

PLSC 30600 - Lab 6 - Instrumental Variables

02/14/2025

Acemoglu et al. (2001): The Effect of Institutions on Economic Development

This is a classic piece on studying the causal effect of institutions on economic development.

The key variables in this paper are:

- `logpgp95` - Outcome: Log GDP Per Capita, PPP, 1995
- `avexpr` - Treatment: Average Protection-Expropriation Risk 1985-95
- `logem4` - Instrument: Log of Settler Mortality

Note: The `avexpr` is the average protection against expropriation risk measured on a scale from 0-10, where a higher score means more protection against expropriation.

To address the endogeneity problem of institution, Acemoglu et al. (2001) uses an IV strategy to isolate exogenous variations in institutions. The instrument is the settler mortality. The idea of the instrument is the following. If the settler mortality is low, Europeans migrated and settled in those colonies and created “Neo-Europes”, which replicated European institutions with strong emphasis on private property and checks against government power. If the settler mortality is high, Europeans set up “extractive states” which does not introduce much protection for private property, nor did they provide checks and balances against government power.

Figure 1: Reduced-Form Relationship ($Y \sim IV$)

We first reproduce Figure 1, which is the reduced form relationship between log settler mortality (Instrument Variable) and income (Outcome). From the figure, we see a negative correlation here, the higher the settler mortality, the lower the income in 1995.

```
# read data
fig1_dta <- read_dta("maketable3.dta")

# make figure
fig1_dta %>% ggplot(aes(x = logem4, y = logpgp95)) +
  geom_point() +
  geom_smooth(method="lm", formula = y ~ x) +
  xlab("Log of Settler Mortality") +
  xlim(3, 8) +
  ylab("Log GDP Per Capita, PPP, 1995")
```

```
## Warning: Removed 307 rows containing non-finite outside the scale range
## (`stat_smooth()`).
```

```
## Warning: Removed 307 rows containing missing values or values outside the scale range
## (`geom_point()`).
```

