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Expansions of GMM statistics that indicate their properties under weak and/or many instruments and the bootstrap

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Preliminary and Incomplete

September 25, 2003

Abstract

We show that the sensitivity of the limit distribution of commonly used GMM statistics to weak and many instruments results from superfluous elements in the higher order expansion of these statistics. When the instruments are strong and their number is small, these elements are of higher order and result in higher order biases. When instruments are weak and/or their number is large, they are, however, of zero-th order and influence the limit distributions of GMM statistics. Edgeworth approximations do not remove these superfluous elements. Expansions of GMM statistics that are robust to weak or many instruments do not possess these superfluous elements. Their robustness is therefore the result of improved higher order properties. This renders an additional reason for usage of these statistics. An Edgeworth expansion of the robust statistics can be constructed so the approximation of their finite sample distribution can be further improved upon by use of the bootstrap. We illustrate the finite sample performance of GMM statistics by constructing power curves for tests on the autocorrelation parameter in a panel autoregressive model using both asymptotic and bootstrap critical values.

JEL classification: C11, C20, C30

1 Introduction

The finite sample distributions of Generalized Method of Moments (GMM) estimators and statistics are affected by the quality and number of instruments, see *e.g.* Hansen *et. al.* (1996) and

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Stock *et. al.* (2002). It has therefore become customary to conduct non-identification pre-tests on the parameters. Pre-testing for parameter non-identification, however, implies that all subsequent inferential procedures are conditional on the outcome of the pre-test. Stock and Yogo (2001), for example, show that 2-step GMM estimators are still considerably biased at the moderate, but significant at the 95% level, values of the non-identification statistics that we typically encounter in practice. Inferential procedures have therefore been developped that are robust to many instruments, see *e.g.* Bekker (1994), and/or weak instruments, see *e.g.* Stock and Wright (2000), Kleibergen (2001,2002a) and Moreira (2003). These robust procedures are advocated to be used in case of many and/or weak instruments.

We construct higher order expressions for a number of different GMM statistics. These higher order expressions indicate the behavior of the different statistics in case of weak and/or many instruments. In case of proper identification, the 2-step Wald statistic from Hansen (1982) and the Lagrange multiplier (LM) statistic of Newey and West (1987a) have higher order elements that distort their limit distributions when the instruments become weak or irrelevant. Edgeworth approximations to the finite sample distributions of these statistics are also sensitive to these higher order elements. The bias caused by the higher order elements implies a further distortion of the limit distribution when the number of instruments gets large. The K-statistic from Kleibergen (2001,2002a) does not possess these higher order elements so its limit distribution is robust to weak and/or many instruments. The Wald statistic that is based on the continuous updating estimator (CUE) of Hansen *et. al.* (1996) does also not possess these higher order elements but is, because it uses an covariance matrix estimator that is evaluated under the unrestricted alternative, only robust to many instruments and not to weak instruments. The absence of the higher order elements implies that the limit distribution of the robust K-statistic is also a better approximation of its finite sample distribution in case of appropriate identified parameters. Its robustness to weak and/or many instruments is just an artifact of this improved approximation.

Tests of misspecification hypothezes can also be based upon the robust K-statistic. The higher order expression of the resulting misspecification statistic also indicates its robustness to weak instruments when compared to misspecification statistics that are based on non-robust statistics. The robustness of this misspecification statistic again results from the improved approximation of the finite sample distribution by the limiting distribution in case of valid instruments. We therefore also advocate the use of robust statistics when the parameters are properly identified. Because the higher order elements of the robust statistics do not depend on the degree of identification, we can use the bootstrap to further improve the approximation of the finite sample distribution.

The outline of the paper is as follows. The second section discusses GMM and states assumptions. The third section states he higher order expressions of the 2-step Wald, CUE Wald, LM and K-statistics under different limit sequences of a GMM concentration parameters and the number of instruments. It shows that an Edgeworth approximation of the finite sample distribution of the 2-step Wald and LM statistic does not remove the sensitivity to higher order elements. The fourth section discusses misspecification statistics. The fifth section shows that an Edgeworth expansion of the K-statistic can be constructed so the finite sample distribution of the K-statistic can be further improved upon by usage of the bootstrap. In the sixth section, we conduct a size and power comparison of the different statistics to test the autoregressive parameter in a panel autoregressive model of order 1. For the K-statistic, we use both asymptotic

and bootstrap critical values. The seventh section concludes.

Throughout the paper we use the notation: $a = \text{vec}(A)$ for the column vectorization of the $n \times m$ matrix A such that for $A = (a_1 \cdots a_m)$, $\text{vec}(A) = (a_1' \cdots a_m')'$, I_m is the $m \times m$ identity matrix, $P_{X,Y} = Y(X'Y)^{-1}X'$, $P_X = P_{X,X}$ and $M_{X,Y} = I_T - P_{X,Y}$, $M_X = I_T - P_X$ for full rank $T \times m$ dimensional matrices X and Y. Furthermore, "$\underset{p}{\rightarrow}$" stands for convergence in probability and "$\underset{d}{\rightarrow}$" for convergence in distribution.

2 Generalized Method of Moments

We consider the estimation of the $m \times 1$ dimensional parameter vector $\theta = (\theta_1 \dots \theta_m)'$, whose parameter region is the $\mathbb{R}^m$, for which the $l \times 1$ dimensional moment equation

$$E\left[\varphi(\theta_0, Y_t)|I_t\right] = 0 \tag{1}$$

holds. The expectation, indicated by E, in (1) is taken with respect to the information set I_t at observation t. The data vector Y_t is observed for observation t. The $l \times 1$ dimensional vector function φ of θ is finite for finite values of θ, continuous and twice continuous differentiable. The specific true value of θ, at which (1) holds, is equal to θ_0. To estimate the parameter θ in (1), we use Hansen's (1982) GMM framework. We involve a k-dimensional vector of instruments X_t that is such that k_f $(= kl)$ exceeds m. The instruments span that part of the information set I_t which is of importance for the estimation of θ and are uncorrelated with $\varphi(\theta_0, Y_t)$,

$$E\left[X_t\varphi(\theta_0, Y_t)'|I_t\right] = E\left[X_t\varphi(\theta_0, Y_t)'\right] = 0. \tag{2}$$

For a data-set $(Y_t, X_t,\, t = 1, \dots, T)$, the objective function in the GMM framework reads

$$Q(\theta) = f_T(\theta, Y)'V_{ff}(\theta)^{-1}f_T(\theta, Y), \tag{3}$$

with $f_T(\theta, Y) = \sum_{t=1}^{T} f_t(\theta)$,

$$f_t(\theta) = \text{vec}\left(X_t\varphi(\theta, Y_t)'\right) = (\varphi(\theta, Y_t) \otimes X_t), \tag{4}$$

and $V_{ff}(\theta)$ is the covariance matrix of $f_T(\theta, Y)$ with $\bar{f}_t(\theta) = f_t(\theta) - E(f_t(\theta))$,

$$V_{ff}(\theta) = \lim_{T\to\infty} E\left\{\tfrac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{T}\bar{f}_t(\theta)\bar{f}_j(\theta)'\right\}. \tag{5}$$

To construct higher order expressions of test statistics, we make an assumption about the behavior of $f_t(\theta)$ and its derivative with respect to θ.

Assumption 1. *The $k_f \times 1$ dimensional derivative of $f_t(\theta_0)$ with respect to θ_i,*

$$p_{i,t}(\theta_0) = \tfrac{\partial f_t(\theta)}{\partial\theta_i}|_{\theta_0} : k_f \times 1, \qquad i = 1, \dots, m, \tag{6}$$

is such that

$$\bar{p}_{i,t}(\theta_0) = A_i\bar{q}_{i,t}(\theta_0) \tag{7}$$

with $\bar{p}_{i,t}(\theta_0) = p_{i,t}(\theta_0) - E(p_{i,t}(\theta_0))$, $q_{i,t}(\theta_0) : k_i \times 1$, $\bar{q}_{i,t}(\theta_0) = q_{i,t}(\theta_0) - E(q_{i,t}(\theta_0))$ *and* A_i *a deterministic full-rank* $k_f \times k_i$ *dimensional matrix,* $k_i \leq k_f$. *The behavior of the sums of the martingale difference series* $\bar{f}_t(\theta_0)$ $(= f_t(\theta_0))$ *and* $\bar{q}_t(\theta_0) = (\bar{q}_{1t}(\theta_0)' \dots \bar{q}_{mt}(\theta_0)')'$ *reads*

$$\tfrac{1}{\sqrt{T}} \sum_{t=1}^{T} \begin{pmatrix} \bar{f}_t(\theta_0) \\ \bar{q}_t(\theta_0) \end{pmatrix} = m_0 + O_p(\tfrac{1}{\sqrt{T}}), \tag{8}$$

where $m_0 : (k_f + k_\theta) \times 1$, $k_\theta = \sum_{i=1}^{m} k_i$; *and*

$$m_0 \underset{d}{\rightarrow} \begin{pmatrix} \psi_f \\ \psi_\theta \end{pmatrix} \tag{9}$$

with $\psi_f : k_f \times 1$, $\psi_\theta : k_\theta \times 1$,

$$\begin{pmatrix} \psi_f \\ \psi_\theta \end{pmatrix} \sim N(0, V(\theta)), \tag{10}$$

and

$$V(\theta) = \begin{pmatrix} V_{ff}(\theta) & V_{f\theta}(\theta) \\ V_{\theta f}(\theta) & V_{\theta\theta}(\theta) \end{pmatrix}, \tag{11}$$

with $V_{ff}(\theta) : k_f \times k_f$, $V_{\theta f}(\theta) = V_{f\theta}(\theta)' : k_\theta \times k_f$, $V_{\theta\theta}(\theta) : k_\theta \times k_\theta$, *and*

$$V(\theta) = \lim_{T\to\infty} E\left\{ \tfrac{1}{T} \sum_{t=1}^{T} \sum_{j=1}^{T} \begin{pmatrix} \bar{f}_t(\theta) \\ \bar{q}_t(\theta) \end{pmatrix} \begin{pmatrix} \bar{f}_j(\theta) \\ \bar{q}_j(\theta) \end{pmatrix}' \right\}. \tag{12}$$

The instruments span that part of the information set which is of importance for the estimation of θ so $E\left[q_{i,t}(\theta)\right] = E\left[q_{i,t}(\theta)|I_t\right]$. Hence, $\bar{q}_t(\theta)$, $t = 1, \dots, T$, is a martingale difference series and Assumption 1 is a central limit theorem for martingale differences. It is therefore satisfied under weak conditions for $\bar{f}_t(\theta_0)$ and $\bar{q}_t(\theta_0)$. Sufficient conditions that ensure such convergence are that: 1. the r-th moment of the absolute value of $\bar{f}_t(\theta_0)$ and $\bar{q}_{i,t}(\theta_0)$, $i = 1, \dots, m$, is finite for some $r > 2$, 2. $V(\theta)$ is well-defined and 3. the average value of the outer-product of $(\bar{f}_t(\theta_0)'$ $\bar{q}_t(\theta_0)')'$ converges in probability to $V(\theta)$, see *e.g.* White (1984).

We use Assumption 1 to determine the convergence rate of the limit behavior of

$$\begin{aligned} D_T(\theta_0, Y) = \; & \big[\; p_{1,T}(\theta_0, Y) - A_1 V_{\theta f,1}(\theta_0) V_{ff}(\theta_0)^{-1} f_T(\theta_0, Y) \quad \cdots \\ & \qquad p_{m,T}(\theta_0, Y) - A_m V_{\theta f,m}(\theta_0) V_{ff}(\theta_0)^{-1} f_T(\theta_0, Y) \;\big], \end{aligned} \tag{13}$$

with $V_{\theta f,i}(\theta_0) : k_i \times k_f$, $i = 1, \dots, m$, $V_{\theta f}(\theta_0) = (V_{\theta f,1}(\theta_0)' \dots V_{\theta f,m}(\theta_0)')'$, $p_{i,T}(\theta_0, Y) : k_f \times 1$, $i = 1, \dots, m$, $p_T(\theta_0, Y) = (p_{1,T}(\theta_0, Y) \dots p_{m,T}(\theta_0, Y))$, $p_{i,T}(\theta_0, Y) = \sum_{i=1}^{T} p_{i,t}(\theta_0)$.

Lemma 1. *When Assumption 1 holds, the behavior of* $T^{-\frac{1}{2}(1+\nu)} D_T(\theta_0, Y)$ *is characterized by*

$$T^{-\frac{1}{2}(1+\nu)} D_T(\theta_0, Y) = D_0 + O_p(T^{-\frac{1}{2}(\nu+1)}), \tag{14}$$

where $D_0 = T^{\frac{1}{2}(1-\nu)} \frac{1}{T} \sum_{t=1}^{T} E(p_t(\theta_0)|I_t) + T^{-\frac{1}{2}\nu}[(m_{0,\theta_1} - A_1 V_{\theta f,1}(\theta_0) V_{ff}(\theta_0)^{-1} m_{0,f}) \cdots (m_{0,\theta_m} - A_m V_{\theta f,m}(\theta_0)\; V_{ff}(\theta_0)^{-1} m_{0,f})]$, $m_0 = (m_{0,f}'\; m_{0,\theta}')$, $m_{0,\theta} = (m_{0,\theta_1}' \dots m_{0,\theta_m}')'$.

Proof. results directly from Assumption 1 when we note that $p_{i,T}(\theta_0, Y) = \sum_{i=1}^{T} \bar{p}_{i,t}(\theta_0)$ and $\bar{p}_{i,t}(\theta_0) = A_i \bar{q}_{i,t}(\theta_0)$. ■

The derivative $D_T(\theta_0, Y)$ is constructed in such a manner that D_0 has a number of convenient properties which we state in the following two corollaries. One of these corollaries deals with the appropriate choice of the convergence rate ν.

Corollary 1. *When Assumption 1 holds,*

$$\text{vec}\left[T^{\frac{1}{2}}\left(T^{-\frac{1}{2}(1-\nu)}D_0 - J_\theta(\theta_0)\right)\right] \quad = m_{0,\theta.f} \tag{15}$$

with

$$J_\theta(\theta_0) = \lim_{T\to\infty} \tfrac{1}{T}\textstyle\sum_{t=1}^{T} E(p_t(\theta_0)|I_t), \tag{16}$$

$m_{0,\theta.f} = m_{0,\theta} - V_{\theta f}(\theta_0)V_{ff}(\theta_0)^{-1}m_{0,f}$ *and*

$$m_{0,\theta.f} \underset{d}{\to} \quad A\psi_{\theta.f} \tag{17}$$

where $A = \text{diag}(A_1, \ldots, A_m)$, $\psi_{\theta.f} = \psi_\theta - V_{\theta f}(\theta_0)V_{ff}(\theta_0)^{-1}\psi_f$ *and*

$$\psi_{\theta.f} \sim N(0, V_{\theta\theta.f}(\theta_0)), \tag{18}$$

with $V_{\theta\theta.f}(\theta_0) = V_{\theta\theta}(\theta_0) - V_{\theta f}(\theta_0)V_{ff}(\theta_0)^{-1}V_{f\theta}(\theta_0)$, *and* $\psi_{\theta.f}$ *is independent of* ψ_f.

Proof. see Kleibergen (2001). ■

Corollary 1 shows that $D_T(\theta_0, Y)$ is an estimator of the Jacobian $J_\theta(\theta_0)$ whose first order limit behavior is independent of the first order limit behavior of $f_T(\theta_0, Y)$.

Corollary 2. *Given* $J_\theta(\theta_0)$, *the convergence rate* ν *in Lemma 1 is such that:*

1. *For a fixed full rank value of* $J_\theta(\theta_0) : \nu = 1$ *so* $D_0 \underset{p}{\to} J_\theta(\theta_0)$ *and*

$$D_0'V_{ff}(\theta_0)^{-1}D_0 \underset{p}{\to} J_\theta(\theta_0)'V_{ff}(\theta_0)^{-1}J_\theta(\theta_0). \tag{19}$$

2. *For a weak value of* $J_\theta(\theta_0)$ *such that* $J_\theta(\theta_0) = J_{\theta,T}$, $J_{\theta,T} = \frac{1}{\sqrt{T}}C$, $C : k_f \times m$ *and* $rank(C) = m : \nu = 0$, $D_0 \underset{d}{\to} C + (A_1\psi_{\theta.f,1} \ldots A_m\psi_{\theta.f,m})$ *and*

$$D_0'V_{ff}(\theta_0)^{-1}D_0 \underset{d}{\to} [C+(A_1\psi_{\theta.f,1} \ldots A_m\psi_{\theta.f,m})]'V_{ff}(\theta_0)^{-1}[C+(A_1\psi_{\theta.f,1} \ldots A_m\psi_{\theta.f,m})]. \tag{20}$$

3. *For a zero value of* $J_\theta(\theta_0)$: $\nu = 0$, $D_0 \underset{d}{\to} (A_1\psi_{\theta.f,1} \ldots A_m\psi_{\theta.f,m})$ *and*

$$D_0'V_{ff}(\theta_0)^{-1}D_0 \underset{d}{\to} (A_1\psi_{\theta.f,1} \ldots A_m\psi_{\theta.f,m})'V_{ff}(\theta_0)^{-1}(A_1\psi_{\theta.f,1} \ldots A_m\psi_{\theta.f,m}). \tag{21}$$

Corollary 2 explains the dependence of the convergence rate of $D_T(\theta_0, Y)$ in Lemma 1 on ν. Since the limit behavior of D_0 is independent of the limit behavior of $m_{0.f}$, the higher order expressions of statistics that test $\text{H}_0 : \theta = \theta_0$ are polynomials of $T^{-\frac{1}{2}\nu}$. Rothenberg (1984) constructs the higher order properties of estimators and test statistics in the linear instrumental variables regression model as a function of the concentration parameter. The statistic $\frac{1}{T^{1+\nu}}D_T(\theta_0, Y)'V_{ff}(\theta_0)^{-1}D_T(\theta_0, Y)$ has a limit behavior that is independent of $m_{0.f}$ and is comparable to the concentration parameter in the linear instrumental variables regression model. We therefore use it to obtain higher order properties of test statistics.

The covariance matrix $V(\theta_0)$ is typically unknown and we therefore replace it with an estimator, $\hat{V}(\theta_0)$. To account for the estimated value of the covariance matrix in the higher order expressions that we construct next, we make an assumption about the convergence properties of the covariance matrix estimator $\hat{V}(\theta_0)$.

Assumption 2: *The convergence of the covariance matrix estimator* $\hat{V}(\theta_0)$ *is such that*

$$T^{\frac{1}{2}\mu}\text{vec}(\hat{V}(\theta_0) - V(\theta_0)) = u_0 + O_p(T^{-\frac{1}{2}\mu}), \tag{22}$$

with μ *the convergence rate of the covariance matrix estimator and* u_0 *(=vec(*U_0*)) converges to a normal distributed random variable,*

$$u_0 \underset{d}{\rightarrow} \psi_u,$$

where $S'_{(m+1)k_f}\psi_u \sim N(0, W(\theta_0))$*, with* $S_j : j^2 \times [\frac{1}{2}j(j+1)]$ *a selection matrix that selects the unique elements of the vectorization of a symmetric* $j \times j$ *matrix and* $W(\theta_0)$ *is the covariance matrix.*

Assumption 2 does not specify the covariance matrix estimator and therefore allows for parametric as well as non-parametric covariance matrix estimators, see *e.g.* Andrews (1991) and Newey and West (1987b). These estimators lead to different convergence rates μ. Also $D_T(\theta_0, Y)$ depends on $V_{ff}(\theta_0)$ so we use the covariance matrix estimator $\hat{V}(\theta_0)$ for $D_T(\theta_0, Y)$ which we indicate by $\hat{D}_T(\theta_0, Y)$.

3 Higher Order Properties of Statistics that test $\mathbf{H}_0 : \theta = \theta_0$.

We analyze the higher order properties of four statistics that test $\text{H}_0 : \theta = \theta_0$:

1. GMM-Wald statistic evaluated at the 2-step GMM estimator, $\hat{\theta}_{2\text{s}}$, see *e.g.* Hansen (1982):[1]

$$\begin{aligned} \text{W}_{2\text{s}}(\theta_0) = & \ (\hat{\theta}_{2\text{s}} - \theta_0)' \left[\tfrac{1}{T} p_T(\hat{\theta}_{2\text{s}}, Y)' \hat{V}_{ff}(\hat{\theta}_{2\text{s}})^{-1} p_T(\hat{\theta}_{2\text{s}}, Y)\right] (\hat{\theta}_{2\text{s}} - \theta_0) \\ \approx & \ \tfrac{1}{T} f_T(\theta_0, Y)' V_{ff}(\hat{\theta}_{2\text{s}})^{-1} p_T(\hat{\theta}_{2\text{s}}, Y) \left[p_T(\hat{\theta}_{2\text{s}}, Y)' V_{ff}(\hat{\theta}_{2\text{s}})^{-1} p_T(\hat{\theta}_{2\text{s}}, Y)\right]^{-1} \\ & p_T(\hat{\theta}_{2\text{s}}, Y)' V_{ff}(\hat{\theta}_{2\text{s}})^{-1} f_T(\theta_0, Y). \end{aligned} \tag{23}$$

2. GMM-Wald statistic evaluated at the continuous updating estimator (CUE), $\hat{\theta}_{\text{cue}}$, of Hansen *et. al.* (1996):

$$\begin{aligned} \text{W}_{\text{cue}}(\theta_0) = & \ (\hat{\theta}_{\text{cue}} - \theta_0)' \left[\tfrac{1}{T} \hat{D}_T(\hat{\theta}_{\text{cue}}, Y)' V_{ff}(\hat{\theta}_{\text{cue}})^{-1} \hat{D}_T(\hat{\theta}_{\text{cue}}, Y)\right] (\hat{\theta}_{\text{cue}} - \theta_0) \\ \approx & \ \tfrac{1}{T} f_T(\theta_0, Y)' V_{ff}(\hat{\theta}_{\text{cue}})^{-1} \hat{D}_T(\hat{\theta}_{\text{cue}}, Y) \left[\hat{D}_T(\hat{\theta}_{\text{cue}}, Y)' \hat{V}_{ff}(\hat{\theta}_{\text{cue}})^{-1} \hat{D}_T(\hat{\theta}_{\text{cue}}, Y)\right]^{-1} \\ & \hat{D}_T(\hat{\theta}_{\text{cue}}, Y)' \hat{V}_{ff}(\hat{\theta}_{\text{cue}})^{-1} f_T(\theta_0, Y). \end{aligned} \tag{24}$$

The first order condition for a minimal value of $Q(\theta)$ is: $\hat{D}_T(\theta, Y)' \hat{V}_{ff}(\theta)^{-1} f_T(\theta, Y) = 0$ so $\hat{D}_T(\hat{\theta}_{cue}, Y)' \hat{V}_{ff}(\hat{\theta}_{cue})^{-1} f_T(\hat{\theta}_{cue}, Y) = 0$, see Kleibergen (2001). This explains the second part of (24), which results from a Taylor approximation, that we use to obtain the higher order properties of $\text{W}_{\text{cue}}(\theta_0)$.

[1] The second expression of $\text{W}_{2s}(\theta_0)$ results from a Taylor approximation of $f_T(\theta_0, Y)$. We use this expression to obtain the higher order properties of $\text{W}_{2s}(\theta_0)$.

3. GMM-Lagrange multiplier (LM) statistic, see Newey and West (1987a):

$$\begin{array}{rl} \mathrm{LM}(\theta_0) = & \frac{1}{T} f_T(\theta_0, Y)' \hat{V}_{ff}(\theta_0)^{-1} p_T(\theta_0, Y) \left[p_T(\theta_0, Y)' \hat{V}_{ff}(\theta_0)^{-1} p_T(\theta_0, Y) \right]^{-1} \\ & p_T(\theta_0, Y)' \hat{V}_{ff}(\theta_0)^{-1} f_T(\theta_0, Y). \end{array} \tag{25}$$

4. K-statistic, see Kleibergen (2001):

$$\begin{array}{rl} \mathrm{K}(\theta_0) = & \frac{1}{T} f_T(\theta_0, Y)' \hat{V}_{ff}(\theta_0)^{-1} \hat{D}_T(\theta_0, Y) \left[\hat{D}_T(\theta_0, Y)' \hat{V}_{ff}(\theta_0)^{-1} \hat{D}_T(\theta_0, Y) \right]^{-1} \\ & \hat{D}_T(\theta_0, Y)' \hat{V}_{ff}(\theta_0)^{-1} f_T(\theta_0, Y). \end{array} \tag{26}$$

Under a fixed full rank of $J_\theta(\theta_0)$, $\mathrm{W}_{2\mathrm{s}}(\theta_0)$, $\mathrm{W}_{\mathrm{cue}}(\theta_0)$ and $\mathrm{LM}(\theta_0)$ have a $\chi^2(m)$ zero-th order limit distribution, see *e.g.* Newey and McFadden (1994). The zero-th order limit distribution of $\mathrm{K}(\theta_0)$ is $\chi^2(m)$ regardless of the value of $J_\theta(\theta_0)$, see Kleibergen (2001).

We construct higher order expressions of $\mathrm{W}_{2\mathrm{s}}(\theta_0)$, $\mathrm{W}_{\mathrm{cue}}(\theta_0)$, $\mathrm{LM}(\theta_0)$ and $\mathrm{K}(\theta_0)$ as functions of the convergence rates of $D_T(\theta_0, Y)' V_{ff}(\theta_0)^{-1} D_T(\theta_0, Y)$ and $\hat{V}(\theta_0)$. We also consider a convergence process where the number of observations and the number of instruments jointly converge to infinity as in Bekker (1994).

3.1 Fixed number of instruments

Theorem 1 states the higher order expressions, see *e.g.* Nagar (1959), that result from Assumptions 1 and 2, of $\mathrm{W}_{2\mathrm{s}}(\theta_0)$, $\mathrm{W}_{\mathrm{cue}}(\theta_0)$, $\mathrm{LM}(\theta_0)$ and $\mathrm{K}(\theta_0)$ in case of a fixed number of instruments. Theorem 1 specifies the higher order expressions as functions of the parameters ν and μ that characterize the convergence rates of $D_T(\theta_0, Y)$, $T^{-\frac{1}{2}(1+\nu)}$, and $\hat{V}(\theta_0)$, $T^{-\frac{1}{2}\mu}$.

Theorem 1. *When the number of instruments k is fixed, Assumptions 1 and 2 imply higher order expressions for $W_{2s}(\theta_0)$, $W_{cue}(\theta_0)$, $LM(\theta_0)$ and $K(\theta_0)$ under $H_0 : \theta = \theta_0$ that are characterized by:*

$$\left.\begin{array}{r} \mathrm{W}_{2s}(\theta_0) \\ \mathrm{W}_{cue}(\theta_0) \\ \mathrm{LM}(\theta_0) \\ \mathrm{K}(\theta_0) \end{array}\right\} = \left\{\begin{array}{ll} n_0 + & \text{:zero-th order} \\ T^{-\frac{\nu}{2}} n_\nu + T^{-\nu} n_{2\nu} + T^{-\frac{3}{2}\nu} n_{3\nu} + & \text{:} D_T(\theta_0, Y) \\ T^{-\frac{\kappa}{2}} n_\kappa + T^{-\kappa} n_{2\kappa} + & \text{:} \hat{V}(\theta_0) \\ T^{-\frac{\nu+\kappa}{2}} n_{\nu+\kappa} + T^{-\frac{1}{2}(2\nu+\kappa)} n_{2\nu+\kappa} + T^{-\frac{1}{2}(\nu+2\kappa)} n_{\nu+2\kappa} + & \text{:mixed} \\ o_p(T^{-\frac{3}{2}\nu}), & \end{array}\right. \tag{27}$$

where:

1. *for* $W_{2s}(\theta_0) : \kappa = \min(\nu, \mu)$ *and*

$$
\begin{aligned}
n_0 &= s_0' G_0^{-1} s_0 \\
D_T(\theta_0, Y) &: \begin{cases} n_\nu = & s_0' Q_1 s_0 + s_{1\nu,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{1\nu,1} \\ n_{2\nu} = & s_{1\nu,1}' Q_1 s_0 + s_0' Q_1 s_{1\nu,1} + s_{1\nu,1}' G_0^{-1} s_{1\nu,1} \\ n_{3\nu} = & s_{1\nu,1}' Q_1 s_{1\nu,1} \end{cases} \\
\hat{V}(\theta_0) &: \begin{cases} n_\kappa = & s_{1\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{1\kappa,1} \\ n_{2\kappa} = & s_{1\kappa,1}' G_0^{-1} s_{1\kappa,1} \end{cases} \\
\text{mixed} &: \begin{cases} n_{\nu+\kappa} = & s_{1\nu,1}' G_0^{-1} s_{1\kappa,1} + s_{1\kappa,1}' G_0^{-1} s_{1\nu,1} + s_{1\kappa,1}' Q_1 s_0 + s_0' Q_1 s_{1\nu+\kappa} + \\ & (s_{\nu+\kappa,1} + s_{\nu+\kappa,2})' G_0^{-1} s_0 + s_0' G_0^{-1} (s_{\nu+\kappa,1} + s_{\nu+\kappa,2}) \\ n_{2\nu+\kappa} = & s_{1\nu,1}' Q_1 s_{1\kappa,1} + s_{1\kappa,1}' Q_1 s_{1\nu,1} + (s_{\nu+\kappa,1} + s_{\nu+\kappa,2})' G_0^{-1} s_{1\nu,1} + \\ & s_{1\nu,1}' G_0^{-1} (s_{\nu+\kappa,1} + s_{\nu+\kappa,2}) \\ n_{\nu+2\kappa} = & (s_{\nu+\kappa,1} + s_{\nu+\kappa,2})' G_0^{-1} s_{1\kappa,1} + s_{1\kappa,1}' G_0^{-1} (s_{\nu+\kappa,1} + s_{\nu+\kappa,2}) + \\ & s_{\nu+2\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{\nu+\kappa,1} + s_{1\kappa,1}' Q_1 s_{1\kappa,1}. \end{cases}
\end{aligned}
\tag{28}
$$

2. *for* $W_{cue}(\theta_0) : \kappa = \min(\nu, \mu)$, *all terms that result from* $D_T(\theta_0, Y) : n_\nu$, $n_{2\nu}$, $n_{3\nu}$ *and* $n_{2\nu+\kappa}$ *are equal to zero and*

$$
\begin{aligned}
n_0 &= s_0' G_0^{-1} s_0 \\
\hat{V}(\theta_0) &: \begin{cases} n_\kappa = & s_0' Q_1 s_0 + s_{1\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{1\kappa,1} \\ n_{2\kappa} = & s_{1\kappa,1}' G_0^{-1} s_{1\kappa,1} + s_{1\kappa,1}' Q_1 s_0 + s_0' Q_1 s_{1\kappa,1} \end{cases} \\
\text{mixed} &: \begin{cases} n_{\nu+\kappa} = & s_{\nu+\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{\nu+\kappa,1} \\ n_{\nu+2\kappa} = & s_{\nu+\kappa,1}' G_0^{-1} s_{1\kappa,1} + s_{1\kappa,1}' G_0^{-1} s_{\nu+\kappa,1} + s_{\nu+2\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{\nu+2\kappa,1} + \\ & s_0' Q_1 s_{\nu+\kappa,1} + s_{\nu+\kappa,1}' Q_1 s_0. \end{cases}
\end{aligned}
\tag{29}
$$

3. *for* $LM(\theta_0)$ *the elements are identical to those for* $W_{2s}(\theta_0)$ *in (28) but with* $\kappa = \mu$.

