Homework 5

Problem 1. In this question, you will derive the asymptotic distribution of the OLS estimator under endogeneity. Consider the usual linear regression model $Y_i = X_i'\beta + U_i$, where β is a $k \times 1$ vector. Assume, however, that X_i's are endogenous:

$$\mathbb{E}X_iU_i = \mu \neq 0,$$

where μ is an unknown $k \times 1$ vector. Let $\hat{\beta}_n$ denote the OLS estimator of β. Make the following additional assumptions:
A1. Data are iid.
A2. $Q = \mathbb{E}X_iX_i'$ is finite and positive definite.
A3. $\mathbb{E}\left(U_i - X_i'\delta\right)^2 X_iX_i'$ is finite and positive definite, where $\delta = Q^{-1}\mu$.

1. Find the probability limit of $\hat{\beta}_n$.
2. Re-write the model as $Y_i = X_i'(\beta + \delta) + (U_i - X_i'\delta)$ and find $\mathbb{E}X_i(U_i - X_i'\delta)$.
3. Using the result in (ii), derive the asymptotic distribution of $\hat{\beta}_n$ and find its asymptotic variance. Explain how this result differs from the asymptotic normality of OLS with exogenous regressors. Hint: To establish asymptotic normality, $\hat{\beta}_n$ must be properly re-centered based on the result in (i).
4. Can $\hat{\beta}_n$ and its asymptotic distribution be used for inference about β? Explain why or why not.
5. Suppose that the errors U_i's are homoskedastic:

   $$\mathbb{E}\left(U_i^2 | X_i\right) = \sigma^2 = const.$$

   Consider the usual estimator of the asymptotic variance of OLS designed for a model with homoskedastic errors and exogenous regressors:

   $$n^{-1}\sum_{i=1}^{n}\left(Y_i - X_i'\hat{\beta}_n\right)^2 \left(n^{-1}\sum_{i=1}^{n} X_iX_i'\right)^{-1}.$$

   Is it consistent for the asymptotic variance of the OLS estimator if X_i's are in fact endogenous? Explain why or why not.
6. Continue to assume that U_i's are homoskedastic as in (v). Consider the usual heteroskedasticity-robust asymptotic variance estimator designed for a model with exogenous regressors:

   $$\left(n^{-1}\sum_{i=1}^{n} X_iX_i'\right)^{-1}\left(n^{-1}\sum_{i=1}^{n}\left(Y_i - X_i'\hat{\beta}_n\right)^2 X_iX_i'\right)\left(n^{-1}\sum_{i=1}^{n} X_iX_i'\right)^{-1}.$$

   Is it consistent for the asymptotic variance of the OLS estimator if X_i's are in fact endogenous? Explain why or why not.

Solution.

1. Write

   $$\hat{\beta}_n = \beta + \left(n^{-1}\sum_{i=1}^{n} X_iX_i'\right)^{-1} n^{-1}\sum_{i=1}^{n} X_iU_i$$

$$
\begin{aligned}
&\to_p \quad \beta + Q^{-1}\mu \\
&= \quad \beta + \delta,
\end{aligned}
$$

where convergence of $n^{-1}\sum_{i=1}^{n} X_i X_i' \to_p Q$ and $n^{-1}\sum_{i=1}^{n} X_i U_i \to_p \mathbb{E}X_i U_i = \mu$ hold by the WLLN, and the result in the second line holds by CMT.

2.

$$
\begin{aligned}
\mathbb{E}X_i(U_i - X_i'\delta) &= \mathbb{E}X_i U_i - \mathbb{E}X_i X_i' Q^{-1}\mu \\
&= \mu - QQ^{-1}\mu \\
&= 0.
\end{aligned}
$$

