Lecture 20: Instrumental Variables Models

ECON 480 - Econometrics - Fall 2018

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Instrumental Variables Models

Two-Stage Least Squares

An Example of 2SLS in R

Instrumental Variables Models

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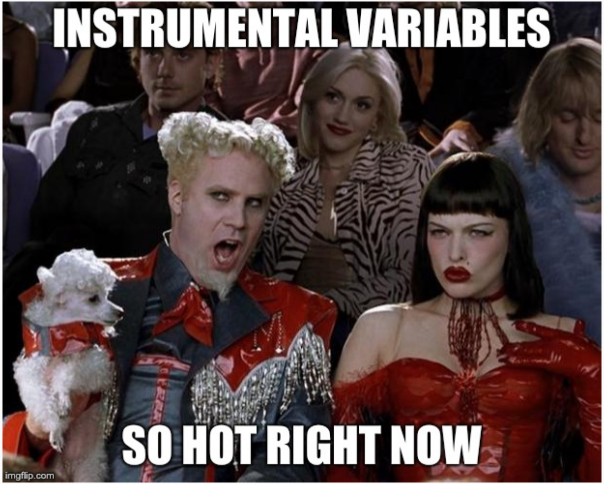
- Another strategy to is to find some source of exogenous variation that removes the endogeneity of a variable, using that source as a instrumental variable


INSTRUMENTAL VARIABLES
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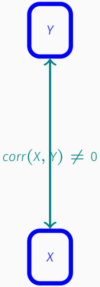
Understanding Instrumental Variables

Y



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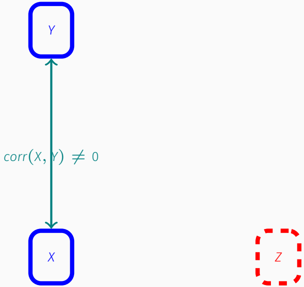

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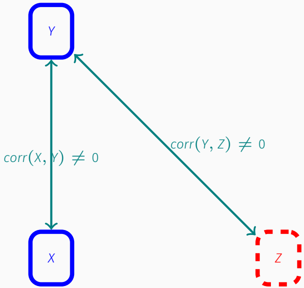

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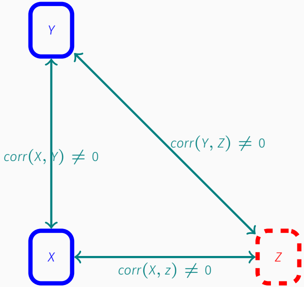

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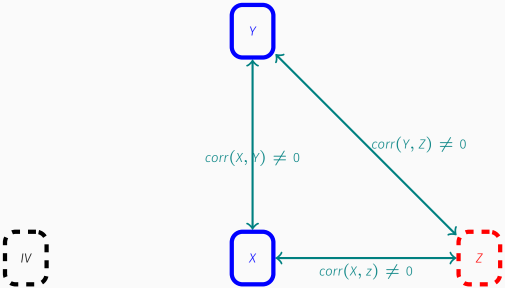

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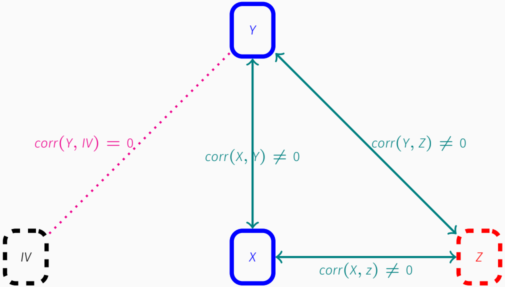

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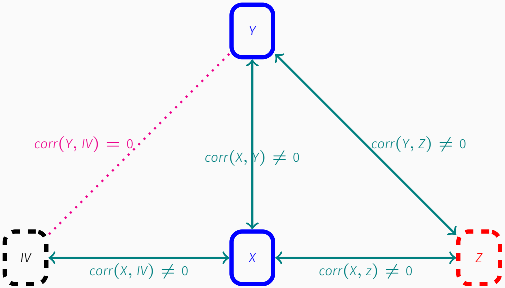

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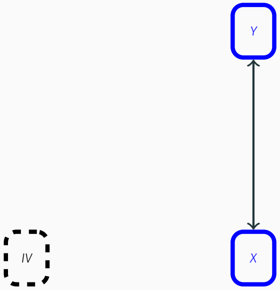

