

Instrumental Variables

matrix-free

1 Introduction

This handout extends the handout on "The Multiple Linear Regression Model" and refers to its definitions and assumptions in section 2. It discusses the violation of the exogeneity assumption (OLS3), its consequences and the potential solution through the use of instrumental variables.

In many applications of the linear model, we suspect that some regressors are endogenous, i.e. one or more regressors are correlated with the error term, $cov(x_{ik}, u_i) \neq 0$. In this situation, OLS cannot consistently estimate the causal effect of the regressor on the dependent variable.

Sometimes, we are able to find exogenous variables z_{il} which are correlated with the endogenous regressor but not correlated with the error term, i.e. $cov(z_{il}, u_i) = 0$. Such variables z_{il} are called *instrumental variables* or *instruments*. If there are enough good such instruments, we can estimate the causal effect of the regressor on the dependent variable.

2 Canonical Examples

2.1 Measurement Errors (Errors in Variables)

Consider the true regression model

$$y_i = \beta_0 + \beta_1 x_i^* + u_i^*$$

which conforms the standard OLS assumptions. Suppose that the variable x^* is only observed with an error

$$x_i = x_i^* + v_i$$

where the error v is uncorrelated with x^* and with u_i^* . The estimated regression model uses x as a proxy for x^*

$$y_i = \beta_0 + \beta_1 x_i + u_i$$

where $u_i = u_i^* - \beta_1 v_i$. The regressor x is therefore correlated with the error term u as both depend on v . Assuming independence between v and u^* , the covariance in the above example is $cov(x, u) = -\beta_1 \sigma_v^2$.

In this special case of a bivariate regression, the OLS estimator is “biased towards zero” as

$$|\text{plim } \hat{\beta}_1| = |\beta_1| \frac{1}{1 + \frac{V(v_i)}{V(x_i)}} < |\beta_1|.$$

2.2 Simultaneity and Reversed Causality

Consider the following system of equations

$$y_{i1} = \alpha_1 + z_{i1}\beta_1 + y_{i2}\gamma_1 + u_{i1}$$

$$y_{i2} = \alpha_2 + z_{i2}\beta_2 + y_{i1}\gamma_2 + u_{i2}$$

where we assume that both z_1 and z_2 are uncorrelated with both u_1 and u_2 . This system is called a *structural simultaneous equation system* since y_1 and y_2 are simultaneously determined. The regressor y_2 depends on y_1 through the second equation. As y_1 is directly dependent on u_1 , the regressor y_2 is also correlated with u_1 and hence endogenous in the first equation. Assuming that u_1 and u_2 are uncorrelated, $cov(y_{i2}, u_{i1}) = \gamma_2 / (1 - \gamma_1 \gamma_2) \sigma_{u_1}^2$. The above equation system is also described as *reversed causality* because the dependent variable y_1 has a feedback effect on the regressor y_2 .

In the above example z_2 and z_1 are straightforward instruments for IV estimation of the first and second equation, respectively.¹

¹Instead of estimating the single structural equations directly by IV it is possible to formulate and estimate a so-called *reduced form* of the above equation system. The RHS of the reduced form equations consists of exogenous variables only. If the system is *identified*, the parameters in the structural form can be deduced from the estimated parameters in the reduced form.

2.3 Omitted Variables

Consider the following regression model

$$y_i = \beta_0 + x_{i1}\beta_1 + x_{i2}\beta_2 + v_i$$

which conforms with standard OLS assumptions. Suppose that the variable x_2 is not observed. The estimated regression model is therefore

$$y_i = \beta_0 + x_{i1}\beta_1 + u_i$$

where $u_i = x_{i2}\beta_2 + v_i$. Regressors x_k in x_1 are therefore correlated with the error term u if they are correlated with the omitted variable x_2 . In case x_{i1} and x_{i2} are scalars, $\text{cov}(x_{ik}, u_i) = \beta_2 \text{cov}(x_{ik}, x_{i2})$.

3 The Econometric Model

Consider the multiple linear regression model for observations $i = 1, \dots, N$

$$y_i = \beta_0 + \beta_1 x_{i1} + \dots + \beta_K x_{iK} + \gamma_1 w_{i1} + \dots + \gamma_M w_{iM} + u_i$$

where y_i is the dependent variable, x_{i1}, \dots, x_{iK} are K endogenous regressors w_{i1}, \dots, w_{iM} are M exogenous regressors, β_k and γ_m are $K + M + 1$ parameters and u_i is the error term. Each observation is furthermore described by L exogenous variables z_{i1}, \dots, z_{iL} , called the *instruments* or *excluded instruments*.

