

Supplemental Material to
A NOTE ON OPTIMAL INFERENCE IN THE LINEAR IV MODEL

By

Donald W. K. Andrews, Vadim Marmer, and Zhengfei Yu

January 2017

COWLES FOUNDATION DISCUSSION PAPER NO. 2073



COWLES FOUNDATION FOR RESEARCH IN ECONOMICS
YALE UNIVERSITY
Box 208281
New Haven, Connecticut 06520-8281

<http://cowles.yale.edu/>

Supplemental Material
for
A Note on Optimal Inference
in the Linear IV Model

Donald W. K. Andrews
Cowles Foundation for Research in Economics
Yale University

Vadim Marmer
Vancouver School of Economics
University of British Columbia

Zhengfei Yu
Faculty of Humanities and Social Sciences
University of Tsukuba

First Version: October 23, 2015

Revised: January 30, 2017

Contents

10 Outline	2
11 Definitions	3
11.1 Densities of \mathbf{Q} when $\beta = \beta_*$ and when $\beta_0 \rightarrow \pm\infty$	3
11.2 POIS2 Test	4
11.3 Structural and Reduced-Form Variance Matrices	4
12 One-Sided Power Bound as $\beta_0 \rightarrow \pm\infty$	5
12.1 Point Optimal Invariant Similar Tests for Fixed β_0 and β_*	6
12.2 One-Sided Power Bound When $\beta_0 \rightarrow \pm\infty$	6
13 Equations (4.1) and (4.2) of AMS	8
14 Proof of Lemma 5.1	10
15 Proof of Theorem 4.1	12
16 Proofs of Theorems 5.2, Corollary 5.3, and Theorem 5.4	17
17 Proof of Theorem 7.1	25
18 Proofs of Theorem 12.1 and Lemmas 13.1 and 13.2	36
19 Power Against Distant Alternatives Compared to Distant Null Hypotheses	39
19.1 Scenario 1 Compared to Scenario 2	39
19.2 Structural Error Variance Matrices under Distant Alternatives and Distant Null Hypotheses	40
20 Transformation of the β_0 Versus β_* Testing Problem to a 0 Versus $\bar{\beta}_*$ Testing Problem	41
21 Transformation of the β_0 Versus β_* Testing Problem to a $\bar{\beta}_0$ Versus 0 Testing Problem	45
22 Additional Numerical Results	46

10 Outline

References to sections, theorems, and lemmas with section numbers less than 10 refer to sections and results in the main paper.

Section 11 of this Supplemental Material (SM) provides expressions for the densities $f_Q(q; \beta_*, \beta_0, \lambda, \Omega)$, $f_{Q_1|Q_T}(q_1|q_T)$, and $f_Q(q; \rho_{uv}, \lambda_v)$, expressions for the POIS2 test statistic and critical value of AMS, and expressions for the one-to-one transformations between the reduced-form and structural variance matrices. Section 12 provides one-sided power bounds for invariant similar tests as $\beta_0 \rightarrow \pm\infty$, where β_0 denotes the null hypothesis value. Section 13 corrects (4.1) of AMS, which concerns the two-point weight function that defines AMS's two-sided AE power envelope.

Section 14 proves Lemma 5.1. Section 15 proves Theorem 4.1 and its Comment (v). Section 16 proves Theorem 5.2 and its Comment (iv), Corollary 5.3 and its Comment (ii), and Theorem 5.4. Section 17 proves Theorem 7.1. Section 18 proves Theorem 12.1 and Lemmas 13.1 and 13.2.

Section 19 contrasts the power properties of tests in the scenario where β_0 is fixed and β_* takes on large (absolute) values, with the scenario where β_* is fixed and β_0 takes on large (absolute) values.

Section 20 shows how the model is transformed to go from a testing problem of $H_0 : \beta = \beta_0$ versus $H_1 : \beta = \beta_*$ for $\pi \in R^k$ and fixed Ω to a testing problem of $H_0 : \bar{\beta} = 0$ versus $H_1 : \bar{\beta} = \bar{\beta}_*$ for some $\bar{\pi} \in R^k$ and some fixed $\bar{\Omega}$ with diagonal elements equal to one. This links the model considered here to the model used in the Andrews, Moreira, and Stock (2006) (AMS) numerical work.

Section 21 shows how the model is transformed to go from a testing problem of $H_0 : \beta = \beta_0$ versus $H_1 : \beta = \beta_*$ for $\pi \in R^k$ and fixed Ω to a testing problem of $H_0 : \bar{\beta} = \bar{\beta}_0$ versus $H_1 : \bar{\beta} = 0$ for some $\bar{\pi} \in R^k$ and some fixed $\bar{\Omega}$ with diagonal elements equal to one. These transformation results imply that there is no loss in generality in the numerical results of the paper to taking $\omega_1^2 = \omega_2^2 = 1$, $\beta_* = 0$, and $\rho_{uv} \in [0, 1]$ (rather than $\rho_{uv} \in [-1, 1]$).

Section 22 provides numerical results that supplement the results given in Tables I-IV in the main paper.

11 Definitions

11.1 Densities of Q when $\beta = \beta_*$ and when $\beta_0 \rightarrow \pm\infty$

In this subsection, we provide expressions for (i) the density $f_Q(q; \beta_*, \beta_0, \lambda, \Omega)$ of Q when the true value of β is β_* , and the null value β_0 is finite, (ii) the conditional density $f_{Q_1|Q_T}(q_1|q_T)$ of Q_1 given $Q_T = q_T$, and (iii) the limit of $f_Q(q; \beta_*, \beta_0, \lambda, \Omega)$ as $\beta_0 \rightarrow \pm\infty$.

Let

$$\xi_{\beta_*}(q) = \xi_{\beta_*}(q; \beta_0, \Omega) := c_{\beta_*}^2 q_S + 2c_{\beta_*} d_{\beta_*} q_{ST} + d_{\beta_*}^2 q_T, \quad (11.1)$$

where $c_{\beta_*} = c_{\beta_*}(\beta_0, \Omega)$ and $d_{\beta_*} = d_{\beta_*}(\beta_0, \Omega)$. As in Section 5, $f_Q(q; \beta_*, \beta_0, \lambda, \Omega)$ denotes the density of $Q := [S : T]'[S : T]$ when $[S : T]$ has the multivariate normal distribution in (2.3) with $\beta = \beta_*$ and $\lambda = \mu'_\pi \mu_\pi$. This noncentral Wishart density is

$$\begin{aligned} f_Q(q; \beta_*, \beta_0, \lambda, \Omega) &= K_1 \exp(-\lambda(c_{\beta_*}^2 + d_{\beta_*}^2)/2) \det(q)^{(k-3)/2} \exp(-(q_S + q_T)/2) \\ &\quad \times (\lambda \xi_{\beta_*}(q))^{-(k-2)/4} I_{(k-2)/2}(\sqrt{\lambda \xi_{\beta_*}(q)}), \text{ where} \\ q &= \begin{bmatrix} q_S & q_{ST} \\ q_{ST} & q_T \end{bmatrix}, \quad q_1 = \begin{pmatrix} q_S \\ q_{ST} \end{pmatrix} \in R^+ \times R, \quad q_T \in R^+, \end{aligned} \quad (11.2)$$

$K_1^{-1} = 2^{(k+2)/2} p_i^{1/2} \Gamma((k-1)/2)$, $I_\nu(\cdot)$ denotes the modified Bessel function of the first kind of order ν , $p_i = 3.1415\dots$, and $\Gamma(\cdot)$ is the gamma function. This holds by Lemma 3(a) of AMS with $\beta = \beta_*$.

By Lemma 3(c) of AMS, the conditional density of Q_1 given $Q_T = q_T$ when $[S : T]$ is distributed as in (2.3) with $\beta = \beta_0$ is

$$f_{Q_1|Q_T}(q_1|q_T) := K_1 K_2^{-1} \exp(-q_S/2) \det(q)^{(k-3)/2} q_T^{-(k-2)/2}, \quad (11.3)$$

which does not depend on β_0 , λ , or Ω .

By Lemma 5.1, the limit of $f_Q(q; \beta_*, \beta_0, \lambda, \Omega)$ as $\beta_0 \rightarrow \pm\infty$ is the density $f_Q(q; \rho_{uv}, \lambda_v)$. As in Section 5, $f_Q(q; \rho_{uv}, \lambda_v)$ denotes the density of $Q := [S : T]'[S : T]$ when $[S : T]$ has a multivariate normal distribution with means matrix in (5.2), all variances equal to one, and all covariances equal to zero. This is a noncentral Wishart density that has following form:

$$\begin{aligned} f_Q(q; \rho_{uv}, \lambda_v) &= K_1 \exp(-\lambda_v(1 + r_{uv}^2)/2) \det(q)^{(k-3)/2} \exp(-(q_S + q_T)/2) \\ &\quad \times (\lambda_v \xi(q; \rho_{uv}))^{-(k-2)/4} I_{(k-2)/2}(\sqrt{\lambda_v \xi(q; \rho_{uv})}), \text{ where} \\ \xi(q; \rho_{uv}) &:= q_S + 2r_{uv} q_{ST} + r_{uv}^2 q_T. \end{aligned} \quad (11.4)$$

This expression for the density holds by the proof of Lemma 3(a) of AMS with means matrix $\mu_\pi \cdot (1/\sigma_v, r_{uv}/\sigma_v)$ in place of the means matrix $\mu_\pi \cdot (c_\beta, d_\beta)$.

11.2 POIS2 Test

Here we define the $POIS2(q_1, q_T; \beta_0, \beta_*, \lambda)$ test statistic of AMS, which is analyzed in Section 5, and its conditional critical value $\kappa_{2, \beta_0}(q_T)$.

Given (β_*, λ) , the parameters (β_{2*}, λ_2) are defined in (5.3), which is the same as (4.2) of AMS. By Cor. 1 of AMS, the optimal average-power test statistic against (β_*, λ) and (β_{2*}, λ_2) is

$$\begin{aligned} POIS2(Q; \beta_0, \beta_*, \lambda) &:= \frac{\psi(Q; \beta_0, \beta_*, \lambda) + \psi(Q; \beta_0, \beta_{2*}, \lambda_2)}{2\psi_2(Q_T; \beta_0, \beta_*, \lambda)}, \text{ where} \\ \psi(Q; \beta_0, \beta, \lambda) &:= \exp(-\lambda(c_\beta^2 + d_\beta^2)/2)(\lambda\xi_\beta(Q))^{-(k-2)/4} I_{(k-2)/2}(\sqrt{\lambda\xi_\beta(Q)}), \\ \psi_2(Q_T; \beta_0, \beta, \lambda) &:= \exp(-\lambda d_\beta^2/2)(\lambda d_\beta^2 Q_T)^{-(k-2)/4} I_{(k-2)/2}(\sqrt{\lambda d_\beta^2 Q_T}), \end{aligned} \quad (11.5)$$

Q and Q_T are defined in (3.1), $c_\beta = c_\beta(\beta, \Omega)$ and $d_\beta = d_\beta(\beta, \Omega)$ are defined in (2.3), $I_\nu(\cdot)$ is defined in (11.2), $\xi_\beta(Q)$ is defined in (11.1) with Q and β in place of q and β_* , and $\lambda := \mu'_\pi \mu_\pi$. Note that $\psi_2(Q_T; \beta_*, \lambda) = \psi_2(Q_T; \beta_{2*}, \lambda_2)$ by (5.3).

Let $\kappa_{2, \beta_0}(q_T)$ denote the conditional critical value of the $POIS2(Q; \beta_0, \beta_*, \lambda)$ test statistic. That is, $\kappa_{2, \beta_0}(q_T)$ is defined to satisfy

$$P_{Q_1|Q_T}(POIS2(Q; \beta_0, \beta_*, \lambda) > \kappa_{2, \beta_0}(q_T) | q_T) = \alpha \quad (11.6)$$

for all $q_T \geq 0$, where $P_{Q_1|Q_T}(\cdot | q_T)$ denotes probability under the density $f_{Q_1|Q_T}(\cdot | q_T)$ defined in (11.3). The critical value function $\kappa_{2, \beta_0}(\cdot)$ depends on $(\beta_0, \beta_*, \lambda, \Omega)$ and k (and (β_{2*}, λ_2) through (β_*, λ)).

11.3 Structural and Reduced-Form Variance Matrices

Let u_i , v_{1i} , and v_{2i} denote the i th elements of u , v_1 , and v_2 , respectively. We have

$$v_{1i} := u_i + v_{2i}\beta \text{ and } \Omega = \begin{bmatrix} \omega_1^2 & \omega_{12} \\ \omega_{12} & \omega_2^2 \end{bmatrix}, \quad (11.7)$$

where β denotes the true value.

Given the true value β and some structural error variance matrix Σ , the corresponding reduced-

form error variance matrix $\Omega(\beta, \Sigma)$ is

$$\begin{aligned}\Omega(\beta, \Sigma) &:= \text{Var} \left(\begin{pmatrix} v_{1i} \\ v_{2i} \end{pmatrix} \right) = \text{Var} \left(\begin{pmatrix} u_i + v_{2i}\beta \\ v_{2i} \end{pmatrix} \right) \\ &= \begin{bmatrix} 1 & \beta \\ 0 & 1 \end{bmatrix} \Sigma \begin{bmatrix} 1 & 0 \\ \beta & 1 \end{bmatrix} = \begin{bmatrix} \sigma_u^2 + 2\sigma_{uv}\beta + \sigma_v^2\beta^2 & \sigma_{uv} + \sigma_v^2\beta \\ \sigma_{uv} + \sigma_v^2\beta & \sigma_v^2 \end{bmatrix}, \text{ where} \\ \Sigma &= \begin{bmatrix} \sigma_u^2 & \sigma_{uv} \\ \sigma_{uv} & \sigma_v^2 \end{bmatrix}.\end{aligned}\tag{11.8}$$

Given the true value β and the reduced-form error variance matrix Ω , the structural variance matrix $\Sigma(\beta, \Omega)$ is

$$\begin{aligned}\Sigma(\beta, \Omega) &:= \text{Var} \left(\begin{pmatrix} u_i \\ v_{2i} \end{pmatrix} \right) = \text{Var} \left(\begin{pmatrix} v_{1i} - v_{2i}\beta \\ v_{2i} \end{pmatrix} \right) \\ &= \begin{bmatrix} 1 & -\beta \\ 0 & 1 \end{bmatrix} \Omega \begin{bmatrix} 1 & 0 \\ -\beta & 1 \end{bmatrix} = \begin{bmatrix} \omega_1^2 - 2\omega_{12}\beta + \omega_2^2\beta^2 & \omega_{12} - \omega_2^2\beta \\ \omega_{12} - \omega_2^2\beta & \omega_2^2 \end{bmatrix}.\end{aligned}\tag{11.9}$$

Let $\sigma_u^2(\beta, \Omega)$, $\sigma_v^2(\beta, \Omega)$, and $\sigma_{uv}(\beta, \Omega)$ denote the (1, 1), (2, 2), and (1, 2) elements of $\Sigma(\beta, \Omega)$. Let $\rho_{uv}(\beta, \Omega)$ denote the correlation implied by $\Sigma(\beta, \Omega)$.

In the asymptotics as $\beta_0 \rightarrow \pm\infty$, we fix β_* and Ω and consider the testing problem as $\beta_0 \rightarrow \pm\infty$. Rather than fixing Ω , one can equivalently fix the structural variance matrix when $\beta = \beta_*$, say at Σ_* . Given β_* and Σ_* , there is a unique reduced-form error variance matrix $\Omega = \Omega(\beta_*, \Sigma_*)$ defined using (11.8). Significant simplifications in certain formulae occur when they are expressed in terms of Σ_* , rather than Ω , e.g., see Lemma 14.1(e) below.

For notational simplicity, we denote the (1, 1), (2, 2), and (1, 2) elements of Σ_* by σ_u^2 , σ_v^2 , and σ_{uv} , respectively, without any $*$ subscripts. As defined in (4.5), $\rho_{uv} := \sigma_{uv}/(\sigma_u\sigma_v)$. Thus, ρ_{uv} is the correlation between the structural and reduced-form errors u_i and v_{2i} when the true value of β is β_* . Note that ρ_{uv} does not change when (β_*, Σ_*) is fixed (or, equivalently, $(\beta_*, \Omega) = (\beta_*, \Omega(\beta_*, \Sigma_*))$ is fixed) and β_0 is changed. Also, note that $\sigma_v^2 = \omega_2^2$ because both denote the variance of v_{2i} under $\beta = \beta_*$ and $\beta = \beta_0$.

12 One-Sided Power Bound as $\beta_0 \rightarrow \pm\infty$

In this section, we provide one-sided power bounds for invariant similar tests as $\beta_0 \rightarrow \pm\infty$ for fixed β_* . The approach is the same as in Andrews, Moreira, and Stock (2004) (AMS04) except that

we consider $\beta_0 \rightarrow \pm\infty$. Also see Mills, Moreira, and Vilela (2014).

12.1 Point Optimal Invariant Similar Tests for Fixed β_0 and β_*

First, we consider the point null and alternative hypotheses:

$$H_0 : \beta = \beta_0 \text{ and } H_1 : \beta = \beta_*, \quad (12.1)$$

where $\pi \in R^k$ (or, equivalently, $\lambda \geq 0$) under H_0 and H_1 .

Point optimal invariant similar (POIS) tests for any given null and alternative parameter values β_0 and β_* , respectively, and any given Ω are constructed in AMS04, Sec. 5. Surprisingly, the same test is found to be optimal for all values of π under H_1 , i.e., for all strengths of identification. The optimal test is constructed by determining the level α test that maximizes conditional power given $Q_T = q_T$ among tests that are invariant and have null rejection probability α conditional on $Q_T = q_T$, for each $q_T \in R$.

By AMS04 (Comment 2 to Cor. 2), the POIS test of $H_0 : \beta = \beta_0$ versus $H_1 : \beta = \beta_*$, for any $\pi \in R^k$ (or $\lambda \geq 0$) under H_1 , rejects H_0 for large values of

$$POIS(Q; \beta_0, \beta_*) := Q_S + 2 \frac{d_{\beta_*}(\beta_0, \Omega)}{c_{\beta_*}(\beta_0, \Omega)} Q_{ST}. \quad (12.2)$$

The critical value for the $POIS(Q; \beta_0, \beta_*)$ test is a conditional critical value given $Q_T = q_T$, which we denote by $\kappa_{\beta_0}(q_T)$. The critical value $\kappa_{\beta_0}(q_T)$ is defined to satisfy

$$P_{Q_1|Q_T}(POIS(Q; \beta_0, \beta_*) > \kappa_{\beta_0}(q_T) | q_T) = \alpha \quad (12.3)$$

for all $q_T \geq 0$, where $P_{Q_1|Q_T}(\cdot | q_T)$ denotes probability under the conditional density $f_{Q_1|Q_T}(q_1 | q_T)$ defined in (11.3). Although the density $f_{Q_1|Q_T}(q_1 | q_T)$ does not depend on β_0 , $\kappa_{\beta_0}(q_T)$ depends on β_0 , as well as (β_*, Ω, k) , because $POIS(Q; \beta_0, \beta_*)$ does.

Note that, although the same $POIS(Q; \beta_0, \beta_*)$ test is best for all strengths of identification, i.e., for all $\lambda = \mu'_\pi \mu_\pi > 0$, the power of this test depends on λ .

12.2 One-Sided Power Bound When $\beta_0 \rightarrow \pm\infty$

Now we consider the best one-sided invariant similar test as $\beta_0 \rightarrow \pm\infty$ keeping (β_*, Ω) fixed. Lemma 14.1 below implies that

$$\lim_{\beta_0 \rightarrow \pm\infty} \frac{d_{\beta_*}(\beta_0, \Omega)}{c_{\beta_*}(\beta_0, \Omega)} = \left(\mp \frac{\rho_{uv}}{\sigma_v(1 - \rho_{uv}^2)^{1/2}} \right) / (\mp 1/\sigma_v) = \frac{\rho_{uv}}{(1 - \rho_{uv}^2)^{1/2}}, \quad (12.4)$$

where ρ_{uv} , defined in (4.5), is the correlation between the structural and reduced-form errors u_i and v_{2i} under β_* . Hence, the limit as $\beta_0 \rightarrow \pm\infty$ of the $POIS(Q; \beta_0, \beta_*)$ test statistic in (12.2) is

$$POIS(Q; \infty, \rho_{uv}) := \lim_{\beta_0 \rightarrow \pm\infty} \left(Q_S + 2 \frac{d_{\beta_*}(\beta_0, \Omega)}{c_{\beta_*}(\beta_0, \Omega)} Q_{ST} \right) = Q_S + 2 \frac{\rho_{uv}}{(1 - \rho_{uv}^2)^{1/2}} Q_{ST}. \quad (12.5)$$

Notice that (i) this limit is the same for $\beta_0 \rightarrow +\infty$ and $\beta_0 \rightarrow -\infty$, (ii) the $POIS(Q; \infty, \rho_{uv})$ statistic depends on $(\beta_*, \Omega) = (\beta_*, \Omega(\beta_*, \Sigma_*))$ only through $\rho_{uv} := Corr(\Sigma_*)$, and (iii) when $\rho_{uv} = 0$, the $POIS(Q; \infty, \rho_{uv})$ statistic is the AR statistic (times k). Some intuition for result (iii) is that $EQ_{ST} = 0$ under the null and $\lim_{|\beta_0| \rightarrow \infty} EQ_{ST} = 0$ under any fixed alternative β_* when $\rho_{uv} = 0$ (see the discussion in Section 5.2). In consequence, Q_{ST} is not useful for distinguishing between H_0 and H_1 when $|\beta_0| \rightarrow \infty$ and $\rho_{uv} = 0$.

Let $\kappa_\infty(q_T)$ denote the conditional critical value of the $POIS(Q; \infty, \rho_{uv})$ test statistic. That is, $\kappa_\infty(q_T)$ is defined to satisfy

$$P_{Q_1|Q_T}(POIS(Q; \infty, \rho_{uv}) > \kappa_\infty(q_T) | q_T) = \alpha \quad (12.6)$$

for all $q_T \geq 0$. The density $f_{Q_1|Q_T}(\cdot | q_T)$ of $P_{Q_1|Q_T}(\cdot | q_T)$ only depends on the number of IV's k , see (11.3). The critical value function $\kappa_\infty(\cdot)$ depends on ρ_{uv} and k .

Let $\phi_{\beta_0}(Q)$ denote a test of $H_0 : \beta = \beta_0$ versus $H_1 : \beta = \beta_*$ based on Q that rejects H_0 when $\phi_{\beta_0}(Q) = 1$. In most cases, a test depends on β_0 because the distribution of Q depends on β_0 , see (2.3) and (3.1), and not because $\phi_{\beta_0}(\cdot)$ depends on β_0 . For example, this is true of the AR, LM, and CLR tests in (3.3) and (3.4). However, we allow for dependence of $\phi_{\beta_0}(\cdot)$ on β_0 in the following result in order to cover all possible sequences of (non-randomized) tests of $H_0 : \beta = \beta_0$.

Theorem 12.1 *Let $\{\phi_{\beta_0}(Q) : \beta_0 \rightarrow \pm\infty\}$ be any sequence of invariant similar level α tests of $H_0 : \beta = \beta_0$ versus $H_1 : \beta = \beta_*$ when Q has density $f_Q(q; \beta, \beta_0, \lambda, \Omega)$ for some $\lambda \geq 0$ and Ω is fixed and known. For fixed true $(\beta_*, \lambda, \Omega)$, the $POIS(Q; \infty, \rho_{uv})$ test satisfies*

$$\limsup_{\beta_0 \rightarrow \pm\infty} P_{\beta_*, \beta_0, \lambda, \Omega}(\phi_{\beta_0}(Q) = 1) \leq P_{\rho_{uv}, \lambda} (POIS(Q; \infty, \rho_{uv}) > \kappa_\infty(Q_T)).$$

Comments. (i). Theorem 12.1 shows that the $POIS(Q; \infty, \rho_{uv})$ test provides an asymptotic power bound as $\beta_0 \rightarrow \pm\infty$ for any invariant similar test for any fixed $(\beta_*, \lambda, \Omega)$. This power bound is strictly less than one. The reason is that $\lim_{\beta_0 \rightarrow \pm\infty} |c_{\beta_*}(\beta_0, \Omega)| \rightarrow \infty$. This is the same reason that the AR test does not have power that converges to one in this scenario, see Section 19. Hence, the bound in Theorem 12.1 is informative.

(ii). The power bound in Theorem 12.1 only depends on $(\beta_*, \lambda, \Omega)$ through ρ_{uv} , the magnitude

of endogeneity under β_* , and λ_v , the concentration parameter.

(iii). As an alternative to the power bound given in Theorem 12.1, one might consider developing a formal limit of experiments result, e.g., along the lines of van der Vaart (1998, Ch. 9). This approach does not appear to work for the sequence of experiments consisting of the two unconditional distributions of $[S : T]$ (or Q) for $\beta = \beta_0, \beta_*$ and indexed by β_0 as $\beta_0 \rightarrow \pm\infty$. The reason is that the likelihood ratio of these two distributions is asymptotically degenerate as $\beta_0 \rightarrow \pm\infty$ (either 0 or ∞ depending on which density is in the numerator) when the truth is taken to be $\beta = \beta_0$. This occurs because the length of the mean vector of T diverges to infinity as $\beta_0 \rightarrow \pm\infty$ (provided $\lambda = \mu'_\pi \mu_\pi > 0$) by (2.3) and Lemma 14.1(c) below. For the sequence of conditional distributions of Q given $Q_T = q_T$, it should be possible to obtain a formal limit of experiments result, but this would not be very helpful because we are interested in the unconditional power of tests and a conditional limit of experiments result would not deliver this.

(iv). The proof of Theorem 12.1 is given in Section 18 below.

13 Equations (4.1) and (4.2) of AMS

This section corrects (4.1) of AMS, which concerns the two-point weight function that defines AMS's two-sided AE power envelope.

Equation (4.1) of AMS is:⁸ given (β_*, λ) , the second point (β_{2*}, λ_2) solves

$$\lambda_2^{1/2} c_{\beta_{2*}} = -\lambda^{1/2} c_{\beta_*} \ (\neq 0) \text{ and } \lambda_2^{1/2} d_{\beta_{2*}} = \lambda^{1/2} d_{\beta_*}. \quad (13.1)$$

AMS states that provided $\beta_* \neq \beta_{AR}$, the solutions to the two equations in (4.1) satisfy the two equations in (4.2) of AMS, which is the same as (5.3) and which we repeat here for convenience:⁹

$$\beta_{2*} = \beta_0 - \frac{d_{\beta_0}(\beta_* - \beta_0)}{d_{\beta_0} + 2r_{\beta_0}(\beta_* - \beta_0)} \text{ and } \lambda_2 = \lambda \frac{(d_{\beta_0} + 2r_{\beta_0}(\beta_* - \beta_0))^2}{d_{\beta_0}^2}, \text{ where} \\ r_{\beta_0} := e'_1 \Omega^{-1} a_0 \cdot (a'_0 \Omega^{-1} a_0)^{-1/2} \text{ and } e_1 := (1, 0)'. \quad (13.2)$$

Equation (4.2) is correct as stated, but (4.1) of AMS is not correct. More specifically, it is not complete. It should be: given (β_*, λ) , the second point (β_{2*}, λ_2) solves either (13.1) or

$$\lambda_2^{1/2} c_{\beta_{2*}} = \lambda^{1/2} c_{\beta_*} \ (\neq 0) \text{ and } \lambda_2^{1/2} d_{\beta_{2*}} = -\lambda^{1/2} d_{\beta_*}. \quad (13.3)$$

⁸Note that (β_*, λ) and (β_{2*}, λ_2) in this paper correspond to (β^*, λ^*) and (β_2^*, λ_2^*) in AMS.

⁹The formulae in (5.3) and (13.2) only hold for $\beta_* \neq \beta_{AR}$, where $\beta_{AR} := (\omega_1^2 - \omega_{12}\beta_0)/(\omega_{12} - \omega_2^2\beta_0)$ provided $\omega_{12} - \omega_2^2\beta_0 \neq 0$ (which necessarily holds for $|\beta_0|$ sufficiently large because $\omega_2^2 > 0$).

For brevity, we write the “either or” conditions in (13.1) and (13.3) as

$$\lambda_2^{1/2} c_{\beta_{2*}} = \mp \lambda^{1/2} c_{\beta_*} \ (\neq 0) \text{ and } \lambda_2^{1/2} d_{\beta_{2*}} = \pm \lambda^{1/2} d_{\beta_*}. \quad (13.4)$$

The reason (4.1) of AMS needs to be augmented by (13.3) is that for some (β_*, λ) , β_0 , and Ω , (4.1) has no real solutions (β_{2*}, λ_2) and the expressions for (β_{2*}, λ_2) in (4.2) of AMS do not satisfy (4.1). Once (4.1) of AMS is augmented by (13.3), there exist real solutions (β_{2*}, λ_2) to the augmented conditions and they are given by the expressions in (4.2) of AMS, i.e., by (13.2). This is established in the following lemma.

Lemma 13.1 *The conditions in (13.4) hold iff the conditions in (4.2) of AMS hold, i.e., iff the conditions in (13.2) holds.*

With (4.1) of AMS replaced by (13.4), the results in Theorem 8(b) and (c) of AMS hold as stated. That is, the two-point weight function that satisfies (13.4) leads to a two-sided weighted average power (WAP) test that is asymptotically efficient under strong IV’s. And, all other two-point weight functions lead to two-sided WAP tests that are not asymptotically efficient under strong IV’s.

Lemma 13.2 *Under the assumptions of Theorem 8 of AMS, i.e., Assumptions SIV-LA and 1-4 of AMS, (a) if (β_{2*}, λ_2) satisfies (13.4), then $LR^*(\widehat{Q}_{1,n}, \widehat{Q}_{T,n}; \beta_*, \lambda) = e^{-\frac{1}{2}(\tau^*)^2} \cosh(\tau^* LM_n^{1/2}) + o_p(1)$, where $\tau^* = \lambda^{1/2} c_{\beta_*}$, which is a strictly-increasing continuous function of LM_n , and (b) if (β_{2*}, λ_2) does not satisfy (13.4), then $LR^*(\widehat{Q}_{1,n}, \widehat{Q}_{T,n}; \beta_*, \lambda) = \eta_2(Q_{ST,n}/Q_{T,n}^{1/2}) + o_p(1)$ for a continuous function $\eta_2(\cdot)$ that is not even.*

Comments. (i). Lemma 13.2(a) is an extension of Theorem 8(b) of AMS; while Lemma 13.2(b) is a correction to Theorem 8(c) of AMS.

(ii). The proofs of Lemma 13.1 and 13.2 are given in Section 18 below.

Having augmented (4.1) by (13.3), the two-point weight function of AMS does not have the property that β_{2*} is necessarily on the opposite side of β_0 from β_* . However, it does have the properties that (i) for any (β_*, λ) , (β_{2*}, λ_2) is the only point that yields a two-point WAP test that is asymptotic efficient in a two-sided sense under strong IV’s, (ii) the marginal distributions of Q_S , Q_T , and Q_{ST} are the same under (β_*, λ) and (β_{2*}, λ_2) , and (iii) the joint distribution of (Q_S, Q_{ST}, Q_T) under (β_*, λ) is the same as that of $(Q_S, -Q_{ST}, Q_T)$ under (β_{2*}, λ_2) .

14 Proof of Lemma 5.1

The proof of Lemma 5.1 and other proofs below use the following lemma.

The distributions of $[S : T]$ under (β_0, Ω) and (β_*, Ω) depend on $c_\beta(\beta_0, \Omega)$ and $d_\beta(\beta_0, \Omega)$ for $\beta = \beta_0$ and β_* . The limits of these quantities as $\beta_0 \rightarrow \pm\infty$ are given in the following lemma.¹⁰

Lemma 14.1 *For fixed β_* and positive definite matrix Ω , we have*

- (a) $\lim_{\beta_0 \rightarrow \pm\infty} c_{\beta_0}(\beta_0, \Omega) = 0.$
- (b) $\lim_{\beta_0 \rightarrow \pm\infty} c_{\beta_*}(\beta_0, \Omega) = \mp 1/\sigma_v.$
- (c) $\lim_{\beta_0 \rightarrow \pm\infty} d_{\beta_0}(\beta_0, \Omega) = \infty.$
- (d) $d_{\beta_0}(\beta_0, \Omega)/|\beta_0| = \frac{\omega_2}{(\omega_1^2\omega_2^2 - \omega_{12}^2)^{1/2}} + o(1) = \frac{1}{\sigma_u(1 - \rho_{uv}^2)^{1/2}} + o(1)$ as $|\beta_0| \rightarrow \infty.$
- (e) $\lim_{\beta_0 \rightarrow \pm\infty} d_{\beta_*}(\beta_0, \Omega) = \pm \frac{\omega_2^2\beta_* - \omega_{12}}{\omega_2(\omega_1^2\omega_2^2 - \omega_{12}^2)^{1/2}} = \mp \frac{\rho_{uv}}{\sigma_v(1 - \rho_{uv}^2)^{1/2}}.$

Comment. The limits in parts (d) and (e), expressed in terms of Σ_* , only depend on ρ_{uv} , σ_u , and σ_v and their functional forms are of a relatively simple multiplicative form. The latter provides additional simplifications of certain quantities that appear below.

