

Econometrics 710
Final Exam, Spring 2017
Sample Answers

1. IV Regression

(a) $\widehat{\beta} = (Z'X)^{-1} Z'Y = \left(\sum_{i=1}^n z_i x_i'\right)^{-1} \left(\sum_{i=1}^n z_i y_i\right)$

(b) Write

$$\widehat{\beta} - \beta = \left(\sum_{i=1}^n z_i x_i'\right)^{-1} \left(\sum_{i=1}^n z_i e_i\right)$$

Then

$$\begin{aligned} E(\widehat{\beta} - \beta | Z, X) &= E\left(\left(\sum_{i=1}^n z_i x_i'\right)^{-1} \left(\sum_{i=1}^n z_i e_i\right) | Z, X\right) \\ &= \left(\sum_{i=1}^n z_i x_i'\right)^{-1} \left(\sum_{i=1}^n z_i E(e_i | Z, X)\right) \\ &= \left(\sum_{i=1}^n z_i x_i'\right)^{-1} \left(\sum_{i=1}^n z_i E(e_i | z_i, x_i)\right) \\ &= 0 \end{aligned}$$

Thus by the law of iterated expectations

$$E(\widehat{\beta}) = \beta$$

and $\widehat{\beta}$ is unbiased for β .

(c) Since $E(\widehat{\beta} | Z, X) = \beta$

$$\begin{aligned} \text{var}(\widehat{\beta} | Z, X) &= E\left((\widehat{\beta} - \beta)(\widehat{\beta} - \beta)' | Z, X\right) \\ &= E\left(\left(\sum_{i=1}^n z_i x_i'\right)^{-1} \left(\sum_{i=1}^n z_i e_i\right) \left(\sum_{i=1}^n e_i z_i'\right) \left(\sum_{i=1}^n x_i z_i'\right)^{-1} | Z, X\right) \\ &= \left(\sum_{i=1}^n z_i x_i'\right)^{-1} \left(\sum_{i=1}^n \sum_{j=1}^n E(z_i e_i e_j z_j' | Z, X)\right) \left(\sum_{i=1}^n x_i z_i'\right)^{-1} \\ &= \left(\sum_{i=1}^n z_i x_i'\right)^{-1} \left(\sum_{i=1}^n E(z_i e_i e_i z_i' | z_i, x_i)\right) \left(\sum_{i=1}^n x_i z_i'\right)^{-1} \\ &= \left(\sum_{i=1}^n z_i x_i'\right)^{-1} \left(\sum_{i=1}^n z_i z_i' \sigma_i^2\right) \left(\sum_{i=1}^n x_i z_i'\right)^{-1} \end{aligned}$$

where

$$\sigma_i^2 = E(e_i^2 | z_i, x_i)$$

Notice that this is the variance conditional on both z and x

2. Control function regression.

- (a) The reduced form equation for x_i is $x_i = \Gamma' z_i + u_i$ so

$$\begin{aligned} E(x_i \varepsilon_i) &= E((\Gamma' z_i + u_i) \varepsilon_i) \\ &= \Gamma' E(z_i \varepsilon_i) + E(u_i \varepsilon_i). \end{aligned}$$

The definition for ε_i is from $e_i = u_i' \gamma + \varepsilon_i$ so $\varepsilon_i = e_i - u_i' \gamma$. Substituting into the first expression on the right side, we find

$$\begin{aligned} E(x_i \varepsilon_i) &= \Gamma' E(z_i (e_i - u_i' \gamma)) + E(u_i \varepsilon_i) \\ &= \Gamma' E(z_i e_i) - \Gamma' E(z_i u_i') \gamma + E(u_i \varepsilon_i) \end{aligned}$$

The three components are each zero. First, $E(z_i e_i) = 0$ by the IV assumption. Second, $E(z_i u_i') = 0$ by the reduced form projection equation. Third, $E(u_i \varepsilon_i) = 0$ by the control function projection equation.

- (b) Derive the asymptotic distribution of $(\hat{\beta}, \hat{\gamma})$. First, write $w_i = (x_i', u_i')'$ so that we can write the estimators as

$$\begin{pmatrix} \hat{\beta} \\ \hat{\gamma} \end{pmatrix} = \left(\sum_{i=1}^n w_i w_i' \right)^{-1} \left(\sum_{i=1}^n w_i y_i \right).$$

Centered and standardized, since $y_i = x_i' \beta + u_i' \gamma + \varepsilon_i$

$$\sqrt{n} \begin{pmatrix} \hat{\beta} - \beta \\ \hat{\gamma} - \gamma \end{pmatrix} = \left(\frac{1}{n} \sum_{i=1}^n w_i w_i' \right)^{-1} \left(\frac{1}{\sqrt{n}} \sum_{i=1}^n w_i \varepsilon_i \right).$$

By the WLLN

$$\frac{1}{n} \sum_{i=1}^n w_i w_i' \rightarrow_p E(w_i w_i') = \begin{pmatrix} E(x_i x_i') & E(x_i u_i') \\ E(u_i x_i') & E(u_i u_i') \end{pmatrix} = Q$$

say. The WLLN applies since w_i are iid, if x_i and u_i have finite second moments.

By the CLT

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n w_i \varepsilon_i \rightarrow_d N(0, \Omega)$$

where

$$\Omega = E(w_i w_i' \varepsilon_i^2) = \begin{pmatrix} E(x_i x_i' \varepsilon_i^2) & E(x_i u_i' \varepsilon_i^2) \\ E(u_i x_i' \varepsilon_i^2) & E(u_i u_i' \varepsilon_i^2) \end{pmatrix}$$

The CLT applies if $w_i \varepsilon_i$ is iid, mean zero, and has finite second moments. The vector $w_i \varepsilon_i$ is iid because it is assumed to be a random sample. It is mean zero since $E(x_i \varepsilon_i) = 0$ by part (a) and $E(u_i \varepsilon_i) = 0$ by the control function projection. The variable $w_i \varepsilon_i$ has finite second moment if the observations have finite fourth moments.

