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ASYMPTOTIC PROPERTIES OF A CORRELATION COEFFICIENT TYPE STATISTIC CONNECTED WITH THE GENERAL LINEAR MODEL.

Laurens de Haan and Elselien Taconis - Haantjes

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#### I. Introduction

The general linear model can be described as follows. The n-dimensional stochastic vector \*J  $\underline{y} = (\underline{y}_i)_{i=1}^n$  has a normal distribution with  $\underline{E}\underline{y} = X\beta$  and  $Cov\ \underline{y} = \sigma^2 I$  where I is the nxn identity matrix and X a known nxk matrix of full rank  $(k \le n)$ ;  $\sigma^2$  and the components of  $\beta$  are unknown parameters. We will be concerned with the situation where the first column of X is  $(1,1,\ldots,1)^T$ . The maximum likelihood estimator of  $\beta$  is  $\hat{\beta} = (X^TX)^{-1}X^T\underline{y}$ .

We follow Theil ([5] p. 163-179, see also [3]) and wish to compare the length of the vectors Ny and NXB where N = I -  $\frac{1}{n}$  11 with 1 = (1,1,...,1). Thus e.g.  $\underline{y}^T N \underline{y} = \Sigma \underline{y}_1^2 - (\Sigma \underline{y}_1)^2$ . In an econometrical context it is usual to consider the quotient:

$$\underline{R}_{n}^{2} = \frac{\hat{\underline{\beta}}^{T} \mathbf{X}^{T} \mathbf{N} \mathbf{X} \hat{\underline{\beta}}}{\mathbf{y}^{T} \mathbf{N} \mathbf{y}}$$

It is wellknown [3] that if for some  $\theta > 0$ 

(1) 
$$\lim_{n\to\infty} \frac{\beta^{T} x^{T} N X \beta}{n\sigma^{2}} = 0$$

then  $\lim_{n\to\infty}\frac{\mathbb{R}^2}{n}=\frac{\theta}{\theta+1}$  in probability. Observe that (1) holds if  $\lim_{n\to\infty}\frac{x^T NX}{\sigma^2}=A$  a positive definite matrix. Write  $\rho^2=\frac{\theta}{\theta+1}$ .

Using the fact that  $\frac{R^2}{n}$  has a non-central  $\beta$ -distribution, we prove (section 2) that  $\frac{R^2}{n}$  is asymptotically normal provided

(2) 
$$\lim_{n\to\infty} \sqrt{n} \left( \frac{\beta^{T} X^{T} N X \beta}{n \sigma^{2}} - \Theta \right) = 0.$$

<sup>\*</sup> J Underlined letters represent random variables (or random vectors).

In view of an adjustment of  $\underline{R}_n^2$  for practical use ((5) p. 178-179) we derive an asymptotic expression for  $\underline{ER}_n^2$  (section 3) under the stronger assumption

(3) 
$$\lim_{n\to\infty} n \left( \frac{\beta^T X^T N X \beta}{n\sigma^2} - \Theta \right) = c$$

for some real c. We were lead to this investigation by our failure to understand Barten's argument [1] leading to a different asymptotic expression for  $ER_n^2$ .

#### II Asymptotic normality

We can write  $\underline{R}_n^2$  as:

$$\underline{R}_{n}^{2} = \frac{\left| n \underline{x} \hat{\underline{\beta}} \right|^{2}}{\left| n \underline{x} \hat{\underline{\beta}} \right|^{2} + \left| \underline{y} - \underline{x} \hat{\underline{\beta}} \right|^{2}}.$$

Here  $|\underline{y} - \underline{x}\underline{\hat{\mu}}|^2/\sigma^2$  has a chi-squared distribution with n-k degrees of freedom. The distribution of  $N\underline{x}\underline{\hat{\mu}} = N\underline{x}(\underline{x}^T\underline{x})^{-1}\underline{x}^T\underline{y}$  is normal with mean vector NXB and covariance matrix  $\sigma^2I$ . The matrix  $N\underline{x}(\underline{x}^T\underline{x})^{-1}\underline{x}^T$  is symmetric and idempotent with rank k-1 so  $|N\underline{x}\underline{\hat{\mu}}|^2/\sigma^2$  has a non-central chi-squared distribution with k-1 degrees of freedom and non-centrality parameter  $\underline{\beta}^T\underline{x}^TN\underline{x}\beta/\sigma^2 = \underline{\theta}_n$ . Furthermore  $\underline{x}\underline{\hat{\mu}}$  and  $|\underline{y}-\underline{x}\underline{\hat{\mu}}|^2$  are independent

so  $\frac{R^2}{n}$  has a non-central  $\beta$ -distribution with k-1 and n-k degrees of freedom and non-centrality parameter  $\theta$  ([2] p. 213).

