Testing for stationarity in heterogeneous panel data in the case of model misspecification

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Abstract

This paper investigates the performance of the tests proposed by Hadri (2000) and by Hadri and Larsson (2005) for testing for stationarity in heterogeneous panel data under model misspecification. The panel tests are based on the well known KPSS test (cf. Kwiatkowski et al. (1992)) *which considers two models: stationarity around a deterministic level and stationarity around a deterministic level and trend.* There is no study, as far as we know, on the statistical properties of the test when the wrong model is used. We also consider the case of the presence of the two types of models simultaneously in a panel. We employ two asymptotics: joint asymptotic, T and $N \to \infty$ simultaneously, and T fixed and N allowed to grow indefinitely. We use Monte Carlo experiments to investigate the effects of misspecification in sample sizes usually used in practice. The results indicate that the assumption that T is fixed rather than asymptotic leads to tests that have less size distortions, particularly for relatively small T with large N panels (micro panels) than the tests derived under the joint asymptotics. We also find that choosing a deterministic trend when a deterministic level is true does not affect significantly the properties of the test. But, choosing a deterministic level when a deterministic trend is true leads to extreme over-rejections. Therefore, when unsure about which model has generated the data, it is suggested to use the model with a trend. We also propose a new statistic for testing for stationarity in mixed panel data where the mixture is known. The performance of this new test is very good for both cases of T asymptotic and T fixed. The statistic for T asymptotic is slightly undersized *when T is very small ($\leq$10).*

Keywords: *Heterogeneous panel data, Model misspecification, Stationarity test.*

JEL classification: C12; C23; C52.

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1 Introduction

An upsurge of interest in testing for nonstationarity in panel data has been witnessed in econometrics literature recently. Since the seminal papers by Breitung and Meyer (1994), Quah (1994), Maddala and Wu (1999), Phillips and Moon (1999), Levin, Lin and Chu (2002), Im, Pesaran and Shin (2003), Hadri (2000) and Hadri and Larsson (2005), panel unit root and stationarity tests, have been applied to a variety of key economic issues with the hope that the increased power of these tests, due to the exploitation of the cross-section dimension, would provide more compelling evidence. Banerjee (1999), Baltagi and Kao (2000), Baltagi (2001) and Breitung and Pesaran (2005) provide comprehensive surveys on the subject. The original panel stationary test suggested by Hadri (2000) is extensively used in empirical work as a complement to standard panel unit root tests. It has also been the subject of further theoretical development by, inter-alia, Hadri and Larsson (2005) for finite T, Carrion-i-Silvestre, J. L., T. Del Barrio and E. López-Bazo (2005) and Hadri and Rao (2007) who extended the test to account for structural breaks in the deterministic components.

These tests are very popular among researchers due to the availability of panel data sets with large T and N, e.g, Penn World Tables data set. The proposed panel tests have been used in many studies including O'Connell (1998), Oh (1996), Papell (1997, 2002), Wu (1996) and Wu and Wu (2001), who focused on testing the existence of purchasing power parity. Culver and Papell (1997) applied panel unit root tests to the inflation rate for a subset of OECD countries. They have also been employed in testing output convergence and more recently in the analysis of business cycle synchronization, house price convergence, regional migration and household income dynamics (cf. Breitung and Pesaran (2005)).

Traditional panel data analysis was mainly applied to micro panel with large N and small T. However, as noted above, the availability of panel data sets with large N and large T led to the development of asymptotics adapted to this type of panels. The main contribution in this area is by Phillips and Moon (1999) who considered three configurations of asymptotics: sequential limits, wherein $T \to \infty$ followed by $N \to \infty$, joint limits where T, $N \to \infty$ simultaneously and the diagonal path limit theory in which the passage to infinity is done along a specific diagonal path. The drawback of sequential limits is that in certain cases, they can give asymptotic results which are misleading. The downside of diagonal path limit theory is that the assumed expansion path $(T(N), N) \to \infty$ may not provide an appropriate approximation for a given (T, N) blend. Finally, the joint limit theory requires, generally, a rate condition on the relative speed of T and N going to infinity. For Hadri (2000) panel stationarity test considered here, the more robust joint asymptotics requires $N/T \to 0$ when $T, N \to \infty$ simultaneously which means that the tests are applicable to panels with T larger than N. This condition therefore limits the applicability of the tests. To overcome this difficulty, Hadri and Larsson (2005) consider a fourth limit theory in which T is fixed and N is allowed to grow indefinitely. *This makes the test applicable even when T is smaller than N.*

