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Testing for Persistence in the Error Component Model: a One-Sided Approach

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Abstract

This paper proposes new simple testing procedures for the joint null hypothesis of absence of persistent effects in the form of random effects and first order serial correlation in the error component model. The fact that the presence of random effects is clearly of a one-sided nature, together with the fact that in many empirical applications researchers worry about positive serial correlation leaves room for a power gain that arises from restricting the parameter space under the alternative hypothesis, compared to existing procedures that allow for two-sided alternatives. A Monte Carlo experiment shows that the proposed statistics have good size and power performance in very small samples like those typically used in applied work in panel data. An empirical example illustrates the usefulness of the proposed statistics.

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1 Introduction

Among the many uses of the basic linear error components model, a particularly relevant one is to provide a flexible structure to explore persistent behavior. For example, the seminal paper by Lillard and Willis (1979) uses a simple error component model with individual random effects and first order serial correlation, to investigate how much of the persistence of poverty is related to time invariant individual factors that make certain persons more prone to be poor (random effects), or to bad shocks experienced by individuals whose effect persist over time (serial correlation).

In the case that all persistences can be captured by observed variables, the null hypothesis of 'no persistence in the unobservables' corresponds to the absence of random effects and serial correlation. Baltagi and Li (1991) proposed a simple procedure to test this hypothesis, based on the Rao score / Lagrange multiplier (LM) principle. Their statistic is designed to detect departures from the null hypothesis in any direction, in the sense that under the alternative hypothesis the parameters controlling each effect (serial correlation and random effects) are different from zero.

The presence of random effects is clearly a one-sided matter since under the null hypothesis the variance of the individual effect is zero, and under the alternative it is a positive number. If, as in the case of the persistence literature, the interest is on positive first order serial correlation, it is then relevant to ask whether the Baltagi and Li procedure can be improved upon by deriving a test that explicitly considers this one-sided nature of the alternative hypothesis.

A first goal of this paper is to derive one-sided versions of a test for the joint null of absence of random effects and positive first order serial correlation. The multiparameter character of the problem introduces a complication since, unlike the single-parameter case, there is not an obvious optimality principle from which to obtain such a test. We rely on results by King and Wu (1997) and Bera and Bilias (2001) to derive asymptotically optimal one-sided tests.

The classic article by Breusch and Pagan (1980) proposes a simple LM based test for the null of no individual random effects allowing for a two-sided alternative; Honda (1985) derived the corresponding one-sided version. These tests implicitly assume no serial correlation in the remaining error component. Bera, Sosa Escudero and Yoon (2001, BSY hereafter) showed that the presence of first order serial correlation makes these test reject the null of no random effects independently of whether it is true or not, and derived a test statistic that is insensitive to the presence of local serial correlation. A similar concern affects the test for first order serial correlation derived by Baltagi and Li (1991), which implicitly assumes no random effects, in the sense that its presence induces spurious rejections of the null of no serial correlation. A robustified version of this test is also provided by BSY (2001).

When the interest is in exploring which source of persistence is active, the testing framework by BSY (2001) is instructive, but the fact that the Breusch-Pagan/Honda and the Baltagi-Li statistics reject their nulls in the presence of random effect or serial correlation suggest that even though they were not explicitly designed for this purpose, they may serve the goal of being informative about departures away of the joint null of no persistence. Hence, it is relevant to consider this family of statistics as valid competitors of the joint tests proposed.

Consequently, a second goal of this paper is to compare the new and existing procedures through a detailed Monte Carlo experiment. The results suggest that the use of one-sided tests result in non-trivial power gains in small samples similar to those commonly used in applied work. Finally, as it is the case of all the previously available procedures discussed above, the new test statistics are computationally very simple, requiring OLS residuals only.

The paper is organized as follows. The next section discusses available procedures to test for persistent effects in the form of tests of random effects and serial correlation. Section 3 presents the theoretical framework used to derive optimal tests for the one-sided multiparameter hypothesis of no random effects nor serial correlation and derives the proposed test statistics. Section 4 illustrates their usefulness with a simple empirical example. The small sample behavior of the proposed procedures is explored in Section 5 through an extensive Monte Carlo experiment. Section 6 concludes.

2 Persistent effects in the error component model

Consider the following one-way error component model which combines random individual effects and first order serial correlation in the disturbance term

$$\begin{aligned} y_{it} &= x'_{it}\beta + u_{it}, \quad i = 1, 2, \dots, N, \ \ t = 1, 2, \dots, T, \\ u_{it} &= \mu_i + \nu_{it}, \\ \nu_{it} &= \rho\nu_{i,t-1} + \epsilon_{it}, \ \ |\rho| < 1, \end{aligned}$$

where β is a $(k \times 1)$ vector of parameters including an intercept, $\mu_i \sim \text{IIDN}(0, \sigma_\mu^2)$ is a random individual component, and $\epsilon_{it} \sim \text{IIDN}(0, \sigma_\epsilon^2)$. μ_i and ν_{it} are assumed to be independent of each other with $\nu_{i,0} \sim N(0, \sigma_\epsilon^2/(1-\rho^2))$. N and T denote the number of individual units and the number of time periods, respectively.