3. Write

$$
\hat{\beta}_n - (\beta + \delta) = \left(n^{-1}\sum_{i=1}^{n} X_i X_i'\right)^{-1} n^{-1}\sum_{i=1}^{n} X_i \epsilon_i,
$$

where

$$
\epsilon_i = U_i - X_i'\delta
$$

and uncorrelated with X_i by the result in (ii). Furthermore, $X_i\epsilon_i$ satisfies the assumptions of the CLT. Hence, this is a regression with all the usual assumptions, however, it has a new regression coefficient $\beta + \delta$ and new errors ϵ_i's. We have:

$$
\sqrt{n}\left(\hat{\beta}_n - (\beta + \delta)\right) \to_d N\left(0, Q^{-1}\left(\mathbb{E}\left(U_i - X_i'\delta\right)^2 X_i X_i'\right) Q^{-1}\right).
$$

Comparing to the case with exogenous regressors, the center of the asymptotic distribution is shifted by δ. Also, the asymptotic variance depends on $X_i'\delta$ through $\mathbb{E}\left(U_i - X_i'\delta\right)^2 X_i X_i'$.

4. Asymptotic inference about β based on the OLS estimator will be invalid since the asymptotic distribution of the OLS estimator is centered at $\beta + \delta$. The OLS estimator can be only used for testing hypotheses about $\beta + \delta$.

5. First, we need to describe the probability limit of the estimator proposed. Write:

$$
\begin{aligned}
n^{-1}\sum_{i=1}^{n}\left(Y_i - X_i'\hat{\beta}_n\right)^2 &= n^{-1}\sum_{i=1}^{n}\left((U_i - X_i'\delta) + X_i'\left(\beta + \delta - \hat{\beta}_n\right)\right)^2 \\
&= n^{-1}\sum_{i=1}^{n}\left(\epsilon_i + X_i'\left(\beta + \delta - \hat{\beta}_n\right)\right)^2,
\end{aligned}
$$

where

$$
\epsilon_i = U_i - X_i'\delta.
$$

In view of the result in (i), $\beta + \delta - \hat{\beta}_n \to_p 0$, and therefore

$$
n^{-1}\sum_{i=1}^{n}\left(Y_i - X_i'\hat{\beta}_n\right)^2 \to_p \mathbb{E}\epsilon_i^2.
$$

Hence, the proposed estimator converges in probability to $\mathbb{E}\left(U_i - X_i'\delta\right)^2 Q^{-1}$. This would be the same as the asymptotic variance in (iii) if the errors $\epsilon_i = U_i - X_i'\delta$ were homoskedastic.
It is given that U_i's are homoskedastic. However, even if U_i's are homoskedastic, $\epsilon_i = U_i - X_i'\delta$ would be heteroskedastic:

$$
\mathbb{E}(\epsilon_i^2|X_i) = \sigma^2 + \left(X_i'\delta\right)^2 - 2\mathbb{E}\left(U_i|X_i\right)X_i'\delta \neq const,
$$

unless $\mathbb{E}(U_i|X_i) = 0.5X_i'\delta$. Since $\delta = Q^{-1}\mu$, $Q = \mathbb{E}X_iX_i'$, and $\mu = \mathbb{E}X_iU_i$, the law of iterated expectation implies that if $\mathbb{E}(U_i|X_i) = 0.5X_i'\delta$, then

$$\begin{aligned}\mu &= \mathbb{E}X_iU_i \\ &= \mathbb{E}(X_i\mathbb{E}(U_i|X_i)) \\ &= \mathbb{E}(X_i \times 0.5X_i'\delta) \\ &= 0.5Q\delta \\ &= 0.5Q \times Q^{-1}\mu \\ &= 0.5\mu.\end{aligned}$$

However, the only solution to $\mu = 0.5\mu$ is $\mu = 0$, which contradicts the assumption that $\mathbb{E}X_iU_i \neq 0$. It follows therefore that $\epsilon_i = U_i - X_i'\delta$ are heteroskedastic. Hence, the estimator would be inconsistent for the asymptotic variance of the OLS estimator.

6. The model $Y_i = X_i'(\beta+\delta) + (U_i - X_i'\delta)$ is the usual linear regression with weakly exogenous regressors. The OLS estimator consistently estimates $\beta+\delta$. Its asymptotic variance has the usual "sandwich" form. Hence, with additional technical assumptions such as finite fourth moments for X_i's and $U_i - X_i'\delta$, the estimator will be consistent.