Proof of Lemma 14.1. Part (a) holds because $c_{\beta_0}(\beta_0, \Omega) = 0$ for all β_0 . Part (b) holds by the following calculations:

$$\begin{aligned}
 \lim_{\beta_0 \rightarrow \pm\infty} c_{\beta_*}(\beta_0, \Omega) &= \lim_{\beta_0 \rightarrow \pm\infty} (\beta_* - \beta_0) \cdot (b_0' \Omega b_0)^{-1/2} \\
 &= \lim_{\beta_0 \rightarrow \pm\infty} (\beta_* - \beta_0) \cdot (\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2\beta_0^2)^{-1/2} \\
 &= \mp 1/\omega_2 \\
 &= \mp 1/\sigma_v.
 \end{aligned} \tag{14.1}$$

Now, we establish part (e). Let $b_* := (1, -\beta_*)'$. We have

$$\begin{aligned}
 \lim_{\beta_0 \rightarrow \pm\infty} d_{\beta_*}(\beta_0, \Omega) &= \lim_{\beta_0 \rightarrow \pm\infty} b_*' \Omega b_0 \cdot (b_0' \Omega b_0)^{-1/2} \det(\Omega)^{-1/2} \\
 &= \lim_{\beta_0 \rightarrow \pm\infty} \frac{\omega_1^2 - \omega_{12}\beta_* - \omega_{12}\beta_0 + \omega_2^2\beta_*\beta_0}{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2\beta_0^2)^{1/2}(\omega_1^2\omega_2^2 - \omega_{12}^2)^{1/2}} \\
 &= \pm \frac{\omega_2^2\beta_* - \omega_{12}}{\omega_2(\omega_1^2\omega_2^2 - \omega_{12}^2)^{1/2}}.
 \end{aligned} \tag{14.2}$$

Next, we write the limit in (14.2) in terms of the elements of the structural error variance matrix

¹⁰Throughout, $\beta_0 \rightarrow \pm\infty$ means $\beta_0 \rightarrow \infty$ or $\beta_0 \rightarrow -\infty$.

Σ_* . The term in the square root in the denominator of (14.2) satisfies

$$\omega_1^2 \omega_2^2 - \omega_{12}^2 = (\sigma_u^2 + 2\sigma_{uv}\beta_* + \sigma_v^2 \beta_*^2) \sigma_v^2 - (\sigma_{uv} + \sigma_v^2 \beta_*)^2 = \sigma_u^2 \sigma_v^2 - \sigma_{uv}^2, \quad (14.3)$$

where the first equality uses $\omega_2^2 = \sigma_v^2$ (since both denote the variance of v_{2i}), $\omega_1^2 = \sigma_u^2 + 2\sigma_{uv}\beta_* + \sigma_v^2 \beta_*^2$, and $\omega_{12} = \sigma_{uv} + \sigma_v^2 \beta_*$ (which both hold by (11.8) with $\beta = \beta_*$ and $\Sigma = \Sigma_*$), and the second equality holds by simple calculations. The limit in (14.2) in terms of the elements of Σ_* is

$$\pm \frac{\omega_2^2 \beta_* - \omega_{12}}{\omega_2 (\omega_1^2 \omega_2^2 - \omega_{12}^2)^{1/2}} = \pm \frac{\sigma_v^2 \beta_* - (\sigma_{uv} + \sigma_v^2 \beta_*)}{\sigma_v (\sigma_u^2 \sigma_v^2 - \sigma_{uv}^2)^{1/2}} = \mp \frac{\rho_{uv}}{\sigma_v (1 - \rho_{uv}^2)^{1/2}}, \quad (14.4)$$

where the first equality uses (14.3), $\omega_2^2 = \sigma_v^2$, and $\omega_{12} = \sigma_{uv} + \sigma_v^2 \beta_*$, and the second inequality holds by dividing the numerator and denominator by $\sigma_u \sigma_v$. This establishes part (e).

For part (c), we have

$$\begin{aligned} \lim_{\beta_0 \rightarrow \pm\infty} d_{\beta_0}(\beta_0, \Omega) &= \lim_{\beta_0 \rightarrow \pm\infty} (b'_0 \Omega b_0)^{1/2} \det(\Omega)^{-1/2} \\ &= \lim_{\beta_0 \rightarrow \pm\infty} \frac{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2 \beta_0^2)^{1/2}}{(\omega_1^2 \omega_2^2 - \omega_{12}^2)^{1/2}} \\ &= \infty. \end{aligned} \quad (14.5)$$

Part (d) holds because, as $|\beta_0| \rightarrow \infty$, we have

$$\begin{aligned} d_{\beta_0}(\beta_0, \Omega)/|\beta_0| &= \frac{(\omega_1^2/\beta_0^2 - 2\omega_{12}/\beta_0 + \omega_2^2)^{1/2}}{(\omega_1^2 \omega_2^2 - \omega_{12}^2)^{1/2}} \\ &= \frac{\omega_2}{(\omega_1^2 \omega_2^2 - \omega_{12}^2)^{1/2}} + o(1) \\ &= \frac{1}{\sigma_u (1 - \rho_{uv}^2)^{1/2}} + o(1), \end{aligned} \quad (14.6)$$

where the last equality uses (14.3) and $\omega_2 = \sigma_v$. \square

Next, we prove Lemma 5.1, which states that for any fixed $(\beta_*, \lambda, \Omega)$, $\lim_{\beta_0 \rightarrow \pm\infty} f_Q(q; \beta_*, \beta_0, \lambda, \Omega) = f_Q(q; \rho_{uv}, \lambda_v)$.

Proof of Lemma 5.1. By Lemma 14.1(b) and (e) and (5.1), we have $\lim_{\beta_0 \rightarrow \pm\infty} c_{\beta_*} = \mp 1/\sigma_v$ and

$\lim_{\beta_0 \rightarrow \pm\infty} d_{\beta_*} = \mp r_{uv}/\sigma_v$. In consequence,

$$\begin{aligned} \lim_{\beta_0 \rightarrow \pm\infty} \lambda(c_{\beta_*}^2 + d_{\beta_*}^2) &= \lambda(1/\sigma_v^2)(1 + r_{uv}^2) = \lambda_v(1 + r_{uv}^2) \text{ and} \\ \lim_{\beta_0 \rightarrow \pm\infty} \lambda \xi_{\beta_*}(q) &= \lim_{\beta_0 \rightarrow \pm\infty} \lambda(c_{\beta_*}^2 q_S + 2c_{\beta_*} d_{\beta_*} q_{ST} + d_{\beta_*}^2 q_T) \\ &= \lambda(1/\sigma_v^2)(q_S + 2r_{uv} q_{ST} + r_{uv}^2 q_T) = \lambda_v \xi(q; \rho_{uv}), \end{aligned} \quad (14.7)$$

using the definitions of λ_v and $\xi(q; \rho_{uv})$ in (5.1) and (11.4), respectively, where the first equality in the third line uses $(\mp 1)(\mp r_{uv}) = r_{uv}$. Combining this with (11.2) and (11.4) proves the result of the lemma. \square

15 Proof of Theorem 4.1

The proof of Theorem 4.1 uses the following lemma.¹¹ Let

$$\begin{aligned} S_{\pm\infty}(Y) &:= (Z'Z)^{-1/2} Z'Y e_2 \cdot \frac{\mp 1}{\sigma_v}, \\ T_{\pm\infty}(Y) &:= (Z'Z)^{-1/2} Z'Y \Omega^{-1} e_1 \cdot (\pm(1 - \rho_{uv}^2)^{1/2} \sigma_u), \text{ and} \\ Q_{\pm\infty}(Y) &:= \begin{bmatrix} e_2' Y' P_Z Y e_2 \cdot \frac{1}{\sigma_v^2} & e_2' Y' P_Z Y \Omega^{-1} e_1 \cdot \frac{\mp(1 - \rho_{uv}^2)^{1/2} \sigma_u}{\sigma_v} \\ e_2' Y' P_Z Y \Omega^{-1} e_1 \cdot \frac{\mp(1 - \rho_{uv}^2)^{1/2} \sigma_u}{\sigma_v} & e_1' \Omega^{-1} Y' P_Z Y \Omega^{-1} e_1 \cdot (1 - \rho_{uv}^2) \sigma_u^2 \end{bmatrix}, \end{aligned} \quad (15.1)$$

where $\rho_{uv} := \text{Corr}(u_i, v_{2i})$, $P_Z := Z(Z'Z)^{-1}Z'$, $e_1 := (1, 0)'$, and $e_2 := (0, 1)'$. Let $Q_{T, \pm\infty}(Y)$ denote the (2, 2) element of $Q_{\pm\infty}(Y)$. As defined in (5.1), $r_{uv} = \rho_{uv}/(1 - \rho_{uv}^2)^{1/2}$.

Lemma 15.1 *For fixed β_* and positive definite matrix Ω , we have*

- (a) $\lim_{\beta_0 \rightarrow \pm\infty} S_{\beta_0}(Y) = S_{\pm\infty}(Y)$,
- (b) $S_{\pm\infty}(Y) \sim N(\mp \frac{1}{\sigma_v} \mu_\pi, I_k)$,
- (c) $\lim_{\beta_0 \rightarrow \pm\infty} T_{\beta_0}(Y) = T_{\pm\infty}(Y) = (Z'Z)^{-1/2} Z'Y \Omega^{-1} e_1 \cdot (\pm(1 - \rho_\Omega^2)^{1/2} \omega_1)$, where $\rho_\Omega := \text{Corr}(v_{1i}, v_{2i})$,
- (d) $T_{\pm\infty}(Y) \sim N(\mp \frac{r_{uv}}{\sigma_v} \mu_\pi, I_k)$,
- (e) $S_{\pm\infty}(Y)$ and $T_{\pm\infty}(Y)$ are independent,
- (f) $\lim_{\beta_0 \rightarrow \pm\infty} Q_{\beta_0}(Y) = Q_{\pm\infty}(Y)$, and
- (g) $Q_{\pm\infty}(Y)$ has a noncentral Wishart distribution with means matrix $\mp \mu_\pi (\frac{1}{\sigma_v}, \frac{r_{uv}}{\sigma_v}) \in R^{k \times 2}$,

identity variance matrix, and density given in (11.4).

Comment. The convergence results in Lemma 15.1 hold for all realizations of Y .

¹¹The proof of Comment (v) to Theorem 4.1 is the same as that of Theorem 4.1(a) and (b) with $[S_{\beta_0}(Y), T_{\beta_0}(Y)]$ and $T_{\beta_0}(Y)$ in place of $Q_{\beta_0}(Y)$ and $Q_{T, \beta_0}(Y)$, respectively.

Proof of Theorem 4.1. First, we prove part (a). We have

$$\begin{aligned}
& 1(RLength(CS_\phi(Y)) = \infty) \\
&= 1(\mathcal{T}(Q_{\beta_0}(Y)) \leq cv(Q_{T,\beta_0}(Y)) \forall \beta_0 \geq K(Y) \text{ for some } K(Y) < \infty) \\
&= \lim_{\beta_0 \rightarrow \infty} 1(\mathcal{T}(Q_{\beta_0}(Y)) \leq cv(Q_{T,\beta_0}(Y))), \tag{15.2}
\end{aligned}$$

where the second equality holds provided the limit as $\beta_0 \rightarrow \infty$ on the rhs exists, the first equality holds by the definition of $CS_\phi(Y)$ in (4.1)-(4.3) and the definition of $RLength(CS_\phi(Q)) = \infty$ in (4.4), and the second equality holds because its rhs equals one (when the rhs limit exists) iff $\mathcal{T}(Q_{\beta_0}(Y)) \leq cv(Q_{T,\beta_0}(Y))$ for $\forall \beta_0 \geq K(Y)$ for some $K(Y) < \infty$, which is the same as its lhs.

Now, we use the dominated convergence theorem to show

$$\begin{aligned}
& \lim_{\beta_0 \rightarrow \infty} E_{\beta_*,\pi,\Omega} 1(\mathcal{T}(Q_{\beta_0}(Y)) \leq cv(Q_{T,\beta_0}(Y))) \\
&= E_{\beta_*,\pi,\Omega} \lim_{\beta_0 \rightarrow \infty} 1(\mathcal{T}(Q_{\beta_0}(Y)) \leq cv(Q_{T,\beta_0}(Y))). \tag{15.3}
\end{aligned}$$

The dominated convergence theorem applies because (i) the indicator functions in (15.3) are dominated by the constant function equal to one, which is integrable, and (ii) $\lim_{\beta_0 \rightarrow \infty} 1(\mathcal{T}(Q_{\beta_0}(Y)) \leq cv(Q_{T,\beta_0}(Y)))$ exists a.s. $[P_{\beta_*,\pi,\Omega}]$ and equals $1(\mathcal{T}(Q_\infty(Y)) \leq cv(Q_{T,\infty}(Y)))$ a.s. $[P_{\beta_*,\pi,\Omega}]$. The latter holds because the assumption that $\mathcal{T}(q)$ and $cv(q_T)$ are continuous at positive definite (pd) q and positive q_T , respectively, coupled with the result of Lemma 15.1(f) (that $Q_{\beta_0}(Y) \rightarrow Q_\infty(Y)$ as $\beta_0 \rightarrow \infty$ for all sample realizations of Y , where $Q_\infty(Y)$ is defined in (15.1)), imply that (a) $\lim_{\beta_0 \rightarrow \infty} \mathcal{T}(Q_{\beta_0}(Y)) = \mathcal{T}(Q_\infty(Y))$ for all realizations of Y for which $Q_\infty(Y)$ is pd, (b) $\lim_{\beta_0 \rightarrow \infty} cv(Q_{T,\beta_0}(Y)) = cv(Q_{T,\infty}(Y))$ for all realizations of Y with $Q_{T,\infty}(Y) > 0$, and hence (c) $\lim_{\beta_0 \rightarrow \infty} 1(\mathcal{T}(Q_{\beta_0}(Y)) \leq cv(Q_{T,\beta_0}(Y))) = 1(\mathcal{T}(Q_\infty(Y)) \leq cv(Q_{T,\infty}(Y)))$ for all realizations of Y for which $\mathcal{T}(Q_\infty(Y)) \neq cv(Q_{T,\infty}(Y))$. We have $P_{\beta_*,\pi,\Omega}(\mathcal{T}(Q_\infty(Y)) = cv(Q_{T,\infty}(Y))) = 0$ by assumption, and $P_{\beta_*,\pi,\Omega}(Q_\infty(Y) \text{ is pd \& } Q_{T,\infty}(Y) > 0) = 1$ (because $Q_\infty(Y)$ has a noncentral Wishart distribution by Lemma 15.1(g)). Thus, condition (ii) above holds and the DCT applies.

Next, we have

$$\begin{aligned}
& 1 - \lim_{\beta_0 \rightarrow \infty} P_{\beta_*,\beta_0,\lambda,\Omega}(\phi(Q) = 1) \\
&= \lim_{\beta_0 \rightarrow \infty} E_{\beta_*,\pi,\Omega} 1(\mathcal{T}(Q_{\beta_0}(Y)) \leq cv(Q_{T,\beta_0}(Y))) \\
&= E_{\beta_*,\pi,\Omega} \lim_{\beta_0 \rightarrow \infty} 1(\mathcal{T}(Q_{\beta_0}(Y)) \leq cv(Q_{T,\beta_0}(Y))) \\
&= P_{\beta_*,\pi,\Omega}(RLength(CS_\phi(Y)) = \infty), \tag{15.4}
\end{aligned}$$

where the first equality holds because the distribution of Q under $P_{\beta_*,\beta_0,\lambda,\Omega}(\cdot)$ equals the distribution of $Q_{\beta_0}(Y)$ under $P_{\beta_*,\pi,\Omega}(\cdot)$ and $\phi(Q) = 0$ iff $\mathcal{T}(Q_{\beta_0}) \leq cv(Q_T)$ by (4.2), the second equality holds by (15.3), and the last equality holds by (15.2). Equation (15.4) establishes part (a).

The proof of part (b) is the same as that of part (a), but with $LLength$, $\forall \beta_0 \leq -K(Y)$, $\beta_0 \rightarrow -\infty$, $Q_{-\infty}(Y)$, and $Q_{T,-\infty}(Y)$ in place of $RLength$, $\forall \beta_0 \geq K(Y)$, $\beta_0 \rightarrow \infty$, $Q_{\infty}(Y)$, and $Q_{T,\infty}(Y)$, respectively.

The proof of part (c) uses the following: (i) $Q_{\infty}(Y)$ and $Q_{-\infty}(Y)$ only differ in the sign of their off-diagonal elements by (15.1), (ii) $\mathcal{T}(Q_{\infty}(Y))$ does not depend on the sign of the off-diagonal element of $Q_{\infty}(Y)$ by assumption, and hence, (iii) $1(\mathcal{T}(Q_{\infty}(Y)) \leq cv(Q_{T,\infty}(Y))) = 1(\mathcal{T}(Q_{-\infty}(Y)) \leq cv(Q_{T,-\infty}(Y)))$ for all sample realizations of Y . We have

$$\begin{aligned}
& 1(RLength(CS_{\phi}(Y)) = \infty \ \& \ LLength(CS_{\phi}(Y)) = \infty) \\
&= 1(\mathcal{T}(Q_{\beta_0}(Y)) \leq cv(Q_{T\beta_0}(Y)) \ \forall \beta_0 \geq K(Y) \ \& \ \forall \beta_0 \leq -K(Y) \ \text{for some } K(Y) < \infty) \\
&= \lim_{\beta_0 \rightarrow \infty} 1(\mathcal{T}(Q_{\beta_0}(Y)) \leq cv(Q_{T,\beta_0}(Y)) \ \& \ \mathcal{T}(Q_{-\beta_0}(Y)) \leq cv(Q_{T,-\beta_0}(Y))) \\
&= 1(\mathcal{T}(Q_{\infty}(Y)) \leq cv(Q_{T,\infty}(Y)) \ \& \ \mathcal{T}(Q_{-\infty}(Y)) \leq cv(Q_{T,-\infty}(Y))) \\
&= 1(\mathcal{T}(Q_{\infty}(Y)) \leq cv(Q_{T,\infty}(Y))) \\
&= \lim_{\beta_0 \rightarrow \infty} 1(\mathcal{T}(Q_{\beta_0}(Y)) \leq cv(Q_{T,\beta_0}(Y))) \tag{15.5}
\end{aligned}$$

where the first two equalities hold for the same reasons as the equalities in (15.2), the third equality holds a.s. $[P_{\beta_*,\pi,\Omega}]$ by result (ii) that follows (15.3) and the same result with $-\beta_0$ and $-\infty$ in place of β_0 and ∞ , respectively, the second last equality holds by condition (iii) immediately above (15.5), and the last equality holds by result (ii) that follows (15.3).

Now, we have

$$\begin{aligned}
& P_{\beta_*,\pi,\Omega}(RLength(CS_{\phi}(Y)) = \infty \ \& \ LLength(CS_{\phi}(Y)) = \infty) \\
&= E_{\beta_*,\pi,\Omega} \lim_{\beta_0 \rightarrow \infty} 1(\mathcal{T}(Q_{\beta_0}(Y)) \leq cv(Q_{T,\beta_0}(Y))) \\
&= 1 - \lim_{\beta_0 \rightarrow \infty} P_{\beta_*,\beta_0,\lambda,\Omega}(\phi(Q) = 1), \tag{15.6}
\end{aligned}$$

where the first equality holds by (15.5) and the second equality holds by the first four lines of (15.4). This establishes the equality in part (c) when $\beta_0 \rightarrow \infty$. The equality in part (c) when $\beta_0 \rightarrow -\infty$ holds because (15.5) and (15.6) hold with $\beta_0 \rightarrow \infty$ replaced by $\beta_0 \rightarrow -\infty$ since the indicator function on the rhs of the second equality in (15.5) depends on β_0 only through $|\beta_0|$. \square

Proof of Lemma 15.1. Part (a) holds because

$$\begin{aligned}
\lim_{\beta_0 \rightarrow \pm\infty} S_{\beta_0}(Y) &= \lim_{\beta_0 \rightarrow \pm\infty} (Z'Z)^{-1/2} Z'Y b_0 \cdot (b_0' \Omega b_0)^{-1/2} \\
&= (Z'Z)^{-1/2} Z'Y \lim_{\beta_0 \rightarrow \pm\infty} \begin{pmatrix} 1 \\ -\beta_0 \end{pmatrix} / (\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2\beta_0^2)^{1/2} \\
&= (Z'Z)^{-1/2} Z'Y e_2 (\mp 1/\sigma_v),
\end{aligned} \tag{15.7}$$

where $e_2 := (0, 1)'$, the first equality holds by (2.3), the second equality holds because $b_0 := (1, -\beta_0)'$, and the third equality holds using $\omega_2 = \sigma_v$.

Next, we prove part (b). The statistic $S_{\pm\infty}(Y)$ has a multivariate normal distribution because it is a linear combination of multivariate normal random variables. The mean of $S_{\pm\infty}(Y)$ is

$$ES_{\pm\infty}(Y) = (Z'Z)^{-1/2} Z'Z[\pi\beta_* : \pi]e_2 \cdot \frac{\mp 1}{\sigma_v} = (Z'Z)^{1/2}\pi \cdot \frac{\mp 1}{\sigma_v} = \mu_\pi \cdot \frac{\mp 1}{\sigma_v}, \tag{15.8}$$

where the first equality holds using (2.2) with $a = (\beta_*, 1)'$ and (15.1). The variance matrix of $S_{\pm\infty}(Y)$ is

$$\begin{aligned}
\text{Var}(S_{\pm\infty}(Y)) &= \text{Var}((Z'Z)^{-1/2} Z'Y e_2) / \sigma_v^2 = \text{Var}\left(\sum_{i=1}^n (Z'Z)^{-1/2} Z_i Y_i' e_2\right) / \sigma_v^2 \\
&= \sum_{i=1}^n \text{Var}((Z'Z)^{-1/2} Z_i Y_i' e_2) / \sigma_v^2 = \sum_{i=1}^n (Z'Z)^{-1/2} Z_i Z_i (Z'Z)^{-1/2} e_2' \Omega e_2 / \sigma_v^2 = I_k,
\end{aligned} \tag{15.9}$$

where the third equality holds by independence across i and the last equality uses $\omega_2^2 = \sigma_v^2$. This establishes part (b).

To prove part (c), we have

$$\begin{aligned}
\lim_{\beta_0 \rightarrow \pm\infty} T_{\beta_0}(Y) &= \lim_{\beta_0 \rightarrow \pm\infty} (Z'Z)^{-1/2} Z'Y \Omega^{-1} a_0 \cdot (a_0' \Omega^{-1} a_0)^{-1/2} \\
&= (Z'Z)^{-1/2} Z'Y \Omega^{-1} \lim_{\beta_0 \rightarrow \pm\infty} \begin{pmatrix} \beta_0 \\ 1 \end{pmatrix} / (\omega^{11}\beta_0^2 + 2\omega^{12}\beta_0 + \omega^{22})^{1/2} \\
&= (Z'Z)^{-1/2} Z'Y \Omega^{-1} e_1 \cdot (\pm 1/\omega^{11})^{1/2} \\
&= (Z'Z)^{-1/2} Z'Y \Omega^{-1} e_1 \cdot (\pm(\omega_1^2\omega_2^2 - \omega_{12}^2)^{1/2}/\omega_2),
\end{aligned} \tag{15.10}$$

where ω^{11} , ω^{12} , and ω^{22} denote the (1, 1), (1, 2), and (2, 2) elements of Ω^{-1} , respectively, $e_1 := (1, 0)'$, the first equality holds by (2.3), the second equality holds because $a_0 := (\beta_0, 1)'$, and the fourth

equality holds by the formula for ω^{11} . In addition, we have

$$(\omega_1^2\omega_2^2 - \omega_{12}^2)^{1/2}/\omega_2 = (1 - \rho_\Omega^2)^{1/2}\omega_1 = (1 - \rho_{uv}^2)^{1/2}\sigma_u, \quad (15.11)$$

where the first equality uses $\rho_\Omega := \omega_{12}/(\omega_1\omega_2)$ and the second equality holds because $\omega_1^2\omega_2^2 - \omega_{12}^2 = \sigma_u^2\sigma_v^2 - \sigma_{uv}^2$ by (14.3) and $\omega_2 = \sigma_v$. Equations (15.10) and (15.11), combined with (15.1), establish part (c).

Now, we prove part (d). Like $S_{\pm\infty}(Y)$, $T_{\pm\infty}(Y)$ has a multivariate normal distribution. The mean of $T_{\pm\infty}(Y)$ is

$$\begin{aligned} ET_{\pm\infty}(Y) &= (Z'Z)^{-1/2}Z'Z[\pi\beta_* : \pi]\Omega^{-1}e_1 \cdot (\pm(1 - \rho_{uv}^2)^{1/2}\sigma_u) \\ &= (Z'Z)^{1/2}\pi(\beta_*\omega^{11} + \omega^{12}) \cdot (\pm(1 - \rho_{uv}^2)^{1/2}\sigma_u), \end{aligned} \quad (15.12)$$

where the equality holds using (2.2) with $a = (\beta_*, 1)'$ and (15.1). In addition, we have

$$\beta_*\omega^{11} + \omega^{12} = \frac{\beta_*\omega_2^2 - \omega_{12}}{\omega_1^2\omega_2^2 - \omega_{12}^2} = \frac{-\sigma_{uv}}{\sigma_u^2\sigma_v^2 - \sigma_{uv}^2} = \frac{-\rho_{uv}}{(1 - \rho_{uv}^2)\sigma_u\sigma_v}, \quad (15.13)$$

where the second equality uses $\omega_1^2\omega_2^2 - \omega_{12}^2 = \sigma_u^2\sigma_v^2 - \sigma_{uv}^2$ by (14.3) and $\beta_*\omega_2^2 - \omega_{12} = -\sigma_{uv}$ by (11.9) with $\beta = \beta_*$. Combining (15.12) and (15.13) gives

$$ET_{\pm\infty}(Y) = \mu_\pi \cdot \frac{\mp\rho_{uv}}{\sigma_v(1 - \rho_{uv}^2)^{1/2}} = \mu_\pi \cdot \frac{\mp r_{uv}}{\sigma_v}. \quad (15.14)$$

The variance matrix of $T_{\pm\infty}(Y)$ is

$$\begin{aligned} \text{Var}(T_{\pm\infty}(Y)) &= \text{Var}((Z'Z)^{-1/2}Z'Y\Omega^{-1}e_1) \cdot (1 - \rho_{uv}^2)\sigma_u^2 \\ &= \text{Var}\left(\sum_{i=1}^n (Z'Z)^{-1/2}Z_iY_i'\Omega^{-1}e_1\right) \cdot (1 - \rho_{uv}^2)\sigma_u^2 = \sum_{i=1}^n \text{Var}((Z'Z)^{-1/2}Z_iY_i'\Omega^{-1}e_1) \cdot (1 - \rho_{uv}^2)\sigma_u^2 \\ &= \sum_{i=1}^n (Z'Z)^{-1/2}Z_iZ_i'(Z'Z)^{-1/2}e_1'\Omega^{-1}e_1 \cdot (1 - \rho_{uv}^2)\sigma_u^2 = I_k \frac{\omega_2^2}{\omega_1^2\omega_2^2 - \omega_{12}^2} \cdot (1 - \rho_{uv}^2)\sigma_u^2 \\ &= I_k \frac{\sigma_v^2}{\sigma_u^2\sigma_v^2 - \sigma_{uv}^2} \cdot (1 - \rho_{uv}^2)\sigma_u^2 = I_k, \end{aligned}$$

where the first equality holds by (15.1), the third equality holds by independence across i , and the second last equality uses $\omega_1^2\omega_2^2 - \omega_{12}^2 = \sigma_u^2\sigma_v^2 - \sigma_{uv}^2$ by (14.3) and $\omega_2^2 = \sigma_v^2$.

Part (e) holds because

$$\begin{aligned} \text{Cov}(S_{\pm\infty}(Y), T_{\pm\infty}(Y)) &= -\sum_{i=1}^n \text{Cov}((Z'Z)^{-1/2} Z_i Y_i' e_2, (Z'Z)^{-1/2} Z_i Y_i' \Omega^{-1} e_1) \cdot (1 - \rho_{uv}^2)^{1/2} \sigma_u / \sigma_v \\ &= \sum_{i=1}^n (Z'Z)^{-1/2} Z_i Z_i' (Z'Z)^{-1/2} e_2' \Omega \Omega^{-1} e_1 \cdot (1 - \rho_{uv}^2)^{1/2} \sigma_u / \sigma_v = 0^k. \end{aligned} \quad (15.15)$$

Part (f) follows from parts (a) and (c) of the lemma and (4.1).

Part (g) holds by the definition of the noncentral Wishart distribution and parts (b), (d), and (e) of the lemma. The density of $Q_{\pm\infty}(Y)$ equals the density in (11.4) because the noncentral Wishart density is invariant to a sign change in the means matrix. \square

16 Proofs of Theorems 5.2, Corollary 5.3, and Theorem 5.4

The following lemma is used in the proof of Theorem 5.2. As above, let $P_{\beta_*, \beta_0, \lambda, \Omega}(\cdot)$ and $P_{\rho_{uv}, \lambda_v}(\cdot)$ denote probabilities under the alternative hypothesis densities $f_Q(q; \beta_*, \beta_0, \lambda, \Omega)$ and $f_Q(q; \rho_{uv}, \lambda_v)$, which are defined in Section 11.1. See (11.2) and (11.4) for explicit expressions for these noncentral Wishart densities.

Lemma 16.1 (a) $\lim_{\beta_0 \rightarrow \pm\infty} P_{\beta_*, \beta_0, \lambda, \Omega}(\text{POIS2}(Q; \beta_*, \beta_0, \lambda) > \kappa_{2, \beta_0}(Q_T)) = P_{\rho_{uv}, \lambda_v}(\text{POIS2}(Q; \infty, |\rho_{uv}|, \lambda_v) > \kappa_{2, \infty}(Q_T)),$

(b) $\lim_{\beta_0 \rightarrow \pm\infty} P_{\beta_{2*}, \beta_0, \lambda_2, \Omega}(\text{POIS2}(Q; \beta_*, \beta_0, \lambda) > \kappa_{2, \beta_0}(Q_T)) = P_{-\rho_{uv}, \lambda_v}(\text{POIS2}(Q; \infty, |\rho_{uv}|, \lambda_v) > \kappa_{2, \infty}(Q_T)),$

(c) $P_{\rho_{uv}, \lambda_v}(\text{POIS2}(Q; \infty, |\rho_{uv}|, \lambda_v) > \kappa_{2, \infty}(Q_T)) = P_{-\rho_{uv}, \lambda_v}(\text{POIS2}(Q; \infty, |\rho_{uv}|, \lambda_v) > \kappa_{2, \infty}(Q_T)),$

(d) $\lim_{\beta_0 \rightarrow \pm\infty} \beta_{2*} = -\beta_* + 2\frac{\omega_{12}}{\omega_2^2} = \beta_* + 2\frac{\sigma_u \rho_{uv}}{\sigma_v},$ and

(e) $\lim_{\beta_0 \rightarrow \pm\infty} \lambda_2 = \lambda.$

The reason that Q has the density $f_Q(q; -\rho_{uv}, \lambda_v)$ (defined in (11.4)) in the limit expression in Lemma 16.1(b) can be seen clearly from the following lemma.

Lemma 16.2 For any fixed $(\beta_*, \lambda, \Omega)$, $\lim_{\beta_0 \rightarrow \pm\infty} f_Q(q; \beta_{2*}, \beta_0, \lambda_2, \Omega) = f_Q(q; -\rho_{uv}, \lambda_v)$ for all 2×2 variance matrices q , where β_{2*} and λ_2 satisfy (5.3) and ρ_{uv} and λ_v are defined in (4.5) and (5.1), respectively.

