The seasonal KPSS test when neglecting seasonal dummies: a Monte Carlo analysis

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Abstract

This paper shows through a Monte Carlo analysis the effect of neglecting seasonal deterministics on the seasonal KPSS test. We found that the test is most of the time heavily oversized and not convergent in this case. In addition, Bartlett-type non-parametric correction of error variances did not signally change the test's rejection frequencies
.

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1 Introduction

Unit root testing in macroeconomic time series has been a focus of interest of several theoretical and applied research over the last three decades. Importantly, unit root tests help assess non-stationarity of many macroeconomic data. In particular, they help determine whether the trend is stochastic, deterministic or a combination of both. Following Nelson and Plosser (1982), many empirical studies have shown that macroeconomic variables have unit root structures.

Although order of integration of time series is usually tested using unit root tests, some authors suggest to change the null hypotheses of these tests and, therefore, proceed to test the null hypothesis of stationarity against the alternative hypothesis of unit roots as a means of consolidating the unit root test results, see e.g. Park (1990). In this respect, one can mention the test of Kwiatkowski et al. (1992), simply called KPSS test, which gained ground in empirical research. In practice, using tests with no seasonal unit root null hypothesis is also recorded albeit in a reduced dimension compared to the use of stationarity tests involving non-seasonal data. In this framework, Lyhagen (2006) proposed a seasonal version of the KPSS test. While being interesting in terms of extension, such a version has a rather complicated asymptotic theory particularly regarding complex unit roots. Khédhiri and El Montasser (2010), through a simulation analysis, show that the seasonal KPSS test is robust to the size and number of outliers and the obtained statistical results reveal a good overall performance of the test's finite-sample properties. In the same vein, Khédhiri and El Montasser (2012) has included in the test's regression-based model dummy variables for a modified test whose null hypothesis is deterministic seasonality and the alternative invoking some seasonal unit roots.

What type of models should we choose for seasonality? This issue has been the subject of several studies in the literature. Several economists agree that the indicator variable model is most appropriate for macroeconomic data. However, many econometricians found seasonal unit roots in a variety of economic time series. This controversy regarding such a presence can be exacerbated by interrelated patterns displayed by both models. For example, when a time series exhibits seasonal unit roots, deterministic seasonality is also usually present at some extent [see Abeysinghe (1994) and Lopes(1999), inter alia]. Recently, Franses, Hylleberg and Lee (1995) pointed out that solely considering seasonality as deterministic while the time series is actually affected by seasonal unit roots results in spurious statistical inference. However, ignoring or avoiding deterministic seasonality in integrated time series should not be drawn from the conclusions of these authors. In fact, Demetrescu and Hassler (2007) found that neglecting seasonally varying means may inflate the size and at the same time reduce the power of the Dickey-Fuller test [DF] (Dickey and Fuller, 1979). Similarly, they have shown that the KPSS test also leads to distorted decisions in presence of neglected seasonal dummies under the null hypothesis. Moreover, using a Monte Carlo analysis, Hassler and Rodrigues (2004) studied the impact of neglecting the structural changes on seasonal unit roots. In this regard, we believe that neglecting structural changes is similar to some extent to neglecting deterministic seasonality in finit sample analyses. The authors have shown indeed that the seasonal unit root test of Hylleberg et al. (1990) as well as an LM variant thereof are asymptotically robust to seasonal mean shifts of finite magnitude.

In this paper, we will extend the analysis of Demetrescu and Hassler (2007) to seasonal stationarity tests. Specifically, we focus, through a Monte Carlo analysis, on the impacts of neglecting seasonal dummies on the seasonal KPSS test which is but the seasonal version of stationarity tests as defined by Busetti and Taylor (2003). Remember that other most commonly used tests of seasonal stationarity adopt also the KPSS framework, either in the specification of the basic regression equation or in the construction of the test statistic. This justifies our choice to study only the seasonal KPSS test.

The rest of the paper is structured as follows. In section 2, we give some preliminaries on the seasonal KPSS test. In section 3, a systematic Monte Carlo analysis, in which quarterly data are simulated, is described to examine the effects of neglecting seasonal dummies on the test statistic. The final section concludes.

