R finance 2018

Bayesian Estimation of stock market VaR using Vine Copula models

Multivariate financial data usually exhibit a complex pattern of dependence; A solution to the treatment of this information is based on copulas.

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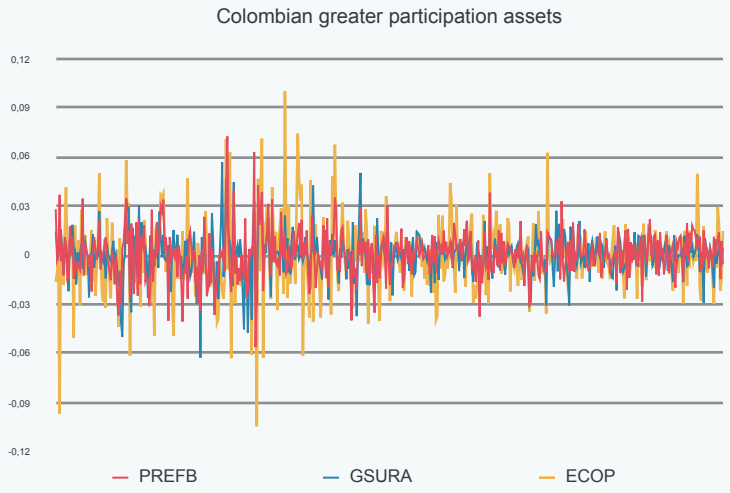
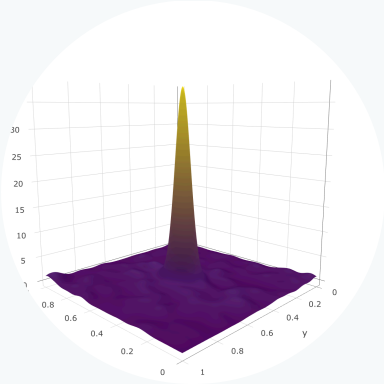
new investments, new opportunities

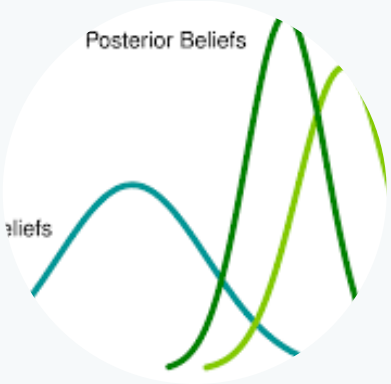
Stock Markets

The **stock market** is defined as the space in which mainly companies deal in equity securities without pre-establishing a particular return. Investors frequently make decisions that seek to maximize the portfolio's expected return and simultaneously minimize the risk of the investment which is frequently exposed. This means the need of calculating VaR which they could take the best investment decision.



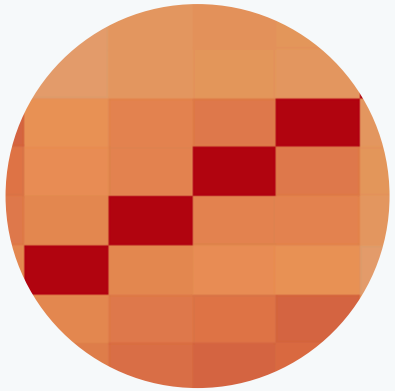
Why Vine Copulas?





Vine Copulas

Allow a joint distribution to be built from bivariate and conditional bivariate copulas arranged together according to the graphical structure of a regular vine, which is a more flexible measure to capture the dependence structure among assets.



Copulas
Multivariate distributions difficult to implement in higher dimensions

Bayesian Estimation
Versatility and good results in comparison to classic statistics

Changes in the market
Help to condense volatility of multivariate assets

Dependency
Handle the complex dependency behavior between multivariate series

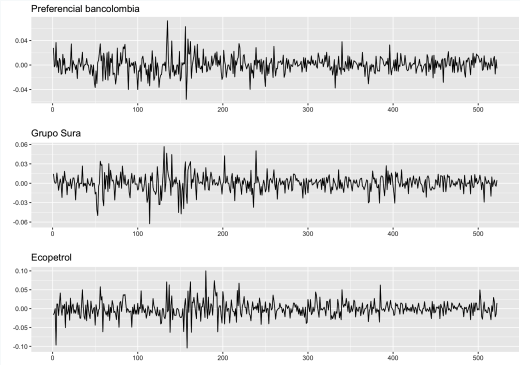
Methodology

How does it work?