The data generation process (dgp) is fully described by the following set of assumptions:

IV1: Linearity

$$y_i = \beta_0 + \beta_1 x_{i1} + \dots + \beta_K x_{iK} + \gamma_1 w_{i1} + \dots + \gamma_M w_{iM} + u_i, E(u_i) = 0$$

IV2: Independence

$$\{x_{i1}, \dots, x_{iK}, w_{i1}, \dots, w_{iM}, z_{i1}, \dots, z_{iL}, y_i\}_{i=1}^N \text{ i.i.d.}$$

IV2 means that regressors, instruments and dependent variables are independent across observations. In practice guaranteed by random sampling.

IV3: Exogeneity

$$\forall m : \text{cov}(w_{im}, u_i) = 0$$

$$\forall \ell : \text{cov}(z_{i\ell}, u_i) = 0$$

IV3 means that the exogenous variables (exogenous regressors and excluded instruments) are uncorrelated with the error term.

IV4: Identifiability

$(\hat{x}_{i1}, \dots, \hat{x}_{iK}, w_{i1}, \dots, w_{iM})$ are not linearly dependent and

$$0 < V(\hat{x}_{ik}) < \infty \text{ for all } k \text{ and}$$

$$0 < V(w_{im}) < \infty \text{ for all } m$$

where \hat{x}_{ik} is predicted by a regression of x_k on $z_1, \dots, z_L, w_1, \dots, w_M$ and a constant

IV4 is also called *instrument relevance* and requires that there are at least as many excluded instruments as endogenous regressors, $L \geq K$, and that the correlation between instruments and endogenous regressors is not zero, that the instruments are not perfectly collinear, that all instruments (but the constant) have non-zero variance and not too many extreme values.

IV5: Error Structure

$$\text{a) } V(u_i | w_{i1}, \dots, w_{iM}, z_{i1}, \dots, z_{iL}) = \sigma^2 < \infty \text{ (homoscedasticity)}$$

$$\text{b) } V(u_i | w_{i1}, \dots, w_{iM}, z_{i1}, \dots, z_{iL}) = \sigma_i^2 = g(w_{i1}, \dots, z_{iL}) < \infty \\ \text{(conditional heteroscedasticity)}$$

4 Estimation with OLS

The OLS estimators β_k and γ_m are biased and inconsistent because *OLS3* is violated.

5 Estimation with IV (2SLS)

The instrumental variables estimator for β_k and γ_m can be estimated in a two-stage procedure:

- (1) Regress each x_k on $z_1, \dots, z_L, w_1, \dots, w_M$ and a constant. Predict \hat{x}_{ik} for each variable k and each observation i .
- (2) Regress y on $\hat{x}_1, \dots, \hat{x}_K, w_1, \dots, w_M$ and a constant.

The estimated coefficients β_k^{IV} and γ_m^{IV} of the 2nd stage are called the instrumental variables (IV) or two-stage least squares (2SLS) estimates.

For the binary regression model with one endogenous regressor and one instrument, $K = L = 1$ and $M = 0$, the IV estimator of β_0 and β_1 can be directly calculated as:

$$\hat{\beta}_1^{IV} = \frac{\sum_{i=1}^N (\hat{x}_i - \bar{\hat{x}})(y_i - \bar{y})}{\sum_{i=1}^N (\hat{x}_i - \bar{\hat{x}})^2} = \frac{\sum_{i=1}^N (z_i - \bar{z})(y_i - \bar{y})}{\sum_{i=1}^N (z_i - \bar{z})(x_i - \bar{x})}$$

$$\hat{\beta}_0^{IV} = \bar{y} - \hat{\beta}_1^{IV} \bar{x}$$

6 Small Sample Properties of the IV Estimator

No small sample properties can be analytically established. The IV estimator is in general biased.

7 Asymptotic Properties of the IV Estimator

The following large sample properties can be established under assumptions *IV1* through *IV5*:

- The IV estimator is consistent:

$$\text{plim } \hat{\beta}_k^{IV} = \beta_k$$

- The IV estimator is asymptotically normally distributed:

$$\sqrt{N}(\hat{\beta}_k^{IV} - \beta_k) \xrightarrow{d} N(0, \varsigma^2)$$

- The IV estimator is therefore approximately normally distributed:

$$\hat{\beta}_k^{IV} \overset{A}{\approx} N(\beta_k, \text{Avar}(\hat{\beta}_k))$$

where the asymptotic variance is $\text{Avar}(\hat{\beta}) = \varsigma^2/N$. For the binary regression model under *IV5a* (homoscedasticity) it can be consistently estimated as