Problem 2. Consider the linear regression model $\boldsymbol{Y} = \boldsymbol{X\beta}+\boldsymbol{e}$, where $\boldsymbol{X}$ is the $n\times k$ matrix of regressors, $\boldsymbol{Y}$ is the n-vector of observations on the dependent variable, and $\boldsymbol{\beta} \in \mathbb{R}^k$ is the vector of unknown parameters. Let $\boldsymbol{Z}$ be the $n \times k$ matrix of instruments. Assume that:

- $\boldsymbol{X}$ and $\boldsymbol{Z}$ are strongly exogenous: $\mathbb{E}(\boldsymbol{e}|\boldsymbol{X},\boldsymbol{Z}) = \boldsymbol{0}$.
- $\boldsymbol{e}$ is homoskedastic: $\mathbb{E}(\boldsymbol{ee}'|\boldsymbol{X},\boldsymbol{Z}) = \sigma^2\boldsymbol{I}_n$.
- $\boldsymbol{X}$ and $\boldsymbol{Z}'\boldsymbol{X}$ have rank k.

Let $\hat{\boldsymbol{\beta}} = (\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{Y}$ and $\tilde{\boldsymbol{\beta}} = (\boldsymbol{Z}'\boldsymbol{X})^{-1}\boldsymbol{Z}'\boldsymbol{Y}$ be the OLS and IV estimators of $\boldsymbol{\beta}$ respectively.

1. Show that $\mathbb{E}(\boldsymbol{e}|\boldsymbol{X}) = \boldsymbol{0}$ and $\mathbb{E}(\boldsymbol{ee}'|\boldsymbol{X}) = \sigma^2\boldsymbol{I}_n$.
2. Show that the OLS and IV estimators are unbiased.
3. Find the exact finite sample conditional variances of $\hat{\boldsymbol{\beta}}$ and $\tilde{\boldsymbol{\beta}}$: $\mathrm{Var}\left(\hat{\boldsymbol{\beta}}|\boldsymbol{X},\boldsymbol{Z}\right)$ and $\mathrm{Var}\left(\tilde{\boldsymbol{\beta}}|\boldsymbol{X},\boldsymbol{Z}\right)$. Show that

$$\begin{aligned}&\mathrm{Var}\left(\tilde{\boldsymbol{\beta}}|\boldsymbol{X},\boldsymbol{Z}\right) - \mathrm{Var}\left(\hat{\boldsymbol{\beta}}|\boldsymbol{X},\boldsymbol{Z}\right) \\ =&\sigma^2(\boldsymbol{Z}'\boldsymbol{X})^{-1}\boldsymbol{Z}'\left(\boldsymbol{I}_n - \boldsymbol{X}(\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\right)\boldsymbol{Z}(\boldsymbol{X}'\boldsymbol{Z})^{-1}.\end{aligned}$$

4. When regressors are exogenous, should the econometrician use IV or OLS ? Explain why using the result in in part (iii).

Solution.

1. The results follow by the law of iterated expectation:

$$\begin{aligned}\mathbb{E}(\boldsymbol{e}|\boldsymbol{X}) &= \mathbb{E}(\mathbb{E}(\boldsymbol{e}|\boldsymbol{X},\boldsymbol{Z})|\boldsymbol{X}) \\ &= \mathbb{E}(\boldsymbol{0}|\boldsymbol{X}) \\ &= \boldsymbol{0}, \\ \mathbb{E}(\boldsymbol{ee}'|\boldsymbol{X}) &= \mathbb{E}(\mathbb{E}(\boldsymbol{ee}'|\boldsymbol{X},\boldsymbol{Z})|\boldsymbol{X}) \\ &= \mathbb{E}(\sigma^2\boldsymbol{I}_n|\boldsymbol{X}) \\ &= \sigma^2\boldsymbol{I}_n.\end{aligned}$$

