Tests for Dynamic Effects in Linear Panel Data Models *

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Abstract

This paper proposes simple tests to detect dynamic and random effects in linear panel data models, in the form of lagged dependent variables and random effects. We use the analytical framework of Bera and Yoon (1993) to derive tests for the presence of random effects, lagged dependent variables, or both. All test statistics can be computed based on pooled OLS estimates, and hence can serve as a useful specification search tool to validate the adoption of a dynamic model.

JEL Classification: C12, C23.
Keywords: Dynamic panel; Random effects; Error components; Local misspecification; Testing.

1 Introduction

One of the most important uses of panel data is to help distinguishing among different sources of persistent behavior. The availability of data for different units along time is a requisite to disentangle whether persistence is due to the relevance of time-invariant, unit-specific unobserved factors, to structural mechanisms that link present values to past

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ones, or to both. The literature has vaguely used the term 'unobserved heterogeneity' to label the first source, and 'state dependence' to the second one.

In the standard linear error component model, individual specific factors induce persistence over time due to the presence of these unmeasured random effects. In a static model, the standard test for random effects originally proposed by Breusch and Pagan (1980), BP(1980) henceforth, serves the purpose of checking for persistent effects due to the presence of random effects. Bera, Sosa-Escudero and Yoon (2001) found that the presence of positive serial correlation confounds the Breusch-Pagan statistic, making it spuriously reject its null even when random effects are absent. The intuition is that the BP(1980) test implicitely assumes only one possible source of persistence in the unobserved terms (the random effect), so serial correlation introduces a second source that is mistakenly perceived as being indicative of the presence of random effects. A symmetric concern affects the test for serial correlation by Baltagi and Li (1991), in the sense that it implicitely assumes no random effects and, hence, is altered along the same lines when this assumption is false. Bera et al. (2001) proposed modified statistics that are insensitive to misspecifications, at least in a local sense, that is, they proposed tests for random effects (serial correlation) that remain unaltered in the presence of *local* serial correlation (random effects). The local nature of the solution seems restrictive, but extensive Monte Carlo experimentation by these authors show that in small samples both tests have good performances even in non-local contexts.

A relevant methodological contribution of the LSE school of dynamic econometrics in the time series context (Hendry, 1995), is to stress the fact that serial correlation should be more appropriately seen as a particular form of dynamic misspecification. The classic article by Hendry and Mizon (1978) emphasizes the point that first order serial correlation is one possible restriction of a more general dynamic specification, hence favoring these general structures as a starting point for specification searches. This is the underlying idea behind the 'general-to-specific' approach advocated by Hendry (1995).

Quite naturally, the same underlying principle applies to the search of dynamic specifications in panel data models. Nevertheless, a major difference is that the extension from a static to a dynamic model is not as straightforward as in the time series context, due to the well known fact that lagged dependent variables are correlated with the unobserved, individual specific error component. This has launched a copious literature on alternative methods to cincurvent this problem. A popular strategy is to use instrumental variable methods, like those based on the results of Anderson and Hsiao (1982) and Arellano and Bond (1991), the latter using a GMM structure to efficiently exploit the valid instruments available due to the dynamic structure of the model. A practical drawback is the poor perfomance of these methods when the time dimension is low, see, for example, Judson and Owen (1999), which has triggered abundant research to improve upon these basic methods.

Consequently, in light of the high implementation costs that dynamic panels impose, in practice it is relevant to pose the basic question of whether static models should be abandoned in favor of dynamic ones. In this paper we adopt a very simple approach, and propose tests for dynamic and random individual effects after simple pooled OLS estimation, with the ultimate goal of helping applied researchers confirm whether persistences can simply be handled with a static random effects specification, or whether a dynamic structure must be adopted. This paper can be seen as a generalization of Bera et al. (2001) to the more general case where dynamics are handled through lagged dependent variables instead of first order serial correlation, the latter arising as a particular 'common factor', non-linear restriction in the dynamic specification.

Some results are the following. As in the case of Bera et al. (2001), random effects confound a simple test for dynamic effects, and the same occurs when the roles of the effects are reversed. In particular, this implies that the classic test for random effects by Breusch-Pagan is affected by dynamic missspecifications in the model, in the sense that the latter make the BP test reject its null in spite of being false. We use the analytical framework by Bera and Yoon (1993) to derive tests that are insensitive to local misspecification, and hence help identifying which source of persistence is active. An extensive Monte Carlo experiment shows that the proposed tests based on simple pooled OLS etimation, have a good performance in small samples, and outperform standard GMM based tests in terms of power.

The paper is organized as follows. Section 2 describes the general analytical framework used to derive the tests. Section 3 obtains several test statistics for dynamic and individual random effects. Section 4 presents the results of a Monte Carlo study to evaluate the small sample performance of the proposed methods, and Section 5 presents concluding remarks.

2 MLE testing under local misspecification

In this section, we present the theoretical framework to derive test statistics. It is based on Bera and Yoon (1993), and we refer to this paper for further details.

We consider a general econometric model represented by the log-likelihood function $L(w;\pi,\psi,\phi)$, where w represents an M-dimensional vector of random variables (the data) whose distribution function is known, π denotes the vector that includes the subset of parameters to be estimated by maximum likelihood, ψ represents the vector of parameters to be included in the null hypothesis, and ϕ is the vector of nuisance parameters. Their respective orders are $[m \times 1]$, $[r \times 1]$, $[s \times 1]$; and we also assume that $(\pi,\psi,\phi) \in \Theta$, a compact subset of $\Re^{(m+r+s)}$. In the rest of this section, we impose on $L(w;\pi,\psi,\phi)$ the standard regularity conditions specified in Bera and Yoon (1993) and the references cited therein.

