

# GMM, Indirect Inference and Bootstrap

Instrumental variables

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# TO IMPROVE

- Slide with inconsistency and forecastability? Do you really need it?
- Make the structure and dimensions of  $W$ ,  $W'u$ ,  $W_t$ ,  $W_t'u_t$  more clear
- Interpretations and structures of  $M_X$ ,  $P_W$

# Instrumental variables

## Preliminaries

- OLS is not consistent and biased if  $E(u_t|X_t) \neq 0$
- Define an information set  $\Omega_t$  (a  $\sigma$ -algebra), such that

$$E(u_t|\Omega_t) = 0$$

- This rationality conditions or moment conditions can be used for estimation
- Variables in  $\Omega_t$  are called **instrumental variables** (or instruments)
- We denote the instrument vector by  $W_t$

# Instrumental variables

## Correlation between errors and disturbances (I)

Errors in variables (e.g. in questionnaires)

- Consider the model

$$y_t = \alpha + \beta x_t^* + \varepsilon_t, \quad \varepsilon_t \sim iid(0, \sigma_\varepsilon^2)$$

- The exogenous variable  $x_t^*$  is unobservable
- We can only observe

$$x_t = x_t^* + v_t$$

where  $v_t \sim iid(0, \sigma_v^2)$  are independent of everything else

- Estimators of  $y_t = \alpha + \beta x_t + u_t$  are inconsistent

[P]

# Instrumental variables

## Correlation between errors and disturbances (II)

### Omitted variables bias

- Let

$$y_t = \alpha + \beta_1 x_{1t} + \beta_2 x_{2t} + \varepsilon_t$$

- If  $x_2$  is unobservable, one estimates

$$y_t = \alpha + \beta_1 x_{1t} + u_t$$

where  $u_t = \beta_2 x_{2t} + \varepsilon_t$

- If  $x_{2t}$  and  $x_{1t}$  are correlated then so are  $u_t$  and  $x_{1t}$

# Instrumental variables

## Correlation between errors and disturbances (III)

### Endogeneity

- Standard example: supply and demand curves determine both price and quantity

$$q_t = \gamma_d p_t + X_t^d \beta_d + u_t^d$$

$$q_t = \gamma_s p_t + X_t^s \beta_s + u_t^s$$

- Solve for  $q_t$  and  $p_t$

$$\begin{bmatrix} q_t \\ p_t \end{bmatrix} = \begin{bmatrix} 1 & -\gamma_d \\ 1 & -\gamma_s \end{bmatrix}^{-1} \left( \begin{bmatrix} X_t^d \beta_d \\ X_t^s \beta_s \end{bmatrix} + \begin{pmatrix} u_t^d \\ u_t^s \end{pmatrix} \right)$$

# Instrumental variables

## Correlation between errors and disturbances (III)

- Since  $q_t$  and  $p_t$  depend on both  $u_t^d$  and  $u_t^s$  single equation OLS estimation of

$$q_t = \gamma_d p_t + X_t^d \beta_d + u_t^d$$

$$q_t = \gamma_s p_t + X_t^s \beta_s + u_t^s$$

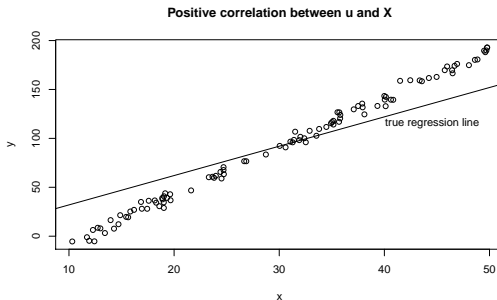
is inconsistent

- The right hand side variable  $p_t$  is correlated with the error term
- The condition  $E(u_t | \Omega_t) = 0$  is violated if  $p_t$  is in  $\Omega_t$

# Instrumental variables

## Correlation between errors and disturbances

- **Warning!** Inconsistency is not always a problem
- If we simply want to forecast, we can use inconsistent estimators
- Trivial example:





# Instrumental variables

## The simple IV estimator

- Let  $W$  denote the  $T \times K$  matrix of instruments
- All columns of  $X$  with  $X_t \in \Omega_t$  should be included in  $W$
- Then  $E(u_t | W_t) = 0$  implies the moment condition

$$E(W'u) = E(W'(y - X\beta)) = 0$$

- The IV estimator is a method of moment estimator
- The solution is

$$\hat{\beta}_{IV} = (W'X)^{-1} W'y$$

# Instrumental variables

## Properties

- The simple IV estimator is consistent if

$$\text{plim} \frac{1}{n} W'X = S_{WX}$$

is deterministic and nonsingular

[P]

- The simple IV estimator is asymptotically normal,

$$\sqrt{n} \left( \hat{\beta}_{IV} - \beta \right) \rightarrow U \sim N \left( 0, \sigma^2 (S_{WX})^{-1} S_{WW} (S'_{WX})^{-1} \right)$$

where  $S_{WW} = \text{plim} \frac{1}{n} W'W$

[P]

# Instrumental variables

## How to find instruments

- Instruments must be
  - ① exogenous, i.e.  $\text{plim}_n \frac{1}{n} W' u = 0$
  - ② valid, i.e.  $\text{plim}_n \frac{1}{n} W' X = S_{WX}$  non-singular
- Natural experiments (weather, earthquakes, ...)
- Angrist and Pischke (2009):

*Good instruments come from a combination of institutional knowledge and ideas about the processes determining the variable of interest.*

# Instrumental variables

## How to find instruments

### Examples

#### Natural experiments

- ① Brückner and Ciccone: Rain and the demographic window of opportunity, *Econometrica* 79 (2011) 923-947
- ② Angrist and Evans: Children and their parents' labor supply: Evidence from exogenous variation in family size, *American Economic Review* 88 (1998) 450-77.

## GMM, Indirect Inference and Bootstrap

└ Instrumental variables

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## Examples

## Natural experiments

- ▣ Brückner and Ciccone: Rain and the demographic window of opportunity, *Econometrica* 79 (2011) 923-947
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- Negative konomische EK-Schocks knnen fr demokratische Verbesserung Instrumente liefern (konomische Rezessionen), Sub-Sahara Afrikanische Lnder, INstrument: Negative Regenschocks
- Endogenitt von Fertilitt, Arbeitsentscheidung nach Geburt. Effekt von Kindergeburt auf Arbeitsangebot. Instrument: Prferenz fr mixed Kinder-Komposition, Eltern mit 2 Mdels probieren noch mal fr Jungen.

# Instrumental variables

## How to find instruments

### Examples

#### Institutional arrangements

- ① Angrist and Krueger: Does Compulsory School Attendance Affect Schooling and Earnings?, Quarterly Journal of Economics 106 (1991) 979-1014.
- ② Levitt: The Effect of Prison Population Size on Crime Rates: Evidence from Prison Overcrowding Litigation, Quarterly Journal of Economics 111 (1996) 319-351.

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## Examples

## Institutional arrangements

- ⌚ Angrist and Krueger: Does Compulsory School Attendance Affect Schooling and Earnings?, *Quarterly Journal of Economics* 106 (1991) 979-1014.
- ⌚ Levitt: The Effect of Prison Population Size on Crime Rates: Evidence from Prison Overcrowding Litigation, *Quarterly Journal of Economics* 111 (1996) 319-351.

- Welcher Monat man geboren ist: Keine Korrelation mit Flügigkeit und Earnings, keine determinante von Flügigkeiten, aber korreliert mit years of schooling. Männer die gezwungen werden zur Schule zu gehen, verdienen mehr
- Gerichtsverfahren. Simultaneität/Endogenität zwischen Gefängnisbevölkerung und Verbrechensraten. Idee: Gefängnisbevölkerung steigt impliziert sinkende Verbrechensrate. Messfehler. IV: Korreliert mit Verurteilung Gef. Bevölkerung aber sonst unrelated to crime rates, state prison overcrowding litigation.

