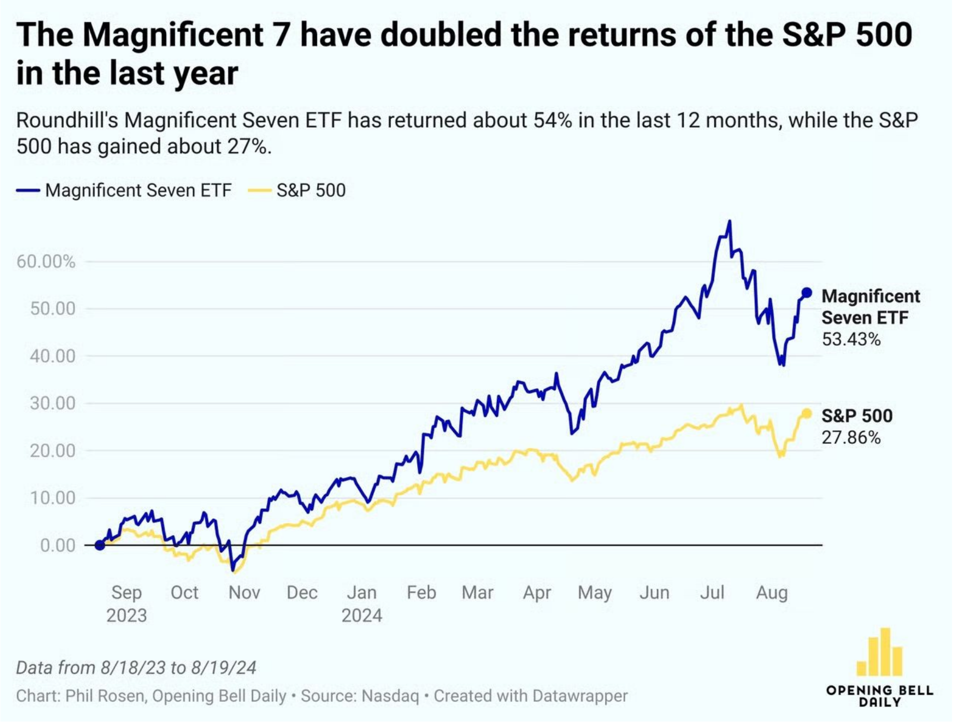
VolForecast: MAG 7 Risk Forecasting

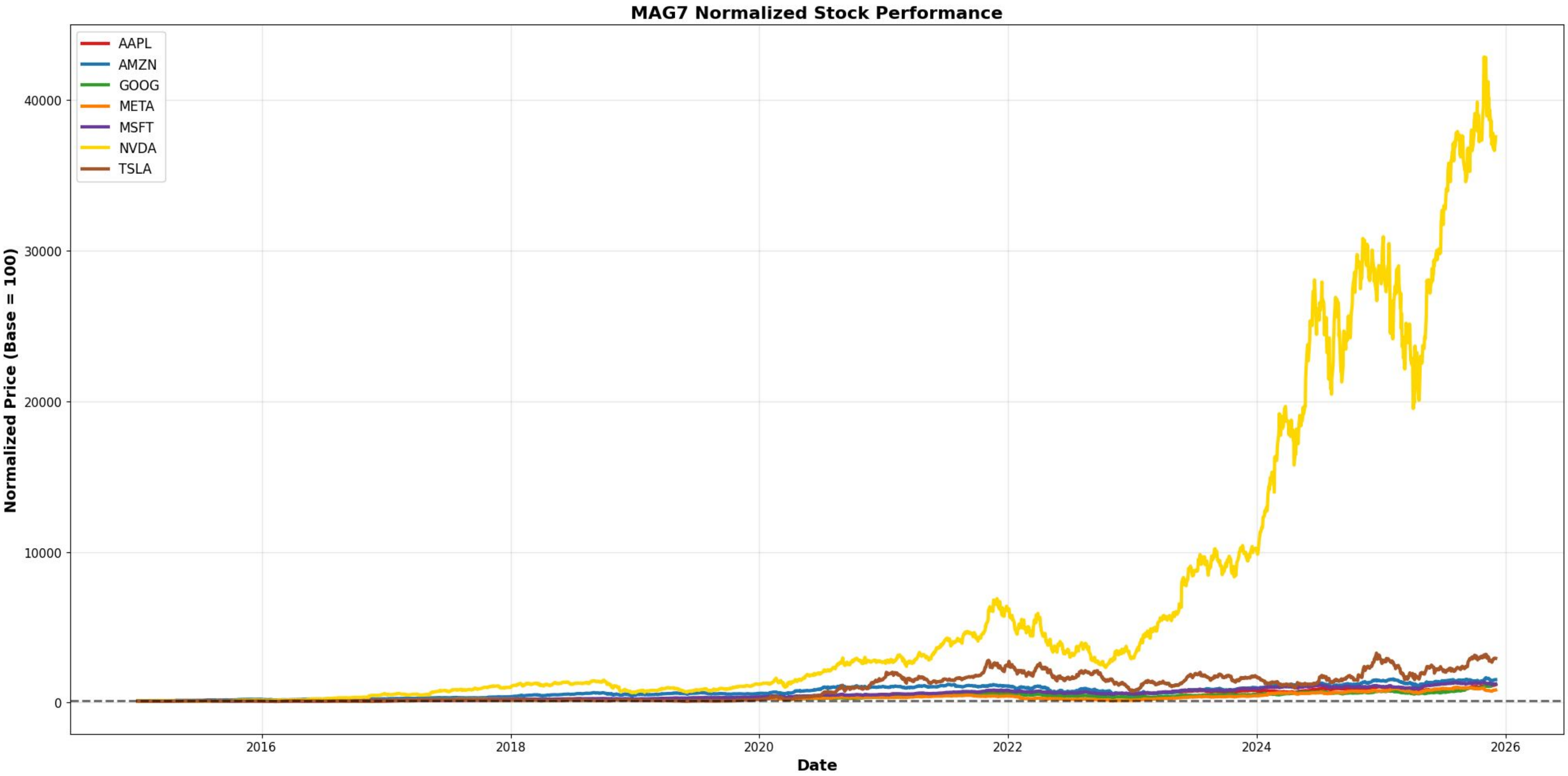
Oorjit Chowdhary • EE 344 Final Project, Fall 2025