2 Seasonal KPSS Test: Preliminaries

Consider a time series y_t with periodicity S. To simplify the presentation, we examine in what follows quarterly data, i.e. $S = 4$. Furthermore, the following model is considered to accommodate the seasonal KPSS statistic:

$$y_t = x_t^{'}\beta + r_t + u_t,\ t = 1, ..., T, \tag{1}$$

with $T = 4N$, $\beta^{'} x_t = \sum_{i=1}^{S} a_i D_{it}$ and the shorthand notation $D_{it} = \delta(i, t - 4[\frac{(t-1)}{4}])$, where we use $[.]$ for the largest integer function and $\delta(i, j)$ for Kroneckerâs δ function. The term u_t is zero mean weakly dependent process with an autocovariogram $\gamma_h = E(u_t u_{t+h})$ and a strictly positive long run variance ω_u^2. r_t is an autoregressive process which may contain seasonal unit roots. For example, if the unit root at the Nyquist frequency is to be tested for quarterly data , the process r_t can be expressed as follows:

$$r_t = -\rho r_{t-1} + v_t, \tag{2}$$

where v_t is weakly dependent and $\rho > 0$. Then, the null hypothesis of the seasonal KPSS test is: $H_0 : \rho = k$, with $k < 1$, under which the time series is stationary and does not contain a Nyquist frequency unit root. The alternative $H_1 : \rho = 1$ indicates the presence of such a unit root.

In general, the process r_t, corresponding to the seasonal unit root in question, can be defined from $\Delta(\theta)$ as the difference operator at frequency $\theta \in [0, \pi]$ and described as follows:

$$\Delta(\theta) = \begin{cases} 1 - \cos\theta L, \ \theta \in \{0, \pi\}, \\ 1 - 2\cos\theta L + L^2, \ \theta \in]0, \pi[, \end{cases} \tag{3}$$

where L is the usual lag operator. The operator $\Delta(\theta)$ is a difference filter having a zero gain at the spectral frequency $\theta \in [0, \pi]$; in other words it removes unit roots at that frequency. Consistent with what, inter alia, Hylleberg et al. (1990), Gregoir (1999), Cubadda (1999) and Busetti (2006) proposed, a real-valued time series process y_t is said to be integrated of order d at frequency $\theta \in [0, \pi]$, denoted $I(d, \theta)$, if its d-th θ-difference,$\Delta(\theta)^d y_t$, is a linear process with a continuous and positive definite spectrum at θ.

At this level, we focus on the seasonal frequencies, i.e., the fundamental one and its harmonics. The seasonal KPSS statistic corresponding to the seasonal frequency $\lambda = \frac{2\pi j}{S}$, $j = 1, ..., [S/2]$, is formulated as follows:

$$\eta_{c,l}^{\lambda} = \frac{1}{T^2} \frac{\sum_{t=1}^{T} \widetilde{S}_t \overline{\widetilde{S}_t}}{\widetilde{\omega}_u^2(l)}, \tag{4}$$

where $\widetilde{S}_t = \sum_{j=1}^{t} \exp^{i\lambda j} \hat{y}_j^c$ and $\hat{y}_j^c = y_j - \overline{y}$. $\hat{y}_j^c$ in (4) implies that series has to be demeaned and not seasonally demeaned to refer to seasonal dummies omission problem. Obviously, if deterministic seasonality is to be tested, the series should be seasonally adjusted using OLS estimates of seasonal coefficients. In this case, the test statistic is denoted $\eta_{d,l}^{\lambda}$; for more details, see Khédhiri and El Montasser (2012). Eq. (4) uses $\widetilde{\omega}_u^2(l)$ the Newey-West nonparametric correction of the long-run variance of the residuals $\hat{y}_t^c$. Note that in testing for seasonal unit roots, this nonparametric correction should not be carried out regardless of the seasonal context. More specifically, $\widetilde{\omega}_u^2(l)$

is the estimator of the spectral generating function is defined as follows:

$$\widetilde{\omega}_u^2(l) = \sum_{\tau=-l}^{l} \omega(\tau, l)\hat{\gamma}_u(\tau) \cos \lambda_j \tau, \tag{5}$$

where $\hat{\gamma}_u(\tau) = T^{-1} \sum_{t=\tau+1}^{T} y_t^c y_{t-\tau}^c$ is the sample autocovariance at lag τ and $\omega(\tau, l)$ is a weighting function or kernel, such as $\omega(\tau, l) = 1 - \frac{|\tau|}{(l+1)}$.

