

UNIFORM INFERENCE WITH GENERAL $AR(p)$ PROCESSES

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Introduction: Magdalinos and Petrova (2026)

- AR(1) process

$$x_t - \mu = \rho (x_{t-1} - \mu) + u_t$$

- Related regression models: Predictive Regression and Local Projection.
- Confidence intervals for ρ with uniform coverage over a parameter space:

$$\Theta = [-M, M], \text{ some } M > 0$$

- Critical regions for parameters in PR and LP models with correct asymptotic size uniformly over Θ
- Combined data-driven instrumentation procedure:
 - no discontinuities in the limit distribution
 - mixed normal limit distribution in all cases
 - standard inference (testing and CIs) based on $\mathcal{N}(0, 1)$
 - uniform size
 - first distribution-free inference procedure in explosive case

This paper

- $AR(p)$ process

$$x_t = \phi_1 x_{t-1} + \dots + \phi_p x_{t-p} + u_t$$

- We wish to do inference on $\phi = (\phi_1, \dots, \phi_p)'$

$$H_0 : H\phi_n = h, \quad \text{rank}(H) = q$$

- Wald statistic for testing H_0

$$W_n = \frac{1}{\hat{\sigma}_n^2} (H\tilde{\phi}_n - h)' H' [H (X' P_Z X)^{-1} H']^{-1} (H\tilde{\phi}_n - h).$$

- $\tilde{\phi}_n$ extension of the MP(2026) IV estimator
- Z extension of the MP(2026) instrument
- Target: get $W_n \rightarrow_d \chi^2(q)$

This paper

- $AR(p)$ process

$$x_t = \phi_1 x_{t-1} + \dots + \phi_p x_{t-p} + u_t$$

- Roots of the characteristic polynomial are the eigenvalues of the companion matrix R :

$$sp(R) = \{\rho_1, \dots, \rho_p\} \subset \mathbb{C}.$$

- Discontinuity in the asymptotics of the OLS estimator of $\phi = (\phi_1, \dots, \phi_p)'$ according to the properties of $sp(R)$.
- $AR(p)$ parameter space:

$$\Theta = \{\rho \in sp(R) : \text{there exist } M, \delta > 0 \text{ s.t. } |\rho| \leq M \text{ and } sp(R) \cap (-1 + \delta, 1 - \delta)^c \subset \mathbb{R}\}$$

- Uniform inference on ϕ requires limit distribution theory along

$$(\rho_{1n}, \dots, \rho_{pn}) \rightarrow (\rho_1, \dots, \rho_p). \quad (1)$$

- Rate of convergence and limit distribution theory depends on:

- 1 the AR category of each $\rho_{in} \rightarrow \rho_i$ in (1)
- 2 the multiplicity of each ρ_{in} in (1)

Categorisation of AR regions

- $sp(R) = \{\rho_1, \dots, \rho_p\}$

$$(\rho_{1n}, \dots, \rho_{pn}) \rightarrow (\rho_1, \dots, \rho_p).$$

- Let $\mathbf{c} := \lim_{n \rightarrow \infty} \mathbf{n}(|\rho_n| - 1)$ exist in $[-\infty, \infty]$.
- Then the eigenvalue ρ_n belongs to one of the following classes:

C(i) *near-stationary* if $\mathbf{c} = -\infty$

C(ii) *LUR* if $\mathbf{c} \in \mathbb{R}$

C(iii) *near-explosive* if $\mathbf{c} = \infty$

Classes C(i)-C(iii) have *regular* and *oscillating* subclasses:

$C(i) = \mathbf{C}_+(i) \cup \mathbf{C}_-(i)$, etc

AR(p) companion matrix

- Companion matrix:

$$R = \begin{bmatrix} \phi_1 & \phi_2 & \cdots & \phi_p \\ 1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

- Simple Jordan form:

$$\text{geometric multiplicity} = \text{algebraic multiplicity} \quad (2)$$

- (2) implies that R is diagonalisable *iff* it has distinct eigenvalues
- In this case, adaptation of MP(2026) is relatively straightforward:
 $AR(p) \simeq p\text{-}AR(1)$ components
- (2) also implies that each group of repeated eigenvalues of R is contained in a single Jordan block which will have size equal to the number of times the eigenvalue is repeated
- Hence, knowing how many times each eigenvalue is repeated is equivalent to knowing the Jordan form of R (up to permutation)

