



Time Series Analysis and Forecasting

Chapter 5: GARCH and Volatility



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Learning Objectives

By the end of this chapter, you will be able to:

1. Understand **volatility clustering** and stylized facts of financial returns
2. Estimate and interpret **ARCH** and **GARCH** models
3. Apply asymmetric models (**EGARCH**, **GJR-GARCH**) for the leverage effect
4. Perform model validation and selection
5. Forecast volatility and calculate **Value at Risk (VaR)**

Practical Skills

- Python implementation with the `arch` package
 - ▶ Estimation, forecasting, and automatic diagnostics
- Interpreting parameters and volatility persistence
- VaR calculation for risk management
 - ▶ Backtesting and forecast validation



Outline

Foundations

- Motivation
- Introduction to Volatility Modeling
- The ARCH Model
- The GARCH Model
- Asymmetric GARCH Models
- Model Selection and Diagnostics

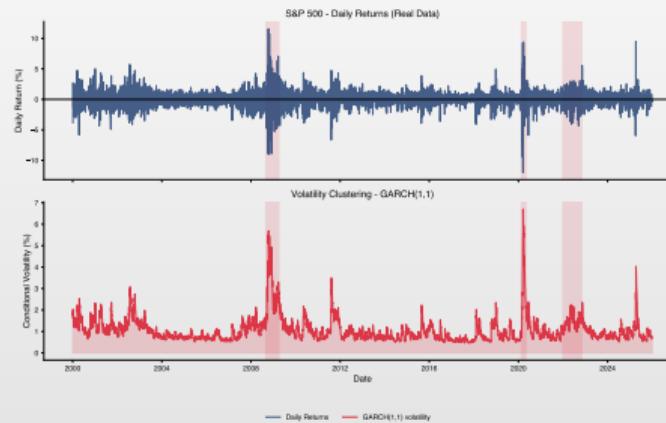
Applications

- Volatility Forecasting
- Python Implementation
- Case Study: S&P 500
- Case Study: Bitcoin
- Summary and Quiz



Volatility Clustering

- High volatility periods are followed by high volatility; calm by calm
- This suggests that **conditional variance** is predictable



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Why Model Volatility?

Empirical Observations in Financial Series

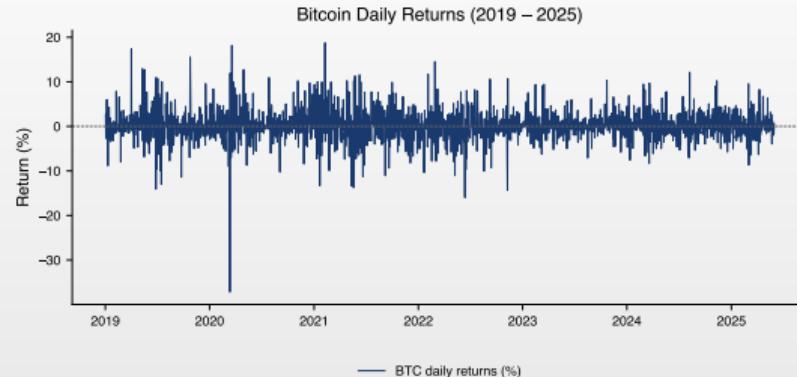
- Financial returns exhibit **volatility clustering** — periods of high volatility tend to be followed by periods of high volatility
- The distribution of returns has **fat tails** (leptokurtosis)
- Return correlation is nearly zero, but correlation of squares is significant
- Volatility responds **asymmetrically** to shocks (leverage effect)

Limitation of ARIMA Models

ARIMA models assume **constant variance** (homoskedasticity), which is not realistic for financial series!



Example: Bitcoin \succ Volatility Clustering



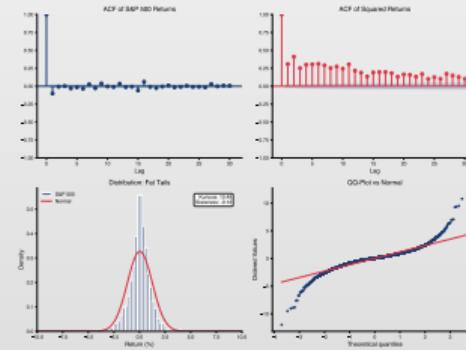
Observations

- ◻ Bitcoin daily returns (2019–2025): extremely pronounced volatility clustering
 - ▶ Returns of $\pm 20\%$ during crisis periods (COVID, Terra/Luna)
- ◻ Bitcoin volatility is significantly higher than traditional assets
 - ▶ Typical $\alpha \approx 0.10\text{--}0.20$ (fast reaction to news)

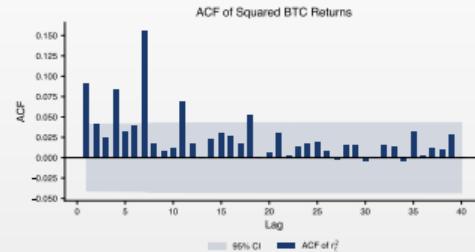
Stylized Facts of Financial Returns

Observed Properties

1. No autocorrelation in returns
2. Autocorrelation in r_t^2 , $|r_t|$
3. Fat tails (kurtosis > 3)
4. Leverage effect
5. Volatility clustering



Example: Bitcoin \succ Evidence for ARCH Effects



Definition 1 (Conditional Variance)

For return series $\{r_t\}$, the **conditional variance** at time t is: $\sigma_t^2 = \text{Var}(r_t | \mathcal{F}_{t-1}) = \mathbb{E}[(r_t - \mu_t)^2 | \mathcal{F}_{t-1}]$ where \mathcal{F}_{t-1} is the information available up to time $t-1$.

General Model

$$r_t = \mu_t + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t, \quad z_t \sim \text{i.i.d.}(0, 1)$$

- μ_t = conditional mean (ARMA); σ_t^2 = conditional variance (GARCH)
- z_t = standardized innovations (Normal, Student-t, GED)

Researcher Spotlight: Engle & Bollerslev



Robert Engle (*1942)
Nobel Prize 2003

Wikipedia



Tim Bollerslev (*1958)

Wikipedia

Biography

- **Robert Engle:** American economist at NYU Stern. Nobel Prize (2003) "for methods of analyzing economic time series with time-varying volatility (ARCH)"
- **Tim Bollerslev:** Danish-American economist at Duke University, PhD student of Engle

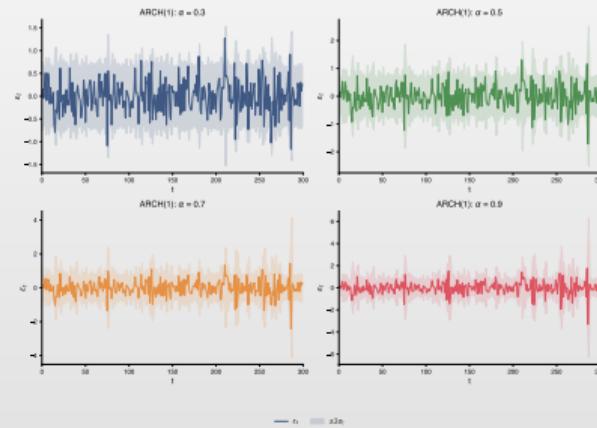
Key Contributions

- **ARCH model** (Engle, 1982) — autoregressive conditional heteroskedasticity
- **GARCH model** (Bollerslev, 1986) — generalized ARCH with persistent volatility
- **Realized volatility** measures and high-frequency econometrics
- Foundation for modern financial risk management (VaR, ES)

ARCH(1) Simulation: Effect of α Parameter

Interpretation

- Higher α means volatility reacts more strongly to recent shocks



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The ARCH(q) Model — Engle (1982)

Definition 2 (ARCH(q))

The Autoregressive Conditional Heteroskedasticity model of order q :

$$\varepsilon_t = \sigma_t z_t, \quad z_t \sim \text{i.i.d.}(0, 1), \quad \sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2$$

Stationarity Restrictions

- $\omega > 0$ (positive base variance), $\alpha_i \geq 0$ (non-negativity)
- $\sum_{i=1}^q \alpha_i < 1$ (stationarity)

Remark 1

Robert Engle received the **Nobel Prize in Economics** in 2003 for developing the ARCH model!



Properties of the ARCH(1) Model

$$\text{ARCH}(1): \sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2$$

- **Unconditional variance:** $\mathbb{E}[\varepsilon_t^2] = \frac{\omega}{1 - \alpha_1}$ (if $\alpha_1 < 1$)
- **Kurtosis:** $\kappa = 3 \cdot \frac{1 - \alpha_1^2}{1 - 3\alpha_1^2}$ (if $\alpha_1^2 < 1/3$)
- Kurtosis > 3 for $\alpha_1 > 0 \Rightarrow$ **fat tails!**

Numerical Example

If $\omega = 0.0001$ and $\alpha_1 = 0.3$:

- Unconditional variance: $\sigma^2 = \frac{0.0001}{1-0.3} = 0.000143$
- Kurtosis: $\kappa = 3 \cdot \frac{1-0.09}{1-0.27} = 3.74 > 3$



Derivation: Unconditional Variance of ARCH(1)

Derivation.

Let $\varepsilon_t = \sigma_t z_t$ with $z_t \sim N(0, 1)$ and $\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2$.

Step 1: Take unconditional expectation:

$$\mathbb{E}[\varepsilon_t^2] = \mathbb{E}[\sigma_t^2 z_t^2] = \mathbb{E}[\sigma_t^2] \cdot \mathbb{E}[z_t^2] = \mathbb{E}[\sigma_t^2]$$

Step 2: Apply expectation to variance equation:

$$\mathbb{E}[\sigma_t^2] = \mathbb{E}[\omega + \alpha_1 \varepsilon_{t-1}^2] = \omega + \alpha_1 \mathbb{E}[\varepsilon_{t-1}^2]$$

Step 3: By stationarity, $\mathbb{E}[\varepsilon_t^2] = \mathbb{E}[\varepsilon_{t-1}^2] = \sigma^2$:

$$\sigma^2 = \omega + \alpha_1 \sigma^2 \quad \Rightarrow \quad \sigma^2(1 - \alpha_1) = \omega$$

Result:
$$\boxed{\sigma^2 = \frac{\omega}{1 - \alpha_1}}$$
 (requires $\alpha_1 < 1$ for stationarity)



Derivation: Kurtosis of ARCH(1)

For $\varepsilon_t = \sigma_t z_t$ with $z_t \sim N(0, 1)$:

Step 1: $\mathbb{E}[\varepsilon_t^4] = \mathbb{E}[\sigma_t^4] \cdot \mathbb{E}[z_t^4] = 3\mathbb{E}[\sigma_t^4]$ (since $\mathbb{E}[z^4] = 3$)

Step 2: Using $\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2$:

$$\mathbb{E}[\sigma_t^4] = \mathbb{E}[(\omega + \alpha_1 \varepsilon_{t-1}^2)^2] = \omega^2 + 2\omega\alpha_1\sigma^2 + \alpha_1^2\mathbb{E}[\varepsilon_{t-1}^4]$$

Step 3: Solving the recursion yields:

$$\kappa = \frac{\mathbb{E}[\varepsilon_t^4]}{(\mathbb{E}[\varepsilon_t^2])^2} = 3 \cdot \frac{1 - \alpha_1^2}{1 - 3\alpha_1^2}$$

Interpretation

- ◻ $\kappa > 3$ for any $\alpha_1 > 0 \Rightarrow$ **fat tails** (leptokurtosis)
- ◻ Requires $\alpha_1 < 0.577$ for finite fourth moment
- ◻ ARCH naturally generates heavy-tailed distributions!