In this paper, we analyze via simulations the robustness of Hadri (2000) and Hadri and Larsson (2005) panel stationarity tests for possible misspecification. More precisely, we assume that for all the cross-sections we have stationarity around a level (Model 1) when the true model is stationarity for all the cross-sections around a trend (Model 2) and vice versa. We also consider the case of mixed models, i.e., the true models are different across cross-sections. The main motivation of this paper is that, in practice, the researcher ignores the true models and does not pre-test[2]. Therefore, the possibility of misspecification is real. The paper seeks to uncover the consequences of misspecification on the statistical properties of the tests. Finally, we also propose a new test for testing for stationarity in mixed panel data where the mixture is known.

The remainder of this paper is organized as follows. Section 2 reviews the related models and test statistics. Section 3 investigates the finite sample properties of the tests under misspecification via Monte Carlo simulations. Section 4 concludes.

2 Panel models and statistics

We recall that the models in Hadri (2000) can be written as follows:

$$\text{Model 1: } y_{it} = r_{it} + \varepsilon_{it}, \tag{1}$$

and

$$\text{Model 2: } \; y_{it} = r_{it} + \beta_i t + \varepsilon_{it}, \tag{2}$$

where r_{it} is a random walk:

$$r_{it} = r_{it-1} + u_{it}.$$

y_{it} $(i = 1, 2, ..., N$ and $t = 1, 2, ..., T)$ are the observed series for which we wish to test the stationarity for all i. The ε_{it} and u_{it} are $i.i.d$ error terms across i and over t with $E[\varepsilon_{it}] = 0$, $E[\varepsilon_{it}^2] = \sigma_{i\varepsilon}^2 > 0$ and $E[u_{it}] = 0$, $E[\sigma_{iu}^2] = \sigma_{iu}^2 \geq 0$. Under the null, $\sigma_{iu}^2 = 0$ for all i, the initial value r_{i0} is treated as fixed unknown and plays the role of an intercept (cf. Abadir (1993) and Abadir and Hadri (2000) for the importance of initial values in autoregressive models). Hence, under the null hypothesis y_{it} is stationary around a level in Model 1 and trend stationary in Model 2.

Suppose $\widehat{\varepsilon}_{it}$ are the residuals from the regression y_{it} on an intercept for Model 1 and on an intercept plus a time trend for Model 2, the panel test statistic is the average of the KPSS test applied to each cross-section (cf. Hadri (2000) for more details) is given by

$$\widehat{LM} = \frac{1}{N} \sum_{i=1}^{N} \frac{\frac{1}{T^2} \sum_{t=1}^{T} S_{it}^2}{\widehat{\sigma}_{i\varepsilon}^2}, \tag{3}$$

[2] Pre-testing has its own problems.

where $\widehat{\sigma}_{i\varepsilon}^2$ is a consistent estimator of $\sigma_{i\varepsilon}^2$. In the absence of serial correlation a consistenr estimator is given by:

$$\widehat{\sigma}_{i\varepsilon}^2 = \frac{1}{T}\sum_{t=1}^{T}\widehat{\varepsilon}_{it}^2. \tag{4}$$

In the presence of serial correlation, $\widehat{\sigma}_{i\varepsilon}^2$ is replace by a consistent estimator of the long-run variance. The panel statistic for the null of stationarity is given by:

$$Z_\mu = \frac{\sqrt{N}(\widehat{LM}_\mu - \xi_\mu)}{\zeta_\mu} \rightarrow N(0,1), \tag{5}$$

and

$$Z_\tau = \frac{\sqrt{N}(\widehat{LM}_\tau - \xi_\tau)}{\zeta_\tau} \rightarrow N(0,1). \tag{6}$$

The indices μ and τ indicate that the statistic corresponds to Model 1 and Model 2 respectively. These results are obtained using the Lindberg-levy central limit theorem exploiting the cross-sectional independence.

