

Behavioral biases and representative agent (or the brain as a central planner with heterogeneous doers)

Elyès Jouini

PIMS, 2008

Homo Economicus

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Interpretation

Axiomatic approach

- Lotteries space X (for instance $R^m \times \Delta_m$)
- $x = (x^1, \pi^1; \dots; x^n, \pi^n)$
- \succeq preference relation on X

Theorem (VNM)

If \succeq is complete, transitive, Archimedean and satisfies

$$x \succeq y \Rightarrow \alpha x + (1 - \alpha)r \succeq \alpha y + (1 - \alpha)r, \quad \forall r, \forall \alpha \in [0, 1]$$

(Independence)

*then $x \succeq y \iff E[u(x)] \geq E[u(y)]$ with $u : R \rightarrow R$
non-decreasing and concave.*

Subjective probabilities

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- Random variables space (payoffs space) X
- \succeq preference relation on X

Theorem (Savage)

If \succeq satisfies the rationality axioms then

$x \succeq y \iff \sum_{j=1}^m \pi^j u(x^j) \geq \sum_{j=1}^m \pi^j u(y^j)$ for some $u : R \rightarrow R$ non-decreasing and concave and some $\pi \in \Delta_m$.

Pareto optimum

- n agents, $i = 1, \dots, n$
- u_i , $i = 1, \dots, n$
- $Q_i = (\pi_i^j)$, $i = 1, \dots, n$
- $U_i(x) = E^{Q_i} [u_i(x)] = E [M_i u_i(x)]$
- total endowment x

Definition

An allocation (x_1, \dots, x_n) such that $\sum_{i=1}^n x_i = x$ is Pareto optimal if there is no (y_1, \dots, y_n) such that $\sum_{i=1}^n y_i = x$ and $U_i(y_i) \geq U_i(x_i)$, $i = 1, \dots, n$, and $U_i(y_j) > U_i(x_j)$ for some j .

Characterization of Pareto optima

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Theorem

(x_1^*, \dots, x_n^*) is a PO iff $\exists (\lambda_i) \in \Delta_n$ s.t.

$$(x_1^*, \dots, x_n^*) = \arg \max_{\sum_{i=1}^n x_i = x} \sum_{i=1}^n \lambda_i U(x_i).$$

For given weights $(\lambda_i) \in \Delta_n$, the social welfare value function is defined by

$$U(x) = \max_{\sum_{i=1}^n x_i = x} \sum_{i=1}^n \lambda_i U_i(x_i) = \sum_{i=1}^n \lambda_i U_i(x_i^*)$$

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- $t = 0, 1, \dots, T$

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- $t = 0, 1, \dots, T$
- $\rho_i, i = 1, \dots, n$

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- $t = 0, 1, \dots, T$
- $\rho_i, i = 1, \dots, n$
- $D_t^i = \exp(-\rho_i t)$

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Interpretation

- $t = 0, 1, \dots, T$
- $\rho_i, i = 1, \dots, n$
- $D_t^i = \exp(-\rho_i t)$
- $M_t^i = \left. \frac{dQ_i}{dP} \right|_{F_t}$

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Interpretation

- $t = 0, 1, \dots, T$
- $\rho_i, i = 1, \dots, n$
- $D_t^i = \exp(-\rho_i t)$
- $M_t^i = \left. \frac{dQ_i}{dP} \right|_{F_t}$
- $U_i(x(0), x(1), \dots, x(T)) = \sum_{t=0}^T \exp(-\rho_i t) U_i(x(t)) = \sum_{t=0}^T E [M_t^i D_t^i u_i(x(t))]$

