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Robust random effects tests for two-way error component models with panel data

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ABSTRACT

In this paper, two test statistics are constructed respectively for individual and time effects in linear panel data models by comparing estimators of the variance of the idiosyncratic error at different robust levels. The resultant tests are one-sided, and asymptotically normally distributed under the null hypothesis. Power study shows that the tests can detect local alternatives that differ from the null hypothesis at the parametric rate. Due to the first difference and orthogonal transformations used in the construction of variance estimators of the idiosyncratic error, the two proposed tests are robust to the presence of one effect and the possible correlation between the covariates and the error components when the other one is tested. Monte Carlo simulations are carried out to provide evidence on the finite sample properties of the tests.

1. Introduction

In econometric analysis of panel data, the random individual and time effects are usually used to capture the heteroscedasticity of individual and time points. In practice, however, people often don't know whether the random effects exist or not, therefore this can lead to the misspecification of the random effects. As a result, some tests for the existence of the two random effects are essential when we use the panel data models with random effects. Breusch and Pagan (1980) proposed several Lagrange multiplier (LM) tests for the existence of two random effects by testing whether their variances are zero or not, which are widely used in both the theory and the application. Given that variances are nonnegative, one-sided tests for such a problem should be more reasonable and powerful than two-sided ones of Breusch and Pagan (1980). Correspondingly, many one-sided tests and their modified versions have been developed for the existence of random effects, e.g. Honda (1985, 1991), Moulton and Randolph (1989), Baltagi et al. (1992), King and Wu (1997), etc. Moreover, Bera et al. (2001) suggested some simple tests based on the ordinary least square (OLS) residuals for random individual effect in the presence of serial correlation. Most of these tests require the normality assumptions of the random effects and the idiosyncratic error, which cannot be guaranteed in practice. Also note that Bera et al. (2001) did not consider the potential time effect which can distort the size of the tests. Montes-Rojas (2010) extended the method of Bera et al. (2001) to spatial panel models. The reader may refer to an excellent monograph by Baltagi (2008) for a detailed review of the existing random effects tests.

Recently, there has been increasing interest in the tests' robustness to the misspecification of various assumptions, conditions and model settings (Bera et al., 2001). Wu and Zhu (2011) proposed two robust random effects tests for the linear panel data models, which are based on the artificial autoregression modelled by the pairwise differenced residuals over the individual and time indices. The simulation results in this paper show that the tests of Wu and Zhu (2011) obtain the robust properties at the cost of low power. Wu and Li (2014) proposed several moment-based tests for the individual and time effects in panel data models. As Wu and Li (2014) argued, these tests have the desired properties as follows. The tests are very simple and easy to compute; the tests for individual effect are robust to the existence of time effect and the possible correlation between the covariates and the error components; the tests for time effect are also robust to the existence of individual effect and the possible correlation between the covariates and the error components. However, since the centering transformation is used in both the construction of the individual effect tests and the determination of the p-values

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of the time effect tests in real applications (see Wu and Li, 2014, Sections 2 and 3), the tests of Wu and Li (2014) cannot be extended to the cases with unbalanced panels. Moreover, since the time effect tests of Wu and Li (2014) are not standard, one needs to center the covariates so that the resultant tests can be performed with p-values of critical values calculated from the standard chi-squared distribution with $T-1$ degrees of freedom. These motivate us to develop some new random effects tests as alternatives for panel data models.

The main contribution of this paper is as follows. To avoid distributional assumptions on the random effects and the idiosyncratic error, we consider a robust method to test for the existence of random effects in linear panel data models. Specifically, we compare two estimators of the variance of the idiosyncratic error at different robust levels, and construct the tests for the existence of random effects in the panel data models with no distributional assumptions. The resultant tests are one-sided, and asymptotically normally distributed under the null hypothesis, which is partly different from those of Wu and Li (2014). Power study shows that the tests can detect local alternatives that differ from the null hypothesis at the parametric rate. Due to the first difference and orthogonal transformations used in the construction of variance estimators of the idiosyncratic error, the two proposed tests are robust to the presence of one effect and the possible correlation between the covariates and the error components when the other one is tested. Moreover, the resultant tests don't need any pretreatment of the data so that the condition $Q'EX_i = 0$ holds (see Wu and Li, 2014, p. 572). In addition, the new tests proposed in this paper can be easily modified to test for the existence of random effects in unbalanced panel data models. The above two properties are main different points between the new tests in this paper and the tests of Wu and Li (2014).

The rest of this paper is organized as follows. In the next section, we introduce some notations and simply describe the involved higher order moment estimation of the idiosyncratic error. In Section 3 , we construct test statistics for the existence of random effects, which are based on the difference of two estimators of the variance of the idiosyncratic error at different robust levels. In this section, the asymptotical behavior of the test statistics is investigated theoretically. In Section 4 , Monte Carlo simulation experiments are carried out for illustration. Some conclusions are given in Section 5 . Proofs of theorems are postponed to the Appendix.

2. Model and notations

Consider the linear panel data model with two-way error components

$$y_{it} = \alpha + X_{it}'\beta + \mu_i + \lambda_t + u_{it}, \quad i = 1,2,\ldots,n, t = 1,2,\ldots,T, \qquad (1)$$

where α is the intercept term, X_{it} is the it-th observation on K covariates, and β is the K-dimensional vector of coefficients of covariates. And, μ_i is the individual effect with zero mean and finite variance (hereafter $\sigma_{\mu_i}^2$) and λ_t is the time effect with zero mean and finite variance (hereafter $\sigma_{\lambda_t}^2$). The variances of random effects μ_i and λ_t are allowed to be heterogeneous so that the model settings are more general. The idiosyncratic error u_{it} varies with individual and time, which is assumed to be independent and identically distributed. The covariates $\{X_{it}, t = 1,2,\ldots,T\}$ are independent and identically distributed across individuals, and predetermined, i.e. $E(X_{it}u_{is}) = 0$ for $s \geq t$. We allow non-zero correlation among the random effects μ_i, λ_t and the covariates X_{it} (see, e.g., Hsiao, 2003, Mundlak, 1978), which is often omitted in the existing random effects tests in the literature. Moreover, when focusing on the existence of one effect, we don't need any informations of the other one. In addition, it is worthwhile to point out that the asymptotic results in this paper are based on the setting that the individual number n goes to infinity and time length T is fixed, which is widely used in the literature (Wu and Li, 2014).

