

# Expected Utility

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Cornell University · Decision Theory · Spring 2017

motivating examples







# POWERBALL EXPECTED PAYOUT

NUMBERS MATCHED	PRIZE	PRIZE - COST	LIKELIHOOD	PROBABILITY	(PRIZE - COST) X PROBABILITY
5 white and red	\$450,000,000	\$449,999,998	1 in 292,201,338	0.0000000034	\$1.54
5 white	\$1,000,000	\$999,998	1 in 11,688,053.52	0.0000000856	\$0.09
4 white and red	\$50,000	\$49,998	1 in 913,129.18	0.0000010951	\$0.05
4 white	\$100	\$98	1 in 36,525.17	0.0000273784	\$0.00
3 white and red	\$100	\$98	1 in 14,494.11	0.0000689935	\$0.01
3 white	\$7	\$5	1 in 579.76	0.0017248517	\$0.01
2 white and red	\$7	\$5	1 in 701.33	0.0014258623	\$0.01
1 white and red	\$4	\$2	1 in 91.98	0.0108719287	\$0.02
Red	\$4	\$2	1 in 38.32	0.0260960334	\$0.05
Nothing	\$0	-\$2	1 in 1.04	0.9597837679	-\$1.92

**EXPECTED VALUE: -\$0.14**

SOURCE: Business Insider calculations with odds from powerball.com

BUSINESS INSIDER

## st. petersburg paradox

- Flip a fair coin until it lands tails
- If we flipped the coin  $n$  times, you get  $\$2^n$
- How much would you be willing to pay to participate?

$$\mathbb{E}[2^n] = \frac{1}{2} \cdot 2 + \frac{1}{4} \cdot 4 + \frac{1}{8} \cdot 8 + \dots = \sum_{n=1}^{\infty} \frac{1}{2^n} \cdot 2^n = \infty$$

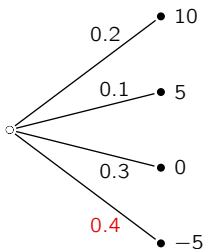
$$\mathbb{E}[\log(2^n)] = \sum_{n=1}^{\infty} \frac{1}{2^n} \cdot \log(2^n) = \log(2) \sum_{n=1}^{\infty} \frac{1}{2^n} \cdot n = 2 \log(2) \approx 0.60$$

von Neumann and Morgenstern



## simple lotteries

- A **simple lottery** is a tuple  $L = (p_1, x_1; p_2, x_2; \dots p_n, x_n)$ 
  - Monetary prizes  $x_1, \dots, x_n \in X \subseteq \mathbb{R}$
  - Probability distribution  $(p_1, \dots, p_n)$ ,  $p_i$  is the probability of  $x_i$
- Let  $\mathcal{L}$  denote the set of simple lotteries
- **Example:**  $L = (10, 0.2; 5, 0.1; 0, 0.3; -5, 0.4)$

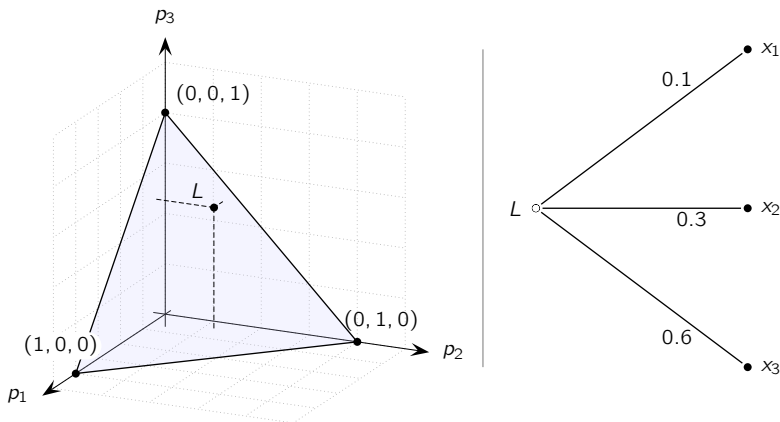




# simplex

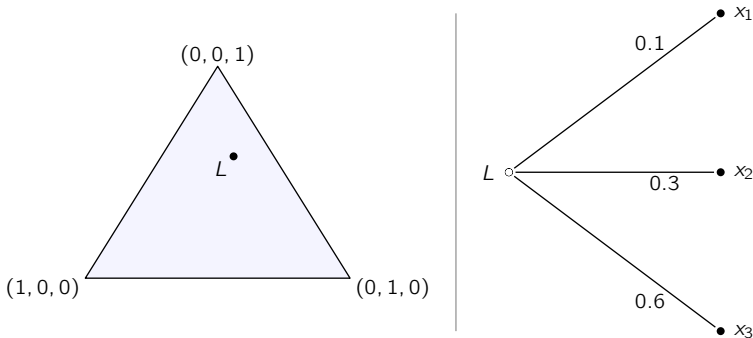
- Simple lotteries given a **fixed** set of prizes  $x_1, \dots, x_n$  correspond to points in the  $n$ -dimensional simplex