Proof of Lemma 16.2. Given (β^*, λ^*) , suppose the second point (β_2^*, λ_2^*) solves (13.1). In this case, by Lemma 14.1(b) and (e), we have

$$\begin{aligned} \lim_{\beta_0 \rightarrow \pm\infty} \lambda_2^{1/2} c_{\beta_{2^*}}(\beta_0, \Omega) &= \lim_{\beta_0 \rightarrow \pm\infty} -\lambda^{1/2} c_{\beta_*}(\beta_0, \Omega) = \pm \lambda^{1/2} / \sigma_v = \pm \lambda_v^{1/2} \text{ and} \\ \lim_{\beta_0 \rightarrow \pm\infty} \lambda_2^{1/2} d_{\beta_{2^*}}(\beta_0, \Omega) &= \lim_{\beta_0 \rightarrow \pm\infty} \lambda^{1/2} d_{\beta_*}(\beta_0, \Omega) = \mp \lambda^{1/2} \frac{\rho_{uv}}{\sigma_v(1 - \rho_{uv}^2)^{1/2}} = \mp \lambda_v^{1/2} r_{uv}. \end{aligned} \quad (16.1)$$

Using (11.1), (11.4), and (16.1), we obtain

$$\begin{aligned} \lim_{\beta_0 \rightarrow \pm\infty} \lambda_2(c_{\beta_{2^*}}^2 + d_{\beta_{2^*}}^2) &= \lambda_v(1 + r_{uv}^2) \text{ and} \\ \lim_{\beta_0 \rightarrow \pm\infty} \lambda_2 \xi_{\beta_{2^*}}(q) &:= \lim_{\beta_0 \rightarrow \pm\infty} \lambda_2(c_{\beta_{2^*}}^2 q_S + 2c_{\beta_{2^*}} d_{\beta_{2^*}} q_{ST} + d_{\beta_{2^*}}^2 q_T) \\ &= \lambda_v(q_S - 2r_{uv} q_{ST} + r_{uv}^2 q_T) \\ &=: \lambda_v \xi(q; -\rho_{uv}), \end{aligned} \quad (16.2)$$

On the other hand, given (β^*, λ^*) , suppose the second point (β_2^*, λ_2^*) solves (13.3). In this case, the minus sign on the rhs side of the first equality on the first line of (16.1) disappears, the quantity on the rhs side of the last equality on the first line of (16.1) becomes $\mp \lambda_v^{1/2}$, a minus sign is added to the rhs side of the first equality on the second line of (16.1), and the quantity on the rhs side of the last equality on the second line of (16.1) becomes $\pm \lambda_v^{1/2} r_{uv}$. These changes leave $\lambda_2 c_{\beta_{2^*}}^2$, $\lambda_2 d_{\beta_{2^*}}^2$, and $\lambda_2 c_{\beta_{2^*}} d_{\beta_{2^*}}$ unchanged from the case where (β_2^*, λ_2^*) solves (13.1). Hence, (16.2) also holds when (β_2^*, λ_2^*) solves (13.3).

Combining (16.2) with (11.2) (with (β_{2^*}, λ_2) in place of (β_*, λ)) and (11.4) proves the result of the lemma. \square

Proof of Theorem 5.2. By Theorem 3 of AMS, for all $(\beta_*, \beta_0, \lambda, \Omega)$,

$$\begin{aligned} &P_{\beta_*, \beta_0, \lambda, \Omega}(\phi_{\beta_0}(Q) = 1) + P_{\beta_{2^*}, \beta_0, \lambda_2, \Omega}(\phi_{\beta_0}(Q) = 1) \\ &\leq P_{\beta_*, \beta_0, \lambda, \Omega}(POIS2(Q; \beta_0, \beta_*, \lambda) > \kappa_{2, \beta_0}(Q_T)) + P_{\beta_{2^*}, \beta_0, \lambda_2, \Omega}(POIS2(Q; \beta_0, \beta_*, \lambda) > \kappa_{2, \beta_0}(Q_T)). \end{aligned} \quad (16.3)$$

That is, the test on the rhs maximizes the two-point average power for testing $\beta = \beta_0$ against (β_*, λ) and (β_{2^*}, λ_2) for fixed known Ω .

Equation (16.3) and Lemma 16.1(a)-(c) establish the result of Theorem 5.2 by taking the $\limsup_{\beta_0 \rightarrow \pm\infty}$ of the lhs and the $\liminf_{\beta_0 \rightarrow \pm\infty}$ of the rhs. \square

The proof of Comment (iv) to Theorem 5.2 is the same as that of Theorem 5.2, but in place of (16.3) it uses the inequality in Theorem 1 of CHJ i.e., $\int P_{\beta_*, \beta_0, \lambda, \mu_\pi / \|\mu_\pi\|, \Omega}(\phi_{\beta_0}(Q) =$

1) $dUnif(\mu_\pi/\|\mu_\pi\|) \leq \int P_{\beta_*,\beta_0,\lambda,\mu_\pi/\|\mu_\pi\|,\Omega}(POIS2(Q; \beta_0, \beta_*, \lambda) > \kappa_{2,\beta_0}(Q_T)) dUnif(\mu_\pi/\|\mu_\pi\|)$, plus the fact that the rhs expression equals $P_{\beta_*,\beta_0,\lambda,\Omega}(POIS2(Q; \beta_0, \beta_*, \lambda) > \kappa_{2,\beta_0}(Q_T))$ because the distribution of Q only depends on μ_π through $\lambda = \mu'_\pi \mu_\pi$.

Proof of Lemma 16.1. To prove part (a), we write

$$\begin{aligned} & P_{\beta_*,\beta_0,\lambda,\Omega}(POIS2(Q; \beta_0, \beta_*, \lambda) > \kappa_{2,\beta_0}(Q_T)) \\ &= \int \int \mathbf{1}(POIS2(q; \beta_0, \beta_*, \lambda) > \kappa_{2,\beta_0}(q_T)) \phi_k(s - c_{\beta_*} \mu_\pi) \phi_k(t - d_{\beta_*} \mu_\pi) ds dt, \text{ and} \\ & P_{\rho_{uv},\lambda_v}(POIS2(Q; \infty, |\rho_{uv}|, \lambda_v) > \kappa_{2,\infty}(Q_T)) \\ &= \int \int \mathbf{1}(POIS2(q; \infty, |\rho_{uv}|, \lambda_v) > \kappa_{2,\infty}(q_T)) \phi_k(s - (\mp 1/\sigma_v) \mu_\pi) \phi_k(t - (\mp r_{uv}/\sigma_v) \mu_\pi) ds dt, \end{aligned} \quad (16.4)$$

where $\phi_k(x)$ for $x \in R^k$ denotes the density of k i.i.d. standard normal random variables, $\lambda = \mu'_\pi \mu_\pi$, $s, t \in R^k$, $q = [s : t]'[s : t]$, $q_T = t't$, $c_{\beta_*} = c_{\beta_*}(\beta_0, \Omega)$, $d_{\beta_*} = d_{\beta_*}(\beta_0, \Omega)$, the \mp signs in the last line are both $+$ or both $-$, and the integral in the last line is the same whether both \mp signs are $+$ or $-$ (by a change of variables calculation).

We have

$$\lim_{\beta_0 \rightarrow \pm\infty} \phi_k(s - c_{\beta_*}(\beta_0, \Omega) \mu_\pi) \phi_k(t - d_{\beta_*}(\beta_0, \Omega) \mu_\pi) = \phi_k(s - (\mp 1/\sigma_v) \mu_\pi) \phi_k(t - (\mp r_{uv}/\sigma_v) \mu_\pi) \quad (16.5)$$

for all $s, t \in R^k$, by Lemma 14.1(b) and (e) and the smoothness of the standard normal density function. By (5.4) and (11.5) and Lemma 14.1(b) and (e), we have

$$\lim_{\beta_0 \rightarrow \pm\infty} POIS2(q; \beta_0, \beta_*, \lambda) = POIS2(q; \infty, |\rho_{uv}|, \lambda_v) \quad (16.6)$$

for all for 2×2 variance matrices q , for given $(\beta_*, \lambda, \Omega)$. In addition, we show below that $\lim_{\beta_0 \rightarrow \pm\infty} \kappa_{2,\beta_0}(q_T) = \kappa_{2,\infty}(q_T)$ for all $q_T \geq 0$. Combining these results gives the following convergence result:

$$\begin{aligned} & \lim_{\beta_0 \rightarrow \pm\infty} \mathbf{1}(POIS2(q; \beta_0, \beta_*, \lambda) > \kappa_{2,\beta_0}(q_T)) \cdot \phi_k(s - c_{\beta_*}(\beta_0, \Omega) \mu_\pi) \phi_k(t - d_{\beta_*}(\beta_0, \Omega) \mu_\pi) \\ &= \mathbf{1}(POIS2(q; \infty, |\rho_{uv}|, \lambda_v) > \kappa_{2,\infty}(q_T)) \cdot \phi_k(s - (\mp 1/\sigma_v) \mu_\pi) \phi_k(t - (\mp r_{uv}/\sigma_v) \mu_\pi) \end{aligned} \quad (16.7)$$

for all $[s : t]$ for which $POIS2(q; \infty, |\rho_{uv}|, \lambda_v) > \kappa_{2,\infty}(q_T)$ or $POIS2(q; \infty, |\rho_{uv}|, \lambda_v) < \kappa_{2,\infty}(q_T)$, where $[s : t]$, q and (q_S, q_{ST}, q_T) are functionally related by $q = [s : t]'[s : t]$ and the definitions in (11.2).

Given Lebesgue measure on the set of points $(s', t') \in R^{2k}$, the induced measure on $(q_S, q_{ST}, q_T) = (s's, s't, t't) \in R^3$ is absolutely continuous with respect to (wrt) Lebesgue measure on R^3 with

positive density only for positive definite q . (This follows from change of variables calculations. These calculations are analogous to those used to show that if $[S : T]$ has the multivariate normal density $\phi_k(s - (\mp 1/\sigma_v)\mu_\pi)\phi_k(t - (\mp r_{uv}/\sigma_v)\mu_\pi)$, then Q has the density $f_Q(q; \rho_{uv}, \lambda_v)$, which, viewed as a function of (q_S, q_{ST}, q_T) , is a density wrt Lebesgue measure on R^3 that is positive only for positive definite q .) The Lebesgue measure of the set of (q_S, q_{ST}, q_T) for which $POIS2(q; \infty, |\rho_{uv}|, \lambda_v) = \kappa_{2,\infty}(q_T)$ is zero. (This holds because (i) the definition of $POIS2(q; \infty, |\rho_{uv}|, \lambda_v)$ in (5.4) implies that the Lebesgue measure of the set of (q_S, q_{ST}) for which $POIS2(q; \infty, |\rho_{uv}|, \lambda_v) = \kappa_{2,\infty}(q_T)$ is zero for all $q_T \geq 0$ and (ii) the Lebesgue measure of the set of (q_S, q_{ST}, q_T) for which $POIS2(q; \infty, |\rho_{uv}|, \lambda_v) = \kappa_{2,\infty}(q_T)$ is obtained by integrating the set in (i) over $q_T \in R$ subject to the constraint that q is positive definite.) In turn, this implies that the Lebesgue measure of the set of $(s', t)'$ for which $POIS2(q; \infty, |\rho_{uv}|, \lambda_v) = \kappa_{2,\infty}(q_T)$ is zero. Hence, (16.7) verifies the a.s. (wrt Lebesgue measure on R^{2k}) convergence condition required for the application of the DCT to obtain part (a) using (16.4).

Next, to verify the dominating function requirement of the DCT, we need to show that

$$\sup_{\beta_0 \in R} |\phi_k(s - c_{\beta_*}(\beta_0, \Omega)\mu_\pi)\phi_k(t - d_{\beta_*}(\beta_0, \Omega)\mu_\pi)| \quad (16.8)$$

is integrable wrt Lebesgue measure on R^{2k} (since the indicator functions in (16.7) are bounded by one). For any $0 < c < \infty$ and $m \in R$, we have

$$\begin{aligned} & \int \sup_{|m| \leq c} \exp(-(x-m)^2/2) dx = 2 \int_0^\infty \sup_{|m| \leq c} \exp(-x^2/2 + mx - m^2/2) dx \\ & \leq 2 \int_0^\infty \exp(-x^2/2 + cx) dx = 2 \int_0^\infty \exp(-(x-c)^2/2 + c^2/2) dx < \infty, \end{aligned} \quad (16.9)$$

where the first equality holds by symmetry. This result yields the integrability of the dominating function in (16.8) because $\phi_k(\cdot)$ is a product of univariate standard normal densities and $\sup_{\beta_0 \in R} |c_{\beta_*}(\beta_0, \Omega)| < \infty$ and $\sup_{\beta_0 \in R} |d_{\beta_*}(\beta_0, \Omega)| < \infty$ are finite by Lemma 14.1(b) and (e) and continuity of $c_{\beta_*}(\beta_0, \Omega)$ and $d_{\beta_*}(\beta_0, \Omega)$ in β_0 .

Hence, the DCT applies and it yields part (a).

It remains to show $\lim_{\beta_0 \rightarrow \pm\infty} \kappa_{2,\beta_0}(q_T) = \kappa_{2,\infty}(q_T)$ for all $q_T \geq 0$. As noted above, $\lim_{\beta_0 \rightarrow \pm\infty} POIS2(q; \beta_0, \beta_*, \lambda) = POIS(q; \infty, |\rho_{uv}|, \lambda_v)$ for all 2×2 variance matrices q . Hence, $1(POIS2(Q; \beta_0, \beta_*, \lambda) \leq x) \rightarrow 1(POIS2(Q; \infty, |\rho_{uv}|, \lambda_v) \leq x)$ as $\beta_0 \rightarrow \pm\infty$ for all $x \in R$ for which $POIS2(Q; \infty, |\rho_{uv}|, \lambda_v) \neq x$. We have $P_{Q_1|Q_T}(POIS2(Q; \infty, |\rho_{uv}|, \lambda_v) = x|q_T) = 0$ for all $q_T \geq 0$ by the absolute continuity of $POIS2(Q; \infty, |\rho_{uv}|, \lambda_v)$ under $P_{Q_1|Q_T}(\cdot|q_T)$ (by the functional form of $POIS2(Q; \infty, |\rho_{uv}|, \lambda_v)$ and the absolute continuity of Q_1 under $P_{Q_1|Q_T}(\cdot|q_T)$, whose density

is given in (11.3)). Thus, by the DCT, for all $x \in R$,

$$\begin{aligned} \lim_{\beta_0 \rightarrow \pm\infty} P_{Q_1|Q_T}(POIS2(Q; \beta_0, \beta_*, \lambda) \leq x|q_T) &= P_{Q_1|Q_T}(POIS2(Q; \infty, |\rho_{uv}|, \lambda_v) \leq x|q_T) \text{ and} \\ POIS2(Q; \beta_0, \beta_*, \lambda) &\rightarrow_d POIS2(Q; \infty, |\rho_{uv}|, \lambda_v) \text{ as } \beta_0 \rightarrow \pm\infty \text{ under } P_{Q_1|Q_T}(\cdot|q_T). \end{aligned} \quad (16.10)$$

The second line of (16.10), coupled with the fact that $POIS2(Q; \infty, |\rho_{uv}|, \lambda_v)$ has a strictly increasing distribution function at its $1 - \alpha$ quantile under $P_{Q_1|Q_T}(\cdot|q_T)$ for all $q_T \geq 0$ (which is shown below), implies that the $1 - \alpha$ quantile of $POIS2(Q; \beta_0, \beta_*, \lambda)$ under $P_{Q_1|Q_T}(\cdot|q_T)$ (i.e., $\kappa_{2,\beta_0}(q_T)$) converges as $\beta_0 \rightarrow \pm\infty$ to the $1 - \alpha$ quantile of $POIS2(Q; \beta_0, \beta_*, \lambda)$ under $P_{Q_1|Q_T}(\cdot|q_T)$ (i.e., $\kappa_{2,\infty}(q_T)$). This can be proved by contradiction. First, suppose $\delta := \limsup_{j \rightarrow \infty} \kappa_{2,j}(q_T) - \kappa_{2,\infty}(q_T) > 0$ (where each $j \in R$ represents some value of β_0 here). Then, there exists a subsequence $\{m_j : j \geq 1\}$ of $\{j : j \geq 1\}$ such that $\delta = \lim_{j \rightarrow \infty} \kappa_{2,m_j}(q_T) - \kappa_{2,\infty}(q_T)$. We have

$$\begin{aligned} \alpha &= \lim_{j \rightarrow \infty} P_{Q_1|Q_T}(POIS2(Q; m_j, \beta_*, \lambda) > \kappa_{2,m_j}(q_T)|q_T) \\ &\leq \lim_{j \rightarrow \infty} P_{Q_1|Q_T}(POIS2(Q; m_j, \beta_*, \lambda) > \kappa_{2,\infty}(q_T) + \delta/2|q_T) \\ &= P_{Q_1|Q_T}(POIS2(Q; \infty, |\rho_{uv}|, \lambda_v) > \kappa_{2,\infty}(q_T) + \delta/2|q_T) \\ &< P_{Q_1|Q_T}(POIS2(Q; \infty, |\rho_{uv}|, \lambda_v) > \kappa_{2,\infty}(q_T)|q_T) \\ &= \alpha, \end{aligned} \quad (16.11)$$

where the first equality holds by the definition of $\kappa_{2,\beta_0}(q_T)$, the first inequality holds by the expression above for δ , the second equality holds by the first line of (16.10) with $x = \kappa_{2,\infty}(q_T) + \delta/2$, the second inequality holds because $\delta > 0$ and the distribution function of $POIS2(Q; \infty, |\rho_{uv}|, \lambda_v)$ is strictly increasing at its $1 - \alpha$ quantile $\kappa_{2,\infty}(q_T)$ under $P_{Q_1|Q_T}(\cdot|q_T)$ for all $q_T \geq 0$, and the last equality holds by the definition of $\kappa_{2,\infty}(q_T)$. Equation (16.11) is a contradiction, so $\delta \leq 0$. An analogous argument shows that $\liminf_{\beta_0 \rightarrow \infty} \kappa_{2,\beta_0}(q_T) - \kappa_{2,\infty}(q_T) < 0$ does not hold. Hence, $\lim_{\beta_0 \rightarrow \infty} \kappa_{2,\beta_0}(q_T) = \kappa_{2,\infty}(q_T)$. An analogous argument shows that $\liminf_{\beta_0 \rightarrow -\infty} \kappa_{2,\beta_0}(q_T) = \kappa_{2,\infty}(q_T)$.

It remains to show that the distribution function of $POIS2(Q; \infty, |\rho_{uv}|, \lambda_v)$ is strictly increasing at its $1 - \alpha$ quantile $\kappa_{2,\infty}(q_T)$ under $P_{Q_1|Q_T}(\cdot|q_T)$ for all $q_T \geq 0$. This holds because (i) $POIS2(Q; \infty, |\rho_{uv}|, \lambda_v)$ is a nonrandom strictly increasing function of $(\xi(Q; \rho_{uv}), \xi(Q; -\rho_{uv}))$ conditional on $T = t$ (specifically, $POIS2(Q; \infty, |\rho_{uv}|, \lambda_v) = C_{q_T} \sum_{j=0}^{\infty} [(\lambda_v \xi(Q; \rho_{uv}))^j + (\lambda_v \xi(Q; -\rho_{uv}))^j] / (4^j j! \Gamma(\nu + j + 1))$, where C_{q_T} is a constant that may depend on q_T , $\nu := (k - 2)/2$, and $\Gamma(\cdot)$ is the gamma function, by (5.4) and (4.8) of AMS, which provides an expression for the modified Bessel function of the first kind $I_\nu(x)$), (ii) $\xi(Q; \rho_{uv}) = (S + r_{uv}T)'(S + r_{uv}T)$ and

$\xi(Q; -\rho_{uv}) = (S - r_{uv}T)'(S - r_{uv}T)$ have the same noncentral χ_k^2 distribution conditional on $T = t$ (because $[S : T]$ has a multivariate normal distribution with means matrix given by (5.2) and identity variance matrix), (iii) $(\xi(Q; \rho_{uv}), \xi(Q; -\rho_{uv}))$ has a positive density on R_+^2 conditional on $T = t$ and also conditional on $Q_T = q_T$ (because the latter conditional density is the integral of the former conditional density over t such that $t't = q_T$), and hence, (iv) $POIS2(Q; \infty, |\rho_{uv}|, \lambda_v)$ has a positive density on R_+ conditional on q_T for all $q_T \geq 0$. This completes the proof of part (a).

The proof of part (b) is the same as that of part (a), but with (i) $-c_{\beta_*}$ and $\pm 1/\sigma_v$ in place of c_{β_*} and $\mp 1/\sigma_v$, respectively, in (16.4), (16.5), and (16.7), and (ii) π_2 in place of π , where

$$\begin{aligned} \pi_2 &:= M e_{1,k}, \quad e_{1,k} := (1, 0, \dots)' \in R^k, \quad M := \frac{\lambda^{1/2} g(\beta_0, \beta_*, \Omega)}{(e_{1,k}' Z' Z e_{1,k})^{1/2}}, \\ g(\beta_0, \beta_*, \Omega) &:= \frac{d_{\beta_0} + 2r_{\beta_0}(\beta_* - \beta_0)}{d_{\beta_0}}, \quad \text{and } \lambda_2 := \mu_{\pi_2}' \mu_{\pi_2}. \end{aligned} \quad (16.12)$$

As defined, λ_2 satisfies (5.3) because

$$\lambda_2 := \mu_{\pi_2}' \mu_{\pi_2} = \pi_2' Z' Z \pi_2 = M^2 e_{1,k}' Z' Z e_{1,k} = \lambda g^2(\beta_0, \beta_*, \Omega). \quad (16.13)$$

In addition, $\lambda_2 \rightarrow \lambda$ as $\beta_0 \rightarrow \pm\infty$ by (16.17) below. With the above changes, the proof of part (a) establishes part (b).

Part (c) holds because the test statistic $POIS2(Q; \infty, |\rho_{uv}|, \lambda_v)$ and critical value $\kappa_{2,\infty}(Q_T)$ only depend on ρ_{uv} and q_{ST} through $|\rho_{uv}|$ and $|q_{ST}|$, respectively, and the density $f_Q(q; \rho_{uv}, \lambda_v)$ of Q only depends on the sign of ρ_{uv} through $r_{uv} q_{ST}$. In consequence, a change of variables from (q_S, q_{ST}, q_T) to $(q_S, -q_{ST}, q_T)$ establishes the result of part (c).

To prove part (d), we have

$$\begin{aligned} d_{\beta_0} &= (a_0' \Omega^{-1} a_0)^{1/2} = \frac{\omega_2^2 \beta_0^2 - 2\omega_{12} \beta_0 + \omega_1^2}{\omega_1^2 \omega_2^2 - \omega_{12}^2} (a_0' \Omega^{-1} a_0)^{-1/2} \quad \text{and} \\ r_{\beta_0} &= e_1' \Omega^{-1} a_0 (a_0' \Omega^{-1} a_0)^{-1/2} = \frac{\omega_2^2 \beta_0 - \omega_{12}}{\omega_1^2 \omega_2^2 - \omega_{12}^2} (a_0' \Omega^{-1} a_0)^{-1/2}, \end{aligned} \quad (16.14)$$

where the first equalities on lines one and two hold by (2.7) of AMS and (5.3), respectively. Next, we have

$$\begin{aligned}
\beta_{2*} &= \beta_0 - \frac{d_{\beta_0}(\beta_* - \beta_0)}{d_{\beta_0} + 2r_{\beta_0}(\beta_* - \beta_0)} \\
&= \frac{d_{\beta_0}(2\beta_0 - \beta_*) + 2r_{\beta_0}(\beta_* - \beta_0)\beta_0}{d_{\beta_0} + 2r_{\beta_0}(\beta_* - \beta_0)} \\
&= \frac{(\omega_2^2\beta_0^2 - 2\omega_{12}\beta_0 + \omega_1^2)(2\beta_0 - \beta_*) + 2(\omega_2^2\beta_0 - \omega_{12})(\beta_*\beta_0 - \beta_0^2)}{(\omega_2^2\beta_0^2 - 2\omega_{12}\beta_0 + \omega_1^2) + 2(\omega_2^2\beta_0 - \omega_{12})(\beta_* - \beta_0)} \\
&= \frac{\beta_0^2(-\omega_2^2\beta_* - 4\omega_{12} + 2\omega_2^2\beta_* + 2\omega_{12}) + O(\beta_0)}{\beta_0^2(\omega_2^2 - 2\omega_2^2) + O(\beta_0)} \\
&= \frac{(\omega_2^2\beta_* - 2\omega_{12}) + o(1)}{-\omega_2^2 + o(1)} \\
&= -\beta_* + \frac{2\omega_{12}}{\omega_2^2} + o(1), \tag{16.15}
\end{aligned}$$

where the third equality uses (16.14) and the two terms involving β_0^3 in the numerator of the rhs of the third equality cancel. Next, we have

$$-\beta_* + \frac{2\omega_{12}}{\omega_2^2} = \frac{2(\omega_{12} - \omega_2^2\beta_*) + \omega_2^2\beta_*}{\omega_2^2} = \frac{2\sigma_{uv} + \sigma_v^2\beta_*}{\sigma_v^2} = \beta_* + 2\frac{\sigma_{uv}}{\sigma_v^2} = \beta_* + 2\frac{\sigma_u\rho_{uv}}{\sigma_v}, \tag{16.16}$$

where the second equality uses (11.9) with $\beta = \beta_*$ and $\omega_2^2 = \sigma_v^2$.

Next, we prove part (e). We have

$$\begin{aligned}
\left(\frac{\lambda_2}{\lambda}\right)^{1/2} &= \left|\frac{d_{\beta_0} + 2r_{\beta_0}(\beta_* - \beta_0)}{d_{\beta_0}}\right| \\
&= \left|\frac{\omega_2^2\beta_0^2 - 2\omega_{12}\beta_0 + \omega_1^2 + 2(\omega_2^2\beta_0 - \omega_{12})(\beta_* - \beta_0)}{\omega_2^2\beta_0^2 - 2\omega_{12}\beta_0 + \omega_1^2}\right| \\
&= \left|\frac{\beta_0^2(\omega_2^2 - 2\omega_2^2) + \beta_0(-2\omega_{12} + 2\omega_2^2\beta_* + 2\omega_{12}) + \omega_1^2 - 2\omega_{12}\beta_*}{\omega_2^2\beta_0^2 - 2\omega_{12}\beta_0 + \omega_1^2}\right| \\
&= 1 + o(1), \tag{16.17}
\end{aligned}$$

where the first equality holds by (5.3) and the second equality uses (16.14). \square

Proof of Corollary 5.3. We have

$$\begin{aligned}
&(P_{\beta_*,\lambda,\Omega}(RLength(CS_\phi(Y)) = \infty) + P_{\beta_{2*},\lambda_2,\Omega}(RLength(CS_\phi(Y)) = \infty))/2 \\
&= 1 - \lim_{\beta_0 \rightarrow \infty} [P_{\beta_*,\beta_0,\lambda,\Omega}(\phi(Q) = 1) + \lim_{\beta_0 \rightarrow \infty} P_{\beta_{2*},\beta_0,\lambda_2,\Omega}(\phi(Q) = 1)]/2 \\
&\geq P_{\rho_{uv},\lambda_v}(POIS2(Q; \infty, |\rho_{uv}|, \lambda_v) > \kappa_{2,\infty}(Q_T)), \tag{16.18}
\end{aligned}$$

where the equality holds by Theorem 4.1(a) with (β_*, λ) and $(\beta_{2*}, \lambda_{2*})$, $P_{\beta_*, \lambda, \Omega}(\cdot)$ is equivalent to $P_{\beta_*, \pi, \Omega}(\cdot)$, which appears in Theorem 4.1(a) (because events determined by $CS_\phi(Y)$ only depend on π through λ , since $CS_\phi(Y)$ is based on rotation-invariant tests), and the inequality holds by Theorem 5.2(a). This establishes the first result of part (a).

The second result of part (a) holds by the same calculations as in (16.18), but with $LLength$ and $\beta_0 \rightarrow -\infty$ in place of $RLength$ and $\beta_0 \rightarrow \infty$, respectively, using Theorem 4.1(b) in place of Theorem 4.1(a).

Part (b) holds by combining Theorem 4.1(c) and Theorem 5.2 because, as noted in Comment (iii) to Theorem 5.2, the limsup on the left-hand side in Theorem 5.2 is the average of two equal quantities. \square

Next, we prove Comment (ii) to Corollary 5.3. The proof is the same as that of Corollary 5.3, but using

$$\int P_{\beta_*, \lambda, \mu_\pi / \|\mu_\pi\|, \Omega}(RLength(CS_\phi(Y)) = \infty) dUniform(\mu_\pi / \|\mu_\pi\|) = 1 - \lim_{\beta_0 \rightarrow \infty} P_{\beta_*, \beta_0, \lambda, \Omega}(\phi(Q) = 1) \quad (16.19)$$

and likewise with (β_{2*}, λ) in place of (β_*, θ) in place of the first equality in (16.18). The proof of (16.19) is the same as the proof of Theorem 4.1(a) but with $Q_{\beta_0}(Y)$ and $Q_{T, \beta_0}(Y)$ replaced by $[S_{\beta_0}(Y), T_{\beta_0}(Y)]$, and $T_{\beta_0}(Y)$, respectively, throughout the proof, with $E_{\beta_*, \pi, \Omega}(\cdot)$ replaced by $\int E_{\beta_*, \lambda, \mu_\pi / \|\mu_\pi\|, \Omega}(\cdot) dUniform(\mu_\pi / \|\mu_\pi\|)$ in (15.3), and using Lemma 15.1(a) and (c) in place of Lemma 15.1(f) when verifying the limit property (ii) needed for the dominated convergence theorem following (15.3).

Proof of Theorem 5.4. The proof is quite similar to, but much simpler than, the proof of part (a) of Lemma 16.1 with $POIS2(q; \beta_0, \beta_*, \lambda) > \kappa_{2, \beta_0}(q_T)$ in (16.4) replaced by $q_S > \chi_{k, 1-\alpha}^2/k$ for the AR test, $q_{ST}^2/q_T > \chi_{1, 1-\alpha}^2$ for the LM test, and $q_S - q_T + ((q_S - q_T)^2 + 4q_{ST}^2)^{1/2} > 2\kappa_{LR, \alpha}(q_T)$ for the CLR test. The proof is much simpler because for the latter three tests neither the test statistics nor the critical values depend on β_0 . The parameter β_0 , for which the limit as $\beta_0 \rightarrow \pm\infty$ is being considered, only enters through the multivariate normal densities in (16.4). The limits of these densities and an integrable dominating function for them have already been provided in the proof of Lemma 16.1(a). The indicator function that appears in (16.7) is bounded by one regardless of which test appears in the indicator function. In addition, $P_{\beta_*, \rho_{uv}, \lambda_v}(AR = \chi_{k, 1-\alpha}^2) = 0$ and $P_{\beta_*, \rho_{uv}, \lambda_v}(LM = \chi_{1, 1-\alpha}^2) = 0$ because the AR statistic has a noncentral χ_k^2 distribution with noncentrality parameter λ_v under $P_{\beta_*, \rho_{uv}, \lambda_v}$ (since $S \sim N(\mu_\pi/\sigma_v, I_k)$ by Lemma 5.1 and (5.2)) and the conditional distribution of the LM statistic given T under $P_{\beta_*, \rho_{uv}, \lambda_v}$ is a noncentral χ^2

distribution.

