Forecasting seasonal data and nonparametric unit-root tests

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Abstract

Nonparametric unit-root tests are a useful addendum to the toolbox of time-series analysis. They tend to trade off power for enhanced robustness features. We consider a variant of the RURS (seasonal range unit roots) test statistic, a variant of the level-crossings count adapted to classes of seasonal patterns, and a new combined test. These tests exploit two main characteristics of seasonal unit-root models, the range expansion typical of integrated processes and the low frequency of changes among main seasonal shapes.

In standard designs, usual parametric tests based on the HEGY (Hylleberg, Engle, Granger, Yoo 1990) dominate nonparametric rival tests in large samples. In small samples, however, surprising local power gains by range tests have been reported. It is of interest whether such power advantages transfer into enhanced predictive accuracy out of sample, particularly as decision rules based on HEHG tests have been shown to offer poor predictive performance.

This contribution explores the consequences of test-based decisions for predictions of seasonal time series. Apart from generating processes with seasonal unit roots and with deterministic seasonality, also processes with seasonal time-deformation are considered.

The nature of seasonal cycles in time series.

Seasonal cycles may be repetitive and well modeled by time-constant deterministic cycles. Changes of basic patterns remain episodic. They may also be rarely but persistently changing. Such behavior is often seen as well modeled via seasonal unit roots.

Nonparametric unit-root tests are a useful addendum to the toolbox for weak deformation (Granger 1980). With seasonal time deformation, none of the prediction models is correct. No seasonal unit-root process is the seasonal random walk (SRW) $x_t = x_{t-1} + \varepsilon_t$ with white-noise ($\varepsilon_t$) for quarterly data.

There exist hypothesis tests for discriminating between these two concepts. These tests have comparatively low power in samples of typical size. We consider two types of tests: parametric tests of the HEYG type and non-parametric tests as inspired by jittered seasonal phase plots.

In a first step, the intra-yearly seasonal patterns are classified into eight shape types. Deterministic seasonality should come to a return to the same class, unit roots present move to different classes.

In a second step, the movements in the classes are checked with nonparametric tests for weak deformation.

Results of the prediction experiments

Forecasts based on the component tests $\varphi_1$ do not perform much better than those based on $\varphi_2$ or on $\varphi_3$.

Most real-life data examples support determinitic seasonal features rather than seasonal unit roots. Dummy-based models tend to predict better than those based on seasonal differencing, even if hypothesis tests support unit roots, as for some economic variables.

Empirical applications

Summary and outlook

• Test power alone does not necessarily imply improved predictive accuracy for test-based selection of forecast models.

• Seasonal differences cannot be blindly recommended: forecast models with fixed seasonal dummies often deliver superior forecasts.

• In standard cases, the non-parametric test competes bravely with the parametric HEYG type tests. In some non-standard cases, the parametric tests reject more often, which then benefit forecasting.

• Testing at 10% is usually better than at 5%: note that the asymptotically forecast-optimizing AIC operates at even more liberal rates.

• Identical power does not necessarily imply improved predictive performance. What are the characteristics of trajectories from the same process that are classified differently by different tests?

• Forecasts based on the component tests $\varphi_1$, $\varphi_2$ do not perform much worse than those based on $\varphi_3$. The optimum weight for prediction may differ from the power-optimizing weight.

• Breaks, outliers, non-normal distributions are often used to advertise non-parametric testing. Does the forecast performance for these cases based on $\varphi_3$ reflect this? Does this help with some realistic variables?

References


Heathrow precipitation

Heathrow temperature

Unemployment rate

Airline Q4

UK GDP

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Empirical applications

variable

% better by

smoother

Airline Q4

79

UK GDP

58

Healthcare precipitation

52

Healthcare temperature

49

Industrial production

49

Unemployment rate

79
