Dealing with Endogeneity: Instrumental Variable

AECN 396/896-002

Before we start

Learning objectives

Understand how instrumental variable (IV) estimation works.

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Endogeneity

Endogeneity

$E[u|x_k] \neq 0$ (the error term is not correlated with any of the independent variables)

Endogenous independent variable

If the error term is, for whatever reason, correlated with the independent variable x_k, then we say that x_k is an endogenous independent variable.

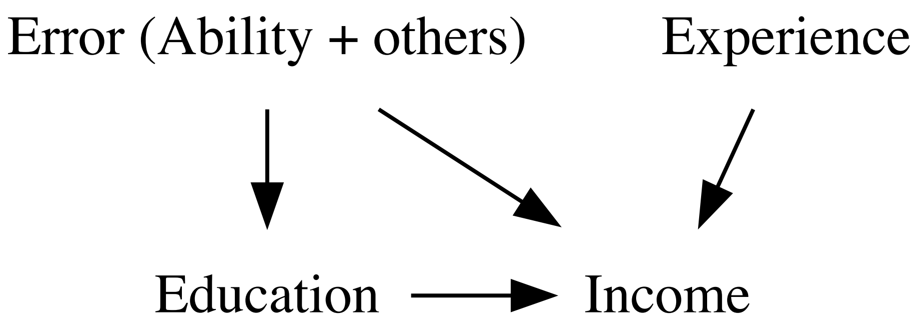
- Omitted variable
- Selection
- Reverse causality
- Measurement error

Instrumental Variable (IV) Approach

Causal Diagram

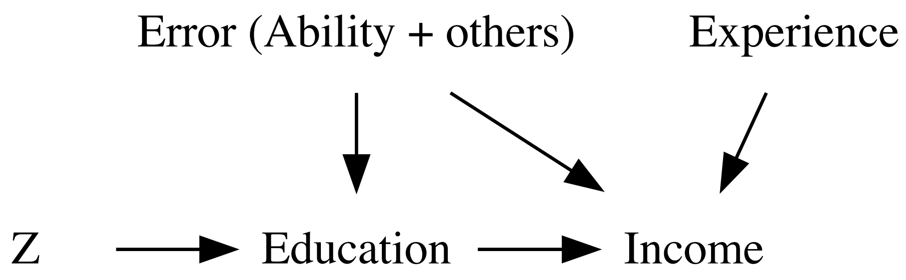
You want to estimate the causal impact of education on income.

- Variable of interest: Education
- Dependent variable: Income



Rough Idea of IV Approach

Find a variable like Z in the diagram below:



- Z does NOT affect income directly
- Z is correlated with the variable of interest (education)
  - does not matter which causes which (associattion is enough)
- Z is NOT correlated with any of the unobservable variables in the error term (including ability) that is making the vairable of interest (education) endogeneous.
  - Z does not affect ability
  - abiliyt does not affect Z

The Model

$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + u$

- x_1 is endogenous: $E[u|x_1] \neq 0$ (or $Cov(u, x_1) \neq 0$)
- x_2 is exogenous: $E[u|x_1] = 0$ (or $Cov(u, x_1) = 0$)

Idea (very loosely put)

Bring in variable(s) (Instrumental variable(s)) that does NOT belong to the model, but IS related with the endogenous variable,

- Using the instrumental variable(s) (which we denote by Z), make the endogenous variable exogenous, which we call instrumented variable(s)
- Use the variation in the instrumented variable instead of the original endogenous variable to estimate the impact of the original variable

IV estimation procedure

Step 1

Using the instrumental variables, make the endogenous variable exogenous, which we call instrumented variable

Step 1: mathematically

- Regress the endogenous variable (x_1) on the instrumental variable(s) $(Z = \{z_1, z_2\}$, two instruments here) and all the other exogenous variables $(x_2$ here)

$$x_1 = \alpha_0 + \sigma_2 x_2 + \alpha_1 z_1 + \alpha_2 z_2 + v$$

- obtain the predicted value of x from the regression

$$\hat{x}_1 = \hat{\alpha}_0 + \hat{\sigma}_2 x_2 + \hat{\alpha}_1 z_1 + \hat{\alpha}_2 z_2$$

