A Note on the Cliff and Ord Test for Spatial Correlation in Panel Models

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March 11, 2009

Abstract

For panel data, we propose to base the Cliff and Ord test for spatial correlation of the disturbances on the estimated residuals of the within estimator. This test can be applied under both the random effects and the fixed effects assumption. We work out its large sample properties and present Monte Carlo evidence that shows that the proposed test works well in finite samples.

Keywords: Moran I test; Panel Data; Within Estimator
JEL Classification: C21; C23

1 Introduction

In panel models, diagnostic tests for spatial correlation of the residuals are unavailable under fixed effects. The existing tests (see e.g. Baltagi, Song and Koh, 2003) utilize the random effects assumption. However, the random effects specification is often implausible and a fixed effects model is warranted. This note suggests to base the Cliff and Ord test for spatial correlation on the within transformed residuals. The resulting test is robust to violations of the random effects assumption. We work out the large sample properties of the test and illustrate its small sample performance.

2 The Cliff and Ord Test in a Panel

We consider the following model:[1]

$$y_{it,N} = \mathbf{x}_{it,N}\boldsymbol{\beta} + u_{it,N}. \tag{1}$$

Index $i = 1,..,N$ denotes the cross-sectional dimension, while $t = 1,...,T$ refers to the time dimension. $y_{it,N}$ is the (scalar) dependent variable, $\mathbf{x}_{it,N}$ is a $1 \times K$ vector of exogenous variables and $\boldsymbol{\beta}$ is the corresponding $K \times 1$ parameter vector. The disturbances $u_{it,N}$ follow a first order spatial autoregressive process,

$$u_{it,N} = \rho \sum_{j=1}^{N} w_{ij,N} u_{jt,N} + \varepsilon_{it,N}, \tag{2}$$

where ρ is a scalar parameter and $w_{ij,N}$ are observable spatial weights. The innovations $\varepsilon_{it,N}$ have the following one-way error component structure:

$$\varepsilon_{it,N} = \mu_{i,N} + \nu_{it,N}, \tag{3}$$

where $\nu_{it,N}$ are independent innovations and the individual effects $\mu_{i,N}$ can be either fixed or random. We sort the data so that the fast index is i and the slow index is t. Our stacked model is

$$\begin{aligned} \mathbf{y}_N &= \mathbf{X}_N\boldsymbol{\beta} + \mathbf{u}_N \\ \mathbf{u}_N &= \rho\left(\mathbf{I}_T \otimes \mathbf{W}_N\right)\mathbf{u}_N + \boldsymbol{\varepsilon}_N, \\ \boldsymbol{\varepsilon}_N &= \left(\boldsymbol{\iota}_T \otimes \mathbf{I}_N\right)\boldsymbol{\mu}_N + \boldsymbol{\nu}_N, \end{aligned} \tag{4}$$

We maintain the following assumptions:

Assumption 1
The elements of $\boldsymbol{\nu}_N$ are independently and identically distributed with zero mean and finite absolute $4 + \delta_\nu$ moments for some $\delta_\nu > 0$. Furthermore, $E\left(\nu_{it,N}^2\right) = \sigma_\nu^2 > 0$.

Assumption 2
The spatial weights collected in $\mathbf{W}_N$ are non-stochastic and

(i) $w_{ii,N} = 0$,

[1] We index all variables by the sample size, since they form triangular arrays.

(ii) the absolute row and column sums of the matrices $\mathbf{W}_N$*, and* $(\mathbf{I}_N - \rho\mathbf{W}_N)^{-1}$ *are uniformly bounded,*

(iii) $|\rho| \leq k_1 < 1/\lambda_{\max}(\mathbf{W}_N)$*, where* $\lambda_{\max}(.)$ *denotes the largest absolute eigenvalue of a matrix,*

(iv) $0 < k_2 \leq N^{-1} tr\left[(\mathbf{W}_N + \mathbf{W}_N')^2\right]$.