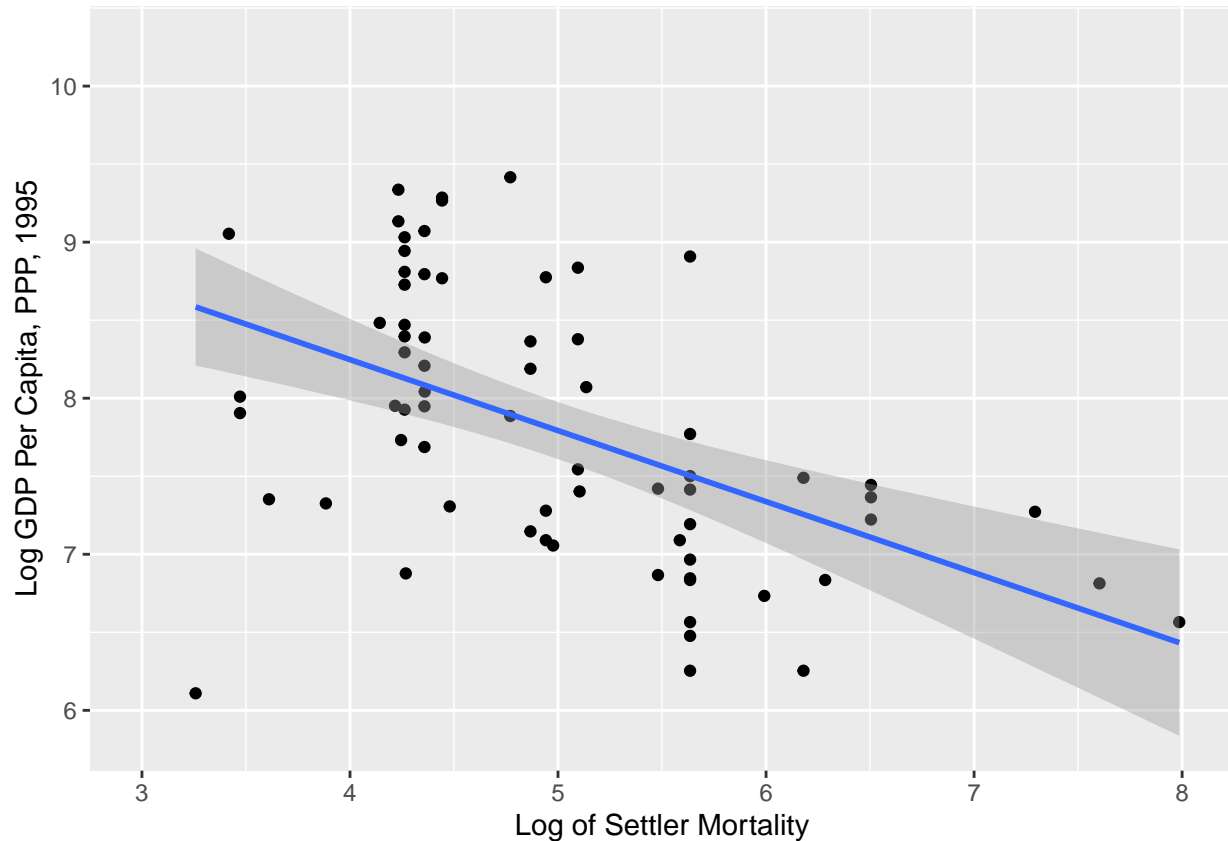


Figure 2: First Stage Plot (D ~ IV) - Correlation between the protection-expropriation risk and mortality

We now reproduce Figure 2. The figure shows a negative correlation between log settler mortality (Instrument Variable) and institutional quality (Treatment).

```
# read data
fig2_dta <- read_dta("maketable3.dta")

# make figure
fig2_dta %>% ggplot(aes(x = logem4, y = avexpr)) +
  geom_point() +
  geom_smooth(method="lm", formula = y ~ x) +
  xlab("Log of Settler Mortality") +
  xlim(3, 8) +
  ylab("Average Protection-Expropriation Risk 1985-95")
```

```
## Warning: Removed 312 rows containing non-finite outside the scale range
```

```
## (`stat_smooth()`).
```

```
## Warning: Removed 312 rows containing missing values or values outside the scale range
```

```
## (`geom_point()`).
```

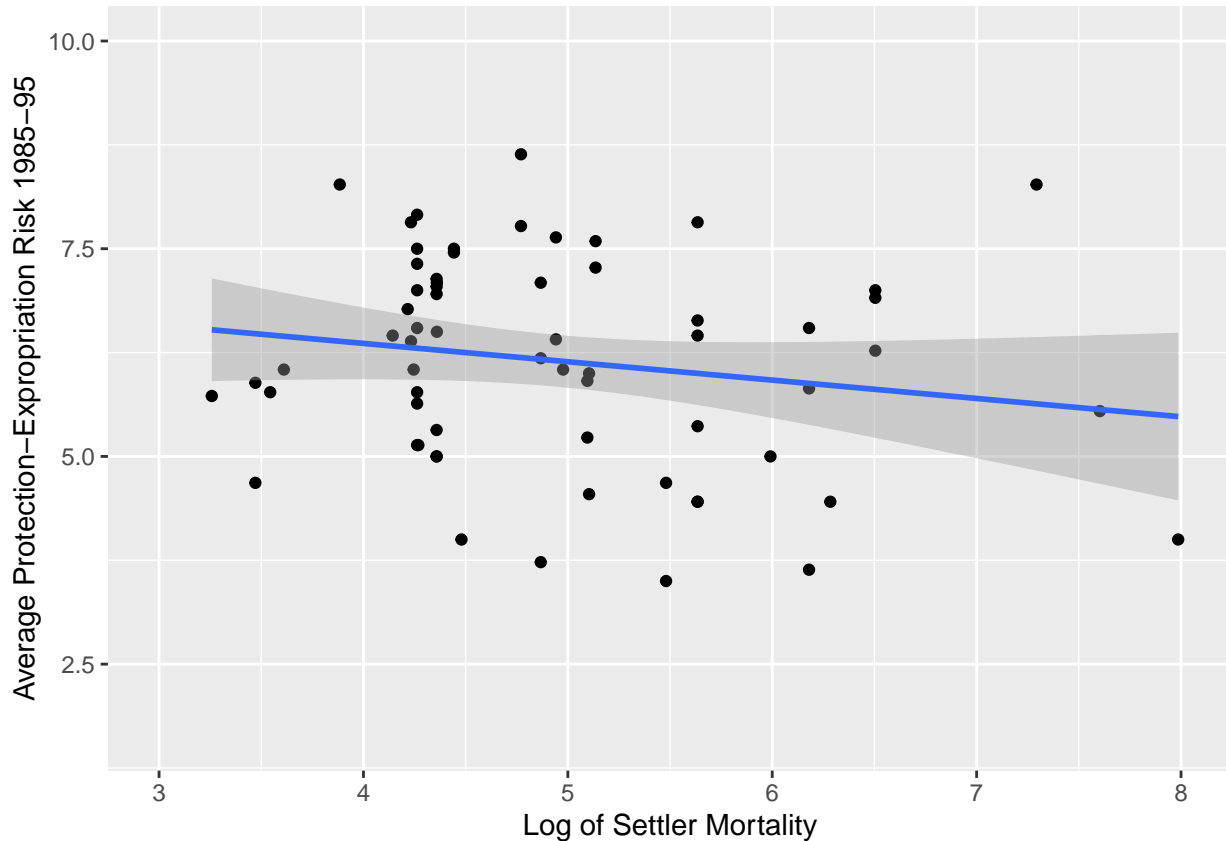


Figure 3: Second Stage plot - Correlation between protection-expropriation risk and income

