Quant II

Lab 6: Instrumental Variables

Giacomo Lemoli

March 2, 2023

House-keeping

- HW2 due Tuesday

House-keeping

- HW2 due Tuesday
- Midterm on Thursday

House-keeping

- HW2 due Tuesday
- Midterm on Thursday
- No lab on Thursday

Today's plan

- Instrumental variables in practice

Today's plan

- Instrumental variables in practice
- Characterize compliers

Today's plan

- Instrumental variables in practice
- Characterize compliers
- Weak instruments

Today's plan

- Instrumental variables in practice
- Characterize compliers
- Weak instruments
- Double ML

Instrumental Variables

Principal Strata:

- Compliers: $D(1) = 1, D(0) = 0$
- Always-takers $D(1) = D(0) = 1$
- Never-takers $D(1) = D(0) = 0$
- Defiers: $D(1) = 0, D(0) = 1$

IV in practice: peasant unrest and representation

American Political Science Review (2018) 112, 1, 125–147
doi:10.1017/S0003055417000454
© American Political Science Association 2017

Collective Action and Representation in Autocracies: Evidence from Russia's Great Reforms

PAUL CASTAÑEDA DOWER *University of Wisconsin–Madison*
EVGENY FINKEL *George Washington University*
SCOTT GEHLBACH *University of Wisconsin–Madison*
STEVEN NAFZIGER *Williams College*

We explore the relationship between capacity for collective action and representation in autocracies with data from Imperial Russia. Our primary empirical exercise relates peasant representation in new institutions of local self-government to the frequency of peasant unrest in the decade prior to reform. To correct for measurement error in the unrest data and other sources of endogeneity, we exploit idiosyncratic variation in two determinants of peasant unrest: the historical incidence of serfdom and religious polarization. We find that peasants were granted less representation in districts with more frequent unrest in preceding years—a relationship consistent with the Acemoglu-Robinson model of political transitions and inconsistent with numerous other theories of institutional change. At the same time, we observe patterns of redistribution in subsequent years that are inconsistent with the commitment mechanism central to the Acemoglu-Robinson model. Building on these results, we discuss possible directions for future theoretical work.

The effect of unrest on representation

```r
library(haven); library(AER); library(stargazer)
data <- read_dta("DFGN_cleaned.dta")

## OLS
olsfit <- lm(peasantrepresentation_1864 ~ afreq + distance_moscow +
               goodsoil + lnurban + lnpopn +
               province_capital, data)

## IV (1): serfdom
ivfit1 <- ivreg(peasantrepresentation_1864 ~ afreq + distance_moscow +
                  goodsoil + lnurban + lnpopn + province_capital | serfperc1 +
                  distance_moscow + goodsoil + lnurban + lnpopn +
                  province_capital, data=data)

## IV (2): religious polarization
ivfit2 <- ivreg(peasantrepresentation_1864 ~ afreq + distance_moscow +
                  goodsoil + lnurban + lnpopn + province_capital | religpolarf4_1870 +
                  distance_moscow + goodsoil + lnurban + lnpopn +
                  province_capital, data=data)

mod <- list(olsfit, ivfit1, ivfit2)
ses <- lapply(mod, function(x) coeftest(x, vcov = vcovHC(x, type = "HC1"))[,"Std. Error"])
labs <- c("", "Z: % serfs", "Z: religious pol.")
```

The effect of peasant unrest on representation

```
stargazer(mod, se = ses, column.labels = labs, omit.stat = c("f", "ser"), type = "text")
```

```
##
## ========================================================
##                            Dependent variable:
##                   --------------------------------------
##                         peasantrepresentation_1864
##                     OLS            instrumental
##                                      variable
##                          Z: % serfs Z: religious pol.
##                     (1)       (2)            (3)
## --------------------------------------------------------
## afreq             -4.249**  -41.999***     -32.770*
##                    (1.830)   (8.509)       (17.352)
##
## distance_moscow    0.379    -7.222***       -5.401
##                    (1.288)   (2.203)        (3.733)
##
## goodsoil           1.127     3.860***       3.101*
##                    (0.811)   (1.317)        (1.801)
##
## lnurban           -2.605*** -1.901***      -2.086***
##                    (0.439)   (0.584)        (0.555)
##
## lnpopn            5.224***   8.291***      7.597***
##                    (1.092)   (1.243)        (1.777)
##
## province_capital -3.345*** -5.177***      -4.689***
##                    (1.281)   (1.679)        (1.642)
##
## Constant           3.633    -23.952*       -17.715
##                   (12.079)  (13.245)       (16.979)
##
##
```

