

# Estimation and Comparison of Correlation-based Measures of Concordance

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July 11, 2020

# MOCs and related questions

- Pearson's linear correlation coefficient  $\rho$  does **not** possess desirable properties for **measuring dependence** (Embrechts et al., 2002).
- Alternatively, **measures of concordance (MOCs)** are widely used to quantify dependence in terms of a single number.
- **Examples:** Spearman's rho  $\rho_S$ , Blomqvist's beta  $\beta$  and Kendall's tau  $\tau$ .

(Q1) **Why are they popular?**

(Q2) **How to compare MOCs? Which one is best to use?**

# Why are $\rho_S$ , $\beta$ and $\tau$ popular?

(A1) They often admit explicit forms for **elliptical** and **Archimedean copulas**.

**Ex:**  $\beta(C_\rho^{\text{Ga}}) = \tau(C_\rho^{\text{Ga}}) = \frac{2}{\pi} \arcsin(\rho)$  for  $\rho \in [-1, 1]$ .

(A2) Because of (A1), they can be used to estimate parameters of these copulas by **method-of-moment-like** estimators.

**Ex:** Estimate  $\tau$  by  $\hat{\tau}$  from data, and find  $\rho \in [-1, 1]$  such that  $\hat{\tau} = \frac{2}{\pi} \arcsin(\rho)$ .

However, benefit of these features is **limited in practice** since these copulas may not always be realistic.

# Interpretability as transformed correlation: 1/2

$\rho_S$ ,  $\beta$  and  $\tau$  admit the forms:

$$\rho_S(C) = 12\mathbb{E}[UV] - 3 = \rho(U, V),$$

$$\beta(C) = 4C(1/2, 1/2) - 1 = \rho(\mathbf{1}_{\{U>1/2\}}, \mathbf{1}_{\{V>1/2\}}),$$

$$\tau(C) = 4 \int_{(0,1)^2} C(u, v) \, dC(u, v) - 1 = \rho(\mathbf{1}_{\{U>\tilde{U}\}}, \mathbf{1}_{\{V>\tilde{V}\}}),$$

where  $(U, V)$  and  $(\tilde{U}, \tilde{V})$  are independent copies from  $C$ . So they are popular partly because...

(A3) They are easy to **interpret** and **explain**!

# Interpretability as transformed correlation: 2/2

This **interpretability** still holds for  $(g_1, g_2)$ -transformed rank correlation coefficients

$$\kappa_{g_1, g_2}(C) = \rho(g_1(U), g_2(V)) \quad \text{for some } g_1, g_2 : [0, 1] \rightarrow \mathbb{R}.$$

**Ex:**  $g_1 = g_2 = G^{-1}$  with  $G$  being...

- Bern(1/2)  $\Rightarrow$  Blomqvist's beta / median correlation coefficient
- Unif(0, 1)  $\Rightarrow$  Spearman's rho
- N(0, 1)  $\Rightarrow$  **van der Waerden's coefficient** / normal score correlation

**We answer which  $g_1$  and  $g_2$  to use in terms of **ease of estimation** / **asymptotic variance**.**

# Literature review

## Comparing MOCs in terms of

- **estimation and robustness** (by numerical experiments); De Winter et al. (2016).
- **influence function**; Croux and Dehon (2010), Boudt et al. (2012), Borroni and Cifarelli (2017) and Raymaekers and Rousseeuw (2019).
- **power in tests of independence**; Bhuchongkul (1964), Behnen (1971), Behnen (1972), Luigi Conti and Nikitin(1999), Rodel and Kossler (2004) and Genest and Verret (2005).
- **tractability**; Schmid and Schmidt (2007).

# Outline

- ① **Preliminaries (cont'd)**
  - Copulas, MOCs and transformed rank correlations.
- ② **Comparison of asymptotic variances**
  - Canonical estimators, optimal shifts, theoretical results for Fréchet copulas and optimality of Blomqvist's beta.
- ③ **Comparison with Kendall's tau**
  - Asymptotic variance for Kendall's tau, its optimality, standardization by sample size.
- ④ **Simulation study**
  - Investigation of asymptotic variances for various copulas and MOCs.

# Notation on copulas

- $\mathcal{C}_2$ : the set of all bivariate copulas.
- $C \preceq C'$ :  $C' \in \mathcal{C}_2$  is **more concordant** than  $C \in \mathcal{C}_2$  if  $C(u, v) \leq C'(u, v)$  for all  $(u, v) \in [0, 1]^2$ .
- $\Pi(u, v) = uv$ : **independence copula**,  $M(u, v) = \min(u, v)$ : **comonotonic copula** and  $W(u, v) = \max(u + v - 1, 0)$ : **countermonotonic copula** such that  $W \preceq C \preceq M, \forall C \in \mathcal{C}_2$ .
- For  $\kappa : \mathcal{C}_2 \rightarrow \mathbb{R}$ , we identify  $\kappa(C)$  for  $C \in \mathcal{C}_2$  with  $\kappa(U, V)$  for a random vector  $(U, V) \sim C$ .
- $\bar{C}(u, v) = \mathbb{P}(U > u, V > v)$  for  $(u, v) \in [0, 1]$  and  $(U, V) \sim C$ : the **survival function** of  $C$ .



# Axioms of MOCs

## Definition 1.1 (Axioms for measures of concordance)

A map  $\kappa : \mathcal{C}_2 \rightarrow \mathbb{R}$  is called a **measure of concordance** if it satisfies the followings axioms.

- ① **Domain:**  $\kappa(C)$  is **defined** for any  $C \in \mathcal{C}_2$ .
- ② **Symmetry:**  $\kappa(V, U) = \kappa(U, V)$  for any  $(U, V) \sim C \in \mathcal{C}_2$ .
- ③ **Monotonicity:** If  $C \preceq C'$  for  $C, C' \in \mathcal{C}_2$ , then  $\kappa(C) \leq \kappa(C')$ .
- ④ **Range:**  $-1 \leq \kappa(C) \leq 1$  and  $\kappa(C) \pm 1$  are attainable.
- ⑤ **Independence:**  $\kappa(\Pi) = 0$  for the independence copula  $\Pi \in \mathcal{C}_2$ .
- ⑥ **Change of sign:**  $\kappa(U, 1 - V) = -\kappa(U, V)$ .
- ⑦ **Continuity:** If  $C_n \rightarrow C$  pointwise for  $C_n, C \in \mathcal{C}_2$ ,  $n \in \mathbb{N}$ , then  $\lim_{n \rightarrow \infty} \kappa(C_n) = \kappa(C)$ .