Behavioral features

- Hyperbolic discounting (Loewenstein and Prelec): ρ_j is not constant and decreases with time

$$\sum_{j=1}^m w^j(x) u(x^j)$$

with

$$w^j(x) = w(p_j + \dots + p_n) - w(p_{j+1} + \dots + p_n).$$

Behavioral features

- Hyperbolic discounting (Loewenstein and Prelec): ρ_i is not constant and decreases with time
- Prospect Theory (Kahneman and Tversky): Probabilities depend upon the prospect $\sum_{j=1}^m w(\pi^j) u(x^j)$

$$\sum_{j=1}^m w^j(x) u(x^j)$$

with

$$w^j(x) = w(p_j + \dots + p_n) - w(p_{j+1} + \dots + p_n).$$

Behavioral features

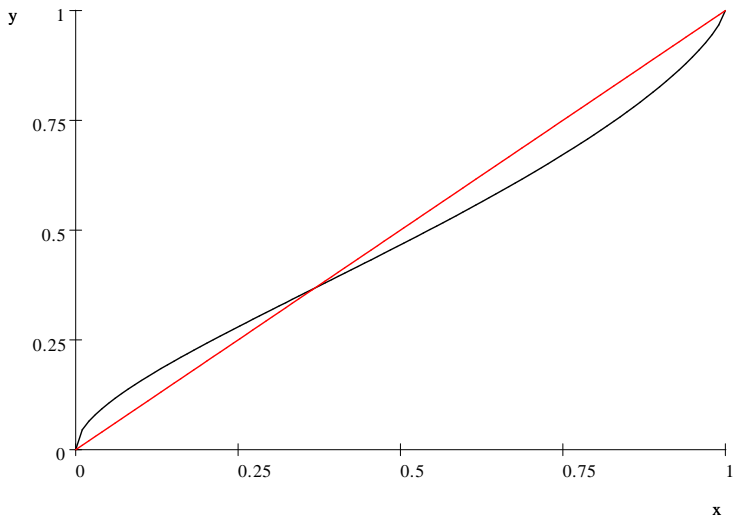
- Hyperbolic discounting (Loewenstein and Prelec): ρ_i is not constant and decreases with time
- Prospect Theory (Kahneman and Tversky): Probabilities depend upon the prospect $\sum_{j=1}^m w(\pi^j) u(x^j)$
- Cumulative Prospect Theory (Tversky and Kahneman), if $x_1 < x_2 < \dots < x_n$

$$\sum_{j=1}^m w^j(x) u(x^j)$$

with

$$w^j(x) = w(p_j + \dots + p_n) - w(p_{j+1} + \dots + p_n).$$

Parametric and non-parametric calibrations



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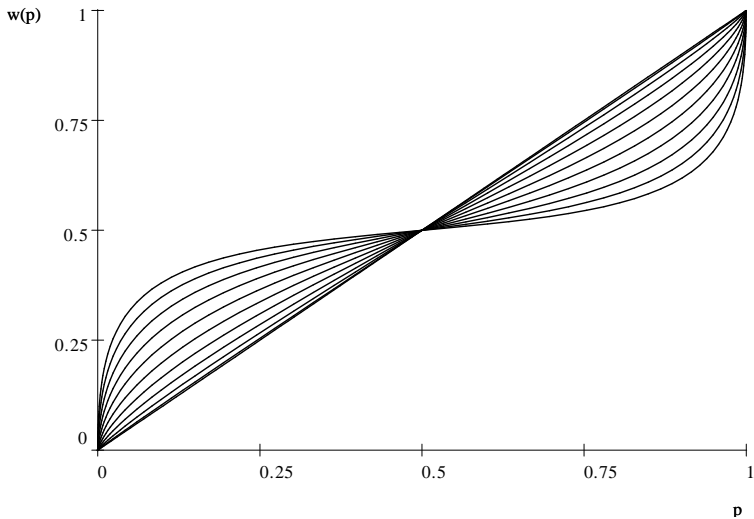
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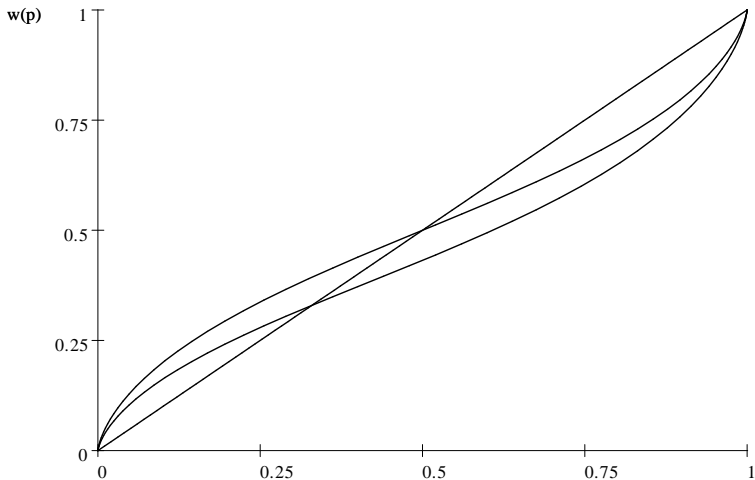
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Representative agent