This model possesses three potential sources of persistent behavior. The first one is the persistence in the explanatory variables, the second one is the presence of μ_i, a time-invariant unobserved individual factor that introduces a source of 'permanent' persistent, and the third one is associated to $\rho > 0$, which induces a 'transitory' persistence due to the stationary character of ν_{it}. In their seminal article, Lillard and Willis (1978) used this structure to study the sources of income persistence. Freije and Portela Souza (2002) or Sosa Escudero et al. (2006) are recent applications of models of this sort.

In this context it is relevant to check whether all persistences can be appropriately captured by observable variables, which corresponds to the null hypothesis of no random effect and serial correlation. A test for this null may serve several purposes. First, under the joint null and if the model is correctly specified, the unknown parameters and their variances can be safely estimated by simple OLS based methods. Second, and in a more general context, the presence of either random effects or serial correlation bias standard OLS based estimates of variances, invalidating inferential methods based on them. In a recent paper Bertrand, Duflo, and Mullainathan (2004) clearly document that panel based difference-in-difference estimates of treatment effects are severely affected by the presence of positive serial correlation, spuriously favoring rejecting the 'no treatment effect' null, hence highlighting the empirical importance of checking for correlated residuals. Third, under random effects or serial correlation, OLS estimates are still unbiased so a possible strategy is to consider alternative consistent estimators for the variances. There is not a trivial strategy to 'robustify' variance estimates under serial correlation and/or random effects, to the point, Bertrand et al. (2004) explore several alternatives, favoring block bootstrap methods when the number of individual units is large. Consequently, powerful tests for the joint null are needed to justify the costs of moving away from standard procedures.

Finally, rejections of the joint null may point towards considering more efficient estimation methods that explicitly contemplate random effects and/or serial correlation. The latter seems to be of a more demanding nature since the presence of serially correlated errors may require more sophisticated dynamic structures, in the sense of the classic paper by Hendry and Mizon (1979) for the standard time series regression context, where serially correlated errors are suggested to arise as a consequence of dynamic misspecifications, which only under very specific conditions, like the presence of common factors, can be fully captured by simple autoregressive structures instead of general dynamic specifications. Estimation and inference in dynamic models for panel data are a complicated matter of active current research and, again, powerful tests that suggest abandoning the null of no persistence may help evaluating this decision.

There are several procedures available to explore persistence in unobservables in the form of random individual effects and serial correlation. Breusch and Pagan's (1980) classic article derives a Lagrange multiplier test for the null $H_0 : \sigma_\mu^2 = 0$ (no random effects) against $H_A : \sigma_\mu^2 \neq 0$. Honda (1985) notes the one-sided nature of the relevant alternative, and proposes a simple test for $H_A : \sigma^2 > 0$, which results in a gain in power by focusing on this more appropriate alternative hypothesis.

These tests are derived in the context of no serial correlation ($\rho = 0$). BSY (2001) found that the presence of positive serial correlation induces spurious rejections of the null of no random effects in the previous testing procedures. The underlying intuition is that the Breusch-Pagan/Honda statistics check for correlations in the residuals of estimating the linear panel model by OLS methods. In the absence of serial correlation in the idiosyncratic term (ν_{it}) the only source of residual correlation is relegated to the presence of μ_i, and the test derives its power by checking this correlation. Obviously, the presence of positive serial correlation introduces an extra source of persistence that confounds the Breusch-Pagan/Honda tests.

Nevertheless, and for the purposes of this paper, it is relevant to stress the fact that the previous concern applies when the interest is in distinguishing which one, if any, of the sources of persistence is present. But when the interest is in checking the null of no persistence, the Breusch-Pagan/Honda statistics may serve the goal of being informative about the validity of the joint null since they have power in all directions away from the joint null (random effects, serial correlation or both), even though, very likely, in a sub optimal way since they were explicitly designed to capture deviations away from the no-random effects null solely.

In the same paper, BSY (2001) proposed modified versions of the Breusch / Pagan and the Honda statistics, that are insensitive to the presence of *local* serial correlation, hence the tests have power only in the direction of the presence of random effects. Of course, when serial correlation can be safely assumed to be inexistent, there is a power cost associated to this robustification, since in such case the Breusch-Pagan/Honda procedures are optimal. BSY (2001) conducted a Monte Carlo experiment that shows that the modified tests work well even in non local contexts, and that the power loss discussed above is relatively small.

Baltagi and Li (1991) proposed a test for the null of no first order serial correlation, assuming no random effects. As expected, the same concern highlighted by BSY (2001) affects this procedure, in the sense that the presence of the random effect adds an extra source of persistence that confounds the check for autocorrelation. BSY (2001) also proposed a robustified version of the Baltagi and Li test, with good performances in their Monte Carlo experiment.

All the previous procedures are designed to check the presence of random effects or serial correlation separately, but when the interest is in the joint null of no persistence in the unosbervables, it is natural to consider *joint* tests that may exploit departures from the null more efficiently. To this purpose, Baltagi and Li (1991) derive an LM test for the joint null of no random effect and serial correlation ($H_0 : \sigma_\mu^2 = 0, \rho = 0$) against the general two-sided alternative $H_0 : \sigma_\mu^2 \neq 0, \rho \neq 0$. As advanced in the Introduction, the presence of random effects is clearly of a one-sided matter, and if the interest lies in the possible presence of persistent effects, applied researchers may want to focus on the relevant alternative of *positive* serial correlation. This appreciation opens the door to consider one-sided versions for the joint null that result in larger power. This is the task of the next section.

