Gov 50: 25. Inference for Linear Regression

Matthew Blackwell

Harvard University

Roadmap

1. Inference for linear regression
2. Presenting OLS regressions
3. Wrapping up the class

1/ Inference for linear regression

Data

- Do political institutions promote economic development?

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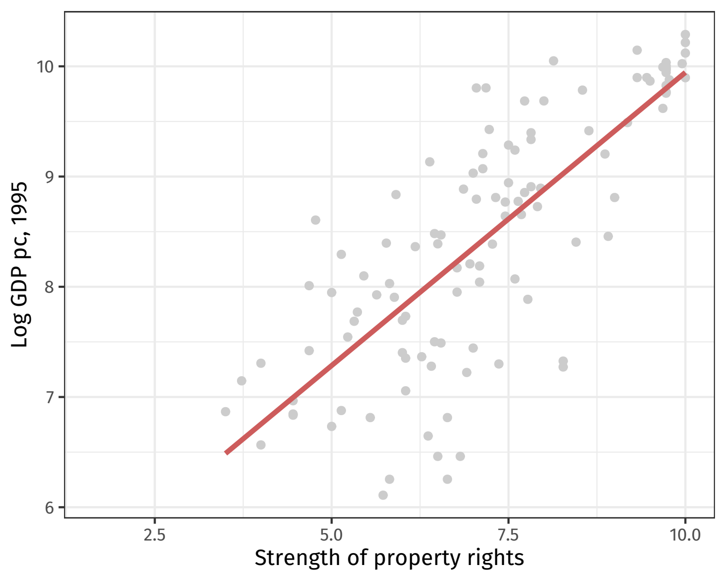
Name	Description
`shortnam`	three-letter country code
`africa`	indicator for if the country is in Africa
`asia`	indicator for if country is in Asia
`avexpr`	strength of property rights (protection against expropriation)
`logpgp95`	log GDP per capita

Loading the data

```r
library(gov50data)
head(ajr)
```

```
## # A tibble: 6 x 15
##   short~1 africa lat_a~2 malfa~3 avexpr logpg~4 logem4  asia
##   <chr>    <dbl>   <dbl>   <dbl>  <dbl>   <dbl>  <dbl> <dbl>
## 1 AFG          0   0.367 0.00372 NA      NA       4.54     1
## 2 AGO          1   0.137 0.950     5.36    7.77   5.63     0
## 3 ARE          0   0.267 0.0123    7.18    9.80  NA        1
## 4 ARG          0   0.378 0         6.39    9.13   4.23     0
## 5 ARM          0   0.444 0       NA        7.68  NA        1
## 6 AUS          0   0.300 0         9.32    9.90   2.15     0
## # ... with 7 more variables: yellow <dbl>, baseco <dbl>,
## #   leb95 <dbl>, imr95 <dbl>, meantemp <dbl>,
## #   lt100km <dbl>, latabs <dbl>, and abbreviated variable
## #   names 1: shortnam, 2: lat_abst, 3: malfal94,
## #   4: logpgp95
```

AJR scatterplot



Simple linear regression model

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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):

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

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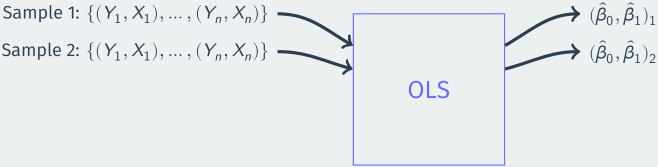

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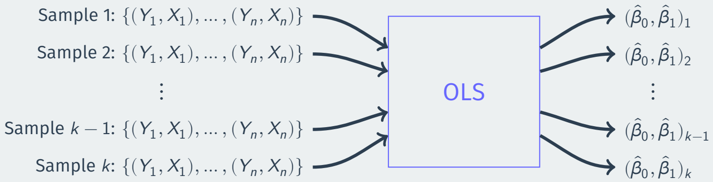

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Sample 2: $\{(Y_1, X_1), \dots, (Y_n, X_n)\}$ → OLS → $(\hat{\beta}_0, \hat{\beta}_1)_2$

$\vdots$

Sample $k-1$: $\{(Y_1, X_1), \dots, (Y_n, X_n)\}$ → OLS → $(\hat{\beta}_0, \hat{\beta}_1)_{k-1}$

