

# Appendices to “Two Stage Least Squares Estimation of Spatial Autoregressive Models with Endogenous Regressors and Many Instruments”

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## A Some Useful Lemmas

To simplify notations, we drop the  $K$  subscript on  $Q_K$ ,  $P_K$  and  $M_K$ . Let MI refer to the Markov inequality, and CSI to the Cauchy-Schwarz inequality.

**Lemma A.1** *For an estimator given by  $\sqrt{n}(\hat{\delta}_n - \delta_0) = \hat{H}_n^{-1}\hat{h}_n$ , suppose there is a decomposition,  $\hat{h}_n = h_n + T^h + Z^h$ ,  $\hat{H}_n = H_n + T^H + Z^H$ ,*

$$(h_n + T^h)(h_n + T^h)' - h_n h_n' H_n^{-1} T^{H'} - T^H H_n^{-1} h_n h_n' = \hat{A}(K) + Z^A(K),$$

*such that  $T^h = o_p(1)$ ,  $h_n = O_p(1)$ ,  $H_n = O(1)$ , the determinant of  $H_n$  is bounded away from zero,  $\rho_{K,n} = \text{tr}(S(K)) = o(1)$ ,  $\|T^H\|^2 = o_p(\rho_{K,n})$ ,  $\|T^h\| \|T^H\| = o_p(\rho_{K,n})$ ,  $\|Z^h\| = o_p(\rho_{K,n})$ ,  $\|Z^H\| = o_p(\rho_{K,n})$ ,  $Z^A(K) = o_p(\rho_{K,n})$ ,  $E[\hat{A}(K)] = \sigma_\epsilon^2 H_n + H_n S(K) H_n + o(\rho_{K,n})$ . Then (2) is satisfied.*

**Proof.** This is Lemma A.1 in Donald and Newey (2001). ■

**Lemma A.2** (i)  $\text{tr}(P) = K$ . (ii) *Suppose that  $\{A_n\}$  is UB. For  $B_n = PA_n$ ,  $\text{tr}(B_n) = O(K)$ ,  $\text{tr}(B_n^2) = O(K)$ , and  $\sum_i (B_{ii})^2 = O(K)$ , where  $B_{ii}$ 's are diagonal elements of  $B_n$ .*

**Proof.** See Liu and Lee (2010). ■

**Lemma A.3** *Under Assumption 4 (iii), we have (i)  $\sum_i P_{ii}^2 = o(K)$ ,  $\sum_{i \neq j} P_{ii} P_{jj} = K^2 + o(K)$ ,  $\sum_{i \neq j} P_{ij} P_{ij} = \sum_{i \neq j} P_{ij} P_{ji} = K + o(K)$ ; (ii)  $\sum_i M_{ii} P_{ii} = o(K)$ ,  $\sum_{i \neq j} M_{ii} P_{jj} = K \text{tr}(M) + o(K) = O(K^2)$ ,  $\sum_{i \neq j} M_{ij} P_{ij} = \sum_{i \neq j} M_{ij} P_{ji} = \text{tr}(M) + o(K) = O(K)$ ; (iii)  $\sum_i M_{ii}^2 = O(K)$ ,  $\sum_{i \neq j} M_{ii} M_{jj} = \text{tr}^2(M) - \sum_i M_{ii}^2 = O(K^2)$ ,  $\sum_{i \neq j} M_{ij} M_{ij} = \text{tr}(MM') - \sum_i M_{ii}^2 = O(K)$ ,  $\sum_{i \neq j} M_{ij} M_{ji} = \text{tr}(M^2) - \sum_i M_{ii}^2 = O(K)$ ; and (iv) if Assumption 5 (ii) also holds,  $\sum_i M_{ii}^2 = o(K)$ .*

**Proof.** (i) is Lemma A.2 in Donald and Newey (2001). For (ii), as  $\text{tr}(MP) = \text{tr}(M) = O(K)$ , it follows that  $|\sum_i M_{ii}P_{ii}| \leq \sum_i |M_{ii}P_{ii}| \leq (\max_i |M_{ii}|)\text{tr}(P) = o(K)$ ,  $\sum_{i \neq j} M_{ii}P_{jj} = \sum_i M_{ii} \sum_j P_{jj} - \sum_i M_{ii}P_{ii} = \text{tr}(M)\text{tr}(P) + o(K) = O(K^2)$ , and  $\sum_{i \neq j} M_{ij}P_{ij} = \sum_{i \neq j} M_{ij}P_{ji} = \sum_{i,j} M_{ij}P_{ji} - \sum_i M_{ii}P_{ii} = \text{tr}(M) + o(K) = O(K)$ . For (iii),  $\sum_i M_{ii}^2 = O(K)$  by Lemma A.2 (ii). As  $\text{tr}(M) = O(K)$ ,  $\text{tr}(MM') = O(K)$ , and  $\text{tr}(M^2) = O(K)$  by Lemma A.2, it follows that  $\sum_{i \neq j} M_{ii}M_{jj} = \sum_{i,j} M_{ii}M_{jj} - \sum_i M_{ii}^2 = \text{tr}^2(M) - \sum_i M_{ii}^2 = O(K^2)$ ,  $\sum_{i \neq j} M_{ij}M_{ij} = \sum_{i,j} M_{ij}M_{ij} - \sum_i M_{ii}^2 = \text{tr}(MM') - \sum_i M_{ii}^2 = O(K)$ , and  $\sum_{i \neq j} M_{ij}M_{ji} = \sum_{i,j} M_{ij}M_{ji} - \sum_i M_{ii}^2 = \text{tr}(M^2) - \sum_i M_{ii}^2 = O(K)$ . For (iv),  $\sum_i M_{ii}^2 \leq (\max_i |M_{ii}|) \sum_i |M_{ii}| = o(K)$ . ■

**Lemma A.4** Under Assumptions 1-4, (i)  $\Delta_K = o(1)$ . (ii)  $F'_n(I_n - P)\epsilon_n/\sqrt{n} = O_p(\Delta_K^{1/2})$  and  $F'_n(I_n - P)V_n/\sqrt{n} = O_p(\Delta_K^{1/2})$ . (iii)

$$E(V'_n P V_n) = \begin{bmatrix} \text{tr}(M'M)(\gamma'_0 \Sigma_u \gamma_0 + 2\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2) & * \\ \text{tr}(M)(\Sigma_u \gamma_0 + \sigma'_{u\epsilon}) & K \Sigma_u \end{bmatrix} = O(K), \quad (1)$$

and  $E(V'_n P \epsilon_n) = [\text{tr}(M)(\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2), K \sigma_{u\epsilon}]' = O(K)$ . (iv)  $E(V'_n P \epsilon_n \epsilon'_n P V_n) - E(V'_n P \epsilon_n)E(\epsilon'_n P V_n) = O(K)$ ,  $E[(V'_n P V_n)^2] - E^2(V'_n P V_n) = O(K)$ , and, if Assumption 5 (ii) also holds,

$$\begin{aligned} & E(V'_n P \epsilon_n \epsilon'_n P V_n) - E(V'_n P \epsilon_n)E(\epsilon'_n P V_n) \\ &= \begin{bmatrix} (\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2)^2 \text{tr}(MM') + \sigma_\epsilon^2 (\gamma'_0 \Sigma_u \gamma_0 + 2\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2) \text{tr}(M^2) & * \\ [(\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2) \sigma'_{u\epsilon} + \sigma_\epsilon^2 (\Sigma_u \gamma_0 + \sigma'_{u\epsilon})] \text{tr}(M) & (\sigma'_{u\epsilon} \sigma_{u\epsilon} + \sigma_\epsilon^2 \Sigma_u) K \end{bmatrix} + o(K). \end{aligned} \quad (2)$$

(v)  $\sqrt{\Delta_K/n} = o(K/n + \Delta_K)$  and  $\sqrt{K\Delta_K/n} = o(K^2/n + \Delta_K)$ . (vi) Let  $\Gamma_n$  be either  $F_n$  or  $(I_n - P)F_n$ ,

$$E\left(\frac{1}{n} \Gamma'_n \epsilon_n \epsilon'_n P V_n\right) = \left[\frac{1}{n} \Gamma'_n \text{vec}_D(M) E(\epsilon_{ni}^2 u_{ni}) \gamma_0 + \frac{1}{n} \Gamma'_n \text{vec}_D(M) \mu_3, \frac{1}{n} \Gamma'_n \text{vec}_D(P) E(\epsilon_{ni}^2 u_{ni})\right],$$

$E\left(\frac{1}{n} F'_n \epsilon_n \epsilon'_n P V_n\right) = O(\sqrt{K/n})$ ,  $E\left[\frac{1}{n} F'_n (I_n - P) \epsilon_n \epsilon'_n P V_n\right] = O(\sqrt{K\Delta_K/n})$ , and  $E\left(\frac{1}{n} h_n h'_n H_n^{-1} V'_n F_n\right) = O(1/n)$ .