Testing for ARCH Effects

Engle's Test for ARCH Effects

Procedure:

1. Estimate the mean model and obtain residuals $\hat{\varepsilon}_t$
2. Calculate $\hat{\varepsilon}_t^2$
3. Regress $\hat{\varepsilon}_t^2$ on its lags:

$$\hat{\varepsilon}_t^2 = \beta_0 + \beta_1 \hat{\varepsilon}_{t-1}^2 + \cdots + \beta_q \hat{\varepsilon}_{t-q}^2 + u_t$$

4. Calculate the statistic $LM = T \cdot R^2 \sim \chi^2(q)$

Hypotheses

- H_0 : No ARCH effects ($\alpha_1 = \cdots = \alpha_q = 0$)
- H_1 : ARCH effects present (at least one $\alpha_i \neq 0$)



Limitations of the ARCH Model

Practical Problems

1. **High order** — many lags are usually needed (large q)
2. **Many parameters** — estimation difficulties
3. **Non-negativity constraints** — difficult to impose for large q
4. **Does not capture persistence** — observed volatility is very persistent

The Solution

The GARCH Model — introduces lags of conditional variance to capture persistence with fewer parameters!



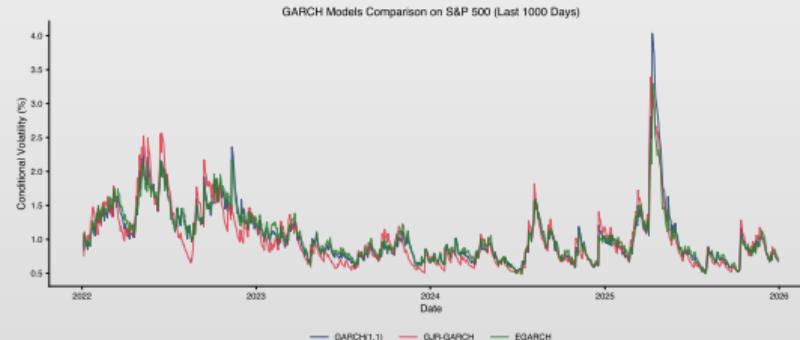
The GARCH(1,1) Model

The Most Popular Volatility Model

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

Restrictions & Properties

- $\omega > 0, \alpha \geq 0, \beta \geq 0; \quad \alpha + \beta < 1$ (stationarity)
- $\bar{\sigma}^2 = \frac{\omega}{1-\alpha-\beta}; \quad \text{Half-life: } HL = \frac{\ln(0.5)}{\ln(\alpha+\beta)}$



The GARCH(p,q) Model — Bollerslev (1986)

Definition 3 (GARCH(p,q))

The Generalized ARCH model:

$$\varepsilon_t = \sigma_t z_t, \quad z_t \sim \text{i.i.d.}(0, 1)$$

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

Interpretation

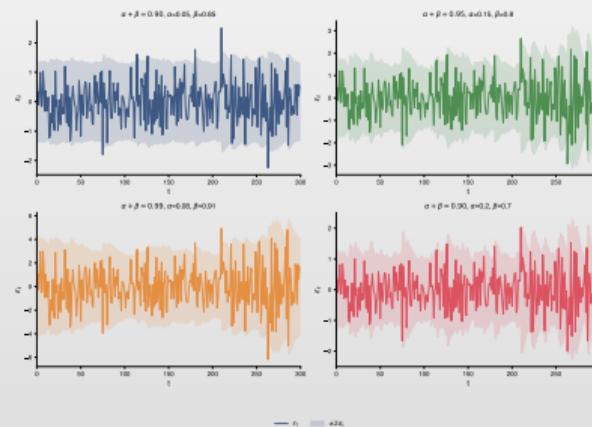
- ω = base level of volatility
- α_i = reaction to recent shocks (news coefficients)
- β_j = volatility persistence (memory)
- $\alpha + \beta$ = total persistence



GARCH(1,1) Simulation: Persistence Effect

Interpretation

- α controls reaction to shocks
- β controls persistence
- The sum $\alpha + \beta$ determines mean-reversion speed



Derivation: Unconditional Variance of GARCH(1,1)

Derivation.

For $\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$:

Step 1: Take unconditional expectation: $\mathbb{E}[\sigma_t^2] = \omega + \alpha \mathbb{E}[\varepsilon_{t-1}^2] + \beta \mathbb{E}[\sigma_{t-1}^2]$

Step 2: By stationarity, $\mathbb{E}[\sigma_t^2] = \mathbb{E}[\sigma_{t-1}^2] = \bar{\sigma}^2$ and $\mathbb{E}[\varepsilon_t^2] = \bar{\sigma}^2$: $\bar{\sigma}^2 = \omega + (\alpha + \beta)\bar{\sigma}^2$

Step 3: Solve: $\bar{\sigma}^2(1 - \alpha - \beta) = \omega \Rightarrow \boxed{\bar{\sigma}^2 = \frac{\omega}{1 - \alpha - \beta}}$

□

Stationarity Condition

Requires $\alpha + \beta < 1$ for finite unconditional variance.



GARCH(1,1) as ARMA for ε_t^2

ARMA(1,1) Representation

Define $\nu_t = \varepsilon_t^2 - \sigma_t^2$ (variance shock). Then:

$$\varepsilon_t^2 = \omega + (\alpha + \beta)\varepsilon_{t-1}^2 + \nu_t - \beta\nu_{t-1}$$

This is an ARMA(1,1) for ε_t^2 !

Implications

- ACF of ε_t^2 decays exponentially (like ARMA)
- Persistence is given by $\alpha + \beta$
- PACF can help identify the order



Derivation: ARMA Representation of GARCH(1,1)

Derivation.

Step 1: Define variance shock: $\nu_t = \varepsilon_t^2 - \sigma_t^2$

- ◻ $\mathbb{E}[\nu_t | \mathcal{F}_{t-1}] = \mathbb{E}[\varepsilon_t^2 | \mathcal{F}_{t-1}] - \sigma_t^2 = \sigma_t^2 - \sigma_t^2 = 0$
- ◻ ν_t is a martingale difference sequence

Step 2: Substitute $\sigma_t^2 = \varepsilon_t^2 - \nu_t$ into GARCH equation:

$$\varepsilon_t^2 - \nu_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta(\varepsilon_{t-1}^2 - \nu_{t-1})$$

Step 3: Rearrange:

$$\varepsilon_t^2 = \omega + (\alpha + \beta)\varepsilon_{t-1}^2 + \nu_t - \beta\nu_{t-1}$$

Result: ARMA(1,1) with AR coefficient $\phi = \alpha + \beta$ and MA coefficient $\theta = -\beta$. □



Derivation: Volatility Persistence and Half-Life

Multi-Step Forecast GARCH(1,1)

- $\mathbb{E}_t[\sigma_{t+h}^2] = \bar{\sigma}^2 + (\alpha + \beta)^{h-1}(\sigma_{t+1}^2 - \bar{\sigma}^2)$

Derivation

- **Step 1:** Let $\phi = \alpha + \beta$ and $q_t = \sigma_t^2 - \bar{\sigma}^2$ (deviation from mean)
- **Step 2:** From the GARCH equation: $\mathbb{E}_t[q_{t+1}] = \phi \cdot q_t$, so $\mathbb{E}_t[q_{t+h}] = \phi^h \cdot q_t$
- **Step 3:** Half-life = time until deviation halves: $\phi^{HL} = 0.5 \Rightarrow HL = \frac{\ln(0.5)}{\ln(\phi)} = \frac{-0.693}{\ln(\alpha+\beta)}$

Example: S&P 500

- With $\alpha + \beta = 0.988$: $HL = \frac{-0.693}{-0.012} \approx 58$ days (shocks persist ~3 months!)



Estimation of GARCH Models

Maximum Likelihood Estimation (MLE)

Log-likelihood (normal): $\ell(\theta) = -\frac{T}{2} \ln(2\pi) - \frac{1}{2} \sum_{t=1}^T \left[\ln(\sigma_t^2) + \frac{\varepsilon_t^2}{\sigma_t^2} \right]$

Alternative Distributions for z_t

- Student-t**: captures fat tails — most common choice
- GED**: flexibility for kurtosis
- Skewed Student-t**: asymmetry and fat tails

Practical Note

Student-t distribution typically provides better fit for financial returns due to fat tails ($kurtosis > 3$).



Typical Values for GARCH(1,1)

Series	α	β	$\alpha + \beta$
S&P 500 daily	0.05–0.10	0.85–0.95	0.95–0.99
EUR/USD daily	0.03–0.08	0.90–0.95	0.95–0.99
Bitcoin daily	0.10–0.20	0.75–0.85	0.90–0.98
Bonds	0.02–0.05	0.90–0.97	0.95–0.99

Observations

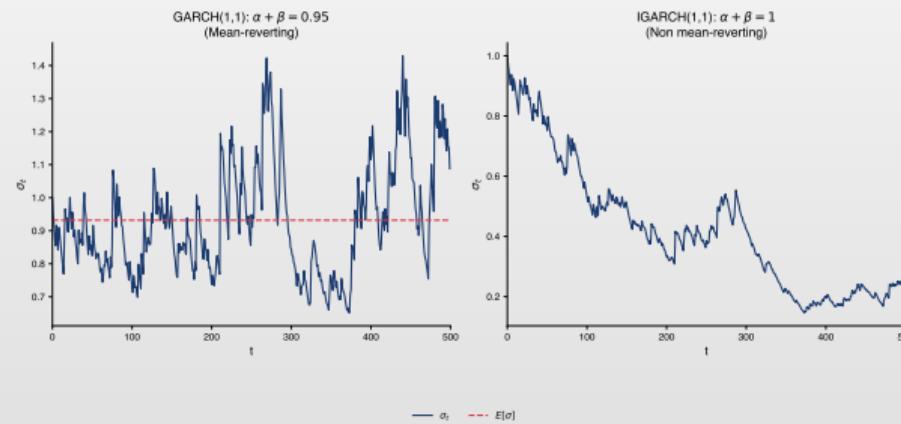
- $\alpha + \beta$ close to 1 \Rightarrow **very persistent volatility**
- Small α , large β \Rightarrow slow reaction to shocks, long memory
- Bitcoin: larger α \Rightarrow faster reaction to news



GARCH vs IGARCH: Persistence Comparison

Interpretation

- Standard GARCH reverts to unconditional mean
- IGARCH has no finite mean \Rightarrow shocks persist indefinitely



IGARCH — Integrated GARCH

Definition 4 (IGARCH(1,1))

When $\alpha + \beta = 1$:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + (1 - \alpha) \sigma_{t-1}^2$$

Properties

- Unconditional variance does not exist (infinite)
- Shocks have **permanent** effect on volatility
- Used for series with extreme persistence
- Useful for **RiskMetrics** (J.P. Morgan): $\alpha = 0.06, \beta = 0.94$

Remark 2

IGARCH is analogous to a unit root in variance!