Sample k: $\{(Y_1, X_1), \dots, (Y_n, X_n)\}$ → OLS → $(\hat{\beta}_0, \hat{\beta}_1)_k$

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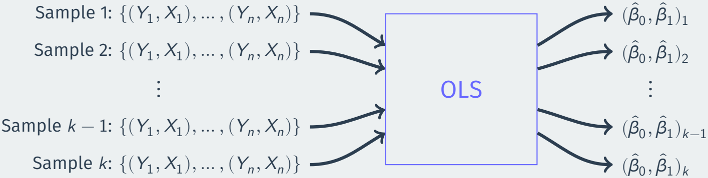

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- $\rightsquigarrow$ sampling distribution with a standard error, etc.

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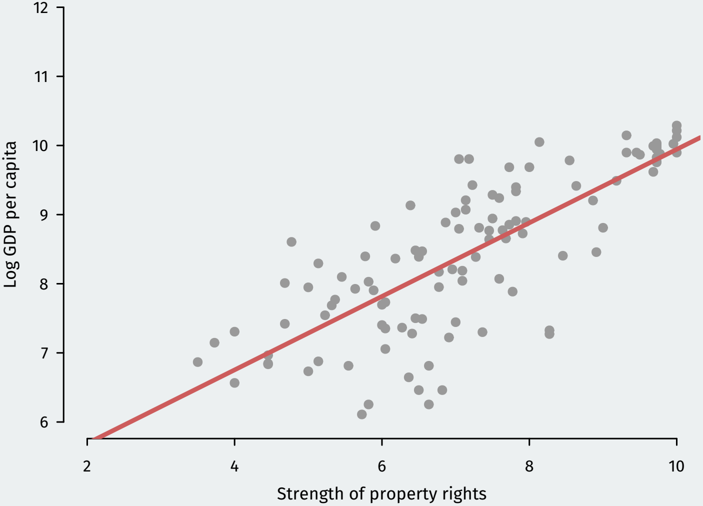
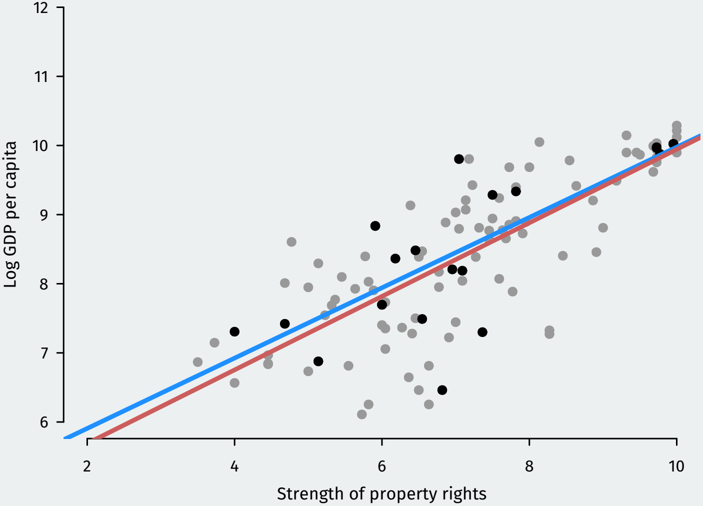
2. Use `lm()` to calculate the OLS estimates of the slope and intercept
3. Plot the estimated regression line

Population regression



Randomly sample from AJR



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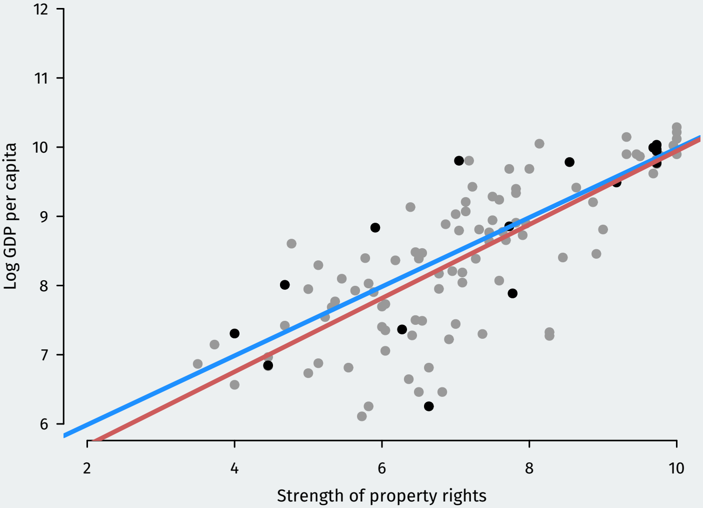

