UGA M1: Econometrics 1
Introduction to Regression

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Part I

Definition and interpretation of regression

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References

- Angrist and Pischke (2014) chapter 2
- Wooldridge (2013) chapter 2
- Stock and Watson (2009) chapter 4-5
- Angrist and Pischke (2009) chapter 3 up to and including section 3.1.2 (pages 27-40)
- Abbring (2001) chapter 3
- Diez, Barr, and Cetinkaya-Rundel (2012) chapter 7
- Bierens (2012)
- Baltagi (2002) chapter 3

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References

- The most useful reference is likely Wooldridge (2013) or Stock and Watson (2009), followed by Angrist and Pischke (2014).
- Angrist and Pischke (2009) is also very nice, but a bit more dense. Diez, Barr, and Cetinkaya-Rundel (2012) is a simple introduction to regression with many examples and not much math.
- Baltagi (2002) is more technical and difficult than Wooldridge, but I think would still be useful.
- Bierens (2012) has many of the proofs that we will go through, but the typesetting is not great.
- Abbring (2001) moves quickly and uses matrix notation.

Section 1

Motivation

General problem

- Often interested in relationship between two (or more) variables, e.g.
  - Wages and education
  - Minimum wage and unemployment
  - Price, quantity, and product characterics
- Usually have:
  1. Variable to be explained or response variable or outcome or regressand or dependent variable.
  2. Regressors or covariates or explanatory variable(s) or independent variables.
- A usual notation for the response variable is Y and for the covariates X.
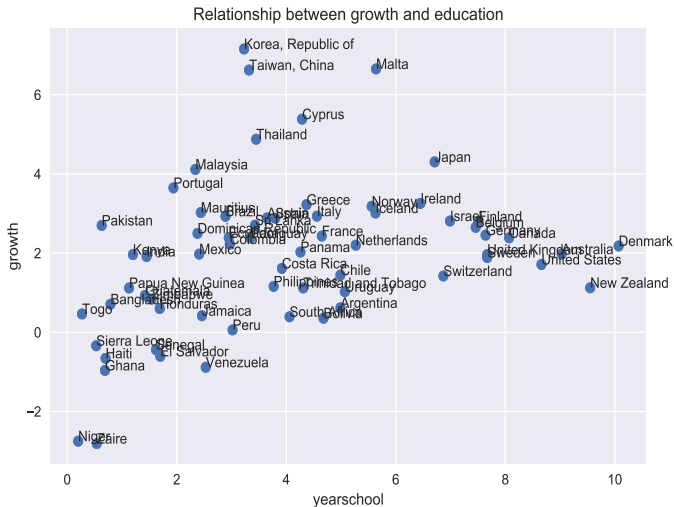- Example:

Response	Covariates
Wage	Education
Unemployment	Minimum wage
Quantity	Price and product characteristics

- For now agnostic about causality, but $\mathbb{E}[Y|X]$ usually is not causal

Example: Growth and GDP

Relationship between growth and gdp
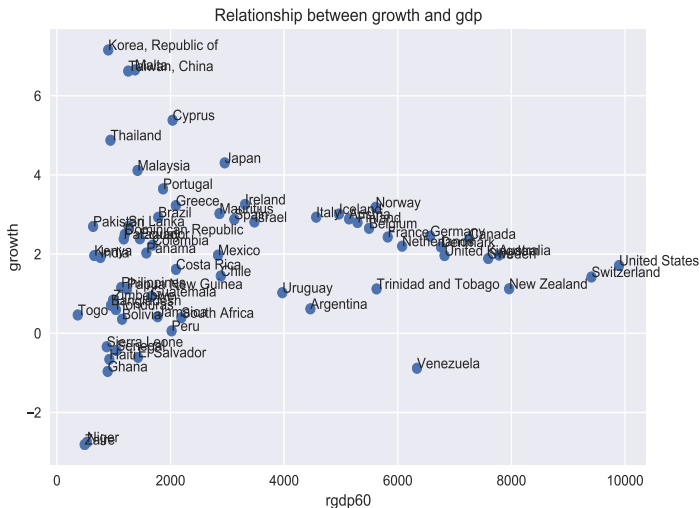
Example: Education and GDP

Relationship between growth and education

Conditional expectation function

- One way to describe relation between two variables is a function,

$$Y = h(X)$$

- Most relationships in data are not deterministic, so look at average relationship,

$$Y = \underbrace{\mathbb{E}[Y|X]}_{\equiv h(X)} + \underbrace{(Y - \mathbb{E}[Y|X])}_{\equiv U}$$

$$= \mathbb{E}[Y|X] + U$$

- Note that $\mathbb{E}[U] = 0$ (by definition of U and iterated expectations)
- $\mathbb{E}[Y|X]$ can be any function, in particular, it need not be linear
- Unrestricted $\mathbb{E}[Y|X]$ hard to work with
    - Hard to estimate
    - Hard to communicate if X a vector (cannot draw graphs)
- Instead use linear regression
    - Easier to estimate and communicate
    - Tight connection to $\mathbb{E}[Y|X]$

Population regression

- The bivariate population regression of Y on X is

$$(\beta_0, \beta_1) = \arg\min_{b_0, b_1} \mathbb{E}[(Y - b_0 - b_1 X)^2]$$

  i.e. β_0 and β_1 are the slope and intercept that minimize the expected square error of $Y - (\beta_0 + \beta_1 X)$