$$\Delta^n = \left\{ (p_1, \dots, p_n) \in \mathbb{R}^n \mid 0 \leq p_i \leq 1 \text{ \& } p_1 + \dots + p_n = 1 \right\}$$



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## lottery mixtures

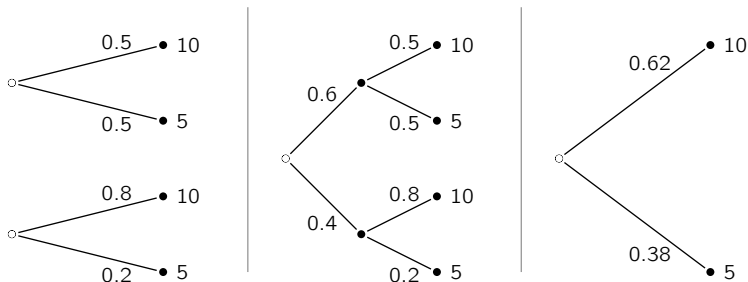
- For  $0 \leq \alpha \leq 1$  and lotteries  $L = (p_1, x_1; p_2, x_2; \dots p_n, x_n)$  and  $M = (q_1, x_1; q_2, x_2; \dots q_n, x_n)$  with the same set of prizes, define

$$\alpha L \oplus (1 - \alpha)M = (r_1, x_1; r_2, x_2; \dots r_n, x_n)$$

where

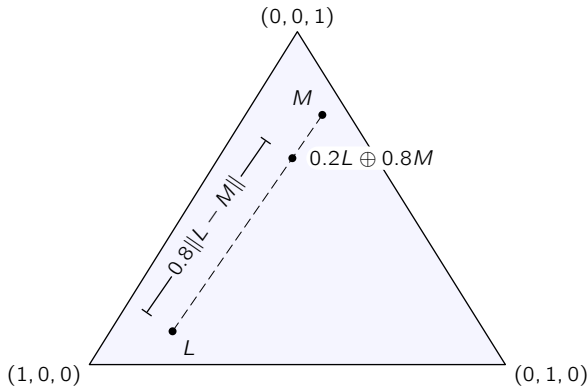
$$r_k = \alpha p_k + (1 - \alpha)q_k$$

- Example:**  $L = (0.5, 10; 0.5, 5)$ ,  $M = (0.8, 10; 0.2, 5)$ ,  $\alpha = 0.6$



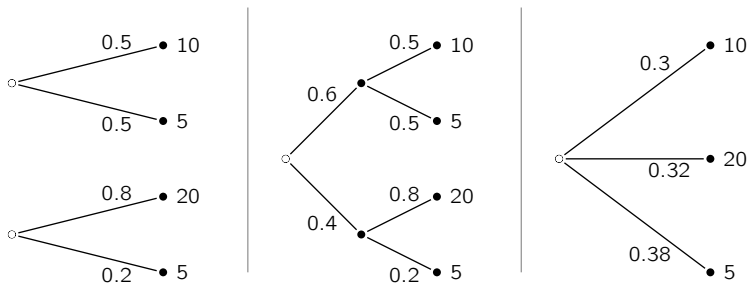
## geometry of mixtures

- With a fixed set of prizes  $x_1, \dots, x_n$ , mixtures between lotteries correspond to points in the line segment between them
- The mixture weights determine the location within the segment



