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TO NONNORMALITY

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Abstract: A comprehensive empirical evaluation is presented of the sensitivity to nonnormality of the main tests for individual effects in a one–way error components panel data model.

Key words: Panel data, Nonnormality, Monte Carlo analysis, Hypothesis testing, Error components model.

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1. Introduction

The use of panel data has become increasingly popular in econometrics over the last decade. Several models and approaches are able to deal with the key features of these data sets (see *Mátyás and Sevestre* [1992]), however, the error components model (especially its one–way version, with individual effects only) remains the most frequently used framework. In the one–way error components model it is crucial to test for the presence of individual effects, because without these effects the usual econometric methods can be applied for estimation and inference, but when present special procedures are needed.

Most of the tests for the presence of individual effects in an error components model assume normally distributed disturbances. One must, however, be concerned with the effects of nonnormalty on the behaviour of these procedures, particularly in small samples, which are characteristic of econometric studies. In a substantial number of empirical applications the normality assumption can be unrealistic. For example, *Baltagi and Levin* [1992] analysed cigarette consumption through a log-linear consumption function. It would be hard to find any evidence to support the underlying assumption on the log-normality of the error terms in the original nonlinear model. It is, therefore, quite likely that the error terms in the estimated model were not normally distributed, and as a result the reported (diagnostic) test results were misleading.

This analysis attempts to evaluate the robustness of the F, one and two sided LM, and the LR tests for individual effects in a panel data context against nonnormality. Using Monte Carlo simulation the power, actual and nominal sizes of the tests are compared.

2. Framework of the analysis

The one–way error components model with individual effects is

$$y = X\beta + u = X\beta + \mu \otimes l_T + v \tag{1}$$

or

$$y_{it} = X'_{it}\beta + u_{it},$$

where

$$y = \begin{pmatrix} y_{11} \\ \vdots \\ y_{1T} \\ \vdots \\ y_{N1} \\ \vdots \\ y_{NT} \end{pmatrix} \quad \text{and} \quad X = \begin{pmatrix} 1 & x_{11}^2 & \cdots & x_{11}^K \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{NT}^2 & \cdots & x_{NT}^K \end{pmatrix},$$

u_{it} can be decomposed as $u_{it} = \mu_i + v_{it}$, μ_i is the random variable of individual effects, μ is the random vector of individual effects $(N \times 1)$, v_{it} is the usual error term, v is the vector of the error terms, l is the vector of ones, N is the number of individuals and T is the length of times series.

We assume that

H_1. The random variables μ_i and v_{it} are independent for all i and t.

H_2. $E(\mu_i) = 0, \quad E(v_{it}) = 0.$

H_3.

$$E(v_{it}v_{i't'}) = \begin{cases} \sigma_v^2 & i = i',\, t = t' \\ 0 & \text{otherwise.} \end{cases}$$

H_4.

$$E(\mu_i\mu_{i'}) = \begin{cases} \sigma_\mu^2 & i = i' \\ 0 & \text{otherwise.} \end{cases}$$

We are interested in testing the null hypothesis $H_0 : \sigma_\mu^2 = 0$ against the alternative hypothesis $H_A : \sigma_\mu^2 \neq 0$.

The *variance decomposition* test (Mátyás [1992]) is based on the test statistic

$$\frac{\widehat{u}'(I_N \otimes \frac{J_T}{T})\widehat{u}\,(N-K)^{-1}}{\widehat{u}'(I_{NT} - (I_N \otimes \frac{J_T}{T}))\widehat{u}\,[N(T-1)-K]^{-1}}$$

2

which is distributed as an $F(N-K, N(T-1)-(K-1))$ random variable under H_0, where $\hat{u}$ is the OLS residual, I is the identity matrix of given size and J is the matrix of ones of given size.

The *two sided LM* test (*Breusch and Pagan* [1980]) is based on the

$$\left(\frac{NT}{2(N-1)}\right)\left(\frac{\hat{u}'(I_N \otimes J_T)\hat{u}}{\hat{u}'\hat{u}} - 1\right)^2$$

test statistic which under H_0 is distributed as a $\mathcal{X}^2$ random variable with 1 degree of freedom.