**Proof.** (i) and the first part of (ii) is in Lemma A.3 of Donald and Newey (2001). For the second part of (ii), let  $\bar{U}_n = (\bar{u}'_{n1}, \dots, \bar{u}'_{nn})'$ , where  $\bar{u}_{ni} = u_{ni} \gamma_0 + \epsilon_{ni}$ .  $E(V_n V'_n) = E(G_n \bar{U}_n \bar{U}'_n G'_n + U_n U'_n) = E(\bar{u}_{ni}^2) G_n G'_n + E(u_{ni} u'_{ni}) I_n = (\gamma'_0 \Sigma_u \gamma_0 + 2\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2) G_n G'_n + \text{tr}(\Sigma_u) I_n$ . Let  $\lambda_{\max}$  be the largest

eigenvalue of  $E(V_n V_n')$ .  $\text{Var}[\frac{1}{\sqrt{n}}F_n'(I_n - P)V_n] = \frac{1}{n}F_n'(I_n - P)E(V_n V_n')(I_n - P)F_n \leq \lambda_{\max} \frac{1}{n}F_n'(I_n - P)F_n = O(\Delta_K)$ . So  $\frac{1}{\sqrt{n}}F_n'(I_n - P)V_n = O_p(\Delta_K^{1/2})$ .

For (iii),

$$E(V_n' P V_n) = \begin{bmatrix} E(\bar{U}_n' M' M \bar{U}_n) & E(\bar{U}_n' M' U_n) \\ * & E(U_n' P U_n) \end{bmatrix},$$

where  $\bar{U}_n = U_n \gamma_0 + \epsilon_n$  and  $M = P G_n$ .  $E(\bar{U}_n' M' M \bar{U}_n) = \text{tr}(M' M)E(\bar{u}_{ni}^2) = \text{tr}(M' M)(\gamma_0' \Sigma_u \gamma_0 + 2\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2)$ ,  $E(\bar{U}_n' M' U_n) = \sum_i M_{ii} E(\bar{u}_{ni} u_{ni}) = \text{tr}(M)(\gamma_0' \Sigma_u + \sigma_{u\epsilon})$  and  $E(U_n' P U_n) = \sum_i P_{ii} E(u_{ni}' u_{ni}) = \text{tr}(P) \Sigma_u = K \Sigma_u$ . As  $\text{tr}(M' M) = O(K)$  and  $\text{tr}(M) = O(K)$  by Lemma A.2,  $E(V_n' P V_n)$  is given by (1). Next,  $E(V_n' P \epsilon_n) = E[\epsilon_n' M' \bar{U}_n, \epsilon_n' P U_n]'$ , where  $E(\epsilon_n' M' \bar{U}_n) = \sum_i M_{ii} E(\bar{u}_{ni} \epsilon_{ni}) = \text{tr}(M)(\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2)$  and  $E(\epsilon_n' P U_n) = \sum_i P_{ii} E(\epsilon_{ni} u_{ni}) = \text{tr}(P) \sigma_{u\epsilon} = K \sigma_{u\epsilon}$ . Hence  $E(V_n' P \epsilon_n) = [\text{tr}(M)(\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2), K \sigma_{u\epsilon}]' = O(K)$  by Lemma A.2.

For (iv),

$$E(V_n' P \epsilon_n \epsilon_n' P V_n) = \begin{bmatrix} E(\bar{U}_n' M' \epsilon_n \epsilon_n' M \bar{U}_n) & E(\bar{U}_n' M' \epsilon_n \epsilon_n' P U_n) \\ * & E(U_n' P \epsilon_n \epsilon_n' P U_n) \end{bmatrix}.$$

It follows by Lemma A.3 that

$$\begin{aligned} & E(\bar{U}_n' M' \epsilon_n \epsilon_n' M \bar{U}_n) \\ &= \sum_i M_{ii}^2 E(\epsilon_{ni}^2 \bar{u}_{ni}^2) + \sum_{i \neq j} (M_{ii} M_{jj} + M_{ji} M_{ij}) E(\bar{u}_{ni} \epsilon_{ni} \epsilon_{nj} \bar{u}_{nj}) + \sum_{i \neq j} M_{ij} M_{ij} E(\epsilon_{ni}^2 \bar{u}_{nj}^2) \\ &= [E(\epsilon_{ni}^2 \bar{u}_{ni}^2) - 2(\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2)^2 - \sigma_\epsilon^2 (\gamma_0' \Sigma_u \gamma_0 + 2\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2)] \sum_i M_{ii}^2 \\ &\quad + (\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2)^2 [\text{tr}^2(M) + \text{tr}(M^2)] + \sigma_\epsilon^2 (\gamma_0' \Sigma_u \gamma_0 + 2\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2) \text{tr}(M' M). \end{aligned}$$

Similarly,  $E(\bar{U}_n' M' \epsilon_n \epsilon_n' P U_n) = (\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2) \sigma_{u\epsilon} K \text{tr}(M) + [(\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2) \sigma_{u\epsilon} + \sigma_\epsilon^2 (\gamma_0' \Sigma_u + \sigma_{u\epsilon})] \text{tr}(M) + o(K)$  and  $E(U_n' P \epsilon_n \epsilon_n' P U_n) = \sigma_{u\epsilon}' \sigma_{u\epsilon} K^2 + (\sigma_{u\epsilon}' \sigma_{u\epsilon} + \sigma_\epsilon^2 \Sigma_u) K + o(K)$ . Hence,  $E(V_n' P \epsilon_n \epsilon_n' P V_n) - E(V_n' P \epsilon_n) E(\epsilon_n' P V_n) = O(K)$  by (iii). Furthermore, under Assumption 5 (ii),  $\sum_i M_{ii}^2 = o(K)$  and (2) follows. On the other hand,  $E[(V_n' P V_n)^2] = E(V_n' M \bar{U}_n \bar{U}_n' M' V_n) + E(V_n' P U_n U_n' P V_n)$ . As  $V_n = [G_n \bar{U}_n, U_n]$ , by similar arguments as above,  $E(\bar{U}_n' M' M \bar{U}_n \bar{U}_n' M' M \bar{U}_n) = (\gamma_0' \Sigma_u \gamma_0 + 2\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2)^2 \text{tr}^2(M) + O(K)$ ,  $E(\bar{U}_n' M' M \bar{U}_n \bar{U}_n' M' U_n) = (\gamma_0' \Sigma_u \gamma_0 + 2\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2) (\gamma_0' \Sigma_u + \sigma_{u\epsilon}) \text{tr}(M' M) \text{tr}(M) + O(K)$ ,  $E(U_n' M \bar{U}_n \bar{U}_n' M' U_n) = (\Sigma_u \gamma_0 + \sigma_{u\epsilon}') (\gamma_0' \Sigma_u + \sigma_{u\epsilon}) \text{tr}^2(M) + O(K)$ ,  $E(\bar{U}_n' M' U_n U_n' M \bar{U}_n) = (\gamma_0' \Sigma_u + \sigma_{u\epsilon}') (\Sigma_u \gamma_0 + \sigma_{u\epsilon}') \text{tr}^2(M) + O(K)$ ,  $E(\bar{U}_n' M' U_n U_n' P U_n) = (\gamma_0' \Sigma_u + \sigma_{u\epsilon}') \Sigma_u K \text{tr}(M) + O(K)$ , and  $E(U_n' P U_n U_n' P U_n) = \Sigma_u^2 K^2 + O(K)$ . Hence,  $E[(V_n' P V_n)^2] - E^2(V_n' P V_n) = O(K)$  by (iii).