## lottery mixtures

- Also possible to mix lotteries with different prizes
- Example:**  $L = (0.5, 10; 0.5, 5)$ ,  $M = (0.8, 20; 0.2, 5)$ ,  $\alpha = 0.6$



$$\alpha L \oplus (1 - \alpha)M = (0.3, 10; 0.32, 20; 0.38, 5)$$

- Reported preferences  $\succ$  on  $\mathcal{L}$
- A utility function  $U : \mathcal{L} \rightarrow \mathbb{R}$  for  $\succ$  is an **expected utility** function if it can be written as

$$U(L) = \sum_{k=1}^n p_i u(x_i)$$

for some function  $u : \mathbb{R} \rightarrow \mathbb{R}$

- If you think of the prizes as a random variable  $\mathbf{x}$ , then

$$U(L) = \mathbb{E}_L [ u(\mathbf{x}) ]$$

- The function  $u$  is called a Bernoulli utility function

## expected utility axioms

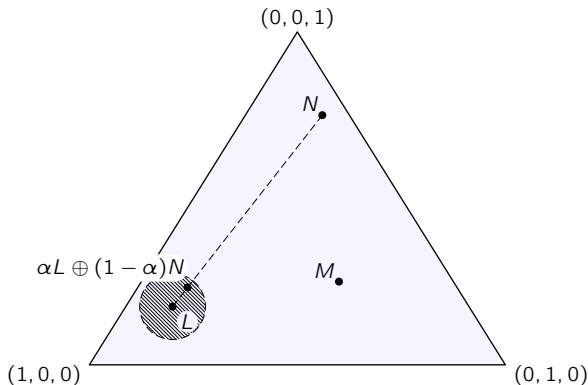
- **Axiom 1:** (Preference order)  $\succ$  is a asymmetric and negatively transitive
- **Axiom 2:** (Continuity) For all simple lotteries  $L, M, N \in \mathcal{L}$ , if  $L \succ M \succ N$  then there exist  $\alpha, \beta \in (0, 1)$  such that

$$\alpha L \oplus (1 - \alpha)N \succ M \succ \beta N \oplus (1 - \beta)N$$

- **Axiom 3:** (Independence) For all lotteries  $L, M, N \in \mathcal{L}$  and  $\alpha \in (0, 1]$ , if  $L \succ M$ , then

$$\alpha L \oplus (1 - \alpha)N \succ \alpha M \oplus (1 - \alpha)N$$

- The continuity axiom can be thought of as requiring that strict preference is preserved by sufficiently small perturbations in the probabilities
  - If  $L \succ M$ , then so are lotteries which are close enough to  $L$  (hatched area)
  - This includes  $\alpha L \oplus (1 - \alpha)N$  with  $\alpha$  close enough to 1

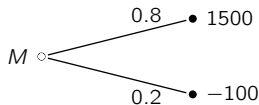
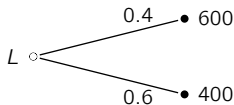




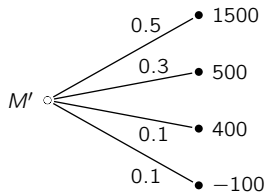
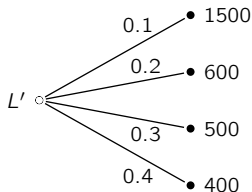
- If  $L$  is preferred to  $M$ , then a mixture of  $L$  with  $N$  is also preferred to a mixture of  $M$  with  $N$  using the same mixing weights
- Independence gives the expected-utility structure
- Similar to the independent-factors requirement from previous notes (expected utility is a form of additive separability)

## example

- How do you rank the following lotteries?



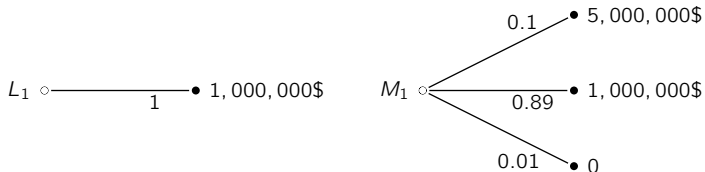
- How do you rank the following lotteries?



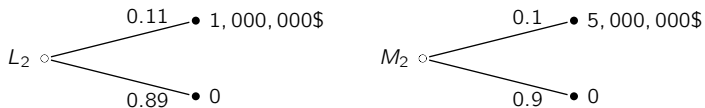
- Independence says that if you prefer  $L$  to  $M$ , then you also prefer  $L'$  to  $M'$
- Note that  $L' = 0.5L \oplus 0.5N$  and  $M' = 0.5M \oplus 0.5N$ , for some lottery  $N$  (which lottery?)

## allais' paradox

- How do you rank the following lotteries?



