Tail-dependence properties of some new types of copula models (part II)

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Abstract We continue the investigation of the tail-dependence behaviour of some new types of copula models, published recently in [5] and [6].

1. Introduction. For the sake of simplicity, we concentrate our investigations to the two-dimensional case. Let U_1, U_2 be standard random variables, i.e. they follow a uniform distribution over the interval [0,1] each. Let further T_1, T_2 be real continuous functions over \mathbb{R}^2 and $W_1 = T_1(U_1, U_2)$, $W_2 = T_2(U_1, U_2)$. If W_1, W_2 already follow a continuous uniform distribution over [0,1] each, then (W_1, W_2) is a representative of a two-dimensional copula. Otherwise, $(V_1, V_2) := (F_1(W_1), F_2(W_2))$ is a representative of a two-dimensional copula if F_i denotes the continuous c.d.f. of W_i , i = 1, 2.

Of particular interest especially for financial markets or risk management is the tail dependence of copulas which was explicitly treated for dependence-of-unity copulas in [2], [3] and [4], and for the new approach in [6], which we shall continue here. The simplest definition of the coefficient λ_U of upper and λ_L of lower tail dependence is

$$\lambda_U = \lim_{t \uparrow 1} \frac{P\left(W_1 > F_1^{-1}(t), W_2 > F_2^{-1}(t)\right)}{1 - t}, \ \lambda_L = \lim_{t \downarrow 0} \frac{P\left(W_1 \le F^{-1}(t), W_2 \le G^{-1}(t)\right)}{t}, \ \text{see e.g. [1], Def.}$$

$$7.36, \text{p.247}.$$

In case that $F_1 = F_2$, i.e. W_1 and W_2 have same distribution, we also have

$$\lambda_{U} = \lim_{s \uparrow \infty} \frac{P(W_1 > s, W_2 > s)}{1 - F(s)}, \ \lambda_{L} = \lim_{s \downarrow -\infty} \frac{P(W_1 \leq s, W_2 \leq s)}{F(s)}.$$

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2. Particular Cases.

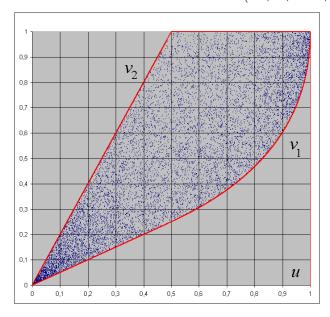
Case 1. Here we consider the choice

$$W_1 = T_1(U_1, U_2) = U_1 + U_2, W_2 = T_2(U_1, U_2) = \max(U_1, U_2).$$

It is easy to see that the corresponding c.d.f.'s are given by

$$F_1(x) = \begin{cases} \frac{x^2}{2}, & 0 \le x \le 1\\ 1 - 2\left(1 - \frac{x}{2}\right)^2, & 1 \le x \le 2. \end{cases}$$
 and
$$F_2(x) = x^2, \quad 0 < x < 1.$$

The following graph shows 10.000 simulations of $(V_1, V_2) = (F_1(W_1), F_2(W_2))$.



The red lines (u,v) represent the (sharp) lower and upper envelopes of the copula, which are given by

$$v_{1} = v_{lower} = \begin{cases} \frac{u}{2}, & \text{if } u \leq \frac{1}{2} \\ \left(1 - \sqrt{\frac{1 - u}{2}}\right)^{2}, & \text{otherwise} \end{cases}$$

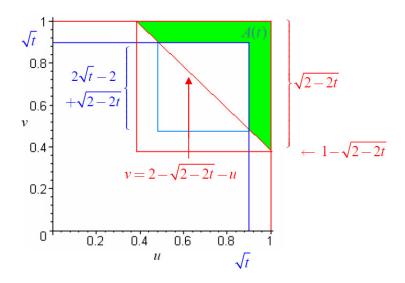
and
$$v_2 = v_{upper} = \begin{cases} 2u, & \text{if } u \le \frac{1}{2} \\ 1, & \text{if } u > \frac{1}{2} \end{cases}$$
,

The lower bound is reached if V_1 and V_2 are close to each other, while the upper bound is reached if one of V_1 or V_2 is close to zero.