Other IV packages

```r
# lfe
library(lfe)
ivfit.felm <- felm(peasantrepresentation_1864 ~ distance_moscow +
                  goodsoil + lnurban + lnpopn + province_capital | 0 | (afreq ~ serfperc1), data=data)

# fixest
library(fixest)
ivfit.feols <- feols(peasantrepresentation_1864 ~ distance_moscow + goodsoil +
                       lnurban + lnpopn + province_capital | afreq ~ serfperc1,
                     vcov = "hc1", data=data)

# Compare
library(modelsummary)
mods <- list(ivfit.felm, ivfit.feols)
vcovs <- list(ivfit.felm$robustvcv, vcov(ivfit.feols))
modelsummary(list(ivfit.felm, ivfit.feols), vcov=vcovs, coef_omit = "^(?!.*fit)", output="markdown")
```

	Model 1	Model 2
afreq(fit)	-41.999	
	(8.509)	
fit_afreq		-41.999
		(8.509)
Num.Obs.	362	362
R2	-0.236	-0.236
R2 Adj.	-0.257	-0.257
R2 Within		
R2 Pseudo		
AIC		2515.8
BIC		2543.1
Log.Lik.		-1250.911

Standard error note

- Robust SE computed by Stata's `ivregress` are the HC0 type

Standard error note

- Robust SE computed by Stata's `ivregress` are the HC0 type
- Here we used HC1 (so SEs slightly different from the paper)

Standard error note

- Robust SE computed by Stata's `ivregress` are the HC0 type
- Here we used HC1 (so SEs slightly different from the paper)
- Make sure you cross-check documentation when translating to another language

IV in Stata

- Classic function: `ivregress`

IV in Stata

- Classic function: `ivregress`
- Now most popular and complete: `ivreg2`

IV in Stata

- Classic function: `ivregress`
- Now most popular and complete: `ivreg2`
- Versions for panel data: `xtivreg` and `ivreghdfe`

Characterize the compliers

- Different strategies, not widely used: see Marbach and Hangartner (2020).

Characterize the compliers

- Different strategies, not widely used: see Marbach and Hangartner (2020).
- Simple regression-based technique:

Characterize the compliers

- Different strategies, not widely used: see Marbach and Hangartner (2020).
- Simple regression-based technique:
  - X: covariate. D: endogenous treatment. Z: instrument.

Characterize the compliers

- Different strategies, not widely used: see Marbach and Hangartner (2020).
- Simple regression-based technique:
  - X: covariate. D: endogenous treatment. Z: instrument.
  - Create $X^* = X * D$ and use it as outcome in the 2SLS model

Characterize the compliers

- Different strategies, not widely used: see Marbach and Hangartner (2020).
- Simple regression-based technique:
  - X: covariate. D: endogenous treatment. Z: instrument.
  - Create $X^* = X * D$ and use it as outcome in the 2SLS model
  - Coefficient of the instrumented D is the mean of Z among the treated compliers

Characterize the compliers

- Different strategies, not widely used: see Marbach and Hangartner (2020).
- Simple regression-based technique:
  - X: covariate. D: endogenous treatment. Z: instrument.
  - Create $X^* = X * D$ and use it as outcome in the 2SLS model
  - Coefficient of the instrumented D is the mean of Z among the treated compliers
- Uses only treated compliers, thus inefficient (Marbach and Hangartner 2020)

Characterize the compliers

- Different strategies, not widely used: see Marbach and Hangartner (2020).
- Simple regression-based technique:
  - X: covariate. D: endogenous treatment. Z: instrument.
  - Create $X^* = X * D$ and use it as outcome in the 2SLS model
  - Coefficient of the instrumented D is the mean of Z among the treated compliers
- Uses only treated compliers, thus inefficient (Marbach and Hangartner 2020)
- To characterize untreated compliers, $X * (1 - D)$ and replace D with $1 - D$