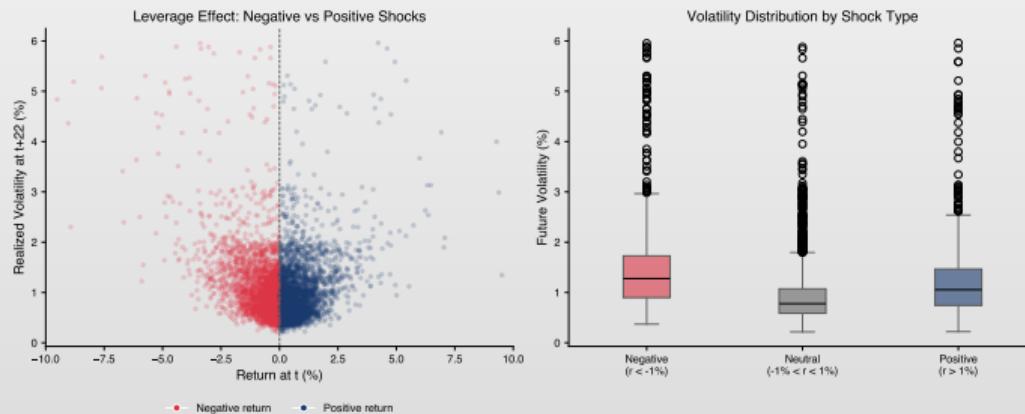
Leverage Effect

Definition

Leverage effect: Negative shocks increase volatility **more** than positive shocks of the same magnitude.

Problem with GARCH

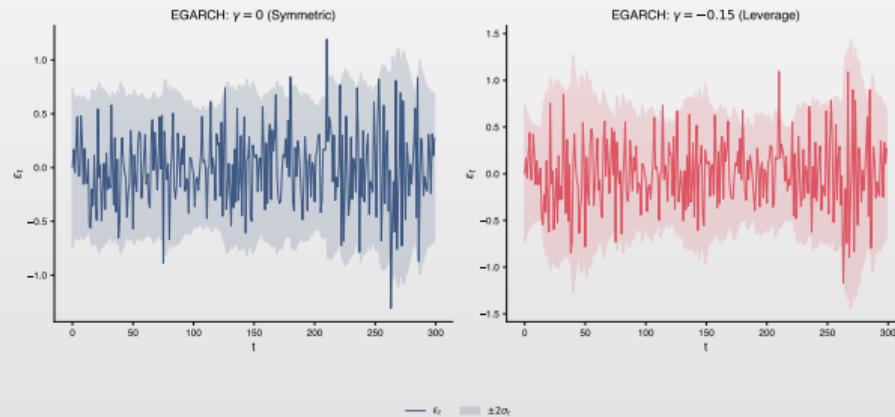
Standard GARCH: $\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$ — only ε_{t-1}^2 matters, sign is lost! Economic intuition: Bad news \Rightarrow stock price falls \Rightarrow debt/equity ratio rises \Rightarrow volatility increases.



EGARCH Simulation: Symmetric vs Asymmetric

Interpretation

- When $\gamma < 0$, negative shocks increase volatility more than positive shocks



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The EGARCH Model — Nelson (1991)

Definition 5 (EGARCH(1,1))

Exponential GARCH:

$$\ln(\sigma_t^2) = \omega + \alpha(|z_{t-1}| - \mathbb{E}[|z_{t-1}|]) + \gamma z_{t-1} + \beta \ln(\sigma_{t-1}^2)$$

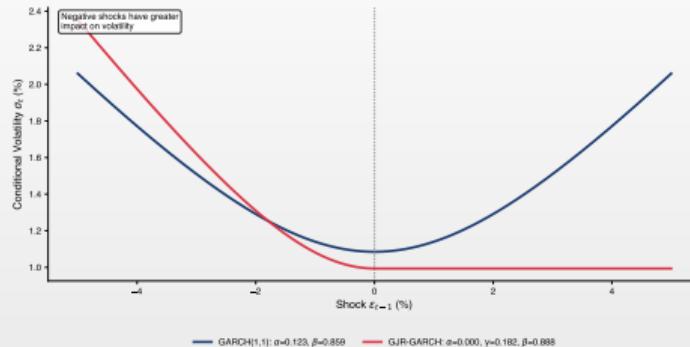
where $z_t = \varepsilon_t / \sigma_t$.

EGARCH Advantages

- No non-negativity constraints required — models $\ln(\sigma_t^2)$
- Captures leverage effect through parameter γ
 - ▶ $\gamma < 0$: negative shocks \Rightarrow higher volatility
 - ▶ $\gamma = 0$: symmetric effect (like GARCH)
- Persistence is given by β



News Impact Curve — EGARCH



Interpretation

- **News Impact Curve:** relationship between ϵ_t and σ_{t+1}^2
- **GARCH:** symmetric curve (parabola)
 - ▶ Positive and negative shocks have the same impact
- **EGARCH:** asymmetric curve
 - ▶ Negative shocks have larger impact on volatility



The GJR-GARCH Model

Definition 6 (GJR-GARCH(1,1))

Glosten, Jagannathan & Runkle (1993): $\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 \cdot I_{t-1} + \beta \sigma_{t-1}^2$ where $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, else 0.

Interpretation

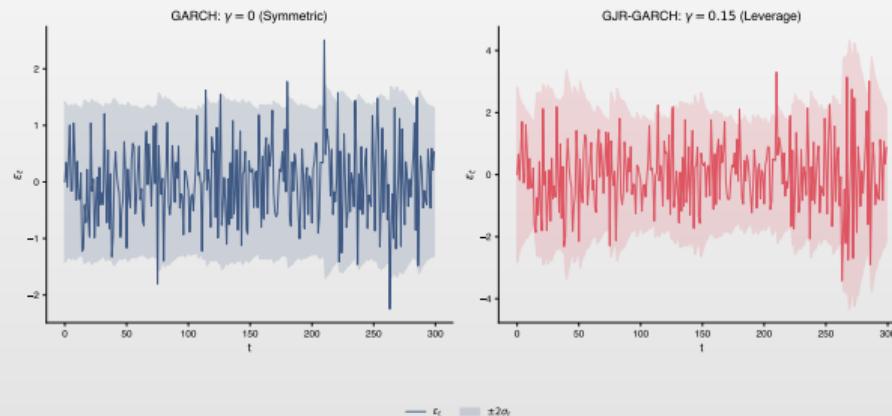
- Positive shocks: impact = α ; Negative shocks: impact = $\alpha + \gamma$
- Leverage effect present if $\gamma > 0$
- Stationarity: $\alpha + \gamma/2 + \beta < 1$



GJR-GARCH/TGARCH Simulation

Interpretation

- GJR-GARCH adds an indicator term to capture asymmetric response to negative shocks



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TGARCH — Threshold GARCH

Definition 7 (TGARCH(1,1))

Zakoian (1994) models standard deviation: $\sigma_t = \omega + \alpha^+ \varepsilon_{t-1}^+ + \alpha^- \varepsilon_{t-1}^- + \beta \sigma_{t-1}$

Comparison of Asymmetric Models

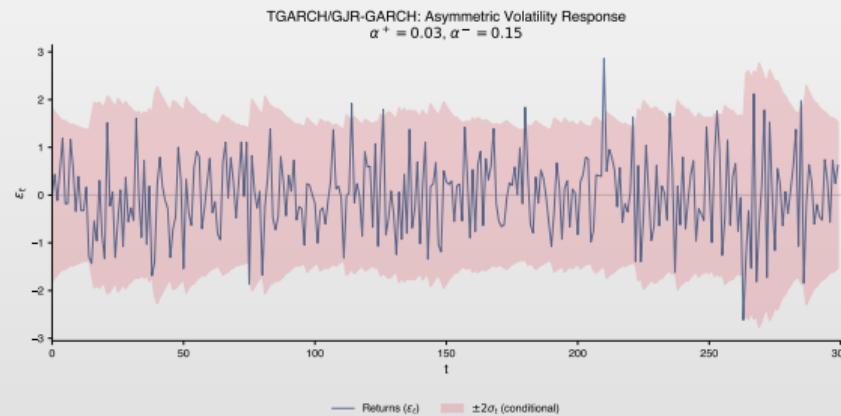
Model	Specification	Leverage
GARCH	σ_t^2	No
EGARCH	$\ln(\sigma_t^2)$	Yes ($\gamma < 0$)
GJR-GARCH	σ_t^2 with indicator	Yes ($\gamma > 0$)
TGARCH	σ_t	Yes ($\alpha^- > \alpha^+$)



TGARCH Simulation: Asymmetric Volatility Response

Interpretation

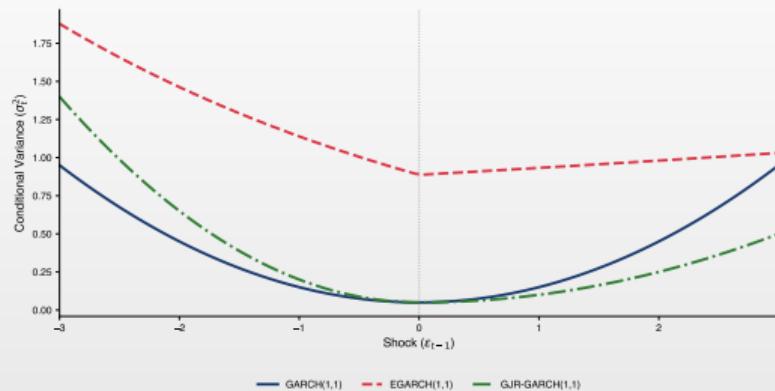
- TGARCH with $\alpha^+ = 0.03$ and $\alpha^- = 0.15 \succ$ negative shocks amplify volatility by 5×
- Volatility bands $\pm 2\sigma$ widen asymmetrically during crisis periods



