4 Financial time series

4.1 Fundamentals of time series analysis

4.1.1 Basic definitions

A *stochastic process* is a family of rvs $(X_t)_{t \in I}$, $I \subseteq \mathbb{R}$, defined on a probability space $(\Omega, \mathcal{F}, \mathbb{P})$. A *time series* is a discrete-time ($I \subseteq \mathbb{Z}$) stochastic process.

Definition 4.1 (Mean function, autocovariance function)
Assuming they exist, the *mean function* $\mu(t)$ and the *autocovariance function* $\gamma(t, s)$ of $(X_t)_{t \in \mathbb{Z}}$ are defined by

$$\mu(t) = \mathbb{E}(X_t), \quad t \in \mathbb{Z},$$
$$\gamma(t, s) = \operatorname{cov}(X_t, X_s) = \mathbb{E}((X_t - \mathbb{E}X_t)(X_s - \mathbb{E}X_s)), \quad t, s, \in \mathbb{Z}.$$

Definition 4.2 ((Weak/strict) stationarity)

1) $(X_t)_{t\in\mathbb{Z}}$ is *(weakly/covariance) stationary* if $\mathbb{E}(X_t^2)<\infty$, $\mu(t)=\mu\in\mathbb{R}$ and $\gamma(t,s)=\gamma(t+h,s+h)$ for all $t,s,h\in\mathbb{Z}$.
2) $(X_t)_{t\in\mathbb{Z}}$ is *strictly stationary* if $(X_{t_1},\dots,X_{t_n}) \overset{\mathrm{d}}{=} (X_{t_1+h},\dots, X_{t_n+h})$ for all $t_1,\dots,t_n,h\in\mathbb{Z}$, $n\in\mathbb{N}$.

Remark 4.3

1) Both types of stationarity formalize the idea that $(X_t)_{t\in\mathbb{Z}}$ behaves similarly in any time period.
2)
   - Strict stationarity $\not\Rightarrow$ stationarity (unless also $\mathbb{E}(X_t^2)$ exists).
   - Stationarity $\not\Rightarrow$ strict stationarity ($\mathbb{E}(|X_t|^p)$, $p>2$, could change).
3) If $(X_t)_{t\in\mathbb{Z}}$ is stationary, $\gamma(0,t-s)=\gamma(s,t)=\gamma(t,s)=\gamma(0,s-t)$, so $\gamma(t,s)$ only depends on the *lag* $h=|t-s|$. We can thus define $\gamma(h):=\gamma(0,|h|)$, $h\in\mathbb{Z}$.

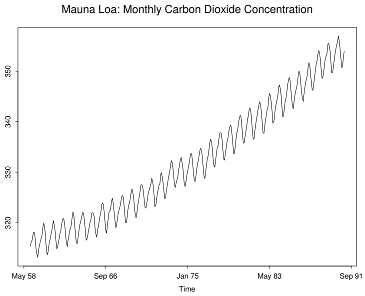
Autocorrelation in stationary time series

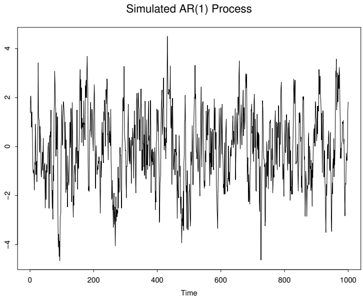
Definition 4.4 (ACF)

The *autocorrelation function (ACF)* (or *serial correlation*) of a stationary time series $(X_t)_{t\in\mathbb{Z}}$ is defined by

$$\rho(h) := \mathrm{corr}(X_0, X_h) = \gamma(h)/\gamma(0), \quad h \in \mathbb{Z}.$$

Stationary?





The study of autocorrelation is known as *analysis in the time domain*.

Another important quantity is the *partial autocorrelation function (PACF)* ϕ, defined by

$$\phi(h) := \operatorname{corr}(X_0 - P_{\mathcal{H}_{h-1}} X_0,\ X_h - P_{\mathcal{H}_{h-1}} X_h),$$

where $P_{\mathcal{H}_{h-1}} X_t$ denotes the best approximation/prediction of X_t from an element of $\mathcal{H}_{h-1} = \{\sum_{k=1}^{h-1} \alpha_k X_{h-k} : \alpha_1, \dots, \alpha_{h-1} \in \mathbb{R}\}$. Note that $\phi(1) = \phi_{1,1} = \gamma(1)/\gamma(0) = \rho(1)$.

- The PACF is the corr between X_0 and X_h with the linear dependence of $X_1, \dots, X_{h-1}$ removed.
- It can be used for model identification of $\mathrm{AR}(p)$ processes similarly to how the ACF is used for $\mathrm{MA}(q)$ processes (see later).
- It can be computed with the Durbin-Levinson algorithm; see the appendix.

White noise processes

Definition 4.5 ((Strict) white noise)

1) $(X_t)_{t\in\mathbb{Z}}$ is a *white noise* process if $(X_t)_{t\in\mathbb{Z}}$ is stationary with $\rho(h) = I_{\{h=0\}}$ (no serial correlation). If $\mu(t) = 0$, $\gamma(0) = \mathrm{var}(X_t) = \sigma^2$, $(X_t)_{t\in\mathbb{Z}}$ is denoted by $(\varepsilon_t)_{t\in\mathbb{Z}} \sim \mathrm{WN}(0, \sigma^2)$.
2) $(X_t)_{t\in\mathbb{Z}}$ is a *strict white noise* process if $(X_t)_{t\in\mathbb{Z}}$ is an iid sequence of rvs with $\gamma(0) = \mathrm{var}(X_t) = \sigma^2 < \infty$. If $\mu(t) = 0$, we write $(Z_t)_{t\in\mathbb{Z}} \sim \mathrm{SWN}(0, \sigma^2)$.

For GARCH processes (see later), we need another notion of noise.

Let $(X_t)_{t\in\mathbb{Z}}$ be a stochastic process on $(\Omega, \mathcal{F}, \mathbb{P})$. A sequence $(\mathcal{F}_t)_{t\in\mathbb{Z}}$ of σ-algebras is called *filtration* if $\mathcal{F}_t \subseteq \mathcal{F}_{t+1} \subseteq \mathcal{F}$, $t \in \mathbb{Z}$. If $\mathcal{F}_t = \sigma(\{X_s : s \le t\})$, we call $(\mathcal{F}_t)_{t\in\mathbb{Z}}$ the *natural filtration* of $(X_t)_{t\in\mathbb{Z}}$. $(X_t)_{t\in\mathbb{Z}}$ is *adapted* to $(\mathcal{F}_t)_{t\in\mathbb{Z}}$ if $X_t \in \mathcal{F}_t$, $t \in \mathbb{Z}$ (X_t is $\mathcal{F}_t$-measurable).

Definition 4.6 (MGDS)

$(X_t)_{t\in\mathbb{Z}}$ is a *martingale-difference sequence (MGDS)* w.r.t. $(\mathcal{F}_t)_{t\in\mathbb{Z}}$ (typically the natural filtration $\mathcal{F}_t = \sigma(\{X_s : s \le t\})$) if $\mathbb{E}|X_t| < \infty$, $t \in \mathbb{Z}$, $(X_t)_{t\in\mathbb{Z}}$ is adapted to $(\mathcal{F}_t)_{t\in\mathbb{Z}}$; and $\mathbb{E}(X_{t+1} \,|\, \mathcal{F}_t) = 0$ for all $t \in \mathbb{Z}$.

- If $\mathbb{E}(X_{t+1}|F_t) = X_t$ a.s., then (X_t) is a (discrete-time) *martingale* and $\varepsilon_t = X_t - X_{t-1}$ is a MGDS (winnings in rounds of a *fair game*).
- One can show that a MGDS $(\varepsilon_t)_{t\in\mathbb{Z}}$ with $\sigma^2 = \mathbb{E}(\varepsilon_t^2) < \infty$ satisfies
  - $\rho(h) = 0$, $h \ne 0$, so $(\varepsilon_t)_{t\in\mathbb{Z}} \sim \mathrm{WN}(0, \sigma^2)$;
  - $\mathbb{E}(\varepsilon_{t+1+k} \,|\, \mathcal{F}_t) = \mathbb{E}(\mathbb{E}(\varepsilon_{t+1+k} \,|\, \mathcal{F}_{t+k}) \,|\, \mathcal{F}_t) = 0$, $k \in \mathbb{N}$.