- Calculating β_0 and β_1:
  - First order conditions:

$$
\begin{aligned}
[b_0] : 0 &= \frac{\partial}{\partial b_0} \mathbb{E}[(Y - b_0 - b_1 X)^2] \\
&= \mathbb{E}\left[\frac{\partial}{\partial b_0}(Y - b_0 - b_1 X)^2\right] \\
&= \mathbb{E}\left[-2(Y - \beta_0 - \beta_1 X)\right]
\end{aligned}
\tag{1}
$$

Population regression

and

$$[b_1] : 0 = \frac{\partial}{\partial b_1} \mathbb{E}[(Y - b_0 - b_1 X)^2]$$

$$= \mathbb{E}\left[\frac{\partial}{\partial b_1}(Y - b_0 - b_1 X)^2\right]$$

$$= \mathbb{E}\left[-2(Y - \beta_0 - \beta_1 X)X\right] \tag{2}$$

- (1) rearranged gives $\beta_0 = \mathbb{E}[Y] - \beta_1 \mathbb{E}[X]$
- Substituting into (2)

$$0 = \mathbb{E}\left[X(-Y + \mathbb{E}[Y] - \beta_1 \mathbb{E}[X] + \beta_1 X)\right]$$

$$= \mathbb{E}\left[X(-Y + \mathbb{E}[Y])\right] + \beta_1 \mathbb{E}\left[X(X - \mathbb{E}[X])\right]$$

$$= -\mathbb{C}(X, Y) + \beta_1 \mathbb{V}(X)$$

$$\beta_1 = \frac{\mathbb{C}(X, Y)}{\mathbb{V}(X)}$$

- $\beta_1 = \frac{\mathbb{C}(X,Y)}{\mathbb{V}(X)}$, $\beta_0 = \mathbb{E}[Y] - \beta_1 \mathbb{E}[X]$

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Population regression approximates $\mathbb{E}[Y|X]$

Lemma 1
The population regression is the minimal mean square error linear
approximation to the conditional expectation function, i.e.

$$\underbrace{\arg\min_{b_0, b_1} \mathbb{E}\left[(Y - (b_0 + b_1 X))^2\right]}_{\textit{population regression}} = \arg\min_{b_0, b_1} \underbrace{\mathbb{E}_X\left[(\mathbb{E}[Y|X] - (b_0 + b_1 X))^2\right]}_{\textit{MSE of linear approximation to } \mathbb{E}[Y|X]}$$

Corollary 2
If $\mathbb{E}[Y|X] = c + mX$, then the population regression of Y on X equals $\mathbb{E}[Y|X]$,
i.e. $\beta_0 = c$ and $\beta_1 = m$

Proof

Proof.

- Let b_0^*, b_1^* be minimizers of MSE of approximation to $\mathbb{E}[Y|X]$
- Same steps as in population regression formula gives

$$0 = \mathbb{E}\left[-2(\mathbb{E}[Y|X] - b_0^* - b_1^* X)\right]$$

and

$$0 = \mathbb{E}\left[-2(\mathbb{E}[Y|X] - b_0^* - b_1^* X)X\right]$$

- Rearranging and combining,

$$b_0^* = \mathbb{E}[\mathbb{E}[Y|X]] - b_1^*\mathbb{E}[X] = \mathbb{E}[Y] - b_1^*\mathbb{E}[X]$$

and

$$
\begin{aligned}
0 =& \mathbb{E}\left[X(-\mathbb{E}[Y|X] + \mathbb{E}[Y] + b_1^*\mathbb{E}[X] - b_1^* X)\right] \\
=& \mathbb{E}\left[X(-\mathbb{E}[Y|X] + \mathbb{E}[Y])\right] + b_1^*\mathbb{E}\left[X(X - \mathbb{E}[X])\right] \\
=& -\mathbb{C}(X, Y) + b_1^*\mathbb{V}(X) \\
b_1^* =& \frac{\mathbb{C}(X, Y)}{\mathbb{V}(X)}
\end{aligned}
$$

□

Econometrics 1: Regression
└─ Population regression
  └─ Interpretation

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Regression interpretation

- Regression = best linear approximation to $\mathbb{E}[Y|X]$
- $\beta_0 \approx \mathbb{E}[Y|X=0]$
- $\beta_1 \approx \frac{d}{dx}\mathbb{E}[Y|X] \approx$ change in average Y per unit change in X
- Not necessarily a causal relationship (usually not)
- Always can be viewed as description of data

Econometrics 1: Regression
 └─ **Population regression**
     └─ **Interpretation**

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Regression with binary X

- Suppose X is binary (i.e. can only be 0 or 1)
- We know $\beta_0 + \beta_1 X =$ best linear approximation to $\mathbb{E}[Y|X]$
- X only takes two values,
    - $\beta_0 = \mathbb{E}[Y|X = 0]$
    - $\beta_0 + \beta_1 = \mathbb{E}[Y|X = 1]$

Sample regression

- Have sample of observations: $\{(Y_i, X_i)\}_{i=1}^N$
- The sample regression (or when unambiguous just "regression") of Y on X is

$$(\hat{\beta}_0, \hat{\beta}_1) = \arg\min_{b_0, b_1} \frac{1}{N} \sum_{i=1}^N (Y_i - b_0 - b_1 X_i)^2$$

  i.e. $\hat{\beta}_0$ and $\hat{\beta}_1$ are the slope and intercept that minimize the sum of squared errors, $(Y_i - (\hat{\beta}_0 + \hat{\beta}_1 X_i))^2$

