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Multiscale inference and long-run variance estimation in non-parametric regression with time series errors. (English summary)

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This article is concerned with a testing problem for certain shape properties of a nonparametric time trend. For T observations of a univariate time series $\{Y_{t,T}\}_{t=1}^T$, the test is built on the nonparametric regression model

$$Y_{t,T} = m\left(\frac{t}{T}\right) + \varepsilon_t,$$

where $m: [0, 1] \rightarrow \mathbb{R}$ is an unknown nonparametric function, and $\{\varepsilon_t\}$ is a zero-mean stationary error process.

The null hypothesis for this test can be formulated as follows. Throughout it is assumed that m is continuously differentiable on $[0, 1]$. Also let $H_0(u, h)$ be the hypothesis that m is constant on the interval $[u - h, u + h]$ for some location u and bandwidth h . It follows that $H_0(u, h) : m'(w) = 0$ for all $w \in [u - h, u + h]$, where m' is the first-order derivative of m . The overall null hypothesis considered in this article is designed to test for constancy of m on many such intervals simultaneously. It is in the form of

$$H_0 : \text{the hypothesis } H_0(u, h) \text{ holds true for all } (u, h) \in \mathcal{G}_T,$$

where \mathcal{G}_T is some large set of points (u, h) that expands with the sample size T in general.

Accordingly, the test statistic for the overall null hypothesis H_0 is constructed from the one for $H_0(u, h)$. For the latter, the following rescaled local linear estimator of the derivative $m'(u)$ is considered:

$$\hat{\psi}_T(u, h) = \sum_{t=1}^T w_{t,T}(u, h) Y_{t,T},$$

where

$$w_{t,T}(u, h) = \frac{\Lambda_{t,T}(u, h)}{\sqrt{\sum_{t=1}^T \Lambda_{t,T}^2(u, h)}},$$

$$\Lambda_{t,T}(u, h) = K\left(\frac{t/T - u}{h}\right) \left\{ S_{T,0}(u, h) \left(\frac{t/T - u}{h}\right) - S_{T,1}(u, h) \right\},$$

$$S_{T,\ell}(u, h) = \frac{1}{Th} \sum_{t=1}^T K\left(\frac{t/T - u}{h}\right) \left(\frac{t/T - u}{h}\right)^\ell$$

for $\ell = 0, 1, 2$, and K is a nonnegative symmetric kernel function with support on $[-1, 1]$. The test statistic for $H_0(u, h)$ is then given by $\hat{\psi}_T(u, h)/\hat{\sigma}$, where $\hat{\sigma}^2$ is some consistent estimator of the long-run variance of $\sigma^2 = \sum_{j=-\infty}^{\infty} E(\varepsilon_t \varepsilon_{t-j})$ of the error process $\{\varepsilon_t\}$. In particular, instead of leaving the dependent structure of the process unspecified, this article assumes that it obeys the class of $\text{AR}(\infty)$ processes and proposes a difference-based long-run variance estimator.

In the end, the test statistic for H_0 is defined as

$$\widehat{\Psi}_T = \max_{(u,h) \in \mathcal{G}_T} \left\{ \left| \frac{\widehat{\psi}_T(u,h)}{\widehat{\sigma}} \right| - \lambda(h) \right\},$$

where $\lambda(h) = \sqrt{2 \log\{1/(2h)\}}$ is the additive correction term that is implied by the distribution of the maximum of standard normal random variables. Because the null distribution of this test statistic is non-standard, critical values should be computed by Monte Carlo simulation. Specifically, $q_T(\alpha)$, the critical value for a given level of significance $\alpha \in (0, 1)$, can be obtained as the $(1 - \alpha)$ -quantile of the empirical distribution of

$$\Phi_T = \max_{(u,h) \in \mathcal{G}_T} \left\{ \left| \frac{\phi_T(u,h)}{\sigma} \right| - \lambda(h) \right\},$$

where $\phi_T(u, h) = \sum_{t=1}^T w_{t,T}(u, h) \sigma Z_t$ for $\{Z_t\}_{t=1}^T \stackrel{iid}{\sim} N(0, 1)$. For such $q_T(\alpha)$, we reject the overall null hypothesis H_0 if $\widehat{\Psi}_T > q_T(\alpha)$. It is also demonstrated that the test has asymptotic power 1 against some local alternatives. *Masayuki Hirukawa*

