Panel Data Unit Roots Tests Using Various Estimation Methods

NAM T. HOANG*and ROBERT F. MCNOWN
Department of Economics - University of Colorado at Boulder

Abstract

In this paper, the performances of panel data unit root tests are considered and various estimation methods under different properties of data are compared. It is shown that weighted symmetric estimation increases the power of the tests without adversely affecting the size, for most data properties and most panels of dimensions N and T. The presence of serial correlation and cross-sectional correlation does not reduce the power of the tests significantly.

Keywords: Panel unit root; cross-section correlation; serial correlation
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*Correspondent author, email: trung.hoang@colorado.edu

1 Introduction

Since Levin and Lin (1993) established the foundations for panel unit root tests, a few tests for panel unit roots have been proposed. Among those, the most common tests in practice are Levin-Lin(LL), Im-Pesaran-Shin (1997)(IPS) and Maddala-Wu (1999)(MW).

Im-Pesaran-Shin (2003) did the Monte-Carlo simulations to compare the test that they proposed (IPS) and the Levin-Lin test, under the assumption of no cross-sectional correlation in panels, and they showed that the IPS test is more powerful than the LL test. Maddala-Wu (1999) also did simulations to compare three tests: LL, IPS and their own test MW. They generated the data with cross-sectional correlation, and the variance-covariance matrix of the cross-section error terms was randomly generated. They found the performance of the LL test to be the worst. Although all three tests exhibit size distortion and low power under cross-sectional dependence, the MW test generally performs better than the LL and IPS tests.

O'Connell (1998) was the first author to note that cross-sectional correlation in panel data will have negative effects on the LL panel unit root test, making the test have substantial size distortion and low power. In his paper, he did a Monte-Carlo simulation to study the impact of cross-section correlation on the size and power of the Levin-Lin test and he proposed using GLS estimators instead of OLS estimators in the Levin-Lin test to increase power.

Kristian (2005) studied the performance of the Levin-Lin test under cross-sectional correlation. In his DGP, he controlled the magnitude of the correlation, and he found results similar to the results of O'Connell (1998). He also proposed to use the panel corrected standard error (PCSE) estimator instead of the OLS standard error in the LL test, arguing that the the PCSE-based test has better size and more power when compared to the LL test. Strauss (2003) did a Monte-Carlo simulation of the IPS test, and found that the magnitude of the contemporaneous correlation is important in the IPS test, and the demeaning procedure across the panel that Im *et al.* (2003) suggest doesn't eliminate this problem.

Of the three popular panel unit roots tests (LL, IPS and MW), the LL test is of limited use, because the null hypothesis and the alternative hypothesis are so strict that it is not realistic in practice. A comparison between the IPS or MW test and the LL test is not valid because the alternative hypotheses of these tests are different. The MW and IPS tests are more directly comparable. The intent of my paper is to perform such a comparison employing both least squares and weighted symmetric estimators.

Comparing the IPS and MW tests in the Maddala and Wu paper (1999), the data generating process is constructed with both serial correlation and contemporaneous correlation, but the serial correlation coefficients are randomly generated and the variance-covariance matrix of contemporaneous errors is also a random positive definite matrix. In this paper, we examine the performance of the IPS and MW tests with different estimation methods under alternative data generating processes. We construct separate DGPs, varying the magnitude of the correlation between cross-sections, to study the impact of serial correlation and contemporaneous correlation separately. In addition, it is well known that a moving-average component in the series will cause size distortion and lower power of unit roots tests. We take this into account to examine the performance of the IPS and MW tests under the moving-average component DGP.

Despite the fact that the IPS and MW test can be performed with any unit-root test (for a single time series in each cross-section), it has been only used with the Dickey-Fuller (DF) or Augmented Dickey-Fuller (ADF) estimation equations until now. We know that although often used, the ADF test (as well the Phillips-Perrons (PP) test) has substantial size distortion and lack of power in some environments. Maddala and Kim (2002) surveyed unit root tests other than the ADF and PP tests, including a weighted symmetric(WS) estimator test. Quoting Maddala and Kim: *"..it is better to use one of these than the ADF and PP tests discussed in previous chapter. It is time now to completely discard the ADF* *and PP test (they are still used often in applied work!)"* (p.145). For this reason, we use both least squares and the weighted symmetric estimation approach with the IPS and MW test, examining their performance under different data properties. The simulation results show that the panel unit root tests with WS estimation have more power with reasonable size properties compared with the tests using DF and ADF estimation in general.

2 Panel data unit roots tests

2.1 The Im-Pesaran-Shin Test

The model is:

$$y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + \epsilon_{i,t} \tag{1}$$

$$t = 1, 2, \ldots, T$$

The null and alternative hypotheses are defined as:

$$H_0 : \rho_i = 1, i = 1, 2, \ldots, N \tag{2}$$

against the alternatives

$$H_A : \rho_i < 1, i = 1, 2, \ldots, N_1; \rho_i = 1, i = N_1 + 1, N_1 + 2, \ldots, N \tag{3}$$

They use separate unit root tests for the N cross-section units. The DF regression:

$$y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + \epsilon_{i,t} \tag{4}$$

$$t = 1, 2, \ldots, T$$

or ADF regression:

$$y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + \sum_{j=1}^{p_i} \theta_{ij} \Delta y_{i,t-j} + \epsilon_{i,t} \tag{5}$$

$$t = 1, 2, \ldots, T$$

is estimated and the t-statistic for testing $\rho_i = 1$ is computed. Let $t_{i,T}(i = 1, 2, \ldots, N)$ denote the t-statistic for testing unit roots in individual series i, and let $E(t_{i,T}) = \mu$ and $V(t_{i,T}) = \sigma^2$. Then

$$\bar{t}_{N,T} = \frac{1}{N} \sum_{i=1}^{N} t_{i,T} \tag{6}$$

and

$$\sqrt{N} \frac{(\bar{t}_{N,T} - \mu)}{\sigma} \overset{N}{\Longrightarrow} \mathrm{N}(0, 1)$$

The IPS test is a way of combining the evidence on the unit root hypothesis from N unit root tests performed on N cross-section units. The test assumption is that T is the same for all cross-section units and hence $E(t_{i,T})$ and $V(t_{i,T})$ are the same for all i, so the IPS test is applied only for balanced panel data. In the case of serial correlation, IPS propose using the ADF t-test for individual series. $E(t_{i,T})$ and $V(t_{i,T})$ will vary as the lag length included in the ADF regression varies. They tabulated $E(t_{i,T})$ and $V(t_{i,T})$ for different lag lengths. In practice, to use their tables one is restricted to using the same lag length for all the ADF regressions for individual series.

In principle, the IPS test also can be used in association with any parametric unit-root test, as long as the panel is balanced and all the t-statistcs for the unit-root in every cross-section are identically distributed so that they will have the same variance and mean. Then the Central Limit Theorem(CLT) can be applied. Although the IPS test requires a balanced panel, it is the test most often used in practice because it is simple and easy to use. Until now, people have only used IPS with the ADF or DF estimation equation. We apply the

IPS test using weighted symmetric estimation. To do this, we estimate by simulation the variances and means of the weighted symmetric t-statistic with different values of T and lag lengths of the ADF equation, and then use these variances and means to compute the test statistics which have the standard normal distribution under the CLT.