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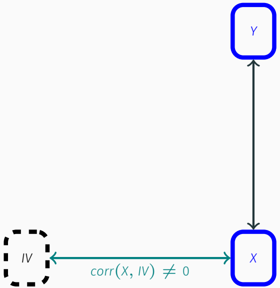

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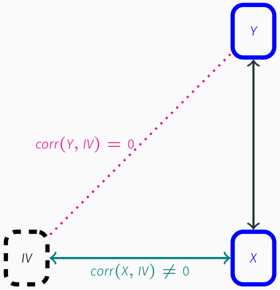

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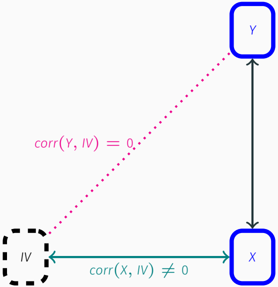
Understanding Instrumental Variables II



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- *IV* **only** affects *Y* **through** *X*

Example
How do police affect crime?

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- Police$\longrightarrow$crime (more police reduces crime)
- Crime$\longrightarrow$Police (high crime areas tend to have more police)
- $corr(Police, \epsilon) \neq 0$: population, income per capita, drug use, recessions, demography, etc.

Example

- Levitt (2002): use number of firefighters as an instrumental variable

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  - These exogenous dynamics affect the number of firefighters in a city—*not* due to crime, but due to excess budgets, etc.
- Isolate that portion of variation in Police that covaries with Firefighters for those *exogenous* changes (i.e. for reasons *other* than crime or its causes), see how *these* changes in Police affect crime

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Two-Stage Least Squares

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- Then substitute in the *predicted* value of $\widehat{X_{1i}}$ for the original regression in the **Second Stage**:

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- Always report the first stage regression results!

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HOOD COLLEGE

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    - If $corr(IV, \epsilon) \neq 0$, we would want IV as a control in the regression (omitted variable bias!)
    - If $corr(IV, \epsilon) = 0$, can't include in the Second Stage regression:

$$\widehat{Y_i} = \widehat{\beta_0} + \widehat{\beta_1} + \widehat{X_{1i}} + \widehat{\beta_2}X_{2i} + \widehat{\beta_3}IV_i + \widehat{\epsilon_i}$$

$\widehat{X_{1i}}$ is a linear function of X_{2i} and IV_i, perfect multicollinearity!

Example

- Levitt's (2002) paper, First Stage:

$$\widehat{ln(Police_{ct})} = \widehat{\gamma}_1 ln(Firefighters_{ct}) + \alpha_c + \tau_t + \widehat{\gamma} Controls_{ct} + \nu_{ct}$$

subscripts for city c at year t, two-way fixed effects: α_c city fixed-effects, τ_t year fixed-effects

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- Second Stage:

$$ln(\widehat{Crime_{ct}}) = \widehat{\beta}_1 ln(\widehat{Police_{ct-1}}) + \alpha_c + \tau_t + \widehat{\beta} Controls_{ct} + \epsilon_{ct}$$

  lag for police (last year's police force determines this year's crime rates)

Instrumental Variables 2SLS Example II

Example

TABLE 2—THE RELATIONSHIP BETWEEN FIREFIGHTE

Variable	First-stage estimates (dependent variable = ln(Police per capita) (i)	(ii)	(iii)
ln(Firefighters per capita)	0.251	0.236	0.206
	(0.050)	(0.054)	(0.050)
ln(Street and highway workers per capita)	—	—	0.014
			(0.014)
ln(State prisoners per capita)	—	−0.101	−0.077
		(0.022)	(0.022)
Unemployment rate	—	0.571	0.265
		(0.276)	(0.314)
State income per capita (×10,000)	—	0.150	0.211
		(0.004)	(0.005)
Effective abortion rate	—	0.033	0.045
(×100)	(0.013)	(0.013)	(0.026)
ln(City population)	—	0.040	−0.014
		(0.040)	(0.047)
Percentage black	—	0.361	0.493
		(0.204)	(0.264)
City-fixed effects and year dummies included?	yes	yes	yes
R^2:	0.947	0.952	0.962
Number of observations:	2,032	2,032	1,445