# Transformed rank correlation coefficients

- Consider a class of maps on  $\mathcal{C}_2$  written as

$$\kappa_{g_1, g_2}(U, V) = \rho(g_1(U), g_2(V)) \quad \text{for } g_1, g_2 : [0, 1] \rightarrow \mathbb{R}.$$

- Hofert and Koike (2019) showed that  $\kappa_{g_1, g_2}$  is MOC only if  $g_1$  and  $g_2$  are **monotone with each other** (w.l.o.g., **increasing**).
- Assuming **left-continuity**,  $g_1$  and  $g_2$  are **quantiles**  $g_1 = G_1^{-1}$  and  $g_2 = G_2^{-1}$  of some cdfs  $G_1, G_2 : \mathbb{R} \rightarrow [0, 1]$ .
- Define the set of **concordance-inducing functions** by

$$\mathcal{G} = \{G : \mathbb{R} \rightarrow [0, 1] : \text{nondegenerate radially symmetric cdfs with finite second moment.}\}.$$

# Properties of $\kappa$

## Proposition 1.2 (Basic properties of $\kappa_{G_1^{-1}, G_2^{-1}}$ )

- ① For cdfs  $G_1$  and  $G_2$ ,  $\kappa_{G_1^{-1}, G_2^{-1}}$  is a measure of concordance **i.f.f.**  $G_1, G_2$  are **of the same type** with some  $G \in \mathcal{G}$ .
- ②  $\kappa_{G_1^{-1}, G_2^{-1}} = \kappa_{G^{-1}, G^{-1}} =: \kappa_G$  (call it the  **$G$ -transformed rank correlation coefficient**).
- ③  $\kappa_G$  is **invariant under location-scale transforms** of  $G$ , that is,  $\kappa_{G_{\mu, \sigma}}(C) = \kappa_G(C)$  where  $G_{\mu, \sigma}(x) = G\left(\frac{x-\mu}{\sigma}\right)$ ,  $\mu \in \mathbb{R}$ ,  $\sigma > 0$ .
- ④  $\kappa_G$  is **linear**, that is,  $\kappa_G(\alpha_1 C_1 + \alpha_2 C_2) = \alpha_1 \kappa_G(C_1) + \alpha_2 \kappa_G(C_2)$  for  $C_1, C_2 \in \mathcal{C}_2$  and  $\alpha_1, \alpha_2 \geq 0$  s.t.  $\alpha_1 + \alpha_2 = 1$ .

**Remark:** Kendall's tau is not included in this class since it is **not linear**.

## 1 Preliminaries (cont'd)

- Copulas, MOCs and transformed rank correlations.

## 2 Comparison of asymptotic variances

- Canonical estimators, optimal shifts, theoretical results for Fréchet copulas and optimality of Blomqvist's beta.

## 3 Comparison with Kendall's tau

- Asymptotic variance for Kendall's tau, its optimality, standardization by sample size.

## 4 Simulation study

- Investigation of asymptotic variances for various copulas and MOCs.

# Canonical estimator of $\kappa_G$

- Assume that  $\mathbb{E}_G[X] = 0$  and  $\text{Var}_G(X) = 1$ .
- Define a **canonical estimator** of  $\kappa_G$

$$\hat{\kappa}_G = \frac{1}{n} \sum_{i=1}^n G^{-1}(U_i)G^{-1}(V_i),$$

where  $(U_1, V_1), \dots, (U_n, V_n) \stackrel{\text{iid}}{\sim} C$ .

- Then the CLT  $\sqrt{n} \{ \hat{\kappa}_G - \kappa_G(C) \} \xrightarrow{d} \text{N}(0, \sigma_G^2(C))$  holds, where

$$\sigma_G^2(C) = \text{Var}(G^{-1}(U)G^{-1}(V))$$

and  $G \in \mathcal{G}_4$  with

$$\mathcal{G}_4 = \{G \in \mathcal{G} : \mathbb{E}_G[X] = 0, \text{Var}_G(X) = 1 \text{ and } \mathbb{E}_G[X^4] < \infty\}.$$

# Optimal asymptotic variances: 1/2

- For  $\mathcal{H} \subseteq \mathcal{G}_4$  and  $\mathcal{D} \subseteq \mathcal{C}_2$ , consider

$$\underline{\sigma}_G^2(\mathcal{D}) = \inf_{C \in \mathcal{D}} \sigma_G^2(C), \quad \bar{\sigma}_G^2(\mathcal{D}) = \sup_{C \in \mathcal{D}} \sigma_G^2(C),$$

and the **optimal best and worst asymptotic variances** and their attainers defined by

$$\underline{\sigma}_*^2(\mathcal{H}, \mathcal{D}) = \inf_{G \in \mathcal{H}} \underline{\sigma}_G^2(\mathcal{D}), \quad \underline{G}_*(\mathcal{H}, \mathcal{D}) = \operatorname{arginf}_{G \in \mathcal{H}} \underline{\sigma}_G^2(\mathcal{D}),$$

$$\bar{\sigma}_*^2(\mathcal{H}, \mathcal{D}) = \inf_{G \in \mathcal{H}} \bar{\sigma}_G^2(\mathcal{D}), \quad \bar{G}_*(\mathcal{H}, \mathcal{D}) = \operatorname{arginf}_{G \in \mathcal{H}} \bar{\sigma}_G^2(\mathcal{D}),$$

respectively.

- Typically  $\mathcal{H} = \mathcal{G}_4$  but can be limited to **continuous** functions or those with **bounded** supports.