IV estimation procedure

Step 2

use the variation in the instrumented variable instead of the original endogenous variable to estimate the impact of the original variable

Step 2: Mathematically

Regress the dependent variable (y) on the instrumented variable $(\hat{x}_1)$,

$$y = \beta_0 + \beta_1 \hat{x_1} + \beta_2 x_2 + \varepsilon$$

to estimate the coefficient on x in the original model

Example

Model of interest

$log(wage) = \beta_0 + \beta_1 educ + \beta_2 exper + (\beta_3 ability + v)$

- Regress $log(wage)$ on $educ$ and $exper$ $(ability$ not included because you do not observe it)
- $(\beta_3 ability + v)$ is the error term
- $educ$ is considered endogenous (correlated with $ability$)
- $exper$ is considered exogenous (not correlated with $ability$)

Instruments (Z)

Suppose you selected the following variables as instruments:

- IQ test score (IQ)
- number of siblings $(sibs)$

Step 1:

Regress $educ$ on $exper$, IQ, and $sibs$:

$$educ = \alpha_0 + \alpha_1 exper + \alpha_2 IQ + \alpha_3 sibs + u$$

Use the coefficient estimates on α_0, α_1, α_2, and α_3 to predict $educ$ as a function of $exper$, IQ, and $sibs$.

$$\hat{educ} = \hat{\alpha}_0 + \hat{\alpha}_1 exper + \hat{\alpha}_2 IQ + \hat{\alpha}_3 sibs$$

```
library(wooldridge)
data("wage2")

#* regress educ on exper, IQ, and sibs
first_reg <- feols(educ ~ exper + IQ + sibs, data = wage2)

#* predict educ as a function of exper, IQ, and sibs
wage2 <- mutate(wage2, educ_hat = first_reg$fitted.values)

#* seed the predicted values
wage2 %>%
  relocate(educ_hat) %>%
  head()
```

```
##    educ_hat wage hours  IQ KWW educ exper tenure age married bl
## 1 13.26398  769    40  93  35   12    11      2  31       1
## 2 14.80686  808    50 119  41   18    11     16  37       1
## 3 14.15410  825    40 108  46   14    11      9  33       1
## 4 12.79569  650    40  96  32   12    13      7  32       1
## 5 10.73631  562    40  74  27   11    14      5  34       1
## 6 14.09006 1400    40 116  43   16    14      2  35       1
```

Step 2:

Use $\hat{educ}$ in place of $educ$ to estimate the model of interest:

$$log(wage) = \beta_0 + \beta_1 \hat{educ} + \beta_2 exper + u$$

```
#* regression with educ_hat in place of educ
second_reg <- feols(wage ~ educ_hat + exper, data = wage2)

#* see the results
second_reg
```

```
## OLS estimation, Dep. Var.: wage
## Observations: 935
## Standard-errors: IID
##                Estimate Std. Error  t value   Pr(>|t|)
## (Intercept) -1269.7880  214.12821 -5.93004 4.2632e-09 ***
## educ_hat      138.1051   13.10586 10.53766  < 2.2e-16 ***
## exper          31.7955    4.14489  7.67101 4.2899e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 382.0   Adj. R2: 0.104547
```

When does IV work?

Just like OLS needs to satisy some conditions for it to consistently estimate the coefficients, IV approach needs to satisy some conditions for it to work.

Estimation Procedure

- Step 1: $\hat{x}_1 = \hat{\alpha}_0 + \hat{\sigma}_2 x_2 + \hat{\alpha}_1 z_1 + \hat{\alpha}_2 z_2$
- Step 2: $y = \beta_0 + \beta_1 \hat{x_1} + \beta_2 x_2 + \varepsilon$

Important question

What are the conditions under which IV estimation is consistent?

The instruments (Z) need to satisfy two conditions, which we will discuss.

Condition 1

Estimation Procedure

- Step 1: $\hat{x}_1 = \hat{\alpha}_0 + \hat{\sigma}_2 x_2 + \hat{\alpha}_1 z_1 + \hat{\alpha}_2 z_2$
- Step 2: $y = \beta_0 + \beta_1 \hat{x_1} + \beta_2 x_2 + \varepsilon$

Question

What happens if Z have no power to explain x_1 $(\alpha_1 = 0$ and $\alpha_2 = 0)$?