The first part of (v) is Lemma A.3 (vi) in Donald and Newey (2001). The second part of (v) is in Liu and Lee (2010). For (vi),  $E(\frac{1}{n}\Gamma'_n\epsilon_n\epsilon'_nPV_n) = [E(\frac{1}{n}\Gamma'_n\epsilon_n\epsilon'_nM\bar{U}_n), E(\frac{1}{n}\Gamma'_n\epsilon_n\epsilon'_nPU_n)]$ , where  $E(\frac{1}{n}\Gamma'_n\epsilon_n\epsilon'_nM\bar{U}_n) = \frac{1}{n}\Gamma'_n\text{vec}_D(M)E(\epsilon_{ni}^2u_{ni})\gamma_0 + \frac{1}{n}\Gamma'_n\text{vec}_D(M)\mu_3$  and  $E(\frac{1}{n}\Gamma'_n\epsilon_n\epsilon'_nPU_n) = \frac{1}{n}\Gamma'_n\text{vec}_D(P)E(\epsilon_{ni}^2u_{ni})$ . On the other hand, let  $T_1 = F'_n(I_n - P)\epsilon_n/\sqrt{n}$  and  $T_2 = V'_nP\epsilon_n/\sqrt{n}$ . By the covariance inequality,  $|E(e'_j h_n T'_2 e_k)| \leq \sqrt{\text{Var}(e'_j h_n)}\sqrt{\text{Var}(e'_k T_2)}$ . As  $\text{Var}(h_n) = O(1)$  and  $\text{Var}(T_2) = E(T_2 T'_2) - E(T_2)E(T'_2) = O(K/n)$  by (iv), it follows that  $E(h_n T'_2) = E(\frac{1}{n}F'_n\epsilon_n\epsilon'_nPV_n) = O(\sqrt{K/n})$ . Similarly,  $|E(e'_j T_1 T'_2 e_k)| \leq \sqrt{\text{Var}(e'_j T_1)}\sqrt{\text{Var}(e'_k T_2)}$ , where  $e_j$  and  $e_k$  are, respectively, the  $j$ th and  $k$ th unit vectors. As  $\text{Var}(T_1) = \sigma_\epsilon^2 F'_n(I_n - P)F_n/n = O(\Delta_K)$  and  $\text{Var}(T_2) = O(K/n)$ , we have  $E(T_1 T'_2) = E[\frac{1}{n}F'_n(I_n - P)\epsilon_n\epsilon'_nPV_n] = O(\sqrt{K\Delta_K/n})$ . Let  $v_{ni}$  be the  $i$ th row of  $V_n$ .  $E(\frac{1}{n}h_n h'_n H_n^{-1}V'_n F_n) = \frac{1}{n^2} \sum_{i,j} E(F'_n e_i \epsilon_{n,i} \epsilon_{n,j} e'_j F_n H_n^{-1} V'_n F_n) = \frac{1}{n^2} \sum_i F'_n e_i e'_i F_n H_n^{-1} E(\epsilon_{ni}^2 v'_{ni}) e'_i F_n = O(\frac{1}{n})$ , because elements of  $F_n$  are uniformly bounded (implied by elements of  $\bar{Z}_{2n}$  being uniformly bounded in Assumption 4 (ii)). ■

**Lemma A.5** *Suppose that  $\{A_n\}$  is a sequence of  $n \times n$  UBC matrices, the elements of the  $n \times k$  matrix  $C_n$  are uniformly bounded, and  $\epsilon_{n1}, \dots, \epsilon_{nn}$  are i.i.d. with zero mean and finite variance  $\sigma^2$ . Then,  $\frac{1}{\sqrt{n}}C'_n A_n \epsilon_n = O_p(1)$  and  $\frac{1}{n}C'_n A_n \epsilon_n = o_p(1)$ . Furthermore, if the limit of  $\frac{1}{n}C'_n A_n A'_n C_n$  exists and is positive definite, then  $\frac{1}{\sqrt{n}}C'_n A_n \epsilon_n \xrightarrow{D} N(0, \sigma^2 \lim_{n \rightarrow \infty} \frac{1}{n}C'_n A_n A'_n C_n)$ .*

**Proof.** See Lee (2004). ■

**Lemma A.6** (i)  $\frac{1}{n}Z'_n P Z_n = H_n + \sum_{i=1}^4 R_i^H$ , where  $R_1^H = -e_F(K) = O(\Delta_K)$ ,  $R_2^H = \frac{1}{n}(F'_n V_n + V'_n F_n) = O(1/\sqrt{n})$ ,  $R_3^H = \frac{1}{n}V'_n P V_n = O(K/n)$ , and  $R_4^H = -\frac{1}{n}[F'_n(I_n - P)V_n + V'_n(I_n - P)F_n] = O(\sqrt{\Delta_K/n}) = o(K/n + \Delta_K)$ ;

(ii)  $[Z'_n P \epsilon_n - E(V'_n P \epsilon_n)]/\sqrt{n} = h_n + \sum_{i=1}^2 R_i^h$ , where  $R_1^h = -F'_n(I_n - P)\epsilon_n/\sqrt{n} = O(\Delta_K^{1/2})$  and  $R_2^h = [V'_n P \epsilon_n - E(V'_n P \epsilon_n)]/\sqrt{n} = O(\sqrt{K/n})$ ;

(iii)  $E(R_1^h R_1^{h'}) = -E(R_1^h h'_n) = -E(h_n h'_n H_n^{-1} R_1^{H'}) = \sigma_\epsilon^2 e_F(K)$  and  $E(h_n h'_n H_n^{-1} R_2^{H'}) = O(1/n)$ .

**Proof.**  $\frac{1}{n}Z'_n P Z_n = \frac{1}{n}(F_n + V_n)'P(F_n + V_n) = \frac{1}{n}F'_n P F_n + \frac{1}{n}(F'_n P V_n + V'_n P F_n) + \frac{1}{n}V'_n P V_n = H_n + \sum_{i=1}^4 R_i^H$ , where  $R_1^H = -\frac{1}{n}F'_n(I_n - P)F_n = -e_F(K) = O(\Delta_K)$ ,  $R_2^H = \frac{1}{n}(F'_n V_n + V'_n F_n) = O(1/\sqrt{n})$  by Lemma A.5,  $R_3^H = \frac{1}{n}V'_n P V_n$ , and  $R_4^H = -\frac{1}{n}[F'_n(I_n - P)V_n + V'_n(I_n - P)F_n] = O(\sqrt{\Delta_K/n}) = o(K/n + \Delta_K)$  by Lemma A.4 (ii) and (v). As  $\frac{1}{n}E(V'_n P V_n) = O(K/n)$  by Lemma A.4 (iii),  $R_3^H = \frac{1}{n}V'_n P V_n = O(K/n)$  by MI.

For (ii),  $[Z'_n P \epsilon_n - E(V'_n P \epsilon_n)]/\sqrt{n} = h_n - F'_n(I_n - P)\epsilon_n/\sqrt{n} + [V'_n P \epsilon_n - E(V'_n P \epsilon_n)]/\sqrt{n} = h_n + R_1^h + R_2^h$ , where  $R_1^h = -F'_n(I_n - P)\epsilon_n/\sqrt{n} = O(\Delta_K^{1/2})$  by Lemma A.4 (ii), and  $R_2^h = [V'_n P \epsilon_n - E(V'_n P \epsilon_n)]/\sqrt{n}$ . As  $E(V'_n P \epsilon_n \epsilon'_n P V_n) - E(V'_n P \epsilon_n)E(\epsilon'_n P V_n) = O(K)$  by Lemma A.4 (iv), it follows that  $R_2^h = O(\sqrt{K/n})$ .

For (iii),  $E(R_1^h R_1^{h'}) = -E(R_1^h h'_n) = -E(h_n h'_n H_n^{-1} R_1^{H'}) = \sigma_\epsilon^2 e_F(K)$  is trivial. By Lemma A.4 (vi),  $E(h_n h'_n H_n^{-1} R_2^{H'}) = O(1/n)$ . ■

**Lemma A.7** *If  $\sup_K \frac{|\hat{S}_\xi(K) - S_\xi(K)|}{S_\xi(K)} \xrightarrow{p} 0$ , then  $\frac{S_\xi(\hat{K})}{\inf_K S_\xi(K)} \xrightarrow{p} 1$ .*

**Proof.** Donald and Newey (2001) Lemma A.9. ■

**Lemma A.8** *Suppose  $\sqrt{n}(\tilde{\delta}_n - \delta_0) = O(1)$ ,  $\tilde{\sigma}'_{u\epsilon} = \frac{1}{n} Z'_{2n}(y_n - Z_n \tilde{\delta}_n)$ , and  $\tilde{\sigma}_\epsilon^2 = \frac{1}{n}(y_n - Z_n \tilde{\delta}_n)'(y_n - Z_n \tilde{\delta}_n)$ . Then, (i)*

$$\sqrt{n}(\tilde{\sigma}_{u\epsilon} - \sigma_{u\epsilon})' = \frac{1}{\sqrt{n}} \bar{Z}'_{2n} \epsilon_n + \sqrt{n} \left( \frac{1}{n} U'_n \epsilon_n - \sigma_{u\epsilon} \right) - \frac{1}{n} [\bar{Z}'_{2n} F_n + E(U'_n V_n)] \sqrt{n} (\tilde{\delta}_n - \delta_0) + o(1) = O(1),$$

$$\text{and (ii) } \sqrt{n}(\tilde{\sigma}_\epsilon^2 - \sigma_\epsilon^2) = \sqrt{n} \left( \frac{1}{n} \epsilon'_n \epsilon_n - \sigma_\epsilon^2 \right) - \frac{2}{n} E(\epsilon'_n V_n) \sqrt{n} (\tilde{\delta}_n - \delta_0) + o(1) = O(1).$$