The *one sided LM* test (*Baltagi et al.* [1992], *Moulton and Randolph* [1989], and *Honda* [1985]) is based on the

$$\left(\frac{NT}{2(N-1)}\right)^{\frac{1}{2}}\left(\frac{\hat{u}'(I_N \otimes J_T)\hat{u}}{\hat{u}'\hat{u}} - 1\right)$$

test statistic which under the null hypothesis $H_0 : \sigma_\mu^2 = 0$ (against the alternative hypothesis $H_A : \sigma_\mu^2 > 0$) has standard normal asymptotic distribution if N & $T \to \infty$.

The *LR* test (*Baltagi et al.* [1992]) is based on the test statistic

$$-2\log\frac{\text{likelihood(restricted)}}{\text{likelihood(unrestricted)}}$$

which has an asymptotic (N & $T \to \infty$) $\mathcal{X}^2$ distribution with 1 degree of freedom. To compute this test the iterative method proposed by *Oberhofer and Kmenta* [1974] and *Breush* [1987] was used.

The basic model used for the Monte Carlo data generation is

$$y_{it} = a_1 x_{it}^{(1)} + a_2 x_{it}^{(2)} + u_{it}$$

where

$u_{it} = \mu_i + v_{it}$ for the analysis of the power, and

$u_{it} = v_{it}$ for the analysis of the size of the given test,

$x_{it}^{(j)} = x_{it-1}^{(j)} + \varepsilon_{it}^{(j)}$ $j = 1, 2$

$\varepsilon_{it}^{(j)} = Uniform[-0.5, 0.5]$ and/or $N(0,1)$, $\varepsilon_{i0}^{(j)} \sim N(0,1)$ $j = 1, 2$,

$i = 1, \ldots N$, $t = 1, \ldots T$, $T = 10, 15, 25$, $N = 25, 100$ and $a_1 = a_2 = 0.5$.

3

Departures from normality are generally considered in terms of kurtosis and skewness. Skewness is measured by $\sqrt{\beta_1} = \nu_3/\nu_2^{3/2}$ where ν_i is the i-th moment about the mean, and for symmetric distributions its value is zero. Kurtosis is measured by $\beta_2 = \nu_4/\nu_2^2$. For the normal distribution its value is 3, with longer tailed distributions having larger values (and vice versa).

The following scenarios are considered:

A) μ_i is nonnormal, v_{it} is $N(0,1)$;

B) μ_i is $N(0,1)$, v_{it} is nonnormal;

C) both μ_i and v_{it} are nonnormal.

The nonnormal distributions used are (more about these distributions can be found in *Evans et al.* [1993]):

1. Exponential distribution (with parameter $= 1$), with skewness 2, and kurtosis 9.

2. Lognormal distribution $(1,1)$ (that is generated from $N(-0.347, 0.833)$) with skewness 4 and kurtosis 41.

3. $t(5)$ distribution, with skewness 0 and kurtosis 9.

4. Cauchy distribution $(0,2)$, with no finite moments.

We also attempt to isolate the effects of skewness and kurtosis on the behaviour of these tests. In a similar way to *Evans* [1992] we use the generalisation of Tukey's lambda distribution introduced by *Ramberg et al.* [1979] (RTDM distribution). The mean is set to zero and the variance to unity, then we generated the RTDM distribution for all the combinations of skewness 0.5 (light right), 0.6 (medium right) and 0.8 (heavy right) and kurtosis 2.4 and 3 (light tail), 5 (medium tail) and 9 (heavy tail).[1]

The most important problem in our analysis is that the distribution of the composite disturbance term in formula (1) is the result of the sum of two independent random variables. It is well known that the sum of two independent normal random variables is also normal. But unfortunately, for the other distributions and the linear combination of these, the analytical derivation of the distribution of the composite disturbance term is quite complex:

$$h(u_{it}) = \int_{-\infty}^{\infty} f(u_{it} - v_{it})g(v_{it})dv_{it} \qquad (2)$$

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[1] Except the case skewness=0.8 and kurtosis=2.4 which is not feasible.

where h, f, and g are the densities of u_{it}, μ_i and v_{it} respectively. So instead of deriving the skewness and kurtosis for the distribution of u_{it} using (2), we characterize it by its empirical skewness and kurtosis.