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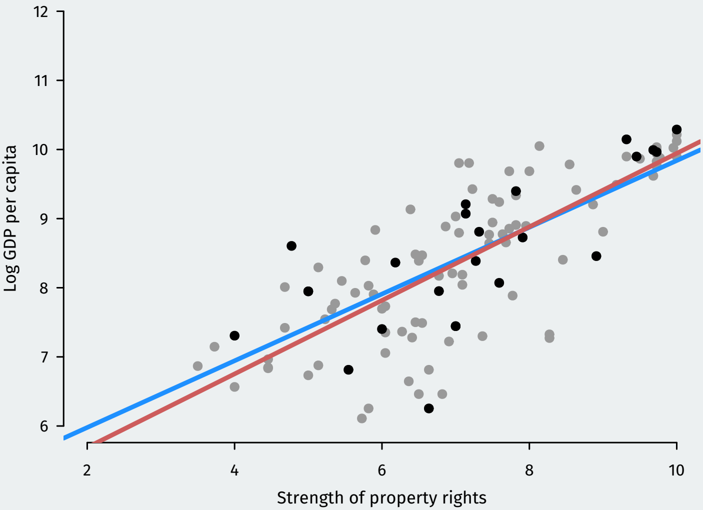

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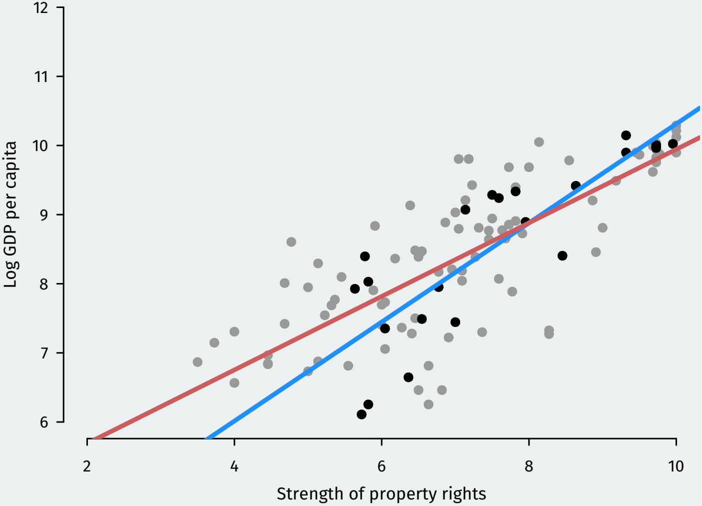

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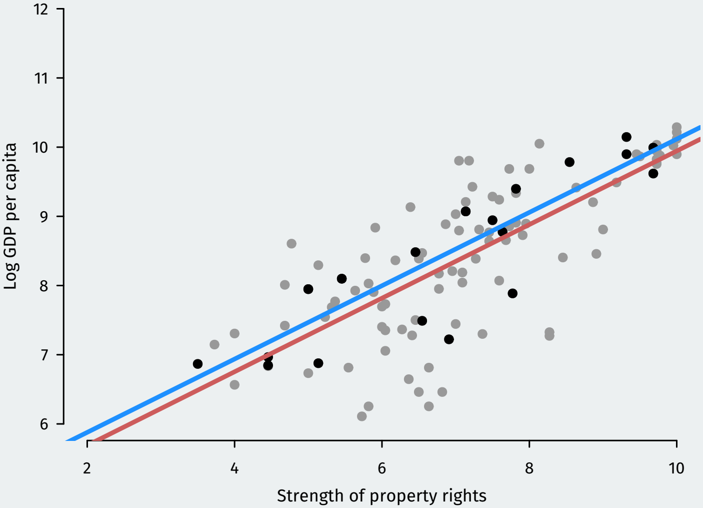

