

# Note 1 to Computer class: The natural logarithm\*

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August 22, 2011

## 1 Logarithms and rates of change

We often make use of the approximation

$$\begin{aligned}\ln\left(1 + \frac{\Delta Y}{Y}\right) &= \ln\left(\frac{Y + \Delta Y}{Y}\right) = \ln(Y + \Delta Y) - \ln Y \\ &\approx \frac{\Delta Y}{Y}, \quad \frac{\Delta Y}{Y} \text{ is small.}\end{aligned}$$

We will see how this approximation works, and how good it is.

When we consider marginal changes we have the precise relationship, i.e., from the derivative of a function

$$\frac{d \ln Y}{dY} = \frac{1}{Y}, \text{ and hence } d \ln Y = \frac{dY}{Y}.$$

To get to the approximation we need the following properties of the logarithmic function:  $\ln X$ :

$$\ln X = \begin{cases} = (X - 1), & X = 1 \\ < (X - 1), & X \neq 1 \end{cases}$$

The relationships holds because the function  $f(X) = (X - 1)$  is a straight line with slope coefficient  $\frac{d(X-1)}{dX} = 1$ , while the function  $g(X) = \ln X$  is concave, with a slope coefficient that decreases with increasing  $X$ :

$$\frac{d \ln X}{dX} = \frac{1}{X} \begin{cases} < 1, X > 1 \\ > 1, X < 1. \end{cases}$$

This result is illustrated in figure 1.

If we let  $X = \frac{Y + \Delta Y}{Y} = 1 + \frac{\Delta Y}{Y}$ , we get the relationship between logarithms and rates of change:

$$\ln\left(1 + \frac{\Delta Y}{Y}\right) = \ln\left(\frac{Y + \Delta Y}{Y}\right) = \ln(Y + \Delta Y) - \ln Y \leq \frac{\Delta Y}{Y}.$$

Changes in logarithms will therefore never give larger values than the exact rates of change. But how good is the approximation, and why does it become poorer when

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\*This note is a translation of Appendix 3.A in Bårdsen and Nymoén (2011).

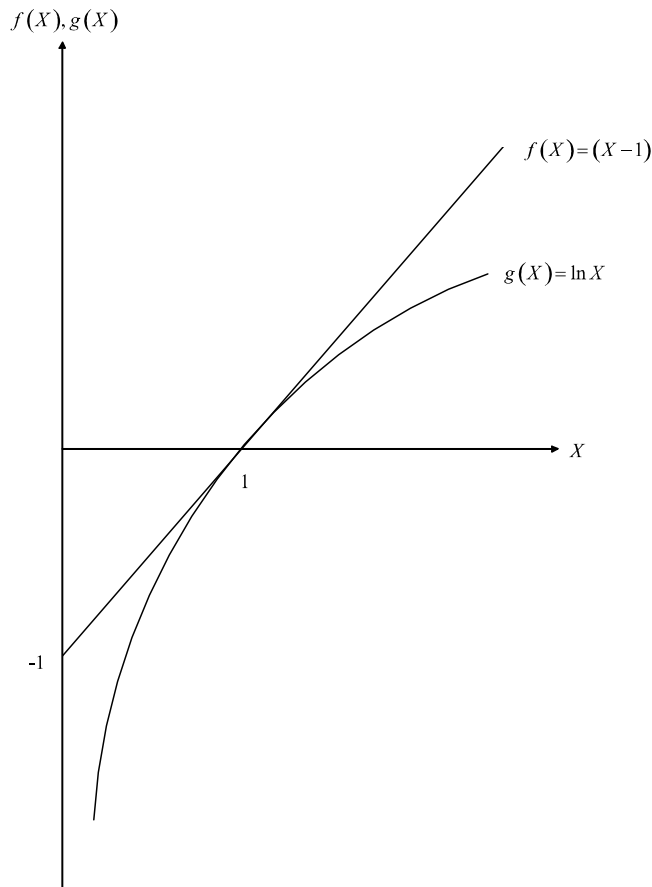


Figure 1: The log-function as a an approximation.

the rate of changes becomes larger? We can investigate this by taking a second order Taylor expansion of  $\ln X$  around the value  $X_0 = 1$ :

$$\begin{aligned}
 \ln X &\approx \ln X_0 + \frac{1}{X_0} (X - X_0) - \left( \frac{1}{X_0^2} \right) \frac{(X - X_0)^2}{2} \\
 &= \ln 1 + 1 (X - 1) - \frac{1}{2} (X - 1)^2 \\
 \ln X &\approx (X - 1) - \frac{1}{2} (X - 1)^2. \tag{1}
 \end{aligned}$$

If we substitute  $X = \frac{Y + \Delta Y}{Y}$ , as above, we can see how close the approximation is, depending on the size of the rate of change:

$$\ln \left( \frac{Y + \Delta Y}{Y} \right) = \ln (Y + \Delta Y) - \ln Y \approx \frac{\Delta Y}{Y} - \frac{1}{2} \left( \frac{\Delta Y}{Y} \right)^2.$$

Clearly the approximation is best for smallish rates of change, but it also works well for a 10 % change in  $Y$ , as the table shows:

$\frac{\Delta Y}{Y}$	0.01	0.05	0.1	0.2	0.5	1
$\ln \left( 1 + \frac{\Delta Y}{Y} \right)$	0.00995	0.04879	0.09531	0.18232	0.405 47	0.693 15

## 2 The standard error of a log-linear model estimated by OLS

Assume that we have estimated a model for  $\ln Y_i$ , so that we can write:

$$\ln Y_i = \ln \hat{Y}_i + \hat{\varepsilon}_i,$$

where  $\hat{Y}_i = e^{\hat{\beta}_0} X_i^{\hat{\beta}_1}$  in the case of a single explanatory variable. The relationship for the variable  $Y_i$  becomes:

$$Y_i = \hat{Y}_i e^{\hat{\varepsilon}_i}.$$

From (1), and by dropping the second order term for simplicity, we have:

$$\ln Y_i - \ln \hat{Y}_i = \hat{\varepsilon}_i \approx \frac{Y_i - \hat{Y}_i}{Y_i}, \quad (2)$$

Equation (2) shows that the residual  $\hat{\varepsilon}_i$  has an interpretation as a relative prediction error. Hence  $100\hat{\varepsilon}_i \approx 100 \left( \frac{Y_i - \hat{Y}_i}{Y_i} \right)$  can be interpreted as percentage prediction error. The standard errors of the regression:

$$\begin{aligned} 100\hat{\sigma}_\varepsilon &= 100 \sqrt{\frac{1}{n-2} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2} \\ &\approx 100 \sqrt{\frac{1}{n-2} \sum_{i=1}^n \left( \frac{Y_i - \hat{Y}_i}{Y_i} \right)^2} \end{aligned}$$

is the percentage unexplained standard deviation in the dependent variable. For example, if we have  $\hat{\sigma}_\varepsilon = 0.01$ , it means that 1 % of the standard deviation of the dependent variable is unexplained by the model we have estimated.

This interpretation is independent of the number of explanatory variables. If we have  $k$  variables, we replace  $n - 2$  by  $n - k - 1$ .

## References

Bårdsen, G. and R. Nymoen (2011). *Innføring i økonometri*. Fagbokforlaget.