3. Simulation results

We focus the evaluation of the simulation results on the power and the size of the tests.

From our point of view there are two important questions to answer:

- as the power of a consistent test converges to one as the sample size increases, what is the speed of this convergence, and

- simultaneously what is the behaviour of the size of the test(s)?

At 5% significance level for most of the distribution combinations of μ_i and v_{it} the power of all tests was 1 even at the smallest sample size analysed ($N = 25$, $T = 10$). The exception was the case when the Cauchy distribution was assumed for v_{it}. In these cases the convergence rate was much slower than for the other pairs of distributions. This is related to the power function, that is how far the null and the alternative hypotheses are from each other. Defining by $\rho = \sigma_\mu^2/(\sigma_\mu^2 + \sigma_v^2)$ the variance ratio, when ρ is close to zero the null is close to the alternative and when it is close to unity the null is well away from the alternative. The ratio ρ is around 0.4–0.5 when v_{it} is not Cauchy or v_{it} and μ_i are both Cauchy, but is near zero if v_{it} is Cauchy but μ_i is not.[2]

Using the RTDM distribution it seems that the skewness and the kurtosis have little effect on the power, given that all the different combinations of skewness and kurtosis lead to power one very quickly. With the RTDM distribution it was also easy to confirm that for a given ρ (ρ=0.01, 0.05, 0.1, 0.2, and 0.5) all the analysed tests have quite similar power behaviour. (See Tables 1–4.) When the null is close to the alternative ($\rho = 0.01$) the F test seems to outperform the other tests, while the two sided LM test seems to be less powerful for all types of distributions, regardless of the sample size. In small samples (see Graphs 1–4) the ranking is systematically F, LM1,

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[2] Using the empirical variance for the Cauchy distribution.

LR, and LM2 tests which reinforces our findings about the good power behaviour of the F test and the poor performance of LM2 test.

All this suggests that there is more interesting action for us in the size of the tests.

We analysed the size of the tests at 5% significance level. The results suggest (see Tables 5–6) that the empirical size of the F test is consistently close to the true 5% size both in small and large samples. While in large samples there is not too much difference between the LM1, LM2, and LR tests, in small samples the LM1 test is performing quite well. The relative fragility of these runner up tests is well illustrated by the fact that we observed for some distributions sizes of 0.29 and 0.71 for the LR test, 0.32 and 0.58 for the LM1 test and 0.30 and 0.62 for the LM2 test. The good news is the robust performance of the F test.

We carried out our experiment using two different types of distributions in the generation of the exogenous variables (ε_{it} normal and uniform). It seems that the choice of this does not affect our main findings. However, the use of the normal distribution led to less stable results: extreme size and power was recorded more frequently for all tests.

It is legitimate to ask why these results. The F test is based on the ration of the Between and Within variances (see *Mátyás* [1992]), whereas the LM tests are based on the ratio between the Between and Total variaces. While they use the same information, the F test takes much more into account the panel feature (or heterogeneity) of the data by using both the Between and Within variances which could be the reason for its robust behaviour. We believe that the poor performance of the LR test is more related to the way this test is carried out than to its theoretical characteristics. The numerical methods available to maximize the (constrained) likelihood in most of the computer packages[3] are slow and not very efficient, which may affect the final outcome of a Monte Carlo simulation where thousands of replications are necessary.

The above results have an additional consequence. In an error components model the usual procedure is to assume that the random (individual) specific effects are independent of the white noise components of the model (in (1) μ_i and v_{it} are assumed to be independent). This (not always realistic) assumption is not really needed anymore. This was necessary to maintain the normality of the overall disturbance term for easy inference. But, in light of our results and those of *Evans* [1992], perhaps there is no more need for this assumption given that there are (nearly) always robust

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[3] Gauss has been used for this evaluation.

