# Limiting Behavior of the Eigenvalues of a Multivariate F Matrix 

Y. Q. Yin<br>China University of Science and Technology<br>and University of Pittsburgh<br>Z. D. BAI<br>China University of Science and Technology<br>P. R. Krishnaiah*<br>University of Pittsburgh<br>Communicated by the Editors

The spectral distribution of a central multivariate $F$ matrix is shown to tend to a limit distribution in probability under certain conditions as the number of variables and the degrees of freedom tend to infinity.

## 1. Introduction

Let $\lambda_{1} \leqslant \cdots \leqslant \lambda_{n}$ denote the eigenvalues of a random matrix $Z=\left(z_{i j}\right): n \times n$. Then, the distribution function $C(x)$ defined by

$$
C(x)=\frac{1}{n} \nRightarrow\left\{i: \lambda_{i} \leqslant x\right\}
$$

is known to be the spectral distribution of the matrix $Z$ where $\#\}$ denotes the number of elements of the set $\{$.$\} . Jonsson [2,3]$ showed that the spectral distribution of the Wishart matrix (divided by its degrees of freedom) has a

Received December 1, 1982.
AMS 1980 Subject Classification Numbers: Primary 62E20; Secondary 62H10.
Key Words and Phrases: Eigenvalues, $F$ matrix, limiting behavior, large dimensional random matrices, and spectral distribution.

* The work of this author is sponsored by the Air Force Office of Scientific Research under Contract F49620-82-K-0001. The U.S. Government's right to retain a nonexclusive royaltyfree license in and to the copyright covering this paper, for governmental purposes, is acknowledged.
limit distribution as the number of variables and the degrees of freedom both tend to infinity such that their ratio tends to a limit. Wachter [4] proved a similar but more general result. Yin and Krishnaiah [5] showed that the spectral distribution of $Z=W T$ tends to a limit distribution under certain conditions when $p$ and $m$ tend to infinity such that their ratio tends to a limit. Here $W: p \times p$ is a Wishart matrix (divided by its degrees of freedom $m$ ) and $T: p \times p$ is a random matrix distributed independent of $W$ and has a limit spectral distribution.

In this paper, we first prove bounds on the distribution functions of the largest and smallest eigenvalues of the Wishart matrix. Then, we prove that the spectral distribution of $n S_{1} S_{2}^{-1}$ tends to a limit distribution in probability as $p, m$ and $n$ tend to infinity such that $(p / m) \rightarrow y$ and $(p / n) \rightarrow y^{\prime}<\frac{1}{2}$; here $S_{1}: p \times p$ and $S_{2}: p \times p$ are distributed independently as central Wishart matrices with $m$ and $n$ degrees of freedom respectively. This is the main result of the paper and it is proved by applying a result of Yin and Krishnaiah [5].

## 2. Preliminaries

We need the following results in the sequel.
Lemma 2.1. If $0<r<\frac{1}{2}$, then the unit ball in $R^{p}$ can be covered by balls of radius $r$ in such a way that the number of these smaller balls does not exceed $C \exp \left\{(p / 2) \log \left(2 \pi e / r^{2}\right)\right\}$ where $C$ is a positive constant.

Proof. First, we cover the unit ball by nonoverlapping $p$-cubes of side length ( $2 r / \sqrt{p}$ ). All these cubes can be included in a bigger ball with radius $1+2 r$. So, the sum of these volumes cannot exceed the volume of the latter ball. Thus the number of these balls cannot exceed $V_{0} / V_{1}$ where $V_{0}$ is the volume of $p$-ball of radius $(1+2 r)$ and $V_{1}$ is the volume of $p$-cube with side $(r / \sqrt{p})$. But,

$$
V_{0}=2 \pi^{p / 2}(1+2 r)^{p} / p \Gamma\left(\frac{p}{2}\right), \quad V_{1}=\left(\frac{r}{\sqrt{p}}\right)^{p}
$$

Now, applying Stirling's formula, we obtain

$$
\begin{equation*}
\frac{V_{0}}{V_{1}} \leqslant C \exp \left\{\left(\frac{p}{2}\right) \log \left(\frac{2 \pi e}{r^{2}}\right)\right\} . \tag{2.1}
\end{equation*}
$$