Next, we show $P_{\beta_*, \rho_{uv}, \lambda_v}(LR = \kappa_{LR, \alpha}(Q_T)) = 0$. Let $J = AR - LM$. Then, $2LR = J + LM - Q_T + ((J + LM - Q_T)^2 + 4LM \cdot Q_T)^{1/2}$. We can write $Q = [S : T]'[S : T]$, where $[S : T]$ has a multivariate normal distribution with means matrix given by (5.2) and identity variance matrix. As shown below, conditional on $T = t$, LM and J have independent noncentral χ^2 distributions with 1 and $k - 1$ degrees of freedom, respectively. This implies that (i) the distribution of LR conditional on $T = t$ is absolutely continuous, (ii) $P_{\beta_*, \rho_{uv}, \lambda_v}(LR = \kappa_{LR, \alpha}(Q_T)|T = t) = 0$ for all $t \in R^k$, and (iii) $P_{\beta_*, \rho_{uv}, \lambda_v}(LR = \kappa_{LR, \alpha}(Q_T)) = 0$. It remains to show that conditional on $Q_T = q_T$, LM and J have independent noncentral χ^2 distributions. We can write $LM = S'P_T S$ and $J = S'(I_k - P_T)S$, where $P_T := T(T'T)^{-1}T'$ and S has a multivariate normal with identity variance matrix. This implies that $P_T S$ and $(I_k - P_T)S$ are independent conditional on $T = t$ and LM and J have independent noncentral χ^2 distributions conditional on $T = t$ for all $t \in R^k$. This completes the proof. \square

17 Proof of Theorem 7.1

The proof of Theorem 7.1(a) uses the following lemma.

Lemma 17.1 *Suppose $b_{1x} = 1 + \delta_x/x$ and $b_{2x} = 1 - \delta_x/x$, where $\delta_x \rightarrow \delta_\infty \neq 0$ as $x \rightarrow \infty$, $K_{j1x} = (b_{jx}x)^\eta$ for some $\eta \in R$ for $j = 1, 2$, and $K_{j2x} \rightarrow K_\infty \in (0, \infty)$ as $x \rightarrow \infty$ for $j = 1, 2$. Then, (a) as $x \rightarrow \infty$,*

$$\begin{aligned} & \log \left(K_{11x}K_{12x}e^{b_{1x}x} + K_{21x}K_{22x}e^{b_{2x}x} \right) - x - \eta \log x - \log K_\infty \\ & \rightarrow \delta_\infty + \log \left(1 + e^{-2\delta_\infty} \right) \text{ and} \end{aligned}$$

(b) *the function $s(y) := y + \log(1 + e^{-2y})$ for $y \in R$ is infinitely differentiable, symmetric about zero, strictly increasing for $y > 0$, and hence, strictly increasing in $|y|$ for $|y| > 0$.*

Proof of Lemma 17.1. Part (a) holds by the following:

$$\begin{aligned} & \log \left(K_{11x}K_{12x}e^{b_{1x}x} + K_{21x}K_{22x}e^{b_{2x}x} \right) - x - \eta \log x - \log K_\infty \\ & = \log \left(K_{11x}K_{12x}e^{b_{1x}x} \left(1 + \frac{K_{21x}K_{22x}}{K_{11x}K_{12x}} e^{(b_{2x}-b_{1x})x} \right) \right) - x - \eta \log x - \log K_\infty \\ & = b_{1x}x + \log K_{11x} + \log(K_{12x}/K_\infty) + \log \left(1 + \frac{K_{21x}K_{22x}}{K_{11x}K_{12x}} e^{(b_{2x}-b_{1x})x} \right) - x - \eta \log x \\ & = \delta_x + \eta \log(b_{1x}) + \log(K_{12x}/K_\infty) + \log \left(1 + \frac{K_{21x}K_{22x}}{K_{11x}K_{12x}} e^{-2\delta_x} \right) \\ & \rightarrow \delta_\infty + \log \left(1 + e^{-2\delta_\infty} \right), \end{aligned} \tag{17.1}$$

where the third equality uses $b_{1x}x - x = \delta_x$, $\log K_{11x} = \eta \log(b_{1x}x) = \eta \log(b_{1x}) + \eta \log(x)$, and $b_{2x} - b_{1x} = -2\delta_x/x$, and the convergence uses $\log(b_{1x}) = \log(1 + o(1)) \rightarrow 0$, $K_{12x}/K_\infty \rightarrow 1$, $K_{21x}/K_{11x} = (b_{2x}/b_{1x})^\eta = 1 + o(1)$, and $K_{22x}/K_{12x} \rightarrow 1$.

The function $s(y)$ is infinitely differentiable because $\log(x)$ and e^{-2y} are. The function $s(y)$ is symmetric about zero because

$$\begin{aligned} y + \log(1 + e^{-2y}) &= -y + \log(1 + e^{2y}) \\ \Leftrightarrow 2y &= \log(1 + e^{2y}) - \log(1 + e^{-2y}) = \log\left(\frac{1 + e^{2y}}{1 + e^{-2y}}\right) = \log(e^{2y}) = 2y. \end{aligned} \quad (17.2)$$

The function $s(y)$ is strictly increasing for $y > 0$ because

$$\frac{d}{dy}s(y) = 1 - \frac{2e^{-2y}}{1 + e^{-2y}} = \frac{1 - e^{-2y}}{1 + e^{-2y}} = \frac{e^{2y} - 1}{e^{2y} + 1}, \quad (17.3)$$

which is positive for $y > 0$. We have $s(y) = s(|y|)$ because $s(y)$ is symmetric about zero, and $(d/d|y|)s(|y|) > 0$ for $|y| > 0$ by (17.3). Hence, $s(y)$ is strictly increasing in $|y|$ for $|y| > 0$. \square

Proof of Theorem 7.1. Without loss in generality, we prove the results for the case where $\text{sgn}(d_{\beta_*})$ is the same for all terms in the sequence as $\lambda d_{\beta_*}^2 \rightarrow \infty$. Given (2.3), without loss of generality, we can suppose that

$$S = c_{\beta_*} \mu_\pi + Z_S \text{ and } T = d_{\beta_*} \mu_\pi + Z_T, \quad (17.4)$$

where Z_S and Z_T are independent $N(0^k, I_k)$ random vectors.

We prove part (c) first. The distribution of Q depends on μ_π only through λ . In consequence, without loss of generality, we can assume that $\Upsilon := \mu_\pi/\lambda^{1/2} \in R^k$ does not vary as $\lambda d_{\beta_*}^2$ and $\lambda^{1/2} c_{\beta_*}$ vary. The following establishes the a.s. convergence of the one-sided *LM* test statistic: as

$\lambda d_{\beta_*}^2 \rightarrow \infty$ and $\lambda^{1/2} c_{\beta_*} \rightarrow c_\infty$,

$$\begin{aligned}
\frac{Q_{ST}}{Q_T^{1/2}} &= \frac{(c_{\beta_*} \mu_\pi + Z_S)'(d_{\beta_*} \mu_\pi + Z_T)}{((d_{\beta_*} \mu_\pi + Z_T)'(d_{\beta_*} \mu_\pi + Z_T))^{1/2}} \\
&= \frac{(c_{\beta_*} \mu_\pi + Z_S)'(d_{\beta_*} \mu_\pi + Z_T)}{(d_{\beta_*}^2 \lambda)^{1/2}(1 + o_{a.s.}(1))} \\
&= \frac{(c_{\beta_*} \mu_\pi / \lambda^{1/2} + Z_S / \lambda^{1/2})'(sgn(d_{\beta_*}) \mu_\pi + O_{a.s.}(1/|d_{\beta_*}|))}{(1 + o_{a.s.}(1))} \\
&= \left(sgn(d_{\beta_*}) \Upsilon' Z_S + sgn(d_{\beta_*}) \lambda^{1/2} c_{\beta_*} + O_{a.s.} \left(\frac{(\lambda c_{\beta_*}^2)^{1/2}}{(\lambda d_{\beta_*}^2)^{1/2}} \right) + O_{a.s.} \left(\frac{1}{(\lambda d_{\beta_*}^2)^{1/2}} \right) \right) \\
&\quad \times (1 + o_{a.s.}(1)) \\
&\rightarrow_{a.s.} sgn(d_{\beta_*}) \Upsilon' Z_S + sgn(d_{\beta_*}) c_\infty \\
&=: LM_{1\infty} \sim N(sgn(d_{\beta_*}) c_\infty, 1), \tag{17.5}
\end{aligned}$$

where the first equality holds by (3.1) and (17.4), the second equality holds using $d_{\beta_*} \mu_\pi + Z_T = (\lambda d_{\beta_*}^2)^{1/2} (d_{\beta_*} \mu_\pi / (\lambda d_{\beta_*}^2)^{1/2} + o_{a.s.}(1))$ since $\lambda d_{\beta_*}^2 \rightarrow \infty$, the convergence holds because $\lambda d_{\beta_*}^2 \rightarrow \infty$ and $\lambda^{1/2} c_{\beta_*} \rightarrow c_\infty$, and the limit random variable $LM_{1\infty}$ has a $N(sgn(d_{\beta_*}) c_\infty, 1)$ distribution because $sgn(d_{\beta_*}) \Upsilon' Z_S \sim N(0, 1)$ (since $Z_S \sim N(0^k, I_k)$ and $\|\Upsilon\| = 1$).

The a.s. convergence in (17.5) implies convergence in distribution by the dominated convergence theorem applied to $1(Q_{ST}/Q_T^{1/2} \leq y)$ for any fixed $y \in R$. In consequence, we have

$$P(LM > \chi_{1,1-\alpha}^2) = P((Q_{ST}/Q_T^{1/2})^2 > \chi_{1,1-\alpha}^2) \rightarrow P(LM_{1\infty}^2 > \chi_{1,1-\alpha}^2) = P(\chi_1^2(c_\infty^2) > \chi_{1,1-\alpha}^2) \tag{17.6}$$

as $\lambda d_{\beta_*}^2 \rightarrow \infty$ and $\lambda^{1/2} c_{\beta_*} \rightarrow c_\infty$, which establishes part (c).

To prove Theorem 7.1(a), we apply Lemma 17.1 to a realization of the random vectors Z_S and Z_T with

$$\begin{aligned}
x &:= (\lambda d_{\beta_*}^2 Q_T)^{1/2}, \\
b_{1x} x &:= (\lambda \xi_{\beta_*}(Q; \beta_0, \Omega))^{1/2} := \lambda^{1/2} (c_{\beta_*}^2 Q_S + 2c_{\beta_*} d_{\beta_*} Q_{ST} + d_{\beta_*}^2 Q_T)^{1/2}, \\
b_{2x} x &:= \lambda^{1/2} (c_{\beta_*}^2 Q_S - 2c_{\beta_*} d_{\beta_*} Q_{ST} + d_{\beta_*}^2 Q_T)^{1/2}, \\
K_{11x} &:= (b_{1x} x)^{-(k-1)/2}, \\
K_{12x} &:= \frac{(b_{1x} x)^{1/2} I_{(k-2)/2}(b_{1x} x)}{e^{b_{1x} x}}, \\
K_{21x} &:= (b_{2x} x)^{-(k-1)/2}, \text{ and} \\
K_{22x} &:= \frac{(b_{2x} x)^{1/2} I_{(k-2)/2}(b_{2x} x)}{e^{b_{2x} x}}, \tag{17.7}
\end{aligned}$$

Thus, we take $\eta := -(k-1)/2$.

We have

$$Q_T = (d_{\beta_*} \mu_\pi + Z_T)'(d_{\beta_*} \mu_\pi + Z_T) = \lambda d_{\beta_*}^2 (1 + o_{a.s.}(1)). \quad (17.8)$$

This implies that $x = (\lambda d_{\beta_*}^2)(1 + o_{a.s.}(1))$. Thus, $x \rightarrow \infty$ a.s. since $\lambda d_{\beta_*}^2 \rightarrow \infty$ by assumption.

The conditions $\lambda d_{\beta_*}^2 \rightarrow \infty$ and $\lambda^{1/2} c_{\beta_*} \rightarrow c_\infty \in R$ imply that $b_{1x} x \rightarrow \infty$ and $b_{2x} x \rightarrow \infty$ as $x \rightarrow \infty$. In consequence, by the properties of the modified Bessel function of the first kind, $I_{(k-2)/2}(x)$ for x large, e.g., see Lebedev (1965, p. 136),

$$\lim_{b_{1x} x \rightarrow \infty} K_{12x} = 1/(2\pi)^{1/2} \text{ and } \lim_{b_{2x} x \rightarrow \infty} K_{22x} = 1/(2\pi)^{1/2}. \quad (17.9)$$

Hence, the assumptions of Lemma 17.1 on K_{j2x} for $j = 1, 2$ hold with $K_\infty = 1/(2\pi)^{1/2}$.

Next, we have

$$\begin{aligned} b_{1x} &= (\lambda c_{\beta_*}^2 Q_S + 2\lambda c_{\beta_*} d_{\beta_*} Q_{ST} + \lambda d_{\beta_*}^2 Q_T)^{1/2} / x \\ &= \left(1 + \frac{2\lambda c_{\beta_*} d_{\beta_*} Q_{ST}}{(\lambda d_{\beta_*}^2 Q_T)^{1/2} x} + \frac{\lambda c_{\beta_*}^2 Q_S}{x^2} \right)^{1/2} \\ &= \left(1 + \frac{2\lambda^{1/2} c_{\beta_*} \operatorname{sgn}(d_{\beta_*}) Q_{ST}}{x Q_T^{1/2}} + \frac{\lambda c_{\beta_*}^2 Q_S}{x^2} \right)^{1/2} \\ &= 1 + (1 + o_{a.s.}(1))^{-1/2} \left(\frac{2\lambda^{1/2} c_{\beta_*} \operatorname{sgn}(d_{\beta_*}) Q_{ST}}{x Q_T^{1/2}} + \frac{\lambda c_{\beta_*}^2 Q_S}{x^2} \right), \end{aligned} \quad (17.10)$$

where the fourth equality holds by the mean value theorem because $\lambda^{1/2} c_{\beta_*} = O(1)$, $x \rightarrow \infty$ a.s., and $Q_{ST}/Q_T^{1/2} = O(1)$ a.s. (by (17.5)) imply that the term in parentheses on the last line of (17.10) is $o_{a.s.}(1)$.

From (17.10), we have

$$\begin{aligned} \delta_x &= (1 + o_{a.s.}(1))^{-1/2} \left(2\lambda^{1/2} c_{\beta_*} \operatorname{sgn}(d_{\beta_*}) \frac{Q_{ST}}{Q_T^{1/2}} + \frac{\lambda c_{\beta_*}^2 Q_S}{x} \right) \\ &\rightarrow 2c_\infty \operatorname{sgn}(d_{\beta_*}) LM_{1\infty} =: \delta_\infty \text{ a.s.} \end{aligned} \quad (17.11)$$

using (17.5). This verifies the convergence condition of Lemma 17.1 on δ_x with $\delta_\infty \neq 0$ a.s. (by the absolute continuity of Z_S). Hence, Lemma 17.1 applies with x, b_{1x}, \dots as in (17.7).

Let ξ_{β_*} abbreviate $\xi_{\beta_*}(Q; \beta_0, \Omega) = c_{\beta_*}^2 Q_S + 2c_{\beta_*} d_{\beta_*} Q_{ST} + d_{\beta_*}^2 Q_T$. Let $\xi_{\beta_{2*}} = c_{\beta_*}^2 Q_S - 2c_{\beta_*} d_{\beta_*} Q_{ST} + d_{\beta_*}^2 Q_T$. So, $b_{1x}x = (\lambda \xi_{\beta_*})^{1/2}$ and $b_{2x}x = (\lambda \xi_{\beta_{2*}})^{1/2}$. Let

$$\begin{aligned} \tau(\beta_*, \lambda, Q_T) &:= -(\lambda d_{\beta_*}^2 Q_T)^{1/2} + \frac{k-1}{2} \log((\lambda d_{\beta_*}^2 Q_T)^{1/2}) - \log K_\infty \\ &= -x - \eta \log x - \log K_\infty, \end{aligned} \tag{17.12}$$

where the equality holds using the definitions in (17.7) and $K_\infty = 1/(2\pi)^{1/2}$ by (17.9).

Given the definitions of $POIS2(Q; \beta_0, \beta_*, \lambda)$ and x, b_{1x}, \dots in (11.5) and (17.7), respectively, Lemma 17.1(a) gives

$$\begin{aligned} &\log(POIS2(Q; \beta_0, \beta_*, \lambda)) + \log(2\psi_2(Q_T; \beta_0, \beta_*, \lambda)) + \tau(\beta_*, \lambda, Q_T) \\ &= \log \left((\lambda \xi_{\beta_*})^{-(k-2)/4} I_{(k-2)/2}((\lambda \xi_{\beta_*})^{1/2}) + (\lambda \xi_{\beta_{2*}})^{-(k-2)/4} I_{(k-2)/2}((\lambda \xi_{\beta_{2*}})^{1/2}) \right) + \tau(\beta_*, \lambda, Q_T) \\ &= \log \left((\lambda \xi_{\beta_*})^{-(k-1)/4} \frac{(\lambda \xi_{\beta_*})^{1/4} I_{(k-2)/2}((\lambda \xi_{\beta_*})^{1/2})}{e^{(\lambda \xi_{\beta_*})^{1/2}}} e^{(\lambda \xi_{\beta_*})^{1/2}} \right. \\ &\quad \left. + (\lambda \xi_{\beta_{2*}})^{-(k-1)/4} \frac{(\lambda \xi_{\beta_{2*}})^{1/4} I_{(k-2)/2}((\lambda \xi_{\beta_{2*}})^{1/2})}{e^{(\lambda \xi_{\beta_{2*}})^{1/2}}} e^{(\lambda \xi_{\beta_{2*}})^{1/2}} \right) + \tau(\beta_*, \lambda, Q_T) \\ &= \log \left(K_{11x} K_{12x} e^{b_{1x}x} + K_{21x} K_{22x} e^{b_{2x}x} \right) - x - \eta \log x - \log K_\infty \\ &\rightarrow_{a.s.} \delta_\infty + \log \left(1 + e^{-2\delta_\infty} \right) \\ &= s(\delta_\infty) \\ &= s(2c_\infty |LM_{1\infty}|), \end{aligned} \tag{17.13}$$

where $\psi_2(Q_T; \beta_0, \beta_*, \lambda)$ is defined in (11.5), $LM_{1\infty}^2 \sim \chi_1^2(c_\infty^2)$ is defined in (17.5), the first equality holds by the definition of $POIS2(Q; \beta_0, \beta_*, \lambda)$ in (11.5), the third equality uses the definitions in (17.7) and (17.12), the convergence holds by Lemma 17.1(a), the second last equality holds by the definition of $s(y)$ in Lemma 17.1(b), and the last equality holds because $\delta_\infty := 2c_\infty \text{sgn}(d_{\beta_*}) LM_{1\infty}$, see (17.11), and $s(y)$ is symmetric around zero by Lemma 17.1(b).

Equation (17.13) and the dominated convergence theorem (applied to $1(\log(POIS2(Q; \beta_0, \beta_*, \lambda)) + \log(2\psi_2(Q_T; \beta_0, \beta_*, \lambda)) + \tau(\beta_*, \lambda, Q_T) \leq w)$ for any $w \in R$) give

$$\log(POIS2(Q; \beta_0, \beta_*, \lambda)) + \log(2\psi_2(Q_T; \beta_0, \beta_*, \lambda)) + \tau(\beta_*, \lambda, Q_T) \rightarrow_d s(\delta_\infty) = s(2c_\infty |LM_{1\infty}|). \tag{17.14}$$

Now we consider the behavior of the critical value function for the POIS2 test, $\kappa_{2, \beta_0}(q_T)$, where q_T denotes a realization of Q_T . We are interested in the power of the POIS2 test. So, we are interested in the behavior of $\kappa_{2, \beta_0}(q_T)$ for q_T sequences as $\lambda d_{\beta_*}^2 \rightarrow \infty$ and $\lambda^{1/2} c_{\beta_*} \rightarrow c_\infty$

that are generated when the true parameters are (β_*, λ) . This behavior is given in (17.8) to be $q_T = \lambda d_{\beta_*}^2 (1 + o(1))$ a.s. under (β_*, λ) .

Up to this point in the proof, the parameters (β_*, λ) have played a dual role. First, they denote the parameter values against which the POIS2 test is designed to have optimal two-sided power and, hence, determine the form of the POIS2 test statistic. Second, they denote the true values of β and λ (because we are interested in the power of the POIS2 test when the (β_*, λ) values for which it is designed are the true values). Here, where we discuss the behavior of the critical value function $\kappa_{2,\beta_0}(\cdot)$, (β_*, λ) only play the former role. The true value of β is β_0 and the true value of λ we denote by λ_0 . The function $\kappa_{2,\beta_0}(\cdot)$ depends on (β_*, λ) because the POIS2 test statistic does, but the null distribution that determines $\kappa_{2,\beta_0}(\cdot)$ does not depend on (β_*, λ) . In spite of this, the values q_T which are of interest to us, do depend on (β_*, λ) as noted in the previous paragraph.

The function $\kappa_{2,\beta_0}(\cdot)$ is defined in (11.6). Its definition depends on the conditional null distribution of Q_1 given $Q_T = q_T$ whose density $f_{Q_1|Q_T}(\cdot|q_T)$ is given in (11.3). This density depends on k , but not on any other parameters, such as β_0 , $\lambda_0 = \mu'_{\pi_0} \mu_{\pi_0}$, or Ω . In consequence, for the purposes of determining the properties of $\kappa_{2,\beta_0}(\cdot)$ we can suppose that $\beta_0 = 0$, $\mu_{\pi_0} = 1^k / \|1^k\|$, $\lambda_0 = 1$, and $\Omega = I_2$. In this case,

$$S = Z_S \sim N(0^k, I_k), \quad T = \mu_{\pi_0} + Z_T \sim N(\mu_{\pi_0}, I_k), \quad (17.15)$$

and S and T are independent (using $d_{\beta_0}(\beta_0, \Omega) = b'_0 \Omega b_0 (b'_0 \Omega b_0)^{-1/2} \det(\Omega)^{-1/2} = 1$ since $b_0 = (1, \beta_0)' = (1, 0)'$).

We now show that $\kappa_{2,\beta_0}(q_T)$ satisfies

$$\log(\kappa_{2,\beta_0}(q_T)) + \log(2\psi_2(q_T; \beta_0, \beta_*, \lambda)) + \tau(\beta_*, \lambda, q_T) \rightarrow s(2|c_\infty|(\chi_{1,1-\alpha}^2)^{1/2}) \text{ as } q_T \rightarrow \infty \quad (17.16)$$

for any sequence of constants $q_T = \lambda d_{\beta_*}^2 (1 + o(1))$ as $\lambda d_{\beta_*}^2 \rightarrow \infty$.

Suppose random variables $\{W_m : m \geq 1\}$ and W satisfy: (i) $W_m \rightarrow_d W$ as $m \rightarrow \infty$, (ii) W has a continuous and strictly increasing distribution function at its $1 - \alpha$ quantile κ_∞ , and (iii) $P(W_m > \kappa_m) = \alpha$ for all $m \geq 1$ for some constants $\{\kappa_m : m \geq 1\}$. Then, $\kappa_m \rightarrow \kappa_\infty$. This holds because if $\limsup_{m \rightarrow \infty} \kappa_m > \kappa_\infty$, then there is a subsequence $\{v_m\}$ of $\{m\}$ such that $\lim_{m \rightarrow \infty} \kappa_{v_m} = \kappa_{\infty+} > \kappa_\infty$ and $\alpha = P(W_{v_m} > \kappa_{v_m}) \rightarrow P(W > \kappa_{\infty+}) < P(W > \kappa_\infty) = \alpha$, which is a contradiction, and likewise $\liminf_{m \rightarrow \infty} \kappa_m < \kappa_\infty$ leads to a contradiction.

We apply the result in the previous paragraph with (a) $\{W_m : m \geq 1\}$ given by $\log(\text{POIS2}(Q; \beta_0, \beta_*, \lambda)) + \log(2\psi_2(q_T; \beta_0, \beta_*, \lambda)) + \tau(\beta_*, \lambda, q_T)$ under the null hypothesis and conditional on $T = t$ with $t = 1^k q_T^{1/2} / k^{1/2}$ for some sequence of constants $q_T = \lambda d_{\beta_*}^2 (1 + o(1)) \rightarrow \infty$ as $\lambda d_{\beta_*}^2 \rightarrow$

∞ , (b) $W = s(2c_\infty|S'1^k/k^{1/2}|)$, where $S'1^k/k^{1/2} \sim N(0,1)$, (c) κ_m equal to $\log(\kappa_{2,\beta_0}(q_T)) + \log(2\psi_2(q_T; \beta_0, \beta_*, \lambda)) + \tau(\beta_*, \lambda, q_T)$, and (d) $\kappa_\infty = s(2|c_\infty|(\chi_{1,1-\alpha}^2)^{1/2})$.

We need to show conditions (i)-(iii) above hold. Condition (ii) holds straightforwardly for W as in (b) given the normal distribution of S , the functional form of $s(y)$, and $c_\infty \neq 0$.

By definition of $\kappa_{2,\beta_0}(q_T)$, under the null hypothesis, $P_{Q_1|Q_T}(POIS2(Q; \beta_0, \beta_*, \lambda) > \kappa_{2,\beta_0}(q_T) | q_T) = \alpha$ for all $q_T \geq 0$, see (11.6). This implies that the invariant POIS2 test is similar. In turn, this implies that under the null hypothesis $P(POIS2(Q; \beta_0, \beta_*, \lambda) > \kappa_{2,\beta_0}(q_T) | T = t) = \alpha$ for all $t \in R^k$ because Theorem 1 of Moreira (2009) shows that any invariant similar test has null rejection probability α conditional on T . This verifies condition (iii) because the log function is monotone and the last two summands of W_m and κ_m defined in (a) and (c) above cancel.

Next, we show that condition (i) holds. Given (17.15) and $t = 1^k q_T^{1/2} / k^{1/2}$, under the null and conditional on $T = t$, we have

$$\frac{Q_{ST}}{Q_T^{1/2}} = \frac{S't}{(t't)^{1/2}} = S'1^k/k^{1/2} \sim \chi_1^2, \quad (17.17)$$

which does not depend on $\lambda d_{\beta_*}^2$ or $\lambda^{1/2} c_{\beta_*}$. Hence, in place of the a.s. convergence result for $Q_{ST}/Q_T^{1/2}$ as $\lambda d_{\beta_*}^2 \rightarrow \infty$ and $\lambda^{1/2} c_{\beta_*} \rightarrow c_\infty$ in (17.5), which applies under the alternative hypothesis with true parameters (β_*, λ) , we have $Q_{ST}/Q_T^{1/2} = S'1^k/k^{1/2}$ under the null hypothesis for all $\lambda d_{\beta_*}^2$ and $\lambda^{1/2} c_{\beta_*}$. Using this in place of (17.5), the unconditional a.s. convergence result in (17.13), established in (17.7)-(17.13), goes through as a conditional on $T = t$ a.s. result without any further changes. In consequence, the convergence in distribution result in (17.14) also holds conditional on $T = t$ a.s., but with $s(2c_\infty|S'1^k/k^{1/2}|)$ in place of $s(2c_\infty|LM_{1\infty}|)$. This verifies condition (i).

Given that conditions (i)-(iii) hold, we obtain $\kappa_m \rightarrow \kappa_\infty$ as $\lambda d_{\beta_*}^2 \rightarrow \infty$ for κ_m and κ_∞ defined in (c) and (d), respectively, above. This establishes (17.16).

Given (17.16), we have

$$\begin{aligned} & P_{\beta_*, \beta_0, \lambda, \Omega}(POIS2(Q; \beta_0, \beta_*, \lambda) > \kappa_{2,\beta_0}(Q_T)) \\ &= P_{\beta_*, \beta_0, \lambda, \Omega}(\log(POIS2(Q; \beta_0, \beta_*, \lambda)) + \log(2\psi_2(Q_T; \beta_0, \beta_*, \lambda)) + \tau(\beta_*, \lambda, Q_T) \\ &\quad > \log(\kappa_{2,\beta_0}(Q_T)) + \log(2\psi_2(Q_T; \beta_0, \beta_*, \lambda)) + \tau(\beta_*, \lambda, Q_T)) \\ &\rightarrow_d P(s(2c_\infty|LM_{1\infty}|) > s(2c_\infty|\chi_{1,1-\alpha}^2|)) \\ &= P(LM_{1\infty}^2 > \chi_{1,1-\alpha}^2) \\ &= P(\chi_1^2(c_\infty^2) > \chi_{1,1-\alpha}^2), \end{aligned} \quad (17.18)$$

where the second last equality uses the fact that $s(y)$ is symmetric and strictly increasing for $y > 0$ by Lemma 17.1(b). Equation (17.18) establishes part (a) of the theorem.

Now we establish part (b) of the theorem. Let

$$J := S'M_T S, \quad (17.19)$$

where $M_T := I_k - P_T$ and $P_T := T(T'T)^{-1}T'$. It follows from (3.3) that

$$LM = S'P_T S \text{ and } Q_S = LM + J. \quad (17.20)$$

By (17.8), $Q_T = \lambda d_{\beta_*}^2 (1 + o_{a.s.}(1)) \rightarrow \infty$ a.s. as $\lambda d_{\beta_*}^2 \rightarrow \infty$ when the true parameters are (β_*, λ) . By (17.20) and some algebra, we have $(Q_S - Q_T)^2 + 4LM \cdot Q_T = (LM - J + Q_T)^2 + 4LM \cdot J$. This and the definition of LR in (3.3) give

$$LR = \frac{1}{2} \left(LM + J - Q_T + \sqrt{(LM - J + Q_T)^2 + 4LM \cdot J} \right). \quad (17.21)$$

Using a mean-value expansion of the square-root expression in (17.21) about $(LM - J + Q_T)^2$, we have

$$\sqrt{(LM - J + Q_T)^2 + 4LM \cdot J} = LM - J + Q_T + (2\sqrt{\zeta})^{-1} 4LM \cdot J \quad (17.22)$$

for an intermediate value ζ between $(LM - J + Q_T)^2$ and $(LM - J + Q_T)^2 + 4LM \cdot J$. It follows that

$$LR = LM + o(1) \text{ a.s.} \quad (17.23)$$

because $Q_T \rightarrow \infty$ a.s., $LM = O(1)$ a.s., and $J = O(1)$ a.s. as $\lambda d_{\beta_*}^2 \rightarrow \infty$ and $\lambda^{1/2} c_{\beta_*} \rightarrow c_\infty \in R$, which imply that $(\sqrt{\zeta})^{-1} = o(1)$ a.s. These properties of LM and J hold because $LM = S'P_T S \leq S'S$, $J = S'M_T S \leq S'S$, and, using (17.4), we have $S'S = (c_{\beta_*} \mu_\pi + Z_S)'(c_{\beta_*} \mu_\pi + Z_S) = O(1)$ a.s. because $\|c_{\beta_*} \mu_\pi\|^2 = \lambda c_{\beta_*}^2 = O(1)$ by assumption.

The critical value function for the CLR test, $\kappa_{LR,\alpha}(\cdot)$, depends only on k and α , see Lemma 3(c) and (3.5) in AMS. It is well known in the literature that $\kappa_{LR,\alpha}(\cdot)$ satisfies $\kappa_{LR,\alpha}(q_T) \rightarrow \chi_{1,1-\alpha}^2$ as $q_T \rightarrow \infty$, e.g., see Moreira (2003, Proposition 1). Hence, we have

$$\begin{aligned} P_{\beta_*, \beta_0, \lambda, \Omega}(LR > \kappa_{LR,\alpha}(Q_T)) &= P_{\beta_*, \beta_0, \lambda, \Omega}(LM + o_{a.s.}(1) > \chi_{1,1-\alpha}^2 + o_{a.s.}(1)) \\ &= P_{\beta_*, \beta_0, \lambda, \Omega}(LM + o_p(1) > \chi_{1,1-\alpha}^2) \rightarrow P(\chi_1^2(c_\infty^2) > \chi_{1,1-\alpha}^2) \end{aligned} \quad (17.24)$$

as $\lambda d_{\beta_*}^2 \rightarrow \infty$ and $\lambda^{1/2} c_{\beta_*} \rightarrow c_\infty$, where the first equality holds by (17.23), $Q_T \rightarrow \infty$ a.s. by (17.8), and $\lim_{q_T \rightarrow \infty} \kappa_{LR,\alpha}(q_T) = \chi_{1,1-\alpha}^2$ and the convergence holds by part (c) of the theorem. This establishes part (b) of the theorem. \square

Proof of Theorem 7.2. First, we establish part (a)(i) of the theorem. By (11.8) with $\beta = \beta_*$ and $\Sigma = \Sigma_*$, we have

$$\Omega(\beta_*, \Sigma_*) = \begin{bmatrix} \omega_1^2 & \omega_{12} \\ \omega_{12} & \omega_2^2 \end{bmatrix} = \begin{bmatrix} \sigma_u^2 + 2\sigma_{uv}\beta_* + \sigma_v^2\beta_*^2 & \sigma_{uv} + \sigma_v^2\beta_* \\ \sigma_{uv} + \sigma_v^2\beta_* & \sigma_v^2 \end{bmatrix}. \quad (17.25)$$

Using this, we obtain, as $\rho_{uv} \rightarrow \pm 1$,

$$\begin{aligned} c_{\beta_*} &= c_{\beta_*}(\beta_0, \Omega(\beta_*, \Sigma_*)) = (\beta_* - \beta_0)(\omega_1^2 - 2\beta_0\omega_{12} + \omega_2^2\beta_0^2)^{-1/2} \\ &= (\beta_* - \beta_0)(\sigma_u^2 + 2\sigma_{uv}\beta_* + \sigma_v^2\beta_*^2 - 2\beta_0(\sigma_{uv} + \sigma_v^2\beta_*) + \sigma_v^2\beta_0^2)^{-1/2} \\ &= (\beta_* - \beta_0)(\sigma_u^2 + 2(\beta_* - \beta_0)\sigma_u\sigma_v\rho_{uv} + (\beta_* - \beta_0)^2\sigma_v^2)^{-1/2} \\ &\rightarrow (\beta_* - \beta_0)(\sigma_u^2 \pm 2(\beta_* - \beta_0)\sigma_u\sigma_v + (\beta_* - \beta_0)^2\sigma_v^2)^{-1/2} \\ &= (\beta_* - \beta_0)/|\sigma_u \pm (\beta_* - \beta_0)\sigma_v|, \end{aligned} \quad (17.26)$$

where the second equality uses (2.3), the convergence only holds if $\sigma_u \pm (\beta_* - \beta_0)\sigma_v \neq 0$, and the fourth equality uses $\sigma_{uv} = \sigma_u\sigma_v\rho_{uv}$. This proves part (a)(i).

