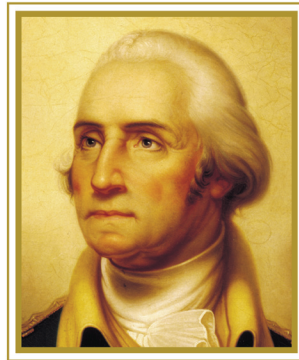


# Lecture on Copulas: Part 2

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# OUTLINE

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1. **ORDINAL MEASURES OF ASSOCIATION: OVERVIEW**
2. ORDINAL MEASURES OF ASSOCIATION: ARCHIMEDEAN
3. ORDINAL MEASURES OF ASSOCIATION: GDB
4. COPULA PARAMETER ELICITATION: ARCHIMEDEAN
5. COPULA PARAMETER ELICITATION: GDB
6. COPULA SELECTION: AN ENTROPY APPROACH
7. A VALUE OF INFORMATION EXAMPLE

# 1. ORDINAL MEASURES OF ASSOCIATION...

## Overview

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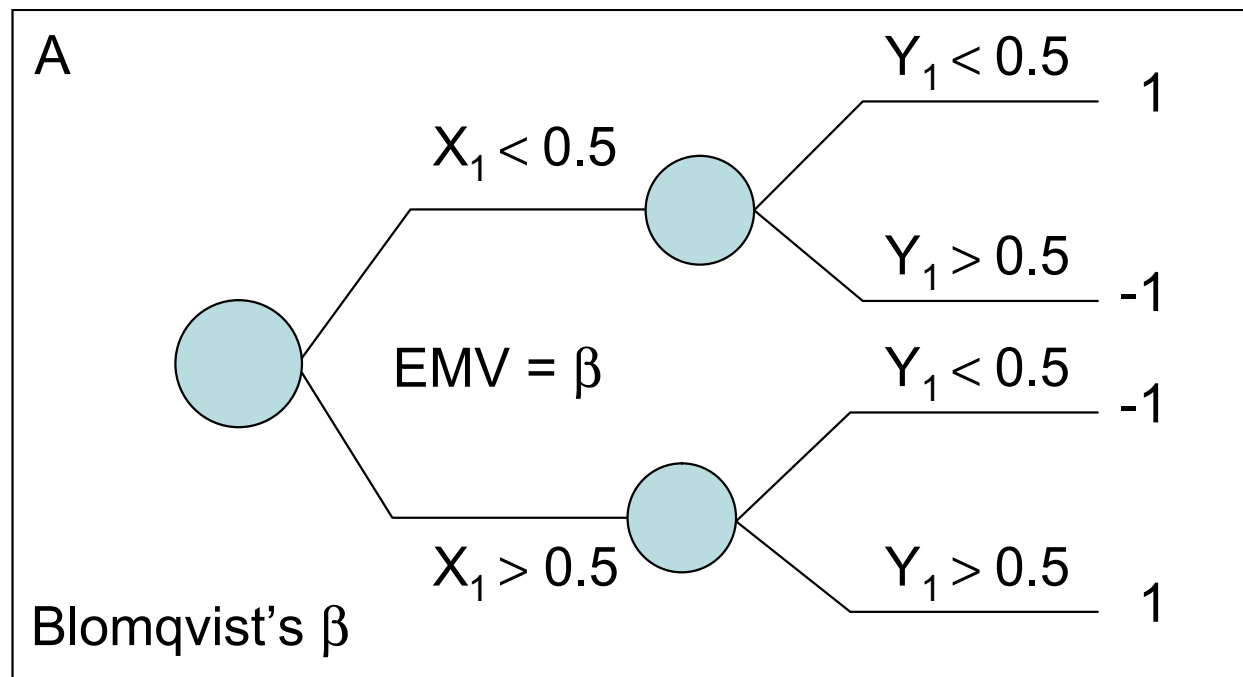
- **Positive (negative) dependence** between  $X' \sim G(\cdot)$  and  $Y' \sim H(\cdot)$  when **large values** of one go with **large (small) values** of the other.
- In case of positive (negative) dependence,  $X'$  and  $Y'$  are said to be **concordant (discordant)**.
- Classical measures for *the degree of positive or negative dependence*:  
**Blomquist's (1950)  $\beta$ , Kendall's (1938)  $\tau$  and Spearman's (1904)  $\rho_s$ .**
- All three measures attain **values ranging from  $-1$  to  $1$** .
- All three are *ordinally invariant*. Hence,  
 **$\rho_s(X', Y') = \rho_s(X, Y)$ , where  $(X, Y) = \{G(X'), H(Y')\}$ , etc.**
- Recall,  $X$  and  $Y \sim U[0, 1]$  and thus the joint pdf of  $(X, Y)$  is a copula.

# 1. ORD. MEASURES OF ASSOCIATION...

## Blomqvist's $\beta$

- **Excellent review** of classical measures  $\beta$ ,  $\tau$  and  $\rho_s$  is given by Kruskal (1958).

$$\beta(X, Y) = 4C\left(\frac{1}{2}, \frac{1}{2}\right) - 1, \text{ where } C(\cdot, \cdot) \text{ is copula cdf}$$

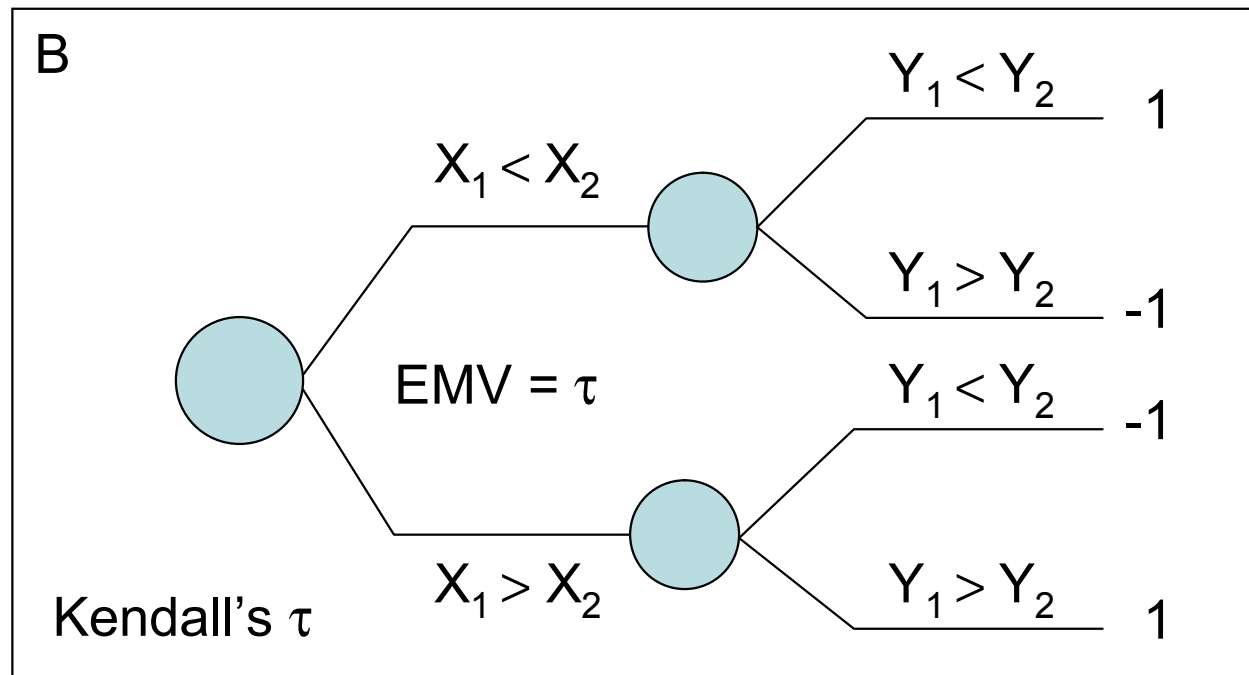


# 1. ORD. MEASURES OF ASSOCIATION...

## Kendall's $\tau$

- Let  $c(\cdot, \cdot)$ ,  $C(\cdot, \cdot)$  be the copula pdf and cdf and let  $(X_i, Y_i) \sim C(\cdot, \cdot)$ ,  $i = 1, 2$  be two independent bivariate samples from the copula.

$$\tau(X, Y) = 4 \int_0^1 \int_0^1 C(x, y)c(x, y)dx dy - 1.$$

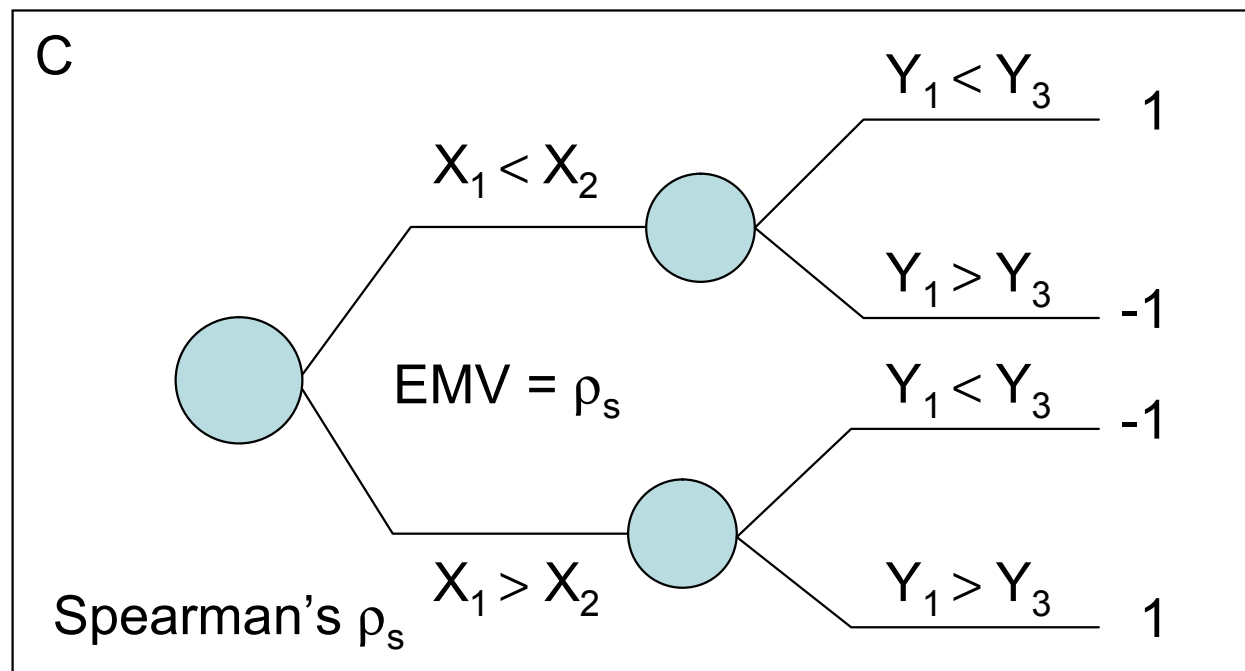


# 1. ORD. MEASURES OF ASSOCIATION...

## Spearman's $\rho_s$

- Let  $c(\cdot, \cdot), C(\cdot, \cdot)$  be the copula pdf let  $(X_i, Y_i) \sim C(\cdot, \cdot), i = 1, 2, 3$  be three independent bivariate samples from the copula.

$$\rho_s(X, Y) = 12 \int_0^1 \int_0^1 xyc(x, y)dx dy - 3.$$



- **Lower and upper tail dependence measures are in vogue**, particularly in problem contexts dealing with modeling **the joint occurrence of extreme events**, such as insurance and modeling of default risk in finance.
- Recent **burst of attention** to the copula approach may be credited to **the Gaussian copula** which has been widely adopted by the "financial quants" .
- Embrechts (2008) even refers to this attention as **"the copula craze"**.
- Unfortunately, some (see, e.g., Salmon, 2009) **blamed** Gaussian copula for the **2008 financial crash**, in part due to **lack of** lower and upper tail dependence.
- These measures too are **ordinal measures of association**, although they focus primarily on modeling positive dependence and not negative dependence.