Under the assumption of $T \rightarrow \infty$, the means ξ_k and the variances ζ_k^2 of the random variable $\int V_k(r)^2$ are obtained by Hadri (2000) using the technique of characteristic functions, where $k = \{\mu, \tau\}$. $V_\mu(r)$ denotes a standard Brownian bridge in Model 1 and $V_\tau(r)$ a second-level Brownian bridge in Model 2.

For Model 1, the mean and variance are

$$\xi_\mu = \frac{1}{6}\ ,\ \zeta_\mu^2 = \frac{1}{45},$$

and for Model 2,

$$\xi_\tau = \frac{1}{15}\ ,\ \zeta_\tau^2 = \frac{11}{6300}. \tag{7}$$

In the case where T is assumed to be fixed, the means and variances of Model 1 and Model 2 are given by:

$$\xi_\mu = \frac{T+1}{6T},\ \zeta_\mu^2 = \frac{T^2+1}{20T^2} - (\frac{T+1}{6T})^2 \text{ and}$$
$$\xi_\tau = \frac{T+2}{15T},\ \zeta_\tau^2 = \frac{(T+2)(13T^2+23)}{2100T^3} - (\frac{T+2}{15T})^2, \tag{8}$$

respectively.

Consider a mixture panel of size N, where we have M time series follow a level case and the remaining $N - M$ time series follow a trend case. Define the proportion

$$\pi = \frac{M}{N}$$

and assume that π remains a known constant proportion.

For a mixture panel of principal concern here, we propose to use the following statistic

$$\widehat{LM}_m = \pi \times \widehat{LM}_\mu + (1-\pi) \times \widehat{LM}_\tau$$

and as a result we obtain the following limiting distribution

$$Z_m = \frac{\sqrt{N}(\widehat{LM}_m - \xi_m)}{\zeta_m} \rightarrow N(0,1) \tag{9}$$

where

$$\begin{aligned} \xi_m &= \pi\xi_\mu + (1-\pi)\xi_\tau \\ \zeta_m^2 &= \pi\zeta_\mu^2 + (1-\pi)\zeta_\tau^2 \end{aligned} \tag{10}$$

The poofs are collected in Appendix.

3 Monte Carlo simulation results

In this section, Monte Carlo experiments are used to evaluate the finite sample performances of the proposed tests in the case of misspecification under both assumptions of T asymptotic and T fixed. Each simulation is based on GAUSS RNDN procedure, using 10000 replications (cf. Hadri and Phillips (1999) for the importance of the number of replications in simulations). The data-generating process (DGP) for Model 1 is:

$$y_{it} = \alpha_i + \varepsilon_{it},$$

and for Model 2 is:

$$y_{it} = \alpha_i + \beta_i t + \varepsilon_{it},$$

where ε_{it} are $i.i.d$ $N(0,1)$ under the null hypothesis. We generated α_i from $U[0,10]$ and β_i from $U[0,2]$. Please note that the results when T is assumed fixed are reported inside brackets in the Tables.

In simulations, when T is assumed asymptotic, the estimator of $\sigma_{i\varepsilon}^2$ is corrected for the number of degree of freedom. Therefore, we use

$$\widehat{\sigma}_{i\varepsilon}^2 = \frac{1}{T-1}\sum_{t=1}^{T} \widehat{\varepsilon}_{it}^2,$$

as an estimator of $\sigma_{i\varepsilon}^2$ for Model 1 and

$$\widehat{\sigma}_{i\varepsilon}^2 = \frac{1}{T-2}\sum_{t=1}^{T} \widehat{\varepsilon}_{it}^2.$$

for Model 2. In the case when T is assumed fixed, we use (4) without any correction.

3.1 Model misspecifications using the same model in all the cross-sections

In this *sub*section, the wrong model is used. Table 1 presents the empirical size at 5% significance level corresponding to the critical value 1.645 (one-sided test). In this case, the true model is Model 2 but we wrongly use the statistic Z_μ, hence, committing a deliberate misspecification. The tests have extremely severe size distortions, all equal to 1. This means that despite that the null hypothesis is true, we will wrongly reject it all the time. The same conclusion is reached when we use the tests where T is assumed finite.