  - Same as population regression but with sample average instead of expectation

- Same calculation as for population regression would show

$$\hat{\beta}_1 = \frac{\widehat{\mathbb{C}}(X, Y)}{\widehat{\mathbb{V}(X)}} = \frac{\frac{1}{N} \sum_{i=1}^N (X_i - \bar{N})(Y_i - \bar{Y})}{\frac{1}{N} \sum_{i=1}^N (X_i - \bar{X})^2}$$

  and

$$\hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{X}$$

Sample regression

- Since $\hat{\beta}_1$ and $\hat{\beta}_0$ come from minimizing a sum of squares, they are called the ordinary least squares estimates, or OLS for short.
- The formulas for $\hat{\beta}_1$ and $\hat{\beta}_0$ come from the first order conditions.
- These estimators minimize the sum of squared differences between the regression line and the observed Y_i,

$$(\hat{\beta}_0, \hat{\beta}_1) = \underset{b_0, b_1}{\arg\min} \frac{1}{N} \sum_{i=1}^{N} (Y_i - b_0 - b_1 X_i)^2.$$

The first order condition for $\hat{\beta}_0$ is:

$$0 = \frac{1}{N} \sum_{i=1}^{N} 2(Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i)$$

Sample regression

which can be rearranged to get

$$\hat{\beta}_0 = \frac{1}{N} \left(\sum_{i=1}^{N} Y_i - \hat{\beta}_1 X_i \right)$$

$$\hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{N}.$$

The first order condition for $\hat{\beta}_1$ is:

$$0 = \frac{1}{N} \sum_{i=1}^{N} 2X_i (Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i).$$

Substituting in the previous expression for $\hat{\beta}_0$ gives

$$0 = \frac{1}{N} \sum_{i=1}^{N} 2X_i (Y_i - \bar{Y} + \hat{\beta}_1 \bar{X} - \hat{\beta}_1 X_i).$$

Sample regression

Rearranging to solve for $\hat{\beta}_1$:

$$\hat{\beta}_1 \sum_{i=1}^{N} X_i(X_i - \bar{X}) = \sum_{i=1}^{N} X_i(Y_i - \bar{Y})$$

$$\hat{\beta}_1 = \frac{\sum_{i=1}^{N} X_i(Y_i - \bar{Y})}{X_i(X_i - \bar{X})} = \frac{\sum_{i=1}^{N}(X_i - \bar{X})(Y_i - \bar{Y})}{(X_i - \bar{X})^2}.$$

Sample regression

- Sample regression is an estimator for the population regression
- Given an estimator we should ask:
  - Unbiased?
  - Variance?
  - Consistent?
  - Asymptotically normal?
- We will address these questions in the next week or two

True linear model approach to regression

- Most authors (like Wooldridge) introduce regression by starting with a linear model for Y:

$$Y = \alpha_0 + \alpha_1 X + \underbrace{U}_{\text{unobserved}}$$

  with $\mathbb{E}[UX] = 0$
    - Perspective: model = true description of data generating process
- Implications:
    - Population regression coefficients = model coefficients, i.e. $\beta_0 = \alpha_0$ and $\beta_1 = \alpha_1$
    - Conditional expectation function is linear

$$\mathbb{E}[Y|X] = \alpha_0 + \alpha_1 X$$

    - $\beta_1 = \alpha_1$ has causal interpretation as long as we believe $\mathbb{E}[UX] = 0$
    - Easier to discuss causality
    - Easier to derive statistical properties

Problems with true linear models

- Usually do not believe models are linear, e.g. no economic theory that says the following should be linear:
    1. $\log(wage_i) = \beta_0 + \beta_1(educ_i) + U_i$
    2. $\log q_t = \beta_0 + \beta_1 \log p_t + U_t$

- Usually do not believe error terms are uncorrelated with covariates, e.g.
    1. Need $\mathbb{E}[U_i educ_i] = 0$, but U_i probably includes IQ, propensity to work hard, etc, which should be correlated with education
    2. Is it supposed to be demand or supply? Either case, changes in q_t from U_t generally also change equilibrium p_t, so $\mathbb{E}[\log p_t U_t] \neq 0$

- Viewing regression as best linear approximation to $\mathbb{E}[Y|X]$ makes it clear what regression tells you about the data even if the true model is not linear and does not have $\mathbb{E}[XU] = 0$

Part II

Properties of regression

Fitted values and residuals

- These algebraic identities about fitted values and residuals are things that we will use repeatedly later.
- I would not recommend spending time trying to memorize these.
- The important ones will come up repeatedly and you will remember them without any special effort.
- The first time we use these identities, we will go through how to get them again. We may even go through them yet again the second and third time we use them.
- Eventually we will use some of these identities so often that you will either be able to quickly derive them or just remember them.
- Fitted values:

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i$$

- Residuals:

$$\hat{U}_i = Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i = Y_i - \hat{Y}_i$$

$$Y_i = \hat{Y}_i + \hat{U}_i$$

Fitted values and residuals

- Sample mean of residuals $= 0$
    - First order condition for $\hat{\beta}_0$,

$$0 = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i)$$

$$0 = \frac{1}{N}\sum_{i=1}^{N}\hat{U}_i$$

- Sample covariance of X and $\hat{U} = 0$
    - First order condition for $\hat{\beta}_1$,

$$0 = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i)X_i$$

$$0 = \frac{1}{N}\sum_{i=1}^{N}\hat{U}_i X_i$$

Fitted values and residuals

- Sample mean of $\hat{Y}_i = \bar{Y} = \hat{\beta}_0 + \hat{\beta}_1\bar{X}$

$$\frac{1}{N}\sum_{i=1}^{N}Y_i = \frac{1}{N}\sum_{i=1}^{N}\hat{Y}_i + \hat{U}_i$$