Jordan form of companion matrix

- $AR(2)$ in companion form:

$$\begin{aligned}\underline{x}_{n,t} &= R_n \underline{x}_{n,t-1} + \underline{u}_{n,t} & R_n &= T_n \Lambda_n T_n^{-1} \\ T_n^{-1} \underline{x}_{n,t} &= \Lambda_n T_n^{-1} \underline{x}_{n,t-1} + T_n^{-1} \underline{u}_{n,t}\end{aligned}$$

- Jordan matrix:

$$\Lambda_n = \begin{bmatrix} \rho_{1n} & 0 \\ 0 & \rho_{2n} \end{bmatrix} \mathbf{1}_{\{\rho_{1n} \neq \rho_{2n}\}} + \begin{bmatrix} \rho_n & 1 \\ 0 & \rho_n \end{bmatrix} \mathbf{1}_{\{\rho_{1n} = \rho_{2n} = \rho_n\}}$$

- Matrix of (generalised) eigenvectors:

$$\begin{aligned}T_n^{-1} &= \frac{1}{\rho_{1n} - \rho_{2n}} \begin{bmatrix} 1 & -\rho_{2n} \\ -1 & \rho_{1n} \end{bmatrix} \mathbf{1}_{\{\rho_{1n} \neq \rho_{2n}\}} \\ &\quad + \begin{bmatrix} \rho_n & -\rho_n^2 \\ 1 & 0 \end{bmatrix} \mathbf{1}_{\{\rho_{1n} = \rho_{2n} = \rho_n\}}\end{aligned}\tag{3}$$

- When $\rho_{1n} \neq \rho_{2n}$, denote

$$S_n := (\rho_{1n} - \rho_{2n}) T_n^{-1} = \begin{bmatrix} 1 & -\rho_{2n} \\ -1 & \rho_{1n} \end{bmatrix}\tag{4}$$

Asymptotic conditioning of eigenvalues

- Data driven criterion for “equality” of ρ_{1n} and ρ_{2n}
- How accurately can we achieve this?

$$\begin{aligned}
 \hat{\rho}_{1n} - \hat{\rho}_{2n} &= \rho_{1n} - \rho_{2n} + \hat{\rho}_{1n} - \rho_{1n} - (\hat{\rho}_{2n} - \rho_{2n}) \\
 &= \rho_{1n} - \rho_{2n} + O_p \left(n^{-1/2} (|\rho_{1n} - 1| \vee |\rho_{2n} - 1|)^{1/2} \right) \\
 &= \rho_{1n} - \rho_{2n} + O_p \left(n^{-1/2} (|\hat{\rho}_{1n} - 1| \vee |\hat{\rho}_{2n} - 1|)^{1/2} \right) \\
 &= \rho_{1n} - \rho_{2n} + O_p (l_n^{-1})
 \end{aligned}$$

- So $|\hat{\rho}_{1n} - \hat{\rho}_{2n}|$ can assess the magnitude of $|\rho_{1n} - \rho_{2n}|$ only up to a l_n^{-1} Pitman drift.
- If $|\rho_{1n} - \rho_{2n}| = O_p(l_n^{-1})$, we design our criterion to give $\rho_{1n} = \rho_{2n}$ even if this may not hold exactly.

Asymptotic conditioning of eigenvalues

- Define the sequence

$$l_n := n^{1/2} \left(|\hat{\rho}_{1n} - 1|^{-1/2} \wedge |\hat{\rho}_{2n} - 1|^{-1/2} \right)$$

and the events

$$\Delta_n = \{l_n |\hat{\rho}_{1n} - \hat{\rho}_{2n}| > L_n\}, \quad \text{some } L_n \rightarrow \infty$$

- Since

$$l_n |\hat{\rho}_{1n} - \hat{\rho}_{2n}| = l_n |\rho_{1n} - \rho_{2n}| + O_p(1),$$

we conclude that:

$$\mathbf{1}_{\Delta_n} \rightarrow_p 0 \quad \text{if } |\rho_{1n} - \rho_{2n}| = O\left(n^{-1/2}(|\rho_{1n} - 1|^{1/2} \wedge |\rho_{2n} - 1|^{1/2})\right) \quad (5)$$