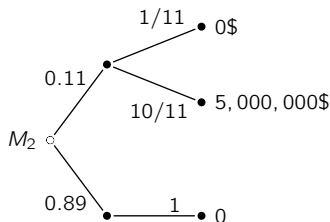
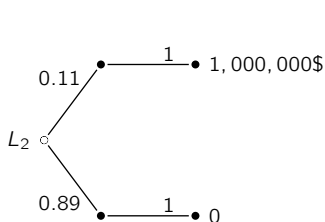
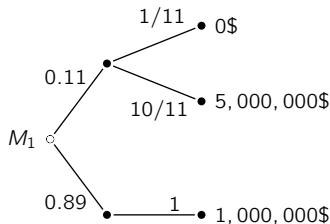
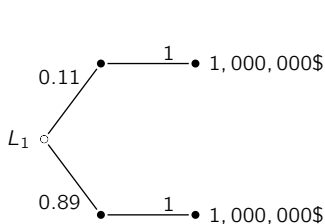
- How do you rank the following lotteries?



- Many people report  $L_1 \succ M_1$  and  $M_2 \succ L_2$

# allais' paradox

- Note that we can write



- Independence would imply that  $L_1 \succ M_1$  if and only if  $L_2 \succ M_2$  (why?)

## von neumann-morgenstern theorem

### Theorem:

- (a) A binary relation  $\succ$  over  $\mathcal{L}$  has an expected utility representation if and only if it satisfies axioms 1–3
- (b) If  $U$  and  $V$  are expected utility representations of  $\succ$ , then there exist constants  $a, b \in \mathbb{R}$ ,  $a > 0$ , such that
$$U(\cdot) = a \cdot V(\cdot) + b$$

## proof of necessity

- Suppose  $U$  is an expected utility representation of  $\succ$
- Axiom 1 follows from the same arguments as before
- For  $0 \leq \alpha \leq 1$  and lotteries  $L = (p_1, x_1; p_2, x_2; \dots p_n, x_n)$  and  $M = (q_1, x_1; q_2, x_2; \dots q_n, x_n)$  note that

$$\begin{aligned} V(\alpha L \oplus (1 - \alpha)M) &= \sum_{i=1}^n [\alpha p_i + (1 - \alpha)q_i] \cdot u(x_i) \\ &= \sum_{i=1}^n [\alpha p_i u(x_i) + (1 - \alpha)q_i u(x_i)] \\ &= \alpha \sum_{i=1}^n p_i u(x_i) + (1 - \alpha) \sum_{i=1}^n q_i u(x_i) \\ &= \alpha V(L) + (1 - \alpha)V(M) \end{aligned}$$

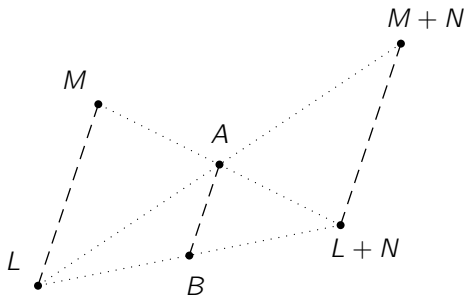
- From here, it is straightforward to show that  $\succ$  satisfies axioms 2 & 3

## independence and linearity

- Fix the set of prizes so that lotteries can be thought of as vectors in  $\Delta^n$
- The following proposition that, under axioms 1–3, preferences are preserved under translations
- This means that the indifference curves are parallel lines

**Proposition:** Given lotteries  $L, M \in \Delta^n$ , and a vector  $N \in \mathbb{R}^n$ , if  $L + N$  and  $M + N$  are also lotteries and  $\succ$  satisfies axioms 1–3, then

$$L \succ M \quad \Leftrightarrow \quad (L + N) \succ (M + N)$$



### Proof sketch:

- If  $(L + N)$  and  $(M + N)$  are lotteries, then so are  $A$  and  $B$
- $A = 0.5M \oplus 0.5(L + N)$  and  $A = 0.5L \oplus 0.5(M + N)$
- Since  $A = 0.5M \oplus 0.5(L + N)$ , independence says that if  $L \succ M$  then  $B \succ A$
- Since  $A = 0.5L \oplus 0.5(M + N)$ , independence says that if  $B \succ A$  then  $(L + N) \succ (M + N)$