# Optimal asymptotic variances: 2/2

- **Interpretation:**  $\underline{G}_*(\mathcal{H}, \mathcal{D})$  and  $\overline{G}_*(\mathcal{H}, \mathcal{D})$  are the **best choices** of  $G$  to accurately estimate  $\kappa_G$  if one believes that  $\mathcal{D}$  is the set of copulas which one wants to quantify and compare in terms of their concordance.
- Does there exist  $G \in \underline{G}_*(\mathcal{H}, \mathcal{D}) \cap \overline{G}_*(\mathcal{H}, \mathcal{D})$ ?
- **Reflection invariance:** By **radial symmetry** of  $G \in \mathcal{G}_4$ ,  $C \mapsto \sigma_G^2(C)$  is **reflection invariant** in the sense that

$$\begin{aligned} \sigma_G^2(U, V) &= \sigma_G^2(1 - U, V) = \sigma_G^2(U, 1 - V) \\ &= \sigma_G^2(1 - U, 1 - V). \end{aligned}$$

# Optimal location shifts of $G$ : 1/3

- $\kappa_G$  is location-scale invariant but its canonical estimator is **not**.
- Let  $G_0 \in \mathcal{G}_4$  be s.t.  $\mathbb{E}_{G_0}[X] = 0$  and  $\text{Var}_{G_0}(X) = 1$ , and let  $G_{\mu,\sigma}(x) = G_0\left(\frac{x-\mu}{\sigma}\right)$  where  $\mu \in \mathbb{R}$  and  $\sigma > 0$ .
- For known  $\mu$  and  $\sigma$ , the **canonical estimator** of  $\kappa_{G_{\mu,\sigma}}$  is

$$\hat{\kappa}_{G_{\mu,\sigma}} = \frac{1}{n} \sum_{i=1}^n \frac{G_{\mu,\sigma}^{-1}(U_i)G_{\mu,\sigma}^{-1}(V_i)}{\sigma^2} - \left(\frac{\mu}{\sigma}\right)^2.$$

- By the CLT, it has the asymptotic variance

$$\sigma_{G_{\mu,\sigma}}^2(C) = \text{Var} \left( \frac{G_{\mu,\sigma}^{-1}(U)G_{\mu,\sigma}^{-1}(V)}{\sigma^2} \right).$$



# Optimal location shifts of $G$ : 2/3

- W.l.o.g, one can take  $\sigma = 1$  since  $G_{\mu,\sigma}^{-1}(u) = G_{\mu/\sigma,1}^{-1}(u)$ .
- Consider  $G_\mu(x) = G_0(x - \mu)$  where  $\mu \in \mathbb{R}$ . Then

$$\sigma_{G_\mu}^2(C) = \text{Var}(G_\mu^{-1}(U)G_\mu^{-1}(V)) = \text{Var}(X_0Y_0 + \mu(X_0 + Y_0))$$

where  $X_0 = G_0^{-1}(U)$ ,  $Y_0 = G_0^{-1}(V)$  and  $(U, V) \sim C$ .

- Provided  $C \neq W$ ,  $\sigma_{G_\mu}^2(C)$  is **minimized** when

$$\mu = \mu_* = \mu_*(G_0, C) = -\frac{\text{Cov}(X_0Y_0, X_0 + Y_0)}{\text{Var}(X_0 + Y_0)}.$$

- We call  $\mu_*$  an **optimal shift** of  $G_0 \in \mathcal{G}_4$  under  $C \in \mathcal{C}_2$ .

# Optimal location shifts of $G$ : 3/3

## Proposition 2.1 (Sufficient condition for $\mu_* = 0$ )

For  $C \in \mathcal{C}_2$  and  $G_0 \in \mathcal{G}_4$  with mean zero and variance one,  $\mu_*(G_0, C) = 0$  holds if  $C$  is **radially symmetric**, that is,

$$(U, V) \stackrel{d}{=} (1 - U, 1 - V) \quad \text{for } (U, V) \sim C.$$

- $\mu_* = 0$  if  $C$  is  $M$ ,  $W$ ,  $\Pi$ , a **Gaussian copula**,  **$t$  copula** or their mixtures.
- $\mu_* \neq 0$  if  $C$  is a **Clayton** or **Gumbel** copula. Nevertheless, we will see that, even in this case,  $\sigma_{G_{\mu_*}}^2(C)$  and  $\sigma_{G_0}^2(C)$  are **very close**.
- In the following we **focus on the case  $\mu = 0$** .

# Asymptotic variances for fundamental copulas

## Proposition 2.2 (Asymptotic variances for fundamental copulas)

- ① Suppose  $\mathcal{D} = \{\Pi\}$ . Then, for any  $\mathcal{H} \subseteq \mathcal{G}_4$ ,

$$\underline{\sigma}_*^2(\mathcal{H}, \{\Pi\}) = \overline{\sigma}_*^2(\mathcal{H}, \{\Pi\}) = 1,$$

$$\underline{G}_*(\mathcal{H}, \{\Pi\}) = \overline{G}_*(\mathcal{H}, \{\Pi\}) = \mathcal{H}.$$

- ② Suppose  $\mathcal{D} = \{M\}$ ,  $\{W\}$  or  $\{M, W\}$ . Then, for  $\mathcal{H} \subseteq \mathcal{G}_4$ ,

$$\underline{\sigma}_*^2(\mathcal{H}, \mathcal{D}) = \overline{\sigma}_*^2(\mathcal{H}, \mathcal{D}) = \inf_{G \in \mathcal{H}} \text{Var}_G(X^2),$$

$$\underline{G}_*(\mathcal{H}, \mathcal{D}) = \overline{G}_*(\mathcal{H}, \mathcal{D}) = \text{arginf}_{G \in \mathcal{H}} \text{Var}_G(X^2).$$

**Proof:** Use  $\sigma_G^2(C) = \text{Var}(XY) = \text{Cov}(X^2, Y^2) + 1 - \text{Cov}(X, Y)^2$ .

# Ordering MOCs for fundamental copulas

Let  $\mathcal{H}_N$ ,  $\mathcal{H}_{\text{Unif}}$  and  $\mathcal{H}_{\text{Bern}}$  be singletons of normal, uniform and Bernoulli distributions with mean zero and variance one, respectively.

## Proposition 2.3 (Orders of MOCs for fundamental copulas)

For  $\mathcal{D}_F = \{\Pi, M, W\}$ , it holds that

$$\underline{\sigma}_*^2(\mathcal{H}_{\text{Bern}}, \{M, W\}) < \underline{\sigma}_*^2(\mathcal{H}_{\text{Unif}}, \{M, W\}) < \underline{\sigma}_*^2(\mathcal{H}_N, \{M, W\}),$$

$$\bar{\sigma}_*^2(\mathcal{H}_{\text{Bern}}, \{M, W\}) < \bar{\sigma}_*^2(\mathcal{H}_{\text{Unif}}, \{M, W\}) < \bar{\sigma}_*^2(\mathcal{H}_N, \{M, W\}).$$

$$\underline{\sigma}_*^2(\mathcal{H}_{\text{Bern}}, \mathcal{D}_F) < \underline{\sigma}_*^2(\mathcal{H}_{\text{Unif}}, \mathcal{D}_F) < \underline{\sigma}_*^2(\mathcal{H}_N, \mathcal{D}_F),$$

$$\bar{\sigma}_*^2(\mathcal{H}_{\text{Bern}}, \mathcal{D}_F) = \bar{\sigma}_*^2(\mathcal{H}_{\text{Unif}}, \mathcal{D}_F) < \bar{\sigma}_*^2(\mathcal{H}_N, \mathcal{D}_F).$$

**Proof:**  $\text{Var}_{G_N}(X^2) = 2$ ,  $\text{Var}_{G_{\text{Unif}}}(X^2) = 0.8$  and  $\text{Var}_{G_{\text{Bern}}}(X^2) = 0$ .