MAG 7 Dataset & Context

ETF of 7 big tech companies

- Apple, Alphabet, Amazon, Meta, Microsoft, Nvidia, and Tesla
- My dataset is the open, high, low, close prices and volume traded of these stocks for each day from the past 10 years
- Fetched from Yahoo Finance
- Organized into a single CSV file

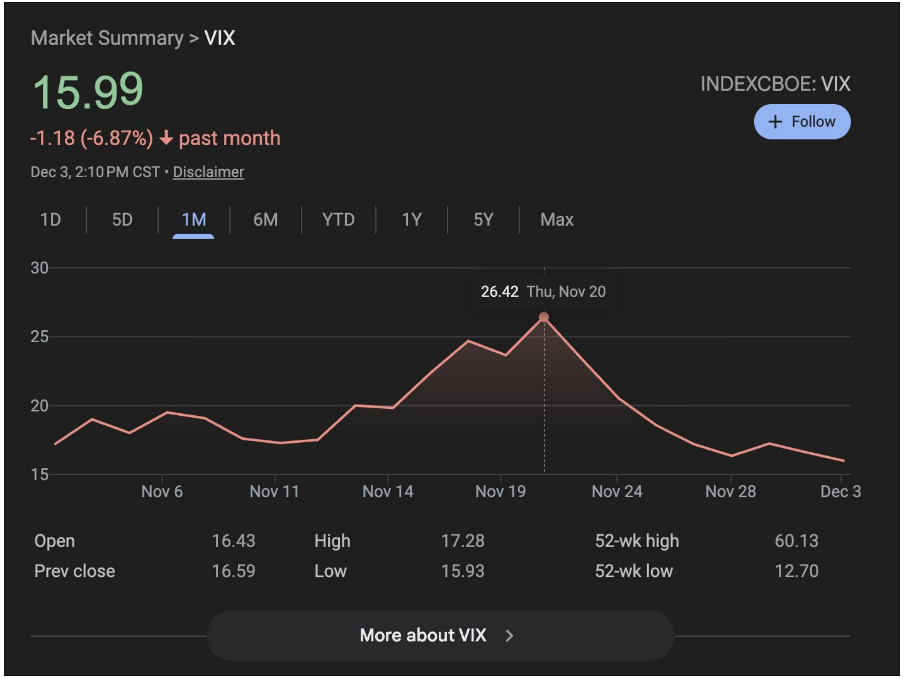




MAG7 Normalized Stock Performance
AAPL
AMZN
GOOG
META
MSFT
NVDA
TSLA
Normalized Price (Base = 100)
40000
30000
20000
10000
0
2016
2018
2020
2022
2024
2026
Date

Motivation

The market was going insane last month



Preprocessing pipeline

Convert raw prices into log returns

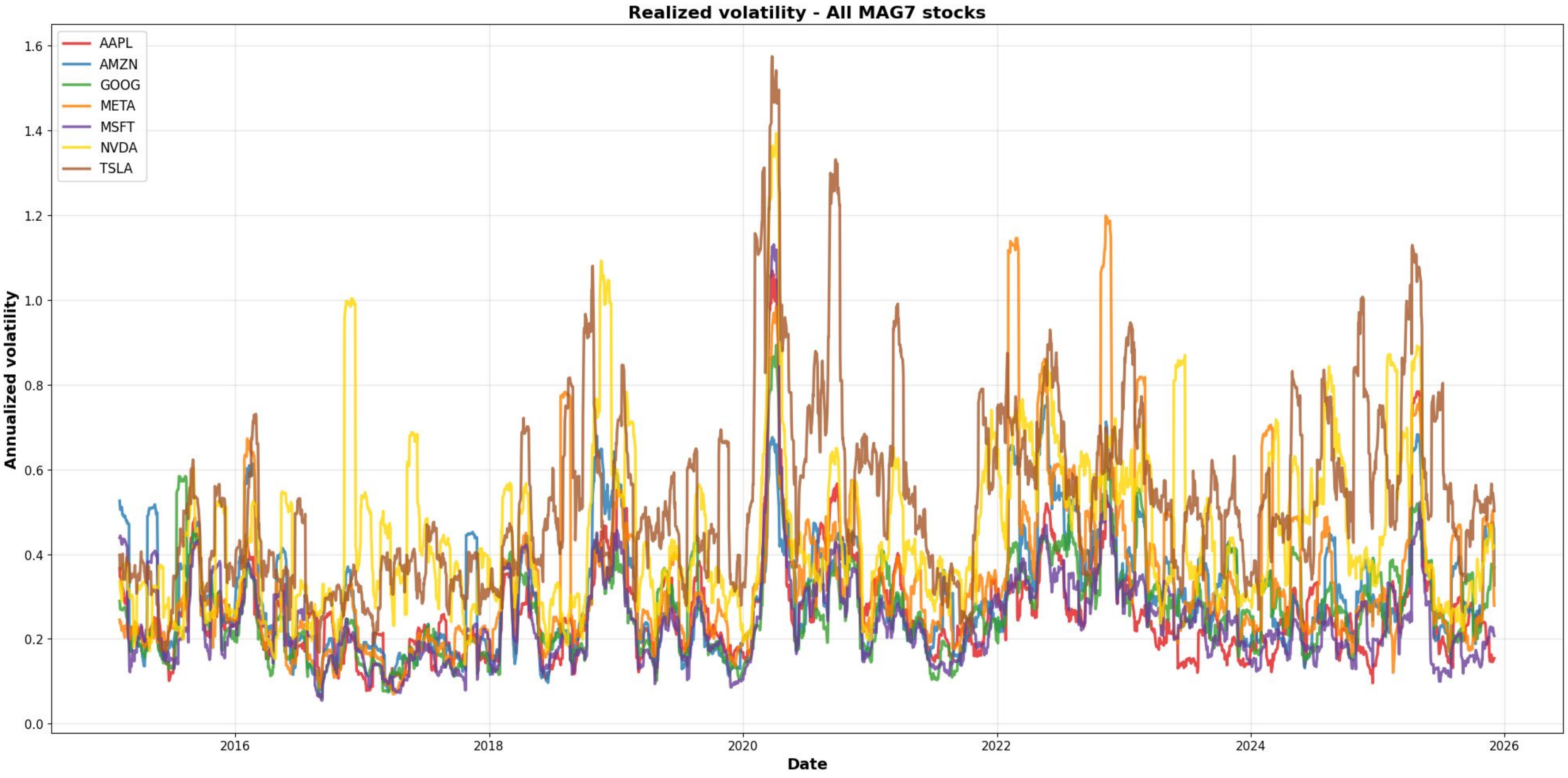
Allows better statistical modeling and aggregation, as log returns are additive, symmetrical, and handle compounding correctly.

