



SOME CONCEPTS OF NEGATIVE DEPENDENCE FOR BIVARIATE DISTRIBUTIONS WITH APPLICATIONS

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ABSTRACT. In this paper, some concepts of negative dependence for bivariate distributions, especially hazard and local negative dependence (HND,LND) are studied. The Clayton-Oakes, φ and γ measures of association and relationship of HND with this measures is studied. In addition, various examples illustrate the usefulness of these notions in some family of distributions.

1. INTRODUCTION

Let X and Y be absolutely continuous random variables having joint density $f(x, y)$ and survival function $\bar{F}(x, y)$. Basu [2] introduced bivariate hazard function, $r(x, y) = f(x, y)/\bar{F}(x, y)$. In the independent case the bivariate hazard function is equal to product of conditional hazard functions, $\frac{\partial}{\partial x}[-\log \bar{F}(x, y)]$ and $\frac{\partial}{\partial y}[-\log \bar{F}(x, y)]$. If equality failed we deal with dependent (positive or negative) random variables. In this paper we used notions of negatively hazard and local dependence, say HND , LND , and have investigated relationship between this concepts with some other concepts of dependence. More details about notions of dependence are in Lehmann[13], Karlin[12], Esary and Proschan[4], Joe[9] and Shaked and Shanthikumar[17]. Oluyede[14], [15] has obtained some properties and inequalities for positively hazard and local dependence. We have obtained some measures of association, like θ -measure (known as Clayton-Oakes measure), φ -measure and γ -measure, and have connected these measures with HND and LND .

Let (X, Y) be an absolutely continuous random vector having distribution (survival) function $F(\bar{F})$. In the next sections we need the following definitions.

DEFINITION 1.1. Absolutely continuous random variables X and Y having a joint density function $f(x, y)$ are hazard negative (positive)dependence, HND(HPD), if and only if

$$\frac{f(x, y)}{\bar{F}(x, y)} \leq (\geq) \int_x^\infty \frac{f(u, y)du}{\bar{F}(x, y)} \int_y^\infty \frac{f(x, v)dv}{\bar{F}(x, y)} \tag{1}$$

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where $\frac{f(x,y)}{\bar{F}(x,y)}$ is the bivariate hazard rate function, $\bar{F}(x,y)$ is bivariate reliability function and

$$\int_x^\infty \frac{f(u,y)du}{\bar{F}(x,y)} = \frac{\partial}{\partial y}[-\log \bar{F}(x,y)], \quad \text{and} \quad \int_y^\infty \frac{f(x,v)dv}{\bar{F}(x,y)} = \frac{\partial}{\partial x}[-\log \bar{F}(x,y)]$$

are conditional hazard functions.

DEFINITION 1.2. Absolutely continuous random variables X and Y having a joint density function $f(x,y)$ are locally negative (positive) dependence, LND(LPD), if and only if

$$F(x,y)f(x,y) \leq (\geq) \int_{-\infty}^x f(u,y)du \int_{-\infty}^y f(x,v)dv, \quad (2)$$

where $F(x,y)$ is joint cumulative distribution of X and Y .

DEFINITION 1.3. A non-negative function h on A^2 , where $A \subseteq \mathbb{R}$, is reverse rule of order 2 (RR_2) if for all $x_1 < x_2$ and $y_1 < y_2$, with $x_i, y_j \in A$ $i = 1, 2$ $j = 1, 2$

$$h(x_1, y_1)h(x_2, y_2) \leq h(x_1, y_2)h(x_2, y_1). \quad (3)$$

DEFINITION 1.4. Let X and Y be continuous random variables. Then X and Y are right corner set decreasing, $RCSD$, if

$$P(X > x, Y > y | X > x', Y > y') \quad (4)$$

is decreasing (non-increasing) in x' and in y' , for all x and y .

DEFINITION 1.5. Let X and Y be continuous random variables. Then X and Y are left corner set increasing, $LCSI$, if

$$P(X \leq x, Y \leq y | X \leq x', Y \leq y') \quad (5)$$

is increasing (non-decreasing) in x' and in y' , for all x and y .