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News Impact Curves Comparison



Interpretation

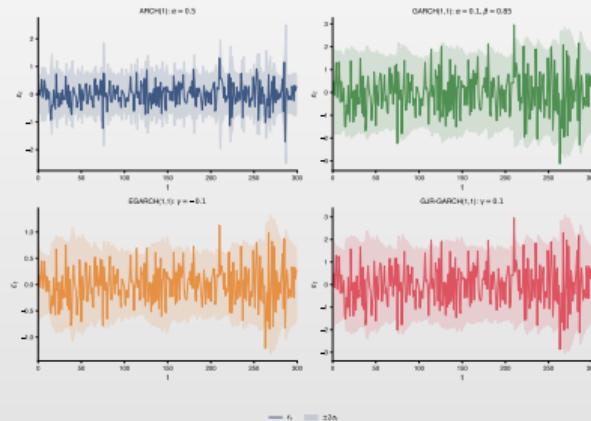
- Standard GARCH:** symmetric
 - ▶ Treats positive and negative shocks identically
- EGARCH and GJR-GARCH:** capture asymmetry
 - ▶ Leverage effect: negative shocks \Rightarrow larger impact



GARCH Family Comparison

Interpretation

- All models capture volatility clustering, but differ in how they model asymmetry



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GARCH-in-Mean (GARCH-M) — Engle, Lilien & Robins (1987)

Definition 8 (GARCH-M)

- Model: Volatility enters directly into the mean equation:

$$\begin{aligned}r_t &= \mu + \delta \cdot g(\sigma_t^2) + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t \\ \sigma_t^2 &= \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2\end{aligned}$$

- Function g : can be σ_t^2 , σ_t , or $\ln(\sigma_t^2)$

Economic Interpretation

- $\delta > 0$: **risk premium** \Rightarrow higher returns when volatility is high
- Formalizes the risk-return relationship (CAPM, Merton ICAPM); test $H_0 : \delta = 0$

Typical Example: Equities

- $r_t = 0.02 + \underbrace{0.15}_{\delta} \cdot \sigma_t + \varepsilon_t \quad \Rightarrow$ At $\sigma_t = 2\%$: $\mathbb{E}[r_t] = 0.023$ (0.3% premium)



GARCH-M: Alternative Specifications

Common Specifications

Risk premium can enter in different forms: (1) $r_t = \mu + \lambda\sigma_t + \varepsilon_t$; (2) $r_t = \mu + \lambda\sigma_t^2 + \varepsilon_t$; (3) $r_t = \mu + \lambda \ln(\sigma_t^2) + \varepsilon_t$

Typical Results for Equity Markets

- Estimated λ often positive but small (0.01–0.10)
- Significance varies across markets and periods
- Variance specification yields larger λ estimates

Remark 3

GARCH-M is used in asset pricing, portfolio optimization, and CAPM testing.



Order Selection

Information Criteria

- AIC** = $-2\ell + 2k$
- BIC** = $-2\ell + k \ln(T)$
- HQIC** = $-2\ell + 2k \ln(\ln(T))$

where ℓ = maximized log-likelihood, k = number of parameters.

Practical Recommendations

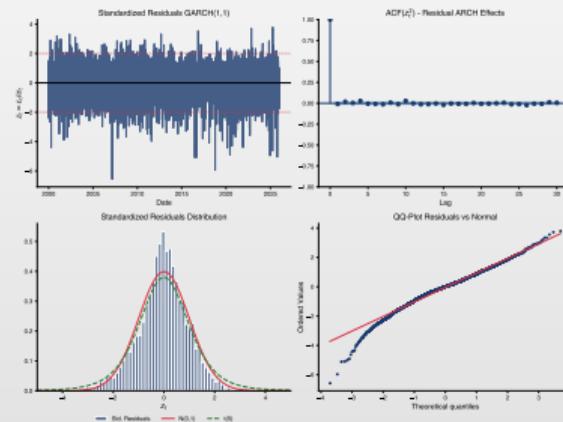
- GARCH(1,1) is sufficient in **90% of cases**
- Check if asymmetric model significantly improves fit
- Choose innovation distribution that minimizes AIC/BIC



Diagnostic Example

Verification

- Standardized residuals should be i.i.d. with no residual ARCH effects



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GARCH Model Diagnostics

Standardized Residuals

$$\hat{z}_t = \frac{\hat{\varepsilon}_t}{\hat{\sigma}_t}$$

If the model is correctly specified, \hat{z}_t should be i.i.d.(0,1).

Diagnostic Checks

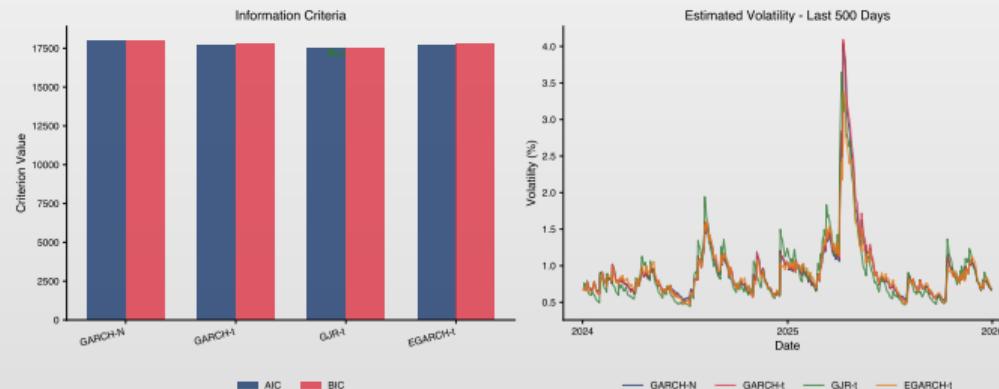
1. **Ljung-Box on \hat{z}_t :** check absence of autocorrelation in mean
2. **Ljung-Box on \hat{z}_t^2 :** check absence of residual ARCH effects
3. **ARCH-LM test on \hat{z}_t :** confirm absence of heteroskedasticity
4. **Histogram + QQ-plot:** verify assumed distribution



GARCH Model Comparison: Validation

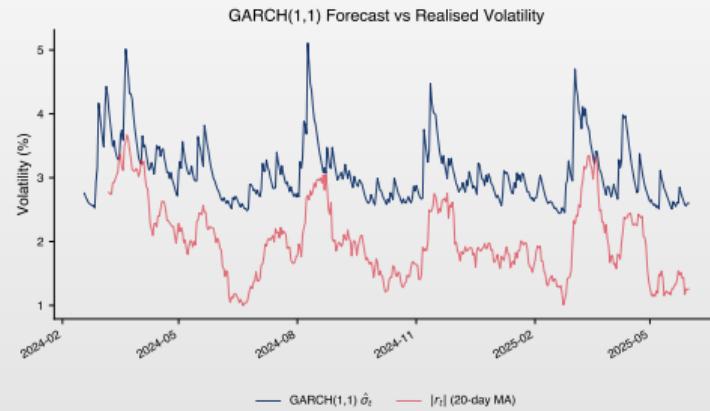
Interpretation

- GARCH(1,1) achieves the lowest MAE on the validation set
 - ▶ More parsimonious and stable than higher-order models
- GARCH(2,1) and GJR-GARCH: similar performance, but more parameters
- **Conclusion:** simplicity wins \succ GARCH(1,1) is hard to beat



Volatility Forecast — Visualization

- Forecast converges exponentially to $\bar{\sigma}^2$; speed depends on $\alpha + \beta$
- The closer $\alpha + \beta$ is to 1, the slower the convergence



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Forecasting with GARCH(1,1)

One-Step-Ahead Forecast

$$\hat{\sigma}_{T+1}^2 = \omega + \alpha \varepsilon_T^2 + \beta \sigma_T^2$$

Multi-Step Forecast

For $h > 1$: $\mathbb{E}_T[\sigma_{T+h}^2] = \bar{\sigma}^2 + (\alpha + \beta)^{h-1}(\sigma_{T+1}^2 - \bar{\sigma}^2)$ where $\bar{\sigma}^2 = \frac{\omega}{1-\alpha-\beta}$ = unconditional variance.

Convergence

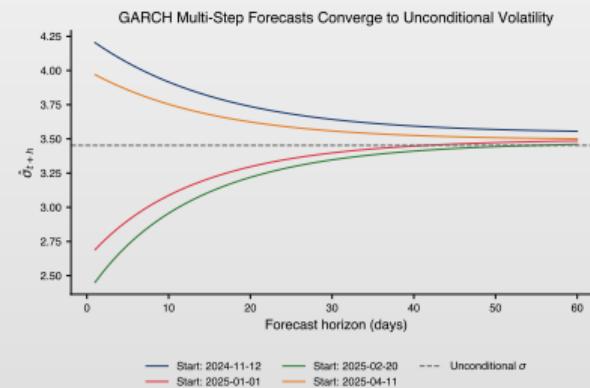
$\lim_{h \rightarrow \infty} \mathbb{E}_T[\sigma_{T+h}^2] = \bar{\sigma}^2$ — forecast converges to unconditional variance!



GARCH Forecast Convergence to Unconditional Variance

Interpretation

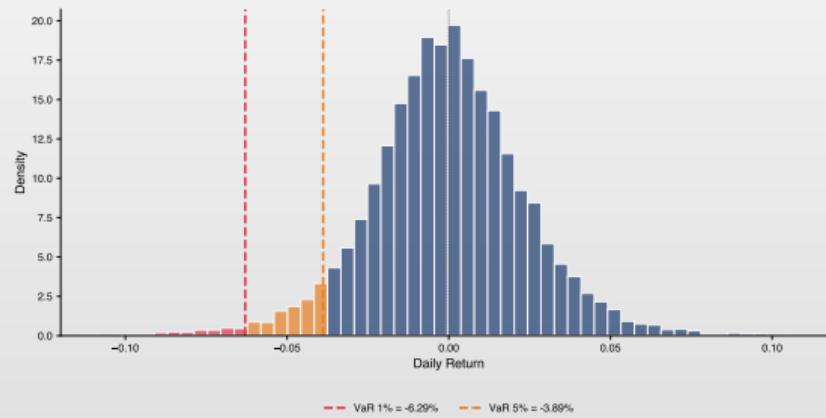
- Multi-step forecast converges exponentially to $\bar{\sigma}^2 = \frac{\omega}{1-\alpha-\beta}$
- The closer $\alpha + \beta$ is to 1, the slower the convergence
 - ▶ S&P 500: $\alpha + \beta \approx 0.99 \succ$ convergence in ~ 50 days
 - ▶ Bitcoin: $\alpha + \beta \approx 0.95 \succ$ faster convergence



VaR and ES: Graphical Illustration

Interpretation

- ☐ VaR 1% = loss exceeded only in 1% of cases
- ☐ Red area = extreme losses (beyond VaR)



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Applications of Volatility Forecasting

Value at Risk (VaR)

$$\text{VaR}_\alpha = z_\alpha \cdot \sigma_{T+1}$$

Maximum loss with probability $1 - \alpha$.

