# Majorization and the Lorenz order in statistics, applied probability, economics and beyond 

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## Introduction

How can we measure
inequality, variability, diversity, disorder ('chaos'), ... ?

Numerous proposals in

- statistics
- economics
- physics
- biology/ecology

Many parallel developments.

## Outline

1. Introduction
2. Majorization
3. Schur convexity
4. Lorenz order
5. Selected applications

Taxes and incomes
Condorcet jury theorems
Portfolio allocation and value at risk
6. Some new results

Lorenz ordering of beta distributions
Spectra of correlation matrices
Schur properties of win-probabilities
7. Concluding remarks

## Majorization

Given two vectors

$$
\mathbf{x}=\left(x_{1}, \ldots, x_{n}\right), \quad \mathbf{y}=\left(y_{1}, \ldots, y_{n}\right)
$$

of equal length $n$ with

$$
\sum_{i=1}^{n} x_{i}=\sum_{i=1}^{n} y_{i}
$$

define majorization as

$$
\mathbf{x} \geqslant_{M} \mathbf{y} \quad: \Longleftrightarrow \quad \sum_{i=1}^{k} x_{(i: n)} \geqslant \sum_{i=1}^{k} y_{(i: n)}, \quad k=1, \ldots, n-1
$$

Here $x_{(1: n)} \geqslant x_{(2: n)} \geqslant \cdots \geqslant x_{(n: n)}$ (decreasing rearrangement).

## Majorization

Basic properties best explained in terms of income (re)distribution.

## Examples.

$$
(1,1,1,1) \leqslant_{M}(2,1,1,0) \leqslant_{M}(3,1,0,0) \leqslant_{M}(4,0,0,0)
$$

Note: ordering irrelevant, also have

$$
(1,1,1,1) \leqslant_{M}(0,2,1,1) \leqslant_{M}(1,0,0,3) \leqslant_{M}(0,4,0,0)
$$

More generally

$$
(\bar{x}, \bar{x}, \ldots, \bar{x}) \leqslant_{M}\left(x_{1}, x_{2}, \ldots, x_{n}\right) \leqslant_{M}\left(x_{1}+x_{2}+\cdots+x_{n}, 0, \ldots, 0\right)
$$

## Majorization

Interpretation. comparison of income distributions

- identical total incomes
(majorization describes distributive aspects)
- identical size of populations

Transition from $x$ to $y$ is result of finitely many "Robin Hood transfers":

Majorization and transfers. The following are equivalent

- $x \geqslant_{M} y$
- $y=T_{1} T_{2} \cdots T_{m} x$, with $T_{i}$ matrix representing 'elementary transfers',
$T=\epsilon I+(1-\epsilon) P(P$ 'elementary' permutation matrix $)$


## Majorization

Some pioneers.

- R. F. Muirhead (1903)
- M. O. Lorenz (1905)
- H. Dalton (1920)
- I. Schur (1923)
- G. H. Hardy, J. E. Littlewood and G. Pólya (1929, 1934)


## Majorization



## Majorization

## Some references.

- PM Alberti and A Uhlmann (1981). Stochasticity and Partial Order, Verlag der Wissenschaften.
- BC Arnold (1987). Majorization and the Lorenz Order, Springer-Verlag.
- R Bhatia (1997). Matrix Analysis, Springer-Verlag.
- GH Hardy, JE Littlewood and G Pólya (1934). Inequalities, Cambridge.
- AW Marshall and I Olkin (1979). Inequalities: Theory of Majorization and Its Applications, Academic Press.
[2nd ed. 2011, with BC Arnold.]
- JM Steele (2004). The Cauchy-Schwarz Masterclass, Cambridge.


## Majorization



# Inequalities: Theory of Majorization and Its Applications 

Second Edition

Springer

## Majorization and Schur convexity

## Schur functions

- $g$ Schur convex iff $x \geqslant_{M} y \quad \Rightarrow \quad g(x) \geqslant g(y)$
- $g$ Schur concave iff ff $\quad x \geqslant_{M} y \quad \Rightarrow \quad g(x) \leqslant g(y)$

Unfortunate terminology ...a monotonicity property.

## HLP characterization (1934)

The following are equivalent:

- $x \geqslant_{M} y$
- $y=P x, P$ doubly stochastic matrix
- $\sum_{i} h\left(x_{i}\right) \geqslant \sum_{i} h\left(y_{i}\right)$ for all (continuous) convex functions $h$

Not every analytic inequality is a consequence of the Schur convexity of some function, but enough are to make familiarity with majorization/Schur convexity a nece[s]sary part of the required background of a respectable mathematical analyst.