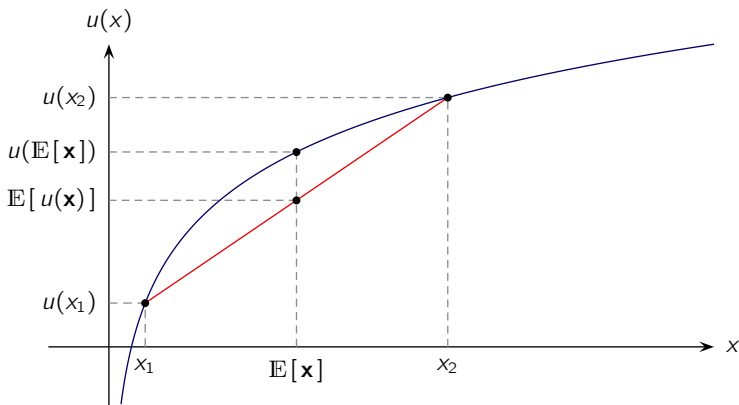
risk aversion



- For the rest of these slides, suppose  $u$  is strictly increasing (our decision maker always prefers more money) and twice continuously differentiable
- Risk-neutral decision maker –  $\mathbb{E}[u(\mathbf{x})] = u(\mathbb{E}[\mathbf{x}])$  for every random variable  $\mathbf{x}$
- Risk-averse decision maker –  $\mathbb{E}[u(\mathbf{x})] \leq u(\mathbb{E}[\mathbf{x}])$  for every r.v.  $\mathbf{x}$
- Risk-loving decision maker –  $\mathbb{E}[u(\mathbf{x})] \geq u(\mathbb{E}[\mathbf{x}])$  for every r.v.  $\mathbf{x}$

## jensen's inequality

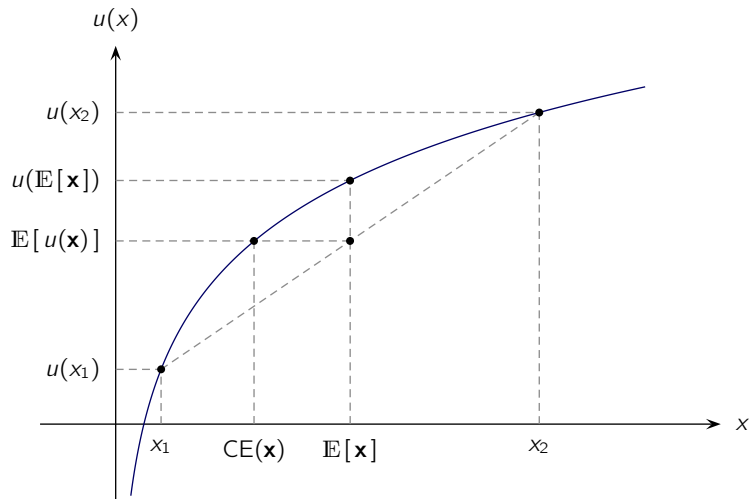
- A set is convex if it contains all the line-segments between its points
- A function is concave if its hypograph is a convex set
- Risk aversion is equivalent to  $u$  being concave



**Definition:** Given  $u$ , the **certainty equivalent** of a lottery  $\mathbf{x}$  is the guaranteed amount of money that an individual with Bernoulli utility function  $u$  would view as equally desirable as  $\mathbf{x}$ , i.e.,

$$CE_u(\mathbf{x}) = u^{-1}(\mathbb{E}[u(\mathbf{x})])$$

- Risk-neutral decision maker –  $CE(L) = \mathbb{E}[\mathbf{x}]$  for every r.v.  $\mathbf{x}$
- Risk-averse decision maker –  $CE(L) \leq \mathbb{E}[\mathbf{x}]$  for every r.v.  $\mathbf{x}$
- Risk-loving decision maker –  $CE(L) \geq \mathbb{E}[\mathbf{x}]$  for every r.v.  $\mathbf{x}$



**Definition:** The arrow-pratt coefficient of **absolute risk aversion** of  $u$  at  $x$  is

$$A_u(x) = -\frac{u''(x)}{u'(x)}$$

- Constant absolute risk aversion (CARA)

$$u(x) = -\exp(-\alpha x)$$

- Indeed  $u'(x) = \alpha u(x)$  and  $u''(x) = \alpha^2 u(x) \Rightarrow A_u(x) = \alpha$

**Theorem:** Given any two strictly increasing Bernoulli utility functions  $u$  and  $v$ , the following are equivalent

- (a)  $A_u(x) \geq A_v(x)$  for all  $x$
- (b)  $CE_u(\mathbf{x}) \leq CE_v(\mathbf{x})$  for all  $\mathbf{x}$
- (c) There exists a strictly increasing concave function  $g$  such that  $u = g \circ v$