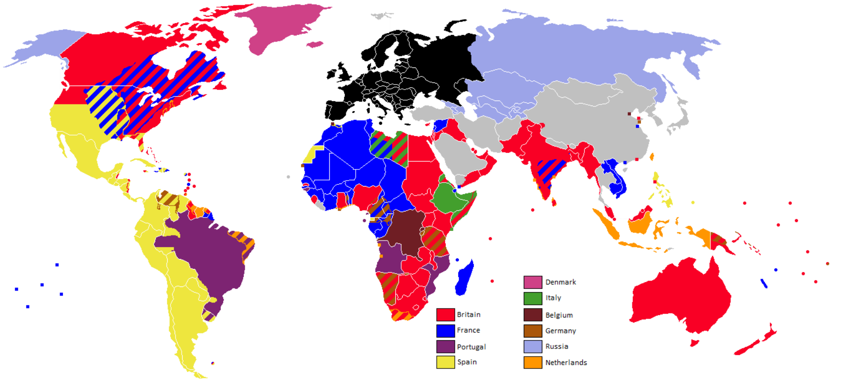
Instrumental Variables 2SLS Example II

Table 3—The Impact of Police on Crime

Variable	Violent crime OLS	Violent crime OLS	Violent crime IV	Property crime OLS	Property crime OLS	Property crime IV
ln(Police per capita)$_{t-1}$	0.562	−0.076	−0.435	0.113	−0.218	−0.501
	(0.056)	(0.061)	(0.231)	(0.038)	(0.052)	(0.235)
ln(State prisoners per capita)$_{t-1}$	0.250	−0.131	−0.171	0.189	−0.273	−0.305
	(0.039)	(0.036)	(0.044)	(0.030)	(0.028)	(0.037)
Unemployment rate	3.573	−0.741	−0.480	1.283	1.023	1.231
	(0.473)	(0.365)	(0.404)	(0.312)	(0.274)	(0.326)
State income per capita (×10,000)	0.050	−0.003	0.003	0.010	0.005	0.009
	(0.005)	(0.006)	(0.007)	(0.003)	(0.004)	(0.006)
Effective abortion rate (×100)	−0.214	−0.150	−0.141	−0.184	−0.118	−0.111
	(0.045)	(0.023)	(0.025)	(0.020)	(0.021)	(0.024)
ln(City population)	0.072	0.203	0.178	−0.064	−0.333	−0.355
	(0.012)	(0.063)	(0.067)	(0.006)	(0.063)	(0.066)
Percentage black	0.627	0.233	0.398	−0.136	0.411	0.517
	(0.074)	(0.334)	(0.345)	(0.057)	(0.271)	(0.291)
City-fixed effects and year dummies included?	only year dummies	yes	yes	only year dummies	yes	yes
R^2:	0.601	0.930	—	0.238	0.819	—
Number of observations:	2,005	2,005	2,005	2,032	2,032	2,032

- A 1% increase in police (last year) leads to a 0.435% decrease in violent crimes, 0.501%

Acemoglu, Johnson, and Robinson (2001): Another Famous IV Model



European Empires at their maximal extents (c.1500-c.1900)

Acemoglu, Daron, Simon Johnson, and James A Robinson, (2001), "The Colonial Origins of Comparative Development: An Empirical Investigation," *American Economic Review* 91(5): 1369-1401

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  - **"Inclusive institutions"**: Europeans facing low mortality rates set up inclusive colonies primarily for settlement and promoting open access to trade and politics
- Those initial colonies carried through to institutions in present countries; inclusive colonies grew wealthy, extractive colonies remain stagnant

Acemoglu, Johnson, and Robinson (2001): Identification Strategy

- Instrument: Settler Mortality in 1500

(potential) settler mortality $\Rightarrow$ settlements

$\Rightarrow$ early institutions $\Rightarrow$ current institutions

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- **Inclusion Restriction**: Settler mortality in 1500 determines risk of expropriation today
- {**Exclusion Restriction**: Settler mortality in 1500 **does not** affect Present GDP
    - Settler mortality in 1500 **only** affects Present GDP **through** institutions determined by historical path set by settler mortality rates

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- First Stage:

$$\widehat{\text{Expropriation}}\ \text{Risk}_i = \widehat{\gamma}_0 + \widehat{\gamma}_1 ln\left(\text{Settler Mortality in 1500}_i\right) + \widehat{\gamma} Controls + \nu_i$$