Expected Shortfall (ES)

$$\text{ES}_\alpha = \mathbb{E}[-r | r < -\text{VaR}_\alpha]$$

Average loss when VaR is exceeded.

Other Applications

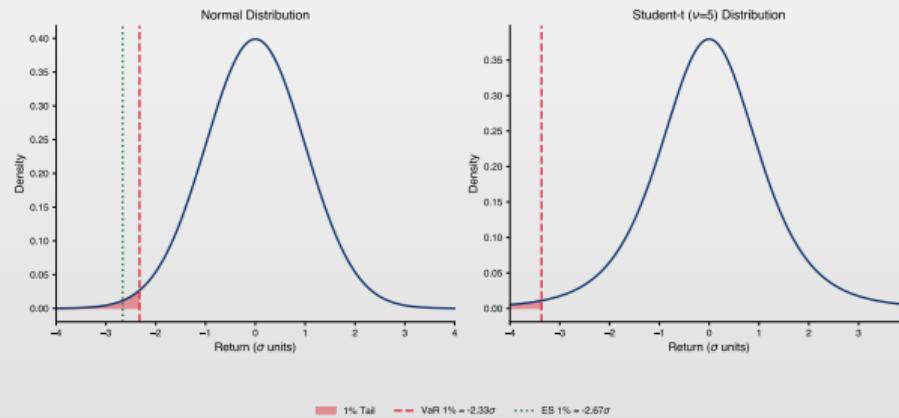
- Option pricing
- Dynamic hedging
- Portfolio allocation
- Stress testing



VaR vs Expected Shortfall: Normal vs Student-t

Interpretation

- ES measures average loss when VaR is exceeded
- Student-t: VaR and ES are larger than under normal distribution



TSA_ch5_var_es



Value at Risk — Numerical Example

VaR Calculation

Portfolio: **1,000,000 EUR**, forecasted volatility $\hat{\sigma}_{T+1} = 1.5\%$

VaR with Normal Distribution

Level	z_α	VaR (%)	VaR (EUR)
5% (1 day)	1.645	2.47%	24,675
1% (1 day)	2.326	3.49%	34,890

Scaling for Longer Periods

$\text{VaR}_{h \text{ days}} = \text{VaR}_{1 \text{ day}} \cdot \sqrt{h}$ — assumes i.i.d. returns



Value at Risk — Student-t Distribution

Why Student-t?

Normal distribution **underestimates** tail risk. Student-t with ν degrees of freedom better captures fat tails ($kurtosis > 3$).

VaR 1% (1 day) Comparison: $\sigma = 1.5\%$, Portfolio = 1M EUR

Distribution	Quantile	VaR (EUR)
Normal	2.326	34,890
Student-t ($\nu = 6$)	3.143	47,145
Student-t ($\nu = 4$)	3.747	56,205

Observation

With $\nu = 6$ (typical for stocks), VaR is **35% higher** than normal!



VaR — Complete Example with GARCH

VaR Calculation Procedure

1. Estimate GARCH(1,1) model with Student-t distribution
2. Obtain volatility forecast: $\hat{\sigma}_{T+1}$
3. Calculate VaR: $\text{VaR}_\alpha = t_\alpha(\nu) \cdot \hat{\sigma}_{T+1} \cdot \sqrt{\frac{\nu-2}{\nu}}$

Example: S&P 500

- Estimated parameters: $\alpha = 0.088$, $\beta = 0.900$, $\nu = 6.4$
- Forecasted volatility: $\hat{\sigma}_{T+1} = 1.2\%$
- Portfolio: 10,000,000 EUR

VaR 1% (1 day): $\text{VaR} = 3.05 \times 0.012 \times 10,000,000 = 366,000 \text{ EUR}$



What is VaR Backtesting?

Definition

- **Backtesting** = ex-post verification of VaR model quality
- Compares realized losses with the forecasted VaR threshold
 - ▶ A **violation** occurs when $r_t < -\text{VaR}_t$

Backtesting Principle

- Violation indicator: $I_t = 1(r_t < -\text{VaR}_{\alpha,t})$
- For a correctly specified model at level α :
 - ▶ Frequency: $\hat{p} = \frac{1}{T} \sum I_t \approx \alpha$; violations **independent**
- VaR 1% over 250 days \Rightarrow expect ~ 2.5 violations/year

Importance

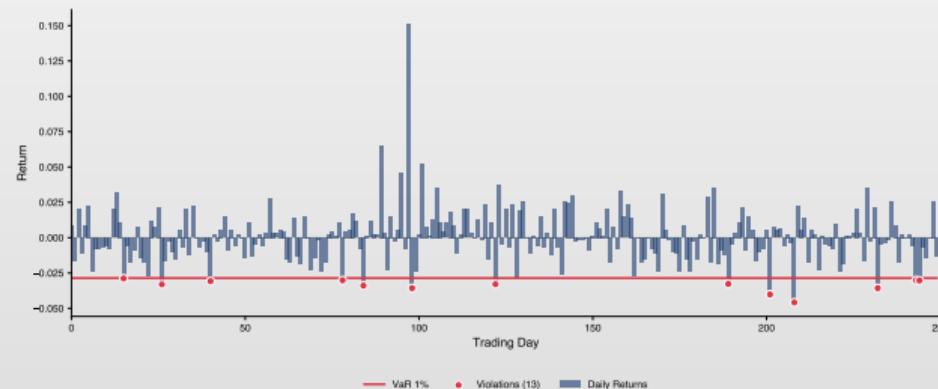
- Regulatory requirement under **Basel III/IV** for banks: backtesting is mandatory



VaR Backtesting: Visual Overview

Interpretation

- Red line: VaR 1% threshold estimated with GARCH(1,1)
- Red dots: 13 violations out of 250 days ($\hat{p} = 5.2\%$)
 - ▶ **Basel red zone** ⇒ model significantly underestimates risk
 - ▶ Solutions: Student-t distribution, EGARCH model, or more conservative VaR level



VaR Backtesting: Basel Traffic Light

Basel III/IV Traffic Light Zones

Zone	Violations/250 days	Interpretation	Penalty
Green	0–4	Model acceptable	No penalty
Yellow	5–9	Needs investigation	Factor k increases
Red	≥ 10	Model inadequate	Maximum penalty

Practical Example

- Portfolio with VaR 1%: 250 days of backtesting
- 3 violations \Rightarrow **Green zone** \Rightarrow model acceptable
- 7 violations \Rightarrow **Yellow zone** \Rightarrow revision needed
- 13 violations \Rightarrow **Red zone** \Rightarrow model rejected



Rolling Window VaR Methodology

Rolling Window Concept

- A **rolling window** of fixed size W (e.g., 500 days) moves day by day
- At each step t : re-estimate GARCH on $[t - W, t - 1]$, forecast $\hat{\sigma}_{t|t-1}$, compute VaR_t

Step-by-Step Procedure (for each day $t = W + 1, \dots, T$)

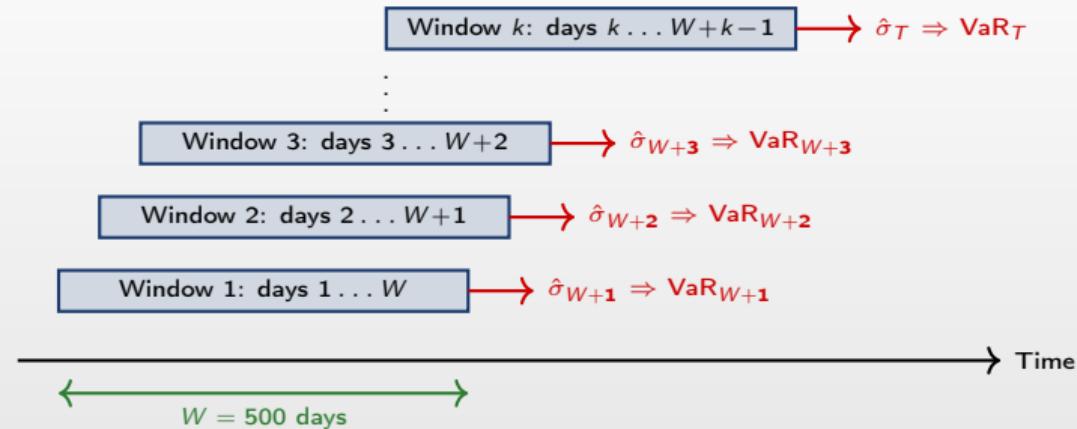
1. Estimate GARCH on $\{r_{t-W}, \dots, r_{t-1}\} \Rightarrow$ parameters $\hat{\omega}, \hat{\alpha}, \hat{\beta}, \hat{\nu}$
2. Forecast: $\hat{\sigma}_{t|t-1}^2 = \hat{\omega} + \hat{\alpha}r_{t-1}^2 + \hat{\beta}\hat{\sigma}_{t-1}^2$
3. Compute: $\text{VaR}_{\alpha,t} = -t_\alpha(\hat{\nu}) \cdot \sqrt{\frac{\hat{\nu}-2}{\hat{\nu}}} \cdot \hat{\sigma}_{t|t-1}$
4. Check violation: $I_t = 1(r_t < -\text{VaR}_{\alpha,t})$

Why Rolling and Not Expanding?

