[Summary]

Others Functional Forms

Subject:	Business Economics
Course:	B. A. (Hons.), 3rd Semester, Undergraduate
Paper No. & Title:	Paper – 304 Basic Econometrics
Unit No. & Title:	Unit – 4 Others Functional Forms
Lecture No. & Title:	Lecture – 1 Others Functional Forms

Summary

Regression analysis is a technique of predicting a dependent variable using one or more independent variables.

We have already studied **Simple regression.** The model has one dependent and one independent variable. Its equation is given as Y = b_0 + b_1 x + e where Y is the response or dependent variable and X is the independent or explanatory or predictor variable.

Here b_0 is the intercept of the line, $b_1$is the regression coefficient and e is the residual or error term.

Logarithmic transformation of variables

Considering the simple bivariate linear model $Y_i = b_0 + b_1 X_i$, there are four possible combinations of transformations involving logarithms: the linear case with no transformations, the linear-log model, the log-linear model, and the log-log model.

Why use logarithmic transformations of variables?

Logarithmically transforming variables in a regression model is a very common way to handle situations where a non-linear relationship exists between the independent and dependent variables. Using the logarithm of one or more variables instead of the un-logged form makes the effective relationship non-linear, while still preserving the linear model. Logarithmic transformations are also a convenient means of transforming a highly skewed variable into one that is more approximately normal. (In fact, there is a distribution called the log-normal distribution defined as a distribution whose logarithm is normally distributed – but whose untransformed scale is skewed.)

Interpreting coefficients in logarithmically models with logarithmic transformations

1 Linear model: $Y_i = b_0 + b_1 X_i$

2 Linear-log model: $Y_i = b_0 + b_1 log X_i$

3 Log-linear model: $log Y_i = b_0 + b_1 X_i$

4 Log-log model: $log Y_i = b_0 + b_1 log X_i$

Reciprocal Transformation: $Y_i = b_0 + b_1 \left(\frac{1}{X_i}\right)$

If the relationship between Y and X is curvilinear, as in the case of the Phillips curve, this model generally gives a good fit.