

Unit Roots in White Noise?!

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Abstract

We show that the empirical distribution of the roots of the vector auto-regression of order n fitted to T observations of a general stationary or non-stationary process, converges to the uniform distribution over the unit circle on the complex plane, when both T and n tend to infinity so that $(\ln T)/n \rightarrow 0$ and $n^3/T \rightarrow 0$.

Granger and Jeon (2006) have found that the roots of auto-regressions fitted to US macroeconomic series when plotted on the complex plane “lie in an indistinct ‘milky-way’ band or ‘halo’, with modulus around 0.8”. They speculate that such a strange pattern is due to the over-fitting and suggest a heuristic partial explanation of the phenomenon. In this paper, we study the roots of the characteristic polynomials of VAR fitted either to stationary or to non-stationary data. We show that the empirical distribution of the roots converges to the uniform distribution over the unit circle when both the sample size T and the order n of the fitted VAR tend to infinity so

that $(\ln T)/n \rightarrow 0$ and $n^3/T \rightarrow 0$. This convergence is independent from the covariance structure of the process approximated by VAR. In particular, even if the process is a white noise, the roots of the estimated vector auto-regression will converge by absolute value to unity.

We consider r -dimensional processes $y_t = (y'_{1t}, y'_{2t})'$ such that its r_1 -dimensional component y_{1t} and r_2 -dimensional component y_{2t} satisfy:

$$\begin{aligned} y_{1t} &= C_1 y_{2t} + u_{1t}, \\ \Delta y_{2t} &= u_{2t}, \end{aligned} \tag{1}$$

where $u_t = (u'_{1t}, u'_{2t})'$ has a VAR(∞) representation:

$$u_t + H_1 u_{t-1} + H_2 u_{t-2} + \dots = \eta_t. \tag{2}$$

Here $\{\dots, \eta_{-1}, \eta_0, \eta_1, \dots\}$ is a sequence of i.i.d. random $r \times 1$ vectors with mean $E\eta_t = 0$, positive definite covariance matrix $E\eta_t \eta'_t = \Sigma_\eta$ and finite fourth moments. We assume that the $r \times r$ coefficient matrices H_j are such that $\sum_{j=1}^{\infty} j \|H_j\| < \infty$, where $\|H_j\|$ is defined as $\sqrt{\text{tr } H_j H'_j}$, and $H(z) \equiv I_r + H_1 z + H_2 z^2 + \dots$ satisfies $\det H(z) \neq 0$ for $|z| \leq 1$. Note that the above DGP spans a wide range of processes from stationary invertible ARMA, when the dimensionality of y_{2t} is zero, to general cointegrated processes.

Let $\hat{A}_1, \dots, \hat{A}_n$ be the OLS estimates of the coefficient matrices of a vector auto-regression of n -th order fitted to T observations of y_t . Consider the estimated characteristic polynomial $\hat{P}_{n,T}(z) = \det \left(I_r z^n - \sum_{j=1}^n \hat{A}_j z^{n-j} \right)$.

Let us denote the number of the roots of $\hat{P}_{n,T}(z)$ that belong to a subset Ω of the complex plane as $N_{n,T}(\Omega)$. For any $0 < \delta < 1$ and $0 \leq \theta < \varphi \leq 2\pi$, let $C_\delta = \{z \in \mathbb{C} : 1 - \delta < |z| < 1 + \delta\}$ be an annulus in the complex plane that contains the unit circle and let $D_{\theta,\varphi} = \{z \in \mathbb{C} : \theta \leq \text{Arg}(z) \leq \varphi\}$ be a sector in the complex plane. Our result is as follows.

Theorem 1. *Let $\{y_t\}$ satisfy (1), and assume that n is chosen as a function of T so that $n^3/T \rightarrow 0$, $(\ln T)/n \rightarrow 0$, and $\sqrt{T}(\|H_n\| + \|H_{n+1}\| + \dots) \rightarrow 0$ as $T \rightarrow \infty$. Then, for any $0 < \delta < 1$ and any $0 \leq \theta < \varphi \leq 2\pi$, as $T \rightarrow \infty$:*

i) $\frac{1}{nr} N_{n,T}(D_{\theta,\varphi}) \xrightarrow{p} \frac{\varphi - \theta}{2\pi},$

ii) $\frac{1}{nr} N_{n,T}(C_\delta) \xrightarrow{p} 1.$

Figure 1 illustrates the result. It shows the roots of $\hat{P}_{n,T}(z)$ for $T = 100, n = 12$ (100 MC replications) and for $T = 1000, n = 48$ (33 MC replications). The upper panel of the Figure corresponds to y_t which is a univariate white noise, the lower panel of the Figure corresponds to y_t which is a univariate random walk. As T and n become larger, the roots stick to the unit circle in a uniform way for both the white noise and the random walk.

