

## GOV 2000 Section 2

Konstantin Kashin<sup>1</sup>  
*Harvard University*

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<sup>1</sup>These notes and accompanying code draw on the notes from Molly Roberts, Maya Sen, Iain Osgood, Brandon Stewart, and TF's from previous years

# OUTLINE

ADMINISTRATIVE DETAILS

REGRESSION

GOODNESS-OF-FIT:  $R^2$

APPENDIX

## PROBLEM SET EXPECTATIONS

- ▶ First problem set distributed yesterday.
- ▶ Due next Tuesday.
- ▶ Must be typeset ( $\text{\LaTeX}$  or Word) and submitted electronically
- ▶ Submit source-able, commented code with journal-quality graphics

## GETTING HELP

1. General questions should go to email list.
2. Response time: 24-response times during week, longer on weekends.
3. Office hours:
  - ▶ Adam: Tuesdays 4-6pm
  - ▶ Andy: Mondays 9-11am
  - ▶ Konstantin: Fridays 2-4pm (EXCEPT FOR THIS WEEK: 11am-1pm)
4. Formula Wiki

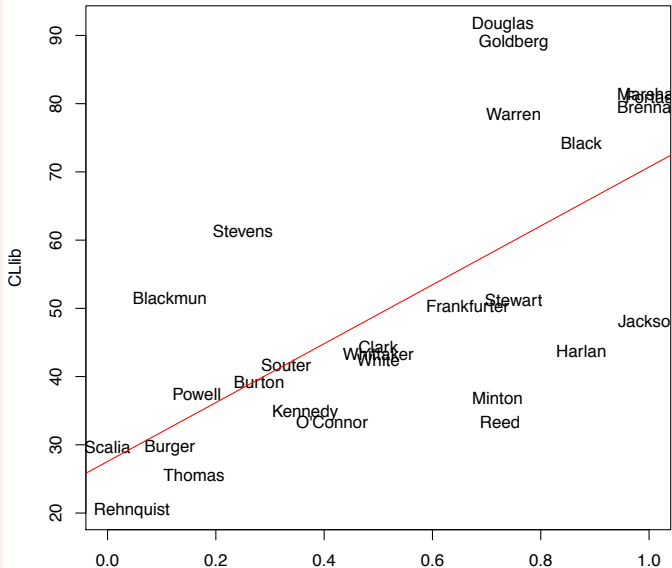
# OUTLINE

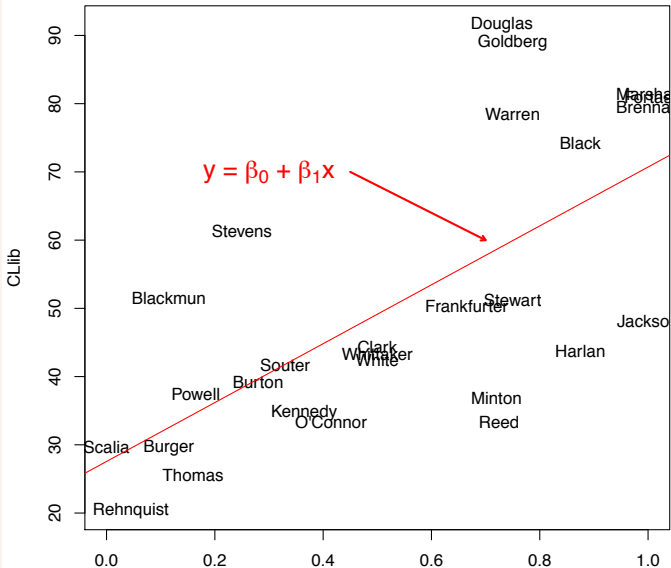
ADMINISTRATIVE DETAILS

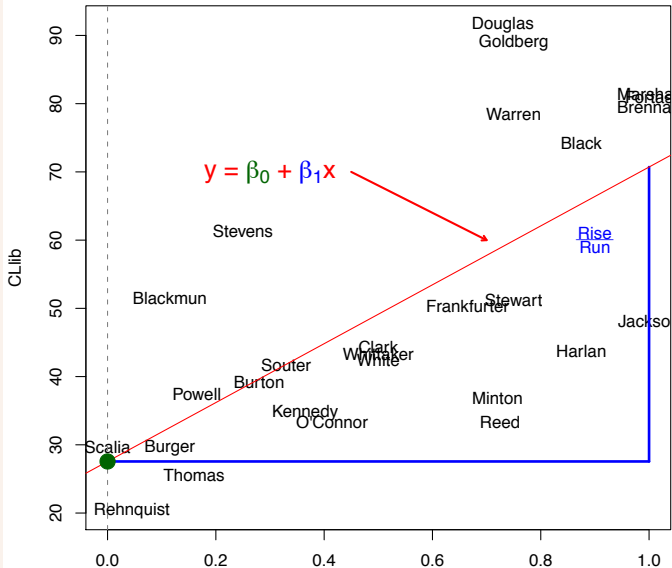
**REGRESSION**

GOODNESS-OF-FIT:  $R^2$

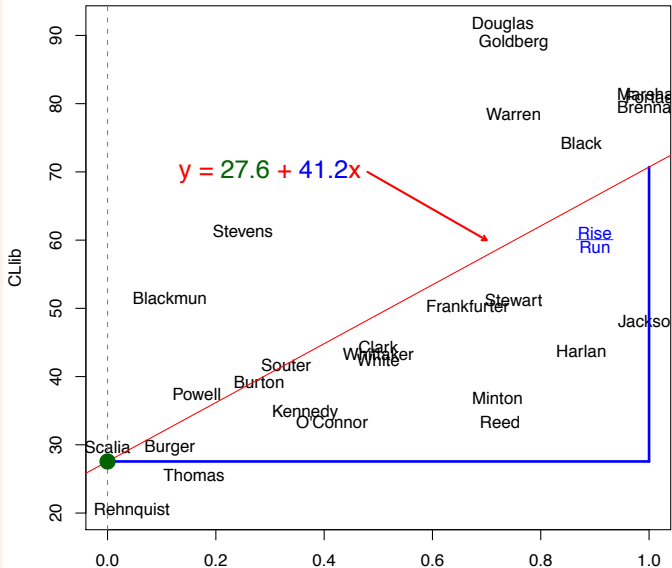
APPENDIX

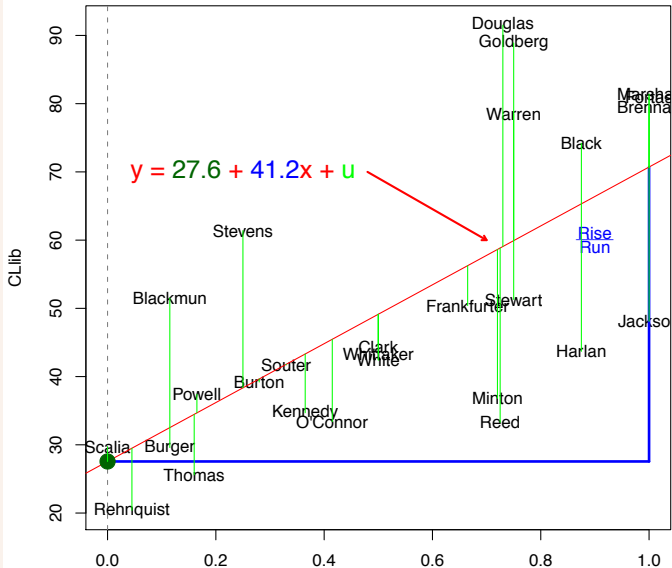












## HOW TO GET $B_0$ AND $B_1$

$$\hat{B}_0 = \bar{y} - \hat{B}_1 \bar{x}.$$

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

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**GOODNESS-OF-FIT:  $R^2$**

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$R^2$ 

How much variance are we explaining?