freedom and non-centrality parameter  $\theta_n$  ([2] p. 213). We will now prove that  $\sqrt{n}$  ( $\underline{R}^2_n - \rho^2$ ) has a limiting normal distribution. Write

$$\underline{R}_{n}^{2} = \frac{\underline{B}^{2}}{\underline{B}^{2} + \underline{C}^{2}}$$

where  $\underline{B}^2 \hookrightarrow \chi^2(k-1,\theta_n)$ ,  $\underline{C}^2 \hookrightarrow \chi^2(n-k)$  and  $\lim_{n\to\infty} n^{-1} \theta_n = \theta = \rho^2/(1-\rho^2)$ .

Now

(4) 
$$\sqrt{n} \left( \underline{R}_{n}^{2} - \rho^{2} \right) = \sqrt{n} \frac{\underline{B}^{2} - \underline{C}^{2}\Theta}{\left( \underline{B}^{2} + \underline{C}^{2} \right) (1 + \Theta)} = \frac{\frac{1}{\sqrt{n}} \underline{B}^{2} - \frac{1}{\sqrt{n}} \underline{C}^{2}\Theta}{\frac{1}{n} (\underline{B}^{2} + \underline{C}^{2}) (1 + \Theta)}.$$

We first consider the denominator. According to the weak law of large numbers  $\frac{1}{n} \underline{c}^2$  converges to 1 in probability. Write  $\frac{1}{n} \underline{B}^2 = \frac{1}{n} |\underline{w} - \sqrt{\Theta_n}|^2$  with  $|\underline{w}|^2 = \sum_{i=1}^{k-1} \underline{w}_i^2$  and  $\underline{w}_i$  are independent and standard normal. It follows  $\lim_{n \to \infty} \frac{1}{n} \underline{B}^2 = \lim_{n \to \infty} \frac{1}{n} \Theta_n = \Theta$ . Hence  $\lim_{n \to \infty} \frac{1}{n} (\underline{B}^2 + \underline{c}^2) (\Theta + 1) = (\Theta + 1)^2$  in probability.

The numerator of (4) can be written as

(5) 
$$\frac{1}{\sqrt{n}} \left( \underline{B}^2 - \Theta_n \right) - \frac{\Theta}{\sqrt{n}} \left( \underline{C}^2 - n \right) + \sqrt{n} \left( \frac{\Theta_n}{n} - \Theta \right).$$

Since  $\frac{1}{\sqrt{n}} (\underline{B}^2 - \theta_n)$  and  $\frac{\theta}{\sqrt{n}} (\underline{C}^2 - n)$  are independent, we have to prove that each part of (5) has a limiting distribution. Now

$$\frac{1}{\sqrt{n}} (\underline{B}^2 - \Theta_n) = \frac{1}{\sqrt{n}} \sum_{i=1}^{k} \underline{w}_i^2 - \frac{2}{\sqrt{n}} \sum_{i=1}^{k-1} w_i \sqrt{\Theta}_n.$$

The first part tends to zero and the second part is  $\mathbb{N}(0,\frac{4\theta}{n})$ . Thus the distribution of  $\frac{1}{\sqrt{n}}(\underline{B}^2 - \theta_n)$  tends to a normal distribution with mean zero and variance  $4\theta$ .

We apply the central limit theorem to find, that the second part  $\frac{\theta}{\sqrt{n}}$  ( $\underline{c}^2$ -n) of (5) is asymptotically N(0,2 $\theta^2$ ).

