Gov 50: 22. Uncertainty in Regressions

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Fall 2018

1/ Today's agenda

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- Learned about uncertainty for sample means and sample difference-in-means.

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  - Final write-up due 12/10
  - We'll learn some key concepts for interpreting regression coefficients today.

2/ Regression review

Data

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- Data:

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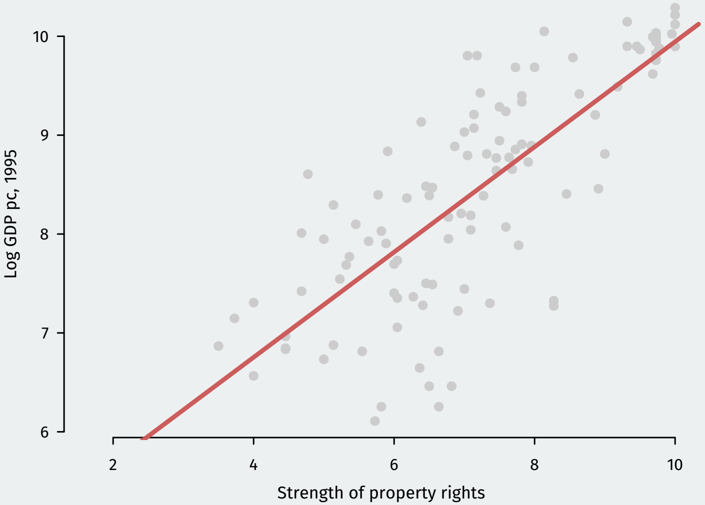
Name	Description
`shortnam`	three-letter country code
`africa`	indicator for if the country is in Africa
`avexpr`	strength of property rights (protection against expropriation)
`logpgp95`	log GDP per capita
`imr95`	infant mortality rate

AJR scatterplot



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  - Population intercept: β_0
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  - Represents all unobserved error factors influencing Y_i other than X_i.

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- Get these estimates by the **least squares method**.
- Minimize the **sum of the squared residuals** (SSR):

$$\text{SSR} = \sum_{i=1}^{n} \widehat{\epsilon}_i^2 = \sum_{i=1}^{n} (Y_i - \widehat{\beta}_0 - \widehat{\beta}_1 X_i)^2$$

3/ OLS as a estimator

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$$\text{Sample 1: } \{(Y_1, X_1), \dots, (Y_n, X_n)\} \longrightarrow \boxed{\text{OLS}} \longrightarrow (\widehat{\beta}_0, \widehat{\beta}_1)_1$$

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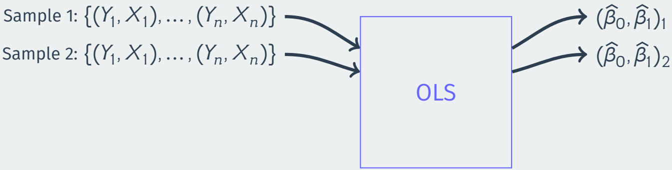

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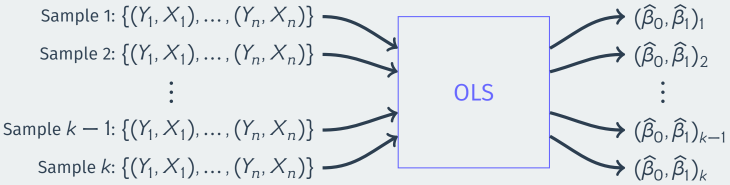

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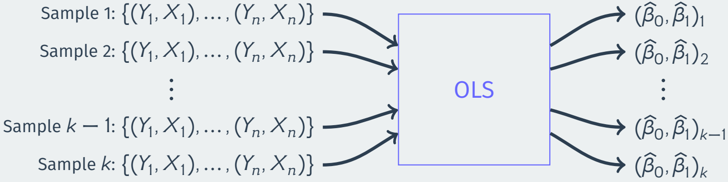