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The subsequent graph explains our arguments for the calculation of the coefficient λ_U of upper tail dependence, which is given by $\lambda_U=0$.

We start with some preliminary inequalitites.



We have, for $t > \frac{1}{2}$, with μ denoting Lebesgue measure,

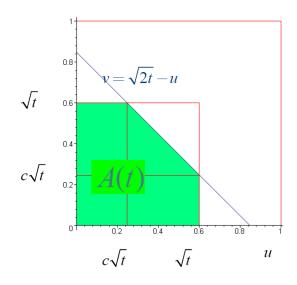
$$\begin{split} P\Big(W_1 > F_1^{-1}(t), W_2 > F_2^{-1}(t)\Big) &= P\Big(\max(U_1, U_2) > \sqrt{t}, \ U_2 > 2 - \sqrt{2 - t} - U_1\Big) \\ &= \mu\Big(A(t)\Big) = \frac{1}{2}\Big(\sqrt{2 - 2t}^2 - \Big(2\sqrt{t} - 2 + \sqrt{2 - 2t}\Big)^2\Big) \end{split}$$

or, by a Taylor expansion around the point t = 1,

$$\mu(A(t)) = \sqrt{2}(1-t)^{3/2} + \mathcal{O}((1-t)^2)$$
, hence $\lambda_U = \lim_{t \to 1} \frac{\mu(A(t))}{1-t} = 0$, as stated.

The subsequent graph explains our arguments for the calculation of the coefficient λ_L of lower tail dependence, which is given by $\lambda_L = 2(\sqrt{2}-1) = 0,828427...$.

We start again with some preliminary inequalitites.



We have, for
$$t > \frac{1}{2}$$
, with $c = \sqrt{2} - 1$,
$$P\left(\max(U_1, U_2) \le F_2^{-1}(t), U_1 + U_2 \le F_1^{-1}(t)\right) = P\left(\max(U_1, U_2) \le \sqrt{t}, U_2 \le \sqrt{2t} - U_1\right)$$
$$= \mu(A(t)) = t - \frac{\left\{(1 - c)\sqrt{t}\right\}^2}{2} = t\left(1 - \frac{(1 - c)^2}{2}\right) = 2ct$$
and hence $\lambda_L = \lim_{t \downarrow 0} \frac{\mu(A(t))}{t} = 2c = 2\left(\sqrt{2} - 1\right) = 0,828427...$, as stated.

Case 2. Here we consider the choice

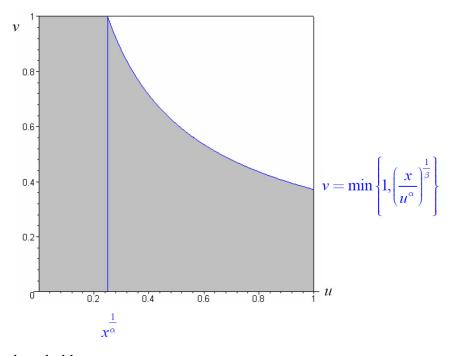
$$W_1 = T_1(U_1, U_2) = U_1^{\alpha} U_2^{\beta}, W_2 = T_2(U_1, U_2) = U_1^{\beta} U_2^{\alpha} \text{ with real } \alpha, \beta > 0.$$

For simplicity, let $U := U_1$, $V := U_2$.

The common c.d.f. of U and V is given by

$$F(x) = \frac{\alpha}{\alpha - \beta} x^{\frac{1}{\alpha}} - \frac{\beta}{\alpha - \beta} x^{\frac{1}{\beta}}, \ 0 < x < 1$$

which can be seen as follows.