As a necessary step, the parameter estimation should be considered firstly. Although there exist more efficient estimators when the effects are not misspecified, we prefer to use the robust within estimator on the misspecification of the random effects,

$$\hat{\beta} = \left[X'\left(I_n - \frac{J_n}{n}\right) \otimes \left(I_T - \frac{J_T}{T}\right)X\right]^{-1} X'\left(I_n - \frac{J_n}{n}\right) \otimes \left(I_T - \frac{J_T}{T}\right)y, \qquad (2)$$

where $y = (y_{11}, y_{12}, \ldots, y_{1T}, y_{21}, y_{22}, \ldots, y_{2T}, \ldots, y_{n1}, y_{n2}, \ldots, y_{nT})'$, $X = (X_{11}, X_{12}, \ldots, X_{1T}, X_{21}, X_{22}, \ldots, X_{2T}, \ldots, X_{n1}, X_{n2}, \ldots, X_{nT})'$, and I_l is an identity matrix of dimension l, J_l denotes a $l \times l$ matrix of ones, and "$\otimes$" denotes the Kronecker product. As Wu and Li (2014) argued, under some regularity conditions, it holds that, regardless of the presence of individual and time effects,

$$\sqrt{n}(\hat{\beta} - \beta) \xrightarrow{D} N(0, \Sigma_1^{-1}\Sigma_2\Sigma_1^{-1})$$

as $n \to \infty$, where $\Sigma_1 = E\left[X_i'\left(I_T - \frac{J_T}{T}\right)X_i\right] - EX_i'\left(I_T - \frac{J_T}{T}\right)EX_i$ and $\Sigma_2 = E\left[(X_i - EX_i)'\left(I_T - \frac{J_T}{T}\right)u_iu_i'\left(I_T - \frac{J_T}{T}\right)(X_i - EX_i)\right]$ with $X_i = (X_{i1}, X_{i2}, \ldots, X_{iT})'$ and $u_i = (u_{i1}, u_{i2}, \ldots, u_{iT})'$. See Wu and Li (2014) or Baltagi (2008) for more details on the within estimator.

As argued in the Introduction, most of the tests for random effects are Lagrange multiplier tests which need the assumptions of normal distribution of the effects and the idiosyncratic error. Wu and Li (2014) proposed several moment-based tests, which don't need distributional assumptions on the error component disturbances. This paper will propose some new moment-based tests as alternatives. Note that Wu and Su (2010) used the first difference over the individual index and the orthogonal transformation over the time index to wipe out the possible time and individual effects and constructed the second order moment estimator (hereafter $\hat{\gamma}_2^u$) and the fourth order moment estimator (hereafter $\hat{\gamma}_4^u$) of the idiosyncratic error. Clearly, the resultant moment estimators are robust to the misspecification of random effects, and they will play a key role in the construction of test statistics for individual and time effects in this paper. In order to save space, we only give the expressions of the two moment estimators $\hat{\gamma}_2^u$ and $\hat{\gamma}_4^u$ of the idiosyncratic error u_{it} as follows (Wu and Su, 2010, p. 1935),

$$\begin{aligned}\hat{\gamma}_2^u &= \frac{1}{n(T-1)}\sum_{j=1}^{m} M_2'\left(\Delta y_{2j} - \Delta X_{2j}\hat{\beta}\right)^{(2)} \\ &= \frac{1}{n(T-1)}\sum_{j=1}^{m}\left(\Delta y_{2j} - \Delta X_{2j}\hat{\beta}\right)'\left(I_T - \frac{J_T}{T}\right)\left(\Delta y_{2j} - \Delta X_{2j}\hat{\beta}\right),\end{aligned} \qquad (3)$$

$$\hat{\gamma}_4^u = \frac{1}{nc_0}\sum_{j=1}^{m} M_4'(\Delta y_{2j} - \Delta X_{2j}\hat{\beta})^{(4)} - 3(\hat{\gamma}_2^u)^2\left[\frac{2(T-1)}{c_0} - 1\right], \qquad (4)$$

where $m = [\frac{n}{2}]$ ($[a]$ being the integer part of a, hereafter), $\hat{\beta}$ is the within estimator of Eq. (2), $c_0 = \sum_{l=2}^{T}\frac{l^2-3l+3}{l(l-1)}$, $M_2 = \sum_{j=2}^{T} q_j^{(2)}$, $M_4 = \sum_{j=2}^{T} q_j^{(4)}$, $q_j = \frac{1}{\sqrt{j(j-1)}}[(j-1)e(j) - \sum_{k=1}^{j-1} e(k)]$, $j = 2,3,\ldots,T$, with $e(k)$ standing for the k-th column vector of the identity matrix I_T. Moreover, $\Delta y_{2j} = (\Delta y_{2j,1}, \Delta y_{2j,2}, \ldots, \Delta y_{2j,T})'$, $\Delta X_{2j} = (\Delta X_{2j,1}, \Delta X_{2j,2}, \ldots, \Delta X_{2j,T})'$ and "Δ" stands for the difference operator over the individual index, i.e. $\Delta y_{2j,t} = y_{2j,t} - y_{2j-1,t}$. Hereafter, we denote $\xi^{(k)} = \underbrace{\xi \otimes \cdots \otimes \xi}_{k}$ for any vector or matrix ξ. Under some moment conditions, the above two estimators are respectively consistent and asymptotically normally distributed. The reader can refer to Wu and Su (2010, p. 1935–1936) for more details.