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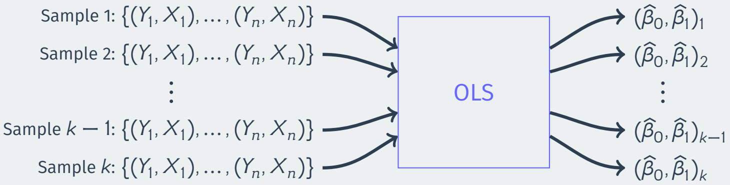

- Just like the sample mean, sample difference in means, or the sample variance
- It has a sampling distribution, with a sampling variance/standard error, etc.

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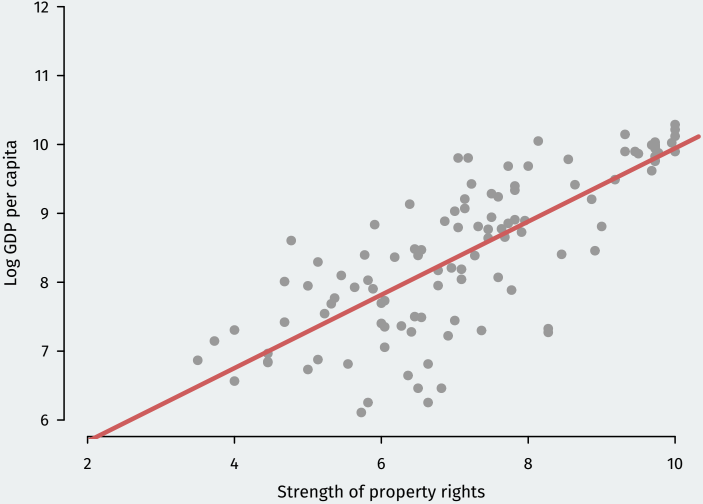
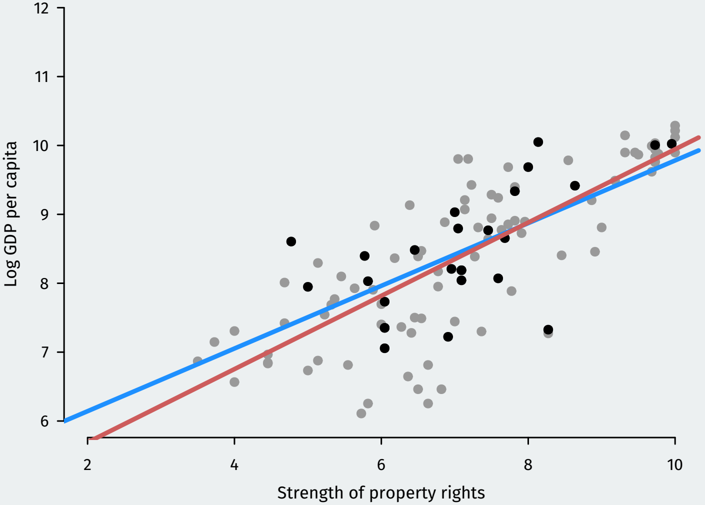
2. Use `lm()` to calculate the OLS estimates of the slope and intercept
3. Plot the estimated regression line

Population regression



Randomly sample from AJR



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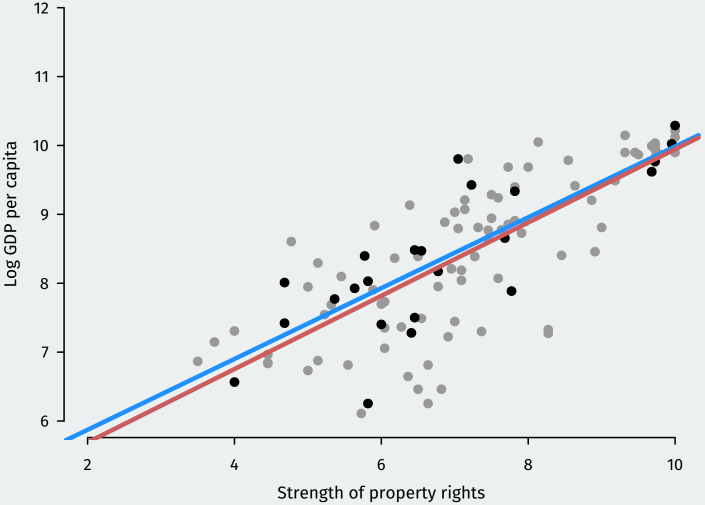