Combining our results and applying (2) we have that  $\sqrt{n}(\underline{R}_n^2 - \rho^2)$  converges in law to

$$N \left(0, \frac{20^2 + 40}{(0+1)^4}\right) = N (0, 2\rho^2 (1-\rho^2)^2 (2-\rho^2)).$$

## III. The limiting behaviour of $\mathbb{E}_n^2$ .

We know that  $\frac{R^2}{n}$  has a non-central  $\beta$ -distribution with non-centrality parameter  $\theta_n$ . So its density  $g(r^2)$  is [4]

$$g(\mathbf{r}^2) = \sum_{\beta=0}^{\infty} e^{-\frac{1}{2}\theta_n} \frac{\left(\frac{1}{2}\theta_n\right)^{\beta}}{\beta!} \frac{\Gamma(\frac{n-1}{2} + \beta)}{\Gamma(\frac{k-1}{2} + \beta)\Gamma(\frac{n-k}{2})}.$$

$$\frac{\frac{k-1}{2} + \beta - 1}{(1-r^2)} \frac{\frac{n-k}{2} - 1}{(1-r^2)}.$$

The expectation of  $\underline{R}_{n}^{2}$  can be written as

$$\mathbb{E}_{\mathbf{n}}^{2} = \sum_{\beta=0}^{\infty} e^{-\frac{1}{2}\theta_{\mathbf{n}}} \frac{\left(\frac{1}{2}\theta_{\mathbf{n}}\right)^{\beta}}{\beta!} \frac{\Gamma(\frac{\mathbf{n}-1}{2}+\beta)}{\Gamma(\frac{\mathbf{k}-1}{2}+\beta)\Gamma(\frac{\mathbf{n}-\mathbf{k}}{2})} \cdot \frac{\Gamma(\frac{\mathbf{k}-1}{2}+\beta)\Gamma(\frac{\mathbf{n}-\mathbf{k}}{2})}{\frac{1}{2}\Gamma(\frac{\mathbf{k}-1}{2}+\beta)\Gamma(\frac{\mathbf{n}-\mathbf{k}}{2})} \cdot \frac{\Gamma(\frac{\mathbf{n}-1}{2}+\beta)}{\frac{1}{2}\Gamma(\frac{\mathbf{n}-1}{2}+\beta)\Gamma(\frac{\mathbf{n}-\mathbf{k}}{2})} \frac{\Gamma(\frac{\mathbf{k}-1}{2}+\beta+1)\Gamma(\frac{\mathbf{n}-\mathbf{k}}{2})}{\Gamma(\frac{\mathbf{n}-1}{2}+\beta)\Gamma(\frac{\mathbf{n}-\mathbf{k}}{2})} = \sum_{\beta=0}^{\infty} e^{-\frac{1}{2}\theta_{\mathbf{n}}} \frac{\left(\frac{1}{2}\theta_{\mathbf{n}}\right)^{\beta}}{\frac{2}{2}\Gamma(\frac{\mathbf{k}-1}{2}+\beta)} \cdot \frac{\frac{\mathbf{k}-1}{2}+\beta}{\frac{2}{2}\Gamma(\frac{\mathbf{n}-1}{2}+\beta)\Gamma(\frac{\mathbf{n}-\mathbf{k}}{2})} \cdot \frac{\Gamma(\frac{\mathbf{n}-1}{2}+\beta+1)\Gamma(\frac{\mathbf{n}-\mathbf{k}}{2})}{\frac{2}{2}\Gamma(\frac{\mathbf{n}-1}{2}+\beta+1)} = \sum_{\beta=0}^{\infty} e^{-\frac{1}{2}\theta_{\mathbf{n}}} \frac{\left(\frac{1}{2}\theta_{\mathbf{n}}\right)^{\beta}}{\frac{2}{2}\Gamma(\frac{\mathbf{n}-1}{2}+\beta)} \cdot \frac{\mathbf{k}-1}{2} + \beta} \cdot \frac{\mathbf{n}-\mathbf{k}}{\mathbf{n}-1} \cdot \frac{\mathbf{n}-\mathbf{k}}{\mathbf{n}-1} \cdot \frac{\mathbf{n}-\mathbf{k}}{\mathbf{n}-1}}{\mathbf{n}-1} \cdot \frac{\mathbf{n}-\mathbf{k}}{\mathbf{n}-1} \cdot \frac{\mathbf{n}-\mathbf{k}}{\mathbf{n}-1} \cdot \frac{\mathbf{n}-\mathbf{k}}{\mathbf{n}-1}}{\mathbf{n}-1} \cdot \frac{\mathbf{n}-\mathbf{k}}{\mathbf{n}-1} \cdot \frac{\mathbf{n}-\mathbf{k}}{\mathbf{n}-1} \cdot \frac{\mathbf{n}-\mathbf{k}}{\mathbf{n}-1}}{\mathbf{n}-1} \cdot \frac{\mathbf{n}-\mathbf{k}}{\mathbf{n}-1} \cdot \frac{\mathbf{n}-1}{\mathbf{n}-1} \cdot \frac{\mathbf{n}-1}{\mathbf{n}-1} \cdot \frac{\mathbf{n}-1$$

