

Simple Linear Regression

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Learning Module 10: Simple Linear Regression

Variation of the Dependent Variable (Sum of Squares total)

$$\text{Variation of } Y \sum_{i=1}^n (Y_i - \bar{Y})^2 \tag{1}$$

Where:

- Y_i : represent an observation of a company's ROA
- \bar{Y} : represent the mean ROA for the sample of size n
- n : sample size

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## Variation of the Dependent Variable (Sum of Squares total)
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\text{Variation of } Y \sum_{i=1}^n (Y_i - \bar{Y})^2 \tag{1}
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Where:
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```
*  $Y_i$ : represent an observation of a company's ROA
```

```
*  $\bar{Y}$ : represent the mean ROA for the sample of size n
*  $n$ : sample size
```

Variation of the Independent Variable

$$\text{Variation of } X = \sum_{i=1}^n (X_i - \bar{X})^2 \tag{2}$$

Where:

- X_i : represent an observation of our explanatory variable
- \bar{X} : sample mean of the independent variable
- n : number of observations

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```
## Variation of the Independent Variable

$$
\text{Variation of } X = \sum_{i=1}^n (X_i - \bar{X})^2 \tag{2}
$$

Where:

*  $X_i$ : represent an observation of our explanatory variable
*  $\bar{X}$ : sample mean of the independent variable
*  $n$ : number of observations
```

Simple Linear Regression Model

$$Y_i = b_0 + b_1 X_i + \varepsilon_i, \dots, n. \tag{3}$$

Where:

- Y_i : dependent variable
- X_i : independent variable
- b_0 : intercept

- b_1 : slope coefficient
- ε : error term

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```
## Simple Linear Regression Model

$$
Y_i = b_0 + b_1 X_i + \varepsilon_i, \dots, n. \tag{3}
$$

Where:

*  $Y_i$ : dependent variable
*  $X_i$ : independent variable
*  $b_0$ : intercept
*  $b_1$ : slope coefficient
*  $\varepsilon$ : error term
```

Sum of Squares Error (SSE)

$$\begin{aligned}
 \text{Sum of squares error} &= \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \\
 &= \sum_{i=1}^n [Y_i - (\hat{b}_0 + \hat{b}_1 X_i)]^2 \\
 &= \sum_{i=1}^n e_i^2
 \end{aligned} \tag{4}$$

Where:

- Y_i : observed value of the dependent variable
- \hat{Y}_i : predicted value of the dependent variable
- \hat{b}_0 : estimated intercept
- \hat{b}_1 : slope coefficient
- e_i : residual for the i th observation

$$- e_i = Y_i - \hat{Y}_i$$

- n : number of observations

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## Sum of Squares Error (SSE)

$$
\text{Sum of squares error } = \sum_{i=1}^n (Y_i - \hat{Y}_i)^2
$$

$$
= \sum_{i=1}^n [ Y_i - ( \hat{b}_0 + \hat{b}_1 X_i ) ]^2 \tag{4}
$$

$$
= \sum_{i=1}^n e_i^2
$$

Where:

*  $Y_i$ : observed value of the dependent variable
*  $\hat{Y}_i$ : predicted value of the dependent variable
*  $\hat{b}_0$ : estimated intercept
*  $\hat{b}_1$ : slope coefficient
*  $e_i$ : residual for the  $i$ th observation
  *  $e_i = Y_i - \hat{Y}_i$ 
*  $n$ : number of observations
```

Ordinary Least Squares Slope Estimator

$$\hat{b}_1 = \frac{\text{Covariance of } Y \text{ and } X}{\text{Variance of } X} = \frac{\frac{\sum_{i=1}^n (Y_i - \bar{Y})(X_i - \bar{X})}{n-1}}{\frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n-1}}$$

Simplifying,

$$\hat{b}_1 = \frac{\sum_{i=1}^n (Y_i - \bar{Y})(X_i - \bar{X})}{\sum_{i=1}^n (X_i - \bar{X})^2} \tag{5}$$

Where:

- \hat{b}_1 : estimated slope coefficient

- Y_i : dependent variable observation
- X_i : independent variable observation
- \bar{Y} : mean of the dependent variable Y
- \bar{X} : mean of the independent variable X
- n : number of observations