References

1. Benner, T. C. (1999) Central England temperatures: long-term variability and teleconnections. *Int. J. Clim.*, **19**, 391–403.
2. Berkes, I., Liu, W. and Wu, W. B. (2014) Komlós-Major-Tusnády approximation under dependence. *Ann. Probab.*, **42**, 794–817. [MR3178474](#)
3. Chaudhuri, P. and Marron, J. S. (1999) SiZer for the exploration of structures in curves. *J. Am. Statist. Ass.*, **94**, 807–823. [MR1723347](#)
4. Chaudhuri, P. and Marron, J. S. (2000) Scale space view of curve estimation. *Ann. Statist.*, **28** 408–428. [MR1790003](#)
5. Chernozhukov, V., Chetverikov, D. and Kato, K. (2014) Gaussian approximation of suprema of empirical processes. *Ann. Statist.*, **42**, 1564–1597. [MR3262461](#)
6. Chernozhukov, V., Chetverikov, D. and Kato, K. (2015) Comparison and anti-concentration bounds for maxima of Gaussian random vectors. *Probab. Theory Reltd Flds*, **162**, 47–70. [MR3350040](#)
7. Chernozhukov, V., Chetverikov, D. and Kato, K. (2017) Central limit theorems and bootstrap in high dimensions. *Ann. Probab.*, **45**, 2309–2352. [MR3693963](#)
8. Cho, H. and Fryzlewicz, P. (2012) Multiscale and multilevel technique for consistent segmentation of nonstationary time series. *Statist. Sin.*, **22**, 207–229. [MR2933173](#)
9. Donoho, D. L., Johnstone, I. M., Kerkycharian, G. and Picard, D. (1995) Wavelet shrinkage: asymptopia (with discussion)? *J. R. Statist. Soc. B*, **57**, 301–369. [MR1323344](#)
10. Dümbgen, L. (2002) Application of local rank tests to nonparametric regression. *J. Nonparam. Statist.*, **14**, 511–537. [MR1929210](#)
11. Dümbgen, L. and Spokoiny, V. G. (2001) Multiscale testing of qualitative hypotheses. *Ann. Statist.*, **29**, 124–152. [MR1833961](#)
12. Dümbgen, L. and Walther, G. (2008) Multiscale inference about a density. *Ann. Statist.*, **36**, 1758–1785. [MR2435455](#)
13. Eckle, K., Bissantz, N. and Dette, H. (2017) Multiscale inference for multivariate deconvolution. *Electron. J. Statist.*, **11**, 4179–4219. [MR3716498](#)
14. Hall, P. and Heckman, N. E. (2000) Testing for monotonicity of a regression mean by calibrating for linear functions. *Ann. Statist.*, **28**, 20–39. [MR1762902](#)
15. Hall, P. and Van Keilegom, I. (2003) Using difference-based methods for inference in nonparametric regression with time series errors. *J. R. Statist. Soc. B*, **65**, 443–456.