Unrest compliers

```r
# Variables used in the analysis
vars <- c("mliteracy_1897", "lingfrac_1897", "popdens1858",
          "percnobleown_1877", "districtfemale_1863")
exvars <- c("distance_moscow", "goodsoil", "lnurban",
            "lnpopn", "province_capital")

# For simplicity, we collapse D and Z to a binary variable
data$D <- ifelse(data$afreq >= quantile(data$afreq, probs = 0.75, na.rm = T), 1, 0)
data$Z1 <- ifelse(data$serfperc1 >= quantile(data$serfperc1, 0.75, na.rm=T), 1, 0)
data$Z2 <- ifelse(data$religpolarf4_1870 >= quantile(data$religpolarf4_1870, 0.75, na.rm=T), 1, 0)
```

Unrest compliers

```
##  Compliers' mean, regression method
mean_comp <- function(var, Z){
  require(AER); require(dplyr)
  data <- mutate(data, Xc = get(var)*D)
  formula <- paste0("Xc", "~", "D", "+", paste(exvars, collapse = " + "),
                    "|", Z, "+", paste(exvars, collapse = " + "))
  fit <- ivreg(as.formula(formula), data=data)
  return(coef(fit)["D"])
}

means_z1_t <- means_z2_t <- rep(NA, length(vars))

# Population distribution
means_full <- round(apply(data[data$zemstvo==1,vars], 2, function(x) mean(x, na.rm=T)), 3)

# Compliers of % serf
for(i in 1:length(vars)){means_z1_t[i] <- round(mean_comp(vars[i], "Z1"), 3)}

# Compliers of rel. pol.
for(i in 1:length(vars)){means_z2_t[i] <- round(mean_comp(vars[i], "Z2"), 3)}
```

Unrest compliers

```
cbind(means_full, means_z1_t, means_z2_t)
```

```
##                      means_full means_z1_t means_z2_t
## mliteracy_1897           47.046     44.819     92.626
## lingfrac_1897             0.183     -0.405      1.794
## popdens1858              68.511     34.258    139.561
## percnobleown_1877        27.389     76.015     29.867
## districtfemale_1863   58729.526  31064.884  10005.480
```

Another application: targeted repression

AMERICAN JOURNAL of POLITICAL SCIENCE

The Geography of Repression and Opposition to Autocracy

Maria Angélica Bautista University of Chicago
Felipe González Pontificia Universidad Católica de Chile
Luis R. Martínez University of Chicago
Pablo Muñoz FGV EPGE Brazilian School of Economics and Finance
Mounu Prem Universidad del Rosario

Abstract: *State repression is a prominent feature of nondemocracies, but its effectiveness in quieting dissent and fostering regime survival remains unclear. We exploit the location of military bases before the coup that brought Augusto Pinochet to power in Chile in 1973, which is uncorrelated to precoup electoral outcomes, and show that counties near these bases experienced more killings and forced disappearances at the hands of the government during the dictatorship. Our main result is that residents of counties close to military bases both registered to vote and voted "No" to Pinochet's continuation in power at higher rates in the crucial 1988 plebiscite that bolstered the democratic transition. Potential mechanisms include informational frictions on the intensity of repression in counties far from bases and shifts in preferences caused by increased proximity to the events. Election outcomes after democratization show no lasting change in political preferences.*

Repression compliers

Table C4: Characterization of compliers

	Treated Compliers	Untreated Compliers	Full sample
	(1)	(2)	(3)
A. Pre-1973 characteristics:			
Houses per capita in 1970	0.19	0.22	0.20
Land inequality 1965 (Gini)	0.85	0.80	0.85
Agrarian reform intensity	0.10	0.24	0.20
Vote share Allende 1970	0.61	0.63	0.27
Vote share Alessandri 1970	-0.19	0.31	0.20
B. Post-1973 characteristics:			
Plebiscite:			
Registration	116.18	89.36	71.16
Vote share "No"	58.79	52.29	54.82
Repression year:			
In 1973	0.66	0.33	0.44
In 1974	0.13	0.14	0.11
≥1975	0.25	0.30	0.33
Profession:			
Laborer	0.44	0.19	0.25
Farmer	0.16	-0.08	0.09
Military	0.09	0.06	0.07

Another approach

- See discussion in MHE (p.166-172)

Another approach

- See discussion in MHE (p.166-172)
- Derive unobservable features of compliers from the other groups

Another approach

- See discussion in MHE (p.166-172)
- Derive unobservable features of compliers from the other groups
- Intuition: "encouraged" never-takers and "non-encouraged" always-takers are observable in the data