**Proof.** For (i),  $\tilde{\sigma}'_{u\epsilon} = \frac{1}{n} Z'_{2n} \epsilon_n - \frac{1}{n} Z'_{2n} Z_n (\tilde{\delta}_n - \delta_0)$ . As  $\frac{1}{n} \bar{Z}'_{2n} V_n = o(1)$ ,  $\frac{1}{n} U'_n F_n = o(1)$ , and  $\frac{1}{n} [U'_n V_n - E(U'_n V_n)] = o(1)$ , we have  $\frac{1}{n} Z'_{2n} Z_n = \frac{1}{n} (\bar{Z}'_{2n} + U'_n)' (F_n + V_n) = \frac{1}{n} [\bar{Z}'_{2n} F_n + E(U'_n V_n)] + o(1)$ . Hence,  $\sqrt{n}(\tilde{\sigma}_{u\epsilon} - \sigma_{u\epsilon})' = \sqrt{n} \left( \frac{1}{n} Z'_{2n} \epsilon_n - \sigma_{u\epsilon} \right) - \left( \frac{1}{n} Z'_{2n} Z_n \right) \sqrt{n} (\tilde{\delta}_n - \delta_0) = \frac{1}{\sqrt{n}} \bar{Z}'_{2n} \epsilon_n + \sqrt{n} \left( \frac{1}{n} U'_n \epsilon_n - \sigma_{u\epsilon} \right) - \frac{1}{n} [\bar{Z}'_{2n} F_n + E(U'_n V_n)] \sqrt{n} (\tilde{\delta}_n - \delta_0) + o(1)$ , where  $\frac{1}{\sqrt{n}} \bar{Z}'_{2n} \epsilon_n = O(1)$ ,  $\sqrt{n} \left( \frac{1}{n} U'_n \epsilon_n - \sigma_{u\epsilon} \right) = O(1)$ , and  $\frac{1}{n} [\bar{Z}'_{2n} F_n + E(U'_n V_n)] = O(1)$ . For (ii),  $\tilde{\sigma}_\epsilon^2 = \frac{1}{n} [\epsilon_n - Z_n (\tilde{\delta}_n - \delta_0)]' [\epsilon_n - Z_n (\tilde{\delta}_n - \delta_0)] = \frac{1}{n} \epsilon'_n \epsilon_n - \frac{2}{n} \epsilon'_n Z_n (\tilde{\delta}_n - \delta_0) + \frac{1}{n} (\tilde{\delta}_n - \delta_0)' Z'_n Z_n (\tilde{\delta}_n - \delta_0)$ . As  $\frac{1}{n} \epsilon'_n F_n = o(1)$  and  $\frac{1}{n} [\epsilon'_n V_n - E(\epsilon'_n V_n)] = o(1)$ , it follows that  $\frac{1}{n} \epsilon'_n Z_n = \frac{1}{n} \epsilon'_n (F_n + V_n) = \frac{1}{n} \epsilon'_n F_n + \frac{1}{n} [\epsilon'_n V_n - E(\epsilon'_n V_n)] + \frac{1}{n} E(\epsilon'_n V_n) = \frac{1}{n} E(\epsilon'_n V_n) + o(1)$ . Hence,  $\sqrt{n}(\tilde{\sigma}_\epsilon^2 - \sigma_\epsilon^2) = \sqrt{n} \left( \frac{1}{n} \epsilon'_n \epsilon_n - \sigma_\epsilon^2 \right) - \frac{2}{n} \epsilon'_n Z_n \sqrt{n} (\tilde{\delta}_n - \delta_0) + \frac{1}{n} (\tilde{\delta}_n - \delta_0)' Z'_n Z_n \sqrt{n} (\tilde{\delta}_n - \delta_0) = \sqrt{n} \left( \frac{1}{n} \epsilon'_n \epsilon_n - \sigma_\epsilon^2 \right) - \frac{2}{n} E(\epsilon'_n V_n) \sqrt{n} (\tilde{\delta}_n - \delta_0) + o(1)$ , where  $\sqrt{n} \left( \frac{1}{n} \epsilon'_n \epsilon_n - \sigma_\epsilon^2 \right) = O(1)$  and  $\frac{1}{n} E(\epsilon'_n V_n) = O(1)$ . ■

## B Proofs

**Proof of Lemma 2.1.** For

$$\pi_K = \begin{pmatrix} \gamma'_0 \pi_q^{0'} & \lambda_0 \gamma'_0 \pi_q^{0'} & \cdots & \lambda_0^p \gamma'_0 \pi_q^{0'} & 0 \\ 0 & 0 & \cdots & 0 & \pi_q^{0'} \end{pmatrix}',$$

$Q_K \pi_K = [(\sum_{j=0}^p \lambda_0^j W_n^{j+1}) \Psi_q(X_n) \pi_q^0 \gamma_0, \Psi_q(X_n) \pi_q^0]$ . Hence, when  $\sup_n \|\lambda_0 W_n\|_\infty < 1$ , we have  $\|F_n - Q_K \pi_K\|_\infty = \|[G_n \bar{Z}_{2n} \gamma_0 - (\sum_{j=0}^p \lambda_0^j W_n^{j+1}) \Psi_q(X_n) \pi_q^0 \gamma_0, \bar{Z}_{2n} - \Psi_q(X_n) \pi_q^0]\|_\infty = \|[G_n (\bar{Z}_{2n} - \Psi_q(X_n) \pi_q^0) \gamma_0 + (G_n - \sum_{j=0}^p \lambda_0^j W_n^{j+1}) \Psi_q(X_n) \pi_q^0 \gamma_0, \bar{Z}_{2n} - \Psi_q(X_n) \pi_q^0]\|_\infty$ , which is  $o(1)$  as  $n, K \rightarrow \infty$ , since  $\|\bar{Z}_{2n} - \Psi_q(X_n) \pi_q^0\|_\infty \rightarrow 0$  and  $\|G_n - \sum_{j=0}^p \lambda_0^j W_n^{j+1}\|_\infty \leq \|\lambda_0 W_n\|_\infty^{p+1} \|G_n\|_\infty \rightarrow 0$ . Finally, as  $\frac{1}{n} \|\cdot\|^2 \leq (\|\cdot\|_\infty)^2$ , the desired result follows. ■

**Proof of Proposition 1.** The 2SLS estimator satisfies  $\sqrt{n}(\hat{\delta}_{2sls,n} - \delta_0 - b_{2sls,n}) = (\frac{1}{n} Z_n' P Z_n)^{-1} [Z_n' P \epsilon_n - E(V_n' P \epsilon_n)] / \sqrt{n}$ , where  $E(V_n' P \epsilon_n) = [\text{tr}(M)(\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2), K \sigma_{u\epsilon}]'$  by Lemma A.4 (iii). As  $K/n \rightarrow 0$  and  $\Delta_K = o(1)$  by Lemma A.4 (i), we have  $\frac{1}{n} Z_n' P Z_n = H_n + o(1) \xrightarrow{p} \bar{H}$  and  $[Z_n' P \epsilon_n - E(V_n' P \epsilon_n)] / \sqrt{n} = h_n + o(1) \xrightarrow{d} N(0, \sigma_\epsilon^2 \bar{H})$  by Lemma A.6. The conclusion then follows by the Slutsky theorem. ■

**Proof of Corollary 2.** (i) and (ii) are trivial. For (iii), because  $0 < \eta < 1$  implies  $K^{2\eta} < K^{1+\eta}$ , therefore  $K^\eta / \sqrt{n} < \sqrt{K^{1+\eta}/n} \rightarrow 0$ . As  $\sqrt{n}(\hat{\delta}_{2sls,n} - \delta_0 - b_{2sls,n}) = O(1)$ ,  $(K^\eta / \sqrt{n}) \sqrt{n}(\hat{\delta}_{2sls,n} - \delta_0 - b_{2sls,n}) = o(1)$ . Note that  $b_{2sls,n} = O(K/n)$  and  $K^\eta b_{2sls,n} = O(K^{1+\eta}/n) = o(1)$ . It follows that  $K^\eta(\hat{\delta}_{2sls,n} - \delta_0) = K^\eta(\hat{\delta}_{2sls,n} - \delta_0 - b_{2sls,n}) + K^\eta b_{2sls,n} = o(1)$ . ■

**Proof of Proposition 3.** The 2SLS estimator satisfies  $\hat{\delta}_{2sls,n} - \delta_0 - b_{2sls,n} = (\frac{1}{n} Z_n' P Z_n)^{-1} \frac{1}{n} [Z_n' P \epsilon_n - E(V_n' P \epsilon_n)]$ . By Lemma A.6,  $(\frac{1}{n} Z_n' P Z_n)^{-1} = O(1)$  and  $\frac{1}{n} [Z_n' P \epsilon_n - E(V_n' P \epsilon_n)] = O(1/\sqrt{n})$ . By Lemma A.4 (iii),  $\frac{1}{n} E(V_n' P \epsilon_n) = O(K/n) = O(1)$ . The conclusion then follows by the Slutsky theorem. ■

