A Simple Panel Stationarity Test in the Presence of serial correlation and a common factor

Kaddour Hadri[1]
Queen's University Management School
Queen's University Belfast

Eiji Kurozumi
Department of Economics
Hitotsubashi University

Abstract

This paper develops a simple test à la Pesaran (2007) for the null hypothesis of stationarity in heterogeneous panel data with cross-sectional dependence in the form of a common factor in the disturbance. We also allow for serial correlation.

JEL classification: C12, C33

Key words: Panel data; stationarity; KPSS test; cross-sectional dependence, common factor.

[1]Corresponding author: Kaddour Hadri, 25 University Square, Queen's University Management School, Queen's University, Belfast, BT7 1NN, UK. Tel +44 (0)28 9097 3286. Fax +44 (0)28 90975156. Email: k.hadri@qub.ac.uk.
This project was supported by JSPS and BA under the Japan-Britain Research Cooperative Program, by the Ministry of Education, Culture, Sports, Science and Technology under Grants-in Aid No. 18730142 and by the Global COE program of the Research Unit for Statistical and Empirical Analysis in Social Sciences, Hitotsubashi University.

1. Introduction

The last two decades have wittenesed an impressive production of unit root and stationarity tests in heterogenous panel data with T and N large. The main motive in transfering single time series unit root and stationarity tests to heterogenous panel data is to increase significantly the power of these tests. The early cohorts of panel unit root and stationary tests were based on the implausible assumption that the cross-sectional units are independent or at least not cross-sectionally correlated. However, in most empirical applications this assumption has been found erroneous. Therefore, it became imperative to develop new tests accounting for the likely possibility of cross-sectional dependence. This led, recently, to a flurry of papers accounting for cross-sectional dependence of different forms in panel unit root tests. For panel stationarity tests, the only contributions so far are Bai and Ng (2005) and Harris, Leybourne and McCabe (2005), both of which corrected for cross-sectional dependence by using the principal component analysis proposed by Bai and Ng (2004). Breitung and Pesaran (2008) give an excellent survey of the first and second generation panel tests. In this paper, we propose a simple test à la Pesaran (2007) for the null hypothesis of stationarity in heterogeneous panel data with cross-sectional dependence in the form of a common factor. We also allow for serial correlation in the disturbance.

The paper is organized as follows. Section 2 sets up the model and assumptions of the panel augmented tests allowing for serial correlation in the error term. In section 3, we examine the finite sample property of the proposed tests via Monte Carlo simulations. Section 4 concludes the paper.

2. Model, Assumption and Test Statistics

Let us consider the following model:

$$y_{it} = z_t'\delta_i + f_t\gamma_i + \varepsilon_{it}, \quad \varepsilon_{it} = \phi_{i1}\varepsilon_{it-1} + \cdots + \phi_{ip}\varepsilon_{it-p} + \nu_{it}. \tag{1}$$

for $i = 1, \cdots, N$ and $t = 1, \cdots, T$ where z_t is deterministic. The commonly used specification of z_t in the literature is either $z_t = z_t^\mu = 1$ or $z_t = z_t^\tau = [1, t]'$. In this paper, we consider these two cases. Accordingly, we define $\delta_i = \alpha_i$ when $z = 1$ and $\delta_i = [\alpha_i, \beta_i]'$ when $z = [1, t]'$. In model (1), $z_t'\delta_i$ is the individual effect while f_t is one dimensional unobserved common factor, γ_i is the loading factor and ε_{it}, the individual-specific (idiosyncratic) error, follows an AR(p) process.

The lag length p may change depending on the cross-sectional units but we suppress the dependence of p on i for notational convenience. Since it is often the case that the observed process can be approximated by an autoregressive (AR) model, we do not consider the error component model as in Hadri (2000) but an AR(p) model instead in this paper[2].

