

Mathematics Review for Public Finance

Econ. 440
Dept. of Economics
University of North Carolina – Chapel Hill

Jonathan B. Hill

The mathematics portion of this documents is merely a review: it is assumed that you have had differential calculus and know what a derivative is (its definition and basic properties and formulas).

A. CALCULUS REVIEW

Denote by $f'(x)$ or $\partial f(x)/\partial x$ or $(\partial/\partial x)f(x)$ the first derivative of function f with respect to its argument.

1. PARTIAL DERIVATIVE

1.1 $f(x) = ax^b$ implies $f'(x) = bax^{b-1}$.

If $b < 1$, then $f'(x)$ is defined for all real x except 0.

1.2 $f(x) = \ln(x)$ implies $f'(x) = 1/x$ for $x > 0$.

1.3 $f(x) = \exp\{ax\} = e^{ax}$ implies $f'(x) = ae^{ax}$.

1.4 $f(x) = a^x$ implies $f'(x) = \ln(a) \times f(x)$.

1.5 If $f(x_1, \dots, x_k)$ has more than one argument then $f_j(x_1, \dots, x_k) = \partial f(x_1, \dots, x_k)/\partial x_j$

If

$$f(x_1, x_2) = \ln(x_1) + ax_2^b, \quad b > 0, x > 0$$

then

$$f_1(x_1, x_2) = 1/x_1 \quad f_2(x_1, x_2) = bax_2^{b-1}$$

If

$$f(x_1, x_2) = Kx_1^\alpha x_2^\beta, \quad \alpha, \beta > 0$$

then

$$f_1(x_1, x_2) = \alpha Kx_1^{\alpha-1} x_2^\beta \quad f_2(x_1, x_2) = \beta Kx_1^\alpha x_2^{\beta-1}$$

2. CHAIN RULE

The derivative of $f(g(x))$ where g is a function is simply

$$\partial f(g(x)) / \partial x = f'(g(x)) \times g'(x)$$

If

$$f(x) = \frac{1}{1 + \ln(x)} \quad (\text{i.e. } f(g(x)) \text{ where } g(x) = \ln(x) \text{ and } f(u) = (1+u)^{-1})$$

then

$$f'(x) = -\frac{1}{(1 + \ln(x))^2} \times \frac{1}{x}$$

If

$$f(x_1, x_2) = g(h(x_1, x_2))$$

then

$$f_1(x_1, x_2) = g'(h(x_1, x_2)) \times h_1(x_1, x_2)$$

3. SECOND DERIVATIVE

The second derivative of f with respect to x is denoted $f''(x)$ or $\partial^2 f(x) / \partial x \partial x$ or $(\partial / \partial x)^2 f(x)$.

If $f(x) = \ln(x)$ then $f''(x) = -1/x^2$.

4. CROSS DERIVATIVE AND YOUNG'S THEOREM

The cross-derivative is a specific second derivative of a multivariate function:

$$f_{1,2}(x_1, x_2) = \frac{\partial^2}{\partial x_1 \partial x_2} f(x_1, x_2)$$

If

$$f(x_1, x_2) = Kx_1^\alpha x_2^\beta, \quad \alpha, \beta > 0$$

then

$$f_{1,2}(x_1, x_2) = \alpha\beta Kx_1^{\alpha-1} x_2^{\beta-1}$$

Young's Theorem states

$$f_{1,2}(x_1, x_2) = f_{2,1}(x_1, x_2)$$

If

$$f(x_1, x_2) = Kx_1^\alpha x_2^\beta, \quad \alpha, \beta > 0$$

then simple inspection from the previous examples shows (compare to $f_{1,2}$ above...)

$$f_{2,1}(x_1, x_2) = \alpha\beta Kx_1^{\alpha-1} x_2^{\beta-1}$$

5. TOTAL DIFFERENTIATION

The total derivative of f is

$$df(x_1, \dots, x_k) = \frac{\partial}{\partial x_1} f(x_1, \dots, x_k) dx_1 + \dots + \frac{\partial}{\partial x_k} f(x_1, \dots, x_k) dx_k$$

Literally, the total amount of change of f , magnified by the amount of change in each argument.