3. Test for random effects

Firstly, we consider the test for the individual effect. Recalling the heterogeneity of individual effect and the nonnegativity of variances, we consider the null hypothesis

$$H_0^{\mu}: D_{\mu} = 0, \tag{5}$$

and the alternative hypotheses

$$H_1^{\mu}: D_{\mu} \geq 0 \quad \text{and} \quad D_{\mu} \neq 0,$$

where $D_{\mu} = \text{diag}(\sigma^2_{\mu_1}, \sigma^2_{\mu_2}, \ldots, \sigma^2_{\mu_n})$, and $\sigma^2_{\mu_i}$ is the variance of μ_i. Under the null hypothesis (5), since there is no individual effect, the orthogonal transformation is not needed in the estimation of the variance of the idiosyncratic error. We only need to eliminate the potential time effect by the first difference over the individual index and then obtain an estimator of the variance of the idiosyncratic error u_{it}, which is denoted by

$$\hat{\gamma}^u_{2,1} = \frac{1}{nT} \sum_{j=1}^{m} (\Delta y_{2j} - \Delta X_{2j}\hat{\beta})'(\Delta y_{2j} - \Delta X_{2j}\hat{\beta}). \tag{6}$$

Note that, the estimator $\hat{\gamma}^u_2$ of Eq. (3) is consistent under both the null hypothesis H_0^{μ} and the alternatives H_1^{μ}. However, the estimator $\hat{\gamma}^u_{2,1}$ of Eq. (6) is only consistent under the null hypothesis H_0^{μ}, and no longer consistent under the alternatives H_1^{μ}. Clearly, the difference of the two estimators should be small under the null hypothesis H_0^{μ} and large under the alternatives H_1^{μ}. In the light of this finding, we construct the following test statistic on the basis of the difference of the two estimators

$$T^{\mu} = \frac{\sqrt{n}}{\sqrt{\Phi_{1n}}} (\hat{\gamma}^u_{2,1} - \hat{\gamma}^u_2),$$

where the scalar Φ_{1n} is used to standardize the statistic and defined in Eq. (13).

Theorem 1. *Suppose that* $E(u^4_{it}) < \infty$, $E \parallel X_i \parallel^4 < \infty$, $|\Sigma_1| > 0$ *and* $cov(X_i'\iota_T, u_i'\iota_T) = 0$. Under the null hypothesis (5), we have

$$T^{\mu} \xrightarrow{D} N(0,1)$$

as $n \to \infty$, *where* $N(0,1)$ *is the standard normal distribution.*

If the null hypothesis (5) is violated, then the test T^{μ} is usually large. In the following, we study theoretically the power properties of T^{μ}, and describe briefly its asymptotic behavior. To check the sensitivity of the test, we consider the local alternatives with homogeneous variance of μ_i

$$H_{1n}^{\mu}: D_{\mu} = C_n I_n, \tag{7}$$

where C_n is a positive constant sequence. In the following, we give two assumptions needed in the power study of the proposed test T^{μ}.

(A) $\{\mu_i\}$ are independent and identically distributed with mean zero and positive variance σ^2_{μ}.
(B) $E(\mu_i u_i) = 0$, $n^{\frac{1}{2}} E(\mu_i^2 \parallel u_i \|^2) < \infty$, and $n^{\frac{1}{4}} E(\mu_i X_i) = \Psi$.

Theorem 2. *Suppose that* $E(u^4_{it}) < \infty$, $E \parallel X_i \parallel^4 < \infty$, $|\Sigma_1| > 0$ *and* $cov(X_i'\iota_T, u_i'\iota_T) = 0$ *and Assumptions (A) and (B) hold. As* $n \to \infty$, *we then have, if* $n^{\gamma} C_n \to q$, $(q \neq 0)$, $0 \leq \gamma < \frac{1}{2}$,

$$T^{\mu} \to +\infty,$$

in probability, and if $n^{\frac{1}{2}} C_n \to \sigma^2_1$,

$$T^{\mu} \xrightarrow{D} N(c^{\mu}, 1),$$

where $N(c^{\mu}, 1)$ *is the non-centrally standard normal distribution with bias* $c^{\mu} = \frac{\sigma_1^2}{\sqrt{\Phi_1}}$, and Φ_1 defined in Eq. (12).

This result shows that the test T^{μ} has asymptotic power 1 for global alternatives ($\gamma = 0$) and local alternatives distinct from the null at a rate $n^{-\gamma}$ with $0 < \gamma < \frac{1}{2}$. It can detect alternatives that converge to the null at a rate $n^{-\frac{1}{2}}$, and then the test is sensitive to alternatives. For the alternatives that are distinct from the null at the rate $n^{-\frac{1}{2}}$, asymptotic p-values can be derived from the standard normal distribution. Moreover, the power of the test is related to the variance of the effect.

Remark 1. The method can also be used to test the time trend of the individual effect in panel data model as follows,

$$y_{it} = X_{it}'\beta + \mu_i + \lambda_t + \xi_i t + u_{it}.$$

Specifically, we use the first order difference across time index to remove the time trend, and then using the same method to estimate the higher order moment as that of Wu and Su (2010). Based on the difference between the new second moment estimator and the moment estimator $\hat{\gamma}^u_2$ of Eq. (3) for the case with no time trend, we can construct a test for the existence of time trend. The details are omitted here.

In the following, we consider the test for the time effect. Recalling that the individual number n is set to large and the time length T small for the panel data considered in this paper. The above method can be adopted to construct test for the time effect, however, the resultant test for time effect should be different from that for individual effect since the two indices n and T are not symmetric. The null hypothesis is

$$H_0^{\lambda}: D_{\lambda} = 0, \tag{8}$$

and the alternative hypotheses

$$H_1^{\lambda}: D_{\lambda} \geq 0 \quad \text{and} \quad D_{\lambda} \neq 0,$$

where $D_{\lambda} = \text{diag}(\sigma^2_{\lambda_1}, \sigma^2_{\lambda_2}, \ldots, \sigma^2_{\lambda_T})$, and $\sigma^2_{\lambda_t}$ is the variance of λ_t. We adopt the same method as the above to construct a statistic to test for time effect

$$T^{\lambda} = \frac{\sqrt{n}}{\sqrt{\Phi_{2n}}} (\hat{\gamma}^u_{2,2} - \hat{\gamma}^u_2),$$

where the scalar Φ_{2n} is used to standardize the statistic and defined in Eq. (15), and

$$\hat{\gamma}^u_{2,2} = \frac{1}{n(T-1)} \sum_{i=1}^{n} \left(y_i - X_i\hat{\beta}\right)' \left(I_T - \frac{J_T}{T}\right) \left(y_i - X_i\hat{\beta}\right). \tag{9}$$

Theorem 3. *Suppose that* $E(u_{it}^2) < \infty$, $E \parallel X_i \parallel^2 < \infty$, $|\Sigma_1| > 0$ *and* $cov(X_i'\iota_T, u_i'\iota_T) = 0$. Under the null hypothesis (8), we have

$$T^\lambda \xrightarrow{D} N(0,1)$$

as $n \to \infty$, *where* $N(0,1)$ *is the standard normal distribution.*

Consider the local alternatives as follows,

$$H_{1n}^\lambda : D_\lambda = C_n I_T, \quad (10)$$

where C_n is a positive constant sequence.