To prove part (a)(ii), we have

$$\begin{aligned} d_{\beta_*} &= d_{\beta_*}(\beta_0, \Omega(\beta_*, \Sigma_*)) = b'_* \Omega b_0 (b'_* \Omega b_0)^{-1/2} \det(\Omega)^{-1/2} \\ &= (\omega_1^2 - \omega_{12}(\beta_0 + \beta_*) + \omega_2^2\beta_0\beta_*) \cdot (\omega_1^2 - 2\beta_0\omega_{12} + \omega_2^2\beta_0^2)^{-1/2} \cdot (\omega_1^2\omega_2^2 - \omega_{12}^2)^{-1/2}, \end{aligned} \quad (17.27)$$

where the second equality holds by (2.3). The second multiplicand on the rhs of (17.27) converges to $|\sigma_u \pm (\beta_* - \beta_0)\sigma_v|^{-1}$ provided $\sigma_u \pm (\beta_* - \beta_0)\sigma_v \neq 0$ by the calculations in (17.26).

The first multiplicand on the rhs of (17.27) satisfies, as $\rho_{uv} \rightarrow \pm 1$,

$$\begin{aligned} &\omega_1^2 - \omega_{12}(\beta_0 + \beta_*) + \omega_2^2\beta_0\beta_* \\ &= \sigma_u^2 + 2\sigma_{uv}\beta_* + \sigma_v^2\beta_*^2 - (\sigma_{uv} + \sigma_v^2\beta_*)(\beta_0 + \beta_*) + \sigma_v^2\beta_0\beta_* \\ &= \sigma_u^2 + \sigma_u\sigma_v\rho_{uv}(\beta_* - \beta_0) \\ &\rightarrow \sigma_u(\sigma_u \pm \sigma_v(\beta_* - \beta_0)), \end{aligned} \quad (17.28)$$

where the first equality uses (17.25) and the second equality holds by simple algebra and $\sigma_{uv} = \sigma_u \sigma_v \rho_{uv}$.

The reciprocal of the square of the third multiplicand on the rhs of (17.27) satisfies, as $\rho_{uv} \rightarrow \pm 1$,

$$\begin{aligned}
\omega_1^2 \omega_2^2 - \omega_{12}^2 &= (\sigma_u^2 + 2\sigma_u \sigma_v \rho_{uv} \beta_* + \sigma_v^2 \beta_*^2) \sigma_v^2 - (\sigma_u \sigma_v \rho_{uv} + \sigma_v^2 \beta_*^2)^2 \\
&\rightarrow (\sigma_u^2 \pm 2\sigma_u \sigma_v \beta_* + \sigma_v^2 \beta_*^2) \sigma_v^2 - (\pm \sigma_u \sigma_v + \sigma_v^2 \beta_*^2)^2 \\
&= (\sigma_u \pm \sigma_v \beta_*)^2 \sigma_v^2 - (\pm \sigma_u + \sigma_v \beta_*)^2 \sigma_v^2 \\
&= 0,
\end{aligned} \tag{17.29}$$

where the first equality holds by (17.25) and $\sigma_{uv} = \sigma_u \sigma_v \rho_{uv}$.

Combining (17.27)-(17.29) and $\lambda > 0$ proves part (a)(ii).

Next, we establish part (b) of the theorem. Using the definition of $c_\beta(\beta_0, \Omega)$ in (2.3), we have

$$\begin{aligned}
\lim_{\rho_\Omega \rightarrow \pm 1} c_{\beta_*}(\beta_0, \Omega) &= \lim_{\rho_\Omega \rightarrow \pm 1} (\beta_* - \beta_0) (b'_0 \Omega b_0)^{-1/2} \\
&= \lim_{\rho_\Omega \rightarrow \pm 1} (\beta_* - \beta_0) (\omega_1^2 - 2\beta_0 \omega_1 \omega_2 \rho_\Omega + \omega_2^2 \beta_0^2)^{-1/2} \\
&= (\beta_* - \beta_0) / |\omega_1 \mp \omega_2 \beta_0|,
\end{aligned} \tag{17.30}$$

where the third equality holds provided $\omega_1 \mp \omega_2 \beta_0 \neq 0$. This establishes part (b)(i) of the theorem.

Using the definition of $d_\beta(\beta_0, \Omega)$ in (2.3) and $b_* := (1, \beta_*)'$, we have

$$\begin{aligned}
\lim_{\rho_\Omega \rightarrow \pm 1} d_{\beta_*}(\beta_0, \Omega) &= \lim_{\rho_\Omega \rightarrow \pm 1} b'_* \Omega b_0 (b'_0 \Omega b_0)^{-1/2} \det(\Omega)^{-1/2} \\
&= \lim_{\rho_\Omega \rightarrow \pm 1} (\omega_1^2 - \omega_1 \omega_2 \rho_\Omega (\beta_0 + \beta_*) + \omega_2^2 \beta_0 \beta_*) \cdot (\omega_1^2 - 2\beta_0 \omega_1 \omega_2 \rho_\Omega + \omega_2^2 \beta_0^2)^{-1/2} \\
&\quad \cdot (\omega_1^2 \omega_2^2 - \omega_1^2 \omega_2^2 \rho_\Omega^2)^{-1/2} \\
&= (\omega_1 \mp \omega_2 \beta_0) (\omega_1 \mp \omega_2 \beta_*) \cdot \frac{1}{|\omega_1 \mp \omega_2 \beta_0|} \cdot \frac{1}{\omega_1 \omega_2} \cdot \lim_{\rho_\Omega \rightarrow \pm 1} \frac{1}{(1 - \rho_\Omega^2)^{1/2}} \\
&= \text{sgn}((\omega_1 \mp \omega_2 \beta_0) (\omega_1 \mp \omega_2 \beta_*)) \cdot \infty,
\end{aligned} \tag{17.31}$$

where the third and fourth equalities hold provided $\omega_1 \mp \omega_2 \beta_0 \neq 0$ and $\omega_1 \mp \omega_2 \beta_* \neq 0$. This and $\lambda > 0$ establish part (b)(ii) of the theorem.

Part (c)(i) is proved as follows:

$$c_{\beta_*} = \frac{\beta_* - \beta_0}{(\sigma_u^2 + 2(\beta_* - \beta_0) \sigma_u \sigma_v \rho_{uv} + (\beta_* - \beta_0)^2 \sigma_v^2)^{1/2}} \rightarrow \mp \frac{1}{\sigma_v} \text{ as } (\rho_{uv}, \beta_0) \rightarrow (1, \pm\infty), \tag{17.32}$$

where the first equality holds by (17.26) and the convergence holds by considering only the dominant β_0 terms. The same result holds as $(\rho_{uv}, \beta_0) \rightarrow (1, \pm\infty)$ because ρ_{uv} enters the middle expression

in (17.32) only through a term that does not affect the limit.

Part (c)(ii) is proved using the expression for d_{β_*} in (17.27). By (17.29), the third multiplicand in (17.27), which does not depend on β_0 , diverges to infinity when $\rho_{uv} \rightarrow 1$ or -1 . The product of the first two multiplicands on the rhs of (17.27) equals

$$\begin{aligned} \frac{\omega_1^2 - \omega_{12}(\beta_0 + \beta_*) + \omega_2^2 \beta_0 \beta_*}{(\omega_1^2 - 2\beta_0 \omega_{12} + \omega_2^2 \beta_0^2)^{1/2}} &= \frac{\sigma_u^2 + \sigma_u \sigma_v \rho_{uv} (\beta_* - \beta_0)}{(\sigma_u^2 + 2(\beta_* - \beta_0) \sigma_u \sigma_v \rho_{uv} + (\beta_* - \beta_0)^2 \sigma_v^2)^{1/2}} \\ &\rightarrow \mp \frac{\sigma_u \sigma_v}{\sigma_v} = \mp \sigma_u \text{ as } (\rho_{uv}, \beta_0) \rightarrow (1, \pm\infty), \end{aligned} \quad (17.33)$$

where the equality uses the calculations in the first three lines of (17.26) and (17.28) and the convergence holds by considering only the dominant β_0 terms. When $(\rho_{uv}, \beta_0) \rightarrow (-1, \pm\infty)$, the limit in (17.33) is $\pm \sigma_u$ because ρ_{uv} enters multiplicatively in the dominant β_0 term in the numerator. In both cases, the product of the first two multiplicands on the rhs of (17.27) converges to a non-zero constant and the third multiplicand diverges to infinity. Hence, d_{β_*} diverges to $+\infty$ or $-\infty$ and $\lambda d_{\beta_*}^2 \rightarrow \infty$ since $\lambda > 0$, which completes the proof.

Part (d)(i) holds because

$$c_{\beta_*} = \frac{\beta_* - \beta_0}{(\omega_1^2 - 2\beta_0 \omega_1 \omega_2 \rho_\Omega + \omega_2^2 \beta_0^2)^{1/2}} \rightarrow \mp \frac{1}{\omega_2} \text{ as } (\rho_\Omega, \beta_0) \rightarrow (1, \pm\infty), \quad (17.34)$$

where the equality uses (17.30). The same convergence holds as $(\rho_\Omega, \beta_0) \rightarrow (1, \pm\infty)$ because ρ_{uv} enters the middle expression in (17.34) only through a term that does not affect the limit.

Part (d)(ii) is proved using the expression for d_{β_*} in (17.31):

$$\begin{aligned} d_{\beta_*} &= \frac{(\omega_1^2 - \omega_1 \omega_2 \rho_\Omega (\beta_0 + \beta_*) + \omega_2^2 \beta_0 \beta_*)}{(\omega_1^2 - 2\beta_0 \omega_1 \omega_2 \rho_\Omega + \omega_2^2 \beta_0^2)^{1/2}} \cdot (\omega_1^2 \omega_2^2 - \omega_1^2 \omega_2^2 \rho_\Omega^2)^{-1/2}, \\ \frac{(\omega_1^2 - \omega_1 \omega_2 \rho_\Omega (\beta_0 + \beta_*) + \omega_2^2 \beta_0 \beta_*)}{(\omega_1^2 - 2\beta_0 \omega_1 \omega_2 \rho_\Omega + \omega_2^2 \beta_0^2)^{1/2}} &\rightarrow \frac{\pm(\omega_2^2 \beta_* - \omega_1 \omega_2)}{\omega_2} = \mp(\omega_1 - \omega_2 \beta_*), \text{ and} \\ (\omega_1^2 \omega_2^2 - \omega_1^2 \omega_2^2 \rho_\Omega^2)^{-1/2} &\rightarrow \infty \text{ as } (\rho_\Omega, \beta_0) \rightarrow (1, \pm\infty). \end{aligned} \quad (17.35)$$

Hence, $\lambda d_{\beta_*}^2 \rightarrow \infty$ as $(\rho_\Omega, \beta_0) \rightarrow (1, \pm\infty)$ provided $\omega_1 - \omega_2 \beta_* \neq 0$. When $(\rho_\Omega, \beta_0) \rightarrow (-1, \pm\infty)$, the limit in the second line of (17.35) is $\pm(\omega_2^2 \beta_* + \omega_1 \omega_2)/\omega_2 = \pm(\omega_1 + \omega_2 \beta_*)$ and, hence, $\lambda d_{\beta_*}^2 \rightarrow \infty$ provided $\omega_1 + \omega_2 \beta_* \neq 0$, which completes the proof. \square

18 Proofs of Theorem 12.1 and Lemmas 13.1 and 13.2

Proof of Theorem 12.1. By Cor. 2 and Comment 2 to Cor. 2 of Andrews, Moreira, and Stock (2004), for all $(\beta_*, \beta_0, \lambda, \Omega)$,

$$P_{\beta_*, \beta_0, \lambda, \Omega}(\phi_{\beta_0}(Q) = 1) \leq P_{\beta_*, \beta_0, \lambda, \Omega}(POIS(Q; \beta_0, \beta_*) > \kappa_{\beta_0}(Q_T)). \quad (18.1)$$

That is, the test on the rhs is the (one-sided) POIS test for testing $H_0 : \beta = \beta_0$ versus $H_1 : \beta = \beta_*$ for fixed known Ω and any $\lambda \geq 0$ under H_1 .

We use the dominated convergence theorem (DCT) to show

$$\lim_{\beta_0 \rightarrow \pm\infty} P_{\beta_*, \beta_0, \lambda, \Omega}(POIS(Q; \beta_0, \beta_*) > \kappa_{\beta_0}(Q_T)) = P_{\rho_{uv}, \lambda_v}(POIS(Q; \infty, \rho_{uv}) > \kappa_{\infty}(Q_T)). \quad (18.2)$$

Equations (18.1) and (18.2) imply that the result of Theorem 12.1 holds.

By (12.2), (12.5), and Lemma 14.1(b) and (e),

$$\lim_{\beta_0 \rightarrow \pm\infty} POIS(q; \beta_0, \beta_*) = POIS(q; \infty, \rho_{uv}) \quad (18.3)$$

for all 2×2 variance matrices q , for given (β_*, π, Ω) .

The proof of (18.2) is the same as the proof of Lemma 16.1(a), but with $POIS(Q; \beta_0, \beta_*)$, $\kappa_{\beta_0}(Q_T)$, $POIS(Q; \infty, \rho_{uv})$, and $\kappa_{\infty}(Q_T)$ in place of $POIS2(Q; \beta_0, \beta_*, \lambda)$, $\kappa_{2, \beta_0}(Q_T)$, $POIS2(Q; \infty, |\rho_{uv}|, \lambda_v)$, and $\kappa_{2, \infty}(Q_T)$, respectively, using (18.3) in place of (16.6), and using the results (established below) that (i) the Lebesgue measure of the set of (q_S, q_{ST}, q_T) for which $POIS(q; \infty, \rho_{uv}) = \kappa_{\infty}(q_T)$ is zero, (ii) $P_{Q_1|Q_T}(POIS(Q; \infty, \rho_{uv}) = x|q_T) = 0$ for all $q_T \geq 0$, and (iii) the distribution function of $POIS(Q; \infty, \rho_{uv})$ is strictly increasing at its $1 - \alpha$ quantile $\kappa_{\infty}(q_T)$ under $P_{Q_1|Q_T}(\cdot|q_T)$ for all $q_T \geq 0$.

Condition (i) holds because (a) $POIS(q; \infty, \rho_{uv}) = q_S + 2r_{uv}q_{ST}$ (see (12.5)) implies that the Lebesgue measure of the set of (q_S, q_{ST}) for which $q_S + 2r_{uv}q_{ST} = \kappa_{\infty}(q_T)$ is zero for all q_T and (b) the Lebesgue measure of the set of (q_S, q_{ST}, q_T) for which $q_S + 2r_{uv}q_{ST} = \kappa_{\infty}(q_T)$ is obtained by integrating the set in (a) over $q_T \in R$ subject to the constraint that q is positive definite.

Condition (ii) holds by the absolute continuity of $POIS(Q; \infty, \rho_{uv})$ under $P_{Q_1|Q_T}(\cdot|q_T)$ (by the functional form of $POIS(Q; \infty, \rho_{uv})$ and the absolute continuity of Q_1 under $P_{Q_1|Q_T}(\cdot|q_T)$, whose density is given in (11.3)).

Condition (iii) holds because we can write $POIS(Q; \infty, \rho_{uv}) = S'S + 2r_{uv}S'T = (S + r_{uv}T)'(S + r_{uv}T) - r_{uv}^2T'T$, where $[S : T]$ has a multivariate normal distribution with means matrix given by (5.2) and identity variance matrix and, hence, $POIS(Q; \infty, \rho_{uv})$ has a shifted noncentral χ^2 distri-

bution conditional on $T = t$. In consequence, it has a positive density on $(r_{uv}^2 t, \infty) = (r_{uv}^2 q_T, \infty)$ conditional on $T = t$ and also conditional on $Q_T = q_T$ (because the latter conditional density is the integral of the former conditional density over t such that $t' = q_T$). This completes the proof. \square

Proof of Lemma 13.1. First, we show that (13.4) implies the equation for λ_2 in (13.2). By the expression $d_\beta = a' \Omega^{-1} a_0 (a_0' \Omega^{-1} a_0)^{-1/2}$ given in (2.7) in AMS, where $a := (\beta, 1)'$ and $a_0 := (\beta_0, 1)'$, for any $\beta \in R$,

$$\begin{aligned} d_\beta - d_{\beta_0} &= (a - a_0)' \Omega^{-1} a_0 (a_0' \Omega^{-1} a_0)^{-1/2} \\ &= (\beta - \beta_0) e_1' \Omega^{-1} a_0 (a_0' \Omega^{-1} a_0)^{-1/2} := (\beta - \beta_0) r_{\beta_0}, \end{aligned} \quad (18.4)$$

where $e_1 := (1, 0)'$ and the last equality holds by the definition of r_{β_0} .

Substituting (18.4) into the second equation in (13.4) gives

$$\begin{aligned} \lambda_2^{1/2} d_{\beta_{2*}} &= \pm \lambda^{1/2} d_{\beta_*} \\ \text{iff } \lambda_2^{1/2} (d_{\beta_0} + r_{\beta_0} (\beta_{2*} - \beta_0)) &= \pm \lambda^{1/2} (d_{\beta_0} + r_{\beta_0} (\beta_* - \beta_0)) \\ \text{iff } \lambda_2^{1/2} d_{\beta_0} &= \pm \lambda^{1/2} (d_{\beta_0} + r_{\beta_0} (\beta_* - \beta_0)) - r_{\beta_0} \lambda_2^{1/2} (\beta_{2*} - \beta_0). \end{aligned} \quad (18.5)$$

Given the definition of c_β in (2.3), the first equation in (13.4) can be written as

$$\lambda_2^{1/2} (\beta_{2*} - \beta_0) = \mp \lambda^{1/2} (\beta_* - \beta_0). \quad (18.6)$$

Substituting this into (18.5) yields

$$\begin{aligned} \lambda_2^{1/2} d_{\beta_{2*}} &= \pm \lambda^{1/2} d_{\beta_*} \\ \text{iff } \lambda_2^{1/2} d_{\beta_0} &= \pm \lambda^{1/2} (d_{\beta_0} + 2r_{\beta_0} (\beta_* - \beta_0)) \\ \text{iff } \lambda_2^{1/2} &= \pm \lambda^{1/2} \frac{d_{\beta_0} + 2r_{\beta_0} (\beta_* - \beta_0)}{d_{\beta_0}}. \end{aligned} \quad (18.7)$$

The square of the equation in the last line in (18.7) is the equation for λ_2 in (13.2).

Next, we show that (13.4) implies the equation for β_{2*} in (13.2). Using (18.6), the first equation in (13.4) can be written as

$$\beta_{2*} = \beta_0 \mp \frac{\lambda^{1/2}}{\lambda_2^{1/2}} (\beta_* - \beta_0). \quad (18.8)$$

This combined with the equation for $\lambda^{1/2}/\lambda_2^{1/2}$ obtained from the last line of (18.7) gives

$$\beta_{2*} = \beta_0 - \frac{d_{\beta_0}}{d_{\beta_0} + 2r_{\beta_0}(\beta_* - \beta_0)}(\beta_* - \beta_0), \quad (18.9)$$

where a minus sign appears because the \mp sign in (18.8) gets multiplied by the \pm sign in the last line of (18.7), which yields a minus sign in both cases. Equation (18.9) is the same as the first condition in (13.2). This completes the proof that (13.4) implies (13.2).

Now, we prove the converse. We suppose (13.2) holds. Taking the square root of the second equation in (13.2) gives

$$\lambda_2^{1/2} = \pm \lambda^{1/2} \frac{d_{\beta_0} + 2r_{\beta_0}(\beta_* - \beta_0)}{d_{\beta_0}}, \quad (18.10)$$

where the \pm sign means that this equation holds either with $+$ or with $-$. Substituting this into the first equation in (13.2) gives (18.8), which is the same as (18.6), and (18.6) is the first equation in (13.4).

The second equation in (13.4) is given by (18.5). Given that the first equation in (13.4) holds, the second equation in (13.4) is given in (18.7). The last line of (18.7) holds by (18.10). This completes the proof that (13.2) implies (13.4). \square

Proof of Lemma 13.2. The proof of part (a) of the lemma is essentially the same as that of Theorem 8(b) in AMS. The only change is to note that when (β_{2*}, λ_2) satisfies (13.3), we have $\tau^* = \tau_2^*$, $\delta^* = -\delta_2^*$, and $\delta_{\max} = |\delta^*| = |\delta_2^*|$ (using the notation in AMS). Because $\delta_{\max} = |\delta^*| = |\delta_2^*|$, we obtain $\sqrt{\delta^2} - \sqrt{\delta_{\max}^2} = 0$ and the remainder of the proof of Theorem 8(b) goes through as is.

The proof of part (b) of the lemma is quite similar to the proof of Theorem 8(c) of AMS. The latter proof first considers the case where “ (β_{2*}, λ_2) does not satisfy the second condition of (13.1).” This needs to be changed to “ (β_{2*}, λ_2) does not satisfy the second condition of (13.1) or (13.3).” With this change, the rest of that part of the proof of Theorem 8(c) goes through unchanged.

The remaining cases (where both (13.1) and (13.3) fail) to consider are (i) when the second condition in (13.1) holds and the first condition in (13.1) fails and (ii) when the second condition in (13.3) holds and the first condition in (13.3) fails. These are mutually exclusive scenarios because the second conditions in (13.1) and (13.3) are incompatible. The proof of Theorem 8(c) of AMS considers case (i) and proves the result of Theorem 8(c) for that case. The proof of Theorem 8(c) for case (ii) is quite similar to that for case (i) using (A.21) in AMS because $\delta^* = -\delta_2^*$, $\delta_{\max} = |\delta^*| = |\delta_2^*| > 0$, and $\tau^* \neq \tau_2^*$ imply that $\text{sgn}(\delta^*) = -\text{sgn}(\delta_2^*)$ and $\tau^* \text{sgn}(\delta^*) \neq -\tau_2^* \text{sgn}(\delta_2^*)$. This last inequality shows that the expression in (A.21) in AMS is a continuous function of $Q_{ST}Q_T^{-1/2}$ that is not even. (Note that (A.21) in AMS has a typo: the quantity $\tau_2^* \text{sgn}(\delta^*)$ in its second summand

should be $\tau_2^* \text{sgn}(\delta_2^*)$. \square

19 Power Against Distant Alternatives Compared to Distant Null Hypotheses

19.1 Scenario 1 Compared to Scenario 2

In this section, we consider the power properties of tests when $|\beta_* - \beta_0|$ is large, where β_* denotes the true value of β . We compare scenario 1, where β_0 is fixed and β_* takes on large (absolute) values, to scenario 2, where β_* is fixed and β_0 takes on large (absolute) values. Scenario 1 yields the power function of a test against distant alternatives. Scenario 2 yields the false coverage probabilities of the CS constructed using the test for distant null hypotheses (from the true parameter value β_*). We show that, while power goes to one in scenario 1 as $\beta_* \rightarrow \pm\infty$ for fixed β_0 , it is not true that power goes to one in scenario 2 as $\beta_0 \rightarrow \pm\infty$ for fixed β_* .

It is convenient to consider the AR test, which is the simplest test. The AR test rejects $H_0 : \beta = \beta_0$ when $S'S > \chi_{k,\alpha}^2$. When the true value is β , the distribution of the $S'S$ statistic is noncentral χ^2 with noncentrality parameter

$$c_\beta^2(\beta_0, \Omega) \cdot \lambda \tag{19.1}$$

and k degrees of freedom. For the fixed null hypothesis $H_0 : \beta = \beta_0$, fixed Ω , and fixed λ , the power at the alternative hypothesis value β_* is determined by $c_{\beta_*}^2(\beta_0, \Omega)$. We have

$$\lim_{|\beta_*| \rightarrow \infty} c_{\beta_*}^2(\beta_0, \Omega) = \lim_{|\beta_*| \rightarrow \infty} (\beta_* - \beta_0)^2 \cdot (b_0' \Omega b_0)^{-1} = \infty. \tag{19.2}$$

Hence, the power of the AR test goes to one as $|\beta_*| \rightarrow \infty$.

On the other hand, if one fixes the alternative hypothesis value β_* and one considers the limit as $|\beta_0| \rightarrow \infty$, then one obtains

$$\begin{aligned} \lim_{|\beta_0| \rightarrow \infty} c_{\beta_*}^2(\beta_0, \Omega) &= \lim_{|\beta_0| \rightarrow \infty} (\beta_* - \beta_0)^2 \cdot (b_0' \Omega b_0)^{-1} \\ &= \lim_{|\beta_0| \rightarrow \infty} (\beta_* - \beta_0)^2 \cdot (\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2\beta_0^2)^{-1} \\ &= 1/\omega_2^2. \end{aligned} \tag{19.3}$$

Hence, the power of the AR test does not go to one as $|\beta_0| \rightarrow \infty$ even though $|\beta_0 - \beta_*| \rightarrow \infty$.

The differing results in (19.2) and (19.3) is easy to show for the AR test, but it also holds for

Kleibergen's and Moreira's LM test and Moreira's CLR test. The numerical power function and power envelope calculations in AMS are all of the type in scenario 1 in (19.2). The difference in the power of the AR (and other) tests between (19.2) and (19.3) suggests that it is worth exploring the properties of tests in scenarios of the latter type as well. We do this in the paper and show that the finding of AMS that the CLR test is essentially on the two-sided AE power envelope and is always at least as powerful as the AR test does not hold when one considers a broader range of null and alternative hypothesis values (β_0, β_*) than considered in the numerical results in AMS.

19.2 Structural Error Variance Matrices under Distant Alternatives and Distant Null Hypotheses

Here, we compute the structural error variance matrices in scenarios 1 and 2 considered in (19.2) and (19.3). By design, the reduced-form variance matrix Ω is the same for β_0 and β_* and, hence, does not vary between these two scenarios.

In scenario 1 in (19.2), the structural error variance matrix under H_0 is $\Sigma(\beta_0, \Omega)$, defined in (11.9). Under $H_1 : \beta = \beta_*$, as $|\beta_*| \rightarrow \infty$, we have

$$\begin{aligned} \lim_{\beta_* \rightarrow \pm\infty} \rho_{uv}(\beta_*, \Omega) &= \lim_{\beta_* \rightarrow \pm\infty} \frac{\omega_{12} - \omega_2^2 \beta_*}{(\omega_1^2 - 2\omega_{12}\beta_* + \omega_2^2 \beta_*^2)^{1/2} \omega_2} = \mp 1 \text{ and} \\ \lim_{|\beta_*| \rightarrow \infty} \sigma_u^2(\beta_*, \Omega) / \sigma_v^2(\beta_*, \Omega) &= \frac{\omega_1^2 - 2\omega_{12}\beta_* + \omega_2^2 \beta_*^2}{\omega_2^2} = \infty, \end{aligned} \quad (19.4)$$

where $\rho_{uv}(\beta_*, \Omega)$, $\sigma_u^2(\beta_*, \Omega)$, and $\sigma_v^2(\beta_*, \Omega)$ are defined just below (11.9). Equation (19.4) shows that, for standard power envelope calculations, when the alternative hypothesis value β_* is large in absolute value the structural variance matrix under H_1 exhibits correlation close to one in absolute value and a large ratio of structural to reduced-form variances.

In scenario 2 in (19.3), the structural error variance error matrix under H_* is $\Sigma(\beta_*, \Omega)$. Under $H_0 : \beta = \beta_0$, by exactly the same argument as in (19.4) with β_0 in place of β_* , we obtain

$$\lim_{\beta_0 \rightarrow \pm\infty} \rho_{uv}(\beta_0, \Omega) = \mp 1 \text{ and } \lim_{|\beta_0| \rightarrow \infty} \sigma_u^2(\beta_0, \Omega) / \sigma_v^2(\beta_0, \Omega) = \infty. \quad (19.5)$$

So, in scenario 2, when the null hypothesis value β_0 is large in absolute value the structural variance matrix under H_0 exhibits correlation close to one in absolute value and a large ratio of structural to reduced-form variances.

From a testing perspective, it is natural and time honored to fix the null hypothesis value β_0 and consider power as the alternative hypothesis value β_* varies. On the other hand, a confidence set is the set of null hypothesis values β_0 for which one does not reject $H_0 : \beta = \beta_0$. Hence, for a

given true value β_* , the false coverage probabilities of the confidence set equal one minus its power as one varies $H_0 : \beta = \beta_0$. Thus, from the confidence set perspective, it is natural to fix β_* and consider power as β_0 varies.

20 Transformation of the β_0 Versus β_* Testing Problem to a 0 Versus $\bar{\beta}_*$ Testing Problem

In this section, we transform the general testing problem of $H_0 : \beta = \beta_0$ versus $H_1 : \beta = \beta_*$ for $\pi \in R^k$ and fixed Ω to a testing problem of $H_0 : \bar{\beta} = 0$ versus $H_1 : \bar{\beta} = \bar{\beta}_*$ for some $\bar{\pi} \in R^k$ and some fixed $\bar{\Omega}$ whose diagonal elements equal one. This is done using the transformations given footnotes 7 and 8 of AMS, which argue that there is no loss in generality in the AMS numerical results to take $\omega_1^2 = \omega_2^2 = 1$ and $\beta_0 = 0$. These results help link the numerical work done in this paper with that done in AMS.

Starting with the model in (2.1), we transform the model based on (y_1, y_2) with parameters (β, π) and fixed reduced-form variance matrix Ω to a model based on (\tilde{y}_1, y_2) with parameters $(\tilde{\beta}, \pi)$ and fixed reduced-form variance matrix $\tilde{\Omega}$, where

$$\begin{aligned} \tilde{y}_1 &:= y_1 - y_2\beta_0, \\ \tilde{\beta} &:= \beta - \beta_0, \text{ and} \\ \tilde{\Omega} &:= \text{Var} \left(\begin{pmatrix} \tilde{y}_1 \\ y_2 \end{pmatrix} \right) = \text{Var} \left(\begin{bmatrix} 1 & -\beta_0 \\ 0 & 1 \end{bmatrix} \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} \right) \\ &= \begin{bmatrix} \omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2\beta_0^2 & \omega_{12} - \omega_2^2\beta_0 \\ \omega_{12} - \omega_2^2\beta_0 & \omega_2^2 \end{bmatrix}. \end{aligned} \tag{20.1}$$

The transformed testing problem is $H_0 : \tilde{\beta} = 0$ versus $H_1 : \tilde{\beta} = \tilde{\beta}_*$, where $\tilde{\beta}_* = \beta_* - \beta_0$, with parameter π and reduced-form variance matrix $\tilde{\Omega}$.

