HW8 QRM

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$\mathbf{Q}\mathbf{1}$

A scatter plot of the pseudo copulas can be seen in figure 1. Log-likelihood maximization with the Clayton and Gumbel models resulted in $\theta_{Clayton} = 3.94 \cdot 10^{-9} \approx 0$ and $\theta_{Gumbel} = 1.00$ respectively. Their associated log-likelihoods were virtually zero. The Frank model however, resulted in a log-likelihood of 825.7331 using $\theta_{Frank} = -3.1301$. For this reason, we can conclude that the data was likely generated using a Frank copula.

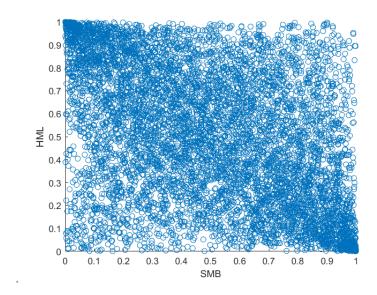


Figure 1: Pseudo copula of the SMB and HML data from the excel file on moodle

By Sklar's theorem, the copula of X and Y is defined by

$$C(u_1, u_2) = F(F_1^{-1}(u_1), F_2^{-1}(u_2)) = F(x, y)$$

where F is the joint CDF and F_1 and F_2 are the marginal CDF's for X and Y respectively. To make use of this theorem, let us first find the marginals. For F_1 it is simple to see

$$F_1(x) = P(X \le x) = \Phi(x)$$

where $\Phi(x)$ is the CDF for the standard normal distribution. Thus $F_1^{-1}(u)$ is simply the inverse of this function. Now for F_2 , where we will use the fact that for $X \sim \mathcal{N}(0,1)$ we have $\Phi(-x) = 1 - \Phi(x)$. This leads to

$$F_2(y) = P(Y \le y) = P(ZX \le y) = P(X \le y|Z = 1)P(Z = 1) + P(-X \le y|Z = -1)P(Z = -1)$$
$$= p\Phi(y) + (1-p)(1-\Phi(-y)) = p\Phi(y) + (1-p)(1-(1-\Phi(y))) = p\Phi(y) + (1-p)\Phi(y) = \Phi(y).$$

Thus we have that

$$F_1^{-1}(u) = F_2^{-1}(u) = \Phi(u)^{-1}.$$

Now we need to find the joint distribution of X and Y:

$$\begin{split} F(x,y) &= P(X \leq x, Y \leq y) = P(X \leq x, X \leq y | Z = 1) \\ P(Z = 1) + P(X \leq x, -X \leq y | Z = -1) \\ P(X \leq x, X \leq y | Z = 1) \\ P(Z = 1) + P(X \leq x, X \geq -y | Z = -1) \\ P(Z \leq \min\{x,y\}) + (1-p) \max\{\Phi(x) - \Phi(-y), 0\} \\ &= p \min\{\Phi(x), \Phi(y)\}) + (1-p) \max\{\Phi(x) - (1-\Phi(y)), 0\} \end{split}$$

Now by inserting $x = F_1^{-1}(u_1)$ and $y = F_2^{-1}(u_2)$ into this expression we obtain

$$C(u_1, u_2) = p \min\{u_1, u_2\} + (1 - p) \max\{u_1 + u_2 - 1, 0\}$$

Which is a parametrization of the comonotonicity copula (p = 1) and the countermonotonicity copula (p = -1).

Q3

LHS of equation:

$$P(U_{1} \leq u_{1},...,U_{d} \leq u_{d}) = \int_{0}^{\infty} P(U_{1} \leq u_{1},...,U_{d} \leq u_{d}|V=v)dG(v) =$$

$$\{=u_{1},...,u_{d} \text{ are conditionally independent given V} = \}$$

$$= \int_{0}^{\infty} \prod_{i=1}^{d} F_{U_{i}|V}(u_{i}|v)dG(v) = \int_{0}^{\infty} e^{-v(\hat{G}^{-1}(u_{1})+,...,+\hat{G}^{-1}(u_{d})}dG(v) =$$

$$\hat{G}(\hat{G}^{-1}(u_{1})+,...+\hat{G}^{-1}(u_{d}))$$
Q.E.D

```
1 clear all
2 close all
4 %Read file
5 table = readtable('Global_3_Factors_Daily.csv', 'PreserveVariableNames', true);
6 data1=table2array(table(:,2));
7 data2=table2array(table(:,3));
8 len=length(data1);
9 [sorted_vals1, indices1] = sort(data1, 'ascend');
10 [sorted_vals2, indices2] = sort(data2, 'ascend');
11 \text{ r} 11 = 1 : \text{len};
12 \text{ r1}(\text{indices1}) = \text{r11};
13 F1=r1/(len+1);
14 \text{ r} 22 = 1: \text{len};
15 \text{ r2} (indices 2) = r22;
16 F2=r2/(len+1);
17 U=[F1, F2, ];
18 % scatter (F1, F2)
19 % xlabel('SMB')
20 % ylabel ('HML')
21
22 initial_theta=6;
23 fun=@(theta) gumbel_target_function(U, theta);
24 [theta, negative_function_value]=fmincon(fun, initial_theta, [], [], [], [], Inf) %
       Change lower bound depending on the family.
25 function target=target_function(U, theta)
26 gumbelpdf=copulapdf('Gumbel', U, theta); % Change here based on which copula
      family is being optimized.
27 boolean=gumbelpdf>0;
                                                 % To avoid problems in log function.
28 gumbelpdf=nonzeros(gumbelpdf.*boolean); % To avoid problems in log function.
                                              \% \ Maximizing \ log-likelihood \ is \ the \ same
29 target=-sum(log(gumbelpdf));
       as \ minimizing \ negative \ log-likelihood.
30 end
```