We now reproduce Figure 3, which is the *raw* correlation ($Y \sim D$) between protection-expropriation risk and income. From the figure, we observe a strong positive correlation between institution quality and economic development.

```
# read data
fig3_dta <- read_dta("maketable2.dta")

# make figure
fig3_dta %>% ggplot(aes(x = avexpr, y = logpgp95)) +
  geom_point() +
  geom_smooth(method="lm", formula = y ~ x) +
  geom_text_repel(aes(label = shortnam), size = 3) +
  xlab("Average Protection-Expropriation Risk 1985-95") +
  xlim(3, 10) +
  ylab("Log GDP Per Capita, PPP, 1995")
```

```
## Warning: Removed 52 rows containing non-finite outside the scale range
## (`stat_smooth()`).
```

```
## Warning: Removed 52 rows containing missing values or values outside the scale range
## (`geom_point()`).
```

```
## Warning: Removed 52 rows containing missing values or values outside the scale range
## (`geom_text_repel()`).
```

```
## Warning: ggrepel: 21 unlabeled data points (too many overlaps). Consider
```

```
## increasing max.overlaps
```

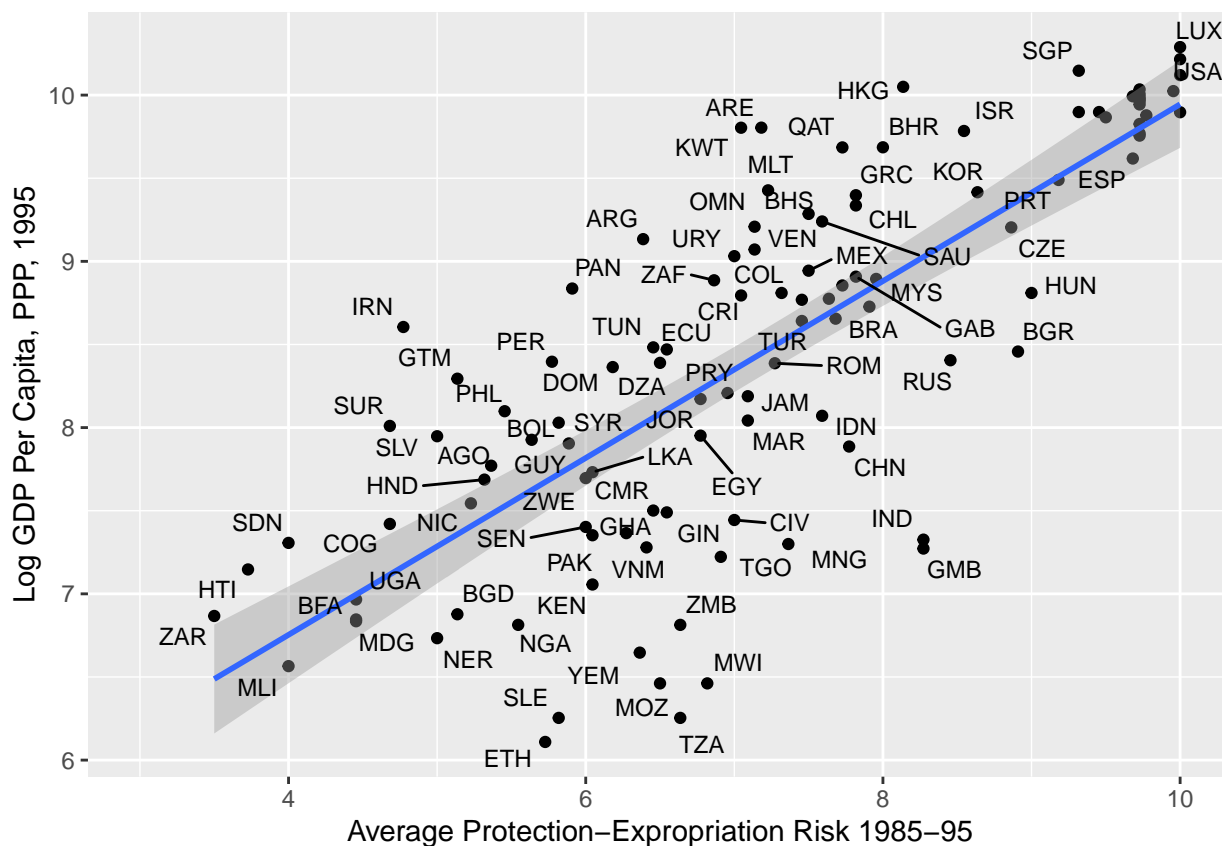


Table 4: Baseline IV Results

We now use the `ivmodel` in `ivmodel` package and `iv_robust` in `estimatr` package to replicate Column (1) in Table 4 in Acemoglu et al. (2001). The results are qualitatively the same with the original results, and the sample size is slightly different. Note that `ivmodel` reports the Anderson-Rubin test results. The test is robust to weak identification, i.e., when IV is weak. The idea is based on inverting the test. For a textbook treatment of the AR test, see section 5.1 in Andrews et al. (2019).

```
# read data
tab4_dta <- read_dta("maketable4.dta")

# use `ivmodel` in `ivmodel` package to reproduce IV estimates
outcome <- as.numeric(tab4_dta$logpgp95)
treatment <- as.numeric(tab4_dta$avexpr)
instrument <- as.numeric(tab4_dta$logem4)

ajr_iv_ivmodel <- ivmodel(Y = outcome, D = treatment, Z = instrument, heteroSE=T)
ajr_iv_ivmodel
```

```