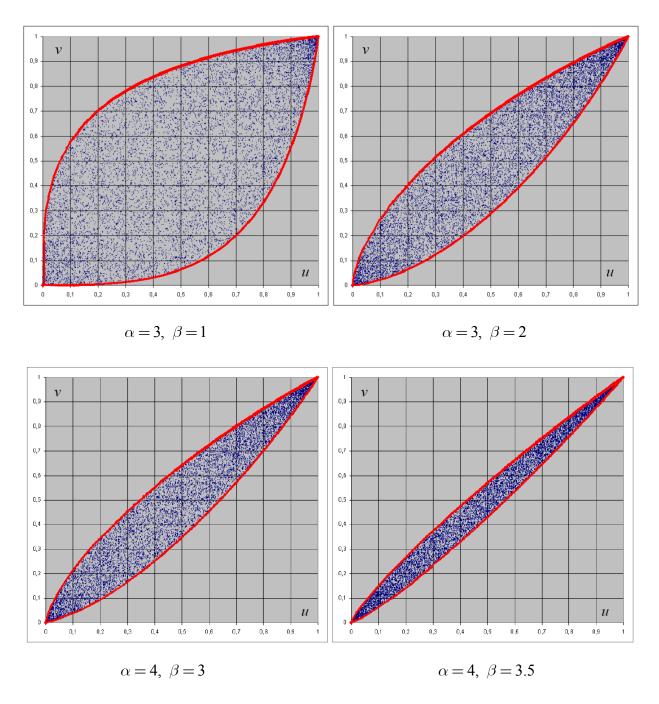
For 0 < x < 1, there holds

$$F(x) = P\left(U^{\alpha}V^{\beta} \le x\right) = P\left(V \le \left(\frac{x}{U^{\alpha}}\right)^{\frac{1}{\beta}}\right) = \int_{0}^{1} P\left(V \le \left(\frac{x}{u^{\alpha}}\right)^{\frac{1}{\beta}}\right) du = \int_{0}^{1} \min\left\{1, \left(\frac{x}{u^{\alpha}}\right)^{\frac{1}{\beta}}\right\} du$$

$$= x^{\frac{1}{\alpha}} + x^{\frac{1}{\beta}} \int_{\frac{1}{x^{\alpha}}}^{1} \frac{1}{u^{\frac{\alpha}{\beta}}} du = x^{\frac{1}{\alpha}} + \frac{\beta}{\beta - \alpha} x^{\frac{1}{\beta}} \left[1 - x^{\left(\frac{1}{\alpha} - \frac{1}{\beta}\right)}\right] = \frac{\alpha}{\alpha - \beta} x^{\frac{1}{\alpha}} - \frac{\beta}{\alpha - \beta} x^{\frac{1}{\beta}} = P\left(U^{\beta}V^{\alpha} \le x\right)$$

by symmetry reasons.

The following graphs show 10,000 simulations each of the copula given by $(F(W_1), F(W_2))$, for different values of α and β .



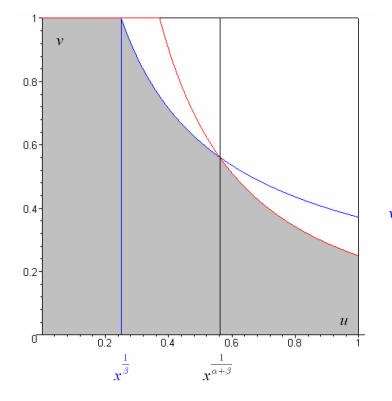
The red lines (u,v) represent the (sharp) lower and upper envelopes of the copula, which are given by

$$v_{lower} = F\left(u^{\frac{\beta}{\alpha}}\right) \text{ and } v_{upper} = F\left(u^{\frac{\alpha}{\beta}}\right), \ 0 < u < 1.$$

Note that for $\alpha \gg \beta$, the copula tends to the independence copula, and for $\alpha \approx \beta$, we obtain the upper Fréchet bound. Note also that the copula is symmetric in α , β .