3 One-sided tests for persistence

This section describes the theoretical framework used to derive one-sided optimal tests for the null hypothesis of no random effects and positive serial correlation in the error component model. It is based on Bera and Bilias (2001) to which we refer for further details.

Assume we are interested in a parametric statistical model for a sample of n observations that can be represented by its log-likelihood function $L(\theta)$, where θ is a p vector of unknown parameters. Let $s(\theta)$ and $I(\theta)$ be, respectively, the score vector and the information matrix, defined as $s(\theta) \equiv \partial L(\theta)/\partial(\theta)$, and $I(\theta) \equiv E\left[s(\theta)s(\theta)'\right]$. We will be interested in testing $H_o : \theta = \theta_0$ against the one-sided alternative H_A :

$\theta > \theta_0$.

The case $p = 1$ corresponds to the *single parameter* case, for which there is a well established theory from where to derive optimal tests. For example, the well known Rao score / Lagrange multiplier principle suggests that a test based on the statistic

$$LM = s(\theta_0)^2 / I(\theta_0)$$

is locally most powerful, and has asymptotic central chi-squared distribution with one degree of freedom under the null hypothesis. Alternatively, Rao and Poti (1946) proposed to use

$$RP = \frac{s(\theta_0)}{\sqrt{I(\theta_0)}}$$

which has asymptotic standard normal distribution under the null, and tests based on it are, naturally, locally most powerful for the one sided alternative. It is interesting to remark that this form of the test can be easily derived directly from the Neyman-Pearson Lemma for local alternatives. See Gourieroux and Monfort (1995, pp. 32-33).

The generalization of the score test for $p > 1$, the *multiparameter* case, is given by

$$LM = s(\theta_0)' I(\theta_0)^{-1} s(\theta_0)$$

which under the null hypotheses has asymptotic chi-squared distribution with p degrees of freedom under the null.

Unfortunately the optimality property of the single-parameter case does not translate directly to the multiparameter case. The problem lies in that optimality for the single parameter case follows from maximizing power in the only direction available under the alternative hypothesis, that is, the direction given by $\theta > \theta_0$. In the multiparameter case there will be a power *surface* defined over the possible values θ can take, and even when one-sided alternatives are considered, there is no obvious direction that should be used to maximize power. There have been many attempts at defining an implementable principle that maximizes power over relevant directions of this power surface. Sen Gupta and Vermeire (1986) and Rao and Mukerjee (1994) are modern references of a literature that dates back to Neyman and Pearson's (1938) work on the issue.

More recently King and Wu (1997) proposed a testing framework for one-sided hypothesis in the multiparameter case. Let i be a p-vector of ones. For the case when $\theta_0 = 0$, so $H_A : \theta > 0$, they propose the following test statistic

$$KW = \frac{i' s(\theta_0)}{\sqrt{i' I(\theta_0) i}},$$

which has an asymptotic standard normal distribution under the null. Tests based on this statistic are shown to be locally *mean* most powerful against $H_A : \theta > 0$.

The King-Wu test is based on a simple unweighted linear combination of the components of the score vector. Bera and Bilias (2001) suggest to weigh the individual scores by their respective precision measures. Denote with $\sqrt{I(\theta_0)^{-1}}$ the square root matrix of $I(\theta_0)^{-1}$, that is, $\sqrt{I(\theta_0)^{-1}}$ is such that $\sqrt{I(\theta_0)^{-1}}' \sqrt{I(\theta_0)^{-1}} = I(\theta_0)^{-1}$. The proposed *sum of normalized scores (SNS)* test statistic is

$$SNS = \frac{i' \sqrt{I(\theta_0)^{-1}} s(\theta_0)}{\sqrt{p}},$$

which also has asymptotic standard normal distribution under the null.

In practice there will be nuisance parameters that have to be estimated. In such case θ is expressed as $\theta = (\theta_1', \theta_2')'$ where θ_1 and θ_2 are respectively $p_1 > 1$ and $p_2 > 0$ vectors of parameters with $p_1 + p_2 = p$, and we will be interested in testing $H_0 : \theta_1 = 0$ against $H_A : \theta_1 > 0$, so θ_2 are nuisance parameters for the testing problem. Let $\tilde{\theta}$ be the maximum likelihood estimator of θ under the restriction imposed by the null hypothesis, that is, for our case, a p vector with its first p_1 components set at 0 and the remaining p_2 components set at the maximum likelihood estimates under the null hypothesis. Let $s_1(\theta)$ be the first p_1 coordinates of the score vector and $G_1(\theta)$ the upper $p_1 \times p_1$ block of the inverse of the information matrix.