**Proof of Proposition 4.** It is sufficient to show that  $\frac{1}{\sqrt{n}}(\hat{b}_{2sls,n} - b_{2sls,n}) = o(1)$ . As  $\tilde{G}_n - G_n = (\tilde{\lambda}_n - \lambda_0) \tilde{G}_n G_n$ ,  $\sqrt{n}(\tilde{\delta}_n - \delta_0) = O(1)$ ,  $\sqrt{n}(\tilde{\sigma}_{u\epsilon} - \sigma_{u\epsilon}) = O(1)$ , and  $\sqrt{n}(\tilde{\sigma}_\epsilon^2 - \sigma_\epsilon^2) = O(1)$  by Lemma A.8,  $\frac{1}{\sqrt{n}}[\text{tr}(P \tilde{G}_n)(\tilde{\sigma}_{u\epsilon} \tilde{\gamma}_n + \tilde{\sigma}_\epsilon^2) - \text{tr}(M)(\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2)] = \frac{1}{\sqrt{n}}(\tilde{\lambda}_n - \lambda_0) \text{tr}(P \tilde{G}_n G_n)(\tilde{\sigma}_{u\epsilon} \tilde{\gamma}_n + \tilde{\sigma}_\epsilon^2) + \frac{1}{\sqrt{n}} \text{tr}(M)[\tilde{\sigma}_{u\epsilon}(\tilde{\gamma}_n - \gamma_0) + (\tilde{\sigma}_{u\epsilon} - \sigma_{u\epsilon}) \gamma_0 + (\tilde{\sigma}_\epsilon^2 - \sigma_\epsilon^2)] = O(K/n) = o(1)$ . Similarly,  $K(\tilde{\sigma}_{u\epsilon} - \sigma_{u\epsilon}) / \sqrt{n} = O(K/n) = o(1)$ . On the other hand, as  $\frac{1}{n} Z_n' P_K Z_n = O(1)$ , the desired result follows. ■

**Proof of Proposition 5.** The 2SLS estimator satisfies  $\sqrt{n}(\hat{\delta}_{2sls,n} - \delta_0) = \hat{H}_n^{-1} \hat{h}_n$ , with  $\hat{H}_n = \frac{1}{n} Z_n' P Z_n$  and  $\hat{h}_n = Z_n' P \epsilon_n / \sqrt{n}$ . By Lemma A.6 (i),  $\hat{H}_n = H_n + T_1^H + T_2^H + Z^H$ , where  $T_1^H = R_1^H = O(\Delta_K)$ ,  $T_2^H = R_2^H = O(1/\sqrt{n})$ ,  $Z^H = R_3^H + R_4^H = O(K/n) + o(K/n + \Delta_K)$ . On the other hand,  $\hat{h}_n = h_n + T_1^h + T_2^h$ , where  $T_1^h = R_1^h = O(\Delta_K^{1/2})$  by Lemma A.6 (ii) and  $T_2^h = V_n' P \epsilon_n / \sqrt{n}$ . As  $E(V_n' P V_n) = O(K)$  by Lemma A.4 (iii) and  $E(\epsilon_n' P \epsilon_n) = \sigma_\epsilon^2 \text{tr}(P) = \sigma_\epsilon^2 K$ , it follows by MI that  $E|V_n' P \epsilon_n| \leq [E(V_n' P V_n)]^{1/2} [E(\epsilon_n' P \epsilon_n)]^{1/2} = O(K)$ . Hence,  $T_2^h = V_n' P \epsilon_n / \sqrt{n} = O(K/\sqrt{n})$ . For

$\rho_{K,n} = \text{tr}(S(K))$ ,  $\rho_{K,n} = O(K^2/n + \Delta_K)$  by Assumption 5 (i). It follows that  $\|Z^H\| = o(\rho_{K,n})$ . For  $T^H = T_1^H + T_2^H$  and  $T^h = T_1^h + T_2^h$ ,  $\|T^H\|^2 = o(\rho_{K,n})$ ,  $\|T^h\| \|T^H\| = o(\rho_{K,n})$ .

Next, by Lemma A.6 (iii),  $E(T_1^h T_1^{h'}) = -E(T_1^h h'_n) = -E(h_n h'_n H_n^{-1} T_1^{H'}) = \sigma_\epsilon^2 e_F(K)$ . By Lemma A.4 (iv),  $E(T_2^h T_2^{h'}) = \frac{1}{n} E(V_n' P \epsilon_n) E(\epsilon_n' P V_n) + O(K/n)$ . When  $\mu_3 = 0$  and  $E(\epsilon_n^2 u_{ni}) = 0$ ,  $E(h_n T_2^{h'}) = \frac{1}{n} E(F_n' \epsilon_n \epsilon_n' P V_n) = 0$ . By Lemma A.4 (v),  $E(T_1^h T_2^{h'}) = -\frac{1}{n} E[F_n' (I_n - P) \epsilon_n \epsilon_n' P V_n] = O(\sqrt{K \Delta_K / n}) = o(\rho_{K,n})$ , and, by Lemma A.6 (iii),  $E(h_n h'_n H_n^{-1} T_2^{H'}) = O(1/n) = o(\rho_{K,n})$ . Then, for  $Z^A(K) = 0$  and  $\hat{A}(K)$  defined in Lemma A.1,  $E[\hat{A}(K)] = E[(h_n + T_1^h + T_2^h)(h_n + T_1^h + T_2^h)' - h_n h'_n H_n^{-1} (T_1^H + T_2^H)' - (T_1^H + T_2^H) H_n^{-1} h_n h'_n] = \sigma_\epsilon^2 H_n + \sigma_\epsilon^2 e_F(K) + \frac{1}{n} E(V_n' P \epsilon_n) E(\epsilon_n' P V_n) + o(\rho_{K,n}) = \sigma_\epsilon^2 H_n + H_n S(K) H_n + o(\rho_{K,n})$ . So all conditions of Lemma A.1 are satisfied. The desired result follows as  $E(V_n' P \epsilon_n) = [\text{tr}(M)(\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2), K \sigma_{u\epsilon}]'$  by Lemma A.4 (iii). ■

**Proof of Proposition 6.** For  $\rho_{K,n} = \text{tr}(S(K))$ ,  $\rho_{K,n} = O(K/n + \Delta_K)$  by Assumption 5 (i). The C2SLS estimator satisfies  $\sqrt{n}(\hat{\delta}_{c2sls,n} - \delta_0) = \hat{H}_n^{-1} \hat{h}_n$ , with  $\hat{H}_n = \frac{1}{n} Z_n' P Z_n$  and  $\hat{h}_n = \frac{1}{\sqrt{n}} Z_n' P \epsilon_n - \frac{1}{\sqrt{n}} [\text{tr}(P \tilde{G}_n) (\tilde{\sigma}_{u\epsilon} \tilde{\gamma}_n + \tilde{\sigma}_\epsilon^2), K \tilde{\sigma}_{u\epsilon}]'$ . By Lemma A.6 (i),  $\hat{H}_n = H_n + \sum_{j=1}^3 T_j^H + Z^H$ , where  $T_1^H = R_1^H = O(\Delta_K)$ ,  $T_2^H = R_2^H = O(1/\sqrt{n})$ ,  $T_3^H = \frac{1}{n} E(V_n' P V_n) = O(K/n)$ , and  $Z^H = \frac{1}{n} V_n' P V_n - \frac{1}{n} E(V_n' P V_n) + R_4^H$ . By Lemma A.4 (iv), we have  $E[(V_n' P V_n)^2] = E^2(V_n' P V_n) + O(K)$ . It follows that  $E[\frac{1}{n} V_n' P V_n - \frac{1}{n} E(V_n' P V_n)]^2 = O(K/n^2) = o(K^2/n^2)$ . Hence,  $\frac{1}{n} V_n' P V_n - \frac{1}{n} E(V_n' P V_n) = o(K/n)$ . As  $R_4^H = o(K/n + \Delta_K)$  by Lemma A.6,  $Z^H = o(\rho_{K,n})$ .