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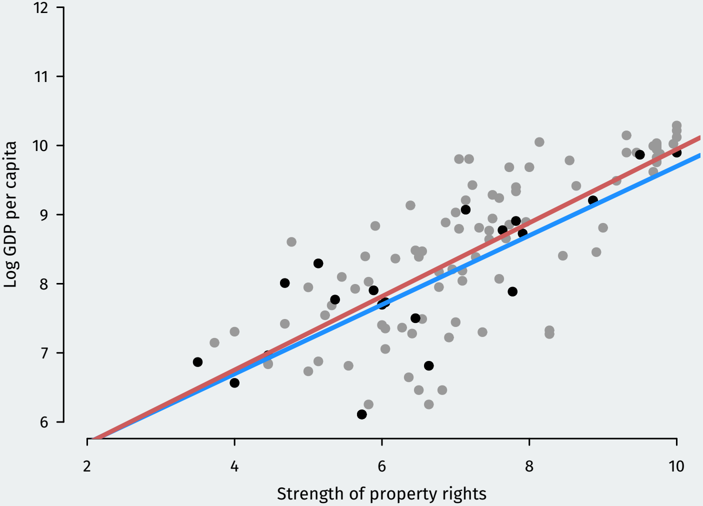

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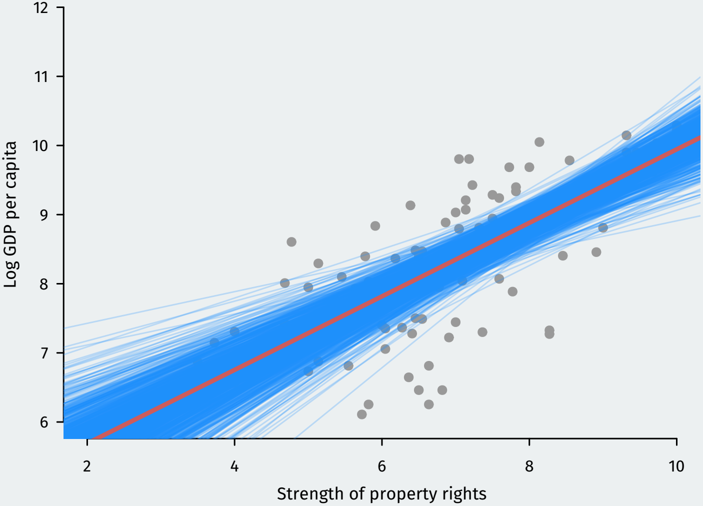
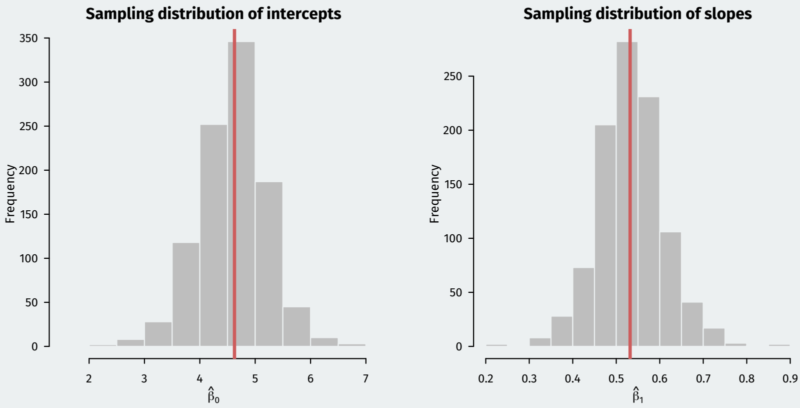


Sampling distribution of OLS

- Estimated slope and intercept vary between samples, centered on truth.



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    - May not represent a causal effect unless causal assumptions hold.

