Stochastic orders: a brief introduction and Bruno's contributions.

Franco Pellerey



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In this presentation:

- A short introduction to the subject
- A description of some of his contributions
- An example of recent applications of his studies

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Here we can not immediately assert which one is the best choice.

Thus, we have to introduce new criteria to choose among different alternatives, taking into account our needs. \rightarrow **Stochastic orders**

Thus, we have to introduce new criteria to choose among different alternatives, taking into account our needs. \rightarrow **Stochastic orders**

In fact, a long list of different stochastic orders have been defined, and applied, in a variety of fields (economics and finance, engineering, medicine, etc.)

They are based on comparisons between:

• The *location*, or *magnitude*, of the random variables to be compared (mainly considered in reliability and survival analysis)

Ex: X is better than Y if $P[X > t] \ge P[Y > t]$ for all $t \in \mathbb{R}$ (usual stochastic order)

• The expectations E[u(X)] and E[u(Y)] of functions of the involved variables (mainly considered in risk theory)

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• Their variability

Ex: X is more dispersed than Y if $X = \phi(Y)$ for some dispersive function ϕ , i.e., such that $\phi(x_2) - x_2 \ge \phi(x_1) - x_1$ whenever $x_1 \le x_2$ (dispersive order).

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• B.B. and Marco Scarsini. **Convex orderings for stochastic** processes. *Comment. Math. Univ. Carolin.* 32 (1991), no. 1, 115–118.

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• B.B., Subhash Kochar and Fabio Spizzichino. Some bivariate notions of IFR and DMRL and related properties. *J. Appl. Probab.* 39 (2002), no. 3, 533–544.

• B.B. and Fabio Spizzichino. **Bivariate survival models with Clayton** aging functions. *Insurance Math. Econom.* 37 (2005), no. 1, 6–12.

• B.B. and Fabio Spizzichino. Relations among univariate aging, bivariate aging and dependence for exchangeable lifetimes. *J. Multivariate Anal.* 93 (2005), no. 2, 313–339.

Let X and Y represent the lifetimes of two items, or individuals.

Recall: X is said to be smaller in the *usual stochastic order* than Y if and only if $P[X > t] \le P[Y > t]$ for all $t \in \mathbb{R}^+$, or, equivalently, if and only if $E[\phi(X)] \le E[\phi(Y)]$ for every increasing function ϕ .

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Apart the usual stochastic order, other comparisons are commonly considered in survival analysis. In particular, different orders have been defined and studied to compare residual lifetimes, i.e., to compare the variables [X - t|X > t] and [Y - t|Y > t], for $t \in \mathbb{R}^+$.

Among them, the *hazard rate order*, the *mean residual life order*, the *likelihood ratio order*, etc.

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By means of these orders, it is possible to provide a list of alternative characterizations of aging, i.e., of the effect of the age in the residual lifetime of the items.

Ex: X has *Increasing Hazard Rate (IHR)* if $[X - t_1|X > t_1] \ge_{st} [X - t_2|X > t_2]$ for all $0 \le t_1 \le t_2$, i.e., if the residual lifetime of X stochastically decreases with the age.

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A clear understanding of the relationships between univariate aging, multivariate aging and dependence

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• The random vector (X, Y) satisfies the *Bivariate Increasing Hazard Rate* (BIHR) property if, and only if, for all $0 \le t_1 \le t_2$,

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• In a similar way, by reversing the inequality, one can define the corresponding negative aging property *Bivariate Decreasing Hazard Rate* (*BDHR*).

• Let us say now that the lifetimes X and Y have *positive dependence* if large (respectively, small) values of X tend to go together (in some stochastic sense) with large (respectively, small) values of Y. Similarly define the *negative dependence*: if large (respectively, small) values of X tend to go together (in some stochastic sense) with small (respectively, large) values of Y. [Formal definitions can be given by means of the *copula* of the vector (X, Y).]

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positive dependence + multivariate positive aging $\label{eq:positive}$ univariate positive aging;

multivariate positive aging + univariate negative aging \Downarrow negative dependence;

etc..

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multivariate positive aging + univariate positive aging ↓↓ positive dependence

• Even if based on stochastic orders, Bruno and Fabio concentrated their studies on applications of comparisons in multivariate aging and survival models, without realizing the effects of their results in other fields. Like, for example, their possible applications in the analysis of the properties of *Joint Stochastic Orders*.

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• Defined and studied for the first time by Shantikumar and Yao (1991), Bivariate characterization of some stochastic order relations. *Adv. in Appl. Prob.*, 23, 642–659, the joint stochastic orders have been introduced in order to compare, marginally, univariate lifetimes, but taking into account their possible mutual dependence.

Ex: Consider a pair (X, Y) of non-independent lifetimes. It is possible to compare the corresponding residual lifetimes considering the inequalities $[X - t|X > t] \leq_{st} [Y - t|Y > t]$ for all $t \in \mathbb{R}^+$ (hazard rate order, \leq_{hr}). This is a comparison based on the marginal distributions of X and Y.

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Otherwise, it is possible to compare their residual lifetimes taking into account survivals of both, i.e., consider the following inequalities:

 $[X-t|\{X>t,Y>t\}] \leq_{st} [Y-t|\{X>t,Y>t\}] \quad \text{for all } t \in \mathbb{R}^+.$

This is a joint stochastic order based on the joint distribution of (X, Y) (*joint weak hazard rate order*, $\leq_{hr:wj}$).

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It can be shown that the stochastic orders above are not equivalent, i.e.,

$$X \leq_{hr} Y \not\Leftrightarrow X \leq_{wj:hr} Y.$$

Actually, the equivalence holds if, and only if, X and Y are independent.