$$= \frac{1}{N}\sum_{i=1}^{N}\hat{Y}_i$$

$$= \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_0 + \hat{\beta}_1 X_i$$

$$= \hat{\beta}_0 + \hat{\beta}_1\bar{X}$$

Fitted values and residuals

- Sample covariance of Y and $\hat{U}$ = sample variance of $\hat{U}$:

$$
\begin{aligned}
\frac{1}{N}\sum_{i=1}^{N}Y_i(\hat{U}_i - \bar{\hat{U}}) &= \frac{1}{N}\sum_{i=1}^{N}Y_i\hat{U}_i \\
&= \frac{1}{N}\sum_{i=1}^{N}(\hat{\beta}_0 + \hat{\beta}_1 X_i + \hat{U}_i)\hat{U}_i \\
&= \hat{\beta}_0\frac{1}{N}\sum_{i=1}^{N}\hat{U}_i + \beta_1\frac{1}{N}\sum_{i=1}^{N}X_i\hat{U}_i + \frac{1}{N}\sum_{i=1}^{N}\hat{U}_i^2 \\
&= \frac{1}{N}\sum_{i=1}^{N}\hat{U}_i^2
\end{aligned}
$$

R^2

- Decompose Y_i

$$Y_i = \hat{Y}_i + \hat{U}_i$$

- Total sum of squares = explained sum of squares + sum of squared residuals

$$\underbrace{\frac{1}{N}\sum_{i=1}^{N}(Y_i - \bar{Y})^2}_{SST} = \underbrace{\frac{1}{N}\sum_{i=1}^{N}(\hat{Y}_i - \bar{Y})^2}_{SSE} + \underbrace{\frac{1}{N}\sum_{i=1}^{N}\hat{U}_i^2}_{SSR}$$

- R-squared: fraction of sample variation in Y that is explained by X

$$R^2 = \frac{SSE}{SST} = 1 - \frac{SSR}{SST} = o\widehat{\text{Corr}}(Y, \hat{Y})$$

  - $0 \leq R^2 \leq 1$
  - If all data on regression line, then $R^2 = 1$
  - Magnitude of R^2 does not have direct bearing on economic importance of a regression

Econometrics 1: Regression
└─ Statistical properties
   └─ Unbiased

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Unbiased

- $\mathbb{E}[\hat{\beta}] = ?$
- Assume:

SLR.1 (linear model) $Y_i = \beta_0 + \beta_1 X_i + U_i$

SLR.2 (independence) $\{(X_i, Y_i)\}_{i=1}^{N}$ is independent random sample

SLR.3 (rank condition) $\widehat{\mathbb{V}}(X) > 0$

SLR.4 (exogeneity) $\mathbb{E}[U|X] = 0$

- Then, $\mathbb{E}[\hat{\beta}_1] = \beta_1$ and $\mathbb{E}[\hat{\beta}_0] = \beta_0$
- It is more important to understand the meaning of these four assumptions (discussed below) than the proof that regression is unbiased.

Regression is unbiased.
We need to calculate $\mathbb{E}[\hat{\beta}]$. First, substitute in the formula for $\hat{\beta}$.

$$\mathbb{E}[\hat{\beta}_1] = \mathbb{E}\left[\frac{\sum_{i=1}^{N}(X_i - \bar{X})Y_i}{\sum_{i=1}^{N}(X_i - \bar{X})X}\right]$$

Next, substitute in the model for Y_i, $Y_i = \beta_0 + \beta_1 X_i + U_i$,

$$\mathbb{E}[\hat{\beta}_1] = \mathbb{E}\left[\frac{\sum_{i=1}^{N}(X_i - \bar{X})(\beta_0 + \beta_1 X_i + U_i)}{\sum_{i=1}^{N}(X_i - \bar{X})X}\right]$$

rearrange

$$= \mathbb{E}\left[\overbrace{\frac{\sum_{i=1}^{N}X_i - \bar{X}}{\sum_{i=1}^{N}(X_i - \bar{X})X}}^{=0}\beta_0 + \overbrace{\left(\frac{\sum_{i=1}^{N}(X_i - \bar{X})X_i}{\sum_{i=1}^{N}(X_i - \bar{X})X}\right)}^{=1}\beta_1 + \frac{\sum_{i=1}^{N}(X_i - \bar{X})U_i}{\sum_{i=1}^{N}(X_i - \bar{X})X}\right]$$

use linearity of expectation

$$= \beta_1 + \mathbb{E}\left[\frac{\sum_{i=1}^{N}(X_i - \bar{x})U_i}{\sum_{i=1}^{N}(X_i - \bar{X})X}\right]$$

use iterated expectations

$$= \beta_1 + \mathbb{E}_X\left[\mathbb{E}_{U|X}\left[\frac{\sum_{i=1}^{N}(X_i - \bar{X})U_i}{\sum_{i=1}^{N}(X_i - \bar{X})X}\bigg| X_1, X_2, ..., X_n\right]\right]$$

conditional on $X_1, ..., X_n$, X_i is constant

$$= \beta_1 + \mathbb{E}_X\left[\frac{\sum_{i=1}^{N}(X_i - \bar{X})\mathbb{E}[U_i|X_1, ..., X_n]}{\sum_{i=1}^{N}(X_i - \bar{X})X}\right]$$

independent observations implies $\mathbb{E}[U_i|X_1, ..., X_n] = \mathbb{E}[U_i|X_i]$

$$= \beta_1 + \mathbb{E}_X\left[\frac{\sum_{i=1}^{N}(X_i - \bar{X})\mathbb{E}[U_i|X_i]}{\sum_{i=1}^{N}(X_i - \bar{X})X}\right]$$

exogeneity assumption says that $\mathbb{E}[U_i|X_i] = 0$.
$$= \beta_1$$

□

Econometrics 1: Regression
└─**Statistical properties**
   └─**Unbiased**

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- Note that the first few steps of the above proof showed that

$$\hat{\beta}_1 = \beta_1 + \frac{\sum_{i=1}^{N}(X_i - \bar{X})U_i}{\sum_{i=1}^{N}(X_i - \bar{X})^2}.$$