In the classic framework, we are interested in verifying a hypothesis such as $H_0 : \psi = \psi_*$ and we assume the absence of nuisance parameters. This means that we are supposing a fixed value for ϕ such that $\phi = \phi_*$ is true. In this context, if we define $\theta = (\pi,\psi,\phi)$ as the vector including all the parameters of the model, $d_\psi(\theta) = \partial L(w;\theta)/\partial\psi$ as the $[r \times 1]$ vector of first derivatives of $L(w;\theta)$ with respect to ψ, and $J(\theta_0) = -E_{\theta_0}[M^{-1}\partial^2 L(w;\theta)/\partial\theta\partial\theta']$ as the Fisher information matrix evaluated at θ_0 and divided by M, the LM statistic can be written as

$$LM_\psi = \frac{1}{M}\, d_\psi(\tilde{\theta})' J^{-1}_{\psi,\pi}(\tilde{\theta}) d_\psi(\tilde{\theta}), \tag{1}$$

where $\tilde{\theta} = (\tilde{\pi},\psi_*,\phi_*)$ denotes the vector of parameters estimated by maximum likelihood under the restrictions of the null model, and assuming the absence of nuisance parameters (i.e. $\phi = \phi_*$), $J_{\psi,\pi}(\theta) = J_\psi(\theta) - J_{\psi\pi}(\theta)J^{-1}_\pi(\theta)J_{\pi\psi}(\theta)$, $J_\psi(\theta) = -E[M^{-1}\partial^2 L(w;\theta)/\partial\psi\partial\psi']$, $J_{\psi\pi}(\theta) = -E[M^{-1}\partial^2 L(w;\theta)/\partial\psi\partial\pi']$, and $J_{\pi\psi}(\theta) = -E[M^{-1}\partial^2 L(w;\theta)/\partial\pi\partial\psi']$. Under the null hypothesis and in the absence of nuisance parameters, a well known result is that LM_ψ converges in distribution to a *central* chi-square with r degrees of freedom. On the other hand, if a nuisance parameter contaminates the model, such as $\phi = \phi_* + \delta/\sqrt{M}$ (with $\delta \neq 0$), the statistic (1) does not converge to a *central* chi-square variable but to a *non-central* one, hence leading to spurious rejections due to the misspecified nuisance parameter and not to the falseness of the null hypothesis (Saikkonen, 1989).

Bera and Yoon (1993) proposed a simple statistic that is robust to the local misspecification of nuisance parameters. Specifically, the modified statistic has the form

$$
\begin{aligned}
LM^*_\psi &= \frac{1}{M}[d_\psi(\tilde{\theta}) - J_{\psi\phi,\pi}(\tilde{\theta})J^{-1}_{\phi,\pi}(\tilde{\theta})d_\phi(\tilde{\theta})]'[J_{\psi,\pi}(\tilde{\theta}) - J_{\psi\phi,\pi}(\tilde{\theta})J^{-1}_{\phi,\pi}(\tilde{\theta})J_{\phi\psi,\pi}(\tilde{\theta})]^{-1} \\
&\quad [d_\psi(\tilde{\theta}) - J_{\psi\phi,\pi}(\tilde{\theta})J^{-1}_{\phi,\pi}(\tilde{\theta})d_\phi(\tilde{\theta})], \qquad (2)
\end{aligned}
$$

where $J_{\psi\phi,\pi}(\theta) = J_{\psi\phi}(\theta) - J_{\psi\pi}(\theta)J^{-1}_{\pi}(\theta)J_{\pi\phi}(\theta)$. As shown by Bera and Yoon (1993), under the null hypothesis and when the nuisance parameter is locally misspecified ($\phi = \phi_* + \delta/\sqrt{M}$, $\delta \neq 0$), when the sample size grows large, the test statistic (2) converges in distribution to a *central* chi-square with r degrees of freedom, implying that the modified statistic is insensitive to the misspecification of the nuisance parameter.

It is important to remark that both, the original and the modified LM tests, can be computed based on the null model, hence the modified version is not computationally more involved than than the simple one.

3 Tests for dynamic panels

We will consider a linear dynamic panel data model that includes the lagged endogenous variable as a regressor, and the random individual effect as a component of the error term. The model can be characterized by the following equations:

$$
\begin{aligned}
y_{it} &= \gamma y_{i,t-1} + x_{it}\beta + u_{it}, \qquad i = 1, 2, ..., N, \qquad t = 1, 2, ..., T, \\
u_{it} &= \mu_i + \varepsilon_{it}. \qquad (3)
\end{aligned}
$$

In this case, y_{it} is the endogenous variable, $y_{i,t-1}$ is the (one period) lagged endogenous variable, μ_i is the random effect component, ε_{it} is the independent and identically distributed observation specific error term, and x_{it} is the $[1 \times k]$ vector of independent variables. β is a $[k \times 1]$ vector of coefficients and γ is a scalar parameter less than one in absolute value.

