# **Delta Method**

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Applied Econometrics II

## **Bootstrap and Delta Method**

- We know how to construct confidence intervals for parameter estimates:  $\hat{\theta}_k \pm 1.96 SE(\hat{\theta}_k)$
- Often we are asked to construct standard errors or confidence intervals around model outputs that are not just parameter estimates: ie:  $h(x_i, \hat{\theta})$ .
- ▶ Sometimes we can't even write  $g(x_i, \theta)$  as an explicit function of  $\theta$  ie:  $\Psi(h(x_i, \theta), \theta) = 0$ .
- ► Two options:
  - 1. Delta Method
  - 2. Bootstrap

#### **Delta Method**

Delta method works by considering a Taylor Expansion of  $g(x_i, \theta)$ .

$$h(z) \approx h(z_0) + h'(z_0)(z - z_0) + o(||z - z_0||)$$

Assume that  $\theta_n$  is asymptotically normally distributed so that:

$$\sqrt{n}(\theta_n-\theta_0)\sim N(0,\Sigma)$$

(How do we get this: OLS? GMM? MLE?). Then we have that

$$\sqrt{n}(h(\theta_n) - h(\theta_0)) \sim N(0, D(\theta)'\Sigma D(\theta))$$

Where  $D(\theta) = \frac{\partial h(x_i, \theta)}{\partial \theta}$  is the Jacobian of g with respect to theta evaluated at  $\theta$ .

We need g to be continuously differentiable around the center of our expansion  $\theta$ .

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### **Delta Method: Examples**

Start with something simple:  $g(\theta) = \overline{X}_1 \cdot \overline{X}_2$  with  $(X_{1i}, X_{2i}) \sim IID$ . We know the CLT applies so that:

$$\sqrt{n} \left( \frac{\overline{X}_1 - \mu_1}{\overline{X}_2 - \mu_2} \right) \sim N \left[ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \Sigma \right]$$

The Jacobian is just 
$$D(\theta) = \begin{pmatrix} \frac{\partial g(\theta)}{\partial \theta_1} \\ \frac{\partial g(\theta)}{\partial \theta_2} \end{pmatrix} = \begin{pmatrix} s_2 \\ s_1 \end{pmatrix}$$

So,

$$V(Y) = D(\theta)' \Sigma D(\theta) = \begin{pmatrix} \mu_2 & \mu_1 \end{pmatrix} \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix} \begin{pmatrix} \mu_2 \\ \mu_1 \end{pmatrix}$$
$$\sqrt{n} (\overline{X}_1 \overline{X}_2 - \mu_1 \mu_2) \sim N(0, \mu_2^2 \sigma_{11}^2 + 2\mu_1 \mu_2 \sigma_{12} + \mu_1^2 \sigma_{22}^2)$$

#### **Delta Method: Examples**

Think about a simple logit:

$$\mathbb{P}(Y_i = 1 | X_i) = \frac{\exp^{\beta_0 + \beta_1 X_i}}{1 + \exp^{\beta_0 + \beta_1 X_i}} \quad \mathbb{P}(Y_i = 0 | X_i) = \frac{1}{1 + \exp^{\beta_0 + \beta_1 X_i}}$$

Remember the "trick" to use GLM (log-odds):

$$\log \mathbb{P}(Y_i = 1|X_i) - \log \mathbb{P}(Y_i = 0|X_i) = \beta_0 + \beta_1 X_i$$

- ▶ Suppose that we have estimated  $\hat{\beta_0}$ ,  $\hat{\beta_1}$  via GLM/MLE but we want to know the confidence interval for the probability:  $P(Y_i = 1|X_i, \hat{\theta})$
- ▶ The derivatives are a little bit tricky, but the idea is the same.
- ▶ This is what STATA should be doing when you type: mfx, compute

## **Delta Method: Other Examples**

Often we have a regression like:

$$log Y_i = \beta_0 + \beta_1 X_i + \gamma Income_i + \epsilon_i$$

And we are interested in  $\beta_1/\gamma$  so that we have  $\beta_i$  in units of "dollars". Again Delta Method Works fine here.

#### **Delta Method: Some Failures**

But we need to be careful. Suppose that  $\theta \approx 0$  and

- h(x) = |X|
- ► h(x) = 1/X
- $h(x) = \sqrt{X}$

These situations can arise in practice when we have weak instruments or other problems.