4.1.2 ARMA processes

Definition 4.7 ($\mathrm{ARMA}(p,q)$)
Let $(\varepsilon_t)_{t\in\mathbb{Z}} \sim \mathrm{WN}(0,\sigma^2)$. $(X_t)_{t\in\mathbb{Z}}$ is a *zero-mean $\mathrm{ARMA}(p,q)$ process* if it is stationary and satisfies, for all $t\in\mathbb{Z}$,

$$X_t - \phi_1 X_{t-1} - \cdots - \phi_p X_{t-p} = \varepsilon_t + \theta_1\varepsilon_{t-1} + \cdots + \theta_q\varepsilon_{t-q}. \qquad (7)$$

$(X_t)_{t\in\mathbb{Z}}$ is $\mathrm{ARMA}(p,q)$ with *mean μ* if $(X_t-\mu)_{t\in\mathbb{Z}}$ is a zero-mean $\mathrm{ARMA}(p,q)$.

Remark 4.8

- If the *innovations* $(\varepsilon_t)_{t\in\mathbb{Z}}$ are $\mathrm{SWN}(0,\sigma^2)$, then $(X_t)_{t\in\mathbb{Z}}$ is strictly stationary (follows from the representation as a linear process below).
- The defining equation (7) can be written as $\phi(B)X_t = \theta(B)\varepsilon_t$, $t\in\mathbb{Z}$, where B denotes the *backshift operator* (such that $B^k X_t = X_{t-k}$) and $\phi(z) = 1-\phi_1 z - \cdots - \phi_p z^p$ and $\theta(z) = 1+\theta_1 z + \cdots + \theta_q z^q$.

Causal processes

For practical purposes, it suffices to consider *causal* ARMA processes $(X_t)_{t\in\mathbb{Z}}$ satisfying

$$X_t = \sum_{k=0}^{\infty} \psi_k \varepsilon_{t-k} \quad \text{(depends on the past/present, not the future)}$$

for $\sum_{k=0}^{\infty} |\psi_k| < \infty$ (*absolute summability condition*; guarantees $\mathbb{E}|X_t| < \infty$).

Proposition 4.9 (ACF for causal processes)
Let $X_t = \sum_{k=0}^{\infty} \psi_k \varepsilon_{t-k}$ with $\sum_{k=0}^{\infty} |\psi_k| < \infty$. This process is stationary with ACF given by

$$\rho(h) = \frac{\sum_{k=0}^{\infty} \psi_k \psi_{k+|h|}}{\sum_{k=0}^{\infty} \psi_k^2}, \quad h \in \mathbb{Z}.$$

Theorem 4.10 (Stationary and causal ARMA solutions)
Let $(X_t)_{t\in\mathbb{Z}}$ be an $\mathrm{ARMA}(p,q)$ process for which $\phi(z), \theta(z)$ have no roots in common. Then (see the appendix for an idea of the proof)

$$(X_t)_{t\in\mathbb{Z}} \text{ is stationary and causal} \quad \Leftrightarrow \quad \phi(z) \neq 0 \quad \forall\, z \in \mathbb{C} : |z| \leq 1.$$

In this case, $X_t = \sum_{k=0}^{\infty} \psi_k \varepsilon_{t-k}$ for $\sum_{k=0}^{\infty} \psi_k z^k = \theta(z)/\phi(z)$, $|z| \leq 1$.

- If $\theta(z) \neq 0,\ |z| \leq 1$ (known as *invertibility condition*), $(X_t)_{t\in\mathbb{Z}}$ is *invertible*, i.e. we can recover ε_t from $(X_s)_{s\leq t}$ (via $\varepsilon_t = \phi(B)X_t/\theta(B)$), so $\varepsilon_t \in \mathcal{F}_t = \sigma(\{X_s : s \leq t\})$.
- An $\mathrm{ARMA}(p,q)$ process with mean μ can be written as $X_t = \mu_t + \varepsilon_t$ for $\mu_t = \mu + \sum_{k=1}^{p} \phi_k (X_{t-k} - \mu) + \sum_{k=1}^{q} \theta_k \varepsilon_{t-k}$. If $(X_t)_{t\in\mathbb{Z}}$ is invertible, $\mu_t \in \mathcal{F}_{t-1}$. If $(\varepsilon_t)_{t\in\mathbb{Z}}$ is a MGDS w.r.t. $(\mathcal{F}_t)_{t\in\mathbb{Z}}$, then $\mu_t = \mathbb{E}(X_t \mid \mathcal{F}_{t-1})$. Therefore, ARMA processes put structure on the conditional mean μ_t given the past. We will see that GARCH processes put structure on $\sigma_t^2 = \mathrm{var}(X_t \mid \mathcal{F}_{t-1})$ (helpful for modeling volatility clustering).

Example 4.11

1) $\mathrm{MA}(q) = \mathrm{ARMA}(0, q)$: $X_t = \varepsilon_t + \sum_{k=1}^{q} \theta_k \varepsilon_{t-k} \underset{\theta_0 := 1}{=} \sum_{k=0}^{q} \theta_k \varepsilon_{t-k}$

$\Rightarrow$ causal, absolute summability condition fulfilled.

- ACF: Proposition 4.9 $\Rightarrow \rho(h) = \frac{\sum_{k=0}^{q-|h|} \theta_k \theta_{k+|h|}}{\sum_{k=0}^{q} \theta_k^2}$, $|h| \in \{1, \dots, q\}$, and $\rho(h) = 0$ for all $|h| > q \Rightarrow$ ACF cuts off after lag q.
- PACF: One can show that for an $\mathrm{MA}(q)$, $\phi(h)$ does not cut off but $|\phi(h)|$ is bounded by an exponentially decreasing function in h.

2) $\mathrm{AR}(p) = \mathrm{ARMA}(p, 0)$: $X_t - \sum_{k=1}^{p} \phi_k X_{t-k} = \varepsilon_t$. ACF: As for general ARMA processes, the ACF can be computed in several ways; see Brockwell and Davis (1991, Section 3.3), e.g. via $X_t = \theta(B)\varepsilon_t/\phi(B) = \psi(B)\varepsilon_t$ from $\rho(h)$ as in Proposition 4.9.

Example: By Theorem 4.10, an $\mathrm{AR}(1)$ has a stationary and causal solution if and only if $1 - \phi_1 z \neq 0$ for all $z \in \mathbb{C} : |z| \leq 1$, so $|\phi_1| < 1$. In this case, $X_t = \phi_1 X_{t-1} + \varepsilon_t = \phi_1(\phi_1 X_{t-2} + \varepsilon_{t-1}) + \varepsilon_t = \dots = \phi_1^n X_{t-n} + \sum_{k=0}^{n-1} \phi_1^k \varepsilon_{t-k} \to \sum_{k=0}^{\infty} \phi_1^k \varepsilon_{t-k}$, so $\psi_k = \phi_1^k$, $k \in \mathbb{N}_0$. By

Proposition 4.9,

$$\rho(h) = \frac{\sum_{k=0}^{\infty} \phi_1^{2k+|h|}}{\sum_{k=0}^{\infty} \phi_1^{2k}} = \phi_1^{|h|}, \quad h \in \mathbb{Z},$$

which decreases exponentially.

For $\mathrm{AR}(p)$, one can show this from a general form of ψ_k (see Brockwell and Davis (1991, p. 92)), possibly with damped sine waves. Furthermore, one can show that the PACF of an $\mathrm{AR}(p)$ cuts off after lag p; it can be computed with the Durbin–Levinson algorithm; see the appendix.