In order to construct tests for this model, we will make the following assumptions. The model (3) generates the variables y_{it}, where y_{i0} is known and exogenous for all i. The variables x_{it} are stochastic, independent of the variables for other individuals, and they are also independent of μ_i and ε_{it}. The matrix $\sum_{i,t} x'_{it}x_{it}$ is invertible with probability approaching one. Finally, to construct the log-likelihood function, it is assumed that $\mu_i \overset{iid}{\sim} N(0,\sigma^2_\mu)$ and $\varepsilon_{it} \overset{iid}{\sim} N(0,\sigma^2_\varepsilon)$. In this context, the null of no random effects corresponds to $\sigma^2_\mu = 0$ and the null of no dynamic effects to $\gamma = 0$.

Defining $e_T = (1,1,...,1)'$ as the T-dimension column vector of ones, I_N as the N-dimension identity matrix, $\omega = \sigma^2_\mu/\sigma^2_\varepsilon$, $H_{NT} = (I_N \otimes e_T e'_T)$, $Y = (y_{11}, y_{12}, .., y_{it}, .., y_{N(T-1)}, y_{NT})'$, the log-likelihood function for this problem has been derived by Bhargava and Sargan (1983, pp. 1641), and is given by:

$$L(Y;\theta) = -\frac{NT}{2}\ln(\sigma^2_\varepsilon) - \frac{N}{2}\ln(1+T\omega) - \frac{u'u}{2\sigma^2_\varepsilon} + \left(\frac{\omega}{1+T\omega}\right)\left(\frac{u'(H_{NT})u}{2\sigma^2_\varepsilon}\right), \quad (4)$$

where $\theta = (\beta', \sigma^2_\varepsilon, \gamma, \omega)'$ and $u = (u_{11}, u_{12}, .., u_{it}, .., u_{N(T-1)}, u_{NT})'$.

We set $\theta_0 = (\beta, \sigma^2_\varepsilon, 0, 0)$, and using the notation of section 2, we define $d_\gamma(\theta_0) = \partial L(Y;\theta)/\partial\gamma$ and $d_\omega(\theta_0) = \partial L(Y;\theta)/\partial\omega$ as the first partial derivatives of $L(Y;\theta)$ with respect to γ (and ω) evaluated at θ_0. It is easy to express them as

$$\begin{aligned} d_\gamma(\theta_0) &= \frac{Y'_{-1}u}{\sigma^2_\varepsilon}, \\ d_\omega(\theta_0) &= -\frac{(NT)}{2} + \frac{u'(H_{NT})u}{2\sigma^2_\varepsilon}. \end{aligned} \quad (5)$$

In addition, using the subindex -1 to represent the application of the one period lag operator over t, and denoting $X = (x'_{11}; x'_{12}; ..; x'_{it}; ..; x'_{N(T-1)}; x'_{NT})'$, and $J(\theta_0) = -(NT)^{-1}E_{\theta_0}\left[\partial^2 L(Y;\theta)/\partial\theta\partial\theta'\right]$ as the expectation of second partial derivatives of $L(Y;\theta)$ with respect to θ evaluated at θ_0, it is straightforward to show that

$$J(\theta_0) = \begin{pmatrix} \frac{X'X}{(NT)\sigma^2_\varepsilon} & 0_{[k\times1]} & \frac{(X'X_{-1})\beta}{(NT)\sigma^2_\varepsilon} & 0_{[k\times1]} \\ 0_{[1\times k]} & \frac{1}{2(\sigma^2_\varepsilon)^2} & 0_{[1\times1]} & \frac{1}{2\sigma^2_\varepsilon} \\ \left[\frac{(X'X_{-1})\beta}{(NT)\sigma^2_\varepsilon}\right]' & 0_{[1\times1]} & \frac{(X_{-1}\beta)'(X_{-1}\beta)}{(NT)\sigma^2_\varepsilon} + 1 & \frac{T-1}{T} \\ 0_{[1\times k]} & \frac{1}{2\sigma^2_\varepsilon} & \frac{T-1}{T} & \frac{T}{2} \end{pmatrix}. \quad (6)$$

For later interpretation of the tests, it is useful to observe that to construct (6), we have used that $E_{\theta_0}[Y_{-1}] = X_{-1}\beta$ and $E_{\theta_0}[Y_{-1}'Y_{-1}] = (X_{-1}\beta)'(X_{-1}\beta) + (NT)\sigma_\varepsilon^2$.

Finally, if we employ the definitions of $J_{\psi,\pi}(\theta)$, $J_{\phi,\pi}(\theta)$ and $J_{\psi\phi,\pi}(\theta)$ detailed in section 2, and if we replace ψ, ϕ and π by γ, ω and $(\beta, \sigma_\varepsilon^2)$, then, for this particular case we can obtain the following terms $J_{\gamma,(\beta,\sigma_\varepsilon^2)}(\theta_0)$, $J_{\omega,(\beta,\sigma_\varepsilon^2)}(\theta_0)$, $J_{(\gamma,\omega),(\beta,\sigma_\varepsilon^2)}(\theta_0)$ and $J_{\gamma\omega,(\beta,\sigma_\varepsilon^2)}(\theta_0)$:

$$
\begin{aligned}
J_{\gamma,(\beta,\sigma_\varepsilon^2)}(\theta_0) &= \frac{(X_{-1}\beta)'Q(X_{-1}\beta)}{(NT)\sigma_\varepsilon^2} + 1, \\
J_{\omega,(\beta,\sigma_\varepsilon^2)}(\theta_0) &= \frac{T-1}{2}, \\
J_{(\gamma,\omega),(\beta,\sigma_\varepsilon^2)}(\theta_0) &= \begin{pmatrix} \frac{(X_{-1}\beta)'Q(X_{-1}\beta)}{(NT)\sigma_\varepsilon^2} + 1 & \frac{T-1}{T} \\ \frac{T-1}{T} & \frac{T-1}{2} \end{pmatrix}, \\
J_{\gamma\omega,(\beta,\sigma_\varepsilon^2)}(\theta_0) &= \frac{T-1}{T},
\end{aligned} \tag{7}
$$

where $Q = (I_{NT} - X(X'X)^{-1}X')$ is the orthogonal projection matrix that projects any vector onto the orthogonal complement of the linear space spanned by the columns of X.