[Table 1 here]

Table 2 shows the reverse situation. The data is generated by Model 1 but we employ on purpose the wrong statistic Z_τ. For the case where T is assumed asymptotic, the size of the test is very close to the nominal value 0.05 for samples with $T > 25$. As expected, as T and N get larger but N is not too large relatively to T, the test becomes less distorted. This is due to the relative rate condition: $N/T \to 0$ when $T, N \to \infty$. For T assumed fixed, the size does not deteriorate even when N is larger than T, as expected.

[Table 2 here]

3.2 Model misspecifications in a mixed stationary panel

In this *sub*section, we investigate the mixed stationary panel data where there are M ($M < N$) cross-sections, which are from Model 1, while the remaining $(N - M)$ cross-sections are generated by Model 2. We apply the panel test statistics Z_μ and Z_τ in turn to a mixed stationary panel data to evaluate their performances.

We have misspecification whether we apply Z_μ or Z_τ statistic in a mixed stationary panel data. Table 3 and Table 4 report the simulation results about the size of Z_μ and Z_τ respectively. Different proportions of each models in a panel are examined.

The results in Table 3, where we use Z_μ statistic, reveal that most results have large size distortion when $M/N < 1$ under both assumptions of T asymptotic and T fixed. We find that there is a tendency for the size to improve when the proportion of level stationary models increases. At the extreme point when $M/N = 1$, that is, all the cross-sections are generated by Model 1, there is no misspecification problem and the sizes are close to the nominal 0.05 as expected. Similar results are obtained when T is assumed fixed.

[Table 3 here]

In Table 4, where we use Z_τ statistic, we find that the calculated sizes are very close to the nominal one for any combination of T, N and M/N when T is assumed fixed. However, for T assumed asymptotic, *the sizes are distorted when T is smaller than N.*

[Table 4 here]

3.2.1 The correct statistic for mixed panel data

Table 5 gives the sizes in a mixed panel data where the correct statistic incorporating the information about the mixture is used. The sizes for both T asymptotic and T fixed are very close to the nominal one. The statistic for T asymptotic is slightly undersized when T is very small ($\leq$10).

[Table 5 here]

4 Conclusion

This paper extends the panel stationarity test proposed by Hadri (2000) and Hadri and Larsson (2005) to the more realistic case of model misspecification. The investigations are based on the assumptions of T asymptotic and T fixed. Monte Carlo simulations are used to analyze the effects of misspecifications. The results suggest that using the statistic corresponding to Model 2 is very robust to misspecification. The statistic under the assumption of T fixed performs better than the statistic where T is assumed asymptotic particularly when T is relatively smaller than N. Finally, we propose a new statistic for testing stationarity in mixed panel data where the mixture is known. The performance of this new test is very good for both cases of T asymptotic and T fixed. The statistic for T asymptotic is slightly undersized when T is very small ($\leq$10).

Appendix

Proof. of equation (10).

We recall that (cf. Hadri (2000)):

$$\widehat{\eta}_{\mu i} = T^{-2}\sum_{t=1}^{T} S_{it}^2/\widehat{\sigma}_{i\epsilon}^2 \rightarrow \int V_\mu(r)^2 dr \quad \text{as} \quad T \rightarrow \infty$$

and

$$\widehat{\eta}_{\tau i} = T^{-2}\sum_{t=1}^{T} S_{it}^2/\widehat{\sigma}_{i\epsilon}^2 \rightarrow \int V_\tau(r)^2 dr \text{ as } T \rightarrow \infty$$

Hence, for Model 1

$$E(\widehat{\eta}_{\mu i}) \rightarrow E\int V_\mu(r)^2 dr = \xi_\mu, \quad V(\widehat{\eta}_{\mu i}) \rightarrow Var(\int V_\mu(r)^2 dr) = \zeta_\mu^2$$

and for Model 2

$$E(\widehat{\eta}_{\tau i}) \rightarrow E\int V_\tau(r)^2 dr = \xi_\tau, \quad V(\widehat{\eta}_{\tau i}) \rightarrow Var(\int V_\tau(r)^2 dr) = \zeta_\tau^2.$$

The values of the above moments are given by (7) and (8) for T asymptotic and T fixed respectively.