3) $\mathrm{ARMA}(1,1)$: $X_t - \phi_1 X_{t-1} = \varepsilon_t + \theta_1 \varepsilon_{t-1}$ for $|\phi_1| < 1$ has a stationary and causal solution (by Theorem 4.10). For determining the ACF, we first write $X_t = \psi(B)\varepsilon_t$, where

$$\psi(z) = \frac{\theta(z)}{\phi(z)} = \frac{1+\theta_1 z}{1-\phi_1 z} = (1+\theta_1 z)\sum_{k=0}^{\infty}(\phi_1 z)^k$$

$$= \sum_{k=0}^{\infty} \phi_1^k z^k + \sum_{k=1}^{\infty} \theta_1 \phi_1^{k-1} z^k = 1 + \sum_{k=1}^{\infty} \phi_1^{k-1}(\phi_1 + \theta_1) z^k,$$

hence $\psi_0 = 1$ and $\psi_k = \phi_1^{k-1}(\phi_1 + \theta_1)$, $k \ge 1$. It follows that

$$\sum_{k=0}^{\infty} \psi_k \psi_{k+h} \underset{h\ge 1}{=} \underbrace{\psi_0 \psi_h}_{=\phi_1^{h-1}(\phi_1+\theta_1)} + \underbrace{\sum_{k=1}^{\infty} \phi_1^{k-1+k+h-1} (\phi_1 + \theta_1)^2}_{=(\phi_1+\theta_1)^2 \phi_1^h \sum_{k=0}^{\infty} \phi_1^{2k}}$$

$$= \phi_1^{h-1}(\phi_1 + \theta_1)(1 + (\phi_1 + \theta_1)\phi_1/(1 - \phi_1^2))$$

$$= \frac{\phi_1^{h-1}}{1 - \phi_1^2}(\phi_1 + \theta_1)(1 + \phi_1\theta_1).$$

Proposition 4.9 then implies that

$$\rho(h) = \phi_1^{h-1} \frac{(\phi_1 + \theta_1)(1 + \phi_1\theta_1)}{1 + 2\phi_1\theta_1 + \theta_1^2} = \phi_1^{h-1}\rho(1) \underset{(h\to\infty)}{\searrow} 0,$$

so that $\rho(h) = \phi_1^{|h|-1}\rho(1)$ for all $h \in \mathbb{Z}\backslash\{0\}$. The PACF can be computed from the Durbin–Levinson algorithm.

Remark 4.12

$(X_t)_{t\in\mathbb{Z}}$ is an ARIMA(p,d,q) (Integrated) process if

$$\underbrace{\phi(B)}_{\text{order } p}\ \overbrace{\underbrace{(1-B)^d}_{\text{order } d}}^{\text{integrated part}}\ X_t = \underbrace{\theta(B)}_{\text{order } q}\,\varepsilon_t, \quad t\in\mathbb{Z}.$$

We see that this is also an $\mathrm{ARMA}(d+p,q)$ process. Extensions to SARIMA (Seasonal) models are available; see the appendix.

4.1.3 Analysis in the time domain

Correlogram

A *correlogram* is a plot of $(h,\hat\rho(h))_{h\ge 0}$ for the sample ACF

$$\hat\rho(h) = \frac{\sum_{t=1}^{n}(X_{t+h}-\bar X_n)(X_t-\bar X_n)}{\sum_{t=1}^{n}(X_t-\bar X_n)^2}, \quad h\in\{0,\dots,n\}.$$

The sample PACF can be computed from $\hat\rho(h)$ via the DL algorithm.

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Theorem 4.13

Let $X_t - \mu = \sum_{k=0}^{\infty} \psi_k Z_{t-k}$ and $(Z_t) \sim \mathrm{SWN}(0, \sigma^2)$. Under suitable conditions,

$$\sqrt{n}\left(\begin{pmatrix}\hat{\rho}(1)\\ \vdots \\ \hat{\rho}(h)\end{pmatrix} - \begin{pmatrix}\rho(1)\\ \vdots \\ \rho(h)\end{pmatrix}\right) \underset{(n\to\infty)}{\overset{\text{d}}{\to}} \mathrm{N}_h(\mathbf{0}, W), \quad h \in \mathbb{N},$$

for a matrix W depending on ρ; see MFE (2015, Theorem 4.13).

If the ARMA process is SWN itself, $\sqrt{n}\begin{pmatrix}\hat{\rho}(1)\\ \vdots \\ \hat{\rho}(h)\end{pmatrix} \underset{(n\to\infty)}{\overset{\text{d}}{\to}} \mathrm{N}_h(\mathbf{0}, I_h)$, so that with probability $1-\alpha$,

$$\hat{\rho}(k) \underset{(n\ \text{large})}{\in} \left[-\frac{q_{1-\alpha/2}}{\sqrt{n}}, \frac{q_{1-\alpha/2}}{\sqrt{n}}\right], \quad k \in \{1, \dots, h\},$$

where $q_{1-\alpha/2} = \Phi^{-1}(1-\alpha/2)$. This interval is usually shown in correlogram. If more than 5% of $\hat{\rho}(k)$, $k \in \{1, \dots, h\}$, lie outside, this is evidence against the (iid) hypothesis of SWN $\Rightarrow$ serial correlation.

Portmanteau tests

- As a formal test of the SWN hypothesis, one can use the Ljung–Box test with test statistic

$$T = n(n+2)\sum_{k=1}^{h}\frac{\hat{\rho}(k)^2}{n-k} \underset{n \text{ large}}{\sim} \chi_h^2; \quad \text{reject if } T > {\chi_h^2}^{-1}(1-\alpha).$$

- If $(X_t)_{t\in\mathbb{Z}}$ is SWN, so is $(X_t^2)_{t\in\mathbb{Z}}$. It is a good idea to also apply the correlogram and Ljung–Box tests to $(|X_t|)_{t\in\mathbb{Z}}$ or $(X_t^2)_{t\in\mathbb{Z}}$.

4.1.4 Statistical analysis of time series

The Box–Jenkins approach

Approach for the statistical analysis of $(X_t)_{t\in\mathbb{Z}}$:

1) Preliminary analysis
   i) Plot the time series ⇒ Does it look stationary?
   ii) If necessary, clean the (e.g. high-frequency) data and plot it again.

iii) Make it stationary by removing trend and seasonality (regime switches etc.). A typical decomposition is

$$X_t = \underbrace{\mu_t}_{\text{trend}} + \underbrace{s_t}_{\text{seasonal component}} + \underbrace{\varepsilon_t}_{\text{residual process}}.$$

- A trend μ_t can be estimated via smoothing with local averages:

$$\begin{aligned}\tilde{X}_t &= \frac{1}{2h+1}\sum_{k=-h}^{h} X_{t+k}\\ &= \underbrace{\sum_{k=-h}^{h}\frac{\mu_{t+k}}{2h+1}}_{\approx \mu_t} + \underbrace{\sum_{k=-h}^{h}\frac{s_{t+k}}{2h+1}}_{\approx 0} + \underbrace{\sum_{k=-h}^{h}\frac{\varepsilon_{t+k}}{2h+1}}_{=\tilde{\varepsilon}_t}\end{aligned}$$

  or exponentially weighted moving averages.

- A seasonal component s_t can be estimated by considering $(\tilde{X}_s)_{s=1}^{S}$ (e.g. for monthly data, $S = 12$) with

$$\tilde{X}_s = \frac{1}{N}\sum_{k=0}^{N-1} X_{s+kS}, \quad s \in \{1, \dots, S\},\ N = \left\lfloor \frac{n}{S} \right\rfloor.$$

Overall, removing μ_t, s_t can be done non-parametrically, via regression, or by taking differences.

2) Analysis in the time domain
   i) Plot ACF, PACF and use the Ljung–Box test for $(X_t)_{t\in\mathbb{Z}}$ (hints at an ARMA) and $(X_t^2)_{t\in\mathbb{Z}}$ (hints at an GARCH). If the SWN hypothesis cannot be rejected, fit a static distribution.
   ii) Do ACF (MA) or PACF (AR) cut off? (determines the order(s))
3) Model fitting
   i) If possible, identify the order and fit the corresponding model; or
   ii) Fit various (low-order) ARMA models (various ways; often (conditional) MLE);
   iii) Model-selection criterion (e.g. minimal AIC, BIC) $\Rightarrow$ select "best" model; see also the automatic procedure by Tsay and Tiao (1984).
4) Residual analysis

i) Consider the residuals

$$\hat{\varepsilon}_t = X_t - \hat{\mu}_t, \quad \hat{\mu}_t = \hat{\mu} + \sum_{k=1}^{p} \hat{\phi}_k (X_{t-k} - \hat{\mu}) + \sum_{k=1}^{q} \hat{\theta}_k \hat{\varepsilon}_{t-k},$$

typically recursively computed (e.g. by letting the first q $\hat{\varepsilon}$'s be 0 and the first p X's be $\bar{X}_n$).

ii) Check the model assumptions via plots, ACF, Ljung–Box, etc.