Graph 1: Power of Test for Normal Dist.
(s=0, k=3.0, N=25 and T=10)

Power

Rho

F-test   LM2-test   LM1-test   LR-test
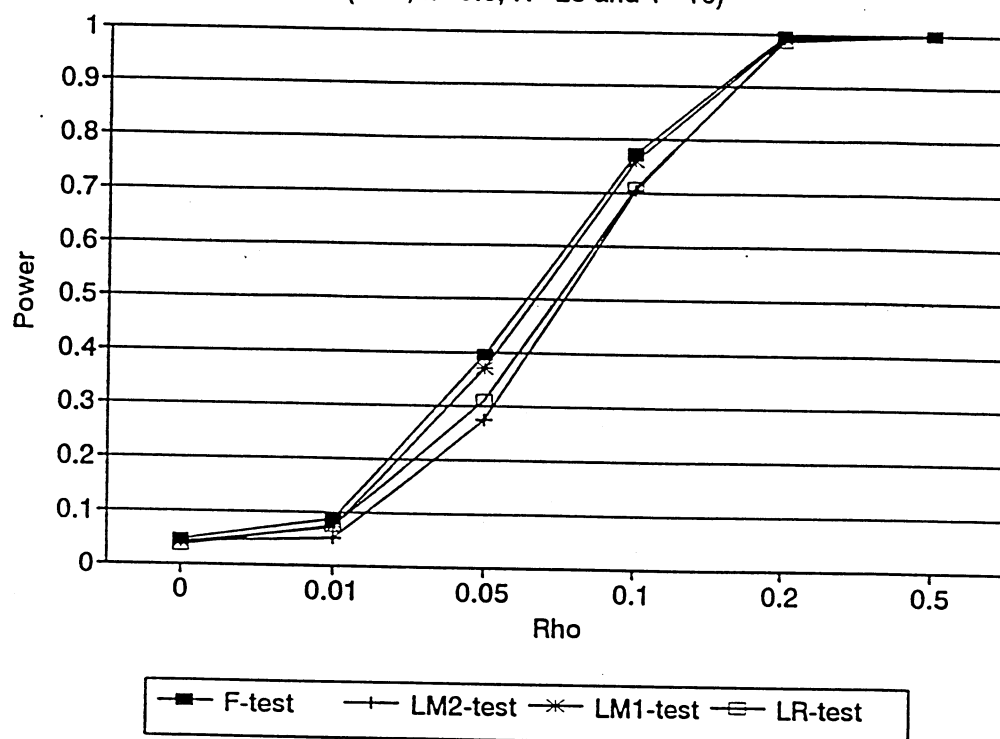
Graph 2: Power, Medium Tail & Skewness
(s=0.6, k=5.0, N=25 and T=10)

Power

Rho

F-test   LM2-test   LM1-test   LR-test

7
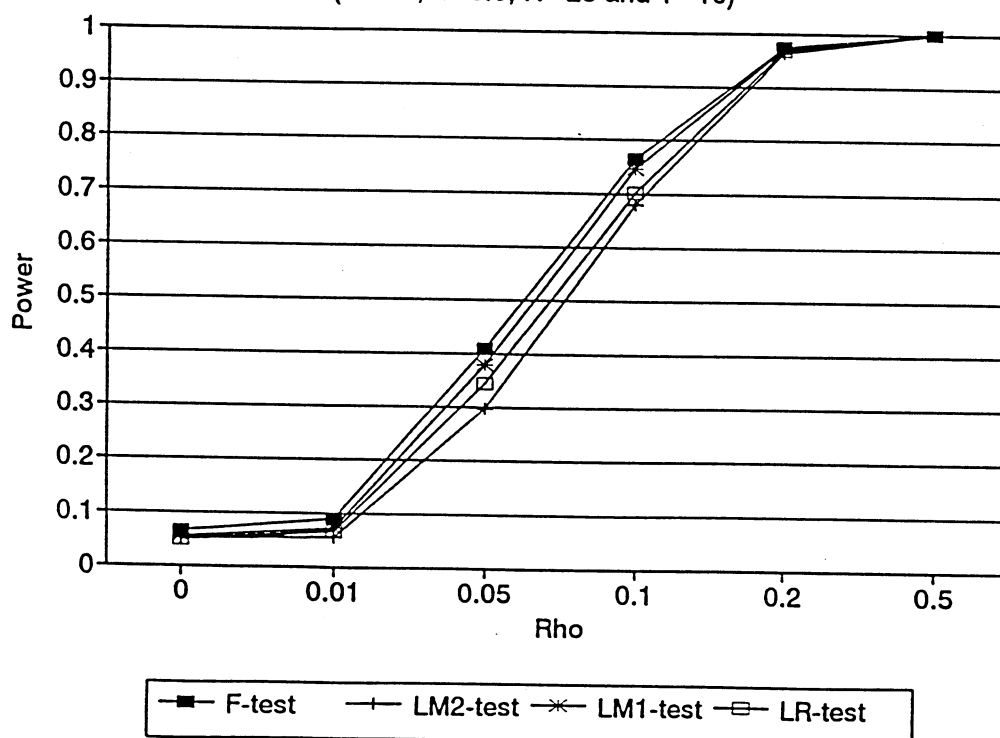
Graph 3: Power, Heavy Tail
(s=0, k=9.0, N=25 and T=10)