Answer

- $\hat{x}_1 = \hat{\alpha}_0 + \hat{\sigma}^2 x_2$
- $\hat{\beta}_1$?

That is, $\hat{x_1}$ has no information beyond the information x_2 possesses.

Condition 1

The instrument(s) Z have jointly significant explanatory power on the endogenous variable x_1 after you control for all the other exogenous variables (here x_2)

Condition 2

Model of interest

$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + u$

Estimation Procedure

- Step 1: $\hat{x}_1 = \hat{\alpha}_0 + \hat{\sigma}_2 x_2 + \hat{\alpha}_1 z_1 + \hat{\alpha}_2 z_2$
- Step 2: $y = \beta_0 + \beta_1 \hat{x_1} + \beta_2 x_2 + \varepsilon$

Remember you can break x_1 into the predicted part and the residuals.

$x_1 = \hat{x}_1 + \hat{\varepsilon}$

where $\hat{\varepsilon}$ is the residual of the first stage estimation.

Plugging in $x_1 = \hat{x}_1 + \hat{\varepsilon}$ into the model of interest,

$$
\begin{aligned}
y &= \beta_0 + \beta_1(\hat{x}_1 + \hat{\varepsilon}) + \beta_2 x_2 + u \\
&= \beta_0 + \beta_1 \hat{x}_1 + \beta_2 x_2 + (\beta_1 \hat{\varepsilon} + u)
\end{aligned}
$$

So, if you regress y on $\hat{x}_1$ and x_2, then the error term is $(\beta_1 \hat{\varepsilon} + u)$.

Second stage regression

$$y = \beta_0 + \beta_1 \hat{x}_1 + \beta_2 x_2 + (\beta_1 \hat{\varepsilon} + u)$$

Question

What is the condition under which the OLS estimation of β_1 in the main model is unbiased?

Answer

$\hat{x}_1$ is not correlated with $(\beta_1 \hat{\varepsilon} + u)$

This in turn means that x_2, z_1, and z_2 are not correlated with u (the error term of the true model.

$(\hat{x}_1$ is always not correlated (orthogonal) with $\varepsilon)$

Condition 2

- z_1 and z_2 do not belong in the main model, meaning they do not have any explanatory power beyond x_2 (they should have been included in the model in the first place as independent variables)

- z_1 and z_2 are not correlated with the error term (there are no unobserved factors in the error term that are correlated with Z)

Question

Do you think we can test condition 2?

Answer

No, because we never observe the error term.

Important

- All we can do is to argue that the instruments are not correlated with the error term.
- In journal articles that use IV method, they make careful arguments as to why their choice of instruments are not correlated with the error term.

Condition 1

- The instrument(s) Z have jointly significant explanatory power on the endogenous variable x_1 after you control for all the other exogenous variables (here x_2)}

Condition 2

- z_1 and z_2 do not belong in the main model, meaning they do not have any explanatory power beyond x_2 (they should have been included in the model in the first place as independent variables)
- z_1 and z_2 are not correlated with the error term (there are no unobserved factors in the error term that are correlated with Z)

Important

- Condition 1 is always testable
- Condition 2 is NOT testable (unless you have more instruments than endogenous variables)

Two-stage Least Square (2SLS)

IV estimator is also called two-stage least squares estimator (2SLS) because it involves two stages of OLS.

- Step 1: $\hat{x}_1 = \hat{\alpha}_0 + \hat{\sigma}_2 x_2 + \hat{\alpha}_1 z_1 + \hat{\alpha}_2 z_2$
- Step 2: $y = \beta_0 + \beta_1 \hat{x_1} + \beta_2 x_2 + \varepsilon$
- 2SLS framework is a good way to understand conceptually why and how instrumental variable estimation works
- But, IV estimation is done in one-step

Instrumental variable validity

The model

$log(wage) = \beta_0 + \beta_1 educ + \beta_2 exper + v \ \ (= \beta_3 ability + u)$

`educ` is endogenous because of its correlation with `ability`.