On the other hand,  $\hat{h}_n = \frac{1}{\sqrt{n}} [Z_n' P \epsilon_n - E(V_n' P \epsilon_n)] - \frac{1}{\sqrt{n}} \{[\text{tr}(P \tilde{G}_n) (\tilde{\sigma}_{u\epsilon} \tilde{\gamma}_n + \tilde{\sigma}_\epsilon^2), K \tilde{\sigma}_{u\epsilon}]' - E(V_n' P \epsilon_n)\}$ .  $\frac{1}{\sqrt{n}} [Z_n' P \epsilon_n - E(V_n' P \epsilon_n)] = h_n + T_1^h + T_2^h$ , where  $T_1^h = R_1^h = O(\Delta_K^{1/2})$  and  $T_2^h = R_2^h = O(\sqrt{K/n})$  by Lemma A.6 (ii). As  $\tilde{G}_n - G_n = (\tilde{\lambda}_n - \lambda_0) \tilde{G}_n G_n$ ,  $\frac{1}{\sqrt{n}} [\text{tr}(P \tilde{G}_n) (\tilde{\sigma}_{u\epsilon} \tilde{\gamma}_n + \tilde{\sigma}_\epsilon^2) - \text{tr}(M)(\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2)] = \frac{1}{\sqrt{n}} (\tilde{\lambda}_n - \lambda_0) \text{tr}(P \tilde{G}_n G_n) (\tilde{\sigma}_{u\epsilon} \tilde{\gamma}_n + \tilde{\sigma}_\epsilon^2) + \frac{1}{\sqrt{n}} \text{tr}(M) [\tilde{\sigma}_{u\epsilon} (\tilde{\gamma}_n - \gamma_0) + (\tilde{\sigma}_{u\epsilon} - \sigma_{u\epsilon}) \gamma_0 + (\tilde{\sigma}_\epsilon^2 - \sigma_\epsilon^2)] = \frac{1}{\sqrt{n}} (\tilde{\lambda}_n - \lambda_0) \text{tr}(P G_n^2) (\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2) + \frac{1}{\sqrt{n}} \text{tr}(M) [\sigma_{u\epsilon} (\tilde{\gamma}_n - \gamma_0) + \gamma_0' (\tilde{\sigma}_{u\epsilon} - \sigma_{u\epsilon}) + (\tilde{\sigma}_\epsilon^2 - \sigma_\epsilon^2)] + o(K/n)$ . Let  $P_0 = Q_0 (Q_0' Q_0)^{-1} Q_0'$ . The preliminary estimator is given by  $\tilde{\delta}_n = (Z_n' P_0 Z_n)^{-1} Z_n' P_0 y_n$ . As  $\frac{1}{n} Q_0' Z_n = \frac{1}{n} Q_0' (F_n + V_n) = \frac{1}{n} Q_0' F_n + o(1)$ ,  $\sqrt{n}(\tilde{\delta}_n - \delta_0) = L_0 + o(1)$ , where  $L_0 = \sqrt{n} (F_n' P_0 F_n)^{-1} F_n' P_0 \epsilon_n$ . By Lemma A.8,  $\sqrt{n}(\tilde{\sigma}_{u\epsilon} - \sigma_{u\epsilon})' = L_1 + o(1)$  and  $\sqrt{n}(\tilde{\sigma}_\epsilon^2 - \sigma_\epsilon^2) = L_2 + o(1)$ , where  $L_1 = \frac{1}{\sqrt{n}} \bar{Z}'_{2n} \epsilon_n + \sqrt{n} (\frac{1}{n} U_n' \epsilon_n - \sigma_{u\epsilon}) - \frac{1}{n} [\bar{Z}'_{2n} F_n + E(U_n' V_n)] L_0$  and  $L_2 = \sqrt{n} (\frac{1}{n} \epsilon_n' \epsilon_n - \sigma_\epsilon^2) - \frac{2}{n} E(\epsilon_n' V_n) L_0$ . Let  $T_3^h = -\frac{1}{n} [a_1, a_2]'$ , where  $a_1 = \text{tr}(P G_n^2) (\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2) e_1' L_0 + \text{tr}(M) [\sigma_{u\epsilon} (0_{m \times 1}, I_m) L_0 + \gamma_0' L_1 + L_2]$  and  $a_2 = K L_1'$ . Let  $Z^h = \frac{1}{\sqrt{n}} [\text{tr}(P \tilde{G}_n) (\tilde{\sigma}_{u\epsilon} \tilde{\gamma}_n + \tilde{\sigma}_\epsilon^2) - \text{tr}(M)(\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2), K (\tilde{\sigma}_{u\epsilon} - \sigma_{u\epsilon})] - T_3^h = o(K/n)$ . Hence,  $\hat{h}_n = h_n + \sum_{j=1}^3 T_j^h + Z^h$ . It follows that, for  $T^H = \sum_{j=1}^3 T_j^H$  and  $T^h = \sum_{j=1}^3 T_j^h$ , we have  $\|T^H\|^2 = o(\rho_{K,n})$ ,  $\|T^h\| \|T^H\| = o(\rho_{K,n})$ ,  $\|Z^h\| = o(\rho_{K,n})$  and  $\|Z^H\| = o(\rho_{K,n})$ .

Next, by Lemma A.6 (iii),  $E(T_1^h T_1^{h'}) = -E(T_1^h h'_n) = -E(h_n h'_n H_n^{-1} T_1^{H'}) = \sigma_\epsilon^2 e_F(K)$ .  $E(T_2^h T_2^{h'}) = \frac{1}{n}[E(V'_n P \epsilon_n \epsilon'_n P V_n) - E(V'_n P \epsilon_n)E(\epsilon'_n P V_n)] = \frac{1}{n}\Pi_1(K) + o(K/n)$ , where  $\Pi_1(K)$  denotes the leading-order matrix given in Lemma A.4 (iv). As  $\mu_3 = 0$  and  $E(\epsilon_{ni}^2 u_{ni}) = 0$ , we have  $E(h_n T_2^{h'}) = 0$ , and  $E(T_1^h T_2^{h'}) = 0$ . By Lemma A.6 (iii),  $E(h_n h'_n H_n^{-1} T_2^{H'}) = O(1/n) = o(\rho_{K,n})$ .  $E(h_n h'_n H_n^{-1} T_3^{H'}) = \frac{1}{n}\sigma_\epsilon^2 E(V'_n P V_n)$ .

$E(L_0 h'_n) = (F'_n P_0 F_n)^{-1} F'_n P_0 E(\epsilon_n \epsilon'_n) F_n = \sigma_\epsilon^2 I_{m+1}$ . As  $E(\epsilon_{ni}^2 u_{ni}) = 0$ ,  $E(L_1 h'_n) = \frac{1}{n} \bar{Z}'_{2n} E(\epsilon_n \epsilon'_n) F_n - \frac{1}{n} [\bar{Z}'_{2n} F_n + E(U'_n V_n)] E(L_0 h'_n) = \frac{1}{n} \sigma_\epsilon^2 \bar{Z}'_{2n} F_n - \frac{1}{n} \sigma_\epsilon^2 [\bar{Z}'_{2n} F_n + E(U'_n V_n)] = -\frac{1}{n} \sigma_\epsilon^2 E(U'_n V_n)$ , where  $E(U'_n V_n) = E[U'_n G_n (U_n \gamma_0 + \epsilon_n), U'_n U_n] = [\text{tr}(G_n)(\Sigma_u \gamma_0 + \sigma'_{u\epsilon}), n \Sigma_u]$ . As  $\mu_3 = 0$ ,  $E(L_2 h'_n) = -\frac{2}{n} E(\epsilon'_n V_n) E(L_0 h'_n) = -\frac{2}{n} \sigma_\epsilon^2 E(\epsilon'_n V_n)$ , where  $E(\epsilon'_n V_n) = E[\epsilon'_n G_n (U_n \gamma_0 + \epsilon_n), \epsilon'_n U_n] = [\text{tr}(G_n)(\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2), n \sigma_{u\epsilon}]$ . It follows that  $E(a_1 h'_n) = \text{tr}(P G_n^2)(\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2) e'_1 E(L_0 h'_n) + \text{tr}(M)[\sigma_{u\epsilon}(0_{m \times 1}, I_m) E(L_0 h'_n) + \gamma_0 E(L_1 h'_n) + E(L_2 h'_n)] = \text{tr}(P G_n^2)(\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2) \sigma_\epsilon^2 e'_1 + \text{tr}(M) \sigma_\epsilon^2 [\sigma_{u\epsilon}(0_{m \times 1}, I_m) - \frac{1}{n} \gamma_0 E(U'_n V_n) - \frac{2}{n} E(\epsilon'_n V_n)] \cdot E(a'_2 h'_n) = K E(L_1 h'_n) = -\frac{K}{n} \sigma_\epsilon^2 E(U'_n V_n)$ . Hence,

$$\begin{aligned} E(T_3^h h'_n) &= -\frac{1}{n} E([a_1, a_2]' h'_n) \\ &= \frac{1}{n} \begin{bmatrix} \frac{1}{n} \text{tr}(M) \text{tr}(G_n) \sigma_\epsilon^2 (\gamma_0' \Sigma_u \gamma_0 + 3 \sigma_{u\epsilon} \gamma_0 + 2 \sigma_\epsilon^2) - \text{tr}(P G_n^2) \sigma_\epsilon^2 (\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2) & \text{tr}(M) \sigma_\epsilon^2 (\gamma_0' \Sigma_u + \sigma_{u\epsilon}) \\ \frac{K}{n} \text{tr}(G_n) \sigma_\epsilon^2 (\Sigma_u \gamma_0 + \sigma'_{u\epsilon}) & K \sigma_\epsilon^2 \Sigma_u \end{bmatrix}. \end{aligned}$$

Then for  $Z^A(K) = [(T_1^h + T_2^h) T_3^{h'}]^s + T_3^h T_3^{h'}$  in Lemma A.1,

$$\begin{aligned} E[\hat{A}(K)] &= E[(h_n + T_1^h + T_2^h)(h_n + T_1^h + T_2^h)' + (T_3^h h'_n)^s - (h_n h'_n H_n^{-1} T^{H'})^s] \\ &= E[h_n h'_n + T_1^h T_1^{h'} + T_2^h T_2^{h'} + (T_1^h h'_n)^s + (T_3^h h'_n)^s - (h_n h'_n H_n^{-1} T^{H'})^s] \\ &= \sigma_\epsilon^2 H_n + \sigma_\epsilon^2 e_F(K) + \frac{1}{n} \Pi_1(K) + E(T_3^h h'_n)^s - \frac{2}{n} \sigma_\epsilon^2 E(V'_n P V_n) + o(\rho_{K,n}) \\ &= \sigma_\epsilon^2 H_n + H_n S(K) H_n + o(\rho_{K,n}). \end{aligned}$$