Compute realized volatility

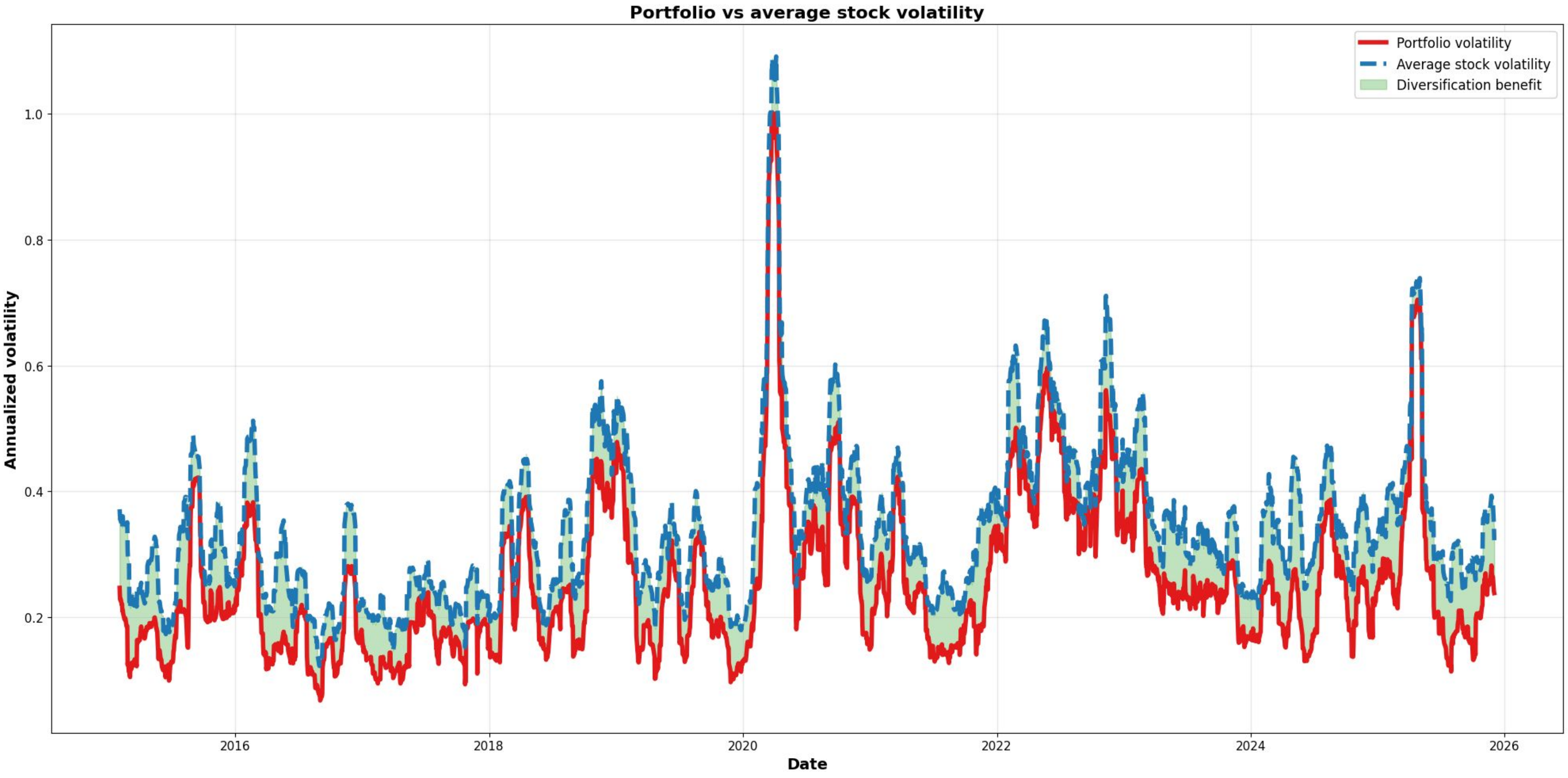
Use 21-day rolling window (1 trading month) to calculate realized volatility (std dev of 21 day log returns annualized) for each stock.