Assumption 3
The elements of $\mathbf{X}_N$ *are non-stochastic and are uniformly bounded in absolute value.*

Our assumptions follow closely those made those in the spatial econometrics literature, see, for example, Mutl and Pfaffermayr (2008) for a detailed discussion.[2]

We define the within transformation as $\mathbf{Q}_{0,N} = (\mathbf{E}_T \otimes \mathbf{I}_N)$, where $\mathbf{E}_T = \left(\mathbf{I}_T - \frac{1}{T}\mathbf{J}_T\right)$ with $\mathbf{J}_T$ being $T \times T$ matrix of ones. The within transformed variables are $\widetilde{\mathbf{y}}_N = \mathbf{Q}_{0,N}\mathbf{y}_N$ and $\widetilde{\mathbf{X}}_N = \mathbf{Q}_{0,N}\mathbf{X}_N$, and the true (unobservable) within transformed residuals are given by $\widetilde{\mathbf{u}}_N = \widetilde{\mathbf{y}}_N - \widetilde{\mathbf{X}}_N\boldsymbol{\beta}$. Suppose that $\widehat{\boldsymbol{\beta}}$ is an initial $\sqrt{n}-$consistent estimator[3] of $\boldsymbol{\beta}$ and denote $\widehat{\widetilde{\mathbf{u}}} = \widetilde{\mathbf{y}}_N - \widetilde{\mathbf{X}}_N\widehat{\boldsymbol{\beta}}$ the estimated disturbances. Our proposed test is then

$$\widehat{I}_N = \frac{\sum_{t=1}^{T} \widehat{\widetilde{\mathbf{u}}}_{t,N}' \mathbf{W}_N \widehat{\widetilde{\mathbf{u}}}_{t,N}}{\widehat{\sigma}_\nu^2 \sqrt{(T-1) tr\left[\left(\mathbf{W}_N + \mathbf{W}_N'\right)\mathbf{W}_N\right]}}. \tag{5}$$

In the Appendix, we show that the square of $\widehat{I}_N$ is equivalent to the LM test for H_0: $\rho = 0$ vs. H_1: $\rho \neq 0$, using the conditional likelihood.[4] The $\widehat{I}_N$ test statistic is also similar to the well known Cliff and Ord test statistic for cross-sectional data (see Moran, 1950, or Burridge, 1980). However, it uses the estimated residuals of the within transformed model and adjusts the normalization appropriately. Moreover, this test can be applied irrespective of whether the random effects model or the fixed effects model is the true data generating process. In contrast, using the residuals of least squares dummy variable estimator, does not lead to a proper test statistic, since σ_ν^2 is not consistently estimated in this model (see also the discussion in Lee and Yu, 2008).

In the Appendix, we establish for the following asymptotic normality result for this test statistic under H_0:

Theorem 1 *Let Assumptions 1-3 hold and let* $\widehat{\widetilde{\mathbf{u}}}_{t,N}$ *be based on a* $\sqrt{n}-$*consistent estimator of* $\boldsymbol{\beta}$*. Then*

(i) $I_N = \frac{Q_N}{\sigma_{Q_N}} \xrightarrow{D} N(0,1)$,
where $Q_N = \widetilde{\mathbf{u}}_N' (\mathbf{I}_T \otimes \mathbf{W}_N) \widetilde{\mathbf{u}}_N$ *and* $\sigma_{Q_N} = \sigma_\nu^2 \sqrt{(T-1)\, tr\left[\left(\mathbf{W}_N + \mathbf{W}_N'\right)\mathbf{W}_N\right]}$,

(ii) $\widehat{I}_N - I_N = o_p(1)$.

Proof. See the Appendix. ■

[2] For discussion of Assumption 2(iv), see e.g. Kelejian and Prucha (2001), equation (4.2).

[3] This could be, for example, the least squares estimator based on the within transformed model. See Mutl and Pfaffermayr (2008) for the proof of consistency of this estimator under both random effects and fixed effects assumptions.

[4] The alternative could also be a spatial MA process, see Burridge (1980).

3 Small Sample Properties

For the Monte Carlo analysis we use the following model:

$$y_{it} = 0.5x_{it} + u_{it}. \tag{6}$$

The explanatory variable is generated as $x_{it} = \zeta_i + z_{it}$ with $\zeta_i \sim i.i.d.\ U[-7.5, 7.5]$ and $z_{it} \sim i.i.d.\ U[-7.5, 7.5]$ with $U[a, b]$ denoting the uniform distribution on the interval $[a, b]$. We generate x_{it} once and keep it fixed in repeated samples. The disturbances are specified as

$$u_{it} = \rho \sum_{j=1}^{N} w_{ij} u_{jt} + \pi\left(\overline{x}_i - \overline{x}\right) + \mu_i + \nu_{it}, \tag{7}$$

where the parameter π induces correlation of the individual-specific effects with x_i. The innovations are generated as independent draws from $\nu_{it} \sim N(0, 10(1-\phi))$ and $\mu_i \sim N(0, 10\phi)$, respectively. $\phi = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\nu^2}$, $(0 < \phi < 1)$, denotes the proportion of the total variance due to the individual-specific effects.

