Stochastic dominance

Motivation

Recall that to apply the expected utility model

$$a^* = \underset{a \in \{a_1, a_2, \dots\}}{\operatorname{argmax}} \mathbb{E}[U(a)],$$

we need both the probability distribution $P(a_i)$ for each a_i and the risk preferences $U(\cdot)$. In reality, we do not necessarily have access to all the required information. Stochastic dominance addresses cases where we know $P(a_i)$ for all a_i but do not know much about $U(\cdot)$ so that we can still make a choice, a^* , in a consistent manner.

Suppose that the domain of the utility function is a closed interval [L, M],

$$U:[L,M]\to\mathbb{R}.$$

Now, consider two risky choices a_f and a_g , whose distributions are characterized by PDFs f(x) and g(x) respectively. We assume

$$f(x) = g(x) = 0$$
 for $x \notin [L, M]$.

Then,

$$a_f \succsim a_g$$
 (1)

$$\Leftrightarrow \qquad \mathbb{E}[U(a_f)] \ge \mathbb{E}[U(a_g)] \tag{2}$$

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$$\Leftrightarrow \qquad \int_L^M U(x)f(x)dx \ge \int_L^M U(x)g(x)dx \tag{3}$$

$$\Leftrightarrow \int_{L}^{M} U(x)[f(x) - g(x)]dx \ge 0 \tag{4}$$

Using stochastic dominance, therefore, we try to deduce either $a_f \gtrsim a_g$ or $a_f \lesssim a_g$ from the sign of the left-hand side of (4) despite the limited information about U.

Key notations & equations

 U_1 : a set of utility functions such that $U \in U_1$ implies U'(x) > 0

 $U_2: U_2 \subseteq U_1$ such that $U \in U_2$ implies U''(x) < 0 $U_3: U_3 \subseteq U_2$ such that $U \in U_3$ implies U'''(x) > 0 For $x \in [L, M]$,

$$f(x), g(x)$$

$$F(x) = \int_{L}^{x} f(t)dt, G(x) = \int_{L}^{x} g(t)dt$$

$$D_{1}(x) = G(x) - F(x)$$

$$D_{2}(x) = \int_{L}^{x} D_{1}(t)dt$$

$$D_{3}(x) = \int_{L}^{x} D_{2}(t)dt$$
(CDF)

We try to determine the sign of (5) by using one of (7), (8) or (9).

$$\mathbb{E}[U(a_f)] - \mathbb{E}[U(a_g)] \tag{5}$$

$$= \int_{L}^{M} U(x)[f(x) - g(x)]dx \tag{6}$$

$$= \int_{L}^{M} U'(x)D_1(x)dx \tag{7}$$

$$= U'(M)D_2(M) - \int_L^M U''(x)D_2(x)dx$$
 (8)

$$= U'(M)[\mathbb{E}[a_f] - \mathbb{E}[a_g]] - U''(M)D_3(M) + \int_L^M U'''(x)D_3(x)dx \tag{9}$$

Please refer to Chavas (2004) for derivation, which is basically a patient application of integration by parts.

As you can see in (7), (8) and (9), when applying stochastic dominance, there is a tradeoff between the required conditions on CDFs (hidden in D_i) and the amount of information assumed on U. Depending on how we balance these competing assumptions, we make different statements.

First-order stochastic dominance

Using (7), we get the following.

With
$$U \in U_1$$
 assumed, $a_f \succsim a_g \iff D_1(x) \ge 0, \forall x$.

This should be obvious and intuitive. $D_1(x) \geq 0$ means that a_f always has a higher chance for a better outcome than a_g . With $U \in U_1$, then, we do not need math to choose a_f .

Second-order stochastic dominance

Here, the mathematical model becomes useful in more complicated situations, i.e. relaxing $D_1(x) \ge 0$ assumption. Using (8),

With
$$U \in U_2$$
 assumed, $a_f \gtrsim a_g \Leftrightarrow D_2(x) \geq 0, \forall x$.

It is easy to see it because $D_2(x) \ge 0$ makes both first term and integrand in (8) positive. Although $D_2(x)$ is already not-so-intuitive a quantity, we can certainly compute it for any pair of random variables. Since $U \in U_2$ is a relatively mild assumption, it is a powerful statement.

Third-order stochastic dominance

In different situations, we may find the following statement more applicable.

With
$$U \in U_3$$
 assumed, $a_f \succsim a_g \iff \mathbb{E}[a_f] \ge \mathbb{E}[a_g]$ and $D_3(x) \ge 0, \forall x$.

Notes

- Above, we motivated stochastic dominance (SD) by using continuous random variables. But, SD holds for discrete random variables as well.
- 1st order SD ⇒ 2nd order SD ⇒ 3rd order SD
 [Proof]
 By definition,

$$U_3 \subseteq U_2 \subseteq U_1$$
.