Construct equal-weighted portfolio

Construct equal exposure basket of 7 stocks and compute annualized realized volatility for this portfolio, increasing diversification for better volatility hedging.



Realized volatility - All MAG7 stocks
AAPL
AMZN
GOOG
META
MSFT
NVDA
TSLA
Annualized volatility
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
2016
2018
2020
2022
2024
2026
Date



Portfolio vs average stock volatility
Portfolio volatility
Average stock volatility
Diversification benefit
Annualized volatility
1.0
0.8
0.6
0.4
0.2
2016
2018
2020
2022
2024
2026
Date

Time-series model: ARIMA

AutoRegressive Integrated Moving Average

- Classical time series forecasting: assumes linear relationships & stationarity and captures autocorrelation patterns
- Failed to explain next-day volatility: zero/negative R-squared, high RMSE
- ARIMA struggles with noisy, heteroskedastic time series data

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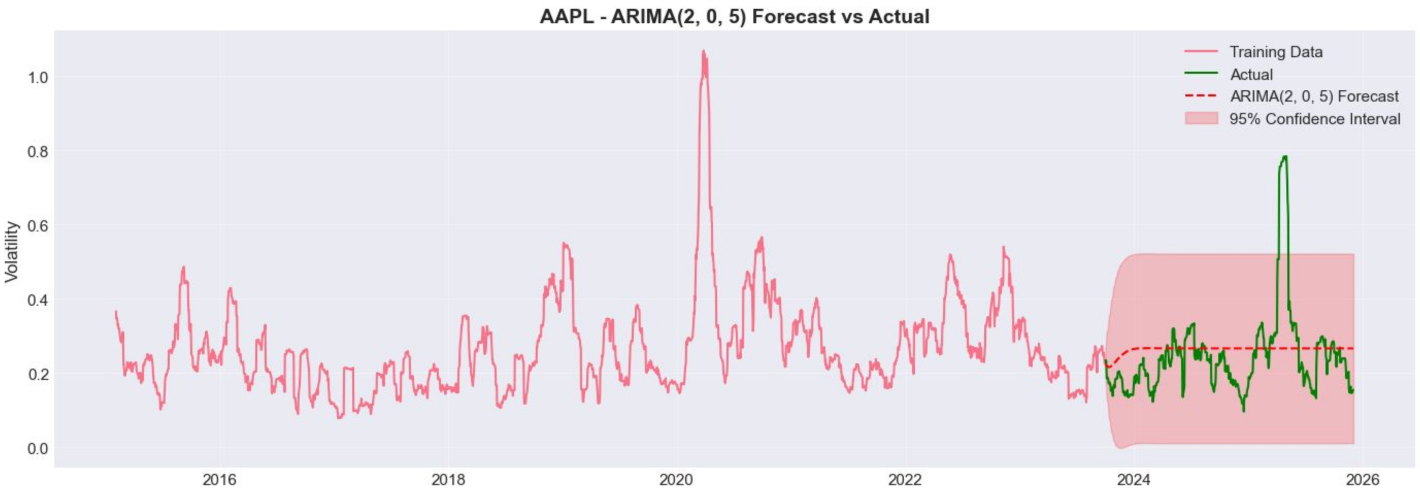
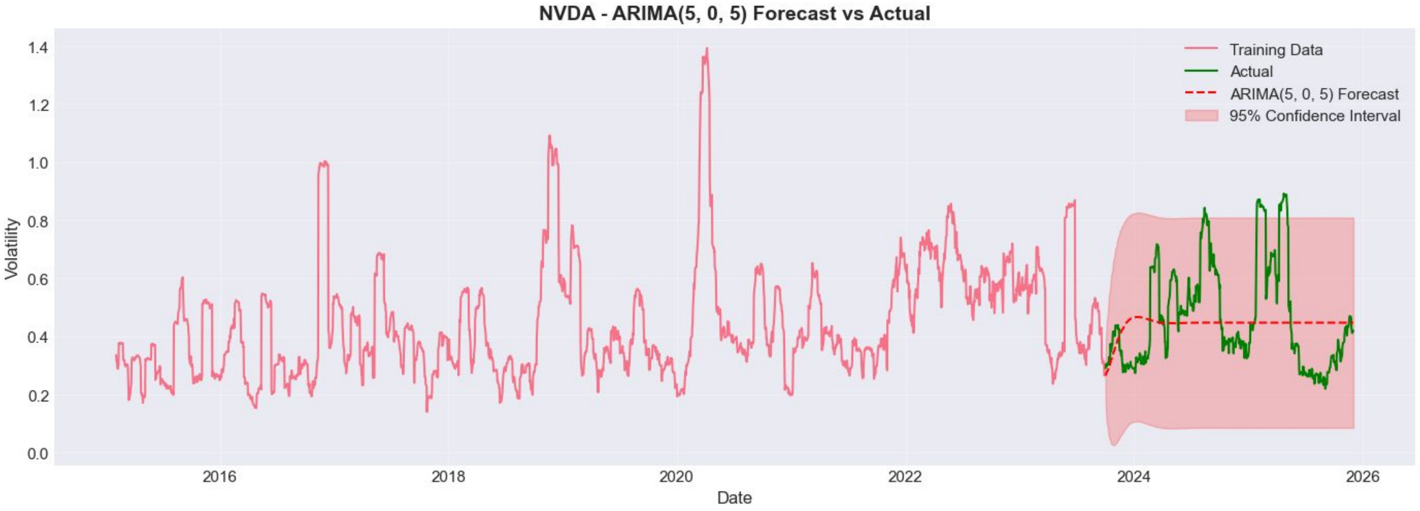
============================================================
AAPL - ARIMA(2, 0, 5)
============================================================