4. *for* $K(\theta_0)$ *the elements are identical to those for* $W_{cue}(\theta_0)$ *in (29) but with* $\kappa = \mu$ *and for all statistics:*

$$
\begin{aligned}
s_0 &= m_{0,f}' V_{ff}(\theta_0)^{-1} D_0 \\
D_T(\theta_0, Y) &: \begin{cases} s_{1\nu,1} = & m_{0,f}' V_{ff}(\theta_0)^{-1} \{ \frac{1}{\sqrt{T}} [p_T(\hat{\theta}, Y) - \hat{D}_T(\hat{\theta}, Y)] \} \\ = & m_{0,f}' V_{ff}(\theta_0)^{-1} [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)] \\ & [I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}] \end{cases} \\
\hat{V}(\theta_0) &: \left\{ s_{1\kappa,1} = \; T^{\frac{\kappa}{2}} m_{0,f}' [\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}] D_0 \right. \\
\text{mixed} &: \begin{cases} s_{\nu+\kappa,1} = & T^{\frac{1}{2}(\kappa-1)} m_{0,f}' V_{ff}(\theta_0)^{-1} [\hat{D}_T(\hat{\theta}, Y) - D_T(\theta_0, Y)] \\ = & T^{\frac{1}{2}\kappa} m_{0,f}' V_{ff}(\theta_0)^{-1} \{ [A_1 \hat{V}_{\theta f,1}(\theta_0) \cdots A_m \hat{V}_{\theta f,m}(\theta_0)] [I_m \otimes \hat{V}_{ff}(\theta_0)^{-1}] \\ & - [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)] [I_m \otimes V_{ff}(\theta_0)^{-1}] \} [I_m \otimes m_{0,f}] \\ s_{\nu+\kappa,2} = & T^{\frac{1}{2}\kappa} m_{0,f}' [\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}] [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)] \\ & [I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}] \\ s_{\nu+2\kappa,1} = & T^{\frac{1}{2}(2\kappa-1)} m_{0,f}' [\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}] [\hat{D}_T(\theta_0, Y) - D_T(\theta_0, Y)], \end{cases}
\end{aligned}
\tag{30}
$$

with $G_0 = D_0' V_{ff}(\theta_0) D_0$ *and the expressions for the remaining* G *and* Q *matrices are given in the Appendix.*

Proof. see the Appendix. ■

The $D_T(\theta_0, Y)$, $\hat{V}(\theta_0)$ and mixed terms in Theorem 1 indicate where the higher order terms orginate from. Unlike the convergence rate μ of the covariance matrix estimator, the convergence rate ν of $D_T(\theta, Y)$ is unknown. The higher order expressions in Theorem 1 therefore depend on the unknown convergence rate of the concentration parameter. The parameter κ in Theorem 1 indicates that the convergence rate of the covariance matrix estimator depends on the involved value of θ. The Wald statistics, $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{W}_{cue}(\theta_0)$, use the covariance matrix estimator at the estimated value of θ, $\hat{\theta}$. The convergence rate of the covariance matrix estimator for the Wald statistics is therefore equal to the minimum of the convergence rate of $\hat{\theta}$, $T^{\frac{1}{2}\nu}$, and $\hat{V}(\theta_0)$, $T^{\frac{1}{2}\mu}$, which we indicate by $T^{\frac{1}{2}\kappa}$ with $\kappa = \min(\mu, \nu)$. The Lagrange multiplier statistics $\mathrm{LM}(\theta_0)$ and $\mathrm{K}(\theta_0)$ use the covariance matrix estimator evaluated at θ_0. The convergence rate of the covariance matrix estimator in these statistics is therefore equal to $T^{\frac{1}{2}\mu}$. Hence, $\kappa = \mu$ for these statistics.

We analyze the higher order expressions from Theorem 2 for both $\nu = 0$ and $\nu = 1$. We first discuss $\nu = 1$ which, as shown in Corollary 2, corresponds with the traditional case of a fixed full rank value of $J_\theta(\theta_0)$. Afterwards we discuss $\nu = 0$ which leads to a first order limit distribution of some of the statistics that depends on nuisance parameters.

3.1.1 Identified parameters or $\nu = 1$

When $\nu = 1$, the zero-th order limit distribution is the same for all statistics in Theorem 1,

$$n_0 = s_0' G_0^{-1} s_0 \underset{d}{\rightarrow} \chi^2(m). \tag{31}$$

The higher order elements in Theorem 1 effect the accuracy of the approximation of the finite sample distribution by the limit of its zero-th order element. Higher order Edgeworth approximations have therefore been proposed to obtain a more accurate approximation of the finite sample distribution, see *e.g.* Bhattacharya and Ghosh (1978), Sargan (1980), Götze and Hipp (1983), Rothenberg (1984) and Phillips and Park (1988). Under a set of regularity conditions, Rothenberg (1984) states that a statistic S whose higher order properties are characterized by

$$S = \quad s_0 + \tfrac{1}{\sqrt{T}} s_1(s_0, y_0) + \tfrac{1}{T} s_2(s_0, y_0) + o_p(\tfrac{1}{T}), \tag{32}$$

with y_0 a vector of sample moments that converges to a random variable different from the random variable where s_0 converges to, has a second order Edgeworth approximation to its finite sample distribution that reads

$$\Pr[S \leq s] \approx F\left[s - \tfrac{1}{\sqrt{T}} s_1(s) + \tfrac{1}{2T}\left\{2 s_1(s)\left[\tfrac{\partial}{\partial s} s_1(s)\right] + c(s) v_1(s) + \left[\tfrac{\partial}{\partial s} v_1(s)\right] - 2 s_2(s)\right\}\right], \tag{33}$$

where F is the distribution function of the limiting distribution of s_0, $c(s) = \frac{\partial}{\partial s} \log[\frac{\partial}{\partial s} F(s)]$, $s_1(s) = E_{y_0}(s_1(s_0, y_0)|s_0 = s)$, $s_2(s) = E_{y_0}(s_2(s_0, y_0)|s_0 = s)$ and $v_1(s) = \mathrm{var}_{y_0}(s_1(s_0, y_0)|s_0 = s)$. The second order Edgeworth approximation (33) removes the approximation errors of the finite sample distribution up to the second order. Hence, the difference between the finite sample distribution and the second order Edgeworth approximation is $O_p(T^{-\frac{3}{2}})$ while the difference between the finite sample distribution and the approximation by the limit of its zero-th order element is $O_p(T^{-\frac{1}{2}})$.

When we assume that $\mu = 1$ and that the regularity conditions for the second order Edgeworth approximation are satisfied, which imply that $\nu = 1$, we can construct the second order Edgeworth approximation for the statistics in Theorem 1. For $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{LM}(\theta_0)$, it amounts to obtaining the conditional expectation of n_v, $n_{2\nu}$, n_κ, $n_{2\kappa}$ and $n_{\nu+\kappa}$ given n_0. We just show that the second order Edgeworth approximation does not perform adequately for $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{LM}(\theta_0)$. We therefore only construct the conditional expectation of n_v and $n_{2\nu}$ and explain why these expressions imply a unsatisfactory performance of the second order Edgeworth approximation. In order to construct the conditional expectations of n_ν and $n_{2\nu}$, we adapt Assumption 2.

Assumption 2*. *The limiting distribution ψ_u from Assumption 2 is independent of ψ_f.*

A sufficient condition for Assumption 2* to hold is that the covariance matrix estimator consists of the residuals of the projection of the moment equations on the instruments. To discuss the properties of the second order Edgeworth approximation, we first obtain the limit expressions of the conditional expectations of n_ν and $n_{2\nu}$ given $\rho = (D_0'V_{ff}(\theta_0)^{-1}D_0)^{-1}D_0'V_{ff}(\theta_0)^{-1}\psi_f$ so $\lim_{T\to\infty} n_0 = \rho' D_0'V_{ff}(\theta_0)^{-1}D_0\rho$. Because of the law of iterated expectations,

$$E[\lim_{T\to\infty} n_{i\nu}|\rho' D_0'V_{ff}(\theta_0)^{-1}D_0\rho = n_0] = \quad E[E[\lim_{T\to\infty} n_{i\nu}|\rho]|\rho' D_0'V_{ff}(\theta_0)^{-1}D_0\rho = n_0]. \tag{34}$$

Hence, $E[\lim_{T\to\infty} n_\nu|\rho]$ and $E[\lim_{T\to\infty} n_{2\nu}|\rho]$ are involved in the second order Edgeworth approximation.

Lemma 2. *When $\mu = \nu = 1$ and Assumptions 1 and 2, 2* hold, the conditional expectations of the limit expressions of n_v and $n_{2\nu}$ given $\rho = (D_0'V_{ff}(\theta_0)^{-1}D_0)^{-1}D_0'V_{ff}(\theta_0)^{-1}\psi_f = (\rho_1 \dots \rho_m)'$ read:*[2]

$$\begin{array}{l} E[\lim_{T\to\infty} n_\nu|\rho] = \\ 3\sum_{i=1}^m \rho_i \rho' D_0'V_{ff}(\theta_0)^{-1}A_iV_{\theta f,i}(\theta_0)V_{ff}(\theta_0)^{-1}D_0\rho + \\ 2\sum_{i=1}^m \rho_i \sum_{j=1}^{k_f-m}\sum_{n=1}^{k_f-m}\left\{\left[(D_{0,\perp}'V_{ff}(\theta_0)D_{0,\perp})^{-1}\right]_{jn}[D_{0,\perp}'A_iV_{\theta f,i}(\theta_0)D_{0,\perp}]_{nj}\right\}, \end{array} \tag{35}$$

with $D_{0,\perp} : k_f \times (k_f - m)$, $D_{0,\perp}'D_0 \equiv 0$, $D_{0,\perp}'D_{0,\perp} \equiv I_{k_f-m}$ and $\left[(D_{0,\perp}'V_{ff}(\theta_0)D_{0,\perp})^{-1}\right]_{jn}$ and $[D_{0,\perp}'A_iV_{\theta f,i}(\theta_0)D_{0,\perp}]_{jn}$ are the jn-th elements of the respective matrix; and

$$\begin{array}{rl} E[\lim_{T\to\infty} n_{2\nu}|\rho] = & a_1 + a_2 + a_3 + a_4 + \\ & \sum_{i=1}^m\sum_{j=1}^m [a_{ij} + b_{ij} + c_{ij} + d_{ij} + e_{ij}](D_0'V_{ff}(\theta_0)^{-1}D_0)^{-1}_{ij}, \end{array} \tag{36}$$

with

$$\begin{array}{rl} a_1 = & \rho' D_0'V_{ff}(\theta_0)^{-1}[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho](D_0'V_{ff}(\theta_0)^{-1}D_0)^{-1} \\ & D_0'V_{ff}(\theta_0)^{-1}[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho]\rho, \\ a_2 = & \mathrm{tr}([\rho \otimes D_{0,\perp}][\sum_{i=1}^{k_f-m}(D_{0,\perp}'V_{ff}(\theta_0)D_{0,\perp})_i^{-1}\rho' D_0'V_{ff}(\theta_0)^{-1}A_1V_{\theta f,1}(\theta_0)_i\cdots \\ & \sum_{i=1}^{k_f-m}\mathrm{tr}\{(D_{0,\perp}'V_{ff}(\theta_0)D_{0,\perp})_i^{-1}\rho' D_0'V_{ff}(\theta_0)^{-1}A_mV_{\theta f,m}(\theta_0)_i](D_0'V_{ff}(\theta_0)^{-1}D_0)^{-1}D_0'V_{ff}(\theta_0)^{-1} \\ & [A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)]), \\ a_3 = & E\{\mathrm{tr}([\rho \otimes D_{0,\perp}(D_{0,\perp}'V_{ff}(\theta_0)D_{0,\perp})^{-1}D_{0,\perp}'[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)] \\ & [I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho](D_0'V_{ff}(\theta_0)^{-1}D_0)^{-1}D_0'V_{ff}(\theta_0)^{-1}[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)]), \\ a_4 = & [\mathrm{tr}(D_{0,\perp}(D_{0,\perp}'V_{ff}(\theta_0)D_{0,\perp})^{-1}D_{0,\perp}'A_1V_{\theta f,1}(\theta_0))\dots\mathrm{tr}(D_{0,\perp}(D_{0,\perp}'V_{ff}(\theta_0)D_{0,\perp})^{-1}D_{0,\perp}'A_m \\ & V_{\theta f,m}(\theta_0))]D_0'V_{ff}(\theta_0)^{-1}D_0)^{-1}D_0'V_{ff}(\theta_0)^{-1}[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho]\rho, \end{array}$$

[2] We note that when $\nu = 1$, $D_0 \underset{p}{\to} J_\theta(\theta_0)$.

and

$$
\begin{aligned}
a_{ij} = \;& \{[\rho' D_0' V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0) V_{ff}(\theta_0)^{-1} D_0 \rho][\rho' D_0' V_{ff}(\theta_0)^{-1} A_j V_{\theta f,j}(\theta_0) V_{ff}(\theta_0)^{-1} D_0 \rho] \\
b_{ij} = \;& 2[\rho' D_0' V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0) V_{ff}(\theta_0)^{-1} D_0 \rho] \mathrm{tr}[D_{0,\perp}(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-1} D_{0,\perp}' A_j V_{\theta f,j}(\theta_0)] \\
c_{ij} = \;& 3 \textstyle\sum_{i_1=1}^{k_f-m} [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}\prime} D_{0,\perp}' A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}}]_{i_1 i_1}^2 + \\
& 2 \textstyle\sum_{i_1=1}^{k_f-m} \sum_{j_1=1, j_1 \neq i_1}^{k_f-m} [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}\prime} D_{0,\perp}' A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}}]_{i_1 i_1} \\
& [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}\prime} D_{0,\perp}' A_j V_{\theta f,j}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}}]_{j_1 j_1} + \\
& 2 \textstyle\sum_{i_1=1}^{k_f-m} \sum_{j_1=1, j_1 \neq i_1}^{k_f-m} [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}\prime} D_{0,\perp}' A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}}]_{i_1 j_1} \\
& [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}\prime} D_{0,\perp}' A_j V_{\theta f,j}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}}]_{i_1 j_1} + \\
& 2 \textstyle\sum_{i_1=1}^{k_f-m} \sum_{j_1=1, j_1 \neq i_1}^{k_f-m} [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}\prime} D_{0,\perp}' A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}}]_{i_1 j_1} \\
& [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}\prime} D_{0,\perp}' A_j V_{\theta f,j}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}}]_{j_1 i_1} \\
d_{ij} = \;& \rho' D_0' V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp} V_{ff}(\theta_0) D_{0,\perp})^{-1} D_{0,\perp} V_{\theta f,j}(\theta_0)' A_j' V_{ff}(\theta_0)^{-1} D_0 \rho \\
e_{ij} = \;& 2\rho' D_0' V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp} V_{ff}(\theta_0) D_{0,\perp})^{-1} D_{0,\perp} V_{\theta f,j}(\theta_0)' A_j' V_{ff}(\theta_0)^{-1} D_0 \rho.
\end{aligned}
$$

Proof. see the Appendix. ■

Lemma 2 states the conditional expectation of n_v and $n_{2\nu}$ given ρ. Because $\lim_{n\to\infty} n_0 = \rho' D_0' V_{ff}(\theta_0)^{-1} D_0 \rho$, we can specify ρ as $\rho = n_0^{\frac{1}{2}} h$ with $h : m \times 1$ and $h' D_0' V_{ff}(\theta_0)^{-1} D_0 h = 1$. To obtain the conditional expectation for the second order Edgeworth approximation, the law of iterated expectations (34) then implies that we construct the expectation of the conditional expectations of n_ν and $n_{2\nu}$ from Lemma 2 with respect to h.

Corollary 3. *Lemma 2 implies that the limiting expressions of the conditional expectations of n_ν and $n_{2\nu}$ given n_0 read*

$$
E[\lim_{T\to\infty} n_\nu | n_0] = \;\; E_h[E[\lim_{T\to\infty} n_\nu | \rho] = 0 \tag{37}
$$

and

$$
\begin{aligned}
& E[\lim_{T\to\infty} n_{2\nu} | n_0] = E_h[E[\lim_{T\to\infty} n_{2\nu} | \rho]] = \\
& E_h[a_2 + a_3 + a_4 | \rho = n_0^{\frac{1}{2}} h] + \textstyle\sum_{i=1}^m \sum_{j=1}^m (D_0' V_{ff}(\theta_0)^{-1} D_0)_{ij}^{-1} \left\{ c_{ij} + E[b_{ij} + d_{ij} + e_{ij} | \rho = n_0^{\frac{1}{2}} h] \right\}.
\end{aligned} \tag{38}
$$

Proof. Because n_0 has a $\chi^2(m)$ limiting distribution and ρ is normally distributed with mean zero, the first and third order moments of h are zero. The expectations of a_1 and a_{ij} from Lemma 2 with respect to h are therefore equal to zero. ■

The elements of the conditional expectation of $n_{2\nu}$ given n_0 (38) are proportional to $(D_0' V_{ff}(\theta_0)^{-1} D_0)^{-1}$ which can be estimated by $(\frac{1}{T^{1+\nu}} D_T(\theta_0, Y)' V_{ff}(\theta_0)^{-1} D_T(\theta_0, Y))^{-1}$. The second order Edgeworth approximation (33) therefore contains, for example, the second order term

$$
\tfrac{1}{T} \textstyle\sum_{i=1}^m \sum_{j=1}^m \left[\frac{1}{T^2} \hat{D}_T(\theta_0, Y)' \hat{V}_{ff}(\theta_0)^{-1} \hat{D}_T(\theta_0, Y) \right]_{ij}^{-1} \hat{c}_{ij}, \tag{39}
$$

which is part of "$-\frac{1}{T} s_2(s)$" in (33) and that assumes that $\nu = 1$. The assumption that $\nu = 1$ is a high level assumption which we can not verify. If $\nu = 0$, (39) becomes a zero-th order

term and the second order Edgeworth approximation then no longer removes all second order approximation errors. The second order Edgeworth approximation thus only removes second order approximation errors when $\nu = 1$ which we need to assume a priori and does not have to hold for the analyzed data.

Alongside the sensitivity of the second order Edgeworth approximation to the value of ν also the number of instruments k_f $(= kl)$ is of importance for the accuracy of the second order Edgeworth approximation. The c_{ij} elements in (38) consist of $(k_f - m)^2$ components and are thus proportional to k_f^2. When k_f^2 is large and proportional to T, the second order term of the Edgeworth approximation becomes a zero-th order term and the second order Edgeworth approximation does then not remove all second order approximation errors.

The sensitivity to the value of ν and the number of instruments k_f shows that a second order Edgeworth approximation does not remove the second order approximation error of the finite sample distribution of $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{LM}(\theta_0)$ in all instances. This indicates that the Edgeworth approximation will not perform satisfactorily for $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{LM}(\theta_0)$ since the improvement of the distributions depends on the unknown parameters of the analyzed model. The n_ν and $n_{2\nu}$ elements are not present in the higher order expressions of $\mathrm{W}_{\mathrm{cue}}(\theta_0)$ and $\mathrm{K}(\theta_0)$. When $\nu = 1$, the quality of the approximation of the finite sample distribution of these statistics by their zero-th order element is therefore less sensitive to the number of instruments. This corresponds with Brown and Newey (1998) and Newey and Smith (2001) where it is shown that the bias of the CUE smaller than that of the 2-step GMM estimator and is much less affected by the number of instruments. Also Donald and Newey (2000) show that the bias of the CUE is smaller than that of the 2step estimator since the CUE works like a jackknife. $\mathrm{W}_{\mathrm{cue}}(\theta_0)$ and $\mathrm{K}(\theta_0)$ are both based upon the CUE and show that the results of Brown and Newey (1998), Donald and Newey (2000) and Newey and Smith (2001) extend to such statistics. These statistics thus contain a considerable part of the corrections that the second order Edgeworth approximation of $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{LM}(\theta_0)$ applies.

Corollary 3 is not only helpful for the analysis of the Edgeworth approximation but also shows that $n_{2\nu}$ is proportional to k_f^2. When k_f and T jointly converge to infinity and k_f^2 is proportional to T, $n_{2\nu}$ therefore becomes a zero-th order term. Hence, in order to preserve the limiting distributions of $\mathrm{W}_{2\mathrm{s}}(\theta_0)$ and $\mathrm{LM}(\theta_0)$ in limiting sequences where k_f and T jointly converge to infinity, $\lim_{T\to\infty,k_f\to\infty} \frac{k_f^2}{T} = 0$ has to hold. We note that the Edgeworth approximation should remove this distortion of the zero-th order behavior of $\mathrm{W}_{2\mathrm{s}}(\theta_0)$ and $\mathrm{LM}(\theta_0)$.

3.1.2 Weak/non-identification or $\nu = 0$

The higher order elements of $\mathrm{W}_{cue}(\theta_0)$ and $\mathrm{K}(\theta_0)$ in Theorem 1 are identical when $\nu = 1$. When $\nu = 0$, the GMM estimators $\hat{\theta}_{2s}$ and $\hat{\theta}_{cue}$ converge to random variables, see *e.g.* Phillips (1989) and Stock and Wright (2000). The covariance matrix estimators involved in the Wald statistics, $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{W}_{cue}(\theta_0)$, are then evaluated at a random variable and are thus inconsistent. The convergence rate κ $(= \min(\mu, \nu))$ in Theorem 1 then equals zero for these statistics and indicates the inconsistency. The covariance matrix estimators involved in $\mathrm{LM}(\theta_0)$ and $\mathrm{K}(\theta_0)$ are evaluated at θ_0 and still converge to the true covariance matrix with convergence rate μ. The convergence rate κ in Theorem 1 is therefore equal to μ for these statistics and we can obtain the limit expression of the zero-th order term of the higher order expression when $\nu = 0$. This expression

is given in Corollary 4.

Corollary 4. *For weak and zero values of $J_\theta(\theta_0)$, for which $\nu = 0$, and a fixed number of instruments, Theorem 1 implies higher order properties for $W_{2s}(\theta_0)$ and $W_{cue}(\theta_0)$ under $H_0 : \theta = \theta_0$ that are characterized by:*

$$\left.\begin{array}{c} \mathrm{W}_{2s}(\theta_0) \\ \mathrm{W}_{cue}(\theta_0) \end{array}\right\} = n_0 + n_\nu + n_\kappa + n_{\nu+\kappa} + n_{2\nu} + n_{2\kappa} + n_{2\nu+\kappa} + n_{\nu+2\kappa} + n_{3\nu}, \ with\ \kappa = 0, \tag{40}$$

for LM(θ_0) :

$$\mathrm{LM}(\theta_0) = n_0 + n_\nu + n_{2\nu} + n_{3\nu} + T^{-\frac{\kappa}{2}}(n_\kappa + n_{\nu+\kappa} + n_{2\nu+\kappa}) + T^{-\kappa}(n_{2\kappa} + n_{\nu+2\kappa}), \ with\ \kappa = \mu, \tag{41}$$

and for K(θ_0) :

$$\mathrm{K}(\theta_0) = n_0 + T^{-\frac{\kappa}{2}}(n_\kappa + n_{\nu+\kappa}) + T^{-\kappa}(n_{2\kappa} + n_{\nu+2\kappa}), \ with\ \kappa = \mu, \tag{42}$$

where the different n-elements are defined in Theorem 1. Given D_0, the zero-th order limiting distribution of $LM(\theta_0)$, or limiting distribution of $n_0 + n_\nu + n_{2\nu} + n_{3\nu}$, reads

$$\begin{array}{l} LM(\theta_0) \underset{d}{\rightarrow} \psi_f' V_{ff}(\theta_0)^{-1}\{D_0 + [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)](I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f)\}[\{D_0 + \\ [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)](I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f)\}' V_{ff}(\theta_0)^{-1}\{D_0 + [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)] \\ (I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f)\}]^{-1}\{D_0 + [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)](I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f)\} V_{ff}(\theta_0)^{-1}\psi_f, \end{array} \tag{43}$$

while the zero-th order limiting distribution of K(θ_0) is $\chi^2(m)$.

We do not give the expressions of the zero-th limiting distributions of $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{W}_{cue}(\theta_0)$ when $\nu = 0$. These Wald statistics involve inconsistent covariance matrix estimators, since the covariance matrix estimators are evaluated at the inconsistent estimator of θ, $\hat{\theta}$. Hence, we could only give limit expressions that involve the inconsistent estimators. The limit distribution of $\mathrm{LM}(\theta_0)$ in (43) is no longer $\chi^2(m)$ and depends on nuisance parameters. The distortion of the limit distribution of $\mathrm{LM}(\theta_0)$, compared to its $\chi^2(m)$ limit distribution when $\nu = 1$ is caused by the higher order terms of the limit distribution when $\nu = 1$. As shown in Corollary 4, some of the higher order terms when $\nu = 1$ become zero-th order terms when $\nu = 0$ and distort the zero-th order limit distribution. The higher order terms of $\mathrm{K}(\theta_0)$ when $\nu = 1$ remain higher order terms when $\nu = 0$ and do therefore not distort the zero-th order limit distribution. The K-statistic is thus a higher order correction of $\mathrm{LM}(\theta_0)$ which overcomes the change of the zero-th order limit distribution of $\mathrm{LM}(\theta_0)$ when $\nu = 0$. Unlike higher order Edgeworth corrections as in (33), the K-statistic does involve the expectation over random variables that are independent, like the conditional expectations of n_ν, $n_{2\nu}$ and $n_{3\nu}$ given n_0, but conditions on the realized values of these independent random variables.

3.2 Number of instruments that goes to infinity

When the number of instruments is proportional to the number of observations, the higher order expressions from Theorem 1 are invalid. We therefore construct higher order expressions when

both the number of observations and the number of instruments jointly converge to infinity as in *e.g.* Bekker (1994). In order to do so, we make an assumption about the convergence behavior of the number of instruments k relative to that of the number of observations T.

Assumption 3. *The joint convergence of the number of instruments k and the number of observations T is such that*

$$\lim_{k,T\to\infty} \tfrac{k}{T^{\alpha}} = c, \tag{44}$$

with c a fixed finite constant.

We construct the convergence rates of the different elements involved in the statistics by means of a sequential convergence scheme in which we first let T converge to infinity and afterwards k. Given a fixed value of k, we have shown in Theorem 1 that all elements converge appropriately when T goes to infinity. Lemma 6 of Phillips and Moon (1999) therefore applies and we can let T and k converge to infinity sequentially, so first T and then k.