- In that case, we say that  $v$  is (weakly) more risk averse than  $u$

- There always exist a strictly increasing and twice continuously differentiable function  $g$  such that  $v = g \circ u$  (why?)
- By the chain-rule of differential calculus

$$v'(x) = g'(u(x))u'(x)$$

$$v''(x) = g'(u(x))u''(x) + g''(u(x))(u'(x))^2$$

- If  $g$  is concave, then  $g'' < 0$  and thus

$$\begin{aligned} A_v(x) &= -\frac{v''(x)}{v'(x)} = -\frac{g'(u(x))u''(x) + g''(u(x))(u'(x))^2}{g'(u(x))u'(x)} \\ &= A_u(x) - \frac{g''(u(x))u'(x)}{g'(u(x))} \geq A_u(x) \end{aligned}$$



- If  $g$  is concave, then Jensen's inequality implies that

$$\begin{aligned} v(CE_v(\mathbf{x})) &= \mathbb{E}[v(\mathbf{x})] = \mathbb{E}[g(u(\mathbf{x}))] \\ &\leq g(\mathbb{E}[u(\mathbf{x})]) = g(u(CE_u(\mathbf{x}))) = v(CE_u(\mathbf{x})) \end{aligned}$$

- Since  $v$  is strictly increasing, this implies that

$$CE_v(\mathbf{x}) \leq CE_u(\mathbf{x})$$

optimal portfolios



## a risky asset

- An expected utility maximizer with initial wealth  $w$  must decide a quantity  $\alpha$  to invest on a risky asset
- The asset has a random gross return of  $\mathbf{z}$  per dollar invested
- The final wealth of the investor will be  $w - \alpha + \alpha\mathbf{z}$
- The optimal investment is the solution to the program

$$\begin{aligned} \max_{\alpha} \quad & \mathbb{E} \left[ u(w + \alpha(\mathbf{z} - 1)) \right] \\ \text{s.t.} \quad & 0 \leq \alpha \leq w \end{aligned}$$

- Let  $\alpha^*$  denote this solution

**Proposition:** A risk averse agent will always invest a positive amount on assets with positive expected return, i.e., if  $\mathbb{E}[\mathbf{z}] > 1$  then  $\alpha^* > 0$

**Proof:**

- Let  $U(\alpha)$  denote the agent's expected utility

$$U'(\alpha) = \mathbb{E}[(\mathbf{z} - 1)u'(w + \alpha(\mathbf{z} - 1))]$$

- If  $\mathbb{E}[\mathbf{z}] > 1$ , then  $U$  is strictly increasing at 0 because

$$U'(0) = \mathbb{E}[(\mathbf{z} - 1)u'(w)] = u'(w)(\mathbb{E}[\mathbf{z}] - 1) > 0$$

- Suppose there are two assets with i.i.d. returns  $\mathbf{z}_1$  and  $\mathbf{z}_2$
- The investor chooses investments  $\alpha_1, \alpha_2 \geq 0$  with  $\alpha_1 + \alpha_2 \leq q$
- Let  $U(\alpha_1, \alpha_2)$  denote the investor's expected utility

$$U(\alpha_1, \alpha_2) = \mathbb{E} \left[ u(w + \alpha_1(\mathbf{z}_1 - 1) + \alpha_2(\mathbf{z}_2 - 1)) \right]$$

**Proposition:** A risk averse agent will always diversify among risky i.i.d. assets with positive returns, i.e., if  $\mathbb{E}[\mathbf{z}_i] > 1$  and  $\mathbb{V}[\mathbf{z}_i] > 0$ , then  $\alpha_1^* > 0$  and  $\alpha_2^* > 0$ .