Another approach

- See discussion in MHE (p.166-172)
- Derive unobservable features of compliers from the other groups
- Intuition: "encouraged" never-takers and "non-encouraged" always-takers are observable in the data
- Under exogenous instrument, they are similar to non-encouraged never-takers and encouraged always-takers (these two are unobservable in the data)

Another approach

- See discussion in MHE (p.166-172)
- Derive unobservable features of compliers from the other groups
- Intuition: "encouraged" never-takers and "non-encouraged" always-takers are observable in the data
- Under exogenous instrument, they are similar to non-encouraged never-takers and encouraged always-takers (these two are unobservable in the data)
- Mean for always-takers: $\mathbb{E}[X|D(1) = D(0) = 1] = \mathbb{E}[X|D = 1, Z = 0]$

Another approach

- See discussion in MHE (p.166-172)
- Derive unobservable features of compliers from the other groups
- Intuition: "encouraged" never-takers and "non-encouraged" always-takers are observable in the data
- Under exogenous instrument, they are similar to non-encouraged never-takers and encouraged always-takers (these two are unobservable in the data)
- Mean for always-takers: $\mathbb{E}[X|D(1) = D(0) = 1] = \mathbb{E}[X|D = 1, Z = 0]$
- Mean for never-takers: $\mathbb{E}[X|D(1) = D(0) = 0] = \mathbb{E}[X|D = 0, Z = 1]$

Another approach

- See discussion in MHE (p.166-172)
- Derive unobservable features of compliers from the other groups
- Intuition: "encouraged" never-takers and "non-encouraged" always-takers are observable in the data
- Under exogenous instrument, they are similar to non-encouraged never-takers and encouraged always-takers (these two are unobservable in the data)
- Mean for always-takers: $\mathbb{E}[X|D(1) = D(0) = 1] = \mathbb{E}[X|D = 1, Z = 0]$
- Mean for never-takers: $\mathbb{E}[X|D(1) = D(0) = 0] = \mathbb{E}[X|D = 0, Z = 1]$
- Overall sample mean is an average of the group means:

$$\begin{aligned}
&\mathbb{E}[X] \\
&= \mathbb{E}[X|D(1) > D(0)]P[D(1) > D(0)]+ \\
&\mathbb{E}[X|D(1) = D(0) = 1]P[D(1) = D(0) = 1]+ \\
&\mathbb{E}[X|D(1) = D(0) = 0]P[D(1) = D(0) = 0]
\end{aligned}$$

Another approach

- Rearrange to find the mean for compliers:

$$\mathbb{E}[X|D(1) > D(0)] = \frac{\mathbb{E}[X]}{P[D=1|Z=1] - P[D=1|Z=0]} - \frac{\mathbb{E}[X|D=1, Z=0]P[D=1|Z=0] - \mathbb{E}[X|D=0, Z=1]P[D=0|Z=1]}{P[D=1|Z=1] - P[D=1|Z=0]}$$

Another approach

- Rearrange to find the mean for compliers:

$$\mathbb{E}[X|D(1) > D(0)] = \frac{\mathbb{E}[X]}{P[D = 1|Z = 1] - P[D = 1|Z = 0]} - \frac{\mathbb{E}[X|D = 1, Z = 0]P[D = 1|Z = 0] - \mathbb{E}[X|D = 0, Z = 1]P[D = 0|Z = 1]}{P[D = 1|Z = 1] - P[D = 1|Z = 0]}$$

- Quantities identified in the data under exogeneity of the instrument

Another approach

- Rearrange to find the mean for compliers:

$$\mathbb{E}[X|D(1) > D(0)] = \frac{\mathbb{E}[X]}{P[D=1|Z=1] - P[D=1|Z=0]} - \frac{\mathbb{E}[X|D=1,Z=0]P[D=1|Z=0] - \mathbb{E}[X|D=0,Z=1]P[D=0|Z=1]}{P[D=1|Z=1] - P[D=1|Z=0]}$$

- Quantities identified in the data under exogeneity of the instrument
- `ivdesc` package in R derives the complier mean

Another approach

- Rearrange to find the mean for compliers:

$$\mathbb{E}[X|D(1) > D(0)] = \frac{\mathbb{E}[X]}{P[D=1|Z=1] - P[D=1|Z=0]} - \frac{\mathbb{E}[X|D=1,Z=0]P[D=1|Z=0] - \mathbb{E}[X|D=0,Z=1]P[D=0|Z=1]}{P[D=1|Z=1] - P[D=1|Z=0]}$$