Note that $\hat{P}_{n,T}(z)$ can be interpreted as a polynomial with random coefficients. Shparo and Shur (1962) prove an equivalent of Theorem 1 for polynomials with i.i.d. coefficients under very general assumptions. For a beautiful geometric discussion of the properties of the roots of random polynomials which provides a piece of intuition for the Shparo and Shur's result see Edelman and Kostlan (1995). The contribution of this paper is to extend

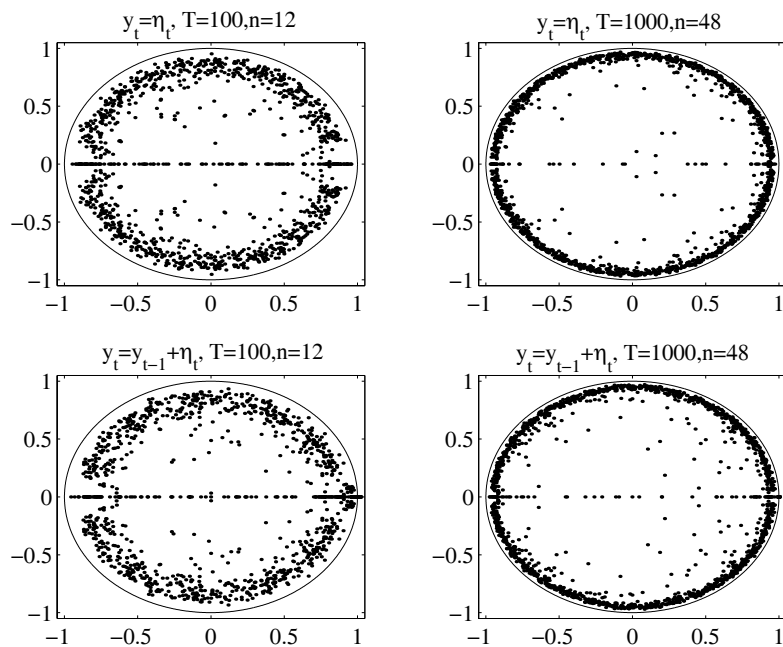


Figure 1: Characteristic roots of $\text{VAR}(n)$ fitted to T observations of different DGPs. Left panel: 100 MC replications, right panel: 33 MC replications.

Shparo and Shur (1962) to $\hat{P}_{n,T}(z)$ whose coefficients are functions of OLS estimates of the auto-regressive parameters, and therefore not i.i.d.

Let us now prove Theorem 1. First, we introduce the following notation. For any matrix M , we denote its j -th singular value, that is the square root of the j -th largest eigenvalue of MM' , as $\sigma_j(M)$. We will now describe useful asymptotic properties of $\hat{A} \equiv [\hat{A}_1, \dots, \hat{A}_n]$. As shown, for example, in Saikkonen and Lütkepohl (1996), y_t has the following VAR representation:

$y_t = A_1 y_{t-1} + \dots + A_n y_{t-n} + e_t$, where

$$\begin{aligned}
e_t &= R \left(\eta_t - \sum_{j=n}^{\infty} H_j u_{t-j} \right), \\
A_1 &= R (Q - H_1) R^{-1}, \\
A_j &= R (-H_j + H_{j-1} Q) R^{-1} \text{ for } j = 2, 3, \dots, n-1, \\
A_n &= -R H_{n-1} Q R^{-1},
\end{aligned} \tag{3}$$

and $R \equiv \begin{pmatrix} I_{r_1} & C_1 \\ 0 & I_{r_2} \end{pmatrix}$, $Q \equiv \begin{pmatrix} 0 & 0 \\ 0 & I_{r_2} \end{pmatrix}$. We have the following:

Lemma 1. *Under the conditions of Theorem 1, we have:*

- i) $\|\hat{A} - A\| = O_p(\sqrt{\frac{n}{T}})$, where $\hat{A} \equiv [\hat{A}_1, \dots, \hat{A}_n]$ and $A \equiv [A_1, \dots, A_n]$,
- ii) $\Pr(\sigma_r(\sqrt{T}(\hat{A}_n - A_n)) > \delta_T) \rightarrow 1$ for any sequence δ_T such that $\delta_T \rightarrow 0$ as $T \rightarrow \infty$.