$$\widehat{\text{Avar}}(\hat{\beta}_1^{IV}) = \frac{\hat{\sigma}^2}{\sum_{i=1}^N (\hat{x}_i - \bar{\hat{x}})^2}$$

with

$$\hat{\sigma}^2 = \frac{1}{N} \sum_{i=1}^N \hat{u}_i^2$$

where $\hat{u}_i = y_i - (\hat{\beta}_0 + \hat{\beta}_1 x_{i1})$. In the general case with K endogenous regressors, M exogenous regressors, L instruments and *IV5b* (heteroscedasticity), $\text{Avar}(\hat{\beta}_k^{IV})$ can be consistently estimated as the *robust* or *Eicker-Huber-White* estimator (see handout on “Heteroscedasticity in the linear Model”).

Note: The estimated asymptotic variance given in the usual output of the 2nd stage OLS regression is incorrect since $\hat{\sigma}^2$ will be based on $\hat{u}_i = y_i - (\hat{\beta}_0 + \hat{\beta}_1 \hat{x}_{i1} + \dots + \hat{\beta}_K \hat{x}_{iK} + \hat{\gamma}_1 w_{i1} + \dots + \hat{\gamma}_M w_{iM})$ rather than $\hat{u}_i = y_i - (\hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \dots + \hat{\beta}_K x_{iK} + \hat{\gamma}_1 w_{i1} + \dots + \hat{\gamma}_M w_{iM})$.

8 What are valid instruments

Valid instruments are typically derived from natural or random experiments (Angrist and Krueger 2001). Instruments are valid if the following two requirements are satisfied:

- (1) *Instrument Exogeneity (IV3)*: Valid instruments are uncorrelated with the error term. This requirement needs a strong theoretical argument and can in general not be tested (see section 9). The theoretical argument has to convincingly
 - (a) describe how the instrument influences the endogenous regressor. This is the influence after controlling for the effect through other included regressors.
 - (b) rule out any direct effect of the instrument on the dependent variable or any effect running through omitted variables. This is sometimes called the *exclusion restriction*.
 - (c) rule out any reverse effect of the dependent variable on the instrument.
- (2) *Instrument Relevance (IV4)*: Valid instruments are highly correlated with the endogenous regressors even after controlling for the exogenous regressors. This requirement can be empirically tested in the first stage regression (see section 10).

In practice the two requirements are often conflicting.

9 Testing for Exogeneity of the Instruments

The exogeneity of the instruments (*IV3*) can in general *not* be tested.

In case we have more instruments than necessary, $L > K$, we can perform a so-called *J*-test for *overidentifying restrictions*. This tests whether all instruments are exogeneous *assuming* that a least one of the instruments is exogenous. The *J*-Test will therefore not necessarily detect a situation in which all instruments are endogenous.

10 Testing for Relevance of the Instruments

Instruments with low correlation between the endogenous regressors are called *weak instruments*. There is empirical and theoretical evidence that IV estimation with weak instruments may perform bad and even poorer than OLS (surveyed in Stock, Wright and Yogo 2002).

The relevance of the instruments is tested in the first-stage regression. As a rule of thumb, the F -statistic of a joint test whether all excluded instruments (z_{i1}, \dots, z_{iL}) are significant should be bigger than 10 in case of a single endogenous regressor. In case of a single instrument and a single endogenous regressor, this implies that the t -value for the instrument should be bigger than 3.2 or the corresponding p -value below 0.0016. This F -Test should always be reported when reporting IV estimates.

11 Testing for Exogeneity of the Regressors

We may also want to know if there is an endogeneity problem in an application. This can be tested by a (Durbin-Wu-)Hausmann test if we have a set of valid instruments at hand. The test is performed by comparing $\hat{\beta}_{OLS}$ and $\hat{\beta}_{IV}$. The Hausmann test statistic

$$H \stackrel{A}{\sim} \chi_J^2$$

follows a χ^2 distribution with $J = K$ degrees of freedom where K is the number of endogenous regressors. The null hypothesis is that there are no endogeneous variables or that endogeneity does not affect the OLS estimator. Under H_0 , $\hat{\beta}_{OLS}$ is consistent and efficient and $\hat{\beta}_{IV}$ is consistent but inefficient; under H_A , $\hat{\beta}_{OLS}$ is inconsistent but $\hat{\beta}_{IV}$ remains consistent.

Note: This is a test for the exogeneity of the regressors x_i and not for the exogeneity of the instruments z_i . If the instruments are not valid, the Hausman test is not valid either. We can only perform this test if we already have the means to solve a potential endogeneity problem by instrumental variables.