- First Stage:

$$\widehat{\text{Expropriation Risk}}_i = \widehat{\gamma}_0 + \widehat{\gamma}_1 ln\big(\text{Settler Mortality in 1500}_i\big) + \widehat{\gamma} Controls + \nu_i$$

- Second Stage:

$$\ln(\text{Present } \widehat{\text{GDP}} \text{ per capita}) = \hat{\beta}_0 + \hat{\beta}_1 \widehat{\text{Expropriation Risk}}_i + \cdots + \hat{\beta}_k \text{Controls} + \epsilon_i$$

ACEMOGLU, JOHNSON, AND ROBINSON (2001): RELATIONSHIP BETWEEN Y AND IV

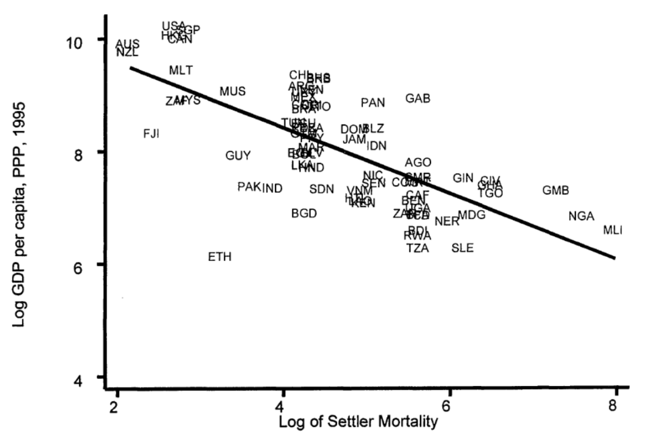

FIGURE 1. REDUCED-FORM RELATIONSHIP BETWEEN INCOME AND SETTLER MORTALITY

Acemoglu, Johnson, and Robinson (2001): Relationship Between X and Y

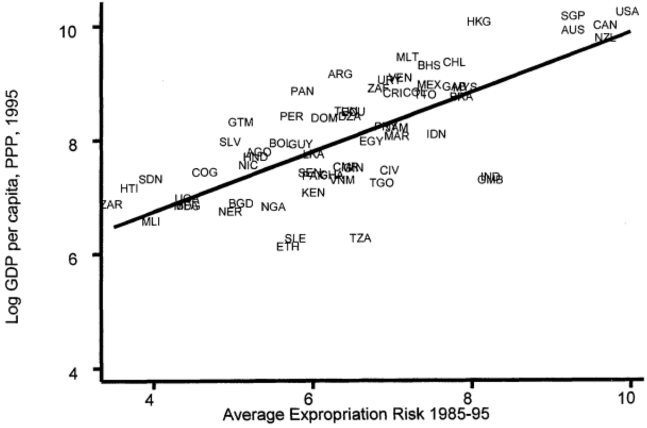

Figure 2. OLS Relationship Between Expropriation Risk and Income

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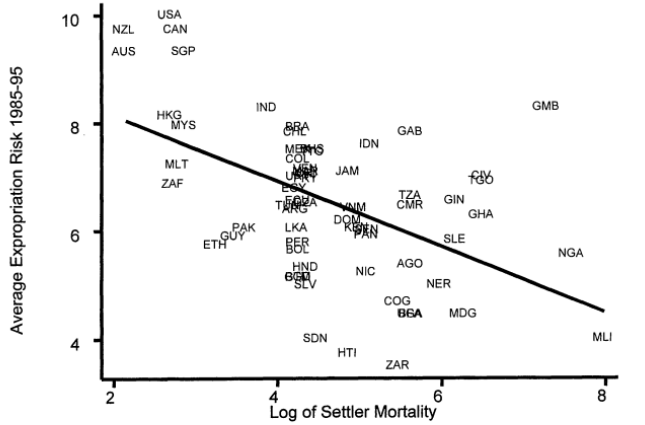