The King-Wu and SNS test statistics for this case will be

$$KW = \frac{i' s_1(\tilde{\theta})}{\sqrt{i' G_1(\tilde{\theta})^{-1} i}} \tag{1}$$

and

$$SNS = \frac{i' \sqrt{G_1(\tilde{\theta})} s_1(\tilde{\theta})}{\sqrt{p}} \tag{2}$$

For the two-sided alternative hypothesis $H_1 : \theta_1 \neq 0$ the standard LM test is

$$LM = s_1(\tilde{\theta})' G_1(\tilde{\theta}) s_1(\tilde{\theta})$$

which under the null has an asymptotic chi-squared distribution with p_1 degrees of freedom.

In order to derive test statistics for the error component model, analytic expressions for the score and the information matrix of this model are given in Baltagi and Li (1991). The information matrix is block diagonal between β and $(\sigma_\mu^2, \rho, \sigma_\epsilon^2)$, so we will concentrate the analysis on the latter. In terms of the notation of the previous section, $\theta_1 = (\sigma_\mu^2, \rho)'$, $\theta_2 = \sigma_\epsilon^2$, $p_1 = 2$, $p_2 = 1$, and $p = 3$. The score vector for these parameters, evaluated at the restricted maximum likelihood estimates is given by

$$s(\tilde{\theta}) = \begin{bmatrix} -\frac{NT}{2\hat{\sigma}_\epsilon^2} A \\ NTB \\ 0 \end{bmatrix}$$

where

$$A = 1 - \frac{\tilde{u}'(I_N \otimes e_T e_T')\tilde{u}}{\tilde{u}'\tilde{u}}$$

and

$$B = \frac{\tilde{u}'\tilde{u}_{-1}}{\tilde{u}'\tilde{u}}.$$

I_N is the identity matrix with dimension N, e_T is a T-vector of ones, $\tilde{u}$ is an NT-vector of OLS residuals from the standard linear model $y_{it} = x_{it}'\beta + u_{it}$, $\tilde{u}_{-1}$ is an NT-vector with typical element $\tilde{u}_{i,t-1}$, and '$\otimes$' denotes the Kronecker product. $\hat{\sigma}_\epsilon^2 = \tilde{u}'\tilde{u}/NT$ is the maximum likelihood estimator of σ_ϵ^2.

The information matrix $I(\theta)$ evaluated at $\tilde{\theta}$ is

$$I(\tilde{\theta}) = \frac{NT}{2\hat{\sigma}_\epsilon^4} \begin{bmatrix} T & \frac{2(T-1)\hat{\sigma}_\epsilon^2}{T} & 1 \\ \frac{2(T-1)\hat{\sigma}_\epsilon^2}{T} & \left(\frac{T-1}{T}\right) 2\hat{\sigma}_\epsilon^4 & 0 \\ 1 & 0 & 1 \end{bmatrix}.$$

Analytic expressions for the inverse of $I(\tilde{\theta})$, its upper 2×2 block $G_1(\tilde{\theta})$, its inverse $G_1(\tilde{\theta})^{-1}$, and $\sqrt{G_1(\tilde{\theta})}$ are given in the Appendix.

Replacing these magnitudes in (1) and (2) we obtain the following expression for the test statistics:

$$KW = \frac{NT\left[2B\hat{\sigma}^2 - A\right]}{\sqrt{2N(T-1)(T + 4\hat{\sigma}_\epsilon^2 + 2\hat{\sigma}_\epsilon^4)}}$$

and

$$SNS = \frac{NT\left[B\left(\sqrt{2(T-2)} - 2\right) - A\right]}{\sqrt{4N(T-1)(T-2)}}.$$

As mentioned before, both statistics have asymptotic standard normal distribution under the joint null. The expression for the joint Baltagi and Li (1991) LM test (labeled JBL) for the two-sided alternative is

$$JBL = \frac{NT^2}{2(T-1)(T-2)}\left[A^2 + 4AB + 2TB^2\right],$$

which has asymptotic Chi-square distribution with 2 degrees of freedom under the null.

4 Empirical illustration

In order to illustrate the usefulness of the testing procedures discussed in this article, we consider a simple example derived from the economic development literature. Consider a simple linear model of the determinants of income inequality. Empirical models of this sort are usually linked to the study of the so-called *Kuznets Hypothesis* that predicts an inverted-U relationship between inequality and development: countries start their development processes with low inequality and as they develop, inequality increases up to a point after which it decreases. There is a copious literature on the subject and a detailed analysis of it is beyond the goals of this paper. Barro (2001) or Gustaffson and Johansson (2001) are recent examples of this literature.

We considered the case of 17 urban regions in Argentina over the period 1993-1999. A more detailed analysis of this empirical model can be found in Gasparini et al. (2001). As explained variable we use the Gini index for each year and region, and the vector of explanatory variables includes mean income and its square, size of industrial sector and of public administration, degree of openness, unemployment rate, population under 64 years old, percentage of population with complete high school, and family size. Regional disparities in inequality are in general persistent over time and a first goal of such a model is to explore whether these persistances can be fully captured by observed factors. The testing procedure is based on a 'null' model where there are no persistances in the unobservables. The test statistics are aimed at learning whether persistence in inequality is still present in its unobservable determinants, and whether, if so, if they are due to region specific and time invariant factors, or to the persistence of idiosyncratic shocks, or to both.

We estimated a simple linear error component model using pooled OLS and implemented several testing procedures. The values of the test statistics and their p-values under their corresponding nulls are shown in Table 1.