F-test   LM2-test   LM1-test   LR-test
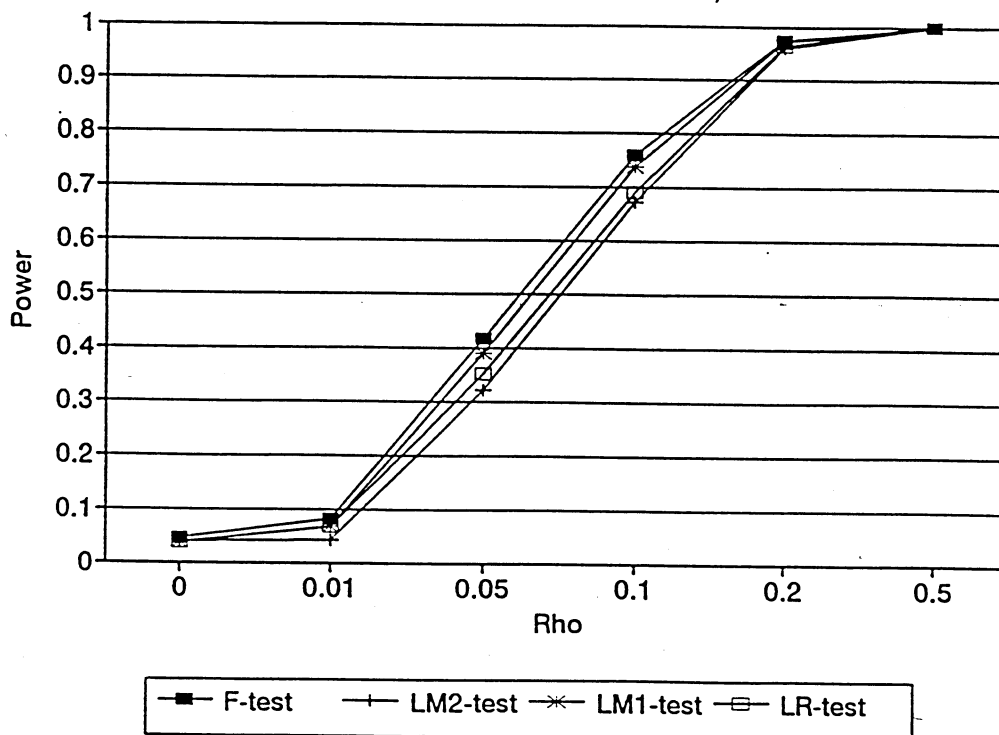
Graph 4: Power, Heavy Skewness
(s=0.8, k=3, N=25 and T=10)

