

## Lecture 18. Estimation of a Ratio and the $\delta$ -method

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# Ratio and its Estimate

Suppose that for each member of a population, **two values** are measured:

$$i^{\text{th}} \text{ member} \rightsquigarrow (x_i, y_i)$$

We are interested in the following **ratio**:

$$r = \frac{\sum_{i=1}^N y_i}{\sum_{i=1}^N x_i}$$

**Ratios arise frequently** in sample surveys.

Example:

Households are sampled. If  $y_i$  is the **number of unemployed males** in the  $i^{\text{th}}$  household, and  $x_i$  is the **total number of males** in the  $i^{\text{th}}$  household, then  $r$  is the **proportion of unemployed males**.

## Estimate of a Ratio

Let  $\begin{pmatrix} X_1 & \cdots & X_n \\ Y_1 & \cdots & Y_n \end{pmatrix}$  be a **sample** from a population.

Then the natural estimate of

$$r = \frac{\sum_{i=1}^N y_i}{\sum_{i=1}^N x_i} = \frac{\frac{1}{N} \sum_{i=1}^N y_i}{\frac{1}{N} \sum_{i=1}^N x_i} = \frac{\mu_y}{\mu_x}$$

is

$$R_n = \frac{\bar{Y}_n}{\bar{X}_n}$$

Our goal: to derive expressions for  $\mathbb{E}[R_n]$  and  $\mathbb{V}[R_n]$

Technical problem: since  $R_n$  a **nonlinear function** of  $\bar{X}_n$  and  $\bar{Y}_n$ , we can't find  $\mathbb{E}[R_n]$  and  $\mathbb{V}[R_n]$  in closed form.

Idea: To approximate  $\mathbb{E}[R_n]$  and  $\mathbb{V}[R_n]$  using the  $\delta$ -**method**.

# The $\delta$ -method

In many applications, the following scenario is typical:

## Problem

$X$  is a *random variable*,  $\mu_X$  and  $\sigma_X^2$  are *known*. The problem is to find the mean and variance of  $Y = f(X)$ , where  $f$  is some (*typically nonlinear*) function.

The  $\delta$ -**method** utilizes a *strategy* that is often used in *applied mathematics*: when confronted with a *nonlinear problem* that we can't solve, we *linearize*.

In the  $\delta$ -method, the *linearization* is carried out through a *Taylor series expansion* of  $f$  about  $\mu_X$ :

$$Y = f(X) \approx f(\mu_X) + (X - \mu_X)f'(\mu_X)$$

We thus obtain the *first order approximations*:

$$\mu_Y \approx f(\mu_X)$$

$$\sigma_Y^2 \approx (f'(\mu_X))^2 \sigma_X^2$$

# The $\delta$ -method

To obtain a **better approximation** for  $\mu_Y$ , we can use the Taylor series expansion to the **2<sup>nd</sup> order**:

$$Y = f(X) \approx f(\mu_X) + (X - \mu_X)f'(\mu_X) + \frac{1}{2}(X - \mu_X)^2 f''(\mu_X)$$

Then the **second order approximations** for  $\mu_Y$  is

$$\mu_Y \approx f(\mu_X) + \frac{1}{2}\sigma_X^2 f''(\mu_X)$$

We can similarly proceed in the case of **two random variables**  $X$  and  $Y$ :

## Problem

*Suppose that  $\mu_X, \mu_Y, \sigma_X^2, \sigma_Y^2, \sigma_{XY} = \text{Cov}(X, Y)$  are known. The problem is to find  $\mu_Z$  and  $\sigma_Z^2$ , where  $Z = f(X, Y)$ .*

# The $\delta$ -method

Using the Taylor series expansion to the first order:

$$Z = f(X, Y) \approx f(\mu) + (X - \mu_X) \frac{\partial f}{\partial x}(\mu) + (Y - \mu_Y) \frac{\partial f}{\partial y}(\mu), \quad \mu = (\mu_X, \mu_Y)$$

Therefore,

$$\mu_Z \approx f(\mu)$$

$$\sigma_Z^2 \approx \sigma_X^2 \left( \frac{\partial f}{\partial x}(\mu) \right)^2 + \sigma_Y^2 \left( \frac{\partial f}{\partial y}(\mu) \right)^2 + 2\sigma_{XY} \frac{\partial f}{\partial x}(\mu) \frac{\partial f}{\partial y}(\mu)$$

To obtain a **better approximation** for  $\mu_Z$ , we can use the Taylor series expansion to the **second order**.

$$\mu_Z \approx f(\mu) + \frac{1}{2}\sigma_X^2 \frac{\partial^2 f}{\partial x^2}(\mu) + \frac{1}{2}\sigma_Y^2 \frac{\partial^2 f}{\partial y^2}(\mu) + \sigma_{XY} \frac{\partial^2 f}{\partial x \partial y}(\mu)$$

# The $\delta$ -method: special case $Z = Y/X$

## Example

If  $Z = Y/X$ , then

$$\mu_Z \approx \frac{\mu_Y}{\mu_X} + \frac{1}{\mu_X^2} \left( \sigma_X^2 \frac{\mu_Y}{\mu_X} - \sigma_{XY} \right) \quad (1)$$

$$\sigma_Z^2 \approx \frac{1}{\mu_X^2} \left( \sigma_X^2 \frac{\mu_Y^2}{\mu_X^2} + \sigma_Y^2 - 2\sigma_{XY} \frac{\mu_Y}{\mu_X} \right) \quad (2)$$