[INSERT TABLE 1 HERE]

The first three statistics are the BSY (2001) robust one-sided tests for random effects (MBP) and serial correlation (MSC), respectively, and the Baltagi-Li joint test for the null of no persistence (JBL). Each of these tests are specifically designed to detect departures away from their nulls and hence are expected to be informative about the presence of persistent effects and its source (random effects, serial correlation of both). The results do not offer conclusive evidence about the falseness of the joint null, in particular, the joint test does not reject the null at a conservative 10% of significance. Next we present results for the new KW and SNS one-sided statistics proposed in this paper, and now *both* tests reject the joint null, with much lower p-values. Interestingly, the one-sided version of the standard Breusch-Pagan (BP) test rejects its null, with a lower p-value than its robust counterpart, and slightly lower than the one-sided SNS test. The one-sided version of the test for serial correlation (SC) rejects at 10% but not at 5%. According to the results of the previous section, this may be due to the presence of random effects more than serial correlation.

The relevant point of this example is the fact that the joint test suggests accepting the null of no persistence, not because of its veracity but very likely because of its inability to detect its falseness. By focusing on the one-sided alternative, the more powerful one-sided test strongly suggest rejecting the null. The example also highlights the fact that 'contaminated' tests may serve the purpose of being informative about departures of the joint null in spite of not being necessarily informative about the direction of the misspecification.

5 Monte Carlo results

We performed a Monte Carlo study to explore the small sample behavior of the proposed test statistics. To facilitate comparison, the adopted experimental design is the same as in previous work on the subject, in particular BSY (2001) and Baltagi et al. (1992) where a more detailed description can be found.

We use a special case of the error component model with random effects and positive first order serial correlation

$$y_{it} \;=\; \alpha + \beta x_{it} + u_{it}, \quad i = 1, 2, \ldots, N, \; t = 1, 2, \ldots, T,$$

$$
\begin{aligned}
u_{it} &= \mu_i + \nu_{it}, \\
\nu_{it} &= \rho\nu_{i,t-1} + \epsilon_{it}, \quad 0 \leq \rho < 1.
\end{aligned}
$$

We set $\alpha = 5$ and $\beta = 0.5$, and x_{it} was generated as a slightly trended autoregressive process as in previously quoted work. The strength of the serial correlation effect is controlled by the parameter ρ whereas that of the random individual effect is controlled by the variance of the random effect as a proportion of the total variance, that is, by $\tau = \sigma_\mu^2/\sigma^2$ with $\sigma^2 = \sigma_\mu^2 + \sigma_\epsilon^2$. We set $\sigma^2 = 20$. Replications of the model were generated for τ and ρ varying over (0,0.4) with increments of 0.05. Sample sizes (N, T) considered are (25,10), (25,20), (50,10) and (50,20), which are similar to those found in empirical applications. The test statistics considered are: the King-Wu (KW) and the sum of normalized scores (*SNS*) one sided joint tests, the Baltagi-Li two sided joint test (*JBL*), the one-sided version of the Baltagi-Li test for serial correlation (SC) and the corresponding modified version by BSY (MSC), the Honda one-sided test for random effects (*BP*) and its robustified version by BSY (*MBP*), the two-sided serial correlation test of Baltagi and Li (*SC2*) and its BSY robustified version (*MSC2*), and finally the Breusch/Pagan two sided test for random effects (*BP2*) and the BSY robustified version (*MBP2*). Analytic expressions of these test statistics are given in the Appendix.

For each sample size and each parameter setting we generated 1000 replications of the model, computed all the test statistics, and counted the proportions of rejections using a nominal size of 0.05 for the corresponding quantiles of the asymptotic distributions of each test statistic under the null.

Under the null hypothesis $H_0 : \sigma_\mu^2 = \rho = 0$, the proposed one-sided statistics have asymptotic standard normal distribution. The statistics generated for these values of the parameters were used to evaluate the accuracy of the normal approximation for the samples sizes considered in the experiment. Table 2 presents the estimated empirical sizes of the tests, using a nominal size of 0.05, that is, we used the 0.95 quantile of the standard normal distribution as the lower limit of the critical region and counted the proportion of rejections. All estimated values are close to the nominal. Since we used 1000 replications, the maximum standard errors for the estimates are $\sqrt{0.5(1-0.5)/1000} \cong 0.015$ so for all cases, a 90% confidence interval includes the nominal value. We also computed Kolmogorov-Smirnov tests (not shown) to explore the null of no differences between the empirical distribution and the standard normal for both tests, and in all cases we do not find significative differences, so the normal approximation seems to be accurate even for very small samples like those considered in the experiment.

[INSERT TABLE 2 HERE]

Regarding power, Table 3 presents results for a sample size of $N = 25, T = 10$, for selected values of the parameters. Estimated rejection probabilities for higher values of τ and ρ are all very close to one, so they are not reported. Besides, the optimality properties of the tests are expected to hold in a small neighborhood of the null hypothesis, so we concentrate the analysis on small values of the alternative. Also, results for sample sizes (25,20), (50,10) and (50,20) only reinforce the conclusions of the (25,10) case, so they are not shown in order to save space, and can be obtained from the author.

