$$\begin{aligned} y_i &= \widehat{\beta}_0 + \widehat{\beta}_1 \ X_{i1} + \cdots + \widehat{\beta}_k \ X_{ik} + \widehat{u}_i \end{aligned}$$

$$\begin{aligned} y_i &= \widehat{\beta}_0 + \widehat{\beta}_1 \ X_{i1} - \overline{X}_1 \) + \cdots + \widehat{\beta}_k \ (X_{ik} - \overline{X}_k) + \widehat{u}_i \end{aligned}$$

$$\begin{aligned} y_i &= \overline{y} &= \widehat{\beta}_1 (X_{i1} - \overline{X}_1) + \cdots + \widehat{\beta}_k (X_{ik} - \overline{X}_k) + \widehat{u}_i \end{aligned}$$

$$\begin{aligned} y_i &= \overline{y} &= \widehat{\beta}_1 \cdot \widehat{\beta}_1 (X_{i1} - \overline{X}_1) + \cdots + \widehat{\beta}_k (X_{ik} - \overline{X}_k) + \widehat{u}_i \\ \widehat{\delta}_y &= \widehat{\delta}_y \cdot \widehat{\beta}_y (X_{ik} - \overline{X}_k) + \widehat{u}_i \\ \widehat{\delta}_y &= \widehat{\delta}_y \cdot \widehat{\beta}_y - \cdots + \widehat{\delta}_k \cdot \widehat{\beta}_k (X_{ik} - \overline{X}_k) + \widehat{u}_i \\ \widehat{\delta}_y &= \widehat{\delta}_y \cdot \widehat{\beta}_y - \cdots + \widehat{\delta}_k \cdot \widehat{\beta}_k (X_{ik} - \overline{X}_k) + \widehat{u}_i \\ \widehat{\delta}_y &= \widehat{\delta}_y \cdot \widehat{\beta}_y - \cdots + \widehat{\delta}_k \cdot \widehat{\beta}_k (X_{ik} - \overline{X}_k) + \widehat{u}_i \\ \widehat{\delta}_y &= \widehat{\delta}_y \cdot \widehat{\beta}_y - \cdots + \widehat{\delta}_k \cdot \widehat{\beta}_k (X_{ik} - \overline{X}_k) + \widehat{u}_i \\ \widehat{\delta}_y &= \widehat{\delta}_y \cdot \widehat{\beta}_y - \cdots + \widehat{\delta}_k \cdot \widehat{\beta}_k (X_{ik} - \overline{X}_k) + \widehat{u}_i \\ \widehat{\delta}_y &= \widehat{\delta}_y \cdot \widehat{\beta}_y - \cdots + \widehat{\delta}_k \cdot \widehat{\beta}_k (X_{ik} - \overline{X}_k) + \widehat{u}_i \\ \widehat{\delta}_y &= \widehat{\delta}_y \cdot \widehat{\beta}_y - \cdots + \widehat{\delta}_k \cdot \widehat{\beta}_k (X_{ik} - \overline{X}_k) + \widehat{u}_i \\ \widehat{\delta}_y &= \widehat{\delta}_y \cdot \widehat{\beta}_y - \cdots + \widehat{\delta}_k \cdot \widehat{\beta}_k (X_{ik} - \overline{X}_k) + \widehat{u}_i \\ \widehat{\delta}_y &= \widehat{\delta}_y \cdot \widehat{\beta}_y - \cdots + \widehat{\delta}_k \cdot \widehat{\beta}_k (X_{ik} - \overline{X}_k) + \widehat{u}_i \\ \widehat{\delta}_y &= \widehat{\delta}_y \cdot \widehat{\beta}_y - \cdots + \widehat{\delta}_k \cdot \widehat{\beta}_k (X_{ik} - \overline{X}_k) + \widehat{u}_i \\ \widehat{\delta}_y &= \widehat{\delta}_y \cdot \widehat{\beta}_y - \widehat{\delta}_y - \widehat{\delta}$$

$$y = \beta_0 + \beta_1 \times_1 + \beta_2 \times_2 + \beta_3 \times_1 \cdot \times_2 + U$$

$$\frac{\Delta V}{\Delta X_2} = \beta_2 + \beta_3 \times_1$$

Reparametrization of interaction effects:

$$y = Q_0 + S_1 \times_1 + S_2 \times_2 + \beta_3 (X_1 - \mu_1)(X_2 - \mu_2) + \mu$$
.

• Reparametrization of interaction effects

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2 + u \quad \text{re}$$

Population means; may be replaced by sample means

$$y = \alpha_0 + \delta_1 x_1 + \delta_2 x_2 + \beta_3 (x_1 - \mu_1)(x_2 - \mu_2) + u$$

Effect of x_2 if all variables take on their mean values

Advantages of reparametrization

- Easy interpretation of all parameters
- Standard errors for partial effects at the mean values available
- If necessary, interaction may be centered at other interesting values

Multiple Regression Analysis: Further Issues



- In models with quadratics, interactions, and other nonlinear functional forms, the partial effect depend on the values of one or more explanatory variables
- Average partial effect (APE) is a summary measure to describe the relationship between dependent variable and each explanatory variable
- After computing the partial effect and plugging in the estimated parameters, average the partial effects for each unit across the sample

$$\frac{\Delta V}{\Delta X_1} = \beta_1 + 2\beta_3 X_1 + \beta_4 X_2$$

$$APE_{X_1} = \hat{\beta}_1 + 2\hat{\beta}_3 \overline{X}_1 + \hat{\beta}_4 \overline{X}_2$$

$$\frac{\Delta y}{\Delta x_2} = \beta_2 + \beta_4 X_1$$