One can use, following the example of Nyblom and Makelainen (1983), the standard variance estimator defined as follows:

$$\hat{\omega}_u^2 = \frac{1}{T} \sum_{t=1}^{T} (\hat{y}_t^c)^2. \tag{6}$$

In this case, the seasonal Kpss statistic will be noted as:

$$\eta_c^\lambda = \frac{1}{T^2} \frac{\sum_{t=1}^{T} \widetilde{S}_t \overline{\widetilde{S}_t}}{\hat{\omega}_u^2}. \tag{7}$$

Similarly, η_d^λ denotes the test statistic obtained by correcting the series for their seasonal means and without using HAC estimators of residual variances. However, it is recognized that the standard variance estimator defined in Eq.(6) is not widely used in literature since the autocorrelation of residuals is a commonly observed feature in empirical applications.

3 Effects of neglected seasonal dummies: a Monte Carlo evidence

We start by specifying the data generating processes (DGPs) considered in this sesction. For the unit root of -1, the DGP follows Eqs. (1) and (2). For complex unit roots, the component r_t in (1) is generated by:

$$r_t = 2\rho \cos \theta r_{t-1} - \rho^2 r_{t-2} + v_t, \tag{8}$$

where θ denotes the fundamental frequency or any harmonic frequency other than the Nyquist one and $\rho \in [0, 1]$. As it was mentioned above, the seasonal periodicities used in this study are the quarterly ones. Our choice to work with this data frequency is motivated by the fact that the seasonal KPSS test was originally introduced for quarterly data. Therefore, it would be useful to see the effects of neglecting seasonal means at this frequency. In addition, the considered sample sizes are $T = 80$ and $T = 200$. Moreover, we chose $\rho = 0.5$ and $\rho = 1$ for respectively size and power experiments. Furthermore, we take into account two choices of the bandwith as in Kwiatkowski et al. (1992):

$$l4 = \left[4(T/100)^{0.25}\right], \quad l12 = \left[12(T/100)^{0.25}\right].$$

All experiments rely on 30000 replications and were performed by means of Matlab. The simulated series to be tested are set up from Eqs. (1), (2) and (8), where the deterministic seasonality is controlled by one parameter a:

$$\begin{array}{rl} (i) & a_1 = a, a_2 = a_3 = a_4 = 0 \\ (ii) & a_1 = -a_2 = a, a_3 = a_4 = 0 \\ (iii) & a_1 = -a_2 = a_3 = -a_4 = a \end{array}$$

We report here the results for $a = 3$. We considered as well other values ranging from 1 to 10 were also considered. The results are not significantly different and are available upon request.

In a similar context, such as structural changes, the level stationarity statistic of the standard KPSS test rejects too often the true null hypothesis when we have a shift in the intercept; see, *inter alia*, Lee *et al.* (1997). This is even true in the seasonal context. Indeed, observing Tables 1, 2, and 3, we note that the statistics η_c^λ, $\eta_{c,l4}^\lambda$ and $\eta_{c,l12}^\lambda$, where λ can be equal to π or $\pi/2$, tend to reject the null hypothesis almost perfectly. Worse, by comparing the rejection frequencies relating to the size and power, it is clear that the test is not convergent. The exception to this observation can be seen in Table 3, where the test relating to the statistic $\eta_c^{\pi/2}$ is very conservative since it never rejects the null hypothesis of seasonal stationarity when $\rho = 0$. This can be interpreted by the fact that the case (iii) promotes trigonometric seasonality attached to the seasonal frequency $\pi/2$, and which has not received any treatment. At this stage, the nonparametric correction of error variances gave rejection frequencies notable enough for $T = 80$, but they tend to 0 when $T = 200$.

On the other hand, the empirical sizes of the statistics η_d^λ built with or without nonparametric correction of error variances are very close to theoretical levels. In this regard, we note that their values did not differ across the three tables. Still, these statistics show very high power slightly superior to that of the statistics η_c^λ.