- We already know that the optimal portfolio cannot be  $(0, 0)$  (why?)
- For any portfolio without diversification  $(\alpha^0, 0)$  we have that

$$\begin{aligned} U(\alpha^0, 0) &= \frac{1}{2}\mathbb{E}[u(w + \alpha^0(\mathbf{z}_1 - 1))] + \frac{1}{2}\mathbb{E}[u(w + \alpha^0(\mathbf{z}_2 - 1))] \\ &= \mathbb{E}\left[\frac{1}{2}u(w + \alpha^0(\mathbf{z}_1 - 1)) + \frac{1}{2}u(w + \alpha^0(\mathbf{z}_2 - 1))\right] \\ &< \mathbb{E}\left[u\left(\frac{1}{2}(w + \alpha^0(\mathbf{z}_1 - 1)) + \frac{1}{2}(w + \alpha^0(\mathbf{z}_2 - 1))\right)\right] \\ &= \mathbb{E}\left[u\left(w + \frac{1}{2}\alpha^0(\mathbf{z}_1 - 1) + \frac{1}{2}\alpha^0(\mathbf{z}_2 - 1)\right)\right] \\ &= U\left(\frac{1}{2}\alpha^0, \frac{1}{2}\alpha^0\right) \end{aligned}$$

comparing distributions

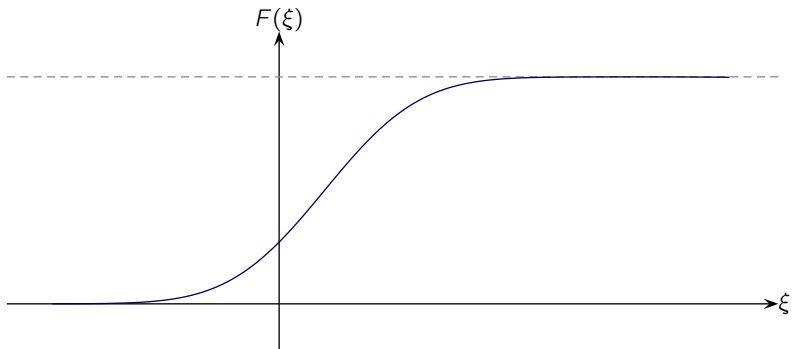


## cumulative distribution functions

- The **cumulative distribution functions** (c.d.f.) of a random variable  $\mathbf{x}$  is the function  $F : \mathbb{R} \rightarrow [0, 1]$  given by

$$F(\xi) = \Pr(\mathbf{x} \leq \xi)$$

- C.d.f.s are non-decreasing, left-continuous, satisfy  $\lim_{\xi \rightarrow -\infty} F(\xi) = 0$  and  $\lim_{\xi \rightarrow \infty} F(\xi) = 1$





## comparing distributions

- Consider random variables  $\mathbf{x}$  and  $\mathbf{y}$  with c.d.f.s  $F$  and  $G$
- That is  $F(\xi) = \Pr(\mathbf{x} \leq \xi)$  and  $G(\xi) = \Pr(\mathbf{y} \leq \xi)$
- When can we say that  $\mathbf{x}$  is “greater” than  $\mathbf{y}$ ?
  - $\mathbb{E}[\mathbf{x}] > \mathbb{E}[\mathbf{y}]$  is probably not enough
  - $\min\{\text{support}(\mathbf{x})\} > \max\{\text{support}(\mathbf{y})\}$  is probably too much
- When can we say that  $\mathbf{x}$  is “riskier” than  $\mathbf{y}$ ?
  - $\mathbb{V}[\mathbf{x}] > \mathbb{V}[\mathbf{y}]$  is probably not enough

## first-order stochastic dominance

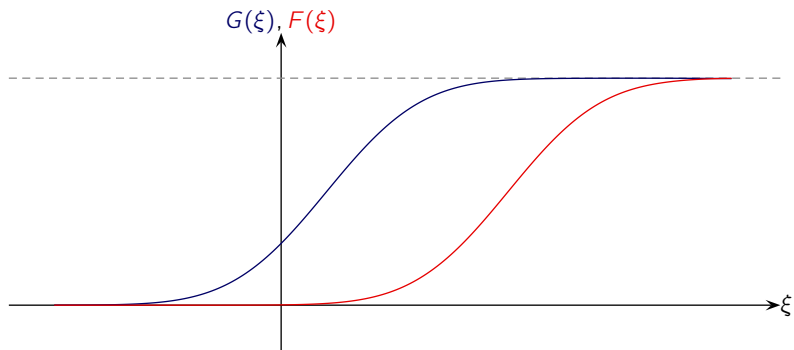
- Say that  $F$  first-order stochastically dominates  $G$  if every expected utility maximizer with monotone preferences would choose  $\mathbf{x}$  over  $\mathbf{y}$

**Definition:** Say that  $F \succ_{\text{FOSD}} G$  if for every non-decreasing function  $u : \mathbb{R} \rightarrow \mathbb{R}$  we have that  $\mathbb{E}[u(\mathbf{x})] \geq \mathbb{E}[u(\mathbf{y})]$