4.1.5 Prediction

Let $X_{t-n+1}, \dots, X_t$ denote the available data at time t and suppose we want to compute $P_t X_{t+1}$. Assume we have the history $\mathcal{F}_t = \sigma(\{X_s : s \leq t\})$ of the underlying ARMA model available (including today t). Two approaches are possible.

Conditional expectation ($\mathbb{E}(X_{t+h}\,|\,\mathcal{F}_t)$ is best L^2 approx. to X_{t+h})

Let the ARMA $(X_t)_{t\in\mathbb{Z}}$ be invertible and $(\varepsilon_t)_{t\in\mathbb{Z}}$ be a MGDS w.r.t. $(\mathcal{F}_t)_{t\in\mathbb{Z}}$. Since $\mathbb{E}(X_{t+h}\,|\,\mathcal{F}_t)$ minimizes $\mathbb{E}((X_{t+h}-\cdot)^2)$, $P_tX_{t+h} = \mathbb{E}(X_{t+h}\,|\,\mathcal{F}_t)$ $\Rightarrow$ Compute $\mathbb{E}(X_{t+h}\,|\,\mathcal{F}_t)$ recursively in terms of $\mathbb{E}(X_{t+h-1}\,|\,\mathcal{F}_t)$. Use that $\mathbb{E}(\varepsilon_{t+h}\,|\,\mathcal{F}_t)=0$ and that $(X_s)_{s\le t}$, $(\varepsilon_s)_{s\le t}$ are "known" at time t (invertibility insures that ε_t can be written as a function of $(X_s)_{s\le t}$).

Example 4.14 (Prediction in the $\mathrm{ARMA}(1,1)$ model)

$\mathrm{ARMA}(1,1)$: $X_t-\mu=\phi_1(X_{t-1}-\mu)+\varepsilon_t+\theta_1\varepsilon_{t-1}$. Then

$$\begin{aligned}
\mathbb{E}(X_{t+1}\,|\,\mathcal{F}_t) &= \mu+\phi_1(X_t-\mu)+\theta_1\varepsilon_t+\underbrace{\mathbb{E}(\varepsilon_{t+1}\,|\,\mathcal{F}_t)}_{\underset{\text{MGDS}}{=}0};\\
\mathbb{E}(X_{t+2}\,|\,\mathcal{F}_t) &= \mu+\phi_1\mathbb{E}(X_{t+1}\,|\,\mathcal{F}_t)-\phi_1\mu\\
&\quad +\theta_1\underbrace{\mathbb{E}(\varepsilon_{t+1}\,|\,\mathcal{F}_t)}_{=0}+\underbrace{\mathbb{E}(\varepsilon_{t+2}\,|\,\mathcal{F}_t)}_{=0}\\
&= \mu+\phi_1(\mathbb{E}(X_{t+1}\,|\,\mathcal{F}_t)-\mu)=\mu+\phi_1^2(X_t-\mu)+\phi_1\theta_1\varepsilon_t;\\
\mathbb{E}(X_{t+h}\,|\,\mathcal{F}_t) &= \ldots = \mu+\phi_1^h(X_t-\mu)+\phi_1^{h-1}\theta_1\varepsilon_t \underset{(h\to\infty)}{\to} \mu.
\end{aligned}$$

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Exponentially weighted moving averages

- Typically directly applied to price series;
- Used for trend estimation and prediction;
- Assume there is no deterministic seasonal component;
- Prediction

$$P_t X_{t+1} = \alpha X_t + (1-\alpha) P_{t-1} X_t = \sum_{k=0}^{n-1} \alpha (1-\alpha)^k X_{t-k}.$$

Increasing $\alpha \in (0,1)$ puts more weight on the last observation.

4.2 GARCH models for changing volatility

- (G)ARCH = (generalized) autoregressive conditionally heteroscedastic
- They are the most important models for daily risk-factor returns.

4.2.1 ARCH processes

Definition 4.15 ($\mathrm{ARCH}(p)$)
Let $(Z_t)_{t\in\mathbb{Z}} \sim \mathrm{SWN}(0,1)$. $(X_t)_{t\in\mathbb{Z}}$ is an $\mathrm{ARCH}(p)$ *process* if it is strictly stationary and satisfies

$$X_t = \sigma_t Z_t,$$

$$\sigma_t^2 = \alpha_0 + \sum_{k=1}^{p} \alpha_k X_{t-k}^2,$$

where $\alpha_0 > 0$, $\alpha_k \geq 0$, $k \in \{1,\dots,p\}$.

Typical examples: $Z_t \overset{\text{ind.}}{\sim} \mathrm{N}(0,1)$ or $Z_t \overset{\text{ind.}}{\sim} t_\nu(0,(\nu-2)/\nu)$.

Remark 4.16

1) σ_{t+1} is $\mathcal{F}_t$-measurable $\Rightarrow \mathbb{E}(X_{t+1}\,|\,\mathcal{F}_t) = \sigma_{t+1}\mathbb{E}(Z_{t+1}\,|\,\mathcal{F}_t) = \sigma_{t+1}\mathbb{E}(Z_{t+1}) = 0$. Thus, $\mathrm{ARCH}(p)$ processes are MGDSs w.r.t. the natural filtration $(\mathcal{F}_t)_{t\in\mathbb{Z}}$. If they are stationary, they are white noise since

$$\begin{aligned}\gamma(h) = \mathbb{E}(X_t X_{t+h}) &\overset{\text{tower}}{\underset{\text{property}}{=}} \mathbb{E}(\mathbb{E}(X_t X_{t+h}\,|\,\mathcal{F}_{t+h-1})) \\ &= \mathbb{E}(X_t\mathbb{E}(X_{t+h}\,|\,\mathcal{F}_{t+h-1})) = 0, \quad h\in\mathbb{N}.\end{aligned}$$

This also applies to GARCH processes; see below.

2) If $(X_t)_{t\in\mathbb{Z}}$ is stationary, then $\mathrm{var}(X_t\,|\,\mathcal{F}_{t-1}) = \mathbb{E}((\sigma_t Z_t)^2\,|\,\mathcal{F}_{t-1}) = \sigma_t^2\mathbb{E}(Z_t^2\,|\,\mathcal{F}_{t-1}) = \sigma_t^2\mathbb{E}(Z_t^2) = \sigma_t^2$.

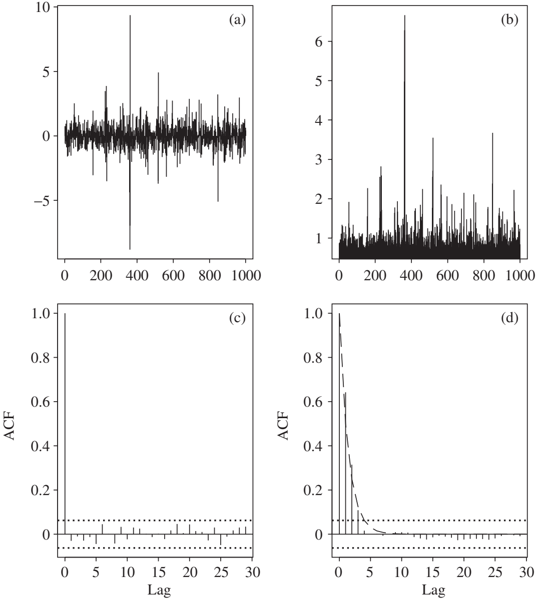
$\Rightarrow$ *Volatility* σ_t (conditional standard deviation) is changing in time, depending on past values of the process. ARCH models can thus capture *volatility clustering* (if one of $|X_{t-1}|,\dots,|X_{t-p}|$ is large, X_t is drawn from a distribution with large variance). This is where "autoregressive conditionally heteroscedastic" comes from.

Example 4.17 ($\mathrm{ARCH}(1)$)

- One can show that an $\mathrm{ARCH}(1)$ process $(X_t)_{t\in\mathbb{Z}}$ is strictly stationary $\Leftrightarrow \mathbb{E}(\log(\alpha_1 Z_t^2)) < 0$. In this case, $X_t^2 = \alpha_0 \sum_{k=0}^{\infty} \alpha_1^k \prod_{j=0}^{k} Z_{t-j}^2$.
- $(X_t)_{t\in\mathbb{Z}}$ is stationary $\Leftrightarrow \alpha_1 < 1$. In this case, $\mathrm{var}(X_t) = \alpha_0/(1-\alpha_1)$.