- Quantities identified in the data under exogeneity of the instrument
- `ivdesc` package in R derives the complier mean
- Standard error computed through bootstrap: reflects uncertainty in the estimation of means and proportions

Another approach

- Rearrange to find the mean for compliers:

$$\mathbb{E}[X|D(1) > D(0)] = \frac{\mathbb{E}[X]}{P[D=1|Z=1] - P[D=1|Z=0]} - \frac{\mathbb{E}[X|D=1,Z=0]P[D=1|Z=0] - \mathbb{E}[X|D=0,Z=1]P[D=0|Z=1]}{P[D=1|Z=1] - P[D=1|Z=0]}$$

- Quantities identified in the data under exogeneity of the instrument
- `ivdesc` package in R derives the complier mean
- Standard error computed through bootstrap: reflects uncertainty in the estimation of means and proportions
- Works for randomized experiments with binary instrument and treatment

ivdesc

Application: field experiment on TV viewership

```
library(icsw); library(ivdesc)
data(FoxDebate)

 with(FoxDebate, ivdesc(X=readnews,D=watchpro,Z=conditn) )  %>% as.data.frame()
```

```
##    group       mu     mu_se         pi      pi_se
## 1 sample 5.500990 0.0896005 1.00000000 0.00000000
## 2     co 5.992418 0.2251350 0.40738261 0.03248977
## 3     nt 5.169014 0.1883447 0.54826255 0.02984220
## 4     at 5.090909 0.6784204 0.04435484 0.01326572
```

kappa-weights

- More general approach (Abadie 2003)
- Following the same principle, constructs a weighting estimator: kappa-weighting

$$\mathbb{E}[X|D(1) > D(0)] = \frac{\mathbb{E}[k_i X_i]}{\mathbb{E}[k_i]}$$

where

$$k_i = 1 - \frac{D_i(1 - Z_i)}{1 - P(Z_i = 1|X_i)} - \frac{(1 - D_i)Z_i}{P(Z_i = 1|X_i)}$$

- Can re-weight the sample to compute moments of the complier distribution
- $P(Z_i = 1|X_i)$ can be estimated with fitted values from LPM

Weak instruments

- Weak instruments: small correlation of the instrument with the endogenous treatment

Weak instruments

- Weak instruments: small correlation of the instrument with the endogenous treatment
- Exacerbate bias and make inference unreliable

Test for weak instruments

- Use the F-statistic of the first-stage regression

Test for weak instruments

- Use the F-statistic of the first-stage regression
- Stock & Yogo (2005): provide critical values for rejecting the null of weak instrument

Test for weak instruments

- Use the F-statistic of the first-stage regression
- Stock & Yogo (2005): provide critical values for rejecting the null of weak instrument
- Results based on assumption of homoskedastic errors, hardly satisfied (Andrews, Stock & Sun 2019)

Test for weak instruments

- Use the F-statistic of the first-stage regression
- Stock & Yogo (2005): provide critical values for rejecting the null of weak instrument
- Results based on assumption of homoskedastic errors, hardly satisfied (Andrews, Stock & Sun 2019)
- Solutions: Robust F statistic. Equivalent to Kleibergen-Paap statistic for the case of a single regressor (Andrews, Stock & Sun 2019)

Test for weak instruments

- Use the F-statistic of the first-stage regression
- Stock & Yogo (2005): provide critical values for rejecting the null of weak instrument
- Results based on assumption of homoskedastic errors, hardly satisfied (Andrews, Stock & Sun 2019)
- Solutions: Robust F statistic. Equivalent to Kleibergen-Paap statistic for the case of a single regressor (Andrews, Stock & Sun 2019)
  - Reported automatically by `ivreg2` in Stata

Test for weak instruments

- Use the F-statistic of the first-stage regression
- Stock & Yogo (2005): provide critical values for rejecting the null of weak instrument
- Results based on assumption of homoskedastic errors, hardly satisfied (Andrews, Stock & Sun 2019)
- Solutions: Robust F statistic. Equivalent to Kleibergen-Paap statistic for the case of a single regressor (Andrews, Stock & Sun 2019)
  - Reported automatically by `ivreg2` in Stata
- Solutions: Effective first-stage F-statistic (Montiel Olea & Pflueger 2013)