DEFINITION 1.6. Let $F_\theta(x)$ be a family of distribution functions. This family is called monotone decreasing likelihood ratio, (MDLR)(monotone increasing likelihood ratio, (MILR)) if for all $\eta > \theta$, $\frac{F_\eta(x)}{F_\theta(x)}$ is decreasing (increasing) in x .

DEFINITION 1.7. (Holland and Wang[8]) Suppose that the mixed partial derivative of $h(x,y)$ exists and h is defined on a Cartesian product set. Then local dependence function, $\gamma_h(x,y)$, define as follows

$$\gamma_h(x,y) = \frac{\partial^2 \text{Log} h(x,y)}{\partial x \partial y} = \frac{1}{h(x,y)} \left\{ h^{11}(x,y) - \frac{h^{10}(x,y)h^{01}(x,y)}{h(x,y)} \right\}, \quad (6)$$

where $h^{ij} = \frac{\partial^{i+j} h(x,y)}{\partial x^i \partial y^j}$, $i, j = 0, 1$.

REMARK 1.8. Let X and Y be continuous random variables with joint distribution (survival) function F (\bar{F}). Then

- a:** $HND(X, Y)(HPD(X, Y)) \Leftrightarrow \gamma_{\bar{F}}(x, y) \leq (\geq)0$.
b: $LND(X, Y)(LPD(X, Y)) \Leftrightarrow \gamma_F(x, y) \leq (\geq)0$.
c: X and Y are independent if and only if equality occur in (1) or (2) or equivalently $\gamma_F(x, y) = 0$ or $\gamma_{\bar{F}}(x, y) = 0$.

2. MAIN RESULTS

In this section we obtain some useful results about HND and LND which show relation of these concepts with some notions of dependence.

PROPOSITION 2.1. *Let (X, Y) be absolutely continuous random vector with distribution $F(x, y)$ and reliability function $\bar{F}(x, y)$. Then*

a: $\bar{F}(x, y)$ is RR_2 if and only if for all $x_1 < x_2$ and $y_1 < y_2$,

$$\begin{aligned} P(X > x_2, Y > y_2) P(x_1 < X \leq x_2, y_1 < Y \leq y_2) \\ \leq P(x_1 < X \leq x_2, Y > y_2) P(X > x_2, y_1 < Y \leq y_2). \end{aligned} \quad (7)$$

b: $F(x, y)$ is RR_2 if and only if for all $x_1 < x_2$ and $y_1 < y_2$,

$$\begin{aligned} P(X \leq x_1, Y \leq y_1) P(x_1 < X \leq x_2, y_1 < Y \leq y_2) \\ \leq P(X \leq x_1, y_1 < Y \leq y_2) P(x_1 < X \leq x_2, Y \leq y_1). \end{aligned} \quad (8)$$

PROOF. We proof part *a*. The part of *b* is similar. We note that $\bar{F}(x, y)$ is RR_2 , i.e. for $x_1 < x_2$ and $y_1 < y_2$

$$\left| \begin{array}{cc} P(X > x_1, Y > y_1) & P(X > x_1, Y > y_2) \\ P(X > x_2, Y > y_1) & P(X > x_2, Y > y_2) \end{array} \right| \leq 0. \quad (9)$$

It is easy to show that (9) is equivalent to

$$\left| \begin{array}{cc} P(x_1 < X \leq x_2, y_1 < Y \leq y_2) & P(x_1 < X \leq x_2, Y > y_2) \\ P(X > x_2, y_1 < Y \leq y_2) & P(X > x_2, Y > y_2) \end{array} \right| \leq 0. \quad (10)$$

and this is equivalent to (7), so that proof is complete. \square

The following Proposition give a relationship between RR_2 and HND(LND).

PROPOSITION 2.2. *Let (X, Y) be absolutely continuous.*

- a:** *If $\bar{F}(x, y)$ is RR_2 , then (X, Y) is HND.*
b: *If $F(x, y)$ is RR_2 , then (X, Y) is LND.*

PROOF.