##
## Call:
## ivmodel(Y = outcome, D = treatment, Z = instrument, heteroSE = T)
## sample size: 70
## -----
##
## First Stage Regression Result:
```

```

##
## F=29.79835, df1=1, df2=68, p-value is 7.2947e-07
## R-squared=0.3046917, Adjusted R-squared=0.2944666
## Residual standard error: 1.304066 on 69 degrees of freedom
## -----
##
## Coefficients of k-Class Estimators:
##
##           k Estimate Std. Error t value Pr(>|t|)
## OLS      0.00000  0.51581    0.04148  12.436 < 2e-16 ***
## Fuller  0.98529  0.85193    0.12775   6.669 5.57e-09 ***
## LIML    1.00000  0.86839    0.13653   6.361 1.97e-08 ***
## TSLS    1.00000  0.86839    0.13653   6.361 1.97e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## -----
##
## Alternative tests for the treatment effect under H_0: beta=0.
##
## Anderson-Rubin test (under F distribution):
## F=66.26733, df1=1, df2=68, p-value is 1.2178e-11
## 95 percent confidence interval:
## [0.667419650762224, 1.22579151622886]
##
## Conditional Likelihood Ratio test (under Normal approximation):
## Test Stat=66.26733, p-value is 1.2178e-11
## 95 percent confidence interval:
## [0.667419562849521, 1.22579179425028]
alternatively <- ivmodelFormula(logpgp95 ~ avexpr | logem4, data= tab4_dta, heteroSE=T)
alternatively

##
## Call:
## ivmodel(Y = Y, D = D, Z = Z, intercept = intercept, beta0 = beta0,
##       alpha = alpha, k = k, manyweakSE = manyweakSE, heteroSE = heteroSE,
##       clusterID = clusterID, deltarange = deltarange, na.action = na.action)
## sample size: 70
## -----
##
## First Stage Regression Result:
##
## F=29.79835, df1=1, df2=68, p-value is 7.2947e-07
## R-squared=0.3046917, Adjusted R-squared=0.2944666
## Residual standard error: 1.304066 on 69 degrees of freedom
## -----
##
## Coefficients of k-Class Estimators:
##
##           k Estimate Std. Error t value Pr(>|t|)
## OLS      0.00000  0.51581    0.04148  12.436 < 2e-16 ***
## Fuller  0.98529  0.85193    0.12775   6.669 5.57e-09 ***
## LIML    1.00000  0.86839    0.13653   6.361 1.97e-08 ***
## TSLS    1.00000  0.86839    0.13653   6.361 1.97e-08 ***
## ---