2. Write

$$\begin{aligned}\hat{\boldsymbol{\beta}} &= \boldsymbol{\beta} + (\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{e},\\ \tilde{\boldsymbol{\beta}} &= \boldsymbol{\beta} + (\boldsymbol{Z}'\boldsymbol{X})^{-1}\boldsymbol{Z}'\boldsymbol{e}.\end{aligned}$$

The results follow since

$$\begin{aligned}\mathbb{E}(\boldsymbol{X}'\boldsymbol{e}|\boldsymbol{X},\boldsymbol{Z}) &= \boldsymbol{X}'\mathbb{E}(\boldsymbol{e}|\boldsymbol{X},\boldsymbol{Z}) = \mathbf{0},\\ \mathbb{E}(\boldsymbol{Z}'\boldsymbol{e}|\boldsymbol{X},\boldsymbol{Z}) &= \boldsymbol{Z}'\mathbb{E}(\boldsymbol{e}|\boldsymbol{X},\boldsymbol{Z}) = \mathbf{0}.\end{aligned}$$

3. For the IV estimator,

$$\begin{aligned}\mathrm{Var}(\tilde{\boldsymbol{\beta}}|\boldsymbol{X},\boldsymbol{Z}) &= \mathrm{Var}\left((\boldsymbol{Z}'\boldsymbol{X})^{-1}\boldsymbol{Z}'\boldsymbol{e}|\boldsymbol{X},\boldsymbol{Z}\right)\\ &= (\boldsymbol{Z}'\boldsymbol{X})^{-1}\boldsymbol{Z}'\mathrm{Var}(\boldsymbol{e}|\boldsymbol{X},\boldsymbol{Z})\boldsymbol{Z}(\boldsymbol{X}'\boldsymbol{Z})^{-1}\\ &= \sigma^2(\boldsymbol{Z}'\boldsymbol{X})^{-1}\boldsymbol{Z}'\boldsymbol{Z}(\boldsymbol{X}'\boldsymbol{Z})^{-1}.\end{aligned}$$

For the OLS estimator, we have the usual expression:

$$\mathrm{Var}(\hat{\boldsymbol{\beta}}|\boldsymbol{X},\boldsymbol{Z}) = \sigma^2(\boldsymbol{X}'\boldsymbol{X})^{-1}.$$

Lastly,

$$\begin{aligned}&(\boldsymbol{Z}'\boldsymbol{X})^{-1}\boldsymbol{Z}'\boldsymbol{Z}(\boldsymbol{X}'\boldsymbol{Z})^{-1} - (\boldsymbol{X}'\boldsymbol{X})^{-1}\\ =\ &(\boldsymbol{Z}'\boldsymbol{X})^{-1}\boldsymbol{Z}'\boldsymbol{Z}(\boldsymbol{X}'\boldsymbol{Z})^{-1} - (\boldsymbol{Z}'\boldsymbol{X})^{-1}(\boldsymbol{Z}'\boldsymbol{X})(\boldsymbol{X}'\boldsymbol{X})^{-1}(\boldsymbol{X}'\boldsymbol{Z})(\boldsymbol{X}'\boldsymbol{Z})^{-1}\\ =\ &\left(\boldsymbol{Z}'\boldsymbol{X}\right)^{-1}\boldsymbol{Z}'\left(\boldsymbol{I}_n - \boldsymbol{X}\left(\boldsymbol{X}'\boldsymbol{X}\right)^{-1}\boldsymbol{X}'\right)\boldsymbol{Z}\left(\boldsymbol{X}'\boldsymbol{Z}\right)^{-1}.\end{aligned}$$