AAPL ARIMA(2, 0, 5) Performance Metrics:
MAE:  0.075083
MSE:  0.014042
RMSE: 0.118499
MAPE: nan%
R²:   0.0009

============================================================
NVDA - ARIMA(5, 0, 5)
============================================================

NVDA ARIMA(5, 0, 5) Performance Metrics:
MAE:  0.144811
MSE:  0.032577
RMSE: 0.180491
MAPE: nan%
R²:   -0.0057
```


AAPL - ARIMA(2, 0, 5) Forecast vs Actual
Training Data
Actual
ARIMA(2, 0, 5) Forecast
95% Confidence Interval
Volatility
0.0
0.2
0.4
0.6
0.8
1.0
2016
2018
2020
2022
2024
2026


NVDA - ARIMA(5, 0, 5) Forecast vs Actual
Training Data
Actual
ARIMA(5, 0, 5) Forecast
95% Confidence Interval
Volatility
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
2016
2018
2020
2022
2024
2026
Date

Time-series model: Exponential Smoothing

Simple Exp Smoothing (SES)

- Classical baseline that models the series as a weighted average of past observations; assumes no trend or seasonality (too restrictive for volatility)
- SES performs worse than ARIMA: R-squared values are negative, MAPE undefined
- SES “smooths away” the spikes that actually matter in 21d volatility data

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============================================================
AAPL – SES
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AAPL SES Performance Metrics:
MAE:  0.069372
MSE:  0.014498
RMSE: 0.120408
MAPE: nan%
R²:   -0.0315

============================================================
NVDA – SES
============================================================

NVDA SES Performance Metrics:
MAE:  0.203239
MSE:  0.072946
RMSE: 0.270085
MAPE: nan%
R²:   -1.2519
```

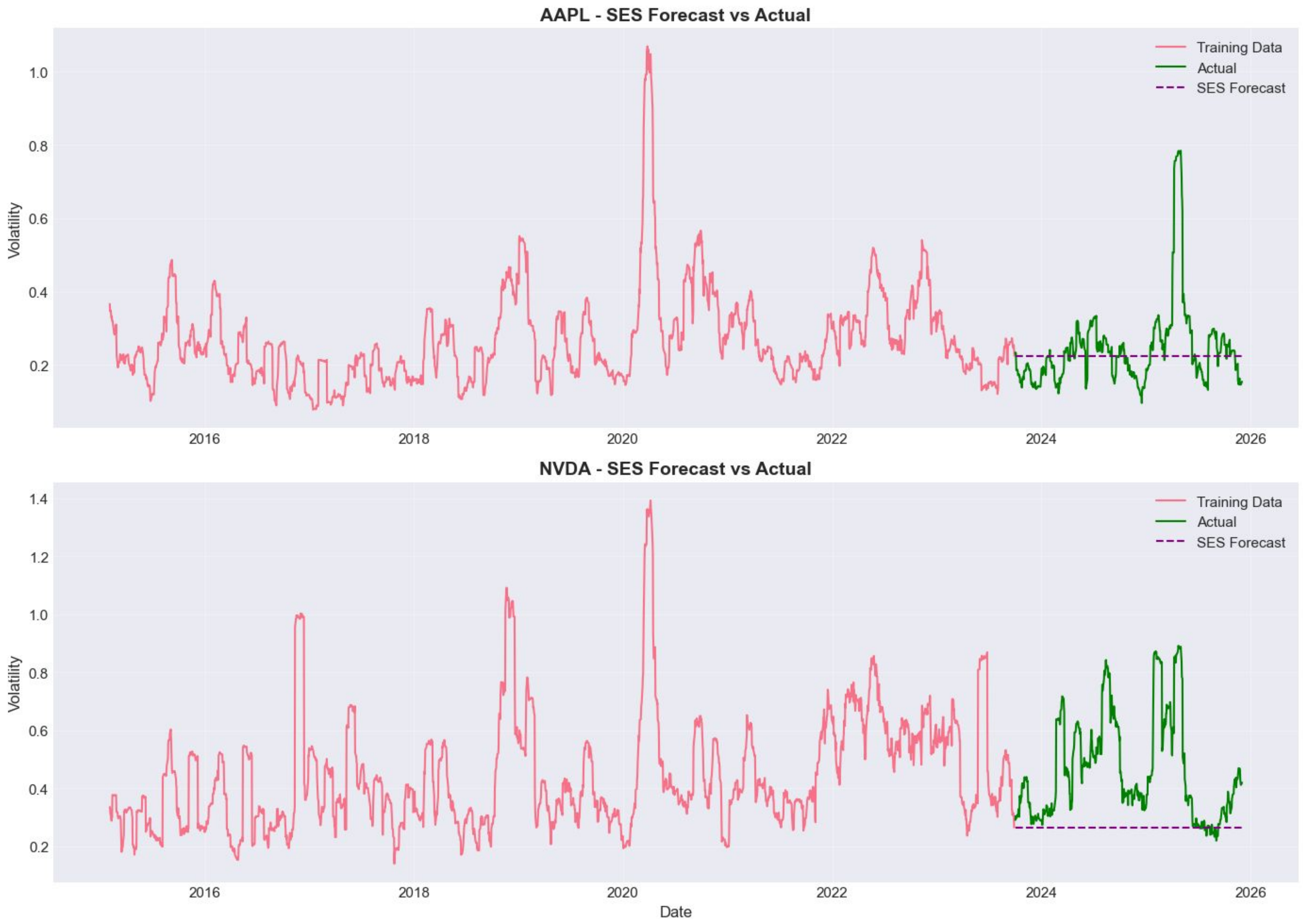
AAPL - SES Forecast vs Actual
Volatility
Date
Training Data
Actual
SES Forecast
0.2
0.4
0.6
0.8
1.0
2016
2018
2020
2022
2024
2026
NVDA - SES Forecast vs Actual
0.2
0.4
0.6
0.8
1.0
1.2
1.4