2.2 Maddala and Wu Test

Maddala and Wu (1999) proposed the use of the Fisher (p_λ) test which is based on combining the p-values of the test-statistic for a unit root in each cross-sectional unit. Let π_i be the p-value from the ith-test such that π_i are $U[0,1]$ and independent, and $-2log_e\pi_i$ has a χ^2 distribution with 2 degrees of freedom. So $p_\lambda = -2\sum_{i=1}^{N} log_e\pi_i$ has a χ^2 distribution with $2N$ degrees of freedom. The null and alternative hypotheses are the same as in the IPS test. Applying the ADF estimation equation in each cross-section, we can compute the ADF t-statistic for each individual series, find the corresponding p-value from the empirical distribution of ADF t-statistic (obtained by Monte-Carlo simulation), and compute the Fisher-test statistics and compare it with the appropriate χ^2 critical value.

The test proposed by Maddala-Wu (1999) using Fisher's test is promising, for the following two reasons: *First*, it can be performed with any unit root test on a single time-series. It should be kept in mind that the MW test does not require using the same unit-root test in each cross section (in practice, one usually uses the same unit root test in each cross-section). *Second*, it does not require a balanced panel as the IPS test does, so T can differ over cross-sections. The main disadvantage of the MW test is that the p-values for each t-statistic in a cross-section have to be derived by Monte-Carlo simulation. Because of this, IPS may be favored over MW, but with more and more powerful computer software available using the MW test is less of problem.

We also apply the weighted symmetric estimation in the context of MW test, and study its performance under various data properties. Simulations are conducted to estimate the empirical weighted symmetric distribution of $\hat{t}_{ws}$ with different values of T.

3 Weighted Symmetric Estimation

3.1 Weighted Symmetric Estimation for AR(1) model

Consider the process:

$$Y_t = \alpha + \rho Y_{t-1} + \epsilon_t \tag{7}$$

$$t = 2, 3, \ldots, T; \epsilon_t \sim N(0, \sigma^2)$$

The idea of the symmetric estimator is that if a stationary process satisfies this equation, then it also satisfies the equation:

$$Y_t = \alpha + \rho Y_{t+1} + u_t \tag{8}$$

$$t = 1, 2, \ldots, (T-1); u_t \sim N(0, \sigma^2)$$

Consider an estimator of ρ that minimizes:

$$Q_w(\rho) = \sum_{t=2}^{T} w_t (y_t - \rho y_{t-1})^2 + \sum_{t=1}^{T-1} (1 - w_{t+1})(y_t - \rho y_{t+1})^2 \tag{9}$$

where w_t , t=2,3,...,T are weights, $y_t = Y_t - \bar{y}$ and $\bar{y} = T^{-1} \sum_{j=1}^{T} y_j$. The estimator obtained by setting $w_t = T^{-1}(t-1)$ is called the weighted symmetric (WS) estimator.

The weighted symmetric estimator of ρ is:

$$\hat{\rho}_{ws} = \frac{\sum_{t=2}^{T} y_t y_{t-1}}{\sum_{t=2}^{T-1} y_t^2 + T^{-1} \sum_{t=1}^{T} y_t^2} \tag{10}$$

and the corresponding t-statistic is:

$$\hat{t}_{ws} = \hat{\sigma}_{ws}^{-1}(\hat{\rho}_{ws} - 1)(\sum_{t=2}^{T-1} y_t^2 + T^{-1}\sum_{t=1}^{T} y_t^2)^{1/2} \tag{11}$$

Where $\hat{\sigma}_{ws}^2 = (T-2)^{-1}Q_w(\hat{\rho}_{ws})$. Park and Fuller (1995) derived the limiting distribution of WS t-statistics:

$$\hat{t}_{ws} \Longrightarrow \left[\int_0^1 W(r)^2 dr - \left[\int_0^1 W(r)dr\right]^2\right]^{-1/2} \times$$

$$\times \left[\frac{W(1)^2 - 1}{2} - W(1)\int_0^1 W(r)^2 dr - \int_0^1 W(r)^2 dr + 2\left[\int_0^1 W(r)dr\right]^2\right]$$

Where $W(r)$ is a standard Wiener process on [0,1].

3.2 Weighted Symmetric Estimation for AR(p) model

Consider the pth order autoregressive time series:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + e_i \tag{12}$$

$$t = p+1, \ldots, T$$

where $\{e_t\}_{t=1}^{\infty}$ is a sequence of normal independent $(0, \sigma^2)$ random variables. The characteristic equation associated with (12) is:

$$m^p - \sum_{i=1}^{p} \alpha_i m^{p-i} = 0 \tag{13}$$

Assume that $|\lambda_i| < 1$, where $\lambda_1, \lambda_2, ..., \lambda_p$ are the roots of the characteristic equation (13). A stationary time series satisfying (12) also satisfies:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t+i} + u_i \tag{14}$$

$$t = 1, 2, \ldots, T - p$$

where $\{u_t\} \sim N(0, \sigma^2)$. We consider a class of estimators of α, obtained by minimizing:

$$Q = \sum_{t=p+1}^{T} w_t \left[Y_t - \alpha_0 - \sum_{i=1}^{p} \alpha_i Y_{t-i} \right]^2 + \sum_{t=1}^{T-p} (1 - w_{t+1}) \left[Y_t - \alpha_0 - \sum_{i=1}^{p} \alpha_i Y_{t+i} \right]^2 \tag{15}$$

where w_t, $t = 1, 2, ..., T$ are weights and $0 \leq w_t \leq 1$. If $w_t = 1$ in (15) we have the ordinary least squares estimator. The estimator that minimizes (15) with $w_t = 0.5$ is called the simple symmetric least squares estimator. The value of α that minimizes (15) with:

$$w_t = \begin{cases} 0 & t = 1, 2, ..., p \\ (T - 2p + 2)^{-1}(t - p) & t = p + 1, p + 2, ..., T - p + 1 \\ 1 & t = T - p + 2, T - p + 3, ..., T \end{cases} \tag{16}$$

is called the weighed symmetric estimator and is denoted $\hat{\alpha}_w$. The estimator $\hat{\alpha}_w$ is closely related to the estimator obtained by maximizing the normal stationary likelihood (Park and Fuller, 1995). By minimizing Q, we can see the idea of weighted symmetric estimator is that we use information of weighted observations based on the time lag and lead of the series: the further the lag of an observation, the smaller is the weighted and the further the lead of an observation, the smaller is the weighted.

Equation (15) can be reparameterized as :

$$Q = \sum_{t=p+1}^{T} w_t \left[Y_t - \theta_0 - \theta_1 Y_{t-1} - \sum_{i=2}^{p} \theta_i \Delta Y_{t-i+1} \right]^2 + \sum_{t=1}^{T-p} (1 - w_{t+1}) \left[Y_t - \theta_0 - \theta_1 Y_{t+1} - \sum_{i=2}^{p} \theta_i (-\Delta Y_{t+i}) \right]^2 \tag{17}$$

Where $\Delta Y_t = Y_t - Y_{t-1}$.