4. We showed that

$$\mathrm{Var}(\tilde{\boldsymbol{\beta}}|\boldsymbol{X},\boldsymbol{Z}) - \mathrm{Var}(\hat{\boldsymbol{\beta}}|\boldsymbol{X},\boldsymbol{Z}) = \sigma^2\boldsymbol{A}'\boldsymbol{M}_{\boldsymbol{X}}\boldsymbol{A},$$

where $\boldsymbol{M}_{\boldsymbol{X}} = \boldsymbol{I}_n - \boldsymbol{X}\left(\boldsymbol{X}'\boldsymbol{X}\right)^{-1}\boldsymbol{X}'$ is symmetric and idempotent and therefore positive semi-definite. Consequently, $\boldsymbol{A}'\boldsymbol{M}_{\boldsymbol{X}}\boldsymbol{A}$ is also positive semi-definite, and it follows that the OLS estimator has a smaller variance than the IV estimator. Since the OLS estimator is also unbiased with exogenous regressors, one should use OLS in this case. Note that the conclusion also follows by Gauss-Markov Theorem.

Problem 3. Consider the model

$$\begin{aligned}Y_i &= \beta_0 + \beta_1 X_i + e_i\\ \mathbb{E}\left(e_i\right) &= 0\\ \mathbb{E}\left(X_i e_i\right) &= 0\end{aligned}$$

with both Y_i and X_i scalar. Assume $\beta_0 > 0$ and $\beta_1 < 0$. Suppose the parameter of interest is the area under the regression curve (e.g., consumer surplus), which is $A = -\frac{\beta_0^2}{2\beta_1}$. Let $\widehat{\boldsymbol{\theta}} = \left(\widehat{\beta}_0, \widehat{\beta}_1\right)'$ be the LS estimator of $\boldsymbol{\theta} = (\beta_0, \beta_1)'$ so that $\sqrt{n}\left(\widehat{\boldsymbol{\theta}} - \boldsymbol{\theta}\right) \to_d N\left(\mathbf{0}, \boldsymbol{V}_{\boldsymbol{\theta}}\right)$. Let $\widehat{\boldsymbol{V}}_{\boldsymbol{\theta}}$ be a standard consistent estimator for $\boldsymbol{V}_{\boldsymbol{\theta}}$. You do not need to write out these estimators.

1. Given the above, describe an estimator of A.
2. Construct an asymptotic $1-\alpha$ coverage probability confidence interval for A.
3. Construct an asymptotic $1-\alpha$ coverage probability bootstrap percentile confidence interval for A.

Solution.

1. The plug-in estimator is $\widehat{A} = -\widehat{\beta}_0^2/2\widehat{\beta}_1$.

2. Define
$$\boldsymbol{a} = \begin{pmatrix} \frac{\partial A}{\partial \beta_0} \\ \frac{\partial A}{\partial \beta_1} \end{pmatrix} = \begin{pmatrix} -\beta_0/\beta_1 \\ \beta_0^2/2\beta_1^2 \end{pmatrix}.$$
By delta method,
$$\sqrt{n}\left(\widehat{\boldsymbol{\theta}} - \boldsymbol{\theta}\right) \to_d N\left(\mathbf{0}, \boldsymbol{a}'\boldsymbol{V}_{\boldsymbol{\theta}}\boldsymbol{a}\right),$$
where $\boldsymbol{V}_{\boldsymbol{\theta}} = \boldsymbol{Q}^{-1}\boldsymbol{\Omega}\boldsymbol{Q}^{-1}$, $\boldsymbol{Q} = \mathbb{E}\left(\boldsymbol{X}_i\boldsymbol{X}_i'\right)$, $\boldsymbol{X}_i = (1, X_i)'$ and $\boldsymbol{\Omega} = \mathbb{E}\left(e_i^2\boldsymbol{X}_i\boldsymbol{X}_i'\right)$. An estimate of the asymptotic variance is $\widehat{\boldsymbol{a}}'\widehat{\boldsymbol{V}}_{\boldsymbol{\theta}}\widehat{\boldsymbol{a}}$, where
$$\widehat{\boldsymbol{a}} = \begin{pmatrix} -\widehat{\beta}_0/\widehat{\beta}_1 \\ \widehat{\beta}_0^2/2\widehat{\beta}_1^2 \end{pmatrix},$$
$\widehat{\boldsymbol{V}}_{\boldsymbol{\theta}} = \widehat{\boldsymbol{Q}}^{-1}\widehat{\boldsymbol{\Omega}}\widehat{\boldsymbol{Q}}^{-1}$, $\widehat{\boldsymbol{Q}} = n^{-1}\sum_{i=1}^n \boldsymbol{X}_i\boldsymbol{X}_i'$, $\widehat{\boldsymbol{\Omega}} = n^{-1}\sum_{i=1}^n \widehat{e}_i^2\boldsymbol{X}_i\boldsymbol{X}_i'$ and $\widehat{e}_i = Y_i - \boldsymbol{X}_i'\widehat{\boldsymbol{\theta}}$. An asymptotic $1-\alpha$ coverage probability confidence interval for A is
$$\left[\widehat{A} - 1.96 \times \sqrt{n^{-1}\widehat{\boldsymbol{a}}'\widehat{\boldsymbol{V}}_{\boldsymbol{\theta}}\widehat{\boldsymbol{a}}}, \widehat{A} + 1.96 \times \sqrt{n^{-1}\widehat{\boldsymbol{a}}'\widehat{\boldsymbol{V}}_{\boldsymbol{\theta}}\widehat{\boldsymbol{a}}}\right].$$