  Proof of necessity. $X_t^2 = \sigma_t^2 Z_t^2 = (\alpha_0 + \alpha_1 X_{t-1}^2) Z_t^2 \Rightarrow \sigma_X^2 = \mathbb{E}(X_t^2) = \alpha_0 + \alpha_1 \mathbb{E}(X_{t-1}^2 Z_t^2) = \alpha_0 + \alpha_1 \sigma_X^2 \Rightarrow \sigma_X^2 = \frac{\alpha_0}{1-\alpha_1}$, $\alpha_1 < 1$. □

  For sufficiency, see MFE (2015, Proposition 4.18).
- Provided that $\mathbb{E}(Z_t^4) < \infty$ and $\alpha_1 < (\mathbb{E}(Z_t^4))^{-1/2}$, one can show that $\kappa(X_t) = \frac{\mathbb{E}(X_t^4)}{\mathbb{E}(X_t^2)^2} = \frac{\kappa(Z_t)(1-\alpha_1^2)}{(1-\alpha_1^2\kappa(Z_t))}$. If $\kappa(Z_t) > 1$, $\kappa(X_t) > \kappa(Z_t)$. For Gaussian or t innovations, $\kappa(X_t) > 3$ (leptokurtic).
- Parallels with the AR(1) process: If $\mathbb{E}(X_t^4) < \infty$, $\alpha_1 < 1$ and $\varepsilon_t = \sigma_t^2(Z_t^2 - 1)$, one can show that $(X_t^2)_{t\in\mathbb{Z}}$ is an $\mathrm{AR}(1)$ of the form $X_t^2 - \frac{\alpha_0}{1-\alpha_1} = \alpha_1(X_{t-1}^2 - \frac{\alpha_0}{1-\alpha_1}) + \varepsilon_t$.



a) $n = 1000$ realizations of an $\mathrm{ARCH}(1)$ process with $\alpha_0 = 0.5$, $\alpha_1 = 0.5$ and Gaussian innovations;
b) Realization of the volatility $(\sigma_t)_{t\in\mathbb{Z}}$;
c) Correlogram of $(X_t)_{t\in\mathbb{Z}}$, compare with Remark 4.16 1);
d) Correlogram of $(X_t^2)_{t\in\mathbb{Z}}$ (AR(1)); dashed line = true ACF

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4.2.2 GARCH processes

Definition 4.18 ($\mathrm{GARCH}(p, q)$)
Let $(Z_t)_{t\in\mathbb{Z}} \sim \mathrm{SWN}(0, 1)$. $(X_t)_{t\in\mathbb{Z}}$ is a $\mathrm{GARCH}(p, q)$ *process* if it is strictly stationary and satisfies

$$X_t = \sigma_t Z_t,$$

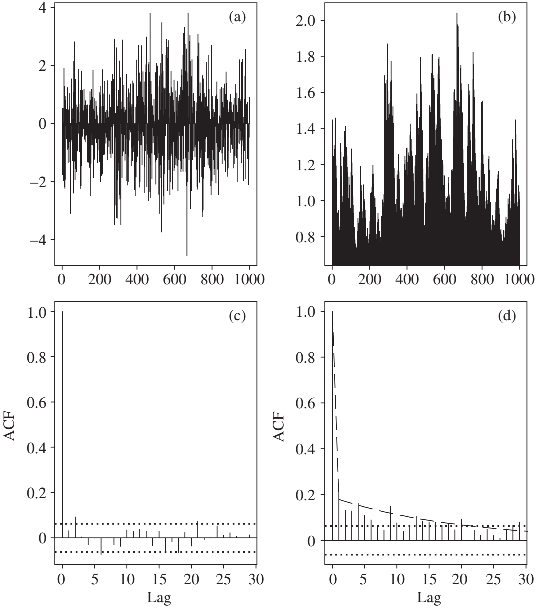
$$\sigma_t^2 = \alpha_0 + \sum_{k=1}^{p} \alpha_k X_{t-k}^2 + \sum_{k=1}^{q} \beta_k \sigma_{t-k}^2,$$

where $\alpha_0 > 0$, $\alpha_k \geq 0$, $k \in \{1, \dots, p\}$, $\beta_k \geq 0$, $k \in \{1, \dots, q\}$.

If one of $|X_{t-1}|, \dots, |X_{t-p}|$ or $\sigma_{t-1}, \dots, \sigma_{t-q}$ is large, X_t is drawn from a distribution with (persistently) large variance. Periods of high volatility tend to be more persistent.

Example 4.19 ($\mathrm{GARCH}(1,1)$)

- One can show (via stoch. recurrence relations) that a $\mathrm{GARCH}(1,1)$ process $(X_t)_{t\in\mathbb{Z}}$ is strictly stationary if $\mathbb{E}(\log(\alpha_1 Z_t^2+\beta_1))<\infty$. In this case, $X_t = Z_t\sqrt{\alpha_0(1+\sum_{k=1}^{\infty}\prod_{j=1}^{k}(\alpha_1 Z_{t-j}^2+\beta_1))}$.
- $(X_t)_{t\in\mathbb{Z}}$ is stationary $\Leftrightarrow$ $\alpha_1+\beta_1<1$. In this case, $\mathrm{var}(X_t)=\frac{\alpha_0}{1-\alpha_1-\beta_1}$.
- $\mathrm{GARCH}(1,1)$ is typically leptokurtic:
  Provided that $\mathbb{E}((\alpha_1 Z_t^2+\beta_1)^2)<1$ (or $(\alpha_1+\beta_1)^2<1-(\kappa(Z_t)-1)\alpha_1^2$), one can show that $\kappa(X_t)=\frac{\kappa(Z_t)(1-(\alpha_1+\beta_1)^2)}{1-(\alpha_1+\beta_1)^2-(\kappa(Z_t)-1)\alpha_1^2}$.
  If $\kappa(Z_t)>1$ (Gaussian, scaled t innovations), $\kappa(X_t)>\kappa(Z_t)$.
- Parallels with the ARMA(1,1) process:
  If $\mathbb{E}(X_t^4)<\infty$, $\alpha_1+\beta_1<1$ and $\varepsilon_t=\sigma_t^2(Z_t^2-1)$, one can show that $(X_t^2)_{t\in\mathbb{Z}}$ is an $\mathrm{ARMA}(1,1)$ of the form $X_t^2-\frac{\alpha_0}{1-\alpha_1-\beta_1}=(\alpha_1+\beta_1)(X_{t-1}^2-\frac{\alpha_0}{1-\alpha_1-\beta_1})+\varepsilon_t-\beta_1\varepsilon_{t-1}$.



a) $n = 1000$ realization of a $\mathrm{GARCH}(1,1)$ process with $\alpha_0 = 0.5$, $\alpha_1 = 0.1$, $\beta_1 = 0.85$ and Gaussian innovations;

b) Realization of the volatility $(\sigma_t)_{t\in\mathbb{Z}}$;

c) Correlogram of $(X_t)_{t\in\mathbb{Z}}$, compare with Remark 4.16 1);

d) Correlogram of $(X_t^2)_{t\in\mathbb{Z}}$ (ARMA(1,1)); dashed line $=$ true ACF

Prediction of GARCH(1,1)

Assume $(X_t)_{t\in\mathbb{Z}}$ is a stationary $\mathrm{GARCH}(1,1)$ with $\mathbb{E}(X_t^4) < \infty$.