Pivotal t-statistics for the unit root hypothesis $\theta_1 = 1$ are constructed by analogy to the pivotal t-statistics for the usual regression analysis:

$$\hat{t}_{ws} = [\hat{V}(\hat{\theta}_1)]^{1/2}(\hat{\theta}_1 - 1) \tag{18}$$

where $\hat{V}(\hat{\theta}_1)$ is the estimated variance of the estimated coefficient of Y_{t-1} in (17). As in the case of the AR(1) model, Park and Fuller (1995) showed that the limiting distribution of $\hat{t}_{ws}$ is:

$$\hat{t}_{ws} \Longrightarrow \left[\int_0^1 W(r)^2 dr - \left[\int_0^1 W(r) dr \right]^2 \right]^{-1/2} \times$$

$$\times \left[\frac{W(1)^2 - 1}{2} - W(1) \int_0^1 W(r)^2 dr - \int_0^1 W(r)^2 dr + 2 \left[\int_0^1 W(r) dr \right]^2 \right]$$

Where $W(r)$ is a standard Wiener process on [0,1].

4 Monte-Carlo Investigation Design

4.1 Testing Procedures

The IPS-DF test

The regression equation for each cross-section i:

$$y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + \epsilon_{i,t} \tag{19}$$

$$t = 2, 3, \ldots, T$$

is estimated for each cross-section $i, i = 1, 2, \ldots, N$, to calculate the t-statistic for $\hat{\rho}_i$ denoted by $t_{i,T}$. The table of $E(t_{i,T})$ and $V(t_{i,T})$ from Im *et al.* (2003, p.60) gives μ and σ^2 for each T. The panel t-statistic is calculated as:

$$t_{DF-N,T} = \sqrt{N}\frac{(\bar{t}_{DF} - \mu)}{\sigma} \overset{N}{\Longrightarrow} \mathrm{N}(0, 1) \tag{20}$$

where

$$\bar{t}_{DF} = \frac{1}{N}\sum_{i=1}^{N} t_{i,T} \tag{21}$$

The standard normal critical values are used to study size and power of the test.

The IPS-ADF test

The regression equation for each cross-section i:

$$y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + \sum_{j=1}^{p} \theta_{ij}\Delta y_{i,t-j} + \epsilon_{i,t} \tag{22}$$

$$t = p + 1, \ldots, T$$

Here, to choose the appropriate lag length, we employed the rule suggested by Schwert (1989): $p = Int[c(T/100)^{1/d}]$ with c=4, d=4.

The steps are similar to the IPS-DF test described above: calculate the t-statistic for $\hat{\rho}_i$, denoted by $t_{i,T}$, then use the table for $E(t_{i,T})$ and $V(t_{i,T})$ available in Im *et al.* (2003, p.66) to get μ and σ^2 for each p and T. The panel t-statistic are calculated as:

$$t_{ADF-N,T} = \sqrt{N}\frac{(\bar{t}_{ADF} - \mu)}{\sigma} \overset{N}{\Longrightarrow} \mathrm{N}(0, 1) \tag{23}$$

where

$$\bar{t}_{ADF} = \frac{1}{N}\sum_{i=1}^{N} t_{i,T} \tag{24}$$

The standard normal critical values are used to study size and power of the test.

The IPS-WS(1) test

To apply WS estimation in the IPS test, we need to compute means and variances of t-statistic for the AR(1) model with different values of T. Table 1 gives the moments of t-statistic of the weighted symmetric estimator for the AR(1) model based on 200,000 simulations, using the formula:

$$\hat{t}_{ws} = \hat{\sigma}_{ws}^{-1}(\hat{\rho}_{ws} - 1)(\sum_{t=2}^{T-1} y_t^2 + T^{-1}\sum_{t=1}^{T} y_t^2)^{1/2} \tag{25}$$

where $\hat{\sigma}^2_{ws} = (T-2)^{-1}Q_w(\hat{\rho}_{ws})$. Then WS estimation is used to compute the $\hat{t}_{ws}$ for each cross-section, follow by the steps of Im *et al.* (2003) as in the IPS-DF test previously described.

The IPS-WS(p) test

Table 2 shows the moments of t-statistics of the weighted symmetric estimator, for the AR(p) model with lags of number p and T. The lag p is calculated by $p = Int[4(T/100)^{1/4}]$. In each cross-section we estimate θ_j which minimize (17). From these estimates, compute the t-statistic for the hypothesis $\theta_1 = 1$ for each cross-section of the panel, and then follow the remaining IPS test procedures.

The MW-ADF test

The ADF equation for each individual series, with the lag length $p = Int[4(T/100)^{1/4}]$, is estimated:

$$y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + \sum_{j=1}^{p} \theta_{ij}\Delta y_{i,t-j} + \epsilon_{i,t} \tag{26}$$

$$t = 1, 2 \ldots, T$$

The MW test requires deriving the distribution of the Dickey-Fuller t-statistic, for which 50,000 simulations were generated for different T and p. Then the p-values π_i for each ADF t-statistic could be derived. Consequently, the MW-ADF statistic p_λ is calculated as: $p_\lambda = -2\sum_{i=1}^{N} log_e \pi_i \sim \chi^2_{2N}$. For the critical values of MW-ADF statistics p_λ for each N, we use the χ^2 table.

The MW-WS test

For this test, the WS estimation was applied for each individual series. For the WS(1) model, the t-statistic were computed by:

$$\hat{t}_{ws} = \hat{\sigma}_{ws}^{-1}(\hat{\rho}_{ws} - 1)(\sum_{t=2}^{T-1} y_t^2 + T^{-1}\sum_{t=1}^{T} y_t^2)^{1/2} \tag{27}$$

For the WS(p) model, the estimation involves minimization of (17), from which the t-statistic for testing the hypothesis $\theta_1 = 1$ was computed. 50,000 simulations were generated to get the empirical WS distribution of $\hat{t}_{ws}$ for different values of p and T. Then based on the WS empirical distribution of $\hat{t}_{ws}$, the p-values π_i of each t-statistic in each cross-section can be derived. After that MW test procedure is followed.

4.2 Data Generation Processes

The basic DGP is:

$$y_{i,t} = (1-\rho)\alpha_i + \rho y_{i,t-1} + \epsilon_{i,t} \tag{28}$$

$$t = 1, 2, \ldots, T; i = 1, 2, \ldots, N$$

where

$$\alpha_i \sim U[0, 1]$$

$$\rho = \begin{cases} 1 & \text{for size} \\ 0.9 & \text{for power} \end{cases} \tag{29}$$

We set $y_{i,0} = 0$. To reduce the influence of the initial condition we generated T+50 time series observations for each cross-section, then eliminated the first 50 observations and used only the last T time series observation for each cross-section. The parameter values adopted here are based on the values used in the Im *et al.* (2003) and the Maddala and Wu (1999) papers. We consider five distinct sets of DGP as following:

a. No serial correlation and no cross-section correlation

$\epsilon_{i,t} \sim N(0, \sigma_i^2)$ and $\sigma_i^2 \sim U[0.5, 1.5]$; $t = 1, 2, \ldots, T; i = 1, 2, \ldots, N$