Question

What conditions would a good instrument (z) satisfy?

Answer

- z has explanatory power on $educ$ after you control for the impact of $epxer$ on $educ$
- z is uncorrelated with v $(ability$ and all the other important unobservables)

The model

$log(wage) = \beta_0 + \beta_1 educ + \beta_2 exper + v \ \ (= \beta_3 ability + u)$

An example of instruments

The last digit of an individual's Social Security Number? (this has been actually used in some journal articles)

Question

- Is it uncorrelated with v ($ability$ and all the other important unobservables)?
- does it have explanatory power on $educ$ after you control for the impact of $epxer$ on $educ$?

The model

$log(wage) = \beta_0 + \beta_1 educ + \beta_2 exper + v \;\; (= \beta_3 ability + u)$

An example of instruments

IQ test score

Question

- Is it uncorrelated with v $(ability$ and all the other important unobservables)?
- does it have explanatory power on $educ$ after you control for the impact of $epxer$ on $educ$?

The model

$log(wage) = \beta_0 + \beta_1 educ + \beta_2 exper + v \;\; (= \beta_3 ability + u)$

An example of instruments

Mother's education

Question

- Is it uncorrelated with v $(ability$ and all the other important unobservables)?
- does it have explanatory power on $educ$ after you control for the impact of $epxer$ on $educ$?

The model

$$log(wage) = \beta_0 + \beta_1 educ + \beta_2 exper + v \quad (= \beta_3 ability + u)$$

An example of instruments

Number of siblings

Question

- Is it uncorrelated with v $(ability$ and all the other important unobservables)?
- does it have explanatory power on $educ$ after you control for the impact of $epxer$ on $educ$?

Implementation of Instrumental Variable (IV) Estimation in R

Model

$$log(wage) = \beta_0 + \beta_1 educ + \beta_2 exper + v \ \ (= \beta_3 ability + u)$$

We believe

- $educ$ is endogenous (x_1)
- $exper$ is exogenous (x_2)
- we use the number of siblings $(sibs)$ and father's education $(feduc)$ as the instruments (Z)

Terminology

- exogenous variable included in the model (here, $exper$) is also called included instruments
- instruments that do not belong to the main model (here, $sibs$ and $feduc$) are also called excluded instruments
- we refer to the collection of included and excluded instruments as instruments

Dataset

```
#--- take a look at the data ---#
wage2 %>%
  select(wage, educ, sibs, feduc) %>%
  head()
```

```
##   wage educ sibs feduc
## 1  769   12    1     8
## 2  808   18    1    14
## 3  825   14    1    14
## 4  650   12    4    12
## 5  562   11   10    11
## 6 1400   16    1    NA
```

We can continue to use the `fixest` package to run IV estimation method.

```
library(fixest)
```

Syntax

```
felm(dep var ~ included instruments|first stage formula, data = dataset)
```

- `included instruments`: exogenous included variables (do not include endogenous variables here)

first stage formula

```
(endogenous vars ~ excluded instruments)
```

Example

```
iv_res <- feols(log(wage) ~ exper | educ ~ sibs + feduc, data = wage2)
```

- `included variable`:
  - exogenous included variables: `exper`
  - endogenous included variables: `educ`
- `instruments`:
  - included instruments: `exper`
  - excluded instruments: `sibs` and `feduc`

IV regression results

```r
iv_res
```

```
## TSLS estimation, Dep. Var.: log(wage), Endo.: educ, Instr.: sibs, feduc
## Second stage: Dep. Var.: log(wage)
## Observations: 741
## Standard-errors: IID
##             Estimate Std. Error  t value   Pr(>|t|)
## (Intercept) 4.507316   0.315735 14.27564  < 2.2e-16 ***
## fit_educ    0.137405   0.019215  7.15104 2.0766e-12 ***
## exper       0.037029   0.005694  6.50306 1.4502e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 0.406208   Adj. R2: 0.049979
## F-test (1st stage), educ: stat = 65.6     , p < 2.2e-16 , on 2 and 737 DoF.
##               Wu-Hausman: stat = 13.2     , p = 3.051e-4, on 1 and 737 DoF.
##                   Sargan: stat =  0.230925, p = 0.630838, on 1 DoF.
```

Note

- When variable `x` is the endogenous variable, `fixest` changes the name of `x` to `x(fit)`.
- Here, `educ` has become `educ(fit)`.