- $X_t = \sigma_t Z_t \Rightarrow \mathbb{E}(X_t \,|\, \mathcal{F}_{t-1}) = \sigma_t \mathbb{E}(Z_t) = 0$, so $(X_t)_{t\in\mathbb{Z}}$ is MGDS and thus, by the tower property, $\mathbb{E}(X_{t+h} \,|\, \mathcal{F}_t) = 0,\ h \in \mathbb{N}$.
- $\mathbb{E}(X_{t+1}^2 \,|\, \mathcal{F}_t) = \sigma_{t+1}^2 \mathbb{E}(Z_{t+1}) = \alpha_0 + \alpha_1 X_t^2 + \beta_1 \sigma_t^2$.
  For $h \geq 2$, X_{t+h}^2 and σ_{t+h}^2 are rvs, and

$$\mathbb{E}(X_{t+h}^2 \,|\, \mathcal{F}_t) \underset{(*)}{=} \mathbb{E}(\sigma_{t+h}^2 \,|\, \mathcal{F}_t)\mathbb{E}(Z_t^2) = \alpha_0 + \alpha_1 \mathbb{E}(X_{t+h-1}^2 \,|\, \mathcal{F}_t)$$

$$+ \beta_1 \underbrace{\mathbb{E}(\sigma_{t+h-1}^2 \,|\, \mathcal{F}_t)}_{\underset{(*)}{=} \mathbb{E}(X_{t+h-1}^2 | \mathcal{F}_t)} = \alpha_0 + (\alpha_1 + \beta_1)\mathbb{E}(X_{t+h-1}^2 \,|\, \mathcal{F}_t)$$

$$= \ldots = \alpha_0 \sum_{k=0}^{h-1} (\alpha_1 + \beta_1)^k + (\alpha_1 + \beta_1)^{h-1}(\alpha_1 X_t^2 + \beta_1 \sigma_t^2).$$

$$\Rightarrow \mathbb{E}(\sigma_{t+h}^2 \,|\, \mathcal{F}_t) \underset{\mathbb{E}(Z_t^2 | F_t) = 1}{=} \mathbb{E}(X_{t+h}^2 \,|\, \mathcal{F}_t) \underset{(h \to \infty)}{\overset{\text{a.s.}}{\to}} \frac{\alpha_0}{1 - \alpha_1 - \beta_1} = \mathrm{var}(X_t).$$

The GARCH(p,q) model

- Higher-order GARCH models have the same general behaviour as $\mathrm{ARCH}(1)$ and $\mathrm{GARCH}(1,1)$ models, but their mathematical analysis becomes more tedious.
- One can show that $(X_t)_{t\in\mathbb{Z}}$ is stationary $\Leftrightarrow \sum_{k=1}^{p} \alpha_k + \sum_{k=1}^{q} \beta_k < 1$.
- A squared $\mathrm{GARCH}(p,q)$ process has the structure

$$X_t^2 = \alpha_0 + \sum_{k=1}^{\max(p,q)} (\alpha_k + \beta_k) X_{t-k}^2 + \varepsilon_t - \sum_{k=1}^{q} \beta_k \varepsilon_{t-k},$$

  where $\varepsilon_t = \sigma_t^2(Z_t^2 - 1)$, $\alpha_k = 0$, $k \in \{p+1, \dots, q\}$ if $q > p$, or $\beta_k = 0$ for $k \in \{q+1, \dots, p\}$ if $p > q$. This resembles the $\mathrm{ARMA}(\max(p,q), q)$ process and is formally such a process provided $\mathbb{E}(X_t^4) < \infty$.
- There are also *IGARCH models* (i.e. non-stationary $\mathrm{GARCH}(p,q)$ models with $\sum_{k=1}^{p} \alpha_k + \sum_{k=1}^{q} \beta_k = 1$; infinite variance).

4.2.3 Simple extensions of the GARCH model

Consider stationary GARCH processes as white noise for ARMA processes.

Definition 4.20 ($\mathrm{ARMA}(p_1, q_1)$ with $\mathrm{GARCH}(p_2, q_2)$ errors)
Let $(Z_t)_{t\in\mathbb{Z}} \sim \mathrm{SWN}(0,1)$. $(X_t)_{t\in\mathbb{Z}}$ is an $\mathrm{ARMA}(p_1, q_1)$ *process with* $\mathrm{GARCH}(p_2, q_2)$ *errors* if it is stationary and satisfies

$$X_t = \mu_t + \varepsilon_t \quad \text{for} \quad \varepsilon_t = \sigma_t Z_t \quad (\text{so } X_t = \mu_t + \sigma_t Z_t),$$

$$\mu_t = \mu + \sum_{k=1}^{p_1} \phi_k (X_{t-k} - \mu) + \sum_{k=1}^{q_1} \theta_k \underbrace{(X_{t-k} - \mu_{t-k})}_{=\varepsilon_{t-k}},$$

$$\sigma_t^2 = \alpha_0 + \sum_{k=1}^{p_2} \alpha_k (X_{t-k} - \mu_{t-k})^2 + \sum_{k=1}^{q_2} \beta_k \sigma_{t-k}^2,$$

where $\alpha_0 > 0$, $\alpha_k \geq 0$, $k \in \{1, \dots, p_2\}$, $\beta_k \geq 0$, $k \in \{1, \dots, q_2\}$, $\sum_{k=1}^{p_2} \alpha_k + \sum_{k=1}^{q_2} \beta_k < 1$.

- ARMA models with GARCH errors are quite flexible models. It is easy to see that the conditional mean of $(X_t)_{t\in\mathbb{Z}}$ is $\mu_t = \mathbb{E}(X_t \,|\, \mathcal{F}_{t-1})$ and that the conditional variance of $(X_t)_{t\in\mathbb{Z}}$ is $\sigma_t^2 = \mathrm{var}(X_t \,|\, \mathcal{F}_{t-1})$.
- Other extensions not futher discussed here:
  - *GJR-GARCH*. These models introduce a parameter in the volatility equation in order for the volatility to react asymmetrically to recent returns (bad news leading to a fall in the equity value of a company tends to increase volatility, the so-called *leverage effect*).
  - *Threshold GARCH (TGARCH)*. More general models (than GJR-GARCH) in which the dynamics at time t depend on whether X_{t-1} (or Z_{t-1}; sometimes even a coefficient) was below/above a threshold.
  - Note that one could also use an asymmetric innovation distribution with mean 0 and variance 1, e.g. from the generalized hyperbolic family or skewed t distribution.

4.2.4 Fitting GARCH models to data

Building the likelihood

- The most widely used approach is maximum likelihood. We first consider $\text{ARCH}(1)$ and $\text{GARCH}(1,1)$ models, the general case easily follows.
- $\text{ARCH}(1)$. Supose we have data $X_0, X_1, \dots, X_n$. The joint density can be written as

$$\begin{aligned} f_{X_0,\dots,X_n}(X_0,\dots,X_n) &= f_{X_0}(X_0)\prod_{t=1}^{n} f_{X_t\,|\,X_{t-1},\dots,X_0}(X_t\,|\,X_{t-1},\dots,X_0)\\ &= f_{X_0}(X_0)\prod_{t=1}^{n} f_{X_t\,|\,X_{t-1}}(X_t\,|\,X_{t-1})\\ &= f_{X_0}(X_0)\prod_{t=1}^{n}\frac{1}{\sigma_t} f_Z\Big(\frac{X_t}{\sigma_t}\Big), \end{aligned}$$

  where $\sigma_t = \sqrt{\alpha_0 + \alpha_1 X_{t-1}^2}$ and f_Z denotes the density of the innovations $(Z_t)_{t\in\mathbb{Z}}$ (mean 0, variance 1; typically $\mathrm{N}(0,1)$ or $t_\nu(0, \frac{\nu-2}{\nu})$). The problem is that f_{X_0} is not known in tractable form. One thus typically considers the conditional likelihood given X_0

$$L(\alpha_0, \alpha_1; X_0, \dots, X_n) = f_{X_1,\dots,X_n | X_0}(X_1, \dots, X_n \,|\, X_0)$$
$$= \frac{f_{X_0,\dots,X_n}(X_0, \dots, X_n)}{f_{X_0}(X_0)} = \prod_{t=1}^{n} \frac{1}{\sigma_t} f_Z\Big(\frac{X_t}{\sigma_t}\Big).$$

Similarly for $\mathrm{ARCH}(p)$ models, one considers the likelihood conditional the first p values.

- $\mathrm{GARCH}(1,1)$. Here we construct the joint density of $X_1, \dots, X_n$ conditional on both X_0 and σ_0, so

$$L(\alpha_0, \alpha_1, \beta_1; X_0, \dots, X_n) = f_{X_1,\dots,X_n | X_0, \sigma_0}(X_1, \dots, X_n \,|\, X_0, \sigma_0)$$
$$= \prod_{t=1}^{n} f_{X_t | X_{t-1},\dots,X_0,\sigma_0}(X_t \,|\, X_{t-1}, \dots, X_0, \sigma_0) = \prod_{t=1}^{n} f_{X_t|\sigma_t}(X_t \,|\sigma_t)$$
$$= \prod_{t=1}^{n} \frac{1}{\sigma_t} f_Z\Big(\frac{X_t}{\sigma_t}\Big), \quad \text{where } \sigma_t = \sqrt{\alpha_0 + \alpha_1 X_{t-1}^2 + \beta_1 \sigma_{t-1}^2}.$$

Note that σ_0^2 is not observed. One typically chooses the sample variance of $X_1, \dots, X_n$ (or 0) as starting values.

