

### 3.3

$$\begin{aligned}
 y_i &= \beta_0 + \beta_1 \bar{x} + \beta_1 x_i - \beta_1 \bar{x} + e_i \\
 y_i &= (\beta_0 + \beta_1 \bar{x}) + \beta_1 (x_i - \bar{x}) + e_i \\
 y_i &= \alpha + \beta_1 (x_i - \bar{x}) + e_i \text{ where } \alpha = \beta_0 + \beta_1 \bar{x}
 \end{aligned}$$

- If we normalize our x around the mean, then  $\alpha$  would be the new intercept of our linear regression line.

- $y_i = \alpha + \beta_1 (x_i - \bar{x}) + e_i$   
 $RSS = \sum_1^N [y_i - \alpha - \beta_1 (x_i - \bar{x})]^2$   
 $\frac{\partial RSS}{\partial \alpha} = 0$   
 $\implies \sum_1^N 2[y_i - \alpha - \beta_1 (x_i - \bar{x})][0 - 1 - 0] = 0$   
 $\implies \sum_1^N [y_i - \alpha - \beta_1 (x_i - \bar{x})] = 0$   
as we know  $\sum_1^N \beta_1 (x_i - \bar{x}) = 0$   
 $\implies \sum_1^N [y_i - \alpha] = 0$   
 $\implies \sum_1^N y_i - N\alpha = 0$   
 $\implies \hat{\alpha} = \frac{\sum_1^N y_i}{N} = \bar{y}$

Now we take derivative against  $\beta_1$   $RSS = \sum_1^N [y_i - \alpha - \beta_1 (x_i - \bar{x})]^2$   
 $\frac{\partial RSS}{\partial \beta_1} = 0$

$$\begin{aligned}
 \implies \sum_1^N 2[y_i - \alpha - \beta_1 (x_i - \bar{x})][-(x_i - \bar{x})] &= 0 \\
 \implies \sum_1^N -2[y_i - \alpha - \beta_1 (x_i - \bar{x})][(x_i - \bar{x})] &= 0 \\
 \implies \sum_1^N [y_i - \alpha - \beta_1 (x_i - \bar{x})][(x_i - \bar{x})] &= 0
 \end{aligned}$$

Now we can replace  $\alpha$  with  $\hat{\alpha}$  i.e.  $\bar{y}$

So,

$$\begin{aligned}
 \implies \sum_1^N [y_i - \bar{y} - \beta_1 (x_i - \bar{x})][(x_i - \bar{x})] &= 0 \\
 \implies \sum_1^N (y_i - \bar{y})(x_i - \bar{x}) - \beta_1 \sum_1^N (x_i - \bar{x})(x_i - \bar{x}) &= 0 \\
 \implies S_{xy} - \beta_1 S_{xx} &= 0 \\
 \implies \hat{\beta}_1 &= \frac{S_{xy}}{S_{xx}}
 \end{aligned}$$

- $\hat{\beta}_1 = \frac{S_{xy}}{S_{xx}}$   
 $\implies \hat{\beta}_1 = \frac{\sum_1^N (y_i - \bar{y})(x_i - \bar{x})}{S_{xx}}$   
 $\implies \hat{\beta}_1 = \frac{\sum_1^N (y_i(x_i - \bar{x}) - \bar{y}(x_i - \bar{x}))}{\frac{S_{xx}}{\sum_1^N (y_i(x_i - \bar{x}) - \bar{y}(x_i - \bar{x}))}}$   
2nd part is 0 and  $\frac{S_{xx}}{\sum_1^N (y_i(x_i - \bar{x}) - \bar{y}(x_i - \bar{x}))}$  is constant  
 $\implies \hat{\beta}_1 = \sum_1^N c_i y_i$   
 $\implies Var(\hat{\beta}_1) = Var(\sum_1^N c_i y_i) = \sum_1^N c_i^2 \sigma^2$   
 $\sum_1^N c_i^2 = \frac{1}{S_{xx}} \implies Var(\hat{\beta}_1) = \frac{\sigma^2}{S_{xx}}$

$$Var(\hat{\alpha}) = Var(\bar{y}) = \frac{\sigma^2}{N}$$

$$\begin{aligned}
Cov(\hat{\alpha}, \hat{\beta}_1) &= Cov(\frac{\sum_1^N y_i}{N}, \sum_1^N c_i) \\
\implies Cov(\hat{\alpha}, \hat{\beta}_1) &= \frac{1}{N} \sum_1^N \sum_1^N c_j Cov(y_i, y_j) \\
\text{for } i <> j \text{ } Cov(y_i, y_j) &= 0 \\
\implies Cov(\hat{\alpha}, \hat{\beta}_1) &= \frac{1}{N} \sum_1^N c_i \implies Cov(\hat{\alpha}, \hat{\beta}_1) = 0
\end{aligned}$$