The matrix $\tilde{\Omega}$ does not have diagonal elements equal to one, so we transform the model based on (\tilde{y}_1, y_2) with parameters $(\tilde{\beta}, \pi)$ and fixed reduced-form variance matrix $\tilde{\Omega}$ to a model based on

(\bar{y}_1, \bar{y}_2) with parameters $(\bar{\beta}, \bar{\pi})$ and fixed reduced-form variance matrix $\bar{\Omega}$, where¹²

$$\begin{aligned}
\bar{y}_1 &:= \frac{\tilde{y}_1}{\tilde{\omega}_1} = \frac{y_1 - y_2\beta_0}{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2\beta_0^2)^{1/2}} \\
\bar{y}_2 &:= \frac{1}{\tilde{\omega}_2}y_2 = \frac{1}{\omega_2}y_2, \\
\bar{\beta} &:= \frac{\tilde{\omega}_2}{\tilde{\omega}_1}\tilde{\beta} = \frac{\omega_2}{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2\beta_0^2)^{1/2}}(\beta - \beta_0), \text{ and} \\
\bar{\pi} &:= \frac{1}{\tilde{\omega}_2}\pi = \frac{1}{\omega_2}\pi.
\end{aligned} \tag{20.2}$$

In addition, we have

$$\begin{aligned}
\bar{\Omega} &:= \text{Var} \begin{pmatrix} \bar{y}_1 \\ \bar{y}_2 \end{pmatrix} = \text{Var} \left(\begin{bmatrix} 1/\tilde{\omega}_1 & 0 \\ 0 & 1/\tilde{\omega}_2 \end{bmatrix} \begin{pmatrix} \tilde{y}_1 \\ y_2 \end{pmatrix} \right) \\
&= \begin{bmatrix} 1/\tilde{\omega}_1 & 0 \\ 0 & 1/\tilde{\omega}_2 \end{bmatrix} \tilde{\Omega} \begin{bmatrix} 1/\tilde{\omega}_1 & 0 \\ 0 & 1/\tilde{\omega}_2 \end{bmatrix} \\
&= \begin{bmatrix} 1/\tilde{\omega}_1 & 0 \\ 0 & 1/\omega_2 \end{bmatrix} \begin{bmatrix} \omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2\beta_0^2 & \omega_{12} - \omega_2^2\beta_0 \\ \omega_{12} - \omega_2^2\beta_0 & \omega_2^2 \end{bmatrix} \begin{bmatrix} 1/\tilde{\omega}_1 & 0 \\ 0 & 1/\omega_2 \end{bmatrix} \\
&= \begin{bmatrix} 1 & \frac{\omega_{12} - \omega_2^2\beta_0}{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2\beta_0^2)^{1/2}\omega_2} \\ \frac{\omega_{12} - \omega_2^2\beta_0}{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2\beta_0^2)^{1/2}\omega_2} & 1 \end{bmatrix}.
\end{aligned} \tag{20.3}$$

The transformed testing problem is $H_0 : \bar{\beta} = 0$ versus $H_1 : \bar{\beta} = \bar{\beta}_*$, where

$$\bar{\beta}_* = \frac{\omega_2}{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2\beta_0^2)^{1/2}}(\beta_* - \beta_0), \tag{20.4}$$

with parameter $\bar{\pi}$ and reduced-form variance matrix $\bar{\Omega}$.

Now, we consider the limit as $\beta_0 \rightarrow \pm\infty$ of the original model and see what it yields in terms of the transformed model. We have

$$\lim_{\beta_0 \rightarrow \pm\infty} \bar{\beta}_* = \mp 1 \text{ and } \lim_{\beta_0 \rightarrow \pm\infty} \bar{\Omega} = \begin{bmatrix} 1 & \mp 1 \\ \mp 1 & 1 \end{bmatrix}. \tag{20.5}$$

So, the asymptotic testing problem as $\beta_0 \rightarrow \pm\infty$ in terms of a model with a null hypothesis $\bar{\beta}$ value of 0 and a reduced-form variance matrix $\bar{\Omega}$ with ones on the diagonal is a test of $H_0 : \bar{\beta} = 0$ versus $H_1 : \bar{\beta} = \mp 1$.

¹²The formula $\bar{\beta} := (\tilde{\omega}_2/\tilde{\omega}_1)\tilde{\beta}$ in (20.2) comes from $\bar{y}_1 := \tilde{y}_1/\tilde{\omega}_1 = (y_2\tilde{\beta} + u)/\tilde{\omega}_1 = y_2\tilde{\beta}/\tilde{\omega}_1 + u/\tilde{\omega}_1 = (y_2/\tilde{\omega}_2)\tilde{\beta}(\tilde{\omega}_2/\tilde{\omega}_1) + u/\tilde{\omega}_1 = \bar{y}_2\bar{\beta} + \bar{u}$, where the last equality holds when $\bar{\beta} := (\tilde{\omega}_2/\tilde{\omega}_1)\tilde{\beta}$ and $\bar{u} := u/\tilde{\omega}_1$.

We get the same expression for the limits as $\beta_0 \rightarrow \pm\infty$ of $c_{\beta_*}(\beta_0, \Omega)$ and $d_{\beta_*}(\beta_0, \Omega)$ written in terms of the transformed parameters $(\bar{\beta}_0, \bar{\beta}_*, \bar{\pi}, \bar{\Omega})$ as in Lemma 14.1 except they are multiplied by σ_v . This occurs because $\mu_{\bar{\pi}} = \mu_{\pi}/\sigma_v$. In consequence, the limits as $\beta_0 \rightarrow \pm\infty$ of $c_{\beta_*}(\beta_0, \Omega)\mu_{\pi}$ and $d_{\beta_*}(\beta_0, \Omega)\mu_{\pi}$ written in terms of the transformed parameters $(\bar{\beta}_0, \bar{\beta}_*, \bar{\pi}, \bar{\Omega})$ are the same as their limits without any transformation.

Lemma 20.1 *Let $\bar{\beta}_* = \bar{\beta}_*(\beta_0)$ and $\bar{\Omega} = \bar{\Omega}(\beta_0)$ be defined in (20.4) and (20.3), respectively. Let $\bar{\beta}_0(\beta_0) = 0$.*

- (a) $\lim_{\beta_0 \rightarrow \pm\infty} c_{\bar{\beta}_*(\beta_0)}(\bar{\beta}_0(\beta_0), \bar{\Omega}(\beta_0)) = \mp 1$.
- (b) $\lim_{\beta_0 \rightarrow \pm\infty} d_{\bar{\beta}_*(\beta_0)}(\bar{\beta}_0(\beta_0), \bar{\Omega}(\beta_0)) = \mp \frac{\rho_{uv}}{(1-\rho_{uv}^2)^{1/2}}$.

Comment. (i). By Lemmas 14.1 and 20.1, the distributions of all of the tests considered in this paper are the same in the model in Section 2 when β_* and Ω are fixed and the null hypothesis value β_0 satisfies $\beta_0 \rightarrow \pm\infty$, and in the transformed model of this section when the null hypothesis $\bar{\beta}_0$ is fixed at 0 and the alternative hypothesis value $\bar{\beta}_* = \bar{\beta}_*(\beta_0)$ and the reduced-form variance $\bar{\Omega} = \bar{\Omega}(\beta_0)$ converge as in (20.5) as $\beta_0 \rightarrow \pm\infty$. (This uses the fact that $\sigma_v = 1$ in Lemma 20.1.)

(ii). AMS footnote 5 notes that there is a special parameter value $\beta = \beta_{AR}$ at which the one-sided point optimal invariant similar test of $H_0 : \beta = \beta_0$ versus $H_1 : \beta = \beta_{AR}$ is the (two-sided) AR test. In footnote 5 β_{AR} is defined to be $\beta_{AR} = \frac{\omega_1^2 - \omega_{12}\beta_0}{\omega_{12} - \omega_2^2\beta_0}$. If we compute β_{AR} for the transformed model (\bar{y}_1, \bar{y}_2) with parameters $(\bar{\beta}, \bar{\pi}, \bar{\Omega})$, where $\bar{\beta}_0 = 0$, we obtain

$$\bar{\beta}_{AR} = \frac{\bar{\omega}_1^2 - \bar{\omega}_{12}\bar{\beta}_0}{\bar{\omega}_{12} - \bar{\omega}_2^2\bar{\beta}_0} = \frac{1}{\bar{\omega}_{12}} = \mp 1, \quad (20.6)$$

which is the same as the limit of $\bar{\beta}_* = \bar{\beta}_*(\beta_0)$ as $\beta_0 \rightarrow \pm\infty$ in (20.2).

Proof of Lemma 20.1. First, we prove part (a). We have

$$\begin{aligned} c_{\bar{\beta}_*}(\bar{\beta}_0, \bar{\Omega}) &= (\bar{\beta}_* - \bar{\beta}_0)(\bar{b}'_0 \bar{\Omega} \bar{b}_0)^{-1/2} \\ &= \frac{\omega_2}{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2\beta_0^2)^{1/2}} (\beta_* - \beta_0)(1 - 2\bar{\omega}_{12}\bar{\beta}_0 + \bar{\beta}_0^2)^{-1/2} \\ &= \frac{\omega_2(\beta_* - \beta_0)}{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2\beta_0^2)^{1/2}} \\ &\rightarrow \mp 1 \text{ as } \beta_0 \rightarrow \pm\infty, \end{aligned} \quad (20.7)$$

where the second equality uses (20.4) and the third equality uses $\bar{\beta}_0 = 0$. Hence, $c_{\bar{\beta}_*}(\bar{\beta}_0, \bar{\Omega})\mu_{\bar{\pi}} \rightarrow \mp(1/\sigma_v)\mu_{\pi}$ as $\beta_0 \rightarrow \pm\infty$ using the expression for $\bar{\pi}$ in (20.2) and $\omega_2 = \sigma_v$.

Next, we prove part (b). Let $\bar{b}_* = (1, -\bar{\beta}_*)'$ and $\bar{b}_0 = (1, -\bar{\beta}_0)'$. We have

$$\begin{aligned} \det(\bar{\Omega}) &= 1 - \bar{\omega}_{12}^2, \\ \bar{\omega}_{12} &= \frac{\omega_{12} - \omega_2^2 \beta_0}{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2 \beta_0^2)^{1/2} \omega_2}, \text{ and} \\ \bar{b}_*' \bar{\Omega} \bar{b}_0 (\bar{b}_0' \bar{\Omega} \bar{b}_0)^{-1/2} &= \frac{1 - \bar{\omega}_{12} \bar{\beta}_0 - \bar{\omega}_{12} \bar{\beta}_* + \bar{\beta}_0 \bar{\beta}_*}{(1 - 2\bar{\omega}_{12} \bar{\beta}_0 + \bar{\beta}_0^2)^{1/2}} = 1 - \bar{\omega}_{12} \bar{\beta}_*, \end{aligned} \quad (20.8)$$

where the second equality on the third line uses $\bar{\beta}_0 = 0$. Next, we have

$$\begin{aligned} 1 - \bar{\omega}_{12} \bar{\beta}_* &= 1 - \frac{\omega_{12} - \omega_2^2 \beta_0}{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2 \beta_0^2)^{1/2} \omega_2} \frac{\omega_2}{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2 \beta_0^2)^{1/2}} (\beta_* - \beta_0) \\ &= 1 - \frac{(\omega_{12} - \omega_2^2 \beta_0)(\beta_* - \beta_0)}{\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2 \beta_0^2} \\ &= \frac{\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2 \beta_0^2 - \omega_{12}\beta_* + \omega_{12}\beta_0 + \omega_2^2 \beta_0 \beta_* - \omega_2^2 \beta_0^2}{\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2 \beta_0^2} \\ &= \frac{\omega_1^2 - \omega_{12}\beta_0 - \omega_{12}\beta_* + \omega_2^2 \beta_0 \beta_*}{\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2 \beta_0^2}, \end{aligned} \quad (20.9)$$

where the first equality uses (20.3) and (20.4).

In addition, we have

$$\begin{aligned} 1 - \bar{\omega}_{12}^2 &= 1 - \frac{(\omega_{12} - \omega_2^2 \beta_0)^2}{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2 \beta_0^2) \omega_2^2} \\ &= \frac{\omega_1^2 \omega_2^2 - 2\omega_{12} \omega_2^2 \beta_0 + \omega_2^4 \beta_0^2 - \omega_{12}^2 + 2\omega_{12} \omega_2^2 \beta_0 - \omega_4 \beta_0^2}{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2 \beta_0^2) \omega_2^2} \\ &= \frac{\omega_1^2 \omega_2^2 - \omega_{12}^2}{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2 \beta_0^2) \omega_2^2}, \end{aligned} \quad (20.10)$$

where the first equality uses (20.8).

Using (20.8)-(20.10), we have

$$\begin{aligned} d_{\bar{\beta}_*}(\bar{\beta}_0, \bar{\Omega}) &= \bar{b}_*' \bar{\Omega} \bar{b}_0 (\bar{b}_0' \bar{\Omega} \bar{b}_0)^{-1/2} \det(\bar{\Omega})^{-1/2} \\ &= \frac{\omega_1^2 - \omega_{12}\beta_0 - \omega_{12}\beta_* + \omega_2^2 \beta_0 \beta_*}{\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2 \beta_0^2} \left(\frac{\omega_1^2 \omega_2^2 - \omega_{12}^2}{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2 \beta_0^2) \omega_2^2} \right)^{-1/2} \\ &= \frac{(\omega_1^2 - \omega_{12}\beta_0 - \omega_{12}\beta_* + \omega_2^2 \beta_0 \beta_*)}{(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2 \beta_0^2)^{1/2} (\omega_1^2 \omega_2^2 - \omega_{12}^2)^{1/2}} \omega_2. \end{aligned} \quad (20.11)$$

The rhs of (20.11) is the same as the expression on the second line of (14.2) multiplied by $\omega_2 = \sigma_v$.

In consequence, the calculations in (14.2)-(14.4) give the result of part (a) of Lemma 20.1. \square

21 Transformation of the β_0 Versus β_* Testing Problem to a $\bar{\beta}_0$ Versus 0 Testing Problem

In this section, we transform the general testing problem of $H_0 : \beta = \beta_0$ versus $H_1 : \beta = \beta_*$ for $\pi \in R^k$ and fixed reduced-form variance matrix Ω to a testing problem of $H_0 : \bar{\beta} = \bar{\beta}_0$ versus $H_1 : \bar{\beta} = 0$ for some $\bar{\pi} \in R^k$ and some fixed $\bar{\Omega}$ with diagonal elements equal to one. These transformation results imply that there is no loss in generality in the numerical results of the paper to taking $\omega_1^2 = \omega_2^2 = 1$ and $\beta_* = 0$. We also show that there is no loss in generality in the numerical results of the paper to taking $\rho_{uv} \in [0, 1]$, rather than $\rho_{uv} \in [-1, 1]$, where ρ_{uv} is the structural variance matrix correlation defined in (4.5).

We consider the same transformations as in Section 20, but with β_* in place of β_0 in (20.1)-(20.3) and with the roles of β_* and β_0 reversed in (20.4) and (20.5). The transformed testing problem given the transformations in (20.1) (with β_* in place of β_0) is $H_0 : \tilde{\beta} = \tilde{\beta}_0$ versus $H_1 : \tilde{\beta} = 0$, where $\tilde{\beta}_0 = \beta_0 - \beta_*$, with parameter π and reduced-form variance matrix $\tilde{\Omega}$. The transformed testing problem given the transformations in (20.1)-(20.3) (with β_* in place of β_0) is $H_0 : \bar{\beta} = \bar{\beta}_0$ versus $H_1 : \bar{\beta} = 0$, where $\bar{\beta}_0 = \beta_0 - \beta_*$, with parameters $\bar{\beta}$, $\bar{\pi}$, and $\bar{\Omega}$ defined in (20.2) and (20.3) (with the roles of β_* and β_0 reversed).

For example, a scenario in which a typical test has high power in the original scenario of testing $H_0 : \beta = \beta_0$ versus $H_1 : \beta = \beta_*$, such as $\beta_0 = 0$ and $|\beta_*|$ large, gets transformed into the testing problem of $H_0 : \bar{\beta} = \bar{\beta}_0$ versus $H_1 : \bar{\beta} = 0$ with correlation $\bar{\omega}_{12}$ (the (1, 2) element of $\bar{\Omega}$) close to ± 1 , because by (20.5) (with the roles of β_* and β_0 reversed) we have

$$\lim_{\beta_* \rightarrow \pm\infty} \bar{\Omega} = \begin{bmatrix} 1 & \mp 1 \\ \mp 1 & 1 \end{bmatrix}. \quad (21.1)$$

In this case, we also have $\lim_{\beta_* \rightarrow \pm\infty} \bar{\beta}_0 = \mp 1$ by (20.5). Also, note that the reduced-form and structural variances matrices are equal when the alternative hypothesis holds in the testing problem $H_0 : \bar{\beta} = \bar{\beta}_0$ versus $H_1 : \bar{\beta} = 0$, so the result in (21.1) also applies to the structural variance matrix $\Sigma(\bar{\beta}, \bar{\Omega})$ when $\bar{\beta} = 0$ whose correlation we denote by $\bar{\rho}_{uv}$, i.e., $\lim_{\beta_* \rightarrow \pm\infty} \bar{\rho}_{uv} = \mp 1$. Here the parameter $\bar{\rho}_{uv}$ is the parameter ρ_{uv} that appears in the tables in the paper. These results are useful in showing how the numerical results of the paper apply to general hypotheses of the form $H_0 : \beta = \beta_0$ versus $H_1 : \beta = \beta_*$.

Next, we show that there is no loss in generality in the numerical results of the paper to taking $\rho_{uv} \in [0, 1]$. We consider the hypotheses $H_0 : \beta = \beta_0$ versus $H_1 : \beta = 0$, as in the numerical results in the paper. When the true β equals 0 and Ω has ones on its diagonal, the reduced-form and

structural variance matrices are equal, see (11.9). Hence, the correlation ω_{12} given by Ω equals the structural variance correlation ρ_{uv} in power calculations in the paper, and it suffices to show that there is no loss in generality in the numerical results of the paper to taking $\omega_{12} \in [0, 1]$.

By (2.3), the distributions of S and T only depend on $c_\beta(\beta_0, \Omega)$, $d_\beta(\beta_0, \Omega)$, and $\mu_\pi := (Z'Z)^{1/2}\pi$. The vector μ_π does not depend on β , β_0 , or Ω . First, note that ω_{12} enters $c_\beta(\beta_0, \Omega) := (\beta - \beta_0)(b'_0\Omega b_0)^{-1/2} = (\beta - \beta_0)(\omega_1^2 - 2\omega_{12}\beta_0 + \omega_2^2\beta_0^2)^{-1/2}$ only through $\omega_{12}\beta_0$. In consequence, the distribution of S is the same under (β_0, ω_{12}) as under $(-\beta_0, -\omega_{12})$. Second, by (2.8) of AMS, $d_\beta(\beta_0, \Omega)$ can be written as $b'\Omega b_0(b'_0\Omega b_0)^{-1/2} \det(\Omega)^{-1/2}$, where $b := (1, -\beta)'$. The distribution of T when $\beta = 0$ depends on $d_0(\beta_0, \Omega) = (1 - \omega_{12}\beta_0)(b'_0\Omega b_0)^{-1/2} \det(\Omega)^{-1/2}$. The first two multiplicands depend on ω_{12} only through $\omega_{12}\beta_0$ and the third multiplicand only depends on ω_{12} through ω_{12}^2 (because $\det(\Omega) = 1 - \omega_{12}^2$). In addition, S and T are independent. Hence, the distribution of $[S : T]$ for given (β_0, ω_{12}) when $\beta = 0$ equals its distribution under $(-\beta_0, -\omega_{12})$ when $\beta = 0$. Thus, the power of a test of $H_0 : \beta = \beta_0$ versus $H_1 : \beta = 0$ when $\omega_{12} < 0$ equals its power for testing $H_0 : \beta = -\beta_0$ versus $H_1 : \beta = 0$ for $-\omega_{12} > 0$.

22 Additional Numerical Results

This section contains Tables SM-I, ..., SM-V and Figure SM-I, which provide additional numerical results to those in Tables I, ..., V in the main paper.

Table SM-I is analogous to Table I, but considers AR and POIS $_\infty$ CS's, in addition to the CLR and POIS2 $_\infty$ CS's. Here, POIS $_\infty$ denotes the CS obtained from the optimal one-sided invariant similar test as $\beta_0 \rightarrow \pm\infty$ defined in (12.5) in Section 12.2. Table SM-I reports probabilities of infinite length, as well as differences in probabilities of infinite length (DPIL's) for CLR and AR, AR and POIS2 $_\infty$, and CLR and POIS2 $_\infty$ CS's. In addition, it reports simulation standard deviations for the first and third DPIL's.

The results for the DPIL's vary greatly with ρ_{uv} . When $\rho_{uv} = 0$, the AR CS is the same as the optimal POIS $_\infty$ CS and the CLR-AR DPIL's range over $[.001, .049]$ as (k, λ) vary. On the other hand, when $\rho_{uv} = .9$, the AR CS is far from optimal and the CLR-AR DPIL's range over $[-.002, -.421]$ as (k, λ) vary. In sum, when $\rho_{uv} \geq .5$, the AR CS can, and typically does, perform noticeably worse than the CLR CS in terms of DPIL's.

Table SM-II reports more detailed results than those given in Table II. Table SM-II reports the maximum power differences (PD's) over β_0 values between the POIS2 power envelope and the CLR test for a grid of (k, ρ_{uv}, λ) values. (In contrast, Table II reports maximum and average PD's over (β_0, λ) values for a grid of (k, ρ_{uv}) values.) Table SM-II shows that the maximum (over β_0) PD's

vary substantially over λ values for $\rho_{uv} \leq .7$ values and less so for $\rho_{uv} = .9$. For example, for $k = 5$ and $\rho_{uv} = .0, .3, .5, .7, .9$, the PD's ranges (over λ values) are [.004, .030], [.008, .034], [.007, .029], [.005, .033], [.001, .017], respectively.

Tables SM-III and SM-IV are the same as Table II except they consider the AR and LM tests, respectively, rather than the CLR test. As noted in the main paper, Tables SM-III and SM-IV show that the power of the AR and LM tests is much farther from the POIS2 power envelope than is the power of the CLR test. Table SM-III(a) shows that the maximum and average (over (β_0, λ)) PD's for the AR test are increasing in k up to $k = 20$, but drop going from $k = 20$ to 40. (This drop may be due to the choice of λ values considered. The choice yields the λ_{\max} value for the AR test to be on the upper bound of the values considered.) Table SM-III(b) shows that the maximum and average (over (β_0, λ)) PD's for the AR test are increasing in ρ_{uv} for all values of k , which is the opposite of the pattern for the CLR test. Table SM-III(b) also shows that the λ_{\max} values are at the boundary of the grid of λ values considered for all k .

Table SM-IV(a) shows that the maximum and average PD's (over (β_0, λ)) for the LM test are clearly increasing in k , except that for $\rho_{uv} = 0, .3$ there is a drop from $k = 20$ to 40 (which may be due to the choice of λ values considered, as for the AR test). Table SM-IV(b) shows that the maximum and average (over (β_0, λ)) PD's for the LM test are decreasing in ρ_{uv} for all values of k , as for the CLR test. Table SM-IV(b) also shows that the λ_{\max} values decrease in ρ_{uv} for each k , as with the CLR test.

Table SM-V is the same as Table III except that it reports results for $k = 2, 5, 10, 20$, and 40, rather than just $k = 5$. It also reports results for a finer grid of β_0 values than in Table IV and it reports the power of the WAP2 test, in addition to the difference in power between the WAP2 and CLR tests.

Figure SM-I provides graphs that are the same as in AMS, but with $\rho_{\Omega} = 0$, rather than $\rho_{\Omega} = .5$ or $.95$. Specifically, these graphs provide the power of the significance level .05 CLR, LM, and AR tests and the POIS2 power envelope for fixed null value $\beta_0 = 0$, varying true value β^* , $k = 2, 5, 10$ and $\lambda = 5, 20$. The number of simulation repetitions used to construct the power functions is 5,000 and 100,000 repetitions are used to compute the null distribution of the POIS2 statistic to obtain its p-values.

Figure SM-I shows that the power of the CLR test is very close to the POIS2 power envelope in the scenarios considered. In fact, the maximum differences are .0074, .0040, .0110, .0062, .0102, and .0090 in the six graphs in Figure SM-I. Note that $\rho_{\Omega} = 0$ is the ρ_{Ω} value that yields many of the largest differences between the power of the CLR test and the POIS2 power envelope when the

true $\beta^* = 0$ is fixed and the null value β_0 varies, as shown in Tables II and SM-II.¹³ The results in Figure SM-I show that standard power graphs with $\beta_0 = 0$ fixed and true β^* varying, as in AMS, do not pick up the relatively large differences between the power of the CLR test and the POIS2 power envelope that appear in some $\rho_\Omega = 0$ parameter configurations considered in Tables II and SM-II.

¹³In Tables II and SM-II, $\rho_{uv} = \rho_\Omega$ for all β_0 values because the true value $\beta^* = 0$.

References

- Andrews, D. W. K., M. J. Moreira, and J. H. Stock (2004): “Optimal Invariant Similar Tests for Instrumental Variables Regression with Weak Instruments,” Cowles Foundation Discussion Paper No. 1476, Yale University.
- (2006): “Optimal Two-sided Invariant Similar Tests for Instrumental Variables Regression,” *Econometrica*, 74, 715–752.
- Lebedev, N. N. (1965): *Special Functions and Their Application*. Englewood Cliffs, NJ: Prentice-Hall.
- Mills, B., M. J. Moreira, and L. P. Vilela (2014): “Tests Based on t-Statistics for IV Regression with Weak Instruments,” *Journal of Econometrics*, 182, 351–363.
- Moreira, M. J. (2009): “Tests with Correct Size When Instruments Can Be Arbitrarily Weak,” *Journal of Econometrics*, 152, 131-140.

TABLE SM-I(a). Probabilities of Infinite-Length Confidence Intervals for $\rho_{uv} = 0$

k	λ	AR	CLR	POIS $_{\infty}$	POIS2 $_{\infty}$	CLR-AR	SD $_1$	AR-POIS2 $_{\infty}$	CLR-POIS2 $_{\infty}$	SD $_2$
2	1	.870	.872	.870	.870	.002	.0007	.000	.002	.0007
2	3	.680	.687	.680	.680	.007	.0009	.000	.007	.0009
2	5	.497	.509	.497	.497	.012	.0010	.000	.012	.0010
2	7	.344	.360	.344	.344	.016	.0010	.000	.016	.0010
2	10	.184	.196	.184	.184	.013	.0008	.000	.013	.0008
2	15	.056	.063	.056	.056	.008	.0006	.000	.008	.0006
2	20	.014	.018	.014	.014	.003	.0003	.000	.003	.0003
5	1	.900	.904	.900	.900	.003	.0008	.000	.003	.0008
5	3	.778	.788	.778	.778	.010	.0011	.000	.010	.0011
5	5	.639	.656	.639	.639	.017	.0012	.000	.017	.0012
5	7	.502	.528	.502	.502	.026	.0012	.000	.026	.0012
5	10	.323	.354	.323	.323	.031	.0012	.000	.031	.0012
5	12	.231	.260	.231	.231	.029	.0011	.000	.029	.0011
5	15	.134	.157	.134	.134	.023	.0009	.000	.023	.0009
5	20	.048	.061	.048	.048	.013	.0007	.000	.013	.0007
5	25	.016	.022	.016	.016	.006	.0004	.000	.006	.0004
10	1	.919	.920	.919	.919	.001	.0008	.000	.001	.0008
10	5	.731	.749	.731	.731	.018	.0012	.000	.018	.0012
10	10	.459	.491	.459	.459	.032	.0013	.000	.032	.0013
10	15	.239	.276	.239	.239	.037	.0012	.000	.037	.0012
10	17	.176	.212	.176	.176	.035	.0011	.000	.035	.0011
10	20	.110	.137	.110	.110	.027	.0010	.000	.027	.0010
10	25	.045	.062	.045	.045	.017	.0007	.000	.017	.0007
10	30	.017	.026	.017	.017	.009	.0005	.000	.009	.0005
20	1	.929	.931	.929	.929	.001	.0009	.000	.001	.0009
20	5	.809	.823	.809	.809	.014	.0012	.000	.014	.0012
20	10	.603	.637	.603	.603	.035	.0014	.000	.035	.0014
20	15	.390	.436	.390	.390	.046	.0014	.000	.046	.0014
20	20	.226	.270	.226	.226	.044	.0012	.000	.044	.0012
20	25	.120	.153	.120	.120	.033	.0010	.000	.033	.0010
20	30	.056	.080	.056	.056	.023	.0008	.000	.023	.0008
20	40	.010	.017	.010	.010	.007	.0004	.000	.007	.0004
40	1	.937	.939	.937	.937	.002	.0008	.000	.002	.0008
40	5	.859	.870	.859	.859	.011	.0011	.000	.011	.0011
40	10	.721	.748	.721	.721	.028	.0013	.000	.028	.0013
40	15	.555	.598	.555	.555	.043	.0014	.000	.043	.0014
40	20	.394	.443	.394	.394	.049	.0014	.000	.049	.0014
40	30	.155	.198	.155	.155	.043	.0012	.000	.043	.0012
40	40	.046	.069	.046	.046	.022	.0008	.000	.022	.0008
40	60	.003	.005	.003	.003	.002	.0002	.000	.002	.0002

TABLE SM-I(b). Probabilities of Infinite-Length Confidence Intervals for $\rho_{uv} = .3$

k	λ	AR	CLR	POIS $_{\infty}$	POIS2 $_{\infty}$	CLR-AR	SD $_1$	AR-POIS2 $_{\infty}$	CLR-POIS2 $_{\infty}$	SD $_2$
2	1	.869	.871	.863	.867	.002	.0007	.003	.004	.0007
2	3	.680	.682	.654	.679	.002	.0010	.001	.003	.0008
2	5	.497	.502	.463	.494	.005	.0010	.002	.008	.0009
2	7	.346	.349	.306	.344	.004	.0011	.002	.005	.0008
2	10	.185	.188	.152	.181	.003	.0009	.003	.006	.0007
2	15	.056	.057	.040	.053	.001	.0006	.002	.004	.0005
2	20	.015	.015	.009	.014	.000	.0004	.001	.001	.0003
5	1	.901	.903	.896	.900	.002	.0008	.000	.003	.0008
5	3	.778	.783	.759	.774	.005	.0011	.005	.010	.0010
5	5	.639	.649	.608	.636	.010	.0013	.003	.012	.0010
5	7	.502	.513	.462	.501	.011	.0013	.001	.012	.0010
5	10	.322	.332	.280	.316	.009	.0013	.006	.016	.0010
5	12	.231	.239	.192	.228	.008	.0012	.003	.011	.0009
5	15	.135	.139	.103	.126	.005	.0010	.008	.013	.0008
5	20	.048	.050	.033	.044	.002	.0007	.005	.007	.0005
5	25	.016	.016	.009	.014	.001	.0005	.002	.002	.0003
10	1	.918	.920	.914	.917	.002	.0009	.000	.002	.0008
10	5	.730	.740	.705	.726	.010	.0013	.005	.015	.0011
10	10	.459	.469	.412	.455	.010	.0014	.003	.014	.0011
10	15	.238	.248	.196	.228	.009	.0013	.010	.020	.0010
10	17	.177	.184	.138	.168	.007	.0012	.009	.017	.0009
10	20	.108	.114	.080	.100	.006	.0010	.008	.014	.0007
10	25	.045	.047	.028	.039	.002	.0007	.005	.008	.0005
10	30	.017	.018	.010	.014	.001	.0005	.003	.004	.0004
20	1	.929	.931	.928	.927	.002	.0008	.001	.003	.0008
20	5	.808	.817	.791	.806	.009	.0012	.002	.011	.0011
20	10	.602	.619	.562	.597	.016	.0015	.005	.022	.0012
20	15	.393	.406	.340	.381	.012	.0015	.013	.025	.0012
20	20	.227	.237	.180	.216	.009	.0013	.012	.021	.0010
20	25	.119	.126	.086	.110	.007	.0011	.009	.016	.0008
20	30	.056	.059	.036	.047	.003	.0009	.009	.012	.0006
20	40	.010	.011	.005	.007	.001	.0004	.003	.003	.0003
40	1	.938	.940	.935	.939	.001	.0008	-.000	.001	.0008
40	5	.860	.867	.848	.858	.007	.0011	.001	.008	.0010
40	10	.718	.735	.691	.715	.017	.0014	.002	.020	.0012
40	15	.554	.570	.509	.547	.016	.0015	.007	.022	.0012
40	20	.392	.409	.337	.380	.017	.0016	.012	.029	.0012
40	30	.154	.163	.114	.143	.009	.0013	.012	.021	.0009
40	40	.045	.049	.028	.037	.004	.0008	.008	.012	.0006
40	60	.002	.003	.001	.001	.001	.0002	.001	.001	.0002