- Similarly for ARMA models with GARCH errors. In this case,

$$L(\boldsymbol{\theta}; X_0, \dots, X_n) = \prod_{t=1}^{n} \frac{1}{\sigma_t} f_Z\Big(\frac{X_t - \mu_t}{\sigma_t}\Big)$$

for the ARMA specification for μ_t and the GARCH specification for σ_t; all parameters are collected in $\boldsymbol{\theta}$, including unknown parameters of the innovation distribution. The *log-likelihood* is thus given by

$$\ell(\boldsymbol{\theta}; X_0, \dots, X_n) = \sum_{t=1}^{n} \ell_t(\boldsymbol{\theta}) = \sum_{t=1}^{n} \log\Big(\frac{1}{\sigma_t} f_Z\Big(\frac{X_t - \mu_t}{\sigma_t}\Big)\Big).$$

- Extensions to models with leverage or threshold effects are also possible.
- The log-likelihood ℓ is typically maximized numerically to obtain $\hat{\boldsymbol{\theta}}_n$.

Model checking

- After model fitting, we check residuals. Consider an ARMA model with GARCH errors $X_t = \mu_t + \varepsilon_t = \mu_t + \sigma_t Z_t$; see Definition 4.20.
- We distinguish two kinds of residuals:
  1) *Unstandardized residuals*. These are the residuals $\hat{\varepsilon}_1, \dots, \hat{\varepsilon}_n$ and should behave like a realization of a GARCH process.
  2) *Standardized residuals*. These are reconstructed realizations of the SWN which drives the GARCH process. They are calculated from the unstandardized residuals via

$$\hat{Z}_t = \hat{\varepsilon}_t / \hat{\sigma}_t, \quad \hat{\sigma}_t^2 = \hat{\alpha}_0 + \sum_{k=1}^{p_2} \hat{\alpha}_k \hat{\varepsilon}_{t-k}^2 + \sum_{k=1}^{q_2} \hat{\beta}_k \hat{\sigma}_{t-k}^2; \tag{8}$$

  starting values for $\hat{\varepsilon}_t$ are taken as 0 and starting values for $\hat{\sigma}_t$ are taken as the sample variance (or 0); ignore the first few values then.
- The standardized residuals should behave like SWN. Check this via correlograms of $(\hat{Z}_t)$ and $(|\hat{Z}_t|)$ and by applying the Ljung–Box test

of strict white noise. In case of no rejection (the dynamics have been satisfactorily captured), the validity of the innovation distribution can also be assessed (e.g. via Q-Q plots or goodness-of-fit tests).

$\Rightarrow$ *Two-stage analysis* possible: First estimate the dynamics via QMLE (known as *pre-whitening* of the data), then model the innovation distribution using the standardized residuals.

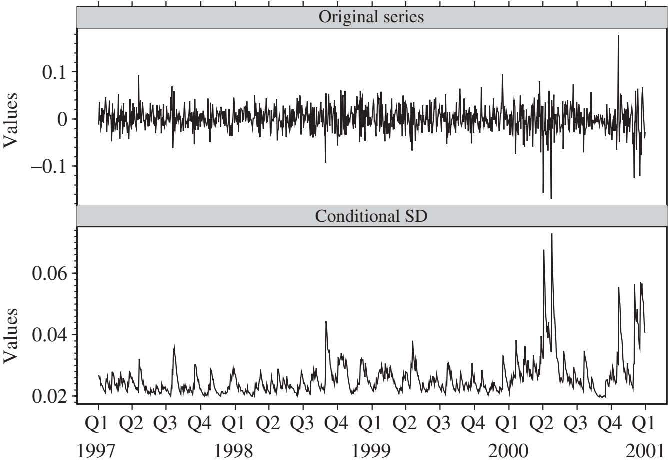
Advantages:
- More transparency in model building;
- Separating of volatility modelling and modelling of shocks that drive the process;
- Practical in higher dimensions.

Drawbacks: ARMA fitting errors propagate through to the fitting of innovations (overall error hard to quantify).

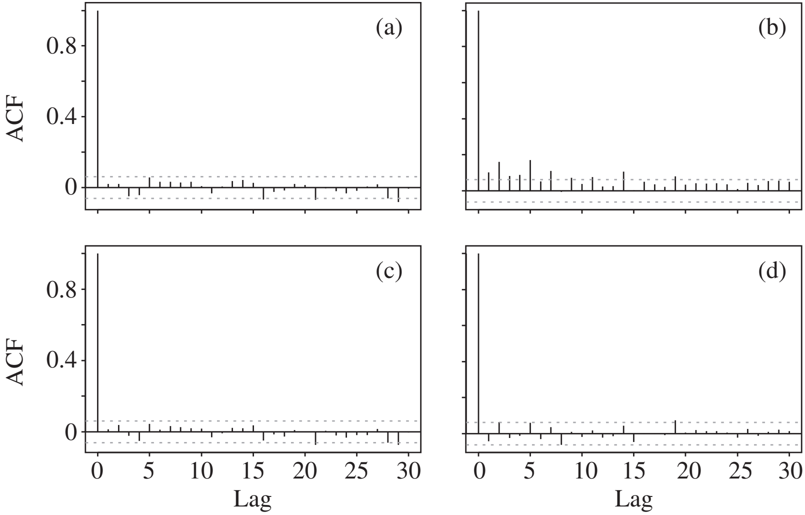
Example 4.21 (GARCH model for Microsoft log-returns)

- Consider Microsoft daily log-returns from 1997–2000 (1009 values). The raw returns show no evidence of serial correlation, the absolute values do (Ljung–Box test based on the first 10 estimated correlations fails at the 5% level).
- Various models with t innovations are fitted via MLE: $\mathrm{GARCH}(1,1)$, $\mathrm{AR}(1)$–$\mathrm{GARCH}(1,1)$, $\mathrm{MA}(1)$–$\mathrm{GARCH}(1,1)$, $\mathrm{ARMA}(1,1)$–$\mathrm{GARCH}(1,1)$. The basic $\mathrm{GARCH}(1,1)$ is favored according to Akaike's information criterion.
- A model GRJ model further improves the fit (both raw and absolute standardized residuals show no serieal correlation; Ljung–Box does not reject).

Microsoft log-returns 1997–2000: Data (top) and estimated volatitlity (bottom) from a $\mathrm{GJR\text{-}GARCH}(1,1)$.



Correlograms of a) (X_t); b) $(|X_t|)$; c) $(\hat{Z}_t)$; and d) $(|\hat{Z}_t|)$



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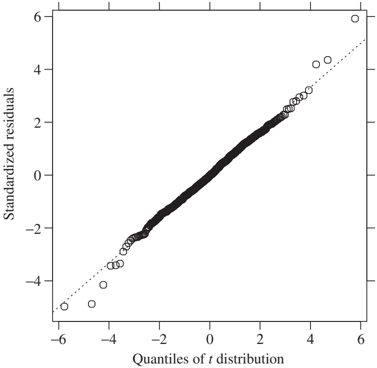
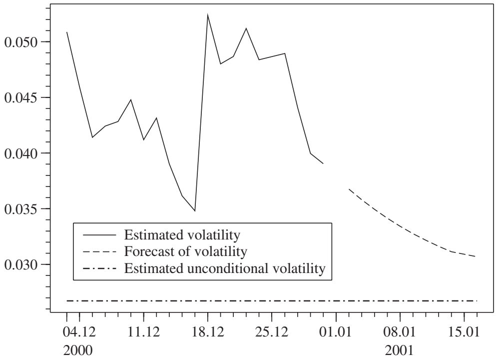
Q-Q plot of the standardized residuals (left); Estimated and predicted volatility (right) for the first 10 days of 2001 for a $\mathrm{GARCH}(1,1)$ model.





