

Sample Mean v. OLS: *Estimation I*

| 1. Estimation | Sample Mean | OLS |
|-------------------------------------|---|--|
| DGM: Data Generation Mechanism | $\{Y_i\}$ <u>iid</u> $E(Y_i) = \mu, Var(Y_i) = \sigma^2$ | $\{Y_i\} = \{\beta_0 + \beta_1 x_i + U_i\}$ <u>indept.</u> $E(Y_i x_i) = \beta_0 + \beta_1 x_i,$ $Var(Y_i x_i) = \sigma^2$ |
| Unknown parameter (to be estimated) | μ | β_1 |
| Linear Estimator | $b_0 + \sum b_i Y_i$ | $b_0 + \sum b_i Y_i$ |
| Linear Unbiased Estimator | $\sum b_i Y_i \sum b_i = 1$ | $\sum b_i Y_i \sum b_i = 0 \ \& \ \sum b_i x_i = 1$ |
| Variance to be minimized | $\sigma^2 \sum b_i^2$ | $\sigma^2 \sum b_i^2$ |
| Constraints | $\sum b_i = 1$ | $\sum b_i = 0 \ \& \ \sum b_i x_i = 1$ |



Sample Mean v. OLS: *Estimation II*

| 1. Estimation, continued | Sample Mean | OLS |
|--------------------------|---|--|
| BLUE | $b_i^* = \frac{1}{n}$ | $b_j^* = \frac{(x_j - \bar{x})}{\sum (x_i - \bar{x})^2}$ |
| Estimator | $M = \frac{1}{n} \sum Y_i$ (unweighted avg. of values) | $B_1 x's = \sum \left\{ \frac{(x_i - \bar{x})^2}{(n-1)S_{xx}} \right\} \frac{(Y_i - \bar{Y})}{(x_i - \bar{x})}$ (weighted avg. of slopes) |
| Estimate | $\hat{\mu} = \frac{1}{n} \sum y_i$ | $\hat{\beta}_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_j - \bar{x})^2}$ |
| Estimator Variance | $\frac{\sigma^2}{n}$ | $\frac{\sigma^2}{\sum (x_j - \bar{x})^2}$ |
| ... Standard Deviation | $sd(M) = \frac{\sigma}{\sqrt{n}}$ | $sd(B_1) = \frac{\sigma}{\sqrt{\sum (x_j - \bar{x})^2}}$ |
| ... Standard Error | $se(M) = \frac{S_Y}{\sqrt{n}}$ | $se(B_1) = \frac{RMSE}{\sqrt{\sum (x_j - \bar{x})^2}}$ |



Sample Mean v. OLS: *Inference I*

| 2. Inference | Sample Mean | OLS |
|---------------------------|---|--|
| Dist. of Y_i | $Y_i \sim N(\mu, \sigma^2)$ | $Y_i x_i \sim N(\beta_0 + \beta_1 x_i, \sigma^2)$ |
| Degrees of Freedom | n-1 | n-2 |
| Distribution of Estimator | $\frac{M - \mu}{sd(M)} \sim N(0,1)$ where $sd(M) = \sigma / \sqrt{n}$ | $\frac{B_1 - \beta_1}{sd(B_1)} \sim N(0,1)$ where $sd(B_1) = \sigma / \sqrt{\sum (x_i - \bar{x})^2}$ |
| t statistic | $\frac{M - \mu}{se(M)} \sim t_{n-1}$ where $se(M)$ $= \frac{S_Y}{\sqrt{n}} = \frac{1}{\sqrt{n}} \sqrt{\frac{\sum (Y_i - \bar{Y})^2}{n-1}}$ | $\frac{B_1 - \beta_1}{se(B_1)} \sim t_{n-2}$ where $se(B_1) = \frac{RMSE}{\sqrt{\sum (x_i - \bar{x})^2}}$ |



Sample Mean v. OLS: *Inference II*

| 2. Inference, continued | Sample Mean | OLS |
|------------------------------------|--|--|
| Confidence Intervals | $[M \pm c \text{se}(M)],$ $P[t_{n-1} < c] = p$ | $[B_1 \pm c \text{se}(B_1)],$ $P[t_{n-2} < c] = p$ |
| Null Hypothesis: | $H_0 : \mu = 0$ | $H_0 : \beta_1 = 0$ |
| t statistic (under Ho) | $\frac{M}{\text{se}(M)}$ | $\frac{B_1}{\text{se}(B_1)}$ |
| t statistic (for the given sample) | $t_{\hat{\mu}} = \frac{\hat{\mu}}{\text{se}(\hat{\mu})}$ | $t_{\hat{\beta}_1} = \frac{\hat{\beta}_1}{\text{se}(\hat{\beta}_1)}$ |
| p value | $P[t_{n-1} > t_{\hat{\mu}})$ | $P[t_{n-2} > t_{\hat{\beta}_1})$ |
| Hypothesis Test: | Reject if $\left \frac{\hat{\mu} - 0}{\text{se}(\hat{\mu})} \right > c$ or $ t_{\hat{\mu}} > c \dots$ or if $p < \alpha$ | Reject if $\left \frac{\hat{\beta}_1 - 0}{\text{se}(\hat{\beta}_1)} \right > c$ or $ t_{\hat{\beta}_1} > c$ or if $p < \alpha$ |