- $X' \sim G(\cdot), Y' \sim H(\cdot)$ , **Lower tail dependence  $\lambda_L$** :

$$\begin{aligned}\lambda_L &= \lim_{x \downarrow 0} Pr\{Y' \leq H^{-1}(x) | X' \leq G^{-1}(x)\} \\ &= \lim_{x \downarrow 0} Pr(Y \leq x | X \leq x) = \lim_{x \downarrow 0} \frac{C(x, x)}{x},\end{aligned}$$

- $X' \sim G(\cdot), Y' \sim H(\cdot)$ , **Upper tail dependence  $\lambda_U$** :

$$\begin{aligned}\lambda_U &= \lim_{x \uparrow 1} Pr\{Y' > H^{-1}(x) | X' > G^{-1}(x)\} \\ &= \lim_{x \uparrow 1} Pr(Y > x | X > x) = \lim_{x \uparrow 1} \frac{1 - 2x + C(x, x)}{1 - x}.\end{aligned}$$

- Clayton and Gumbel copulae exhibit lower and upper tail dependence, respectively.



- **For GDB copula cdf  $C\{x, y|p(\cdot|\Psi)\}$  we have  $\lambda_L = \lambda_U = 0$** , similar to the Gaussian copulae (Embrechts et. al, 2002).
- Blomquist's  $\beta$ , Kendall's  $\tau$  and Spearman's  $\rho_S$  are more applicable in contexts dealing with **the modeling of joint events in general, not extremes per se.**
- Blomquist's  $\beta$ , Kendall's  $\tau$  and Spearman's  $\rho_S$  pertain to full copula support and not just to their asymptotic extreme values.
- **Caution** to those who believe that the Clayton and Gumbel copulae could serve as the panacea as an alternative to the Gaussian Copula.
- Heteroscedastic behavior of financial processes **suggests** their dependence cannot be modelled using a copula with **a constant correlation over time, regardless** of a copula displaying tail dependence or not.

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## 2. ORD. MEAS. OF ASSOC...

### Archimedean Copula

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- **Population expressions for  $\beta$ ,  $\tau$ ,  $\rho_s$ ,  $\lambda_L$  and  $\lambda_U$  are:**

$$\left\{ \begin{array}{l} \beta(X, Y) = 4C(\frac{1}{2}, \frac{1}{2}) - 1, \\ \tau(X, Y) = 4\int_0^1 \int_0^1 C(x, y)c(x, y)dxdy - 1, \\ \rho_s(X, Y) = 12\int_0^1 \int_0^1 xyc(x, y)dxdy - 3, \end{array} \right. \quad \left\{ \begin{array}{l} \lambda_L = \lim_{x \downarrow 0} \frac{C(x, x)}{x} \\ \lambda_U = \lim_{x \uparrow 1} \frac{1-2x+C(x, x)}{1-x} \end{array} \right.$$

- Archimedean copula with **generator function pdf  $\varphi(\cdot)$  (e.g Genest and Mackay, 1986):**

$$\left\{ \begin{array}{l} \beta\{X, Y|\alpha\} = 4\varphi^{-1}\{\varphi(\frac{1}{2}) + \varphi(\frac{1}{2})\} - 1, \\ \tau\{X, Y|\alpha\} = 4\int_0^1 \frac{\varphi(t)}{\varphi'(t)} dt + 1, \\ \rho_s\{X, Y|\alpha\}: \text{No expression available.} \end{array} \right. \quad \left\{ \begin{array}{l} \lambda_L = \lim_{x \downarrow 0} \frac{\varphi^{-1}\{2\varphi(x)\}}{x} \\ \lambda_U = \lim_{x \uparrow 1} \frac{1-2x+\varphi^{-1}\{2\varphi(x)\}}{1-x} \end{array} \right.$$

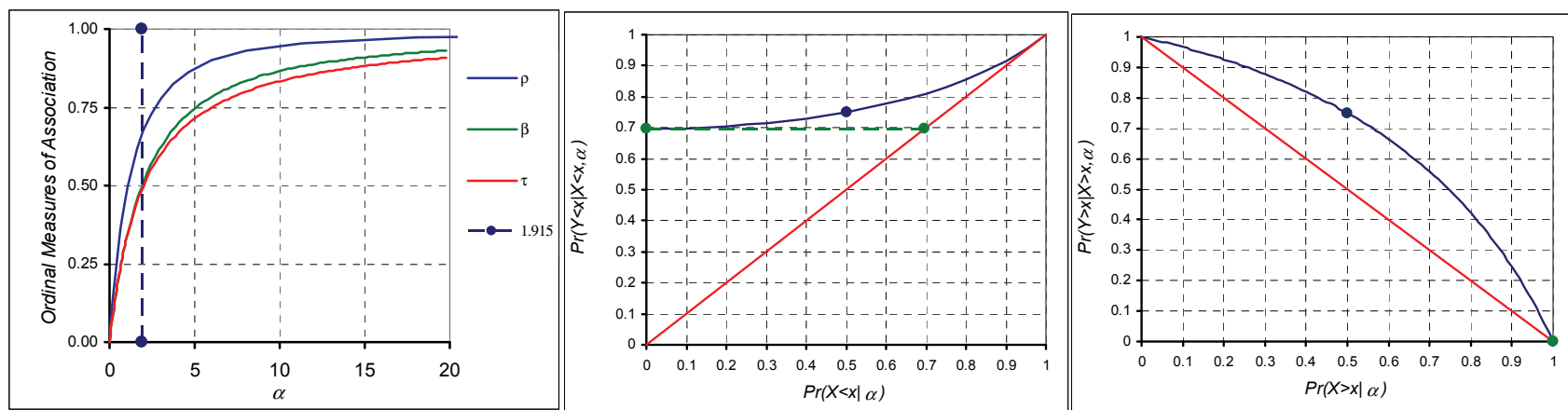
## 2. ORD. MEAS. OF ASSOC...

## Archimedean Copula

- Clayton Copula:**  $\varphi(t) = t^{-\alpha} - 1, \alpha \in (0, \infty)$

$$\left\{ \begin{array}{l} \beta(X, Y) = 4 \left[ 2^{\alpha+1} - 1 \right]^{-1/\alpha} - 1 \in [0, 1], \\ \tau(X, Y) = \frac{\alpha}{\alpha+2} \in [0, 1], \\ \rho_s(X, Y): \text{No expression available,} \\ \lambda_L = 2^\alpha, \lambda_U = 0 \end{array} \right.$$

$$\alpha \approx 1.915 \Rightarrow Pr(Y \leq 0.5 | X \leq 0.5) = Pr(Y > 0.5 | X > 0.5) = 0.75$$



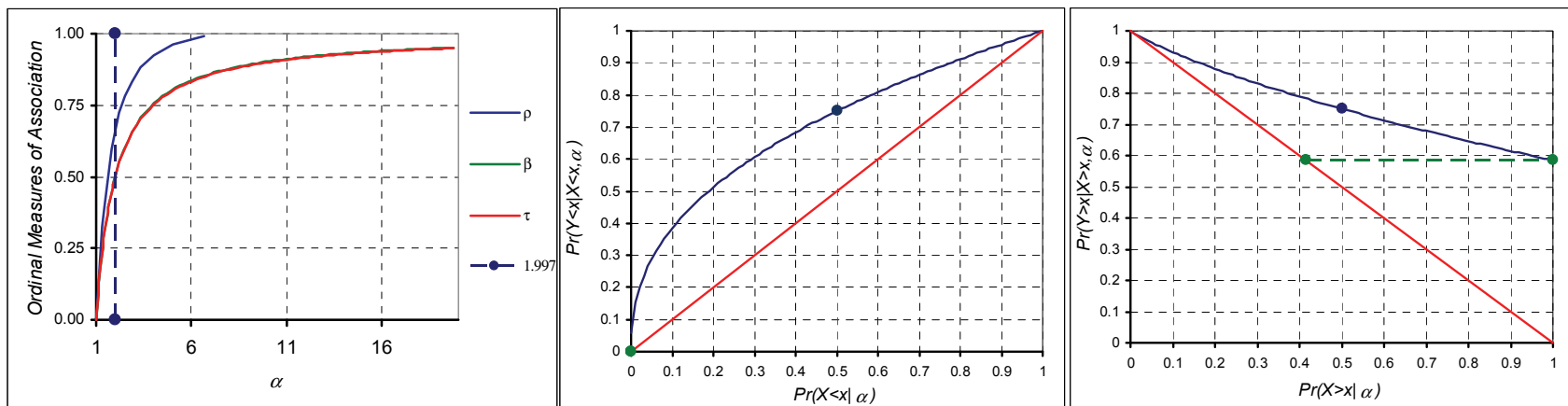
## 2. ORD. MEAS. OF ASSOC...

### Archimedean Copula

- Gumbel Copula:**  $\varphi(t) = t^{-\alpha} - 1, \alpha \in (0, \infty)$

$$\begin{cases} \beta(X, Y) = 4 \times (1/2)^{(2^{1/\alpha})} - 1 \in [0, 1], \\ \tau(X, Y) = \frac{\alpha-1}{\alpha} \in [0, 1], \\ \rho_s(X, Y): \text{No expression available,} \\ \lambda_L = 0, \lambda_U = 2 - 2^\alpha \end{cases}$$

$$\alpha \approx 1.997 \Rightarrow Pr(Y \leq 0.5 | X \leq 0.5) = Pr(Y > 0.5 | X > 0.5) = 0.75$$



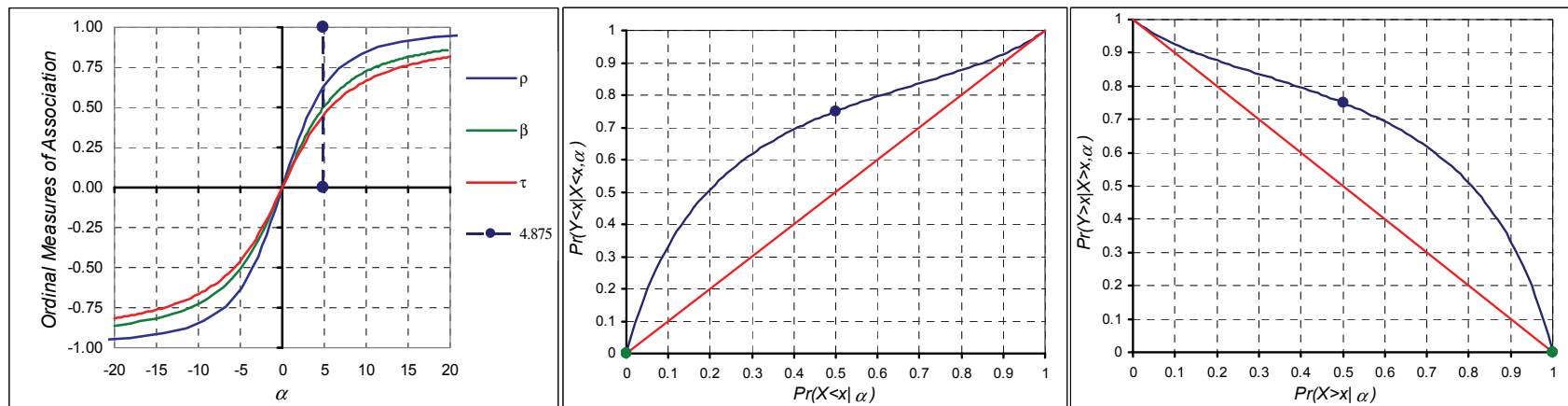
## 2. ORD. MEAS. OF ASSOC...