FIGURE 3. FIRST-STAGE RELATIONSHIP BETWEEN SETTLER MORTALITY AND EXPROPRIATION RISK

TABLE 4—IV REGRESSIONS OF LOG GDP PER CAPITA

	Base sample (1)	Base sample (2)	Base sample without Neo-Europes (3)	Base sample without Neo-Europes (4)	Base sample without Africa (5)	Base sample without Africa (6)	Base sample with continent dummies (7)	Base sample with continent dummies (8)	Base sample, dependent variable is log output per worker (9)
Panel A: Two-Stage Least Squares									
Average protection against expropriation risk 1985–1995	0.94	1.00	1.28	1.21	0.58	0.58	0.98	1.10	0.98
	(0.16)	(0.22)	(0.36)	(0.35)	(0.10)	(0.12)	(0.30)	(0.46)	(0.17)
Latitude		−0.65		0.94		0.04		−1.20	
		(1.34)		(1.46)		(0.84)		(1.8)	
Asia dummy							−0.92	−1.10	
							(0.40)	(0.52)	
Africa dummy							−0.46	−0.44	
							(0.36)	(0.42)	
"Other" continent dummy							−0.94	−0.99	
							(0.85)	(1.0)	
Panel B: First Stage for Average Protection Against Expropriation Risk in 1985–1995									
Log European settler mortality	−0.61	−0.51	−0.39	−0.39	−1.20	−1.10	−0.43	−0.34	−0.63
	(0.13)	(0.14)	(0.13)	(0.14)	(0.22)	(0.24)	(0.17)	(0.18)	(0.13)
Latitude		2.00		−0.11		0.99		2.00	
		(1.34)		(1.50)		(1.43)		(1.40)	
Asia dummy							0.33	0.47	
							(0.49)	(0.50)	
Africa dummy							−0.27	−0.26	
							(0.41)	(0.41)	
"Other" continent dummy							1.24	1.1	
							(0.84)	(0.84)	
R^2	0.27	0.30	0.13	0.13	0.47	0.47	0.30	0.33	0.28
Panel C: Ordinary Least Squares									
Average protection against expropriation risk 1985–1995	0.52	0.47	0.49	0.47	0.48	0.47	0.42	0.40	0.46
	(0.06)	(0.06)	(0.08)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)
Number of observations	64	64	60	60	37	37	64	64	61

An Example of 2SLS in R

Example

Does economic growth reduce the odds of civil conflict? Data ('RainIV.dta' on Blackboard) on 41 African countries between 1981-1999.

- `Internalconflict`: =1 if civil war ($<$ 25 deaths), else =0
- `LaggedGDPGrowth`: 1st lag of GDP growth
- `LagggedRainfallGrowth`: 1st lag of change in mm of rain from previous year
- Other controls

```r
# normal regression
reg1<-lm(InternalConflict~LaggedGDPGrowth, data=rain)
summary(reg1)
```

```
##
## Call:
## lm(formula = InternalConflict ~ LaggedGDPGrowth, data = rain)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.2999 -0.2689 -0.2660  0.7228  0.7876
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.26738    0.01631  16.389   <2e-16 ***
## LaggedGDPGrowth -0.08206    0.22485  -0.365    0.715
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4434 on 741 degrees of freedom
## Multiple R-squared:  0.0001797,  Adjusted R-squared:  -0.00117
## F-statistic: 0.1332 on 1 and 741 DF,  p-value: 0.7152
```

```r
# normal regression with controls
reg2<-lm(InternalConflict~LaggedGDPGrowth+InitialGDP+Democracy+Mountains+EthnicFrac+ReligiousFrac, data=rain)
summary(reg2)
```

```
##
## Call:
## lm(formula = InternalConflict ~ LaggedGDPGrowth + InitialGDP +
##     Democracy + Mountains + EthnicFrac + ReligiousFrac, data = rain)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.5654 -0.2811 -0.2221  0.4570  0.9459
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.0703555  0.0731012   0.962  0.33614
## LaggedGDPGrowth -0.1087977  0.2200999  -0.494  0.62123
## InitialGDP      -0.0569091  0.0182258  -3.122  0.00186 **
## Democracy        0.0012242  0.0028894   0.424  0.67193
## Mountains        0.0038654  0.0009527   4.057 5.49e-05 ***
## EthnicFrac       0.3247931  0.0918181   3.537  0.00043 ***
## ReligiousFrac    0.0105162  0.0958907   0.110  0.91270
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4334 on 736 degrees of freedom
## Multiple R-squared:  0.05106,    Adjusted R-squared:  0.04332
```