Table 1: Rejection frequencies of the seasonal KPSS test, case (i)

		T=80			T=200		
		1%	5%	10%	1%	5%	10%
$\rho = 0$	η_c^π	0.9863	0.9994	0.9999	1	1	1
	η_d^π	0.0112	0.0535	0.1103	0.0091	0.0501	0.1010
	$\eta_c^{\pi/2}$	1	1	1	1	1	1
	$\eta_d^{\pi/2}$	0.0081	0.0487	0.1044	0.0103	0.0523	0.1036
	$\eta_{c,l4}^\pi$	0.9998	1	1	1	1	1
	$\eta_{d,l4}^\pi$	0.0197	0.0717	0.1291	0.0134	0.0598	0.1127
	$\eta_{c,l4}^{\pi/2}$	1	1	1	1	1	1
	$\eta_{d,l4}^{\pi/2}$	0.0225	0.0778	0.1367	0.0171	0.0660	0.1219
	$\eta_{c,l12}^\pi$	0.9996	1	1	1	1	1
	$\eta_{d,l12}^\pi$	0.0474	0.1214	0.1923	0.0243	0.0822	0.1414
	$\eta_{c,l12}^{\pi/2}$	1	1	1	1	1	1
	$\eta_{d,l12}^{\pi/2}$	0.0691	0.1578	0.2314	0.0357	0.1025	0.1684
$\rho = -1$	η_c^π	0.8613	0.9373	0.9667	0.9716	0.9910	0.9968
	η_d^π	0.9598	0.9895	0.9962	0.9972	0.9998	1
	$\eta_c^{\pi/2}$	0.9351	0.9724	0.9863	0.9941	0.9988	0.9996
	$\eta_d^{\pi/2}$	0.9844	0.9962	0.9986	0.9998	1	1
	$\eta_{c,l4}^\pi$	0.9982	0.9997	0.9999	0.9999	1	1
	$\eta_{d,l4}^\pi$	0.9997	1	1	1	1	1
	$\eta_{c,l4}^{\pi/2}$	0.9998	0.9999	1	1	1	1
	$\eta_{d,l4}^{\pi/2}$	0.9997	1	1	1	1	1
	$\eta_{c,l12}^\pi$	0.9990	0.9998	1	1	1	1
	$\eta_{d,l12}^\pi$	1	1	1	1	1	1
	$\eta_{c,l12}^{\pi/2}$	0.9999	0.9999	1	1	1	1
	$\eta_{d,l12}^{\pi/2}$	0.9999	1	1	1	1	1

Note: $\eta_{c,l4}^\lambda$ and $\eta_{c,l2}^\lambda$, $\lambda \in \{\pi, \pi/2\}$, stand for seasonal KPSS statistics in (7)with respectively nonparametric corrections of variance errors $l4$ and $l12$. Nevertheless $\eta_{c,l4}^\lambda$ and $\eta_{c,l2}^\lambda$, $\lambda \in \{\pi, \pi/2\}$, stand for seasonal KPSS statistics constructed from demeaned residuals and with nonparametric corrections of variance errors $l4$ and $l12$ respectively.

Table 2: Rejection frequencies of the seasonal KPSS test, case (ii)

		T=80			T=200		
		1%	5%	10%	1%	5%	10%
$\rho = 0$	η_c^{π}	1	1	1	1	1	1
	η_d^{π}	0.0112	0.0535	0.1103	0.0091	0.0501	0.1010
	$\eta_c^{\pi/2}$	1	1	1	1	1	1
	$\eta_d^{\pi/2}$	0.0081	0.0487	0.1044	0.0103	0.0523	0.1036
	$\eta_{c,l4}^{\pi}$	1	1	1	1	1	1
	$\eta_{d,l4}^{\pi}$	0.0197	0.0717	0.1291	0.0134	0.0598	0.1127
	$\eta_{c,l4}^{\pi/2}$	1	1	1	1	1	1
	$\eta_{d,l4}^{\pi/2}$	0.0225	0.0778	0.1367	0.0171	0.0660	0.1219
	$\eta_{c,l12}^{\pi}$	1	1	1	1	1	1
	$\eta_{d,l12}^{\pi}$	0.0474	0.1214	0.1923	0.0243	0.0822	0.1414
	$\eta_{c,l12}^{\pi/2}$	1	1	1	1	1	1
	$\eta_{d,l12}^{\pi/2}$	0.0691	0.1578	0.2314	0.0357	0.1025	0.1684
$\rho = -1$	η_c^{π}	0.8573	0.9322	0.9601	0.9698	0.9902	0.9961
	η_d^{π}	0.9598	0.9895	0.9962	0.9972	0.9998	1
	$\eta_c^{\pi/2}$	0.9179	0.9596	0.9774	0.9915	0.9976	0.9992
	$\eta_d^{\pi/2}$	0.9844	0.9962	0.9986	0.9998	1	1
	$\eta_{c,l4}^{\pi}$	0.9987	0.9996	0.9998	0.9997	0.9999	1
	$\eta_{d,l4}^{\pi}$	0.9997	1	1	1	1	1
	$\eta_{c,l4}^{\pi/2}$	0.9998	0.9999	1	1	1	1
	$\eta_{d,l4}^{\pi/2}$	0.9997	1	1	1	1	1
	$\eta_{c,l12}^{\pi}$	0.9991	0.9998	1	1	1	1
	$\eta_{d,l12}^{\pi}$	1	1	1	1	1	1
	$\eta_{c,l12}^{\pi/2}$	0.9999	0.9999	1	1	1	1
	$\eta_{d,l12}^{\pi/2}$	0.9999	1	1	1	1	1