DATA TREATMENT

returns 3 stocks

starting from June 10th, 2015 - 2017, stationary series.



Bancolombia, Grupo Sura, Ecopetrol are the three selected assets in the portfolio.

TIME SERIES MODELING

mean & variance

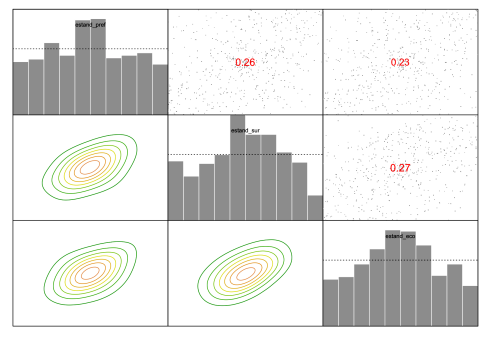
ARFIMA-GARCH models were implemented

In order to express the mean & variance of the model the **Rugarch** package was implemented.

RESIDUALS

form

Estimation of degrees of freedom for the t student distribution using **Rjags** with discrete priors.



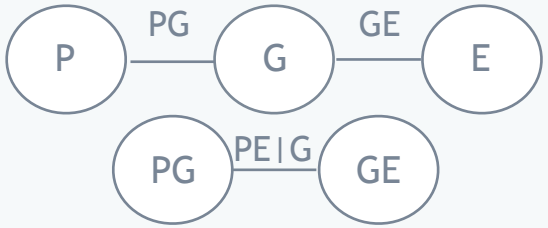
Identification of the possible copulas in each tree of the structure using **RVineStructureSelect** function of **VineCopula** package.

10000 iterations were performed with one markov chain, excluding the first thousand generated numbers and taking one observation every 4 values.

VINE COPULA STRUCTURE

d-vine

Authoritatively cultivate out-of-the-box processes after emerging products.



BAYESIAN ESTIMATION

parameters

Implementing Random-Walk-Metropolis-Hastings the parameters for both trees are found, first tree with 2 frank copulas and second with a t copula.

First tree estimated assuming normal priors, 10000 iterations, then the pseudo-observations are transformed in copula data with Montecarlo integration using Important sampling to feed the next tree.