The First Stage

- Use `LaggedRainfallGrowth` as an instrument for `LaggedGDPGrowth`

```
rain.corr<-rain %>%
  select(InternalConflict, LaggedGDPGrowth, LaggedRainfallGrowth)

cor(rain.corr)
```

```
##                      InternalConflict LaggedGDPGrowth LaggedRainfallGrowth
## InternalConflict            1.0000000      -0.0134064           -0.0506118
## LaggedGDPGrowth            -0.0134064       1.0000000            0.1263399
## LaggedRainfallGrowth       -0.0506118       0.1263399            1.0000000
```

- Use `LaggedRainfallGrowth` as an instrument for `LaggedGDPGrowth`
  - **Inclusion restriction**: $corr(LaggedGDPGrowth, LaggedRainfallGrowth) \neq 0$

```
rain.corr<-rain %>%
  select(InternalConflict, LaggedGDPGrowth, LaggedRainfallGrowth)

cor(rain.corr)
```

```
##                      InternalConflict LaggedGDPGrowth LaggedRainfallGrowth
## InternalConflict            1.0000000      -0.0134064           -0.0506118
## LaggedGDPGrowth            -0.0134064       1.0000000            0.1263399
## LaggedRainfallGrowth       -0.0506118       0.1263399            1.0000000
```

- Use `LaggedRainfallGrowth` as an instrument for `LaggedGDPGrowth`
  - **Inclusion restriction**: $corr(LaggedGDPGrowth, LaggedRainfallGrowth) \neq 0$
  - **Exclusion restriction**: $corr(LaggedGDPGrowth, \epsilon) = 0$

```
rain.corr<-rain %>%
  select(InternalConflict, LaggedGDPGrowth, LaggedRainfallGrowth)

cor(rain.corr)
```

```
##                       InternalConflict LaggedGDPGrowth LaggedRainfallGrowth
## InternalConflict             1.0000000      -0.0134064           -0.0506118
## LaggedGDPGrowth             -0.0134064       1.0000000            0.1263399
## LaggedRainfallGrowth        -0.0506118       0.1263399            1.0000000
```

The First Stage II

```r
# normal regression with controls
firststage<-lm(LaggedGDPGrowth~LaggedRainfallGrowth+InitialGDP+Democracy+Mountains+EthnicFrac+ReligiousFrac, data=rain)
summary(firststage)
```

```
##
## Call:
## lm(formula = LaggedGDPGrowth ~ LaggedRainfallGrowth + InitialGDP +
##     Democracy + Mountains + EthnicFrac + ReligiousFrac, data = rain)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.46563 -0.03051  0.00459  0.03159  0.66704
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)          -0.0058041  0.0121558  -0.477 0.633168
## LaggedRainfallGrowth  0.0439770  0.0128127   3.432 0.000632 ***
## InitialGDP           -0.0008056  0.0030287  -0.266 0.790327
## Democracy             0.0005373  0.0004798   1.120 0.263080
## Mountains             0.0001087  0.0001582   0.687 0.492435
## EthnicFrac            0.0031603  0.0152584   0.207 0.835976
## ReligiousFrac        -0.0017176  0.0159357  -0.108 0.914197
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07201 on 736 degrees of freedom
## Multiple R-squared:  0.01844,    Adjusted R-squared:  0.01044
```

From First to Second Stage in R

```r
# save predicted values of first stage
gdp.hat<-fitted.values(firststage)

# run second stage regression using gdp.hat instead of gdp
secondstage<-lm(InternalConflict~gdp.hat+InitialGDP+Democracy+Mountains+EthnicFrac+ReligiousFrac, data=rain)
summary(secondstage)
```

```
##
## Call:
## lm(formula = InternalConflict ~ gdp.hat + InitialGDP + Democracy +
##     Mountains + EthnicFrac + ReligiousFrac, data = rain)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.5653 -0.2830 -0.2237  0.4748  0.9952
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)    0.0625061  0.0733775   0.852 0.394579
## gdp.hat       -2.0631528  1.7522115  -1.177 0.239394
## InitialGDP    -0.0580798  0.0182415  -3.184 0.001514 **
## Democracy      0.0023613  0.0030592   0.772 0.440438
## Mountains      0.0040694  0.0009691   4.199 3.01e-05 ***
## EthnicFrac     0.3288508  0.0918180   3.582 0.000364 ***
## ReligiousFrac  0.0047242  0.0959548   0.049 0.960746
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```