[MR1983757](#)

16. Hannig, J. and Marron, J. S. (2006) Advanced distribution theory for SiZer. *J. Am. Statist. Ass.*, **101**, 484–499. [MR2256169](#)
17. Herrmann, E., Gasser, T. and Kneip, A. (1992) Choice of bandwidth for kernel regression when residuals are correlated. *Biometrika*, **79**, 783–795. [MR1209478](#)
18. Inselberg, A. (1985) The plane with parallel coordinates. *Visl Comput.*, **1**, 69–91. [MR2548611](#)
19. Morice, C. P., Kennedy, J. J., Rayner, N. A. and Jones, P. D. (2012) Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: the HadCRUT4 data set. *J. Geophys. Res.*, **117**.
20. Mudelsee, M. (2010) *Climate Time Series Analysis: Classical Statistical and Bootstrap Methods*. New York: Springer. [MR3307724](#)
21. Müller, H.-G. and Stadtmüller, U. (1988) Detecting dependencies in smooth regression models. *Biometrika*, **75**, 639–650. [MR0995108](#)
22. Park, C., Hannig, J. and Kang, K.-H. (2009) Improved SiZer for time series. *Statist. Sin.*, **19**, 1511–1530. [MR2589195](#)
23. Park, C., Marron, J. S. and Rondonotti, V. (2004) Dependent SiZer: goodness-of-fit tests for time series models. *J. Appl. Statist.*, **31**, 999–1017. [MR2100426](#)
24. Parker, D. E., Legg, T. P. and Folland, C. K. (1992) A new daily central England temperature series, 1772–1991. *Int. J. Clim.*, **12**, 317–342.
25. Proksch, K., Werner, F. and Munk, A. (2018) Multiscale scanning in inverse problems. *Ann. Statist.*, **46**, 3569–3602. [MR3852662](#)
26. Qiu, D., Shao, Q. and Yang, L. (2013) Efficient inference for autoregressive coefficients in the presence of trends. *J. Multiv. Anal.*, **114**, 40–53. [MR2993872](#)
27. Rahmstorf, S., Foster, G. and Cahill, N. (2017) Global temperature evolution: recent trends and some pitfalls. *Environ. Res. Lett.*, **12**, article 054001.
28. Rohde, A. (2008) Adaptive goodness-of-fit tests based on signed ranks. *Ann. Statist.*, **36**, 1346–1374. [MR2418660](#)
29. Rondonotti, V., Marron, J. S. and Park, C. (2007) SiZer for time series: a new approach to the analysis of trends. *Electron. J. Statist.*, **1**, 268–289. [MR2336034](#)
30. Rufibach, K. and Walther, G. (2010) The block criterion for multiscale inference about a density, with applications to other multiscale problems. *J. Computatn Graph. Statist.*, **19**, 175–190. [MR2654403](#)
31. Schmidt-Hieber, J., Munk, A. and Dümbgen, L. (2013) Multiscale methods for shape constraints in deconvolution: confidence statements for qualitative features. *Ann. Statist.*, **41**, 1299–1328. [MR3113812](#)
32. Shao, Q. and Yang, L. J. (2011) Autoregressive coefficient estimation in nonparametric analysis. *J. Time Ser. Anal.*, **32**, 587–597. [MR2846558](#)
33. Tecuapetla-Gómez, I. and Munk, A. (2017) Autocovariance estimation in regression with a discontinuous signal and m -dependent errors: a difference-based approach. *Scand. J. Statist.*, **44**, 346–368. [MR3658518](#)
34. Truong, Y. K. (1991) Nonparametric curve estimation with time series errors. *J. Statist. Planng Inf.*, **28**, 167–183. [MR1115816](#)
35. Von Sachs, R. and MacGibbon, B. (2000) Non-parametric curve estimation by Wavelet thresholding with locally stationary errors. *Scand. J. Statist.*, **27**, 475–499. [MR1795776](#)
36. Wu, W. B. (2005) Nonlinear system theory: another look at dependence. *Proc. Natn. Acad. Sci. USA*, **102**, 14150–14154. [MR2172215](#)
37. Wu, W. B. and Shao, X. (2004) Limit theorems for iterated random functions. *J. Appl. Probab.*, **41**, 425–436. [MR2052582](#)
38. Wu, W. B., Woodrooffe, M. and Mentz, G. (2001) Isotonic regression: another look

at the changepoint problem. *Biometrika*, **88**, 793–804. [MR1859410](#)

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