3. percentile bootstrap
   - Step 1: Generate an i.i.d. sample $\{(Y_i^*, X_i^*)\}_{i=1}^n$ by drawing with replacement from the sample $\{(Y_i, X_i) : i = 1, ..., n\}$.
   - Step 2: Use the bootstrap sample to calculate $\widehat{\boldsymbol{\theta}}^* = \left(\widehat{\beta}_0^*, \widehat{\beta}_1^*\right)' = \left(\sum_{i=1}^n \boldsymbol{X}_i^*\boldsymbol{X}_i^{*\prime}\right)^{-1}\left(\sum_{i=1}^n \boldsymbol{X}_i^* Y_i^*\right)$ $(\boldsymbol{X}_i^* = (1, X_i^*)')$ and $\widehat{A}^* = -\widehat{\beta}_0^{*2}/2\widehat{\beta}_1^*$.
   - Step 3: Repeat B times. Collect B replications: $\widehat{A}^{*1}, ..., \widehat{A}^{*B}$.
   - Step 4: Order the B values of $\widehat{A}^{*1}, ..., \widehat{A}^{*B}$. Denote the ordered values by $\widehat{A}_{(1)}^*, ..., \widehat{A}_{(B)}^*$. Suppose $B = 1000$. The bootstrap percentile confidence interval is $\left[\widehat{A}_{(25)}^*, \widehat{A}_{(975)}^*\right]$.

Problem 4. Consider a regression model with potentially endogenous regressors:
$$Y_i = X_i'\beta + U_i, \quad \beta \in \mathbb{R}^k.$$
Let Z_i be the l-vector of instruments such that $l \geq k$,
$$\begin{aligned} \text{rank}(\mathbb{E}Z_iX_i') &= k, \\ \mathbb{E}Z_iU_i &= 0. \end{aligned}$$
Let R be a $q \times k$ matrix of rank q, and let r be a $q \times 1$ vector; both R and r are known. Let W_n be an $l \times l$ matrix such that
$$W_n \to_p W,$$
where W is symmetric and positive definite. Let $\tilde{\beta}_n$ be the restricted GMM estimator: $\tilde{\beta}_n$ minimizes the GMM criterion function $(Y - Xb)'ZW_nZ'(Y - Xb)$ subject to the restriction $Rb - r = 0$, where
$$Y = \begin{pmatrix} Y_1 \\ \vdots \\ Y_n \end{pmatrix}, \quad X = \begin{pmatrix} X_1' \\ \vdots \\ X_n' \end{pmatrix}, \quad Z = \begin{pmatrix} Z_1' \\ \vdots \\ Z_n' \end{pmatrix}.$$

1. Show that $\tilde{\beta}_n$ solves
$$-X'ZW_nZ'(Y - X\tilde{\beta}_n) + R'\tilde{\lambda}_n = 0,$$
where $\tilde{\lambda}_n$ is the q-vector of Lagrange multipliers.