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## Ordinary Least Squares Slope Estimator
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```
\hat{b}_1 = \frac{\text{Covariance of } Y \text{ and } X}{\text{Variance of } X} =
\frac{\frac{\sum_{i=1}^n (Y_i - \bar{Y})(X_i - \bar{X})}{n - 1}}{\frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n - 1}}
```

```
Simplifying,
```

```
$$
```

```
\hat{b}_1 = \frac{\sum_{i=1}^n (Y_i - \bar{Y})(X_i - \bar{X})}{\sum_{i=1}^n (X_i - \bar{X})^2}
```

```
Where:
```

- * \hat{b}_1 : estimated slope coefficient
- * Y_i : dependent variable observation
- * X_i : independent variable observation
- * \bar{Y} : mean of the dependent variable Y
- * \bar{X} : mean of the independent variable X
- * n : number of observations

Ordinary Least Squares Intercept Estimator

$$\hat{b}_0 = \bar{Y} - \hat{b}_1 \bar{X} \quad (6)$$

Where:

- \hat{b}_0 : estimated intercept
- \bar{Y} : mean of the dependent variable Y
- \bar{X} : mean of the independent variable X
- \hat{b}_1 : estimated slope

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```
## Ordinary Least Squares Intercept Estimator

$$
\hat{b}_0 = \bar{Y} - \hat{b}_1 \bar{X} \tag{6}
$$

Where:

*  $\hat{b}_0$ : estimated intercept
*  $\bar{Y}$ : mean of the dependent variable  $Y$ 
*  $\bar{X}$ : mean of the independent variable  $X$ 
*  $\hat{b}_1$ : estimated slope
```

Sample Correlation

$$r = \frac{\text{Covariance of } Y \text{ and } X}{(\text{Standard deviation of } Y)(\text{Standard deviation of } X)} \quad (7)$$

Where:

- r : sample correlation
- Covariance of Y and X : covariance between X and Y
- Standard deviation of X : standard deviation of the independent variable
- Standard deviation of Y : standard deviation of the dependent variable

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```
## Sample Correlation

$$
r = \frac{\text{Covariance of } Y \text{ and } X}{(\text{Standard deviation of } Y)(\text{Standard deviation of } X)}
$$

Where:

*  $r$ : sample correlation
*  $\text{Covariance of } Y \text{ and } X$ : covariance between  $X$  and  $Y$ 
*  $\text{Standard deviation of } X$ : standard deviation of the independent variable
*  $\text{Standard deviation of } Y$ : standard deviation of the dependent variable
```

Homoskedasticity Assumption

$$E(\varepsilon_i^2) = \sigma_\varepsilon^2, \quad i = 1, \dots, n \tag{8}$$

Where:

- ε_i :
- σ_ε^2 :
- E :

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```
## Homoskedasticity Assumption

$$
E(\varepsilon_i^2) = \sigma_\varepsilon^2, \quad i = 1, \dots, n \tag{8}
$$

Where:

*  $\varepsilon_i$ :
*  $\sigma_\varepsilon^2$ :
*  $E$ :
```

Sum of Squares Regression (SSR)

$$\sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2 \tag{9}$$

Where:

- \hat{Y}_i : predicted value of the dependent variable
- \bar{Y} : mean of the dependent variable
- n : number of observations

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```
## Sum of Squares Regression (SSR)

$$
\sum_{i=1}^n \left( \hat{Y}_i - \bar{Y} \right)^2 \tag{9}
$$
```

Where:

- * \hat{Y}_i : predicted value of the dependent variable
- * \bar{Y} : mean of the dependent variable
- * n : number of observations

Coefficient of Determination (R^2)

$$\text{Coefficient of determination} = \frac{\text{Sum of squares regression}}{\text{Sum of squares total}}$$

$$\text{Coefficient of determination} = \frac{\sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} \tag{10}$$

Where:

- coefficient of determination: is the percentage of the variation of the dependent variable that is explained by the independent variable
- \hat{Y}_i : predicted value of the dependent variable
- Y_i : observed value of the dependent variable
- \bar{Y} : mean of the dependent variable
- n : number of observations

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```
## Coefficient of Determination  $(R^2)$ 

$$
\text{Coefficient of determination} = \frac{\text{Sum of squares regression}}{\text{Sum of squares total}}
$$

$$
\text{Coefficient of determination} = \frac{\sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2}
$$
```