- All agents have the same CRRA utility function

$$u(s) = \frac{s^{1-\frac{1}{\eta}}}{1-\frac{1}{\eta}}.$$

- The number of agents can be finite or infinite

Theorem

If the characteristics $(M_t^i, D_t^i, \lambda_i)_{i \in I}$ are independent, then

$$U(x) = E [M_t D_t u(x)]$$

with

$$M_t = \left(\frac{1}{|I|} \sum_{i \in I} (M_t^i)^\eta \right)^{\frac{1}{\eta}} \quad \text{and} \quad D_t = \left(\frac{1}{|I|} \sum_{i \in I} (D_t^i)^\eta \right)^{\frac{1}{\eta}}.$$

Our aim

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Interpretation

- We start from a standard model of Pareto optimality

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Interpretation

- We start from a standard model of Pareto optimality
- We analyze the behavioral properties of the representative agent

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Interpretation

- We start from a standard model of Pareto optimality
- We analyze the behavioral properties of the representative agent
- It can be seen as a model of individual decision making if $RA = \text{individual}$ and $\text{agents} = \text{processes}$

Distribution of x for the representative agent

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Interpretation

We denote by Q the representative agent probability

Theorem

$$f_t = \left(\frac{1}{|I|} \sum_{i \in I} (f_t^i)^\eta \right)^{\frac{1}{\eta}}$$

- If $\eta = 1$, $E^Q [x] = \frac{1}{|I|} \sum_{i \in I} E^{Q_i} [x]$ and $E^Q [x] = E^P [x]$ if no bias

Distribution of x for the representative agent

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$$f_t = \left(\frac{1}{|I|} \sum_{i \in I} (f_t^i)^\eta \right)^{\frac{1}{\eta}}$$

- If $\eta = 1$, $E^Q [x] = \frac{1}{|I|} \sum_{i \in I} E^{Q_i} [x]$ and $E^Q [x] = E^P [x]$ if no bias
- If $\eta = 1$, $Var^Q [x] = Var^P [x] + Var_i [E^{Q_i} [x]]$

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Interpretation

- $\log x \sim \mathcal{N}((\mu, \sigma^2))$

Theorem

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- $\log x \sim \mathcal{N}((\mu, \sigma^2))$
- $\log x \sim_{Q_i} \mathcal{N}(\mu_i, \sigma^2)$

Theorem

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Interpretation

- $\log x \sim \mathcal{N}((\mu, \sigma^2))$
- $\log x \sim_{Q_i} \mathcal{N}(\mu_i, \sigma^2)$
- If $\mu_i \leq \mu$, i is pessimistic and if $\mu_i \geq \mu$, i is optimistic

Theorem

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Theorem

- 1 *If agents' beliefs are heterogeneous enough, the distribution of $\log x$ is bimodal.*

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Theorem

- 1 *If agents' beliefs are heterogeneous enough, the distribution of $\log x$ is bimodal.*
- 2 *More variance, excess kurtosis and same mean (if no bias),*

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Theorem

- 1 *If agents' beliefs are heterogeneous enough, the distribution of $\log x$ is bimodal.*
- 2 *More variance, excess kurtosis and same mean (if no bias),*
- 3 *$\text{Var}^Q [\log x]$ increases with the level or risk tolerance η .*

