



# Title

## Subtitle

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2025-07-02

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# First section





Wow, this is a slide.

The music experience has been cancelled.

This quote is from the Severance TV-show



Touying equation with pause:

$$f(x) =$$

Touying equation is very simple.

Touying equation with pause:

$$f(x) = x^2 + 2x + 1 =$$

Touying equation is very simple.

Touying equation with pause:

$$f(x) = x^2 + 2x + 1 = (x + 1)^2$$

Touying equation is very simple.



At subslide 1, we can

use  $\text{reserve\_space}$  for reserving space,

use  $\text{no\_reserve\_space}$  for not reserving space,

call  $\text{choose\_one}$  multiple times  $\sigma$  for choosing one of the alternatives.





At subslide 2, we can

use `#uncover` function for reserving space,

use `#only` function for not reserving space,

use `#alternatives` function ✓ for choosing one of the alternatives.



At subslide 3, we can

use `#uncover` function for reserving space,

use `#only` function for not reserving space,

use `#alternatives` function ✓ for choosing one of the alternatives.

If you have “animations” in your presentation, you can set “handout” to “true” in the config and only include the last subslide.

```
#import "@preview/ucph-nielsine-touying" as uc
#import "@preview/touying:0.6.1" as ty
show: uc.ucph-metropolis-theme.with(
  // ...
  ,
  ty.config-common(handout: true)
)
```

First column.

Second column. Schelling ([1971](#))<sup>1</sup>

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<sup>1</sup>a footnote

# The OLS estimator

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For a multiple linear regression model, the equation can be written in matrix form as:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

where:

- $\mathbf{y}$  is an  $n \times 1$  vector of observed dependent variables.
- $\mathbf{X}$  is an  $k \times (k + 1)$  matrix of independent variables (including a column of ones for the intercept).
- $\boldsymbol{\beta}$  is a vector of unknown coefficients.
- $\boldsymbol{\varepsilon}$  is an  $n \times 1$  vector of error terms.

Implying we have a vector of residuals given by:

$$\varepsilon = \mathbf{y} - \mathbf{X}\beta$$

Our objective is to minimize the sum of squared residuals:

$$\begin{aligned}\min_{\beta} \varepsilon^T \varepsilon &= (\mathbf{y} - \mathbf{X}\beta)^T (\mathbf{y} - \mathbf{X}\beta) \leftrightarrow \\ &= \underbrace{\mathbf{y}^T \mathbf{y}}_{\perp \beta} - \mathbf{y}^T \mathbf{X}\beta - \beta^T \mathbf{X}^T \mathbf{y} + \beta^T \mathbf{X}^T \mathbf{X}\beta \leftrightarrow \\ &= -2\beta^T \mathbf{X}^T \mathbf{y} + \beta^T \mathbf{X}^T \mathbf{X}\beta\end{aligned}$$

*Note:* By multiple a vector with itself transposed with just a scalar, or in this case  $\varepsilon^T \varepsilon$  which is the sum of squared error terms.

$$\frac{\partial}{\partial \beta} (-2\beta^T \mathbf{X}^T \mathbf{y} + \beta^T \mathbf{X}^T \mathbf{X} \beta) = 0 \Leftrightarrow$$

$$2\mathbf{X}^T \mathbf{X} \beta = 2\mathbf{X}^T \mathbf{y} \Leftrightarrow$$

$$\mathbf{X}^T \mathbf{X} \beta = \mathbf{X}^T \mathbf{y} \Leftrightarrow$$

Multiply both sides with  $(\mathbf{X}^T \mathbf{X})^{-1}$ :

$$\underbrace{(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{X}}_{=I} \beta = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y} \Leftrightarrow$$

$$\hat{\beta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$





## The OLS estimator

$$\hat{\beta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

- This is very important.
- Remember this.

# Colors



# Let me show you the colors



Dark red #901a1e	Dark blue #122947	Dark petroleum #0a5963	Dark green #39641c	Dark grey #3d3d3d
Red #c73028	Blue #425570	Petroleum #197f8e	Green #4b8325	Grey #666666
Light red #db3b0a	Light blue #bac7d9	Light petroleum #b7d7de	Light green #becaa8	Light grey #e1dfdf

Wake up!

Wake up with a gradient!

Schelling, T.C. (1971) “Dynamic models of segregation,” *Journal of mathematical sociology*, 1(2), pp. 143–186.

# Appendix

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## Page layout

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Header

Margin→

Content

Footer