Assumption 1 *(i) There exist real numbers M_1, $\underline{M}$ and $\overline{M}$ such that $|\gamma_i| < M_1 < \infty$ for all i and $0 < \underline{M} < |\bar{\gamma}| < \overline{M} < \infty$ for all N, where $\bar{\gamma} = N^{-1} \sum_{i=1}^N \gamma_i$.*
(ii) The stochastic process f_t is stationary with a finite fourth moment and the functional central limit theorem (FCLT) holds for the partial sum process of f_t. (iii) The stochastic process ν_{it} is independent of f_t and i.i.d.$(0, \sigma^2_{\nu i})$ across i and t with a finite fourth moments.

Assumption 1(i) is concerned with the weights of the common factor f_t. This assumption implies that each individual is possibly affected by the common factor with the finite weight γ_i and that the absolute value of the average of γ_i is bounded away from 0 and above both in finite samples and in asymptotics. The latter property is important in order to eliminate the common factor effect from the regression. A similar assumption is also entertained in Pesaran (2007). Assumption 1(ii and iii) allow the common factor to be stationary but still presumes that it is independent of the idiosyncratic errors, which are finite order AR processes with i.i.d. innovations.

Since our interest is whether y_{it} are (trend) stationary or unit root processes, the testing problem is given by

$$H_0' : \ \phi_i(1) \neq 0 \ \ \forall i \quad \text{v.s.} \quad H_1' : \ \phi_i(1) = 0 \quad \text{for some } i,$$

[2] We do not consider a general linear process instead of an AR(p) model because in the case of a general linear process the long-run variance estimator based on Toda and Yamamoto (1995), used here, will diverge to infinity at a rate T^2 under the alternative when the process is AR(∞). As a result, our test based on the lag-augmented method becomes inconsistent.

where $\phi_i(L) = 1 - \phi_{i1}L - \cdots - \phi_{ip}L^p$.

For the correction of cross-sectional dependence, for each i, we regress y_{it} on $w_t = [z_t', \bar{y}_t, \bar{y}_{t-1}, \cdots, \bar{y}_{t-p}]$ because ε_{it} are AR(p) processes and construct the test statistic in the same way as Hadri (2000). That is,

$$Z_A = \frac{\sqrt{N}(\overline{ST} - \xi)}{\zeta}, \tag{2}$$

$$\text{where} \quad \overline{ST} = \frac{1}{N}\sum_{i=1}^{N} ST_i \quad \text{with} \quad ST_i = \frac{1}{\hat{\sigma}_i^2 T^2}\sum_{t=1}^{T}(S_{it}^w)^2 \quad \text{where} \quad S_{it}^w = \sum_{s=1}^{t}\widehat{\varepsilon}_{is},$$

$\hat{\sigma}_i^2$ is the estimator of the long-run variance defined later,

$$\text{and} \quad \begin{cases} \xi = \xi_\mu = \frac{1}{6}, \quad \zeta^2 = \zeta_\mu^2 = \frac{1}{45} & \text{when } z_t = z_t^\mu = 1, \\ \xi = \xi_\tau = \frac{1}{15}, \quad \zeta^2 = \zeta_\tau^2 = \frac{11}{6300} & \text{when } z_t = z_t^\tau = [1, t]', \end{cases}$$

with $\widehat{\varepsilon}_{it}$ obtained for each i by regressing y_{it} on $w_t = [z_t', \bar{y}_t, \bar{y}_{t-1}, \cdots, \bar{y}_{t-p}]$ for $t = 1, \cdots, T$.

From (2) we can see that $\overline{ST}$ is the average of the KPSS test statistic across i and Z_A is normalized so that we obtain a limiting distribution. We call Z_A the panel augmented KPSS test statistic and construct S_{it}^w using these regression residuals. In this case it is not difficult to see that the numerator of each ST_i weakly converges to

$$\frac{1}{T^2}\sum_{t=1}^{T}(S_{it}^w)^2 \overset{T}{\Longrightarrow} \sigma_i^2 \int_0^1 (V_i^\varepsilon(r) + \tilde{\gamma}_i R_N)^2\, dr$$

where $\tilde{\gamma}_i = \gamma_i/\bar{\gamma}$, R_N is $O_p(1/\sqrt{N})$ uniformly over $0 \le r \le 1$ and does not depend on the subscript i, $\sigma_i^2 = \sigma_{\nu i}^2/(1-\phi_{i1}-\cdots-\phi_{ip})^2$ and $V_i^\varepsilon(r) = B_i^\varepsilon(r) - \int_0^r z(t)'dt \left(\int_0^1 z(t)z(t)'dt\right)^{-1} \int_0^1 z(t)dB_i^\varepsilon(t)$ with $B_i^\varepsilon(t)$ are independent standard Brownian motions. This suggests that we should divide the numerator of each ST_i by a consistent estimator of the long-run variance σ_i^2 in order to correct for serial correlation.