- This is a very useful expression that can be used as a starting point for calculating the variance of $\hat{\beta}_1$, and thinking about what happens if exogeneity fails and $\mathbb{E}[U|X] \neq 0$.

Econometrics 1: Regression
└─ **Statistical properties**
　　└─ **Variance**

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Variance

- $\mathbb{V}(\hat{\beta})$?
- Assume SLR.1-4 and
  SLR.5 (homoskedasticity) $\mathbb{V}(U|X) = \sigma^2$
- Then,

$$\mathbb{V}(\hat{\beta}_1|\{X_i\}_{i=1}^n) = \frac{\sigma^2}{\sum_{i=1}^n (X_i - \bar{X})^2}$$

and

$$\mathbb{V}(\hat{\beta}_0|\{X_i\}_{i=1}^N) = \frac{\sigma^2 \frac{1}{N}\sum_{i=1}^N X_i^2}{\sum_{i=1}^N (X_i - \bar{X})^2}$$

Econometrics 1: Regression
└─ Statistical properties
  └─ Variance

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Variance

- As in the proof that regression is unbiased,

$$\hat{\beta}_1 = \beta_1 + \frac{\sum_{i=1}^{N}(X_i - \bar{X})U_i}{\sum_{i=1}^{N}(X_i - \bar{X})^2}.$$

- We now want to take the variance of this expression.
- Before doing so, it will be useful to review some properties of the variance of a sum of random variables.

Lemma 3

Let a, b, and c be constants, and Z and W be random variables. Then,

$$\mathbb{V}(a + bZ + cW) = b^2\mathbb{V}(Z) + c^2\mathbb{V}(W) + 2bc\mathbb{C}(Z, W).$$

Econometrics 1: Regression
└─Statistical properties
  └─Variance

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- We can prove this using the definition of variance.

Proof.

$$
\begin{aligned}
\mathbb{V}(a + bZ + cW) &= \mathbb{E}\left[(a + bZ + cW - \mathbb{E}[a + bZ + cW])^2\right] \\
&= \mathbb{E}\left[(a + bZ + cW - a - b\mathbb{E}[Z] - c\mathbb{E}[W])^2\right] \\
&= \mathbb{E}\left[(b(Z - \mathbb{E}[Z]) + c(W - \mathbb{E}[W]))^2\right] \\
&= \mathbb{E}\left[b^2(Z - \mathbb{E}[Z])^2 + 2bc(Z - \mathbb{E}[Z])(W - \mathbb{E}[W])\right. \\
&\quad \left. + c^2(W - \mathbb{E}[W])^2\right] \\
&= b^2\mathbb{E}\left[(Z - \mathbb{E}[Z])^2\right] + 2bc\mathbb{E}\left[(Z - \mathbb{E}[Z])(W - \mathbb{E}[W])\right] \\
&\quad + c^2\mathbb{E}\left[(W - \mathbb{E}[W])^2\right] \\
&= b^2\mathbb{V}(Z) + c^2\mathbb{V}(W) + 2bc\mathbb{C}(Z, W)
\end{aligned}
$$

$\square$

Econometrics 1: Regression
  └─**Statistical properties**
      └─**Variance**

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- Generalizing the above to the sum of more than two random variables, we have

Corollary 4

Let $a_1, ..., a_n$ be constants, and $Z_1, ..., Z_n$ be random variables, then,

$$\mathbb{V}\left(\sum_{i=1}^{N} a_i Z_i\right) = \sum_{i=1}^{N} \sum_{j=1}^{N} a_i a_j \mathbb{C}(Z_i, Z_j)$$

Furthermore, if Z_i and Z_j are independent (or just uncorrelated) for $i \neq j$, then

$$\mathbb{V}\left(\sum_{i=1}^{N} a_i Z_i\right) = \sum_{i=1}^{N} a_i^2 \mathbb{V}(Z_i)$$

Econometrics 1: Regression
└─ Statistical properties
  └─ Variance

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- We can apply this corollary to

$$
\begin{aligned}
\mathbb{V}(\hat{\beta}_1|x) &= \mathbb{V}\left(\beta_1 + \frac{\sum_{i=1}^{N}(X_i - \bar{X})U_i}{\sum_{i=1}^{N}(X_i - \bar{X})^2}\,\middle|\, x\right) \\
&= \mathbb{V}\left(\sum_{i=1}^{N}\underbrace{\frac{X_i - \bar{X}}{\sum_{i=1}^{N}(X_i - \bar{X})^2}}_{a_i}\underbrace{U_i}_{Z_i}\,\middle|\, x\right) \quad \text{using the corollary} \\
&= \sum_{i=1}^{N}\sum_{j=1}^{N}\frac{X_i - \bar{X}}{\sum_{i=1}^{N}(X_i - \bar{X})^2}\frac{x_j - \bar{X}}{\sum_{i=1}^{N}(X_i - \bar{X})^2}\mathbb{C}(U_i, U_j|X) \quad \text{independence} \\
&= \sum_{i=1}^{N}\left(\frac{X_i - \bar{X}}{\sum_{i=1}^{N}X_i - \bar{X}}\right)^2\mathbb{V}(U_i|X) \quad \text{homoskedasticity} \\
&= \sum_{i=1}^{N}\frac{(X_i - \bar{X})^2}{\left(\sum_{i=1}^{N}(X_i - \bar{X})^2\right)^2}\sigma_U^2 \\
&= \frac{\sigma_U^2}{\sum_{i=1}^{N}(X_i - \bar{X})^2}.
\end{aligned}
$$