A proof of Lemma 1 is available from us upon request. It uses the same techniques as proofs in Saikkonen and Lütkepohl (1996). For stationary DGP, the lemma follows from the proof of Theorem 1 and from Theorem 4 of Lewis and Reinsel (1985).

Now we are ready to prove statement i) of Theorem 1. Our main technical apparatus is the following lemma:

Lemma 2. *(Erdős and Turán, 1950) Let a_k , $k = 0, 1, \dots, rn$, be arbitrary complex numbers not all of which are equal to zero, and let $N(\theta, \varphi)$ denote the number of zeros of $F_{rn}(z) = \sum_{k=0}^{rn} a_k z^k$ that lie in the sector $0 \leq \theta \leq \arg z \leq \varphi$. Then, for $a_0 a_{rn} \neq 0$: $\left| N(\theta, \varphi) - \frac{(\varphi - \theta)rn}{2\pi} \right| < 16 \left[rn \ln \frac{\sum_{k=0}^{rn} |a_k|}{|a_0 a_{rn}|^{1/2}} \right]^{1/2}$.*

Taking $F_{rn}(z) \equiv \sum_{k=0}^{rn} a_k z^k = \det \left(z^n I_r - \sum_{j=1}^n \hat{A}_j z^{n-j} \right)$, we have: $a_0 a_{rn} = \det \left(-\hat{A}_n \right)$. Note that $\left| \det \left(\sqrt{T} \hat{A}_n \right) \right|^{1/r} \geq \sigma_r \left(\sqrt{T} \left(\hat{A}_n - A_n \right) \right) - \sqrt{T} \|A_n\|$. The second term in the latter difference converges to zero by the assumption that $\sqrt{T} (\|H_n\| + \|H_{n+1}\| + \dots) \rightarrow 0$. The first term satisfies Lemma lii) with, say, $\delta_T = n^{-1/2} + \sqrt{T} \|A_n\|$. Therefore,

$$\Pr \left(|a_0 a_{rn}| > (nT)^{-r/2} \right) \rightarrow 1. \quad (4)$$

By definition of the determinant, $F_{rn}(z) = \sum_{\tau} (-1)^{|\tau|} P_{1\tau(1)}(z) \dots P_{r\tau(r)}(z)$, where the summation is over all permutations of $1, 2, \dots, r$ and $P_{ij}(z) \equiv z^n - \hat{A}_{1,ij} z^{n-1} - \dots - \hat{A}_{n,ij}$. Such a representation implies that $\sum_{k=0}^{nr} |a_k| \leq \sum_{\tau} \prod_{i=1}^r \left(1 + \sum_{j=1}^n |\hat{A}_{j,i\tau(i)}| \right) \leq \sum_{\tau} \prod_{i=1}^r \left(1 + \sqrt{n} \|\hat{A} - A\| + \sum_{j=1}^n \|A_j\| \right)$, where the latter inequality uses the fact that for any vector $v = (v_1, \dots, v_n)$, $\sum_{j=1}^n |v_j| \leq \sqrt{n} \|v\|$. But formulas (3) and the assumption that $\sum_{j=1}^{\infty} j \|H_j\| < \infty$ imply that $\sum_{j=1}^{\infty} \|A_j\| < \infty$, and by Lemma li) $\sqrt{n} \|\hat{A} - A\| = o_p(1)$. Therefore, there exists a constant M such that $\Pr \left(\sum_{k=0}^{nr} |a_k| \leq M \right) \rightarrow 1$. Combining the latter convergence with (4), we obtain: $\Pr \left(\frac{\sum_{k=0}^{rn} |a_k|}{|a_0 a_{rn}|^{1/2}} < M (nT)^{r/4} \right) \rightarrow 1$.

This fact and Lemma 2 imply that

$\Pr \left(\left| \frac{N(\theta, \varphi)}{rn} - \frac{(\varphi - \theta)}{2\pi} \right| < 16 \sqrt{\frac{\ln M}{rn} + \frac{\ln T + \ln n}{4n}} \right) \rightarrow 1$ which proves statement i) of Theorem 1 because $\ln T/n \rightarrow 0$ by assumption.