# Fréchet copulas

- A bivariate **Fréchet copula** is defined by

$$C_{\mathbf{p}}^{\text{F}} = p_M M + p_{\Pi} \Pi + p_W W, \quad \mathbf{p} = (p_M, p_{\Pi}, p_W) \in \Delta_3,$$

where  $\Delta_3 = \{(p_1, p_2, p_3) \in \mathbb{R}_+^3 : p_1 + p_2 + p_3 = 1\}$ .

- Let  $\mathcal{C}^{\text{F}} = \{C_{\mathbf{p}}^{\text{F}} : \mathbf{p} \in \Delta_3\}$ .
- Fréchet copulas can be **applied in insurance and finance**, and for **approximating bivariate copulas** (Yang et. al, 2006).
- $\kappa_G(C_{\mathbf{p}}^{\text{F}})$  can **take any value in  $[-1, 1]$**  for any  $G \in \mathcal{G}$ ;

$$\begin{aligned} \kappa_G(C_{\mathbf{p}}^{\text{F}}) &= p_M \kappa_G(M) + p_{\Pi} \kappa_G(\Pi) + p_W \kappa_G(W) \\ &= p_M - p_W \in [-1, 1]. \end{aligned}$$

# Asymptotic variances for Fréchet copulas

## Proposition 2.4 (Asymptotic variances for Fréchet copulas)

For  $G \in \mathcal{G}_4$ , we have that

$$\bar{\sigma}_G^2(\mathcal{C}^F) = 1 + \text{Var}_G(X^2) \quad \text{and} \quad \underline{\sigma}_G^2(\mathcal{C}^F) = 1 \wedge \text{Var}_G(X^2)$$

with the maximum and minimum attained, respectively, by

$$C_{\max} = \begin{cases} \frac{M+W}{2} & \text{if } \text{Var}_G(X^2) > 0, \\ p \frac{M+W}{2} + (1-p)\Pi \text{ for any } p \in [0, 1] & \text{if } \text{Var}_G(X^2) = 0, \end{cases}$$

$$C_{\min} = \begin{cases} M, W & \text{if } 0 \leq \text{Var}_G(X^2) < 1, \\ M, W, \Pi & \text{if } \text{Var}_G(X^2) = 1, \\ \Pi & \text{if } 1 < \text{Var}_G(X^2). \end{cases}$$

# Optimal asymptotic variances for Fréchet copulas

## Corollary 2.5 (Optimal asymptotic variances for Fréchet copulas)

For  $\mathcal{H} \subseteq \mathcal{G}_4$  and  $\mathcal{D} = \mathcal{C}^F$ , it holds that

$$\overline{\sigma}_*^2(\mathcal{H}, \mathcal{C}^F) = 1 + \inf_{G \in \mathcal{H}} \text{Var}_G(X^2),$$

$$\underline{\sigma}_*^2(\mathcal{H}, \mathcal{C}^F) = 1 \wedge \inf_{G \in \mathcal{H}} \text{Var}_G(X^2),$$

$$\overline{G}_*(\mathcal{H}, \mathcal{C}^F) = \operatorname{arginf}_{G \in \mathcal{H}} \text{Var}_G(X^2),$$

$$\underline{G}_*(\mathcal{H}, \mathcal{C}^F) = \begin{cases} \operatorname{arginf}_{G \in \mathcal{H}} \text{Var}_G(X^2), & \text{if } \inf_{G \in \mathcal{H}} \text{Var}_G(X^2) < 1, \\ \mathcal{H}, & \text{if } \inf_{G \in \mathcal{H}} \text{Var}_G(X^2) \geq 1. \end{cases}$$

**Remark:** Again  $\text{Var}_G(X^2)$  determines the order. The upper bound increases but the lower bound is unchanged.

# Proof of Prop 2.4 and Cor 2.5

- For  $C_{\mathbf{p}}^{\mathbb{F}} \in \mathcal{C}^{\mathbb{F}}$  with  $\mathbf{p} = (p_M, p_{\Pi}, p_W) \in \Delta_3$  and  $v = \text{Var}_G(X^2)$ ,  

$$\sigma_G^2(C_{\mathbf{p}}^{\mathbb{F}}) = (p_M + p_W)v + 1 - (p_M - p_W)^2 =: f(p_M, p_W).$$
- Taking  $(p_M, p_W) = (p - r, r)$  where  $0 \leq r \leq p \leq 1$ ,  

$$f(p - r, r) = -4 \left( r - \frac{p}{2} \right)^2 + pv + 1 \quad (\text{parabolic cylinder}).$$

$$\Rightarrow \text{optimize over } 0 \leq r \leq p \leq 1.$$

**Remark:** (Restrictions of  $\mathcal{C}^{\mathbb{F}}$ ) One can consider  $\mathcal{D} = \mathcal{C}_{\underline{k}, \bar{k}}^{\mathbb{F}}(G)$  where

$$\mathcal{C}_{\underline{k}, \bar{k}}^{\mathbb{F}}(G) = \{C \in \mathcal{C}^{\mathbb{F}} : \underline{k} \leq \kappa_G(C) \leq \bar{k}\}, \quad -1 \leq \underline{k} \leq \bar{k} \leq 1.$$

Then the problem reduces to optimizing  $f(p_M, p_W)$  subject to  
 $0 \leq p_M, p_W, p_M + p_W \leq 1$  and  $\underline{k} \leq p_M - p_W \leq \bar{k}$ .



# Asymptotic variance for Blomqvist's beta

Let  $p(C) = C(1/2, 1/2) + \bar{C}(1/2, 1/2)$  for  $C \in \mathcal{C}_2$ .  $C$  is called **balanced** if  $p(C) = 1/2$ , **imbalanced** if  $p(C) \neq 1/2$ , **totally positively imbalanced (TPI)** if  $p(C) = 1$  and **totally negatively imbalanced (TNI)** if  $p(C) = 0$ .