- "Estimate" the Jordan form of R as

$$\begin{bmatrix} \rho_{1n} & 0 \\ 0 & \rho_{2n} \end{bmatrix} \mathbf{1}_{\Delta_n} + \begin{bmatrix} \rho_n & 1 \\ 0 & \rho_n \end{bmatrix} \mathbf{1}_{\Delta_n^c}$$

- An error of considering $\rho_{1n} \neq \rho_{2n}$ when in fact $\rho_{1n} = \rho_{2n}$ occurs with prob. tending to 0
- We need to show that asymptotic theory under Δ_n^c works when $|\rho_{1n} - \rho_{2n}|$ satisfies (5)

AR(2) instrumentation

- AR(2) in companion form:

$$\begin{aligned}\underline{x}_{n,t} &= R_n \underline{x}_{n,t-1} + \underline{u}_{n,t} & R_n &= T_n \Lambda_n T_n^{-1} \\ T_n^{-1} \underline{x}_{n,t} &= \Lambda_n T_n^{-1} \underline{x}_{n,t-1} + T_n^{-1} \underline{u}_{n,t}\end{aligned}\quad (6)$$

- Estimated Jordan form of R_n :

$$\hat{\Lambda}_n := \begin{bmatrix} \rho_{1n} & 0 \\ 0 & \rho_{2n} \end{bmatrix} \mathbf{1}_{\Delta_n} + \begin{bmatrix} \rho_n & 1 \\ 0 & \rho_n \end{bmatrix} \mathbf{1}_{\Delta_n^c} \quad (7)$$

- We are trying to build an instrument process that follows (6) as closely as possible subject to the MP(2026) instrumentation and information on the integration order provided by (7):

$$\underline{z}_{n,t} = \tilde{\Lambda}_n \underline{z}_{n,t-1} + \tilde{\underline{u}}_{n,t}$$

$$\tilde{\Lambda}_n := \begin{bmatrix} \varphi_{1n} & 0 \\ 0 & \varphi_{2n} \end{bmatrix} \mathbf{1}_{\Delta_n} + \begin{bmatrix} \varphi_n & 1 \\ 0 & \varphi_n \end{bmatrix} \mathbf{1}_{\Delta_n^c}$$

- φ_{1n} , φ_{2n} and φ_n are artificial AR roots chosen as in MP(2026).
- Selection of $\tilde{\underline{u}}_{n,t}$ requires estimation of T_n^{-1} by OLS in (3).

AR(2) instrumentation: root selection

- Instrument process:

$$\underline{z}_{n,t} = \tilde{\Lambda}_n \underline{z}_{n,t-1} + \tilde{u}_{n,t}$$

$$\tilde{\Lambda}_n = \begin{bmatrix} \varphi_{1n} & 0 \\ 0 & \varphi_{2n} \end{bmatrix} \mathbf{1}_{\Delta_n} + \begin{bmatrix} \varphi_n & 1 \\ 0 & \varphi_n \end{bmatrix} \mathbf{1}_{\Delta_n^c}$$

- For $i \in \{1, 2\}$:

$$\varphi_{in} = \lambda_{in} \mathbf{1}_{F_{in}^+} + \lambda_{in}^- \mathbf{1}_{F_{in}^-} + \Lambda_{in} \mathbf{1}_{\bar{F}_{in}^+} + \Lambda_{in}^- \mathbf{1}_{\bar{F}_{in}^-}$$

where: $\lambda_{in} \in C_+(i)$, $\lambda_{in}^- \in C_-(i)$, $\Lambda_{in} \in C_+(iii)$, $\Lambda_{in}^- \in C_-(iii)$

- Events F_{in} defined as in MP(2026) for each eigenvalue ρ_{1n}, ρ_{2n} :

$$F_{in} = \{n (|\hat{\rho}_{in}| - 1) \leq 0\} \quad \bar{F}_{in} = \{n (|\hat{\rho}_{in}| - 1) > 0\}$$

$$\begin{aligned} F_{in}^+ &= F_{in} \cap \{\hat{\rho}_{in} \geq 0\} & F_{in}^- &= F_{in} \cap \{\hat{\rho}_{in} < 0\} \\ \bar{F}_{in}^+ &= \bar{F}_{in} \cap \{\hat{\rho}_{in} \geq 0\} & \bar{F}_{in}^- &= \bar{F}_{in} \cap \{\hat{\rho}_{in} < 0\} \end{aligned}$$