Econometrics 1: Regression
└─ Statistical properties
  └─ Distribution

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Distribution with normal errors

- Assume SLR.1-SLR.5 and
  SLR.6 (normality) $U_i|X_i \sim N(0, \sigma^2)$
- Then $Y|X \sim N(\beta_0 + \beta_1 X, \sigma^2)$, and

$$\hat{\beta}_1 | \{X_i\}_{i=1}^N \sim N\left(\beta_1, \frac{\sigma^2}{\sum_{i=1}^N (X_i - \bar{X})^2}\right)$$

- Even without assuming normality, the central limit theorem implies $\hat{\beta}$ is asymptotically normal (details in a later lecture)

Econometrics 1: Regression
└─ Statistical properties
  └─ Distribution

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Distribution with normal errors

- An important property of normal random variables is that if Z and W are independent, and $Z \sim N(\mu_z, \sigma_z^2)$ and $W \sim N(\mu_w, \sigma_w^2)$, then

$$a + bZ + cW \sim N(a + b\mu_z + c\mu_w, b^2\sigma_z^2 + c^2\sigma_w^2).$$

- If we assume that U_i is normally distributed conditional on X, then since $\hat{\beta}_1$ is just a sum of the U_i,[1] $\hat{\beta}_1$ will also be normally distributed.

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[1]Specifically, $\hat{\beta}_1 = \beta_1 + \frac{\sum_{i=1}^{N}(x_i - \bar{x})U_i}{\sum_{i=1}^{N}(x_i - \bar{x})^2}$.

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Summary

- Simple linear regression model assumptions:

SLR.1 (linear model) $Y_i = \beta_0 + \beta_1 X_i + U_i$

SLR.2 (independence) $\{(X_i, Y_i)\}_{i=1}^n$ is independent random sample

SLR.3 (rank condition) $\widehat{\mathbb{V}}(X) > 0$

SLR.4 (exogeneity) $\mathbb{E}[U|X] = 0$

SLR.5 (homoskedasticity) $\mathbb{V}(U|X) = \sigma^2$

SLR.6 (normality) $U_i|X_i \sim N(0, \sigma^2)$

- $\hat{\beta}$ unbiased if SLR.1-SLR.4

- If also SLR.5, then $\mathbb{V}(\hat{\beta}_1|\{X_i\}_{i=1}^N) = \frac{\sigma^2}{\sum_{i=1}^N (X_i - \bar{X})^2}$

- If also SLR.6, then $\hat{\beta}_1|\{X_i\}_{i=1}^N \sim N\left(\beta_1, \frac{\sigma^2}{\sum_{i=1}^N (X_i - \bar{X})^2}\right)$

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Discussion of assumptions

SLR.1 Having a linear model makes it easier to state the other assumptions, but
we could instead start by saying let $\beta_1 = \frac{\mathbb{C}(X,Y)}{\mathbb{V}(X)}$ and $\beta_0 = \mathbb{E}[Y] - \beta_1 \mathbb{E}[X]$
be the population regression coefficients and define $U_i = Y_i - \beta_0 - \beta_1 X_i$

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Discussion of assumptions

- To say whether an estimator is unbiased, we first have to define what parameter we want to estimate.
- Assuming that there is a linear model defines the parameter we want to estimate.
- This linear model could be population regression, in which case, $\beta_1 = \frac{\mathbb{C}(X,Y)}{\mathbb{V}(X)}$, and by construction we must have $\mathbb{E}[XU] = 0$.
- However, the linear model may also be motivated by economic theory.
- For example, consider a Cobb-Douglass production function with only one input, labor,

$$Y = AL^{\alpha},$$

where Y is output, L is labor, and A is productivity.

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- If we take logs, then

$$\log Y = \log A + \alpha \log L.$$

If we rearrange slightly, we get something that looks just like a linear regression model,

$$\underbrace{\log Y_i}_{Y_i} = \underbrace{\mathbb{E}[\log A]}_{\beta_0} + \underbrace{\alpha}_{\beta_1} \underbrace{\log L_i}_{X_i} + \underbrace{(\log A_i - \mathbb{E}[\log A])}_{U_i}.$$

- If this is the model we want to estimate, then U_i is not the error term in the population regression.
- Instead U_i is the difference between the log productivity of firm i and average log productivity.
- It is unlikely that this U_i would be uncorrelated with $\log L_i$.
- More productive firms generally choose to use more inputs, so we should suspect that U_i and $\log L_i$ are positively correlated.