# Instrumental variables

## How to find instruments

- In a time series context, one can sometimes use lagged endogenous regressors as instrumental variables
- Example:

$$y_t = \alpha + \beta x_t + u_t$$

with  $E(u_t|x_t) \neq 0$

- If  $\text{Cov}(x_t, x_{t-1}) \neq 0$  but  $\text{Cov}(u_t, x_{t-1}) = 0$ , then  $x_{t-1}$  can be used as instrumental variable
- Attention:  $\text{Cov}(u_t, x_{t-1}) = 0$  is not always obvious



# Instrumental variables

## How to find instruments

### Example (Measurement error in time series)

Consider the model

$$y_t = \alpha + \beta x_t^* + u_t$$

$$x_t^* = \rho x_{t-1}^* + \varepsilon_t$$

$$x_t = x_t^* + v_t.$$

Then  $x_{t-1}$  is a valid instrument for a regression of  $y_t$  on  $x_t$ , and  $\alpha$  and  $\beta$  will be estimated consistently.

[IVLags.R]

# Instrumental variables

## How to find instruments

### Example (Omitted variable bias in time series)

Consider the model

$$y_t = \alpha + \beta_1 x_{1t} + \beta_2 x_{2t} + u_t$$

$$x_{1t} = \rho_{11}x_{1,t-1} + \rho_{12}x_{2,t-1} + \varepsilon_{1t}$$

$$x_{2t} = \rho_{21}x_{1,t-1} + \rho_{22}x_{2,t-1} + \varepsilon_{2t}$$

Then  $x_{1,t-1}$  is **not** a valid instrument for a regression of  $y_t$  on  $x_{1t}$ , and  $\alpha$  and  $\beta_1$  will **not** be estimated consistently.

[IVLags.R]

# Instrumental variables

## How to find instruments

### Example (Endogeneity in time series)

Consider the model

$$\begin{aligned}y_t &= \alpha + \beta_1 x_t + \beta_2 y_{t-1} + u_t \\x_t &= \gamma + \delta_1 y_t + \delta_2 x_{t-1} + v_t\end{aligned}$$

Then  $x_{1,t-1}$  is a valid instrument for a regression of  $y_t$  on  $x_t$  and  $y_{t-1}$ , and  $\alpha$ ,  $\beta_1$  and  $\beta_2$  will be estimated consistently.

[IVLags.R]

# Instrumental variables

## Generalized IV estimation

- If the number of instruments  $L$  is larger than the number of parameters  $K$ , the model is **overidentified**
- Right-multiply the  $T \times L$  matrix  $W$  by an  $L \times K$  matrix  $J$  to obtain an  $T \times K$  instrument matrix  $WJ$
- Linear combinations of the instruments in  $W$
- One can show that the asymptotically optimal matrix is  $J = (W'W)^{-1} W'X$ , see Davidson and MacKinnon.

# Instrumental variables

## Generalized IV estimation

- The generalized IV estimator is

$$\begin{aligned}\hat{\beta}_{GIV} &= ((WJ)'X)^{-1} (WJ)'y \\ &= \left( X'W (W'W)^{-1} W'X \right)^{-1} X'W (W'W)^{-1} W'y \\ &= (X'P_W X)^{-1} X'P_W y\end{aligned}$$

with  $P_W = W (W'W)^{-1} W'$

- Consistency and asymptotic normality still hold

# Instrumental variables

## Generalized IV estimation

- The two-stage-least-squares (2SLS) interpretation
- The matrix  $J$  is similar to  $\hat{\beta}$  in the standard OLS model,

$$J = (W'W)^{-1} W'X$$

- Hence,  $WJ$  is similar to  $X\hat{\beta}$
- The optimal instruments are obtained if we regress the endogenous regressors on the instruments (1st stage), and then use the fitted values as regressors (2nd stage)

# Instrumental variables

## Finite sample properties

- The finite sample properties of IV estimators are complex
- In the overidentified case, the first  $L - K$  moments exist, but higher moments do not
- If the expectation exists, IV estimators are in general biased
- The simple IV estimator has **very** heavy tails, even the first moment does not exist!
- The estimator can be extremely far off the true value

[ivfinite.R]