We use spatial weighting matrices based on a regular lattice with 144 and 289 cells, respectively, containing one observation each. The first weighting scheme is a rook design, where every unit is surrounded by four neighbors. Alternatively, the distance between two neighboring cells is defined as 1 and $w_{ij} = \frac{1/d_{ij}}{\max_i \sum_{j=1}^{N} 1/d_{ij}}$, with $d_{ii} = 0$. Both spatial weighting matrices are maximum-row normalized. In each experiment we calculate the size of the test as the share of rejections at $\rho = 0$. The power of the test is given by the share of rejections under the alternative $\rho \neq 0$.

===== Table 1 =====

In the first experiment we compare the performance of our test with the LM test for the random effects models as proposed by Baltagi, Song and Koh (2003)[5], using the rook design with $N = 144$, $T = 5$ and $\phi = 0.5$. Table 1 shows that under the random effects assumption ($\pi = 0$) both tests exhibit the correct size at nominal level $\alpha = 0.05$, but the LM-test exhibits somewhat higher power as one would expect. However, the LM-test becomes oversized if $\pi > 0$. The size distortion is more pronounced at a larger weight of the between variation (i.e., a higher ϕ). In contrast, the panel Cliff and Ord by construction is robust to the violation of the random effects assumption.

Experiments 1-6 in Table 2 refer to the rook design, indicating that the panel Cliff and Ord test is nearly correctly sized and it possesses power against the alternative. Doubling the number of observations either in the cross-section dimension or the time dimension (Experiments 2 and 3) improves the power as expected. In Experiment 4 we look at a lower variance ($\sigma_v^2 = 2.5, \phi = 0.75$) of the remainder error, observing some improvement in the size of the test, but the power remains the same as in the baseline (Experiment 1). In Experiments 5 and 6 we consider non-normal disturbances. We assume log-normal disturbances $\varepsilon_{it} = \frac{e^{\xi_{it}} - e^{0.5}}{\sqrt{e^2 - e^1}}$, where $\xi_{it} \sim i.i.d.\ N(0, 1)$ (Experiment 5). Alternatively, we allow for fatter tails than the normal and assume $\varepsilon_{it} \sim i.i.d\ t(5)$ (Experiment 6). In both cases the performance of the panel Cliff and Ord test is comparable to that under normal disturbances.

[5] The LM test for H_0: $\rho = 0$ is given by $LM_\lambda = \frac{0.5\widehat{u}'\left(\frac{\sigma_v^2}{\sigma_1^2}(\overline{\mathbf{J}}_T \otimes (\mathbf{W}_N + \mathbf{W}'_N)) + \frac{1}{\sigma_v^2}(\overline{\mathbf{E}}_T \otimes (\mathbf{W}'_N + \mathbf{W}_N))\right)\widehat{u}}{\sqrt{(T - 1 + \sigma_v^4/\sigma_1^4) tr((\mathbf{W}'_N + \mathbf{W}_N)\mathbf{W}_N)}}$.

===== Tables 2 =====

Lastly, we repeat all experiments using the distance based spatial weights (Experiments 7-12). This weighting scheme implies much higher spatial correlation of the disturbances. In these experiments the panel Cliff and Ord test also performs well in terms of size. However, it exhibits lower power than under the rook design. Specifically, the power now is considerably smaller if ρ is negative but large in absolute value. Experiments 8 and 9 show that the power increases much faster with T than with N.