### Archimedean Copula

- Frank Copula:**  $\varphi(t) = \ln \frac{e^{\alpha t} - 1}{e^{\alpha} - 1}$ ,  $\alpha \in \mathbb{R} \setminus \{0\}$

$$\left\{ \begin{array}{l} \beta(X, Y) = -\frac{4}{\alpha} \ln \left\{ 1 + \frac{(e^{-\frac{\alpha}{2}} - 1)^2}{e^{-\alpha} - 1} \right\} - 1 \in [-1, 1], \\ \tau(X, Y) = 1 - \frac{4}{\alpha} [1 - D(\alpha)] \in [-1, 1], \quad D(\alpha) = \frac{1}{\alpha} \int_0^\alpha \frac{t}{e^t - 1} dt, \\ \rho_s(X, Y): \text{No expression available,} \\ \lambda_L = 0, \lambda_U = 0. \end{array} \right.$$

$$\alpha \approx 4.875 \Rightarrow Pr(Y \leq 0.5 | X \leq 0.5) = Pr(Y > 0.5 | X > 0.5) = 0.75$$



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### 3. ORD. MEAS. OF ASSOC...

### GDB Copula with TS Gen. PDF

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- **Population expressions for  $\beta$ ,  $\tau$  and  $\rho_s$  are**

$$\left\{ \begin{array}{l} \beta(X, Y) = 4C(\frac{1}{2}, \frac{1}{2}) - 1, \\ \tau(X, Y) = 4\int_0^1 \int_0^1 C(x, y)c(x, y)dxdy - 1, \\ \rho_s(X, Y) = 12\int_0^1 \int_0^1 xyc(x, y)dxdy - 3, \end{array} \right. \quad \left\{ \begin{array}{l} \lambda_L = \lim_{x \downarrow 0} \frac{C(x, x)}{x} \\ \lambda_U = \lim_{x \uparrow 1} \frac{1-2x+C(x, x)}{1-x} \end{array} \right.$$

- We have for GDB copula with **TS pdf with generating pdf  $p(\cdot | \Psi)$  and  $Z \sim P(\cdot | \Psi)$ ,  $P(\cdot | \Psi)$  the generating cdf:**

$$\left\{ \begin{array}{l} \beta\{X, Y|p(\cdot | \Psi)\} = 2E[Z|\Psi] - 1, \\ \tau\{X, Y|p(\cdot | \Psi)\} = 2E[Z^2|\Psi] - 2\int_0^1 P^2(s|\Psi)ds + 4\int_0^1 sP^2(s|\Psi)ds - 1, \\ \rho_s\{X, Y|p(\cdot | \Psi)\} = -4E[Z^3|\Psi] + 6E[Z^2|\Psi] - 1. \\ \lambda_L = 0, \lambda_U = 0 \end{array} \right.$$



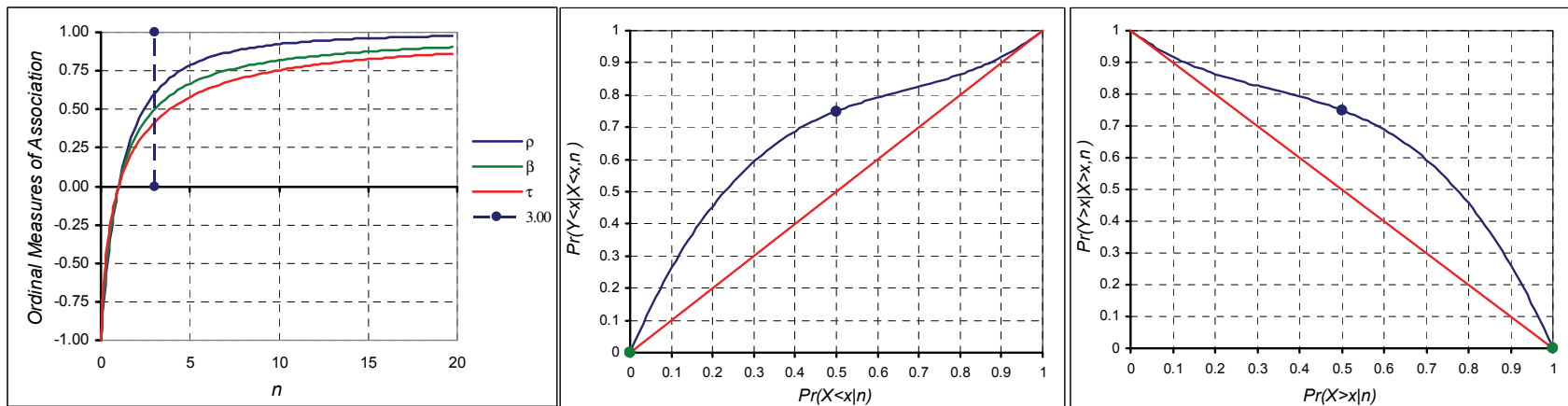
### 3. ORD. MEAS. OF ASSOC...

### GDB Copula with TS Gen. PDF

- Power pdf:  $p(z|n) = nz^{n-1}, n > 0,$

$$\begin{cases} \beta\{X, Y|p(\cdot|n)\} = \frac{n-1}{n+1}, & \in [-1, 1], \\ \tau\{X, Y|p(\cdot|n)\} = \frac{n-1}{n+2} + \frac{n-1}{(n+1)(n+2)(2n+1)}, & \in [-1, 1], \\ \rho_s\{X, Y|p(\cdot|n)\} = \frac{(n-1)(n+6)}{(n+2)(n+3)}, & \in [-1, 1]. \\ \lambda_L = 0, \lambda_U = 0 \end{cases}$$

$$n = 3 \Rightarrow Pr(Y \leq 0.5|X \leq 0.5) = Pr(Y > 0.5|X > 0.5) = 0.75$$



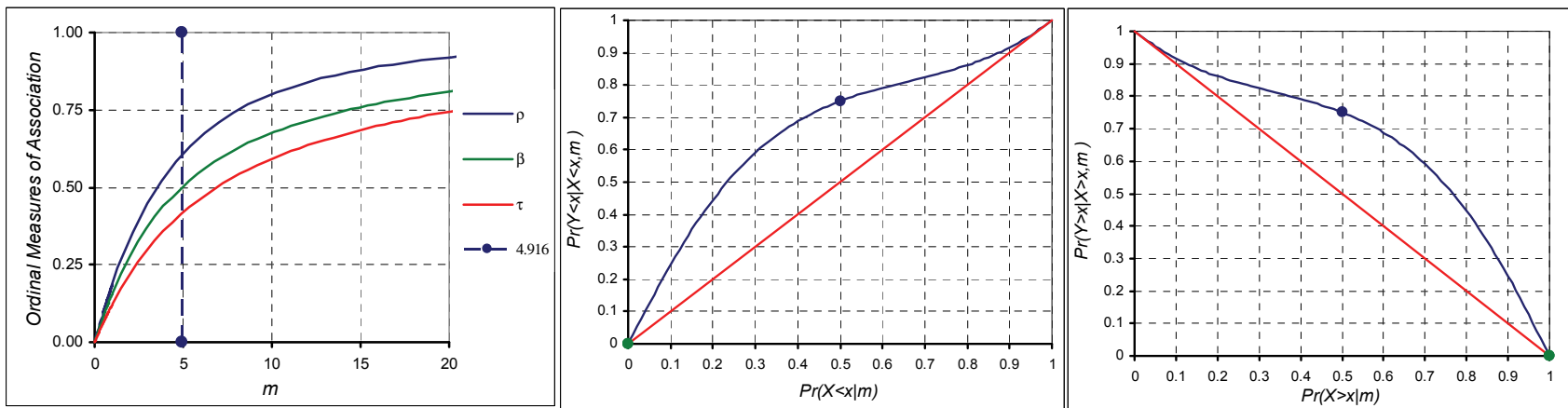
### 3. ORD. MEAS. OF ASSOC...

### GDB Copula with TS Gen. PDF

- Ogive pdf:  $p(z|m) = \frac{m+2}{3m+4} \{2(m+1)\sqrt{z^m} - mz^{m+1}\}, m > 0,$

$$\left\{ \begin{array}{l} \beta\{X, Y|p(\cdot|m)\} = \frac{m(m+1)(3m+8)}{(m+3)(m+4)(3m+4)}, \quad \in [0, 1], \\ \tau\{X, Y|p(\cdot|m)\} = \frac{m(m+1)(162m^6+2643m^5+18132m^4+66108m^3+140032m+58880)}{(m+3)(m+4)(m+6)(2m+5)(3m+4)^2(3m+8)(3m+10)}, \quad \in [0, 1], \\ \rho_s\{X, Y|p(\cdot|m)\} = \frac{m(m+1)(3m^3+70m^2+424m+736)}{(m+4)(m+5)(m+6)(m+8)(3m+4)}, \quad \in [0, 1]. \\ \lambda_L = 0, \lambda_U = 0 \end{array} \right.$$

$$m = 4.916 \Rightarrow Pr(Y \leq 0.5|X \leq 0.5) = Pr(Y > 0.5|X > 0.5) = 0.75$$



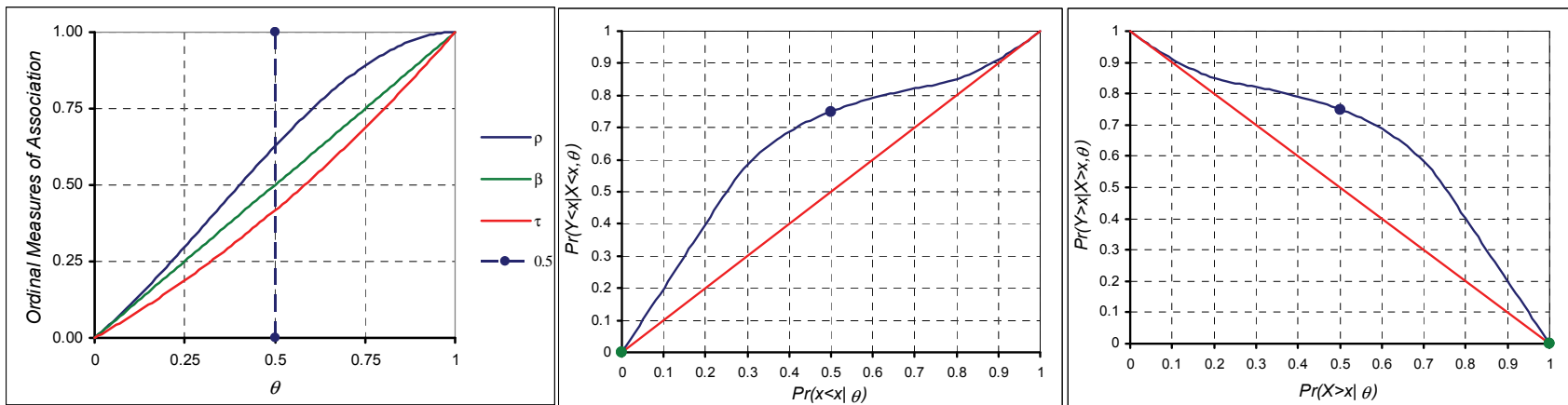
### 3. ORD. MEAS. OF ASSOC...