[INSERT TABLE 3 HERE]

Table 3 shows the estimated rejection frequencies for different tests. First we compare the power performance of the proposed one-sided statistics (KW and *SNS*) with that of the two-sided LM test of Baltagi and Li (*JBL*). Results are shown graphically in Figure 1. Each plot presents differences in power for selected tests, for several relevant values of the alternative hypothesis. Regarding the comparison between the KW and the *JBL* tests, overall the difference in power is positive, suggesting a power gain by focusing on the one sided alternative, except along the $\tau > 0, \rho = 0$ axis (random effects but no serial correlation), where the *JBL* procedure dominates. Similarly the *SNS* test induces, overall, positive power differences when compared to the *JBL* test, except along the positive serial correlation but no random effects axis. It is important to remark that along each axis of the alternative hypothesis, all the joint tests are, obviously, dominated by the single parameter procedures designed specifically for that purpose. When both serial correlation and random effects are present, the one-sided joint tests unambiguously dominate the two-sided joint version, with the *SNS* test inducing larger power gains in the direction of random effects and the KW in the direction of serial correlation.

[INSERT FIGURE 1 HERE]

As stressed in section 2, single parameter tests have power against random effects and serial correlation and hence may compete against the joint tests. We concentrate the analysis on the Honda one-sided test for random effects (BP), and the one-sided version of the Baltagi-Li test for serial correlation (SC). Since these tests are by construction optimal in the presence of the misspecification they were designed to test for (solely random effects in the Honda test and serial correlation for the Baltagi/Li test), the relevant comparison with the joint test is when both sources of misspecification are present. Figure 2 presents these comparisons graphically. The KW and SNS tests have larger power than both the SC and the BP tests when both misspecifications are present. It is interesting to see that the KW overall dominates the sc test in most directions away from the null, and that the SNS does similarly with the BP test.

[INSERT FIGURE 2 HERE]

To summarize, the montecarlo experiment suggests that the KW test favors the presence of serial correlation, with almost no power costs compared to the SC test, specifically designed to detect this type of misspecification. The SNS favors random effects, and performs no worse than the Honda test, the one with highest power along this direction. When both sources of persistence are active, the proposed one-sided tests have the highest power.

6 Concluding remarks

This paper proposes simple tests for the null of no serial correlation and random effects in the error component model. As stressed in Davidson and MacKinnon (1993, pp. 428), tests that do not reject the null are more reliable if they are known to have high power against relevant alternatives. Since the presence of random effects is essentially a one-sided matter, and given that in the context of persistence models researchers are usually worried about positive serial correlation, the proposed statistics exploit this one-sided character of the alternative hypothesis, in contrast to existing procedures that take the alternative as two-sided.

Monte Carlo results show that, as expected, the use of one-sided tests imply a power gain with respect to the two-sided Baltagi and Li (1991) test, specially when the alternative moves in the direction of both serial correlation and random effects. In all cases the two-sided test is dominated in power by at least one of the one-sided alternative procedures. Also, the results suggest that 'single parameter' tests for random effects and serial correlation, though unable to detect the source of misspecification, may serve the purpose of indicating deviations away from the joint null.

We share with some recent literature, in particular Inoue and Solon (2006), the concern that checks for serial correlation in panel data are not as popular as their time series regression counterparts, where such tests are part of the toolkit that accompanies standard regression output. As dramatically highlighted by Bertrand et al. (2006), neglected correlations in the error term may affect statistical inference severely, for which we believe it is relevant to check the validity of standard methods using powerful tests.

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Table 1: Empirical Example

	Statistic	P-value
Random Effect One-Sided Robust: MBP	1.492	0.067
Serial Correlation One-Sided Robust: MSC	0.433	0.332
Joint Two-Sided: JBL	4.350	0.113
Joint One-Sided: KW	2.040	0.020
Joint One-Sided: SNS	2.085	0.018
Random Effect One-Sided: BP	2.040	0.020
Serial Correlation One-Sided: SC	1.456	0.072

Table 2: Empirical Sizes (nominal size=0.05)

	Tests	
(N,T)	KW	SNS
(25,10)	0.053	0.054
(25,20)	0.051	0.045
(50,10)	0.059	0.057
(50,20)	0.049	0.047

Table 3: Estimated rejection probabilities of different tests
Sample size: N=25; T=10