## Majorization and Schur convexity

How to recognize Schur concave/convex functions?

## Schur's criterion (1923)

Continuously differentiable $g$, permutation symmetric, is Schur convex (concave) if, for all $i, j$,

$$
\left(x_{i}-x_{j}\right)\left(\frac{\partial g(x)}{\partial x_{i}}-\frac{\partial g(x)}{\partial x_{j}}\right) \geqslant(\leqslant) \quad 0
$$

Remark on terminology: (convexity connection)
Why 'convex'? For $f$ convex, composite function

$$
g(x):=\sum_{i} f\left(x_{i}\right)
$$

is Schur convex. Also have various representations involving doubly stochastic matrices, specific convex functions, etc.

## Majorization and Schur convexity

Examples: Classical inequality measures are Schur convex in incomes

- Gini

$$
G=2 \cdot \text { concentration area }
$$

- coefficient of variation (squared)

$$
C V^{2}=\frac{1}{n} \sum_{i}\left(\frac{x_{i}}{\bar{x}}-1\right)^{2}
$$

- Theil

$$
T=\frac{1}{n} \sum_{i} \frac{x_{i}}{\bar{x}} \log \frac{x_{i}}{\bar{x}}
$$

- Atkinson

$$
A_{\epsilon}=1-\left\{\frac{1}{n} \sum_{i}\left(\frac{x_{i}}{\bar{x}}\right)^{1-\epsilon}\right\}^{1 /(1-\epsilon)}
$$

## The Lorenz order

Majorization not sufficiently general for many tasks:

- identical population size?
- identical total incomes?

Suggestion of Max Otto Lorenz (1905):

## Lorenz curve

For $\mathbf{x}=\left(x_{1}, \ldots, x_{n}\right), x_{i} \geqslant 0, \sum_{i=1}^{n} x_{i}>0$, define Lorenz curve via linear interpolation of ( $x_{i: n}$ increasingly ordered)

$$
L\left(\frac{k}{n}\right)=\frac{\sum_{i=1}^{k} x_{i: n}}{\sum_{i=1}^{n} x_{i: n}}, \quad k=0,1, \ldots, n .
$$

Interpretation:
"poorest $\frac{k}{n} \cdot 100 \%$ possess $\frac{\sum_{i=1}^{k} x_{i: n}}{\sum_{i=1}^{n} x_{i: n}}$ of total income"

## The Lorenz order

$$
x=(1,3,5,11)
$$



## The Lorenz order

a) modern

c) Chatelain (1907)

u
b) Lorenz (1905)

d) ROC style


## The Lorenz order

## Lorenz curve (Pietra 1915, Piesch 1967, Gastwirth 1971)

For non-negative $X$ with $0<E(X)<\infty$, set

$$
L_{X}(u)=\frac{1}{E(X)} \int_{0}^{u} F_{X}^{-1}(t) d t, \quad u \in[0,1] .
$$

## Properties.

- $L$ continuous on $[0,1]$, with $L(0)=0$ and $L(1)=1$,
- $L$ monotonically increasing, and
- $L$ convex.


## Lorenz order

$X_{1}$ more unequal (... or more spread out . . . or more variable) than $X_{2}$ in the Lorenz sense, if $L_{1}(u) \leqslant L_{2}(u)$ for all $u \in[0,1]$. Notation:

$$
X_{1} \geqslant_{L} X_{2} \quad: \Longleftrightarrow \quad L_{1} \leqslant L_{2}
$$

## The Lorenz order

## Lorenz curves



## The Lorenz order



## Applications of majorization and the Lorenz order

'Random' paper in statistical distribution theory:
Kochar and Xu (J Mult Anal 2010) show for exponential distribution:

Suppose $X_{i} \sim \operatorname{Exp}\left(\lambda_{i}\right)$ independent.
If $\left(1 / \lambda_{1}, \ldots, 1 / \lambda_{n}\right) \geqslant_{M}\left(1 / \lambda_{1}^{*}, \ldots, 1 / \lambda_{n}^{*}\right)$, then

$$
\sum_{i=1}^{n} X_{\lambda_{i}} \quad \geqslant_{L} \quad \sum_{i=1}^{n} X_{\lambda_{i}^{*}}
$$

Nice: Majorization and Lorenz order!