```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## -----
##
## Alternative tests for the treatment effect under H_0: beta=0.
##
## Anderson-Rubin test (under F distribution):
## F=66.26733, df1=1, df2=68, p-value is 1.2178e-11
## 95 percent confidence interval:
## [0.667419650762224, 1.22579151622886]
##
## Conditional Likelihood Ratio test (under Normal approximation):
## Test Stat=66.26733, p-value is 1.2178e-11
## 95 percent confidence interval:
## [0.667419562849521, 1.22579179425028]
```

Purpose of the Anderson-Rubin Test

The Anderson-Rubin test is used to test the joint null hypothesis that the coefficients on the endogenous explanatory variables are zero in an instrumental variables regression model. It is robust to weak instruments in that the distribution of the test statistic does not depend on the strength of the instruments. That is, the Anderson-Rubin test remains valid even in the presence of weak instruments.

How the Anderson-Rubin Test Works

1. **Null Hypothesis (H0):** The null hypothesis of the Anderson-Rubin test is that the coefficients on the endogenous explanatory variables are zero.
2. **Test Statistic:** The test is based on the distribution of a particular test statistic (often an F-statistic) that compares the fit of a restricted model (under H0) with the fit of the full model.
3. **Inference:** If the test statistic is large enough to reject the null hypothesis, it suggests that the coefficients on the endogenous variables are significantly different from zero.

```
# use `iv_robust` in `estimatr` package to reproduce IV estimates
ajr_iv_ivreg <- iv_robust(logpgp95 ~ avexpr | logem4, data = tab4_dta, se_type = "HCO")
summary(ajr_iv_ivreg)
```

```
##
## Call:
## iv_robust(formula = logpgp95 ~ avexpr | logem4, data = tab4_dta,
##           se_type = "HCO")
##
## Standard error type:  HCO
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF
## (Intercept)    2.3702     0.9283   2.553 1.292e-02  0.5178   4.222 68
## avexpr         0.8684     0.1365   6.361 1.972e-08  0.5960   1.141 68
##
## Multiple R-squared:  0.3045 ,    Adjusted R-squared:  0.2942
## F-statistic: 40.46 on 1 and 68 DF,  p-value: 1.972e-08
ajr_iv_ivreg_coef <- iv_robust(logpgp95 ~ avexpr | logem4,
                              data = tab4_dta)$coefficients[2]
ajr_iv_ivreg_coef

##      avexpr
```

```
## 0.8683933
```

Do Not Compute the Bootstrap Standard Error for Instrumental Variable

Hahn and Liao (2021) shows that the bootstrap standard error is usually too “large.” In their simulation, they use an exactly identified IV model to illustrate this theoretical point. Moreover, with infinite samples, the 2SLS estimator may not have a finite second moment, which implies that bootstrap standard error estimates are unstable and unreliable (Hansen, 2021).

Now, let us examine how this phenomenon is reflected in the data from Acemoglu et al. (2001). In this example, the bootstrap standard error (Bootstrap SE = 0.2037) is approximately 1.5 times larger than the standard error reported by `ivmodel` (Heteroskedasticity-Robust SE = 0.1365) and `iv_robust` (Heteroskedasticity-Robust SE = 0.1365).

```
# set seed to make results replicable
set.seed(60637)

# create bootstrap vector
n_iteration <- 5000
iv_boot <- rep(NA, n_iteration)

# bootstrap iteration
for(i in 1:n_iteration){

  # resample with replacement
  tab4_dta_boot <- tab4_dta[sample(1:nrow(tab4_dta),
                                  nrow(tab4_dta),
                                  replace=T),]

  # run iv model using `iv_robust` with the bootstrap data
  iv <- iv_robust(logpgp95 ~ avexpr | logem4, data = tab4_dta_boot)$coefficients[2]
  iv_boot[i] <- iv

}

# display bootstrap standard error and associated confidence interval
boot_iv_se <- sd(iv_boot)
boot_iv_se

## [1] 0.2036732

c(ajr_iv_ivreg_coef - qnorm(.975)*boot_iv_se,
  ajr_iv_ivreg_coef + qnorm(.975)*boot_iv_se)

##      avexpr      avexpr
## 0.4692013 1.2675854

# bootstrap percentile method
quantile(iv_boot, c(0.025, 0.975))

##      2.5%      97.5%
## 0.6735169 1.3722130

# compare with the CI from `iv_robust`
c(ajr_iv_ivreg_coef - qnorm(.975)*0.1365,
  ajr_iv_ivreg_coef + qnorm(.975)*0.1365)

##      avexpr      avexpr
```

0.6008582 1.1359284

References

Acemoglu, Daron, Simon Johnson, and James A. Robinson. “The colonial origins of comparative development: An empirical investigation.” *American Economic Review* 91, no. 5 (2001): 1369-1401.

Andrews, Isaiah, James H. Stock, and Liyang Sun. “Weak instruments in instrumental variables regression: Theory and practice.” *Annual Review of Economics* 11 (2019): 727-753.

Hahn, Jinyong, and Zhipeng Liao. “Bootstrap standard error estimates and inference.” *Econometrica* 89, no. 4 (2021): 1963-1977.

Hansen, Bruce. “Econometrics.” Unpublished Manuscript, (2021).