Test for weak instruments

- Use the F-statistic of the first-stage regression
- Stock & Yogo (2005): provide critical values for rejecting the null of weak instrument
- Results based on assumption of homoskedastic errors, hardly satisfied (Andrews, Stock & Sun 2019)
- Solutions: Robust F statistic. Equivalent to Kleibergen-Paap statistic for the case of a single regressor (Andrews, Stock & Sun 2019)
  - Reported automatically by `ivreg2` in Stata
- Solutions: Effective first-stage F-statistic (Montiel Olea & Pflueger 2013)
- Equivalent to robust F in the just-identified case

Test for weak instruments

- Use the F-statistic of the first-stage regression
- Stock & Yogo (2005): provide critical values for rejecting the null of weak instrument
- Results based on assumption of homoskedastic errors, hardly satisfied (Andrews, Stock & Sun 2019)
- Solutions: Robust F statistic. Equivalent to Kleibergen-Paap statistic for the case of a single regressor (Andrews, Stock & Sun 2019)
  - Reported automatically by `ivreg2` in Stata
- Solutions: Effective first-stage F-statistic (Montiel Olea & Pflueger 2013)
- Equivalent to robust F in the just-identified case
- Post-estimation command `weakivtest` in Stata (`ssc install weakivtest`)

Test for weak instruments

- Use the F-statistic of the first-stage regression
- Stock & Yogo (2005): provide critical values for rejecting the null of weak instrument
- Results based on assumption of homoskedastic errors, hardly satisfied (Andrews, Stock & Sun 2019)
- Solutions: Robust F statistic. Equivalent to Kleibergen-Paap statistic for the case of a single regressor (Andrews, Stock & Sun 2019)
  - Reported automatically by `ivreg2` in Stata
- Solutions: Effective first-stage F-statistic (Montiel Olea & Pflueger 2013)
- Equivalent to robust F in the just-identified case
- Post-estimation command `weakivtest` in Stata (`ssc install weakivtest`)
- With one instrument, Effective F can be compared to Stock & Yogo critical values

Test for weak instruments

- Use the F-statistic of the first-stage regression
- Stock & Yogo (2005): provide critical values for rejecting the null of weak instrument
- Results based on assumption of homoskedastic errors, hardly satisfied (Andrews, Stock & Sun 2019)
- Solutions: Robust F statistic. Equivalent to Kleibergen-Paap statistic for the case of a single regressor (Andrews, Stock & Sun 2019)
  - Reported automatically by `ivreg2` in Stata
- Solutions: Effective first-stage F-statistic (Montiel Olea & Pflueger 2013)
- Equivalent to robust F in the just-identified case
- Post-estimation command `weakivtest` in Stata (`ssc install weakivtest`)
- With one instrument, Effective F can be compared to Stock & Yogo critical values
- With multiple instruments, use the critical values in Montiel Olea & Pflueger

Test for weak instruments

```
. qui ivreg2 peasantrepresentation_1864 (afreq = serfperc) distance_moscow goodsoil lnurban lnpopn provinc
> e_capital, robust

. weakivtest
(obs=362)

Montiel-Pflueger robust weak instrument test
--------------------------------------------
Effective F statistic:        49.697
Confidence level alpha:           5%
--------------------------------------------


--------------------------------------------
Critical Values                 TSLS      LIML
--------------------------------------------
% of Worst Case Bias
tau=5%                        37.418    37.418
tau=10%                       23.109    23.109
tau=20%                       15.062    15.062
tau=30%                       12.039    12.039
--------------------------------------------

.
```

Inference with weak instruments

- In just-identified case Anderson-Rubin test is efficient (Andrews, Stock & Sun 2019)

Inference with weak instruments

- In just-identified case Anderson-Rubin test is efficient (Andrews, Stock & Sun 2019)
- `weakiv` package in Stata computes the AR confidence set (`ssc install weakiv`)

Inference with weak instruments

- In just-identified case Anderson-Rubin test is efficient (Andrews, Stock & Sun 2019)
- `weakiv` package in Stata computes the AR confidence set (`ssc install weakiv`)
- For the over-identified case, debate still ongoing