Also, remember a property of integral:

$$f \ge 0 \Rightarrow \int f \ge 0.$$

So, by each difinition of D_1 , D_2 and D_3 ,

$$D_1(x) \ge 0 \Rightarrow D_2(x) \ge 0 \Rightarrow D_3(x) \ge 0.$$

Finally,

$$D_2(x) \ge 0 \Rightarrow D_2(M) \ge 0 \Leftrightarrow \mathbb{E}[a_f] - \mathbb{E}[a_g] \ge 0.$$

Because,

$$\mathbb{E}[a_f] - \mathbb{E}[a_g] = \int_L^M x[f(x) - g(x)] dx$$

$$= x[F(x) - G(x)] \Big|_L^M - \int_L^M [F(x) - G(x)] dx$$

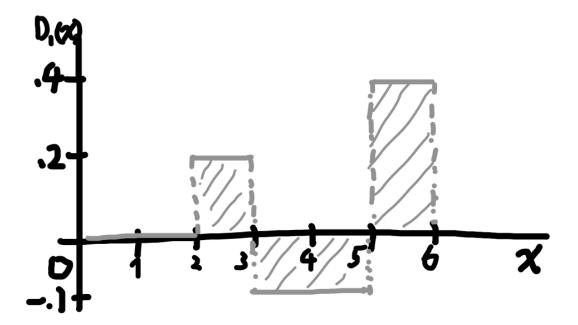
$$= 0 + \int_L^M [G(x) - F(x)] dx$$

$$= \int_L^M D_1(x) dx$$

$$= D_2(M)$$

• An example of D_1 , D_2 and D_3 for discrete random variables. Suppose that we have the following information about two risky choices, characterized by CDFs, F(x) and G(x).

x	1	2	3	4	5	6
F(x)	0	0.2	0.5	0.5	1	1
$\overline{G(x)}$	0	0	0.6	0.6	0.6	1
$D_1(x)$	0	0.2	-0.1	-0.1	0.4	0



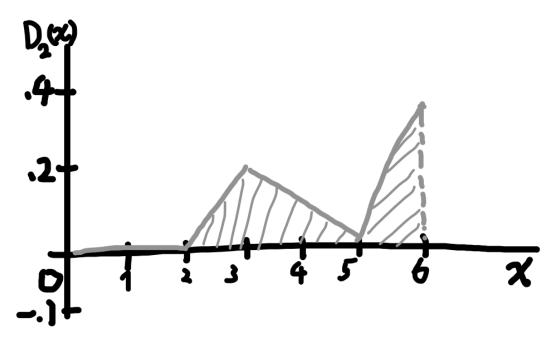
Remember that an integral is the area under a curve. So, the total area is

$$D_2(6) = \int_0^6 D_1(t)dt$$
$$= \int_2^3 D_1(t)dt + \int_3^5 D_1(t)dt + \int_5^6 D_1(t)dt$$

Instead of calculating the total area, how about calculating up to some point $x \leq 6$? We can do this intuitively by combining rectangles.

$$D_2(x) = \begin{cases} 0 & 0 \le x \le 2\\ 0.2(x-2) & 2 \le x \le 3\\ 0.2 - 0.1(x-3) & 3 \le x \le 5\\ 0.2 + (-0.2) + 0.4(x-5) & 5 \le x \le 6 \end{cases}$$
$$= \begin{cases} 0 & 0 \le x \le 2\\ 0.2x - 0.4 & 2 \le x \le 3\\ -0.1x + 0.5 & 3 \le x \le 5\\ 0.4x - 2 & 5 \le x \le 6 \end{cases}$$

This is a piece-wise linear function.



Do the same for D_3 by combining triangles and trapezoids.

$$D_3(6) = \int_0^6 D_2(t)dt$$

$$= \int_2^3 D_2(t)dt + \int_3^5 D_2(t)dt + \int_5^6 D_2(t)dt$$

$$D_3(x) = \begin{cases} 0 & 0 \le x \le 2\\ 0.5(x-2) \times D_2(x) & 2 \le x \le 3\\ 0.1 + 0.5(x-3) \times [0.2 + D_2(x)] & 3 \le x \le 5\\ 0.3 + 0.5(x-5) \times D_2(x) & 5 \le x \le 6 \end{cases}$$

$$= \begin{cases} 0 & 0 \le x \le 2\\ 0.5(x-2) \times [0.2x - 0.4] & 2 \le x \le 3\\ 0.1 + 0.5(x-3) \times [0.2 - 0.1x + 0.5] & 3 \le x \le 5\\ 0.3 + 0.5(x-5) \times [0.4x - 2] & 5 \le x \le 6 \end{cases}$$

Rearranging, you see it as a piece-wise quadratic function.