12 Implementation in Stata 11.0

Stata calculates the IV (2SLS) estimator by the command

```
ivregress 2sls depvar [varlist1] (varlist2=varlist3)
```

where *varlist1* are exogeneous regressors (w_{i1}, \dots, w_{iM}), *varlist2* are endogenous regressors (x_{i1}, \dots, x_{iK}) and *varlist3* are excluded instruments (z_{i1}, \dots, z_{iL}). For example, load data

```
webuse hsng2
```

and regress median monthly rents (*rent*) of census divisions on the share of urban population (*pcturban*) and the median housing value (*hsngval*)

```
ivregress 2sls rent pcturban (hsngval = faminc reg2-reg4)
```

Housing values are likely endogeneous and therefore instrumented by median family income (*faminc*) and 3 regional dummies (*reg2*, *reg4*, *reg4*).

The Eicker-Huber-White covariance estimator which is robust to heteroscedastic error terms is reported after estimation with the option `vce(robust)`. The option `first` requests that the first-stage regression results be displayed. First stage results are also provided by the postestimation command

```
estat firststage
```

which includes the F -statistic to assess weak instruments in case of $K = 1$ or the so-called rank F -statistic in case of $K > 1$.

The Hausman test for exogeneity can be calculated by estimating OLS and IV and then comparing the estimates. For example,

```
regress rent pcturban hsngval
estimates store b_ols
ivregress 2sls rent pcturban (hsngval = faminc reg2-reg4), first
estimates store b_iv
hausman b_iv b_ols, constant sigmamore
```

Tests for overidentifying restrictions are reported with the postestimation command

```
estat overid
```

13 Implementation R 2.13

The IV (2SLS) estimator is conveniently implemented in the R package AER as command

```
> ivreg(y ~ x1 + x2 + w1 + w2 | z1 + z2 + z3 + w1 + w2)
```

where x_1 and x_2 are endogenous regressors, w_1 and w_2 exogeneous regressors, and z_1 to z_3 are excluded instruments. For example, load data

```
> library(foreign)
> hsng2 <- read.dta("http://www.stata-press.com/data/r11/hsng2.dta")
```

and regress median monthly rents (`rent`) of census divisions on the share of urban population (`pcturban`) and the median housing value (`hsngval`)

```
> library(foreign)
> hsng2 <- read.dta("http://www.stata-press.com/data/r11/hsng2.dta")
> fiv <- ivreg(rent~hsngval+pcturban|pcturban+faminc+reg2+reg3+reg4,
  data = hsng2)
> summary(fiv)
```

Housing values are likely endogeneous and therefore instrumented by median family income (`faminc`) and 3 regional dummies (`reg2`, `reg3`, `reg4`).

The Eicker-Huber-White covariance estimator which is robust to heteroscedastic error terms is reported after estimation with

```
> library(sandwich)
> library(lmtest)
> coefest(fm, vcov=sandwich)
```

First stage results are reported by explicitly estimating them. E.g,

```
> first <- lm(hsngval~pcturban+faminc+reg2+reg3+reg4, data = hsng2)
> summary(first)
```

In case of a single endogenous variable ($K = 1$), the F -statistic to assess weak instruments is reported after estimating the first stage with e.g.

```
> waldtest(first, .~.-faminc-reg2-reg3-reg4)
```

or in case of heteroscedastic errors

```
> waldtest(first, .~.-faminc-reg2-reg3-reg4, vcov=sandwich)
```

References

Introductory textbooks

Stock, James H. and Mark W. Watson (2011), Introduction to Econometrics, 3rd ed., Pearson Addison-Wesley. Chapter 12.

Wooldridge, Jeffrey M. (2009), Introductory Econometrics: A Modern Approach, 4th ed., South-Western Cengage Learning. Chapter 15.

Advanced textbooks

Cameron, A. Colin and Pravin K. Trivedi (2005), Microeconometrics: Methods and Applications, Cambridge University Press. Sections 4.8-4.9.

Wooldridge, Jeffrey M. (2002), Econometric Analysis of Cross Section and Panel Data, MIT Press. Chapter 5.

Davidson and MacKinnon (2004), Econometric Theory and Methods, Oxford University Press, chapter 8.

On IV and Measurement Errors

Jerry Hausman (2001), Mismeasured Variables in Econometric analysis: Problem form the Right and from the Left, *Journal of Economics Perspectives*, 15/4, 57-67.

On IV and Omitted Variables

Angrist Joshua and Alan Krueger (2001), Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments, *Journal of Economics Perspectives*, 15/4, 69-85.

On weak instruments

Stock, J. H., J. H. Wright and M. Yogo (2002) A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments, *Journal of Business and Economic Statistics*, 20(4), 518-29.