$$= \sum_{\beta=0}^{\infty} e^{-\frac{1}{2}\Theta_{n}} \frac{\left(\frac{1}{2}\Theta_{n}\right)^{\beta}}{\beta!} \frac{\frac{k-1}{2} + \beta}{\frac{n-1}{2} + \beta}$$

So 
$$1 - \mathbb{E}\mathbb{E}_{n}^{2} = \frac{n-k}{n-1} \sum_{\beta=0}^{\infty} e^{-\frac{1}{2}\Theta_{n}} \frac{\left(\frac{1}{2}\Theta_{n}\right)^{\beta}}{\beta!} \frac{1}{1 + \frac{2\beta}{n-1}}$$

We write 
$$\int_{0}^{\infty} e^{\frac{-2\beta}{n-1} \cdot x - x} dx \text{ for } (1 + \frac{2\beta}{n-1})^{-1} \text{ and obtain}$$

$$1 - \mathbb{E}_{n}^{2} = \frac{n-k}{n-1} \int_{0}^{\infty} e^{-x} \int_{\beta=0}^{\infty} e^{-\frac{1}{2}\theta_{n}} \frac{(\frac{1}{2}\theta_{n})^{\beta}}{\beta!} e^{\frac{-2\beta x}{n-1}} dx$$

$$= \frac{n-k}{n-1} \int_{0}^{\infty} e^{-x} e^{-\frac{1}{2}\theta_{n}} \exp \left[\frac{-\frac{2x}{n-1}}{\frac{1}{2}\theta_{n}e^{-x}}\right] dx$$

First we prove that 
$$\lim_{n\to\infty} n \{(1-\rho_n^2) - (1-\underline{ER}^2)\} = constant$$

where 
$$1 - \rho_n^2 = \frac{n-k}{n-1} \left(1 + \frac{\Theta}{n-1}\right)^{-1} = \frac{n-k}{n-1} \int_{0}^{\infty} e^{-x(1 + \frac{\Theta}{n-1})} dx$$
.

Now 
$$n \{(1-\rho_n^2) - (1-\mathbb{E}_n^2)\} = n \begin{cases} \frac{n-k}{n-1} \int_0^\infty e^{-x(1+\frac{\Theta_n}{n-1})} dx + \end{cases}$$

$$-\frac{n-k}{n-1}\int_{0}^{\infty}e^{-x}e^{-\frac{1}{2}\theta}n\exp\left[\frac{1}{2}\theta_{n}e^{-\frac{1}{2}\theta}\right]dx$$

$$=n\frac{n-k}{n-1}\int_{0}^{\infty}e^{-x}\left[\frac{-x\theta_{n}}{n-1}e^{-\frac{1}{2}\theta_{n}}e^$$

(6) 
$$= n \frac{n-k}{n-1} \int_{0}^{\infty} e^{-x(1 + \frac{\theta}{n-1})} \left[ 1 - \exp \frac{1}{2}\theta_{n} \left( e^{-x} - 1 + \frac{2x}{n-1} \right) \right] dx.$$

The next step is to compare this integral with the following expression

(7) 
$$-n \frac{n-k}{n-1} \int_{0}^{\infty} e^{-x\left(1 + \frac{\Theta}{n-1}\right)} \left[ \frac{-2x}{n-1} \right]_{e} dx$$

which can be evaluated explicitly and converges to  $\frac{-20}{(1+0)^3}$  as  $n\to\infty$ . We will show that the difference between (7) and (6) tends to zero. This difference can be written as

(8) 
$$\frac{n-k}{n-1} \int_{0}^{\infty} -x(1+\frac{\theta_{n}}{n-1}) \left[ g_{n}(x) - 1 - g_{n}(x) \right] dx$$

with 
$$g_n(x) = \frac{-2x}{n-1}$$
 with  $g_n(x) = \frac{1}{2}\Theta_n(e^{-1} + \frac{2x}{n-1})$ .