The bimodal representative agent distribution

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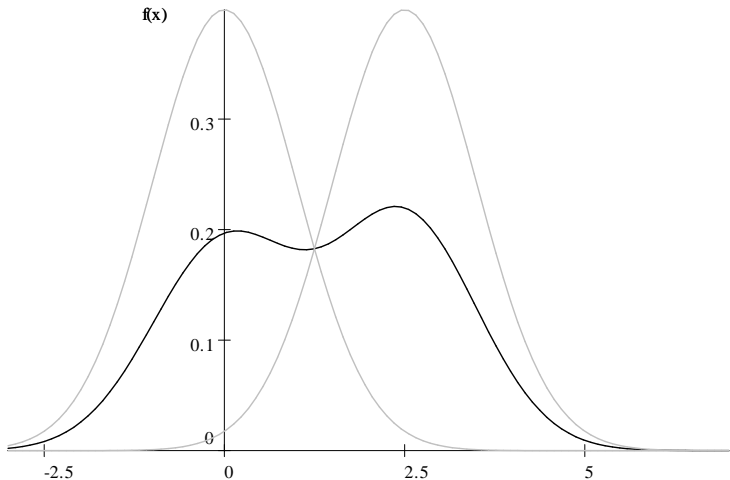
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Properties of the representative agent's belief

Theorem

If I is made of both optimistic and pessimistic agents.

- 1 *The representative agent can neither be (everywhere) optimistic, nor (everywhere) pessimistic*

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- 3 *The representative agent behaves like the more pessimistic individual for low values and behaves like the more optimistic individual for high values*

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- 3 *The representative agent behaves like the more pessimistic individual for low values and behaves like the more optimistic individual for high values*
- 4 *The representative agent acts as if he had fear (need for security) for very bad events and hope (desire for potential) for very good events (SP/A Theory, Lopes)*

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- 4 *The representative agent acts as if he had fear (need for security) for very bad events and hope (desire for potential) for very good events (SP/A Theory, Lopes)*
- 5 *The transformation w is inverse S-shaped (Abdellaoui, Gonzalez and Wu, Prelec)*

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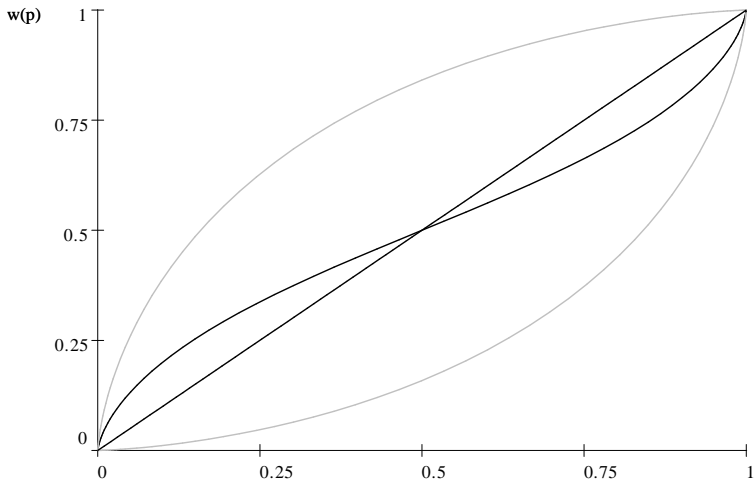
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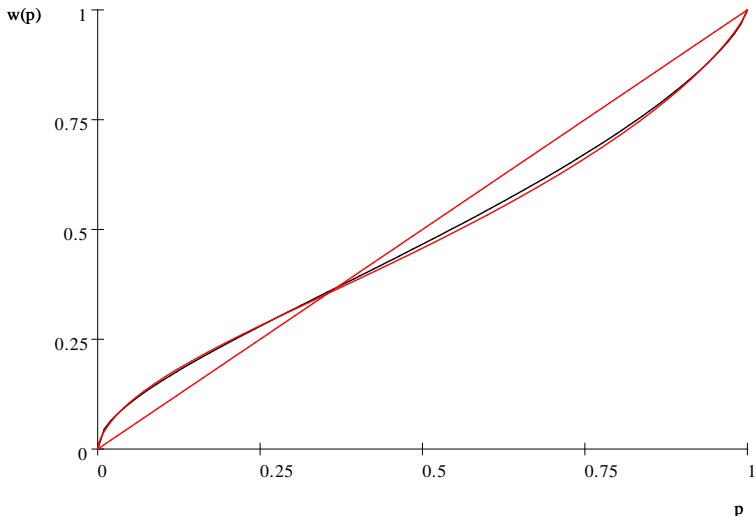
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The transformation w



Prelec's function



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Theorem

If all the agents have log-utility functions then a left shift on the distribution of (μ_i) increases attractiveness and a symmetric spread on the distribution of (μ_i) decreases discriminability.