Note: See Table 1.

Table 3: Rejection frequencies of the seasonal KPSS test, case (iii)

		T=80			T=200		
		1%	5%	10%	1%	5%	10%
$\rho = 0$	η_c^{π}	1	1	1	1	1	1
	η_d^{π}	0.0112	0.0535	0.1103	0.0091	0.0501	0.1010
	$\eta_c^{\pi/2}$	0	0	0	0	0	0
	$\eta_d^{\pi/2}$	0.0081	0.0487	0.1044	0.0103	0.0523	0.1036
	$\eta_{c,l4}^{\pi}$	1	1	1	1	1	1
	$\eta_{d,l4}^{\pi}$	0.0197	0.0717	0.1291	0.0134	0.0598	0.1127
	$\eta_{c,l4}^{\pi/2}$	0.0217	0.0806	0.1443	0	0.0003	0.0016
	$\eta_{d,l4}^{\pi/2}$	0.0225	0.0778	0.1367	0.0171	0.0660	0.1219
	$\eta_{c,l12}^{\pi}$	1	1	1	1	1	1
	$\eta_{d,l12}^{\pi}$	0.0474	0.1214	0.1923	0.0243	0.0822	0.1414
	$\eta_{c,l12}^{\pi/2}$	0.0532	0.1392	0.2151	0.0020	0.0162	0.0396
	$\eta_{d,l12}^{\pi/2}$	0.0691	0.1578	0.2314	0.0357	0.1025	0.1684
$\rho = -1$	η_c^{π}	0.9103	0.9675	0.9836	0.9825	0.9960	0.9984
	η_d^{π}	0.9598	0.9895	0.9962	0.9972	0.9998	1
	$\eta_c^{\pi/2}$	0.7880	0.8765	0.9115	0.9767	0.9918	0.9956
	$\eta_d^{\pi/2}$	0.9844	0.9962	0.9986	0.9998	1	1
	$\eta_{c,l4}^{\pi}$	0.9990	0.9997	0.999	0.9999	1	1
	$\eta_{d,l4}^{\pi}$	0.9997	1	1	1	1	1
	$\eta_{c,l4}^{\pi/2}$	0.9992	0.9998	0.9999	0.9998	1	1
	$\eta_{d,l4}^{\pi/2}$	0.9997	1	1	1	1	1
	$\eta_{c,l12}^{\pi}$	0.9994	0.9999	0.9999	1	1	1
	$\eta_{d,l12}^{\pi}$	1	1	1	1	1	1
	$\eta_{c,l12}^{\pi/2}$	0.9994	0.9999	1	1	1	1
	$\eta_{d,l12}^{\pi/2}$	0.9999	1	1	1	1	1

Note: See Table 1.

Overall, our results confirm those of Demetrescu and Hassler (2007) for the standard KPSS test. Still, if we neglect the determinist seasonality, the seasonal KPSS test undergoes serious size distortions.

4 Conclusion

The belief that deterministic seasonality had nothing to do with testing for the long-run propreties of the data is invalid. Moreover, the fact of neglecting this type of seasonality can seriously affect stationarity tests. The seasonal extension ended with the same observations. This paper showed that neglecting deterministic seasonality using seasonal stationarity tests may lead us to the wrong conclusions. It is in this sense that these tests reject too often the null hypothesis. More specifically, when neglecting seasonal dummies, the seasonal KPSS test suffers large size distortions. However, if one takes into account the deterministic seasonal variable, the empirical test sizes closely approximate their theoretical levels.

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