- Fixed window: parameters reflect the **current regime** of volatility
- Old data ($> W$ days) may be irrelevant (structural changes, crises)



Rolling Window VaR: Procedure Diagram



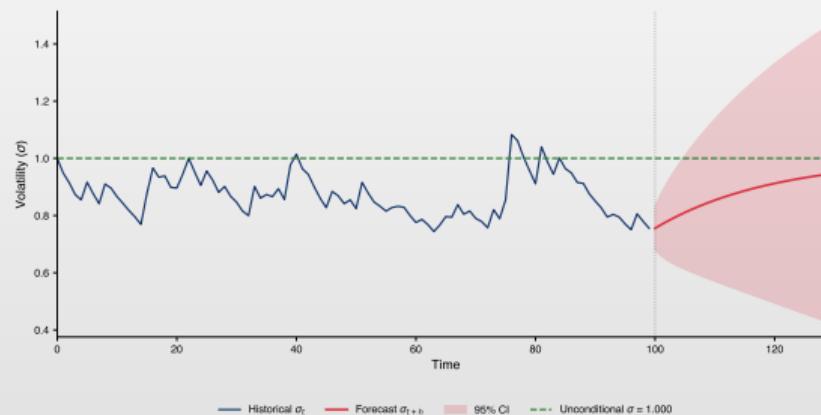
Result

- We obtain the series $\{\text{VaR}_{\alpha,t}\}_{t=W+1}^T \Rightarrow$ a **different** threshold every day
- VaR adapts to the current regime: increases during volatile periods, decreases during calm ones
- Compare r_t with $-\text{VaR}_{\alpha,t}$ to identify violations

Volatility Forecast with Confidence Intervals

Interpretation

- Forecast converges to $\bar{\sigma}$
- Uncertainty increases with forecast horizon



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Rolling Forecast: Step-by-Step Prediction

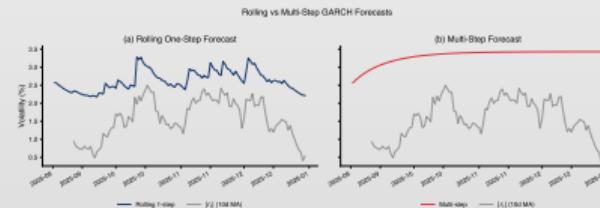
Procedure

S&P 500, W=500, GARCH(1,1)-t

- Re-estimate GARCH on $[t-W, t-1]$; forecast $\hat{\sigma}_{t|t-1}$
- Compare with realized vol. (20-day rolling std.)

Results (2015 days OOS)

- $\rho = 0.938 \succ$ excellent tracking; MAE = 0.15%, RMSE = 0.24%
- COVID-19: temporary under-prediction, rapid adaptation



VaR Backtesting: Kupiec Test

Unconditional Coverage Test

Tests whether the observed violation rate equals the expected rate p (e.g., 1% for VaR 1%).

Let N = number of VaR violations, T = total observations, $\hat{p} = N/T$.

Likelihood Ratio Statistic:

$$LR_{uc} = -2 \ln \left[\frac{(1-p)^{T-N} p^N}{(1-\hat{p})^{T-N} \hat{p}^N} \right] \sim \chi^2(1)$$

Hypotheses

- $H_0: \hat{p} = p$ (VaR model is correctly calibrated)
- $H_1: \hat{p} \neq p$ (VaR model under- or over-estimates risk)



VaR Backtesting: Christoffersen Test

Conditional Coverage Test

Tests both **unconditional coverage** and **independence** of violations.

Violations should be independent — no clustering of exceptions!

Test Components

- Independence test (LR_{ind})**: Tests if violations are serially independent
- Conditional coverage**: $LR_{cc} = LR_{uc} + LR_{ind} \sim \chi^2(2)$

Interpretation

- Reject LR_{uc} : wrong frequency
- Reject LR_{ind} : clustered violations
- Reject LR_{cc} : model fails



Full Backtesting: Results and Decision

Application S&P 500 (T=500, VaR 1%)

Typical Output

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ARMA-GARCH: Joint Mean and Variance Modeling

Why Joint Modeling?

Serial correlation \Rightarrow ARMA for mean; **Volatility clustering** \Rightarrow GARCH for variance.

Definition 9 (ARMA(p,q)-GARCH(r,s))

Mean equation: $r_t = \mu + \sum_{i=1}^p \phi_i(r_{t-i} - \mu) + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t$

Variance equation: $\varepsilon_t = \sigma_t z_t, \quad \sigma_t^2 = \omega + \sum_{i=1}^r \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^s \beta_j \sigma_{t-j}^2$



ARMA-GARCH: Model Selection Strategy

Step-by-Step Approach

1. **Identify mean model:** Check ACF/PACF of returns for ARMA structure
2. **Test for ARCH effects:** Apply ARCH-LM test to residuals
3. **Specify variance model:** Usually GARCH(1,1) is sufficient
4. **Joint estimation:** Estimate both equations via MLE
5. **Diagnostic checking:** Standardized residuals should be i.i.d.

Common Specifications

- Stock returns:** AR(1)-GARCH(1,1) or ARMA(1,1)-GARCH(1,1)
- Exchange rates:** Often just GARCH(1,1) (no mean dynamics)
- Interest rates:** AR(1)-EGARCH(1,1) for leverage effects



Step 1: Data — S&P 500 Daily Returns

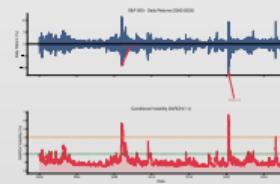
Data Description

- Source: Yahoo Finance, S&P 500, daily data 2000–2024 ($T > 6000$)
- Returns: $r_t = \ln(P_t/P_{t-1}) \times 100$

Descriptive Statistics

Mean	Std. Dev.	Skewness	Kurtosis	Min	Max
0.034%	1.21%	-0.29	13.8	-12.8%	+11.0%

- Fat tails (kurtosis $\gg 3$) and negative skewness \Rightarrow ARCH effects



Step 2: Testing for ARCH Effects

Python Code — ARCH-LM and Ljung-Box on r_t^2

Results

Test	Statistic	p-value
ARCH-LM (10 lags)	892.4	< 0.0001
Ljung-Box r_t^2 (lag 20)	4217.6	< 0.0001

- Conclusion: Strong ARCH effects \Rightarrow significant heteroskedasticity



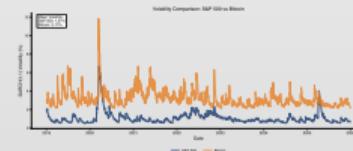
Step 3: Estimated Parameters — Comparison

Estimated Parameters Table

Model	ω	α	β	γ	$\alpha+\beta$	ν	HL
GARCH-N	0.011	0.088	0.901	—	0.989	—	60 days
GARCH-t	0.011	0.088	0.900	—	0.989	6.42	60 days
EGARCH-t	0.003	0.103	0.987	-0.120	—	6.38	—
GJR-t	0.010	0.022	0.906	0.126	0.991	6.51	78 days

Interpretation

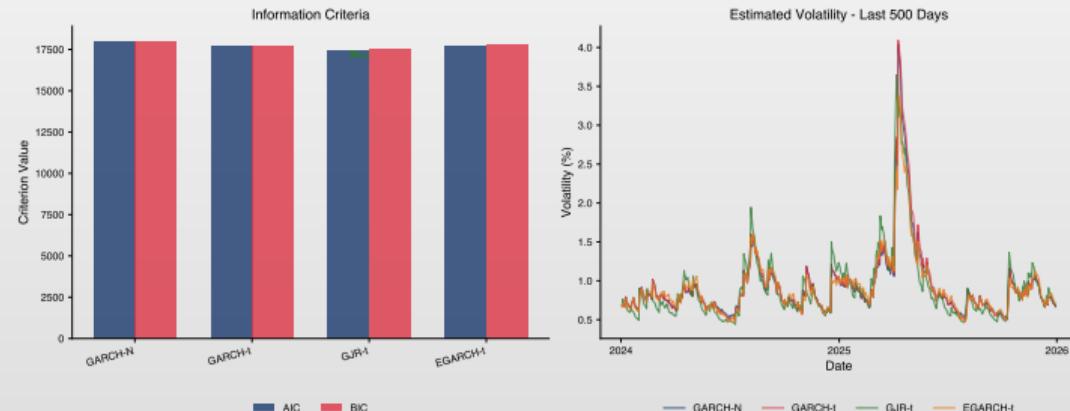
- EGARCH $\gamma = -0.12$ significant \Rightarrow leverage effect confirmed
- GJR: $\alpha_{\text{neg}} = \alpha + \gamma = 0.148$ vs $\alpha_{\text{pos}} = 0.022$ \Rightarrow strong asymmetry



Step 5: Leverage Effect — Visualization

GARCH vs EGARCH — Volatility Differences

- EGARCH produces **higher** volatility after negative shocks (2008, 2020)
- Symmetric GARCH **underestimates** risk during crisis periods
- Difference: up to 2–3 percentage points in daily volatility



Step 4: Model Selection — AIC/BIC

Information Criteria

Model	Log-Lik	AIC	BIC	Rank
GARCH(1,1)-N	-8042.3	16090.6	16111.0	4
GARCH(1,1)-t	-7981.5	15971.0	15997.8	3
EGARCH(1,1)-t	-7964.2	15938.4	15971.6	1
GJR-GARCH(1,1)-t	-7968.1	15946.2	15979.4	2

Decision

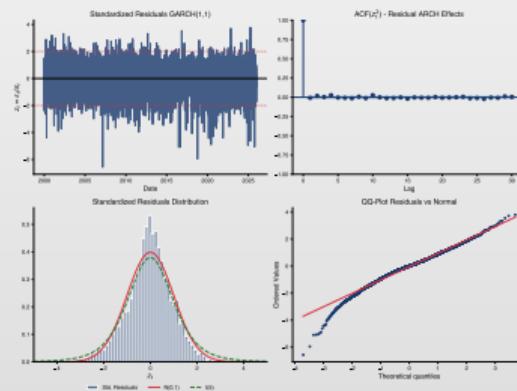
- EGARCH(1,1)-t wins:** lowest AIC and BIC
- Student-t superior to Normal ($\Delta\text{AIC} \approx 120$) \Rightarrow fat tails matter!
- Leverage effect justifies asymmetric models ($\Delta\text{AIC} \approx 33$ vs GARCH-t)



Step 5: Diagnostics — EGARCH(1,1)-t

Checks on Standardized Residuals $z_t = \varepsilon_t / \hat{\sigma}_t$

- Ljung-Box on z_t : p-value = 0.38 — no residual autocorrelation
- Ljung-Box on z_t^2 : p-value = 0.52 — **ARCH effects eliminated**
- Q-Q plot: points follow the theoretical Student-t line
- Conclusion: EGARCH(1,1)-t adequately captures volatility dynamics



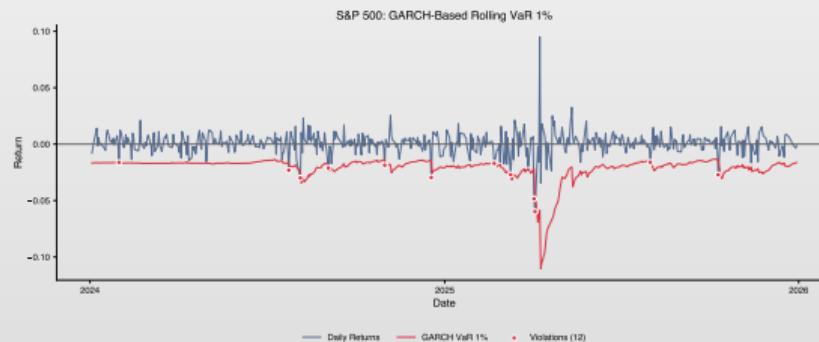
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Step 6: Backtesting Rolling VaR — S&P 500