Time preference rates

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Interpretation

- $D_t = \left(\sum_{i \in I} \frac{1}{|I|} (D_t^i)^\eta \right)^{\frac{1}{\eta}}$ where $D_t^i \equiv \exp(-\rho_i t)$.

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Interpretation

- $D_t = \left(\sum_{i \in I} \frac{1}{|I|} (D_t^i)^\eta \right)^{\frac{1}{\eta}}$ where $D_t^i \equiv \exp(-\rho_i t)$.
- Representative agent marginal and average time preference rates ρ_m and ρ_a

$$\rho_m^D(t) = -\frac{D'_t}{D_t}$$

$$\rho_a^D(t) = -\frac{1}{t} \log D_t$$

Behavioral properties of the rep. agent's rates

Theorem

ρ_m and ρ_a are given by

$$\rho_a^D(t) = -\frac{1}{t} \log \left[\frac{1}{N} \sum_{i=1}^N \exp(-\eta \rho_i t) \right]^{1/\eta}$$

$$\rho_m^D(t) = \sum_{i=1}^N \frac{\exp(-\eta \rho_i t)}{\sum_{i=1}^N \exp(-\eta \rho_i t)} \rho_i$$

They are lower than the average of the time preference rates

$$\rho_m^D(t) < \frac{1}{N} \sum_{i=1}^N \rho_i \quad \text{and} \quad \rho_a^D(t) < \frac{1}{N} \sum_{i=1}^N \rho_i$$

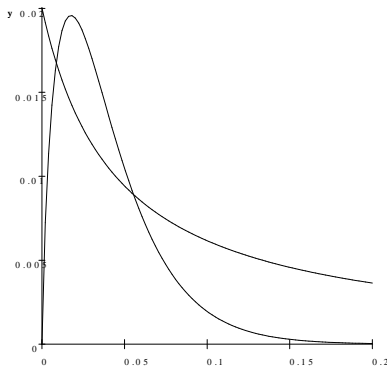
“Behavioral Properties” (Lengwiler, Gollier-Zeckhauser): ρ_m and ρ_a decrease with time and

$$\lim_{t \rightarrow \infty} \rho_m^D(t) = \lim_{t \rightarrow \infty} \rho_a^D(t) = \rho(-)$$

Specific Distributions

If we assume a Gamma distribution with mean m and variance v for the ρ_i s we obtain (hyperbolic discounting)

$$\rho_m^D(t) = \frac{m^2}{m + \eta v^2 t}$$



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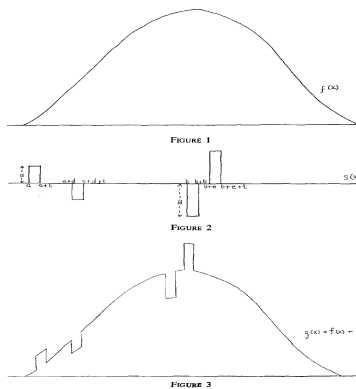
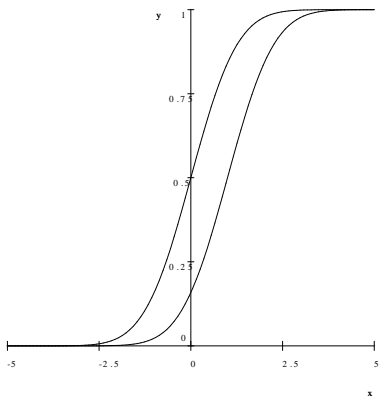
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FSD and SSD shifts

A FSD (resp. SSD) dominated shift on the distribution f_ρ of individual marginal time preference rates decreases the representative agent average time preference rate ρ_a^D .