τ	ρ	KW	SNS	JBL	SC	MSC	BP	MBP	SC2	MSC2	BP2	MBP2
0.00	0.00	0.052	0.036	0.074	0.056	0.078	0.042	0.038	0.098	0.086	0.032	0.042
0.05	0.00	0.200	0.124	0.134	0.216	0.216	0.096	0.060	0.142	0.152	0.074	0.064
0.10	0.00	0.438	0.298	0.326	0.456	0.438	0.194	0.074	0.346	0.320	0.136	0.092
0.15	0.00	0.706	0.466	0.566	0.708	0.666	0.300	0.094	0.612	0.550	0.218	0.106
0.20	0.00	0.882	0.624	0.778	0.892	0.824	0.390	0.084	0.838	0.762	0.298	0.116
0.25	0.00	0.988	0.834	0.946	0.988	0.978	0.558	0.166	0.982	0.958	0.484	0.170
0.00	0.05	0.200	0.364	0.268	0.184	0.074	0.388	0.354	0.128	0.076	0.294	0.250
0.05	0.05	0.520	0.590	0.444	0.484	0.208	0.528	0.372	0.370	0.152	0.426	0.290
0.10	0.05	0.708	0.682	0.578	0.688	0.398	0.578	0.338	0.572	0.288	0.490	0.298
0.15	0.05	0.882	0.806	0.780	0.870	0.682	0.682	0.372	0.820	0.534	0.610	0.334
0.20	0.05	0.966	0.898	0.914	0.962	0.870	0.766	0.400	0.936	0.796	0.690	0.326
0.25	0.05	0.996	0.962	0.986	0.996	0.962	0.854	0.440	0.994	0.932	0.806	0.374
0.00	0.10	0.574	0.810	0.704	0.496	0.070	0.814	0.768	0.380	0.052	0.752	0.672
0.05	0.10	0.728	0.864	0.778	0.696	0.210	0.854	0.716	0.592	0.150	0.790	0.624
0.10	0.10	0.892	0.916	0.844	0.864	0.416	0.876	0.728	0.786	0.290	0.818	0.648
0.15	0.10	0.968	0.964	0.948	0.962	0.696	0.922	0.714	0.934	0.568	0.878	0.646
0.20	0.10	0.988	0.978	0.972	0.986	0.868	0.932	0.732	0.980	0.786	0.910	0.668
0.25	0.10	0.998	0.988	0.996	0.998	0.958	0.956	0.756	0.996	0.932	0.932	0.688
0.00	0.15	0.770	0.926	0.884	0.676	0.070	0.934	0.900	0.580	0.044	0.906	0.876
0.05	0.15	0.888	0.960	0.916	0.834	0.236	0.952	0.906	0.754	0.136	0.934	0.866
0.10	0.15	0.968	0.984	0.960	0.948	0.462	0.976	0.890	0.918	0.340	0.960	0.856
0.15	0.15	0.992	0.994	0.984	0.988	0.680	0.978	0.874	0.976	0.560	0.960	0.844
0.20	0.15	0.996	0.988	0.994	0.994	0.856	0.980	0.878	0.992	0.772	0.974	0.844
0.25	0.15	1.000	1.000	1.000	1.000	0.962	0.994	0.884	1.000	0.910	0.986	0.862
0.00	0.20	0.918	0.992	0.980	0.850	0.094	0.992	0.986	0.784	0.060	0.984	0.974
0.05	0.20	0.954	0.988	0.980	0.940	0.216	0.986	0.980	0.906	0.108	0.986	0.966
0.10	0.20	0.988	0.994	0.980	0.982	0.460	0.994	0.968	0.966	0.324	0.984	0.944
0.15	0.20	1.000	1.000	0.994	1.000	0.696	0.994	0.964	0.994	0.572	0.992	0.948
0.20	0.20	1.000	0.998	0.998	1.000	0.868	0.992	0.954	1.000	0.784	0.990	0.946
0.25	0.20	1.000	1.000	1.000	1.000	0.958	0.994	0.966	1.000	0.908	0.994	0.956
0.00	0.25	0.966	0.996	0.998	0.934	0.080	0.998	1.000	0.894	0.038	0.998	0.998
0.05	0.25	0.988	0.996	0.992	0.986	0.252	0.998	0.990	0.970	0.148	0.992	0.982
0.10	0.25	0.996	0.998	0.996	0.994	0.486	0.998	0.988	0.994	0.336	0.998	0.984
0.15	0.25	1.000	1.000	0.998	1.000	0.680	0.998	0.982	1.000	0.526	0.996	0.978
0.20	0.25	0.998	0.998	0.998	0.998	0.872	0.996	0.984	0.998	0.786	0.994	0.976
0.25	0.25	1.000	1.000	1.000	1.000	0.942	1.000	0.992	1.000	0.898	1.000	0.986