Because of its properties, the *joint weak hazard rate order* has interesting applications is different fields, like in reliability (*optimal allocation of components*), in actuarial sciences, in portfolio theory or in medicine (*crossover clinical trials*).

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Ex: Let (X, Y) be such that $X \leq_{hr:wj} Y$. It can be shown that in this case

 $E[g(X,Y)] \geq E[g(Y,X)]$

for all function $g:\mathbb{R}^2
ightarrow \mathbb{R}$ such that

$$\Delta g(x,y) = g(x,y) - g(y,x)$$

is supermodular in the set $\mathcal{U} = \{(x, y) \in \mathbb{R}^2, x \ge y\}.$

Consider now a pair (X, Y) of non-independent financial returns, and consider the two portfolios

$$Z_1 = \alpha Y + (1 - \alpha)X$$
 and $Z_2 = (1 - \alpha)Y + \alpha X$, $\alpha \in [0, 1]$.

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Because of the previous property, for $lpha \geq 1/2$ one has

$$X \leq_{hr:wj} Y \implies E[u(Z_1)] \geq E[u(Z_2)]$$

for every logarithmic utility function u (like, e.g., $u(t) = \ln(1 + t)$). [The proof easily follows letting $g(x, y) = u(\alpha y + (1 - \alpha)x)$.]

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Another interesting property of the joint weak hazard rate order is that it is closed with respect to mixtures (while the standard hazard rate order is not)

Studying the properties of this particular order, we verified that a relationship between the joint weak hazard rate order and the standard hazard rate order can be stated by making use of a notion defined and analyzed by Bruno and Fabio in their works.

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Definition

A bivariate copula $C : [0, 1]^2 \longrightarrow [0, 1]$ is called *supermigrative* (*submigrative*) if it is symmetric, i.e. C(u, v) = C(v, u) for every $(u, v) \in [0, 1]^2$, and it satisfies

$$C(u, \gamma v) \geq (\leq) C(\gamma u, v)$$

for all $u \leq v$ and $\gamma \in (0, 1)$.



As shown by Bruno and Fabio, examples of copulas satisfying the supermigrative property are the Archimedean ones having log-convex inverse generators. Thus, e.g., the Gumbel-Hougaard copula, and the Frank and Clayton copulas with positive value of the parameter θ . The Farlie-Gumbel-Morgenstern copula, with posite value of the parameter, satisfies this property as well.

It can be shown that the following holds.

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Theorem

Let the survival copula $\overline{C}_{(X,Y)}$ of (X,Y) be supermigrative. Then $X \leq_{hr} Y \implies X \leq_{hr:wj} Y$. Viceversa, if the survival copula $\overline{C}_{(X,Y)}$ of (X,Y) is submigrative, then $X \leq_{hr:wj} Y \implies X \leq_{hr} Y$.

Results similar to the previous one can be proved also for the other well-know joint orders.

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Definition

Let \mathcal{D} be the set of functions $\mathcal{D} = \{g \mid g : \mathbb{R}^2 \to \mathbb{R}\}$. We denote:

- $\mathcal{G}_{hr} = \{g \in \mathcal{D} \mid g(x, y) g(y, x) \text{ is non-decreasing in } x \forall y \leq x\};$
- $\mathcal{G}_{lr} = \{g \in \mathcal{D} \mid g(x, y) \ge g(y, x) \text{ for all } y \le x\}.$

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•
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Definition

Given two random variables X and Y as above, X is said to be greater than Y

- in the joint hazard rate order (denoted $X \ge_{hr:j} Y$) if $E[g(X, Y)] \ge E[g(Y, X)]$ for all $g \in \mathcal{G}_{hr}$;
- in the joint likelihood ratio order (denoted $X \ge_{lr:j} Y$) if $E[g(X, Y)] \ge E[g(Y, X)]$ for all $g \in \mathcal{G}_{lr}$.

Recall the definition of standard joint likelihood ratio:

$$X \ge_{lr} Y \iff [X - t \mid t \le X \le t + s] \ge_{st} [Y - t \mid t \le Y \le t + s]$$

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for all $t \in \mathbb{R}, s \in \mathbb{R}^+$.

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Theorem

Let (X, Y) be a random vector with an absolutely continuous survival copula $\widehat{C}_{(X,Y)}$. Assume that

- $\widehat{C}_{(X,Y)}$ is exchangeable (symmetric);
- The density c
 _(X,Y)(u, v) is non-increasing in u and non-decreasing in v for all u ≥ v.

Then $X \ge_{lr} [\ge_{hr}] Y$ implies $X \ge_{lr:j} [\ge_{hr:j}] Y$.

The second assumption appearing in this statement has an immediate interpretation: it essentially means that for every point (u, v) below the diagonal and for any point (\hat{u}, \hat{v}) contained in the closed triangle with vertices (u, v), (u, u) and (v, v) it holds $\hat{c}_{(X,Y)}(\hat{u}, \hat{v}) \geq \hat{c}_{(X,Y)}(u, v)$ (and similarly for points above the diagonal).



Roughly speaking, it is satisfied by copulas having probability mass mainly concentrated around the diagonal, thus describing *positive dependence*, as the copulas having density uniformly distributed on regions like the ones shown in the following figure.



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Such an assumption can be further weakened in order to let the relation $X \ge_{lr} Y \Rightarrow X \ge_{lr:j} Y$ be satisfied also for survival copulas having a singularity on the diagonal v = u, like Cuadras-Augé copulas or Frechét copulas.

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A larger class of copulas satisfying this property has been defined and studied in Durante (2006), A new class of symmetric bivariate copulas, *J* of Nonparametrical Statistics, **18**, 499–510.