4.2.5 Volatility forecasting and risk measure estimation

- Consider a weakly and strictly stationary time series $(X_t)_{t\in\mathbb{Z}}$ of the form

$$X_t = \mu_t + \sigma_t Z_t$$

  adapted to a filtration $(\mathcal{F}_t)_{t\in\mathbb{Z}}$, where $\mu_t, \sigma_t \in \mathcal{F}_{t-1}$ and $\mathbb{E}Z_t = 0$, $\operatorname{var} Z_t = 1$, independent of $\mathcal{F}_{t-1}$ (e.g. $(X_t)_{t\in\mathbb{Z}}$ could be a GARCH model or ARMA model with GARCH errors).
- Assume we know $X_{t-n+1}, \dots, X_t$ and want to compute $P_t\sigma_{t+h}$, $h \ge 1$, a forecast of volatility based on these data.
- Since $\mathbb{E}(\sigma_{t+h}^2 \,|\, \mathcal{F}_t) = \mathbb{E}((X_{t+h} - \mu_{t+h})^2 \,|\, \mathcal{F}_t)$ our forecasting problem is related to the problem of predicting $(X_{t+h} - \mu_{t+h})^2$.
- We consider two approaches: (1) calculating conditional expectations (optimal squared error forecasts) using model of GARCH type; (2) the more ad hoc exponentially weighted moving average (EWMA) approach.

Conditional expectation

The general procedure becomes clear from examples.

Example 4.22 (Prediction in the $\mathrm{GARCH}(1,1)$ model)

- A $\mathrm{GARCH}(1,1)$ model is of type $X_t = \mu_t + \sigma_t Z_t$ for $\mu_t = 0$. Since $\mathbb{E}(X_{t+h} \,|\, \mathcal{F}_t) = 0$, $\hat{\mu}_{t+h} = P_t X_{t+h} = 0$ for all $h \in \mathbb{N}$.
- A natural prediction of X_{t+1}^2 based on $\mathcal{F}_t$ is its conditional mean
$$\mathbb{E}(X_{t+1}^2 \,|\, \mathcal{F}_t) = \sigma_{t+1}^2 = \alpha_0 + \alpha_1 X_t^2 + \beta_1 \sigma_t^2.$$
If $\mathbb{E}(X_t^4) < \infty$, this is the optimal squared error prediction.
- We thus obtain the one-step-ahead forecast
$$\hat{\sigma}_{t+1}^2 = \widehat{\mathbb{E}(X_{t+1}^2 \,|}\, \mathcal{F}_t) = \alpha_0 + \alpha_1 X_t^2 + \beta_1 \hat{\sigma}_t^2.$$
- If $h > 1$, σ_{t+h}^2 and X_{t+h}^2 are rvs. Their predictions (coincide and) are
$$\begin{aligned}\mathbb{E}(\sigma_{t+h}^2 \,|\, \mathcal{F}_t) &= \alpha_0 + \alpha_1 \mathbb{E}(X_{t+h-1}^2 \,|\, \mathcal{F}_t) + \beta_1 \mathbb{E}(\sigma_{t+h-1}^2 \,|\, \mathcal{F}_t) \\ &= \alpha_0 + (\alpha_1 + \beta_1)\mathbb{E}(\sigma_{t+h-1}^2 \,|\, \mathcal{F}_t)\end{aligned}$$

so that a general formula is

$$\mathbb{E}(\sigma_{t+h}^2 \,|\, \mathcal{F}_t) = \alpha_0 \sum_{k=0}^{h-1} (\alpha_1 + \beta_1)^k + (\alpha_1 + \beta_1)^{h-1} (\alpha_1 X_t^2 + \beta_1 \sigma_t^2).$$

Note that for $h \to \infty$, $\mathbb{E}(\sigma_{t+h}^2 \,|\, \mathcal{F}_t) \overset{\text{a.s.}}{\to} \frac{\alpha_0}{1-\alpha_1-\beta_1}$, so the prediction of squared volatility converges to the unconditional variance of the process.

Example 4.23 (Prediction in the $\mathrm{ARMA}(1,1)$–$\mathrm{GARCH}(1,1)$ model)
Let $X_t = \mu_t + \sigma_t Z_t = \mu_t + \varepsilon_t$ as before. It follows from Examples 4.14 and 4.22 that

$$\mathbb{E}(X_{t+h} \,|\, \mathcal{F}_t) = \mu + \phi_1^h (X_t - \mu) + \phi_1^{h-1} \theta_1 \varepsilon_t,$$

$$\mathrm{var}(X_{t+h} \,|\, \mathcal{F}_t) = \alpha_0 \sum_{k=0}^{h-1} (\alpha_1 + \beta_1)^k + (\alpha_1 + \beta_1)^{h-1} (\alpha_1 \varepsilon_t^2 + \beta_1 \sigma_t^2).$$

For ε_t, σ_t, substitute values obtained from (8).

Exponentially weighted moving averages

- A one-period ahead forecast $P_t Y_{t+1}$ of a generic Y_{t+1} based on $\mathcal{F}_t$ is given by

$$P_0 Y_1 = 0, \quad P_t Y_{t+1} = \alpha Y_t + (1-\alpha) P_{t-1} Y_t, \quad t \geq 1. \tag{9}$$

  With $Y_{t+1} = (X_{t+1} - \mu_{t+1})^2$ one obtains

$$P_t (X_{t+1} - \mu_{t+1})^2 = \alpha (X_t - \mu_t)^2 + (1-\alpha) P_{t-1} (X_t - \mu_t)^2. \tag{10}$$

- Since $\sigma_{t+1}^2 = \mathbb{E}((X_{t+1} - \mu_{t+1})^2 \mid \mathcal{F}_t)$, we can use (10) as exponential smoothing scheme for the unobserved squared volatility σ_{t+1}^2. This yields a recursive scheme for the one-step-ahead volatility forecast given by

$$\hat{\sigma}_{t+1}^2 = \alpha (X_t - \hat{\mu}_t)^2 + (1-\alpha) \hat{\sigma}_t^2,$$

  which is then iterated.
- α is typically small (e.g. RiskMetrics: $\alpha = 0.06$); $\hat{\mu}_t$ is usually set to 0 (see Chapter 3).

Forecasting VaR_α and ES_α

- Suppose we now want to forecast $\mathrm{VaR}_\alpha^{t+1}$, ES_α^{t+1}, risk measures based on the conditional df $F_{X_{t+1}|\mathcal{F}_t}$; think of $\mathcal{F}_t$ as all random quantities known/observed up to and including t.
- If $Z_t \overset{\text{ind.}}{\sim} F_Z$, this $\mathcal{F}_t$-measurability of μ_{t+1} and σ_{t+1}, and $X_{t+1} = \mu_{t+1} + \sigma_{t+1} Z_{t+1}$ imply that

$$F_{X_{t+1}|\mathcal{F}_t}(x) = \mathbb{P}(\mu_{t+1} + \sigma_{t+1} Z_{t+1} \le x \,|\, \mathcal{F}_t) = F_Z\Big(\frac{x - \mu_{t+1}}{\sigma_{t+1}}\Big),$$

  so

$$\mathrm{VaR}_\alpha^{t+1} = \mu_{t+1} + \sigma_{t+1} F_Z^{\leftarrow}(\alpha),$$
$$\mathrm{ES}_\alpha^{t+1} = \mu_{t+1} + \sigma_{t+1} \mathrm{ES}_\alpha(Z).$$

- If we have estimated σ_{t+1} (and μ_{t+1}; often taken as 0) it only remains to estimate $F_Z^{\leftarrow}(\alpha)$ and $\mathrm{ES}_\alpha(Z)$.
  - For GARCH-type models it is easy to calculate $F_Z^{\leftarrow}(\alpha)$ and $\mathrm{ES}_\alpha(Z)$ (typically $Z \overset{\text{ind.}}{\sim} \mathrm{N}(0,1)$ or $t_\nu(0, \nu/(\nu-2))$).

- If we use exponential smoothing or QMLE to estimate μ_{t+1}, σ_{t+1}, we can use the residuals

$$\hat{Z}_s = (X_s - \hat{\mu}_s)/\hat{\sigma}_s, \quad s \in \{t-n+1, \dots, n\},$$

to estimate $F_Z^{\leftarrow}(\alpha)$ and $\mathrm{ES}_\alpha(Z)$.

References

Brockwell, P. J. and Davis, R. A. (1991), Time Series: Theory and Methods, 2nd, New York: Springer.

Tsay, R. S. and Tiao, G. C. (1984), Consistent estimates of autoregressive parameters and extended sample autocorrelation function for stationary and nonstationary ARMA models, *Journal of the American Statistical Association*, 79, 84–96.