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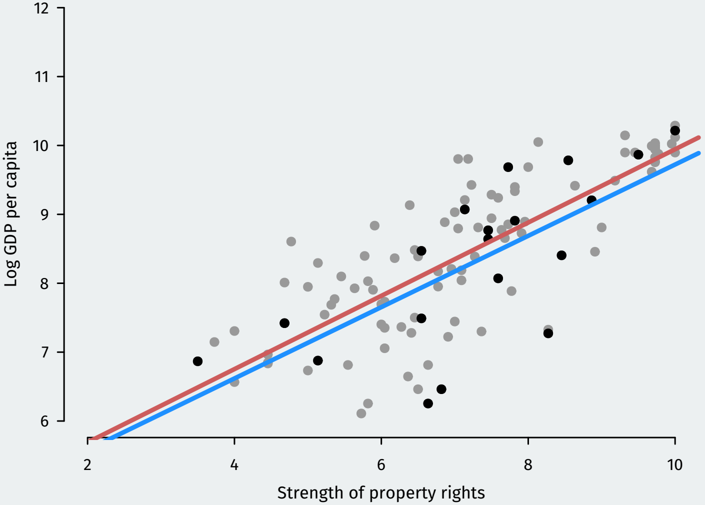

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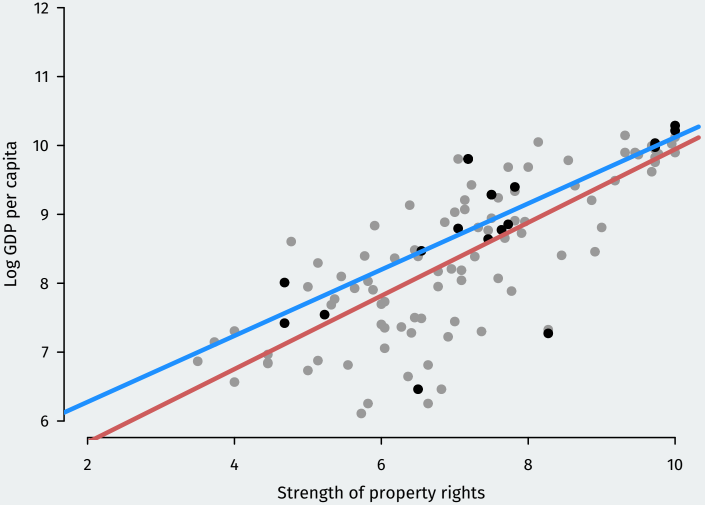

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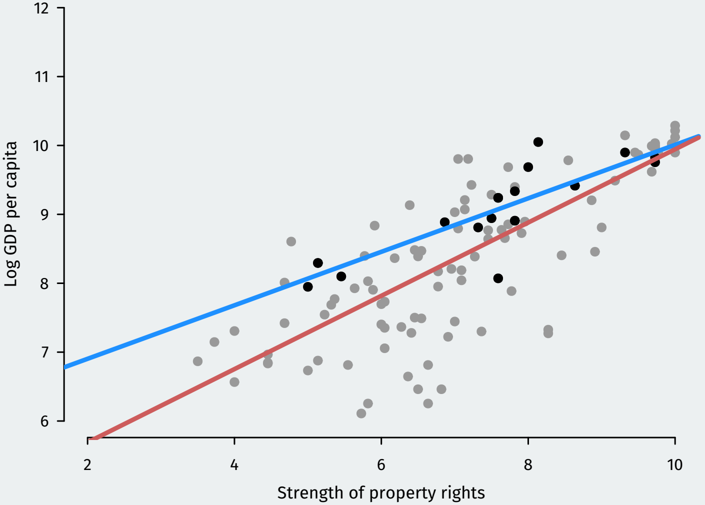