A Appendix

To show that the proposed test is the LM test we consider the conditional likelihood of the model (see e.g. Lee and Yu, 2008, p. 5, eq. 2.4)

$$\begin{aligned} L_N(\boldsymbol{\theta}) &= -\tfrac{N(T-1)}{2}\ln 2\pi - \tfrac{N(T-1)}{2}\ln\sigma_\nu^2 + (T-1)(\ln\det \mathbf{B}_N) \\ &\quad -\tfrac{1}{2\sigma_\nu^2}\sum_{t=1}^{T}(\widetilde{\mathbf{y}}_{t,N}-\widetilde{\mathbf{X}}_{t,N}\boldsymbol{\beta})'\mathbf{B}_N'\mathbf{B}_N(\widetilde{\mathbf{y}}_{t,N}-\widetilde{\mathbf{X}}_{t,N}\boldsymbol{\beta}), \end{aligned} \tag{A.1}$$

where $\mathbf{B}_N = \mathbf{I}_{NT} - \rho\mathbf{W}_N$ and $\boldsymbol{\theta} = (\sigma_\nu^2, \rho, \boldsymbol{\beta}')'$. The partial derivative of the likelihood w.r.t. ρ is then

$$\frac{\partial L}{\partial\rho} = -(T-1)\,tr(\mathbf{W}_N\mathbf{B}_N^{-1}) - \tfrac{1}{\sigma_\nu^2}\sum_{t=1}^{T}(\widetilde{\mathbf{y}}_{t,N}-\widetilde{\mathbf{X}}_{t,N}\boldsymbol{\beta})'\mathbf{W}_N\mathbf{B}_N(\widetilde{\mathbf{y}}_{t,N}-\widetilde{\mathbf{X}}_{t,N}\boldsymbol{\beta}).$$

Under H_0: $\rho = 0$, we have $\mathbf{B}_N = \mathbf{I}_N$ and the score is given by

$$\left.\frac{\partial L}{\partial\rho}\right|_{\rho=0} = -\tfrac{1}{\sigma_\nu^2}\sum_{t=1}^{T}(\widetilde{\mathbf{y}}_{t,N}-\widetilde{\mathbf{X}}_{t,N}\boldsymbol{\beta})'\mathbf{W}_N(\widetilde{\mathbf{y}}_{t,N}-\widetilde{\mathbf{X}}_{t,N}\boldsymbol{\beta}), \tag{A.2}$$

and as shown in the proof of Theorem 1 below, the variance of the score is

$$E\left[\left(\frac{\partial L}{\partial\rho}\right)^2\right]\Bigg|_{\rho=0} = 2\sigma_\nu^4\,(T-1)\,tr\left[(\mathbf{W}_N+\mathbf{W}_N')\,\mathbf{W}_N\right].$$

Hence we obtain that the LM test statistics

$$LM = \frac{\left(\frac{1}{\sigma_\nu^2}\sum_{t=1}^{T}\widetilde{\mathbf{u}}_{t,N}'\mathbf{W}_N\widetilde{\mathbf{u}}_{t,N}\right)^2}{(T-1)\,tr\left[(\mathbf{W}_N+\mathbf{W}_N')\,\mathbf{W}_N\right]} \tag{A.3}$$

with $LM = (I_N)^2$.

To derive the asymptotic distribution of I_N, we use following central limit theorem for triangular arrays of quadratic forms:

Lemma 2 *Let Assumption 1 hold and let the sequence of $N\times N$ symmetric matrices $\mathbf{A}_N$ satisfy Assumption 2. Consider the sequence of quadratic forms $R_N = \boldsymbol{\nu}_N'(\mathbf{B}\otimes\mathbf{A}_N)\boldsymbol{\nu}_N$, where $\mathbf{B}$ is a symmetric nonsingular $T\times T$ matrix whose elements do not depend on N. Then $E(R_N) = 0$ and the variance of R_N is*

$$\sigma_R^2 = E\left(R_N^2\right) = 2\left(\sigma_\nu^2\right)^2\cdot tr\left(\mathbf{B}\mathbf{B}\right)\cdot tr\left(\mathbf{A}_N\mathbf{A}_N\right).$$

Furthermore,

$$\frac{R_N}{\sigma_R} \xrightarrow{d} N(0,1).$$

Proof: Observe that the assumptions of the Lemma guarantee that Assumptions 1-3 in Kelejian and Prucha (2001) are satisfied. The expressions for the mean and variance of R_N then follow from their equation 3.2. Next, note that by Assumption 2(iv),

$$N^{-1}\sigma_R^2 = N^{-1}2\left(\sigma_\nu^2\right)^2 \cdot tr\left(\mathbf{BB}\right) \cdot tr\left(\mathbf{A}_N\mathbf{A}_N\right) \geq k_2 > 0, \tag{A.4}$$

for some positive constant k_2, since $\sigma_\nu^2 > 0$ and $\mathbf{B}$ is nonsingular. The claim then follows from Theorem 1 in Kelejian and Prucha (2001).■