Comparison of OLS and IV Estimation Results

	Model 1	Model 2
(Intercept)	5.503***	4.507***
	(0.112)	(0.316)
educ	0.078***	
	(0.007)	
exper	0.020***	0.037***
	(0.003)	(0.006)
fit_educ		0.137***
		(0.019)
Num.Obs.	935	741
R2	0.131	0.053
Std. errors	IID	IID

* p < 0.1, ** p < 0.05, *** p < 0.01

Question

Do you think $sibs$ and $feduc$ are good instruments?

- Condition 1: weak instruments?
- Condition 2: uncorrelated with the error term?

Weak Instrument Test

We can always test if the excluded instruments are weak or not (test of condition 1).

How

- Run the 1st stage regression

$educ = \alpha_0 + \alpha_1 exper + \alpha_2 sibs + \alpha_3 feduc + v$

- test the joint significance of α_2 and α_3 $(F$-test)

If excluded instruments $(sibs$ and $feduc)$ are jointly significant, then it would mean that $sibs$ and $feduc$ are not weak instruments, satisfying condition 1.

When we ran the IV estimation using `fixest::feols()` earlier, it automatically calculated the F-statistic for the weak instrument test.

```r
iv_res
```

```
## TSLS estimation, Dep. Var.: log(wage), Endo.: educ, Instr.: sibs, feduc
## Second stage: Dep. Var.: log(wage)
## Observations: 741
## Standard-errors: IID
##             Estimate Std. Error  t value   Pr(>|t|)
## (Intercept) 4.507316   0.315735 14.27564  < 2.2e-16 ***
## fit_educ    0.137405   0.019215  7.15104 2.0766e-12 ***
## exper       0.037029   0.005694  6.50306 1.4502e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 0.406208   Adj. R2: 0.049979
## F-test (1st stage), educ: stat = 65.6     , p < 2.2e-16 , on 2 and 737 DoF.
##               Wu-Hausman: stat = 13.2     , p = 3.051e-4, on 1 and 737 DoF.
##                   Sargan: stat =  0.230925, p = 0.630838, on 1 DoF.
```

Here, F-test for the null hypothesis of the excluded instruments (`sibs` and `feduc`) do not have any explanatory power on the endogenous variable (`educ`) beyond the included instrument (`exper`) is rejected.

Alternatively, you can access the `iv_first_stage` component of the regression results.

```
iv_res$iv_first_stage
```

```
## $educ
## TSLS estimation, Dep. Var.: educ, Endo.: educ, Instr.: sibs, feduc
## First stage: Dep. Var.: educ
## Observations: 741
## Standard-errors: IID
##              Estimate Std. Error   t value   Pr(>|t|)
## (Intercept) 14.075273   0.358595  39.25116  < 2.2e-16 ***
## sibs        -0.131009   0.030800  -4.25357 2.3749e-05 ***
## feduc        0.205169   0.021909   9.36459  < 2.2e-16 ***
## exper       -0.191535   0.016373 -11.69819  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 1.84505   Adj. R2: 0.319802
## F-test (1st stage): stat = 65.6, p < 2.2e-16, on 2 and 737 DoF.
```

Notes

- It is generally recommended that you have F-stat of over 10 (this is not a clear-cut criteria that applied to all the empirical cases)
- Even if you reject the null if F-stat is small, you may have a problem
- You know nothing about if your excluded instruments satisfy Condition 2.
- If you cannot reject the null, it is a strong indication that your instruments are weak. Look for other instruments.
- Always, always report this test. There is no reason not to.