- a:** Let $x_1 = x$, $x_2 = x + \Delta x$, $y_1 = y$, $y_2 = y + \Delta y$ where $\Delta x, \Delta y > 0$. By using (7) and dividing the result by $\Delta x \Delta y$ and letting $\Delta x \rightarrow 0, \Delta y \rightarrow 0$, the result follows.
b: Proof is similar. \square

THEOREM 2.3. *Let X, Y be continuous random variables having distribution function $F(x, y)$ and reliability function $\bar{F}(x, y)$.*

a: X, Y are $RCSD(X, Y)$ if and only if $\bar{F}(x, y)$ is RR_2 .

b: X, Y $LCSI(X, Y)$ if and only if $F(x, y)$ is RR_2 .

PROOF. The first part is proved, the second is similar.

$RCSD \Rightarrow RR_2$: Let (X, Y) be $RCSD$ then by definition (1.4), for all $(x, y) \in \mathbb{R}^2$, $P(X > x, Y > y | X > x', Y > y')$ is decreasing in x' and in y' . So that for $y = -\infty$, $P(X > x | X > x', Y > y')$ decreasing in x' and in y' , for all x . Therefore if $x > x'$, then $P(X > x | X > x', Y > y') = \frac{P(X > x, Y > y')}{P(X > x', Y > y')}$ is decreasing in y' and hence for $y' < y$,

$$\frac{P(X > x, Y > y)}{P(X > x', Y > y)} \leq \frac{P(X > x, Y > y')}{P(X > x', Y > y')} \quad (11)$$

which is equivalent to (3) with $h = \bar{F}$.

$RR_2 \Rightarrow RCSD$: Since $\bar{F}(x, y)$ is RR_2 hence for $x > x'$ and $y > y'$, (11) valid and so for $x > x'$ $P(X > x | X > x', Y > y') = \frac{P(X > x, Y > y')}{P(X > x', Y > y')}$ is decreasing in y' . Similarly for $y > y'$ by RR_2 -property of $\bar{F}(x, y)$

$$P(Y > y | X > x', Y > y') \geq P(Y > y | X > x, Y > y')$$

i.e. $P(Y > y | X > x', Y > y')$ is decreasing in x' . Now, if $x > x'$, $y < y'$

$$\begin{aligned} P(X > x, Y > y | X > x', Y > y') &= \frac{P(X > x, Y > y')}{P(X > x', Y > y')} \\ &\leq \frac{P(X > x, Y > y)}{P(X > x', Y > y)} \\ &= P(X > x, Y > y | X > x', Y > y), \end{aligned}$$

thus $P(X > x, Y > y | X > x', Y > y')$ is decreasing in y' . Similarly for $x \leq x'$, $y > y'$, $P(X > x, Y > y | X > x', Y > y')$ is decreasing in x' . Also for $x < x'$, $y < y'$, $P(X > x, Y > y | X > x', Y > y') = 1$, therefore (X, Y) is $RCSD$. \square

COROLLARY 2.4. *Under the assumptions of Theorem 2.3 and Proposition 2.2*

a: $RCSD(X, Y) \Rightarrow HND(X, Y)$.

b: $LCSI(X, Y) \Rightarrow LND(X, Y)$.

THEOREM 2.5. *Let $F_\theta(x)$ and $G_\theta(y)$ be two families of distribution functions. For any mixing distribution K , consider the distribution*

$$H(x, y) = \int_{\Omega} F_\theta(x) G_\theta(y) dK(\theta),$$

where Ω is a Borel set in \mathbb{R}^n and K is a probability measure on Ω .

(i): *If one of the family is MILR and the other is MDLR, then $H(x, y)$ is LND.*

(ii): *If $F_\theta(x)$ and $G_\theta(y)$ are both MDLR or MILR, then $H(x, y)$ is LPD.*

PROOF. We prove part (i). The proof of part (ii) is similar. Let $F_\theta(x)$ be *MDLR* and $G_\theta(y)$ be *MILLR*, so that for $x < x'$, $y < y'$ and $\eta > \theta$ ($\eta, \theta \in \Omega$), we have

$$[F_\eta(x)F_\theta(x') - F_\eta(x')F_\theta(x)][G_\eta(y)G_\theta(y') - G_\eta(y')G_\theta(y)] \leq 0.$$