Kupiec + Christoffersen Results (2015 days out-of-sample)

Test	Statistic	p-value	Decision
Violations	27/2015 ($\hat{p} = 1.34\%$)	—	Green zone
Kupiec (uc)	2.13	0.145	Accepted
Christoffersen (ind)	0.79	0.375	Accepted
Combined (cc)	2.91	0.233	Accepted



Step 7: Conclusions — S&P 500 Case Study

Step-by-Step Methodology Summary

1. **Data:** log returns, descriptive statistics \Rightarrow fat tails, skewness
2. **ARCH test:** ARCH-LM + Ljung-Box on $r_t^2 \Rightarrow$ significant ARCH effects
3. **Estimation:** 4 candidate models (symmetric/asymmetric \times Normal/Student-t)
4. **Selection:** AIC/BIC \Rightarrow **EGARCH(1,1)-t** winner
5. **Diagnostics:** standardized residuals \Rightarrow model adequate
6. **VaR:** rolling window + Kupiec/Christoffersen backtesting \Rightarrow model **validated**

Key Lessons

- Student-t distribution is **essential** for financial data
- Leverage effect: asymmetric models **mandatory** for equities
- Systematic backtesting: not just “looks good”, but **statistically tested**



Step 1: Data — Bitcoin Daily Returns

Data Description

- Source: Yahoo Finance (BTC-USD), daily data 2018–2024
- Log returns: mean $\approx 0.05\%$, volatility $\approx 3.5\%$

Descriptive Statistics

Mean	Std. Dev.	Skewness	Kurtosis	Min	Max
0.05%	3.48%	-0.72	12.1	-46.5%	+22.5%

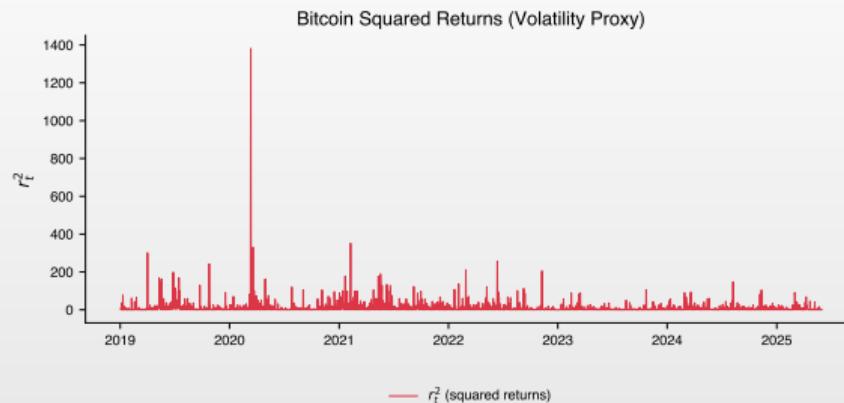
- Volatility $\sim 3 \times$ higher than S&P 500
- Extreme kurtosis — high risk of large losses



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Step 2: Testing for ARCH Effects — Bitcoin



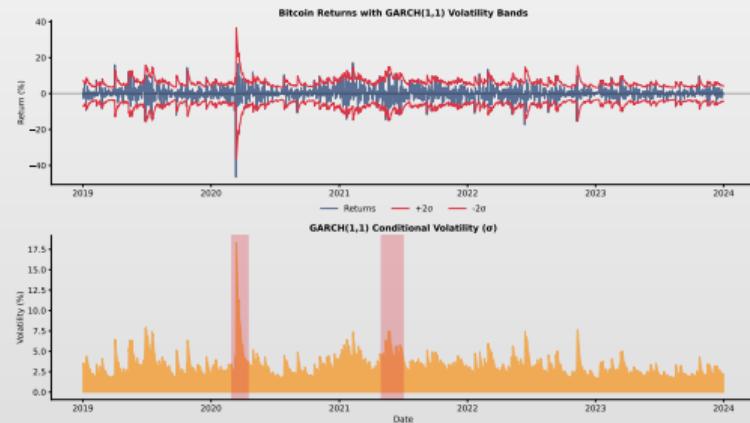
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Step 5: Conditional Volatility — Bitcoin

GJR-GARCH(1,1)-t Diagnostics

- ◻ Ljung-Box on z_t^2 : p-value = 0.41 — **ARCH effects eliminated**
- ◻ Volatility peaks: March 2020 (COVID), May 2022 (Terra/Luna)
- ◻ Daily volatility: from 1% (calm periods) to >15% (crises)



Q TSA_ch5_btc_garch



Steps 3–4: Estimation and Model Selection — Bitcoin

Estimated Parameters

Model	ω	α	β	γ	$\alpha+\beta$	ν	AIC
GARCH-t	0.42	0.131	0.848	—	0.979	4.82	9284
EGARCH-t	0.08	0.184	0.976	-0.061	—	4.79	9276
GJR-t	0.40	0.088	0.854	0.078	0.976	4.85	9271

Interpretation

- **GJR-GARCH-t wins** (lowest AIC)
- $\nu \approx 4.8$: **much heavier tails** than S&P 500 ($\nu = 6.4$)
- $\alpha = 0.131$ (BTC) vs 0.088 (S&P) — Bitcoin reacts faster to news
- Leverage effect weaker than for stocks ($\gamma_{\text{BTC}} = 0.078$ vs 0.126)



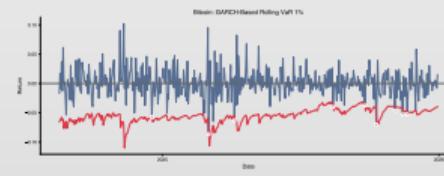
Step 6: Backtesting Rolling VaR — Bitcoin

Statistical Tests (2421 days out-of-sample)

Test	Statistic	p-value	Decision
Violations	28/2421 ($\hat{p} = 1.16\%$)	—	Green zone
Kupiec (uc)	0.57	0.450	Accepted
Christoffersen (ind)	0.94	0.333	Accepted
Combined (cc)	1.51	0.471	Accepted

Interpretation

- Volatility ranges from 3% to 38% — rolling window is **essential**
- All tests **accepted**: model valid for risk management



Step 6: VaR Rolling Window — Bitcoin

Rolling Window GJR-GARCH-t (W=500 days, VaR 1%)

Rolling VaR Characteristics Bitcoin (2018–2024)

- Mean VaR: 9.34% (\approx EUR 93,400 / 1M EUR)
- Max VaR: 37.54% \Rightarrow COVID crash March 2020
- Min VaR: 2.90% \Rightarrow calm period
- Bitcoin: rolling VaR $\sim 4\times$ larger than S&P 500 at same exposure



Final Comparison: S&P 500 vs Bitcoin

Comparative Summary

	S&P 500	Bitcoin
Average volatility	1.2%	3.5%
Kurtosis	13.8	12.1
Student-t ν	6.42	4.82
Best model	EGARCH(1,1)-t	GJR-GARCH(1,1)-t
Leverage effect	Strong ($\gamma = -0.12$)	Moderate ($\gamma = 0.078$)
Half-life	~ 60 days	~ 42 days
Rolling VaR 1% mean	2.53%	9.34%
Rolling VaR 1% max	22.02% (COVID)	37.54% (COVID)
Kupiec	Accepted ($p=0.145$)	Accepted ($p=0.450$)
Christoffersen (ind)	Accepted ($p=0.375$)	Accepted ($p=0.333$)

General Conclusion

- ☐ Re-estimating GARCH at each step: Kupiec + Christoffersen **accepted**
- ☐ Rolling window VaR: **mandatory** — static VaR is completely inadequate
- ☐ Student-t + asymmetric model: **essential** for both markets



Key Formulas

Volatility Models

- **ARCH(q):** $\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2$
- **GARCH(1,1):** $\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$
- **EGARCH:** $\ln(\sigma_t^2) = \omega + \alpha(|z_{t-1}| - \mathbb{E}[|z|]) + \gamma z_{t-1} + \beta \ln(\sigma_{t-1}^2)$
- **GJR-GARCH:** $\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \beta \sigma_{t-1}^2$

Properties and Measures

- **Unconditional variance:** $\bar{\sigma}^2 = \frac{\omega}{1-\alpha-\beta}$ **Half-life:** $HL = \frac{\ln(0.5)}{\ln(\alpha+\beta)}$
- **VaR:** $\text{VaR}_\alpha = z_\alpha \cdot \sigma_{T+1}$ **Stationarity:** $\alpha + \beta < 1$
- **ARCH-LM:** $LM = T \cdot R^2 \sim \chi^2(q)$



AI Exercise: Critical Thinking

Prompt to test in ChatGPT / Claude / Copilot

"Using yfinance, download daily closing prices for S&P 500 (^GSPC) from 2018-01-01 to 2024-12-31 (approx. 1,750 observations). Compute daily log returns. Test for ARCH effects, fit a GARCH(1,1) model, and forecast volatility for the next 20 trading days. Give me complete Python code."

Exercise:

1. Run the prompt in an LLM of your choice and critically analyze the response.
2. Does it compute log returns correctly? Does it remove the mean before fitting GARCH?
3. How does it test for ARCH effects? Does it use Engle's LM test?
4. Does it separate the mean equation from the variance equation?
5. Does it discuss asymmetric effects (GJR-GARCH, EGARCH)? Are VaR estimates computed from the conditional distribution?

Warning: AI-generated code may run without errors and look professional. *That does not mean it is correct.*



Summary → Chapter 5: Volatility Models

Key Concepts

- **ARCH(q)**: conditional variance depends on past squared errors (Nobel 2003)
- **GARCH(p,q)**: adds variance lags for persistence (GARCH(1,1) in 90% of cases)
- **EGARCH**: allows leverage effect, no positivity constraints
- **GJR-GARCH/TGARCH**: captures asymmetry with indicator variables

Applications

- Risk measurement and forecasting (VaR, ES)
- Derivative pricing, dynamic hedging, portfolio management

Practical Tip

- Start with GARCH(1,1), check for leverage, choose distribution minimizing AIC/BIC!
 - ▶ Student-t often superior to normal distribution



Question 1

Question

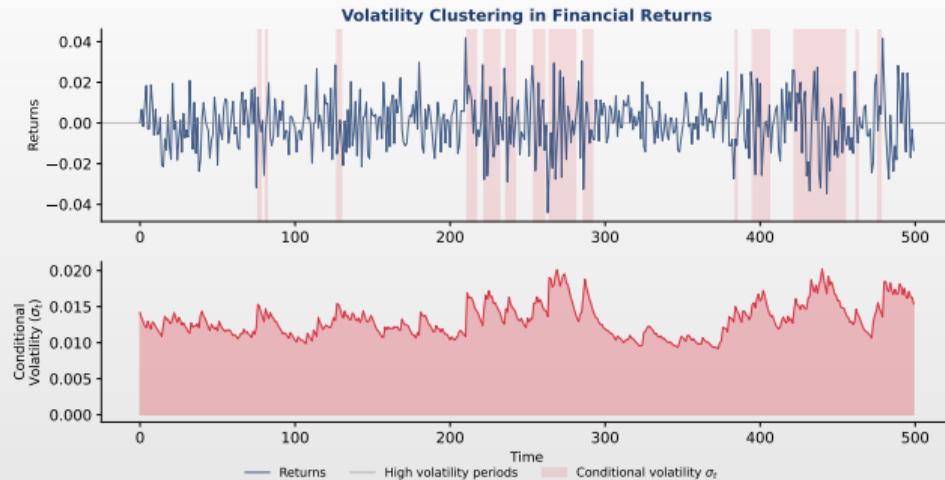
- What best describes the phenomenon of *volatility clustering* in financial series?