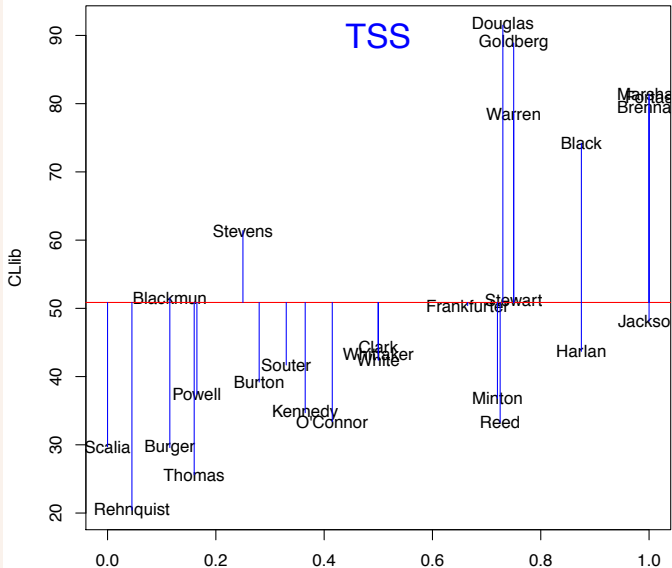
To calculate  $R^2$ , we need to think about the following two quantities:

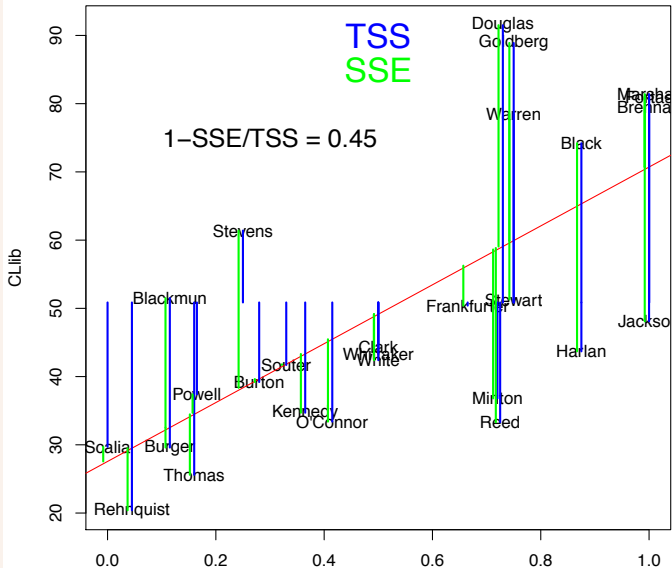
1. TSS: Total sum of squares
2. SSR: Sum of squared residuals

$$TSS = \sum_{i=1}^n (y_i - \bar{y})^2.$$

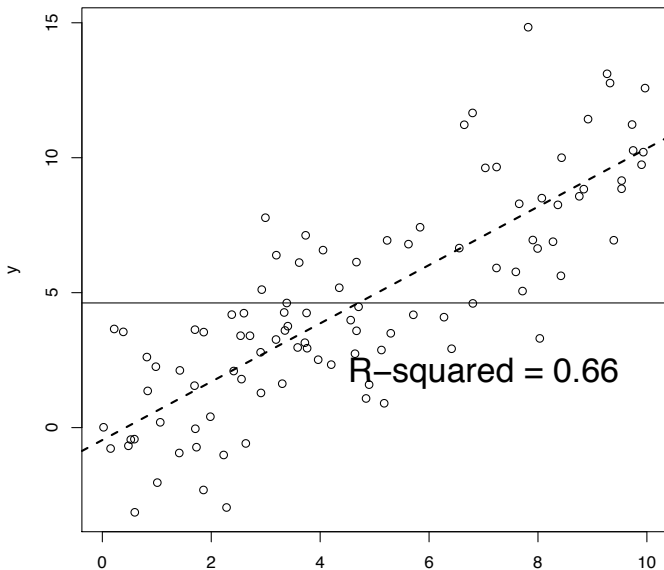
$$SSR = \sum_{i=1}^n (y_i - \hat{y}_i)^2.$$

