E C O N O M I C S   B U L L E T I N

Choosing Between Panel Data Stationarity Tests

Kristian Jönsson
National Institute of Economic Research

Abstract

When testing for stationarity in panel data several tests are available. These tests differ in degree to which they allow for serial correlation in the series under the null hypothesis. In the current paper, a serial correlation test for panel data is proposed. The suggested test can be used to choose between the available stationarity tests, and provides a statistical ground for choosing an appropriate framework when investigating the stationarity hypothesis in panel data situations.

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1 Introduction

When testing for stationarity in panel data, one can choose from a variety of tests. Hadri (2000) suggests a test that is valid asymptotically, e.g. as the time-series dimension (T) tends to infinity followed by the cross-sectional dimension (N), regardless of whether or not serial correlation is present in the considered series under the null hypothesis. For finite-sample situations, more specifically for the case of a fixed time-series dimension, Hadri and Larsson (2005) suggest a test that can be used when no serial correlation is present. For a third case where serial correlation is allowed for, while the time-series dimension is finite, Jönsson (2005) suggests a modification of the Hadri (2000) test that can be used to improve its finite-T size properties.

All of these panel data stationarity tests are based on the stationarity test of Kwiatkowski et al. (1992).[1] As such, the tests are not only sensitive to the actual presence of serial correlation, but also sensitive to the use of the so-called long-run variance estimator, even if no serial correlation is present. If no serial correlation is present, the use of the long-run variance estimator, and hence the choice of a test that allows for serial correlation, reduces the power of the test by inflating the variance of the test statistic under the null hypothesis. Since all of the properties of the KPSS test carries over to the panel data stationarity setting, and even aggregates over cross sections, the test Hadri (2000) and Jönsson (2005) incur unnecessary power losses if no serial correlation is present but allowed for. On the other hand, is serial correlation is present but not accounted for, the tests will have exhibit nuisance parameter-dependence and size distortions that remain even asymptotically. Hence, it is of great interest to test whether or not serial correlation is present in a cross section of time series before choosing the appropriate panel data stationarity test.

In this paper, a panel data test for serial correlation is suggested. The proposed test assists the researcher when choosing between the available panel data stationarity tests. The test that we suggest is very easy to calculate and obtained by pooling the p-values for cross-section specific serial correlation tests, along the lines of reasoning suggested by Maddala and Wu (1999). Monte Carlo simulations reveal that the autocorrelation test has good size and power properties in small-sample situations, making the test useful for practitioners that are to choose a stationarity test in the panel data framework.

The rest of this paper is organized as follows. In Section 2, the econometric framework is presented, while the serial correlation test is discussed in Section 3. In Section 4, we present finite-sample size and power properties of the test obtained from Monte Carlo simulations. Finally, Section 5 offers some concluding remarks.

2 The panel data model

In this paper, we consider a panel data test for serial correlation in the following econometric model:

$$y_{i,t} = \delta_{0,i} + \delta_{1,i}t + \varepsilon_{i,t} \tag{1}$$

[1] The test of Kwiatkowski et al. (1992) is often referred to as the KPSS test, so also in this paper.

In (1), $y_{i,t}$ are the series that are stationary under the null hypothesis of Hadri (2000), Hadri and Larsson (2005) and Jönsson (2005). α_i denotes an intercept in the series $y_{i,t}$, while the term $\delta_i t$ is a time trend. Finally, $\varepsilon_{i,t}$ is a stochastic disturbance term, which is assumed to be normally distributed, independent across cross sections and fulfill the linear process assumption of Phillips and Solo (1992).

The expression in (1), describes the evolvement of a stationary time series in the context of Kwiatkowski et al. (1992), Hadri (2000), Hadri and Larsson (2005) and Jönsson (2005). A key question when choosing between these tests are whether or not the disturbance series $\varepsilon_{i,t}$ are serially correlated. If this is the case, a long-run variance estimator, such as the the one suggested by Newey and West (1987), has to be employed to test the null hypothesis of stationarity. The appropriate panel data stationarity test would be that of Hadri (2000) or Jönsson (2005). If no serial correlation is present, the variance estimator $\hat{\sigma}^2_{\varepsilon,i} = T^{-1}\sum_{t=1}^{T}\hat{\varepsilon}^2_{i,t}$ can be used and the panel stationarity test of Hadri and Larsson (2005) can be employed. The use of the latter estimator reduces the number of parameters that have to be estimated when performing the stationarity test. Hence, once size has been controlled for, power gains can be obtained by not having to embark in long-run variance estimation. Such power gains aggregates across cross sections and becomes larger as the cross-sectional dimension of the panel increases. However, in order to abandon the long-run variance estimator, the researcher has to make sure that no autocorrelation is present in $\varepsilon_{i,t}$. This issue is addressed next.