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Discussion of assumptions

SLR.2 Independent observations is a good assumption for data from a simple
random sample

- Common situations where it fails in economics are when we have a time
  series of observations,
- e.g. $\{(X_t, Y_t)\}_{t=1}^N$ could be unemployment and GDP of Canada for many
  different years; and clustering,
- e.g. the data could be students test scores and hours studying and our
  sample consists of randomly chosen courses or schools—students in the
  same course would not be independent, but across different courses they
  might be.
- Still have $\mathbb{E}[\hat{\beta}_1] = \beta_1$ with non-independent observations as long as
  $\mathbb{E}[Un_i|X_1, ..., X_N] = 0$
- The variance of $\hat{\beta}_1$ will change with non-independent observations

- Independence says that knowing the values of x_1 and y_1 tells you nothing
  about the distribution of x_2 and y_2 (or any other observation).

- When we have cross-sectional data, this assumption usually makes sense.

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- In economics, we sometimes deal with time-series data, where (x_1, y_1) would be the observation of something at time 1 and (x_2, y_2) is the observation that same thing at time 2. In this case, independence is unlikely to hold.

- Another common situation is panel data, where we observe a sample of individuals over time, so (x_{it}, y_{it}) would be what we observe from individual i at time t.

- Again, it is likely that these observations would be independent over time.

- Later in the course, we will talk about how to deal with non-independent observations.

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Discussion of assumptions

SLR.3 If $\widehat{\mathbb{V}}(X) = 0$, then $\hat{\beta}_1$ involves dividing by 0

- If there is no variation in X, then we cannot see how Y is related to X

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Discussion of assumptions

SLR.4 To think about mean independence of U from X we should have a model motivating the regression

- If the model we want is just a population regression, then automatically $\mathbb{E}[UX] = 0$, and $\mathbb{E}[U|X] = 0$ if the conditional expectation function is linear; if conditional expectation nonlinear maybe still a useful approximation
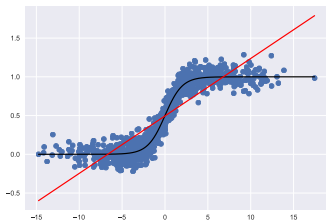
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Discussion of assumptions

SLR.4 To think about mean independence of U from X we should have a model
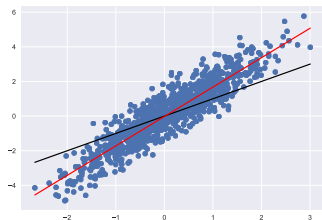motivating the regression

- If the model we want is anything
  else, then maybe $\mathbb{E}[UX] \neq 0$
  (and $\mathbb{E}[U|X] \neq 0$), e.g.
  - Demand curve

    $$P_i = \beta_0 + \beta_1 Q_i + U_i$$

    U_i = everything that affects
    price other than quantity. Q_i
    determined in equilibrium
    implies $\mathbb{E}[U_i|Q_i] \neq 0$
  - $\mathbb{E}[\hat{\beta}_1] \neq \beta_1$ and $\hat{\beta}_1$ does not
    tell us what we want

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Discussion of assumptions

- Exogeneity is the most important assumption underlying regression.
- In fact, estimating any economic model using any method will involve some kind of exogeneity assumption.
- By this, we mean that every estimation method requires assuming some error term is either completely independent of some observable ($F_{U|X}(u|x) = F_U(u)$), mean independent of some observable ($\mathbb{E}[U|X] = 0$), or at least uncorrelated with an observable ($\mathbb{E}[UX] = 0$).
- Much of what separates good empirical work in economics from bad is how plausible are the exogeneity assumptions.
- Often, economic theory can help us decide whether or not an exogeneity assumption is plausible. Consider the production function example from earlier,

$$\underbrace{\log Y_i}_{Y_i} = \underbrace{\mathbb{E}[\log A]}_{\beta_0} + \underbrace{\alpha}_{\beta_1} \underbrace{\log L_i}_{X_i} + \underbrace{(\log A_i - \mathbb{E}[\log A])}_{U_i}.$$

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Discussion of assumptions

- To think about whether mean independence of the error term, $\mathbb{E}[(\underbrace{\log A - \mathbb{E}[\log A]}) \mid \log L] = 0$, makes sense in this model, we should

  think about how L is determined.

- The firm chooses how much labor to use. Suppose the firm faces output price P and wage W.

- If the firm chooses L knowing its productivity, then the firm solves,

$$\max_L PAL^{\alpha} - WL$$

The first order condition is

$$PA\alpha L^{\alpha-1} - W = 0.$$

If we solve for A, we get

$$A = \frac{W}{P\alpha} L^{1-\alpha}$$

$$\log A = \log\left(\frac{W}{P\alpha}\right) + (1-\alpha)\log L$$

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so

$$\mathbb{E}[\log A \mid \log L] = (1 - \alpha) \log L + \mathbb{E}\left[\log\left(\frac{W}{p\alpha} \right) \middle| \log L \right]$$

- This will not be a constant unless $\alpha = 1$ and $\frac{W}{p}$ is mean independent of $\log L$.

- Both of these are unlikely to hold.

- Unless $\mathbb{E}[\log A \mid \log L]$ is constant, $\mathbb{E}[\underbrace{(\log A - \mathbb{E}[\log A])}{} \mid \log L] \neq 0$.