b. Serial correlation but no cross-section correlation

$$\epsilon_{i,t} = \lambda_i \epsilon_{i,t-1} + u_{i,t} \tag{30}$$

$$t = 1, 2, \ldots, T; i = 1, 2, \ldots, N$$

where

$$\lambda_i \sim U[0.2, 0.4]$$

$$u_{i,t} \sim N(0, \sigma_i^2)$$

$$\sigma_i^2 \sim U[0.5, 1.5]$$

c. Moving-average serial correlation

$$\epsilon_{i,t} = e_{i,t} - \theta_i e_{i,t-1} \tag{31}$$

$$t = 1, 2, \ldots, T; i = 1, 2, \ldots, N$$

where

$$\theta_i \sim U[0.2, 0.4]$$

$$e_i \sim N(0, \sigma_i^2)$$

$$\sigma_i^2 \sim U[0.5, 1.5]$$

d. Cross-section correlation but no serial correlation

$$\epsilon_t = [\epsilon_{1,t}, \epsilon_{2,t}, ..., \epsilon_{N,t}]' \sim \mathbf{N}(\mathbf{0}_{N\times1}, \Sigma_{N\times N}) \tag{32}$$

where

$$\Sigma = (\sigma_{ij})_{i,j=1}^{N} \tag{33}$$

Σ is the variance-covariance matrix of vector ϵ_t. The non-zero terms on the off-diagonal terms in Σ represent the existence of cross-section correlations. The effect of different degrees of cross-section correlation is investigated by altering the elements of Σ. In all the simulations we set the diagonal elements of Σ equal to one, and alter the off-diagonal. The off-diagonal elements are set to 0.25; 0.50 and 0.75. So $\sigma_{ij} \in (0.25; 0.50; 0.75)$ if $i \neq j$, and $\sigma_{ij} = 1$ if $i = j$.

To construct vectors ϵ_t, $t = 1, 2, \ldots, N$, which satisfy $\epsilon_t \sim \mathbf{N}(\mathbf{0}_{N\times1}, \Sigma_{N\times N})$ we use the Cholesky decomposition of Σ.

e. Serial correlation and cross-section correlation

$$\epsilon_{i,t} = \lambda_i \epsilon_{i,t-1} + u_{i,t} \tag{34}$$

$$t = 1, 2, \ldots, T; i = 1, 2, \ldots, N$$

where

$$\lambda_i \sim U[0.2, 0.4]$$

and

$$\mathbf{u}_t = [u_{1,t}, u_{2,t}, ..., u_{N,t}]' \sim \mathbf{N}(\mathbf{0}_{N\times 1}, \Sigma_{N\times N}) \tag{35}$$

with $\sigma_{ij} = 0.5$ if $i \neq j$, and $\sigma_{ij} = 1$ if $i = j$.

5 Size and Power of Tests

The results of the simulation experiments are reported in Tables 3-7. In all cases, 3000 trials are used to examine the size and power properties.

Table 3[1] presents the first set of experiments when there is no serial correlation in individual series and no cross-section correlation between series. The critical value of the 5% significance level is used to calculate the size and power of the tests. For all five tests , the size is close to 5% of the nominal size, and the size does not change much when N and T are increased. In every case, the empirical size lies between 0.04 and 0.06. In this table the IPS-ADF and MW-ADF tests are over-parameterized, which adversely affects their power, but not the size. We can see that the power of the tests vary, but for every combination of N and T, the IPS-WS(1) test has the most power. The second most powerful test is the MW-WS(1) test. Compared to the IPS-DF, the IPS-ADF and MW-ADF are less powerful because of their over-parameterization. When the number of cross-sections N or number of observations T increases, the power of all five tests increase. Power increases faster with T than with N so that cases with large N (50) and small T (10) show low power overall. The power varies more across the tests when N and T are small, so that with $N = 10$ and $T = 25$, the power of the IPS-WS(1) test is 56%, compared with 40% for the MW-WS(1),

[1] All simulations are performed by using Matlab 7.0 on a 3.44 GHz, 2GB Ram PC. The programs are available upon requested.

28% for the IPS-DF and only 16% for the MW-ADF. The IPS-WS(1) seems to be the best choice in the case of no serial correlation and no cross-sectional correlation but if the panel is unbalanced, the MW-WS(1) test may be preferred.

Table 4 summarizes the size and power of tests in the case when there is serial correlation but no cross-sectional correlation. The IPS-DF test has strong size distortion towards zero, which worsens when N and T increase. The reason is the under-parameterization of the DF estimation equation in a series which is serially correlated. The IPS-ADF and MW-ADF tests remain almost as good for size as in Table 3 but are somewhat over sized for small T. The size of IPS-WS(p) and MW-WS(p) tests are still close to the nominal 5%, but are a little under sized with small T. The greatest size distortion for all tests is when T is small, and it increases when N increases, but when T increases as well, the size becomes acceptable again. Size distortion is not severe in this table for all tests except the IPS-DF test. The IPS-WS(p) test is a little deficient in size, but it tends to reduce the probability of a type I error in testing a hypothesis.

For the power of the tests, we see that the IPS-WS(p) test consistently has the the best power, and the power of the MW-WS(p) test is the second highest. The IPS-DF test is very weak in power especially when T is small, so this test should not be used in the case of serial correlation. When T and N are small, the WS(p) estimation brings more power to the tests as compared with the ADF estimation. When $T = 100$ and $N \geq 25$ all of the tests' power tends to 1. They are different when $T \leq 50$. The IPS-WS(p) test should be chosen in this case, unless the panel is unbalanced, in which case the MW-WS(p) test should be used. Power rises more strongly with increases in T, compared with increases in N. Power is low for $T = 10$, even when $N = 50$.

Table 5 reports the size and power of the tests when there is a moving-average component in the errors of each individual series. The IPS-DF test has a very serious size distortion, which grows quickly when T is increasing. The other four tests show some size distortion, tending to be a little above the nominal 5% size in some cases. The IPS-WS(p) and MW-WS(p) tests have slightly more distortion compared with the IPS-ADF and MW-ADF tests. When $N = 50$, $T = 10$ and $T = 25$, they have the most distortions, which are 0.148, 0.143 for IPS-WS(p) and 0.105, 0.136 for MW-WS(p). The IPS-ADF and the MW-ADF show least size distortion. WS tests show greatest distortion when N is large and T is small.

For the power of the test, the IPS-DF test power looks good, but this test can not be used because it has a serious size distortion with probabilities of a type I error near one. Of all four remaining tests, the IPS-WS(p) test has the strongest power for every value of N and T, followed by the MW-WS(p), IPS-ADF and the MW-ADF test. With the small trade off in size distortion (allowing greater risk of type I error) one may use the IPS-WS(p) or MW-WS(p) test to have a higher power, which reduces a probability of committing a type II error. To avoid type I error, the MW-ADF or IPS-ADF tests may be preferred in this case, although power is much lower.

Table 6A reports the size and power of the tests when there is a cross-sectional correlation coefficient of $[\sigma = 0.25]$ and no serial correlation. In this case, O'Connell (1998) found that the size of the Levin-Lin test is distorted upwards. In contrast to this, all five tests presented here have sizes distorted downwards with all sizes close to zero, especially the IPS-WS(p) and MW-WS(p) tests. This shows that the normal distribution locus of the IPS-WS(p) test shifts to the right, and the chi-squared distribution locus of the MW-WS(p) test shifts to the left. With all sizes close to zero, the probability of a type I error is lower. It is interesting that the power of all the tests seems not to be affected much compared with the results in Table 3 (under no serial and cross-sectional correlation). The order from the most powerful to the least powerful of tests is the same as in Table 3, which is: IPS-WS(p), MW-WS(p), IPS-DF, IPS-ADF and MW-ADF. The tests' power in this table are a little less than those in Table 3. The reason for this may be because of the over-parameterization in ADF and WS(p) estimations. It is also of note here that the over-parameterization is less serious than the under-parameterization problem. In this case the IPS-DF may be preferred to test the hypothesis of a unit- root, because it has the best size and relatively good power when $T \geq 25$.