When we construct the higher order expressions with a number of instruments that converges to infinity, we maintain the properties of Assumption 1 that

$$\tfrac{1}{T^{1+\nu}} D_T(\theta_0,Y)' V_{ff}(\theta_0)^{-1} D_T(\theta_0,Y) \;\; = D_0' V_{ff}(\theta_0)^{-1} D_0 + o_p(1) \tag{45}$$

and

$$\tfrac{1}{\sqrt{T^{2+\nu}}} f_T(\theta_0,Y)' V_{ff}(\theta_0)^{-1} D_T(\theta_0,Y) \;\; = m_{0,f}' V_{ff}(\theta_0)^{-1} D_0 + o_p(1). \tag{46}$$

Because

$$\begin{aligned} D_T(\theta_0,Y) = \;\; & \big[\; p_{1,T}(\theta_0,Y) - A_1 V_{\theta f,1}(\theta_0) V_{ff}(\theta_0)^{-1} f_T(\theta_0,Y) \;\; \cdots \\ & \qquad p_{m,T}(\theta_0,Y) - A_m V_{\theta f,m}(\theta_0) V_{ff}(\theta_0)^{-1} f_T(\theta_0,Y) \;\big], \end{aligned} \tag{47}$$

and

$$\tfrac{1}{k} m_0' V(\theta_0)^{-1} m_0 = \;\; (m+1)l + o_p(1), \tag{48}$$

since $k_f = kl$, we do have to assume, however, that $\nu \geq \alpha$ since (45) and (46) can not hold otherwise. Bekker (1994) constructs the limit distribution of the CUE in the linear instrumental variables regression model under a limit sequence where the number of instruments is proportional to the number of observations, so $\alpha = 1$, and

$$\tfrac{1}{T} \left[\textstyle\sum_{t=1}^{T} E(p_t(\theta_0)|I_t)\right]' V_{ff}(\theta_0)^{-1} \left[\textstyle\sum_{t=1}^{T} E(p_t(\theta_0)|I_t)\right]$$

goes to a constant when k and T converge to infinity. Lemma 1 shows that

$$\begin{aligned} & T^{-\frac{1}{2}(1+\nu)} D_T(\theta_0,Y) = \tfrac{1}{T^{\frac{1}{2}(1+\nu)}} \textstyle\sum_{t=1}^{T} E(p_t(\theta_0)|I_t) + \\ & T^{-\frac{1}{2}\nu}[(m_{0,\theta_1} - A_1 V_{\theta f,1}(\theta_0) V_{ff}(\theta_0)^{-1} m_{0,f}) \cdots (m_{0,\theta_m} - A_m V_{\theta f,m}(\theta_0) V_{ff}(\theta_0)^{-1} m_{0,f})]. \end{aligned} \tag{49}$$

Because of (48), the convergence scheme of Bekker (1994) corresponds with $\alpha = 1$ and $\nu = 1$ in our specification.

Theorem 2 states the higher order expressions of $\mathrm{W}_{2s}(\theta_0)$, $\mathrm{W}_{cue}(\theta_0)$, $\mathrm{LM}(\theta_0)$ and $\mathrm{K}(\theta_0)$ when the number of instruments gets large according to Assumption 3.

Theorem 2. *When the number of instruments k converges to infinity according to Assumption 3 with $\nu \geq \alpha$, Assumptions 1 and 2 imply higher order properties of $W_{2s}(\theta_0)$, $W_{cue}(\theta_0)$, $LM(\theta_0)$ and $K(\theta_0)$ under $H_0 : \theta = \theta_0$ that are characterized by:*

$$\left.\begin{array}{r}\mathrm{W}_{2s}(\theta_0)\\ \mathrm{W}_{cue}(\theta_0)\\ \mathrm{LM}(\theta_0)\\ \mathrm{K}(\theta_0)\end{array}\right\} = \left\{\begin{array}{ll} n_0+ & : \text{zero-th order}\\ T^{-\frac{\nu-2\alpha}{2}} n_{\nu-2\alpha} + T^{-(\nu-\alpha)} n_{2(\nu-\alpha)} + T^{-(\nu-2\alpha)} n_{2(\nu-2\alpha)}+ & : \begin{array}{l} D_T(\theta_0, Y)+\\ \text{instruments}\end{array}\\ T^{-(\nu-\alpha)} n_{2(\nu-\alpha)}+ & \\ T^{-\nu} n_{\nu}+ & : D_T(\theta_0, Y)\\ T^{-\frac{\kappa}{2}} n_{\kappa} + T^{-\kappa} n_{2\kappa}+ & : \hat{V}(\theta_0)\\ T^{-\frac{1}{2}(\nu+\kappa-2\alpha)} n_{\nu+\kappa-2\alpha} + T^{-\frac{1}{2}(\nu+\kappa)} n_{\nu+\kappa}+ & \\ +T^{-\frac{1}{2}(\nu+2(\kappa-\alpha))} n_{\nu+2(\kappa-\alpha)}+ & \\ T^{-\frac{1}{2}(2\nu+\kappa-2\alpha)} n_{2\nu+\kappa-2\alpha} + T^{-(\nu+\kappa-\alpha)} n_{2(\nu+\kappa-\alpha)}+ & : \text{mixed}\\ T^{-\frac{1}{2}\kappa+2(\nu-2\alpha)} n_{\kappa+2(\nu-2\alpha)} + T^{-(\nu+\kappa-2\alpha)} n_{2(\nu+\kappa-2\alpha))} & \end{array}\right. \tag{50}$$

where:

1. *for $W_{2s}(\theta_0)$: $\kappa = \min(\mu, \nu)$, and*

$$\begin{array}{rcl} n_0 & = & s_0' G_0^{-1} s_0 \\ D_T(\theta_0, Y)+ \text{ instruments} & : & \left\{\begin{array}{rl} n_{\nu-2\alpha} = & s_{\nu-2\alpha,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{\nu-2\alpha,1} \\ n_{2(\nu-2\alpha)} = & s_{\nu-2\alpha,1}' G_0^{-1} s_{\nu-2\alpha,1} \\ n_{2(\nu-\alpha)} = & s_{\nu-2\alpha,1}' Q_1 s_0 + s_0' Q_1 s_{\nu-2\alpha,1} \end{array}\right. \\ D_T(\theta_0, Y) & : & \left\{ n_\nu = \; s_0' Q_1 s_0 \right. \\ \hat{V}(\theta_0) & : & \left\{\begin{array}{rl} n_\kappa = & s_{1\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{1\kappa,1} \\ n_{2\kappa} = & s_{1\kappa,1}' G_0^{-1} s_{1\kappa,1} \end{array}\right. \\ \text{mixed} & : & \left\{\begin{array}{rl} n_{\nu+\kappa-2\alpha} = & (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2})' G_0^{-1} s_0 + s_{\nu-2\alpha,1}' G_0^{-1} s_{1\kappa,1} + \\ & s_0' G_0^{-1} (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2}) + s_{1\kappa,1}' G_0^{-1} s_{\nu-2\alpha,1} \\ n_{\nu+\kappa} = & s_{1\kappa,1}' Q_1 s_0 + s_0' Q_1 s_{1\kappa,1} \\ n_{\nu+2(\kappa-\alpha)} = & (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2})' G_0^{-1} s_{1\kappa,1} + s_{\nu+2\kappa-2\alpha,1}' G_0^{-1} s_0 + \\ & s_{1\kappa,1}' G_0^{-1} (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2}) + s_0' G_0^{-1} s_{\nu+2\kappa-2\alpha,1} \\ n_{2\nu+\kappa-2\alpha} = & (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2})' Q_1 s_0 + s_0' Q_1 (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2}) \\ n_{2(\nu+\kappa-\alpha)} = & s_{\nu+2(\kappa-\alpha),1}' Q_1 s_0 + (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2})' Q_1 s_{1\kappa,1} + \\ & s_{1\kappa,1}' Q_1 (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2}) + s_0' Q_1 s_{\nu+2(\kappa-\alpha),1} \\ n_{\kappa+2(\nu-2\alpha)} = & s_{\nu-2\alpha,1}' Q_1 s_{\nu-2\alpha,1} \\ n_{2(\nu+\kappa-2\alpha)} = & (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2})' G_0^{-1} (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2}) \end{array}\right. \end{array} \tag{51}$$

2. *for $W_{cue}(\theta_0)$: $\kappa = \min(\mu, \nu)$, $n_{\nu-2\alpha} = n_{2(\nu-2\alpha)} = n_v = n_{\nu+\kappa} = n_{2(\nu-\alpha)} = n_{2\nu+\kappa-2\alpha} =$*

$$n_{2(\nu+\kappa-\alpha)} = n_{\kappa+2(\nu-2\alpha)} = 0,$$

$$\begin{array}{rcl}
n_0 & = & s_0' G_0^{-1} s_0 \\
\hat{V}(\theta_0) & : & \left\{ \begin{array}{rl} n_\kappa = & s_0' Q_1 s_0 + s_{1\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{1\kappa,1} \\ n_{2\kappa} = & s_{1\kappa,1}' G_0^{-1} s_{1\kappa,1} + s_{1\kappa,1}' Q_1 s_0 + s_0' Q_1 s_{1\kappa,1} \\ n_{3\kappa} = & s_{1\kappa,1}' Q_1 s_{1\kappa,1} \end{array} \right. \\
\text{mixed} & : & \left\{ \begin{array}{rl} n_{\nu+\kappa-2\alpha} = & s_{\nu+\kappa-2\alpha,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{\nu+\kappa-2\alpha,1} \\ n_{\nu+2(\kappa-\alpha)} = & s_{\nu+\kappa-2\alpha,1}' G_0^{-1} s_{1\kappa,1} + s_{1\kappa,1}' G_0^{-1} s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,1}' Q_1 s_0 + \\ & s_0' Q_1 s_{\nu+\kappa-2\alpha,1} + s_{\nu+2\kappa-2\alpha,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{\nu+2\kappa-2\alpha,1} \\ n_{2\nu+\kappa-2\alpha} = & s_{\nu+\kappa-2\alpha,1}' G_0^{-1} s_{\nu+\kappa-2\alpha,1}. \end{array} \right.
\end{array} \tag{52}$$

3. *for LM(θ_0) the elements are identical to those for $W_{2s}(\theta_0)$ in (51) but with $\kappa = \mu$.*

4. *for K(θ_0) the elements are identical to those for $W_{cue}(\theta_0)$ in (52) but with $\kappa = \mu$*

and for all statistics

$$\begin{array}{rcl}
s_0 = & m_{0,f}' V_{ff}(\theta_0)^{-1} D_0 \\
s_{\nu-2\alpha,1} = & m_{0,f}' V_{ff}(\theta_0)^{-1} \{ \frac{1}{\sqrt{T}} [p_T(\hat{\theta}, Y) - \hat{D}_T(\hat{\theta}, Y)] \} \\
= & \frac{1}{k} m_{0,f}' V_{ff}(\theta_0)^{-1} [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}] \\
s_{1\kappa,1} = & T^{\frac{1}{2}\kappa} m_{0,f}' [V_{ff}(\hat{\theta})^{-1} - V_{ff}(\theta_0)^{-1}] D_0 \\
s_{\nu+\kappa-2\alpha,1} = & \frac{T^{\frac{1}{2}\kappa}}{k} m_{0,f}' V_{ff}(\theta_0)^{-1} \{ [A_1 \hat{V}_{\theta f,1}(\theta_0) \cdots A_m \hat{V}_{\theta f,m}(\theta_0)][I_m \otimes \hat{V}_{ff}(\theta_0)^{-1}] \\
& - [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}] \} [I_m \otimes m_{0,f}] \\
s_{\nu+\kappa-2\alpha,2} = & \frac{T^{\frac{1}{2}\kappa}}{k} m_{0,f}' [\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}] [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)] \\
& [I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}] \\
s_{\nu+2(\kappa-\alpha),1} = & \frac{T^{\frac{1}{2}(2\kappa-1)}}{k} m_{0,f}' [\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}] [\hat{D}_T(\theta_0, Y) - D_T(\theta_0, Y)],
\end{array} \tag{53}$$

with $G_0 = D_0' V_{ff}(\theta_0)^{-1} D_0$ and the remaining expressions of the G and Q matrices are given in the Appendix.

Proof. see the Appendix. ■

When $\alpha = 0$, the higher order expressions in Theorem 2 are identical to those in Theorem 1 that were constructed for a fixed number of instruments. An important difference with the elements of the higher order expressions in Theorem 1 results from the convergence of

$$s_{\nu-2\alpha,1} = \frac{1}{k} m_{0,f}' V_{ff}(\theta_0)^{-1} [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}]. \tag{54}$$

When k and T converge to infinity,

$$s_{\nu-2\alpha,1} \underset{p}{\longrightarrow} \omega(\theta_0), \tag{55}$$

where $\omega(\theta_0) = (\omega_1(\theta_0) \ldots \omega_m(\theta_0))$ and

$$\omega_i(\theta_0) = \lim_{k\to\infty} \frac{1}{k} \mathrm{tr}(V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0)). \tag{56}$$

The convergence of $s_{\nu-2\alpha,1}$ towards a constant implies that ν needs to exceed 2α for the $\chi^2(m)$ limiting distribution to remain valid for $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{LM}(\theta_0)$. Otherwise, $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{LM}(\theta_0)$ converge to $\lim_{k,T\to\infty} n_{2(\nu-2\alpha)} = \omega(\theta_0)' G_0^{-1} \omega(\theta_0)$ because $2(\nu-2\alpha) < (\nu-2\alpha)$ when $\nu < 2\alpha$. This sensitivity to the number of instruments of $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{LM}(\theta_0)$ is also indicated by Corollary 3 where the conditional expectation of higher order elements of $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{LM}(\theta_0)$ depends on the number of instruments. Theorem 2 further emphasizes this sensitivity to the number of instruments of $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{LM}(\theta_0)$. Even for values of ν that correspond with a well-identified θ_0, $\nu \geq 1$, the limiting distributions of $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{LM}(\theta_0)$ can be affected by the number of instruments.

Theorem 2 assumes that $\nu \geq \alpha$. The number of instruments can therefore affect the limiting distribution of $\mathrm{W}_{cue}(\theta_0)$ and $\mathrm{K}(\theta_0)$ when $\alpha \geq \mu$. Corollary 5 states these distortions for a stylized setting in which $\nu = \alpha = \mu = 1$.

Corollary 5. *When $\nu = \alpha = \mu = 1$, the higher order expressions of $W_{cue}(\theta_0)$ and $K(\theta_0)$ that result from Theorem 2 read*

$$\left.\begin{matrix} \mathrm{W}_{cue}(\theta_0) \\ \mathrm{K}(\theta_0) \end{matrix}\right\} = \; n_0 + n_{\nu+\kappa-2\alpha} + n_{2(\nu+\kappa-2\alpha)} + T^{-\frac{1}{2}}(n_\kappa + n_{\nu+2(\kappa-\alpha)}) + T^{-1} n_{2\kappa} + o_p(T^{-1}) \tag{57}$$

where the expressions of the n-elements are stated in Theorem 2.

Corollary 5 shows that additional zero-th order elements, *i.e.* $n_{\nu+\kappa-2\alpha} + n_{2(\nu+\kappa-2\alpha)}$, appear when $\nu = \alpha = \mu = 1$. Both $n_{\nu+\kappa-2\alpha}$ and $n_{2(\nu+\kappa-2\alpha)}$ consists of, alongside s_0, $s_{\nu+\kappa-2\alpha,1}$. We therefore state the limiting distribution of $s_{\nu+\kappa-2\alpha,1}$ in Lemma 3.

Lemma 3. *When k and T converge to infinity, and Assumption 1, 2, 2* and 3 hold, the convergence of $s_{\nu+\kappa-2\alpha,1}$ defined in Theorem 3 is characterized by*

$$s_{\nu+\kappa-2\alpha,1} \underset{d}{\to} \; \lambda, \tag{58}$$

where $\lambda \sim N(0, \Sigma(\theta_0))$ and independent of ψ_f with $\Sigma(\theta_0) = \{\sigma_{ij}(\theta_0)\}_{i,j=1,\ldots,m}$ and

$$\begin{aligned} \sigma_{ij}(\theta_0) = \; & \lim_{k\to\infty} \left[\tfrac{1}{\sqrt{k}} \psi_f' V_{ff}(\theta_0)^{-1} \otimes \tfrac{1}{\sqrt{k}} \psi_f' V_{ff}(\theta_0)^{-1} A_i\right]' \bar{W}_{ij}(\theta_0) \\ & \left[\tfrac{1}{\sqrt{k}} \psi_f' V_{ff}(\theta_0)^{-1} \otimes \tfrac{1}{\sqrt{k}} \psi_f' V_{ff}(\theta_0)^{-1} A_j\right] \end{aligned} \tag{59}$$

with

$$\bar{W}_{ij}(\theta_0) = \; \lim_{T\to\infty} E[\mathrm{vec}(U_{\theta f,i} - V_{\theta f,i}(\theta_0) V_{ff}(\theta_0)^{-1} U_{ff}) \mathrm{vec}(U_{\theta f,j} - V_{\theta f,j}(\theta_0) V_{ff}(\theta_0)^{-1} U_{ff})'], \tag{60}$$

which expression results from Assumption 2.

Proof. see the Appendix. ■

Lemma 3 indicates that the zero-th order term from Corollary 5 does not have a $\chi^2(m)$ limiting distribution when $\nu = \mu = \alpha = 1$. We can account for the distortion of the $\chi^2(m)$ limiting distribution by including an estimate of $\Sigma(\theta_0)$ in the covariance matrix estimators involved in

$\mathrm{W}_{cue}(\theta_0)$ and $\mathrm{K}(\theta_0)$. Bekker (1994) proposes such a covariance matrix estimator for $\mathrm{W}_{cue}(\theta_0)$ in the linear instrumental variables regression model for a limit sequence with $\nu = \mu = \alpha = 1$.

The elements $\sigma_{ij}(\theta_0)$ (59), that we need to incorporate in $\mathrm{W}_{cue}(\theta_0)$ and $\mathrm{K}(\theta_0)$ to preserve their $\chi^2(m)$ limit distributions in a limit sequence with $\nu = \mu = \alpha = 1$, are of order $T^{2\alpha+\mu}$ $(= k^2 T^{\mu})$. In case k is fixed, so $\alpha = 0$, $\nu = 0$ and $\mu = 1$, this order equals T and is identical to the convergence rate of $D_T(\theta_0, Y)' V_{ff}(\theta_0)^{-1} D_T(\theta_0, Y)$. The robustness of the limiting distribution of $\mathrm{W}_{cue}(\theta_0)$ and $\mathrm{K}(\theta_0)$ to limit sequences where $\nu = \mu = \alpha = 1$ comes therefore at the price of non-robustness of the limiting distribution of $\mathrm{W}_{cue}(\theta_0)$ and $\mathrm{K}(\theta_0)$ to limit sequences where $\nu = \alpha = 0$, see also Bekker and Kleibergen (2003). The limiting distribution of $\mathrm{W}_{cue}(\theta_0)$ is non-robust to such limit sequences but the limiting distribution of $\mathrm{K}(\theta_0)$ is robust to these limit sequences. Hence, robustifying $\mathrm{K}(\theta_0)$ to allow for $\nu = \mu = \alpha = 1$ means losing the robustness to $\nu = \alpha = 0$. Without adapting the covariance matrix estimator, the limiting distribution of $\mathrm{K}(\theta_0)$ remains $\chi^2(m)$ when $\mu > \alpha$.

4 Higher Order Properties of Statistics that test H_e : $E(f_t(\theta)) = 0$.

Alongside tests of hypothezes specified on the parameter θ, like $\mathrm{H}_0 : \theta = \theta_0$, it is customary to test whether Assumption 1 holds so the model is not misspecified: $\mathrm{H}_e : E(f_t(\theta)) = 0$ or to conduct a joint test of H_0 and H_e. For the latter kind of joint hypothezes, we can use the objective function evaluated at θ_0, which is Stock and Wright's (2000) S-statistic:

$$\mathrm{S}(\theta_0) = \tfrac{1}{T} f_T(\theta_0, Y)' \hat{V}_{ff}(\theta_0)^{-1} f_T(\theta_0, Y). \tag{61}$$

Under H_0 and H_e, $\mathrm{S}(\theta_0)$ has a $\chi^2(k_f)$ limit distribution regardless of the value of $J_\theta(\theta_0)$.

To obtain that part of $\mathrm{S}(\theta_0)$ that tests H_e, we can use a J-statistic, see *e.g.* Hansen (1982), that results from substracting one of the statistics $\mathrm{W}_{2s}(\theta_0)$, $\mathrm{W}_{cue}(\theta_0)$, $\mathrm{LM}(\theta_0)$ or $\mathrm{K}(\theta_0)$ from $\mathrm{S}(\theta_0)$:

$$\begin{array}{rl} \mathrm{J}_{2s}(\theta_0) = & \mathrm{S}(\theta_0) - \mathrm{W}_{2s}(\theta_0) \\ \mathrm{J}_{cue}(\theta_0) = & \mathrm{S}(\theta_0) - \mathrm{W}_{cue}(\theta_0) \\ \mathrm{J}_{LM}(\theta_0) = & \mathrm{S}(\theta_0) - \mathrm{LM}(\theta_0) \\ \mathrm{J}_{K}(\theta_0) = & \mathrm{S}(\theta_0) - \mathrm{K}(\theta_0). \end{array} \tag{62}$$

Under H_0 and H_e, all J-statistics in (62) have $\chi^2(k_f - m)$ limiting distributions when $J_\theta(\theta_0)$ has a fixed full rank value. Only $\mathrm{J}_K(\theta_0)$ has a $\chi^2(k_f - m)$ limiting distribution for any value of $J_\theta(\theta_0)$, see Kleibergen (2001,2002b). When $J_\theta(\theta_0)$ has a fixed full rank value, the J-statistics that are commonly used, *i.e.* $\mathrm{J}_{2s}(\hat{\theta}_{2s})$ and $\mathrm{J}_{cue}(\hat{\theta}_{cue})$, have under H_e only a $\chi^2(k_f - m)$ limiting distribution. Theorem 3 states the higher order expressions of the S and J-statistics for a fixed number of instruments. Because the S and J-statistics have limiting distributions that depend on the number of instruments, we do not construct their higher order expressions in a limit sequence where the number of instruments and the number of observations jointly converge to infinity.

Theorem 3. *Assumptions 1, 2 and Theorem 1 imply higher order expressions for the S-statistic (61) and J-statistics (62) that read:*

$$S(\theta_0) = \quad n_0 + n_{0,\perp} + T^{-\frac{\mu}{2}} w_\mu + o_p(T^{-\frac{\mu}{2}}), \tag{63}$$

with $w_\mu = T^{\frac{\mu}{2}} m'_{0.f}[\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}]m_{0.f}$, $n_0 = m'_{0.f}V_{ff}(\theta_0)^{-1}D_0(D'_0V_{ff}(\theta_0)^{-1}D_0)^{-1}D'_0 V_{ff}(\theta_0)^{-1}m_{0.f}$ *and* $n_{0,\perp} = m'_{0.f}D_{0,\perp}(D'_{0,\perp}V_{ff}(\theta_0)D_{0,\perp})^{-1}D'_{0,\perp}m_{0.f}$ *, where* $D_{0,\perp} : k_f \times (k_f - m)$, $D'_{0,\perp}D_0 \equiv 0$, $D'_{0,\perp}D_{0,\perp} \equiv I_{k_f-m}$; *and*

$$\left.\begin{array}{r} \mathrm{J}_{2s}(\theta_0) \\ \mathrm{J}_{cue}(\theta_0) \\ \mathrm{J}_{LM}(\theta_0) \\ \mathrm{J}_{\mathrm{K}}(\theta_0) \end{array}\right\} = n_{0,\perp} + T^{-\frac{\mu}{2}}w_\mu - \left\{\begin{array}{l} T^{-\frac{\nu}{2}}n_\nu + T^{-\frac{\kappa}{2}}n_\kappa + T^{-\frac{\nu+\kappa}{2}}n_{\nu+\kappa} + T^{-\nu}n_{2\nu} + T^{-\kappa}n_{2\kappa} + \\ T^{-\frac{1}{2}(2\nu+\kappa)}n_{2\nu+\kappa} + T^{-\frac{1}{2}(\nu+2\kappa)}n_{\nu+2\kappa} + T^{-\frac{3}{2}\nu}n_{3\nu} + o_p(T^{-\frac{3}{2}\nu}), \end{array}\right. \tag{64}$$

where the specification of the different n-elements for a specific statistic is given in Theorem 1.

Proof. see the Appendix. ■

Theorem 3 shows that the J-statistics (62) possess similar higher order properties as the statistics whose properties are stated in Theorem 1. Since

$$n_{0,\perp} \underset{d}{\rightarrow} \chi^2(k_f - m),$$

all J-statistics converge to a $\chi^2(k_f - m)$ distributed random variable when $\nu = 1$ but only $\mathrm{J}_{\mathrm{K}}(\theta_0)$ converges to such a random variable when $\nu = 0$. Identical to the statistics in Theorem 1, the distortion of the limit distribution when $\nu = 0$ results from elements that are of higher order when $\nu = 1$. These elements are not present amongst the higher order elements of $\mathrm{J}_K(\theta_0)$ and can therefore not alter the limit distribution of $\mathrm{J}_K(\theta_0)$ when ν becomes equal to zero. We conclude from Theorems 1 and 3 that the statistics whose higher order properties do not depend on ν, *i.e.* $\mathrm{S}(\theta_0)$, $\mathrm{K}(\theta_0)$ and $\mathrm{J}_K(\theta_0)$, are also optimal from a higher order perspective since they posses less and "smaller", in a bias or variance sense, higher order elements.

The higher order properties of the commonly used J-statistics, $\mathrm{J}_{2s}(\hat{\theta}_{2s})$ and $\mathrm{J}_{cue}(\hat{\theta}_{cue})$, are similar to those of $\mathrm{J}_{2s}(\theta_0)$ and $\mathrm{J}_{cue}(\theta_0)$ in Theorem 3. A $\chi^2(k_f - m)$ limiting distribution is therefore only valid for these statistics when $\nu = 1$ and thus for full rank values of $J_\theta(\theta_0)$. Because $\mathrm{J}_{2s}(\hat{\theta}_{2s})$ results from $\mathrm{W}_{2s}(\theta_0)$ that can be severly biased when the number of instruments and/or the correlation is large, we also for other reasons have to be careful with the use of $\mathrm{J}_{2s}(\hat{\theta}_{2s})$.

Theorems 1 and 3 show that the limiting distributions of $\mathrm{K}(\theta_0)$ and $\mathrm{J}_K(\theta_0)$ are robust to the value of ν. Since $\mathrm{K}(\theta_0)$ is a score or Lagrange multiplier statistic, it suffers from a spurious power decline around values of θ where the objective function is maximal or has an inflexion point. The J-statistic $\mathrm{J}_K(\theta_0)$ has discriminatory power at these values of θ and is since its limiting distribution is independently distributed from $\mathrm{K}(\theta_0)$ ideally suited to be combined with $\mathrm{K}(\theta_0)$, see Kleibergen (2001,2002b). These statistics can be combined in a unconditional or in a conditional manner. A unconditional manner implies that we use fixed significance levels for $\mathrm{K}(\theta_0)$ and $\mathrm{J}_K(\theta_0)$, α_K and α_{J_K}, that add up to the significance level α by which we want to test, $\alpha = \alpha_K + \alpha_{J_K}$. A conditional manner implies that we use an additional independently distributed statistic to combine $\mathrm{K}(\theta_0)$ and $\mathrm{J}_K(\theta_0)$. The conditional likelihood ratio statistic of Moreira (2003) in the linear instrumental variables regression model with $m = 1$ operates in such manner. Its conditional limiting distribution is the sum of the limiting distributions of $\mathrm{K}(\theta_0)$ and a weighted value of $\mathrm{J}_{\mathrm{K}}(\theta_0)$. It uses $D_T(\theta_0, Y)'V_{ff}(\theta)^{-1}D_T(\theta_0, Y)$ as the independently distributed conditioning statistic. When $D_T(\theta_0, Y)'V_{ff}(\theta)^{-1}D_T(\theta_0, Y)$ is large, the conditional limiting distribution is identical to that of $\mathrm{K}(\theta_0)$ while it resembles $\mathrm{K}(\theta_0)$+$\mathrm{J}_K(\theta_0)$ (=$\mathrm{S}(\theta_0)$)

when $D_T(\theta_0, Y)' V_{ff}(\theta)^{-1} D_T(\theta_0, Y)$ is small. Because the conditional likelihood ratio statistic has a conditional limiting distribution, it is less straightforward to show that its robustness to the value of ν results from higher order elements. Furthermore, we can only approximate the conditional likelihood ratio statistic in GMM, see Kleibergen (2001,2002b). We therefore refer from constructing the higher order properties of Moreira's (2003) conditional likelihood ratio statistic.

5 Bootstrapping robust statistics

Theorems 1 and 3 show that the zero-th order elements of some of the statistics that we consider depend on the value of ν. For these statistics we can therefore not use the bootstrap to approximate the finite sample distribution. The zero-th order elements of $\mathrm{K}(\theta_0)$, $\mathrm{J}_K(\theta_0)$ and $\mathrm{S}(\theta_0)$ do not depend on ν. The higher order expressions of these statistics in Theorems 1 and 3 indicate that we can construct a higher order Edgeworth approximation of the finite sample distribution. The higher order Edgeworth approximation indicates if the bootstrap improves upon the approximation of the finite sample distribution by its zero-th order element, see *e.g.* Horowitz (2001). We therefore analyze the Edgeworth approximation of the statistics whose zero-th elements do not depend on ν, *i.e.* $\mathrm{K}(\theta_0)$, $\mathrm{J}_K(\theta_0)$ and $\mathrm{S}(\theta_0)$. We also discuss how the bootstrap can be implemented for these statistics.