3 The serial correlation test

In order to test the null hypothesis that no serial correlation up until order k is present in the disturbances $\varepsilon_{i,t}$ for any $i \in \{1, \dots, N\}$, we suggest that the Ljung and Box (1978) statistic in (2) should be calculated for each cross-section and for each $l \in \{1, \dots, k\}$.

$$Q_{i,l} = T(T+2)(T-l)^{-1}\frac{\sum_{j=l+1}^{T} e_{i,j}e_{i,j-l}}{\sum_{j=1}^{T} e_{i,j}e_{i,j}} \tag{2}$$

In (2), $e_{i,t}$ is the least squares estimate of $\varepsilon_{i,t}$ in (1), which is obtained by detrending $y_{i,t}$ with either an intercept or an intercept and a time trend. The test statistic in (2) can now be used to construct a cross-section test statistic, $Q_i = \sum_{l=1}^{k} Q_{i,l}$, which can be applied to test the null hypothesis of serially uncorrelated disturbances up until order k against the alternative that there exist serial correlation in the error terms for some order $0 < l \leq k$ for cross section i.

The test statistic, Q_i, has been shown to have an asymptotic $\chi^2_{(k)}$ distribution as $T \to \infty$. However, basing a serial correlation test on Q_i for some $i \in \{1, \dots, N\}$, implies that a test for serial correlation in the i:th cross section, not in the entire panel, is performed. In order to obtain a panel data test for serial correlation, the p-values of the cross-section specific Q_i statistics could be pooled over cross sections. More specifically, in the current papers it is suggested that the 'combining p-values test' of Maddala and Wu (1999) should be used to test the null hypothesis that none of the cross-sectional disturbance series are serially correlated against the alternative that at least one of the cross-section disturbance series display serial correlation. The suggested panel data test statistic is given in (3).

$$\lambda = -2\sum_{i=1}^{N} ln(\pi_i) \tag{3}$$

In (3), π_i is the p-value for Q_i, which is obtained from the $\chi^2_{(k)}$ distribution. The test statistic λ will have an asymptotic $\chi^2_{(2N)}$ distribution as $T \to \infty$ for fixed N (see e.g. Maddala and Wu, 1999).

The fact that approximate p-values are readily obtainable for the cross-section specific test statistics, Q_i, together with the fact that both critical values and p-values are easy to obtain for the panel data serial correlation test, makes the test very easy to calculate and hence very attractive to implement. However, the attractiveness of the test in finite-T situation depends critically on the small-sample performance of the test.

In the next section, it is investigated how well the asymptotic approximations, needed to obtain p-values and critical values for the panel data test, work in finite samples. Furthermore, the power properties of the test are also investigated.

4 Monte Carlo simulation

The computational simplicity of the panel data serial correlation test presented in the previous section is of course very attractive. However, the price paid for the easy calculations is approximation errors that arise as a consequence of the fact that the individual test statistics, Q_i, have a finite-sample distribution that may differ from the asymptotic one. In order to assess the importance of such discrepancies, we simulate the size of the panel data serial correlation test of Section 3.

To investigate the size of the serial correlation test we set $k = 1$, and generate data series under the null hypothesis that no serial correlation is present. More specifically, the series are constructed as $y_{i,t} = \alpha_{0,i} + \alpha_{1,i}t + \epsilon_{i,t}$, where $\alpha_{0,i} \sim U[0, 10]$, $\alpha_{1,i} \sim U[0, 2]$ and $\epsilon_{i,t} \sim IIDN(0, 1)$.[2] When only an intercept is considered, we let $\alpha_{1,i} = 0\ \forall i$. The data is generated for $i \in \{1, 2, \ldots, N\}$ and $t \in \{1, 2, \ldots, T\}$, where $N \in \{5, 10, 15, 20\}$ and $T \in \{50, 100, 250\}$. Both the size and the power properties presented below are based on 5,000 generated data sets.

In Table 1, we present the size of the panel data serial correlation test, at the 5% significance level. As seen in the table, the size of the panel data serial correlation test is very close to 5% for all sample sizes when only an intercept is present. The small size distortions that are observed become smaller as the ratio N/T decreases. When both an intercept and a time trend are present, the size distortions for the panel data serial correlation test become somewhat larger. However, the size distortions are small in absolute value and quickly becomes smaller as N/T decreases. For example when $T = 100$, the largest size distortion is 2.1 percentage points, while it is only 0.3 percentage points when T=250.

Besides having good size properties, it is desirable that the panel data serial correlation test has good power properties. That is, when disturbances of at least one cross-sectional

[2]We let $U[a, b]$ denote the uniform distribution over the interval $[a, b]$.

unit displays serial correlation, the test should reject the null hypothesis that *all* cross-sectional units have serially uncorrelated disturbances.