Theorem 4. *Suppose that* $E(u_{it}^2) < \infty$, $E \parallel X_i \parallel^2 < \infty$, $|\Sigma_1| > 0$ *and* $cov(X_i'\iota_T, u_i'\iota_T) = 0$. *As* $n \to \infty$, *we have, if* $n^\gamma C_n \to q$ $(q \neq 0)$, $0 \le \gamma < \frac{1}{2}$,

$$T^\lambda \to +\infty,$$

in probability, and if $n^{\frac{1}{2}} C_n \to \sigma_2^2$,

$$T^\lambda \xrightarrow{D} N(c^\lambda, 1),$$

where $N(c^\lambda, 1)$ *is the non-centrally standard normal distribution with bias* $c^\lambda = \frac{\tilde{\sigma}_2^2}{\sqrt{\Phi_2}}$, *and the expressions of* Φ_2 *and* $\tilde{\sigma}_2^2$ can be found in Eqs. (14) and (16), respectively.

Remark 2. The conditions $|\Sigma_1| > 0$ and $cov(X_i'\iota_T, u_i'\iota_T) = 0$ in Theorems 1–4 are to guarantee the root-n consistency and asymptotic normality of the within estimator $\hat{\beta}$. In fact, in the proofs of the theorems we only need the property of root-n consistency of parameter estimator $\hat{\beta}$. And correspondingly, the within estimator $\hat{\beta}$ can be replaced by the other ones only if they are root-n consistent whether the random effects exist or not.

4. Finite sample properties via simulations

In the following, we conduct some simulation experiments to examine the performance of the resultant tests in the above section. Consider the panel model as follows

$$y_{it} = \alpha + X_{it}'\beta + \mu_i + \lambda_t + u_{it}, \quad (11)$$

where $\alpha = 0.5, \beta = (1,2)'$, $X_{it} \overset{i.i.d.}{\sim} N(0, I_2)$ and $\mu_i \overset{i.i.d.}{\sim} c_1 U(-1,1)$ (the uniform distribution on the interval $[-1,1]$), $\lambda_t \overset{i.i.d.}{\sim} c_2 U(-1,1)$. As to the idiosyncratic error term, we consider the two distribution settings: $u_{it} \overset{i.i.d.}{\sim} N(0,1)$ and $u_{it} \overset{i.i.d.}{\sim} (\chi_1^2 - 1)$ (χ_1^2 being the standard chi-square distribution with 1 degree of freedom). Firstly, we consider the individual effect test. Let $c_1 = 0.0, 0.2, 0.4, 0.6, 0.8, 1.0$, where $c_1 = 0.0$ corresponds to the null and $c_1 \neq 0.0$ to the alternatives. To show the test's robustness on the existence of time effect, we let $c_2 = 0.0$ and 1.0, where $c_2 = 0.0$ or 1.0 stands for the absence or presence of time effect. Secondly, we carry out the simulation for the time effect test, and consider the similar settings as the above. The sample sizes are designed as all the combinations of $n = 100, 200$, and $T = 10, 20$, and the simulation results are based on 1000 replications of the experiments. The simulation results show that our tests perform well. It is noteworthy that, regardless of the existence of time effect, the empirical size of the individual effect test is close to the nominal size and the empirical power is high even when the sample size is moderate or small. The time effect test has the similar simulation results. See Tables 1 and 2 for more details.

Nextly, we compare seven existing tests in the literature with our tests using simulation experiments. For the sake of statements, we first present their expressions. Denoted by $\tilde{u}$ the residuals from the standard linear panel data model without random effects, let

$$A = 1 - \frac{\tilde{u}'(I_n \otimes J_T)\tilde{u}}{\tilde{u}'\tilde{u}} \quad \text{and} \quad B = \frac{\tilde{u}'\tilde{u}_{-1}}{\tilde{u}'\tilde{u}}.$$

The LM test (BP_μ) for random individual effect developed by Breusch and Pagan (1980) is

$$BP_\mu = \frac{nTA^2}{2(T-1)}.$$

Under the null hypothesis of no individual effect, the test is asymptotically distributed as χ_1^2. As the test for random effects should be one-sided, Honda (1985) suggested the modified version of the two-sided test BP_μ, which is denoted by H_μ,

$$H_\mu = -\sqrt{\frac{nT}{2(T-1)}}A.$$

Bera et al. (2001) made some adjustments and obtained two robust versions of the above two tests, which are denoted by $BSY1$ and $BSY2$, respectively,

$$BSY1 = \frac{nT^2(A+2B)^2}{2(T-1)(T-2)}, \quad BSY2 = -\sqrt{\frac{nT^2}{2(T-1)(T-2)}}(A-2B).$$