Several consistent estimators of the long-run variance[3] for parametric model have been proposed in the literature for univariate time series. For example, Leybourne and McCabe

[3] We cannot use here the estimator of the long-run variance proposed in Perron and Ng (1998), despite its good properties in finite samples, because it is consistent under the null of a unit root but not under the null of stationarity which we are considering in this paper.

(1994) propose to correct the stationarity test for serial correlation by estimating the AR coefficients based on the ML method for the ARIMA model. Their method is also applied to panel data with no cross-sectional dependence by Shin and Snell (2006). However, our preliminary simulation shows that this method does not work well in finite samples and we do not use this method in this paper.

We next consider to make use of the new truncation rule proposed by Sul, Phillips and Choi (2005). Their method is originally developed for the prewhitening method, but it is also applicable to parametric model. We first estimate the AR(p) model augmented by the lags of $\bar{y}_t$ for each i by the least squares method

$$y_{it} = z_t'\hat{\delta}_i + \hat{\phi}_{i1} y_{it-1} + \cdots + \hat{\phi}_{ip} y_{it-p} + \hat{\psi}_{i0}\bar{y}_t + \cdots + \hat{\psi}_{ip}\bar{y}_{t-p} + \hat{\nu}_{it},$$

and construct the estimator of the long-run variance by

$$\hat{\sigma}^2_{iSPC} = \frac{\hat{\sigma}^2_{\nu i}}{(1-\hat{\phi}_i)^2} \quad \text{where} \quad \hat{\phi}_i = \min\left\{1 - \frac{1}{\sqrt{T}}, \sum_{j=1}^{p}\hat{\phi}_{ij}.\right\} \quad \text{and} \quad \hat{\sigma}^2_{\nu i} = \frac{1}{T}\sum_{t=1}^{T}\hat{\nu}^2_{it}.$$

We then propose to construct the test statistic (2) using

$$ST_i^{SPC} = \frac{1}{\hat{\sigma}^2_{iSPC}T^2}\sum_{t=1}^{T}(S_{it}^w)^2.$$

We denote this test statistic as Z_A^{SPC}.

The other method we consider is the lag-augmented method proposed by Choi (1993) and Toda and Yamamoto (1995). According to these papers, we intentionally add an additional lag of y_t and estimate an AR($p+1$) model instead of an AR(p) model:

$$y_{it} = z_t'\tilde{\delta}_i + \tilde{\phi}_{i1} y_{it-1} + \cdots + \tilde{\phi}_{ip} y_{it-p} + \tilde{\phi}_{ip+1} y_{it-p-1} + \tilde{\psi}_{i0}\bar{y}_t + \cdots + \tilde{\psi}_{ip}\bar{y}_{t-p} + \tilde{\nu}_{it},$$

and construct the test statistic using

$$ST_i^{LA} = \frac{1}{\hat{\sigma}^2_{iLA}T^2}\sum_{t=1}^{T}(S_{it}^w)^2 \quad \text{where} \quad \hat{\sigma}^2_{iLA} = \frac{\hat{\sigma}^2_{\nu i}}{(1-\tilde{\phi}_{i1}-\cdots-\tilde{\phi}_{ip})^2}.$$

We denote this test statistic as Z_A^{LA}.

The consistency of $\hat{\sigma}^2_{iSPC}$ and $\hat{\sigma}^2_{iLA}$ under the null hypothesis is established in the standard way and we omit here the details. On the other hand, they are shown to diverge to infinity at a rate of T under the alternative, so that ST_i can be seen as a consistent stationarity test for univariate time series. It is also shown that the null distributions of Z_A^{SPC} and Z_A^{LA} are asymptotically standard normal[4] while they diverge to infinity under the alternative.

