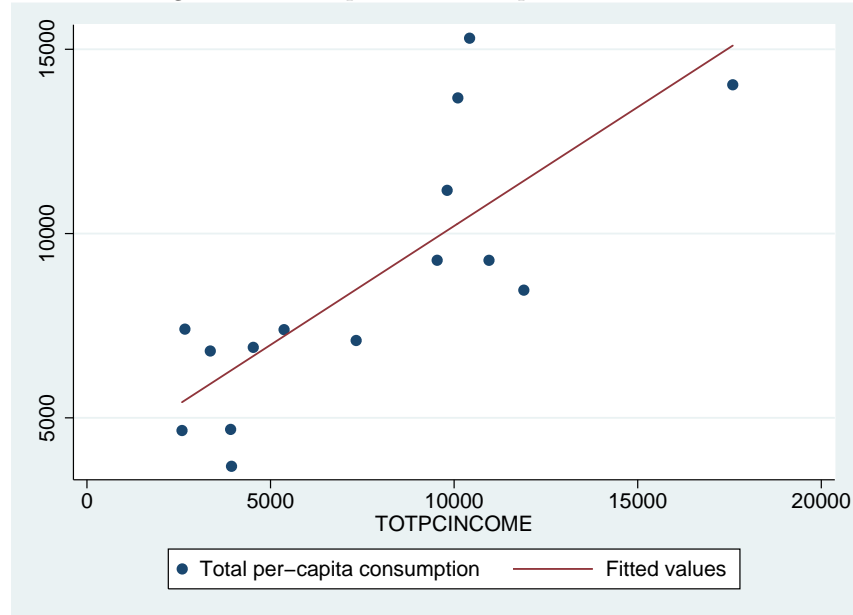


# Calculation of $\beta$ 's parameters

Consider individual data

$$y_i = \beta_0 + \beta_1 x_i + u_i \quad \text{where } i = 1, 2, \dots, n \quad (3)$$

Figure 1: Scatterplot of consumption and income



Now, recalling that

$$E(u) = 0 \quad (4)$$

then

$$Cov(x, u) = E(xu) = 0 \quad (5)$$

and by substitution

$$E(y - \beta_0 - \beta_1 x) = 0 \quad (6)$$

$$E[x(y - \beta_0 - \beta_1 x)] = 0 \quad (7)$$

Now taking the sample values of 6 and 7

$$n^{-1} \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i) = 0 \quad (8)$$

$$n^{-1} \sum_{i=1}^n x_i (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i) = 0 \quad (9)$$

Here we applied the *method of moments*, but other approaches could also be used.

Now, let's solve 8 and 9 by  $\hat{\beta}_0$  and  $\hat{\beta}_1$ .

Equation 8 can be expressed as:

$$\bar{y} = \hat{\beta}_0 + \hat{\beta}_1 \bar{x} \quad (10)$$

and then

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} \quad (11)$$

This is the **sample intercept**.

To get  $\hat{\beta}_1$ , let's substitute the expression of  $\hat{\beta}_0$  from 11 into 9 (we can drop  $n^{-1}$  as it's only a rescaling parameter which doesn't affect the slope). After some algebraic transformations, using summation properties, and given that:

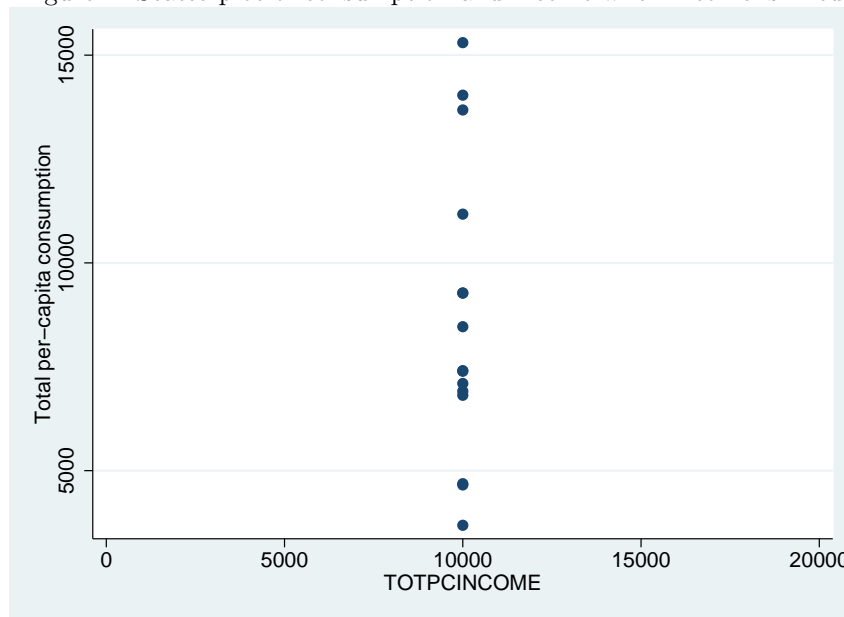
$$\sum_{i=1}^n (x_i - \bar{x})^2 > 0 \quad (12)$$

we get

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (13)$$

the **estimated slope**, that is the sample counterpart of the covariance between  $x$  and  $y$  divided by the variance of  $x$ . If  $x$  and  $y$  are positively correlated, then  $\hat{\beta}_1$  is positive, if they are negatively correlated  $\hat{\beta}_1$  will be negative.

Figure 2: Scatterplot of consumption and income when income is fixed



The expressions 11 and 13 are the **Ordinary Least Squares (OLS)** estimates of  $\beta_0$  and  $\beta_1$ . To get a particular **fitted** value of  $y$  when  $x = x_i$ :

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i \quad (14)$$

For each value  $y = y_i$  there is a fitted value in 14. The distance between the fitted  $\hat{y}$  and the actual value  $y_i$  is the **residual**, expressed by:

$$\hat{u}_i = y_i - \hat{y}_i = y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i \quad (15)$$

Are  $\hat{u}_i$  the same as  $u_i$  in equation 3?

Once we get  $\hat{\beta}_0$  and  $\hat{\beta}_1$

$$\sum_{i=1}^n \hat{u}_i^2 = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2 \quad (16)$$

There are particular values of  $\hat{\beta}_0$  and  $\hat{\beta}_1$  which minimize 16, the **sum of squared residuals**.

Quite coincidentally, these values are given by 8 and 9 (apart from  $n^{-1}$ ). Instead of the methods of moments, we could have applied a minimization of 16, deriving the **First Order Conditions (FOC)** for the OLS, whose solutions are 11 and 13. This is why they are called “ordinary least squares”.

Now we get everything for the regression line of graph 1:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x. \quad (17)$$

This is also called the **sample regression function (SRF)**, why?

Because it is the sample counterpart of equation 2. With a different sample, we would get different values of  $\hat{\beta}_0$  and  $\hat{\beta}_1$  in equation 17.

Economists always focus on  $\hat{\beta}_1$ , as they are interested in the change in  $\hat{y}$  for a unit change in  $x$ . In fact, being

$$\hat{\beta}_1 = \Delta \hat{y} / \Delta x \quad (18)$$

then

$$\Delta \hat{y} = \hat{\beta}_1 \Delta x \quad (19)$$

Let’s look at an empirical example.

Figure 3: Scatterplot of consumption and income, sample and population