\$\$

Where:

- * coefficient of determination: is the percentage of the variation of the dependent variable
- * \hat{Y}_i : predicted value of the dependent variable
- * Y_i : observed value of the dependent variable
- * \bar{Y} : mean of the dependent variable
- * n : number of observations

Relationship Between r^2 and R^2

$$r^2 = \frac{\sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} = R^2 \quad (11)$$

Where:

- r : sample correlation coefficient
- R^2 : coefficient of determination

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## Relationship Between  $r^2$  and  $R^2$ 
```

```
$$
```

```
 $r^2 = \frac{\sum_{i=1}^n \left( \hat{Y}_i - \bar{Y} \right)^2}{\sum_{i=1}^n \left( Y_i - \bar{Y} \right)^2}$ 
```

```
Where:
```

- ```
* r : sample correlation coefficient
* R^2 : coefficient of determination
```

## Mean Square Regression (MSR) with k Parameters

$$\text{MSR} = \frac{\text{Sum of squares regression}}{k} = \frac{\sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2}{1} \quad (12)$$

Where:

- MSR: mean square regression
- $k$ : number of independent variables

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Mean Square Regression (MSR) with k Parameters
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```
\text{MSR} = \frac{\text{Sum of squares regression}}{k} = \frac{\sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2}{1}
```

```
$$
```

```
Where:
```

- ```
* $\text{MSR}$: mean square regression  
* $k$: number of independent variables
```

Mean Square Regression (MSR)

$$\text{MSR} = \sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2 \quad (13)$$

Where:

- MSR: mean square regression
- \hat{Y}_i : predicted value of the dependent variable
- \bar{Y} : mean of the dependent variable
- n : number of observations

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Mean Square Regression (MSR)

\$\$

$$\text{MSR} = \sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2 \tag{13}$$

\$\$

Where:

- * MSR : mean square regression
- * \hat{Y}_i : predicted value of the dependent variable
- * \bar{Y} : mean of the dependent variable
- * n : number of observations

Mean Square Error (MSE)

$$\text{MSE} = \frac{\text{Sum of squares error}}{n - k - 1}$$

$$\text{MSE} = \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{n - 2} \tag{14}$$

Where:

- MSE: mean square error
- Y_i : observed value of the dependent variable
- \hat{Y}_i : predicted value of the dependent variable
- n : number of observations

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Mean Square Error (MSE)

\$\$

$$\text{MSE} = \frac{\text{Sum of squares error}}{n - k - 1}$$

\$\$

\$\$

$$\text{MSE} = \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{n - 2} \tag{14}$$

\$\$

Where:

- * MSE : mean square error
- * Y_i : observed value of the dependent variable
- * \hat{Y}_i : predicted value of the dependent variable
- * n : number of observations

F-distributed test statistic (MSR/MSE)

$$F = \frac{\frac{\text{Sum of squares regression}}{k}}{\frac{\text{Sum of squares error}}{n-k-1}} = \frac{\text{MSR}}{\text{MSE}}$$
$$F = \frac{\frac{\sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2}{1}}{\frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{n-2}} \quad (15)$$

Where:

- F : F-statistic for testing overall regression significance
- \hat{Y}_i : predicted value of the dependent variable
- Y_i : observed value of the dependent variable
- \bar{Y} : mean of the dependent variable
- $n - 2$: degrees of freedom
- n : number of observations

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## F-distributed test statistic (MSR/MSE)
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```
F = \frac{\frac{\text{Sum of squares regression}}{k}}{\frac{\text{Sum of squares error}}{n -
```

```
$$
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$$
```

```
F = \frac{\frac{\sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2}{1}}{\frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{n - 2}}
```

```
$$
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Where:

- * F : F-statistic for testing overall regression significance
- * \hat{Y}_i : predicted value of the dependent variable
- * Y_i : observed value of the dependent variable
- * \bar{Y} : mean of the dependent variable
- * $n - 2$: degrees of freedom
- * n : number of observations

t-Test Statistic for Slope Coefficient

$$t = \frac{\hat{b}_1 - B_1}{s_{\hat{b}_1}} \tag{16}$$

Where:

- t : t-statistic for hypothesis test of the slope
- \hat{b}_1 : estimated slope coefficient
- B_1 : hypothesized population slope
- $s_{\hat{b}_1}$: standard error of the slope coefficient

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```
## t-Test Statistic for Slope Coefficient
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t = \frac{\hat{b}_1 - B_1}{s_{\hat{b}_1}} \tag{16}  
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Where:

- * t : t-statistic for hypothesis test of the slope
 - * \hat{b}_1 : estimated slope coefficient
 - * B_1 : hypothesized population slope
 - * $s_{\hat{b}_1}$: standard error of the slope coefficient
-

Standard Error of the Slope Coefficient

$$s_{\hat{b}_1} = \frac{s_e}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2}} \quad (17)$$

Where:

- $s_{\hat{b}_1}$: standard error of the slope estimate
- s_e : standard error of the estimate
- X_i :
- \bar{X} :
- n : number of observations

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```
## Standard Error of the Slope Coefficient

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s_{\hat{b}_1} = \frac{s_e}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2}} \tag{17}
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Where:

- * $s_{\hat{b}_1}$: standard error of the slope estimate
- * s_e : standard error of the estimate
- * X_i :
- * \bar{X} :
- * n : number of observations

t-Test Statistic for Correlation

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \quad (18)$$

Where:

- t : t-statistic for testing correlation significance
- r : sample correlation coefficient
- n : number of observations

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```
## t-Test Statistic for Correlation
```

```
$$  
t = \frac{r\sqrt{n - 2}}{\sqrt{1 - r^2}} \tag{18}  
$$
```

Where:

- * t : t-statistic for testing correlation significance
- * r : sample correlation coefficient
- * n : number of observations

Standard error of the intercept

$$s_{\hat{b}_0} = S_e \sqrt{\frac{1}{n} + \frac{\bar{X}^2}{\sum_{i=1}^n (X_i - \bar{X})^2}} \tag{19}$$

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```
## Standard error of the intercept
```

```
$$  
s_{\hat{b}_0} = S_e \sqrt{\frac{1}{n} + \frac{\bar{X}^2}{\sum_{i=1}^n (X_i - \bar{X})^2}}  
$$
```

Intercept

$$t_{\text{intercept}} = \frac{\hat{b}_0 - B_0}{s_{\hat{b}_0}} = \frac{\hat{b}_0 - B_0}{S \sqrt{\frac{1}{n} + \frac{\bar{X}^2}{\sum_{i=1}^n (X_i - \bar{X})^2}}} \tag{20}$$

Where:

- B_0 : hypothesized value

- \hat{b}_0 : estimated intercept
- $s_{\hat{b}_0}$ standard error of the intercept

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```
## Intercept

$$
t_{\{\text{intercept}\}} = \frac{\hat{b}_0 - B_0}{s_{\{\hat{b}_0\}}} = \frac{\hat{b}_0 - B_0}{S \sqrt{\dots}}
$$

Where:

* $B_0$: hypothesized value
* $\hat{b}_0$: estimated intercept
* $s_{\{\hat{b}_0\}}$ standard error of the intercept
```

Hypothesis Tests of Slope When the Independent Variable Is an Indicator Variable

$$RET_i = b_0 + b_1 EARN_i + \varepsilon_i \tag{21}$$

Where:

- RET: monthly returns
- EARN: Indicator variable

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```
## Hypothesis Tests of Slope When the Independent Variable Is an Indicator Variable

$$
\text{RET}_i = b_0 + b_1 \text{EARN}_i + \varepsilon_i \tag{21}
$$

Where:

* RET: monthly returns
* EARN: Indicator variable
```

Standard Error of the Estimate

$$\text{Standard error of the estimate } (s_e) = \sqrt{\text{MSE}} = \sqrt{\frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{n - 2}} \quad (22)$$

Where:

- s_e : standard error of the estimate
 - The s_e is a measure of the distance between the observed values of the dependent variable and those predicted from the estimated regression—the smaller the s_e , the better the fit of the model

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```
## Standard Error of the Estimate

$$
\text{Standard error of the estimate } (s_e) = \sqrt{\text{MSE}} = \sqrt{\frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{n - 2}}
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Where:

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* The  $s_e$  is a measure of the distance between the observed values of the dependent variable and those predicted from the estimated regression—the smaller the  $s_e$ , the better the fit of the model
```

Forecasted Value of the Dependent Variable

$$\hat{Y}_f = \hat{b}_0 + \hat{b}_1 X_f \quad (23)$$

Where:

- \hat{Y}_f : forecasted value of the dependent variable
- X_f : forecasted independent variable

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```
## Forecasted Value of the Dependent Variable
```

```
$$
```

```
\hat{Y}_f = \hat{b}_0 + \hat{b}_1 X_f \tag{23}
```

```
$$
```

Where:

* \hat{Y}_f : forecasted value of the dependent variable

* X_f : forecasted independent variable

Standard Error of the Forecast

estimated variance of the prediction error

$$s_f^2 = s_e^2 \left[1 + \frac{1}{n} + \frac{(X_f - \bar{X})^2}{(n-1)s_X^2} \right] = s_e^2 \left[1 + \frac{1}{n} + \frac{(X_f - \bar{X})^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \right]$$

Where:

s_f^2 : estimated variance of the prediction error

Standard Error of the Forecast

$$s_f = s_e \sqrt{1 + \frac{1}{n} + \frac{(X_f - \bar{X})^2}{\sum_{i=1}^n (X_i - \bar{X})^2}} \tag{24}$$

Where:

- s_f : standard error of the forecast
- s_e : standard error of the estimate
- X_f : forecast value of the independent variable

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Standard Error of the Forecast

****estimated variance of the prediction error****

\$\$

$$s_f^2 = s_e^2 \left[1 + \frac{1}{n} + \frac{(X_f - \bar{X})^2}{(n-1)s_X^2} \right]$$
$$= s_e^2 \left[1 + \frac{1}{n} + \frac{(X_f - \bar{X})^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \right]$$

\$\$

Where:

s_f^2 : estimated variance of the prediction error

****Standard Error of the Forecast****

\$\$

$$s_f = s_e \sqrt{1 + \frac{1}{n} + \frac{(X_f - \bar{X})^2}{\sum_{i=1}^n (X_i - \bar{X})^2}}$$

\$\$

Where:

- * s_f : standard error of the forecast
- * s_e : standard error of the estimate
- * X_f : forecast value of the independent variable

Log-Lin Model

$$\ln Y_i = b_0 + b_1 X_i \quad (25)$$

Where:

- Y_i : dependent variable
 - is in logarithmic form
- X_i : independent variable
 - not in logarithmic form
- b_0 : intercept
- b_1 : slope coefficient

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```
## Log-Lin Model

$$
\ln Y_i = b_0 + b_1 X_i \tag{25}
$$

Where:

*  $Y_i$ : dependent variable
  * is in logarithmic form
*  $X_i$ : independent variable
  * not in logarithmic form
*  $b_0$ : intercept
*  $b_1$ : slope coefficient
```

Lin-Log Model

$$Y_i = b_0 + b_1 \ln X_i \tag{26}$$

Where:

- Y_i : dependent variable
 - not in logarithmic form
- X_i : independent variable
 - is in logarithmic form
- b_0 : intercept
- b_1 : slope coefficient

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```
## Lin-Log Model

$$
Y_i = b_0 + b_1 \ln X_i \tag{26}
$$
```

Where:

- * Y_i : dependent variable
- * not in logarithmic form
- * X_i : independent variable
- * is in logarithmic form
- * b_0 : intercept
- * b_1 : slope coefficient

Log-Log Model

$$\ln Y_i = b_0 + b_1 \ln X_i \tag{27}$$

Where:

- Y_i : dependent variable
 - logarithmic form
- X_i : independent variable
 - logarithmic form
- b_0 : intercept
- b_1 : slope coefficient
- This model is useful in calculating elasticities because the slope coefficient is the relative change in the dependent variable for a relative change in the independent variable.

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```
## Log-Log Model

$$
\ln Y_i = b_0 + b_1 \ln X_i \tag{27}
$$

Where:

*  $Y_i$ : dependent variable
  * logarithmic form
*  $X_i$ : independent variable
```

- * logarithmic form
 - * b_0 : intercept
 - * b_1 : slope coefficient
 - * This model is useful in calculating elasticities because the slope coefficient is the relative change in the dependent variable for a relative change in the independent variable.
-