Inference with weak instruments

```
. qui ivreg2 peasantrepresentation_1864 (afreq = serfperc) distance_moscow goodsoil lnurban lnpopn provinc
> e_capital, robust

. weakiv
Estimating confidence sets over 100 grid points
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50
..................................................   100

Weak instrument robust tests and confidence sets for linear IV
H0: beta[peasantrepresentation_1864:afreq] = 0
```

Test	Statistic			p-value	Conf. level	Conf. Set
AR	chi2(1)	=	33.66	0.0000	95%	[-63.0172,-28.3202]
Wald	chi2(1)	=	24.85	0.0000	95%	[-58.5132,-25.4844]

```
Confidence sets estimated for 100 points in [-75.0276,-8.96998].
Number of obs N = 362.
Method = lagrange multiplier (LM).
Tests robust to heteroskedasticity.
Wald statistic in last row is based on ivreg2 estimation and is not robust to weak instruments.

.
```

Double ML

- Goal: estimation of treatment effect relaxing linear functional form assumption

Double ML

- Goal: estimation of treatment effect relaxing linear functional form assumption
- Idea: Estimate conditional mean functions of D and Y with potentially complex functions of covariates

Double ML

- Goal: estimation of treatment effect relaxing linear functional form assumption
- Idea: Estimate conditional mean functions of D and Y with potentially complex functions of covariates
- Then residua-residual regression of $\tilde{Y}$ on $\tilde{D}$

Double ML

- Goal: estimation of treatment effect relaxing linear functional form assumption
- Idea: Estimate conditional mean functions of D and Y with potentially complex functions of covariates
- Then residua-residual regression of $\tilde{Y}$ on $\tilde{D}$
- ML: "learn" functional form that best fits the data from data itself

Double ML

`DoubleML` package

- Several algorithms available for selecting the functional form

Double ML

`DoubleML` package

- Several algorithms available for selecting the functional form
- Basic intuitions (details in Quant 3):

Double ML

`DoubleML` package

- Several algorithms available for selecting the functional form
- Basic intuitions (details in Quant 3):
- LASSO: shrinkage/regularization for selecting predictors

Double ML

`DoubleML` package

- Several algorithms available for selecting the functional form
- Basic intuitions (details in Quant 3):
- LASSO: shrinkage/regularization for selecting predictors
- Random trees/forest: predict through random splitting of sample

Double ML

```r
library(DoubleML); library(data.table); library(mlr3); library(mlr3learners)

### Initialize the data ###
## Covariates to use
X <- c("longitude", "latitude", "latitude2", "longitude2", "lingfrac_1897", "mliteracy_1897")

## Data for the model: need to be in data.table format
## and must not have missing values

data_dml <- select(data, c(peasantrepresentation_1864, D, all_of(X))) %>% as.data.table() %>% na.omit()

data_dml <- DoubleMLData$new(data_dml,
                             y_col = "peasantrepresentation_1864",
                             d_cols = "D")
```

Double ML

```r
# Initialize learners
set.seed(123)
lasso <- lrn("regr.cv_glmnet", nfolds = 3, s = "lambda.min")
lasso_class <- lrn("classif.cv_glmnet", nfolds = 3, s = "lambda.min")

# Initialize DoubleMLPLR model
dml_plr_lasso <- DoubleMLPLR$new(data_dml,
                                ml_l = lasso,
                                ml_m = lasso_class,
                                n_folds = 3)
dml_plr_lasso$fit()
```

```
## INFO  [15:57:07.658] [mlr3] Applying learner 'regr.cv_glmnet' on task 'nuis_l' (iter 1/3)
## INFO  [15:57:07.816] [mlr3] Applying learner 'regr.cv_glmnet' on task 'nuis_l' (iter 2/3)
## INFO  [15:57:07.858] [mlr3] Applying learner 'regr.cv_glmnet' on task 'nuis_l' (iter 3/3)
## INFO  [15:57:08.039] [mlr3] Applying learner 'classif.cv_glmnet' on task 'nuis_m' (iter 1/3)
## INFO  [15:57:08.245] [mlr3] Applying learner 'classif.cv_glmnet' on task 'nuis_m' (iter 2/3)
## INFO  [15:57:08.382] [mlr3] Applying learner 'classif.cv_glmnet' on task 'nuis_m' (iter 3/3)
```

```r
dml_plr_lasso$summary()
```

```
## Estimates and significance testing of the effect of target variables
##   Estimate. Std. Error t value Pr(>|t|)
## D   -0.7106     0.6344   -1.12    0.263
```