MODELING STOCK RETURN VOLATILITY USING SAS TIME SERIES ECONOMETRICS

1. Overview

Client:

An asset management firm focused on U.S. technology sector ETFs

Objective:

To model and forecast return volatility for major tech stocks using SAS time series econometrics. The analysis aimed to support portfolio hedging decisions and enhance risk-adjusted performance metrics.

2. Background

High-frequency volatility in technology stocks poses a risk to portfolio returns, especially during market corrections. The client sought a statistically robust, time series-based forecasting model to inform dynamic risk allocation strategies. SAS was chosen for its stability, transparency, and strong econometric capabilities.

3. Data Summary

Dataset:

Daily adjusted closing prices for top 5 NASDAQ-100 technology stocks (e.g., AAPL, MSFT, NVDA, AMZN, GOOG)
Timeframe: January 2018 – December 2022 (1,250 trading days per stock)

Derived Variables:

Variable	**Type**	**Description**
Log_Return	Continuous	log(Pt/Pt−1)\log(P_t / P_{t-1}), daily return series
Squared_Return	Continuous	Proxy for conditional variance
VIX_Index	Exogenous	Used for model comparison and validation

4. Methodology

Software Used:

SAS 9.4 (TSM + ETS modules)

SAS Workflow:

1. **Preprocessing:**
   - Imported price series via PROC IMPORT
   - Calculated log returns in DATA step
   - Conducted stationarity checks using PROC ARIMA (ADF test)
2. **Univariate Modeling (ARIMA):**
   - Identified ARIMA structure using PROC ARIMA with identify, estimate, and forecast statements
   - Residual diagnostics to check for remaining autocorrelation
3. **Volatility Modeling (GARCH):**
   - Used PROC AUTOREG and PROC VARMAX for initial model calibration
   - Final model in PROC AUTOREG:
   - proc autoreg data=tech_returns;
   - model Log_Return = / garch=(q=1, p=1);
   - output out=Forecasts p=Predicted r=Residual h=Variance;
   - run;
4. **Model Evaluation:**
   - Assessed AIC/BIC, Ljung-Box, and ARCH LM tests
   - Plotted conditional variance over time
   - Compared forecasted volatility with VIX movements

5. Key Results

Stock	**ARIMA Model**	**GARCH Coefficients**	**AIC**	**Observations**
AAPL	ARIMA(1,0,1)	$\alpha = 0.09$, $\beta = 0.87$	–5120	High volatility persistence ($\alpha+\beta > 0.95$)

NVDA	ARIMA(2,0,1)	$\alpha = 0.14$, $\beta = 0.81$	–5034	Responds faster to volatility shocks
MSFT	ARIMA(1,0,1)	$\alpha = 0.11$, $\beta = 0.88$	–5111	Stable with moderate mean reversion

Common Insights:

- All tech stocks showed high persistence in volatility
- GARCH(1,1) outperformed static volatility assumptions
- Conditional volatility spikes aligned with key market events (e.g., March 2020 COVID crash)

6. Visual Outputs (from SAS)

- Time series plots of log returns with GARCH volatility bands
- Conditional variance forecasts with market event overlays
- Residual ACF and PACF for model diagnostics
- Actual vs. forecasted volatility comparison with VIX trend

7. Deliverables

- Modular .sas code files for ARIMA and GARCH modeling
- Full econometrics report (22 pages), including:
    - Model selection rationale
    - Technical output with interpretation
    - Volatility risk insights for portfolio managers
- Risk analytics dashboard (5 slides) for CIO briefing:
    - Stock-wise volatility forecasts
    - Correlation with market indicators
    - Suggested allocation adjustments

8. Client Outcome & Application

- GARCH volatility forecasts integrated into daily VAR (Value at Risk) models

- Used in quarterly rebalancing decisions for tech-heavy ETFs
- Helped client improve Sharpe ratio by reallocating during high-volatility signals

9. Strategic Value Delivered

- Enabled **forward-looking risk awareness** based on econometric volatility models
- Supported **quantitative risk budgeting** in line with portfolio goals
- Delivered a **scalable SAS solution** with high interpretability and model transparency