However, none of these tests is feasible when the potential time effect λ_t exists. Baltagi et al. (1992) derived a LM test for individual effect, which has the validity of the Breusch-Pagan statistic and allows for the presence (or absence) of time effect. Their individual effect test is as follows,

$$BCL_\mu = \frac{\sqrt{2}\tilde{\sigma}_2^2\tilde{\sigma}_\nu^2}{\sqrt{T(T-1)\left[\tilde{\sigma}_\nu^4 + (n-1)\tilde{\sigma}_2^4\right]}}\tilde{D}_\mu,$$

$$\tilde{D}_\mu = \frac{T}{2}\left\{\frac{1}{\tilde{\sigma}_2^2}\left[\frac{\tilde{u}'(\bar{J}_n \otimes \bar{J}_T)\tilde{u}}{\tilde{\sigma}_2^2} - 1\right] + \frac{n-1}{\tilde{\sigma}_\nu^2}\left[\frac{\tilde{u}'(E_n \otimes \bar{J}_T)\tilde{u}}{(n-1)\tilde{\sigma}_\nu^2} - 1\right]\right\},$$

where $\tilde{\sigma}_2^2 = \frac{\tilde{u}'(\bar{J}_n \otimes I_T)\tilde{u}}{T}$ and $\tilde{\sigma}_\nu^2 = \frac{\tilde{u}'(E_n \otimes I_T)\tilde{u}}{T(n-1)}$ with $E_n = I_n - \bar{J}_n$ and $\bar{J}_n = \frac{J_n}{n}$. Moreover, the above tests need normality assumptions for the random effects and the idiosyncratic error, which cannot be guaranteed in practice. Wu and Zhu (2011) proposed a residual-based random effect test as follows,

$$WZ_\mu = \sqrt{m(T-1)}\left(\sum_{i=1}^m\sum_{t=2}^T \xi_{2i,t-1}^2\right)^{-1}\sum_{i=1}^m\sum_{t=2}^T \xi_{2i,t-1}\xi_{2i,t},$$

where $\xi_{2i,t} = \Delta y_{2i,t} - \hat{\beta}'\Delta X_{2i,t}$ and $m = [\frac{n}{2}]$. Wu and Li (2014) proposed a moment-based individual effect test as follows,

$$WL_\mu = \sqrt{\frac{nT(T-1)}{2}}\left(\frac{\hat{\sigma}_{1u}^2}{\hat{\sigma}_{0u}^2} - 1\right),$$

where $\hat{\sigma}_{1u}^2$ and $\hat{\sigma}_{0u}^2$ are respectively the two estimators of the variance of the idiosyncratic error at different robust levels, see Wu and Li (2014, p. 570–571) for more details.

For the sake of comparison, we consider the same data generating process (DGP) as those of Wu and Li (2014). That is, the DGP is

Table 1
The empirical size and power of the test T^{μ} for individual effect in model (11). The nominal size is 5%.

Error distribution	n	T	c_2	$c_1=0.0$	$c_1=0.2$	$c_1=0.4$	$c_1=0.6$	$c_1=0.8$	$c_1=1.0$
$N(0,1)$	100	10	0	0.058	0.178	0.720	0.991	1.000	1.000
	100	20	0	0.048	0.357	0.971	1.000	1.000	1.000
	200	10	0	0.052	0.236	0.903	1.000	1.000	1.000
	200	20	0	0.051	0.563	1.000	1.000	1.000	1.000
	100	10	1	0.060	0.208	0.713	0.998	1.000	1.000
	100	20	1	0.051	0.371	0.979	1.000	1.000	1.000
	200	10	1	0.052	0.231	0.904	1.000	1.000	1.000
	200	20	1	0.052	0.564	1.000	1.000	1.000	1.000
χ_1^2-1	100	10	0	0.059	0.116	0.377	0.787	0.968	0.998
	100	20	0	0.053	0.195	0.729	0.986	1.000	1.000
	200	10	0	0.049	0.140	0.533	0.963	1.000	1.000
	200	20	0	0.048	0.234	0.920	1.000	1.000	1.000
	100	10	1	0.053	0.111	0.382	0.771	0.982	0.996
	100	20	1	0.048	0.187	0.721	0.995	1.000	1.000
	200	10	1	0.053	0.133	0.552	0.939	1.000	1.000
	200	20	1	0.053	0.269	0.925	1.000	1.000	1.000

still from the model (11), but some settings such as the distribution assumptions are different from the above. Denote $X_{it}=(X_{1,it},X_{2,it})'$, and assume that $X_{1,it}, X_{2,it}$, μ_i and λ_t follow the normal distributions with mean zero, $\text{var}(X_{1,it})=\text{var}(X_{2,it})=1$, $\text{var}(\mu_i)=\sigma_\mu^2$, $\text{var}(\lambda_t)=\sigma_\lambda^2$, $\text{corr}(X_{1,it},\mu_i)=\rho$, and u_{it} follows the standard normal distribution, $N(0,1)$, or $\sqrt{0.6}t_5$ (the Student t-distribution with 5 degrees of freedom). When $\rho\neq 0$, $X_{1,it}$ and $X_{1,is}$ are also correlated for $t\neq s$, and then we further set $\text{corr}(X_{1,it},X_{1,is})=\rho^2$. Note that $\sigma_\mu=0$ or >0 corresponds respectively to the size or the power, and $\sigma_\lambda=0$ or >0 to the absence or the presence of the time effect. Let $X_{1,i}=(X_{1,i1},\ldots,X_{1,iT})'$. Sequences $\{X_{1,i}\}$, $\{X_{2,it}\}$, $\{\mu_i\}$, $\{\lambda_t\}$ and $\{u_{it}\}$ are set to be *i.i.d.*, and are independent of each other except for $\{X_{1,i}\}$ and $\{\mu_i\}$ with $\rho\neq 0$. The sample sizes are $(n,T)=(100,10)$ and $(200,10)$, the experiments are replicated 1000 times to obtain the empirical sizes and powers of the tests. We check the different performances of the tests in various cases including the correlation coefficient ρ between the covariates and random effects. Table 3 lists the empirical sizes and powers of the test T^{μ} and other tests for the individual effect in the case with normally distributed errors. Since the results are similar to those in Table 3 we do not report the results in the case with t-distributed errors to save space. From the results in Table 3 we can obtain some conclusions as follows. When there are no time effect and no correlation between the covariates and the random effects (i.e. $\rho=0.00$), all the tests including $BP_\mu, H_\mu, BSY1, BSY2$ and BCL_μ have the desired empirical sizes and high powers. When the potential time effect exists and there is no correlation between the covariates and the random effects, the four tests $BP_\mu, H_\mu, BSY1, BSY2$ have worse performance, in contrast, the test BCL_μ still performs well. For the correlated setting (e.g. $\rho=0.50$), however, all the above five tests have distorted empirical sizes. In contrast, the tests WZ_μ, WL_μ and T^{μ} perform well in various settings and are robust to the misspecification of the random effects and the correlation between the covariates and the random effects. Among the three robust tests, the power of the tests T^{μ} and WL_μ are significantly higher power than that of the test WZ_μ, which is consistent with our expectations. Although both the two tests T^{μ} and WL_μ have the desired performance in various cases, the latter performs slightly better than the former in the simulation study.