F-test   LM2-test   LM1-test   LR-test
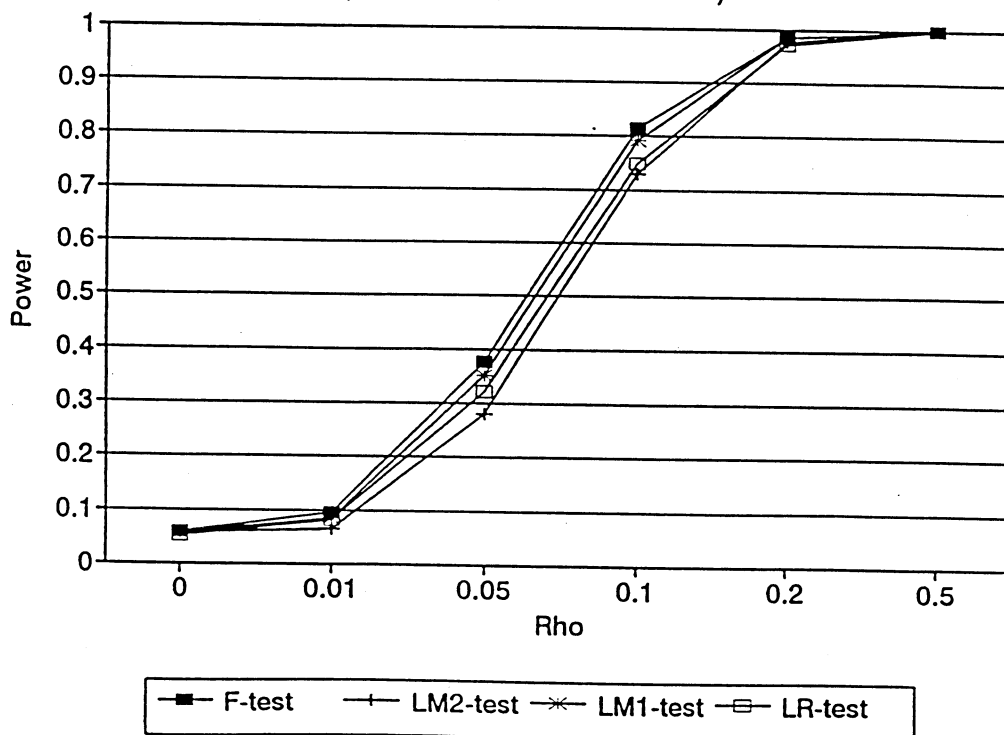
TABLE 1

Power of tests for the standard normal distribution

(skewness = 0;   kurtosis = 3)

T	Test	N=25				N=100			
		F	LM2	LM1	LR	F	LM2	LM1	LR
10	$\rho = 0$	45	42	39	35	55	45	53	65
	$\rho = 0.01$	86	49	72	73	170	114	163	153
	$\rho = 0.05$	395	274	370	310	882	802	871	825
	$\rho = 0.1$	772	703	759	707	999	995	995	995
	$\rho = 0.2$	994	983	991	985	1000	1000	1000	1000
	$\rho = 0.5$	1000	1000	1000	1000	1000	1000	1000	1000
15	$\rho = 0$	57	35	45	38	47	50	41	42
	$\rho = 0.01$	127	81	108	106	261	165	249	236
	$\rho = 0.05$	633	532	614	562	986	972	985	981
	$\rho = 0.1$	940	918	935	910	1000	1000	1000	1000
	$\rho = 0.2$	996	998	997	1000	1000	1000	1000	1000
	$\rho = 0.5$	1000	1000	1000	1000	1000	1000	1000	1000
25	$\rho = 0$	46	45	43	43	53	51	49	64
	$\rho = 0.01$	203	116	189	141	463	344	455	425
	$\rho = 0.05$	882	823	870	828	1000	1000	1000	1000
	$\rho = 0.01$	993	992	994	991	1000	1000	1000	1000
	$\rho = 0.2$	1000	1000	1000	1000	1000	1000	1000	1000
	$\rho = 0.5$	1000	1000	1000	1000	1000	1000	1000	1000

(ε_{it} has a uniform distribution)

TABLE 2

Power of tests for medium tail and medium skewness

(skewness = 0.6; kurtosis = 5.0)

T	Test	N=25				N=100			
		F	LM2	LM1	LR	F	LM2	LM1	LR
10	$\rho = 0$	65	49	54	47	43	43	38	45
	$\rho = 0.01$	88	54	71	65	172	119	162	156
	$\rho = 0.05$	408	297	377	344	879	805	874	819
	$\rho = 0.1$	762	679	745	700	999	997	999	999
	$\rho = 0.2$	973	962	971	866	1000	1000	1000	1000
	$\rho = 0.5$	1000	1000	1000	1000	1000	1000	1000	1000
15	$\rho = 0$	51	33	42	41	52	42	49	60
	$\rho = 0.01$	135	73	122	101	247	173	238	215
	$\rho = 0.05$	629	543	609	548	978	963	979	969
	$\rho = 0.1$	904	854	890	856	1000	1000	1000	1000
	$\rho = 0.2$	997	995	997	1000	1000	1000	1000	1000
	$\rho = 0.5$	1000	1000	1000	1000	1000	1000	1000	1000
25	$\rho = 0$	44	30	37	36	53	48	51	60
	$\rho = 0.01$	193	118	179	144	449	368	445	426
	$\rho = 0.05$	851	791	834	796	1000	1000	1000	1000
	$\rho = 0.01$	982	772	980	970	1000	1000	1000	1000
	$\rho = 0.2$	1000	1000	1000	1000	1000	1000	1000	1000
	$\rho = 0.5$	1000	1000	1000	1000	1000	1000	1000	1000