Table 6B shows the results of the experiment that is the same as in Table 6A, except the cross-section correlation coefficient now is $[\sigma = 0.5]$. The size now is slightly higher in all three tests using DF or ADF estimations. It tends to exceed the 5% nominal size when T=10, and it drops below 5% when T increases. The power of all the tests are slightly higher than those in Table 6A when T is small and get smaller than those in Table 6A when N and T increase. We see that when σ is larger, all of the tests' powers are better for small values of T, and a bit less power for larger T. The power of the IPS-WS(p) and MW-WS(p) tests still dominate the other three tests for almost every value of N and T.

In Table 6C, the cross-section correlation coefficient is chosen as $[\sigma = 0.75]$. As we see in the table, most of the sizes are higher than those in Table 6B. All tests using DF and ADF estimations have greater than 5% size when T=10 but their size drops to 5% and lower when T increases. The size of IPS-WS(p) and MW-WS(p) tests is slightly increased but they are still very close to zero for all value of N and T. The power of tests are better than those in Table 6A when $N \leq 10$ and $T \leq 25$, but they slightly decrease when N and T are larger. The power of the IPS-WS(p) test still dominates for all cases of N and T.

Combining tables 6A, 6B and 6C, we see that when the magnitude of the cross-section correlation coefficient increases, the size of all three tests using DF or ADF estimation becomes larger. Especially when N=10, the power of the tests gets stronger for small T and getting weaker for large T as cross-sectional correlation is increasing. The size of the two tests using WS(p) estimation are close to zero, which means the locus of these tests' distributions shifts away from a standard position (to the right for IPS-WS test, and to the left for MW-WS test). In the case when there is cross-sectional correlation and no serial correlation in the panel, and when $N \geq 10$ and $T \geq 50$, the IPS-DF test may be a better choice, as it has both good size and power. When T or N is small, we can use the IPS-WS(p) test with a balanced panel or the MW-WS(p) test with an unbalanced panel to get more power in testing the hypothesis of nonstationarity in the panel.

The last set of experiments is shown in Table 7, where in the DGP, both serial correlation and cross-sectional correlation are allowed, with the cross-sectional correlation coefficient set to $[\sigma = 0.5]$. Compared to the results in the case of Table 6B, adding serial correlation seriously affects the performance of the IPS-DF test, but it does not affect the performances of the other four tests very much. The size of the IPS-DF test is closer to 0.05 than those in Table 4, even though DF estimation is also under-parameterized in this case. It may be because the presence of cross-sectional correlation remedies the size distortion of DF estimation, but the power of the IPS-DF test drops dramatically. The other four tests IPS-ADF, IPS-WS(p), MW-ADF and MW-WS(p) perform pretty much the same as they do in the case of Table 6B, which is without serial correlation. We can see here that over-parameterization in Table 6B does not impact the size and power of the tests very much compared with the correct-parameterization in the case of Table 7. The IPS-WS(p) test is the most powerful, followed by the MW-WS(p) in every case of N and T.

For all tests using ADF or WS(p) estimation, serial correlation in individual series is not a serious problem. The presence of cross-sectional correlation affects all tests. It usually lowers the size of tests when T increases, but it does not change the power of the tests very much compared with the case with no cross-sectional correlation.

6 Conclusions

In this paper, we consider the use of weighted symmetric estimation in the context of stationary testing in panel data. The Monte-Carlo simulations are made to investigate the performance of the IPS and MW unit root tests in panels without time trend under different data properties. The of moments of t-statistic for weighted symmetric estimators are computed for use with the IPS test. The weighted symmetric estimation is compared to DF and ADF estimation, two commonly used estimation methods. We found that in the case of panel data without cross-sectional correlation, tests using weighted symmetric estimation dominate those using the DF and ADF estimation in terms of power of the test, regardless of whether there is serial correlation in each series or not. Tests using weighted symmetric estimation also have the best power when there is a moving-average in the errors. When there is cross-sectional correlation between individual series, in most cases the size of tests using weighted symmetric estimation is zero, which reduces a probability to commit a type I error in testing hypotheses, and the power of tests using weighted symmetric estimation is still better than those using DF or ADF estimation. Across all environments there appear to be strong gains in powers afforded by use of the weighted symmetric procedure in panel unit root tests.

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TABLE 1: Moments of t-statistics of the weighted symmetric estimator for the AR(*1*) model

T	MEAN	VARIANCE
5	-1.4541	1.1948
6	-1.3996	1.0120
7	-1.3619	0.9511
8	-1.3349	0.9170
9	-1.3118	0.8777
10	-1.2962	0.8638
15	-1.2460	0.8182
20	-1.2092	0.7970
25	-1.2104	0.7927
30	-1.2002	0.7935
40	-1.1884	0.7820
50	-1.1817	0.7741
60	-1.1753	0.7758
70	-1.1758	0.7727
80	-1.1642	0.7693
90	-1.1680	0.7715
100	-1.1665	0.7726
150	-1.1614	0.7684
200	-1.1599	0.7681
500	-1.1571	0.7681
1000	-1.1575	0.7660

NOTES: means and variances in this table are computed by stochastic simulations with 200,000 replications. The underlying data is generated by $y_t = y_{t-1} + \epsilon_t$, where $\epsilon_t \sim N(0, \sigma^2)$ with $\sigma^2 \sim U[0.5, 1.5]$. *T+50* observations are generated and the first 50 observations are eliminated, using only the last T observations.

TABLE 2: Moments of t-statistics of the weighted symmetric estimator for the AR(p) model

p	T	MEAN	VARIANCE
2	7	-0.7209	1.0078
2	8	-0.7520	1.0331
2	9	-0.7734	1.0369
2	10	-0.7932	1.0531
2	15	-0.8708	1.0702
2	20	-0.9235	1.0611
2	25	-0.9608	1.0442
2	30	-0.9873	1.0316
3	40	-1.0078	1.0067
3	50	-1.0319	0.9957
3	60	-1.0483	0.9778
3	70	-1.0605	0.9704
3	80	-1.0765	0.9550
3	90	-1.0814	0.9545
4	100	-1.0604	0.9566
4	150	-1.0894	0.9319
4	200	-1.1022	0.9162

NOTES: means and variances in this table are computed by stochastic simulations with 200,000 replications. The underlying data is generated by $y_t = y_{t-1} + \epsilon_t$, where $\epsilon_t \sim N(0, \sigma^2)$ with $\sigma^2 \sim U[0.5, 1.5]$. *T+50* observations are generated and the first *50* observations are eliminated, using only the last T observations. p is decided by $p = Int[c(T/100)^{1/d}]$ with c=4, d=4.