Answer Choices

- (A)** Financial returns are normally distributed and independent
- (B)** Periods of high volatility are followed by high volatility, and vice versa
- (C)** Volatility is constant over time (homoscedasticity)
- (D)** Correlation between returns is always positive



Question 1: Answer



Answer: (B)

- Volatility clustering is a fundamental stylized fact of financial series. It implies that conditional variance is **predictable**, motivating ARCH/GARCH models.



Question 2

Question

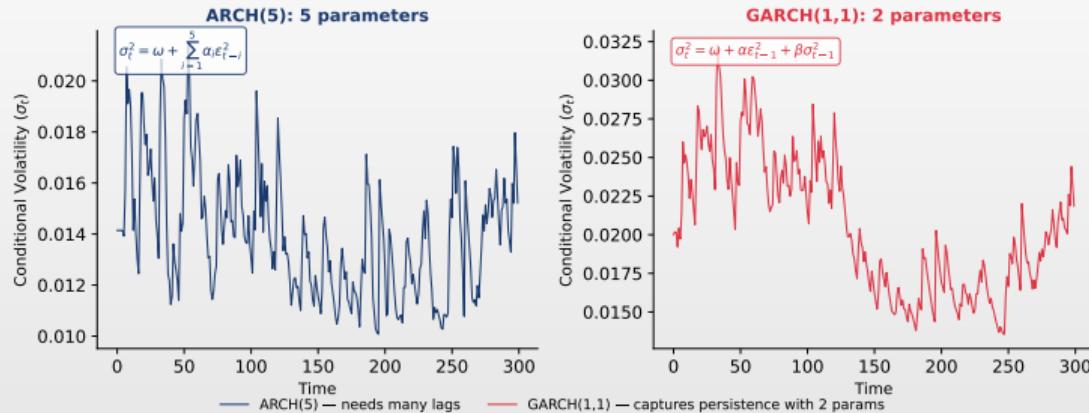
- What is the main difference between an ARCH(q) and a GARCH(p,q) model?

Answer Choices

- (A)** GARCH models the conditional mean, ARCH models the variance
- (B)** ARCH includes lags of conditional variance, GARCH does not
- (C)** GARCH adds lags of conditional variance (σ_{t-j}^2) beyond squared errors
- (D)** ARCH is more parsimonious than GARCH

Question 2: Answer

ARCH vs GARCH: Parsimony



Answer: (C)

- GARCH(1,1) captures the same persistence as ARCH(q) with only 2 parameters instead of q . In practice, GARCH(1,1) is sufficient in 90% of cases.



Question 3

Question

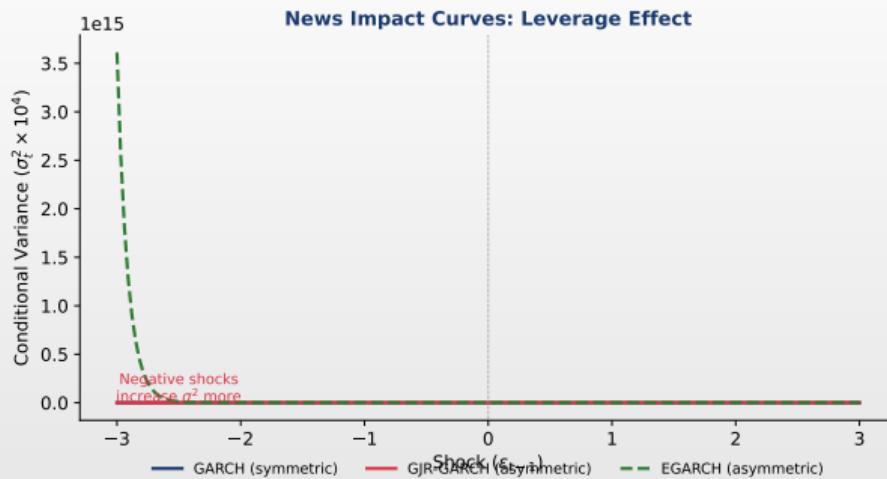
- What is the *leverage effect* and which GARCH models capture it?

Answer Choices

- (A)** Positive shocks increase volatility more; captured by standard GARCH
- (B)** Negative shocks increase volatility more; captured by EGARCH and GJR-GARCH
- (C)** Volatility is symmetric; captured by all GARCH models
- (D)** Financial leverage effect on stock prices; captured by IGARCH



Question 3: Answer



Answer: (B)

- Price drops increase volatility **more** than equivalent price increases. Standard GARCH uses ε_{t-1}^2 , losing the sign information.



Question 4

Question

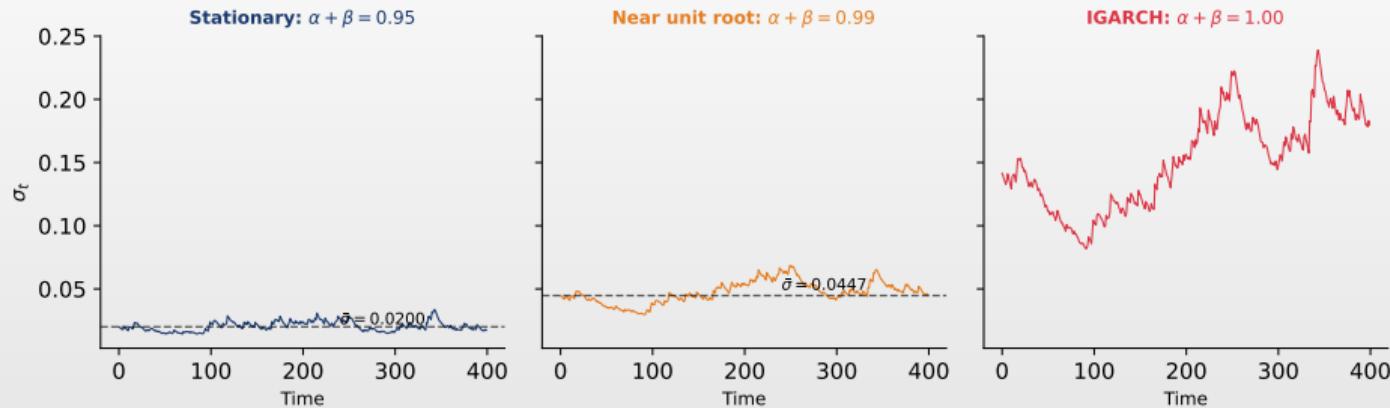
- What is the stationarity condition for a GARCH(1,1) model?

Answer Choices

- (A)** $\alpha + \beta = 1$
- (B)** $\alpha > 0$ and $\beta > 0$
- (C)** $\alpha + \beta < 1$, with $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$
- (D)** $\alpha \cdot \beta < 1$

Question 4: Answer

GARCH(1,1) Stationarity: $\alpha + \beta < 1$



Answer: (C)

- This ensures a finite unconditional variance $\bar{\sigma}^2 = \frac{\omega}{1-\alpha-\beta}$. When $\alpha + \beta = 1$ (IGARCH), variance is infinite.



Question 5

Question

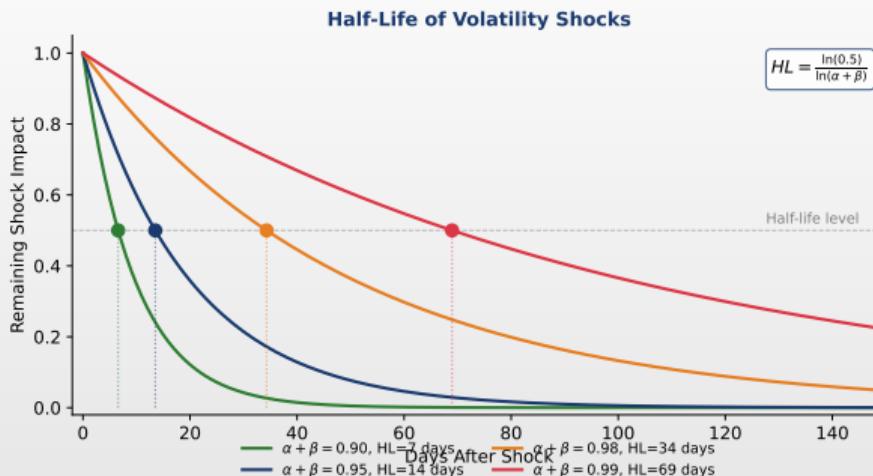
- What does the *half-life* of volatility represent in a GARCH(1,1) model?

Answer Choices

- (A) The time needed for the price to return to its mean
- (B) The number of periods until volatility becomes zero
- (C) The number of periods for a volatility shock to decay to half its initial impact
- (D) The average duration of a high-volatility episode



Question 5: Answer



Answer: (C)

- $HL = \frac{\ln(0.5)}{\ln(\alpha + \beta)}$. Example: S&P 500 with $\alpha + \beta = 0.988$ gives $HL \approx 58$ days (shocks persist ~ 3 months).

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- Glosten, L.R., Jagannathan, R., & Runkle, D.E. (1993). On the Relation Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks, *Journal of Finance*, 48(5), 1779–1801.
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- Franke, J., Härdle, W.K., & Hafner, C.M. (2019). *Statistics of Financial Markets*, 4th ed., Springer.
- McNeil, A.J., Frey, R., & Embrechts, P. (2015). *Quantitative Risk Management*, 2nd ed., Princeton University Press.

Online Resources and Code

- **Quantlet:** <https://quantlet.com> ↗ Code repository for statistics
- **Quantinar:** <https://quantinar.com> ↗ Learning platform for quantitative methods
- **GitHub TSA:** https://github.com/QuantLet/TSA/tree/main/TSA_ch5 ↗ Python code for this chapter



Thank You!

Questions?

Course materials available at: <https://danpele.github.io/Time-Series-Analysis/>