4.2. Finite sample property

In this section we conduct Monte Carlo simulations to investigate the finite sample properties of the panel augmented KPSS test using the long-run variance estimated by the SPC or the LA methods in order to correct for serial correlation in the innovations. The data generating process in this subsection is given as follows:

$$y_{it} = z_t'\delta_i + f_t\gamma_i + \varepsilon_{it}, \quad \varepsilon_{it} = \phi_i\varepsilon_{it-1} + \nu_{it},$$

where $f_t \sim i.i.d.N(0,1)$, $\nu_{it} \sim i.i.d.N(0,1)$, f_t and ν_{it} are independent of each other, $\delta_i = \alpha_i$ for the constant case while $\delta_i = [\alpha_i, \beta_i]'$ for the trend case with α_i and β_i being drawn from independent $U(0, 0.02)$, γ_i are drawn from $-1+U(0,4)$ for strong cross-sectional correlation case (SCC) and from $U(0, 0.02)$ for weak cross-sectional correlation case (WCC), and α_i, β_i and γ_i are fixed throughout the iterations. The ϕ_i are drawn from $0.1+U(0, 0.8)$ under the null hypothesis and they remain fixed throughout the iterations. On the other hand, the ϕ_i are set to be equal to 1 for all i under the alternative. For the purpose of comparison, we also calculate the test statistic proposed by Harris, Leybourne and McCabe (2005) (HLM hereafter).

[4] Note that the central limit theorem can be applied to our panel augmented KPSS test whereas it cannot be to Pesaran's (2007) panel unit root tests. The reason is that, in the case of the unit root tests, the common factor f_t accumulates in y_t so that its effect remains even asymptotically. As a result, individual unit root test statistics have a common component generated by f_t and therefore they are not independent asymptotically. Because of this correlation, the central limit theorem cannot be applied to the panel unit root tests. On the other hand, the common factor f_t does not permanently accumulate in y_t because y_t is stationary under the null hypothesis. This leads to the asymptotic independence of individual statistics ST_i and thus we can apply the central limit theorem to the panel stationarity tests.

Table 1 reports the sizes of the tests. There are no entries for HLM test when $T = 10$ because the time dimension is too short to calculate their test statistic. When only a constant is included in the model, the panel augmented KPSS test corrected by the SPC method tends to be undersized for moderate size of T for SCC (strong cross-correlation) case while it is oversized for small or large size of T, although the over-rejection is not so severe when $N = 100$ and $T = 200$. For WCC (weak cross-correlation) case Z_A^{SPC} is undersized[5] except for the case of $T = 10$. The augmented KPSS test corrected by the LA method has a similar property as Z_A^{SPC} for SCC case while the size of the test is relatively well controlled for WCC case. On the other hand, the size of HLM test seems to be better controlled for moderate or large size of T, although the test becomes undersized for large size of N and small or moderate size of T.

When both a constant and a linear trend are included in the model, the overall property of Z_A^{SPC} and Z_A^{LA} is preserved while HLM test tends to be undersized for N larger than 20.

Table 2 shows the nominal powers of the tests. Because of the size distortion of the tests it is not easy to compare the powers of these tests but we observe that all the tests are less powerful for the moderate size of T due to the undersize property of the tests. In some cases the panel augmented KPSS test apparently dominates HLM test but the reversed relation is observed in other cases. For example, the empirical sizes of Z_A^{SPC}, Z_A^{LA} and HLM test are 0.009, 0.022 and 0.078 when $N = 10$ and $T = 30$ for the constant case with SCC, while the powers of these tests are 0.437, 0.262 and 0.218. On the other hand, the sizes of these tests are 0.058, 0.076 and 0.054 when $N = 10$ and $T = 100$ for the constant case with WCC while the powers are 0.878, 0.812 and 1.00.