So all conditions of Lemma A.1 are satisfied. Let  $\Pi_2(K) = n E(T_3^h h'_n)^s - 2 \sigma_\epsilon^2 E(V'_n P V_n)$ .

$$\Pi_2(K) = \begin{bmatrix} \Pi_{2,11} & * \\ [\frac{K}{n} \text{tr}(G_n) - \text{tr}(M)] \sigma_\epsilon^2 (\Sigma_u \gamma_0 + \sigma'_{u\epsilon}) & 0 \end{bmatrix},$$

where  $\Pi_{2,11} = 2[\frac{1}{n} \text{tr}(M) \text{tr}(G_n) - \text{tr}(M' M)] \sigma_\epsilon^2 (\gamma_0' \Sigma_u \gamma_0 + 2 \sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2) + 2[\frac{1}{n} \text{tr}(M) \text{tr}(G_n) - \text{tr}(P G_n^2)] \sigma_\epsilon^2 (\sigma_{u\epsilon} \gamma_0 + \sigma_\epsilon^2)$ . ■



**Proof of Proposition 7.** Let  $\Omega_{1\xi} = \xi' H_n^{-1} \Omega_1 H_n^{-1} \xi$ ,  $\Omega_{2\xi} = \xi' H_n^{-1} \Omega_2 H_n^{-1} \xi$ ,  $\Pi = \Pi_1(K) + \Pi_2(K)$  and  $\Pi_\xi = \xi' H_n^{-1} \Pi H_n^{-1} \xi$ . Let  $\hat{\Omega}_{1\xi} = \xi' \hat{H}_n^{-1} \hat{\Omega}_1 \hat{H}_n^{-1} \xi$ ,  $\hat{\Omega}_{2\xi} = \xi' \hat{H}_n^{-1} \hat{\Omega}_2 \hat{H}_n^{-1} \xi$  and  $\hat{\Pi}_\xi = \xi' \hat{H}_n^{-1} \hat{\Pi} \hat{H}_n^{-1} \xi$ . Let  $\tilde{R}(K) = \frac{1}{n} [Z_n'(I_n - P)Z_n + \hat{\Omega}_2 - V_n' V_n]$  and  $\tilde{R}_\xi(K) = \xi' \hat{H}_n^{-1} \tilde{R}(K) \hat{H}_n^{-1} \xi$ . Let  $\tilde{S}_\xi(K) = \frac{1}{n} \hat{\Omega}_{1\xi} + \hat{\sigma}_\epsilon^2 \tilde{R}_\xi(K)$  for 2SLS and  $\tilde{S}_\xi(K) = \frac{1}{n} \hat{\Pi}_\xi + \hat{\sigma}_\epsilon^2 \tilde{R}_\xi(K)$  for C2SLS. As  $\frac{1}{n} V_n' V_n$  does not depend on  $K$ ,  $\hat{K} = \arg \min_K \hat{S}_\xi(K) = \arg \min_K \tilde{S}_\xi(K)$ . Let  $R(K) = \frac{1}{n} F_n'(I_n - P)F_n$ ,  $R_\xi(K) = \xi' H_n^{-1} R(K) H_n^{-1} \xi$ . We have  $S_\xi(K) = \frac{1}{n} \Omega_{1\xi} + \sigma_\epsilon^2 R_\xi(K)$  for 2SLS and  $S_\xi(K) = \frac{1}{n} \Pi_\xi + \sigma_\epsilon^2 R_\xi(K)$  for C2SLS. By Lemma A.7, we only need to show  $\sup_K \frac{|\hat{S}_\xi(K) - S_\xi(K)|}{S_\xi(K)} \xrightarrow{p} 0$ ,  $\frac{|\hat{S}_\xi(K) - S_\xi(K)|}{S_\xi(K)} \leq \frac{1}{n} \frac{A}{S_\xi(K)} + \hat{\sigma}_\epsilon^2 \frac{|\tilde{R}_\xi(K) - R_\xi(K)|}{S_\xi(K)} + |\hat{\sigma}_\epsilon^2 - \sigma_\epsilon^2| \frac{R_\xi(K)}{S_\xi(K)}$ , where  $A = |\hat{\Omega}_{1\xi} - \Omega_{1\xi}|$  for 2SLS and  $A = |\hat{\Pi}_\xi - \Pi_\xi|$  for C2SLS. Let  $\tilde{G}_n = G_n(\tilde{\lambda}_n)$ . As  $\tilde{G}_n - G_n = (\tilde{\lambda}_n - \lambda_0) \tilde{G}_n G_n$ , we have  $\text{tr}(\tilde{M} - M) = (\tilde{\lambda}_n - \lambda_0) \text{tr}(P \tilde{G}_n G_n) = o(K)$  and  $\text{tr}(P \tilde{G}_n^2 - P G_n^2) = \text{tr}(P \tilde{G}_n^2 - P \tilde{G}_n G_n + P \tilde{G}_n G_n - P G_n^2) = (\tilde{\lambda}_n - \lambda_0) \text{tr}(P \tilde{G}_n^2 G_n) + (\tilde{\lambda}_n - \lambda_0) \text{tr}(P \tilde{G}_n G_n^2) = o(K)$ . Similarly,  $\text{tr}(\hat{M}^2 - M^2) = o(K)$  and  $\text{tr}(\hat{M}' \hat{M} - M' M) = o(K)$ . It follows that  $|\hat{\Omega}_{1\xi} - \Omega_{1\xi}| = o(K^2)$  and  $|\hat{\Pi}_\xi - \Pi_\xi| = o(K)$ . For 2SLS,  $|n S_\xi(K)| \geq c \cdot K^2$  by Assumption 6 (ii), which implies  $\frac{1}{n} |\hat{\Omega}_{1\xi} - \Omega_{1\xi}| / S_\xi(K) = o(1)$ , uniformly in  $K$ . On the other hand, for C2SLS,  $|n S_\xi(K)| \geq c \cdot K$  by Assumption 6 (iii), which implies  $\frac{1}{n} |\hat{\Pi}_\xi - \Pi_\xi| / S_\xi(K) = o(1)$ . As  $R_\xi(K) / S_\xi(K) = O(1)$  uniformly in  $K$  for both 2SLS and C2SLS because  $0 < R_\xi(K) / S_\xi(K) < 1$  for all  $K$ , it remains to show that  $\sup_K \frac{|\tilde{R}_\xi(K) - R_\xi(K)|}{S_\xi(K)} \xrightarrow{p} 0$ . As  $|n S_\xi(K)| \geq c(K + n \Delta_K)$  for 2SLS and C2SLS,  $\sup_K \frac{|\tilde{R}_\xi(K) - R_\xi(K)|}{S_\xi(K)} \xrightarrow{p} 0$  can be proved by the same argument for both estimators as follows.

For subsequent analysis, it is useful to consider a more general form,  $\sup_K \frac{|\tilde{R}_*(K) - R_*(K)|}{S_\xi(K)}$ , where  $\tilde{R}_*(K) = \xi'_{1n} \tilde{R}(K) \xi_{2n}$  and  $R_*(K) = \xi'_{1n} R(K) \xi_{2n}$  for any arbitrary (random) vectors  $\xi_{1n}$  and  $\xi_{2n}$  which converge (in probability) to well defined limits. As  $\tilde{R}(K) - R(K) = \frac{1}{n} [F_n'(I_n - P)V_n]^s - \frac{1}{n} (V_n' P V_n - \Omega_2) + \frac{1}{n} (\hat{\Omega}_2 - \Omega_2)$ , we have  $\tilde{R}_*(K) - R_*(K) = \frac{1}{n} \xi'_{1n} [F_n'(I_n - P)V_n]^s \xi_{2n} - \frac{1}{n} \xi'_{1n} (V_n' P V_n - \Omega_2) \xi_{2n} + \frac{1}{n} \xi'_{1n} (\hat{\Omega}_2 - \Omega_2) \xi_{2n}$ .