We need the following lemma in the sequel:

Lemma 2.2. For $M>0$ and $\varepsilon>0$

$$
\begin{align*}
& P\left[\chi_{n}^{2} \geqslant n M\right] \leqslant \exp \{-n(M-\log 4) / 4\}  \tag{2.2}\\
& P\left[\chi_{n}^{2} \leqslant n \varepsilon\right] \leqslant C \exp \left\{-\frac{n}{2} \log (1 / e \varepsilon)\right\} \tag{2.3}
\end{align*}
$$

where $\chi^{2}$ is distributed as chi-square with $n$ degrees of freedom.
Lemma 2.3. If $A \geqslant 0$ is a $p \times p$ matrix, and $\bar{\lambda}$ is the largest eigenvalue of $A$, then

$$
\begin{equation*}
\left|x^{\prime} A x-y^{\prime} A y\right| \leqslant \bar{\lambda}|x-y||x+y| \tag{2.4}
\end{equation*}
$$

for any vectors $x$ and $y$ of order $p \times 1$ where $|x|$ denotes Eucledian norm.
Throughout this paper, the transpose of a matrix $B$ is denoted by $B^{\prime}$.

## 3. Bounds on the Extreme Eigenvalues of the Wishart Matrix

Let $\left\{Y_{i j} ; i, j=1,2, \ldots\right\}$ be a double sequence of independent random variables which are distributed normally with mean zero and variance one. Also, let $Y_{n}$ denote the $p \times n$ matrix ( $Y_{i j}(i=1,2, \ldots, p, j=1,2, \ldots, n)$. Here $p=p(n)$ and the ratio $p / n$ has a finite limit $y>0$ as $n$ tends to infinity. Next, let $\bar{\lambda}_{n}$ and $\underline{\lambda}_{n}$ respectively denote the largest and smallest eigenvalues of $A_{n}=Y_{n} Y_{n}^{\prime} / n$. We now establish the following bound on the distribution function of $\bar{\lambda}_{n}$.

Theorem 3.1. There are positive constants $C, D$ and $M_{0}$ such that

$$
\begin{equation*}
P\left\{\bar{\lambda}_{n} \geqslant M\right\} \leqslant C \exp \{-D M n\} \tag{3.1}
\end{equation*}
$$

when $M>M_{0}$ and $n=1,2, \ldots$
Proof. Let $M_{1}>0$ be such that $\sqrt{2 \pi e} \exp (-M / 64)<1 / 12$ when $M \geqslant M_{1}$. Also, let $M_{0}=\max \left(M_{1}, 64 \log 2\right)$. Now, let $M>M_{0}$ and $r=\sqrt{2 \pi e} \exp (-M / 64)$. Then $0<r<1 / 2$ and $r(r+2)<1 / 4$. We cover the unit ball $B_{p}(0,1)$ in $R^{p}$ with the origin as center by balls of radius $r$. Suppose, these smaller balls are $B_{p}\left(x_{1}, r\right), \ldots, B_{p}\left(x_{q}, r\right)$ with centers $x_{1}, \ldots, x_{q}$, respectively. By Lemma 2.1 , we can choose the covering in such a way that

$$
q \leqslant C \exp \left\{\frac{p}{2} \log \left(2 \pi e / r^{2}\right)\right\}
$$

Also,

$$
\begin{aligned}
P\left[\bar{\lambda}_{n} \geqslant M\right] & =P\left[\max _{z \in B_{p}(0,1)} z^{\prime} A_{n} z \geqslant M\right] \\
& \leqslant \sum_{k=1}^{m} P\left\{\max _{z \in B_{p}\left(x_{k}, r\right) \cap B_{p}(0,1)} z^{\prime} A_{n} z \geqslant M, \bar{\lambda}_{n} \leqslant 2 M\right\}+P\left\{\bar{\lambda}_{n} \geqslant 2 M\right\} .
\end{aligned}
$$