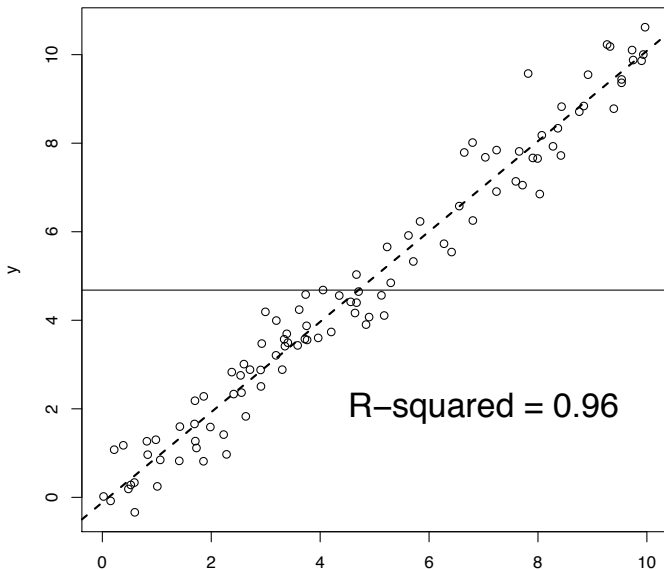
$$R^2 = 1 - \frac{SSR}{TSS}.$$

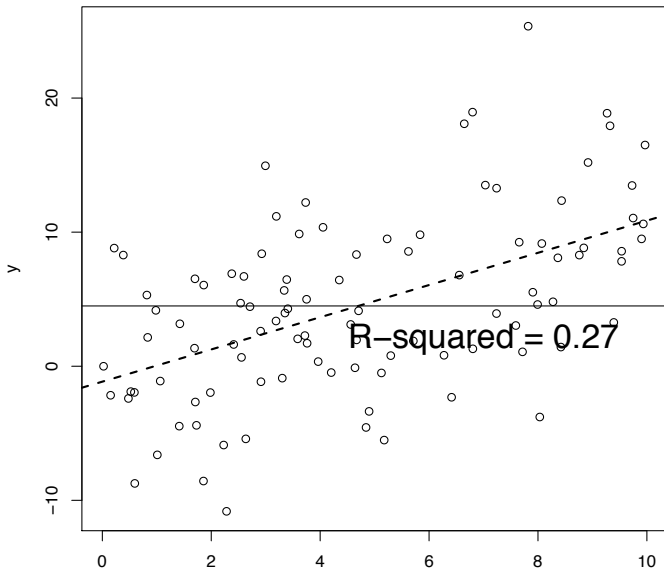












Questions?

# OUTLINE

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## DERIVING THE LINEAR LEAST SQUARES ESTIMATOR

Let  $\tilde{\beta}_0$  and  $\tilde{\beta}_1$  be possible values for  $\beta_0$  and  $\beta_1$  respectively, and

$$S(\tilde{\beta}_0, \tilde{\beta}_1) = \sum_{i=1}^n (y_i - \tilde{\beta}_0 - x_i \tilde{\beta}_1)^2.$$

1. Take partial derivatives of  $S$  with respect to  $\tilde{\beta}_0$  and  $\tilde{\beta}_1$ .
2. Set each of the partial derivatives to 0
3. Substitute  $\hat{\beta}_0$  and  $\hat{\beta}_1$  for  $\tilde{\beta}_0$  and  $\tilde{\beta}_1$  and solve for  $\hat{\beta}_0$  and  $\hat{\beta}_1$