- Therefore, exogeneity is not a good assumption in this model, and regression will not give an unbiased estimate of the production function.
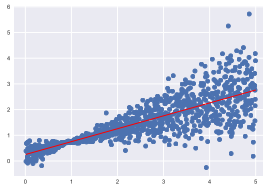
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Discussion of assumptions

SLR.5 Homoskedasticity: variance of U does not depend on X
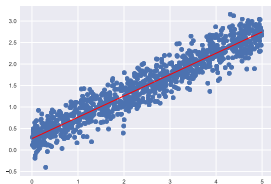
<div align="center">Homoskedastic   Heteroskedastic</div>

- Heteroskedasticity is when $\mathbb{V}(U|X)$ varies with X
- If there is heteroskedasticity, the variance of $\hat{\beta}_1$ is different, but we can fix it
- "robust standard errors" / "heteroscedasticity-consistent (HC) standard errors" / "Eicker–Huber–White standard errors"

- Homoskedasticity is a strong assumption that is usually not very plausible.
- Therefore, in practice economists almost always calculate heteroscedasticity-robust standard errors.

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## Discussion of assumptions

SLR.6 If $U_i|X_i \sim N$, then $\hat{\beta}_1 \sim N$
- What if U_i not normally distributed?
- We will see that $\hat{\beta}_1$ still asymptotically normal

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Example: convergence in growth

- Data on average growth rate from 1960-1995 for 65 countries along with GDP in 1960, average years of schooling in 1960, and other variables
- From http: //wps.aw.com/aw_stock_ie_2/50/13016/3332253.cw/index.html, originally used in Beck, Levine, and Loayza (2000)
- Question: has there been in convergence, i.e. did poorer countries in 1960 grow faster and catch-up?

GDP in 1960 and growth: $\hat{\beta}_0 = 1.7958$, $\hat{\beta}_1 = 4.735e - 05$.

OLS fitted values
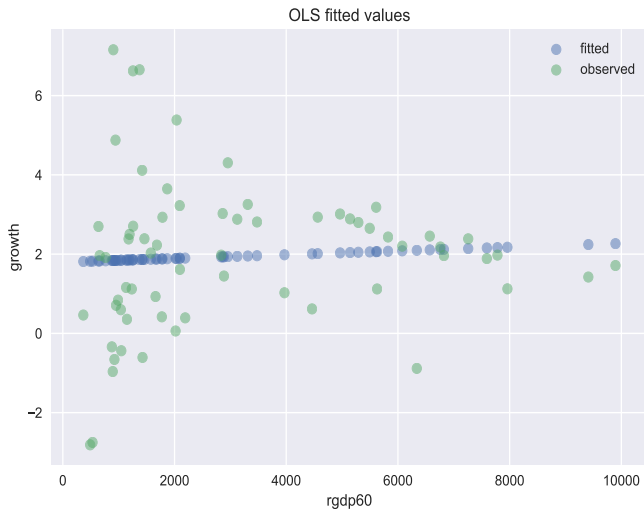
Years of schooling in 1960 and growth: $\hat{\beta}_0 = 0.9583$, $\hat{\beta}_1 = 0.2470$.

OLS fitted values
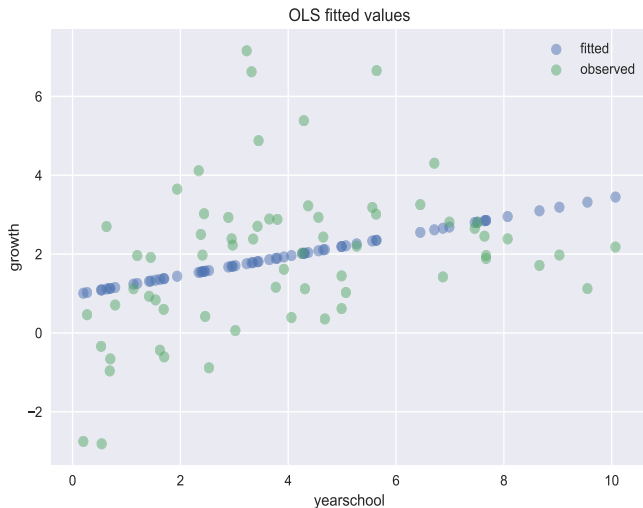
Education and earnings(Card (1993)), : $\hat{\beta}_0 = 5.5709$, $\hat{\beta}_1 = 0.0521$.

OLS fitted values

References

Abbring, Jaap. 2001. "An Introduction to Econometrics: Lecture notes." URL http://jabbring.home.xs4all.nl/courses/b44old/lect210.pdf.

Angrist, J.D. and J.S. Pischke. 2009. *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Angrist, Joshua D and Jörn-Steffen Pischke. 2014. *Mastering 'Metrics: The Path from Cause to Effect*. Princeton University Press.

Baltagi, BH. 2002. *Econometrics*. Springer, New York. URL http://gw2jh3xr2c.search.serialssolutions.com/?sid=sersol&SS_jc=TC0001086635&title=Econometrics.

Beck, T., R. Levine, and N. Loayza. 2000. "Finance and the Sources of Growth." *Journal of financial economics* 58 (1):261–300. URL http://www.sciencedirect.com/science/article/pii/S0304405X00000726.

Bierens, Herman J. 2012. "The Two-Variable Linear Regression Model." URL http://personal.psu.edu/hxb11/LINREG2.PDF.

References

Card, David. 1993. "Using geographic variation in college proximity to estimate the return to schooling." Tech. rep., National Bureau of Economic Research. URL http://www.nber.org/papers/w4483.

Diez, David M, Christopher D Barr, and Mine Cetinkaya-Rundel. 2012. *OpenIntro Statistics*. OpenIntro. URL http://www.openintro.org/stat/textbook.php.

Stock, J.H. and M.W. Watson. 2009. *Introduction to Econometrics, 2/E*. Addison-Wesley.

Wooldridge, J.M. 2013. *Introductory econometrics: A modern approach*. South-Western.