### GDB Copula with TS Gen. PDF

- $U[\theta, 1]$  pdf :  $p(z|\theta) = \frac{1}{1-\theta}, \theta \leq z \leq 1, 0 \leq \theta \leq 1,$

$$\begin{cases} \beta\{X, Y|p(\cdot|\theta)\} = \theta, & \in [0, 1], \\ \tau\{X, Y|p(\cdot|\theta)\} = \theta(\theta + 2)/3, & \in [0, 1], \\ \rho_s\{X, Y|p(\cdot|\theta)\} = \theta(1 + \theta - \theta^2), & \in [0, 1]. \\ \lambda_L = 0, \lambda_U = 0 \end{cases}$$

$$\theta = 0.5 \Rightarrow Pr(Y \leq 0.5|X \leq 0.5) = Pr(Y > 0.5|X > 0.5) = 0.75$$



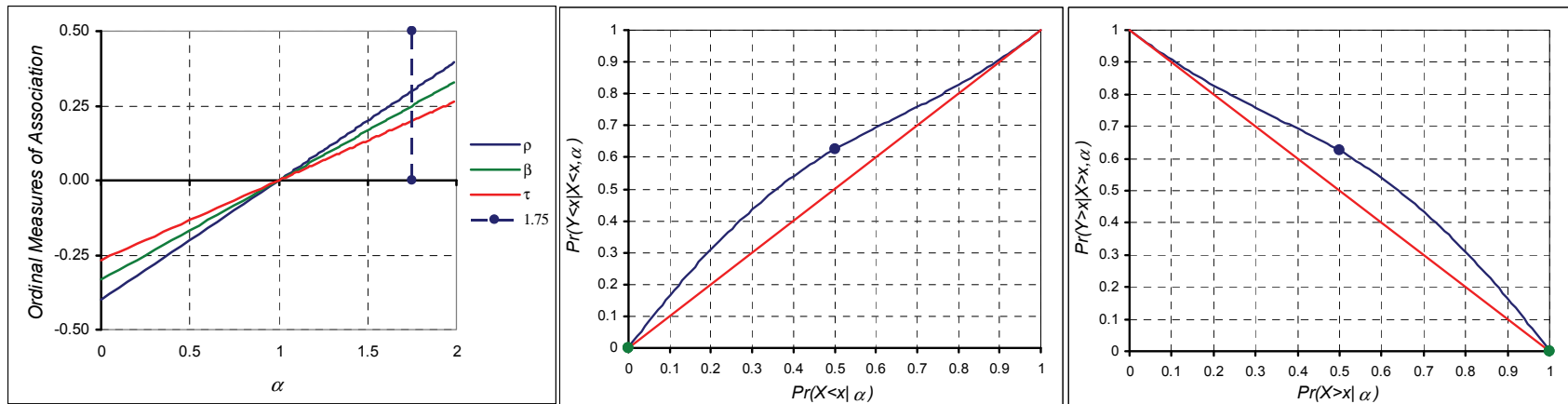
### 3. ORD. MEAS. OF ASSOC...

### GDB Copula with TS Gen. PDF

- Slope pdf:  $p(z|\alpha) = 2 - \alpha + 2(\alpha - 1)z$ ,  $0 \leq \alpha \leq 2$ ,

$$\begin{cases} \beta\{X, Y|p(\cdot|\alpha)\} = -\frac{1}{3} + \frac{1}{3}\alpha, & \in \left[-\frac{1}{3}, \frac{1}{3}\right], \\ \tau\{X, Y|p(\cdot|\alpha)\} = -\frac{4}{15} + \frac{4}{15}\alpha, & \in \left[-\frac{4}{15}, \frac{4}{15}\right], \\ \rho_s\{X, Y|p(\cdot|\alpha)\} = -\frac{2}{5} + \frac{2}{5}\alpha, & \in \left[-\frac{2}{5}, \frac{2}{5}\right]. \\ \lambda_L = 0, \lambda_U = 0 \end{cases}$$

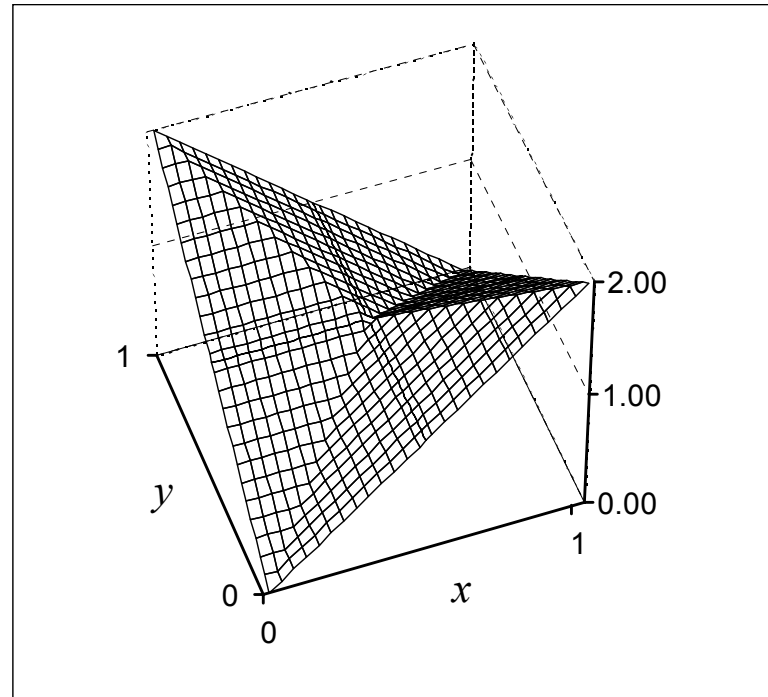
$$\alpha = 1.75 \Rightarrow Pr(Y \leq 0.5|X \leq 0.5) = Pr(Y > 0.5|X > 0.5) = 0.625$$



### 3. ORD. MEAS. OF ASSOC...

### Reflection Property

- Let  $q(z|\Psi)$  be pdf  $Z' = 1 - Z, Z \sim p(z|\Psi) \Rightarrow q(z|\Psi) = p(1 - z|\Psi)$ .
- $c\{x, y|q(z|\Psi)\} = c\{x, y|p(1 - z|\Psi)\}$  obtained via **a right angle rotation**.



Graph of rotated copula using  $p(1 - z|\Psi) = 2(1 - z)$ .

### 3. ORD. MEAS. OF ASSOC...

### Reflection Property

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- We have for GDB copula with **TS gen. pdf**  $p(\cdot | \Psi)$  and  $Z \sim p(\cdot | \Psi)$ :

$$\begin{cases} \beta\{X, Y | p(\cdot | \Psi)\} = 2E[Z | \Psi] - 1, \\ \tau\{X, Y | p(\cdot | \Psi)\} = 2E[Z^2] - 2\int_0^1 P^2(s | \Psi) ds + 4\int_0^1 sP^2(s | \Psi) ds - 1, \\ \rho_s\{X, Y | p(\cdot | \Psi)\} = -4E[Z^3 | \Psi] + 6E[Z^2 | \Psi] - 1. \end{cases}$$

- **Let**  $q(z | \Psi)$  **be pdf**  $Z' = 1 - Z$ ,  $Z \sim p(z | \Psi) \Rightarrow$

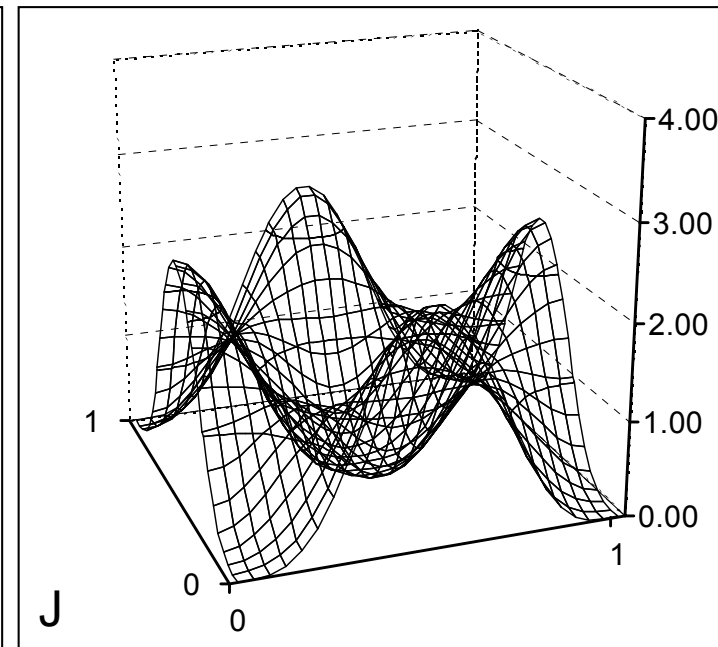
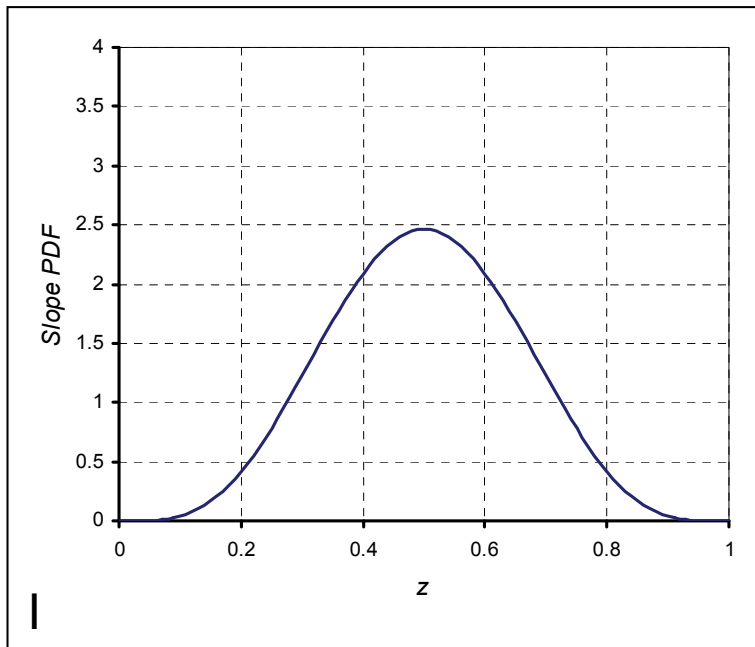
$$\begin{cases} \beta\{X, Y | q(z | \Psi)\} = \beta\{X, Y | p(1 - z | \Psi)\} = -\beta\{X, Y | p(z | \Psi)\}, \\ \tau\{X, Y | q(z | \Psi)\} = \tau\{X, Y | p(1 - z | \Psi)\} = -\tau\{X, Y | p(z | \Psi)\}, \\ \rho_s\{X, Y | q(z | \Psi)\} = \rho_s\{X, Y | p(1 - z | \Psi)\} = -\rho_s\{X, Y | p(z | \Psi)\}. \end{cases}$$

- $p(z | \Psi)$  **symmetric** on  $[0, 1] \Rightarrow p(1 - z | \Psi) = p(z | \Psi) \Rightarrow \beta, \tau, \rho_s \equiv 0$

### 3. ORD. MEAS. OF ASSOC...

### Reflection Property

$$p(z|a) = \frac{\Gamma(2a)}{\Gamma(a)\Gamma(a)} x^{a-1}(1-x)^{a-1}, a > 0 \Rightarrow \beta, \tau, \rho_s \equiv 0, \forall a > 0$$



**G: Beta generating pdf; H: GDB Copula with TS Gen. PDF in A.**

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## 4. COPULA PARAM. ELICITATION...