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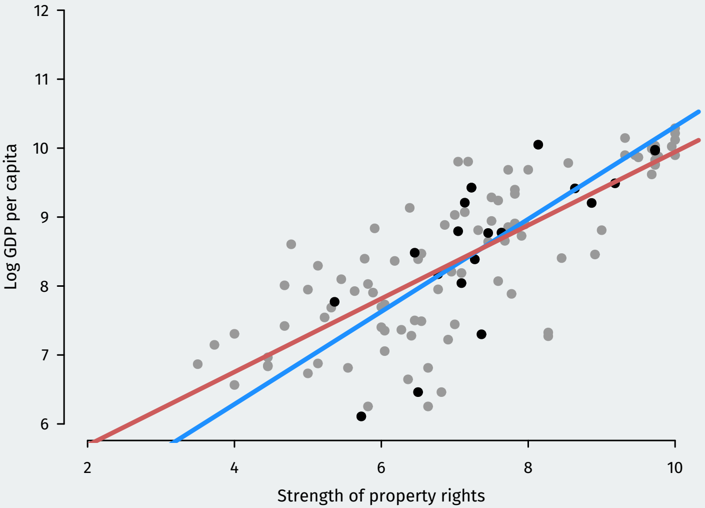

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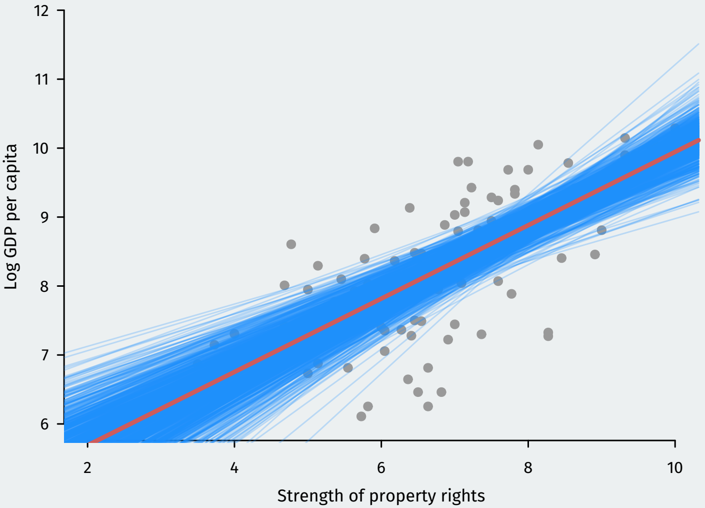
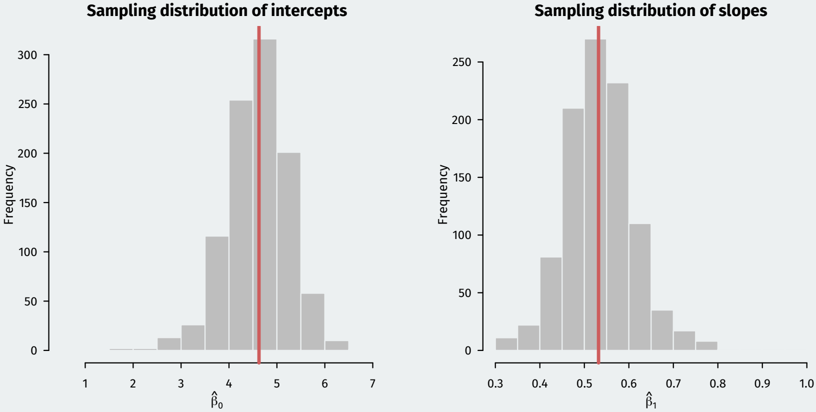


Sampling distribution of OLS

- You can see that the estimated slopes and intercepts vary from sample to sample, but that the “average” of the lines looks about right.