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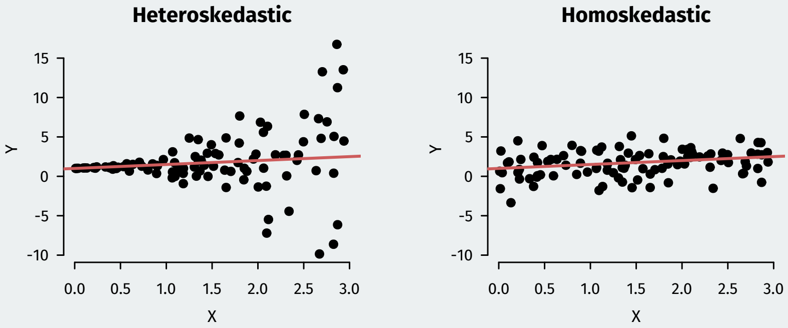

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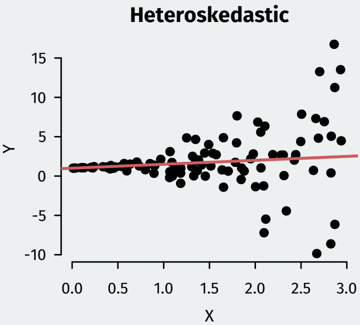
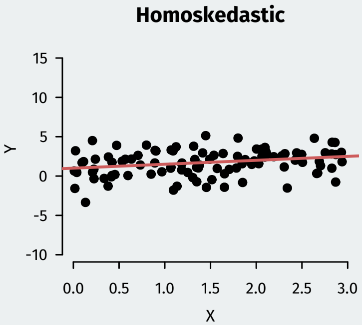
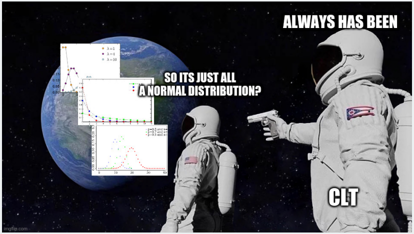




Relatively easy fixes exist, but beyond the scope of this class.

Tests and CIs for regression



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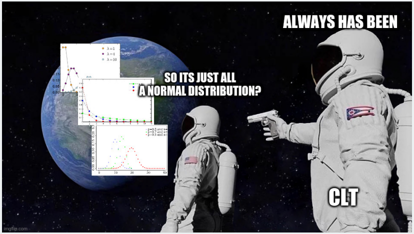

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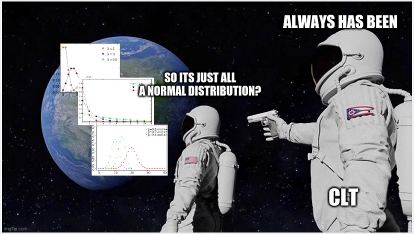

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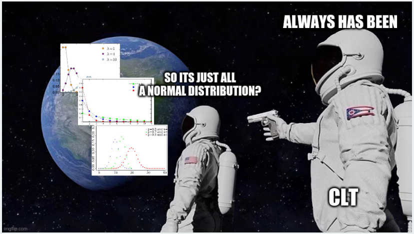

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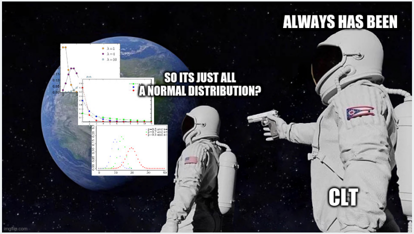

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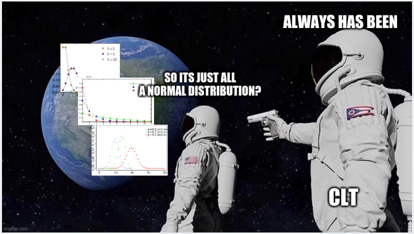

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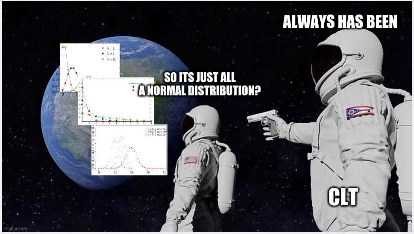

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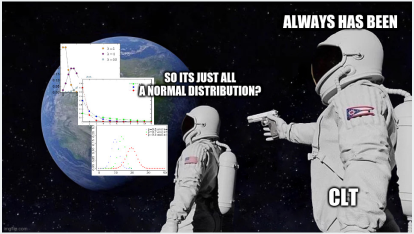

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    - Usual test is of $\beta_1 = 0$.
    - $\hat{\beta}_1$ is **statistically significant** if its p-value from this test is below some threshold (usually 0.05)

```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
```

Using broom with regression

```r
library(broom)
tidy(ajr.reg)
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)    4.63     0.301       15.4 4.28e-29
## 2 avexpr         0.532    0.0406      13.1 4.16e-24
```

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$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip} + \epsilon_i$$

- Interpretation of β_j: an increase in the outcome associated with a one-unit increase in X_{ij} when other variables don't change their values
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  - Hypothesis tests done exactly the same for $\hat{\beta}_j$
  - $\rightsquigarrow$ interpret p-values the same as before.