## Approximations of $\mathbb{E}[R_n]$ and $\mathbb{V}[R_n]$

The estimate of  $r = \frac{\mu_y}{\mu_x}$  is

$$R_n = \frac{\bar{Y}_n}{\bar{X}_n}$$

To use the  $\delta$ -method to approximate  $\mathbb{E}[R_n]$  and  $\mathbb{V}[R_n]$ , we need to know  $\mu_{\bar{X}_n}, \mu_{\bar{Y}_n}, \sigma_{\bar{X}_n}^2, \sigma_{\bar{Y}_n}^2$ , and  $\text{Cov}(\bar{X}_n, \bar{Y}_n)$ . In previous Lectures, we found that

- $\mu_{\bar{X}_n} = \mu_x$
- $\mu_{\bar{Y}_n} = \mu_y$
- $\sigma_{\bar{X}_n}^2 = \frac{\sigma_x^2}{n} \left(1 - \frac{n-1}{N-1}\right)$
- $\sigma_{\bar{Y}_n}^2 = \frac{\sigma_y^2}{n} \left(1 - \frac{n-1}{N-1}\right)$

It can be shown that

- $\text{Cov}(\bar{X}_n, \bar{Y}_n) = \frac{\sigma_{xy}}{n} \left(1 - \frac{n-1}{N-1}\right)$ , where  $\sigma_{xy}$  is the population covariance of  $x$  and  $y$ ,  $\sigma_{xy} = \frac{1}{N} \sum_{i=1}^N (x_i - \mu_x)(y_i - \mu_y)$ .



# Approximations of $\mathbb{E}[R_n]$ and $\mathbb{V}[R_n]$

Using approximations (1) and (2) from the  $\delta$ -method, we obtain

## Theorem

*The expectation and variance of  $R_n$  are given by*

$$\mathbb{E}[R_n] \approx r + \frac{1}{n} \left( 1 - \frac{n-1}{N-1} \right) \frac{1}{\mu_x^2} (r\sigma_x^2 - \sigma_{xy}) \quad (3)$$

$$\mathbb{V}[R_n] \approx \frac{1}{n} \left( 1 - \frac{n-1}{N-1} \right) \frac{1}{\mu_x^2} (r^2\sigma_x^2 + \sigma_y^2 - 2r\sigma_{xy}) \quad (4)$$

In **applications**, population parameters  $\mu_x, \sigma_x, \sigma_y, \sigma_{xy}$  are **unknown**. To compute the **estimated** values of  $\mathbb{E}[R_n]$  and  $\mathbb{V}[R_n]$ , we use (3) and (4) together with

- $r \approx R_n$      $\mu_x \approx \bar{X}_n$
- $\sigma_x^2 \approx \hat{\sigma}_{x,\text{unbiased}}^2 = \frac{N-1}{Nn-N} \sum_{i=1}^n (X_i - \bar{X}_n)^2$
- $\sigma_y^2 \approx \hat{\sigma}_{y,\text{unbiased}}^2 = \frac{N-1}{Nn-N} \sum_{i=1}^n (Y_i - \bar{Y}_n)^2$
- $\sigma_{xy} \approx \frac{N-1}{Nn-N} \sum_{i=1}^n (X_i - \bar{X}_n)(Y_i - \bar{Y}_n)$

# Summary

- Ratios  $r = \mu_y/\mu_x$  arise frequently in sample surveys
- The natural estimate of  $r$  is  $R_n = \bar{Y}_n/\bar{X}_n$
- We can find expressions for  $\mathbb{E}[R_n]$  and  $\mathbb{V}[R_n]$  using the  $\delta$ -method:

$$\mathbb{E}[R_n] \approx r + \frac{1}{n} \left( 1 - \frac{n-1}{N-1} \right) \frac{1}{\mu_x^2} (r\sigma_x^2 - \sigma_{xy})$$

$$\mathbb{V}[R_n] \approx \frac{1}{n} \left( 1 - \frac{n-1}{N-1} \right) \frac{1}{\mu_x^2} (r^2\sigma_x^2 + \sigma_y^2 - 2r\sigma_{xy})$$

- To compute the estimated values of  $\mathbb{E}[R_n]$  and  $\mathbb{V}[R_n]$ , we use:
  - ▶  $r \approx R_n$      $\mu_x \approx \bar{X}_n$
  - ▶  $\sigma_x^2 \approx \hat{\sigma}_{x,\text{unbiased}}^2 = \frac{N-1}{Nn-N} \sum_{i=1}^n (X_i - \bar{X}_n)^2$
  - ▶  $\sigma_y^2 \approx \hat{\sigma}_{y,\text{unbiased}}^2 = \frac{N-1}{Nn-N} \sum_{i=1}^n (Y_i - \bar{Y}_n)^2$
  - ▶  $\sigma_{xy} \approx \frac{N-1}{Nn-N} \sum_{i=1}^n (X_i - \bar{X}_n)(Y_i - \bar{Y}_n)$