[5] It seems that the long-run variance is well estimated by the method proposed by Sul *et al.* (2005). But it is well known that the numerator of the KPSS statistic has a downward bias (cf *inter alia* Shin and Snell (2006) and Kurozumi and Tanaka (2010)). As a result, each test statistic ST_i is downward biased. These downward biases accumulate as N increases leading to the undersize of the tests based on Z_A^{SPC}. Another problem is that the centering and scaling constants are derived asymptotically, $T \to \infty$. When T is finite these constants may be inappropriate. We did some additional simulations employing the bias corrections proposed by Kurozumi and Tanaka (2010) and the centering and scaling constants for fixed T suggested by Hadri and Larsson (2005). We found that the results after corrections are very similar to those before corrections except for the case where $T = 10$. In the latter case, the finite sample corrections are effective in reducing the severe over-size distorsions.

Although our simulations are limited, it is difficult to recommend one of these tests because none of them dominates the others. It seems that HLM test tends to work relatively well in the constant case because the size of the test is more or less controlled in many cases and it has moderate power, whereas the panel augmented KPSS test with SPC correction seems to perform best in many cases corresponding to the trend case (all the other tests tend to be undersized in this case) and is most powerful in many cases.

5. Conclusion

In this paper we extended Hadri's (2000) test to correct for cross-sectional dependence à la Pesaran (2007) in the presence of serial correlation. The panel augmented KPSS test with SPC correction seems to perform best in many instances corresponding to the trend case (all the other tests tend to be undersized in this case) and is most powerful in many cases.

References

[1] Bai, J. and S. Ng (2005). A new look at panel testing of stationarity and the PPP hypothesis, D. W. K. Andrews and J. H. Stock, ed., *Identification and Inference for Econometric Models. Essays in Honor of Thomas Rothenberg.* Cambridge University Press, Cambridge.

[2] Breitung, J. and Pesaran, M. H. (2008). Unit roots and cointegration in panels. In: L. Matyas and P. Sevestre (eds): *The Econometrics of Panel Data: Fundamentals and Recent Developments in Theory and Practice. Dordrecht:* Kluwer Academic Publishers, 3rd edition, Chapt. 9, pp. 279-322.

[3] Chang, Y. (2004). Bootstrap unit root tests in panels with cross-sectional dependency. *Journal of Econometrics 110,* 261-292.

[4] Choi, I. (1993). Asymptotic normality of the least-squares estimates for higher order autoregressive integrated processes with some applications. *Econometric Theory 9,* 263-282.

[5] de Silva, S., K. Hadri and A. R. Tremayne (2009). Panel unit root tests in the presence of cross-sectional dependence: Finite sample performance and an application, *Econometrics Journal,* Vol 12, 2, 340-366.

[6] Hadri, K. (2000). Testing for stationarity in heterogeneous panel data. *Econometrics Journal 3,* 148-161.

[7] Hadri, K. and Larsson, R. (2005). Testing for stationarity in heterogeneous panel data where the time dimension is finite. *Econometrics Journal 8,* 55-69.

[8] Harris, D., S. Leybourne and B. McCabe (2005). Panel stationarity tests for purchasing power parity with cross-sectional dependence. *Journal of Business and Economic Statistic* 23, 395-409.

[9] Kurozumi, E. and S. Tanaka (2010). Reducing the size distortion of the KPSS test, *Journal of Time Series Analysis 31,* 415-426.

[10] Kwiatkowski, D., P. C. B. Phillips, P. Schmidt and Y. Shin (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics 54,* 159-178.

[11] Leybourne, S J & McCabe, B P M, 1994. "A Consistent Test for a Unit Root," Journal of Business & Economic Statistics, vol. 12(2), pages 157-66, April.

[12] Perron, P. and S. Ng (1998). An autoregressive spectral density estimator at frequency zero for non-stationary tests. *Econometric Theory*, Vol. 4(05), 560-603.

[13] Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics 22,* 265-312.

[14] Shin, Y. and A. Snell (2006). Mean group tests for stationarity in heterogeneous panels. *Econometrics Journal 9,* 123-158.

[15] Sul, D., P. C. B. Phillips and C. Y. Choi (2005). Prewhitening bias in HAC estimation. *Oxford Bulletin of Economics and Statistics 67,* 517-546.

[16] Toda, H. Y., and T. Yamamoto (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics 66,* 225-250.