Based on these definitions, in the rest of this section we use the LM_ψ and LM_ψ^* statistics (detailed in section 2) to construct simple tests for model (3). The parameters to be estimated by restricted maximum likelihood will be β and σ_ε^2 and the restrictions will be $\gamma = 0$ and $\omega = 0$. Then, if we use $\tilde{\theta} = (\tilde{\beta}, \tilde{\sigma}_\varepsilon^2, 0, 0)$ to denote the restricted maximum likelihood estimator (i.e. the argument that maximizes $L(Y;\theta)$ subject to $\gamma = 0$ and $\omega = 0$), it is clear that $\tilde{\beta}$ is the pooled OLS estimator of regressing of y_{it} on x_{it}, while $\tilde{\sigma}_\varepsilon^2 = (NT)^{-1}\sum_{i,t}\tilde{u}_{it}^2$ with $\tilde{u}_{it} = y_{it} - x_{it}\tilde{\beta}$. Or equivalently, if we define $\tilde{u} = (\tilde{u}_{11}, \tilde{u}_{12}, .., \tilde{u}_{it}, .., \tilde{u}_{N(T-1)}, \tilde{u}_{NT})'$, $\tilde{u} = QY$ and $\tilde{\sigma}_\varepsilon^2 = (NT)^{-1}\tilde{u}'\tilde{u}$.

With these results, we can apply (1) and (2) to derive a test to detect dynamic effects (random effects) in the presence of local random effects (dynamic effects). Naturally, it is also possible to construct tests to identify the presence of dynamic effects in the absence of random effects, and, jointly the presence of both dynamic and random effects.

Since in the rest of the section the parameters to be estimated by maximum likelihood will be β and σ_ε^2, we can fix $\pi = (\beta, \sigma_\varepsilon^2)$. Furthermore, we will always have that $\psi_* = \phi_* = 0$, thus the computation of the tests will be very simple. Specifically, to compute all the statistics, it will be sufficient to estimate the restricted model by pooled OLS, so it will not be necessary to rely on more complex GMM based methods.

Test for dynamic effects robust to the presence of random effects

Employing the notation of section 2 to this particular case, we have that the nuisance parameter is ω, and we can set $\pi = (\beta, \sigma_\varepsilon^2)'$, $\psi = \gamma$, $\psi_* = 0$, $\phi = \omega$, and $\phi_* = 0$. Since we are assuming the existence of a nuisance parameter, we have that $\phi = \phi_* + \delta/\sqrt[2]{NT}$ (with $\delta \neq 0$), or equivalently, $\omega = \delta/\sqrt[2]{NT}$.

Using the log-likelihood function and the results described before, we can obtain a particular version of the statistic (2):

$$LM_\gamma^* \;=\; (NT)\frac{[B + (A/T)]^2}{C - \frac{2(T-1)}{T^2}}, \tag{8}$$

where $A = (1 - \frac{\tilde{u}'(H_{NT})\tilde{u}}{\tilde{u}'\tilde{u}})$, $B = \frac{Y'_{-1}\tilde{u}}{\tilde{u}'\tilde{u}}$, and $C = [\frac{(X_{-1}\tilde{\beta})'Q(X_{-1}\tilde{\beta})}{(\tilde{u}'\tilde{u})} + 1]$. By the arguments described at the end of section 2, the asymptotic distribution of LM_γ^*, under the null of absence of dynamic effects and under the presence of local random effects, is *central* chi-square with one degree of freedom.

Test for random effects robust to the presence of dynamic effects

The nuisance parameter in this case is γ, so using the notation of section 2, we have that $\pi = (\beta, \sigma_\varepsilon^2)'$, $\psi = \omega$, $\psi_* = 0$, $\phi = \gamma$, and $\phi_* = 0$. Since we are assuming the existence of a nuisance parameter, we have that $\phi = \phi_* + \delta/\sqrt[2]{NT}$ (with $\delta \neq 0$), or equivalently, $\gamma = \delta/\sqrt[2]{NT}$. The test statistic is

$$LM_\omega^* \;=\; (NT)\frac{\left[\frac{A}{2} + \frac{(T-1)B}{TC}\right]^2}{\frac{T-1}{2} - \frac{(T-1)^2}{T^2 C}}, \tag{9}$$

and its asymptotic distribution under the null of absence of random effects and under the local presence of dynamic effects, is *central* chi-square with one degree of freedom.