Figure 1: Power Comparisson with Joint Two-Sided Test

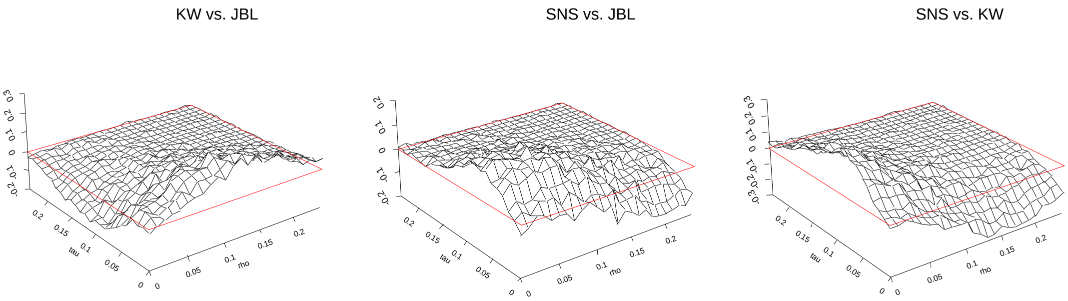
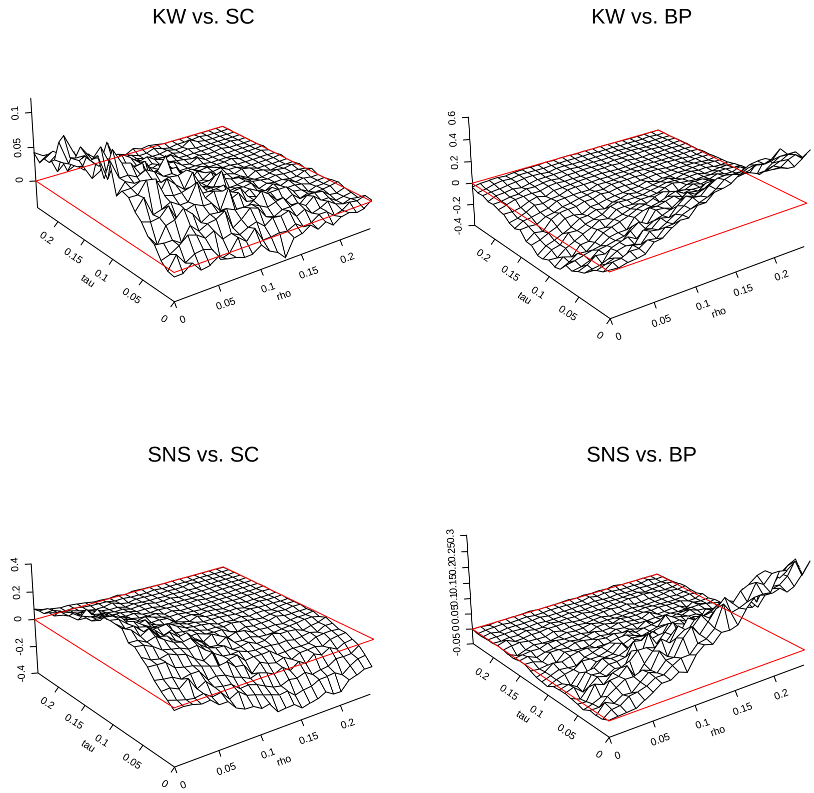


Figure 2: Power Comparisson with Single Parameter One-Sided Tests



Appendix: Algebraic Details and Test Statistics

This appendix gives the analytic expressions used to derive the new test statistics in the paper.

$$I(\tilde{\theta})^{-1} = \frac{2\hat{\sigma}_\epsilon^4}{N(T-1)(T-2)} \begin{bmatrix} 1 & -1/\sigma_\epsilon^2 & -1 \\ -1/\sigma_\epsilon^2 & T/2\sigma_\epsilon^4 & -1/\sigma_\epsilon^2 \\ -1 & -1/\sigma_\epsilon^2 & \frac{T^2-2T+2}{T} \end{bmatrix}$$

$$G_1(\tilde{\theta}) = \frac{2\hat{\sigma}_\epsilon^4}{N(T-1)(T-2)} \begin{bmatrix} 1 & -1/\sigma_\epsilon^2 \\ -1/\sigma_\epsilon^2 & T \end{bmatrix}$$

$$G_1(\tilde{\theta})^{-1} = \frac{N(T-1)(T-2)}{2\hat{\sigma}_\epsilon^4} \begin{bmatrix} T & 2\sigma_\epsilon^2 \\ \sigma_\epsilon^2 & \sigma_\epsilon^4 \end{bmatrix}$$

For the square root matrix we used the Cholesky factor P of $G_1(\tilde{\theta})$:

$$P = \frac{\sqrt{2}\hat{\sigma}_\epsilon^2}{\sqrt{N(T-1)(T-2)}} \begin{bmatrix} 1 & 1/\sigma_\epsilon^2 \\ 0 & \sqrt{T-2}/\left(\sqrt{2}\sigma_\epsilon^2\right) \end{bmatrix}$$

Regarding analytic expressions for the test statistics used in this paper, besided the ones decribed in Section 3, we used the following. The two-sided LM statistic test for random effects of Breusch and Pagan (1980) is

$$BP2 = \frac{NTA^2}{2(T-1)},$$

and its adjusted version in BSY (2001) is

$$MBP2 = \frac{NT(A+2B)^2}{2(T-1)(1-\frac{2}{T})},$$

where A and B are defined as in Section 3. The one-sided version of the Breusch-Pagan statistic was derived by Honda(1985) and is given by:

$$BP = -\sqrt{\frac{NT}{2(T-1)}}A$$

and the corresponding one-sided version is derived by BSY(2001):

$$MBP = -\sqrt{\frac{NT}{2(T-1)(1-\frac{2}{T})}}(A-2B).$$

The two-sided LM statistic to test the null of no serial correlation assuming no random effects is given in Baltagi and Li (1991):

$$SC2 = \frac{NT^2B^2}{T-1},$$

and its adjusted version by BSY (2000), valid under random effects, is

$$MSC2 = \frac{NT^2(B + \frac{A}{T})^2}{(T-1)(1-\frac{2}{T})}.$$

The one-sided versions are derived following BSY (2001), by taking the *signed* squared roots of the two-sided statistics, and are given by

$$SC = \frac{\sqrt{N}TB}{\sqrt{T-1}},$$

and

$$MSC = \sqrt{\frac{NT^2}{(T-1)(1-2/T)}} \left(B + \frac{A}{T} \right).$$