Proof of Theorem 1: Observe that under H_0 we have

$$\begin{aligned} Q_N &= \widetilde{\mathbf{u}}_N'\left(\mathbf{I}_T \otimes \mathbf{W}_N\right)\widetilde{\mathbf{u}}_N = \boldsymbol{\nu}_N'\left(\mathbf{E}_T \otimes \mathbf{W}_N\right)\boldsymbol{\nu}_N \\ &= \frac{1}{2}\boldsymbol{\nu}_N'\left[\mathbf{E}_T \otimes \left(\mathbf{W}_N + \mathbf{W}_N'\right)\right]\boldsymbol{\nu}_N. \end{aligned} \tag{A.5}$$

Given our assumptions, the conditions of Lemma 2 are satisfied and hence

$$\begin{aligned} E\left(Q_N^2\right) &= 2\left(\frac{1}{2}\right)^2\left(\sigma_\nu^2\right)^2 \cdot tr\left(\mathbf{E}_T\mathbf{E}_T\right) \cdot tr\left[\left(\mathbf{W}_N + \mathbf{W}_N'\right)\left(\mathbf{W}_N + \mathbf{W}_N'\right)\right] \\ &= \left(\sigma_\nu^2\right)^2(T-1) \cdot tr\left[\left(\mathbf{W}_N + \mathbf{W}_N'\right)\mathbf{W}_N\right] = \sigma_{Q_N}^2. \end{aligned} \tag{A.6}$$

Therefore, Lemma 2 implies that under H_0

$$I_N = \frac{Q_N}{\sigma_{Q_N}} \xrightarrow{d} N(0,1). \tag{A.7}$$

It remains to be shown that $\widehat{I}_N \xrightarrow{p} I_N$. Since $\widehat{\boldsymbol{\beta}}$ is $\sqrt{N}$- consistent, Lemma 1 in Kelejian and Prucha (2001) implies

$$\tfrac{1}{\sqrt{NT}}\widehat{\widetilde{\mathbf{u}}}_N'\mathtt{W}_N\widehat{\widetilde{\mathbf{u}}}_N - \tfrac{1}{\sqrt{NT}}\widetilde{\mathbf{u}}_N'\mathtt{W}_N\widetilde{\mathbf{u}}_N = \tfrac{1}{NT}\widetilde{\mathbf{u}}_N'\left(\mathtt{W}_N + \mathtt{W}_N'\right)\widetilde{\mathbf{X}}_N\sqrt{NT}\left(\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}_0\right) + o_p(1), \tag{A.8}$$

where we define $\mathtt{W}_N = \left(\mathbf{I}_T \otimes \mathbf{W}_N\right)$. Furthermore,

$$E\left(\tfrac{1}{NT}\widetilde{\mathbf{u}}_N'\mathtt{W}_N\widetilde{\mathbf{X}}_N\right) = 0, \tag{A.9}$$

and

$$Var\left(\tfrac{1}{NT}\widetilde{\mathbf{u}}_N'\mathtt{W}_N\widetilde{\mathbf{X}}_N\right) = \frac{\sigma_\nu^2}{NT^2}\widetilde{\mathbf{X}}_N'\mathtt{W}_N\mathbf{Q}_{0,N}\mathtt{W}_N\widetilde{\mathbf{X}}_N, \tag{A.10}$$

which is uniformly bounded in absolute value by Assumptions 1-3. Hence,

$$\tfrac{1}{\sqrt{NT}}\widehat{\widetilde{\mathbf{u}}}_N'\mathtt{W}_N\widehat{\widetilde{\mathbf{u}}}_N - \tfrac{1}{\sqrt{NT}}\widetilde{\mathbf{u}}_N'\mathtt{W}_N\widetilde{\mathbf{u}}_N = o_p(1). \tag{A.11}$$

As shown above, σ_{Q_N} is uniformly bounded away from zero. Observe that $(NT)^{-1}\widehat{\sigma}_{Q_N}^2 - (NT)^{-1}\sigma_{Q_N}^2 = o_p(1)$, since $\widehat{\sigma}_\nu^2 - \sigma_\nu^2 = o_p(1)$ and $(NT)^{-1} tr\left[\left(\mathbf{W}_N + \mathbf{W}_N'\right)\mathbf{W}_N\right] = O(1)$. Theorem 2 in Kelejian and Prucha (2001) then implies that $\widehat{I}_N \xrightarrow{p} I_N$. ■