Time-series model: Facebook Prophet

Additive Trend + Seasonality Model

- Designed for business-scale time series with strong trend/seasonality patterns
- Assumes smooth changes over time: not suited for noisy, regime-shifting volatility
- Prophet performs no better than ARIMA/SES, with negative R^2 values and high MAPE

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AAPL - Prophet
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AAPL Prophet Performance Metrics:
MAE:  0.073184
MSE:  0.015488
RMSE: 0.124452
MAPE: 30.50%
R²:   -0.1020

============================================================
NVDA - Prophet
============================================================

NVDA Prophet Performance Metrics:
MAE:  0.222478
MSE:  0.066573
RMSE: 0.258017
MAPE: 59.34%
R²:   -1.0552
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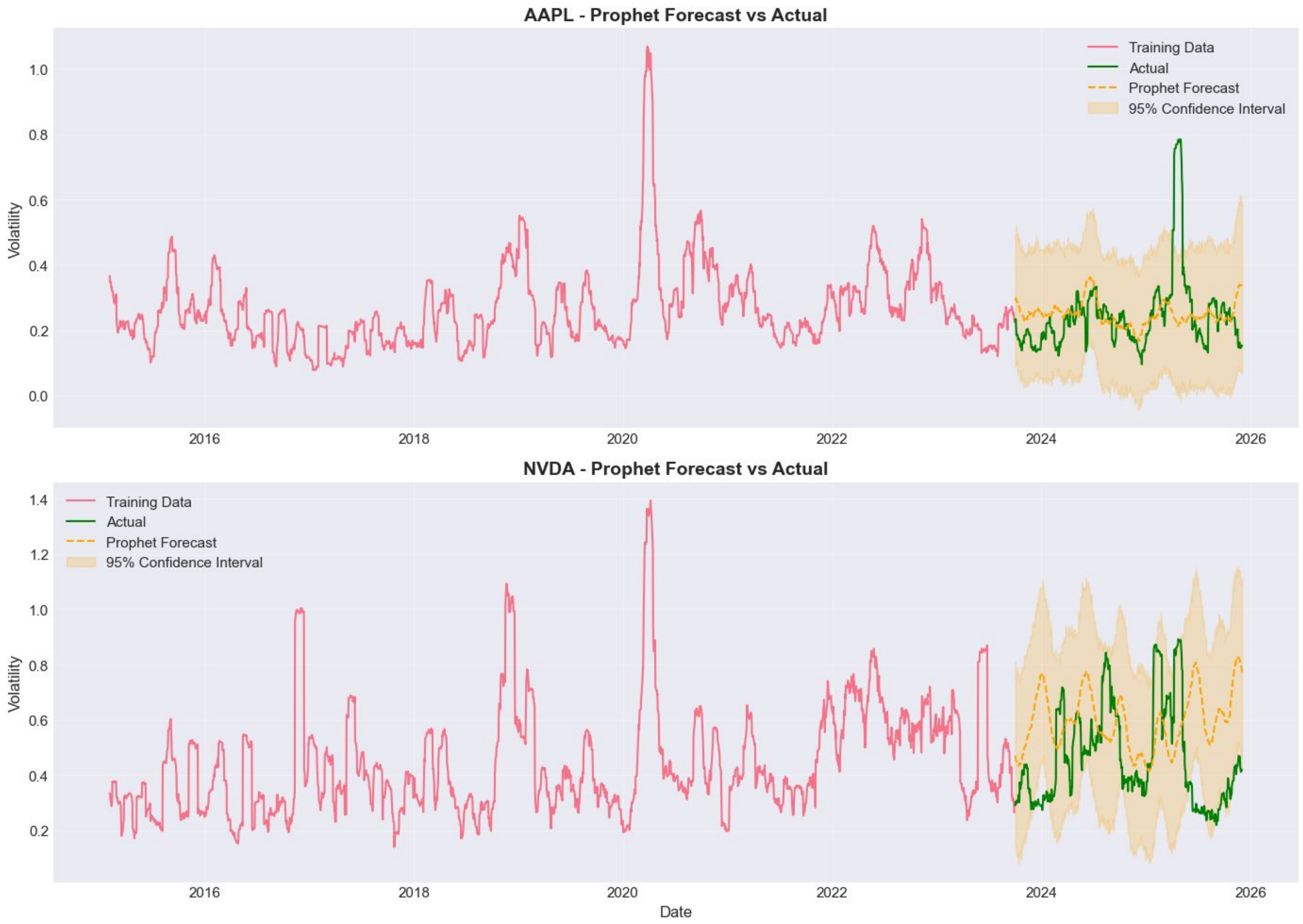

AAPL - Prophet Forecast vs Actual
Training Data
Actual
Prophet Forecast
95% Confidence Interval
Volatility
1.0
0.8
0.6
0.4
0.2
0.0
2016
2018
2020
2022
2024
2026
NVDA - Prophet Forecast vs Actual
Training Data
Actual
Prophet Forecast
95% Confidence Interval
Volatility
1.4
1.2
1.0
0.8
0.6
0.4
0.2
2016
2018
2020
2022
2024
2026
Date

Observations & causes for failure

Volatility isn’t a smooth series

Classical time-series models expect gradual changes, trend, or seasonality, but volatility has sudden jumps, long quiet stretches, and regime macroeconomic shifts.