Remark. Since 2000 dozens (hundreds?) of papers on distributional inequalities for linear combinations, order statistics etc from heterogeneous populations. Many involve majorization.

## Applications of majorization and the Lorenz order

- Mathematics, statistics, actuarial science
- eigenvalues and diagonal elements of matrices
- distributions of quadratic forms
- power functions of tests in multivariate analysis
- inequalities for special functions
- distributions of aggregate losses (= random sums)
- value at risk
- ...
- Social sciences
- tax progression and income redistribution
- Condorcet jury theorems
- "fair representation" in parliaments
- ...


## Applications of majorization and the Lorenz order

- Often variations on the main theme:
- majorization of transformations (logarithms, ...)
- weak majorization (super- or submajorization)
- Especially Lorenz ordering results often require background on further stochastic orders to exploit interrelations
- there are hundreds of stochastic orders in statistics, economics, reliability theory, actuarial science, ...
- Examples include stochastic dominance (of various orders), convex order, increasing convex/concave order, star-shaped order, mean residual life (or mean excess) order, hazard rate order, likelihood ratio order, excess wealth order, total time on test, superadditive order, ...


## Applications: Taxes and incomes

Framework. Given

- vector of incomes $\mathbf{x}=\left(x_{1}, \ldots, x_{n}\right)$
- tax schedule $t(x)$ Call $\{1-t(x)\} x$ after-tax income ("residual income")

Goal. Comparison of before- and after-tax incomes wrt. inequality. Majorization not applicable because

$$
\sum_{i} x_{i} \neq \sum_{i}\left\{1-t\left(x_{i}\right)\right\} x_{i}
$$

Use Lorenz order instead.
Question. What does a 'Lorenz-equalizing' tax look like?

## Applications: Taxes and incomes

Theorem (Eichhorn, Funke, Richter, J Math Econ 1984)

$$
x \quad \geqslant_{L} \quad\{1-t(x)\} x
$$

iff

- $t(x)$ increasing and
- $\{1-t(x)\} x$ increasing.

Interpretation. Income tax is inequality-reducing iff

- progressive and
- incentive preserving


## Applications: Condorcet jury theorems

Framework. Jury of $n$ 'experts' faces binary decision.

- Suppose $X_{i} \in\{0,1\}$ decision of expert $i$ and $p_{i}=P\left(X_{i}=1\right)$, $i=1, \ldots, n$. Call $p_{i}$ competence/ability of expert $i$.
- Consider number of correct decisions

$$
S:=\sum_{i=1}^{n} X_{i}
$$

If all experts equally competent $\left(p_{i} \equiv p\right)$ and independent,

$$
P(S \geqslant k)=\sum_{i=k}^{n}\binom{n}{i} p^{i}(1-p)^{n-i}
$$

a binomial probability.

- Decision is via majority voting.

To avoid ties, set $n=2 m+1$, hence $k=m+1$.

## Applications: Condorcet jury theorems



## Applications: Condorcet jury theorems

## Setting of classical CJT.

- two alternatives
- common preferences
(one alternative is superior in the light of full information)
- independent decisions
- homogeneous competences
- decision rule is simple majority voting


## Applications: Condorcet jury theorems

Classical CJTs. (Boland, JRSS D 1989)

## Non-asymptotic CJT

Under majority voting with $p>1 / 2$ ("experts") have

$$
P(S \geqslant m+1) \quad>\quad p
$$

Proof: use Beta integral representation of binomial probabilities

$$
P(S \geqslant m+1)=\frac{1}{B(m+1, m+1)} \int_{0}^{p} t^{m}(1-t)^{m} d t
$$

NB. There is also an asymptotic CJT, but not needed here.

## Applications: Condorcet jury theorems



## Applications: Condorcet jury theorems

## Extensions of basic version.

- supermajority voting (also called special majority voting)
- heterogeneous experts
- dependent experts ("opinion leaders")
- juries of different sizes
- direct vs indirect majority voting ( $\rightarrow$ US presidential elections)


## Applications: Condorcet jury theorems

Framework. Jury $J$ characterized by vector of probabilities ("competences")

$$
\mathbf{p}=\left(p_{1}, \ldots, p_{n}\right) \quad \in[0,1]^{n}
$$

Question. Given 2 juries $J_{1}$ und $J_{2}$ of equal size, with competences $\mathbf{p}_{1}$ and $\mathbf{p}_{\mathbf{2}}$, when will $J_{1}$ do better?