AR(2) instrumentation: quasi-innovation selection

- Instrument process:

$$\underline{z}_{n,t} = \tilde{\Lambda}_n \underline{z}_{n,t-1} + \underline{\tilde{u}}_{n,t}$$

- Direction selection:

$$\begin{aligned}\hat{T}_n^{-1} &= \frac{1}{\hat{\rho}_{1n} - \hat{\rho}_{2n}} \begin{bmatrix} 1 & -\hat{\rho}_{2n} \\ -1 & \hat{\rho}_{1n} \end{bmatrix} \mathbf{1}_{\Delta_n} + \begin{bmatrix} \hat{\rho}_{2n} & -\hat{\rho}_{2n}^2 \\ 1 & 0 \end{bmatrix} \mathbf{1}_{\Delta_n^c} \\ \hat{S}_n &= (\hat{\rho}_{1n} - \hat{\rho}_{2n}) \hat{T}_n^{-1}\end{aligned}$$

- $\underline{\tilde{u}}_{n,t} = \underline{\tilde{u}}_{n,t}^{(d)} \mathbf{1}_{\Delta_n} + \underline{\tilde{u}}_{n,t}^{(r)} \mathbf{1}_{\Delta_n^c}$
- Discrete eigenvalues:

$$\begin{aligned}\underline{\tilde{u}}_{n,t}^{(d)} &= \mathbb{I}_{F_n^+} \hat{S}_n \Delta \underline{x}_{n,t} + \mathbb{I}_{F_n^-} \hat{S}_n \nabla \underline{x}_{n,t} + \mathbb{I}_{\bar{F}_n^+ \cup \bar{F}_n^-} \hat{S}_n \hat{u}_{n,t} \\ \mathbb{I}_{F_n^+} &= \text{diag} \left(\mathbf{1}_{F_{1n}^+}, \mathbf{1}_{F_{2n}^+} \right), \mathbb{I}_{\bar{F}_n^+ \cup \bar{F}_n^-} = \text{diag} \left(\mathbf{1}_{\bar{F}_{1n}^+ \cup \bar{F}_{1n}^-}, \mathbf{1}_{\bar{F}_{2n}^+ \cup \bar{F}_{2n}^-} \right)\end{aligned}$$

- Repeated eigenvalues:

$$\underline{\tilde{u}}_{n,t}^{(r)} = \hat{T}_n^{-1} \Delta \underline{x}_{n,t} \mathbf{1}_{F_{1n}^+} + \hat{T}_n^{-1} \nabla \underline{x}_{n,t} \mathbf{1}_{F_{1n}^-} + \hat{T}_n^{-1} \hat{u}_{n,t} \mathbf{1}_{\bar{F}_{1n}^+ \cup \bar{F}_{1n}^-}$$

AR(2) with distinct characteristic roots

- $\underline{x}_t = R\underline{x}_{t-1} + \underline{u}_t$
- R diagonalisable: $X_t = S_n \underline{x}_t$

$$S_n = (\rho_{1n} - \rho_{2n}) T_n^{-1} = \begin{bmatrix} 1 & -\rho_{2n} \\ -1 & \rho_{1n} \end{bmatrix} = \begin{bmatrix} S'_{1n} \\ S'_{2n} \end{bmatrix}$$

implies that

$$\begin{bmatrix} X_{1t} \\ X_{2t} \end{bmatrix} = \begin{bmatrix} \rho_{1n} & 0 \\ 0 & \rho_{2n} \end{bmatrix} \begin{bmatrix} X_{1t-1} \\ X_{2t-1} \end{bmatrix} + \begin{bmatrix} u_t \\ -u_t \end{bmatrix}$$