- First-order stochastic dominance can be characterized in terms of distribution functions
- The following proposition asserts that  $\mathbf{x} \succ_{\text{FOSD}} \mathbf{y}$  if for every number  $\xi$ ,  $\mathbf{y}$  taking a value **smaller** than  $\xi$  is more likely than  $\mathbf{x}$  taking a value smaller than  $\xi$

**Proposition:**  $\mathbf{x} \succ_{\text{FOSD}} \mathbf{y}$  if and only if  $F(\xi) \leq G(\xi)$

## first order stochastic dominance



$$F \succ_{\text{FOSD}} G$$

- Suppose  $F(\xi) > G(\xi)$  for some  $\xi$ 
  - Let  $u : \mathbb{R} \rightarrow \mathbb{R}$  be the Bernoulli utility function

$$u(x) = \begin{cases} 1 & \text{if } x > \xi \\ 0 & \text{otherwise} \end{cases}$$

- Then  $\mathbb{E}[u(\mathbf{x})] = 1 - F(\xi) < 1 - G(\xi) = \mathbb{E}[u(\mathbf{y})]$
- Suppose  $F(\xi) \leq G(\xi)$  for all  $\xi$  and  $u$ ,  $F$  and  $G$  are differentiable
  - Integrating by parts:

$$\mathbb{E}[u(\mathbf{x})] = - \int_{-\infty}^{\infty} u'(\xi) F(\xi) d\xi$$

- Therefore

$$\mathbb{E}[u(\mathbf{x})] - \mathbb{E}[u(\mathbf{y})] = - \int_{-\infty}^{\infty} u'(\xi) (F(\xi) - G(\xi)) d\xi \geq 0$$

## second order stochastic dominance

- First-order stochastic dominance is a very incomplete ranking
- More comparisons if we further restrict the set of utility functions
- Say that  $F$  second-order stochastically dominates  $G$  if every expected utility maximizer with monotone **and concave** preferences would choose  $\mathbf{x}$  over  $\mathbf{y}$

**Definition:** Say that  $F \succ_{\text{SOSD}} G$  if for every non-decreasing and concave function  $u : \mathbb{R} \rightarrow \mathbb{R}$  we have that  $\mathbb{E}[u(\mathbf{x})] \geq \mathbb{E}[u(\mathbf{y})]$

- Since concavity is a measure of risk-aversion, second-order stochastic dominance helps us to rank distributions by how much risk they involve

## mean preserving spreads

- Say that  $\mathbf{y}$  is a **mean preserving spread** of  $\mathbf{x}$  if we can write

$$\mathbf{y} = \mathbf{x} + \varepsilon$$

where  $\mathbb{E}[\varepsilon|\mathbf{x}] = 0$

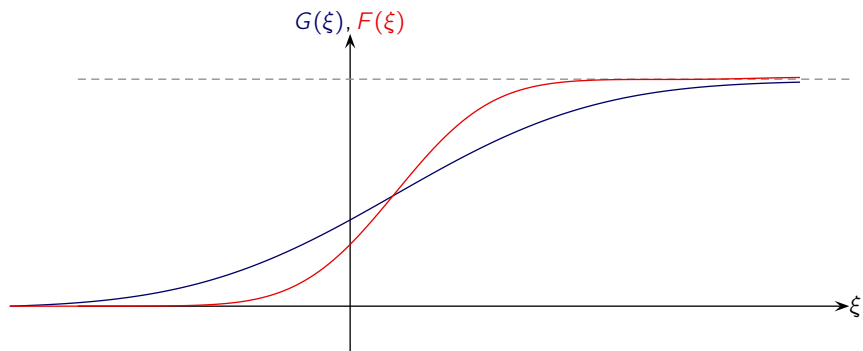
- That is,  $\mathbf{y}$  equals  $\mathbf{x}$  plus “noise”

**Proposition:** The following are equivalent

- (a)  $F \succ_{\text{SOSD}} G$
- (b) There exist random variables  $\mathbf{x}$  and  $\mathbf{y}$  with c.d.f.s  $F$  and  $G$ , resp., such that  $\mathbf{y}$  is a mean preserving spread of  $\mathbf{x}$
- (c) For every number  $\xi$

$$\int_{-\infty}^{\xi} F(x) dx \leq \int_{-\infty}^{\xi} G(y) dy$$

## second order stochastic dominance



$$F \succ_{\text{SOSD}} G$$