Consequences of weak instruments

Data generation

```
set.seed(73289)
N <- 500 # number of observations

u_common <- runif(N) # the term shared by the endogenous variable and the error term
z_common <- runif(N) # the term shared by the endogenous variable and instruments
x_end <- u_common + z_common + runif(N) # the endogenous variable
z_strong <- z_common + runif(N) # strong instrument
z_weak <- 0.01 * z_common + 0.99995 * runif(N) # weak instrument
u <- u_common + runif(N) # error term
y <- x_end + u # dependent variable

data <- data.frame(y, x_end, z_strong, z_weak)
```

Correlation

```
cor(data)
```

```
##                    y       x_end    z_strong       z_weak
## y          1.0000000  0.86492868 0.298704509 -0.108007146
## x_end      0.8649287  1.00000000 0.419011491 -0.074224622
## z_strong   0.2987045  0.41901149 1.000000000  0.003839565
## z_weak    -0.1080071 -0.07422462 0.003839565  1.000000000
```

Estimation with the strong instrumental variable

```r
#--- IV estimation (strong) ---#
iv_strong <- feols(y ~ 1 | x_end ~ z_strong, data = data)
```

Estimation with the weak instrumental variable

```r
#--- IV estimation (weak) ---#
iv_weak <- feols(y ~ 1 | x_end ~ z_weak, data = data)
```

```r
#--- coefs (strong) ---#
tidy(iv_strong)
```

```
## # A tibble: 2 × 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)    0.883    0.133       6.64 8.20e-11
## 2 fit_x_end      1.09     0.0856     12.7  2.96e-32
```

```r
#--- coefs (weak) ---#
tidy(iv_weak)
```

```
## # A tibble: 2 × 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)   -0.862     1.10     -0.784 0.434
## 2 fit_x_end      2.22      0.714     3.11  0.00197
```

Question

Any notable differences?

The coefficient estimate on x_end is far away from the true value in the weak instrument case.

Comparison of the weak instrument tests

```r
#--- diagnostics (strong) ---#
iv_strong$iv_first_stage
```

```
## $x_end
## TSLS estimation, Dep. Var.: x_end, Endo.: x_end, Instr.: z_strong
## First stage: Dep. Var.: x_end
## Observations: 500
## Standard errors: IID
```

```r
#--- diagnostics (weak) ---#
iv_weak$iv_first_stage
```

```
## $x_end
## TSLS estimation, Dep. Var.: x_end, Endo.: x_end, Instr.: z_weak
## First stage: Dep. Var.: x_end
## Observations: 500
## Standard errors: IID
```

Question

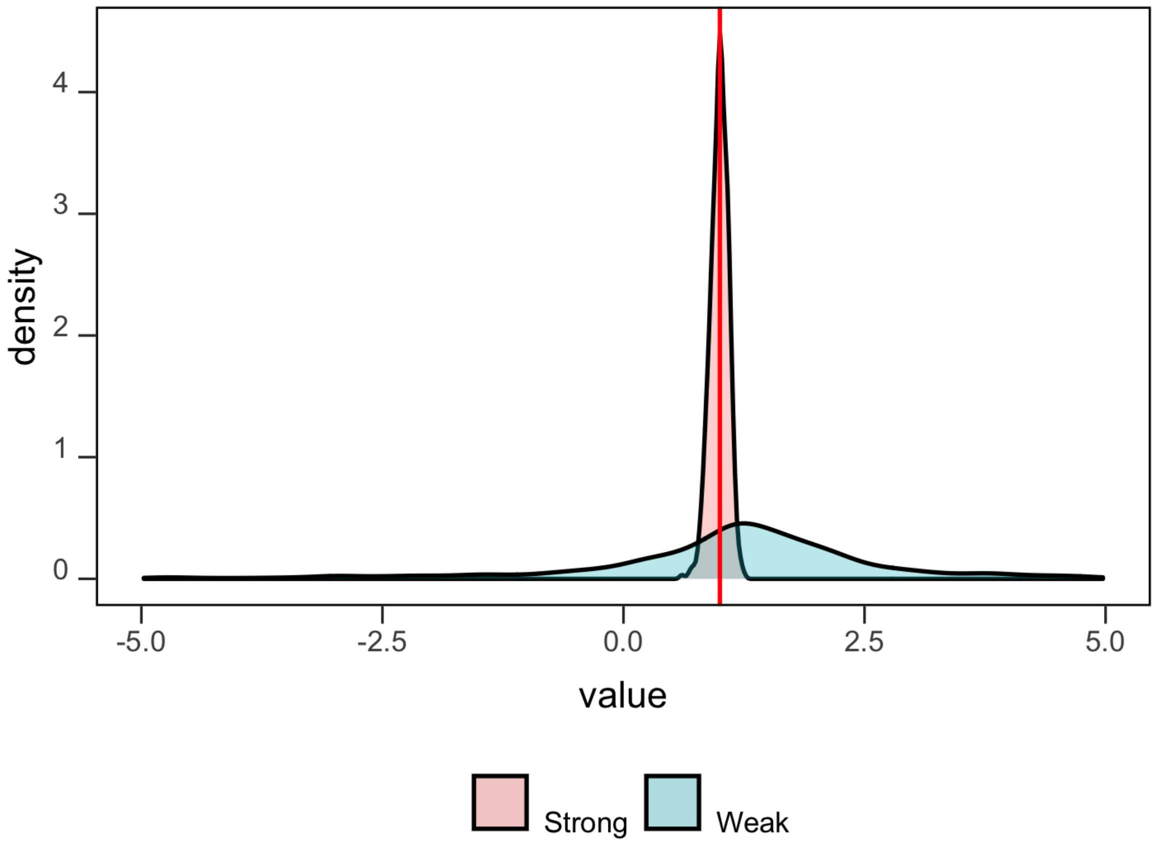
Any notable differences?