## Proposition 2.6 (Asymptotic variance for Blomqvist's beta)

For any  $\mathcal{D} \subseteq \mathcal{C}_2$ , we have that

$$0 \leq \underline{\sigma}_*^2(\mathcal{H}_{\text{Bern}}, \mathcal{D}) \leq \bar{\sigma}_*^2(\mathcal{H}_{\text{Bern}}, \mathcal{D}) = 1.$$

The upper bound is attained i.f.f.  $\mathcal{D}$  contains a **balanced copula**, and the lower bound is attained i.f.f.  $\mathcal{D}$  contains a **TPI or TNI copula**.

**Proof:** By calculation,  $\sigma_{G_{\text{Bern}}}^2(C) = 4p(C)(1 - p(C))$ .

# Optimality of Blomqvist's beta

## Corollary 2.7 (Optimality of Blomqvist's beta)

Consider  $\mathcal{D} \subseteq \mathcal{C}_2$  and  $\mathcal{H}_{\text{Bern}} \subseteq \mathcal{H}$  for  $\mathcal{H} \subseteq \mathcal{G}_4$ . If  $\Pi \in \mathcal{D}$ , then

$$\bar{\sigma}_*^2(\mathcal{H}, \mathcal{D}) = 1 \text{ and } \mathcal{H}_{\text{Bern}} \subseteq \bar{G}_*(\mathcal{H}, \mathcal{D}).$$

If  $\mathcal{D}$  includes **at least one TPI or TNI copula**, then

$$\underline{\sigma}_*^2(\mathcal{H}, \mathcal{D}) = 0 \text{ and } \mathcal{H}_{\text{Bern}} \subseteq \underline{G}_*(\mathcal{H}, \mathcal{D}).$$

**Proof:** For any  $G \in \mathcal{G}_4$ ,  $1 = \sigma_G^2(\Pi) \leq \sup_{C \in \mathcal{D}} \sigma_G^2(C)$  for  $\bar{\sigma}_*^2(\mathcal{H}, \mathcal{D})$ , and  $0 \leq \inf_{C \in \mathcal{D}} \sigma_G^2(C)$  for  $\underline{\sigma}_*^2(\mathcal{H}, \mathcal{D})$ .

**Remark:** Blomqvist's beta attains the optimum when  $\mathcal{D}$  is, for e.g.,  $\mathcal{C}_2$ ,  $\mathcal{C}_2^{\succeq} = \{C \in \mathcal{C}_2 : C \succeq \Pi\}$  or  $\mathcal{C}_2^{\preceq} = \{C \in \mathcal{C}_2 : C \preceq \Pi\}$ .

# Non-uniqueness of the optimality of $\beta$

$G \in \underline{G}_*(\mathcal{H}, \mathcal{D}) \Leftrightarrow$  there exists  $C \in \mathcal{D}$  s.t.  $\sigma_G^2(C) = 0$

$\Leftrightarrow G^{-1}(U)G^{-1}(V) \stackrel{\text{a.s.}}{=} \exists a \in \mathbb{R}$  and  $(U, V) \sim \exists C \in \mathcal{D}$ .

## Proposition 2.8 (Necessary conditions on $G \in \underline{G}_*(\mathcal{H}, \mathcal{D})$ )

Let  $G \in \underline{G}_*(\mathcal{H}, \mathcal{D})$ . Then  $C \in \mathcal{D}$  and  $a \in \mathbb{R}$  above satisfy the followings.

(C1) If  $\mathbb{P}(X = 0) > 0$  for  $X \sim G$ , then  $a = 0$  and  $\mathbb{P}(X = 0) \geq 1/2$ .

(C2) If  $\mathbb{P}(X = 0) = 0$ , then  $a \neq 0$  and the copula  $C$  is either TPI or TNI with  $0 < a \leq 1$  if  $C$  is TPI and  $-1 \leq a < 0$  if  $C$  is TNI.

Moreover, the distribution function  $G_+(x) = 2G(x) - 1$ ,  $x > 0$  satisfies  $\mathbb{E}_{G_+}[Z] \geq |a|^{1/2}$ ,  $Z \sim G_+$ , and

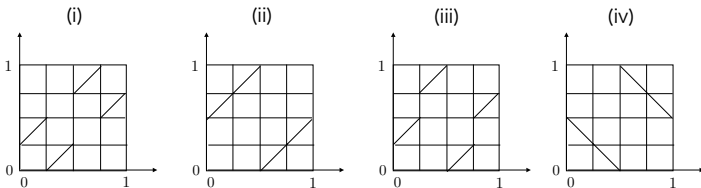
$$G_+(x) = 1 - G_+(|a|/x-), \quad x > 0.$$

# Examples of $G \in \underline{G}_*(\mathcal{H}, \mathcal{D})$

Consider  $X_+ \sim G_+$  where

$$(C1) \quad X_+ = \begin{cases} 0 & \text{w.p. } 1/2, \\ U \sim \text{Unif}(0, \sqrt{6}) & \text{w.p. } 1/2, \end{cases} \quad (C2) \quad X_+ = \begin{cases} \sqrt{1 - \sqrt{2}/2} & \text{w.p. } 1/2, \\ 1/\sqrt{2} - \sqrt{2} & \text{w.p. } 1/2, \end{cases}$$

and four shuffles of  $M$  copulas



Then  $(C1) + (i), (ii), (iii)$  and  $(C2) + (iv)$  attain  $\sigma_G^2(C) = 0$ .

# Discussion on $G \in \overline{G}_*(\mathcal{H}, \mathcal{D})$

- **Much less is known** for  $G \in \overline{G}_*(\mathcal{H}, \mathcal{D})$  compared to  $\underline{G}_*(\mathcal{H}, \mathcal{D})$ .
- Assuming that  $\Pi \in \mathcal{D}$  and  $\mathcal{H}_{\text{Bern}} \subseteq \mathcal{H}$ , we have that

$$\begin{aligned}
 G \in \overline{G}_*(\mathcal{H}, \mathcal{D}) &\Leftrightarrow \sigma_G^2(C) \leq 1 \quad \text{for all } C \in \mathcal{D} \\
 &\Leftrightarrow \text{Cov}(X^2, Y^2) \leq \text{Cov}(X, Y)^2 \quad (= \kappa_G(C)^2).
 \end{aligned}$$

- If  $M$  or  $W$  is in  $\mathcal{D}$ , then

$$\text{Var}_G(X^2) \leq 1$$

is a sufficient condition for  $G \in \overline{G}_*(\mathcal{H}, \mathcal{D})$ .