5.1 Edgeworth Approximation of the finite sample distribution of $\mathbf{K}(\theta_0)$, $\mathbf{J}_K(\theta_0)$ and $\mathbf{S}(\theta_0)$

The specification of the covariance matrix estimator $\hat{V}(\theta_0)$ determines the convergence rate μ. The higher order expression of $\mathrm{K}(\theta_0)$ in case of a fixed number of instruments is stated in Theorem 1:

$$\mathrm{K}(\theta_0) = \; n_0 + T^{-\frac{1}{2}\kappa} n_\kappa + T^{-\frac{\nu+\kappa}{2}} n_{\nu+\kappa} + T^{-\kappa} n_{2\kappa} + T^{-\frac{\nu+2\kappa}{2}} n_{\nu+2\kappa} + T^{-\frac{3\kappa}{2}} n_{3\kappa} + o_p(T^{-\frac{3\kappa}{2}}), \qquad (65)$$

with $\kappa = \mu$. The higher order expression (65) depends on the value of ν which indicates the convergence rate of $D_T(\theta_0, Y)$, see Lemma 1. Because the limit behavior D_0 of $T^{-\frac{1}{2}(1+\nu)} D_T(\theta_0, Y)$ is independent of the limit behavior of n_0, as shown in Corollaries 1 and 2, we can condition on D_0 and consequently ν in the higher order expression (65) to specify it as

$$\mathrm{K}(\theta_0) = \; n_0 + T^{-\frac{1}{2}\kappa}(n_\kappa + T^{-\frac{1}{2}\nu} n_{\nu+\kappa}) + T^{-\kappa}(n_{2\kappa} + T^{-\frac{1}{2}\nu} n_{\nu+2\kappa}) + T^{-\frac{3\kappa}{2}} n_{3\kappa} + o_p(T^{-\frac{3}{2}}). \qquad (66)$$

Higher order expression (66) is identical to (32) when $\kappa = 1$. Hence, we can construct a 2κ-th order Edgeworth approximation of the finite sample distribution of $\mathrm{K}(\theta_0)$ by using (33). It amounts to constructing the expressions of the different elements of (66) and their conditional

expectations and variances given n_0. For example, the expression for $n_\kappa + T^{-\frac{1}{2}\nu} n_{\nu+\kappa}$ reads,

$$n_\kappa + T^{-\frac{1}{2}\nu} n_{\nu+\kappa} = T^{\frac{\kappa}{2}}\{m'_{0,f}\{[\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}]D_T(\theta_0, Y) + V_{ff}(\theta_0)^{-1}[\hat{D}_T(\hat{\theta}, Y) - D_T(\theta_0, Y)]\}[D_T(\theta_0, Y)' V_{ff}(\theta_0)^{-1} D_T(\theta_0, Y)]^{-1} D_T(\theta_0, Y)' V_{ff}(\theta_0)^{-1} m_{0.f} + m'_{0.f} V_{ff}(\theta_0)^{-1} D_T(\theta_0, Y)[D_T(\theta_0, Y)' V_{ff}(\theta_0)^{-1} D_T(\theta_0, Y)]^{-1}\{[\hat{D}_T(\hat{\theta}, Y) - D_T(\theta_0, Y)]V_{ff}(\theta_0)^{-1} + D_T(\theta_0, Y)[\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}]\} m_{0.f} + m'_{0.f} V_{ff}(\theta_0)^{-1} D_T(\theta_0, Y)[D_T(\theta_0, Y)' V_{ff}(\theta_0)^{-1} D_T(\theta_0, Y)]^{-1} D_T(\theta_0, Y)' [\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}] D_T(\theta_0, Y)[D_T(\theta_0, Y)' V_{ff}(\theta_0)^{-1} D_T(\theta_0, Y)]^{-1} D_T(\theta_0, Y)' V_{ff}(\theta_0)^{-1} m_{0.f}\}, \tag{67}$$

which also shows that ν is not present in it. Similar to Lemma 2, it is convenient to use the law of iterated expectations (34) and first construct the conditional expectation given $\rho = (D_0' V_{ff}(\theta_0)^{-1} D_0)^{-1} D_0' V_{ff}(\theta_0)^{-1} \psi_f$. Because of Assumption 2*, the conditional expectation of $n_\kappa + T^{-\frac{1}{2}\nu} n_{\nu+\kappa}$ given ρ equals zero so $s_1(s_0, y_0)$ in (33) is equal to zero. Since it is also possible to obtain the expression of $s_2(s_0, y_0)$, from which we refrain here, the 2κ-th order Edgeworth approximation to the finite sample distribution of $\mathrm{K}(\theta_0)$ can be constructed. We do not construct the explicit expression of the 2κ-th order Edgeworth approximation. We only use that because of its existence the bootstrap leads to an improvement of the approximation of the finite sample distribution of $\mathrm{K}(\theta_0)$ over the limit of its zero-th order element, see Horowitz (2001).

In an identical manner as outlined above for $\mathrm{K}(\theta_0)$, it is possible to obtain 2κ-th order Edgeworth approximations to the finite sample distributions of $\mathrm{J}_K(\theta_0)$ and $\mathrm{S}(\theta_0)$. Hence, also for these statistics the bootstrap leads to an improvement of the approximation of the finite sample distribution.

5.2 Bootstraps

$\mathbf{K}(\theta_0)$. To construct a bootstrap approximation of the finite sample distribution of $\mathrm{K}(\theta_0)$, that tests $\mathrm{H}_0 : \theta = \theta_0$, we consider the moment condition where $\mathrm{K}(\theta_0)$ is based on:

$$E[J_\theta(\theta_0)' V_{ff}(\theta_0)^{-1} f_t(\theta_0)] = J_\theta(\theta_0)' V_{ff}(\theta_0)^{-1} E[f_t(\theta_0)] = 0. \tag{68}$$

The bootstrap uses the empirical distribution instead of the unknown true distribution. When evaluated using the empirical distribution, the moment condition (68) reads

$$\hat{D}_T(\theta, Y)' \hat{V}_{ff}(\theta)^{-1} f_T(\theta, Y) = 0, \tag{69}$$

since $\hat{D}_T(\theta, Y)$, $\hat{V}_{ff}(\theta)$ and $f_T(\theta, Y)$ are the analogs of $J_\theta(\theta_0)$, $V_{ff}(\theta_0)$ and $E[f_t(\theta_0)]$ when evaluated using the empirical distribution. The empirical moment condition (69) holds at the CUE of θ, $\hat{\theta}_{cue}$. We therefore use $\hat{\theta}_{cue}$ to construct bootstrap samples on which we test $\mathrm{H}_0^* : \theta = \hat{\theta}_{cue}$ using $\mathrm{K}(\hat{\theta}_{cue})$. Hence, we replace $\mathrm{H}_0 : \theta = \theta_0$ by $\mathrm{H}_0^* : \theta = \hat{\theta}_{cue}$ for which the empirical moment condition (69) is satisfied. Although the empirical moment condition holds at $\hat{\theta}_{cue}$, we use recentered moments of $f_t(\hat{\theta}_{cue})$:

$$\bar{f}_t(\hat{\theta}_{cue}) = f_t(\hat{\theta}_{cue}) - \tfrac{1}{T} \textstyle\sum_{j=1}^{T} f_j(\hat{\theta}_{cue}), \tag{70}$$

to obtain bootstrap samples of $\mathrm{K}(\hat{\theta}_{cue})$. We need to use the recentered moments (70) because the theoretical moment condition $E[f_t(\theta_0)] = 0$ does not hold for the empirical distribution. The covariance matrix involved in $\mathrm{K}(\hat{\theta}_{cue})$ would therefore be in error when we do not use the recentered moments (70), see *e.g.* Hall and Horowitz (1996). Depending on whether $[f_t(\theta)' \; q_t(\theta)']'$,

$t = 1, \ldots, T$, are independently distributed, we can use several different manners to construct a bootstrap sample of $\mathrm{K}(\theta_0)$. Because GMM does not make any assumptions about the distribution of $[f_t(\theta)' \; q_t(\theta)']'$, $t = 1, \ldots, T$, we only use the empirical distribution of $[f_t(\theta)' \; q_t(\theta)']'$, $t = 1, \ldots, T$, in the bootstrap.

When $[f_t(\theta)' \; q_t(\theta)']'$, $t = 1, \ldots, T$, are independently distributed, two different manners to obtain a bootstrap distribution of $\mathrm{K}(\theta_0)$ are:

1. (a) Obtain bootstrap sample $\{[\tilde{f}_t(\hat{\theta}_{cue})' \; \tilde{q}_t(\hat{\theta}_{cue})']', t = 1, \ldots, T\}$ by drawing from $\{[\bar{f}_t(\hat{\theta}_{cue})' \; q_t(\hat{\theta}_{cue})']', \; t = 1, \ldots, T\}$ with replacement.

   (b) Construct: $\tilde{V}(\hat{\theta}_{cue})$, $\tilde{D}_T(\hat{\theta}_{cue}, Y)$ and $\tilde{f}_T(\hat{\theta}_{cue}, Y)$ from the bootstrap sample $\{[\tilde{f}_t(\hat{\theta}_{cue})' \; \tilde{q}_t(\hat{\theta}_{cue})']', \; t = 1, \ldots, T\}$.

   (c) Compute:

$$\begin{aligned} \mathrm{K}(\hat{\theta}_{cue}) = \; & \tfrac{1}{T}\tilde{f}_T(\hat{\theta}_{cue}, Y)'\tilde{V}_{ff}(\hat{\theta}_{cue})^{-1}\tilde{D}_T(\hat{\theta}_{cue}, Y)[\tilde{D}_T(\hat{\theta}_{cue}, Y)'\tilde{V}_{ff}(\hat{\theta}_{cue})^{-1} \\ & \tilde{D}_T(\hat{\theta}_{cue}, Y)]^{-1}\tilde{D}_T(\hat{\theta}_{cue}, Y)'\tilde{V}_{ff}(\hat{\theta}_{cue})^{-1}\tilde{f}_T(\hat{\theta}_{cue}, Y). \end{aligned}$$

2.

   (a) Obtain bootstrap sample $\{\tilde{f}_t(\hat{\theta}_{cue}), \; t = 1, \ldots, T\}$ by drawing from $\{\bar{f}_t(\hat{\theta}_{cue}), \; t = 1, \ldots, T\}$ with replacement.

   (b) Construct: $\tilde{V}_{ff}(\hat{\theta}_{cue})$ and $\tilde{f}_T(\hat{\theta}_{cue}, Y)$ from the bootstrap sample $\{\tilde{f}_t(\hat{\theta}_{cue}), t = 1, \ldots, T\}$.

   (c) Compute:

$$\begin{aligned} \mathrm{K}(\hat{\theta}_{cue}) = \; & \tfrac{1}{T}\tilde{f}_T(\hat{\theta}_{cue}, Y)'\tilde{V}_{ff}(\hat{\theta}_{cue})^{-1}\tilde{D}_T(\hat{\theta}_{cue}, Y)[\tilde{D}_T(\hat{\theta}_{cue}, Y)'\tilde{V}_{ff}(\hat{\theta}_{cue})^{-1} \\ & \tilde{D}_T(\hat{\theta}_{cue}, Y)]^{-1}\tilde{D}_T(\hat{\theta}_{cue}, Y)'\tilde{V}_{ff}(\hat{\theta}_{cue})^{-1}\tilde{f}_T(\hat{\theta}_{cue}, Y). \end{aligned}$$

The first bootstrap algorithm incorporates the construction of $\hat{D}_T(\hat{\theta}_{cue}, Y)$ while the second bootstrap algorithm treats $\hat{D}_T(\hat{\theta}_{cue}, Y)$ as fixed and exogenous. Because of the independence of the first order behavior of D_0 from n_0, the approximation error of both bootstrap algorithms of the finite sample distribution of $\mathrm{K}(\theta_0)$ is of the same order and both should perform in a similar manner. We illustrate the performance of the bootstrap algorithms in Section 6 for a dynamic panel data model. When $[f_t(\theta)' \; q_t(\theta)']'$, $t = 1, \ldots, T$, are dependent, we draw blocks of consecutive realizations of $[f_t(\hat{\theta}_{cue})' \; q_t(\hat{\theta}_{cue})']'$ in step a of the bootstrap algorithms, see *e.g.* Hall and Horowitz (1996). By drawing blocks of the appropriate length, we incorporate the dependence of $[f_t(\hat{\theta}_{cue})' \; q_t(\hat{\theta}_{cue})']'$, $t = 1, \ldots, T$, into the bootstrap.

When we analyze time-series data and lagged observations are used as instruments, we generate the instruments by the bootstrap as well and adapt step a of the bootstrap algorithms. Instead of sampling $[\tilde{f}_t(\hat{\theta}_{cue})' \; \tilde{q}_t(\hat{\theta}_{cue})']'$, either as a single realization or as a block of consecutive realizations, from $\{[f_t(\hat{\theta}_{cue})' \; q_t(\hat{\theta}_{cue})']', \; t = 1, \ldots, T\}$ with replacement, we then sample $[\tilde{\varphi}(\hat{\theta}_{cue}, Y_t)' \; \mathrm{vec}\{\frac{\partial}{\partial \theta'}\tilde{\varphi}(\hat{\theta}_{cue}, Y_t)\}']'$ from $\{[\tilde{\varphi}(\hat{\theta}_{cue}, Y_t)' \; \mathrm{vec}\{\frac{\partial}{\partial \theta'}\tilde{\varphi}(\hat{\theta}_{cue}, Y_t)\}']', \; t = 1, \ldots, T\}$ with replacement. From the generated $[\tilde{\varphi}(\hat{\theta}_{cue}, Y_t)' \; \mathrm{vec}\{\frac{\partial}{\partial \theta'}\tilde{\varphi}(\hat{\theta}_{cue}, Y_t)\}']'$, we construct $[\tilde{f}_t(\hat{\theta}_{cue})' \; \tilde{q}_t(\hat{\theta}_{cue})']' = \{[\tilde{\varphi}(\hat{\theta}_{cue}, Y_t)' \; \mathrm{vec}\{\frac{\partial}{\partial \theta'}\tilde{\varphi}(\hat{\theta}_{cue}, Y_t)\}']' \otimes \tilde{X}_t)$ and solve for future values of the bootstrapped instruments, $\tilde{X}_{t+h}$, $h = 1, \ldots, H$, from $[\tilde{\varphi}(\hat{\theta}_{cue}, Y_t)' \; \mathrm{vec}\{\frac{\partial}{\partial \theta'}\tilde{\varphi}(\hat{\theta}_{cue}, Y_t)\}']'$.

$\mathbf{S}(\theta_0)$. The S-statistic $\mathrm{S}(\theta_0)$ is based on tests of the theoretical moment:

$$E[f_t(\theta_0)] = 0. \tag{71}$$

Because there is no value of θ_0 where this moment condition is satisfied when we use the corresponding empirical moment

$$\tfrac{1}{T} f_T(\theta_0, Y) = \tfrac{1}{T} \textstyle\sum_{t=1}^{T} f_t(\theta_0), \tag{72}$$

we use the value of θ that leads to the minimal value of (72), when scaled by its covariance matrix estimator $\hat{V}_{ff}(\theta)$, which is the CUE, $\hat{\theta}_{cue}$. We then use the recentered moments $\bar{f}_t(\hat{\theta}_{cue})$ to obtain bootstrap samples of $\mathrm{S}(\hat{\theta}_{cue})$. When $\bar{f}_t(\hat{\theta}_{cue})$, $t = 1, \ldots, T$, are independent, a bootstrap distribution of $\mathrm{S}(\hat{\theta}_{cue})$ is constructed by means of:

1. (a) Obtain bootstrap sample $\{\tilde{f}_t(\hat{\theta}_{cue}),\ t = 1, \ldots, T\}$ by drawing from $\{\bar{f}_t(\hat{\theta}_{cue}),\ t = 1, \ldots, T\}$ with replacement.
   (b) Construct: $\tilde{V}_{ff}(\hat{\theta}_{cue})$ and $\tilde{f}_T(\hat{\theta}_{cue}, Y)$ from the bootstrap sample $\{\tilde{f}_t(\hat{\theta}_{cue}), t = 1, \ldots, T\}$.
   (c) Compute:
$$\mathrm{S}(\hat{\theta}_{cue}) = \ \tfrac{1}{T} \tilde{f}_T(\hat{\theta}_{cue}, Y)' \tilde{V}_{ff}(\hat{\theta}_{cue})^{-1} \tilde{f}_T(\hat{\theta}_{cue}, Y).$$

When $\bar{f}_t(\hat{\theta}_{cue})$, $t = 1, \ldots, T$, are dependent, we generate blocks of consecutive realizations of $\tilde{f}_t(\hat{\theta}_{cue})$ in step a of the above bootstrap algorithm.

$\mathbf{J}_K(\theta_0)$. The J-statistic $\mathrm{J}_K(\theta_0)$ is based on the moment condition:

$$J(\theta_0)_\perp' E[f_t(\theta_0)] = 0, \tag{73}$$

with $J(\theta_0)_\perp : k_f \times (k_f - m)$, $J(\theta_0)_\perp' J(\theta_0) \equiv 0$, $J(\theta_0)_\perp' J(\theta_0)_\perp \equiv I_{k_f - m}$. Its corresponding empirical moment condition,

$$\hat{D}_T(\theta_0, Y)_\perp' f_T(\theta_0, Y) = 0, \tag{74}$$

with $\hat{D}_T(\theta_0, Y)_\perp : k_f \times (k_f - m)$, $\hat{D}_T(\theta_0, Y)_\perp' \hat{D}_T(\theta_0, Y) \equiv 0$, $\hat{D}_T(\theta_0, Y)_\perp' \hat{D}_T(\theta_0, Y)_\perp \equiv I_{k_f - m}$, is not satisfied for any value of θ_0. We therefore use the value of θ that leads to the minimal value of this empirical moment when scaled by its variance. This value of θ is the CUE, $\hat{\theta}_{cue}$. We recenter the moments based on the CUE:

$$f_t^*(\hat{\theta}_{cue}) = \ f_t(\hat{\theta}_{cue}) - V_{ff}(\hat{\theta}_{cue}) \hat{D}_T(\hat{\theta}_{cue}, Y)_\perp [\hat{D}_T(\hat{\theta}_{cue}, Y)_\perp' V_{ff}(\hat{\theta}_{cue}) \hat{D}_T(\hat{\theta}_{cue}, Y)_\perp]^{-1} \hat{D}_T(\hat{\theta}_{cue}, Y)_\perp' f_t(\hat{\theta}_{cue}) \tag{75}$$

and $f_T^*(\hat{\theta}_{cue}, Y) = \sum_{t=1}^{T} f_t^*(\hat{\theta}_{cue})$. For the recentered moments, the empirical moment condition (74) is satisfied at the CUE. An algorithm for obtaining a bootstrap distribution of $\mathrm{J}_K(\theta_0)$, when $[f_t(\theta)'\ q_t(\theta)']'$, $t = 1, \ldots, T$, are independently distributed, then reads:

1. (a) Obtain bootstrap sample $\{[\tilde{f}_t^*(\hat{\theta}_{cue})'\ \tilde{q}_t(\hat{\theta}_{cue})']',\ t = 1, \ldots, T\}$ by drawing from $\{[f_t^*(\hat{\theta}_{cue})'\ q_t(\hat{\theta}_{cue})']',\ t = 1, \ldots, T\}$ with replacement.
   (b) Construct: $\tilde{V}(\hat{\theta}_{cue})$, $\tilde{D}_T(\hat{\theta}_{cue}, Y)$ and $\tilde{f}_T^*(\hat{\theta}_{cue}, Y)$ from the bootstrap sample $\{[\tilde{f}_t^*(\hat{\theta}_{cue})'\ \tilde{q}_t(\hat{\theta}_{cue})']',\ t = 1, \ldots, T\}$.

(c) Compute:

$$\mathrm{J}_K(\hat{\theta}_{cue}) = \frac{1}{T}\tilde{f}_T^*(\hat{\theta}_{cue},Y)'\tilde{D}_T(\hat{\theta}_{cue},Y)_\perp[\tilde{D}_T(\hat{\theta}_{cue},Y)'_\perp\tilde{V}_{ff}(\hat{\theta}_{cue})^{-1}\tilde{D}_T(\hat{\theta}_{cue},Y)_\perp]^{-1}\tilde{D}_T(\hat{\theta}_{cue},Y)'_\perp\tilde{f}_T^*(\hat{\theta}$$

2.

(a) Obtain bootstrap sample $\{\tilde{f}_t^*(\hat{\theta}_{cue}),\ t = 1,\ldots,T\}$ by drawing from $\{f_t^*(\hat{\theta}_{cue}),\ t = 1,\ldots,T\}$ with replacement.

(b) Construct: $\tilde{V}_{ff}(\hat{\theta}_{cue})$ and $\tilde{f}_T^*(\hat{\theta}_{cue},Y)$ from the bootstrap sample $\{\tilde{f}_t(\hat{\theta}_{cue}), t = 1,\ldots,T\}$.

(c) Compute:

$$\mathrm{J}_K(\hat{\theta}_{cue}) = \frac{1}{T}\tilde{f}_T^*(\hat{\theta}_{cue},Y)'\tilde{D}_T(\hat{\theta}_{cue},Y)_\perp[\tilde{D}_T(\hat{\theta}_{cue},Y)'_\perp\tilde{V}_{ff}(\hat{\theta}_{cue})^{-1}\tilde{D}_T(\hat{\theta}_{cue},Y)_\perp]^{-1}\tilde{D}_T(\hat{\theta}_{cue},Y)'_\perp\tilde{f}_T^*(\hat{\theta}$$

In case of dependent data, we replace the generation of a single realization in step a of the bootstrap algorithms with a block of consecutive realizations. The recentered realizations $\bar{f}_t(\hat{\theta}_{cue})$ are also used to compute $\mathrm{K}(\hat{\theta}_{cue})$ in the algorithm for the bootstrap distribution of $\mathrm{J}_K(\hat{\theta}_{cue})$.

6 Power comparison for Panel AR(1) Model

Panel AR(1) model. We compare power curves of different statistics to test hypotheses on the autoregressive parameter in a panel autoregressive model of order 1 (AR(1)). For $\mathrm{K}(\theta_0)$, we use both critical values that result from the limiting distribution of its zero-th order element and from the bootstraps from Section 5. An elaborate literature on panel autoregressive (AR) models exists, see *e.g.* Anderson and Hsiao (1981), Arellano and Bond (1991) and Arellano and Honoré (2001). In panel data models the cross-section dimension N exceeds the time series dimension T. In line with the literature on panel data models, we therefore indicate the sample size by N. In the previous sections, the sample size was indicated by T.

For individual n at time t, the panel AR(1) model reads

$$y_{t,n} = \mu_n + \theta y_{t-1,n} + \varepsilon_{t,n} \qquad t = 1,\ldots,T,\ n = 1,\ldots,N. \tag{76}$$

The disturbances $\varepsilon_{t,n}$ are assumed to be independent with mean zero. We take first differences to remove individual specific constants:

$$\Delta y_{t,n} = \theta \Delta y_{t-1,n} + \Delta\varepsilon_{t,n} \qquad t = 2,\ldots,T,\ n = 1,\ldots,N, \tag{77}$$

with $\Delta y_{t,n} = y_{t,n} - y_{t-1,n}$. Estimation of the parameter θ in (77) by means of least squares leads to a biased estimator in samples with a finite value of T, see *e.g.* Nickel (1981). We therefore estimate it using GMM. The moment equation (1) for the panel AR(1) reads

$$E(\varphi(\theta,y_{t,n})|I_t) = E(\Delta\varepsilon_{t,n}|I_t) = E(\Delta y_{t,n} - \theta\Delta y_{t-1,n}|I_t) = 0 \qquad t = 2,\ldots,T,\ n = 1,\ldots,N. \tag{78}$$

A common choice of the instruments is to use all two period and more lagged level values of $y_{t,n}$, *i.e.* $X_{t,n} = (y_{t-2,n}\cdots y_{1,n})'$, see *e.g.* Arellano and Bond (1991). This leads to the specification of the moment equation $f_n(\theta)$,

$$f_n(\theta) = X_n\varphi_n(\theta) : \tfrac{1}{2}(T-1)(T-2)\times 1 \qquad n = 1,\ldots,N, \tag{79}$$

with $\varphi_n(\theta) = (\Delta y_{3,n} - \theta \Delta y_{2,n} \ldots \Delta y_{T,n} - \theta \Delta y_{T-1,n})'$ and

$$X_n = \begin{pmatrix} y_{1,n} & 0 \ldots 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 \ldots 0 & \begin{pmatrix} y_{1,n} \\ \vdots \\ y_{T-2,n} \end{pmatrix} \end{pmatrix} : \tfrac{1}{2}(T-1)(T-2) \times (T-2). \tag{80}$$

Besides the independence of $\varepsilon_{t,n}$ and finite fourth order moments, we make no assumptions about the covariance structure of $\varepsilon_{t,n}$. We therefore use White's (1980) covariance matrix estimator:

$$\hat{V}_{ff}(\theta) = \tfrac{1}{N} \textstyle\sum_{n=1}^{N} f_n(\theta) f_n(\theta)' : \tfrac{1}{2}(T-1)(T-2) \times \tfrac{1}{2}(T-1)(T-2). \tag{81}$$

We also use White's (1980) non-parametric covariance matrix estimator for $\hat{V}_{\theta f}(\theta)$ which is involved in $\mathrm{K}(\theta_0)$:

$$\hat{V}_{\theta f}(\theta) = \tfrac{1}{N} \textstyle\sum_{n=1}^{N} X_n [\frac{\partial}{\partial \theta} \varphi_n(\theta) - E(\frac{\partial}{\partial \theta} \varphi_n(\theta) | X_n)] f_n(\theta)' : \tfrac{1}{2}(T-1)(T-2) \times \tfrac{1}{2}(T-1)(T-2), \tag{82}$$

with

$$\tfrac{\partial}{\partial \theta} \varphi_n(\theta) - E(\tfrac{\partial}{\partial \theta} \varphi_n(\theta) | X_n) = \; - \begin{pmatrix} \Delta y_{2,n} - y_{1,n} \hat{\alpha}_1 \\ \vdots \\ \Delta y_{T-1,n} - (y_{1,n} \ldots y_{T-2,n}) \, \hat{\alpha}_{T-2} \end{pmatrix}, \tag{83}$$

where $\hat{\alpha}_1 : 1 \times 1, \ldots, \hat{\alpha}_{T-2} : (T-2) \times 1$, and

$$\begin{pmatrix} \hat{\alpha}_1 \\ \vdots \\ \hat{\alpha}_{T-2} \end{pmatrix} = \left(\textstyle\sum_{n=1}^{N} X_n X_n' \right)^{-1} \textstyle\sum_{n=1}^{N} X_n \begin{pmatrix} \Delta y_{2,n} \\ \vdots \\ \Delta y_{T-1,n} \end{pmatrix}. \tag{84}$$

The derivative $\frac{\partial}{\partial \theta} \varphi_n(\theta) = -(\Delta y_{2,n} \ldots \Delta y_{T-1,n})'$ is a white noise series when $\theta = 1$. The parameter θ is therefore not identified when it is equal to one. Weak identified values of θ then occur when it is close to one relative to the sample size, *i.e.* when $\frac{1-\theta}{N}$ is small. It implies that the statistics in Theorem 1 whose zero-th order elements depend on ν become size distorted when θ_0 is close to one relative to the sample size. We analyze this by computing power curves for the different statistics for various values of θ_0 and N.

Power comparison. We use the moment equations and covariance matrix estimators for the panel AR(1) model to conduct a size and power comparison of the different statistics discussed previously. We therefore compute power curves for $\mathrm{W}_{2s}(\theta_0)$, $\mathrm{W}_{cue}(\theta_0)$, $\mathrm{LM}(\theta_0)$ and $\mathrm{K}(\theta_0)$ that test $\mathrm{H}_0 : \theta = \theta_0$ with the covariance matrix estimators (81)-(82) and a 95% asymptotic critical value that results from the limiting distribution of the zero-th order term. We also compute the power curve of $\mathrm{K}(\theta_0)$ when we use the 95% critical values that result from the two bootstrap procedures discussed in Section 5.

We compute power curves of the different statistics using a data generating process that has independent disturbances $\varepsilon_{t,n}$ which are generated from a student t distribution with 10

degrees of freedom and mean zero and variance one. The bootstrap critical values are computed using 100 bootstrap realizations from the empirical distribution for each simulated dataset. The number of simulated datasets equals 1000. Panel 1 shows the power curves when $N = 50$, Panel 2 when $N = 100$ and Panel 3 when $N = 250$. The number of time periods is equal to six in all three panels, $T = 6$. All three panels contain the power curves for hypothezes that test for four different values of θ : 0.5, 0.7, 0.9 and 0.95.

Panel 1 shows the power curves for data sets with $T = 6$ and $N = 50$. It is clear from Panel 1 that $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{W}_{cue}(\theta_0)$ are size distorted when $N = 50$ and $T = 6$. The size distortion becomes more prominent for larger values of θ_0. This is in line with the deteriorating degree of identification of θ when it converges to one. Because of the absence of correlation between $f_n(\theta)$ and $\frac{\partial}{\partial\theta} f_n(\theta)$, $\mathrm{W}_{cue}(\theta_0)$ does not necessarily improve upon $\mathrm{W}_{2s}(\theta_0)$ which is expected from the higher order expressions in Theorem 1. The size distortion of $\mathrm{LM}(\theta_0)$ is much smaller than that of $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{W}_{cue}(\theta_0)$ and is also increasing when θ_0 approaches one. This indicates that a considerable part of the size distortion results from the covariance matrix estimator $\hat{V}(\theta)$ (81). $\mathrm{LM}(\theta_0)$ evaluates $\hat{V}(\theta)$ at θ_0 while $\mathrm{W}_{2s}(\theta_0)$ and $\mathrm{W}_{cue}(\theta_0)$ evaluate it at $\hat{\theta}_{2s}$ and $\hat{\theta}_{cue}$ resp.. Hence, a large part of the size distortion results from evaluating $\hat{V}(\theta)$ at an estimate of θ instead of the true value, see also Bond and Windmeijer (2003). The size distortion of $\mathrm{K}(\theta_0)$ when we use the asymptotic critical value is again smaller than that of $\mathrm{LM}(\theta_0)$ as is to be expected from the higher order expressions in Theorem 1. Also the size distortion of $\mathrm{K}(\theta_0)$ is somewhat increasing when θ_0 approaches one. This again results from $\hat{V}(\theta)$ whose importance for the size of $\mathrm{K}(\theta_0)$ increases as θ_0 approaches one. When we use either one of the two bootstrap critical values instead of the asymptotic critical value, the size distortion of $\mathrm{K}(\theta_0)$ only minorly depends on the value of θ. Both bootstrap critical values therefore improve the size of $\mathrm{K}(\theta_0)$. The power curves of $\mathrm{K}(\theta_0)$ using the bootstrap critical values are identical. The two bootstrap procedures from Section 5 therefore both perform adequately in correcting the size of $\mathrm{K}(\theta_0)$.