After some simple calculation we obtain $H(x, y)H(x', y') \leq H(x, y')H(x', y)$. Therefore the distribution function H is *RR₂*, and hence H is *LND*. \square

3. EXAMPLES AND MEASURES OF DEPENDENCE

In this section we first introduce the Clayton-Oakes association measure (θ -measure) and ψ -measure and drive the relationship of these measures with hazard negative dependence, then we give some examples. Clayton[3] and Oakes[16] defined the following associated measure:

$$\theta(x, y) = \frac{\bar{F}(x, y)D_{12}\bar{F}(x, y)}{D_1\bar{F}(x, y)D_2\bar{F}(x, y)}, \quad (12)$$

where $D_{12}\bar{F}(x, y) = \frac{\partial^2}{\partial x \partial y}\bar{F}(x, y)$, $D_1\bar{F}(x, y) = \frac{\partial}{\partial x}\bar{F}(x, y)$ and $D_2\bar{F}(x, y) = \frac{\partial}{\partial y}\bar{F}(x, y)$. The function $\theta(x, y)$ measures the degree of association between X and Y , and has direct relation to local dependence function, $\gamma_{\bar{F}}(x, y)$. $\theta(x, y) = 1$ if and only if $\gamma_{\bar{F}}(x, y) = 0$ i.e X and Y are independent, $\theta(x, y) > 1$ if and only if $\gamma_{\bar{F}}(x, y) > 0$ i.e X and Y have positively dependent and $\theta(x, y) < 1$ if and only if $\gamma_{\bar{F}}(x, y) < 0$ or equivalently X and Y are negatively dependent.

Let us define some quantities to formulate $\theta(x, y)$.

$$r_1(x, y) := -\frac{\partial}{\partial x}[\log \bar{F}(x, y)] = -\frac{D_1\bar{F}(x, y)}{\bar{F}(x, y)}, r_2(x, y) := -\frac{\partial}{\partial y}[\log \bar{F}(x, y)] = -\frac{D_2\bar{F}(x, y)}{\bar{F}(x, y)}$$

By using (6) we can write:

$$\frac{\partial^2}{\partial x \partial y} \log \bar{F}(x, y) = r_1(x, y)r_2(x, y)(\theta(x, y) - 1). \quad (13)$$

So, from (12) we drive;

$$r(x, y) = r_1(x, y)r_2(x, y)\theta(x, y), \quad (14)$$

where $r(x, y) = \frac{f(x, y)}{F(x, y)}$ is Basu's failure rate. More detail about formulate of θ is found in Gupta [6], [7].

Another measure for appearance of dependence is ψ -measure which is defined as follows:

$$\psi(x, y) = \frac{P(X > x | Y > y)}{P(X > x)} = \frac{\bar{F}(x, y)}{\bar{F}_1(x)\bar{F}_2(y)} \quad (15)$$

Under the some regular conditions, the following statements are valid for ψ -measure in (14);

- $\psi(x, y) = 1 \Leftrightarrow X$ and Y are independent.
- $\frac{\partial^2}{\partial x \partial y} \psi(x, y) = \gamma_{\bar{F}}(x, y)$.
- If $\psi(x, y) > 1$ then (X, Y) is *PQD*.

- If $\psi(x, y) < 1$ then (X, Y) is *NQD*.
- If $\theta(x, y) < (>)1$ then $\psi(x, y) < (>)1$ (the converse is not true).

The following proposition gives relationship between dependence measures.

PROPOSITION 3.1. *Let (X, Y) be an absolutely continuous random vector having reliability function $\bar{F}(x, y)$. One can verify that the following are equivalent*

- (i): $\theta(x, y) < 1$,
- (ii): $\gamma_{\bar{F}}(x, y) < 0$,
- (iii): $\frac{\partial^2}{\partial x \partial y} \psi(x, y) < 0$,
- (iv): $r(x, y) < r_1(x, y)r_2(x, y)$,
- (v): (X, Y) is *HND*.