Volatility typically clusters around

A high volatility index today usually implies high volatility tomorrow, but classical models treat each point as roughly independent noise, so the forecasts collapsed to a flat line.

Classical models forecast the level of the series, not its variance

Volatility is a variance process, rather than a standard time series value. Classical models tried to fit volatility as prices, sales numbers, or temperature data, which failed because volatility is a second-order property of how much a (stock) price moves.

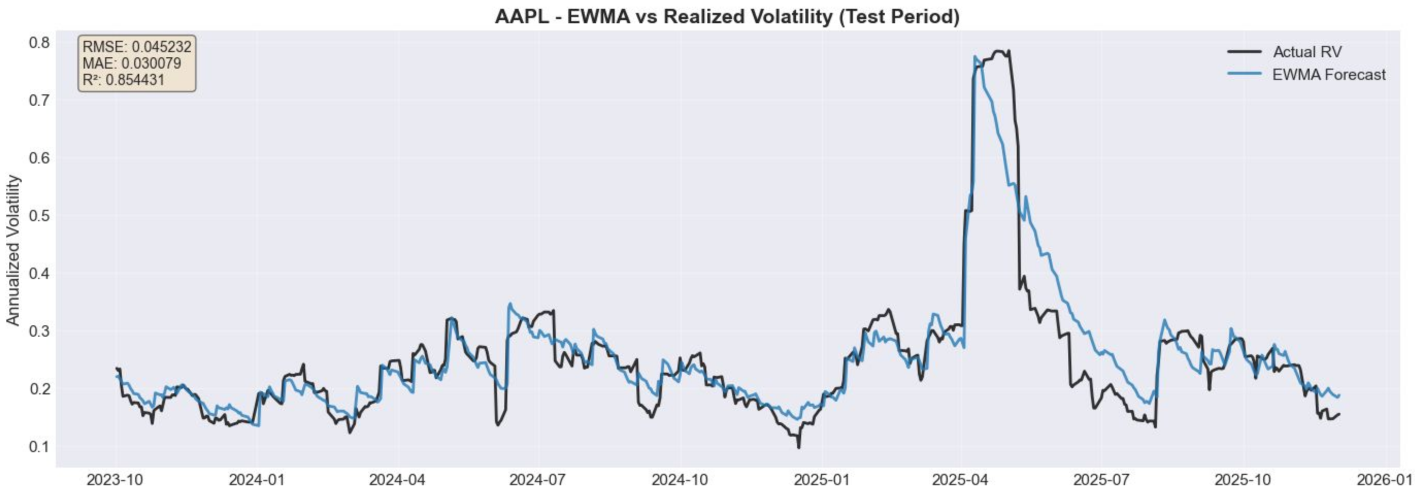
Quant finance models: EWMA & GARCH

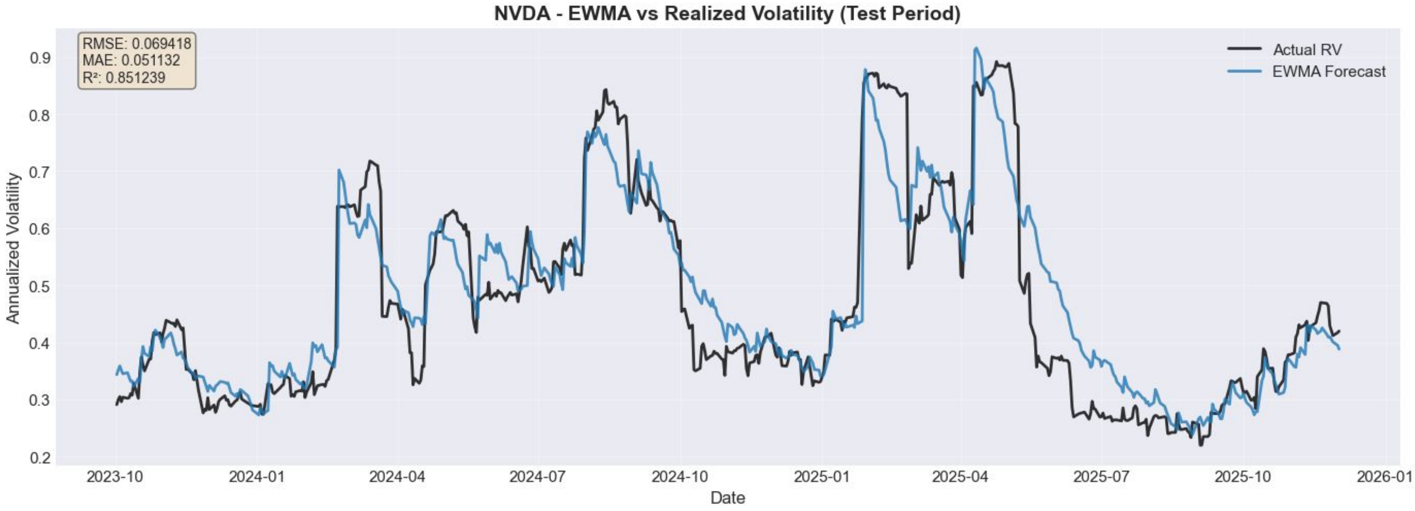
Exponential Weighted Moving Average

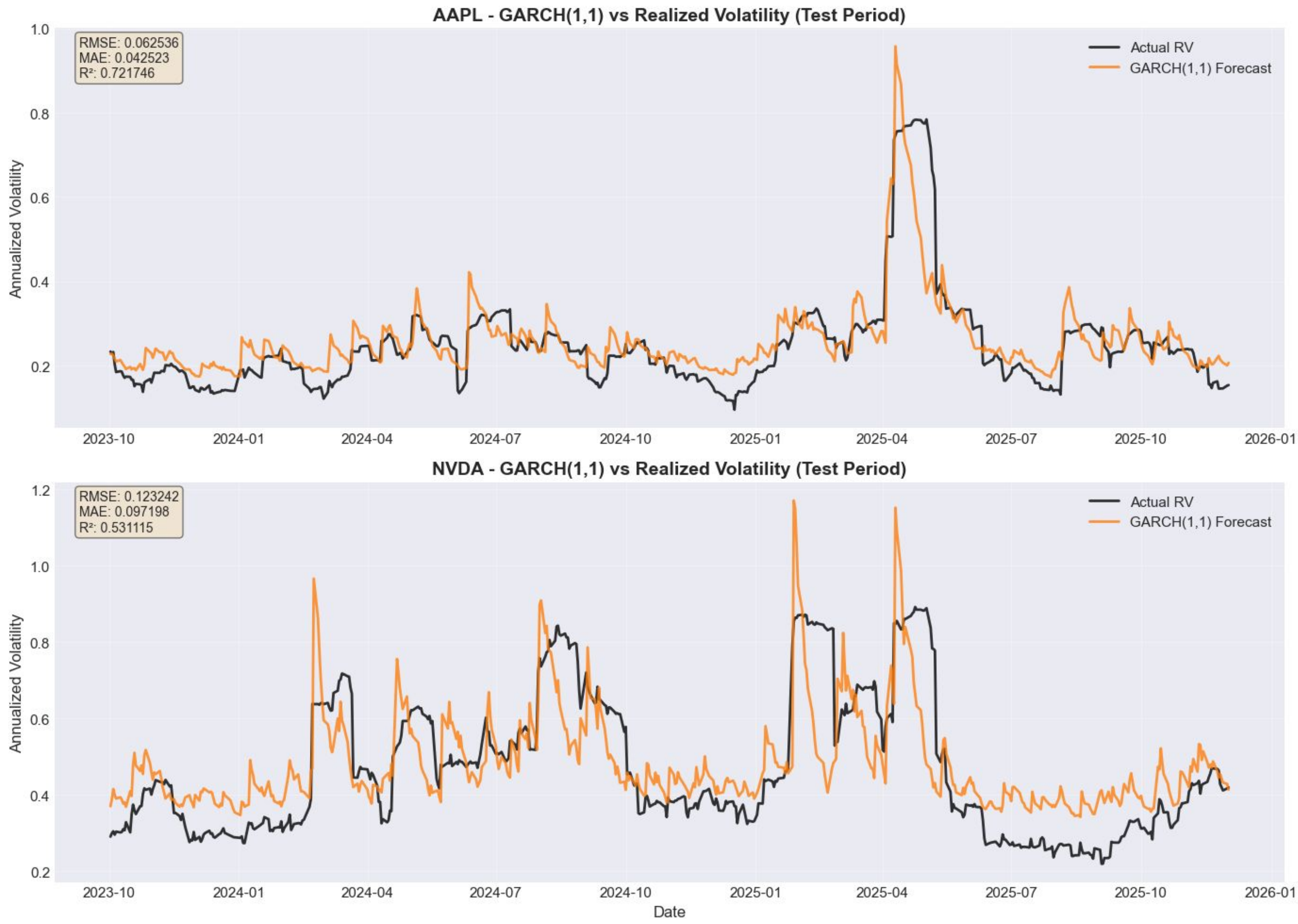
- Designed specifically for financial volatility, not generic time-series data
- Gives more weight to recent market moves, reacts quickly when volatility spikes
- Captures the fact that markets show volatility clustering (calm periods stay calm, turbulent periods stay turbulent)

Generalized AutoRegressive Conditional Heteroskedasticity

- A more structured volatility model that adds persistence and mean-reversion
- Smooths out noise while still tracking longer volatility cycles
- Good at modeling regime behavior (long periods of low or high volatility)
- Handles market dynamics that generic forecasting models don’t consider