Test for dynamic effects in the absence of random effects

In this case, we fix the parameters of the model at $\pi = (\beta, \sigma_\varepsilon^2)'$, $\psi = \gamma$, $\psi_* = 0$, $\phi = \omega$, and $\phi_* = 0$. Since we are assuming the absence of nuisance parameters, we have that $\phi = \phi_*$ (i.e. $\omega = 0$). As result of the arguments discussed above, we have that

$$LM_\gamma = (NT)\frac{B^2}{C}, \tag{10}$$

under the null hypothesis of $\gamma = 0$ and if $\omega = 0$, the asymptotic distribution of LM_γ is *central* chi-square with one degree of freedom.

Test for random effects in the absence of dynamic effects

For this case, the parameters are set as follows: $\pi = (\beta, \sigma_\varepsilon^2)'$, $\psi = \omega$, $\psi_* = 0$, $\phi = \gamma$, and $\phi_* = 0$. In this case, there are not nuisance parameters, and naturally the statistic reduces to the classic Breusch-Pagan test for random effects. Specifically,

$$LM_\omega = (NT)\frac{A^2}{2(T-1)}, \tag{11}$$

and when $\gamma = 0$, the asymptotic distribution of LM_ω, under the null hypothesis of $\omega = 0$, is central chi-square with one degree of freedom.

Test for dynamic and random individual effects

Finally, we re-define the parameters of the model as $\pi = (\beta, \sigma_\varepsilon^2)'$, $\psi = (\gamma, \omega)'$, and $\psi_* = (0, 0)'$. It is important to remark that there are no possible nuisance parameters in this situation because all the parameters are involved in the null hypothesis or are estimated by maximum likelihood. Then, we have that the relevant test statistics is

$$LM_{\gamma,\omega} = (NT)\frac{[B + (A/T)]^2}{C - \frac{2(T-1)}{T^2}} + (NT)\frac{A^2}{2(T-1)}, \tag{12}$$

and its asymptotic distribution under the null $\gamma = \omega = 0$ is central chi-square with two degrees of freedom.

4 Monte Carlo Experiment

With the aim of evaluating the small sample behavior of the tests described in the precedent section, we report the results of a Monte Carlo experiment. We use an experimental design similiar to the one used in previous work on the subject, in particular, Bera et al. (2001) and Baltagi, Chang and Li (1992), we refer to these papers for further details.

The specific purpose of these simulations is to analyze the finite sample properties of the previous tests for different values of ω (random effect) and γ (dynamic effect). In the experiments the model has been set as special case of (3), and the variables ε_{it} and μ_i have been generated following a Gaussian distribution. The data generation process is:

$$\begin{aligned} y_{it} &= \gamma y_{it-1} + \alpha + x_{it}\beta + u_{it}, \qquad i = 1, 2, ..., N, \quad t = 1, 2, ..., T, \\ u_{it} &= \mu_i + \varepsilon_{it}, \end{aligned} \tag{13}$$

where $\mu_i \overset{iid}{\sim} N(0, 20\omega)$ and $\varepsilon_{it} \overset{iid}{\sim} N(0, 20)$. The values and distributions for the fixed parameters are $\alpha = 5$ and $\beta = 0.5$, while the independent variable x_{it} was generated *a la* Nerlove (1971), as $x_{it} = 0.1t + 0.5x_{it-1} + w_{it}$, where w_{it} is uniformly distributed on the interval $[-0.5, 0.5]$. The experiment was performed for different values of ω and γ. The number of replications was 2000 and the nominal size of these tests was set in 0.05.

In each replication, the unknown coefficients are estimated by pooled OLS and the proposed statistics are computed. For comparisson, we also compute the GMM based test statistic LM_γ^G of $H_0 : \gamma = 0$ after estimating the dynamic model using the the Arellano and Bond (1991) estimator. We use a standard GMM based LM test statistic, see Wooldridge (2002, pp. 426-427).

Tables 1 and 2 report the results of simulations for different values of γ and ω. We report results for sample sizes $(N, T) = (50, 10)$ and $(N, T) = (100, 15)$. Results for other sample sizes only reinforce the conclusions, and to save space, are omited and made available upon request. Specifically, the numbers reported in each column are the proportions of rejections of the null hypothesis corresponding to each test.

Regarding size, the tests for dynamic effects (LM_γ and LM_γ^* are a bit undersized for $N = 50$ and $T = 10$, as compared to tests for random effects (LM_ω and LM_ω^*, the joint test is also undersized and, finally, the GMM based test has empirical size larger than the nominal (0.072). As expected, size performance improves when a larger sample size is considered, as can be seen in Table 2.

In terms of power, consider first the case of no random effects ($\omega = 0$) when the relative importance of the lagged dependent variable is increased gradually, as measured by γ. A first relevant result is the very poor performance of the GMM based test LM_γ^G as compared to the LM based test for lagged dependent variables in the absence of random effects, LM_γ. In both cases power increases with ω though in the case of LM_γ^G not monotonically. What is relevant is that LM_γ has substantially larger power. As advanced in the Introduction, the poor performance of the GMM based test is severely affected when the sample size is low, and hence the LM based test is a much more powerful alternative.

Is is also interesting to observe that the robust version LM_γ^* has a very good performance. It is relevant to remark that in the absence of random effects, LM_γ^* is by construction sub-optimal and hence is expected to perfom worse. Nevertheles, the ‘robustification cost’, that is, the power loss compared to the ‘optimal’ LM_γ test, seems to be small.