We compare our time effect test with the existing tests in the literature such as the two-sided test BP_λ (Breusch and Pagan, 1980), the modified one-sided test H_λ (Honda, 1985), the conditional LM test BCL_λ (Baltagi et al., 1992), the residual-based test WZ_λ (Wu and Zhu, 2011) and the moment-based test WL_λ (Wu and Li, 2014). The simulation results are similar to those of the individual effect tests and then not reported here to save space.

5. Conclusions

On the basis of the comparison of various estimators of the variance of the idiosyncratic error, two new tests are constructed for the existence of random effects in linear panel data models with

Table 2
The empirical size and power of the test T^{λ} for time effect in model (11). The nominal size is 5%.

Error distribution	n	T	c_1	$c_2=0.0$	$c_2=0.2$	$c_2=0.4$	$c_2=0.6$	$c_2=0.8$	$c_2=1.0$
$N(0,1)$	100	10	0	0.061	0.095	0.323	0.738	0.945	0.991
	100	20	0	0.053	0.142	0.495	0.930	0.997	1.000
	200	10	0	0.052	0.121	0.486	0.888	0.980	1.000
	200	20	0	0.053	0.153	0.691	0.987	0.999	1.000
	100	10	1	0.061	0.095	0.336	0.724	0.951	0.989
	100	20	1	0.049	0.137	0.490	0.941	0.997	1.000
	200	10	1	0.052	0.112	0.485	0.884	0.983	0.992
	200	20	1	0.052	0.158	0.706	0.990	1.000	1.000
χ_1^2-1	100	10	0	0.061	0.080	0.160	0.389	0.669	0.885
	100	20	0	0.054	0.100	0.229	0.548	0.889	0.987
	200	10	0	0.053	0.100	0.223	0.544	0.845	0.959
	200	20	0	0.055	0.107	0.353	0.797	0.983	1.000
	100	10	1	0.060	0.085	0.165	0.377	0.684	0.868
	100	20	1	0.045	0.081	0.207	0.551	0.893	0.990
	200	10	1	0.053	0.085	0.231	0.556	0.843	0.956
	200	20	1	0.053	0.102	0.338	0.771	0.973	0.999

Table 3
Empirical size and power of the test T^{μ} and other seven tests for individual effect in model (11). The nominal size is 5%.

ρ	σ_λ	σ_μ	BP_μ	$BSY1$	H_μ	$BSY2$	BCL_μ	WZ_μ	WL_μ	T^{μ}
(n,T) = (100,10)										
0.00	0.00	0.00	0.054	0.048	0.040	0.045	0.038	0.062	0.050	0.058
	0.00	0.10	0.099	0.081	0.157	0.138	0.144	0.087	0.193	0.150
	0.00	0.20	0.656	0.584	0.763	0.707	0.743	0.205	0.795	0.550
	0.50	0.00	0.268	0.281	0.005	0.011	0.046	0.052	0.054	0.060
	0.50	0.10	0.149	0.185	0.013	0.021	0.171	0.068	0.193	0.147
	0.50	0.20	0.163	0.219	0.211	0.232	0.741	0.203	0.762	0.542
	1.00	0.00	0.909	0.658	0.000	0.006	0.053	0.046	0.064	0.066
	1.00	0.10	0.836	0.626	0.000	0.014	0.190	0.067	0.205	0.171
	1.00	0.20	0.512	0.488	0.017	0.063	0.763	0.239	0.786	0.586
0.50	0.00	0.10	0.035	0.038	0.045	0.033	0.043	0.061	0.057	0.067
	0.00	0.20	0.068	0.063	0.089	0.094	0.086	0.081	0.200	0.156
	0.00	0.20	0.292	0.250	0.383	0.349	0.372	0.204	0.765	0.544
	0.50	0.00	0.284	0.280	0.003	0.011	0.066	0.060	0.077	0.068
	0.50	0.10	0.198	0.224	0.003	0.024	0.106	0.088	0.214	0.168
	0.50	0.20	0.077	0.145	0.057	0.085	0.421	0.199	0.770	0.555
	1.00	0.00	0.907	0.655	0.000	0.010	0.057	0.044	0.079	0.069
	1.00	0.10	0.858	0.607	0.000	0.007	0.120	0.093	0.218	0.168
	1.00	0.20	0.713	0.528	0.001	0.034	0.430	0.244	0.773	0.588
(n,T) = (200,10)										
0.00	0.00	0.00	0.043	0.045	0.045	0.036	0.040	0.045	0.056	0.055
	0.00	0.10	0.148	0.133	0.223	0.200	0.215	0.075	0.256	0.181
	0.00	0.20	0.870	0.811	0.921	0.875	0.913	0.322	0.933	0.767
	0.50	0.00	0.498	0.396	0.000	0.008	0.062	0.047	0.065	0.060
	0.50	0.10	0.249	0.268	0.006	0.041	0.243	0.096	0.260	0.183
	0.50	0.20	0.296	0.372	0.348	0.387	0.959	0.326	0.965	0.795
	1.00	0.00	0.969	0.781	0.000	0.015	0.062	0.052	0.069	0.066
	1.00	0.10	0.929	0.721	0.001	0.036	0.238	0.077	0.249	0.168
	1.00	0.20	0.658	0.564	0.015	0.096	0.936	0.313	0.939	0.753
0.50	0.00	0.00	0.046	0.058	0.047	0.057	0.041	0.061	0.063	0.064
	0.00	0.10	0.076	0.077	0.123	0.127	0.117	0.085	0.269	0.207
	0.00	0.20	0.493	0.433	0.608	0.537	0.598	0.318	0.925	0.760
	0.50	0.00	0.476	0.397	0.001	0.005	0.062	0.048	0.068	0.055
	0.50	0.10	0.343	0.331	0.004	0.019	0.126	0.099	0.271	0.208
	0.50	0.20	0.133	0.222	0.084	0.129	0.626	0.293	0.935	0.750
	1.00	0.00	0.973	0.760	0.000	0.009	0.043	0.057	0.058	0.066
	1.00	0.10	0.942	0.743	0.000	0.019	0.123	0.087	0.267	0.191
	1.00	0.20	0.834	0.658	0.001	0.049	0.616	0.306	0.933	0.733

no distributional assumptions. The resultant tests are one-sided, and asymptotically normally distributed under the null hypothesis. Power study shows that the tests can detect local alternatives distinct at the parametric rate from the null. Due to the first difference and orthogonal transformations used in the construction of variance estimators of the idiosyncratic error, the two proposed tests are robust to the presence of one effect and the possible correlation between the covariates and the error components when the other one is tested.