In order to test the power of the test, we generate $N-1$ cross-sectional units with serially uncorrelated disturbances and 1 cross-sectional unit with serially correlated disturbances. The latter cross-section time series are generated as described above, with the only difference being that $\epsilon_{i,t}$ is generated either according to an AR(1) or a MA(1) process. The AR and the MA parameters are set to 0.5, while the innovation driving the processes are set to be $IIDN(0,1)$.

By letting only one cross section have serially correlated disturbances, we study the power of the test under a minimal deviation from the null hypothesis that all time series have serially uncorrelated disturbances.

In Table 2, we present the power of the serial correlation test. As seen in the table, the power is high, around 65%, when $N=5$ and $T=50$ in the case of AR(1) disturbances, and somewhat lower, although still high, when errors are of the MA(1) form. From Table 2, it can also be seen that the power decreases as the number of cross sections increase. This is a natural consequence of the fact that only one cross section with serially correlated disturbances is considered, regardless of the total number of cross sections in the panel. Hence, the influence that the one and only cross-section time series generated under the alternative hypothesis have on the panel data test decreases as N increases. If more cross sections were to displays serially correlated disturbances, the power of the test would increase correspondingly.

From Table 2 it can also be seen that the power of the panel data serial correlation test is somewhat lower when a linear trend is present, as compared to the case when only an intercept is present, but as before the power increases as T becomes larger.

The overall conclusion from studying Table 2 is that the test has good power to detect situations where serially correlated disturbances are present. The high power reduces the risk of incurring size distortions, due to erroneous omission of serial correlation, in the panel data stationarity framework.

The good size and power properties of the panel data serial correlation test, together with its computational simplicity, makes it a valuable tool when we are to choose tests in the panel data stationarity testing framework.

5 Concluding remarks

The current paper suggests a panel data test for serial correlation that can be applied to choose between panel data stationarity tests. The panel data serial correlation test provides guidance when choosing panel data stationarity test in such a way that serially correlated disturbances are not neglected when present, but neither superfluously accounted for when absent. The former aspect of the test helps preserve the size of the panel data stationarity test, while the latter avoids the risk of unnecessary reductions in power. Finite-sample simulations indicate that the serial correlation test has good size properties in small samples, while still providing power when only one cross-sectional unit displays serial correlation.

As a final remark it should be noted that the results in the current paper can be generalized without altering the main results of the paper.

First, the current test for serial correlation can be implemented also in the panel data unit root test of Im et al. (2003) when choosing the number of lagged first differences that are to be used for augmenting the Dickey-Fuller test regressions.

Second, the number of autocorrelations, k, that are used to test for serial correlation in the disturbance terms, needs not to homogeneous over the cross section. That is, the number can vary between cross sections, as long as the degrees of freedom that are used to obtain the p-values are altered correspondingly.

Third, under some circumstances, it can be unrealistic to assume that all cross-section time series are serially uncorrelated. However, the test proposed in the current paper, can be equally well used to test the null hypothesis that a subset of the cross sections have serially uncorrelated series. If it is found that some of the cross-sectional unit consist of serially uncorrelated series, the panel data stationarity test is implemented by using the variance estimator of Section 2 for these cross sections, while e.g. the Newey and West (1987) estimator is applied for the cross-sectional units that display serially correlated time series.

Finally, the current test can be used also when allowing cross-sectional correlation in the panel data stationarity framework, as long as the cross-sectional correlation is handled prior to implementing the test (e.g. through defactoring the cross-section time series along the lines of Shin and Snell (2006) or Bai and Ng (2004).

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Table 1: Size of panel data serial correlation test.

	Intercept		
	T=50	T=100	T=250
N=5	0.052	0.048	0.047
10	0.051	0.049	0.046
15	0.052	0.053	0.047
20	0.052	0.048	0.051
	Intercept and trend		
	T=50	T=100	T=250
N=5	0.064	0.059	0.046
10	0.071	0.059	0.053
15	0.076	0.064	0.055
20	0.079	0.071	0.053

Table 2: Power of panel data serial correlation test.[a]

AR(1) disturbances							
	Intercept				Intercept and trend		
	T=50	T=100	T=250		T=50	T=100	T=250
N=5	0.682	0.970	1.000	N=5	0.620	0.958	1.000
10	0.520	0.906	1.000	10	0.478	0.885	1.000
15	0.428	0.843	1.000	15	0.402	0.817	1.000
20	0.373	0.788	0.999	20	0.370	0.760	0.999
MA(1) disturbances							
	Intercept				Intercept and trend		
	T=50	T=100	T=250		T=50	T=100	T=250
N=5	0.462	0.869	1.000	N=5	0.422	0.846	1.000
10	0.323	0.711	0.999	10	0.318	0.696	0.998
15	0.266	0.611	0.992	15	0.276	0.605	0.992
20	0.240	0.521	0.983	20	0.252	0.516	0.980

Notes: [a]The power is studied by letting one of the cross-section time series contain serial correlation.