As in Bera et al. (2001) the standard Breusch-Pagan test for random effects LM_ω is affected by the presence of an unconsidered source of persistence, in this case, the lagged dependent variable. When $\omega = 0$ (no random effects), the empirical rejection frequencies of LM_ω should be close to the chosen nominal size (0.05). This is certainly not the case: when γ increases, rejections increase rapidly, hence leading to spurious rejections of the null of no random effects due to the relevance of the lagged dependent variable. This is an important result, since it implies that dynamic misspecifications bias the standard Breusch-Pagan test towards rejecting the null of no random effects, not due to its falsness but to the effect of ignored dynamic terms. This result can be seen as a generalization of that of Bera et al. (2001) who restricted the analysis to the case of the harmful effects of the ignored first-order serial correlation, the latter being a particular case of a more general dynamic misspecification.

The robust version LM_ω^* preserves size well in the presence of small values of γ, in both sample sizes considered. Its rejection frequencies are substantially below those of its non-robust counterpart. For example, when $\gamma = 0.2$, LM_ω rejects the null 54% of the cases, compared to only 16.1% for the robust version.

Similar remarks hold for the symmetric case of random effects with no lagged dependent variables. LM_γ has unwanted power when the strength of the random effect is increased, hence leading to spurious rejections of the null of no dynamic effects. Surprisinigly, the robust version LM_γ^* preserves size quite well, even in non-local context, a result similar to that obtained by Bera et al. (2001) for their test of serial correlation. By construction

LM_{γ}^{G} is robust to the presence of random effects, and hence its size is not affected.

5 Final remarks

In this paper we suggest simple tests to detect persistences in the form of pure dynamic terms and random individual effects. Both tests are based on pooled OLS estimation of the joint null model. Since statistics are derived in the Bera and Yoon (1993) framework, they are insensitive to local misspecifications, and hence they are informative about the source of misspecification when they reject their nulls.

These statistcs should be helpful in applied work, when researchers are doubtful about the dynamic structure of a model and hence the effects of adopting a dynamic specification, possibly involving GMM estimation and inference strategies, may be costly. Since the proposed tests are based on simple OLS estimation, they may serve the purpose of cheking whether a simple random effects structure suffice to handle persistences, or, instead, whether the costs of relying on more complex estimation methods should be accepted in order to allow for richer dynamic models.

Quite interestingly, our Monte Carlo results show that GMM based tests have very low power to detect dynamic effects, so the proposed new statistics, which imply a considerable power gain, are more informative when they tend to accept the null of no dynamic effects.

Finally, this paper stresses the fact that the methodological concerns of Hendry and Mizon (1978) in their classic article, where serial correlation is seen as a particular form of a more general dynamic model, apply naturally to the case of panels. From this perspective, this paper generalizes the results of Bera et al (2001) to a more flexible dynamic framework where persistent behavior is allowed to arise from a dynamic model instead from a static one with serial correlation.

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Appendix (not to be published)

A.1 First and second partial derivatives of $L(Y;\theta)$

The first partial derivatives of the function $L(Y;\theta)$ with respect to θ are:

$$
\begin{aligned}
\frac{\partial L(\theta)}{\partial \beta} &= \frac{X'u}{\sigma_\varepsilon^2} - \frac{\omega}{\sigma_\varepsilon^2(1+T\omega)}(X'H_{NT}u) \\
\frac{\partial L(\theta)}{\partial \sigma_\varepsilon^2} &= -\frac{NT}{2\sigma_\varepsilon^2} + \frac{u'u}{2(\sigma_\varepsilon^2)^2} - \frac{\omega}{2(\sigma_\varepsilon^2)^2(1+T\omega)}(u'H_{NT}u) \\
\frac{\partial L(\theta)}{\partial \gamma} &= \frac{Y_{-1}'u}{\sigma_\varepsilon^2} - \frac{\omega}{\sigma_\varepsilon^2(1+T\omega)}(Y_{-1}'H_{NT}u) \\
\frac{\partial L(\theta)}{\partial \omega} &= -\frac{NT}{2(1+T\omega)} + \frac{u'H_{NT}u}{2(\sigma_\varepsilon^2)(1+T\omega)^2}
\end{aligned}
\tag{A.1}
$$

Therefore, if we evaluate these derivatives at θ_0, it is easy to obtain the results detailed in (5). In addition, the second derivatives of the function $L(Y;\theta)$ with respect to θ are:

$$
\begin{aligned}
\frac{\partial^2 L(\theta)}{\partial^2 \beta} &= -\frac{X'X}{\sigma_\varepsilon^2} + \frac{\omega}{\sigma_\varepsilon^2(1+T\omega)}(X'H_{NT}X) \\
\frac{\partial^2 L(\theta)}{\partial \beta \partial \sigma_\varepsilon^2} &= -\frac{X'u}{(\sigma_\varepsilon^2)^2} + \frac{\omega}{(\sigma_\varepsilon^2)^2(1+T\omega)}(X'H_{NT}u) \\
\frac{\partial^2 L(\theta)}{\partial \beta \partial \gamma} &= -\frac{X'Y_{-1}}{\sigma_\varepsilon^2} + \frac{\omega}{\sigma_\varepsilon^2(1+T\omega)}(X'H_{NT}Y_{-1}) \\
\frac{\partial^2 L(\theta)}{\partial \beta \partial \omega} &= -\frac{1}{\sigma_\varepsilon^2(1+T\omega)^2}(X'H_{NT}u) \\
\frac{\partial^2 L(\theta)}{\partial^2 \sigma_\varepsilon^2} &= \frac{NT}{2(\sigma_\varepsilon^2)^2} - \frac{u'u}{(\sigma_\varepsilon^2)^3} + \frac{\omega}{(\sigma_\varepsilon^2)^3(1+T\omega)}(u'H_{NT}u) \\
\frac{\partial^2 L(\theta)}{\partial \sigma_\varepsilon^2 \partial \gamma} &= -\frac{Y_{-1}'u}{(\sigma_\varepsilon^2)^2} + \frac{\omega}{(\sigma_\varepsilon^2)^2(1+T\omega)}(Y_{-1}'H_{NT}u) \\
\frac{\partial^2 L(\theta)}{\partial \sigma_\varepsilon^2 \partial \omega} &= -\frac{u'H_{NT}u}{2(\sigma_\varepsilon^2)^2(1+T\omega)^2} \\
\frac{\partial^2 L(\theta)}{\partial^2 \gamma} &= -\frac{Y_{-1}'Y_{-1}}{\sigma_\varepsilon^2} + \frac{\omega}{\sigma_\varepsilon^2(1+T\omega)}(Y_{-1}'H_{NT}Y_{-1}) \\
\frac{\partial^2 L(\theta)}{\partial \gamma \partial \omega} &= -\frac{Y_{-1}'H_{NT}u}{\sigma_\varepsilon^2(1+T\omega)^2} \\
\frac{\partial^2 L(\theta)}{\partial^2 \omega} &= \frac{NT^2}{2(1+T\omega)^2} - \frac{T}{(\sigma_\varepsilon^2)(1+T\omega)^3}(u'H_{NT}u)
\end{aligned}
\tag{A.2}
$$

Similarly, if we evaluate $(NT)^{-1}E[\partial^2 L(Y;\theta)/\partial\theta\partial\theta']$ at θ_0, it is simple to obtain the results detailed in (6). Finally, after applying the definitions of section 2 to the matrix $J(\theta_0)$, it is straightforward to obtain the results of (7).

Table 1: Empirical rejection probabilities of different tests. N=50, T=10.

ω	γ	LM_{γ}	LM^{*}_{γ}	LM_{ω}	LM^{*}_{ω}	$LM_{\gamma,\omega}$	LM^{G}_{γ}
0,00	0,00	0,039	0,031	0,055	0,044	0,034	0,072
	0,05	0,117	0,105	0,078	0,057	0,103	0,013
	0,10	0,448	0,349	0,176	0,082	0,360	0,009
	0,15	0,814	0,665	0,333	0,117	0,722	0,036
	0,20	0,968	0,897	0,540	0,161	0,940	0,107
	0,25	0,997	0,977	0,727	0,241	0,994	0,260
	0,30	1,000	0,998	0,852	0,351	1,000	0,410
	0,35	1,000	1,000	0,943	0,465	1,000	0,564
0,05	0,00	0,033	0,033	0,052	0,049	0,037	0,062
	0,05	0,132	0,102	0,105	0,074	0,120	0,012
	0,10	0,457	0,347	0,203	0,088	0,383	0,009
	0,15	0,824	0,655	0,376	0,131	0,744	0,037
	0,20	0,962	0,890	0,567	0,178	0,941	0,103
	0,25	0,998	0,974	0,730	0,246	0,993	0,224
	0,30	1,000	0,994	0,874	0,361	1,000	0,389
	0,35	1,000	1,000	0,961	0,508	1,000	0,574
0,10	0,00	0,035	0,036	0,067	0,063	0,047	0,072
	0,05	0,179	0,100	0,173	0,100	0,174	0,016
	0,10	0,525	0,335	0,295	0,128	0,458	0,012
	0,15	0,838	0,633	0,465	0,185	0,784	0,028
	0,20	0,978	0,872	0,669	0,260	0,960	0,101
	0,25	0,997	0,975	0,823	0,332	0,996	0,229
	0,30	1,000	0,995	0,918	0,486	1,000	0,377
	0,35	1,000	1,000	0,968	0,591	1,000	0,535
0,15	0,00	0,063	0,031	0,155	0,146	0,132	0,068
	0,05	0,247	0,114	0,265	0,185	0,286	0,018
	0,10	0,615	0,320	0,441	0,234	0,582	0,008
	0,15	0,893	0,629	0,631	0,317	0,862	0,033
	0,20	0,983	0,864	0,788	0,410	0,972	0,086
	0,25	1,000	0,975	0,901	0,520	0,999	0,217
	0,30	1,000	0,996	0,959	0,618	1,000	0,381
	0,35	1,000	1,000	0,989	0,750	1,000	0,506
0,20	0,00	0,089	0,032	0,277	0,285	0,251	0,073
	0,05	0,369	0,095	0,476	0,364	0,492	0,020
	0,10	0,742	0,311	0,667	0,450	0,760	0,011
	0,15	0,941	0,621	0,809	0,525	0,933	0,033
	0,20	0,995	0,883	0,918	0,614	0,992	0,116
	0,25	1,000	0,967	0,966	0,731	1,000	0,203
	0,30	1,000	0,998	0,989	0,793	1,000	0,340
	0,35	1,000	1,000	0,998	0,903	1,000	0,460
0,25	0,00	0,190	0,026	0,514	0,522	0,507	0,078
	0,05	0,511	0,075	0,694	0,621	0,711	0,014
	0,10	0,854	0,298	0,828	0,664	0,888	0,010
	0,15	0,979	0,609	0,925	0,744	0,983	0,028
	0,20	0,998	0,871	0,972	0,816	0,999	0,090
	0,25	1,000	0,963	0,988	0,873	1,000	0,184
	0,30	1,000	0,993	0,998	0,928	1,000	0,324
	0,35	1,000	1,000	0,999	0,964	1,000	0,451
0,30	0,00	0,301	0,027	0,737	0,749	0,738	0,070
	0,05	0,691	0,080	0,876	0,822	0,892	0,016
	0,10	0,925	0,280	0,942	0,863	0,970	0,010
	0,15	0,992	0,583	0,978	0,898	0,999	0,024
	0,20	1,000	0,842	0,994	0,941	1,000	0,082
	0,25	1,000	0,959	1,000	0,959	1,000	0,170
	0,30	1,000	0,990	0,999	0,976	1,000	0,282
	0,35	1,000	1,000	1,000	0,992	1,000	0,405