$$\begin{aligned} S(\tilde{\beta}_0, \tilde{\beta}_1) &= \sum_{i=1}^n (y_i - \tilde{\beta}_0 - x_i \tilde{\beta}_1)^2 \\ &= \sum_{i=1}^n (y_i^2 - 2y_i \tilde{\beta}_0 - 2y_i \tilde{\beta}_1 x_i + \tilde{\beta}_0^2 + 2\tilde{\beta}_0 \tilde{\beta}_1 x_i + \tilde{\beta}_1^2 x_i^2) \end{aligned}$$

$$\frac{\partial S(\tilde{\beta}_0, \tilde{\beta}_1)}{\partial \tilde{\beta}_0} = \sum_{i=1}^n (-2y_i + 2\tilde{\beta}_0 + 2\tilde{\beta}_1 x_i)$$

and

$$\frac{\partial S(\tilde{\beta}_0, \tilde{\beta}_1)}{\partial \tilde{\beta}_1} = \sum_{i=1}^n (-2y_i x_i + 2\tilde{\beta}_0 x_i + 2\tilde{\beta}_1 x_i^2)$$

We set the partial derivatives to zero

$$\frac{\partial S(\tilde{\beta}_0, \tilde{\beta}_1)}{\partial \tilde{\beta}_0} = \sum_{i=1}^n (-2y_i + 2\tilde{\beta}_0 + 2\tilde{\beta}_1 x_i)$$

becomes

$$\hat{\beta}_0 n = \left( \sum_{i=1}^n y_i \right) - \hat{\beta}_1 \left( \sum_{i=1}^n x_i \right)$$

and

$$\frac{\partial S(\tilde{\beta}_0, \tilde{\beta}_1)}{\partial \tilde{\beta}_1} = \sum_{i=1}^n (-2y_i x_i + 2\tilde{\beta}_0 x_i + 2\tilde{\beta}_1 x_i^2)$$

becomes

$$\hat{\beta}_1 \sum_{i=1}^n x_i^2 = \left( \sum_{i=1}^n x_i y_i \right) - \hat{\beta}_0 \left( \sum_{i=1}^n x_i \right)$$



**Normal Equations:** Two equations, two unknowns.

$$\hat{\beta}_0 n = \left( \sum_{i=1}^n y_i \right) - \hat{\beta}_1 \left( \sum_{i=1}^n x_i \right)$$

$$\hat{\beta}_1 \sum_{i=1}^n x_i^2 = \left( \sum_{i=1}^n x_i y_i \right) - \hat{\beta}_0 \left( \sum_{i=1}^n x_i \right)$$

Solving for  $\hat{\beta}_0$  is straight forward:

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

Let's solve for  $\hat{\beta}_1$ . We have two equations. We can manipulate them by multiplying the first by  $\sum_{i=1}^n x_i$  and the second one by  $n$ .

$$\hat{\beta}_0 n \sum_{i=1}^n x_i + \hat{\beta}_1 \left( \sum_{i=1}^n x_i \right) \sum_{i=1}^n x_i = \left( \sum_{i=1}^n y_i \right) \sum_{i=1}^n x_i$$

$$\hat{\beta}_0 n \left( \sum_{i=1}^n x_i \right) + n \hat{\beta}_1 \sum_{i=1}^n x_i^2 = n \left( \sum_{i=1}^n x_i y_i \right)$$

Putting them together

$$\hat{\beta}_1 \left( \left( \sum_{i=1}^n x_i \right) \sum_{i=1}^n x_i - n \sum_{i=1}^n x_i^2 \right) = \left( \sum_{i=1}^n y_i \right) \sum_{i=1}^n x_i - n \left( \sum_{i=1}^n x_i y_i \right)$$

Rearranging we get

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

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

$$\hat{\beta}_1 = \frac{\text{Cov}(x, y)}{\text{Var}(x)}$$

We also have from the assumptions the  $E(\epsilon) = 0$  and  $Cov(X_i\epsilon_j) = 0$  that

$$\sum_{i=1}^n \hat{u}_i = 0$$

$$\sum_{i=1}^n x_i \hat{u}_i = 0$$

$$\sum_{i=1}^n \hat{y}_i \hat{u}_i = 0$$