- MP(2022) instrumentation:

$$\begin{bmatrix} Z_{1t} \\ Z_{2t} \end{bmatrix} = \begin{bmatrix} \varphi_{1n} & 0 \\ 0 & \varphi_{2n} \end{bmatrix} \begin{bmatrix} Z_{1t-1} \\ Z_{2t-1} \end{bmatrix} + \begin{bmatrix} \tilde{u}_{1t} \\ -\tilde{u}_{2t} \end{bmatrix} \quad (8)$$

- $n(|\hat{\rho}_{in}| - 1) \leq 0 \implies \varphi_{in}$ near-stationary and $\tilde{u}_{it} = \Delta x_t$
- $n(|\hat{\rho}_{in}| - 1) > 0 \implies \varphi_{in}$ near-explosive and $\tilde{u}_{it} = \hat{u}_t$
- Feasibility: need to estimate the *directions* S_{1n} and S_{2n}

AR(2) with distinct characteristic roots

- Estimate the *directions*

$$X_{1t} \simeq \hat{S}'_{1n} \underline{x}_t \quad \text{and} \quad X_{2t} \simeq \hat{S}'_{2n} \underline{x}_t$$

where

$$\hat{S}_n = (\hat{\rho}_{1n} - \hat{\rho}_{2n}) \hat{T}_n^{-1} = \begin{bmatrix} 1 & -\hat{\rho}_{2n} \\ -1 & \hat{\rho}_{1n} \end{bmatrix} = \begin{bmatrix} \hat{S}'_{1n} \\ \hat{S}'_{2n} \end{bmatrix}$$

- IV residuals:

$$\begin{aligned} \tilde{u}_{1t} &= \hat{S}'_{1n} \Delta \underline{x}_t \mathbf{1}_{F_{1n}^+} + \hat{S}'_{1n} \nabla \underline{x}_t \mathbf{1}_{F_{1n}^-} + \hat{u}_t \mathbf{1}_{\bar{F}_{1n}^+ \cup \bar{F}_{1n}^-} \\ \tilde{u}_{2t} &= \hat{S}'_{2n} \Delta \underline{x}_t \mathbf{1}_{F_{2n}^+} + \hat{S}'_{2n} \nabla \underline{x}_t \mathbf{1}_{F_{2n}^-} + \hat{u}_t \mathbf{1}_{\bar{F}_{2n}^+ \cup \bar{F}_{2n}^-} \end{aligned}$$

- Eigenvector estimation error $\hat{S}_{in}$ is controllable because it only depends on the estimation error of $\hat{\rho}_{in}$

Eigenvector estimation error

- IV residuals:

$$\tilde{u}_{1t} = \Delta X_{1t} \mathbf{1}_{F_{1n}^+} + \nabla X_{1t} \mathbf{1}_{F_{1n}^-} + \hat{u}_t \mathbf{1}_{F_{1n}^+ \cup F_{1n}^-} - r_{1t}^{(n)}$$

$$\tilde{u}_{2t} = \Delta X_{2t} \mathbf{1}_{F_{2n}^+} + \nabla X_{2t} \mathbf{1}_{F_{2n}^-} - \hat{u}_t \mathbf{1}_{F_{2n}^+ \cup F_{2n}^-} + r_{2t}^{(n)}$$

where

$$r_{1t}^{(n)} = (\hat{\rho}_{2n} - \rho_{2n}) \left(\Delta x_{t-1} \mathbf{1}_{F_{1n}^+} + \nabla x_{t-1} \mathbf{1}_{F_{1n}^-} \right) \quad (9)$$

$$r_{2t}^{(n)} = (\hat{\rho}_{1n} - \rho_{1n}) \left(\Delta x_{t-1} \mathbf{1}_{F_{2n}^+} + \nabla x_{t-1} \mathbf{1}_{F_{2n}^-} \right) \quad (10)$$

- If ρ_{2n} is explosive and ρ_{1n} is stable, x_t is explosive, but:
 - the exponential decay of $\hat{\rho}_{2n} - \rho_{2n}$ controls (9)
 - the arbitrary decay of $\mathbf{1}_{F_{2n}^+}$ and $\mathbf{1}_{F_{2n}^-}$ controls (10) (Lemma 2 of MP(2026)).
- The above ensures the feasibility of the instrumentation in (8).