Panel 1: Power curves of $W_{2s}(\theta_0)$ (solid with stars), $W_{cue}(\theta_0)$ (solid with plusses), $LM(\theta_0)$ (dashed), $K(\theta_0)$ (solid) that test $H_0 : \theta = \theta_0$ with 95% significance using asymptotic critical value and bootstrap critical values 1 (dashed-dotted) and 2 (dotted) for $K(\theta_0)$, $T = 6$, $N = 50$.

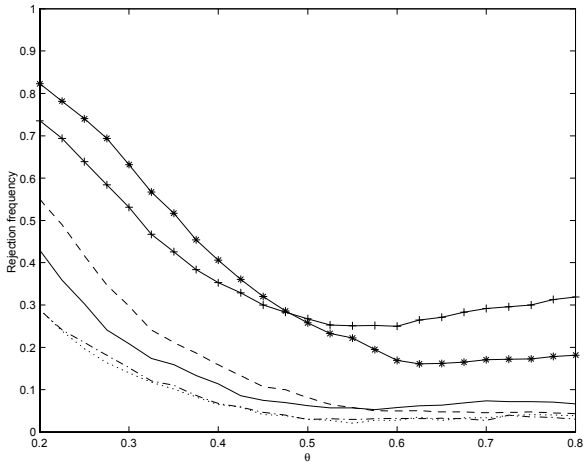

Figure 1.1: $\theta_0 = 0.5$

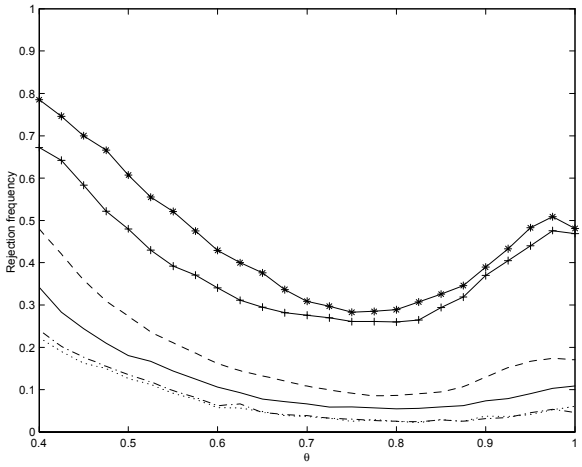

Figure 1.2: $\theta_0 = 0.7$

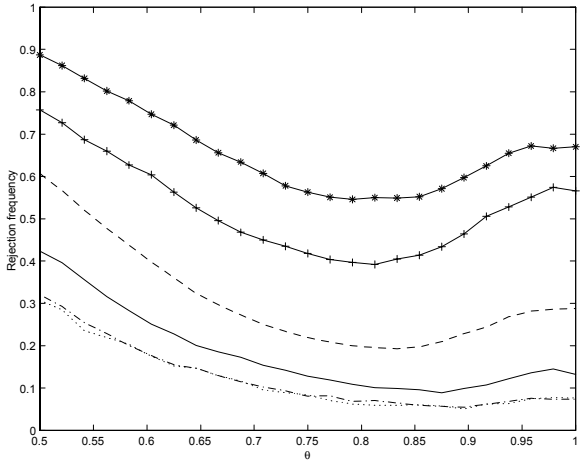

Figure 1.3: $\theta_0 = 0.9$

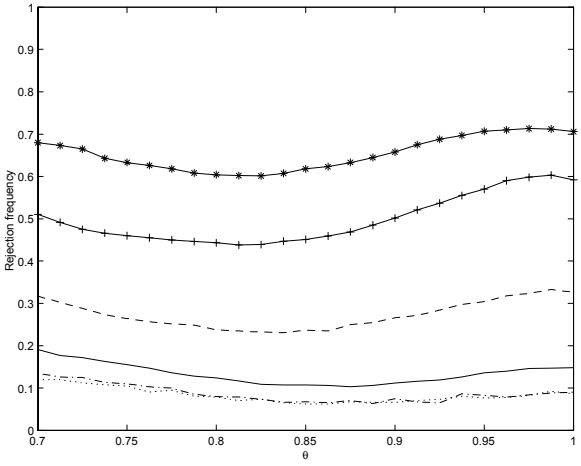

Figure 1.4: $\theta_0 = 0.95$

Panels 2 and 3 show that the size distortion of the different statistics reduces when N increases. The size of $K(\theta_0)$ with the bootstrap critical values remains the same but its power has, because of the larger number of observations, increased. Still the size distortion of most statistics remains considerable when $N = 100$ and for large values of θ_0 when $N = 250$. The power of these statistics, $W_{2s}(\theta_0)$, $W_{cue}(\theta_0)$ and $LM(\theta_0)$, is also distorted at $\theta = 1$ where θ is non-identified so the power should equal the size of 5%. The power of $W_{2s}(\theta_0)$, $W_{cue}(\theta_0)$ and $LM(\theta_0)$ for all values of θ_0 in Panels 1-3 does not equal 5% at $\theta = 1$ and is therefore erroneous. Panels 1-3 show that this erroneous power depends only to a minor extent on the sample size N. For large values of values N, we can, although their size-distortion becomes rather small, therefore still not interpret $W_{2s}(\theta_0)$, $W_{cue}(\theta_0)$ and $LM(\theta_0)$ in a trustworthy manner. The power of $K(\theta_0)$ is approximately equal to the size at $\theta = 1$ when we use the asymptotic critical value. Panels 1-3 show that the approximation error between the power at $\theta = 1$, when we use the asymptotic critical value,

and the size reduces when N increases. It is also hardly present when we use bootstrap critical values instead of asymptotic ones. This shows that the bootstrap works adequately in reducing the error in the size of $\mathrm{K}(\theta_0)$. Panel 3 shows that, as expected, the power curves of $\mathrm{K}(\theta_0)$ that result from using asymptotic or bootstrap critical values become indistinguishable when N gets large.

Panel 2: Power curves of $\mathrm{W}_{2s}(\theta_0)$ (solid with stars), $\mathrm{W}_{cue}(\theta_0)$ (solid with plusses), $\mathrm{LM}(\theta_0)$ (dashed), $\mathrm{K}(\theta_0)$ (solid) that test $\mathrm{H}_0 : \theta = \theta_0$ with 95% significance using asymptotic critical value and bootstrap critical values 1 (dashed-dotted) and 2 (dotted) for $\mathrm{K}(\theta_0)$, $T = 6$, $N = 100$.

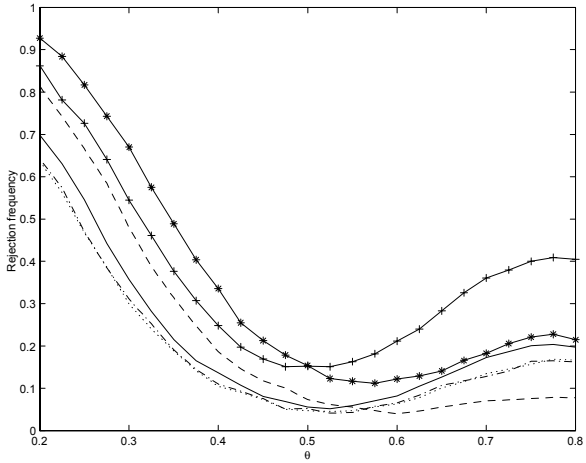

Figure 2.1: $\theta_0 = 0.5$

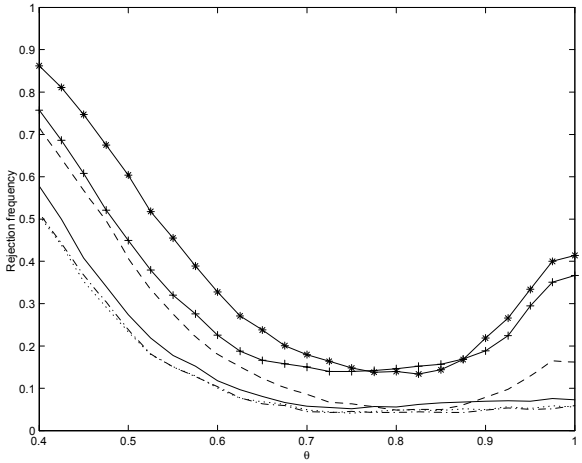

Figure 2.2: $\theta_0 = 0.7$

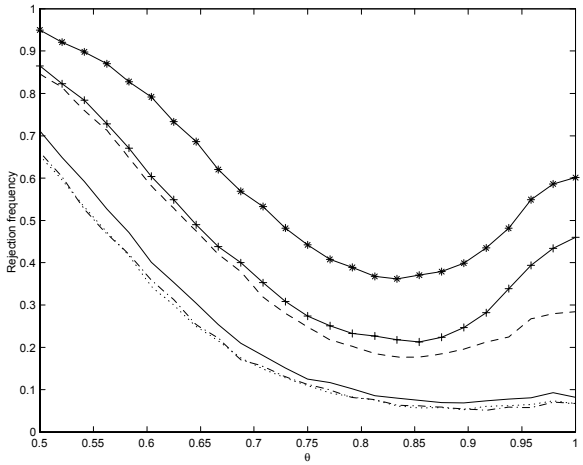

Figure 2.3: $\theta_0 = 0.9$

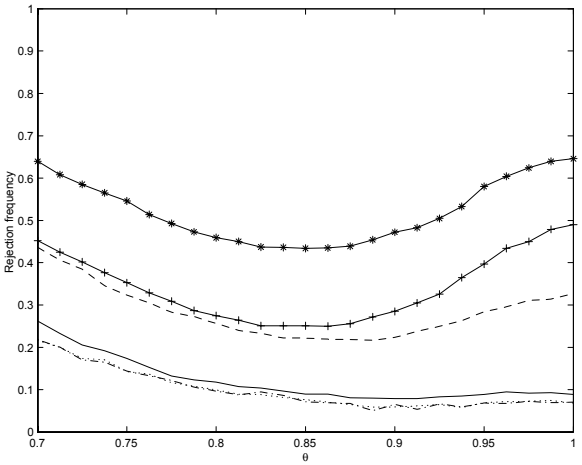

Figure 2.4: $\theta_0 = 0.95$

Panel 3: Power curves of $\mathrm{W}_{2s}(\theta_0)$ (solid with stars), $\mathrm{W}_{cue}(\theta_0)$ (solid with plusses), $\mathrm{LM}(\theta_0)$ (dashed), $\mathrm{K}(\theta_0)$ (solid) that test $\mathrm{H}_0 : \theta = \theta_0$ with 95% significance using asymptotic critical value and bootstrap critical values 1 (dashed-dotted) and 2 (dotted) for $\mathrm{K}(\theta_0)$, $T = 6,\ N = 250$.

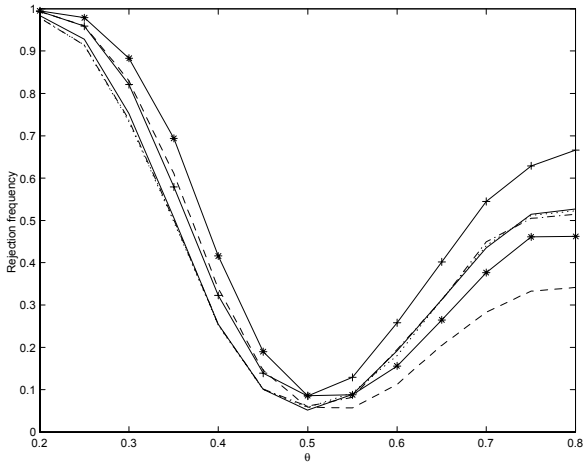

Figure 3.1: $\theta_0 = 0.5$

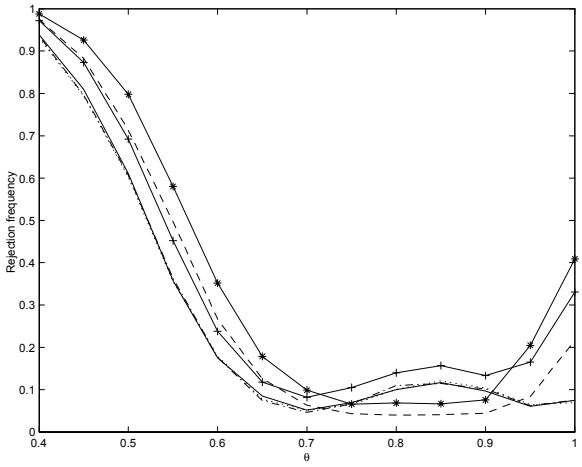

Figure 3.2: $\theta_0 = 0.7$

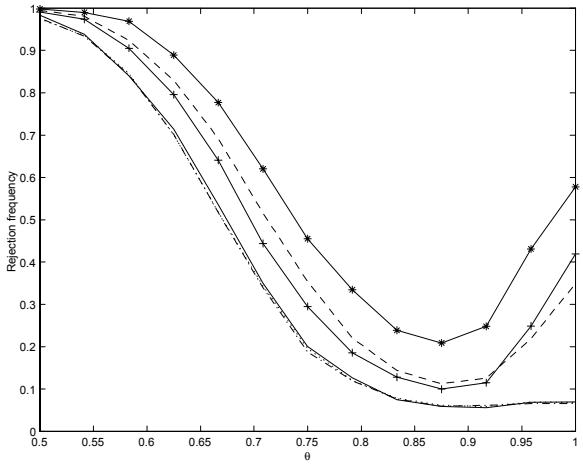

Figure 3.3: $\theta_0 = 0.9$

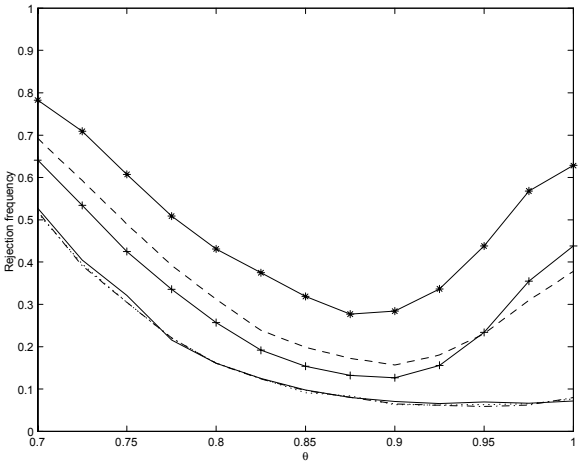

Figure 3.4: $\theta_0 = 0.95$

7 Conclusions

Appendix

Proof of Theorem 1.

We construct the higher order properties of the statistics (1, 2, 3 and 4) in a sequence of steps. First, we obtain the higher order properties of the score vectors involved in the different statistics, step a. Secondly, we obtain the higher order properties of the inverse of the covariance matrix, step b. We combine the different elements of the score vectors and the covariance matrix to obtain the higher order properties of the statistics, step c.

1a. Higher order properties of $f_T(\theta_0,Y)'V_{ff}(\hat\theta_{2s})^{-1}p_T(\hat\theta_{2s},Y)$ used in $\mathbf{W}_{2s}(\theta_0)$. To obtain the higher order elements for the 2-step Wald-statistic, we use that

$$(\hat\theta-\theta_0)\approx\ \ [p_T(\hat\theta_{2s},Y)'\hat V_{ff}(\hat\theta_{2s})^{-1}p_T(\hat\theta_{2s},Y)]^{-1}p_T(\hat\theta_{2s},Y)'\hat V_{ff}(\hat\theta_{2s})^{-1}f_T(\theta_0,Y).$$

We specify $p_T(\hat\theta_{2s},Y)$ as

$$p_T(\hat\theta_{2s},Y)=D_T(\theta_0,Y)+p_T(\hat\theta_{2s},Y)-\hat D_T(\hat\theta_{2s},Y)+\hat D_T(\hat\theta_{2s},Y)-D_T(\theta_0,Y),$$

with

$$\begin{aligned}&p_T(\hat\theta_{2s},Y)-\hat D_T(\hat\theta_{2s},Y)\\&=\Big[A_1\hat V_{\theta f,1}(\hat\theta_{2s})\hat V_{ff}(\hat\theta_{2s})^{-1}f_T(\hat\theta_{2s},Y)\cdots A_m\hat V_{\theta f,m}(\hat\theta_{2s})\hat V_{ff}(\hat\theta_{2s})^{-1}f_T(\hat\theta_{2s},Y)\Big]\\&=[A_1\hat V_{\theta f,1}(\hat\theta_{2s})\cdots A_m\hat V_{\theta f,m}(\hat\theta_{2s})][I_m\otimes\hat V_{ff}(\hat\theta_{2s})^{-1}f_T(\hat\theta_{2s},Y)]\end{aligned}$$

and $\hat V(\hat\theta_{2s})=V(\theta_0)+[\hat V(\hat\theta_{2s})-\hat V(\theta_0)]+[\hat V(\theta_0)-V(\theta_0)]=V(\theta_0)+[\hat V(\hat\theta_{2s})-V(\hat\theta_{2s})]+[V(\hat\theta_{2s})-V(\theta_0)]$. The convergence rate of $\hat V_{ff}(\hat\theta)-V_{ff}(\theta_0)$ and $\hat D_T(\hat\theta_{2s},Y)-D_T(\theta_0,Y)$ is therefore equal to $T^{-\frac12\kappa}$, with $\kappa=\min(\mu,\nu)$.

Using Assumption 1, $\frac{1}{\sqrt T}f_T(\theta_0,Y)'\hat V_{ff}(\hat\theta_{2s})^{-1}[T^{-\frac12(1+\nu)}p_T(\hat\theta_{2s},Y)]$ then reads

$$\begin{aligned}\tfrac{1}{\sqrt T}f_T(\theta_0,Y)'\hat V_{ff}(\hat\theta_{2s})^{-1}[T^{-\frac12(1+\nu)}p_T(\hat\theta_{2s},Y)]=\ \ &s_0+T^{-\frac{\nu}{2}}s_{1\nu,1}+T^{-\frac{\kappa}{2}}s_{1\kappa,1}+\\&T^{-\frac12(\nu+\kappa)}(s_{\nu+\kappa,1}+s_{\nu+\kappa,2})+T^{-\frac12(\nu+2\kappa)}s_{\nu+2\kappa,1}+o_p(T^{-\frac12}),\end{aligned}$$

with $\kappa=\min(\mu,\nu)$ and

$$\begin{aligned}s_0=\ &m_{0,f}'V_{ff}(\theta_0)^{-1}D_0\\s_{1\nu,1}=\ &m_{0,f}'V_{ff}(\theta_0)^{-1}\{\tfrac{1}{\sqrt T}[p_T(\hat\theta,Y)-\hat D_T(\hat\theta,Y)]\}\\=\ &m_{0,f}'V_{ff}(\theta_0)^{-1}[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m\otimes V_{ff}(\theta_0)^{-1}m_{0,f}]\\s_{1\kappa,1}=\ &T^{\frac{\kappa}{2}}m_{0,f}'[\hat V_{ff}(\theta_0)^{-1}-V_{ff}(\theta_0)^{-1}]D_0\\s_{\nu+\kappa,1}=\ &T^{\frac12(\kappa-1)}m_{0,f}'V_{ff}(\theta_0)^{-1}[\hat D_T(\hat\theta,Y)-D_T(\theta_0,Y)]\\=\ &T^{\frac12\kappa}m_{0,f}'V_{ff}(\theta_0)^{-1}\{[A_1\hat V_{\theta f,1}(\theta_0)\cdots A_m\hat V_{\theta f,m}(\theta_0)][I_m\otimes\hat V_{ff}(\theta_0)^{-1}]\\&-[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m\otimes V_{ff}(\theta_0)^{-1}]\}[I_m\otimes m_{0,f}]\\s_{\nu+\kappa,2}=\ &T^{\frac12\kappa}m_{0,f}'[\hat V_{ff}(\theta_0)^{-1}-V_{ff}(\theta_0)^{-1}][A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m\otimes V_{ff}(\theta_0)^{-1}m_{0,f}]\\s_{\nu+2\kappa,1}=\ &T^{\frac12(2\kappa-1)}m_{0,f}'[\hat V_{ff}(\theta_0)^{-1}-V_{ff}(\theta_0)^{-1}][\hat D_T(\theta_0,Y)-D_T(\theta_0,Y)],\end{aligned}$$

We also used that

$$m'_{0,f}V_{ff}(\theta_0)^{-1}[\hat{D}_T(\hat{\theta},Y) - D_T(\theta_0,Y)] =$$
$$m'_{0,f}V_{ff}(\theta_0)^{-1}[p_T(\hat{\theta},Y) - p_T(\theta_0,Y)] + m'_{0,f}V_{ff}(\theta_0)^{-1}\{[A_1V_{\theta f,1}(\hat{\theta})\cdots A_mV_{\theta f,m}(\hat{\theta})][I_m \otimes V_{ff}(\hat{\theta})^{-1}] -$$
$$[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}]\}[I_m \otimes V_{ff}(\theta_0)^{-1}m_{0,f}].$$

The convergence of $\hat{p}_T(\hat{\theta},Y) - p_T(\theta_0,Y)$ is of order $T^{\frac{1}{2}\nu}$ and therefore $T^{-\frac{1}{2}(1+\nu)}[\hat{p}_T(\hat{\theta},Y) - p_T(\theta_0,Y)]$ is of a lower order, $T^{-(1+\upsilon)}$, than the other elements. We have therefore left it out. The convergence rate of $m'_{0,f}V_{ff}(\theta_0)^{-1}[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}m_{0,f}]$ results from

$$E[\lim_{T\to\infty}\tfrac{1}{T}(f_T(\theta_0,Y)' \otimes f_T(\theta_0,Y)')] = \quad \mathrm{vec}[E(\lim_{T\to\infty}\tfrac{1}{T}f_T(\theta_0,Y)f_T(\theta_0,Y)'] = \mathrm{vec}[V_{ff}(\theta_0)],$$

so we obtain the expression for the limiting expectation:

$$\begin{aligned}
&E\{\lim_{T\to\infty}\tfrac{1}{T}f_T(\theta_0,Y)'V_{ff}(\theta_0)^{-1}[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}f_T(\theta_0,Y)]\}\\
&= [\{I_m \otimes \{E[\lim_{T\to\infty}\tfrac{1}{T}f_T(\theta_0,Y)' \otimes f_T(\theta_0,Y)']\}\\
&\qquad \mathrm{vec}[V_{ff}(\theta_0)^{-1}[A_1V_{\theta f,1}(\theta_0)V_{ff}(\theta_0)^{-1}\cdots A_mV_{\theta f,m}(\theta_0)V_{ff}(\theta_0)^{-1}]]]'\\
&= \{I_m \otimes \mathrm{vec}[V_{ff}(\theta_0)]'\}\mathrm{vec}[V_{ff}(\theta_0)^{-1}[A_1V_{\theta f,1}(\theta_0)V_{ff}(\theta_0)^{-1}\cdots A_mV_{\theta f,m}(\theta_0)V_{ff}(\theta_0)^{-1}]]\\
&= \mathrm{vec}[V_{ff}(\theta_0)^{-1}[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)]],
\end{aligned}$$

which shows the appropriate convergence rate.

2a. Higher order properties of $f_T(\theta_0,Y)'\hat{V}_{ff}(\hat{\theta}_{cue})^{-1}\hat{D}_T(\hat{\theta}_{cue},Y)$ used in $\mathbf{W}_{cue}(\theta_0)$.

$$\begin{aligned}
\tfrac{1}{\sqrt{T}}f_T(\theta_0,Y)'\hat{V}_{ff}(\hat{\theta}_{cue})^{-1}[T^{-\frac{1}{2}(1+\nu)}\hat{D}_T(\hat{\theta}_{cue},Y)] = \quad & s_0 + T^{-\frac{\kappa}{2}}s_{1\kappa,1} + T^{-\frac{1}{2}(\nu+\kappa)}s_{\nu+\kappa,1} +\\
& T^{-\frac{1}{2}(\nu+2\kappa)}s_{\nu+2\kappa,1} + o_p(T^{-\frac{1}{2}}),
\end{aligned}$$

with $\kappa = \min(\nu,\mu)$.

3a. Higher order properties of $f_T(\theta_0,Y)'V_{ff}(\theta_0)^{-1}p_T(\theta_0,Y)$ used in $\mathbf{LM}(\theta_0)$.

$$\begin{aligned}
\tfrac{1}{\sqrt{T}}f_T(\theta_0,Y)'\hat{V}_{ff}(\theta_0)^{-1}[T^{-\frac{1}{2}(1+\nu)}p_T(\theta_0,Y)] = \quad & s_0 + T^{-\frac{\nu}{2}}s_{1\nu,1} + T^{-\frac{\kappa}{2}}s_{1\kappa,1} + T^{-\frac{1}{2}(\nu+\kappa)}(s_{\nu+\kappa,1} + s_{\nu+\kappa,2}) +\\
& T^{-\frac{1}{2}(\nu+2\kappa)}s_{\nu+2\kappa,1} + o_p(T^{-\frac{1}{2}}),
\end{aligned}$$

with $\kappa = \mu$ since we evaluate all elements in θ_0 only.

4a. Higher order properties of $f_T(\theta_0,Y)'V_{ff}(\theta_0)^{-1}D_T(\theta_0,Y)$ used in $\mathbf{K}(\theta_0)$.

$$\begin{aligned}
\tfrac{1}{\sqrt{T}}f_T(\theta_0,Y)'\hat{V}_{ff}(\theta_0)^{-1}[T^{-\frac{1}{2}(1+\nu)}D_T(\theta_0,Y)] = \quad & s_0 + T^{-\frac{\kappa}{2}}s_{1\kappa,1} + T^{-\frac{1}{2}(\nu+\kappa)}s_{\nu+\kappa,1} +\\
& T^{-\frac{1}{2}(\nu+2\kappa)}s_{\nu+2\kappa,1},
\end{aligned}$$

with $\kappa = \mu$ since we evaluate all elements in θ_0 only.

1b. Higher order properties of $p_T(\hat{\theta},Y)'\hat{V}_{ff}(\hat{\theta})^{-1}p_T(\hat{\theta},Y)$ used in $\mathbf{W}_{2s}(\theta_0)$.

$$\begin{aligned}
&[T^{-\frac{1}{2}(1+\nu)}p_T(\hat{\theta}_{2s},Y)]'\hat{V}_{ff}(\hat{\theta}_{2s})^{-1}[T^{-\frac{1}{2}(1+\nu)}p_T(\hat{\theta}_{2s},Y)] = G_0 + T^{-\frac{\nu}{2}}G_{1\nu,1} + T^{-\frac{\kappa}{2}}G_{1\kappa,1} +\\
&T^{-\nu}G_{2\nu,1} + T^{-\frac{1}{2}(\nu+\kappa)}(G_{\nu+\kappa,1} + G_{\nu+\kappa,2}) + T^{-\frac{1}{2}(2\nu+\kappa)}(G_{2\nu+\kappa,1} + G_{2\nu+\kappa,2}) +\\
&T^{-\frac{1}{2}(\nu+2\kappa)}G_{\nu+2\kappa,1} + T^{-(\nu+\kappa)}(G_{2(\nu+\kappa),1} + G_{2(\nu+\kappa),2}) + T^{-\frac{2\nu+3\kappa}{2}}G_{2\nu+3\kappa,1} + O_p(T^{-\frac{1}{2}(2\nu+1)}),
\end{aligned}$$

with $\kappa = \min(\nu, \mu)$ and

$$\begin{aligned}
G_0 = \;& D_0' V_{ff}(\theta_0)^{-1} D_0 \\
G_{1\nu,1} = \;& D_0' V_{ff}(\theta_0)^{-1} [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}] + \\
& [I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}]' [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)]' V_{ff}(\theta_0)^{-1} D_0 \\
G_{1\kappa,1} = \;& T^{\frac{\kappa}{2}} D_0' [\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}] D_0 \\
G_{2\nu,1} = \;& [I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}]' [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)]' V_{ff}(\theta_0)^{-1} \\
& [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}] \\
G_{\nu+\kappa,1} = \;& T^{\frac{\kappa}{2}} D_0' [\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}] [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}] + \\
& T^{\frac{\kappa}{2}} [I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}]' [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)]' [\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}] D_0 \\
G_{\nu+\kappa,2} = \;& T^{\frac{1}{2}(\kappa-1)} [\hat{D}_T(\theta_0, Y) - D_T(\theta_0, Y)]' V_{ff}(\theta_0)^{-1} D_0 + \\
& T^{\frac{1}{2}(\kappa-1)} D_0' V_{ff}(\theta_0)^{-1} [\hat{D}_T(\theta_0, Y) - D_T(\theta_0, Y)] \\
G_{2\nu+\kappa,1} = \;& T^{\frac{1}{2}\kappa} [I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}]' [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)]' [\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}] \\
& [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}]
\end{aligned}$$

$$\begin{aligned}
G_{2\nu+\kappa,2} = \;& T^{\frac{1}{2}(\kappa-1)} [\hat{D}_T(\theta_0, Y) - D_T(\theta_0, Y)]' V_{ff}(\theta_0)^{-1} [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)] \\
& [I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}] + T^{\frac{1}{2}(\kappa-1)} [I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}]' [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)]' \\
& V_{ff}(\theta_0)^{-1} [\hat{D}_T(\theta_0, Y) - D_T(\theta_0, Y)] \\
G_{\nu+2\kappa,3} = \;& T^{\frac{1}{2}(2\kappa-1)} [\hat{D}_T(\theta_0, Y) - D_T(\theta_0, Y)]' [\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}] D_0 + \\
& T^{\frac{1}{2}(2\kappa-1)} D_0' [\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}] [\hat{D}_T(\theta_0, Y) - D_T(\theta_0, Y)] \\
G_{2\nu+2\kappa,1} = \;& T^{\frac{1}{2}(2\kappa-1)} [\hat{D}_T(\theta_0, Y) - D_T(\theta_0, Y)]' [\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}] [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)] \\
& [I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}] + T^{\frac{1}{2}(2\kappa-1)} [I_m \otimes V_{ff}(\theta_0)^{-1} m_{0,f}]' [A_1 V_{\theta f,1}(\theta_0) \cdots A_m V_{\theta f,m}(\theta_0)]' \\
& [\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}] [\hat{D}_T(\theta_0, Y) - D_T(\theta_0, Y)] \\
G_{2\nu+2\kappa,2} = \;& T^{(\kappa-1)} [\hat{D}_T(\theta_0, Y) - D_T(\theta_0, Y)]' V_{ff}(\theta_0)^{-1} [\hat{D}_T(\theta_0, Y) - D_T(\theta_0, Y)] \\
G_{2\nu+3\kappa,1} = \;& T^{\frac{1}{2}(3\kappa-2)} [D_T(\hat{\theta}, Y) - D_T(\theta_0, Y)]' [V_{ff}(\hat{\theta})^{-1} - V_{ff}(\theta_0)^{-1}] [D_T(\hat{\theta}, Y) - D_T(\theta_0, Y)]
\end{aligned}$$

Hence,

$$T^{(1+\nu)} [p_T(\hat{\theta}, Y)' V_{ff}(\theta_0)^{-1} p_T(\hat{\theta}, Y)]^{-1} = G_0^{-1} + T^{-\frac{\nu}{2}} Q_1,$$

with

$$Q_1 = -G_0^{-1} [(G_{1\nu,1} + T^{-\frac{\nu}{2}} H)^{-1} + T^{-\frac{\nu}{2}} G_0^{-1}]^{-1} G_0^{-1},$$

where $H = T^{-\frac{\kappa-2\nu}{2}} G_{1\kappa,1} + G_{2\nu,1} + T^{-\frac{1}{2}(\kappa-\nu)} (G_{\nu+\kappa,1} + G_{\nu+\kappa,2}) + T^{-\frac{1}{2}\kappa} (G_{2\nu+\kappa,1} + G_{2\nu+\kappa,2}) + T^{-\frac{1}{2}(2\kappa-\nu)} G_{\nu+2\kappa,1} + T^{-\kappa} (G_{2(\nu+\kappa),1} + G_{2(\nu+\kappa),2}) + T^{-\frac{3\kappa}{2}} G_{2\nu+3\kappa,1}$.