The subsequent graph explains our arguments for the calculation of the coefficient λ_L of lower tail dependence, which is given by $\lambda_L = 0$. First notice that for 0 < x < 1, the intersection point of

$$\left(\frac{x}{u^{\alpha}}\right)^{\frac{1}{\beta}}$$
 and $\left(\frac{x}{u^{\beta}}\right)^{\frac{1}{\alpha}}$ is given by $u_x = x^{\frac{1}{\alpha+\beta}}$ with value u_x .



$$v = \left(\frac{x}{u^{\beta}}\right)^{\alpha}$$

$$v = \left(\frac{x}{u^{\alpha}}\right)^{\frac{1}{\beta}}$$

Next we have

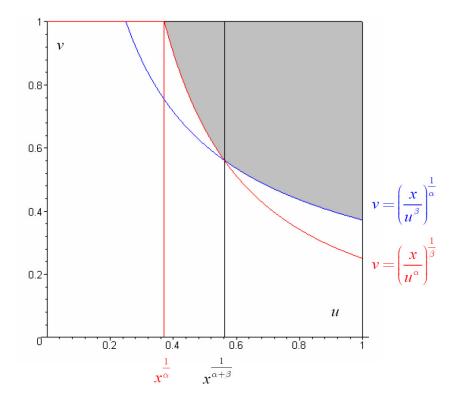
$$P\left(U^{\alpha}V^{\beta} \leq x, \ U^{\beta}V^{\alpha} \leq x\right) = x^{\frac{1}{\beta}} + \int_{x^{\frac{1}{\alpha+\beta}}}^{\frac{1}{\alpha+\beta}} \left(\frac{x}{u^{\beta}}\right)^{\frac{1}{\alpha}} du + \int_{x^{\frac{1}{\alpha+\beta}}}^{1} \left(\frac{x}{u^{\alpha}}\right)^{\frac{1}{\beta}} du = x^{\frac{2}{\alpha+\beta}}$$

with

$$\frac{F(x)}{P(U^{\alpha}V^{\beta} \le x, \ U^{\beta}V^{\alpha} \le x)} = \frac{\alpha}{\alpha - \beta} x^{\frac{\beta - \alpha}{\alpha \cdot (\alpha + \beta)}} - \frac{\beta}{\alpha - \beta} x^{\frac{\alpha - \beta}{\alpha \cdot (\alpha + \beta)}} \text{ and hence}$$

$$\lim_{x\to 0} \frac{F(x)}{P\left(U^{\alpha}V^{\beta} \leq x, \ U^{\beta}V^{\alpha} \leq x\right)} = \infty, \text{ i.e. } \lim_{x\to 0} \frac{P\left(U^{\alpha}V^{\beta} \leq x, \ U^{\beta}V^{\alpha} \leq x\right)}{F(x)} = 0 = \lambda_{L}.$$

The subsequent graph explains our arguments for the calculation of the coefficient λ_U of upper tail dependence, which is given by $\lambda_U = \frac{2\beta}{\alpha + \beta} > 0$ if $\alpha > \beta$.



If $\alpha > \beta$,

$$P\left(U^{\alpha}V^{\beta} > x, \ U^{\beta}V^{\alpha} > x\right) = 1 - x^{\frac{1}{\alpha}} - \int_{\frac{1}{x^{\frac{1}{\alpha+\beta}}}}^{\frac{1}{\alpha+\beta}} \left(\frac{x}{u^{\alpha}}\right)^{\frac{1}{\beta}} du - \int_{\frac{1}{x^{\alpha+\beta}}}^{1} \left(\frac{x}{u^{\beta}}\right)^{\frac{1}{\alpha}} du = 1 - \frac{2\alpha}{\alpha-\beta} x^{\frac{1}{\alpha}} + \frac{\beta}{\alpha-\beta} x^{\frac{2}{\alpha+\beta}}$$

With, by a Taylor expansion around x = 1,

$$\frac{P\left(U^{\alpha}V^{\beta} > x, \ U^{\beta}V^{\alpha} > x\right)}{1 - F(x)} = \frac{2\beta}{\alpha + \beta} - \frac{2(\alpha - \beta)}{3(\alpha + \beta)^2}(x - 1) + \mathcal{O}\left((x - 1)^2\right), \text{ hence } \lambda_U = \frac{2\beta}{\alpha + \beta} > 0.$$

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