IV estimator (distinct characteristic roots)

- IV estimator $\tilde{\phi}_n$ of ϕ : $\tilde{\phi}_n = (\sum_{t=1}^n \underline{z}_{t-1} \underline{x}'_{t-1})^{-1} \sum_{t=1}^n \underline{z}_{t-1} x_t$

$$T_n = (\rho_{1n} - \rho_{2n})^{-1} \begin{bmatrix} \rho_{1n} & \rho_{2n} \\ 1 & 1 \end{bmatrix}.$$

- Diagonal normalisation matrices $D_n(\rho_{1n}, \rho_{2n})$ and $D_n(\varphi_{1n}, \varphi_{2n})$ depending on the AR regime of ρ_{1n}, ρ_{2n} :

$$D_n T'_n (\tilde{\phi}_n - \phi) = (D_{nz}^{-1} \sum_{t=1}^n Z_{t-1} X'_{t-1} D_n^{-1})^{-1} D_{nz}^{-1} \sum_{t=1}^n Z_{t-1} u_t$$

Theorem

When $\varphi_{1n} = r \varphi_{2n}$ for $r \in (0, 1)$, the limit distribution of $\tilde{\phi}_n$ is given by

$$D_n T'_n (\tilde{\phi}_n - \phi) \rightarrow_d \mathcal{MN} \left(0, \sigma^2 (V_{xz}^{-1})' V_{zz} V_{xz}^{-1} \right)$$

where $V_{zz} > 0$ and $\det(V_{xz}) \neq 0$ a.s.

AR(2) with repeated characteristic root

- ρ_n repeated characteristic root

$$J(\rho_n) = \begin{bmatrix} \rho_n & 0 \\ 1 & \rho_n \end{bmatrix}, \quad T^{-1}(\rho_n) = \begin{bmatrix} \rho_n & -\rho_n^2 \\ 1 & 0 \end{bmatrix}$$

and $X_t := T^{-1}(\rho_n) \underline{x}_t$, the Jordan decomposition gives

$$X_t = J(\rho_n) X_{t-1} + U_t, \quad U_t = u_t \begin{bmatrix} \rho_n \\ 1 \end{bmatrix} \quad (11)$$

- Instrument (11) by

$$Z_t = J(\varphi_n) Z_{t-1} + \tilde{u}_t \begin{bmatrix} \varphi_n \\ 1 \end{bmatrix}$$

- $F_n = \{n(|\hat{\rho}_n| - 1) \leq 0\} \Rightarrow \varphi_n$ near-stationary, $\tilde{u}_t = \Delta^2 x_t$
- $\bar{F}_n = n(|\hat{\rho}_n| - 1) > 0 \Rightarrow \varphi_n$ near-explosive, $\tilde{u}_t = \hat{u}_t$

OLS limit theory with near-stationary repeated ch. root

- Fixed parameter $AR(p)$: Chan and Wei (1988, AoS)
- Extension to $\rho_n \rightarrow 1$ in C(i):

$$D(\rho_n) = \text{diag} \left[(1 - \rho_n^2)^{-1/2}, (1 - \rho_n^2)^{-3/2} \right]$$

$$D(\rho_n)^{-1} \frac{1}{n} \sum_{t=1}^n X_{t-1} X'_{t-1} D(\rho_n)^{-1} \rightarrow_p \sigma^2 \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} > 0 \quad (12)$$

- Since $Z_t \simeq X_t$ when $(\rho_n - 1) / (\varphi_n - 1) \rightarrow \infty$ and Z_t behaves asymptotically as

$$Z_t = J(\varphi_n) Z_{t-1} + u_t \begin{bmatrix} \varphi_n \\ 1 \end{bmatrix} \quad \text{when } (\rho_n - 1) / (\varphi_n - 1) \rightarrow 0$$

(12) with $(D(\rho_n), X_{t-1})$ replaced by $(D(\varphi_n), Z_{t-1})$ establishes $Z'Z$ asymptotic instrument validity.