AAPL - EWMA vs Realized Volatility (Test Period)
RMSE: 0.045232
MAE: 0.030079
R²: 0.854431
Actual RV
EWMA Forecast
Annualized Volatility
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
2023-10
2024-01
2024-04
2024-07
2024-10
2025-01
2025-04
2025-07
2025-10
2026-01


NVDA - EWMA vs Realized Volatility (Test Period)
RMSE: 0.069418
MAE: 0.051132
R²: 0.851239
Actual RV
EWMA Forecast
Annualized Volatility
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
2023-10
2024-01
2024-04
2024-07
2024-10
2025-01
2025-04
2025-07
2025-10
2026-01
Date



AAPL - GARCH(1,1) vs Realized Volatility (Test Period)
RMSE: 0.062536
MAE: 0.042523
R²: 0.721746
Actual RV
GARCH(1,1) Forecast
Annualized Volatility
1.0
0.8
0.6
0.4
0.2
2023-10
2024-01
2024-04
2024-07
2024-10
2025-01
2025-04
2025-07
2025-10
2026-01
NVDA - GARCH(1,1) vs Realized Volatility (Test Period)
RMSE: 0.123242
MAE: 0.097198
R²: 0.531115
Actual RV
GARCH(1,1) Forecast
Annualized Volatility
1.2
1.0
0.8
0.6
0.4
0.2
2023-10
2024-01
2024-04
2024-07
2024-10
2025-01
2025-04
2025-07
2025-10
2026-01
Date

Next steps for final deliverable

1. Finish analyzing the constructed equal-weight portfolio beyond individual stocks
2. Consider cross validation with rolling test/train splits
3. Look into Value at Risk and Conditional Value at Risk target variables (if time permits)
4. Any suggestions?