### Procedure

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- $X' \sim G(\cdot), Y' \sim H(\cdot), \{G(X'), H(Y')\} = (X, Y) \sim C\{x, y|p(\cdot|\Psi)\}$

- Elicit:  $Pr(Y' \leq y'_{0.5}|X' \leq x'_{0.5}) = Pr(Y \leq 0.5|X \leq 0.5) = \pi.$

- This *elicitation procedure* falls within **the conditional fractile estimation method for eliciting degree of dependence** - Clemen and Reilly (1999).

- We have for Blomquist's  $\beta$

$$\beta\{X, Y\} = 2Pr(Y \leq 0.5|X \leq 0.5) - 1 = 2\pi - 1$$

- Hence, elicitation of  $\pi$  is equivalent to **an indirect elicitation of Blomquist's  $\beta$**  which has a more straightforward interpretation as  $\tau$  and  $\rho_s$ .

## 4. COPULA PARAM. ELICITATION...

### Archimedean Copulas

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- **General expression for Archimedean Copulas with generator  $\varphi(\cdot|\alpha)$ :**

$$\begin{aligned}\pi(X, Y|\alpha) &= Pr(Y \leq 0.5|X \leq 0.5) = 2C\left(\frac{1}{2}, \frac{1}{2}|\alpha\right) \\ &= 2 \times \varphi^{-1}\left\{\varphi\left(\frac{1}{2}\right) + \varphi\left(\frac{1}{2}\right)\right\}\end{aligned}$$

- **For different Archimedean Copulas with generator  $\varphi(\cdot|\alpha)$  herein :**

$$\pi(X, Y|\alpha) = \begin{cases} (2^{\alpha+1} - 1)^{-1/\alpha} \in [0.5, 1], & \text{Clayton Copula,} \\ (1/2)^{2^{1/\alpha}} \in [0.5, 1], & \text{Gumbel Copula,} \\ -\frac{1}{\alpha} \ln\left\{1 + \frac{(e^{-\alpha/2} - 1)^2}{e^{-\alpha} - 1}\right\} \in [0.5, 1], & \text{Frank Copula,} \end{cases}$$

- Having elicited  $\pi$  one solves for  $\alpha$  using a numerical procedure, except in case of Gumbel copula.

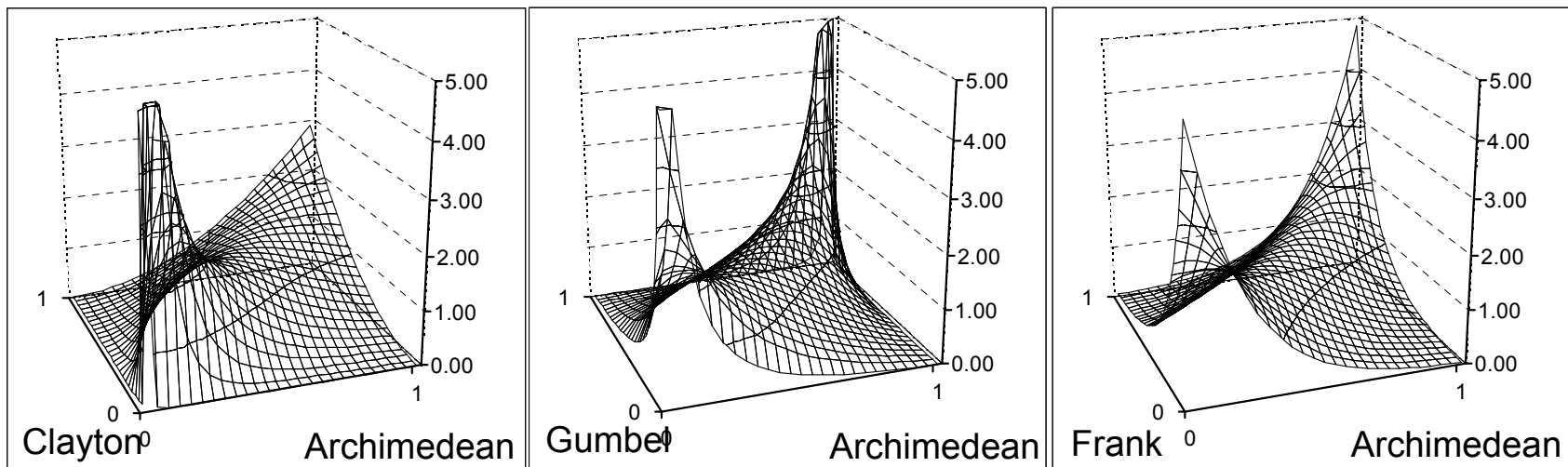
## 4. COPULA PARAM. ELICITATION...

### Archimedean Copulas

- Assume that an expert has assessed a value :

$$\pi\{X, Y|p(\cdot|\Psi)\} = Pr(Y \leq 0.5|X \leq 0.5) = 0.75 \Rightarrow$$

$$\left\{ \begin{array}{ll} \text{Clayton Copula,} & \alpha \approx 1.915, \\ \text{Gumbel Copula,} & \alpha \approx 1.997, \\ \text{Frank Copula,} & \alpha \approx 4.875. \end{array} \right.$$



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## 5. COPULA PARAM. ELICITATION...

### GDB Copulas

$$C\{x, y|p(\cdot|\Psi)\} = \begin{cases} x - \frac{1}{2} \int_{1-x-y}^{1+x-y} P(z|\Psi) dz, & (x, y) \in A_1, \\ y - \frac{1}{2} \int_{1-x-y}^{1-x+y} P(z|\Psi) dz, & (x, y) \in A_2, \\ x - \frac{1}{2} \int_{x+y-1}^{1+x-y} P(z|\Psi) dz, & (x, y) \in A_3, \\ y - \frac{1}{2} \int_{x+y-1}^{1-x+y} P(z|\Psi) dz, & (x, y) \in A_4. \end{cases} \Rightarrow$$

$$\frac{1}{2}\pi = Pr(Y \leq 0.5, X \leq 0.5) = C\left\{\frac{1}{2}, \frac{1}{2}|p(\cdot|\Psi)\right\} = \frac{1}{2} \int_0^1 \{1 - P(z|\Psi)\} dz$$

- With  $Z \sim P(z|\Psi)$ ,  $E[Z|\Psi] = \int_0^1 \{1 - P(z|\Psi)\} dz$ , thus we have:

$$\pi\{X, Y|p(\cdot|\Psi)\} = E[Z|\Psi]. \quad (12)$$

- Thus, having elicited  $\pi$  one solves for  $\psi$  using **the method of moments**.

## 5. COPULA PARAM. ELICITATION...

### GDB Copulas

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- For different GDB Copulas with generating pdf's  $p(\cdot | \cdot)$  herein

$$\pi\{X, Y | p(\cdot | \Psi)\} = \begin{cases} (2 + \alpha)/6 \in [\frac{1}{3}, \frac{2}{3}], & p(z|\alpha), & \text{Slope pdf,} \\ n/(n + 1) \in [0, 1], & p(z|n), & \text{Power pdf,} \\ \frac{(m+2)^2}{3m+4} \left[ \frac{3m+6}{(m+4)(m+3)} \right] \in [0.5, 1], & p(z|m), & \text{Ogive pdf,} \\ (\theta + 1)/2 \in [0.5, 1], & p(z|\theta), & \text{U}[\theta, 1] \text{ pdf.} \end{cases}$$

- Having elicited  $\pi$  one solves for  $\alpha$ ,  $n$  and  $\theta$  in closed form for GDB copula with slope, power or  $U[\theta, 1]$  generating pdf.
- Having elicited  $\pi$  one solves for  $m$  using a numerical procedure in case of GDB copula with Ogive generating pdf.

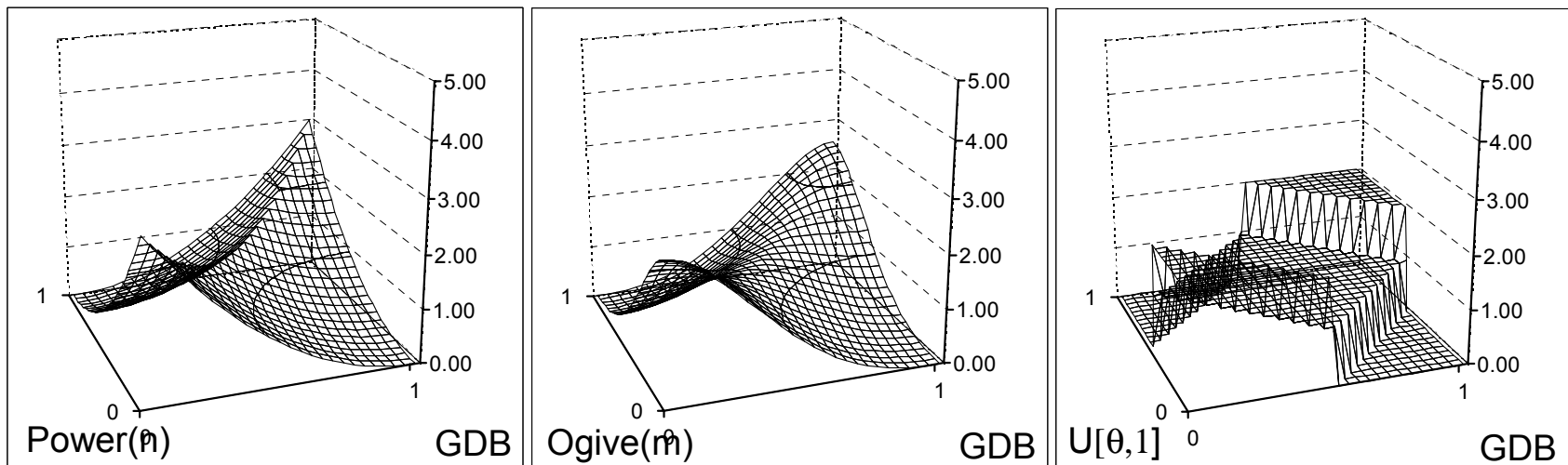
## 4. COPULA PARAM. ELICITATION...