Table 1. Size of the tests: serially correlated case

		constant case						trend case					
		SCC			WCC			SCC			WCC		
N	T	Z_A^{SPC}	Z_A^{LA}	HLM	Z_A^{SPC}	Z_A^{LA}	HLM	Z_A^{SPC}	Z_A^{LA}	HLM	Z_A^{SPC}	Z_A^{LA}	HLM
10	10	0.075	0.338	-	0.062	0.262	-	0.289	0.650	-	0.535	0.800	-
	20	0.004	0.068	0.033	0.004	0.069	0.038	0.001	0.029	0.027	0.003	0.039	0.034
	30	0.009	0.022	0.078	0.009	0.036	0.086	0.006	0.021	0.059	0.011	0.029	0.068
	50	0.040	0.062	0.086	0.018	0.046	0.079	0.030	0.050	0.056	0.014	0.034	0.056
	100	0.061	0.101	0.064	0.024	0.070	0.064	0.045	0.085	0.033	0.014	0.060	0.033
	200	0.109	0.124	0.058	0.058	0.076	0.054	0.120	0.135	0.051	0.053	0.073	0.053
20	10	0.081	0.425	-	0.080	0.338	-	0.437	0.859	-	0.759	0.922	-
	20	0.002	0.059	0.011	0.002	0.067	0.015	0.001	0.021	0.010	0.001	0.036	0.013
	30	0.002	0.008	0.043	0.004	0.033	0.058	0.001	0.008	0.023	0.006	0.022	0.031
	50	0.025	0.048	0.088	0.009	0.042	0.075	0.013	0.026	0.037	0.006	0.025	0.031
	100	0.041	0.087	0.074	0.013	0.072	0.072	0.026	0.059	0.024	0.006	0.044	0.022
	200	0.122	0.150	0.055	0.040	0.071	0.055	0.121	0.154	0.036	0.029	0.063	0.038
30	10	0.088	0.499	-	0.085	0.386	-	0.488	0.930	-	0.832	0.948	-
	20	0.001	0.068	0.003	0.001	0.063	0.006	0.001	0.020	0.003	0.002	0.039	0.007
	30	0.001	0.005	0.026	0.003	0.029	0.040	0.001	0.006	0.009	0.004	0.016	0.016
	50	0.020	0.045	0.076	0.007	0.041	0.064	0.010	0.027	0.019	0.006	0.023	0.014
	100	0.034	0.078	0.062	0.013	0.063	0.063	0.017	0.050	0.014	0.004	0.036	0.014
	200	0.131	0.176	0.058	0.027	0.071	0.059	0.145	0.187	0.028	0.020	0.059	0.031
50	10	0.089	0.635	-	0.103	0.444	-	0.603	0.984	-	0.917	0.980	-
	20	0.001	0.045	0.000	0.002	0.057	0.002	0.000	0.017	0.001	0.004	0.042	0.003
	30	0.000	0.001	0.013	0.001	0.029	0.020	0.000	0.002	0.003	0.002	0.012	0.005
	50	0.009	0.032	0.050	0.002	0.041	0.042	0.002	0.013	0.005	0.002	0.016	0.004
	100	0.030	0.076	0.059	0.006	0.049	0.060	0.017	0.040	0.010	0.004	0.029	0.009
	200	0.089	0.122	0.056	0.023	0.061	0.058	0.082	0.118	0.025	0.016	0.045	0.026
100	10	0.097	0.752	-	0.163	0.529	-	0.877	1.000	-	0.986	0.996	-
	20	0.000	0.040	0.000	0.001	0.054	0.000	0.000	0.014	0.000	0.007	0.059	0.000
	30	0.000	0.001	0.001	0.001	0.035	0.002	0.000	0.001	0.000	0.001	0.008	0.000
	50	0.003	0.018	0.018	0.001	0.032	0.013	0.001	0.003	0.000	0.001	0.007	0.000
	100	0.028	0.067	0.045	0.005	0.050	0.049	0.015	0.030	0.002	0.001	0.019	0.002
	200	0.084	0.124	0.049	0.016	0.049	0.056	0.078	0.114	0.013	0.009	0.032	0.014