2b. Higher order properties of $p_T(\hat{\theta}, Y)' V_{ff}(\hat{\theta})^{-1} p_T(\hat{\theta}, Y)$ used in $\mathbf{W}_{cue}(\theta_0)$.

$$\begin{aligned}
& [T^{-\frac{1}{2}(1+\nu)} p_T(\hat{\theta}, Y)]' \hat{V}_{ff}(\hat{\theta})^{-1} [T^{-\frac{1}{2}(1+\nu)} p_T(\hat{\theta}, Y)] = G_0 + T^{-\frac{\kappa}{2}} G_{1\kappa,1} + T^{-\frac{1}{2}(\nu+\kappa)} G_{\nu+\kappa,2} + \\
& T^{-\frac{1}{2}(\nu+2\kappa)} G_{\nu+2\kappa,1} + T^{-(\nu+\kappa)} G_{2(\nu+\kappa),2} + T^{-\frac{1}{2}(2\nu+3\kappa)} G_{2\nu+3\kappa,1} + O_p(T^{-\frac{1}{2}(2\nu+1)}),
\end{aligned}$$

with $\kappa = \min(\nu, \mu)$. Hence,

$$T^{(1+\nu)} [p_T(\hat{\theta}, Y)' V_{ff}(\hat{\theta})^{-1} p_T(\hat{\theta}, Y)]^{-1} = G_0^{-1} + T^{-\frac{\kappa}{2}} Q_1,$$

with

$$Q_1 = \; -G_0^{-1} [(G_{1\kappa,1} + T^{-\frac{\kappa}{2}} H)^{-1} + T^{-\frac{\kappa}{2}} G_0^{-1}]^{-1} G_0^{-1},$$

where $H = T^{-\frac{1}{2}\nu}G_{\nu+\kappa,2} + T^{-\kappa}G_{\nu+2\kappa,1} + T^{-\frac{1}{2}(\nu+2\kappa)}G_{2(\nu+\kappa),2} + T^{-\frac{1}{2}(\nu+3\kappa)}G_{2\nu+3\kappa,1}$.

3b. Higher order properties of $p_T(\theta_0, Y)'\hat{V}_{ff}(\theta_0)^{-1}p_T(\theta_0, Y)$ used in LM(θ_0).

$$[T^{-\frac{1}{2}(1+\nu)}p_T(\theta_0, Y)]'\hat{V}_{ff}(\theta_0)^{-1}[T^{-\frac{1}{2}(1+\nu)}p_T(\theta_0, Y)] = G_0 + T^{-\frac{\nu}{2}}G_{1\nu,1} + T^{-\frac{\kappa}{2}}G_{1\kappa,1} + T^{-\nu}G_{2\nu,1} + T^{-\frac{1}{2}(\nu+\kappa)}(G_{\nu+\kappa,1} + G_{\nu+\kappa,2}) + T^{-\frac{1}{2}(2\nu+\kappa)}(G_{2\nu+\kappa,1} + G_{\nu+\kappa,2}) + T^{-\frac{1}{2}(\nu+2\kappa)}G_{\nu+2\kappa,1} + T^{-(\nu+\kappa)}(G_{2(\nu+\kappa),1} + G_{2(\nu+\kappa),2}) + T^{-\frac{1}{2}(2\nu+3\kappa)}G_{2\nu+3\kappa,1} + O_p(T^{-\frac{1}{2}(2\nu+1)}),$$

with $\kappa = \mu$. Hence,

$$T^{(1+\nu)}[p_T(\theta_0, Y)'\hat{V}_{ff}(\theta_0)^{-1}p_T(\theta_0, Y)]^{-1} = G_0^{-1} + T^{-\frac{\nu}{2}}Q_1,$$

with

$$Q_1 = \; -G_0^{-1}[(G_{1\kappa,1} + T^{-\frac{\nu}{2}}H)^{-1} + T^{-\frac{\nu}{2}}G_0^{-1}]^{-1}G_0^{-1},$$

where $H = T^{-\frac{\kappa-2\nu}{2}}G_{1\kappa,1} + G_{2\nu,1} + T^{-\frac{1}{2}(\kappa-\nu)}(G_{\nu+\kappa,1} + G_{\nu+\kappa,2}) + T^{-\frac{1}{2}\kappa}(G_{2\nu+\kappa,1} + G_{\nu+\kappa,2}) + T^{-\frac{1}{2}(2\kappa-\nu)}G_{\nu+2\kappa,1} + T^{-\kappa}(G_{2(\nu+\kappa),1} + G_{2(\nu+\kappa),2}) + T^{-\frac{3\kappa}{2}}G_{2\nu+3\kappa,1}$,

4b. Higher order properties of $\hat{D}_T(\theta_0, Y)'\hat{V}_{ff}(\theta_0)^{-1}\hat{D}_T(\theta_0, Y)$ used in K(θ_0).

$$[T^{-\frac{1}{2}(1+\nu)}\hat{D}_T(\theta_0, Y)]'\hat{V}_{ff}(\theta_0)^{-1}[T^{-\frac{1}{2}(1+\nu)}\hat{D}_T(\theta_0, Y)] = G_0 + T^{-\frac{\kappa}{2}}G_{1\kappa,1} + T^{-\frac{1}{2}(\nu+\kappa)}G_{\nu+\kappa,2} + T^{-\frac{1}{2}(\nu+2\kappa)}G_{\nu+2\kappa,1} + T^{-(\nu+\kappa)}G_{2(\nu+\kappa),2} + T^{-\frac{1}{2}(2\nu+3\kappa)}G_{2\nu+3\kappa,1} + O_p(T^{-\frac{1}{2}(2\nu+1)}),$$

with $\kappa = \mu$. Hence,

$$T^{(1+\nu)}\left[\hat{D}_T(\theta_0, Y)'\hat{V}_{ff}(\theta_0)^{-1}\hat{D}_T(\theta_0, Y)\right]^{-1} = G_0^{-1} + T^{-\frac{\kappa}{2}}Q_1,$$

with

$$Q_1 = \; -G_0^{-1}[(G_{1\kappa,1} + T^{-\frac{\kappa}{2}}H)^{-1} + T^{-\frac{\kappa}{2}}G_0^{-1}]^{-1}G_0^{-1},$$

where $H = T^{-\frac{1}{2}(\nu-\kappa)}G_{\nu+\kappa,2} + T^{-\frac{1}{2}\nu}G_{\nu+2\kappa,1} + T^{-\nu}G_{2(\nu+\kappa),2} + T^{-(\nu+\frac{1}{2}\kappa)}G_{2\nu+3\kappa,1}$.

1c. The higher order components of $\mathrm{W}_{2s}(\theta_0)$ that result from m_0 in Assumption 1 can be specified as:

$$\begin{aligned}\mathrm{W}_{2s}(\theta_0) = \; & n_0 + T^{-\frac{\nu}{2}}n_\nu + T^{-\frac{\kappa}{2}}n_\kappa + T^{-\frac{\nu+\kappa}{2}}n_{\nu+\kappa} + T^{-\nu}n_{2\nu} + T^{-\kappa}n_{2\kappa} \\ & + T^{-\frac{1}{2}(2\nu+\kappa)}n_{2\nu+\kappa} + T^{-\frac{1}{2}(\nu+2\kappa)}n_{\nu+2\kappa} + O_p(T^{-\frac{3}{2}\nu})\end{aligned}$$

with

$$\begin{aligned}
n_0 &= s_0'G_0^{-1}s_0 \\
n_\nu &= s_0'Q_1s_0 + s_{1\nu,1}'G_0^{-1}s_0 + s_0'G_0^{-1}s_{1\nu,1} \\
n_\kappa &= s_{1\kappa,1}'G_0^{-1}s_0 + s_0'G_0^{-1}s_{1\kappa,1} \\
n_{\nu+\kappa} &= s_{1\nu,1}'G_0^{-1}s_{1\kappa,1} + s_{1\kappa,1}'G_0^{-1}s_{1\nu,1} + s_{1\kappa,1}'Q_1s_0 + s_0'Q_1s_{1\nu+\kappa} + \\
&\quad (s_{\nu+\kappa,1} + s_{\nu+\kappa,2})'G_0^{-1}s_0 + s_0'G_0^{-1}(s_{\nu+\kappa,1} + s_{\nu+\kappa,2}) \\
n_{2\nu} &= s_{1\nu,1}'Q_1s_0 + s_0'Q_1s_{1\nu,1} + s_{1\nu,1}'G_0^{-1}s_{1\nu,1} \\
n_{2\kappa} &= s_{1\nu,\kappa}'G_0^{-1}s_{1\kappa,1} \\
n_{2\nu+\kappa} &= s_{1\nu,\kappa}'Q_1s_{1\kappa,1} + s_{1\kappa,1}'Q_1s_{1\nu,1} + (s_{\nu+\kappa,1} + s_{\nu+\kappa,2})'G_0^{-1}s_{1\nu,1} + s_{1\nu,1}'G_0^{-1}(s_{\nu+\kappa,1} + s_{\nu+\kappa,2}) \\
n_{\nu+2\kappa} &= (s_{\nu+\kappa,1} + s_{\nu+\kappa,2})'G_0^{-1}s_{1\kappa,1} + s_{1\kappa,1}'G_0^{-1}(s_{\nu+\kappa,1} + s_{\nu+\kappa,2}) + s_{\nu+2\kappa,1}'G_0^{-1}s_0 + \\
&\quad s_0'G_0^{-1}s_{\nu+\kappa,1} + s_{1\kappa,1}'Q_1s_{1\kappa,1}
\end{aligned}$$

and $\kappa = \min(\nu, \mu)$.

2c. The higher order components of $\mathrm{W}_{cue}(\theta_0)$ that result from m_0 in Assumption 1 can be specified as:

$$\mathrm{W}_{cue}(\theta_0) = \; n_0 + T^{-\frac{\kappa}{2}} n_\kappa + T^{-\frac{\nu+\kappa}{2}} n_{\nu+\kappa} + T^{-\kappa} n_{2\kappa} + T^{-\frac{\nu+2\kappa}{2}} n_{\nu+2\kappa} + T^{-\frac{3}{2}\kappa} n_{3\kappa} + o_p(T^{-\frac{3\kappa}{2}})$$

with

$$\begin{aligned}
n_0 &= s_0' G_0^{-1} s_0 \\
n_\kappa &= s_0' Q_1 s_0 + s_{1\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{1\kappa,1} \\
n_{\nu+\kappa} &= s_{\nu+\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{\nu+\kappa,1} \\
n_{2\kappa} &= s_{1\kappa,1}' G_0^{-1} s_{1\kappa,1} + s_{1\kappa,1}' Q_1 s_0 + s_0' Q_1 s_{1\kappa,1} \\
n_{\nu+2\kappa} &= s_{\nu+\kappa,1}' G_0^{-1} s_{1\kappa,1} + s_{1\kappa,1}' G_0^{-1} s_{\nu+\kappa,1} + s_0' G_0^{-1} s_{\nu+2\kappa,1} \\
&\quad s_0' Q_1 s_{\nu+\kappa,1} + s_{\nu+\kappa,1}' Q_1 s_0 + s_{\nu+2\kappa,1}' G_0^{-1} s_0 \\
n_{3\kappa} &= s_{1\kappa,1}' Q_1 s_{1\kappa,1}
\end{aligned}$$

and $\kappa = \min(\mu, \nu)$.

3c. The higher order components of $\mathrm{LM}(\theta_0)$ that result from m_0 in Assumption 1 can be specified as:

$$\begin{aligned}
\mathrm{LM}(\theta_0) = \; & n_0 + T^{-\frac{\nu}{2}} n_\nu + T^{-\frac{\kappa}{2}} n_\kappa + T^{-\frac{\nu+\kappa}{2}} n_{\nu+\kappa} + T^{-\nu} n_{2\nu} + T^{-\kappa} n_{2\kappa} \\
& + T^{-\frac{1}{2}(2\nu+\kappa)} n_{2\nu+\kappa} + T^{-\frac{1}{2}(\nu+2\kappa)} n_{\nu+2\kappa} + O_p(T^{-\frac{3}{2}\nu})
\end{aligned}$$

with $\kappa = \mu$ and

$$\begin{aligned}
n_0 &= s_0' G_0^{-1} s_0 \\
n_\nu &= s_0' Q_1 s_0 + s_{1\nu,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{1\nu,1} \\
n_\kappa &= s_{1\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{1\kappa,1} \\
n_{\nu+\kappa} &= s_{1\nu,1}' G_0^{-1} s_{1\kappa,1} + s_{1\kappa,1}' G_0^{-1} s_{1\nu,1} + s_{1\kappa,1}' Q_1 s_0 + s_0' Q_1 s_{1\kappa,1} + \\
&\quad s_{\nu+\kappa,2}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{\nu+\kappa,2} \\
n_{2\nu} &= s_{1\nu,1}' G_0^{-1} s_{1\nu,1} + s_{1\nu,1}' Q_1 s_0 + s_0' Q_1 s_{1\nu,1} \\
n_{2\kappa} &= s_{1\kappa,1}' G_0^{-1} s_{1\kappa,1} \\
n_{2\nu+\kappa} &= s_{1\kappa,1}' Q_1 s_{1\nu,1} + s_{1\nu,1}' Q_1 s_{1\kappa,1} + s_{\nu+\kappa,2}' Q_1 s_0 + s_{\nu+\kappa,2}' G_0^{-1} s_{\nu,1} + s_0' Q_1 s_{\nu+\kappa,2} + s_{1\nu,1}' G_0^{-1} s_{\nu+\kappa,2} \\
n_{\nu+2\kappa} &= s_{\nu+2\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{\nu+2\kappa,1} + s_{1\kappa,1}' Q_1 s_{1\kappa,1} + s_{\nu+\kappa,2}' G_0^{-1} s_{1\kappa,1} + s_{1\kappa,1}' G_0^{-1} s_{\nu+\kappa,2}
\end{aligned}$$

4c. The higher order components of $\mathrm{K}(\theta_0)$ that result from m_0 in Assumption 1 can be specified as:

$$\mathrm{K}(\theta_0) = \; n_0 + T^{-\frac{\kappa}{2}} n_\kappa + T^{-\frac{\nu+\kappa}{2}} n_{\nu+\kappa} + T^{-\kappa} n_{2\kappa} + T^{-\frac{\nu+2\kappa}{2}} n_{\nu+2\kappa} + T^{-\frac{3}{2}\kappa} n_{3\kappa} + o_p(T^{-\frac{3\kappa}{2}})$$

with $\kappa = \mu$ and

$$\begin{aligned}
n_0 &= s_0' G_0^{-1} s_0 \\
n_\kappa &= s_{1\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{1\kappa,1} + s_0' Q_1 s_0 \\
n_{\nu+\kappa} &= s_{\nu+\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{\nu+\kappa,1} \\
n_{2\kappa} &= s_{1\kappa,1}' G_0^{-1} s_{1\kappa,1} + s_{1\kappa,1}' Q_1 s_0 + s_0' Q_1 s_{1\kappa,1} \\
n_{\nu+2\kappa} &= s_{\nu+2\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{\nu+2\kappa,1} + s_{\nu+\kappa,1}' G_0^{-1} s_{1\kappa,1} + s_{1\kappa,1}' G_0^{-1} s_{\nu+\kappa,2} + \\
&\quad s_0' Q_1 s_{\nu+\kappa,1} + s_{\nu+\kappa,1}' Q_1 s_0 \\
n_{3\kappa} &= s_{1\kappa,1}' Q_1 s_{1\kappa,1}.
\end{aligned}$$

Lemma 2. We construct the conditional expectation of the limit expressions of n_ν and $n_{2\nu}$ given ρ when the number of observations converges to infinity. We begin with n_v which consists of two parts: $s'_{1\nu,1}G_0^{-1}s_0$ and $s'_0Q_1s_0$:
$\mathbf{s}'_{1\nu,1}\mathbf{G}_0^{-1}\mathbf{s}_0$: We specify ψ_f as

$$V_{ff}(\theta_0)^{-\frac{1}{2}}\psi_f = \quad V_{ff}(\theta_0)^{-\frac{1}{2}}D_0\rho + V_{ff}(\theta_0)^{\frac{1}{2}}D_{0,\perp}\lambda,$$

with $\rho = (D_0'V_{ff}(\theta_0)^{-1}D_0)^{-1}D_0'V_{ff}(\theta_0)^{-1}\psi_f$ and $\lambda = (D_{0,\perp}'V_{ff}(\theta_0)D_{0,\perp})^{-1}D_{0,\perp}'\psi_f$ and $D_{0,\perp} : k_f \times (k_f - m)$, $D_{0,\perp}'D_0 \equiv 0$, $D_{0,\perp}'D_{0,\perp} \equiv I_{k_f-m}$ so ρ and λ are independent and $\rho \sim N(0, (D_0'V_{ff}(\theta_0)^{-1}D_0)^{-1})$, $\lambda \sim N(0, (D_{0,\perp}'V_{ff}(\theta_0)D_{0,\perp})^{-1})$. This implies that $\lim_{T\to\infty}s'_{1\nu,1}G_0^{-1}s_0$ can be specified as:

$$\begin{aligned}
&\lim_{T\to\infty} s'_{1\nu,1}G_0^{-1}s_0 \\
&= \psi_f'V_{ff}(\theta_0)^{-1}[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f]\rho \\
&= [\lambda'D_{0,\perp}' + \rho'D_0'V_{ff}(\theta_0)^{-1}][A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][\rho \otimes \{V_{ff}(\theta_0)^{-1}D_0\rho + D_{0,\perp}\lambda\}] \\
&= \mathrm{tr}\{[\rho \otimes \{V_{ff}(\theta_0)^{-1}D_0\rho + D_{0,\perp}\lambda\}][\lambda'D_{0,\perp}' + \rho'D_0'V_{ff}(\theta_0)^{-1}][A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)]\},
\end{aligned}$$

since $[I_m \otimes d]c = [d'c_1 \ldots d'c_m]' = [c \otimes d]$ with c and d $m \times 1$ and $k_f \times 1$ vectors. Because

$$\begin{aligned}
&E\{[\rho \otimes \{V_{ff}(\theta_0)^{-1}D_0\rho + D_{0,\perp}\lambda\}][\lambda'D_{0,\perp} + \rho'D_0'V_{ff}(\theta_0)^{-1}]|\rho\} \\
&= E\{\rho \otimes V_{ff}(\theta_0)^{-1}D_0\rho\lambda'D_{0,\perp}|\rho\} + E\{\rho \otimes V_{ff}(\theta_0)^{-1}D_0\rho\rho'D_0'V_{ff}(\theta_0)^{-1}|\rho\} + \\
&\quad E\{\rho \otimes D_{0,\perp}\lambda\lambda'D_{0,\perp}|\rho\} + E\{\rho \otimes D_{0,\perp}\lambda\rho'D_0'V_{ff}(\theta_0)^{-1}|\rho\} \\
&= E\{\rho \otimes V_{ff}(\theta_0)^{-1}D_0\rho\rho'D_0'V_{ff}(\theta_0)^{-1}|\rho\} + E\{\rho \otimes D_{0,\perp}\lambda\lambda'D_{0,\perp}'|\rho\} \\
&= [\rho \otimes V_{ff}(\theta_0)^{-1}D_0\rho\rho'D_0'V_{ff}(\theta_0)^{-1}] + [\rho \otimes D_{0,\perp}(D_{0,\perp}'V_{ff}(\theta_0)D_{0,\perp})^{-1}D_{0,\perp}']
\end{aligned}$$

where we used that $E(\lambda) = 0$, $E(\rho|\rho) = \rho$ and $E(\lambda\lambda') = (D_{0,\perp}'V_{ff}(\theta_0)D_{0,\perp})^{-1}$, we obtain that

$$\begin{aligned}
&E[\lim_{T\to\infty} s'_{1\nu,1}G_0^{-1}s_0|\rho] \\
&= \mathrm{tr}\{[\rho \otimes V_{ff}(\theta_0)^{-1}D_0\rho\rho'D_0'V_{ff}(\theta_0)^{-1}][A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)]\} + \\
&\quad \mathrm{tr}\{[\rho \otimes D_{0,\perp}(D_{0,\perp}'V_{ff}(\theta_0)D_{0,\perp})^{-1}D_{0,\perp}'][A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)]\} \\
&= \textstyle\sum_{i=1}^m \mathrm{tr}\{\rho_iV_{ff}(\theta_0)^{-1}D_0\rho\rho'D_0'V_{ff}(\theta_0)^{-1}A_iV_{\theta f,i}(\theta_0)\} + \\
&\quad \textstyle\sum_{i=1}^m \mathrm{tr}\{\rho_iD_{0,\perp}(D_{0,\perp}'V_{ff}(\theta_0)D_{0,\perp})^{-1}D_{0,\perp}'A_iV_{\theta f,i}(\theta_0)\} \\
&= \textstyle\sum_{i=1}^m \rho_i\rho'D_0'V_{ff}(\theta_0)^{-1}A_iV_{\theta f,i}(\theta_0)V_{ff}(\theta_0)^{-1}D_0\rho + \\
&\quad \textstyle\sum_{i=1}^m \rho_i \sum_{j=1}^{k_f-m}\sum_{n=1}^{k_f-m}\left[(D_{0,\perp}'V_{ff}(\theta_0)D_{0,\perp})^{-1}\right]_{jn}[D_{0,\perp}'A_iV_{\theta f,i}(\theta_0)D_{0,\perp}]_{nj},
\end{aligned}$$

where $\left[(D_{0,\perp}'V_{ff}(\theta_0)D_{0,\perp})^{-1}\right]_{jn}$ and $[D_{0,\perp}'A_iV_{\theta f,i}(\theta_0)D_{0,\perp}]_{jn}$ are the jn-th element of the respective matrix.
$\mathbf{s}_0'\mathbf{Q}_1\mathbf{s}_0$: We assume that $\nu = \mu = 1$,

$$\begin{aligned}
&\lim_{T\to\infty} Q_1 = \lim_{T\to\infty} G_0^{-1}(G_{1\nu,1} + G_{1\kappa,1})G_0^{-1} = (D_0'V_{ff}(\theta_0)^{-1}D_0)^{-1}[D_0'V_{ff}(\theta_0)^{-1} \\
&[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m \otimes \{V_{ff}(\theta_0)^{-1}D_0\rho + D_{0,\perp}\lambda\}] + [I_m \otimes \{V_{ff}(\theta_0)^{-1}D_0\rho + D_{0,\perp}\lambda\}]' \\
&[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)]'V_{ff}(\theta_0)^{-1}D_0 + D_0'\Psi_uD_0](D_0'V_{ff}(\theta_0)^{-1}D_0)^{-1}
\end{aligned}$$

and

$$\begin{aligned}
&\lim_{T\to\infty} s_0'Q_1s_0 = \\
&\rho'\{[D_0'V_{ff}(\theta_0)^{-1}[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m \otimes \{V_{ff}(\theta_0)^{-1}D_0\rho + D_{0,\perp}\lambda\}] + \\
&[I_m \otimes \{V_{ff}(\theta_0)^{-1}D_0\rho + D_{0,\perp}\lambda\}]'[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)]'V_{ff}(\theta_0)^{-1}D_0 + D_0'\Psi_uD_0\}\rho \\
&= \rho'D_0'V_{ff}(\theta_0)^{-1}[A_1V_{\theta f,1}(\theta_0)\{V_{ff}(\theta_0)^{-1}D_0\rho + D_{0,\perp}\lambda\}\cdots A_mV_{\theta f,m}(\theta_0)\{V_{ff}(\theta_0)^{-1}D_0\rho + D_{0,\perp}\lambda\}]\rho + \\
&\rho'[A_1V_{\theta f,1}(\theta_0)\{V_{ff}(\theta_0)^{-1}D_0\rho + D_{0,\perp}\lambda\}\cdots A_mV_{\theta f,m}(\theta_0)\{V_{ff}(\theta_0)^{-1}D_0\rho + D_{0,\perp}\lambda\}]'V_{ff}(\theta_0)^{-1}D_0\rho + \\
&\rho'D_0'\Psi_uD_0\rho.
\end{aligned}$$

The conditional expectation of $\rho' D_0' \Psi_u D_0 \rho_0$ given ρ equals zero because, by Assumption 2, Ψ_u is independent of ψ_f. The conditional expectation of the remaining part of $s_0' Q_1 s_0$,

$$\begin{array}{l} E[\rho'\{D_0' V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes \{V_{ff}(\theta_0)^{-1} D_0\rho + D_{0,\perp}\lambda\}]\}\rho|\rho] \\ = \rho' D_0' V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][\rho \otimes V_{ff}(\theta_0)^{-1} D_0\rho] \\ = \sum_{i=1}^m \rho_i \rho' D_0' V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0) V_{ff}(\theta_0)^{-1} D_0\rho, \end{array}$$

which we have shown for the expression of $s_{1\nu,1}' G_0^{-1} s_0$ so

$$\lim_{T\to\infty} E[s_0' Q_1 s_0|\rho] = \sum_{i=1}^m \rho_i \rho' D_0' V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0) V_{ff}(\theta_0)^{-1} D_0\rho$$

and

$$\begin{array}{rl} \lim_{T\to\infty} E[n_\nu|\rho] = & 3\sum_{i=1}^m \rho_i \rho' D_0' V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0) V_{ff}(\theta_0)^{-1} D_0\rho + \\ & 2\sum_{i=1}^m \rho_i \sum_{j=1}^{k_f-m}\sum_{n=1}^{k_f-m} \left[(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-1}\right]_{jn} [D_{0,\perp}' A_i V_{\theta f,i}(\theta_0) D_{0,\perp}]_{nj}. \end{array}$$

$n_{2\nu}$ consists of $s_{1\nu,1}' Q_1 s_0$ and $s_{1\nu,1}' G_0^{-1} s_{1\nu,1}$. We construct the limit expressions of the conditional expectations of both of these expressions given ρ.
$\mathbf{s}_{1\nu,1}' \mathbf{Q}_1 \mathbf{s}_0$. We assume that $\nu = \mu = 1$,

$$\begin{array}{l} \lim_{T\to\infty} Q_1 = \lim_{T\to\infty} G_0^{-1}(G_{1\nu,1} + G_{1\kappa,1}) G_0^{-1} \\ = (D_0' V_{ff}(\theta_0)^{-1} D_0)^{-1}[D_0' V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes \{V_{ff}(\theta_0)^{-1} D_0\rho + D_{0,\perp}\lambda\}] \\ +[I_m \otimes \{V_{ff}(\theta_0)^{-1} D_0\rho + D_{0,\perp}\lambda\}]'[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)]' V_{ff}(\theta_0)^{-1} D_0 + \\ D_0' \Psi_u D_0](D_0' V_{ff}(\theta_0)^{-1} D_0)^{-1} \end{array}$$

so

$$\begin{array}{l} \lim_{T\to\infty} s_{1\nu,1}' Q_1 s_0 = \\ = \psi_f' V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f](D_0' V_{ff}(\theta_0)^{-1} D_0)^{-1}\{D_0' V_{ff}(\theta_0)^{-1} \\ [A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f] + [I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f]' \\ [A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)]' V_{ff}(\theta_0)^{-1} D_0 + D_0' \Psi_u D_0\}\rho. \end{array}$$