### GDB Copulas

- Assume that an expert has assessed a value :

$$\pi\{X, Y|p(\cdot|\Psi)\} = Pr(Y \leq 0.5|X \leq 0.5) = 0.75 \Rightarrow$$

$$\left\{ \begin{array}{ll} \text{GDB - Power Gen. Density,} & n = 3, \\ \text{GDB - Ogive Gen. Density,} & m \approx 4.916, \\ \text{GDB - } U[\theta, 1] \text{ Gen. Density,} & \theta = 0.5. \end{array} \right.$$



# OUTLINE

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1. ORDINAL MEASURES OF ASSOCIATION: OVERVIEW
2. ORDINAL MEASURES OF ASSOCIATION: ARCHIMEDEAN
3. ORDINAL MEASURES OF ASSOCIATION: GDB
4. COPULA PARAMETER ELICITATION: ARCHIMEDEAN
5. COPULA PARAMETER ELICITATION: GDB
- 6. COPULA SELECTION: AN ENTROPY APPROACH**
7. A VALUE OF INFORMATION EXAMPLE

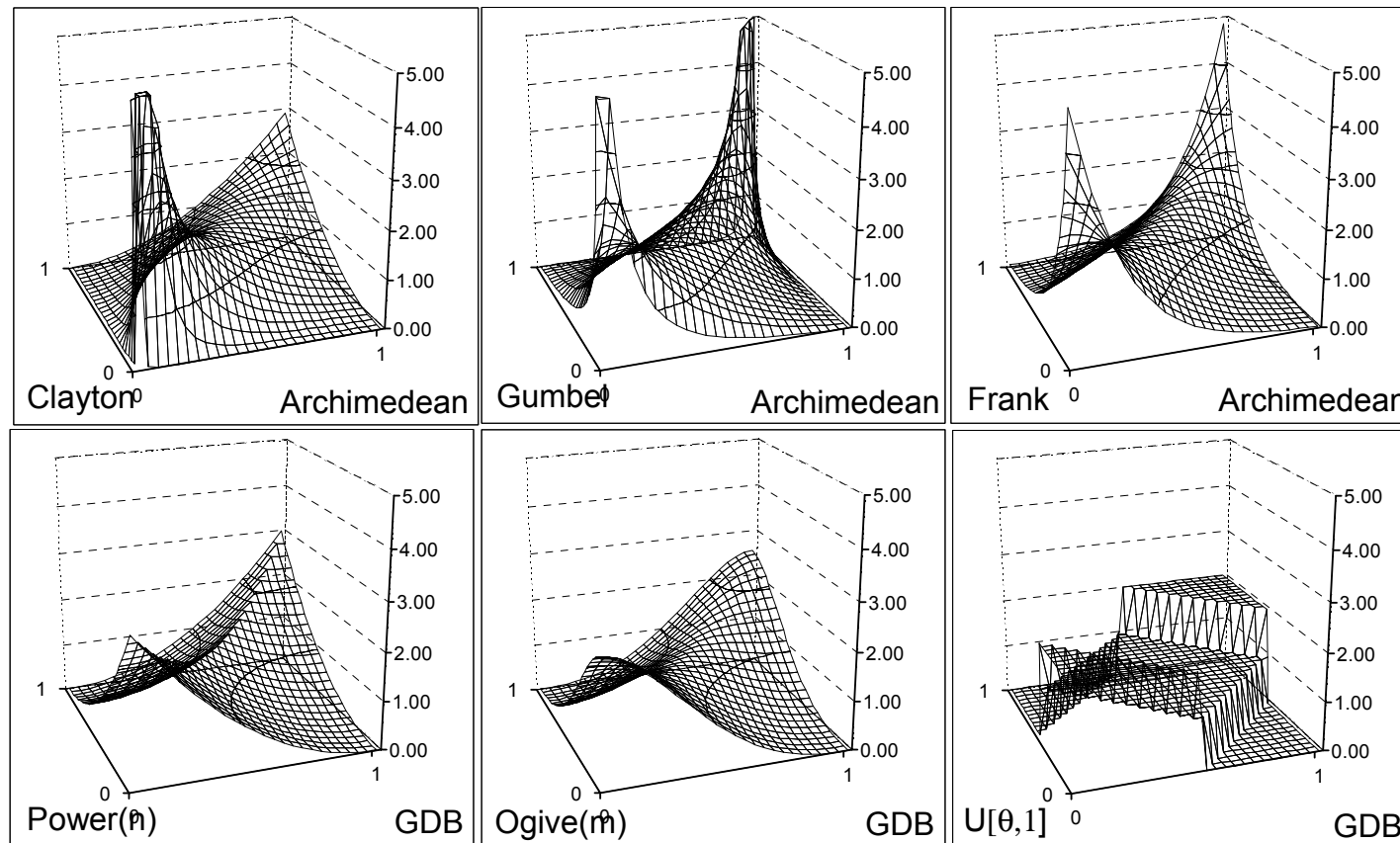


## 6. COPULA SELECTION...

How to pick one?

- Assume that an expert has assessed a value

$$\pi\{X, Y|p(\cdot|\Psi)\} = Pr(Y \leq 0.5|X \leq 0.5) = 0.75.$$



## 6. COPULA SELECTION...

How to pick one?

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- **All six copulas above match the constraint:**

$$\pi\{X, Y|p(\cdot|\Psi)\} = Pr\{Y < 0.5|X < 0.5\} = 0.75$$

- Lower tail dependence  $\Rightarrow$  Pick Clayton Copula
- Upper tail dependence  $\Rightarrow$  Pick Gumbel Copula

- **If neither is required, pick one that is uniform as possible?**

Clayton :  $\alpha \approx 1.915 \Rightarrow \rho_s \approx 0.6625, \beta = 0.5, \tau \approx 0.489$

Gumbel :  $\alpha \approx 1.997 \Rightarrow \rho_s \approx 0.6616, \beta = 0.5, \tau = 0.5$

Frank :  $\alpha \approx 4.875 \Rightarrow \rho_s \approx 0.6244, \beta = 0.5, \tau \approx 0.448$

Power( $n$ ) :  $n = 3 \Rightarrow \rho_s(n) = 0.6000, \beta = 0.5, \tau = 0.414,$

Ogive( $m$ ) :  $m \approx 4.916 \Rightarrow \rho_s(m) = 0.6059, \beta = 0.5, \tau = 0.415,$

DB( $\theta$ ) :  $\theta = 0.5 \Rightarrow \rho_s(\theta) = 0.6250, \beta = 0.5, \tau = 0.417,$

## 6. COPULA SELECTION...

Smallest  $\rho_s$ ?

- 
- **Can we select the one with the smallest rank correlation in general?**
  - Pdf  $p(\cdot | \Psi)$  symmetric on  $[0, 1] \Rightarrow E[Z|\psi] = \pi\{X, Y|p(\cdot | \Psi)\} = \frac{1}{2}$ .
  - Pdf  $p(\cdot | \Psi)$  symmetric on  $[0, 1] \Rightarrow \rho_s \equiv 0, \beta \equiv 0, \tau \equiv 0$ .
  - When elicited  $\pi\{X, Y|p(\cdot | \Psi)\} = Pr(Y \leq 0.5|X \leq 0.5) = \frac{1}{2}$  it seems to intuitive to select copula with independent uniform marginals.
  - **Hence, answer is: No.**

## 6. COPULA SELECTION...

### Max. Entropy?

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- Select copula that **minimizes distance** between it and copula with independent uniform marginals.
- **Kullback-Liebler distance** measures **the relative information** of one candidate pdf  $f(x, y)$  with respect to pdf  $g(x, y)$  given by

$$I(f|g) = \int \int f(x, y) \ln\{f(x, y)/g(x, y)\} dx dy.$$

- Setting  $f(x, y) = c\{x, y\}$  and  $g(x, y) = u(x, y) = 1$ , yields:

$$I(c|u) = \int \int_{s_c} c(x, y) \ln\{c(x, y)\} dx dy, \quad (40)$$

- The quantity  $E = -I(c|u) \geq$  is known as **the entropy** of the pdf  $c(x, y)$ .
- Bedford and Meeuwissen (1997) constructed **maximum entropy copulae given a correlation constraint** that are *minimally informative*.

## 6. COPULA SELECTION...

### Max. Entropy

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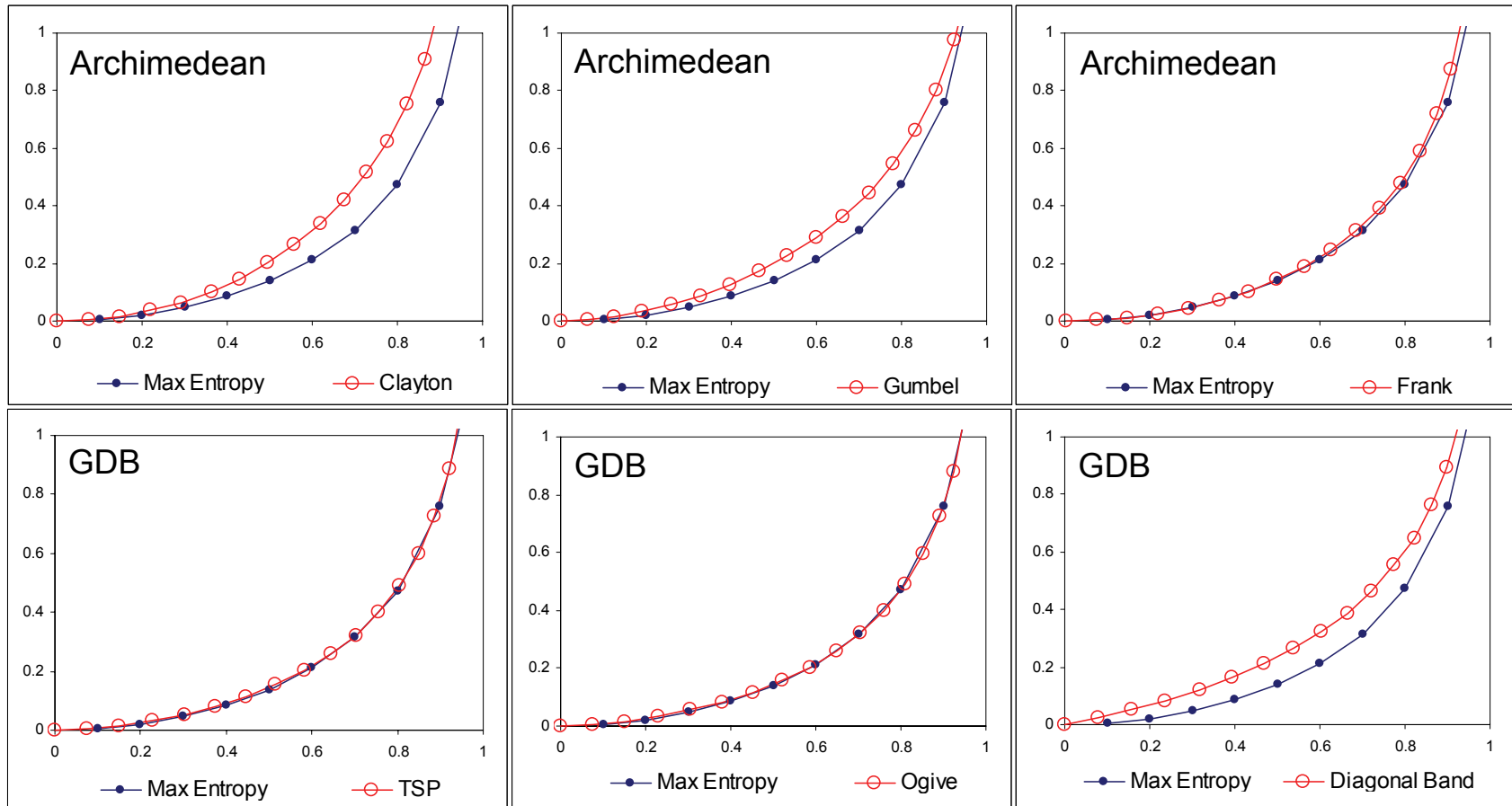
- Bedford and Meeuwissen's (1997) **maximum entropy copulae given a correlation constraint**, do not possess closed form pdf and cdf.
- Select amongst a set of GDB copula that matches a specified constraint that one that is **minimally informative** (or has maximum entropy).
- Utilizing **numerical integration** over a 100 by 100 grid over  $[0, 1]^2$ , we have

$$I\{c(x, y)|p(\cdot|\psi)\} = \begin{cases} 0.2136, & p(z|n), n = 3, & \text{Power pdf,} \\ 0.2222, & p(z|m), m = 4.916, & \text{Ogive pdf} \\ 0.3400, & p(z|\theta), \theta = 0.5. & \text{U}[\theta, 1] \text{ pdf} \end{cases}$$

- Summarizing, given *the constraint* set by  $\pi = Pr(Y \leq 0.5|X \leq 0.5) = 0.75$ , the relative information approach above would suggest to **use the GDB copula with the power( $n$ ) generating pdf (26) with  $n = 3$ .**