You cannot reject the null hypothesis of weak instrument in the weak instrument case.

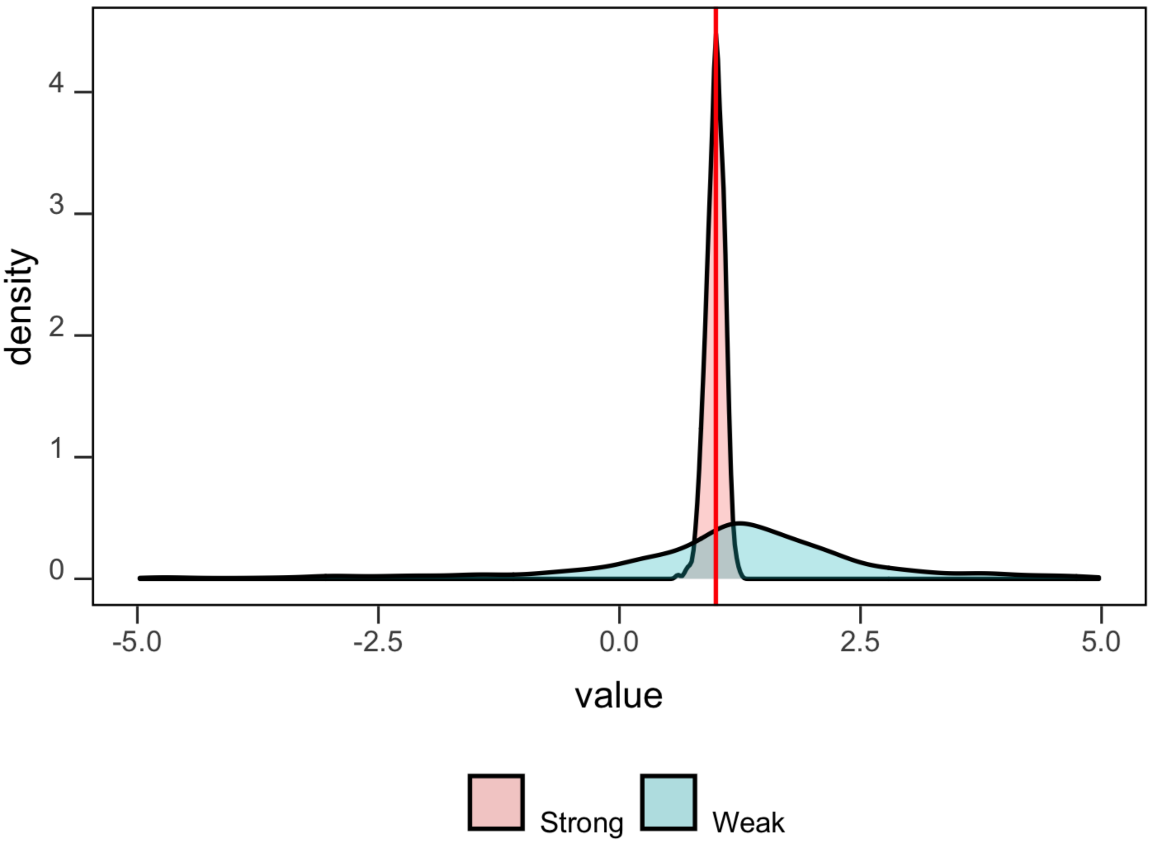
MC simulation

```r
B <- 1000 # the number of experiments
beta_hat_store <- matrix(0, B, 2) # storage of beta hat

for (i in 1:B) {

  #--- data generation ---#
  u_common <- runif(N)
  z_common <- runif(N)
  x_end <- u_common + z_common + runif(N)
  z_strong <- z_common + runif(N)
  z_weak <- 0.01 * z_common + 0.99995 * runif(N)
  u <- u_common + runif(N)
  y <- x_end + u
  data <- data.table(y, x_end, z_strong, z_weak)

  #--- IV estimation with a strong instrument ---#
  iv_strong <- feols(y ~ 1 | x_end ~ z_strong, data = data)
  beta_hat_store[i, 1] <- iv_strong$coefficients[2]

  #--- IV estimation with a weak instrument ---#
  iv_weak <- feols(y ~ 1 | x_end ~ z_weak, data = data)
  beta_hat_store[i, 2] <- iv_weak$coefficients[2]
}
```