Calculations of the mean and variance of $\widehat{LM}_\mu$ and $\widehat{LM}_\tau$ are as follows. For Model 1, since

$$\widehat{LM}_\mu = \frac{1}{M}(\sum_{i=1}^{M} \frac{\frac{1}{T^2}(\sum_{t=1}^{T} S_{it}^2)}{\widehat{\sigma}_{i\varepsilon,1}^2}) = \frac{1}{M}\sum_{i=1}^{M}(\widehat{\eta}_{\mu i}),$$

therefore

$$E[\widehat{LM}_\mu] = \frac{1}{M}\sum_{i=1}^{M} E(\widehat{\eta}_{\mu i}) = \xi_\mu,$$

and

$$\begin{aligned} Var(\widehat{LM}_\mu) &= Var(\frac{1}{M}(\sum_{i=1}^{M}\widehat{\eta}_{\mu i}) \\ &= \frac{1}{M^2}\sum_{i=1}^{M} Var(\widehat{\eta}_{\mu i}) \\ &= \frac{1}{M}\zeta_\mu^2. \end{aligned}$$

For Model 2, we have

$$\begin{aligned} \widehat{LM}_\tau &= \frac{1}{N-M}(\sum_{i=M+1}^{N} \frac{\frac{1}{T^2}(\sum_{t=1}^{T} S_{it}^2)}{\widehat{\sigma}_{i\varepsilon,1}^2}) \\ &= \frac{1}{N-M}\sum_{i=M+1}^{N}(\widehat{\eta}_{\tau i}), \end{aligned}$$

so we can find

$$E(\widehat{LM}_\tau) = \frac{1}{N-M}\sum_{i=M+1}^{N} E(\widehat{\eta_{\tau i}}) = \xi_\tau$$

and

$$\begin{aligned} Var(\widehat{LM}_\tau) &= Var(\frac{1}{N-M}\sum_{i=M+1}^{N}\widehat{\eta}_{\tau i}) \\ &= \frac{1}{(N-M)^2}\sum_{i=M+1}^{N} Var(\widehat{\eta}_{\tau i}) \\ &= \frac{1}{N-M}\zeta_\tau^2 \end{aligned}$$

Derivation of the mean and variance of $\widehat{LM}_m$ are as follows:

$$\widehat{LM}_m = \frac{M}{N}(\widehat{LM}_\mu) + \frac{N-M}{N}(\widehat{LM}_\tau),$$

$$\begin{aligned} E[\widehat{LM}_m] &= \frac{M}{N}(E[\widehat{LM}_\mu]) + \frac{N-M}{N}(E[\widehat{LM}_\tau]) \\ &= \frac{M}{N}(\xi_\mu) + \frac{N-M}{N}(\xi_\tau) \\ &= \xi_m \end{aligned}$$

and

$$\begin{aligned} Var[\widehat{LM}_m] &= \frac{M^2}{N^2}(Var[\widehat{LM}_\mu]) + \frac{(N-M)^2}{N^2}(Var[\widehat{LM}_\tau]) \\ &= \frac{M^2}{N^2}\frac{1}{M}(\zeta_\mu^2) + \frac{(N-M)^2}{N^2}\frac{1}{N-M}(\zeta_\tau^2) \\ &= \frac{M}{N^2}(\zeta_\mu^2) + \frac{N-M}{N^2}(\zeta_\tau^2) \\ &= \frac{1}{N}\zeta_m^2. \end{aligned}$$

Recall that as $M \to \infty$ and $N - M \to \infty$ (while π remains constant)

$$Z_\mu = \frac{\sqrt{M}(\widehat{LM}_\mu - \xi_\mu)}{\zeta_\mu} \to N(0,1)$$

and as

$$Z_\tau = \frac{\sqrt{N-M}(\widehat{LM}_\tau - \xi_\tau)}{\zeta_\tau} \to N(0,1)$$

It follows that $\widehat{LM}_m$ which is a weighted average of $\widehat{LM}_\mu$ and $\widehat{LM}_\tau$ has the following limiting distribution

$$Z_m = \frac{\sqrt{N}(\widehat{LM}_m - \xi_m)}{\zeta_m} \to N\,(0,1)$$

where

$$\begin{aligned} \xi_m &= \frac{M \times \xi_\mu + (N-M) \times \xi_\tau}{N} = \pi\xi_\mu + (1-\pi)\xi_\tau \\ \zeta_m^2 &= \frac{M\zeta_\mu^2 + (N-M)\zeta_\tau^2}{N} = \pi\zeta_\mu^2 + (1-\pi)\zeta_\tau^2 \end{aligned} \qquad (11)$$