Together, we obtain

$$\sqrt{n} \begin{pmatrix} \widehat{\beta} - \beta \\ \widehat{\gamma} - \gamma \end{pmatrix} \rightarrow_d Q^{-1} N(0, \Omega) = N(0, Q^{-1} \Omega Q^{-1}).$$

In addition, this requires that Q^{-1} exists.

3. GMM criterion

(a) Evaluated at the true value β_0 ,

$$\overline{m}_n(\beta_0) = \frac{1}{n} \sum_{i=1}^n z_i e_i$$

which is the average of iid random vectors with mean zero (by assumption). Standardized, the CLT implies

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n z_i e_i \rightarrow_d Z \sim N(0, \Omega)$$

where

$$\Omega = E(z_i z_i' e_i^2)$$

It follows that

$$J_n(\beta_0) = \sqrt{n} \overline{m}_n(\beta_0)' W \sqrt{n} \overline{m}_n(\beta_0) \rightarrow_d Z' W Z$$

- (b) If $W = \Omega^{-1}$ then the limit distribution is $Z' \Omega^{-1} Z \sim \chi_\ell^2$ where ℓ is the dimension of z_i .
- (c) An estimator which takes advantage of H_0 is $\widetilde{\Omega} = \frac{1}{n} \sum_{i=1}^n z_i z_i' \widetilde{e}_i^2$ where $\widetilde{e}_i = y_i - x_i' \beta_0$ and $\widetilde{W} = \widetilde{\Omega}^{-1}$. The estimator $\widetilde{\Omega}$ is unbiased for Ω , and \widetilde{W} is consistent for $W = \Omega^{-1}$ under H_0 . This is different than the standard estimator $\widehat{\Omega} = \frac{1}{n} \sum_{i=1}^n z_i z_i' \widehat{e}_i^2$ and $\widehat{W} = \widehat{\Omega}^{-1}$ where $\widehat{e}_i = y_i - x_i' \widehat{\beta}$ and $\widehat{\beta}$ is a consistent estimator of β , for example $\widehat{\beta} = (X'Z(Z'Z)^{-1}Z'X)^{-1}(X'Z(Z'Z)^{-1}Z'Y)$. This does not take advantage of H_0 .
- (d) An asymptotic test rejects H_0 in favor of H_1 at level α if $J_n(\beta_0) > c$ where c is the $1 - \alpha$ quantile of the distribution of χ_ℓ^2 . This test has asymptotic level of α since

$$P(J_n(\beta_0) > c | H_0) \rightarrow P(\chi_\ell^2 > c) = \alpha$$

(e) A $1 - \alpha$ confidence region for β is the set β for which the test does not reject. It is

$$C = \{\beta : J_n(\beta) \leq c\}$$

where c is the $1 - \alpha$ quantile of the distribution of χ_ℓ^2 . When $\widetilde{W}(\beta) = \widetilde{\Omega}(\beta)^{-1} = \frac{1}{n} \sum_{i=1}^n z_i z_i' (y_i - x_i' \beta)^2$ then the weight matrix depends on β and the confidence region is

$$C = \left\{ \beta : (Y'Z - \beta' X'Z)' \widetilde{\Omega}(\beta)^{-1} (Z'Y - Z'X\beta) \leq nc \right\}$$

which is not an ellipse.

(f) For a bootstrap test, sample (y_i^*, x_i^*, z_i^*) iid from the data. If the estimator $\widetilde{\Omega}$ was used,

then we set

$$\begin{aligned}
J_n^* &= n\bar{m}_n^{*'}\tilde{\Omega}^{*-1}\bar{m}_n^* \\
\bar{m}_n^* &= \frac{1}{n}\sum_{i=1}^n z_i^* \left(y_i^* - x_i^{*'}\hat{\beta} \right) \\
\tilde{\Omega}^* &= \frac{1}{n}\sum_{i=1}^n z_i^* z_i^{*'} \tilde{e}_i^{*2} \\
\tilde{e}_i^* &= y_i^* - x_i^{*'}\hat{\beta}
\end{aligned}$$

where $\hat{\beta}$ is either 2SLS or GMM on the original sample. This is appropriate because $\hat{\beta}$ is the analog of β_0 in the bootstrap distribution.

If the estimator $\hat{\Omega}$ was used then we would alternatively set

$$\begin{aligned}
J_n^* &= n\bar{m}_n^{*'}\hat{\Omega}^{*-1}\bar{m}_n^* \\
\hat{\Omega}^* &= \frac{1}{n}\sum_{i=1}^n z_i^* z_i^{*'} \hat{e}_i^{*2} \\
\hat{e}_i^* &= y_i^* - x_i^{*'}\hat{\beta}^* \\
\hat{\beta}^* &= \left(X^{*'}Z^* (Z^{*'}Z^*)^{-1} Z'^* X^* \right)^{-1} \left(X'^* Z^* (Z'^* Z^*)^{-1} Z'^* Y^* \right)
\end{aligned}$$

That is, \hat{e}_i^* is calculated using the bootstrap estimate $\hat{\beta}^*$

In either case, we obtain B replications of the statistic J_{nb}^* by simulation. The p-value for the test is then calculated as

$$p_n^* = \frac{1}{B} \sum_{b=1}^B 1(J_{nb}^* > J_n(\beta_0))$$

The bootstrap test rejects H_0 at level α if $p_n^* < \alpha$, otherwise it does not reject H_0 .