Practical 2: GJR-copula

Quantitative Risk Management

Introduction

The aim of this practical is to model stock returns by taking into account heteroskedasticity as well as the non-normality of innovations with a GJR model, and the possibly nontrivial crosssectional dependence via a copula model. Specifically, we assume that the stock log-returns follow:

$$x_{i,t} = \mu_i + \varepsilon_{i,t}, \quad i = 1, \dots, D, \quad t = 1, \dots, T$$
(1)

where $\varepsilon_{i,t} = \sigma_{i,t} z_{i,t}$, μ_i is the mean, $\sigma_{i,t}^2$ is the time-*t* conditional variance, and $z_{i,t}$ is an innovation. The variance follows the GJR-GARCH(1,1,1) model given by:

$$\sigma_{i,t}^2 = \omega_i + (\alpha_i + \gamma_i \mathbf{1}_{\{\varepsilon_{i,t-1} < 0\}})\varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2,$$
(2)

where the indicator function $\mathbf{1}_{\{x\}}$ equals to 1 if condition x is satisfied and 0 otherwise. The model has the following constraints to satisfy the stationarity and positivity:

for each stock i,

- $\omega_i > 0$
- $\alpha_i, \beta_i \ge 0$
- $\alpha_i + \gamma_i \ge 0$
- $\alpha_i + \gamma_i + \beta_i < 1.$

The innovations $z_{i,t}$ are independent identically distributed (i.i.d.) and follow marginal distribution given by cumulative distribution function $(cdf) F_{\delta_i}$. Furthermore, the joint innovations follow copula C_{θ} :

$$(z_1^T,\ldots,z_D^T)^T \sim C_\theta$$

Useful toolboxes

You are encouraged to code everything by yourself, but you might consider employing the following libraries. The libraries are already installed in Jupyter application at the Nuvolos.

- scipy.stats does not contain a class for the Hansen's skewed t-distribution. However, you may find all necessary methods in SkewStudent class from skewstudent toolbox.¹
- arch_model class from arch.univariate library² has .fit() method for estimation of univariate marginals (Exercise 2-a).

¹https://github.com/khrapovs/skewstudent

²https://arch.readthedocs.io/en/latest/univariate/introduction.html

Exercise 1: simulation

- a) Hand-write an algorithm that generates a GJR-GARCH as in (1)-(2) using the inverse method: $z_{i,t} = F_{\delta_i}^{-1}(u_{i,t})$, where u is a realization of a uniform random variable $U \sim \mathcal{U}(0, 1)$.
- b) Using a), write a code to generate (1)-(2) with innovations distributed according to the Student's t-distribution. Use the inverse *cdf* for the Student's t-distribution.
- c) As in b), but the innovations follow the Hansen's skewed t-distribution. The probability density function (pdf) of the skewed t-distribution is given by:

$$f(z; \eta, \lambda) = \begin{cases} bc \left(1 + \frac{1}{\eta - 2} \left(\frac{bz + a}{1 - \lambda}\right)^2\right)^{-\frac{\eta + 1}{2}}, & \text{if } z < -a/b\\ bc \left(1 + \frac{1}{\eta - 2} \left(\frac{bz + a}{1 + \lambda}\right)^2\right)^{-\frac{\eta + 1}{2}}, & \text{if } z \ge -a/b, \end{cases}$$
(3)

where $a = 4\lambda c \frac{\eta-2}{\eta-1}$, $b^2 = 1 + 3\lambda^2 - a^2$, and $c = \frac{\Gamma(\frac{\eta+1}{2})}{\sqrt{\pi(\eta-2)}\Gamma(\frac{\eta}{2})}$ with $\Gamma(\cdot)$ being the gamma function. The parameters η ($\eta > 2$) and λ ($-1 < \lambda < 1$) are degrees of freedom and a skewness parameter, respectively. What happens if $\lambda = 0$? Generation of the Hansen's skewed t-random variable with the inverse method is obtained using the following equation

$$z = \begin{cases} \frac{1}{b} \left[(1-\lambda)\sqrt{\frac{\eta-2}{\eta}} F_{\eta}^{-1} \left(\frac{u}{1-\lambda}\right) - a \right], & \text{if } u < \frac{1-\lambda}{2}, \\ \frac{1}{b} \left[(1+\lambda)\sqrt{\frac{\eta-2}{\eta}} F_{\eta}^{-1} \left(\frac{u+\lambda}{1+\lambda}\right) - a \right], & \text{if } u \ge \frac{1-\lambda}{2}, \end{cases}$$
(4)

where F_{η}^{-1} is the inverse *cdf* of the Student's t-distribution with η degrees of freedom.

- d) Using your code of Practical 1, generate first a Clayton copula of size n = 1000 and D = 2 with $\theta = 3$, and then generate a GJR-GARCH with the Student's t-innovations using b) and plot the two time series side-by-side. What can you tell about the extreme events?
- e) Repeat d) with the Hansen's t-distribution of point c).

Exercise 2: model fit by IFM

The IFM, or Inference For Margins, is a two-steps maximum likelihood method to fit a copula. Use the sample generated in Exercice 1-e).

- a) Fit each marginal x_i (i = 1, 2) with the GJR-GARCH defined in (1)-(2) and the Hansen's skewed t-innovations.
- **b)** Compute estimated innovations $\hat{z}_{i,t} = \frac{x_{i,t} \hat{\mu}_i}{\hat{\sigma}_{i,t}}$ and plot them.
- c) Compute the estimated probabilities by using

$$\hat{u} = \begin{cases} (1-\lambda)F_{\eta}\left(\frac{b\hat{z}+a}{1-\lambda}\sqrt{\frac{\eta}{\eta-2}}\right), & \text{if } \hat{z} < -a/b, \\ (1+\lambda)F_{\eta}\left(\frac{b\hat{z}+a}{1+\lambda}\sqrt{\frac{\eta}{\eta-2}}\right) - \lambda, & \text{if } \hat{z} \ge -a/b. \end{cases}$$
(5)

d) Fit the Clayton copula to the \hat{u} 's as in Exercise 4 of Practical 1.

Exercise 3: fit comparison

Repeat Exercise 2 M = 1000 times and compare the estimators $\hat{\theta}$ with those obtained in Exercise 5 of Practical 1. Is the variance of $\hat{\theta}$ the same?