We are going to use the following simple properties

(9) 
$$\frac{e^{x}-1-x}{x^{2}}$$
 is an increasing function of x when x > 0,

(10) 
$$0 < e^{-y} - 1 + y \le y$$
 if  $y > 0$  and

(11) 
$$0 < e^{-y} - 1 + y < \frac{1}{2}y^2 \text{ if } y > 0.$$

We split the integral (8) into two parts 
$$\int_{0}^{\infty} = \int_{0}^{f_{n}} + \int_{n}^{\infty}$$

and will prove that both integrals converge to zero. First we consider the second part, then (use (10))

$$0 < \int_{n}^{\infty} e^{-x(1 + \frac{\Theta_{n}}{n-1})} \left[ g_{n}(x) - 1 - g_{n}(x) \right] dx$$

$$\frac{1}{2} \int_{0}^{\infty} e^{-x(1+\frac{\Theta}{n-1})} \left[ \frac{\frac{\Theta}{n}x}{\frac{n-1}{n-1}} - \frac{\Theta}{n-1}x \right] dx$$

$$\leq \int_{f_n}^{\infty} e^{-x(1+\frac{\Theta_n}{n-1})} \frac{\frac{\Theta_n x}{n-1}}{n} dx = \begin{bmatrix} -x \end{bmatrix}_{f_n}^{\infty} = n e^{-f_n}.$$

Let for instance  $f_n = 2 \log n$  then  $\lim_{n \to \infty} n = \lim_{n \to \infty} e_n = 0$ 

Next consider the first part, then (use (11) and (9) successively)

$$0 < \int_{0}^{f} e^{-x(1 + \frac{\Theta_{n}}{n-1})} \left[ g_{n}(x) - 1 - g_{n}(x) \right] dx$$

$$\leq \int_{0}^{n} e^{-x(1 + \frac{\Theta_{n}}{n-1})} \left[ \frac{2\Theta_{n}x^{2}}{e^{(n-1)^{2}} - 1 - \frac{2\Theta_{n}x^{2}}{(n-1)^{2}}} \right] dx$$

$$\leq \int_{0}^{f_{n}} n \left[ \frac{\frac{2\theta_{n}x^{2}}{(n-1)^{2}}}{e^{-1} - \frac{2\theta_{n}x^{2}}{(n-1)^{2}}} \right] dx$$

$$\frac{\frac{2\theta_{n}f_{n}^{2}}{(n-1)^{2}}}{e^{\frac{2\theta_{n}f_{n}^{2}}{(n-1)^{2}}}} \int_{0}^{f_{n}} \frac{\int_{u_{n}}^{f_{n}} \int_{u_{n}}^{f_{n}} dx}{\int_{u_{n}}^{4\theta_{n}f_{n}} \int_{u_{n}}^{f_{n}} dx}$$

$$= \frac{\frac{2\theta_{n}f_{n}^{2}}{(n-1)^{2}}}{\frac{4\theta_{n}^{2}f_{n}^{4}}{(n-1)^{4}}} \cdot \frac{\frac{2\theta_{n}f_{n}^{2}}{(n-1)^{4}}}{\frac{4n\theta_{n}^{2}f_{n}^{5}}{(n-1)^{4}}}.$$

Hence the first part also converges to zero as n→∞ and thus

$$\lim_{n\to\infty} n \{(1-\rho_n^2)-(1-\mathbb{E}_n^2)\} = \frac{-2\theta}{(1+\theta)^3} = -2\rho^2(1-\rho^2)^2.$$

Up to now we only used assumption (1). We get

$$\lim_{n\to\infty} n \{(1-\rho^2)-(1-\mathbb{E}_n^2)\} = (1-\rho^2)\{k-1+(c-2\rho^2)(1-\rho^2)\}$$

provided assumption (3) holds i.e.

$$\lim_{n\to\infty} n \left( \frac{\beta^T x^T N X \beta}{n \sigma^2} - \Theta \right) = c.$$

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- [5] Theil H. (1971). Principles of Econometrics. North Holland Publishing Company, Amsterdam.