# 6. COPULA SELECTION...

## Max. Entropy



**X-Axis: Rank Correlation**

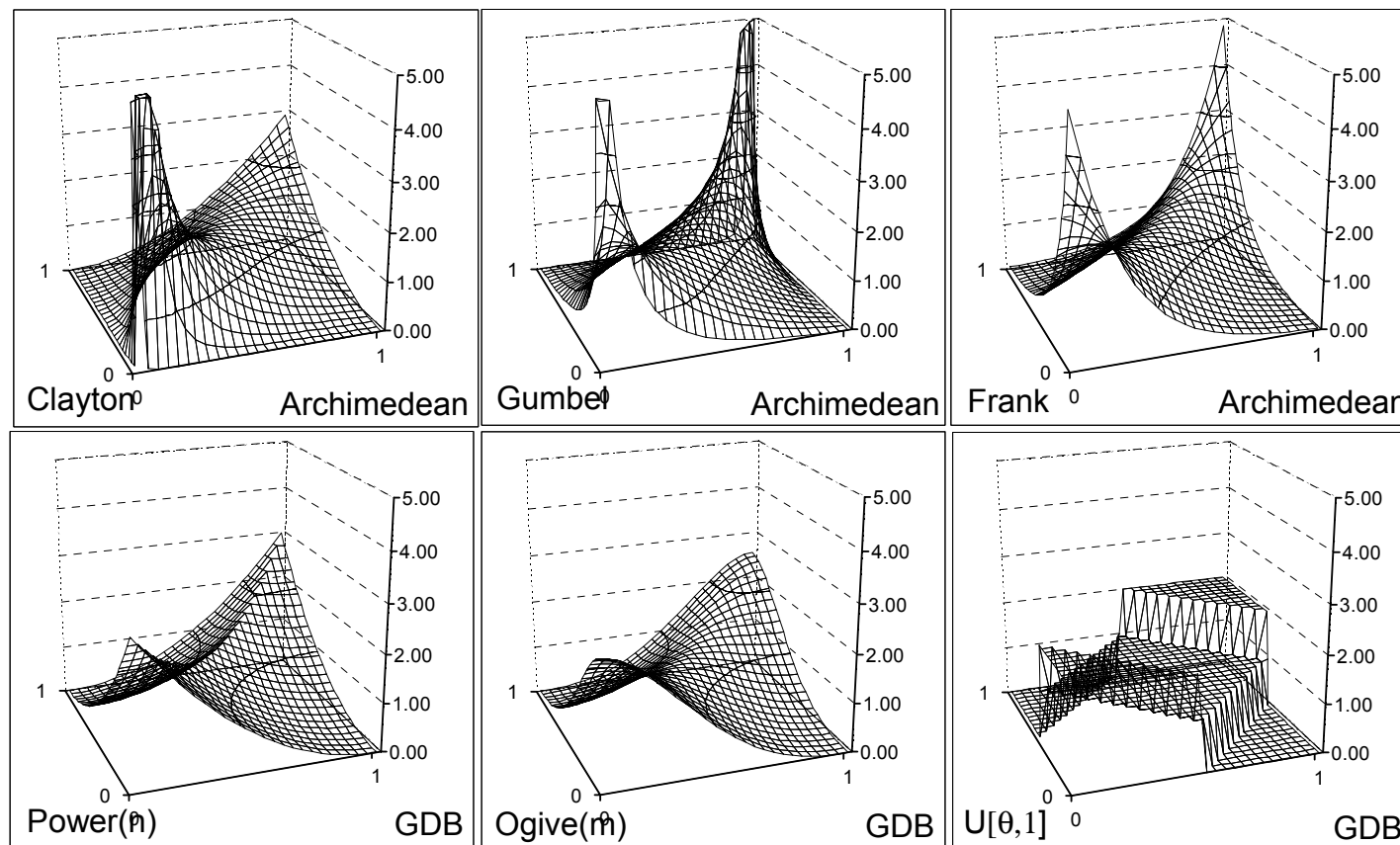
**Y-Axis: Relative Information = - Entropy**

## 6. COPULA SELECTION...

How to pick one?

- Assume that an expert has assessed a value

$$\pi\{X, Y|p(\cdot|\Psi)\} = Pr(Y \leq 0.5|X \leq 0.5) = 0.75.$$



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7. **A VALUE OF INFORMATION EXAMPLE**



## 7. A VALUE OF INFORMATION EXAMPLE...

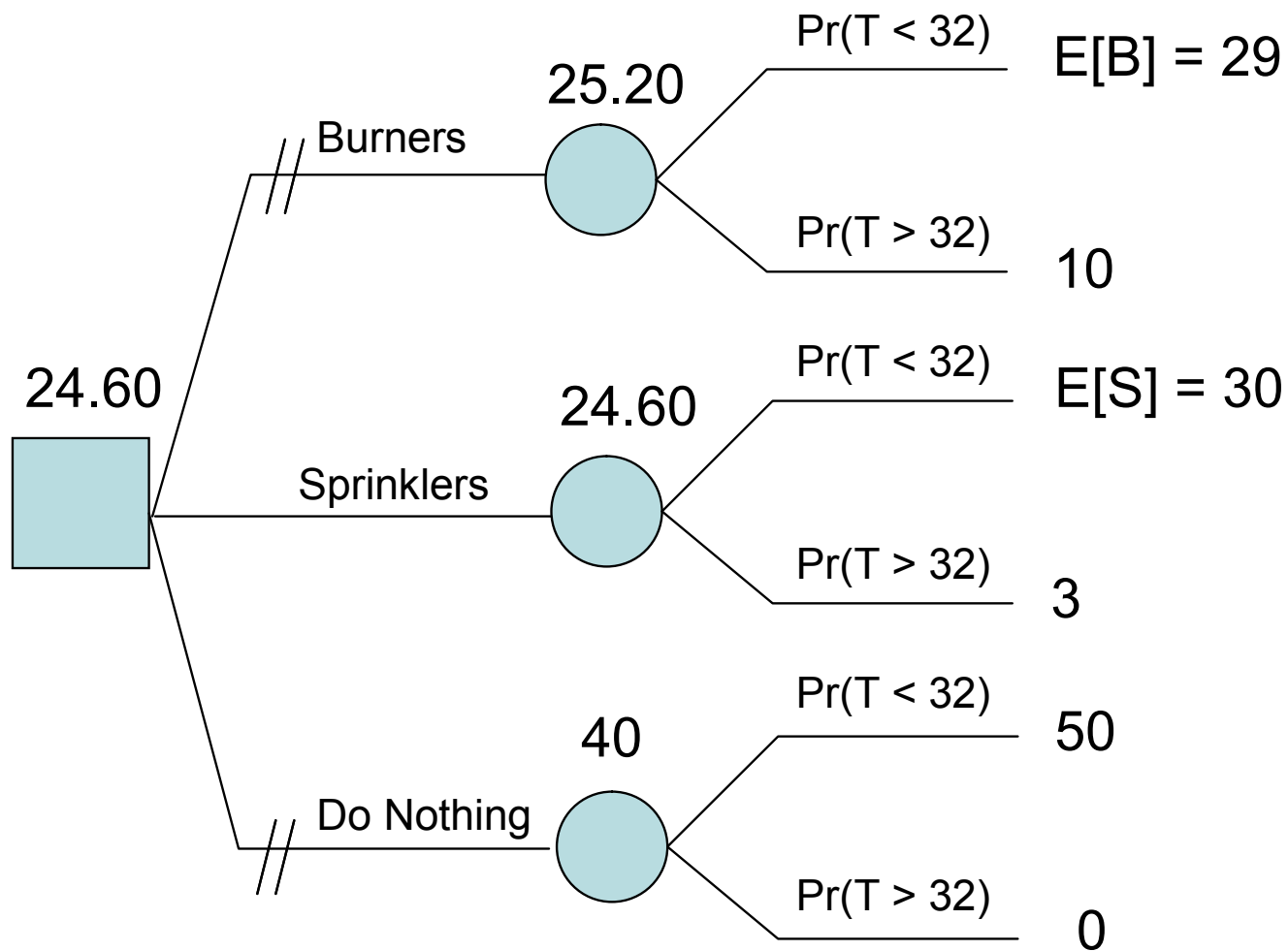
### Description

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- The farmer needs to **protecting his/her crop of oranges** (with a total worth of \$50,000) against freezing weather with the objective of **minimizing losses**.
- **Temperature  $T$**  (in Fahrenheit)  $\sim U[24, 34]$  that night.
- $T < 32$  (below freezing)  $\Rightarrow$  Farmer loses entire crop **without protection**.
- Two protection alternatives: **Burners** or **Sprinklers** with \$10,000 or \$3,000, respectively, in mobilization cost.
- Effectiveness of both is uncertain. Farmer assesses **all-in loss  $B(S)$**  to vary between  $a = \$25,000$  (\$28,000) and  $b = \$35,000$  (\$33,000) with a most likely value of  $m = \$27,000$  (\$29,000) **if it freezes**.
- Assume  $B$  and  $S$  to be **triangular distributed**  $\Rightarrow E[B] = \$29,000$ ,  $E[S] = \$30,000$ .

## 7. A VALUE OF INFORMATION EXAMPLE...

### Decision Tree



## 7. A VALUE OF INFORMATION EXAMPLE...

### Dependence on $T$

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- **Effectiveness sprinkler** option is based on an **insular layer of freezing water** on the oranges.
- **Effectiveness burner** option is based on **gas usage**.
- The farmer assesses a 90% chance (60% chance) that the burning loss  $B$  (sprinkler loss  $S$ ) is **above its median value**  $b_{0.5}$  ( $s_{0.5}$ ) when the temperature  $T$  is **below its median value**  $29F$ . Hence, we have:

$$Pr(B > b_{0.5} | T < 29) = 0.9, Pr(S > s_{0.5} | T < 29) = 0.6,$$

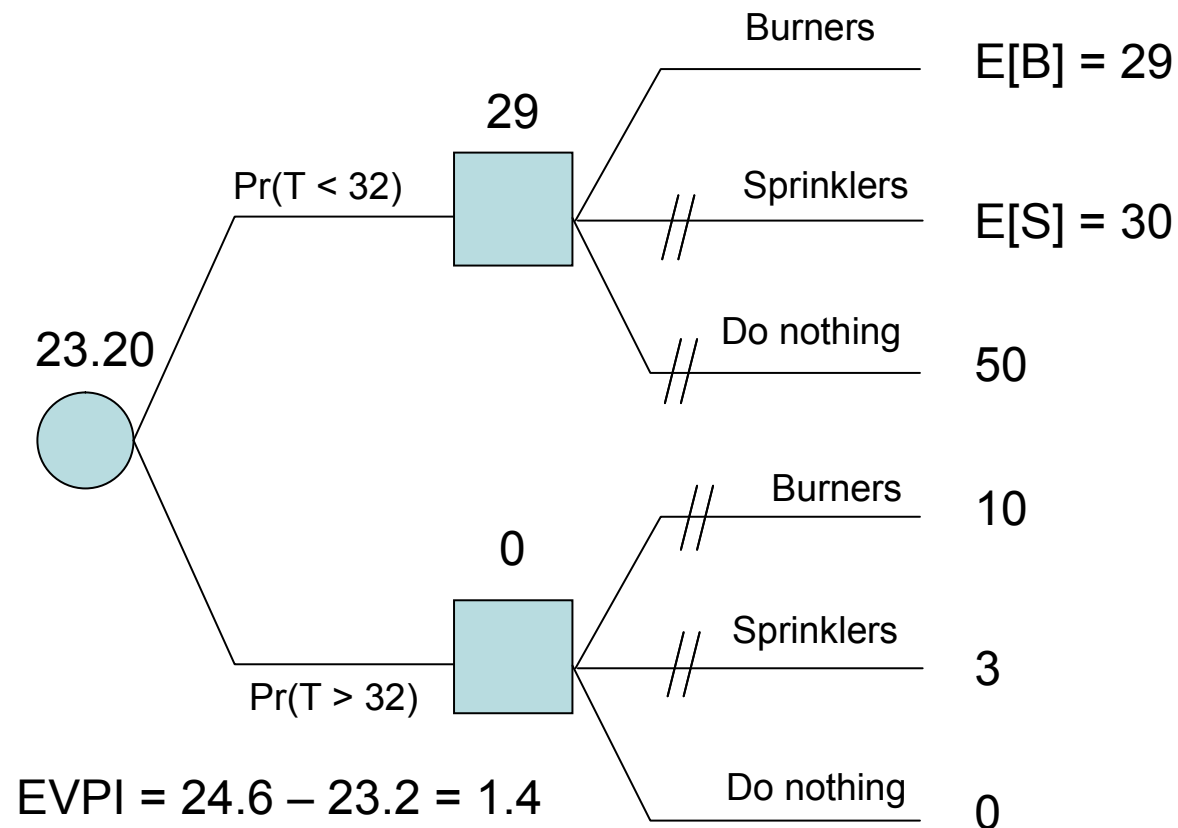
where  $b_{0.5} \approx \$28,675$  and  $s_{0.5} \approx \$29,838$ .