(ε_{it} has a uniform distribution)

TABLE 3

Power of tests for heavy tail

(skewness = 0; kurtosis = 9.0)

T	Test	N=25				N=100			
		F	LM2	LM1	LR	F	LM2	LM1	LR
10	$\rho = 0$	45	39	38	37	42	33	41	47
	$\rho = 0.01$	81	41	68	66	179	121	174	159
	$\rho = 0.05$	415	321	388	350	850	786	846	804
	$\rho = 0.1$	759	672	737	689	998	995	997	996
	$\rho = 0.2$	973	959	971	962	1000	1000	1000	1000
	$\rho = 0.5$	1000	1000	1000	1000	1000	1000	1000	1000
15	$\rho = 0$	40	38	35	36	48	46	47	60
	$\rho = 0.01$	127	74	110	95	247	157	237	209
	$\rho = 0.05$	604	520	578	540	985	968	982	976
	$\rho = 0.1$	897	836	879	841	1000	1000	1000	1000
	$\rho = 0.2$	996	989	991	989	1000	1000	1000	1000
	$\rho = 0.5$	1000	1000	1000	1000	1000	1000	1000	1000
25	$\rho = 0$	43	34	36	40	42	42	41	38
	$\rho = 0.01$	212	143	194	158	489	373	481	426
	$\rho = 0.05$	838	777	826	781	1000	997	999	996
	$\rho = 0.01$	979	963	976	969	1000	1000	1000	1000
	$\rho = 0.2$	1000	1000	1000	1000	1000	1000	1000	1000
	$\rho = 0.5$	1000	1000	1000	1000	1000	1000	1000	1000

(ε_{it} has a uniform distribution)

TABLE 4

Power of tests for heavy skewness

(skewness = 0.8; kurtosis = 3)

T	Test	N=25				N=100			
		F	LM2	LM1	LR	F	LM2	LM1	LR
10	$\rho = 0$	59	56	56	53	46	37	42	50
	$\rho = 0.01$	94	64	84	181	168	110	159	170
	$\rho = 0.05$	376	280	350	321	887	828	881	848
	$\rho = 0.1$	813	729	791	748	1000	999	1000	1000
	$\rho = 0.2$	985	976	984	971	1000	1000	1000	1000
	$\rho = 0.5$	1000	1000	1000	1000	1000	1000	1000	1000
15	$\rho = 0$	44	34	36	35	53	49	52	59
	$\rho = 0.01$	139	69	118	102	273	182	258	239
	$\rho = 0.05$	637	526	617	549	990	979	989	978
	$\rho = 0.1$	936	907	930	904	1000	1000	1000	1000
	$\rho = 0.2$	1000	1000	1000	999	1000	1000	1000	1000
	$\rho = 0.5$	1000	1000	1000	1000	1000	1000	1000	1000
25	$\rho = 0$	37	33	32	29	43	31	42	50
	$\rho = 0.01$	203	150	207	176	492	393	480	456
	$\rho = 0.05$	870	814	860	813	1000	1000	1000	1000
	$\rho = 0.01$	994	987	993	988	1000	1000	1000	1000
	$\rho = 0.2$	1000	1000	1000	1000	1000	1000	1000	1000
	$\rho = 0.5$	1000	1000	1000	1000	1000	1000	1000	1000

(ε_{it} has a uniform distribution)

TABLE 5

Size of tests for different skewness and kurtosis

(at 5% level, N = 25, in %.)

