

Fredrik Andersson

September 16, 2009

Advanced Microeconomic Analysis – some useful mathematics

Random variables A random variable, X , can take a set of values, x_i , $i = 1, \dots, n$ (for a finite random variable generalizations to infinitely many or a continuum of outcomes are obvious but inessential for grasping the concept). Letting p_i , $i = 1, \dots, n$ denote the probabilities, the *expected value* is

$$E(X) = \sum_{i=1}^n p_i x_i.$$

Importantly, the expected value is a linear function of a random variable, i.e. for constants a and b ,

$$E(aX + b) = aE(X) + b.$$

A few applications:

- *Jensen's inequality.* Let $\bar{x} = E(X)$. For a suitably twice differentiable function, f , (using a Taylor series expansion; see below)

$$f(x_i) = f(\bar{x}) + f'(\bar{x})(x_i - \bar{x}) + f''(\xi_i) \frac{(x_i - \bar{x})^2}{2}, \text{ with } \xi_i \in [\bar{x}, x_i];$$

now, for a concave function ($f'' < 0$)

$$f(x_i) < f(\bar{x}) + f'(\bar{x})(x_i - \bar{x})$$

for all i , and taking expectations (using the fact that the expectation is linear¹)

$$E[f(x_i)] < f(\bar{x});$$

this is Jensen's inequality.

- The *Cumulative Distribution Function* (CDF) of a random variable, X , is defined by

$$F(x) = \Pr \{X \leq x\};$$

it is a general property of a CDF that it is a non-decreasing function defined on the real line bounded by $0 \leq F(x) \leq 1$.²

¹I.e. $E[f'(\bar{x})(x_i - \bar{x})] = f'(\bar{x})E[(x_i - \bar{x})] = f'(\bar{x})[(\bar{x} - \bar{x})] = 0$.

²Depending on the nature of the underlying distribution, a density function, $f(x) = F'(x)$ (continuous distribution) or probability function (discrete distribution) can be derived from the CDF.

Taylor series expansions If a function f is differentiable on an interval $[x_0, x_1]$, $x_0 < x_1$, then by the mean-value theorem,

$$f(x_1) = f(x_0) + f'(\xi)(x_1 - x_0), \text{ for some } \xi \in [x_0, x_1];$$

a Taylor series expansion generalizes this to

$$f(x_1) = f(x_0) + f'(x_0)(x_1 - x_0) + f''(\xi)\frac{(x_1 - x_0)^2}{2}, \text{ for some } \xi \in [x_0, x_1],$$

and beyond.³

Comparative statics – optimization problems Put generally and abstractly, an maximization problem where x is the choice variable and where there is a parameter π that affects the problem. The original objective function can then be expressed $U(x; \pi)$. The first-order condition(s) require that

$$\frac{\partial U(x; \pi)}{\partial x} = 0$$

as an identity (i.e. for all combinations of x and π that solve the equation); this defines x as a function of π , $x(\pi)$, and differentiating with respect to π gives

$$\frac{\partial^2 U(x; \pi)}{\partial x^2} \frac{dx}{d\pi} + \frac{\partial^2 U(x; \pi)}{\partial x \partial \pi} = 0$$

from which

$$\frac{dx}{d\pi} = -\frac{\partial^2 U(x; \pi)/\partial x \partial \pi}{\partial^2 U(x; \pi)/\partial x^2}.$$

Since, moreover, the second-order condition for a maximum is $\partial^2 U(x; \pi)/\partial x^2 < 0$, one can note that generally

$$\text{sign } \frac{dx}{d\pi} = \text{sign } \frac{\partial^2 U}{\partial x \partial \pi};$$

this is, obviously, reversed for a minimization problem.

³That is, $(f^{(k)})$ is the k 'th derivative of f)

$$f(x_1) = \sum_{k=0}^{n-1} f^{(k)}(x_0) \frac{(x_1 - x_0)^k}{k!} + f^{(n)}(\xi) \frac{(x_1 - x_0)^n}{n!}.$$