Table 2: Empirical rejection probabilities of different tests. N=100, T=15.

ω	γ	LM_{γ}	LM_{γ}^{*}	LM_{ω}	LM_{ω}^{*}	$LM_{\gamma,\omega}$	LM_{γ}^{G}
0,00	0,00	0,035	0,036	0,047	0,047	0,041	0,067
	0,05	0,419	0,352	0,122	0,065	0,333	0,025
	0,10	0,942	0,906	0,310	0,096	0,909	0,262
	0,15	1,000	0,999	0,571	0,145	0,998	0,771
	0,20	1,000	1,000	0,832	0,217	1,000	0,971
	0,25	1,000	1,000	0,936	0,328	1,000	1,000
	0,30	1,000	1,000	0,988	0,502	1,000	1,000
	0,35	1,000	1,000	0,997	0,635	1,000	1,000
0,05	0,00	0,051	0,044	0,051	0,057	0,057	0,073
	0,05	0,464	0,363	0,160	0,091	0,366	0,023
	0,10	0,957	0,890	0,412	0,130	0,922	0,257
	0,15	1,000	0,998	0,678	0,216	0,999	0,727
	0,20	1,000	1,000	0,886	0,289	1,000	0,966
	0,25	1,000	1,000	0,958	0,399	1,000	0,999
	0,30	1,000	1,000	0,995	0,532	1,000	1,000
	0,35	1,000	1,000	1,000	0,736	1,000	1,000
0,10	0,00	0,057	0,034	0,156	0,166	0,134	0,061
	0,05	0,538	0,352	0,360	0,199	0,538	0,026
	0,10	0,975	0,882	0,614	0,284	0,948	0,242
	0,15	1,000	0,999	0,851	0,375	1,000	0,712
	0,20	1,000	1,000	0,958	0,503	1,000	0,956
	0,25	1,000	1,000	0,993	0,633	1,000	0,997
	0,30	1,000	1,000	0,999	0,781	1,000	1,000
	0,35	1,000	1,000	1,000	0,880	1,000	1,000
0,15	0,00	0,108	0,043	0,433	0,448	0,390	0,082
	0,05	0,695	0,324	0,719	0,549	0,798	0,028
	0,10	0,991	0,891	0,882	0,640	0,987	0,210
	0,15	1,000	0,998	0,968	0,727	1,000	0,695
	0,20	1,000	1,000	0,997	0,819	1,000	0,951
	0,25	1,000	1,000	1,000	0,893	1,000	0,995
	0,30	1,000	1,000	1,000	0,952	1,000	1,000
	0,35	1,000	1,000	1,000	0,979	1,000	1,000
0,20	0,00	0,239	0,035	0,832	0,844	0,818	0,071
	0,05	0,861	0,293	0,935	0,875	0,956	0,020
	0,10	0,999	0,867	0,984	0,915	1,000	0,208
	0,15	1,000	0,994	1,000	0,950	1,000	0,672
	0,20	1,000	1,000	0,999	0,968	1,000	0,956
	0,25	1,000	1,000	1,000	0,984	1,000	0,991
	0,30	1,000	1,000	1,000	0,996	1,000	1,000
	0,35	1,000	1,000	1,000	0,999	1,000	1,000
0,25	0,00	0,503	0,026	0,980	0,986	0,978	0,078
	0,05	0,962	0,291	0,993	0,988	0,997	0,016
	0,10	0,999	0,843	0,999	0,996	1,000	0,208
	0,15	1,000	0,996	1,000	0,994	1,000	0,664
	0,20	1,000	1,000	1,000	1,000	1,000	0,942
	0,25	1,000	1,000	1,000	1,000	1,000	0,995
	0,30	1,000	1,000	1,000	1,000	1,000	0,999
	0,35	1,000	1,000	1,000	1,000	1,000	1,000
0,30	0,00	0,762	0,032	0,999	0,999	1,000	0,083
	0,05	0,993	0,242	1,000	1,000	1,000	0,021
	0,10	1,000	0,844	1,000	1,000	1,000	0,191
	0,15	1,000	0,999	1,000	1,000	1,000	0,636
	0,20	1,000	1,000	1,000	1,000	1,000	0,918
	0,25	1,000	1,000	1,000	1,000	1,000	0,991
	0,30	1,000	1,000	1,000	1,000	1,000	0,998
	0,35	1,000	1,000	1,000	1,000	1,000	1,000