But, if $z \in B_{p}\left(x_{k}, r\right) \cap B_{p}(0,1), z^{\prime} A_{n} z \geqslant M, \bar{\lambda}_{n} \leqslant 2 M$, then

$$
\begin{aligned}
x_{k}^{\prime} A_{n} x_{k} & \geqslant z^{\prime} A_{n} z-\left|z^{\prime} A_{n} z-x_{k}^{\prime} A_{n} x_{k}\right| \\
& \geqslant M-2 M\left|z-x_{k}\right|\left|z+x_{k}\right| \\
& \geqslant M-2 M r(1+1+r) \geqslant \frac{M}{2}
\end{aligned}
$$

by using (2.3). So,

$$
\begin{equation*}
P\left(\bar{\lambda}_{n} \geqslant M\right) \leqslant \sum_{k=1}^{q} P\left\{x_{k}^{\prime} A_{n} x_{k} \geqslant \frac{M}{2}\right\}+P\left(\bar{\lambda}_{n} \geqslant 2 M\right) . \tag{3.2}
\end{equation*}
$$

By a well-known property of the Wishart matrix, we observe that

$$
\begin{equation*}
P\left(x_{k}^{\prime} A_{n} x_{k} \geqslant M / 2\right)=P\left\{\chi_{n}^{2} \geqslant \frac{n M}{2 x_{k}^{\prime} x_{k}}\right\} \leqslant P\left\{\chi_{n}^{2} \geqslant \frac{n M}{2(1+r)^{2}}\right\} . \tag{3.3}
\end{equation*}
$$

Applying Lemma 2.2, we have

$$
\begin{equation*}
P\left(x_{k}^{\prime} A_{n} x_{k} \geqslant \frac{M}{2}\right) \leqslant \exp \left(-\frac{n}{4}\left(\frac{M}{8}-\log 4\right)\right\} \tag{3.4}
\end{equation*}
$$

Thus,

$$
\begin{align*}
P\left(\bar{\lambda}_{n} \geqslant M\right)-P\left(\bar{\lambda}_{n} \geqslant 2 M\right) & \leqslant q \exp \left\{-\frac{n}{4}\left(\frac{M}{8}-\log 4\right)\right\} \\
& \leqslant C \exp \left\{\frac{p}{2} \log \frac{2 \pi e}{r^{2}}-\frac{n}{4}\left(\frac{M}{8}-\log 4\right)\right\} \\
& \leqslant C \exp \left\{\frac{n}{2}\left[y \log \frac{2 \pi e}{r^{2}}-\frac{M}{16}+\log 2\right]\right\} \\
& \leqslant C \exp \left\{\frac{n}{2}\left[\frac{M y}{32}-\frac{M}{16}+\log 2\right]\right\} \\
& \leqslant C \exp \left\{\frac{n}{2}\left[-\frac{M}{32}+\log 2\right]\right\} \\
& \leqslant C \exp \left\{\frac{n}{2}\left\{-\frac{M}{64}\right\}\right\} \tag{3.5}
\end{align*}
$$

by using (3.2), (3.4) and Lemma 2.1.

Replace $M$ by $2^{k} M$, and add these inequalities together to get the result required. We now prove a bound on the distribution function of $\lambda_{n}$.

Theorem 3.2. Let $y<\frac{1}{2}$. Then

$$
\begin{equation*}
P\left(\lambda_{n} \leqslant \varepsilon\right) \leqslant C D^{n} \varepsilon^{a n}, \quad 0<\varepsilon \leqslant \varepsilon_{0}, \tag{3.6}
\end{equation*}
$$

where $C, D$ and $\alpha$ are positive constants.
Proof. Let $1<\beta<1 / 2 y, \alpha=1 / 2 y-\beta, \gamma=\varepsilon^{\beta} / 3$ and $K=\varepsilon^{1-\beta}$. Also, let $B_{p}\left(x_{1}, r\right), \ldots, B_{p}\left(x_{q}, r\right)$ be $p$-balls with radius $r$ and centers $x_{1}, \ldots, x_{q}$ respectively, which cover the unit $p$-sphere $S_{p}(0,1)$. In addition, let $q$ satisfy the inequality

$$
\begin{equation*}
q \leqslant C \exp \left\{\frac{p}{2} \log \frac{2 \pi e}{r^{2}}\right\} . \tag{3.7}
\end{equation*}
$$