Visualization of the MC Results



Visualization of the MC Results



Flow of IV Estimation in Practice

- Identify endogenous variable(s) and included instrument(s)
- Identify potential excluded instrument(s)
- Argue why the excluded instrument(s) you pick is uncorrelated with the error term (**condition 2**)
- Once you decide what variable(s) to use as excluded instruments, test whether the excluded instrument(s) is weak or not (**condition 1**)
- Implement IV estimation and report the results

You can include fixed effects in your IV estimation.

Syntax

```
feols(dep var ~ included instruments | FE | 1st stage formula, data = dataset)
```

Example

Include `married` and `south` as fixed effects.

```
feols(log(wage) ~ exper | married + south | educ ~ feduc + sibs, data = wage2)
```

```
## TSLS estimation, Dep. Var.: log(wage), Endo.: educ, Instr.: feduc, sibs
## Second stage: Dep. Var.: log(wage)
## Observations: 741
## Fixed-effects: married: 2,  south: 2
## Standard-errors: Clustered (married)
##          Estimate Std. Error t value Pr(>|t|)
## fit_educ 0.124355   0.003627 34.2906 0.018560 *
## exper    0.032128   0.002260 14.2144 0.044713 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 0.391178     Adj. R2: 0.116588
##                  Within R2: 0.069595
## F-test (1st stage), educ: stat = 61.1     , p < 2.2e-16 , on 2 and 736 DoF.
##               Wu-Hausman: stat =  8.98498 , p = 0.002814, on 1 and 735 DoF.
##                   Sargan: stat =  0.169226, p = 0.6808  , on 1 DoF.
```

Clustered SE? You can just add `cluster =` option just like we previously did.

```r
feols(log(wage) ~ exper | married + south | educ ~ feduc + sibs, cluster = ~black, data = wage2)
```

```
## TSLS estimation, Dep. Var.: log(wage), Endo.: educ, Instr.: feduc, sibs
## Second stage: Dep. Var.: log(wage)
## Observations: 741
## Fixed-effects: married: 2,  south: 2
## Standard-errors: Clustered (black)
##          Estimate Std. Error t value Pr(>|t|)
## fit_educ 0.124355   0.005258 23.6526 0.026899 *
## exper    0.032128   0.002798 11.4842 0.055295 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 0.391178     Adj. R2: 0.116588
##                  Within R2: 0.069595
## F-test (1st stage), educ: stat = 61.9     , p < 2.2e-16 , on 2 and 735 DoF.
##               Wu-Hausman: stat =  8.98498 , p = 0.002814, on 1 and 735 DoF.
##                   Sargan: stat =  0.169226, p = 0.6808  , on 1 DoF.
```