2. Show that
$$\tilde{\beta}_n = \hat{\beta}_n - (X'ZW_nZ'X)^{-1}R'\tilde{\lambda}_n,$$
where $\hat{\beta}_n$ is the unconstrained GMM estimator, i.e.
$$\hat{\beta}_n = \arg\min_{b\in\mathbb{R}^k}(Y - Xb)'ZW_nZ'(Y - Xb).$$

3. Using the the result from (ii) and the fact that $\tilde{\beta}_n$ satisfies the constraint, show that
$$\tilde{\beta}_n = \hat{\beta}_n - (X'ZW_nZ'X)^{-1}R'(R(X'ZW_nZ'X)^{-1}R')^{-1}(R\hat{\beta}_n - r).$$

4. Suppose that data are iid, and the instruments and regressors have finite second moments. Find the probability limit of the restricted GMM estimator, i.e. find the expression for β^* in
$$\tilde{\beta}_n \to_p \beta^*.$$
Under what condition the restricted GMM estimator $\tilde{\beta}_n$ is consistent?

5. Suppose that $R\beta = r$. Find the probability limit of $\tilde{\lambda}_n/n^2$. Explain how the result can be used for testing $H_0 : R\beta = r$ against $H_1 : R\beta \neq r$. You do not have to figure out the details of such a test, only to explain why the probability limit of $\tilde{\lambda}_n/n^2$ is useful for construction of the test.

Solution.

1. The Lagrangian is given by
$$L(b, \lambda) = (Y - Xb)'ZW_nZ'(Y - Xb) + 2\lambda'(Rb - r).$$
The derivative of $L(b, \lambda)$ with respect to b is
$$\frac{\partial L(b, \lambda)}{\partial b} = -2X'ZW_nZ'(Y - Xb) + 2R'\lambda.$$
Hence, $\tilde{\beta}_n$ and $\tilde{\lambda}_n$ must satisfy
$$-X'ZW_nZ'(Y - X\tilde{\beta}_n) + R'\tilde{\lambda}_n = 0.$$

2. From (i),
$$X'ZW_nZ'X\tilde{\beta}_n = X'ZW_nZ'Y - R'\tilde{\lambda}_n,$$
or
$$\begin{aligned}\tilde{\beta}_n &= (X'ZW_nZ'X)^{-1}\left(X'ZW_nZ'Y - R'\tilde{\lambda}_n\right) \\ &= \hat{\beta}_n - (X'ZW_nZ'X)^{-1}R'\tilde{\lambda}_n, \qquad (1)\end{aligned}$$
since
$$\hat{\beta}_n = (X'ZW_nZ'X)^{-1}X'ZW_nZ'Y.$$

3. Since $\tilde{\beta}_n$ is the solution to the constrained optimization problem, it must satisfy the constraint:

$$R\tilde{\beta}_n - r = 0.$$

From the result in (ii),

$$\begin{aligned} r &= R\tilde{\beta}_n \\ &= R\left(\hat{\beta}_n - (X'ZW_nZ'X)^{-1}R'\tilde{\lambda}_n\right) \\ &= R\hat{\beta}_n - R(X'ZW_nZ'X)^{-1}R'\tilde{\lambda}_n. \end{aligned}$$

Hence,

$$\tilde{\lambda}_n = \left(R(X'ZW_nZ'X)^{-1}R'\right)^{-1}\left(R\hat{\beta}_n - r\right). \tag{2}$$

The result follows from equations (1) and (2).