Such balls exist by Lemma 2.1. We have

$$
P\left\{\underline{\lambda}_{n} \leqslant \varepsilon\right\} \leqslant \sum_{k=1}^{q} P\left\{_{z \in B_{p}\left(x_{k}, r\right) \cap s_{p}(0,1)} z^{\prime} A_{n} z \leqslant \varepsilon, \bar{\lambda}_{n}<K\right\}+P\left\{\bar{\lambda}_{n} \geqslant K\right\} .
$$

If $z \in B_{p}\left(x_{k}, r\right) \cap S_{p}(0,1), z^{\prime} A_{n} z \leqslant \varepsilon, \bar{\lambda}_{n}<K$, then

$$
\begin{aligned}
x_{k}^{\prime} A_{n} x_{k} & \leqslant z^{\prime} A_{n} z+\left|x_{k}^{\prime} A_{n} x_{k}-z^{\prime} A_{n} z\right| \\
& \leqslant \varepsilon+\bar{\lambda}_{n}\left|x_{k}-z\right|\left|x_{k}+z\right| \\
& \leqslant \varepsilon+K \cdot r(2+r) \leqslant 2 \varepsilon .
\end{aligned}
$$

Thus

$$
P\left(\lambda_{n} \leqslant \varepsilon\right) \leqslant \sum_{k=1}^{q} P\left\{x_{k}^{\prime} A_{n} x_{k} \leqslant 2 \varepsilon\right\}+P\left\{\bar{\lambda}_{n} \geqslant K\right\} .
$$

But,

$$
\begin{aligned}
P\left\{x_{k}^{\prime} A_{n} x_{k} \leqslant 2 \varepsilon\right\} & =P\left\{\chi_{n}^{2} \leqslant \frac{2 n \varepsilon}{x_{k}^{\prime} x_{k}}\right\} \leqslant P\left\{\chi_{n}^{2} \leqslant \frac{2 n \varepsilon}{(1-r)^{2}}\right\} \\
& \leqslant C \exp \left\{-\frac{n}{2} \log \frac{(1-r)^{2}}{2 e \varepsilon}\right\},
\end{aligned}
$$

by Lemma 2.2. Therefore

$$
\begin{aligned}
P\left(\lambda_{n} \leqslant \varepsilon\right) & \leqslant C \exp \left\{\frac{p}{2} \log \frac{2 \pi e}{r^{2}}\right\} \exp \left\{-\frac{n}{2} \log \frac{(1-r)^{2}}{2 e \varepsilon}\right\}+P\left\{\bar{\lambda}_{n} \geqslant K\right\} \\
& \leqslant C\left(\frac{2 \pi e}{r^{2}}\right)^{n y / 2} \cdot \frac{\varepsilon^{n / 2}(2 e)^{n / 2}}{(1-r)^{n}}+C e^{-D_{1} K n} \\
& \leqslant C D_{2}^{n} \varepsilon^{-\beta y n+n / 2}+C e^{-n \varepsilon^{1-B D_{1}}} \\
& \leqslant C D_{2}^{n} \varepsilon^{\alpha n}+C \exp \left\{-n \varepsilon^{-\delta} D_{1}\right\}, \quad \text { if } \quad 0<\varepsilon \leqslant \varepsilon_{0}
\end{aligned}
$$

Here $\alpha=\frac{1}{2}-\beta y>0, \delta=\beta-1>0$. But,

$$
D_{2}^{n} \varepsilon^{\alpha n} \exp \left\{n \varepsilon^{-\delta} D_{1}\right\} \geqslant 1
$$

as $\varepsilon$ is small. So

$$
P\left(\lambda_{n} \leqslant \varepsilon\right) \leqslant C D^{n} \varepsilon^{\alpha n}
$$

for $0<\varepsilon \leqslant \varepsilon_{0}$, and for some constant $\varepsilon_{0}$.
Geman [1] showed that $\bar{\lambda}_{n}$ tends to $\left(1+y^{1 / 2}\right)^{2}$ a.s. where $\lim _{p, n \rightarrow \infty}(p / n)=y$ and $0<y<\infty$.

## 4. Proof of the Main Theorem

We now apply the following theorem of Yin and Krishnaiah [5] to prove our main theorem.