VALUE AT RISK

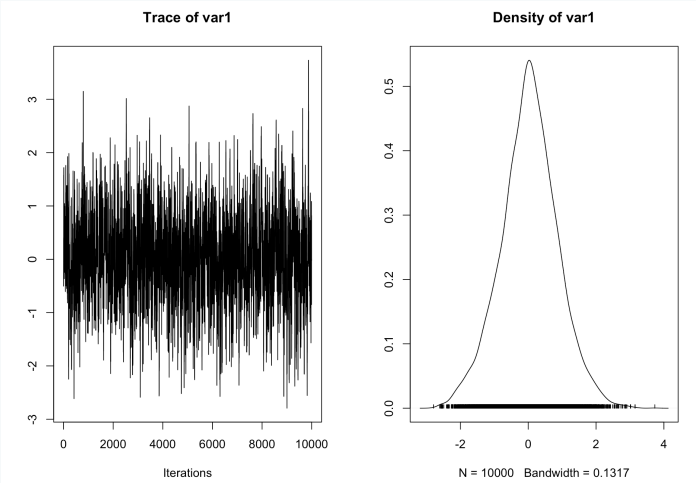
losses

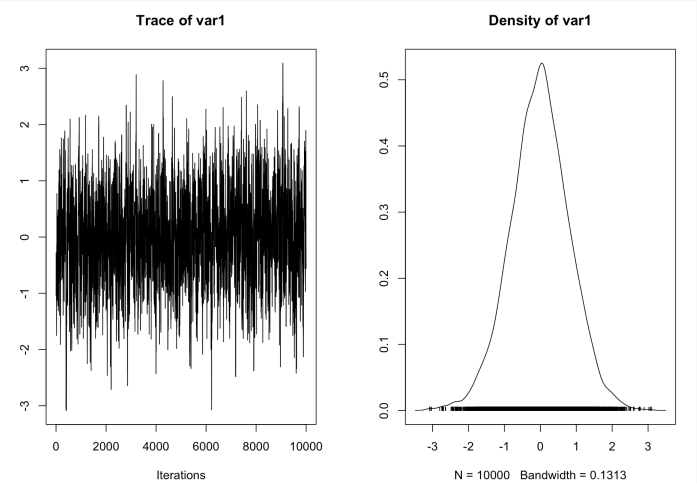
Finally value at risk is calculated following the structure of the coefficients made with **Rugarch** using **RVineMatrix** and **RVineSim** triples generated by the VineCopula structure previously estimated.

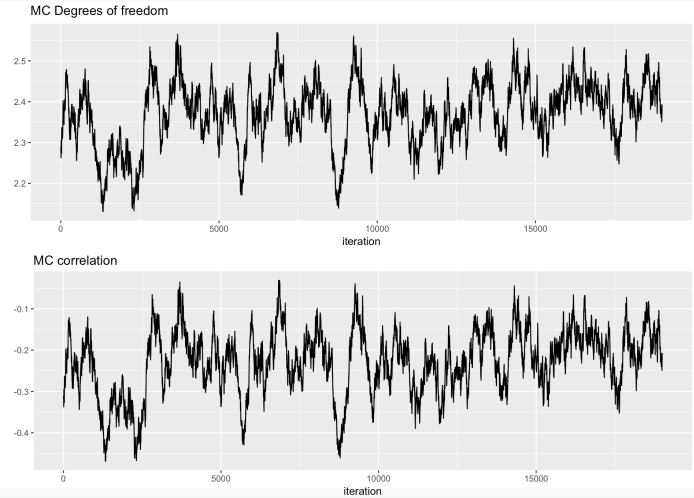
Value at risk is calculated at 90%, 95% and 99% confidence level with equal weights for the returns.

Vine Copula parameter estimation

Bayesian Estimation results







01

Frank copula PG

- Acceptation rate 0.6867687
- Estimation: 0.03275

02

Frank copula GE

- Acceptation rate 0.6991699
- Estimation: –0.0146

03

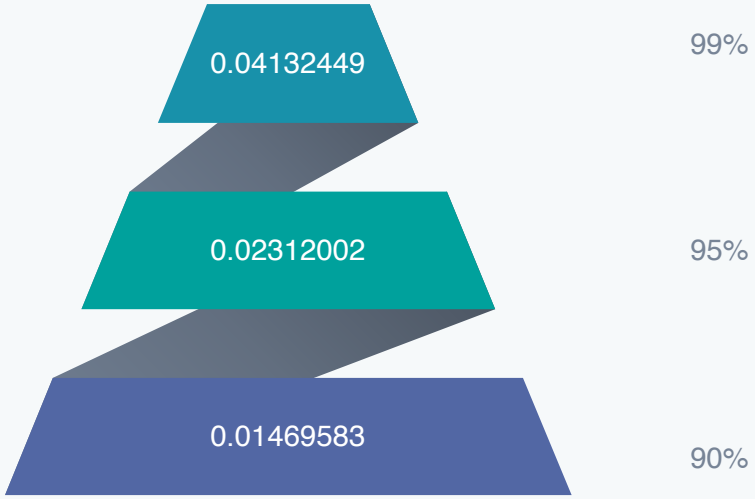
t Copula PEIG

- Acceptation rate (Degrees of freedom): 0.704557
- Acceptation rate (Correlation): 0.7126471
- Degrees of freedom: 2.37158
- Correlation coefficient: -0.22841

Finally the estimation

Value at Risk

Considering the structure of the ARFIMA-GARCH model provided in **Rugarch** package in order to asses the accuracy of VaR estimates. We backtested the method at 90%, 95% and 99% confidence level as follows:



It was possible to implement algorithms of Bayesian inference to obtain samples from the posterior distributions and made the estimates of the parameters of the proposed model, this last allowed us to calculate the Value at Risk taking into account the non-linear dependency structure between the assets with Vine Copula graphs .

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Thank you!

US Traveler

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