As argued in Remark 1, the method can be used to construct tests for a time trend. Moreover, different from the method of Wu and Li (2014), the method suggested in this paper can be easily extended to construct test statistics for the existence of random effects in the two-way error component models with unbalanced panels. Specifically, we use the difference operator to eliminate the time effect and then use the same method of Wu et al. (2015) to construct test statistics for the existence of random effects in the error component models with unbalanced panels. We leave this for further study.

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Appendix A. Technical details

The proof of Theorem 1. By the same proof as that of Wu and Li (2014), we can show that $\hat{\beta}$ is asymptotically normal regardless of the existence of random effects under the conditions with $|\Sigma_1| > 0$ and $\text{cov}(X_i'\iota_T, u_i'\iota_T) = 0$. Let $U_1 = diag\{E(1,1), E(2,2), \cdots, E(T,T)\}$ be a partitioning diagonal matrix, and

$$U_2 = \begin{pmatrix} I_T & E(1,2)+E(2,1) & \cdots & E(1,T)+E(T,1) \\ E(1,2)+E(2,1) & I_T & \cdots & E(2,T)+E(T,2) \\ \vdots & \vdots & \vdots & \vdots \\ E(1,T)+E(T,1) & E(2,T)+E(T,2) & \cdots & I_T \end{pmatrix},$$

where $E(i,j)$ is a $T \times T$ matrix with element $(i,j) = 1$, and zero otherwise. Under the null hypothesis (5), by Eqs. (3) and (6) and Taylor series expansion, we have

$$\hat{\gamma}^{u}_{2,1} - \hat{\gamma}^{u}_{2} = \frac{1}{n}\sum_{j=1}^{m} O'\Delta u_{2j} \otimes \Delta u_{2j} + o_p\left(n^{-\frac{1}{2}}\right),$$

where $O = \frac{1}{T}\mathrm{vec}(I_T) - \frac{1}{T-1}M_2$. It then follows from the conditions $E(u_{it}^4) < \infty$, $E \parallel X_i \parallel^4 < \infty$, and the central limit theorem that,

$$\sqrt{n}(\hat{\gamma}_{2,1}^u - \hat{\gamma}_2^u) \xrightarrow{D} N(0, \Phi_1)$$

as $n \to \infty$, where

$$\Phi_1 = O'\left[\left(\gamma_4^u + (\gamma_2^u)^2\right)U_1 + 2(\gamma_2^u)^2 U_2\right]O. \tag{12}$$

Therefore, we have

$$\frac{\sqrt{n}}{\sqrt{\Phi_{1n}}}\left(\hat{\gamma}_{2,1}^u - \hat{\gamma}_2^u\right) \xrightarrow{D} N(0,1)$$

as $n \to \infty$, where Φ_{1n} is the empirical version of the limit variance Φ_1,

$$\Phi_{1n} = O'\left[\left(\hat{\gamma}_4^u + \left(\hat{\gamma}_2^u\right)^2\right)U_1 + 2\left(\hat{\gamma}_2^u\right)^2 U_2\right]O, \tag{13}$$

and the definitions of $\hat{\gamma}_2^u$ and $\hat{\gamma}_4^u$ are respectively from the equations of (3)–(4).

The proof of Theorem 2. Note that $\hat{\beta}$ is asymptotically normal regardless of the existence of random effects under the conditions with $|\Sigma_1| > 0$ and $\mathrm{cov}(X_i'\iota_T, u_i'\iota_T) = 0$. Under the alternatives (7), by Eqs. (3) and (6) and Taylor series expansion, we have that

$$\hat{\gamma}_{2,1}^u - \hat{\gamma}_2^u = \frac{1}{n}\sum_{j=1}^{m}\left(O'\Delta u_{2j} \otimes \Delta u_{2j} + \Delta\mu_{2j}'\Delta\mu_{2j} + \frac{2}{T}\iota_T'\Delta\mu_{2j}\Delta u_{2j}\right) + o_p\left(n^{-\frac{1}{2}}\right),$$

where $O = \frac{1}{T}\mathrm{vec}(I_T) - \frac{1}{T-1}M_2$. If $n^\gamma C_n \to q(q \neq 0)$, $0 \le \gamma < \frac{1}{2}$, it then follows from Assumptions (A) and (B) that, in probability,

$$T^\mu = \sqrt{n}\left(\hat{\gamma}_{2,1}^u - \hat{\gamma}_2^u\right) = C_n n^{\frac{1}{2}} + O_p(1) \to +\infty.$$

In the case with $n^{\frac{1}{2}}C_n \to \sigma_1^2$, it follows from Assumptions (A) and (B), $E(u_{it}^4) < \infty$, $E \parallel X_i \parallel^4 < \infty$, and the central limit theorem that, as $n \to \infty$,

$$\sqrt{n}\left(\hat{\gamma}_{2,1}^u - \hat{\gamma}_2^u\right) = \sigma_1^2 + \frac{1}{\sqrt{n}}\sum_{j=1}^{m} O'\Delta u_{2j}^{(2)} + o_p(1) \xrightarrow{D} N\left(\sigma_1^2, \Phi_1\right).$$

So, we have,

$$\frac{\sqrt{n}}{\sqrt{\Phi_{1n}}}\left(\hat{\gamma}_{2,1}^u - \hat{\gamma}_2^u\right) \xrightarrow{D} N(c^\mu, 1)$$

as $n \to \infty$, where Φ_{1n} is the empirical version of the limit variance Φ_1, and $c^\mu = \frac{\sigma_1^2}{\sqrt{\Phi_1}}$, see (Eqs. (12)–(13)) for the expressions of Φ_1 and Φ_{1n}.