- **Model dependence** between  $B$  ( $S$ ) and  $T$  using a GDB copula with a power (slope) generating density with  $n = 1/11$  ( $\alpha = 0.4$ ).

## 7. A VALUE OF INFORMATION EXAMPLE...

### EVPI Freezing

- To reduce losses further, the farmer considers consulting either a *clairvoyant Expert A* on "**Freezing**" or a *clairvoyant Expert B* on **the temperature  $T$** .



## 7. A VALUE OF INFORMATION EXAMPLE...

### EVPI Temperature $T$

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- EVPI on the temperature  $T$  from Expert B is **more complicated** since it requires **evaluation of  $E[B|t]$  and  $E[S|t]$** .

- Given  $t$ , we evaluate  $E[B|t]$  using  $s = 2500$  realizations using the steps:

Step 1:  $x = \frac{t-24}{34-24}$  (Recall,  $T \sim Uniform[24, 34]$ )

Step 2: **Sample quantile levels  $y_i, i = 1, \dots, s$**  from GDB( $X, Y$ ) copula with power( $n$ ) generating density for  $B, n = 1/11$ .

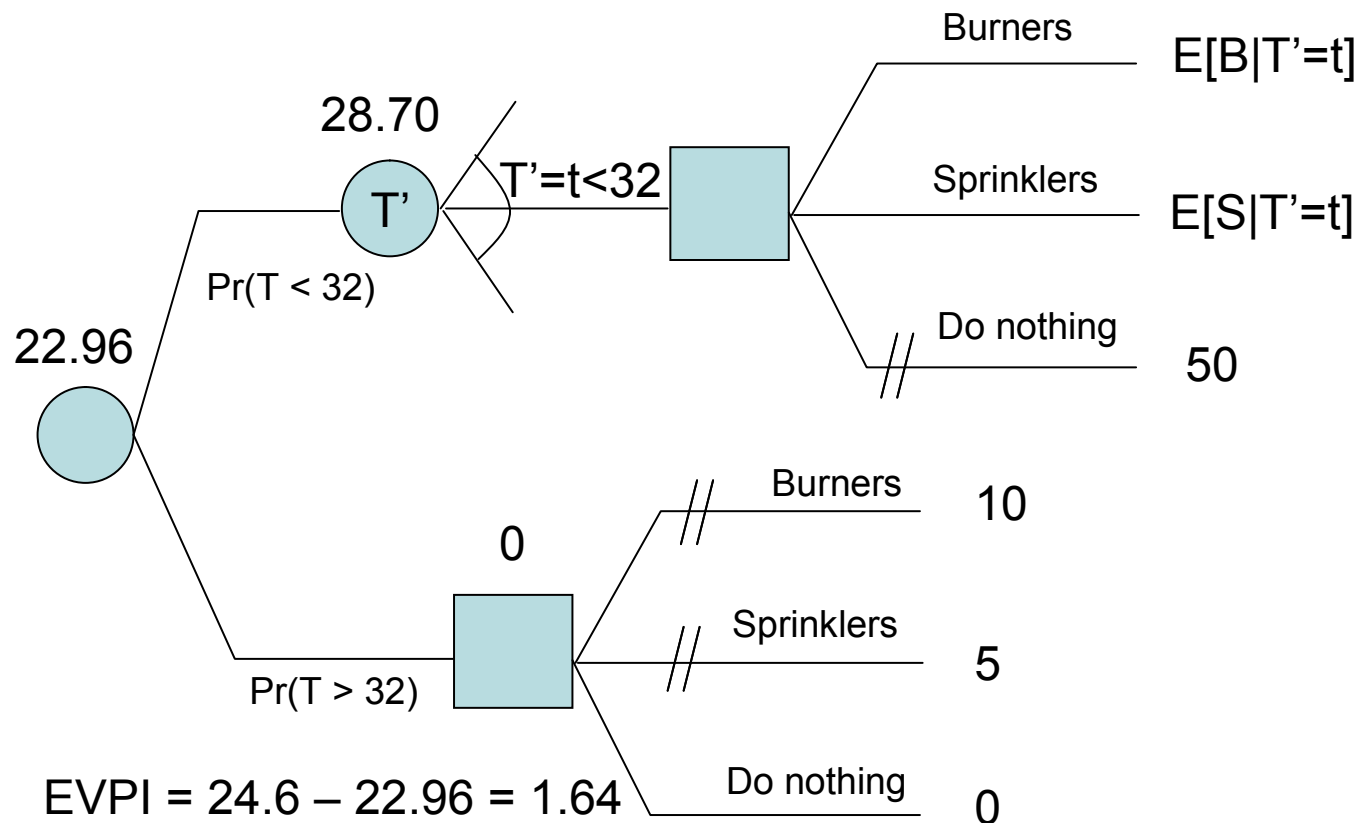
Step 3:  $E[B|t] = \frac{1}{s} \sum_{i=1}^s H^{-1}(y_i),$

- $B \sim Triang(\$25,000; \$27,000; \$35,000)$ ,  $H^{-1}(\cdot)$  is the inverse cdf or quantile function of  $B$ .  $S \sim Triang(\$28,000; \$29,000; \$33,000)$ . Evaluation of  $E[S|t]$  is analogous.

## 7. A VALUE OF INFORMATION EXAMPLE...

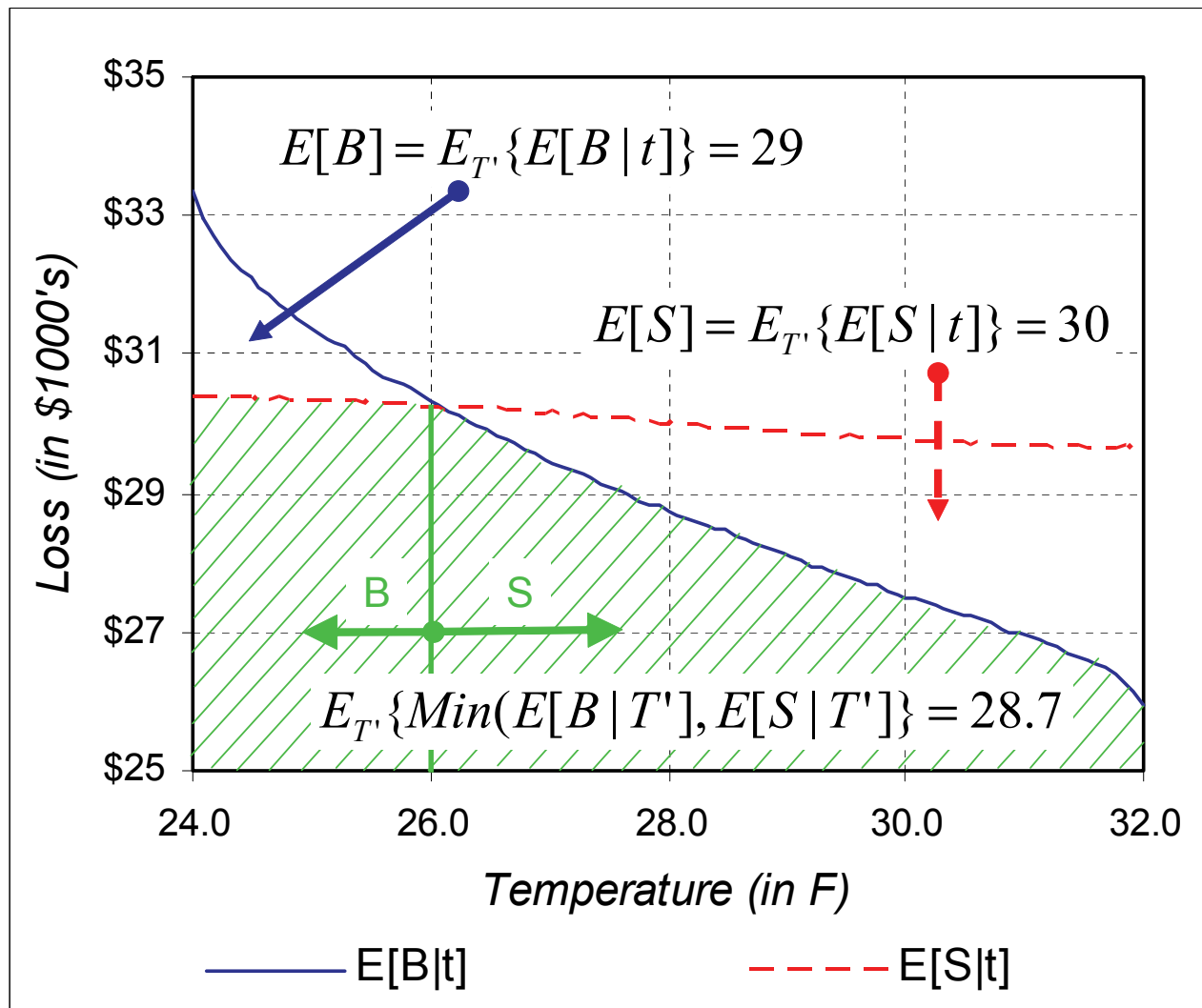
### EVPI Temperature $T$

- $T' = (T|T < 32) \sim U[24, 32]$  since  $T \sim U[24, 34]$ .



## 7. A VALUE OF INFORMATION EXAMPLE...

EVPI Temperature  $T$



## 7. A VALUE OF INFORMATION EXAMPLE...

### EVPI Temperature $T$

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- EVPI "freezing"  $\approx$  \$1,400, EVPI "freezing"  $\approx$  \$1,640
- Summarizing, the farmer is willing to pay \$240 dollars more for perfect information on the temperature  $T$ .
- Optimal decision switches to Sprinkler option when *Expert A* provides "Freezing" information.
- Optimal decision switches to Sprinkler option when *Expert B* provides "temperature  $t$ " information, where  $26 < t < 32$ .
- When *Expert B* provides "temperature  $t$ " information, where  $24 < t < 26$ , the optimal decision remains the Burner option.

## QUESTIONS?



## 7. COPULAS...

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