Theorem 4.1 (Yin-Krishnaiah [5]). Let $\left\{X_{i j} ; i=1,2, \ldots, j=1,2, \ldots\right\}$ and $X_{m}: p \times m$ be as defined in Section 3. Also, let $W_{p}=(1 / m) X_{m} X_{m}^{T}$. In addition, let $T_{p}$ be a symmetrie $p \times p$ matrix of random variables with spectral distribution $G_{p}(x)$. We assume that the following conditions are satisfied:
(1) $\left\{X_{i j}\right\}$ and $T_{p}$ are independent for each $p$,
(2) $\lim (p / m)=y$ exists and finite,
(3) $\int x^{k} d G_{p}(x) \rightarrow H_{k} \quad$ exists in $\quad L^{2}(P)$, for $\quad k=1,2, \ldots$, and $\sum H_{2 k}^{-1 / 2 k}=+\infty$,
Then the spectral distribution of $W_{p} T_{p}, F_{p}(x)$, tends to a limit $F(x)$ (nonrandom) in probability for each $x$.

We will verify that the conditions of the above theorem in Yin and Krishnaiah [5] are satisfied for our case.

In this section, we prove the following main theorem of our paper:
Theorem 4.2. Suppose $\left\{X_{i j}, Y_{k l}, i, j, k, l=1,2, \ldots\right\}$ are iid, $X_{11} \sim N(0,1)$, $X_{m}=\left(X_{i j}, i=1, \ldots, p ; j=1, \ldots, m\right), Y_{n}=\left(Y_{k l}, k=1, \ldots, p ; l=1, \ldots, n\right)$. Then, the spectral distribution of $\left((1 / m) X_{m} X_{m}^{\prime}\right)\left((1 / n) Y_{n} Y_{n}^{\prime}\right)^{-1}$ has a nonrandom limit distribution (in probability) as $p \rightarrow \infty$, if $p / m \rightarrow y^{\prime}, p / n \rightarrow y<\frac{1}{2}$ exist.

Theorem 4.3. $\quad(1 / p) \operatorname{tr} T_{p}^{k} \rightarrow H_{k}$ in $L^{2}(P)$, as $p \rightarrow \infty$, and

$$
\sum H_{2 k}^{-1 / 2 k}=\infty
$$

Proof. Let $F_{n}(x)$ be the spectral distribution of the matrix ( $1 / n$ ) $Y_{n} Y_{n}^{\prime}=$ $T_{p}^{-1}$. By Jonsson's theorem [2, Theorem 2.1], $F_{n}(x) \rightarrow F_{y}(x)$ where $F_{y}(x)$ is a distribution function with density function

$$
\begin{aligned}
f_{y}(x) & =\frac{\sqrt{(x-a)(b-x)}}{2 \pi x y}, & & a<x<b, \\
& =0, & & \text { otherwise }
\end{aligned}
$$

with $a=(1-\sqrt{y})^{2}, b=(1+\sqrt{y})^{2}$. Since

$$
\frac{1}{p} \operatorname{tr} T_{p}^{k}=\int_{0}^{\infty} x^{-k} d F_{n}(x)
$$

it is sufficient to prove

$$
\int_{0}^{\infty} x^{-k} d F_{n}(x) \rightarrow \int_{0}^{\infty} x^{-k} d F_{y}(x) \quad \text { in } \quad L^{2}(P)
$$

and

$$
\sum_{k}\left\{\int_{0}^{\infty} x^{-2 k} d F_{y}(x)\right\}^{-1 / 2 k}=+\infty
$$

The latter requirement is easy to see. We have

$$
\int_{0}^{\infty} x^{-2 k} d F_{y}(x)=\int_{a}^{b} x^{-2 k} d F_{y}(x) \leqslant a^{-2 k}
$$

Therefore

$$
\sum\left\{\int_{0}^{\infty} x^{-2 k} d F_{y}(x)\right\}^{-1 / 2 k} \geqslant \sum_{k=1}^{\infty} a=+\infty
$$