Table 2. Power of the tests: serially correlated case

		constant case						trend case					
		SCC			WCC			SCC			WCC		
N	T	Z_A^{SPC}	Z_A^{LA}	HLM	Z_A^{SPC}	Z_A^{LA}	HLM	Z_A^{SPC}	Z_A^{LA}	HLM	Z_A^{SPC}	Z_A^{LA}	HLM
10	10	0.229	0.564	-	0.092	0.315	-	0.186	0.537	-	0.373	0.726	-
	20	0.323	0.282	0.033	0.162	0.269	0.040	0.000	0.044	0.004	0.000	0.070	0.006
	30	0.437	0.262	0.218	0.267	0.324	0.231	0.003	0.041	0.001	0.002	0.079	0.001
	50	0.695	0.373	0.740	0.454	0.461	0.739	0.039	0.086	0.000	0.023	0.155	0.001
	100	0.843	0.521	0.985	0.669	0.631	0.984	0.374	0.207	0.113	0.260	0.357	0.113
	200	0.944	0.672	1.000	0.878	0.812	1.000	0.831	0.413	0.890	0.700	0.636	0.894
20	10	0.312	0.748	-	0.123	0.392	-	0.222	0.705	-	0.508	0.857	-
	20	0.511	0.445	0.004	0.205	0.336	0.008	0.000	0.035	0.000	0.000	0.068	0.001
	30	0.609	0.407	0.194	0.336	0.413	0.200	0.000	0.036	0.000	0.001	0.085	0.000
	50	0.862	0.587	0.894	0.503	0.541	0.890	0.042	0.100	0.000	0.021	0.187	0.000
	100	0.944	0.748	1.000	0.714	0.722	1.000	0.606	0.297	0.083	0.344	0.464	0.084
	200	0.993	0.861	1.000	0.930	0.903	1.000	0.965	0.606	0.987	0.790	0.777	0.986
30	10	0.367	0.814	-	0.146	0.420	-	0.251	0.817	-	0.586	0.899	-
	20	0.608	0.574	0.001	0.231	0.376	0.002	0.000	0.030	0.000	0.000	0.064	0.000
	30	0.659	0.512	0.151	0.369	0.450	0.160	0.000	0.029	0.000	0.000	0.080	0.000
	50	0.898	0.716	0.949	0.525	0.578	0.950	0.046	0.114	0.000	0.019	0.195	0.000
	100	0.962	0.844	1.000	0.728	0.762	1.000	0.710	0.390	0.063	0.394	0.518	0.060
	200	0.996	0.921	1.000	0.947	0.930	1.000	0.981	0.765	0.998	0.831	0.844	0.999
50	10	0.449	0.928	-	0.167	0.452	-	0.288	0.919	-	0.703	0.945	-
	20	0.807	0.739	0.000	0.267	0.410	0.000	0.000	0.020	0.000	0.000	0.072	0.000
	30	0.762	0.612	0.114	0.399	0.490	0.126	0.000	0.018	0.000	0.000	0.088	0.000
	50	0.977	0.872	0.989	0.546	0.610	0.989	0.051	0.107	0.000	0.019	0.222	0.000
	100	0.995	0.943	1.000	0.752	0.788	1.000	0.895	0.469	0.028	0.456	0.582	0.028
	200	1.000	0.980	1.000	0.967	0.962	1.000	0.999	0.874	1.000	0.858	0.893	1.000
100	10	0.556	0.980	-	0.197	0.490	-	0.393	0.987	-	0.837	0.978	-
	20	0.872	0.870	0.000	0.294	0.440	0.000	0.000	0.010	0.000	0.000	0.074	0.000
	30	0.816	0.739	0.055	0.423	0.526	0.065	0.000	0.012	0.000	0.000	0.092	0.000
	50	0.986	0.947	1.000	0.575	0.646	1.000	0.050	0.118	0.000	0.019	0.254	0.000
	100	0.999	0.977	1.000	0.775	0.825	1.000	0.953	0.659	0.008	0.514	0.650	0.007
	200	1.000	0.993	1.000	0.981	0.979	1.000	1.000	0.973	1.000	0.887	0.938	1.000