Because of the independence of Ψ_u and ρ, the conditional expectation of the part of $s_{1\nu,1}' Q_1 s_0$ that contains Ψ_u equals zero and can be left aside. We construct the conditional expectation of

the remaining two parts of $s'_{1\nu,1}Q_1 s_0$ given ρ :

$$
\begin{aligned}
&E\{\psi'_f V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}\\
&D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f]\rho|\rho\}\\
&= E\{\rho' D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}\\
&D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f]\rho|\rho\}+\\
&E\{\lambda' D'_{0,\perp}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}D'_0 V_{ff}(\theta_0)^{-1}\\
&[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f]\rho|\rho\}\\
&= E\{\rho' D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}\\
&D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f]\rho|\rho\} + E\{\rho' D'_0 V_{ff}(\theta_0)^{-1}\\
&[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes D_{0,\perp}\lambda](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}D'_0 V_{ff}(\theta_0)^{-1}\\
&[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f]\rho|\rho\} + E\{\lambda' D'_{0,\perp}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)]\\
&[I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)]\\
&[I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f]\rho|\rho\} + E\{\lambda' D'_{0,\perp}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes D_{0,\perp}\lambda]\\
&(D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f]\rho|\rho\}\\
&= \rho' D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}\\
&D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho]\rho + E\{\rho' D'_0 V_{ff}(\theta_0)^{-1}\\
&[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes D_{0,\perp}\lambda](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}D'_0 V_{ff}(\theta_0)^{-1}\\
&[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes D_{0,\perp}\lambda]\rho|\rho\} + E\{\lambda' D'_{0,\perp}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)]\\
&[I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)]\\
&[I_m \otimes D_{0,\perp}\lambda]\rho|\rho\} + E\{\lambda' D'_{0,\perp}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes D_{0,\perp}\lambda]\\
&(D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho]\rho|\rho\}\\
&= a_1 + a_2 + a_3 + a_4,
\end{aligned}
$$

because all other elements contain first and third order moments of λ which are equal to zero. The expressions for different a-terms read:

$$
\begin{aligned}
&a_1 = \rho' D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}\\
&D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho]\rho,
\end{aligned}
$$

$$
\begin{aligned}
&a_2 = E\{\rho' D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes D_{0,\perp}\lambda](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}\\
&D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][\rho \otimes D_{0,\perp}\lambda]|\rho\}\\
&= E\{\mathrm{tr}([\rho \otimes D_{0,\perp}\lambda][\rho' D'_0 V_{ff}(\theta_0)^{-1}A_1 V_{\theta f,1}(\theta_0)D_{0,\perp}\lambda\cdots\rho' D'_0 V_{ff}(\theta_0)^{-1}A_m V_{\theta f,m}(\theta_0)D_{0,\perp}\lambda]\\
&(D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)])|\rho\}\\
&= E\{\mathrm{tr}([\rho \otimes D_{0,\perp}][\lambda\rho' D'_0 V_{ff}(\theta_0)^{-1}A_1 V_{\theta f,1}(\theta_0)D_{0,\perp}\lambda\cdots\lambda\rho' D'_0 V_{ff}(\theta_0)^{-1}A_m V_{\theta f,m}(\theta_0)D_{0,\perp}\lambda]\\
&(D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)])|\rho\}\\
&= \mathrm{tr}([\rho \otimes D_{0,\perp}][\textstyle\sum_{i=1}^{k_f-m}(D_{0,\perp}V_{ff}(\theta_0)D_{0,\perp})_i^{-1}\rho' D'_0 V_{ff}(\theta_0)^{-1}A_1 V_{\theta f,1}(\theta_0)_i\cdots\\
&\textstyle\sum_{i=1}^{k_f-m}\mathrm{tr}\{(D_{0,\perp}V_{ff}(\theta_0)D_{0,\perp})_i^{-1}\rho' D'_0 V_{ff}(\theta_0)^{-1}A_m V_{\theta f,m}(\theta_0)_i](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}D'_0 V_{ff}(\theta_0)^{-1}\\
&[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)])
\end{aligned}
$$

since

$$E(\lambda b'\lambda) = \quad E(\lambda \textstyle\sum_{i=1}^{k_f-m} b_i\lambda_i) = \sum_{i=1}^{k_f-m}(D_{0,\perp}V_{ff}(\theta_0)D_{0,\perp})_i^{-1}b_i,$$

with b_i the i-th element of the $(k_f-m)\times 1$ vector b and $(D_{0,\perp}V_{ff}(\theta_0)D_{0,\perp})_i^{-1}$ the i-th column of

$(D_{0,\perp}V_{ff}(\theta_0)D_{0,\perp})^{-1}$.

$a_3 = E\{\lambda' D'_{0,\perp}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}$
$D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes D_{0,\perp}\lambda]\rho|\rho\} = E\{\mathrm{tr}([\rho \otimes D_{0,\perp}\lambda\lambda' D'_{0,\perp}$
$[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}D'_0 V_{ff}(\theta_0)^{-1}$
$[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)])|\rho\} = E\{\mathrm{tr}([\rho \otimes D_{0,\perp}(D_{0,\perp}V_{ff}(\theta_0)D_{0,\perp})^{-1}D'_{0,\perp}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)]$
$[I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)]),$

and

$a_4 = E\{\lambda' D'_{0,\perp}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes D_{0,\perp}\lambda](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}$
$D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho]\rho|\rho\} =$
$E\{[\lambda' D'_{0,\perp}A_1 V_{\theta f,1}(\theta_0)D_{0,\perp}\lambda\cdots\lambda' D'_{0,\perp}A_m V_{\theta f,m}(\theta_0)D_{0,\perp}\lambda](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}D'_0 V_{ff}(\theta_0)^{-1}$
$[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho]\rho|\rho\} =$
$[\mathrm{tr}(D_{0,\perp}(D_{0,\perp}V_{ff}(\theta_0)D_{0,\perp})^{-1}D'_{0,\perp}A_1 V_{\theta f,1}(\theta_0))\ldots\mathrm{tr}(D_{0,\perp}(D_{0,\perp}V_{ff}(\theta_0)D_{0,\perp})^{-1}D'_{0,\perp}A_m V_{\theta f,m}(\theta_0))]$
$(D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}D'_0 V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}D_0\rho]\rho,$

so $\lim_{T\to\infty} E(s'_{1\nu,1}Q_1 s_0|\rho) = a_1 + a_2 + a_3 + a_4$.
$\mathbf{s}'_{1\nu,1}\mathbf{G}_0^{-1}\mathbf{s}_{1\nu,1}$:

$$\lim_{T\to\infty}\mathbf{s}'_{1\nu,1}\mathbf{G}_0^{-1}\mathbf{s}_{1\nu,1} = E\{\psi'_f V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f]$$
$$(D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}[I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f]'[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)]' V_{ff}(\theta_0)^{-1}\psi_f|\rho\}.$$

We construct the conditional expectation given ρ by substituting $V_{ff}(\theta_0)^{-\frac{1}{2}}\psi_f = V_{ff}(\theta_0)^{-\frac{1}{2}}D_0\rho + V_{ff}(\theta_0)^{\frac{1}{2}}D_{0,\perp}\lambda$,

$\{\psi'_f V_{ff}(\theta_0)^{-1}[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}$
$[I_m \otimes V_{ff}(\theta_0)^{-1}\psi_f]'[A_1 V_{\theta f,1}(\theta_0)\cdots A_m V_{\theta f,m}(\theta_0)]' V_{ff}(\theta_0)^{-1}\psi_f|\rho\} =$
$E\{[\psi'_f V_{ff}(\theta_0)^{-1}A_1 V_{\theta f,1}(\theta_0)V_{ff}(\theta_0)^{-1}\psi_f\cdots\psi'_f V_{ff}(\theta_0)^{-1}A_m V_{\theta f,m}(\theta_0)V_{ff}(\theta_0)^{-1}\psi_f](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}$
$[\psi'_f V_{ff}(\theta_0)^{-1}A_1 V_{\theta f,1}(\theta_0)V_{ff}(\theta_0)^{-1}\psi_f\cdots\psi'_f V_{ff}(\theta_0)^{-1}A_m V_{\theta f,m}(\theta_0)V_{ff}(\theta_0)^{-1}\psi_f]'|\rho\} =$
$= \sum_{i=1}^m\sum_{j=1}^m E\{[\psi'_f V_{ff}(\theta_0)^{-1}A_i V_{\theta f,i}(\theta_0)V_{ff}(\theta_0)^{-1}\psi_f][\psi'_f V_{ff}(\theta_0)^{-1}A_j V_{\theta f,j}(\theta_0)V_{ff}(\theta_0)^{-1}\psi_f]|\rho\}$
$(D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}_{ij}$
$= \sum_{i=1}^m\sum_{j=1}^m E\{[(\rho' D'_0 V_{ff}(\theta_0)^{-1} + \lambda' D'_{0,\perp})A_i V_{\theta f,i}(\theta_0)(V_{ff}(\theta_0)^{-1}D_0\rho + D_{0,\perp}\lambda)]$
$[(\rho' D'_0 V_{ff}(\theta_0)^{-1} + \lambda' D'_{0,\perp})A_j V_{\theta f,j}(\theta_0)(V_{ff}(\theta_0)^{-1}D_0\rho + D_{0,\perp}\lambda)]|\rho\}(D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}_{ij}$
$= \sum_{i=1}^m\sum_{j=1}^m\{[\rho' D'_0 V_{ff}(\theta_0)^{-1}A_i V_{\theta f,i}(\theta_0)V_{ff}(\theta_0)^{-1}D_0\rho][\rho' D'_0 V_{ff}(\theta_0)^{-1}A_j V_{\theta f,j}(\theta_0)V_{ff}(\theta_0)^{-1}D_0\rho] +$
$2[\rho' D'_0 V_{ff}(\theta_0)^{-1}A_i V_{\theta f,i}(\theta_0)V_{ff}(\theta_0)^{-1}D_0\rho]\mathrm{tr}[D_{0,\perp}(D'_{0,\perp}V_{ff}(\theta_0)D_{0,\perp})^{-1}D'_{0,\perp}A_j V_{\theta f,j}(\theta_0)] +$
$E\{\mathrm{tr}[D_{0,\perp}\lambda\lambda' D'_{0,\perp}A_i V_{\theta f,i}(\theta_0)]\mathrm{tr}[D_{0,\perp}\lambda\lambda' D'_{0,\perp}A_j V_{\theta f,j}(\theta_0)] +$
$[\rho' D'_0 V_{ff}(\theta_0)^{-1}A_i V_{\theta f,i}(\theta_0)D_{0,\perp}\lambda][\rho' D'_0 V_{ff}(\theta_0)^{-1}A_j V_{\theta f,j}(\theta_0)D_{0,\perp}\lambda] + 2[\rho' D'_0 V_{ff}(\theta_0)^{-1}A_i V_{\theta f,i}(\theta_0)D_{0,\perp}\lambda]$
$[\lambda' D'_{0,\perp}A_j V_{\theta f,j}(\theta_0)V_{ff}(\theta_0)^{-1}D_0\rho]|\rho\}\}(D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}_{ij}$
$= \sum_{i=1}^m\sum_{j=1}^m[a_{ij} + b_{ij} + c_{ij} + d_{ij} + e_{ij}](D'_0 V_{ff}(\theta_0)^{-1}D_0)^{-1}_{ij},$

with

$$
\begin{aligned}
a_{ij} = \;& \{[\rho' D_0' V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0) V_{ff}(\theta_0)^{-1} D_0 \rho][\rho' D_0' V_{ff}(\theta_0)^{-1} A_j V_{\theta f,j}(\theta_0) V_{ff}(\theta_0)^{-1} D_0 \rho] \\
b_{ij} = \;& 2[\rho' D_0' V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0) V_{ff}(\theta_0)^{-1} D_0 \rho] \mathrm{tr}[D_{0,\perp}(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-1} D_{0,\perp}' A_j V_{\theta f,j}(\theta_0)] \\
c_{ij} = \;& 3 \textstyle\sum_{i_1=1}^{k_f-m} [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}\prime} D_{0,\perp}' A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}}]_{i_1 i_1}^2 + \\
& 2 \textstyle\sum_{i_1=1}^{k_f-m} \sum_{j_1=1, j_1 \neq i_1}^{k_f-m} [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}\prime} D_{0,\perp}' A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}}]_{i_1 i_1} \\
& [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}\prime} D_{0,\perp}' A_j V_{\theta f,j}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}}]_{j_1 j_1} + \\
& 2 \textstyle\sum_{i_1=1}^{k_f-m} \sum_{j_1=1, j_1 \neq i_1}^{k_f-m} [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}\prime} D_{0,\perp}' A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}}]_{i_1 j_1} \\
& [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}\prime} D_{0,\perp}' A_j V_{\theta f,j}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}}]_{i_1 j_1} + \\
& 2 \textstyle\sum_{i_1=1}^{k_f-m} \sum_{j_1=1, j_1 \neq i_1}^{k_f-m} [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}\prime} D_{0,\perp}' A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}}]_{i_1 j_1} \\
& [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}\prime} D_{0,\perp}' A_j V_{\theta f,j}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}}]_{j_1 i_1} \\
d_{ij} = \;& \rho' D_0' V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp} V_{ff}(\theta_0) D_{0,\perp})^{-1} D_{0,\perp} V_{\theta f,j}(\theta_0)' A_j' V_{ff}(\theta_0)^{-1} D_0 \rho \\
e_{ij} = \;& 2\rho' D_0' V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp} V_{ff}(\theta_0) D_{0,\perp})^{-1} D_{0,\perp} V_{\theta f,j}(\theta_0)' A_j' V_{ff}(\theta_0)^{-1} D_0 \rho.
\end{aligned}
$$

since all first and third order moments with respect to λ are equal to zero and

$$
\begin{aligned}
& E\{\mathrm{tr}[D_{0,\perp}\lambda\lambda' D_{0,\perp}' A_i V_{\theta f,i}(\theta_0)] \mathrm{tr}[D_{0,\perp}\lambda\lambda' D_{0,\perp}' A_j V_{\theta f,j}(\theta_0)] | \rho\} = \\
& E\{\lambda' D_{0,\perp}' A_i V_{\theta f,i}(\theta_0) D_{0,\perp} \lambda\lambda' D_{0,\perp}' A_j V_{\theta f,j}(\theta_0) D_{0,\perp}\lambda\} = \\
& E\{\zeta' (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}\prime} D_{0,\perp}' A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}} \zeta \\
& \zeta' (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}\prime} D_{0,\perp}' A_j V_{\theta f,j}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}} \zeta\} = \\
& \textstyle\sum_{i_1=1}^{k_f-m} \sum_{i_2=1}^{k_f-m} \sum_{j_1=1}^{k_f-m} \sum_{j_2=1}^{k_f-m} \zeta_{i_1}\zeta_{i_2}\zeta_{j_1}\zeta_{j_2} [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}\prime} D_{0,\perp}' A_i V_{\theta f,i}(\theta_0) D_{0,\perp} \\
& (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}}]_{i_1 i_2} [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}\prime} D_{0,\perp}' A_j V_{\theta f,j}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}}]_{j_1 j_2} = \\
& 3 \textstyle\sum_{i_1=1}^{k_f-m} [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}\prime} D_{0,\perp}' A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}}]_{i_1 i_1}^2 + \\
& 2 \textstyle\sum_{i_1=1}^{k_f-m} \sum_{j_1=1, j_1 \neq i_1}^{k_f-m} [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}\prime} D_{0,\perp}' A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}}]_{i_1 i_1} \\
& [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}\prime} D_{0,\perp}' A_j V_{\theta f,j}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}}]_{j_1 j_1} + \\
& 2 \textstyle\sum_{i_1=1}^{k_f-m} \sum_{j_1=1, j_1 \neq i_1}^{k_f-m} [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}\prime} D_{0,\perp}' A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}}]_{i_1 j_1} \\
& [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}\prime} D_{0,\perp}' A_j V_{\theta f,j}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}}]_{i_1 j_1} + \\
& 2 \textstyle\sum_{i_1=1}^{k_f-m} \sum_{j_1=1, j_1 \neq i_1}^{k_f-m} [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}\prime} D_{0,\perp}' A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}}]_{i_1 j_1} \\
& [(D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}\prime} D_{0,\perp}' A_j V_{\theta f,j}(\theta_0) D_{0,\perp} (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{\frac{1}{2}}]_{j_1 i_1},
\end{aligned}
$$

where we used that $\zeta = (D_{0,\perp}' V_{ff}(\theta_0) D_{0,\perp})^{-\frac{1}{2}} \lambda \sim N(0, I_{k-m})$. Only second and fourth order moments of the same elements of ζ are therefore non-zero.

$$
\begin{aligned}
& E\{[\rho' D_0' V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0) D_{0,\perp}\lambda][\rho' D_0' V_{ff}(\theta_0)^{-1} A_j V_{\theta f,j}(\theta_0) D_{0,\perp}\lambda] | \rho\} \\
& = E\{[\rho' D_0' V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0) D_{0,\perp}\lambda][\lambda' D_{0,\perp} V_{\theta f,j}(\theta_0)' A_j' V_{ff}(\theta_0)^{-1} D_0 \rho | \rho\} \\
& = \rho' D_0' V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp} V_{ff}(\theta_0) D_{0,\perp})^{-1} D_{0,\perp} V_{\theta f,j}(\theta_0)' A_j' V_{ff}(\theta_0)^{-1} D_0 \rho
\end{aligned}
$$

and

$$
\begin{aligned}
& E\{[\rho' D_0' V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0) D_{0,\perp}\lambda][\lambda' D_{0,\perp}' A_j V_{\theta f,j}(\theta_0) V_{ff}(\theta_0)^{-1} D_0 \rho] | \rho\} = \\
& = \rho' D_0' V_{ff}(\theta_0)^{-1} A_i V_{\theta f,i}(\theta_0) D_{0,\perp} (D_{0,\perp} V_{ff}(\theta_0) D_{0,\perp})^{-1} D_{0,\perp} V_{\theta f,j}(\theta_0)' A_j' V_{ff}(\theta_0)^{-1} D_0 \rho.
\end{aligned}
$$

The conditional expectation of $n_{2\nu}$ given ρ therefore reads:

$$
E[\lim_{T\to\infty} n_{2\nu} | \rho] = \; a_1 + a_2 + a_3 + a_4 + \textstyle\sum_{i=1}^{m} \sum_{j=1}^{m} [a_{ij} + b_{ij} + c_{ij} + d_{ij} + e_{ij}].
$$

Proof of Theorem 2.

1a. $\mathbf{W}_{2s}(\theta_0)$. Because $m_{0,f}$ is stochastically bounded and converges to ψ_f when T goes to infinity, the results of Lemma 6 of Phillips and Moon (1999) apply and we can let T and k converge to infinity sequentially, so first T and then k. We construct the order of the different elements of $\mathrm{W}_{2s}(\theta_0)$ when T and k jointly converge to infinity for which we assume that $D_T(\theta_0,Y)'V_{ff}(\theta_0)^{-1}D_T(\theta_0,Y)$ is of the order $T^{1+\nu}$ and $D_T(\theta_0,Y)'V_{ff}(\theta_0)^{-1}f_T(\theta_0,Y)$ is of order $T^{\frac{1}{2}(2+\nu)}$.

When k goes to infinity proportional to T^α and $\nu \geq \alpha$,

$$\begin{array}{l}\frac{1}{\sqrt{T}}f_T(\theta_0,Y)'V_{ff}(\hat{\theta}_{2s})^{-1}[T^{-\frac{1}{2}(1+\nu)}p_T(\hat{\theta}_{2s},Y)] = s_0 + T^{-\frac{\nu-2\alpha}{2}}s_{\nu-2\alpha,1} + T^{-\frac{\kappa}{2}}s_{1\kappa,1} + \\ T^{-\frac{1}{2}(\nu+\kappa-2\alpha)}(s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2}) + T^{-\frac{1}{2}(\nu+2(\kappa-\alpha))}s_{\nu+2(\kappa-\alpha),1},\end{array}$$

with $\kappa = \min(\nu,\mu)$ and

$$\begin{array}{rl}
s_0 = & m_{0,f}'V_{ff}(\theta_0)^{-1}D_0 \\
s_{\nu-2\alpha,1} = & m_{0,f}'V_{ff}(\theta_0)^{-1}\{\frac{1}{\sqrt{T}}[p_T(\hat{\theta},Y) - \hat{D}_T(\hat{\theta},Y)]\} \\
= & \frac{1}{k}m_{0,f}'V_{ff}(\theta_0)^{-1}[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}m_{0,f}] \\
s_{1\kappa,1} = & T^{\frac{1}{2}\kappa}m_{0,f}'[V_{ff}(\hat{\theta})^{-1} - V_{ff}(\theta_0)^{-1}]D_0 \\
s_{\nu+\kappa-2\alpha,1} = & \frac{T^{\frac{1}{2}\kappa}}{k}m_{0,f}'V_{ff}(\theta_0)^{-1}\{[A_1\hat{V}_{\theta f,1}(\theta_0)\cdots A_m\hat{V}_{\theta f,m}(\theta_0)][I_m \otimes \hat{V}_{ff}(\theta_0)^{-1}] \\
& -[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}]\}[I_m \otimes m_{0,f}] \\
s_{\nu+\kappa-2\alpha,2} = & \frac{T^{\frac{1}{2}\kappa}}{k}m_{0,f}'[\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}][A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m \otimes V_{ff}(\theta_0)^{-1}m_{0,f}] \\
s_{\nu+2(\kappa-\alpha),1} = & \frac{T^{\frac{1}{2}(2\kappa-1)}}{k}m_{0,f}'[\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}][\hat{D}_T(\theta_0,Y) - D_T(\theta_0,Y)],
\end{array}$$

which we obtained by fixing the convergence rate of $f_T(\theta_0,Y)'V_{ff}(\theta_0)^{-1}D_T(\theta_0,Y)$ to $T^{-\frac{1}{2}(2+\nu)}$, with $\nu \geq \alpha$, and use the results that $\frac{1}{k}m_{0,f}'V_{ff}(\theta_0)^{-1}m_{0,f} \underset{p}{\longrightarrow} l$.

2a. $\mathbf{W}_{cue}(\theta_0)$.

$$\begin{array}{rl}\frac{1}{\sqrt{T}}f_T(\theta_0,Y)'\hat{V}_{ff}(\hat{\theta})^{-1}[T^{-\frac{1}{2}(1+\nu)}D_T(\hat{\theta},Y)] = & s_0 + T^{-\frac{\kappa}{2}}s_{1\kappa,1} + T^{-\frac{1}{2}(\nu+\kappa-2\alpha)}s_{\nu+\kappa-2\alpha,1} + \\ & T^{-\frac{1}{2}(\nu+2(\kappa-\alpha))}s_{\nu+2(\kappa-\alpha),1},\end{array}$$

with $\kappa = \min(\nu,\mu) \geq \alpha$.

3a. LM(θ_0).

$$\begin{array}{l}\frac{1}{\sqrt{T}}f_T(\theta_0,Y)'\hat{V}_{ff}(\theta_0)^{-1}[T^{-\frac{1}{2}(1+\nu)}p_T(\theta_0,Y)] = s_0 + T^{-\frac{\nu-2\alpha}{2}}s_{\nu-2\alpha,1} + T^{-\frac{\kappa}{2}}s_{1\kappa,1} + \\ T^{-\frac{1}{2}(\nu+\kappa-2\alpha)}(s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2}) + T^{-\frac{1}{2}(\nu+2(\kappa-\alpha))}s_{\nu+2(\kappa-\alpha),1},\end{array}$$

with $\kappa = \mu$.

4a. K(θ_0).

$$\begin{array}{rl}T^{-\frac{1}{2}(1+\alpha)}f_T(\theta_0,Y)'\hat{V}_{ff}(\theta_0)^{-1}[T^{-\frac{1}{2}(1+\nu)}D_T(\theta_0,Y)] = & s_0 + T^{-\frac{\kappa}{2}}s_{1\kappa,1} + T^{-\frac{1}{2}(\nu+\kappa-2\alpha)}s_{\nu+\kappa-2\alpha,1} + \\ & T^{-\frac{1}{2}(\nu+2(\kappa-\alpha))}s_{\nu+2(\kappa-\alpha),1},\end{array}$$

with $\kappa = \mu$.

1b. $\mathbf{W}_{2s}(\theta_0)$.

$$[T^{-\frac{1}{2}(1+\nu)}p_T(\hat{\theta}_{2s},Y)]'V_{ff}(\hat{\theta}_{2s})^{-1}[T^{-\frac{1}{2}(1+\nu)}p_T(\hat{\theta}_{2s},Y)] = G_0 + T^{-\frac{\nu}{2}}G_{1\nu,1} + T^{-\frac{\kappa}{2}}G_{1\kappa,1} + T^{-(\nu-\alpha)}G_{2(\nu-\alpha),1} + T^{-\frac{1}{2}(\nu+\kappa)}(G_{\nu+\kappa,1}+G_{\nu+\kappa,2}) + T^{-\frac{2\nu+\kappa-2\alpha}{2}}(G_{2\nu+\kappa-2\alpha,1}+G_{2\nu+\kappa-2\alpha,2}) + T^{-\frac{\nu+2\kappa}{2}}G_{\nu+2\kappa,1} + T^{-(\nu+\kappa-\alpha)}(G_{2(\nu+\kappa-\alpha),1}+G_{2(\nu+\kappa-\alpha),2}) + T^{-\frac{1}{2}(2\nu+3\kappa-\alpha)}G_{2\nu+3\kappa-2\alpha,1}$$

with $\kappa = \min(\nu,\mu)$ and

$$\begin{aligned}
G_0 = {} & D_0'V_{ff}(\theta_0)^{-1}D_0 \\
G_{1\nu,1} = {} & D_0'V_{ff}(\theta_0)^{-1}[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m\otimes V_{ff}(\theta_0)^{-1}m_{0,f}] + \\
& [I_m\otimes V_{ff}(\theta_0)^{-1}m_{0,f}]'[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)]'V_{ff}(\theta_0)^{-1}D_0 \\
G_{1\kappa,1} = {} & T^{\frac{\kappa}{2}}D_0'[V_{ff}(\hat{\theta})^{-1}-V_{ff}(\theta_0)^{-1}]D_0 \\
G_{2(\nu-\alpha),1} = {} & \tfrac{1}{k}[I_m\otimes V_{ff}(\theta_0)^{-1}m_{0,f}]'[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)]'V_{ff}(\theta_0)^{-1} \\
& [A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m\otimes V_{ff}(\theta_0)^{-1}m_{0,f}] \\
G_{\nu+\kappa,1} = {} & T^{\frac{\kappa}{2}}D_0'[V_{ff}(\hat{\theta})^{-1}-V_{ff}(\theta_0)^{-1}][A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m\otimes V_{ff}(\theta_0)^{-1}m_{0,f}] + \\
& T^{\frac{\kappa}{2}}[I_m\otimes V_{ff}(\theta_0)^{-1}m_{0,f}]'[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)]'V_{ff}(\theta_0)^{-1}D_0 \\
G_{\nu+\kappa,2} = {} & T^{\frac{1}{2}(\kappa-1)}[D_T(\hat{\theta},Y)-D_T(\theta_0,Y)]'V_{ff}(\theta_0)^{-1}D_0 + \\
& T^{\frac{1}{2}(\nu-1)}D_0'V_{ff}(\theta_0)^{-1}[D_T(\hat{\theta},Y)-D_T(\theta_0,Y)]
\end{aligned}$$

$$\begin{aligned}
G_{2\nu+\kappa-2\alpha,1} = {} & \tfrac{1}{k}T^{\frac{1}{2}\kappa}[I_m\otimes V_{ff}(\theta_0)^{-1}m_{0,f}]'[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)]' \\
& [V_{ff}(\hat{\theta})^{-1}-V_{ff}(\theta_0)^{-1}][A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m\otimes V_{ff}(\theta_0)^{-1}m_{0,f}] \\
G_{2\nu+\kappa-2\alpha,2} = {} & \tfrac{1}{k}T^{\frac{1}{2}(\kappa-1)}[D_T(\hat{\theta},Y)-D_T(\theta_0,Y)]'V_{ff}(\theta_0)^{-1}[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)] \\
& [I_m\otimes V_{ff}(\theta_0)^{-1}m_{0,f}] + \tfrac{1}{k}T^{\frac{1}{2}(\kappa-1)}[I_m\otimes V_{ff}(\theta_0)^{-1}m_{0,f}]' \\
& [A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)]'V_{ff}(\theta_0)^{-1}[D_T(\hat{\theta},Y)-D_T(\theta_0,Y)] \\
G_{\nu+2\kappa,1} = {} & T^{\frac{1}{2}(2\kappa-1)}[D_T(\hat{\theta},Y)-D_T(\theta_0,Y)]'[V_{ff}(\hat{\theta})^{-1}-V_{ff}(\theta_0)^{-1}]D_0 + \\
& T^{\frac{1}{2}(2\kappa-1)}D_0'[V_{ff}(\hat{\theta})^{-1}-V_{ff}(\theta_0)^{-1}][D_T(\hat{\theta},Y)-D_T(\theta_0,Y)] \\
G_{2(\nu+\kappa-\alpha),1} = {} & \tfrac{1}{k}T^{\frac{1}{2}(2\kappa-1)}[D_T(\hat{\theta},Y)-D_T(\theta_0,Y)]'[V_{ff}(\hat{\theta})^{-1}-V_{ff}(\theta_0)^{-1}] \\
& [A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m\otimes V_{ff}(\theta_0)^{-1}m_{0,f}] + T^{\frac{1}{2}(2\kappa-1)}[I_m\otimes V_{ff}(\theta_0)^{-1}m_{0,f}]' \\
& [A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)]'[V_{ff}(\hat{\theta})^{-1}-V_{ff}(\theta_0)^{-1}][D_T(\hat{\theta},Y)-D_T(\theta_0,Y)] \\
G_{2(\nu+\kappa-\alpha),2} = {} & \tfrac{1}{k}T^{(\kappa-1)}[D_T(\hat{\theta},Y)-D_T(\theta_0,Y)]'V_{ff}(\theta_0)^{-1}[D_T(\hat{\theta},Y)-D_T(\theta_0,Y)] \\
G_{2\nu+3\kappa-2\alpha,1} = {} & \tfrac{1}{k}T^{\frac{1}{2}(3\kappa-2\alpha)}[D_T(\hat{\theta},Y)-D_T(\theta_0,Y)]'[V_{ff}(\hat{\theta})^{-1}-V_{ff}(\theta_0)^{-1}][D_T(\hat{\theta},Y)-D_T(\theta_0,Y)]
\end{aligned}$$

Hence,

$$T^{(1+\nu)}[p_T(\hat{\theta},Y)'V_{ff}(\hat{\theta})^{-1}p_T(\hat{\theta},Y)]^{-1} = G_0^{-1} + T^{-\frac{\nu}{2}}Q_1,$$

with

$$Q_1 = \; -G_0^{-1}[(G_{1\nu,1}+H)^{-1} + T^{-\frac{\nu}{2}}G_0^{-1}]^{-1}G_0^{-1}$$

where $H = T^{-\frac{\kappa-\nu}{2}}G_{1\kappa,1} + T^{-(\frac{1}{2}\nu-\alpha)}G_{2(\nu-\alpha),1} + T^{-\frac{1}{2}\kappa}(G_{\nu+\kappa,1}+G_{\nu+\kappa,2}) + T^{-\frac{\nu+\kappa-2\alpha}{2}}(G_{2\nu+\kappa-2\alpha,1} + G_{2\nu+\kappa-2\alpha,2}) + T^{-\kappa}G_{\nu+2\kappa,1} + T^{-(\frac{1}{2}\nu+\kappa-\alpha)}(G_{2(\nu+\kappa-\alpha),1}+G_{2(\nu+\kappa-\alpha),2}) + T^{-\frac{1}{2}(\nu+3\kappa-\alpha)}G_{2\nu+3\kappa-2\alpha,1}$.