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  - easy fix for this, but beyond the scope of this class.

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  - Estimated standard errors are unbiased

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  - $\widehat{\beta}_1$ is **statistically significant** if its p-value from this test is below some threshold (usually 0.05)

```r
ajr.reg <- lm(logpgp95 ~ avexpr, data = ajr)
summary(ajr.reg)
```

```
##
## Call:
## lm(formula = logpgp95 ~ avexpr, data = ajr)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -1.902 -0.316  0.138  0.422  1.441
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   4.6261     0.3006    15.4   <2e-16 ***
## avexpr        0.5319     0.0406    13.1   <2e-16 ***
## ---
## Signif. codes:
## 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.718 on 109 degrees of freedom
##   (52 observations deleted due to missingness)
## Multiple R-squared:  0.611,  Adjusted R-squared:  0.608
## F-statistic:  171 on 1 and 109 DF,  p-value: <2e-16
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  - Hypothesis tests done exactly the same for $\widehat{\beta}_j$

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- Inference:
    - Confidence intervals constructed exactly the same for $\widehat{\beta}_j$
    - Hypothesis tests done exactly the same for $\widehat{\beta}_j$
    - $\rightsquigarrow$ interpret p-values the same as before.

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##     Min      1Q  Median      3Q     Max
## -1.3928 -0.2708  0.0865  0.2749  1.1652
##
## Coefficients:
##             Estimate Std. Error t value   Pr(>|t|)
## (Intercept)  7.01362    0.40445   17.34    < 2e-16 ***
## avexpr       0.28872    0.05046    5.72 0.00000043 ***
## africa      -0.02069    0.18622   -0.11       0.91
## imr95       -0.01549    0.00271   -5.71 0.00000045 ***
## ---
## Signif. codes:
## 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.492 on 56 degrees of freedom
##   (103 observations deleted due to missingness)
## Multiple R-squared:  0.778,  Adjusted R-squared:  0.766
## F-statistic: 65.4 on 3 and 56 DF,  p-value: <2e-16
```

Regression tables

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- Standard errors, p-values, sample size, and R^2 may be reported as well.

AJR regression table

TABLE 2—OLS REGRESSIONS

	Whole world (1)	Base sample (2)	Whole world (3)	Whole world (4)	Base sample (5)	Base sample (6)	Whole world (7)	Base sample (8)
	Dependent variable is log GDP per capita in 1995						Dependent variable is log output per worker in 1988	
Average protection against expropriation risk, 1985–1995	0.54	0.52	0.47	0.43	0.47	0.41	0.45	0.46
	(0.04)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.04)	(0.06)
Latitude			0.89	0.37	1.60	0.92		
			(0.49)	(0.51)	(0.70)	(0.63)		
Asia dummy				−0.62		−0.60		
				(0.19)		(0.23)		
Africa dummy				−1.00		−0.90		
				(0.15)		(0.17)		
"Other" continent dummy				−0.25		−0.04		
				(0.20)		(0.32)		
R^2	0.62	0.54	0.63	0.73	0.56	0.69	0.55	0.49
Number of observations	110	64	110	110	64	64	108	61

4/ Wrapping up

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  - A particular sample or result could be due to random chance $\rightsquigarrow$ use hypothesis tests and confidence intervals to assess
  - Be skeptical of causal claims unless groups are really comparable.
  - Think carefully about sampling biases when people make claims.

Want more?

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- Outside classes:
  - Work with faculty on research projects!

Thanks!

Thanks for a really fun and engaging semester! Good luck with your final projects!