4. Note that by usual results for GMM, the unconstrained estimator is consistent:

$$\hat{\beta}_n \to_p \beta.$$

Moreover, by the WLLN,

$$\frac{Z'X}{n} \to_p Q = \mathbb{E}Z_iX_i'.$$

Hence,

$$\begin{aligned} \tilde{\beta}_n &= \hat{\beta}_n - \left(\frac{X'Z}{n}W_n\frac{Z'X}{n}\right)^{-1}R'\left(R\left(\frac{X'Z}{n}W_n\frac{Z'X}{n}\right)^{-1}R'\right)^{-1}(R\hat{\beta}_n - r) \\ &\to_p \beta - \left(Q'WQ\right)^{-1}R'\left(R(Q'WQ)^{-1}R'\right)^{-1}(R\beta - r), \end{aligned}$$

i.e.

$$\beta^* = \beta - \left(Q'WQ\right)^{-1}R'\left(R(Q'WQ)^{-1}R'\right)^{-1}(R\beta - r).$$

Thus, the restricted estimator is in general inconsistent as $\beta^* \neq \beta$. However, when the restriction is true, $R\beta - r = 0$, $\beta^* = \beta$ and the estimator becomes consistent.

5. We have

$$\begin{aligned} \tilde{\lambda}_n/n^2 &= \left(n^2R(X'ZW_nZ'X)^{-1}R'\right)^{-1}\left(R\hat{\beta}_n - r\right) \\ &= \left(R\left(\frac{X'Z}{n}W_n\frac{Z'X}{n}\right)^{-1}R'\right)^{-1}\left(R\hat{\beta}_n - r\right) \\ &\to_p \left(R(Q'WQ)^{-1}R'\right)^{-1}(R\beta - r) \\ &= 0. \end{aligned}$$

Let

$$\tilde{\lambda}_n/n^2 \to_p \lambda^*.$$

When $H_0 : R\beta = r$ is true, $\lambda^* = 0$. Hence, we can test the same hypothesis by testing

$$\lambda^* = 0.$$

Problem 5. Consider the following regression model:

$$Y = X\beta + U,$$

where Y is an $n \times 1$ vector of observations on the dependent variable and X is an $n \times k$ matrix of observations on the regressors. Let Z be an $n \times l$ matrix of observations on the instruments, $l \geq k$. The 2SLS estimator of β can be written as $\hat{\beta} = (X'P_Z X)^{-1} X'P_Z Y$, where $P_Z = Z(Z'Z)^{-1}Z'$. Let $\tilde{\beta}$ be the OLS estimator of the coefficients on X in the regression of Y against X and $\hat{V}$:

$$Y = X\beta + \hat{V}\gamma + U,$$

where $\hat{V}$ is the matrix of the fitted residuals from the regression of X against Z,

$$X = Z\hat{\Pi} + \hat{V},$$

and $\hat{\Pi} = (Z'Z)^{-1}Z'X$ is the OLS estimator from the regression of X against Z. Show that $\tilde{\beta} = \hat{\beta}$ by following the steps below:

1. Use the partitioned regression result to write $\tilde{\beta} = (X'MX)^{-1}X'MY$, and define the matrix M in terms of $\hat{V}$.
2. Using the definition of M from part (i) and the definition of $\hat{V}$, show that $X'MX = X'P_Z X$.
3. Repeat the same steps as in (ii) to show that $X'MY = X'P_Z Y$.

Solution.
Write

$$\tilde{\beta} = (X'M_{\hat{V}}X)^{-1}X'M_{\hat{V}}Y,$$

where

$$\begin{aligned} M_{\hat{V}} &= I - \hat{V}(\hat{V}'\hat{V})^{-1}\hat{V}' \\ &= I - M_Z X(X'M_Z X)^{-1}X'M_Z. \end{aligned}$$

Therefore,

$$\begin{aligned} X'M_{\hat{V}}X &= X'X - X'M_Z X(X'M_Z X)^{-1}X'M_Z X \\ &= X'X - X'M_Z X \\ &= X'(I - M_Z)X \\ &= X'P_Z X. \end{aligned}$$

Similarly,

$$\begin{aligned} X'M_{\hat{V}}Y &= X'Y - X'M_Z X(X'M_Z X)^{-1}X'M_Z Y \\ &= X'Y - X'M_Z Y \\ &= X'(I - M_Z)Y \\ &= X'P_Z Y. \end{aligned}$$