Need conditions for

$$
P\left(S_{1} \geqslant m+1\right) \geqslant P\left(S_{2} \geqslant m+1\right) \text { for } \mathbf{p}_{\mathbf{i}} \in \mathcal{P} \subseteq[0,1]^{n}
$$

- New problem: distribution of sums of independent, but not identically distributed Bernoulli variables
- Goal: stochastic comparisons with e.g. binomial distribution
- Classical paper: Hoeffding (Ann Math Stat 1956)


## Applications: Condorcet jury theorems

In Hoeffding (1956) purely probabilistic point of view.
Sums of heterogeneous Bernoullis arise in many contexts

- CJTs
- reliability of " $k$ out of $n$ " systems (unequal default probabilities)
- portfolios of credit risks


## Applications: Condorcet jury theorems

Point of reference. average competence $\bar{p}$

## Hoeffding's inequality (Hoeffding 1956)

Suppose $k>0$ with $\bar{p} \geqslant k / n$. Then

$$
P(S \geqslant k) \geqslant \sum_{i=k}^{n}\binom{n}{i} \bar{p}^{i}(1-\bar{p})^{n-i}
$$

This gives
Boland's CJT (Boland 1989)
Suppose $n \geqslant 3, \bar{p} \geqslant 1 / 2+1 /(2 n)$. Then

$$
P(S \geqslant m+1) \quad>\quad \bar{p}
$$

## Applications: Condorcet jury theorems

Generalization of Hoeffding's inequality:
Gleser's inequality (Ann Prob 1975)
Let $\mathbf{p}_{1} \geqslant_{M} \mathbf{p}_{2}$. Then

$$
P\left(S \leqslant k \mid \mathbf{p}_{1}\right) \leqslant P\left(S \leqslant k \mid \mathbf{p}_{2}\right), \quad k \leqslant\lfloor n \bar{p}-2\rfloor
$$

This gives

## CJT under heterogeneity

Let $n \geqslant 7$ and $\bar{p} \geqslant 1 / 2+5 /(2 n)$. If $\mathbf{p}_{1} \geqslant_{M} \mathbf{p}_{2}$ then

$$
P\left(S \geqslant m+1 \mid \mathbf{p}_{1}\right) \geqslant P\left(S \geqslant m+1 \mid \mathbf{p}_{2}\right)
$$

Note: need large $\bar{p}$ for superiority of majority voting!

## Applications: Condorcet jury theorems

Further generalization of Hoeffding's inequality:

## Boland and Proschan's inequality (Ann Prob 1983)

Let $\mathbf{p}_{1} \geqslant_{M} \mathbf{p}_{2}$. Then
$P\left(S \leqslant k \mid \mathbf{p}_{1}\right) \leqslant P\left(S \leqslant k \mid \mathbf{p}_{2}\right), \quad$ all $\quad p_{i} \in[(k-1) /(n-1), 1]^{n}$
This gives

## CJT under heterogeneity

Let $p_{i} \in[1 / 2,1]^{n}$ with $\mathbf{p}_{1} \geqslant_{M} \mathbf{p}_{2}$. Then

$$
P\left(S \geqslant m+1 \mid \mathbf{p}_{1}\right) \geqslant P\left(S \geqslant m+1 \mid \mathbf{p}_{2}\right)
$$

This differs from the Gleser version!
Can be generalized to supermajority voting.

## Applications: Condorcet jury theorems

Visualization via Lorenz curves

$$
L\left(\frac{k}{n}\right)=\frac{\sum_{i=1}^{k} x_{i: n}}{\sum_{i=1}^{n} x_{i: n}}, \quad k=0,1, \ldots, n,
$$

where $x_{i: n} i$ th smallest income $\rightarrow$ consider probabilities as incomes
Example: $\quad n=9, \bar{p}=0.6$
$\mathrm{p} 1<-c(1.0,1.0,1.0,0.7,0.7,0.7,0.5,0.5,0.5)$
$\mathrm{p} 2<-\mathrm{c}(1.0,0.9,0.9,0.8,0.8,0.6,0.6,0.5,0.5)$

## Applications: Condorcet jury theorems

majorization of competences


## Portfolio allocation and value at risk

Conventional wisdom in portfolio allocation:

## Diversification reduces risk.

Q. Really ...?

## Schur properties of VaR (Ibragimov, Quant Fin 2009)

Consider portfolios $Y_{a}=\sum_{i} a_{i} Y_{i}$ and $Y_{b}=\sum_{i} b_{i} Y_{i}$, and $\alpha<\frac{1}{2}$. Then

- $a \geqslant_{M} b \quad \Longrightarrow \quad \operatorname{VaR}_{\alpha}\left(Y_{a}\right) \geqslant \operatorname{VaR}_{\alpha}\left(Y_{b}\right)$ for $Y_{i}$ light-tailed.
- $a \geqslant_{M} b \quad \Longrightarrow \quad \operatorname{VaR}_{\alpha}\left(Y_{a}\right) \leqslant \operatorname{Va}_{\alpha}\left(Y_{b}\right)$ for $Y_{i}$ (very) heavy-tailed.


## Applications: Lorenz ordering of beta distributions

Consider beta distribution $\beta(p, q)$

$$
f(x)=\frac{1}{B(p, q)} x^{p-1}(1-x)^{q-1}, \quad x \in[0,1] .
$$

Q. Let $X_{i} \sim \beta\left(p_{i}, q_{i}\right), i=1,2$. When do we have $X_{1} \geqslant_{L} X_{2}$ ?

Many applications: Order statistics, reliability, actuarial science, ...

## Partial results:

- $X_{1} \geqslant_{L} X_{2}$ implies $p_{1} \leqslant p_{2}$ and $p_{1} / p_{2} \leqslant q_{1} / q_{2}$
- $\beta(p, q) \geqslant_{L} \beta(q, p) \Longleftrightarrow p \leqslant q$
- Let $X_{i} \sim \beta\left(p_{i}, p_{i}\right), i=1,2$. Then $X_{1} \geqslant_{L} X_{2} \Longleftrightarrow p_{1} \leqslant p_{2}$.
- $p_{1} \leqslant p_{2}$ and $q_{1} \geqslant q_{2}$ imply $X_{1} \geqslant_{L} X_{2}$.

Tools: relations for tailweight, log-concavity, beta-gamma algebra.
Remark. Can be translated into (obscure?) inequalities for regularized incomplete beta function.

## Applications: Lorenz ordering of beta distributions


$\beta(1,3) \geqslant_{L} \beta(2,2)$ (proof!)

$\beta(1,2) \geqslant_{L} \beta(2,3)$ (no proof ...)

## Applications: Spectra of correlation matrices

Q: How to compare correlation matrices of time series models?
Consider AR(1) process

$$
y_{t}=\rho y_{t-1}+\varepsilon_{t}
$$

and (auto)correlation matrix

$$
R_{\rho}=\left(\rho^{|i-j|}\right)_{i, j=1, \ldots, T}
$$

Obvious: process is more persistent for larger $\rho$.
Can say more: Spectra of correlation matrices are ordered

$$
\rho_{1} \leqslant \rho_{2} \quad \Longrightarrow \quad \lambda\left(R_{\rho_{1}}\right) \leqslant M \quad \lambda\left(R_{\rho_{2}}\right)
$$

Further examples:

- MA(1) processes
- equicorrelation matrices $(1-\rho) I+\rho 11^{\top}$

Ingredients: Majorization inequalities for Schur products.

## Applications: Spectra of correlation matrices

two AR(1) spectra ( $\mathrm{T}=100$ )


## Applications: Win-probabilities

Consider random variables $X_{1}, \ldots, X_{k}$, independent.
Win-probability for 'treatment' $X_{k}$ is

$$
\begin{aligned}
W^{U}(k ; 1, \ldots, k-1) & =P\left(X_{k}>\max _{1 \leqslant j \leqslant k-1} X_{j}\right) \\
& =\int_{\mathbb{R}} f_{k}(x) \prod_{j=1}^{k-1} F_{j}(x) d x
\end{aligned}
$$

Example: Let $k=3$ and $X_{j} \sim \operatorname{Exp}\left(\lambda_{j}\right)$, independent.
With $\rho_{i}=\lambda_{i} / \lambda_{3}, i=1,2$, have

$$
W^{U}(3 ; 1,2 \mid \rho)=1-\frac{1}{\rho_{1}+1}-\frac{1}{\rho_{2}+1}+\frac{1}{\rho_{1}+\rho_{2}+1}
$$

This is Schur-concave in $\rho=\left(\rho_{1}, \rho_{2}\right)^{\top}$. Thus

$$
\rho \geqslant_{M} \tau \quad \Longrightarrow \quad W^{U}(\ldots \mid \rho) \leqslant W^{U}(\ldots \mid \tau)
$$