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Table 1: Share of rejections of the panel Cliff and Ord test and the LM test for H_0: $\rho=0$ in 10000 replications

	Panel Cliff and Ord test						LM test					
	$\phi=0.50$			$\phi=0.75$			$\phi=0.50$			$\phi=0.75$		
ρ/π	0	1	2	0	1	2	0	1	2	0	1	2
-0,3	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	0,999	0,999	1,000
-0,2	0,948	0,949	0,950	0,951	0,947	0,949	0,963	0,976	0,983	0,955	0,946	0,974
-0,1	0,430	0,439	0,422	0,440	0,430	0,434	0,464	0,588	0,621	0,452	0,594	0,672
0,0	0,053	0,049	0,048	0,050	0,052	0,053	0,052	0,065	0,072	0,050	0,124	0,128
0,1	0,429	0,432	0,437	0,432	0,435	0,428	0,444	0,229	0,233	0,432	0,042	0,036
0,2	0,948	0,949	0,949	0,952	0,948	0,947	0,958	0,849	0,857	0,953	0,353	0,378
0,3	0,999	1,000	1,000	1,000	1,000	1,000	1,000	0,997	0,999	0,999	0,855	0,887

Notes: The spatial weighting matrix is maximum row normalized. The LM-test is based on the random effects model and derived by Baltagi, Song and Koh (2003). The setup refers to Experiment 1 with normal disturbances, N=144, T=5, $\sigma^2_\mu+\sigma^2_\nu=10$, $\theta=\sigma^2_\mu/(\sigma^2_\mu+\sigma^2_\nu)$. The paramter π measures the violation of the random effects assumption.

Table 2: Share of rejections of the panel Cliff and Ord test for H_0: $\rho=0$ in 10000 replications

	Rook design						Distance based spatial weights					
ρ	1	2	3	4	5	6	7	8	9	10	11	12
-0,9	1,000	1,000	1,000	1,000	1,000	1,000	0,237	0,346	0,783	0,241	0,224	0,226
-0,6	1,000	1,000	1,000	1,000	1,000	1,000	0,098	0,144	0,418	0,091	0,086	0,099
-0,4	1,000	1,000	1,000	1,000	1,000	1,000	0,046	0,067	0,196	0,044	0,035	0,047
-0,3	1,000	1,000	1,000	0,999	0,998	1,000	0,028	0,044	0,115	0,027	0,024	0,032
-0,2	0,948	0,999	1,000	0,947	0,946	0,948	0,022	0,030	0,062	0,025	0,020	0,021
-0,1	0,430	0,708	0,761	0,427	0,446	0,433	0,027	0,026	0,036	0,027	0,023	0,028
0,0	0,053	0,050	0,050	0,048	0,047	0,050	0,046	0,046	0,047	0,047	0,040	0,044
0,1	0,429	0,699	0,765	0,434	0,401	0,434	0,081	0,092	0,108	0,090	0,082	0,088
0,2	0,948	0,999	1,000	0,945	0,960	0,950	0,168	0,168	0,233	0,158	0,153	0,170
0,3	0,999	1,000	1,000	1,000	1,000	0,999	0,274	0,280	0,445	0,284	0,274	0,276
0,4	1,000	1,000	1,000	1,000	1,000	1,000	0,426	0,440	0,663	0,426	0,423	0,422
0,6	1,000	1,000	1,000	1,000	1,000	1,000	0,743	0,754	0,944	0,746	0,757	0,750
0,9	1,000	1,000	1,000	1,000	1,000	1,000	0,985	0,987	1,000	0,984	0,988	0,985

Notes: The spatial weighting matrix is maximum row normalized.

Experiment 1,7: Normal disturbances, N=144, T=5, $\sigma^2_\nu=5$.

Experiment 2,8: Normal disturbances, N=289, T=5, $\sigma^2_\nu=5$.

Experiment 3,9: Normal disturbances, N=144, T=10, $\sigma^2_\nu=5$.

Experiment 4,10: Normal disturbances, N=144, T=5, $\sigma^2_\nu=2.5$.

Experiment 5, 11: log-normal disturbances, N=144, T=5, $\sigma^2_\nu=5$.

Experiment 6,12: t(5) disturbances, N=144, T=5, $\sigma^2_\nu=5$.