TABLE 3: Size and power of panel unit root tests with
no serial correlation and no cross-sectional correlation

N	T	IPS-DF	IPS-ADF	IPS-WS(1)	MW-ADF	MW-WS(1)
				SIZE		
5	10	0.048	0.048	0.054	0.046	0.049
	25	0.051	0.045	0.050	0.044	0.051
	50	0.046	0.043	0.047	0.046	0.050
	100	0.049	0.046	0.054	0.054	0.053
10	10	0.057	0.059	0.053	0.053	0.050
	25	0.047	0.052	0.052	0.054	0.047
	50	0.043	0.042	0.043	0.046	0.047
	100	0.045	0.045	0.048	0.051	0.048
25	10	0.054	0.046	0.058	0.044	0.056
	25	0.045	0.048	0.050	0.046	0.057
	50	0.042	0.044	0.048	0.044	0.051
	100	0.044	0.041	0.045	0.050	0.046
50	10	0.060	0.055	0.050	0.053	0.051
	25	0.058	0.054	0.051	0.049	0.044
	50	0.048	0.043	0.047	0.046	0.053
	100	0.052	0.050	0.057	0.055	0.052
				POWER		
5	10	0.073	0.064	0.103	0.058	0.088
	25	0.169	0.126	0.320	0.107	0.243
	50	0.459	0.318	0.787	0.243	0.661
	100	0.969	0.857	1.000	0.762	0.996
10	10	0.093	0.083	0.156	0.071	0.126
	25	0.279	0.214	0.563	0.158	0.407
	50	0.777	0.604	0.982	0.439	0.924
	100	1.000	0.994	1.000	0.967	1.000
25	10	0.143	0.126	0.290	0.095	0.212
	25	0.565	0.450	0.924	0.260	0.759
	50	0.991	0.943	1.000	0.787	1.000
	100	1.000	1.000	1.000	1.000	1.000
50	10	0.221	0.188	0.483	0.114	0.343
	25	0.825	0.712	0.998	0.434	0.960
	50	1.000	0.999	1.000	0.972	1.000
	100	1.000	1.000	1.000	1.000	1.000

NOTES: This table reports the size and power of the tests. The underlying data is generated by $y_{i,t} = (1-\rho)\alpha_i + \rho y_{i,t-1} + \epsilon_{i,t}$, where $\alpha_i \sim U[0,1]$ and $\epsilon_{it} \sim N(0,\sigma_i^2)$ with $\sigma_i^2 \sim U[0.5,1.5]$. α_i and σ_i^2 are generated once and fixed in all replications, there is no serial correlation and no cross-sectional correlation. $\rho = 1$ for size and $\rho = 0.9$ for power. WS(1) denotes the weighted symmetric estimation for AR(1) model. *T+50* observations are generated and the first *50* observations are eliminated, using only last T observations. Number of replications is set to 3,000 for computing the empirical size and power of all five tests. The size and power of tests are computed at the 5% nominal level.

TABLE 4: Size and power of panel unit root tests with serial correlation but no cross-sectional correlation

N	T	IPS-DF	IPS-ADF	IPS-WS(p)	MW-ADF	MW-WS(p)
				SIZE		
5	10	0.017	0.059	0.053	0.059	0.048
	25	0.010	0.045	0.048	0.050	0.052
	50	0.005	0.043	0.043	0.046	0.050
	100	0.007	0.050	0.047	0.055	0.058
10	10	0.012	0.066	0.044	0.069	0.042
	25	0.003	0.051	0.046	0.052	0.051
	50	0.001	0.042	0.046	0.046	0.047
	100	0.001	0.046	0.042	0.053	0.050
25	10	0.002	0.063	0.038	0.072	0.046
	25	0.000	0.057	0.041	0.057	0.050
	50	0.000	0.046	0.038	0.043	0.045
	100	0.000	0.042	0.039	0.055	0.054
50	10	0.000	0.057	0.030	0.073	0.034
	25	0.000	0.050	0.037	0.064	0.047
	50	0.000	0.043	0.042	0.052	0.049
	100	0.000	0.046	0.043	0.056	0.056
				POWER		
5	10	0.025	0.080	0.096	0.072	0.080
	25	0.017	0.120	0.233	0.110	0.193
	50	0.030	0.305	0.584	0.241	0.483
	100	0.190	0.827	0.961	0.724	0.931
10	10	0.015	0.097	0.119	0.085	0.098
	25	0.013	0.208	0.416	0.161	0.322
	50	0.036	0.570	0.864	0.403	0.759
	100	0.432	0.990	1.000	0.951	0.999
25	10	0.005	0.143	0.188	0.123	0.146
	25	0.006	0.422	0.755	0.270	0.617
	50	0.046	0.921	0.999	0.755	0.986
	100	0.869	1.000	1.000	1.000	1.000
50	10	0.002	0.199	0.274	0.169	0.218
	25	0.001	0.671	0.954	0.443	0.865
	50	0.058	0.998	1.000	0.962	1.000
	100	0.999	1.000	1.000	1.000	1.000

NOTES: This table reports the size and power of the tests. The underlying data is generated by $y_{i,t} = (1-\rho)\alpha_i + \rho y_{i,t-1} + \epsilon_{i,t}$, where $\alpha_i \sim U[0,1]$ and ϵ_{it}'s follow the AR(1) processes: $\epsilon_{i,t} = \lambda_i \epsilon_{i,t-1} + e_{i,t}$ where $\lambda_i \sim U[0.2, 0.4]$ and $e_{i.t} \sim N(0, \sigma_i^2)$, $\sigma_i^2 \sim U[0.5, 1.5]$. *T+50* observations are generated and the first *50* observations are eliminated, using only the last T observations. λ_i, α_i and σ_i^2 are generated once and fixed in all replications, so there is serial correlation but no cross-sectional correlation in the DGP. $\rho = 1$ for size and $\rho = 0.9$ for power. WS(p) denotes the weighted symmetric estimation for the AR(p) model, p is decided by $p = Int[c(T/100)^{1/d}]$ with c=4, d=4. Number of replications is set to 3,000 for computing the empirical size and power of all five tests. The size and power of tests are computed at the 5% nominal level.

TABLE 5: Size and power of panel unit root tests with a moving-average component in errors

N	T	IPS-DF	IPS-ADF	IPS-WS(p)	MW-ADF	MW-WS(p)
		SIZE				
5	10	0.282	0.053	0.076	0.047	0.064
	25	0.496	0.062	0.071	0.056	0.075
	50	0.489	0.044	0.051	0.047	0.055
	100	0.629	0.052	0.052	0.055	0.059
10	10	0.432	0.055	0.083	0.044	0.063
	25	0.653	0.062	0.076	0.059	0.072
	50	0.803	0.054	0.067	0.056	0.064
	100	0.847	0.052	0.053	0.055	0.061
25	10	0.736	0.065	0.099	0.049	0.079
	25	0.964	0.078	0.103	0.066	0.095
	50	0.992	0.057	0.072	0.046	0.066
	100	0.997	0.055	0.055	0.055	0.064
50	10	0.949	0.073	0.148	0.041	0.105
	25	0.999	0.092	0.143	0.067	0.136
	50	1.000	0.058	0.091	0.058	0.081
	100	1.000	0.047	0.064	0.052	0.071
		POWER				
5	10	0.394	0.060	0.140	0.051	0.109
	25	0.838	0.159	0.341	0.124	0.274
	50	0.994	0.360	0.701	0.279	0.575
	100	1.000	0.895	0.983	0.815	0.968
10	10	0.625	0.090	0.203	0.068	0.142
	25	0.977	0.273	0.572	0.193	0.428
	50	1.000	0.684	0.947	0.508	0.854
	100	1.000	0.996	1.000	0.979	1.000
25	10	0.926	0.143	0.375	0.083	0.251
	25	1.000	0.593	0.927	0.369	0.810
	50	1.000	0.971	1.000	0.854	0.997
	100	1.000	1.000	1.000	1.000	1.000
50	10	0.996	0.228	0.604	0.104	0.425
	25	1.000	0.874	0.999	0.635	0.978
	50	1.000	1.000	1.000	0.992	1.000
	100	1.000	1.000	1.000	1.000	1.000