The proof of Theorem 3. Recalling the asymptotic normality of $\hat{\beta}$ regardless of the existence of random effects under the conditions with $|\Sigma_1| > 0$ and $\mathrm{cov}(X_i'\iota_T, u_i'\iota_T) = 0$. Under the null hypothesis (8), by Eqs. (3), (9) and Taylor series expansion, we obtain that

$$\begin{aligned}\hat{\gamma}_{2,2}^u - \hat{\gamma}_2^u &= \frac{1}{n(T-1)}\sum_{j=1}^{m} M_2'(u_{2j-1} \otimes u_{2j-1} + u_{2j} \otimes u_{2j} - \Delta u_{2j} \otimes \Delta u_{2j}) \\ &\quad + o_p(n^{-\frac{1}{2}}) \\ &= \frac{1}{n(T-1)}\sum_{j=1}^{m} M_2'(u_{2j-1} \otimes u_{2j} + u_{2j} \otimes u_{2j-1}) + o_p(n^{-\frac{1}{2}}).\end{aligned}$$

Let

$$U_3 = \begin{pmatrix} E(1,1) & E(2,1) & \cdots & E(T,1) \\ E(1,2) & E(2,2) & \cdots & E(T,2) \\ \vdots & \vdots & \vdots & \vdots \\ E(1,T) & E(2,T) & \cdots & E(T,T) \end{pmatrix},$$

where $E(i,j)$ is a $T \times T$ matrix with element $(i,j) = 1$, and zero otherwise. Further, by the conditions $E(u_{it}^2) < \infty$, $E \parallel X_i \parallel^2 < \infty$, and the central limit theorem, we have that,

$$\sqrt{n}\left(\hat{\gamma}_{2,2}^u - \hat{\gamma}_2^u\right) \xrightarrow{D} N(0, \Phi_2)$$

as $n \to \infty$, where

$$\Phi_2 = \frac{(\gamma_2^u)^2}{(T-1)^2}M_2'(I_{T^2} + U_3)M_2. \tag{14}$$

Therefore, we have

$$T^\lambda = \frac{\sqrt{n}}{\sqrt{\Phi_{2n}}}\left(\hat{\gamma}_{2,2}^u - \hat{\gamma}_2^u\right) \xrightarrow{D} N(0,1)$$

as $n \to \infty$, where Φ_{2n} is the empirical version of the limit variance Φ_2,

$$\Phi_{2n} = \frac{\left(\hat{\gamma}_2^u\right)^2}{(T-1)^2}M_2'(I_{T^2} + U_3)M_2. \tag{15}$$

The proof of Theorem 4. Recalling the asymptotic normality of $\hat{\beta}$ regardless of random effects under the conditions with $|\Sigma_1| > 0$ and $\mathrm{cov}(X_i'\iota_T, u_i'\iota_T) = 0$. Under the alternatives (10), by Eqs. (3) and (9) and Taylor series expansion, we have that

$$\begin{aligned}\hat{\gamma}_{2,2}^u - \hat{\gamma}_2^u = &\frac{1}{n(T-1)}\sum_{j=1}^{m} M_2'(u_{2j-1} \otimes u_{2j} + u_{2j} \otimes u_{2j-1} + 2\lambda \otimes \lambda + u_{2j-1} \otimes \lambda \\ &+ \lambda \otimes u_{2j} + u_{2j} \otimes \lambda + \lambda \otimes u_{2j-1}) + o_p(n^{-\frac{1}{2}}),\end{aligned}$$

where $u_i = (u_{i1}, u_{i2}, \ldots, u_{iT})'$ and $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_T)'$. If $n^\gamma C_n \to q(q \neq 0)$, $0 \le \gamma < \frac{1}{2}$, it then follows easily that, in probability, as $n \to \infty$,

$$T^\lambda = \sqrt{n}\left(\hat{\gamma}_{2,2}^u - \hat{\gamma}_2^u\right) = C_n n^{\frac{1}{2}} + O_p(1) \to +\infty.$$

In the case with $n^{\frac{1}{2}}C_n \to \sigma_2^2$, it follows from $E(u_{it}^2) < \infty$, $E \parallel X_i \parallel^2 < \infty$, and the central limit theorem that,

$$\sqrt{n}(\hat{\gamma}_{2,2}^u - \hat{\gamma}_2^u) = \tilde{\sigma}_2^2 + \frac{1}{\sqrt{n}}\sum_{j=1}^{m}\frac{1}{T-1}M_2'(u_{2j-1}\otimes u_{2j} + u_{2j}\otimes u_{2j-1}) + o_p(1) \xrightarrow{D} N(\tilde{\sigma}_2^2, \Phi_2)$$

as $n \to \infty$, where Φ_2 is defined in Eq. (14), and

$$\tilde{\sigma}_2^2 = \frac{1}{T-1}\sum_{t=1}^{T}\left(\lambda_t^* - \bar{\lambda}^*\right)^2, \quad \bar{\lambda}^* = \frac{1}{T}\sum_{t=1}^{T}\lambda_t^*, \tag{16}$$

and $\lambda_t^* = n^{\frac{1}{4}}\lambda_t$ being the random variable with mean zero and variance σ_2^2. So, we have

$$T^\lambda = \frac{\sqrt{n}}{\sqrt{\Phi_{2n}}}\left(\hat{\gamma}_{2,2}^u - \hat{\gamma}_2^u\right) \xrightarrow{D} N(c^\lambda, 1)$$

as $n \to \infty$, where Φ_{2n} is the empirical version of the limit variance Φ_2, and $c^\lambda = \frac{\tilde{\sigma}_2^2}{\sqrt{\Phi_2}}$, see (Eqs. (14)–(16)) for the expressions of Φ_2, Φ_{2n} and $\tilde{\sigma}_2^2$. □

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