Now in order to apply this new test, we have just to replace the appropriate above moments in (9). ■

Table 1. Size of Z_μ in the case of model misspecification

	$N=5$	$N=10$	$N=15$	$N=25$	$N=50$	$N=100$
$T=10$	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
$T=20$	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
$T=50$	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
$T=100$	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
$T=200$	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)

Table 2. Size of Z_τ in the case of misspecification

	$N=5$	$N=10$	$N=15$	$N=25$	$N=50$	$N=100$
$T=10$	0.0079	0.0052	0.0049	0.0023	0.0012	0.0002
	(0.1021)	(0.1145)	(0.1146)	(0.1244)	(0.1256)	(0.1290)
$T=20$	0.0336	0.0322	0.0313	0.0223	0.0226	0.0193
	(0.0848)	(0.0922)	(0.0962)	(0.0911)	(0.0917)	(0.0916)
$T=50$	0.0572	0.0496	0.0502	0.0503	0.0427	0.0362
	(0.0746)	(0.0699)	(0.0775)	(0.0794)	(0.0733)	(0.0615)
$T=100$	0.0618	0.0556	0.0551	0.0545	0.0547	0.0500
	(0.0687)	(0.0639)	(0.0676)	(0.0682)	(0.0673)	(0.0644)
$T=200$	0.0606	0.0575	0.0544	0.0561	0.0536	0.0546
	(0.0659)	(0.0645)	(0.0576)	(0.0625)	(0.0609)	(0.0616)

Table 3 Size of Z_μ in model of mixed stationary panel series

	M/N	0.25	0.50	0.75	1
$N = 20$	$T = 10$	1.0000	1.0000	0.77899	0.0255
		(1.0000)	(1.0000)	(0.9970)	(0.0583)
	$T = 20$	1.0000	1.0000	1.0000	0.0419
		(1.0000)	(1.0000)	(1.0000)	(0.0618)
	$T = 50$	1.0000	1.0000	1.0000	0.0544
		(1.0000)	(1.0000)	(1.0000)	(0.0628)
	$T = 100$	1.0000	1.0000	1.0000	0.0603
		(1.0000)	(1.0000)	(1.0000)	(0.0633
$N = 40$	$T = 10$	1.0000	1.0000	1.0000	0.0195
		(1.0000)	(1.0000)	(1.0000)	(0.0553)
	$T = 20$	1.0000	1.0000	1.0000	0.0362
		(1.0000)	(1.0000)	(1.0000)	(0.0571)
	$T = 50$	1.0000	1.0000	1.0000	0.0499
		(1.0000)	(1.0000)	(1.0000)	(0.0570)
	$T = 100$	1.0000	1.0000	1.0000	0.0530
		(1.0000)	(1.0000)	(1.0000)	(0.0570)
$N = 60$	$T = 10$	1.0000	1.0000	1.0000	0.0187
		(1.0000)	(1.0000)	(1.0000)	(0.0569)
	$T = 20$	1.0000	1.0000	1.0000	0.0380
		(1.0000)	(1.0000)	(1.0000)	(0.0571)
	$T = 50$	1.0000	1.0000	1.0000	0.0529
		(1.0000)	(1.0000)	(1.0000)	(0.0613)
	$T = 100$	1.0000	1.0000	1.0000	0.0518
		(1.0000)	(1.0000)	(1.0000)	(0.0558)
$N = 100$	$T = 10$	1.0000	1.0000	1.0000	0.0139
		(1.0000)	(1.0000)	(1.0000)	(0.0493)
	$T = 20$	1.0000	1.0000	1.0000	0.0357
		(1.0000)	(1.0000)	(1.0000)	(0.0549)
	$T = 50$	1.0000	1.0000	1.0000	0.0488
		(1.0000)	(1.0000)	(1.0000)	(0.0571)
	$T = 100$	1.0000	1.0000	1.0000	0.0509
		(1.0000)	(1.0000)	(1.0000)	(0.0540)