NOTES: This table reports the size and power of the tests. The underlying data is generated by $y_{i,t} = (1-\rho)\alpha_i + \rho y_{i,t-1} + \epsilon_{i,t}$, where $\alpha_i \sim U[0,1]$ and ϵ_{it}'s follow the MA(1) processes: $\epsilon_{i,t} = e_{i,t} - \psi_i e_{i,t-1}$ where $\psi_i \sim U[0.2, 0.4]$ and $e_{i.t} \sim N(0, \sigma_i^2)$, $\sigma_i^2 \sim U[0.5, 1.5]$. *T+50* observations are generated and the first *50* observations are eliminated, using only the last T observations. ψ_i, α_i and σ_i^2 are generated once and fixed in all replications, there is no cross-section correlation. $\rho = 1$ for size and $\rho = 0.9$ for power. WS(p) denotes the weighted symmetric estimation for the AR(p) model, p is decided by $p = Int[c(T/100)^{1/d}]$ with c=4, d=4. Number of replications is set to 3,000 for computing the empirical size and power of all five tests. The size and power of tests are computed at the 5% nominal level.

TABLE 6A: Size and power of panel unit root tests with cross-sectional correlation [$\sigma = 0.25$] but no serial correlation

N	T	IPS-DF	IPS-ADF	IPS-WS(p)	MW-ADF	MW-WS(p)
				SIZE		
5	10	0.037	0.037	0.009	0.036	0.009
	25	0.017	0.018	0.000	0.022	0.001
	50	0.007	0.010	0.000	0.011	0.000
	100	0.003	0.004	0.000	0.006	0.000
10	10	0.042	0.040	0.002	0.040	0.002
	25	0.012	0.018	0.000	0.020	0.000
	50	0.003	0.004	0.000	0.004	0.000
	100	0.003	0.002	0.000	0.001	0.000
25	10	0.029	0.031	0.000	0.035	0.000
	25	0.006	0.008	0.000	0.011	0.000
	50	0.002	0.003	0.000	0.003	0.000
	100	0.001	0.001	0.000	0.002	0.000
50	10	0.023	0.030	0.000	0.034	0.000
	25	0.007	0.006	0.000	0.006	0.000
	50	0.002	0.004	0.000	0.004	0.000
	100	0.002	0.002	0.000	0.003	0.000
				POWER		
5	10	0.088	0.083	0.120	0.074	0.097
	25	0.157	0.138	0.283	0.110	0.225
	50	0.472	0.338	0.614	0.270	0.498
	100	0.958	0.835	0.957	0.742	0.924
10	10	0.127	0.094	0.172	0.081	0.135
	25	0.301	0.248	0.471	0.172	0.354
	50	0.745	0.601	0.864	0.437	0.763
	100	0.995	0.972	0.997	0.932	0.993
25	10	0.217	0.176	0.290	0.122	0.212
	25	0.568	0.458	0.759	0.295	0.607
	50	0.941	0.881	0.980	0.731	0.947
	100	1.000	0.998	1.000	0.990	0.999
50	10	0.326	0.274	0.431	0.183	0.335
	25	0.743	0.660	0.876	0.448	0.787
	50	0.976	0.944	0.990	0.861	0.980
	100	1.000	0.999	1.000	0.998	1.000

NOTES: This table reports the size and power of the tests. The underlying data is generated by $y_{i,t} = (1-\rho)\alpha_i + \rho y_{i,t-1} + \epsilon_{i,t}$, where $\alpha_i \sim U[0,1]$. *T+50* observations are generated and the first *50* observations are eliminated, using only the last T observations. No serial correlation but there is contemporaneous correlation between $\epsilon_{i,t}$'s, which means $\epsilon_{i,t}$'s satisfy $cov(\epsilon_{i,t}, \epsilon_{j,t}) = \sigma_{ij}\ \forall t = 1, 2, ..., T$, in this table $\sigma_{ij} = 0.25$ if $i \neq j$ and $\sigma_{ij} = 1$ if $i = j$. $\rho = 1$ for size and $\rho = 0.9$ for power. α_i is generated once and fixed in all replications. WS(p) denotes the weighted symmetric estimation for the AR(p) model, p is decided by $p = Int[c(T/100)^{1/d}]$ with c=4, d=4. Number of replications is set to 3,000 for computing the empirical size and power of all five tests. The size and power of tests are computed at the 5% nominal level.

TABLE 6B: Size and power of panel unit root tests with cross-sectional correlation [$\sigma = 0.5$] but no serial correlation

N	T	IPS-DF	IPS-ADF	IPS-WS(p)	MW-ADF	MW-WS(p)
				SIZE		
5	10	0.054	0.055	0.016	0.053	0.018
	25	0.037	0.039	0.000	0.035	0.000
	50	0.019	0.014	0.000	0.013	0.000
	100	0.015	0.015	0.000	0.014	0.000
10	10	0.059	0.077	0.008	0.069	0.007
	25	0.029	0.040	0.000	0.033	0.000
	50	0.022	0.024	0.000	0.018	0.000
	100	0.011	0.014	0.000	0.012	0.000
25	10	0.067	0.092	0.003	0.078	0.002
	25	0.032	0.038	0.000	0.034	0.000
	50	0.020	0.026	0.000	0.019	0.000
	100	0.014	0.017	0.000	0.015	0.000
50	10	0.071	0.090	0.002	0.081	0.000
	25	0.028	0.043	0.000	0.035	0.000
	50	0.021	0.024	0.000	0.018	0.000
	100	0.015	0.021	0.000	0.018	0.000
				POWER		
5	10	0.117	0.109	0.164	0.096	0.128
	25	0.205	0.176	0.328	0.141	0.249
	50	0.492	0.370	0.607	0.286	0.494
	100	0.910	0.781	0.916	0.678	0.872
10	10	0.191	0.160	0.235	0.121	0.183
	25	0.366	0.311	0.497	0.217	0.379
	50	0.692	0.580	0.807	0.440	0.701
	100	0.977	0.920	0.976	0.845	0.955
25	10	0.327	0.261	0.358	0.199	0.288
	25	0.561	0.504	0.697	0.358	0.564
	50	0.830	0.778	0.916	0.622	0.845
	100	0.993	0.975	0.993	0.942	0.986
50	10	0.413	0.362	0.459	0.269	0.373
	25	0.656	0.609	0.766	0.448	0.661
	50	0.895	0.840	0.930	0.716	0.882
	100	0.999	0.985	0.996	0.963	0.991

NOTES: This table reports the size and power of the tests. The underlying data is generated by $y_{i,t} = (1-\rho)\alpha_i + \rho y_{i,t-1} + \epsilon_{i,t}$, where $\alpha_i \sim U[0,1]$. *T+50* observations are generated and the first *50* observations are eliminated, using only the last T observations. No serial correlation but there is contemporaneous correlation between $\epsilon_{i,t}$'s, which means $\epsilon_{i,t}$'s satisfy $cov(\epsilon_{i,t}, \epsilon_{j,t}) = \sigma_{ij}\ \forall t = 1, 2, ..., T$, in this table $\sigma_{ij} = 0.5$ if $i \neq j$ and $\sigma_{ij} = 1$ if $i = j$. $\rho = 1$ for size and $\rho = 0.9$ for power. α_i is generated once and fixed in all replications. WS(p) denotes the weighted symmetric estimation for the AR(p) model, p is decided by $p = Int[c(T/100)^{1/d}]$ with c=4, d=4. Number of replications is set to 3,000 for computing the empirical size and power of all five tests. The size and power of tests are computed at the 5% nominal level.