First, we show  $\sup_K \frac{|\frac{1}{n} \xi'_{1n} F_n'(I_n - P)V_n \xi_{2n}|}{S_\xi(K)} \xrightarrow{p} 0$ , where  $V_n = G_n \bar{U}_n e_1 + U_n(0_{m \times 1}, I_m)$ . Given any  $\alpha > 0$  and positive integer  $r$ , by Chebyshev's inequality, we have  $\Pr(\sup_K \frac{|\frac{1}{n} \xi'_{1n} F_n'(I_n - P)V_n \xi_{2n}|}{S_\xi(K)} > \alpha) \leq \sum_K \frac{(e_1' \xi_{2n})^{2r} \mathbb{E}[\xi'_{1n} F_n'(I_n - P)G_n \bar{U}_n]^{2r}}{\alpha^{2r} [n S_\xi(K)]^{2r}}$ . Let  $\lambda_{G, \max}$  be the largest eigenvalue of  $G_n G_n'$ . By Theorem 2 of Whittle (1960), for positive constants  $c_1, c_2$  and  $c$ ,  $\mathbb{E}[\xi'_{1n} F_n'(I_n - P)G_n \bar{U}_n]^{2r} \leq c_1 [\xi'_{1n} F_n'(I_n - P)G_n G_n'(I_n - P)F_n \xi_{1n}]^r \leq c_1 [\lambda_{G, \max} \xi'_{1n} F_n'(I_n - P)F_n \xi_{1n}]^r = O(n \Delta_K)^r \leq c_2 [n S_\xi(K)]^r$ . Hence, for  $r = 1$ ,  $\Pr(\sup_K \frac{|\xi'_{1n} F_n'(I_n - P)G_n \bar{U}_n e_1 \xi_{2n}|}{n S_\xi(K)} > \alpha) \leq c \cdot \alpha^{-2r} \sum_K [n S_\xi(K)]^{-r} \rightarrow 0$  by Assumption 7. Similarly, we have  $\sup_K \frac{|\xi'_{1n} F_n'(I_n - P)U_n(0_{m \times 1}, I_m) \xi_{2n}|}{n S_\xi(K)} \xrightarrow{p} 0$ . Thus,  $\sup_K \frac{|\xi'_{1n} F_n'(I_n - P)V_n \xi_{2n}|}{n S_\xi(K)} \xrightarrow{p} 0$ .

Next, we show  $\sup_K \frac{|\xi'_{1n} (V_n' P V_n - \Omega_2) \xi_{2n}|}{n S_\xi(K)} \xrightarrow{p} 0$ . Given any  $\alpha > 0$  and positive integer  $r$ , by Cheby-

shev's inequality, we have

$$\begin{aligned} & \Pr(\sup_K \frac{|\frac{1}{n}\xi'_{1n}e_1[\bar{U}'_n G'_n P G_n \bar{U}_n - E(\bar{U}'_n G'_n P G_n \bar{U}_n)]e'_1 \xi_{2n}|}{S_\xi(K)} > \alpha) \\ & \leq \sum_K \frac{(\xi'_{1n}e_1)^{2r}(e'_1 \xi_{2n})^{2r} E[\bar{U}'_n G'_n P G_n \bar{U}_n - E(\bar{U}'_n G'_n P G_n \bar{U}_n)]^{2r}}{\alpha^{2r} [nS_\xi(K)]^{2r}}. \end{aligned}$$

For some positive constants  $c_3, c_4$ ,  $E[\bar{U}'_n G'_n P G_n \bar{U}_n - E(\bar{U}'_n G'_n P G_n \bar{U}_n)]^{2r} \leq c_3 \text{tr}[(G'_n P G_n)^2]^r = O(K^r) \leq c_4 [nS_\xi(K)]^r$ , where the first inequality follows by Theorem 2 of Whittle (1960), the equality follows by Lemma A.2 (ii), and the last inequality follows as  $|nS_\xi(K)| \geq c \cdot K$ . Hence, for  $r = 1$ ,  $\Pr(\sup_K \frac{|\frac{1}{n}\xi'_{1n}e_1[\bar{U}'_n G'_n P G_n \bar{U}_n - E(\bar{U}'_n G'_n P G_n \bar{U}_n)]e'_1 \xi_{2n}|}{S_\xi(K)} > \alpha) \leq c \cdot \alpha^{-2r} \sum_K [nS_\xi(K)]^{-r} \rightarrow 0$ .

On the other hand, let  $U_{1n} = U_n(0_{m \times 1}, I_m)\xi_{1n}$  and  $U_{2n} = U_n(0_{m \times 1}, I_m)\xi_{2n}$ . Given any  $\alpha > 0$ , by Chebyshev's inequality, we have  $\Pr(\sup_K \frac{|U'_{1n} P U_{2n} - E(U'_{1n} P U_{2n})|}{nS_\xi(K)} > \alpha) \leq \sum_K \frac{E[U'_{1n} P U_{2n} - E(U'_{1n} P U_{2n})]^2}{\alpha^2 [nS_\xi(K)]^2}$ . By an argument similar to that in the proof of Lemma A.4 (iv),  $E[U'_{1n} P U_{2n} - E(U'_{1n} P U_{2n})]^2 = O(K) \leq c \cdot nS_\xi(K)$ . Hence,  $\Pr(\sup_K \frac{|U'_{1n} P U_{2n} - E(U'_{1n} P U_{2n})|}{nS_\xi(K)} > \alpha) \leq c \cdot \alpha^{-2} \sum_K [nS_\xi(K)]^{-1} \rightarrow 0$ . Similarly,  $\Pr(\sup_K \frac{|\frac{1}{n}\xi'_{1n}e_1[\bar{U}'_n G'_n P U_{2n} - E(\bar{U}'_n G'_n P U_{2n})]|}{S_\xi(K)} > \alpha) \rightarrow 0$ .

Lastly, as  $\frac{1}{n}|\xi'_{1n}(\hat{\Omega}_2 - \Omega_2)\xi_{2n}| = o(K/n)$  and  $|nS_\xi(K)| \geq c \cdot K$ , we have  $\sup_K \frac{|\xi'_{1n}(\hat{\Omega}_2 - \Omega_2)\xi_{2n}|}{nS_\xi(K)} \xrightarrow{p} 0$ . In summary, we have  $\sup_K \frac{|\tilde{R}_*(K) - R_*(K)|}{S_\xi(K)} \xrightarrow{p} 0$ . As  $\xi_{1n}$  and  $\xi_{2n}$  can be arbitrary vectors, we have shown, in particular, that each component of  $\frac{\tilde{R}(K) - R(K)}{S_\xi(K)}$  converges to 0 uniformly in  $K$ .

Note that  $\tilde{R}_\xi(K) - R_\xi(K) = \xi' \hat{H}_n^{-1} \tilde{R}(K) (\hat{H}_n^{-1} - H_n^{-1}) \xi + \xi' (\hat{H}_n^{-1} - H_n^{-1}) \tilde{R}(K) H_n^{-1} \xi + \frac{1}{n} \xi' H_n^{-1} [F'_n (I_n - P) V_n]^s H_n^{-1} \xi - \frac{1}{n} \xi' H_n^{-1} (V'_n P V_n - \Omega_2) H_n^{-1} \xi + \frac{1}{n} \xi' H_n^{-1} (\hat{\Omega}_2 - \Omega_2) H_n^{-1} \xi$ , where  $\frac{|\xi' \hat{H}_n^{-1} \tilde{R}(K) (\hat{H}_n^{-1} - H_n^{-1}) \xi|}{S_\xi(K)} \leq \frac{|\xi' \hat{H}_n^{-1} [\tilde{R}(K) - R(K)] (\hat{H}_n^{-1} - H_n^{-1}) \xi|}{S_\xi(K)} + \frac{|\xi' \hat{H}_n^{-1} R(K) (\hat{H}_n^{-1} - H_n^{-1}) \xi|}{S_\xi(K)}$ . As  $\hat{H}_n^{-1} - H_n^{-1} = o(1)$  and each component of  $\frac{\tilde{R}(K) - R(K)}{S_\xi(K)}$  converges to 0 uniformly in  $K$ , we have  $\sup_K \frac{|\xi' \hat{H}_n^{-1} [\tilde{R}(K) - R(K)] (\hat{H}_n^{-1} - H_n^{-1}) \xi|}{S_\xi(K)} \xrightarrow{p} 0$ . On the other hand, as  $\hat{H}_n^{-1} - H_n^{-1} = o(1)$  and  $R(K)/S_\xi(K) = O(1)$  uniformly in  $K$ , we have  $\sup_K \frac{|\xi' \hat{H}_n^{-1} R(K) (\hat{H}_n^{-1} - H_n^{-1}) \xi|}{S_\xi(K)} \xrightarrow{p} 0$ . Hence,  $\sup_K \frac{|\xi' \hat{H}_n^{-1} \tilde{R}(K) (\hat{H}_n^{-1} - H_n^{-1}) \xi|}{S_\xi(K)} \xrightarrow{p} 0$ . Similarly, we have  $\sup_K \frac{|\xi' (\hat{H}_n^{-1} - H_n^{-1}) \tilde{R}(K) H_n^{-1} \xi|}{S_\xi(K)} \xrightarrow{p} 0$ . Hence,  $\sup_K \frac{|\tilde{R}_\xi(K) - R_\xi(K)|}{S_\xi(K)} \xrightarrow{p} 0$ , and the desired result follows. ■

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