# Instrumental variables

## Hypothesis testing

- Exact hypothesis tests are usually not feasible
- Asymptotic tests are based on the asymptotic normality
- An estimator of the covariance matrix of  $\hat{\beta}_{IV}$  is

$$\widehat{Cov}(\hat{\beta}_{IV}) = \hat{\sigma}^2 (X' P_W X)^{-1}$$

with

$$\begin{aligned} P_W &= W (W' W)^{-1} W' \\ \hat{\sigma}^2 &= \frac{1}{n} (y - X \hat{\beta}_{IV})' (y - X \hat{\beta}_{IV}) \end{aligned}$$



# Instrumental variables

## Hypothesis testing

- Asymptotic  $t$ -test

$$H_0 : \beta_i = \beta_{i0}$$

$$H_1 : \beta_i \neq \beta_{i0}$$

- Under the null hypothesis, the test statistic

$$t = \frac{\hat{\beta}_i - \beta_{i0}}{\sqrt{\widehat{Var}(\hat{\beta}_i)}}$$

is asymptotically  $N(0, 1)$

# Instrumental variables

## Hypothesis testing

- Asymptotic Wald test (similar to an  $F$ -test)

$$H_0 : \beta_2 = \beta_{20}, \quad H_1 : \beta_2 \neq \beta_{20}$$

where  $\beta_2$  is a length  $L$  subvector of  $\beta$

- Under the null hypothesis, the test statistic

$$W = \left( \hat{\beta}_2 - \beta_{20} \right)' \left[ \widehat{\text{Cov}} \left( \hat{\beta}_2 \right) \right]^{-1} \left( \hat{\beta}_2 - \beta_{20} \right)$$

is asymptotically  $\chi^2$  with  $L$  degrees of freedom

# Instrumental variables

## Hypothesis testing

- Testing overidentifying restrictions
- The identifying restrictions are

$$E(u_t|W_t) = 0$$

or  $E(W'u) = 0$

- If the model is just identified the validity of the restriction cannot be tested
- If the model is overidentified, one can test if the overidentifying restrictions hold, i.e. if the instruments are valid and exogenous

# Instrumental variables

## Hypothesis testing

- Basic test idea: Check if the IV residuals can be explained by the full set of instruments
- Compute the IV residuals  $\hat{u}$
- Regress the residuals on all instruments  $W$
- Under the null hypothesis, the test statistic

$$nR^2 \sim \chi_m^2$$

where  $m$  is the degree of overidentification

Davidson and MacKinnon (2004, p. 338):

*Even if we do not know quite how to interpret a significant value of the overidentification test statistic, it is always a good idea to compute it. If it is significantly larger than it should be by chance under the null hypothesis, one should be extremely cautious in interpreting the estimates, because it is quite likely either that the model is specified incorrectly or that some of the instruments are invalid.*

- Durbin-Wu-Hausman test

$$H_0 : E(X'u) = 0$$

$$H_1 : E(W'u) = 0$$

- Test if IV estimation is really necessary or if OLS would do
- Under  $H_0$ , OLS is consistent and efficient, but IV is just consistent
- Under  $H_1$ , OLS is inconsistent, but IV is still consistent
- Basic test idea: Compare  $\hat{\beta}_{OLS}$  and  $\hat{\beta}_{IV}$ . If they are 'too different', reject  $H_0$

- The difference between the estimators is

$$\begin{aligned} & \hat{\beta}_{IV} - \hat{\beta}_{OLS} \\ &= (X'P_WX)^{-1} X'P_Wy - (X'X)^{-1} X'y \\ &= (X'P_WX)^{-1} \left( X'P_Wy - (X'P_WX) (X'X)^{-1} X'y \right) \\ &= (X'P_WX)^{-1} \left( X'P_W \left( I - X (X'X)^{-1} X' \right) y \right) \\ &= (X'P_WX)^{-1} (X'P_WM_X y) \end{aligned}$$

# Instrumental variables

## Hypothesis testing

- We need to test if  $X'P_W M_X y$  is significantly different from 0
- This term is identically equal to zero for all variables in  $X$  that are instruments (i.e. that are also in  $W$ )
- Denote by  $\tilde{X}$  all possibly endogenous regressors
- To test if  $\tilde{X}'P_W M_X y$  is significantly different from zero, perform a Wald test of  $\delta = 0$  in the regression

$$y = X\beta + P_W \tilde{X}\delta + u$$