OLS limit theory with near-explosive repeated ch. root

- Fixed explosive parameter $AR(p)$: Jeganathan (1988, AoS)
- Extension to $\rho_n \rightarrow 1$ in C(iii):

$$(\rho_n^2 - 1) D(\rho_n)^{-1} J(\rho_n)^{-n} \sum_{t=1}^n X_{t-1} X'_{t-1} J'(\rho_n)^{-n} D(\rho_n)^{-1} \rightarrow_d M(\xi_1, \xi_2) \quad (13)$$

$$M(\xi_1, \xi_2) = \begin{bmatrix} \xi_1^2 & \xi_1 \xi_2 \\ \xi_1 \xi_2 & \xi_1^2 + \xi_2^2 \end{bmatrix} > 0$$

$$(\xi_1, \xi_2)' \sim \mathcal{N}\left(0, \sigma^2 \begin{bmatrix} 1 & -1 \\ -1 & 2 \end{bmatrix}\right)$$

- Since the instrument process Z_t behaves asymptotically as

$$Z_t = J(\varphi_n) Z_{t-1} + u_t \begin{bmatrix} \varphi_n \\ 1 \end{bmatrix}$$

(13) with $(D(\rho_n), X_{t-1})$ replaced by $(D(\varphi_n), Z_{t-1})$ establishes $Z'Z$ asymptotic instrument validity.

Signal matrix summary

- Key result:

$$D_n^{-1} \frac{1}{n} \sum_{t=1}^n X_{t-1} Z'_{t-1} D(\varphi_n)^{-1} \rightarrow_d \Psi, \quad \det(\Psi) \neq 0 \text{ a.s.}$$

where

$$D(\varphi_n) = \text{diag} \left[|1 - \varphi_n^2|^{-1/2}, |1 - \varphi_n^2|^{-3/2} \right]$$

- D_n is a *non-diagonal stochastic* normalisation matrix satisfying

$$\|D_n\| \rightarrow \infty$$

- D_n depends stochastically only on the partial sum process $B_n(t)$ of u_t
- Guarantees asymptotic independence of

$$n^{-1/2} D(\varphi_n)^{-1} \sum_{t=1}^n Z_{t-1} u_t \quad \text{and} \quad [D_n, B_n(t)]$$

Wald statistic

- Under H_0 , the Wald statistic satisfies

$$W_n = v_n' P_{\tilde{H}_n'} v_n, \quad \tilde{H}_n = H (T_n')^{-1} (D_n')^{-1} \left(V_{xz}^{(n)'} \right)^{-1} \left(V_{zz}^{(n)} \right)^{1/2}$$

- “Score”:

$$v_n = \frac{1}{\hat{\sigma}_n} \left(V_{zz}^{(n)} \right)^{-1/2} n^{-1/2} D(\varphi_n)^{-1} \sum_{t=1}^n Z_{t-1} u_t \rightarrow_d N(0, I_p).$$

- Critical region: $\mathcal{R}_{n,\alpha} = \left\{ W_n > \chi_q^2 (1 - \alpha)^{-1} \right\}$
- $AR(p)$ parameter space:

$$\Theta = \left\{ \rho \in sp(R) : \text{there exist } M, \delta > 0 \text{ s.t. } |\rho| \leq M \text{ and } sp(R) \cap (-1 + \delta, 1 - \delta)^c \subset \mathbb{R} \right\}$$

Theorem (?)

$$\lim_{n \rightarrow \infty} \sup_{\theta \in \Theta} \mathbb{P}_{\theta}(\mathcal{R}_{n,\alpha}) = \alpha$$

Conclusion

- Question marks:
 - approximate the IV limit distribution under Δ_n^c (non-trivial Jordan form) when eigenvalues are close but not equal
 - Done for local to unit roots $\rho_{1n} = 1 + c_1/n$ and $\rho_{2n} = 1 + c_2/n$
 - Scale up the analysis of

$$D_n^{-1} \frac{1}{n} \sum_{t=1}^n X_{t-1} Z'_{t-1} D(\varphi_n)^{-1} \rightarrow_d \Psi, \quad \det(\Psi) \neq 0 \text{ a.s.}$$

from the $AR(2)$ to the $AR(p)$ case

- The method provides inference for $AR(p)$ processes without knowledge of:
 - type of eigenvalues (stable/unit/explosive)
 - integration order of the $AR(p)$ ranging from $I(0)$ to $I(p)$
- Extension to $VAR(p)$ interesting but difficult: in general, we lose the advantage of not having to worry about convergence of sequences of eigenvectors...