Turning to the proof of statement ii), define $Z = [z^{-1} I_r, z^{-2} I_r, \dots, z^{-n} I_r]'$. Then $\hat{P}_{n,T}(z) = z^{rn} \det \left(I_r - AZ - (\hat{A} - A)Z \right)$, and therefore $\left| \hat{P}_{n,T}(z) \right|^{1/r} \geq$

$|z|^n \left(\sigma_r(I_r - AZ) - \sigma_1 \left((\hat{A} - A)Z \right) \right)$. Using (3), we get: $I_r - AZ = (I_r - Qz^{-1}) \left(I_r + \sum_{j=1}^{n-1} H_j z^{-j} \right)$. Note that the second term in the latter product converges to $H(z^{-1})$ uniformly outside the unit circle. Since $\det H(z) \neq 0$ for $|z| \leq 1$ and since $\sigma_r(I_r - Qz^{-1}) \geq 1 - |z|^{-1}$, there exists a positive constant c such that for any $|z| > 1 + \delta$ and large enough T , $\sigma_r(I_r - AZ) > c$. Further, $\sigma_1 \left((\hat{A} - A)Z \right) \leq \left\| \hat{A} - A \right\| \sigma_1(Z) = \left\| \hat{A} - A \right\| \sqrt{r \frac{1 - |z|^{-2n}}{|z|^2 - 1}} \leq \left\| \hat{A} - A \right\| \sqrt{\frac{r}{2\delta}} = o_p(1)$ uniformly over $|z| > 1 + \delta$. Summing up, $\min_{|z| > 1 + \delta} \left| \hat{P}_{n,T}(z) \right|^{1/r} \geq \min_{|z| > 1 + \delta} |z|^n (c - o_p(1)) > 0$ with probability arbitrarily close to one for large enough T . Hence, for any $\delta > 0$:

$$\Pr(N_{n,T}(B_{1+\delta}) = rn) \rightarrow 1, \quad (5)$$

where $B_{1+\delta}$ is the ball of radius $1 + \delta$ in the complex plane.

It remains to be shown that $\frac{1}{nr} N_{n,T}(B_{1-\delta}) \xrightarrow{p} 0$, or, in other words, that for any $\varepsilon > 0$, $\Pr\left(\frac{1}{nr} N_{n,T}(B_{1-\delta}) < \varepsilon\right) \rightarrow 1$ as $T \rightarrow \infty$. Let us fix an $\varepsilon > 0$ and let $\tau > 0$ be such that

$$-\ln(1 + \tau) / \ln(1 - \delta) = \varepsilon/2. \quad (6)$$

Let z_1, \dots, z_{rn} be the roots of $\hat{P}_{n,T}(z)$ so that $\hat{P}_{n,T}(z) = \prod_{i=1}^{rn} (z - z_i)$. Note that $\det(-\hat{A}_n)$ equals $(-1)^{rn} \prod_{i=1}^{rn} z_i$, and therefore, $\left| \det(\hat{A}_n) \right| = \prod_{i=1}^{rn} |z_i|$. Replacing δ by τ in (5), we see that all of $|z_i|$ are no larger than $1 + \tau$ with probability arbitrarily close to one for large enough T . Furthermore, by defi-

nition, there are $N_{n,T}(B_{1-\delta})$ of $|z_i|$ which are less than or equal $1 - \delta$. Thus, $\Pr\left(\left|\det\left(\sqrt{T}\hat{A}_n\right)\right| < T^{r/2}(1-\delta)^{N_{n,T}(B_{1-\delta})}(1+\tau)^{rn}\right) \rightarrow 1$. Using this convergence and (4), we have: $\Pr\left(n^{-r/2} < T^{r/2}(1-\delta)^{N_{n,T}(B_{1-\delta})}(1+\tau)^{rn}\right) \rightarrow 1$. Taking logarithms of the both sides of the latter inequality, rearranging and recalling (6), we get: $\Pr\left(\frac{1}{nr}N_{n,T}(B_{1-\delta}) < \frac{\varepsilon}{2} + \frac{1}{2n} \frac{\ln T + \ln n}{-\ln(1-\delta)}\right) \rightarrow 1$ which implies that $\Pr\left(\frac{1}{nr}N_{n,T}(B_{1-\delta}) < \varepsilon\right) \rightarrow 1$.

Q.E.D.

In conclusion, we would like to point out that the striking ubiquity of unit roots established by Theorem 1 does not have negative implications for the econometric procedures not directly based on the estimated roots. For example, univariate stationary processes that satisfy the conditions of Theorem 1 would satisfy Berk's (1974) conditions for the consistency and asymptotic normality of the auto-regressive spectral estimates. For another example, the critical coefficient in the "long" augmented Dickey-Fuller regression would not behave peculiarly because it is related to the characteristic roots of the regression only through their sum.

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