PROOF. By (6), (11), (12), (13) and (14) the proposition proved immediately. \square

EXAMPLE 3.2. (*Farli-Gumble-Morganstern [4] distribution (FGM)*) Consider the family bivariate distributions

$$F(x, y) = F_1(x)F_2(y)[1 + \alpha(1 - F_1(x))(1 - F_2(y))]$$

where $|\alpha| \leq 1$ and $F_1(x)$ and $F_2(y)$ are continuous distributions.

$$\gamma_F(x, y) \leq 0 \Leftrightarrow \alpha f_1(x)f_2(y) \leq 0 \Leftrightarrow -1 \leq \alpha \leq 0.$$

Therefor the above bivariate family of distributions is *LND* if and only if $-1 \leq \alpha \leq 0$.

EXAMPLE 3.3. In the previous example the reliability function for *FGM* distribution is

$$\bar{F}(x, y) = \bar{F}_1(x)\bar{F}_2(y)[1 + \alpha F_1(x)F_2(y)], \quad |\alpha| \leq 1$$

$$\gamma_{\bar{F}}(x, y) = \frac{\alpha f_1(x)f_2(y)}{[1 + \alpha F_1(x)F_2(y)]^2} \leq 0 \Leftrightarrow -1 \leq \alpha \leq 0,$$

therefore (X, Y) is *HND* if and only if $-1 \leq \alpha \leq 0$.

EXAMPLE 3.4. (*Gumbel's bivariate exponential distribution*) The reliability function of Gumbel's bivariate distribution is

$$\bar{F}(x, y) = \exp\{-\alpha_1 x - \alpha_2 y - \beta xy\}, \quad \alpha_1, \alpha_2 > 0 \quad \text{and} \quad 0 \leq \beta \leq \alpha_1 \alpha_2.$$

For $x < x'$ and $y < y'$;

$$\begin{aligned} \bar{F}(x, y)\bar{F}(x', y') - \bar{F}(x, y')\bar{F}(x', y) \\ = \exp\{-\alpha_1(x + x') - \alpha_2(y + y')\} \\ \times \left[\exp\{-\beta(xy + x'y')\} - \exp\{-\beta(xy' + x'y)\} \right] \leq 0. \end{aligned}$$

Since $xy + x'y' \geq xy' + x'y$, hence \bar{F} is *RR₂*, and this implies that (X, Y) is *HND*.

EXAMPLE 3.5. (*Ali-Mikhail-Haq distribution*) Consider Ali-Mikhail-Haq[1] family of distribution

$$F(x, y) = \frac{F_1(x)F_2(y)}{1 - \beta \bar{F}_1(x)\bar{F}_2(y)}, \quad |\beta| \leq 1$$

where F_1 and F_2 are continuous distribution functions and $\bar{F}_i = 1 - F_i$ $i = 1, 2$. The above family of distribution is *LND* if and only if $-1 \leq \beta \leq 0$, since

$$\gamma_F(x, y) = \frac{\beta f_1(x)f_2(y)}{[1 - \beta \bar{F}_1(x)\bar{F}_2(y)]^2} \leq 0 \quad \Leftrightarrow \quad -1 \leq \beta \leq 0.$$

REMARK 3.6. In the example 3.4 we can use the proposition 3.1 and obtain

$$\begin{aligned} r_1(x, y) &= -\frac{\partial}{\partial x}[\log \bar{F}(x, y)] = \alpha_1 + \beta y \\ r_2(x, y) &= -\frac{\partial}{\partial y}[\log \bar{F}(x, y)] = \alpha_2 + \beta x \\ r(x, y) &= \frac{f(x, y)}{\bar{F}(x, y)} = (\alpha_1 + \beta y)(\alpha_2 + \beta x) - \beta \\ \theta(x, y) &= \frac{r(x, y)}{r_1(x, y)r_2(x, y)} = \frac{(\alpha_1 + \beta y)(\alpha_2 + \beta x) - \beta}{(\alpha_1 + \beta y)(\alpha_2 + \beta x)} \end{aligned}$$

since $\alpha_i > 0$, $i = 1, 2$ and $\beta \geq 0$, therefore Proposition (3.1) implies that (X, Y) is *HND*.

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Presentation