## 1 Preliminaries (cont'd)

- Copulas, MOCs and transformed rank correlations.

## 2 Comparison of asymptotic variances

- Canonical estimators, optimal shifts, theoretical results for Fréchet copulas and optimality of Blomqvist's beta.

## 3 Comparison with Kendall's tau

- Asymptotic variance for Kendall's tau, its optimality, standardization by sample size.

## 4 Simulation study

- Investigation of asymptotic variances for various copulas and MOCs.

# Canonical estimator of $\tau$

- For  $(U, V), (\tilde{U}, \tilde{V}) \stackrel{\text{iid}}{\sim} C$ , **Kendall's tau** admits

$$\tau(C) = \rho(g(U, \tilde{U}), g(V, \tilde{V})) \quad \text{where} \quad g(l, m) = \begin{cases} 1 & \text{if } l \leq m, \\ -1 & \text{if } l > m. \end{cases}$$

- The **canonical estimator** of  $\tau(C)$  is defined by

$$\hat{\tau} = \frac{1}{n} \sum_{i=1}^n g(U_i, \tilde{U}_i) g(V_i, \tilde{V}_i) \quad \text{where} \quad (U_i, V_i), (\tilde{U}_i, \tilde{V}_i), i = 1, \dots, n, \stackrel{\text{iid}}{\sim} C.$$

- By the CLT,  $\hat{\tau}$  satisfies the **asymptotic normality**

$$\sqrt{n} \{ \hat{\tau} - \tau(C) \} \xrightarrow{d} N(0, \sigma_{\tau}^2(C)) \quad \text{where} \quad \sigma_{\tau}^2(C) = \text{Var}(g(U, \tilde{U})g(V, \tilde{V})).$$

# Asymptotic variances of $\tau$

## Proposition 3.1 (Asymptotic variances of $\tau$ )

- 1 For all  $C \in \mathcal{C}_2$ , it holds that  $0 \leq \sigma_\tau^2(C) \leq 1$ .
- 2 For a given  $C \in \mathcal{C}_2$ ,  $\sigma_\tau^2(C) = 1$  i.f.f.  $\tau(C) = 0$ , which holds, for example, when  $C = \Pi$  or  $C = (M + W)/2$ . More generally,  $\sigma_\tau^2(C) = 1$  if  $C$  satisfies  $(U, 1 - V) \stackrel{d}{=} (U, V)$  or  $(1 - U, V) \stackrel{d}{=} (U, V)$  for  $(U, V) \sim C$ .
- 3 For a given  $C \in \mathcal{C}_2$ ,  $\sigma_\tau^2(C) = 0$  i.f.f.  $\tau(C) = 1$  or  $-1$ , i.e.,  $C = M$  or  $W$ , resp.

**Proof:**  $\sigma_\tau^2(C) = 4p_\tau(C)(1 - p_\tau(C))$  where  $p_\tau(C) = \frac{1}{2}(\tau(C) + 1)$ .

**Remark:** Attainers of  $\sigma_\tau^2(C) = 0$  are characterized but those of  $\sigma_\tau^2(C) = 1$  are not.



# Optimality of Kendall's tau

For  $\mathcal{D} \subseteq C_2$ , define

$$\underline{\sigma}_\tau^2(\mathcal{D}) = \inf_{C \in \mathcal{D}} \sigma_\tau^2(C) \quad \text{and} \quad \bar{\sigma}_\tau^2(\mathcal{D}) = \sup_{C \in \mathcal{D}} \sigma_\tau^2(C).$$

## Proposition 3.2 (Optimality of $\tau$ )

- 1 Suppose  $\mathcal{H}_{\text{Bern}} \subseteq \mathcal{H}$  and  $\Pi \in \mathcal{D}$ . Then  $\bar{\sigma}_\tau^2(\mathcal{D}) = \bar{\sigma}_*^2(\mathcal{H}, \mathcal{D}) = 1$ .
- 2 Suppose  $\mathcal{H}_{\text{Bern}} \subseteq \mathcal{H}$ , and  $M \in \mathcal{D}$  or  $W \in \mathcal{D}$ . Then  $\underline{\sigma}_\tau^2(\mathcal{D}) = \underline{\sigma}_*^2(\mathcal{H}, \mathcal{D}) = 0$ .

Considering the drawback of  $\beta$  that it depends only on the local value  $C(1/2, 1/2)$ , Kendall's tau can be a **good alternative** of  $\beta$ .

# Characterization of the attainers of $\bar{\sigma}_\tau^2(\mathcal{C}^F)$

Characterization of attainers of  $\bar{\sigma}_\tau^2(\mathcal{D})$  is in general not known but is known when  $\mathcal{D} = \mathcal{C}^F$ .

## Proposition 3.3 (Characterization of copulas attaining $\bar{\sigma}_\tau^2(\mathcal{C}^F)$ )

A Fréchet copula  $C = C_{(p_M, p_\Pi, p_W)}^F \in \mathcal{C}^F$  attains  $\bar{\sigma}_\tau^2(\mathcal{C}^F) = 1$  i.f.f.  $p_M = p_W \in [0, 1/2]$ . Equivalently,

$$C = p \frac{M + W}{2} + (1 - p)\Pi, \quad p \in [0, 1].$$

**Proof:** Solve  $\tau(C_{(p_M, p_\Pi, p_W)}^F) = (p_M - p_W)(p_M + p_W + 2)/3 = 0$ .

# Standardization by sample size

- $\hat{\tau}$  requires **twice** more samples than  $\hat{\kappa}_G$  for  $G \in \mathcal{G}_4$ .
- If only  $n$  i.i.d. samples are given, then

$$\text{Var}(\hat{\kappa}_G) = \frac{\sigma_G^2(C)}{n} \quad \text{and} \quad \text{Var}(\hat{\tau}) = \frac{\sigma_\tau^2(C)}{n/2} = \frac{2\sigma_\tau^2(C)}{n}.$$

Thus  $\sigma_G^2(C)$  should be compared with  $\sigma_\tau^{2*}(C) = 2\sigma_\tau^2(C)$ .