Using knitr::kable to produce tables

```
ajr.multreg <- lm(logpgp95 ~ avexpr + lat_abst + asia + africa, data = ajr)
tidy(ajr.multreg) |>
  knitr::kable(digits = 3)
```

term	estimate	std.error	statistic	p.value
(Intercept)	5.840	0.339	17.239	0.000
avexpr	0.394	0.050	7.843	0.000
lat_abst	0.312	0.444	0.703	0.484
asia	-0.170	0.153	-1.108	0.270
africa	-0.930	0.165	-5.628	0.000

2/ Presenting OLS regressions

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    - Might differ by independent variables, dependent variables, sample, etc.
- 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 (0.04)	0.52 (0.06)	0.47 (0.06)	0.43 (0.05)	0.47 (0.06)	0.41 (0.06)	0.45 (0.04)	0.46 (0.06)
Latitude			0.89 (0.49)	0.37 (0.51)	1.60 (0.70)	0.92 (0.63)		
Asia dummy				−0.62 (0.19)		−0.60 (0.23)		
Africa dummy				−1.00 (0.15)		−0.90 (0.17)		
"Other" continent dummy				−0.25 (0.20)		−0.04 (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

modelsummary() to produce tables

We can use modelsummary() to produce a table. It takes a list of outputs from lm and aligns them in the correct way.

```
modelsummary::modelsummary(list(ajr.reg, ajr.multreg))
```

Output

```r
modelsummary::modelsummary(list(ajr.reg, ajr.multreg))
```

	Model 1	Model 2
(Intercept)	4.626	5.840
	(0.301)	(0.339)
avexpr	0.532	0.394
	(0.041)	(0.050)
lat_abst		0.312
		(0.444)
asia		−0.170
		(0.153)
africa		−0.930
		(0.165)
Num.Obs.	111	111
R2	0.611	0.713
R2 Adj.	0.608	0.703
AIC	245.4	217.6
BIC	253.5	233.8
Log.Lik.	−119.709	−102.795
RMSE	0.71	0.61

Cleaning up the goodness of fit statistics

```
modelsummary::modelsummary(
  list(ajr.reg, ajr.multreg),
  gof_map = c("nobs", "r.squared", "adj.r.squared"))
```

	Model 1	Model 2
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Cleaning up the variable names

We can also map the variable names to more readable names using the `coef_map` argument. But first, we should do the mapping in a vector. Any term omitted from this vector will be omitted from the table

```
var_labels <- c(
  "avexpr" = "Avg. Expropriation Risk",
  "lat_abst" = "Abs. Value of Latitude",
  "asia" = "Asian country",
  "africa" = "African country"
)
var_labels
```

```
##                    avexpr                  lat_abst
## "Avg. Expropriation Risk"  "Abs. Value of Latitude"
##                      asia                    africa
##           "Asian country"         "African country"
```

Nice table

```
modelsummary::modelsummary(
  list(ajr.reg, ajr.multreg),
  coef_map = var_labels,
  gof_map = c("nobs", "r.squared", "adj.r.squared"))
```

	Model 1	Model 2
Avg. Expropriation Risk	0.532	0.394
	(0.041)	(0.050)
Abs. Value of Latitude		0.312
		(0.444)
Asian country		−0.170
		(0.153)
African country		−0.930
		(0.165)
Num.Obs.	111	111
R2	0.611	0.713
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3/ Wrapping up the class

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Important takeaways from the course:

1. Data wrangling and data visualizations are really important skills that you now have!
2. Causality is hugely important in the world but difficult to establish.
3. Really important to understand and assess statistical uncertainty when working with data.

I’m really proud of you!

You’ve come a long way! Hopefully the tools you learned in this course will help you throughout your life and career!

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- More CS approach to data science: CS109 (Data Science 1)

Thanks!

Fill out your evaluations!