## Applications: Win-probabilities

## Remarks:

- works for $k>3$
- works for Pareto
- works for Weibull with common shape
- similar for $W^{L}$ 'lower win (lose?) probability'
- related to stress-strength models in reliability


## Concluding remarks

Majorization has many applications, not only in mathematics.
Classical problem: (majorization)

$$
a \geqslant_{M} b \quad \Longrightarrow \quad f(a) \geqslant(\leqslant) f(b)
$$

Open problem: (Lorenz order)

$$
a \geqslant_{L} b \quad ? \quad f(a) \geqslant(\leqslant) f(b)
$$

- Lorenz order is less widely known but potentially more useful
- Lorenz curve is useful for visualizing majorization inequalities .... and for hypothesizing theorems (!)
- many majorization and Lorenz ordering results remain to be discovered


## Applications: Chemistry

bubble sizes


## Applications: Schur-Horn theorem

Problem. Relation between eigenvalues $\lambda_{i}$ and diagonal elements $a_{i i}$ of a symmetric matrix $A$ ?

Note $\operatorname{tr}(A)=\sum_{j} \lambda_{j}$, hence majorization meaningful.
Schur (1923) shows

$$
\left(a_{11}, a_{22}, \ldots, a_{n n}\right) \quad \leqslant M \quad\left(\lambda_{1}, \lambda_{2}, \ldots, \lambda_{n}\right)
$$

This implies Hadamard's inequality:
For any real, symmetric matrix

$$
\prod_{i} a_{i i} \geqslant \prod_{i} \lambda_{i}
$$

## Applications: Schur-Horn theorem

But there is more:

Schur-Horn theorem. Suppose $a, b \in \mathbb{R}^{n}$ with $a \leqslant_{M} b$.
Then there exists a real, symmetric matrix $A$ with diagonal $a$ and eigenvalues $b$.

Recent abstract version: majorization of sequences implies existence of compact operator with suitable eigenvalues, etc.

## Applications: Credit risks

Framework. $\quad n$ credit risks $X_{i}$ described by sizes $a_{i}, i=1, \ldots, n$, and (possibly distinct) default probabilities $p_{i}$.

Quantities of interest:

- number of defaults $\sum_{i} X_{i}, X_{i} \sim \operatorname{Bin}\left(1, p_{i}\right)$
- aggregate losses $\sum_{i} a_{i} X_{i}, X_{i} \sim \operatorname{Bin}\left(1, p_{i}\right)$

Result on number of defaults.
If $\mathbf{p}_{(\mathbf{1})} \geqslant_{M} \mathbf{p}_{(\mathbf{2})}$ and risks independent, then

$$
\operatorname{Var}\left(\sum_{i} X_{i} \mid \mathbf{p}_{(\mathbf{1})}\right) \leqslant \operatorname{Var}\left(\sum_{i} X_{i} \mid \mathbf{p}_{(\mathbf{2})}\right)
$$

Proof: variance is Schur concave in $p$
Can also use Hoeffding etc bounds ... but they provide lower bounds on probabilities.

## Applications: Credit risks

Result on aggregate losses.
This requires assumption on $a_{i}$ s. Suppose $a_{i}$ decreasing in $p_{i}$.
Assume

$$
a_{i} p_{i} \approx \text { const. }=: a
$$

hence consider

$$
\sum a_{i} X_{i}=a \sum \frac{1}{p_{i}} X_{i}, \quad \text { wlog } a=1
$$

If $\mathbf{p}_{(\mathbf{1})} \geqslant_{M} \mathbf{p}_{(\mathbf{2})}$ and risks independent, then

$$
\operatorname{Var}\left(\sum_{i} a_{i} X_{i} \mid p_{(1)}\right) \geqslant \operatorname{Var}\left(\sum_{i} a_{i} X_{i} \mid p_{(2)}\right)
$$

Proof: variance is Schur concave in $p$

## Majorization and Schur convexity

Axiomatic approach to inequality measurement.
For a scalar measure of inequality $I$, require (at least) the following properties:

- $I(x)=I(\lambda x)$ for $\lambda>0$ (homogeneity of degree 0)
- for $x \geqslant_{M} y$ must have $I(x) \geqslant I(y)$
- $I((x, x))=I(x)$
(Schur convexity)
(population principle)