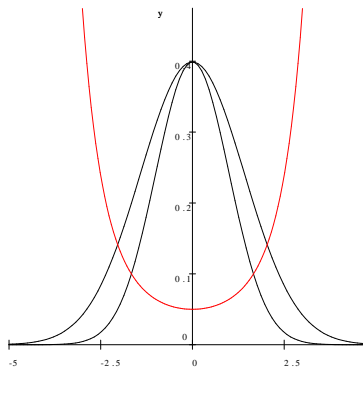
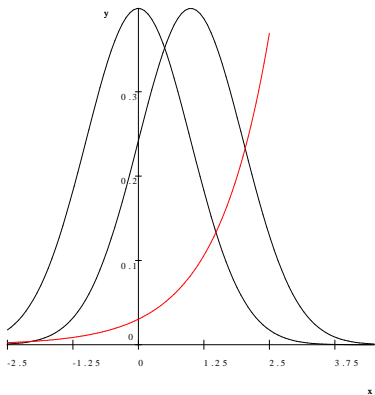


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MLR and PD shifts

A MLR (resp. PD) dominated shift on the distribution f_ρ of individual marginal time preference rates decreases the representative agent average time preference rate ρ_m^D .



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Optimism and pessimism

Definition

An agent is said to be optimistic (resp. pessimistic) if $\frac{f_i}{f}$ is nondecreasing. Agent i is said to be more optimistic than agent j and we denote by $f_i \succcurlyeq f_j$ if and only if $\frac{f_i}{f_j}$ is nondecreasing.

The probability weighting function g_i transforms the objective decumulative distribution function F into the agent's subjective decumulative distribution function F_i , i.e. $F_i = g_i \circ F$.

- $\frac{f_i}{f}$ is nondecreasing (resp. nonincreasing) if and only if g_i is convex (resp. concave). (Diecidue and Wakker, 2001) in a RDEU framework.

Optimism and pessimism

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- A MLR dominated shift for a given distribution reduces the mean.

Behavioral properties

Theorem

If there are at least one optimistic agent and one pessimistic agent

- 1 *The representative agent can neither be optimistic, nor pessimistic.*

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- 2 *The representative agent overestimates the weight of the “good states of the world” as well as the weight of “bad states of the world”*
- 3 *The representative agent acts as if he had fear (need for security) for very bad events and hope (desire for potential) for very good events*
- 4 $f_M \sim_{\infty} f_{opt}^{\max}$ and $f_M \sim_{-\infty} f_{pess}^{\max}$.

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Theorem

If there are at least one optimistic agent and one pessimistic agent

- 1 *The representative agent can neither be optimistic, nor pessimistic.*
- 2 *The representative agent overestimates the weight of the “good states of the world” as well as the weight of “bad states of the world”*
- 3 *The representative agent acts as if he had fear (need for security) for very bad events and hope (desire for potential) for very good events*
- 4 $f_M \sim_{\infty} f_{opt}^{\max}$ and $f_M \sim_{-\infty} f_{pess}^{\max}$.
- 5 *The probability weighting function is concave for small probabilities, and convex for high probabilities.*

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Theorem

- 1 *If log-utilities and if agent's density functions are totally ordered with respect to the FSD order then a FSD dominated shift in agents' density functions distribution leads to a less attractive density function for the representative agent.*

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- 1 *If log-utilities and if agent's density functions are totally ordered with respect to the FSD order then a FSD dominated shift in agents' density functions distribution leads to a less attractive density function for the representative agent.*
- 2 *If the set $(f_i)_{i \in I}$ of agent's density functions is totally ordered with respect to the MLR order then a MLR dominated shift in agents' density functions distribution leads to a more pessimistic representative agent.*

Interpretation

- Individual behavior can be represented as the aggregate behavior of a collection of individuals

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- Individual behavior can be represented as the aggregate behavior of a collection of individuals
- Is there a way to interpret the brain as a collection of processes?

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- Is there a way to interpret the brain as a collection of processes?
- Each process has its own belief and its own time preference rate (level of impatience)

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- The attribution is made in order to maximize the total utility (specialization of the processes)
- Other models in the literature (Carillo-Brocas): asymmetric information