For the first requirement, by Minkowski's inequality, we have

$$
\begin{aligned}
E^{1 / 2} & \left|\int_{0}^{\infty} x^{-k} d F_{n}(x)-\int_{0}^{\infty} x^{-k} d F_{y}(x)\right|^{2} \\
& \leqslant E^{1 / 2}\left|\int_{0}^{\varepsilon} x^{-k} d F_{n}(x)\right|^{2}+E^{1 / 2} \mid \int_{\varepsilon}^{K} x^{-k} d\left[F_{n}(x)-F_{y}(x)| |^{2}\right. \\
& +E^{1 / 2}\left|\int_{K}^{\infty} x^{-k} d F_{n}(x)\right|^{2}=I_{1}^{1 / 2}+I_{2}^{1 / 2}+I_{3}^{1 / 2},
\end{aligned}
$$

if $0<\varepsilon<a<b<K$. Now we consider $I_{1}$ :

$$
\begin{aligned}
I_{1} & =E\left[\left|\int_{0}^{\varepsilon} x^{-k} d F_{n}(x)\right|^{2} ; \underline{\lambda}_{n} \leqslant \varepsilon\right] \leqslant E\left[\underline{\lambda}_{n}^{-2 k} ; \underline{\lambda}_{n} \leqslant \varepsilon\right] \\
& =\int_{0}^{\varepsilon} x^{-2 k} d P\left(\lambda_{n} \leqslant x\right) .
\end{aligned}
$$

Integrating by parts, and using Theorem 2.2, we see that

$$
\begin{aligned}
I_{1} & \leqslant \int_{0}^{\varepsilon} x^{-2 k} d P\left(\lambda_{n} \leqslant x\right) \leqslant \varepsilon^{-2 k} P\left(\lambda_{n} \leqslant \varepsilon\right)+2 k C D^{n} \frac{\varepsilon^{n \alpha-2 k}}{n \alpha-2 k} \\
& \leqslant C D^{n} \varepsilon^{n \alpha-2 k}+k C D^{n} \frac{\varepsilon^{n \alpha-2 k}}{n \alpha-2 k} \rightarrow 0
\end{aligned}
$$

as $n \rightarrow \infty$, if we choose $\varepsilon^{a}<1 / D$.
For $I_{2}$, we have

$$
\begin{aligned}
I_{2}^{1 / 2} \leqslant & E^{1 / 2}\left|K^{-k}\left(F_{n}(K)-F_{y}(K)\right)\right|^{2} \\
& +E^{1 / 2}\left|\varepsilon^{-k}\left(F_{n}(\varepsilon)-F_{y}(\varepsilon)\right)\right|^{2} \\
& +E^{1 / 2}\left|k \int_{\varepsilon}^{K} x^{-k-1}\left(F_{n}(x)-F_{y}(x)\right) d x\right|^{2} \\
= & J_{1}+J_{2}+J_{3} .
\end{aligned}
$$

By Jonsson's theorem, $F_{n}(c)-F_{y}(c) \rightarrow 0$ in prob. for any $c$, and thus $J_{1}, J_{2}$ both tend to 0 . Also,

$$
\begin{aligned}
J_{3}^{2} & \leqslant k^{2} \int_{\epsilon}^{K} x^{-2 k-2} d x E \int_{\varepsilon}^{K}\left(F_{n}(x)-F_{y}(x)\right)^{2} d x \\
& =k \varepsilon^{-2 k-2}(K-\varepsilon) \cdot \int_{0}^{K} E\left(F_{n}(x)-F_{y}(x)\right)^{2} d x \\
& \rightarrow 0 \quad \text { as } \quad n \rightarrow \infty .
\end{aligned}
$$

Thus, Theorem 4.3 is proved. Therefore the main theorem is proved.

## References

[1] Geman, S. (1980). A limit theorem for the norm of random matrices. Ann. Probab. 8, 252-261.
[2] Jonsson, D. (1976). Some limit theorems for the eigenvalues of a sample covariance matrix. Technical Report No. 6, Department of Mathematics, Uppsala University, Uppsala.
[3] Jonsson, D. (1976). Some limit theorems for the eigenvalues of a sample covariance matrix. J. Multivar. Anal. 12, 1-38.
[4]. Wachter, K. W. (1978). The strong limits of random matrix spectra for sample matrices of independent elements. Ann. Probab. 6, 1-18.
[5] Yin, Y. Q., and Krishnaiah, P. R. (1983). Limit theorems for the eigenvalues of product of two random matrices. J. Multivar. Anal. 13, 489-507.