2b. $\mathbf{W}_{cue}(\theta_0)$.

$$[T^{-\frac{1}{2}(1+\nu)}\hat{D}_T(\hat{\theta},Y)]'V_{ff}(\hat{\theta})^{-1}[T^{-\frac{1}{2}(1+\nu)}\hat{D}_T(\hat{\theta},Y)] = G_0 + T^{-\frac{\kappa}{2}}G_{1\kappa,1} + T^{-\frac{1}{2}(\nu+\kappa)}G_{\nu+\kappa,2} + T^{-\frac{\nu+2\kappa}{2}}G_{\nu+2\kappa,1} + T^{-(\nu+\kappa-\alpha)}G_{2(\nu+\kappa-\alpha),1} + T^{-\frac{1}{2}(2\nu+3\kappa-\alpha)}G_{2\nu+3\kappa-2\alpha,1},$$

with $\kappa = \min(\mu, \nu)$. Hence,

$$T^{(1+\nu)}[\hat{D}_T(\hat{\theta}, Y)' V_{ff}(\hat{\theta})^{-1} \hat{D}_T(\hat{\theta}, Y)]^{-1} = G_0^{-1} + T^{-\frac{\kappa}{2}} Q_1,$$

with

$$Q_1 = \ -G_0^{-1}[G_{1\kappa,1} + H)^{-1} + T^{-\frac{\nu}{2}} G_0^{-1}]^{-1} G_0^{-1}$$

where $H = T^{-\frac{1}{2}\nu} G_{\nu+\kappa,2} + T^{-\frac{\nu+\kappa}{2}} G_{\nu+2\kappa,1} + T^{-(\nu+\frac{1}{2}\kappa-\alpha)} G_{2(\nu+\kappa-\alpha),1} + T^{-\frac{1}{2}(2\nu+2\kappa-\alpha)} G_{2\nu+3\kappa-2\alpha,1}$.
3b. LM(θ_0):

$$[T^{-\frac{1}{2}(1+\nu)} p_T(\theta_0, Y)]' \hat{V}_{ff}(\theta_0)^{-1} [T^{-\frac{1}{2}(1+\nu)} p_T(\theta_0, Y)] = G_0 + T^{-\frac{\nu}{2}} G_{1\nu,1} + T^{-\frac{\kappa}{2}} G_{1\kappa,1} +$$
$$T^{-(\nu-\alpha)} G_{2(\nu-\alpha),1} + T^{-\frac{1}{2}(\nu+\kappa)} (G_{\nu+\kappa,1} + G_{\nu+\kappa,2}) + T^{-\frac{2\nu+\kappa-2\alpha}{2}} (G_{2\nu+\kappa-2\alpha,1} + G_{2\nu+\kappa-2\alpha,2}) +$$
$$T^{-\frac{\nu+2\kappa}{2}} G_{\nu+2\kappa,1} + T^{-(\nu+\kappa-\alpha)} (G_{2(\nu+\kappa-\alpha),1} + G_{2(\nu+\kappa-\alpha),2}) + T^{-\frac{1}{2}(2\nu+3\kappa-\alpha)} G_{2\nu+3\kappa-2\alpha,1}$$

with $\kappa = \mu$. Hence,

$$T^{(1+\nu)}[p_T(\theta_0, Y)' \hat{V}_{ff}(\theta_0)^{-1} p_T(\theta_0, Y)]^{-1} = G_0^{-1} + T^{-\frac{\nu}{2}} Q_1,$$

with

$$Q_1 = \ -G_0^{-1}[(G_{1\nu,1} + H)^{-1} + T^{-\frac{\nu}{2}} G_0^{-1}]^{-1} G_0^{-1},$$

with $H = T^{-\frac{\kappa-\nu}{2}} G_{1\kappa,1} + T^{-(\frac{1}{2}\nu-\alpha)} G_{2(\nu-\alpha),1} + T^{-\frac{1}{2}\kappa} (G_{\nu+\kappa,1} + G_{\nu+\kappa,2}) + T^{-\frac{\nu+\kappa-2\alpha}{2}} (G_{2\nu+\kappa-2\alpha,1} + G_{2\nu+\kappa-2\alpha,2}) + T^{-\kappa} G_{\nu+2\kappa,1} + T^{-(\frac{1}{2}\nu+\kappa-\alpha)} (G_{2(\nu+\kappa-\alpha),1} + G_{2(\nu+\kappa-\alpha),2}) + T^{-\frac{1}{2}(\nu+3\kappa-\alpha)} G_{2\nu+3\kappa-2\alpha,1}$.
4b. K(θ_0):

$$[T^{-\frac{1}{2}(1+\nu)} \hat{D}_T(\theta_0, Y)]' \hat{V}_{ff}(\theta_0)^{-1} [T^{-\frac{1}{2}(1+\nu)} \hat{D}_T(\theta_0, Y)] = G_0 + T^{-\frac{\kappa}{2}} G_{1\kappa,1} +$$
$$T^{-\frac{1}{2}(\nu+\kappa)} G_{\nu+\kappa,2} + T^{-\frac{\nu+2\kappa}{2}} G_{\nu+2\kappa,1} + T^{-(\nu+\kappa-\alpha)} G_{2(\nu+\kappa-\alpha),2} + T^{-\frac{1}{2}(2\nu+3\kappa-\alpha)} G_{2\nu+3\kappa-2\alpha,1},$$

with $\kappa = \mu$. Hence,

$$T^{(1+\nu)} \left[\hat{D}_T(\theta_0, Y)' \hat{V}_{ff}(\theta_0)^{-1} \hat{D}_T(\theta_0, Y)\right]^{-1} = G_0^{-1} + T^{-\frac{\kappa}{2}} Q_1$$

and

$$Q_1 = \ -G_0^{-1}[(G_{1\nu,1} + H)^{-1} + T^{-\frac{\nu}{2}} G_0^{-1}]^{-1} G_0^{-1},$$

with $H = T^{-\frac{1}{2}\nu} G_{\nu+\kappa,2} + T^{-\frac{\nu+\kappa}{2}} G_{\nu+2\kappa,1} + T^{-(\nu+\frac{1}{2}\kappa-\alpha)} G_{2(\nu+\kappa-\alpha),2} + T^{-\frac{1}{2}(2\nu+2\kappa-\alpha)} G_{2\nu+3\kappa-2\alpha,1}$.
1c. $\mathbf{W}_{2s}(\theta_0)$:

$$\begin{aligned} \mathrm{W}_{2s}(\theta_0) = \ & n_0 + T^{-\frac{\nu-2\alpha}{2}} n_{\nu-2\alpha} + T^{-(\nu-\alpha)} n_{2(\nu-\alpha)} + T^{-(\nu-2\alpha)} n_{2(\nu-2\alpha)} + T^{-\frac{\nu}{2}} n_\nu + T^{-\frac{\kappa}{2}} n_\kappa + T^{-\kappa} n_{2\kappa} + \\ & T^{-\frac{1}{2}(\nu+\kappa-2\alpha)} n_{\nu+\kappa-2\alpha} + T^{-\frac{1}{2}(\nu+\kappa)} n_{\nu+\kappa} + T^{-(\nu-\alpha)} n_{2(\nu-\alpha)} + T^{-\frac{1}{2}(\nu+2(\kappa-\alpha))} n_{\nu+2(\kappa-\alpha)} + \\ & T^{-\frac{1}{2}(2\nu+\kappa-2\alpha)} n_{2\nu+\kappa-2\alpha} + T^{-(\nu+\kappa-\alpha)} n_{2(\nu+\kappa-\alpha)} + T^{-\frac{1}{2}\kappa+2(\nu-2\alpha)} n_{\kappa+2(\nu-2\alpha)} + T^{-(\nu+\kappa-2\alpha)} n_{2(\nu+\kappa-2\alpha)}, \end{aligned}$$

with $\kappa = \min(\mu, \nu)$,

$$\begin{aligned}
n_0 &= s_0' G_0^{-1} s_0 \\
n_{\nu-2\alpha} &= s_{\nu-2\alpha,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{\nu-2\alpha,1} \\
n_{2(\nu-2\alpha)} &= s_{\nu-2\alpha,1}' G_0^{-1} s_{\nu-2\alpha,1} \\
n_{\nu} &= s_0' Q_1 s_0 \\
n_{\kappa} &= s_{1\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{1\kappa,1} \\
n_{\nu+\kappa-2\alpha} &= (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2})' G_0^{-1} s_0 + s_0' G_0^{-1} (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2}) + \\
&\quad s_{\nu-2\alpha,1}' G_0^{-1} s_{1\kappa,1} + s_{1\kappa,1}' G_0^{-1} s_{\nu-2\alpha,1} \\
n_{2\kappa} &= s_{1\kappa,1}' G_0^{-1} s_{1\kappa,1} \\
n_{\nu+\kappa} &= s_{1\kappa,1}' Q_1 s_0 + s_0' Q_1 s_{1\kappa,1} \\
n_{2(\nu-\alpha)} &= s_{\nu-2\alpha,1}' Q_1 s_0 + s_0' Q_1 s_{\nu-2\alpha,1} \\
n_{\nu+2(\kappa-\alpha)} &= (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2})' G_0^{-1} s_{1\kappa,1} + s_{1\kappa,1}' G_0^{-1} (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2}) + \\
&\quad s_{\nu+2\kappa-2\alpha,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{\nu+2\kappa-2\alpha,1} \\
n_{2\nu+\kappa-2\alpha} &= (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2})' Q_1 s_0 + s_0' Q_1 (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2}) \\
n_{2(\nu+\kappa-\alpha)} &= s_{\nu+2(\kappa-\alpha),1}' Q_1 s_0 + s_0' Q_1 s_{\nu+2(\kappa-\alpha),1} + (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2})' Q_1 s_{1\kappa,1} + \\
&\quad s_{1\kappa,1}' Q_1 (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2}) \\
n_{\kappa+2(\nu-2\alpha)} &= s_{\nu-2\alpha,1}' Q_1 s_{\nu-2\alpha,1} \\
n_{2(\nu+\kappa-2\alpha)} &= (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2})' G_0^{-1} (s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,2})
\end{aligned}$$

2c. $\mathbf{W}_{cue}(\theta_0)$:

$$\begin{aligned}
\mathrm{W}_{cue}(\theta_0) = \; & n_0 + T^{-\frac{\kappa}{2}} n_\kappa + T^{-\kappa} n_{2\kappa} + T^{-\frac{3}{2}\kappa} n_{3\kappa} + T^{-\frac{1}{2}(\nu+\kappa-2\alpha)} n_{\nu+\kappa-2\alpha} + \\
& T^{-\frac{1}{2}(\nu+\kappa-2\alpha)} n_{\nu+\kappa-2\alpha} + T^{-\frac{1}{2}(\nu+2(\kappa-\alpha))} n_{\nu+2(\kappa-\alpha)}
\end{aligned}$$

with $\kappa = \min(\mu, \nu)$,

$$\begin{aligned}
n_0 &= s_0' G_0^{-1} s_0 \\
n_{\kappa} &= s_0' Q_1 s_0 + s_{1\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{1\kappa,1} \\
n_{2\kappa} &= s_{1\kappa,1}' G_0^{-1} s_{1\kappa,1} + s_{1\kappa,1}' Q_1 s_0 + s_0' Q_1 s_{1\kappa,1} \\
n_{3\kappa} &= s_{1\kappa,1}' Q_1 s_{1\kappa,1} \\
n_{\nu+\kappa-2\alpha} &= s_{\nu+\kappa-2\alpha,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{\nu+\kappa-2\alpha,1} \\
n_{\nu+2(\kappa-\alpha)} &= s_{\nu+\kappa-2\alpha,1}' G_0^{-1} s_{1\kappa,1} + s_{1\kappa,1}' G_0^{-1} s_{\nu+\kappa-2\alpha,1} + s_{\nu+\kappa-2\alpha,1}' Q_1 s_0 + \\
&\quad s_0' Q_1 s_{\nu+\kappa-2\alpha,1} + s_{\nu+2\kappa-2\alpha,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{\nu+2\kappa-2\alpha,1} \\
n_{2(\nu+\kappa-2\alpha)} &= s_{\nu+\kappa-2\alpha,1}' G_0^{-1} s_{\nu+\kappa-2\alpha,1}
\end{aligned}$$

3c. $\mathbf{LM}(\theta_0)$:

$$\begin{aligned}
\mathrm{LM}(\theta_0) = \; & n_0 + T^{-\frac{\nu-2\alpha}{2}} n_{\nu-2\alpha} + T^{-(\nu-\alpha)} n_{2(\nu-\alpha)} + T^{-(\nu-2\alpha)} n_{2(\nu-2\alpha)} + T^{-\frac{\nu}{2}} n_\nu + T^{-\frac{\kappa}{2}} n_\kappa + T^{-\kappa} n_{2\kappa} + \\
& T^{-\frac{1}{2}(\nu+\kappa-2\alpha)} n_{\nu+\kappa-2\alpha} + T^{-\frac{1}{2}(\nu+\kappa)} n_{\nu+\kappa} + T^{-(\nu-\alpha)} n_{2(\nu-\alpha)} + T^{-\frac{1}{2}(\nu+2(\kappa-\alpha))} n_{\nu+2(\kappa-\alpha)} + \\
& T^{-\frac{1}{2}(2\nu+\kappa-2\alpha)} n_{2\nu+\kappa-2\alpha} + T^{-(\nu+\kappa-\alpha)} n_{2(\nu+\kappa-\alpha)} + T^{-\frac{1}{2}\kappa+2(\nu-2\alpha)} n_{\kappa+2(\nu-2\alpha)} + o_p(T^{-(\nu+\kappa-\alpha)})
\end{aligned}$$

with $\kappa = \mu$,

$$\begin{aligned}
n_0 &= s_0' G_0^{-1} s_0 \\
n_{\nu-2\alpha} &= s_{\nu-2\alpha,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{\nu-2\alpha,1} \\
n_{2(\nu-2\alpha)} &= s_{\nu-2\alpha,1}' G_0^{-1} s_{\nu-2\alpha,1} \\
n_{\nu} &= s_0' Q_1 s_0 \\
n_{\kappa} &= s_{1\kappa,1}' G_0^{-1} s_0 + s_0' G_0^{-1} s_{1\kappa,1}
\end{aligned}$$

$$
\begin{aligned}
n_{\nu+\kappa-2\alpha} = \; & (s_{\nu+\kappa-2\alpha,1}+s_{\nu+\kappa-2\alpha,2})'G_0^{-1}s_0+s_0'G_0^{-1}(s_{\nu+\kappa-2\alpha,1}+s_{\nu+\kappa-2\alpha,2})+\\
& s_{\nu-2\alpha,1}'G_0^{-1}s_{1\kappa,1}+s_{1\kappa,1}'G_0^{-1}s_{\nu-2\alpha,1}\\
n_{2\kappa} = \; & s_{1\kappa,1}'G_0^{-1}s_{1\kappa,1}\\
n_{\nu+\kappa} = \; & s_{1\kappa,1}'Q_1s_0+s_0'Q_1s_{1\kappa,1}\\
n_{2(\nu-\alpha)} = \; & s_{\nu-2\alpha,1}'Q_1s_0+s_0'Q_1s_{\nu-2\alpha,1}\\
n_{\nu+2(\kappa-\alpha)} = \; & (s_{\nu+\kappa-2\alpha,1}+s_{\nu+\kappa-2\alpha,2})'G_0^{-1}s_{1\kappa,1}+s_{1\kappa,1}'G_0^{-1}(s_{\nu+\kappa-2\alpha,1}+s_{\nu+\kappa-2\alpha,2})+\\
& s_{\nu+2\kappa-2\alpha,1}'G_0^{-1}s_0+s_0'G_0^{-1}s_{\nu+2\kappa-2\alpha,1}\\
n_{2\nu+\kappa-2\alpha} = \; & (s_{\nu+\kappa-2\alpha,1}+s_{\nu+\kappa-2\alpha,2})'Q_1s_0+s_0'Q_1(s_{\nu+\kappa-2\alpha,1}+s_{\nu+\kappa-2\alpha,2})\\
n_{2(\nu+\kappa-\alpha)} = \; & s_{\nu+2(\kappa-\alpha),1}'Q_1s_0+s_0'Q_1s_{\nu+2(\kappa-\alpha),1}+(s_{\nu+\kappa-2\alpha,1}+s_{\nu+\kappa-2\alpha,2})'Q_1s_{1\kappa,1}+\\
& s_{1\kappa,1}'Q_1(s_{\nu+\kappa-2\alpha,1}+s_{\nu+\kappa-2\alpha,2})\\
n_{\kappa+2(\nu-2\alpha)} = \; & s_{\nu-2\alpha,1}'Q_1s_{\nu-2\alpha,1}
\end{aligned}
$$

4c. $\mathbf{K}(\theta_0)$:

$$
\begin{aligned}
\mathrm{K}(\theta_0) = \; & n_0+T^{-\frac{\kappa}{2}}n_\kappa+T^{-\kappa}n_{2\kappa}+T^{-\frac{3}{2}\kappa}n_{3\kappa}+T^{-\frac{1}{2}(\nu+\kappa-2\alpha)}n_{\nu+\kappa-2\alpha}+\\
& T^{-\frac{1}{2}(\nu+\kappa-2\alpha)}n_{\nu+\kappa-2\alpha}+T^{-\frac{1}{2}(\nu+2(\kappa-\alpha))}n_{\nu+2(\kappa-\alpha)}
\end{aligned}
$$

with $\kappa=\mu$,

$$
\begin{aligned}
n_0 = \; & s_0'G_0^{-1}s_0\\
n_\kappa = \; & s_0'Q_1s_0+s_{1\kappa,1}'G_0^{-1}s_0+s_0'G_0^{-1}s_{1\kappa,1}\\
n_{2\kappa} = \; & s_{1\kappa,1}'G_0^{-1}s_{1\kappa,1}+s_{1\kappa,1}'Q_1s_0+s_0'Q_1s_{1\kappa,1}\\
n_{3\kappa} = \; & s_{1\kappa,1}'Q_1s_{1\kappa,1}\\
n_{\nu+\kappa-2\alpha} = \; & s_{\nu+\kappa-2\alpha,1}'G_0^{-1}s_0+s_0'G_0^{-1}s_{\nu+\kappa-2\alpha,1}\\
n_{\nu+2(\kappa-\alpha)} = \; & s_{\nu+\kappa-2\alpha,1}'G_0^{-1}s_{1\kappa,1}+s_{1\kappa,1}'G_0^{-1}s_{\nu+\kappa-2\alpha,1}+s_{\nu+\kappa-2\alpha,1}'Q_1s_0+\\
& s_0'Q_1s_{\nu+\kappa-2\alpha,1}+s_{\nu+2\kappa-2\alpha,1}'G_0^{-1}s_0+s_0'G_0^{-1}s_{\nu+2\kappa-2\alpha,1}.
\end{aligned}
$$

Lemma 3. Convergence of

$$
\begin{aligned}
s_{\nu+\kappa-2\alpha,1} = \; & \tfrac{T^{\frac{1}{2}\kappa}}{k}m_{0,f}'V_{ff}(\theta_0)^{-1}\{[A_1\hat{V}_{\theta f,1}(\theta_0)\cdots A_m\hat{V}_{\theta f,m}(\theta_0)][I_m\otimes\hat{V}_{ff}(\theta_0)^{-1}]\\
& -[A_1V_{\theta f,1}(\theta_0)\cdots A_mV_{\theta f,m}(\theta_0)][I_m\otimes V_{ff}(\theta_0)^{-1}]\}[I_m\otimes m_{0,f}]\\
= \; & (s_{\nu+\kappa-2\alpha,1,1}\ldots s_{\nu+\kappa-2\alpha,1,m})
\end{aligned}
$$

with

$$
\begin{aligned}
s_{\nu+\kappa-2\alpha,1,i} = \; & \tfrac{T^{\frac{1}{2}\kappa}}{k}m_{0,f}'V_{ff}(\theta_0)^{-1}A_i[\hat{V}_{\theta f,i}(\theta_0)V_{ff}()^{-1}-V_{\theta f,i}(\theta_0)V_{ff}(\theta_0)^{-1}]m_{0,f}\\
= \; & \tfrac{T^{\frac{1}{2}\kappa}}{k}m_{0,f}'V_{ff}(\theta_0)^{-1}A_i[\hat{V}_{\theta f,i}(\theta_0)-V_{\theta f,i}(\theta_0)]\hat{V}_{ff}(\theta_0)^{-1}m_{0,f}-\\
& \tfrac{T^{\frac{1}{2}\kappa}}{k}m_{0,f}'V_{ff}(\theta_0)^{-1}A_iV_{\theta f,i}(\theta_0)V_{ff}(\theta_0)^{-1}[\hat{V}_{ff}(\theta_0)-V_{ff}(\theta_0)]\hat{V}_{ff}(\theta_0)^{-1}m_{0,f}\\
= \; & \tfrac{1}{k}m_{0,f}'V_{ff}(\theta_0)^{-1}A_i[U_{\theta f,i}-V_{\theta f,i}(\theta_0)V_{ff}(\theta_0)^{-1}U_{ff}]V_{ff}(\theta_0)^{-1}m_{0,f}+o_p(1)\\
= \; & \tfrac{1}{k}m_{0,f}'V_{ff}(\theta_0)^{-1}A_iU_{\theta.f,i}V_{ff}(\theta_0)^{-1}m_{0,f}+o_p(1)\\
= \; & (\tfrac{1}{\sqrt{k}}m_{0,f}'V_{ff}(\theta_0)^{-1}\otimes\tfrac{1}{\sqrt{k}}m_{0,f}'V_{ff}(\theta_0)^{-1}A_i)\mathrm{vec}(U_{\theta.f,i})+o_p(1).
\end{aligned}
$$

where $U_{\theta.f,i}=U_{\theta f,i}-V_{\theta f,i}(\theta_0)U_{ff}$. Because of Assumption 2*,

$$
\begin{aligned}
s_{\nu+\kappa-2\alpha,1,i} = \; & (\tfrac{1}{\sqrt{k}}m_{0,f}'V_{ff}(\theta_0)^{-1}\otimes\tfrac{1}{\sqrt{k}}m_{0,f}'V_{ff}(\theta_0)^{-1}A_i)\mathrm{vec}(U_{\theta.f,i})+o_p(1)\\
\underset{d}{\to} \; & \lambda_i,
\end{aligned}
$$

with$\lambda_i \sim N(0, \sigma_{ii}(\theta_0)$ and $\sigma_{ij}(\theta_0) = \lim_{k\to\infty}(\frac{1}{\sqrt{k}} m'_{0,f} V_{ff}(\theta_0)^{-1} \otimes \frac{1}{\sqrt{k}} m'_{0,f} V_{ff}(\theta_0)^{-1} A_i)' \bar{W}_{ij}(\theta_0)(\frac{1}{\sqrt{k}} m'_{0,f} V_{ff}(\theta_0)^{-1}$ $\frac{1}{\sqrt{k}} m'_{0,f} V_{ff}(\theta_0)^{-1} A_j)$, where

$$\begin{aligned} \bar{W}_{ij}(\theta_0) = &\ \lim_{T\to\infty} E[\mathrm{vec}(U_{\theta f,i} - V_{\theta f,i}(\theta_0) V_{ff}(\theta_0)^{-1} U_{ff}) \mathrm{vec}(U_{\theta f,j} - V_{\theta f,j}(\theta_0) V_{ff}(\theta_0)^{-1} U_{ff})'], \\ = &\ E[(\psi_{u,\theta_i f} - V_{\theta f,i}(\theta_0) V_{ff}(\theta_0)^{-1} S_{k_f(m+1)} \psi_{u,ff})(\psi_{u,\theta_i f} - V_{\theta f,i}(\theta_0) V_{ff}(\theta_0)^{-1} S_{k_f(m+1)} \psi_{u,ff})'], \end{aligned}$$

which expression can be further constructed using Assumption 2*.

Proof of Theorem 3. The convergence of $S(\theta_0)$ is characterized by

$$S(\theta_0) = \ w_0 + T^{-\frac{\mu}{2}} w_\mu + o_p(T^{-\frac{\mu}{2}}),$$

with $w_0 = m'_{0.f} V_{ff}(\theta_0)^{-1} m_{0.f}$, $w_\mu = T^{\frac{\mu}{2}} m'_{0.f}[\hat{V}_{ff}(\theta_0)^{-1} - V_{ff}(\theta_0)^{-1}] m_{0.f}$. By decomposing $V_{ff}(\theta_0)^{-\frac{1}{2}} m_{0.f}$ as

$$V_{ff}(\theta_0)^{-\frac{1}{2}} m_{0.f} = \ V_{ff}(\theta_0)^{-\frac{1}{2}} D_0 \rho_0 + V_{ff}(\theta_0)^{\frac{1}{2}} D_{0,\perp} \lambda_0$$

with $\rho_0 = (D'_0 V_{ff}(\theta_0)^{-1} D_0)^{-1} D'_0 V_{ff}(\theta_0)^{-1} m_{0.f}$ and $\lambda_0 = (D'_{0,\perp} V_{ff}(\theta_0) D_{0,\perp})^{-1} D'_{0,\perp} m_{0.f}$ and $D_{0,\perp}$: $k_f \times (k_f - m)$, $D'_{0,\perp} D_0 \equiv 0$, $D'_{0,\perp} D_{0,\perp} \equiv I_{k_f - m}$; we can specify the higher order properties of $\mathrm{S}(\theta_0)$ also by

$$S(\theta_0) = \ n_0 + n_{0,\perp} + T^{-\frac{\mu}{2}} w_\mu + o_p(T^{-\frac{\mu}{2}}),$$

with

$$\begin{aligned} n_0 = &\ m'_{0.f} V_{ff}(\theta_0)^{-1} D_0 (D'_0 V_{ff}(\theta_0)^{-1} D_0)^{-1} D'_0 V_{ff}(\theta_0)^{-1} m_{0.f}, \\ n_{0,\perp} = &\ m'_{0.f} D_{0,\perp} (D'_{0,\perp} V_{ff}(\theta_0) D_{0,\perp})^{-1} D'_{0,\perp} m_{0.f}. \end{aligned}$$

The higher order properties of the J-statistics result from substracting the higher order properties from Theorem 1 from the S-statistic. Consequently,

$$\left.\begin{array}{r} \mathrm{J}_{2s}(\theta_0) \\ \mathrm{J}_{cue}(\theta_0) \\ \mathrm{J}_{LM}(\theta_0) \\ \mathrm{J}_{\mathrm{K}}(\theta_0) \end{array}\right\} = n_{0,\perp} + T^{-\frac{\mu}{2}} w_\mu - \left\{ \begin{array}{l} T^{-\frac{\nu}{2}} n_\nu + T^{-\frac{\kappa}{2}} n_\kappa + T^{-\frac{\nu+\kappa}{2}} n_{\nu+\kappa} + T^{-\nu} n_{2\nu} + T^{-\kappa} n_{2\kappa} + \\ T^{-\frac{1}{2}(2\nu+\kappa)} n_{2\nu+\kappa} + T^{-\frac{1}{2}(\nu+2\kappa)} n_{\nu+2\kappa} + T^{-\frac{3}{2}\nu} n_{3\nu} + o_p(T^{-\frac{3}{2}\nu}), \end{array} \right.$$

where all the components for the respective statistics are defined in Theorem 1.

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