TABLE SM-I(c). Probabilities of Infinite-Length Confidence Intervals for $\rho_{uv} = .5$

k	λ	AR	CLR	POIS $_{\infty}$	POIS2 $_{\infty}$	CLR-AR	SD $_1$	AR-POIS2 $_{\infty}$	CLR-POIS2 $_{\infty}$	SD $_2$
2	1	.868	.869	.847	.865	.000	.0008	.003	.003	.0006
2	3	.678	.674	.613	.672	-.004	.0010	.006	.002	.0006
2	5	.496	.486	.408	.483	-.010	.0012	.013	.003	.0006
2	7	.345	.330	.255	.329	-.015	.0012	.016	.001	.0006
2	10	.186	.168	.113	.166	-.018	.0010	.020	.002	.0005
2	15	.056	.047	.025	.046	-.008	.0007	.010	.002	.0003
2	20	.015	.012	.005	.011	-.003	.0004	.004	.001	.0002
5	1	.901	.902	.888	.900	.001	.0008	.001	.002	.0007
5	3	.779	.775	.726	.769	-.004	.0012	.010	.006	.0007
5	5	.641	.626	.552	.622	-.015	.0014	.019	.004	.0007
5	7	.501	.478	.394	.474	-.023	.0015	.026	.003	.0007
5	10	.322	.291	.215	.286	-.031	.0015	.036	.005	.0007
5	12	.233	.199	.136	.196	-.034	.0014	.037	.003	.0007
5	15	.135	.106	.065	.101	-.029	.0012	.034	.005	.0006
5	20	.048	.034	.017	.030	-.014	.0008	.018	.003	.0004
5	25	.016	.010	.004	.008	-.006	.0005	.007	.001	.0002
10	1	.919	.919	.907	.917	.000	.0009	.002	.002	.0008
10	5	.730	.720	.659	.712	-.010	.0014	.018	.008	.0008
10	10	.457	.420	.333	.417	-.037	.0016	.040	.003	.0008
10	15	.240	.194	.131	.185	-.045	.0015	.055	.009	.0007
10	17	.176	.136	.087	.129	-.040	.0014	.048	.008	.0007
10	20	.109	.077	.044	.071	-.032	.0012	.039	.006	.0006
10	25	.045	.027	.012	.023	-.018	.0008	.021	.003	.0004
10	30	.016	.008	.003	.006	-.008	.0005	.010	.002	.0002
20	1	.928	.929	.923	.927	.001	.0008	.002	.002	.0008
20	5	.808	.804	.758	.798	-.004	.0013	.009	.006	.0008
20	10	.601	.576	.484	.565	-.025	.0016	.036	.011	.0009
20	15	.393	.340	.255	.329	-.053	.0017	.063	.011	.0009
20	20	.228	.176	.113	.165	-.053	.0016	.064	.011	.0008
20	25	.118	.078	.044	.072	-.040	.0013	.046	.006	.0006
20	30	.057	.031	.014	.026	-.026	.0009	.031	.005	.0004
20	40	.010	.004	.002	.003	-.006	.0004	.007	.001	.0002
40	1	.938	.939	.932	.938	.001	.0008	.000	.001	.0008
40	5	.861	.859	.824	.855	-.001	.0012	.006	.005	.0008
40	10	.717	.705	.627	.696	-.012	.0016	.021	.009	.0009
40	15	.552	.513	.419	.502	-.038	.0018	.050	.011	.0009
40	20	.390	.334	.244	.321	-.056	.0018	.069	.013	.0009
40	30	.155	.103	.059	.092	-.052	.0014	.062	.011	.0007
40	40	.045	.022	.010	.017	-.023	.0009	.028	.005	.0004
40	60	.002	.001	.000	.000	-.001	.0002	.001	.000	.0001

TABLE SM-I(d). Probabilities of Infinite-Length Confidence Intervals for $\rho_{uv} = .7$

k	λ	AR	CLR	POIS $_{\infty}$	POIS2 $_{\infty}$	CLR-AR	SD $_1$	AR-POIS2 $_{\infty}$	CLR-POIS2 $_{\infty}$	SD $_2$
2	1	.867	.865	.822	.863	-.002	.0008	.004	.002	.0003
2	3	.678	.657	.557	.656	-.021	.0012	.022	.001	.0005
2	5	.495	.457	.345	.455	-.038	.0013	.040	.002	.0005
2	7	.346	.299	.202	.298	-.047	.0013	.048	.001	.0005
2	10	.187	.143	.084	.142	-.043	.0012	.044	.001	.0004
2	15	.057	.037	.017	.035	-.020	.0008	.021	.001	.0003
2	20	.015	.008	.003	.008	-.007	.0004	.007	.000	.0002
5	1	.900	.899	.871	.898	-.001	.0009	.003	.002	.0004
5	3	.778	.752	.667	.751	-.026	.0014	.028	.002	.0006
5	5	.640	.578	.463	.576	-.062	.0016	.064	.003	.0008
5	7	.499	.409	.301	.407	-.091	.0018	.092	.001	.0007
5	10	.323	.224	.143	.221	-.099	.0017	.102	.004	.0006
5	12	.232	.140	.082	.140	-.092	.0016	.093	.000	.0005
5	15	.136	.065	.034	.062	-.070	.0013	.073	.003	.0004
5	20	.049	.017	.007	.016	-.031	.0009	.032	.001	.0003
5	25	.015	.004	.001	.004	-.011	.0005	.012	.000	.0001
10	1	.918	.917	.895	.916	-.001	.0009	.002	.001	.0005
10	5	.730	.673	.572	.667	-.057	.0017	.063	.005	.0008
10	10	.456	.325	.223	.320	-.131	.0019	.136	.005	.0008
10	15	.240	.115	.066	.111	-.124	.0017	.129	.004	.0006
10	17	.177	.072	.038	.069	-.104	.0016	.107	.003	.0005
10	20	.110	.035	.016	.032	-.076	.0013	.078	.002	.0004
10	25	.045	.009	.003	.008	-.036	.0009	.037	.001	.0002
10	30	.016	.002	.001	.002	-.014	.0005	.014	.000	.0001
20	1	.928	.927	.915	.926	-.001	.0009	.003	.002	.0006
20	5	.808	.769	.684	.766	-.039	.0015	.042	.003	.0008
20	10	.600	.472	.354	.463	-.127	.0020	.137	.010	.0009
20	15	.391	.223	.139	.215	-.168	.0020	.176	.008	.0008
20	20	.227	.085	.044	.080	-.142	.0018	.147	.005	.0006
20	25	.117	.027	.012	.025	-.090	.0014	.092	.002	.0004
20	30	.056	.008	.003	.007	-.048	.0010	.050	.001	.0002
20	40	.011	.001	.000	.001	-.010	.0005	.010	.000	.0001
40	1	.937	.938	.926	.937	.001	.0009	-.000	.001	.0007
40	5	.860	.839	.772	.838	-.021	.0014	.022	.001	.0007
40	10	.719	.623	.504	.614	-.095	.0019	.104	.009	.0010
40	15	.550	.382	.268	.372	-.168	.0021	.178	.009	.0009
40	20	.390	.195	.119	.186	-.195	.0021	.204	.009	.0008
40	30	.155	.032	.014	.028	-.123	.0016	.127	.004	.0004
40	40	.045	.004	.001	.003	-.041	.0009	.043	.001	.0002
40	60	.002	.000	.000	.000	-.002	.0002	.002	.000	.0000

TABLE SM-I(e). Probabilities of Infinite-Length Confidence Intervals for $\rho_{uv} = .9$

k	λ	AR	CLR	POIS $_{\infty}$	POIS2 $_{\infty}$	CLR-AR	SD $_1$	AR-POIS2 $_{\infty}$	CLR-POIS2 $_{\infty}$	SD $_2$
2	1	.868	.852	.774	.850	-.016	.0010	.018	.002	.0006
2	3	.679	.613	.491	.613	-.065	.0015	.066	.001	.0004
2	5	.494	.411	.295	.410	-.083	.0016	.084	.001	.0003
2	7	.344	.262	.169	.262	-.083	.0015	.082	-.000	.0003
2	10	.183	.122	.069	.122	-.061	.0013	.061	.000	.0002
2	15	.055	.030	.014	.029	-.025	.0008	.025	.001	.0001
2	20	.015	.006	.002	.007	-.008	.0004	.008	-.000	.0001
5	1	.901	.884	.822	.882	-.017	.0012	.019	.002	.0007
5	3	.775	.675	.555	.671	-.101	.0018	.104	.004	.0006
5	5	.636	.465	.345	.466	-.172	.0021	.171	-.001	.0004
5	7	.500	.302	.202	.304	-.198	.0021	.196	-.002	.0004
5	10	.325	.146	.085	.144	-.180	.0019	.181	.002	.0003
5	12	.232	.085	.046	.086	-.147	.0017	.146	-.001	.0003
5	15	.136	.037	.018	.036	-.099	.0014	.099	.001	.0002
5	20	.049	.008	.003	.008	-.041	.0009	.041	.000	.0001
5	25	.015	.002	.000	.001	-.014	.0005	.014	.000	.0001
10	1	.918	.904	.853	.904	-.013	.0011	.013	.000	.0007
10	5	.730	.530	.406	.526	-.201	.0022	.205	.004	.0006
10	10	.456	.177	.106	.176	-.279	.0022	.280	.001	.0004
10	15	.241	.046	.022	.046	-.195	.0018	.195	.000	.0003
10	17	.180	.025	.012	.025	-.154	.0017	.155	.000	.0002
10	20	.110	.010	.004	.010	-.099	.0014	.099	.000	.0002
10	25	.044	.002	.001	.002	-.042	.0009	.042	.000	.0001
10	30	.016	.000	.000	.000	-.015	.0006	.015	-.000	.0000
20	1	.927	.919	.884	.919	-.008	.0010	.009	.000	.0007
20	5	.806	.626	.498	.620	-.180	.0021	.186	.006	.0007
20	10	.599	.247	.159	.246	-.352	.0023	.353	.001	.0004
20	15	.390	.073	.039	.073	-.317	.0022	.318	.001	.0004
20	20	.224	.019	.008	.018	-.205	.0018	.205	.000	.0002
20	25	.116	.004	.002	.004	-.112	.0014	.112	.000	.0001
20	30	.056	.001	.000	.001	-.055	.0010	.055	.000	.0001
20	40	.010	.000	.000	.000	-.010	.0005	.010	.000	.0000
40	1	.936	.934	.905	.934	-.002	.0010	.002	.000	.0006
40	5	.859	.727	.605	.717	-.132	.0020	.142	.009	.0009
40	10	.720	.356	.246	.354	-.364	.0024	.366	.002	.0006
40	15	.551	.130	.074	.129	-.421	.0023	.422	.001	.0005
40	20	.388	.039	.018	.038	-.349	.0022	.350	.001	.0003
40	30	.154	.002	.001	.002	-.152	.0016	.152	.000	.0001
40	40	.046	.000	.000	.000	-.046	.0009	.046	.000	.0000
40	60	.002	.000	.000	.000	-.002	.0002	.002	.000	.0000

TABLE SM-II(a). Maximum Power Differences over λ and β_0 Values between POIS2 and CLR Tests for Fixed Alternative $\beta^* = 0$ for $\rho_{uv} = 0.00$

k	λ	$\beta_{0,\max}$	$\rho_{uv,0}$	POIS2	POIS2-CLR
2	1	-5.00	.98	.133	.009
2	3	100.00	-1.00	.314	.012
2	5	-10.00	1.00	.499	.019
2	7	-10000.00	1.00	.663	.021
2	10	7.50	-.99	.814	.018
2	15	10.00	-1.00	.950	.009
2	20	-1.25	.78	.923	.004
5	1	-10.00	1.00	.095	.004
5	3	-5.00	.98	.209	.012
5	5	-1000.00	1.00	.363	.017
5	7	-10.00	1.00	.501	.025
5	10	-50.00	1.00	.680	.030
5	15	-10000.00	1.00	.870	.025
5	20	-50.00	1.00	.953	.015
10	1	2.00	-.89	.078	.003
10	3	3.75	-.97	.161	.012
10	5	10.00	-1.00	.268	.021
10	7	100.00	-1.00	.379	.028
10	10	-10000.00	1.00	.540	.030
10	15	-50.00	1.00	.760	.038
10	20	50.00	-1.00	.888	.025
20	1	-2.75	.94	.064	.006
20	3	-100.00	1.00	.116	.007
20	5	100.00	-1.00	.180	.016
20	7	5.00	-.98	.252	.028
20	10	-100.00	1.00	.389	.040
20	15	10.00	-1.00	.596	.042
20	20	100.00	-1.00	.770	.040
20	22	100.00	-1.00	.820	.038
20	25	-10000.00	1.00	.878	.035
40	1	-0.25	.24	.054	.011
40	3	2.50	-.93	.095	.011
40	5	-7.50	.99	.149	.020
40	7	-50.00	1.00	.201	.024
40	10	-100.00	1.00	.287	.035
40	15	-7.50	.99	.441	.041
40	20	50.00	-1.00	.608	.058
40	22	-50.00	1.00	.664	.059
40	25	1000.00	-1.00	.742	.056

TABLE SM-II(b). Maximum Power Differences over λ and β_0 Values between POIS2 and CLR Tests for Fixed Alternative $\beta^* = 0$ for $\rho_{uv} = 0.30$

k	λ	$\beta_{0,\max}$	$\rho_{uv,0}$	POIS2	POIS2-CLR
2	1	10.00	-1.00	.140	.009
2	3	7.50	-.99	.335	.012
2	5	3.50	-.96	.543	.016
2	7	2.25	-.90	.692	.018
2	10	3.75	-.96	.860	.019
2	15	2.25	-.90	.966	.009
2	20	-1.75	.91	.920	.004
5	1	3.75	-.96	.102	.008
5	3	2.75	-.93	.239	.017
5	5	7.50	-.99	.387	.018
5	7	3.00	-.94	.546	.023
5	10	3.50	-.96	.732	.034
5	15	2.75	-.93	.901	.023
5	20	4.00	-.97	.971	.014
10	1	3.00	-.94	.090	.003
10	3	3.00	-.94	.181	.014
10	5	2.75	-.93	.296	.023
10	7	3.75	-.96	.417	.026
10	10	3.00	-.94	.590	.032
10	15	3.50	-.96	.806	.032
10	20	3.50	-.96	.921	.025
20	1	-50.00	1.00	.067	.006
20	3	3.50	-.96	.126	.009
20	5	4.00	-.97	.195	.019
20	7	3.00	-.94	.285	.030
20	10	3.25	-.95	.432	.038
20	15	3.50	-.96	.655	.045
20	20	2.75	-.93	.817	.038
20	22	3.00	-.94	.863	.034
20	25	3.75	-.96	.915	.031
40	1	-0.25	.50	.051	.008
40	3	1.50	-.78	.097	.008
40	5	2.75	-.93	.153	.014
40	7	5.00	-.98	.215	.020
40	10	4.00	-.97	.312	.036
40	15	3.00	-.94	.485	.042
40	20	3.75	-.96	.663	.059
40	22	4.00	-.97	.724	.061
40	25	3.75	-.96	.798	.052

TABLE SM-II(c). Maximum Power Differences over λ and β_0 Values between POIS2 and CLR Tests for Fixed Alternative $\beta^* = 0$ for $\rho_{uv} = 0.50$

k	λ	$\beta_{0,\max}$	$\rho_{uv,0}$	POIS2	POIS2-CLR
2	1	2.00	-.87	.162	.006
2	3	2.50	-.92	.399	.014
2	5	2.00	-.87	.635	.016
2	7	2.50	-.92	.782	.013
2	10	2.25	-.90	.922	.012
2	15	-10.00	1.00	.943	.004
2	20	-1.25	.90	.804	.003
5	1	1.75	-.82	.112	.007
5	3	2.00	-.87	.291	.019
5	5	2.50	-.92	.475	.022
5	7	2.50	-.92	.638	.028
5	10	2.25	-.90	.821	.029
5	15	1.75	-.82	.951	.014
5	20	1.00	-.50	.969	.007
10	1	2.00	-.87	.097	.003
10	3	1.75	-.82	.215	.014
10	5	2.00	-.87	.362	.028
10	7	1.75	-.82	.500	.028
10	10	2.00	-.87	.697	.037
10	15	2.00	-.87	.887	.023
10	20	2.25	-.90	.968	.018
20	1	5.00	-.98	.071	.008
20	3	2.00	-.87	.148	.011
20	5	3.00	-.94	.233	.024
20	7	2.00	-.87	.355	.034
20	10	1.75	-.82	.533	.046
20	15	2.00	-.87	.769	.040
20	20	2.00	-.87	.905	.031
20	22	2.25	-.90	.934	.025
20	25	2.25	-.90	.963	.014
40	1	-0.25	.65	.051	.007
40	3	1.50	-.76	.117	.008
40	5	2.00	-.87	.184	.014
40	7	3.25	-.95	.256	.026
40	10	2.00	-.87	.381	.035
40	15	1.75	-.82	.594	.050
40	20	1.75	-.82	.776	.049
40	22	2.00	-.87	.835	.049
40	25	2.00	-.87	.897	.040

TABLE SM-II(d). Maximum Power Differences over λ and β_0 Values between POIS2 and CLR Tests for Fixed Alternative $\beta^* = 0$ for $\rho_{uv} = 0.70$

k	λ	$\beta_{0,\max}$	$\rho_{uv,0}$	POIS2	POIS2-CLR
2	1	1.75	-.83	.214	.006
2	3	2.25	-.91	.528	.013
2	5	1.50	-.75	.811	.016
2	7	1.25	-.61	.927	.009
2	10	-2.75	.98	.672	.005
2	15	-4.00	.99	.896	.003
2	20	-1.00	.92	.671	.002
5	1	2.00	-.88	.142	.005
5	3	1.75	-.83	.413	.020
5	5	1.50	-.75	.669	.033
5	7	1.50	-.75	.834	.029
5	10	1.50	-.75	.949	.016
5	15	7.50	-.99	.971	.003
5	20	-2.50	.98	.897	.003
10	1	1.25	-.61	.117	.004
10	3	1.50	-.75	.320	.028
10	5	1.25	-.61	.521	.030
10	7	1.50	-.75	.711	.036
10	10	1.50	-.75	.878	.021
10	15	1.75	-.83	.979	.010
10	20	0.50	.27	.757	.007
20	1	2.00	-.88	.087	.007
20	3	1.50	-.75	.212	.025
20	5	1.50	-.75	.377	.038
20	7	1.25	-.61	.544	.042
20	10	1.50	-.75	.754	.036
20	15	1.50	-.75	.935	.024
20	20	-1.25	.94	.582	.007
20	22	-1.00	.92	.546	.007
20	25	-7.50	1.00	.952	.005
40	1	-100.00	1.00	.071	.006
40	3	2.25	-.91	.158	.015
40	5	1.75	-.83	.275	.030
40	7	1.25	-.61	.393	.038
40	10	1.50	-.75	.588	.049
40	15	1.50	-.75	.837	.050
40	20	1.50	-.75	.948	.026
40	22	1.50	-.75	.967	.017
40	25	-3.25	.98	.817	.009

TABLE SM-II(e). Maximum Power Differences over λ and β_0 Values between POIS2 and CLR Tests for Fixed Alternative $\beta^* = 0$ for $\rho_{uv} = 0.90$

k	λ	$\beta_{0,\max}$	$\rho_{uv,0}$	POIS2	POIS2-CLR
2	0.7	1.25	-.63	.359	.010
2	0.8	1.00	-.22	.412	.015
2	0.9	1.25	-.63	.461	.017
2	1	1.25	-.63	.505	.013
2	3	1.25	-.63	.947	.005
2	5	-7.50	1.00	.497	.002
2	7	-5.00	1.00	.600	.001
2	10	-3.50	1.00	.702	.001
2	15	-50.00	1.00	.967	.001
2	20	-3.75	1.00	.950	.001
5	0.7	1.00	-.22	.256	.013
5	0.8	1.00	-.22	.292	.017
5	0.9	1.00	-.22	.331	.017
5	1	1.00	-.22	.365	.015
5	3	1.00	-.22	.870	.015
5	5	1.00	-.22	.985	.004
5	7	0.75	.33	.975	.004
5	10	10.00	-1.00	.916	.002
5	15	-10.00	1.00	.934	.001
5	20	-1.75	.99	.815	.001
10	1	1.00	-.22	.273	.017
10	3	1.25	-.63	.766	.027
10	5	1.25	-.63	.956	.014
10	7	2.00	-.93	.964	.005
10	10	-50.00	1.00	.812	.004
10	15	-1.50	.98	.618	.003
10	20	-2.75	.99	.895	.003
20	1	1.00	-.22	.183	.015
20	3	1.00	-.22	.607	.032
20	5	1.25	-.63	.882	.022
20	7	5.00	-.99	.705	.008
20	10	3.00	-.98	.951	.005
20	15	-3.25	.99	.769	.003
20	20	-1.75	.99	.766	.003
20	22	-3.75	1.00	.931	.003
20	25	-3.25	.99	.946	.002
40	1	1.00	-.22	.146	.016
40	3	1.00	-.22	.440	.027
40	5	1.25	-.63	.750	.040
40	7	1.25	-.63	.919	.022
40	10	3.75	-.99	.844	.009
40	15	-3.00	.99	.674	.005
40	20	-2.25	.99	.770	.004
40	22	-2.75	.99	.857	.002
40	25	-0.25	.94	.151	.001

TABLE SM-III. Maximum and Average Power Differences over λ and β_0 Values between POIS2 and AR Tests for Fixed Alternative $\beta^* = 0$

(a) Across k patterns for fixed ρ_{uv}

ρ_{uv}	k	λ_{\max}	$\beta_{0,\max}$	$\rho_{uv,0}$	POIS2	POIS2-AR	
						max	average
.0	2	20	0.50	-.45	.49	.079	.012
.0	5	20	0.75	-.60	.66	.151	.014
.0	10	20	-0.75	.60	.57	.183	.015
.0	20	25	0.75	-.60	.57	.217	.016
.0	40	25	-0.75	.60	.42	.161	.011
.3	2	20	0.50	-.21	.60	.084	.014
.3	5	20	-0.75	.74	.56	.163	.020
.3	10	20	-1.00	.81	.61	.201	.022
.3	20	25	0.50	-.21	.47	.231	.024
.3	40	25	-1.00	.81	.47	.194	.019
.5	2	20	-0.75	.82	.58	.090	.020
.5	5	20	0.50	.00	.66	.182	.031
.5	10	20	-1.00	.87	.59	.232	.038
.5	20	25	-1.00	.87	.60	.285	.044
.5	40	25	-1.25	.90	.54	.248	.040
.7	2	20	-0.75	.90	.54	.094	.030
.7	5	20	-1.25	.94	.72	.208	.054
.7	10	20	-1.25	.94	.67	.281	.069
.7	20	25	-1.25	.94	.71	.361	.084
.7	40	25	-2.00	.97	.73	.351	.085
.9	2	20	-1.00	.97	.64	.105	.033
.9	5	20	-1.25	.98	.70	.237	.068
.9	10	20	-1.50	.98	.75	.340	.133
.9	20	25	-1.25	.98	.76	.455	.160
.9	40	25	-1.75	.99	.82	.513	.179

(b) Across ρ_{uv} patterns for fixed k

k	ρ_{uv}	λ_{\max}	$\beta_{0,\max}$	$\rho_{uv,0}$	POIS2	POIS2-AR	
						max	average
2	.0	20	0.50	-.45	.49	.079	.012
2	.3	20	0.50	-.21	.60	.084	.014
2	.5	20	-0.75	.82	.58	.090	.020
2	.7	20	-0.75	.90	.54	.094	.030
2	.9	20	-1.00	.97	.64	.105	.033
5	.0	20	0.75	-.60	.66	.151	.014
5	.3	20	-0.75	.74	.56	.163	.020
5	.5	20	0.50	.00	.66	.182	.031
5	.7	20	-1.25	.94	.72	.208	.054
5	.9	20	-1.25	.98	.70	.237	.068
10	.0	20	-0.75	.82	.58	.090	.020
10	.3	20	-1.00	.81	.61	.201	.022
10	.5	20	-1.00	.87	.59	.232	.038
10	.7	20	-1.25	.94	.67	.281	.069
10	.9	20	-1.50	.98	.75	.340	.133
20	.0	25	0.75	-.60	.57	.183	.015
20	.3	25	0.50	-.21	.47	.201	.022
20	.5	25	-1.00	.87	.60	.232	.038
20	.7	25	-1.25	.94	.71	.361	.084
20	.9	25	-1.25	.98	.76	.455	.160
40	.0	25	-0.75	.60	.42	.161	.011
40	.3	25	-1.00	.81	.47	.194	.019
40	.5	25	-1.25	.90	.54	.248	.040
40	.7	25	-2.00	.97	.73	.351	.085
40	.9	25	-1.75	.99	.82	.513	.179

TABLE SM-IV. Maximum and Average Power Differences over λ and β_0 Values between POIS2 and LM Tests for Fixed Alternative $\beta^* = 0$

(a) Across k patterns for fixed ρ_{uv}

ρ_{uv}	k	λ_{\max}	$\beta_{0,\max}$	$\rho_{uv,0}$	POIS2	POIS2-LM	
						max	average
.0	2	15	50.00	-1.00	.95	.312	.117
.0	5	20	1000.00	-1.00	.95	.538	.173
.0	10	20	10000.00	-1.00	.89	.611	.174
.0	20	25	10000.00	-1.00	.88	.687	.203
.0	40	25	10000.00	-1.00	.74	.621	.173
.3	2	15	3.75	-.96	.97	.309	.103
.3	5	20	3.25	-.95	.97	.536	.155
.3	10	20	3.50	-.96	.92	.628	.161
.3	20	25	3.25	-.95	.91	.710	.187
.3	40	25	3.25	-.95	.80	.671	.168
.5	2	10	2.00	-.87	.92	.311	.077
.5	5	15	2.00	-.87	.95	.538	.121
.5	10	20	2.00	-.87	.97	.639	.133
.5	20	25	2.00	-.87	.96	.734	.153
.5	40	25	2.00	-.87	.90	.750	.152
.7	2	7	1.50	-.75	.93	.310	.041
.7	5	10	1.50	-.75	.95	.531	.070
.7	10	15	1.50	-.75	.98	.621	.084
.7	20	20	1.50	-.75	.99	.721	.089
.7	40	22	1.50	-.75	.97	.784	.107
.9	2	3	1.25	-.63	.95	.242	.010
.9	5	3	1.00	-.22	.87	.422	.016
.9	10	5	1.25	-.63	.96	.474	.023
.9	20	5	1.25	-.63	.88	.562	.021
.9	40	7	1.25	-.63	.92	.620	.031

(b) Across ρ_{uv} patterns for fixed k

k	ρ_{uv}	λ_{\max}	$\beta_{0,\max}$	$\rho_{uv,0}$	POIS2	POIS2-LM	
						max	average
2	.0	15	50.00	-1.00	.95	.312	.117
2	.3	15	3.75	-.96	.97	.309	.103
2	.5	10	2.00	-.87	.92	.311	.077
2	.7	7	1.50	-.75	.93	.310	.041
2	.9	3	1.25	-.63	.95	.242	.010
5	.0	20	1000.00	-1.00	.95	.538	.173
5	.3	20	3.25	-.95	.97	.536	.155
5	.5	15	2.00	-.87	.95	.538	.121
5	.7	10	1.50	-.75	.95	.531	.070
5	.9	3	1.00	-.22	.87	.422	.016
10	.0	20	10000.00	-1.00	.89	.611	.174
10	.3	20	3.50	-.96	.92	.628	.161
10	.5	20	2.00	-.87	.97	.639	.133
10	.7	15	1.50	-.75	.98	.621	.084
10	.9	5	1.25	-.63	.96	.474	.023
20	.0	25	10000.00	-1.00	.88	.687	.203
20	.3	25	3.25	-.95	.91	.710	.187
20	.5	25	2.00	-.87	.96	.734	.153
20	.7	20	1.50	-.75	.99	.721	.089
20	.9	5	1.25	-.63	.88	.562	.021
40	.0	25	10000.00	-1.00	.74	.621	.173
40	.3	25	3.25	-.95	.80	.671	.168
40	.5	25	2.00	-.87	.90	.750	.152
40	.7	22	1.50	-.75	.97	.784	.107
40	.9	7	1.25	-.63	.92	.620	.031

TABLE SM-V(a). Average (over λ) Power Differences for $\lambda \in \{2.5, 5.0, \dots, 90.0\}$ between the WAP2 and CLR Tests for $k = 2$

β_0	$\rho_{uv,0}$		WAP2					WAP2-CLR				
	$\rho_{uv} = 0$.9	$\rho_{uv} = 0$.3	.5	.7	.9	$\rho_{uv} = 0$.3	.5	.7	.9
-10000.00	1.00	1.00	.946	.950	.951	.955	.958	.003	.002	.001	.001	.001
-1000.00	1.00	1.00	.946	.950	.951	.955	.958	.003	.002	.001	.001	.001
-100.00	1.00	1.00	.946	.949	.951	.954	.957	.003	.002	.001	.000	.001
-50.00	1.00	1.00	.946	.949	.950	.953	.956	.003	.002	.001	.001	.001
-10.00	1.00	1.00	.946	.945	.945	.947	.948	.003	.002	.001	.000	.001
-7.50	.99	1.00	.945	.944	.943	.944	.945	.003	.002	.001	.000	.000
-5.00	.98	1.00	.944	.941	.938	.938	.937	.003	.001	.001	.001	.000
-4.00	.97	1.00	.943	.938	.935	.933	.931	.003	.001	.001	.001	.000
-3.75	.97	1.00	.942	.937	.933	.931	.929	.003	.001	.001	.001	.001
-3.50	.96	1.00	.941	.936	.932	.929	.927	.002	.001	.001	.001	.001
-3.25	.96	.99	.940	.934	.930	.926	.923	.002	.001	.001	.001	.001
-3.00	.95	.99	.940	.933	.927	.923	.920	.003	.001	.001	.001	.000
-2.75	.94	.99	.938	.930	.925	.920	.916	.003	.001	.001	.000	.000
-2.50	.93	.99	.937	.928	.922	.916	.911	.002	.001	.001	.001	.000
-2.25	.91	.99	.935	.925	.918	.910	.904	.002	.001	.001	.001	.000
-2.00	.89	.99	.932	.920	.912	.904	.896	.002	.002	.001	.001	.001
-1.75	.87	.99	.928	.914	.904	.895	.885	.002	.001	.001	.001	.000
-1.50	.83	.98	.921	.905	.893	.881	.870	.001	.001	.001	.001	.000
-1.25	.78	.98	.910	.890	.876	.861	.847	.001	.002	.001	.001	.001
-1.00	.71	.97	.895	.866	.845	.827	.809	.002	.002	.001	.001	.001
-0.75	.60	.97	.851	.814	.788	.762	.738	.001	.002	.002	.001	.001
-0.50	.45	.95	.736	.681	.646	.613	.584	.002	.002	.002	.002	.001
-0.25	.24	.94	.366	.329	.310	.293	.279	.002	.002	.002	.001	.001
0.25	-.24	.83	.366	.410	.447	.488	.544	.001	.001	.002	.002	.001
0.50	-.45	.68	.737	.804	.848	.892	.937	.002	.002	.001	.001	.000
0.75	-.60	.33	.851	.899	.928	.959	.989	.002	.001	.001	.001	.000
1.00	-.71	-.22	.892	.928	.951	.975	.997	.001	.001	.001	.001	.000
1.25	-.78	-.63	.911	.942	.959	.979	.997	.001	.002	.001	.001	.000
1.50	-.83	-.81	.921	.948	.963	.980	.995	.001	.002	.002	.001	.000
1.75	-.87	-.89	.928	.950	.965	.979	.993	.002	.002	.002	.002	.000
2.00	-.89	-.93	.932	.953	.965	.978	.991	.001	.002	.002	.002	.000
2.25	-.91	-.95	.935	.953	.965	.976	.989	.002	.002	.002	.001	.000
2.50	-.93	-.96	.937	.954	.964	.975	.986	.002	.003	.002	.001	.000
2.75	-.94	-.97	.938	.955	.964	.973	.985	.003	.003	.002	.001	.000
3.00	-.95	-.98	.939	.955	.963	.973	.983	.002	.003	.002	.001	.000
3.25	-.96	-.98	.940	.954	.963	.972	.982	.003	.003	.002	.001	.000
3.50	-.96	-.99	.941	.954	.962	.970	.980	.003	.003	.002	.000	.000
3.75	-.97	-.99	.942	.955	.962	.970	.979	.003	.003	.002	.001	.000
4.00	-.97	-.99	.942	.954	.962	.969	.978	.003	.002	.002	.001	.000
5.00	-.98	-.99	.944	.954	.960	.967	.974	.003	.002	.002	.001	.000
7.50	-.99	-1.00	.945	.953	.957	.964	.970	.003	.002	.001	.001	.000
10.00	-1.00	-1.00	.946	.952	.956	.961	.967	.004	.002	.002	.001	.000
50.00	-1.00	-1.00	.946	.950	.952	.956	.960	.003	.002	.001	.000	.001
100.00	-1.00	-1.00	.946	.950	.952	.955	.959	.003	.002	.002	.001	.001
1000.00	-1.00	-1.00	.946	.950	.951	.955	.958	.003	.002	.001	.001	.001
10000.00	-1.00	-1.00	.946	.950	.951	.955	.958	.003	.002	.001	.001	.001