TABLE 6C: Size and power of panel unit root tests with cross-sectional correlation [$\sigma = 0.75$] but no serial correlation

N	T	IPS-DF	IPS-ADF	IPS-WS(p)	MW-ADF	MW-WS(p)
				SIZE		
5	10	0.086	0.085	0.026	0.072	0.022
	25	0.056	0.060	0.001	0.050	0.002
	50	0.032	0.044	0.000	0.036	0.000
	100	0.022	0.029	0.000	0.022	0.000
10	10	0.111	0.111	0.021	0.089	0.015
	25	0.063	0.078	0.000	0.060	0.000
	50	0.041	0.049	0.000	0.034	0.000
	100	0.033	0.040	0.000	0.027	0.000
25	10	0.134	0.146	0.023	0.117	0.014
	25	0.070	0.083	0.001	0.062	0.000
	50	0.057	0.059	0.000	0.044	0.000
	100	0.039	0.045	0.000	0.035	0.000
50	10	0.118	0.157	0.016	0.123	0.007
	25	0.062	0.089	0.001	0.069	0.000
	50	0.046	0.059	0.000	0.039	0.000
	100	0.042	0.057	0.000	0.039	0.000
				POWER		
5	10	0.176	0.152	0.210	0.129	0.161
	25	0.268	0.142	0.374	0.189	0.276
	50	0.482	0.402	0.616	0.311	0.493
	100	0.851	0.717	0.874	0.621	0.801
10	10	0.263	0.237	0.317	0.182	0.243
	25	0.406	0.361	0.520	0.257	0.394
	50	0.634	0.557	0.734	0.432	0.603
	100	0.933	0.837	0.935	0.733	0.878
25	10	0.370	0.347	0.423	0.260	0.339
	25	0.522	0.509	0.633	0.369	0.499
	50	0.744	0.688	0.824	0.554	0.714
	100	0.972	0.924	0.971	0.837	0.936
50	10	0.456	0.434	0.476	0.322	0.390
	25	0.608	0.581	0.697	0.442	0.573
	50	0.809	0.747	0.877	0.617	0.775
	100	0.983	0.943	0.977	0.867	0.950

NOTES: This table reports the size and power of the tests. The underlying data is generated by $y_{i,t} = (1-\rho)\alpha_i + \rho y_{i,t-1} + \epsilon_{i,t}$, where $\alpha_i \sim U[0,1]$. *T+50* observations are generated and the first *50* observations are eliminated, using only the last T observations. No serial correlation but there is contemporaneous correlation between $\epsilon_{i,t}$'s, which means $\epsilon_{i,t}$'s satisfy $cov(\epsilon_{i,t}, \epsilon_{j,t}) = \sigma_{ij}\ \forall t = 1, 2, ..., T$, in this table $\sigma_{ij} = 0.75$ if $i \neq j$ and $\sigma_{ij} = 1$ if $i = j$. $\rho = 1$ for size and $\rho = 0.9$ for power. α_i is generated once and fixed in all replications. WS(p) denotes the weighted symmetric estimation for the AR(p) model, p is decided by $p = Int[c(T/100)^{1/d}]$ with c=4, d=4. Number of replications is set to 3,000 for computing the empirical size and power of all five tests. The size and power of tests are computed at the 5% nominal level.

TABLE 7: Size and power of panel unit root tests with both cross-sectional correlation [$\sigma = 0.5$] and serial correlation

N	T	IPS-DF	IPS-ADF	IPS-WS(p)	MW-ADF	MW-WS(p)
				SIZE		
5	10	0.074	0.074	0.012	0.071	0.012
	25	0.060	0.035	0.001	0.033	0.000
	50	0.045	0.019	0.000	0.017	0.000
	100	0.035	0.011	0.000	0.011	0.000
10	10	0.089	0.088	0.010	0.085	0.007
	25	0.064	0.040	0.000	0.038	0.000
	50	0.061	0.025	0.000	0.021	0.000
	100	0.045	0.017	0.000	0.016	0.000
25	10	0.097	0.092	0.004	0.086	0.003
	25	0.060	0.042	0.000	0.040	0.000
	50	0.052	0.028	0.000	0.024	0.000
	100	0.053	0.021	0.000	0.016	0.000
50	10	0.108	0.108	0.008	0.108	0.004
	25	0.068	0.045	0.000	0.038	0.000
	50	0.063	0.032	0.000	0.026	0.000
	100	0.053	0.024	0.000	0.020	0.000
				POWER		
5	10	0.045	0.123	0.143	0.112	0.114
	25	0.042	0.186	0.309	0.147	0.237
	50	0.075	0.352	0.594	0.272	0.486
	100	0.254	0.760	0.910	0.663	864
10	10	0.057	0.179	0.219	0.147	0.177
	25	0.068	0.299	0.474	0.213	0.366
	50	0.118	0.562	0.774	0.433	0.668
	100	0.464	0.900	0.970	0.811	0.945
25	10	0.097	0.271	0.336	0.227	0.269
	25	0.101	0.489	0.653	0.357	0.536
	50	0.240	0.754	0.890	0.616	0.816
	100	0.683	0.972	0.991	0.927	0.982
50	10	0.122	0.364	0.420	0.299	0.353
	25	0.148	0.604	0.728	0.454	0.637
	50	0.318	0.833	0.930	0.710	0.886
	100	0.823	0.982	0.992	0.950	0.989

NOTES: This table reports the size and power of the tests. The underlying data is generated by $y_{i,t} = (1-\rho)\alpha_i + \rho y_{i,t-1} + \epsilon_{i,t}$, where $\alpha_i \sim U[0,1]$. *T+50* observations are generated and the first *50* observations are eliminated, using only the last T observations. There are both serial correlation and contemporaneous correlation between $\epsilon_{i,t}$'s, which means: $\epsilon_{i,t} = \lambda_i \epsilon_{i,t-1} + u_{i,t}$ where $\lambda_i \sim U[0.2, 0.4]$ and $u_{i,t}$'s satisfy the contemporaneous correlation $cov(u_{i,t}, u_{j,t}) = \sigma_{ij}, \forall t = 1, 2, ..., T$, in this table $\sigma_{ij} = 0.5$ if $i \neq j$ and $\sigma_{ij} = 1$ if $i = j$. $\rho = 1$ for size and $\rho = 0.9$ for power. α_i and λ_i are generated once and fixed in all replications. WS(p) denotes the weighted symmetric estimation for the AR(p) model, p is decided by $p = Int[c(T/100)^{1/d}]$ with c=4, d=4. Number of replications is set to 3,000 for computing the empirical size and power of all five tests. The size and power of tests are computed at the 5% nominal level.