- Optimality of  $\tau$  in terms of the **worst asymptotic variance** is **valid** with this modification since

$$\underline{\sigma}_\tau^{2*}(\mathcal{D}) = 2\underline{\sigma}_\tau^2(\mathcal{D}) = 0 = \underline{\sigma}_*^2(\mathcal{G}_4, \mathcal{D}).$$

- That of the **best asymptotic variance** becomes **invalid** since

$$\bar{\sigma}_\tau^{2*}(\mathcal{D}) = 2\bar{\sigma}_\tau^2(\mathcal{D}) = 2 > 1 = \bar{\sigma}_*^2(\mathcal{G}_4, \mathcal{D}).$$

## 1 Preliminaries (cont'd)

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## 2 Comparison of asymptotic variances

- Canonical estimators, optimal shifts, theoretical results for Fréchet copulas and optimality of Blomqvist's beta.

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## 4 Simulation study

- Investigation of asymptotic variances for various copulas and MOCs.

# Simulation study

## 1 Set

$$\rho = -0.99 + 1.98 \frac{k}{49}, \quad k = 0, 1, \dots, 49,$$

$\nu = 5$  and  $\theta = 2\rho/(1 - \rho)$  (so that  $\tau(C_\theta^{\text{Cl}}) = \rho$ ) in  $C = C_\rho^{\text{Ga}}$  (Gauss),  $C_{\rho,\nu}^t$  ( $t$ ) and  $C_\theta^{\text{Cl}}$  (Clayton).

2 For each  $C$ , simulate  $(U_1, V_1), \dots, (U_n, V_n) \stackrel{\text{iid}}{\sim} C$ ,  $n = 10^5$ .

3 Estimate  $\sigma_G^2(C)$  and  $\sigma_\tau^2(C)$  by the sample variances of  $G^{-1}(U_i)G^{-1}(V_i)$ ,  $i = 1, \dots, n$ , and of  $g(U_i, U_{i+n/2})g(V_i, V_{i+n/2})$ ,  $i = 1, \dots, n/2$ , where  $G$  is a **standardized**, and **optimally shifted Bernoulli, uniform, normal,  $t(10)$  and Beta(0.5, 0.5)** distribution function.

Results and discussion

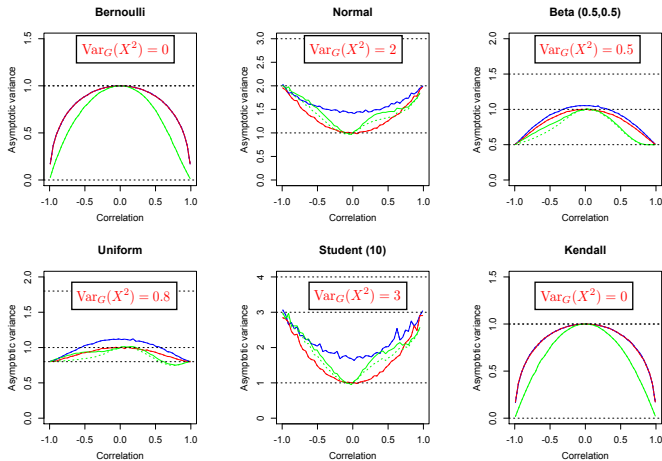


Figure: Standardized (solid) and optimally shifted (dotted)  $\sigma_G^2(C)$  for  $C = C_{\rho}^{\text{Ga}}$ ,  $C_{\rho, \nu}^t$  and  $C_{\theta}^{\text{Cl}}$ . The black dotted lines are  $y = 1$ ,  $\text{Var}_G(X^2)$  and  $\text{Var}_G(X^2) + 1$ .

# Discussion: 1/2

- **Shapes of the curves:** The curves of  $\sigma_G^2(C)$  against  $\rho \in [-1, 1]$  are **symmetric around  $\rho = 0$** , **convex** when  $\text{Var}_G(X^2) > 1$  and **concave** when  $\text{Var}_G(X^2) < 1$ .
- **Upper and lower bounds:** For all the cases of  $G$ , the upper and lower bounds are  $1 \vee \text{Var}_G(X^2)$  and  $1 \wedge \text{Var}_G(X^2)$ , resp. The upper bound  $1 + \text{Var}_G(X^2)$  is **not attained** except for the case where  $\text{Var}_G(X^2) = 0$  (Blomqvist and Kendall)
- **Choices of  $G$ :** **Smaller  $\text{Var}_G(X^2)$**  is more **preferable**. **Normal** (van der Waerden) is better than  $t$  and **Beta(0.5, 0.5)** outperforms uniform (Spearman).

# Discussion: 2/2

- **Blomqvist's beta and Kendall's tau:** The curves seem to **coincide** for all choices of  $C$ . Some theoretical results are known:

$$\beta(C_\rho^{\text{Ga}}) = \tau(C_\rho^{\text{Ga}}) = \beta(C_{\rho,\nu}^t) = \tau(C_{\rho,\nu}^t) = \frac{2}{\pi} \arcsin(\rho),$$
$$\sigma_{G_{\text{Bern}}}^2(C) = 1 - \beta^2(C) \quad (\text{Schmid and Schmidt, 2007}).$$

- **Strength of dependence and model of copula:** The **strength of dependence** affects  $\sigma_G^2(C)$ . Among the **models of  $C$**  with the same strength of dependence, differences of  $\sigma_G^2(C)$  are **small**.
- **Effect of optimal shifts:** As theoretically shown,  $\sigma_G^2(C)$  is **not reduced** by the optimal shift of  $G$  when  $C = C_\rho^{\text{Ga}}$  or  $C_{\rho,\nu}^t$ . Even when the copula is  $C_\theta^{\text{Cl}}$ , only a **small reduction** was observed.



## Concluding remarks

- We proposed a framework for comparing **transformed rank correlations** in terms of the **asymptotic variances  $\sigma_G^2(C)$  of their canonical estimators**.
- **Blomqvist's beta  $\beta$**  was shown to be optimal.
- **Kendall's tau** is also optimal if not standardized by sample size.
- The curve of  $\sigma_G^2(C)$  against the strength of dependence is typically **symmetric convex** or **concave**.
- **Smaller  $\text{Var}_G(X^2)$  is more preferable**.
- Normal (**van der Waerden's coefficient**) is better than  $t$ . Beta  $(0.5, 0.5)$  is more preferable than uniform (**Spearman's rho**).