Table 4. Size of $Z\tau$ in model of mixed stationary panel series

	M/N	0.25	0.50	0.75	1
$N=20$	$T=10$	0.0031	0.0034	0.0034	0.0032
		(0.0548)	(0.0558)	(0.0595)	(0.0564)
	$T=20$	0.0252	0.0250	0.0285	0.0281
		(0.0579)	(0.0567)	(0.0567)	(0.0583)
	$T=50$	0.0501	0.0451	0.0488	0.0498
		(0.0620)	(0.0582)	(0.0596)	(0.0611)
	$T=100$	0.0537	0.0530	0.0536	0.0542
		(0.0604)	(0.0585)	(0.0597)	(0.0596)
$N=40$	$T=10$	0.0013	0.0014	0.0016	0.0019
		(0.0575)	(0.0563)	(0.0550)	(0.0563)
	$T=20$	0.0200	0.0198	0.0223	0.0198
		(0.0556)	(0.0538)	(0.0573)	(0.0583)
	$T=50$	0.0445	0.0462	0.0453	0.0458
		(0.0555)	(0.0594)	(0.0590)	(0.0573)
	$T=100$	0.0471	0.0511	0.0511	0.0510
		(0.0527)	(0.0576)	(0.0580)	(0.0567)
$N=60$	$T=10$	0.0010	0.0018	0.0010	0.0010
		(0.0537)	(0.0521)	(0.0518)	(0.0537)
	$T=20$	0.0217	0.0197	0.0203	0.0208
		(0.0541)	(0.0551)	(0.0563)	(0.0578)
	$T=50$	0.0432	0.0414	0.0436	0.0415
		(0.0577)	(0.0542)	(0.0575)	(0.0537)
	$T=100$	0.0521	0.0486	0.0498	0.0493
		(0.0573)	(0.0548)	(0.0560)	(0.0546)
$N=100$	$T=10$	0.0004	0.0003	0.0003	0.0005
		(0.0518)	(0.0496)	(0.0543)	(0.0515)
	$T=20$	0.0198	0.0183	0.0170	0.0166
		(0.0575)	(0.0551)	(0.0556)	(0.0526)
	$T=50$	0.0406	0.0428	0.0412	0.0421
		(0.0544)	(0.0561)	(0.0548)	(0.0564)
	$T=100$	0.0472	0.0503	0.0436	0.0489
		(0.0528)	(0.0576)	(0.0497)	(0.0565)

Table 5 Size of Z_m in mixed stationary panel series

	M/N	0.25	0.50	0.75
$N = 20$	$T = 10$	0.0191	0.0240	0.0227
		(0.0665)	(0.0622)	(0.0586)
	$T = 20$	0.0401	0.0402	0.0426
		(0.0608)	(0.0609)	(0.0587)
	$T = 50$	0.0618	0.0590	0.0567
		(0.0702)	(0.0655)	(0.0644)
	$T = 100$	0.0606	0.0608	0.0588
		(0.0644)	(0.0643)	(0.0623)
$N = 40$	$T = 10$	0.0151	0.0193	0.0154
		(0.0599)	(0.0586)	(0.0552)
	$T = 20$	0.0410	0.0366	0.0365
		(0.0648)	(0.0571)	(0.0555)
	$T = 50$	0.0569	0.0525	0.0544
		(0.0649)	(0.0617)	(0.0612)
	$T = 100$	0.0580	0.0569	0.0511
		(0.0612)	(0.0604)	(0.0552)
$N = 60$	$T = 10$	0.0123	0.0141	0.0183
		(0.0574)	(0.0564)	(0.0632)
	$T = 20$	0.0368	0.0357	0.0369
		(0.0571)	(0.0567)	(0.0563)
	$T = 50$	0.0512	0.0492	0.0516
		(0.0605)	(0.0566)	(0.0595)
	$T = 100$	0.0555	0.0539	0.0529
		(0.0591)	(0.0575)	(0.0567)
$N = 100$	$T = 10$	0.0085	0.0134	0.0154
		(0.0560)	(0.0571)	(0.0559)
	$T = 20$	0.0337	0.0348	0.0343
		(0.0588)	(0.0565)	(0.0543)
	$T = 50$	0.0505	0.0507	0.0492
		(0.0594)	(0.0592)	(0.0580)
	$T = 100$	0.0558	0.0538	0.0539
		(0.0598)	(0.0574)	(0.0578)

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