test Distribution	T = 10				T = 15				T = 25			
	F	LM2	LM1	LR	F	LM2	LM1	LR	F	LM2	LM1	LR
S=0, K=3.0	45	37	40	38	45	38	36	32	48	31	37	41
S=0, K=2.4	57	40	50	48	43	50	41	43	51	40	44	41
S=0, K=5.0	55	43	45	36	43	34	32	29	53	54	47	34
S=0, K=9.0	45	39	38	37	40	38	35	36	43	34	36	40
S=0.5, K=2.4	58	37	51	41	49	38	48	48	67	55	52	47
S=0.5, K=3.0	51	39	36	41	51	44	46	34	57	46	54	60
S=0.5, K=5.0	44	42	36	36	48	32	43	43	47	44	47	43
S=0.5, K=9.0	56	34	49	47	58	40	58	54	57	33	45	49
S=0.6, K=2.4	55	33	42	39	49	33	39	37	63	44	54	42
S=0.6, K=3.0	44	36	34	39	46	23	39	38	42	41	36	49
S=0.6, K=3.0	53	42	47	47	47	32	36	34	43	36	39	33
S=0.6, K=5.0	65	49	54	47	51	33	42	41	44	30	37	36
S=0.8, K=3.0	59	56	56	53	44	34	36	35	37	33	32	29
S=0.8, K=5.0	47	41	40	53	37	47	46	71	54	62	55	55
S=0.8, K=9.0	52	48	42	41	48	39	40	32	37	32	33	40
Mean	52.4	41.0	44.0	42.8	46.6	37.0	41.1	40.4	49.5	41.0	43.2	42.6
Std. Dev.	6.34	6.11	6.90	5.82	5.04	6.70	6.51	10.7	8.97	9.83	8.06	8.33

S : Skewness (ε_{it} has a uniform distribution)

K : Kurtosis (normal distribution: S = 0, K = 3.0)

TABLE 6

Size of tests for different skewness and kurtosis
(at 5% level, N = 100, in %.)

test \ Distribution	T = 10				T = 15				T = 25			
	F	LM2	LM1	LR	F	LM2	LM1	LR	F	LM2	LM1	LR
S=0, K=3.0	53	42	51	52	40	45	39	47	55	42	50	45
S=0, K=2.4	46	48	43	63	45	46	43	54	40	44	38	49
S=0, K=5.0	48	50	42	55	44	44	42	50	48	57	44	56
S=0, K=9.0	42	33	41	47	48	46	47	60	42	42	41	38
S=0.5, K=2.4	52	44	48	75	47	50	44	58	48	52	45	41
S=0.5, K=3.0	49	49	46	52	54	52	54	58	46	40	47	49
S=0.5, K=5.0	41	48	37	49	48	53	48	52	60	54	58	56
S=0.5, K=9.0	47	47	45	50	51	41	48	58	44	51	42	50
S=0.6, K=2.4	44	42	42	45	42	38	40	46	51	55	50	60
S=0.6, K=3.0	55	55	51	56	47	42	44	47	44	37	41	60
S=0.6, K=5.0	43	43	38	45	52	42	49	60	53	48	51	60
S=0.6, K=9.0	44	41	41	49	47	47	44	58	45	40	41	58
S=0.8, K=3.0	46	37	42	50	53	49	52	59	43	31	42	50
S=0.8, K=5.0	56	58	53	60	59	51	55	60	55	57	52	61
S=0.8, K=9.0	48	52	46	54	40	39	37	53	43	44	41	61
Mean	47.6	45.9	44.4	53.4	47.8	45.6	45.7	54.6	47.8	46.2	45.5	52.9
Std. Dev.	4.65	6.62	4.76	7.83	5.33	4.70	5.35	5.16	5.79	7.87	5.57	7.56

S : Skewness   (ε_{it} has a uniform distribution)

K : Kurtosis   (normal distribution: S = 0, K = 3.0)

procedures available to carry out basic hypothesis testing in an error components model.

3. Conclusion

It has been shown in this paper that amongst the testing procedures available to test for individual effects in an error components framework the F test is robust against nonnormality while the one and two sided LM and the LR tests may be quite fragile. So *Baltagi and Levin* [1992] may have been right with their inference, after all. It has also been suggested that the usual assumption of independence of the random components of the composed disturbance term may not be needed for correct inference.

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