If

$$f(x_1, x_2) = Kx_1^\alpha x_2^\beta, \quad \alpha, \beta > 0$$

then

$$df_1(x_1, x_2) = \alpha Kx_1^{\alpha-1} x_2^\beta dx_1 + \beta Kx_1^\alpha x_2^{\beta-1} dx_2$$

We can solve for relative magnitude of change in the arguments x_1 and x_2 required to make the total change in f zero:

$$df(x_1, x_2) = f_1(x_1, x_2) dx_1 + f_2(x_1, x_2) dx_2 = 0 \quad \rightarrow \quad \frac{dx_2}{dx_1} = - \frac{f_1(x_1, x_2)}{f_2(x_1, x_2)} \quad \forall \{x_1, x_2\} : f_2(x_1, x_2) \neq 0$$

If

$$f(x_1, x_2) = Kx_1^\alpha x_2^\beta, \quad \alpha, \beta > 0$$

then

$$\frac{dx_2}{dx_1} = - \frac{\alpha Kx_1^{\alpha-1} x_2^\beta}{\beta Kx_1^\alpha x_2^{\beta-1}} = - \frac{\alpha x_2}{\beta x_1}$$

B. GROWTH

1. COMPOUNDING ONCE PER PERIOD AND LOGARITHMS

Suppose A_t is a discretely valued variable, indexed by time t (e.g. aggregate savings). If A_t grows at rate a and is compounded once per time period t then

$$A_t = (1+a)^t A_0$$

Notice

$$\begin{aligned} \% \Delta A_{t+1} &= \frac{A_{t+1} - A_t}{A_t} = \frac{(1+a)^{t+1} - (1+a)^t}{(1+a)^t} = \frac{(1+a)^{t+1} / (1+a)^t - (1+a)^t / (1+a)^t}{(1+a)^t / (1+a)^t} \\ &= 1 + a - 1 = a \end{aligned}$$

$$\ln A_t = t \times \ln(1+a) + \ln(A_0) \quad \rightarrow \quad \ln A_t \approx \beta_0 + \beta_1 t \quad \text{where } \beta_1 = a \text{ denotes growth}$$

$$\begin{aligned} \ln A_{t+1} - \ln A_t &= (t+1) \times \ln(1+a) - t \times \ln(1+a) \\ &\approx (t+1)a - t \times a = a \end{aligned}$$

where we use the approximation $\ln(1+a) \approx a$ when a is small, due to $\ln(1) = 0$. This follows from an exact Taylor expansion, invoking the mean-value-theorem:

$$f(x) = f(a) + f'(a)|_{a=a^*} (x - a)$$

for some $a^* \in [a, x]$. Now look at the natural log:

$$\ln(1+a) = \ln(1) + \frac{1}{1+a^*} a = \frac{1}{1+a^*} a \approx a \text{ for small } a \text{ because } a^* \in [0, a]$$

Thus, the log-difference $\ln(X_{t+1}) - \ln(X_t)$ of a time series X_t is synonymously its growth.

And, $\ln(X_t)$ should be close to a linear function of the growth rate of X_t .

2. CONSTANT GROWTH AS LINEAR TREND

If growth is a constant then $\ln(X_t)$ will appear to increase linearly. Suppose

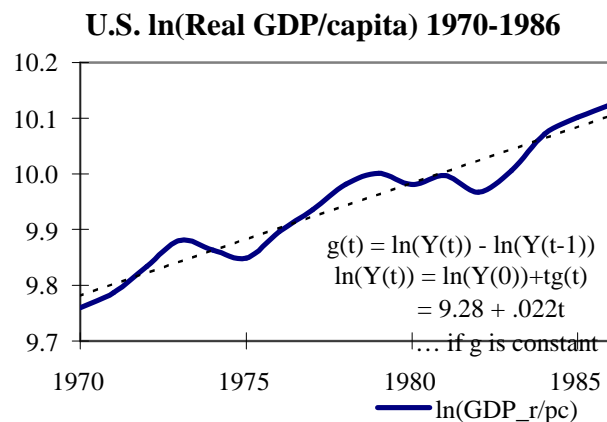
$$g = \ln(X_t) - \ln(X_{t-1})$$

a constant for all periods. Then iterate to get

$$\begin{aligned} \ln(X_t) &= g + \ln(X_{t-1}) \\ &= g + g + \ln(X_{t-2}) \\ &= \dots \\ &= g + \dots + g + \ln(X_0) \\ &= g \times t + \ln(X_0) \\ &= \ln(X_0) + g \times t \\ &= a + b \times t \end{aligned}$$

This is simply a linear function of time (i.e. a **Linear Trend**), with intercept $\ln(X_0)$ and slope g . In other words, *if growth is constant then a macroeconomic time series will increase linearly*, with subtle deviations due to business cycles.

Example: The plot below shows real $\ln(\text{GDP}_t)$ and plots a linear trend $a + bt$. Notice how well $\ln(\text{GDP}_t)$ cycles up and down the trend line.



The small peaks and troughs above and below trend are the business cycles.