# Future work

- Comparison of  $\kappa_G$  to **Gini's gamma** and other MOCs.
- **Parametric classes** of  $G$  (e.g., **Beta**( $\alpha, \alpha$ )).
- Optimal  $G$  and  $\sigma_G^2(C)$  for more **practical choices** of  $\mathcal{D}$  (e.g.,  $\mathcal{D}_\epsilon(C^*) = \{C \in \mathcal{C}_2 : d(C, C^*) \leq \epsilon\}$ ).
- Comparison of **multivariate MOCs** and **matrices of pairwise MOCs**.
- Comparison based on **pseudo-samples** (when the margins are unknown and estimated non-parametrically).
- Effect of **optimal shifts**.

*Thank you for your attention!*

**References:** see [Koike and Hofert \(2020+\)](#).  
Available at: <https://arxiv.org/abs/2006.13975>

**Website:** <https://uwaterloo.ca/scholar/tkoike/home>

(The paper and these slides are also available here.)

# Appendix I: Alternative estimators of Kendall's tau

- Consider

$$\hat{\tau}^{\boxtimes} = \frac{1}{n} \sum_{i=1}^n g(U_i, U_{i+1})g(V_i, V_{i+1}), \quad (U_i, V_i) \stackrel{\text{iid}}{\sim} C.$$

- The **Markov chain CLT** holds with the asymptotic variance

$$\begin{aligned} \sigma_{\tau}^{2\boxtimes}(C) = & \text{Var}(g(U_1, U_2)g(V_1, V_2)) \\ & + \text{Cov}(g(U_1, U_2)g(V_1, V_2), g(U_2, U_3)g(V_2, V_3)). \end{aligned}$$

- $\sigma_{\tau}^{2\boxtimes}(C)$  can be **directly compared** to  $\sigma_G^2(C)$  as  $\frac{n+1}{n} \rightarrow 1$ .
- $\underline{\sigma}_{\tau}^{2\boxtimes}(\mathcal{D}) = 0 = \underline{\sigma}_*^2(\mathcal{G}_4, \mathcal{D})$  if  $M \in \mathcal{D}$  or  $W \in \mathcal{D}$ .
- $\overline{\sigma}_{\tau}^{2\boxtimes}(C) \leq \overline{\sigma}_{\tau}^{2*}(\mathcal{D}) = 2$  so  $\hat{\tau}^{\boxtimes}$  is **not worse** than  $\hat{\tau}$ .

## Appendix II: A class of discrete $G$ functions

- Let  $G_{m,z,p} \in \mathcal{G}$  take  $-z_m, \dots, -z_1, 0, z_1, \dots, z_m \in \mathbb{R}$  with probs  $p_m, \dots, p_1, p_0, p_1, \dots, p_m \in \mathbb{R}_+$  s.t.  $\sum_{i=1}^m p_i z_i^2 = 1/2$ .
- Then  $\kappa_{G_{m,z,p}}(C)$  and  $\sigma_{G_{m,z,p}}^2(C)$  admits

$$\kappa_{G_{m,z,p}}(C) = \sum_{(i,j) \in \{-m, \dots, m\}} z_i z_j \mathbf{V}_C(I_i \times I_j),$$

$$\sigma_{G_{m,z,p}}^2(C) = \sum_{(i,j) \in \{-m, \dots, m\}} z_i^2 z_j^2 \mathbf{V}_C(I_i \times I_j) - \left( \sum_{(i,j) \in \{-m, \dots, m\}} z_i z_j \mathbf{V}_C(I_i \times I_j) \right)^2,$$

where  $z_{-i} = -z_i$ ,  $p_+ = p_1 + \dots + p_m$ ,

$$I_{-i} = [p_+ - \sum_{j=1}^i p_j, p_+ - \sum_{j=1}^{i-1} p_j], \quad I_0 = [p_+, p_+ + p_0],$$

$$I_i = [p_+ + p_0 + \sum_{j=1}^{i-1} p_j, p_+ + p_0 + \sum_{j=1}^i p_j], \quad i = 1, \dots, m.$$

# Appendix III: Joint distribution of $(X^2, Y^2)$

- By radial symmetry of  $G$ ,

$$G^{[2]}(x) = \mathbb{P}(X^2 \leq x) = 2G(\sqrt{x}) - 1, \quad x \geq 0.$$

- Suppose  $G$  is **continuous**. Then the copula of  $(X^2, Y^2)$  is

$$C^{[2]}(u, v) = \sum_{\varphi \in \{\nu_1, \nu_2, \nu_1 \circ \nu_2\}} \bar{C}_\varphi \left( \frac{1}{2}, \frac{1}{2} \right) C_{\varphi, (1/2, 1/2)} \left( \frac{u+1}{2}, \frac{v+1}{2} \right),$$

where  $\nu_1(C)(u, v) = v - C(1 - u, v)$ ,  $\nu_2(C)(u, v) = u - C(u, 1 - v)$ ,  
 $C_{\varphi, (1/2, 1/2)}(u, v) = \mathbb{P}(U_\varphi \leq u, V_\varphi \leq v \mid U_\varphi > 1/2, V_\varphi > 1/2)$ ,  
 $(U_\varphi, V_\varphi) \sim C_\varphi = \varphi(C)$ .

- Examples:**  $M^{[2]} = W^{[2]} = M$  and  $\Pi^{[2]} = \Pi$ .

## Appendix IV: Linearity of $C \mapsto \sigma_G^2(C)$

Suppose  $G \in \mathcal{G}_4$  is **continuous**. For  $p \in [0, 1]$  and  $C, C' \in \mathcal{C}_2$ ,

$$\tilde{C}_p^{[2]} = pC^{[2]} + (1-p)C'^{[2]} \quad \text{where} \quad \tilde{C}_p = pC + (1-p)C'.$$

This yields the following proposition.

### Proposition (Linearity of $\sigma_G^2(C)$ )

For any  $G \in \mathcal{G}_4$  and  $k \in [-1, 1]$ , the map  $C \mapsto \sigma_G^2(C)$  is **linear** on  $\mathcal{C}_G(k) = \{C \in \mathcal{C}_2 : \kappa_G(C) = k\}$ , that is,

$$\sigma_G^2(pC + (1-p)C') = p\sigma_G^2(C) + (1-p)\sigma_G^2(C')$$

for  $p \in [0, 1]$  and  $C, C' \in \mathcal{C}_2$  s.t.  $\kappa_G(C) = \kappa_G(C') = k$ .