TABLE SM-V(b). Average (over λ) Power Differences for $\lambda \in \{2.5, 5.0, \dots, 90.0\}$ between the WAP2 and CLR Tests for $k = 5$

β_0	$\rho_{uv,0}$		WAP2					WAP2-CLR				
	$\rho_{uv} = 0$.9	$\rho_{uv} = 0$.3	.5	.7	.9	$\rho_{uv} = 0$.3	.5	.7	.9
-10000.00	1.00	1.00	.923	.924	.929	.939	.953	.005	.002	.001	.001	.000
-1000.00	1.00	1.00	.923	.924	.929	.939	.953	.005	.002	.001	.001	.000
-100.00	1.00	1.00	.923	.923	.929	.939	.952	.005	.002	.001	.001	.000
-50.00	1.00	1.00	.923	.923	.929	.938	.951	.005	.003	.001	.001	.000
-10.00	1.00	1.00	.922	.920	.924	.931	.942	.005	.002	.001	.000	.000
-7.50	.99	1.00	.921	.918	.922	.929	.938	.004	.002	.000	.000	.000
-5.00	.98	1.00	.919	.915	.917	.923	.931	.004	.001	.000	.000	.000
-4.00	.97	1.00	.918	.912	.913	.917	.924	.003	.001	.000	-.000	.000
-3.75	.97	1.00	.917	.911	.911	.915	.922	.003	.002	.000	-.000	-.000
-3.50	.96	1.00	.917	.910	.910	.913	.920	.003	.001	-.000	-.000	.000
-3.25	.96	.99	.916	.909	.908	.910	.917	.003	.001	.000	.000	-.000
-3.00	.95	.99	.916	.907	.906	.907	.914	.003	.001	.000	.000	-.000
-2.75	.94	.99	.914	.905	.903	.904	.910	.002	.001	.000	.000	-.000
-2.50	.93	.99	.913	.902	.899	.900	.904	.002	.001	.001	-.000	.000
-2.25	.91	.99	.910	.898	.895	.894	.897	.002	.000	.001	-.000	-.000
-2.00	.89	.99	.907	.893	.888	.887	.888	.002	.001	.000	.001	-.000
-1.75	.87	.99	.903	.886	.880	.877	.877	.001	.001	.001	.000	.000
-1.50	.83	.98	.896	.877	.868	.863	.863	.001	.001	.001	.000	.000
-1.25	.78	.98	.885	.861	.850	.842	.839	.002	.001	.001	.000	.000
-1.00	.71	.97	.865	.836	.820	.808	.800	.001	.000	-.000	-.000	-.000
-0.75	.60	.97	.823	.783	.760	.741	.727	.000	-.000	.001	-.000	-.000
-0.50	.45	.95	.705	.649	.618	.592	.572	-.000	-.000	-.001	-.001	-.000
-0.25	.24	.94	.340	.311	.294	.282	.272	-.001	-.001	-.001	-.000	-.000
0.25	-.24	.83	.347	.390	.428	.476	.536	-.000	-.001	-.001	-.000	-.001
0.50	-.45	.68	.711	.777	.825	.877	.931	.001	.000	.000	.000	.000
0.75	-.60	.33	.827	.873	.908	.944	.985	.000	.001	.001	.001	.000
1.00	-.71	-.22	.868	.904	.930	.960	.994	.002	.001	.001	.001	.000
1.25	-.78	-.63	.887	.915	.940	.966	.994	.001	.001	.004	.003	.001
1.50	-.83	-.81	.897	.922	.943	.966	.992	.001	.002	.003	.003	.001
1.75	-.87	-.89	.904	.926	.945	.965	.989	.002	.003	.004	.003	-.000
2.00	-.89	-.93	.907	.928	.945	.963	.986	.002	.003	.004	.002	.000
2.25	-.91	-.95	.910	.930	.945	.961	.984	.001	.004	.004	.001	.000
2.50	-.93	-.96	.912	.931	.945	.960	.981	.001	.005	.004	.001	-.000
2.75	-.94	-.97	.914	.931	.944	.958	.979	.003	.005	.004	.001	.000
3.00	-.95	-.98	.915	.931	.943	.957	.977	.003	.005	.003	.001	.000
3.25	-.96	-.98	.916	.931	.942	.956	.976	.003	.004	.003	.001	.000
3.50	-.96	-.99	.917	.931	.942	.955	.974	.003	.005	.003	.001	-.000
3.75	-.97	-.99	.918	.931	.941	.954	.973	.003	.004	.002	.001	.000
4.00	-.97	-.99	.919	.931	.940	.954	.972	.004	.005	.002	.001	.000
5.00	-.98	-.99	.920	.930	.939	.951	.968	.004	.005	.002	.000	.000
7.50	-.99	-1.00	.922	.929	.936	.948	.963	.005	.004	.001	.001	.000
10.00	-1.00	-1.00	.922	.928	.935	.946	.960	.005	.003	.001	.001	.000
50.00	-1.00	-1.00	.923	.925	.930	.941	.955	.005	.003	.001	.000	-.000
100.00	-1.00	-1.00	.923	.924	.930	.940	.954	.005	.003	.001	.000	.000
1000.00	-1.00	-1.00	.923	.924	.929	.939	.953	.005	.002	.001	.001	.000
10000.00	-1.00	-1.00	.923	.924	.929	.939	.953	.005	.002	.001	.001	.000

TABLE SM-V(c). Average (over λ) Power Differences for $\lambda \in \{2.5, 5.0, \dots, 90.0\}$ between the WAP2 and CLR Tests for $k = 10$

β_0	$\rho_{uv,0}$		WAP2					WAP2-CLR				
	$\rho_{uv} = 0$.9	$\rho_{uv} = 0$.3	.5	.7	.9	$\rho_{uv} = 0$.3	.5	.7	.9
-10000.00	1.00	1.00	.901	.903	.910	.924	.946	.011	.006	.003	.001	.000
-1000.00	1.00	1.00	.901	.903	.910	.924	.946	.011	.006	.003	.001	.000
-100.00	1.00	1.00	.901	.902	.910	.924	.945	.011	.006	.003	.002	.001
-50.00	1.00	1.00	.901	.902	.909	.923	.944	.011	.006	.003	.002	.001
-10.00	1.00	1.00	.900	.898	.904	.916	.935	.011	.005	.003	.001	.001
-7.50	.99	1.00	.900	.896	.902	.913	.932	.010	.005	.003	.002	.001
-5.00	.98	1.00	.897	.892	.897	.907	.924	.008	.004	.003	.002	.001
-4.00	.97	1.00	.895	.889	.893	.902	.918	.007	.004	.002	.002	.001
-3.75	.97	1.00	.894	.888	.891	.900	.916	.007	.004	.002	.001	.001
-3.50	.96	1.00	.893	.886	.889	.898	.914	.007	.004	.002	.002	.001
-3.25	.96	.99	.892	.884	.888	.896	.911	.006	.003	.003	.002	.001
-3.00	.95	.99	.891	.882	.885	.893	.908	.006	.004	.002	.001	.001
-2.75	.94	.99	.890	.881	.882	.889	.904	.007	.005	.002	.001	.001
-2.50	.93	.99	.888	.878	.879	.886	.899	.006	.004	.002	.002	.001
-2.25	.91	.99	.885	.874	.874	.881	.892	.006	.003	.002	.002	.001
-2.00	.89	.99	.881	.869	.868	.873	.884	.004	.003	.002	.002	.001
-1.75	.87	.99	.876	.862	.860	.863	.872	.005	.003	.003	.002	.001
-1.50	.83	.98	.869	.853	.847	.848	.857	.005	.003	.002	.001	.002
-1.25	.78	.98	.858	.837	.829	.827	.834	.003	.003	.003	.002	.002
-1.00	.71	.97	.838	.809	.799	.794	.796	.003	.003	.002	.002	.002
-0.75	.60	.97	.793	.756	.738	.727	.724	.003	.003	.003	.002	.002
-0.50	.45	.95	.676	.623	.596	.580	.572	.004	.004	.003	.003	.004
-0.25	.24	.94	.323	.294	.282	.274	.272	.003	.004	.003	.002	.003
0.25	-.24	.83	.326	.370	.408	.460	.530	.004	.004	.004	.003	.002
0.50	-.45	.68	.674	.743	.796	.857	.923	.003	.003	.002	.002	.001
0.75	-.60	.33	.794	.845	.885	.929	.979	.003	.003	.003	.002	.001
1.00	-.71	-.22	.838	.878	.910	.948	.989	.003	.004	.003	.003	.002
1.25	-.78	-.63	.857	.891	.920	.953	.989	.003	.005	.005	.005	.002
1.50	-.83	-.81	.870	.899	.927	.955	.986	.004	.005	.007	.005	.001
1.75	-.87	-.89	.877	.904	.929	.953	.983	.005	.007	.008	.004	.001
2.00	-.89	-.93	.881	.906	.929	.951	.980	.005	.007	.008	.004	.001
2.25	-.91	-.95	.884	.909	.929	.950	.978	.005	.009	.008	.003	.001
2.50	-.93	-.96	.887	.910	.928	.948	.975	.006	.009	.008	.003	.001
2.75	-.94	-.97	.888	.910	.928	.946	.973	.006	.009	.008	.003	.001
3.00	-.95	-.98	.890	.911	.927	.945	.971	.006	.010	.008	.002	.001
3.25	-.96	-.98	.892	.911	.925	.944	.969	.007	.010	.007	.002	.000
3.50	-.96	-.99	.893	.912	.925	.943	.968	.007	.010	.007	.002	.001
3.75	-.97	-.99	.893	.912	.924	.942	.967	.007	.010	.006	.002	.000
4.00	-.97	-.99	.894	.912	.923	.942	.966	.008	.010	.006	.002	.000
5.00	-.98	-.99	.896	.910	.921	.939	.962	.009	.009	.005	.002	.001
7.50	-.99	-1.00	.899	.908	.918	.934	.957	.009	.008	.004	.002	.000
10.00	-1.00	-1.00	.900	.907	.916	.932	.954	.011	.008	.004	.002	.000
50.00	-1.00	-1.00	.901	.903	.912	.926	.948	.010	.006	.003	.002	.001
100.00	-1.00	-1.00	.901	.903	.911	.925	.947	.011	.006	.003	.002	.001
1000.00	-1.00	-1.00	.901	.903	.910	.925	.946	.011	.006	.003	.001	.000
10000.00	-1.00	-1.00	.901	.903	.910	.924	.946	.011	.006	.003	.001	.000

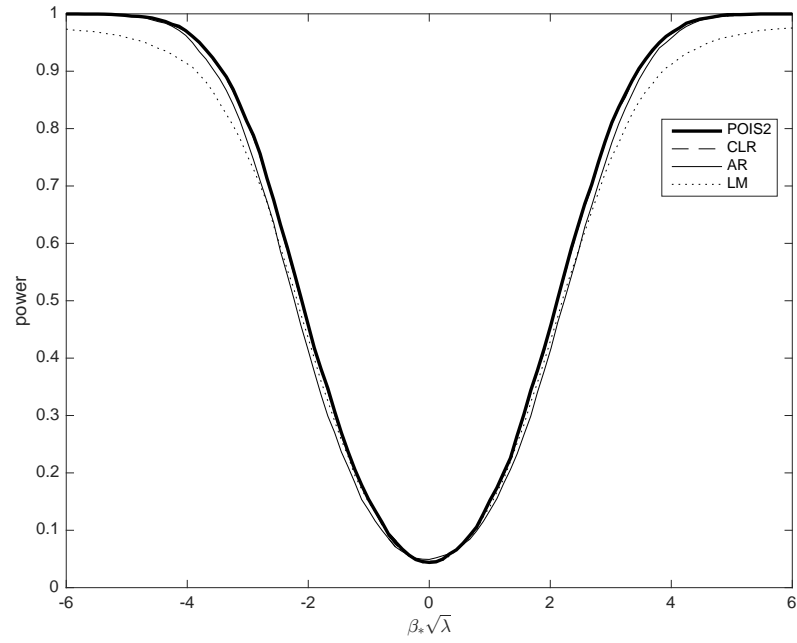
TABLE SM-V(d). Average (over λ) Power Differences for $\lambda \in \{2.5, 5.0, \dots, 90.0\}$ between the WAP2 and CLR Tests for $k = 20$

β_0	$\rho_{uv,0}$		WAP2					WAP2-CLR				
	$\rho_{uv} = 0$.9	$\rho_{uv} = 0$.3	.5	.7	.9	$\rho_{uv} = 0$.3	.5	.7	.9
-10000.00	1.00	1.00	.862	.865	.878	.901	.934	.013	.008	.004	.001	.000
-1000.00	1.00	1.00	.862	.865	.878	.900	.934	.013	.008	.004	.001	.000
-100.00	1.00	1.00	.862	.864	.877	.900	.933	.013	.007	.003	.002	.000
-50.00	1.00	1.00	.862	.864	.876	.899	.932	.013	.007	.003	.002	.000
-10.00	1.00	1.00	.860	.860	.870	.892	.923	.012	.007	.002	.002	.001
-7.50	.99	1.00	.859	.858	.867	.889	.919	.012	.007	.002	.002	.000
-5.00	.98	1.00	.856	.853	.862	.881	.911	.010	.006	.003	.001	.000
-4.00	.97	1.00	.854	.849	.858	.876	.905	.009	.005	.003	.002	.000
-3.75	.97	1.00	.853	.847	.856	.875	.902	.009	.005	.003	.003	-.000
-3.50	.96	1.00	.852	.845	.854	.872	.900	.009	.004	.003	.003	.000
-3.25	.96	.99	.851	.843	.852	.869	.897	.009	.004	.003	.002	-.000
-3.00	.95	.99	.849	.841	.849	.866	.893	.008	.004	.003	.002	.000
-2.75	.94	.99	.847	.839	.846	.862	.889	.008	.005	.003	.001	-.000
-2.50	.93	.99	.845	.836	.842	.857	.884	.007	.004	.003	.002	.000
-2.25	.91	.99	.842	.832	.837	.851	.877	.006	.004	.002	.002	.000
-2.00	.89	.99	.838	.826	.830	.843	.869	.006	.004	.003	.002	.000
-1.75	.87	.99	.833	.818	.820	.832	.857	.005	.004	.003	.002	.000
-1.50	.83	.98	.825	.807	.806	.817	.841	.005	.005	.003	.002	.000
-1.25	.78	.98	.811	.789	.787	.794	.816	.005	.004	.004	.002	.001
-1.00	.71	.97	.787	.760	.752	.757	.776	.004	.004	.003	.001	.001
-0.75	.60	.97	.739	.701	.688	.688	.704	.004	.002	.002	.001	.000
-0.50	.45	.95	.615	.567	.549	.543	.556	.002	.002	.001	.001	.001
-0.25	.24	.94	.286	.263	.258	.257	.263	.001	.001	.002	.001	.000
0.25	-.24	.83	.286	.328	.367	.428	.512	.002	.003	.001	.001	.001
0.50	-.45	.68	.617	.692	.757	.829	.912	.004	.003	.003	.002	.000
0.75	-.60	.33	.743	.800	.849	.906	.971	.004	.004	.003	.003	.001
1.00	-.71	-.22	.790	.837	.877	.927	.983	.004	.005	.004	.003	.002
1.25	-.78	-.63	.812	.853	.889	.936	.983	.004	.005	.005	.007	.002
1.50	-.83	-.81	.824	.861	.897	.936	.980	.004	.006	.008	.007	.001
1.75	-.87	-.89	.832	.867	.900	.934	.976	.006	.007	.010	.006	.001
2.00	-.89	-.93	.838	.870	.900	.931	.972	.006	.009	.010	.004	.001
2.25	-.91	-.95	.842	.872	.900	.930	.969	.007	.010	.010	.004	.001
2.50	-.93	-.96	.845	.873	.899	.927	.967	.008	.011	.010	.003	.001
2.75	-.94	-.97	.848	.874	.897	.925	.965	.008	.011	.009	.002	.001
3.00	-.95	-.98	.849	.875	.896	.924	.963	.008	.011	.008	.002	.001
3.25	-.96	-.98	.851	.875	.895	.922	.961	.009	.012	.008	.002	.000
3.50	-.96	-.99	.852	.875	.894	.921	.960	.009	.012	.007	.002	.001
3.75	-.97	-.99	.853	.875	.893	.920	.958	.009	.012	.007	.002	.001
4.00	-.97	-.99	.854	.875	.893	.919	.957	.009	.012	.007	.002	.001
5.00	-.98	-.99	.857	.874	.890	.916	.954	.010	.012	.006	.002	.001
7.50	-.99	-1.00	.859	.872	.887	.911	.948	.012	.010	.005	.002	.001
10.00	-1.00	-1.00	.860	.870	.885	.909	.945	.012	.010	.005	.002	.001
50.00	-1.00	-1.00	.862	.866	.879	.902	.936	.013	.008	.004	.002	.001
100.00	-1.00	-1.00	.862	.865	.879	.901	.935	.013	.008	.004	.001	.000
1000.00	-1.00	-1.00	.862	.865	.878	.901	.934	.013	.008	.004	.001	.000
10000.00	-1.00	-1.00	.862	.865	.878	.901	.934	.013	.008	.004	.001	.000

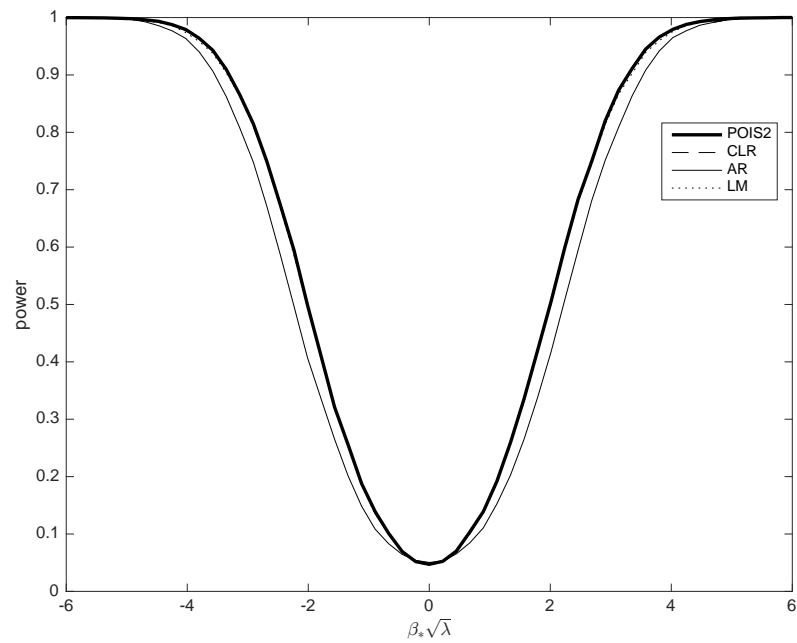
TABLE SM-V(e). Average (over λ) Power Differences for $\lambda \in \{2.5, 5.0, \dots, 90.0\}$ between the WAP2 and CLR Tests for $k = 40$

β_0	$\rho_{uv,0}$		WAP2					WAP2-CLR				
	$\rho_{uv} = 0$.9	$\rho_{uv} = 0$.3	.5	.7	.9	$\rho_{uv} = 0$.3	.5	.7	.9
-10000.00	1.00	1.00	.817	.819	.835	.869	.919	.024	.013	.006	.004	.001
-1000.00	1.00	1.00	.817	.819	.835	.869	.919	.023	.013	.006	.004	.001
-100.00	1.00	1.00	.817	.818	.834	.867	.917	.023	.013	.006	.004	.001
-50.00	1.00	1.00	.817	.817	.833	.867	.916	.023	.012	.005	.004	.001
-10.00	1.00	1.00	.814	.810	.826	.858	.905	.022	.010	.005	.003	.000
-7.50	.99	1.00	.812	.807	.823	.853	.901	.020	.010	.005	.003	.001
-5.00	.98	1.00	.808	.802	.816	.845	.892	.018	.009	.005	.003	.000
-4.00	.97	1.00	.804	.797	.810	.838	.884	.016	.008	.004	.003	.000
-3.75	.97	1.00	.802	.796	.808	.836	.882	.015	.008	.004	.004	.000
-3.50	.96	1.00	.801	.794	.806	.834	.879	.014	.008	.004	.003	-.000
-3.25	.96	.99	.799	.792	.803	.831	.876	.013	.008	.004	.003	.000
-3.00	.95	.99	.797	.790	.800	.828	.872	.012	.008	.004	.004	.000
-2.75	.94	.99	.795	.786	.796	.823	.867	.012	.007	.004	.003	.001
-2.50	.93	.99	.792	.783	.792	.817	.861	.011	.007	.005	.002	.001
-2.25	.91	.99	.788	.777	.786	.811	.854	.011	.006	.004	.003	.000
-2.00	.89	.99	.783	.772	.778	.802	.846	.009	.007	.005	.004	.001
-1.75	.87	.99	.777	.761	.767	.790	.833	.009	.006	.004	.003	-.000
-1.50	.83	.98	.768	.749	.754	.773	.816	.008	.006	.004	.003	.001
-1.25	.78	.98	.752	.730	.730	.750	.791	.007	.006	.004	.003	.000
-1.00	.71	.97	.727	.698	.694	.709	.751	.007	.007	.004	.003	-.000
-0.75	.60	.97	.672	.633	.624	.632	.675	.006	.005	.004	.001	-.000
-0.50	.45	.95	.536	.490	.480	.489	.524	.004	.004	.002	.001	-.002
-0.25	.24	.94	.233	.217	.215	.221	.242	.001	.001	-.000	-.001	-.002
0.25	-.24	.83	.237	.275	.318	.383	.491	.001	.000	.000	-.002	-.002
0.50	-.45	.68	.539	.621	.697	.788	.892	.004	.004	.004	.003	.001
0.75	-.60	.33	.672	.741	.804	.876	.958	.004	.005	.005	.004	.001
1.00	-.71	-.22	.727	.784	.837	.901	.974	.005	.006	.006	.006	.003
1.25	-.78	-.63	.754	.803	.853	.911	.974	.006	.008	.010	.009	.004
1.50	-.83	-.81	.769	.815	.861	.913	.969	.007	.012	.014	.011	.002
1.75	-.87	-.89	.779	.824	.865	.910	.965	.008	.016	.016	.008	.001
2.00	-.89	-.93	.785	.828	.866	.905	.961	.009	.017	.016	.006	.001
2.25	-.91	-.95	.790	.831	.866	.903	.958	.010	.019	.017	.006	.001
2.50	-.93	-.96	.794	.833	.864	.901	.955	.011	.020	.016	.005	.001
2.75	-.94	-.97	.797	.834	.862	.898	.953	.012	.020	.015	.004	.001
3.00	-.95	-.98	.799	.834	.861	.896	.950	.013	.021	.014	.004	.001
3.25	-.96	-.98	.801	.834	.859	.894	.949	.014	.021	.013	.004	.001
3.50	-.96	-.99	.803	.835	.858	.893	.947	.015	.021	.013	.004	.001
3.75	-.97	-.99	.805	.834	.857	.892	.946	.016	.021	.013	.004	.001
4.00	-.97	-.99	.806	.834	.855	.890	.944	.016	.021	.012	.004	.001
5.00	-.98	-.99	.810	.831	.852	.887	.940	.018	.019	.011	.004	.001
7.50	-.99	-1.00	.814	.828	.847	.881	.933	.021	.017	.009	.004	.001
10.00	-1.00	-1.00	.815	.826	.844	.878	.929	.022	.016	.009	.004	.002
50.00	-1.00	-1.00	.817	.820	.837	.871	.921	.023	.014	.007	.004	.001
100.00	-1.00	-1.00	.817	.820	.836	.870	.920	.023	.014	.007	.005	.001
1000.00	-1.00	-1.00	.817	.819	.836	.869	.919	.024	.013	.006	.004	.001
10000.00	-1.00	-1.00	.817	.819	.835	.869	.919	.024	.013	.006	.004	.001

FIGURE SM-I(a). Power of the significance level .05 CLR, LM, and AR tests and the POIS2 power envelope for fixed null value $\beta_0 = 0$, varying true value β_* , $k = 2$, $\rho_\Omega = 0$, and $\lambda = 5, 20$

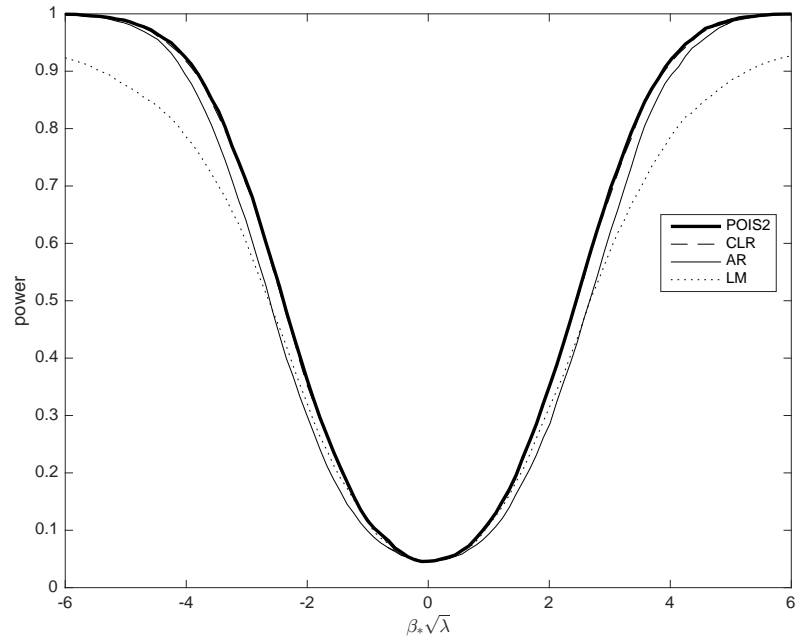


(i) $\lambda = 5$

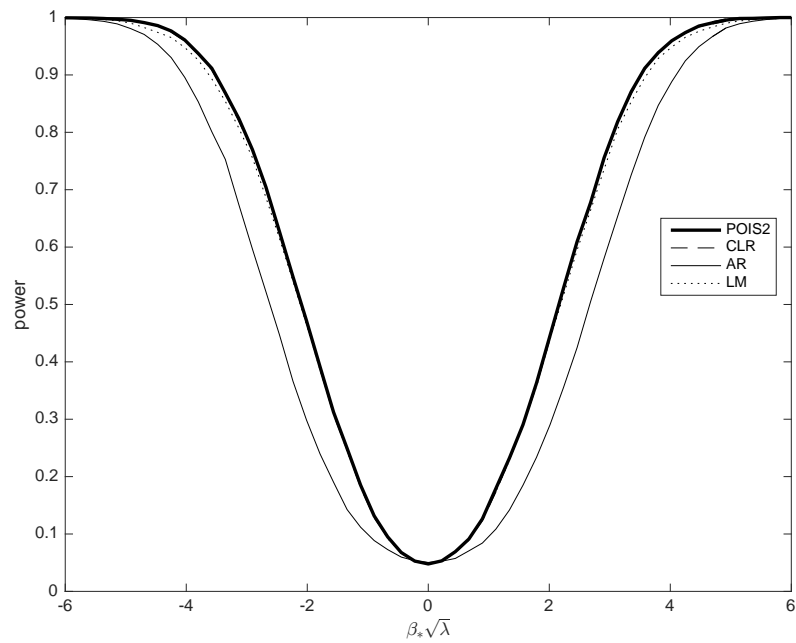


(ii) $\lambda = 20$

FIGURE SM-I(b). Power of the significance level .05 CLR, LM, and AR tests and the POIS2 power envelope for fixed null value $\beta_0 = 0$, varying true value β_* , $k = 5$, $\rho_\Omega = 0$, and $\lambda = 5, 20$

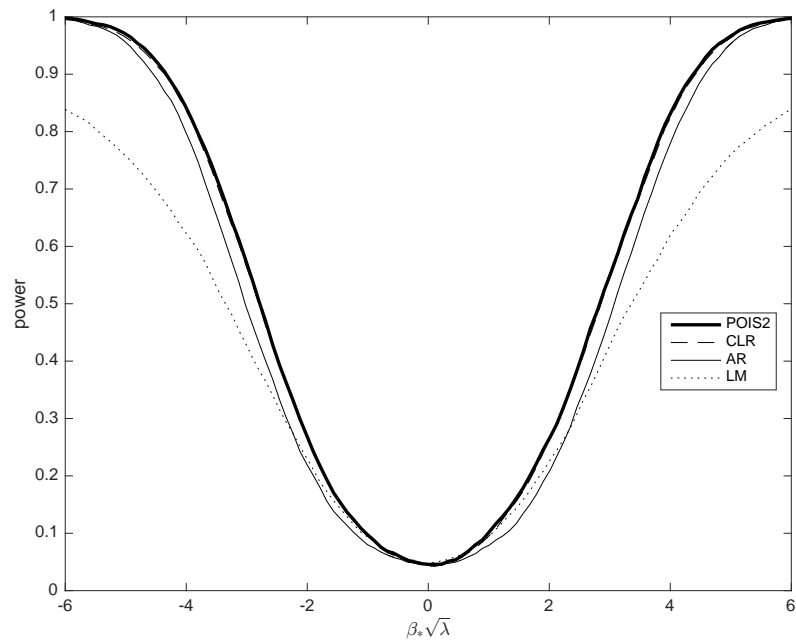


(i) $\lambda = 5$

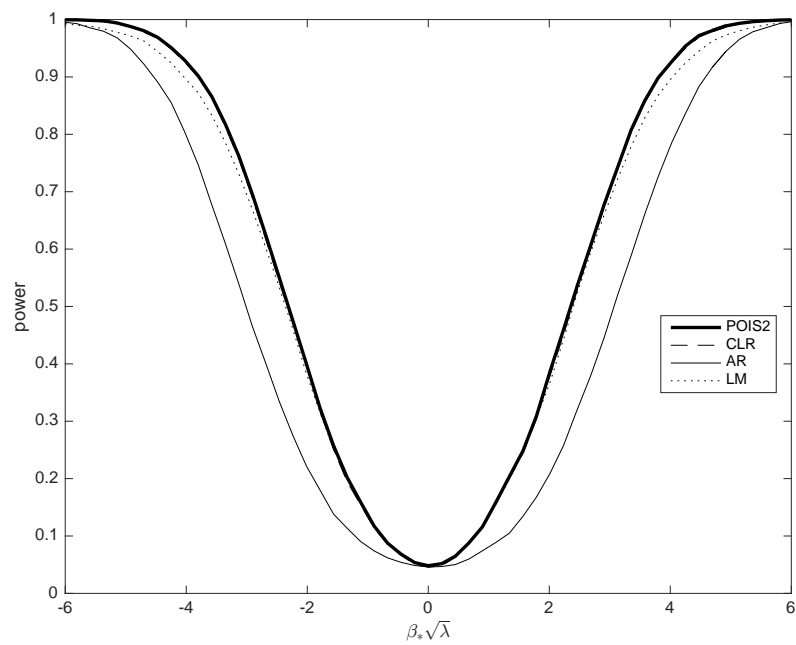


(ii) $\lambda = 20$

FIGURE SM-I(c). Power of the significance level .05 CLR, LM, and AR tests and the POIS2 power envelope for fixed null value $\beta_0 = 0$, varying true value β_* , $k = 10$, $\rho_\Omega = 0$, and $\lambda = 5, 20$



(i) $\lambda = 5$



(ii) $\lambda = 20$