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**Kurusu, Daisuke** (J-TOKYTE-IEC); **Otsu, Taisuke** (4-LSE-EC)

**On linearization of nonparametric deconvolution estimators for repeated measurements model. (English summary)**

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This article is concerned with nonparametric density deconvolution estimation for the classical measurement error model. Let a scalar variable  $Y$  be generated by  $Y = X + \epsilon$ , where  $X$  is the error-free latent variable having an unknown density  $f_X$ ,  $\epsilon$  is the measurement error with a density  $f_\epsilon$  and  $E(\epsilon) = 0$ , and  $X$  and  $\epsilon$  are independent. Suppose that we are primarily interested in estimating  $f_X$  nonparametrically, given the noisy measurement  $Y$ . The deconvolution problem has been typically studied either under the assumption that the distribution of  $\epsilon$  is known or under the one that prior information about its shape is available (e.g., symmetry) even though the distribution is unknown.

In contrast, leaving both  $f_X$  and  $f_\epsilon$  unspecified, T. Li and Q. H. Vuong [*J. Multivariate Anal.* **65** (1998), no. 2, 139–165; MR1625869] demonstrated that these densities can be estimated nonparametrically via repeated measurements. For  $n$  pairs of i.i.d. noisy measurements  $\{(Y_{1j}, Y_{2j})\}_{j=1}^n = \{(X_j + \epsilon_{1j}, X_j + \epsilon_{2j})\}_{j=1}^n$ , define the empirical characteristic function of  $(Y_1, Y_2)$  and its derivative with respect to the first argument as

$$\begin{aligned}\widehat{\psi}(u_1, u_2) &= \frac{1}{n} \sum_{j=1}^n \exp\{i(u_1 Y_{1j} + u_2 Y_{2j})\} \quad \text{and} \\ \widehat{\psi}_1(u_1, u_2) &= \frac{\partial \widehat{\psi}(u_1, u_2)}{\partial u_1} = \frac{1}{n} \sum_{j=1}^n i Y_{1j} \exp\{i(u_1 Y_{1j} + u_2 Y_{2j})\},\end{aligned}$$

respectively, where  $i = \sqrt{-1}$ . Then, relying on I. I. Kotlarski's [*Pacific J. Math.* **20** (1967), 69–76; MR0203769] identity, Li and Vuong [op. cit.] proposed to estimate the characteristic functions of  $X$  and  $\epsilon$  as

$$\widehat{\varphi}_X(u) = \exp \int_0^u \frac{\widehat{\psi}_1(0, u_2)}{\widehat{\psi}(0, u_2)} du_2 \quad \text{and} \quad \widehat{\varphi}_\epsilon(u) = \frac{\widehat{\psi}(0, u)}{\widehat{\varphi}_X(u)},$$

respectively. Finally, two densities  $f_X$  and  $f_\epsilon$  can be estimated by

$$\widehat{f}_a(t) = \frac{1}{2\pi} \int_{\mathbb{R}} e^{-iut} \widehat{\varphi}_a(u) \widehat{\varphi}_K(hu) du$$

for  $a \in \{X, \epsilon\}$ , where  $\widehat{\varphi}_K(u) = \int_{\mathbb{R}} e^{iux} K(x) dx$  is the Fourier transform of a kernel function  $K$ , and  $h$  is the bandwidth.

In this article, it is demonstrated that  $\widehat{f}_X - f_X$  and  $\widehat{f}_\epsilon - f_\epsilon$  can be represented in an asymptotic linear form uniformly over a given compact interval. Four results are available, depending on whether the distributions of  $X$  and  $\epsilon$  may be ordinary smooth or supersmooth. These results are obtained via intermediate Gaussian approximations. An advantage of utilizing such approximations is faster uniform convergence rates of  $\widehat{f}_X$  and  $\widehat{f}_\epsilon$  than not only those derived by Li and Vuong [op. cit.] but also those obtained in yet another article by the authors [*Econometric Theory* **38** (2022), no. 1, 172–193, doi:10.1017/S0266466620000572] via maximal inequalities. On the other hand, approx-

imation errors in the sample counterparts of linearization terms have slow convergence rates. Therefore, the authors recommend using subsample-based bootstrap counterparts of the linearization terms to construct bootstrap confidence bands for  $\hat{f}_X$  and  $\hat{f}_\epsilon$ .

*Masayuki Hirukawa*

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### References

1. K. Adusumilli, D. Kurisu, T. Otsu, Y.-J. Whang, Inference on distribution functions under measurement error, *J. Econometrics* 215 (2020) 131–164. [MR4066070](#)
2. D.W. Andrews, Empirical process methods in econometrics, *Handb. Econometrics* 4 (1994) 2247–2294. [MR1315972](#)
3. N. Bissantz, L. Dümbgen, H. Holzmann, A. Munk, Non-parametric confidence bands in deconvolution density estimation, *J. R. Stat. Soc. Ser. B Stat. Methodol.* 69 (2007) 483–506. [MR2323764](#)
4. S. Bonhomme, J.-M. Robin, Generalized non-parametric deconvolution with an application to earnings dynamics, *Rev. Econom. Stud.* 77 (2) (2010) 491–533. [MR2650495](#)
5. V. Chernozhukov, D. Chetverikov, K. Kato, Gaussian approximation of suprema of empirical processes, *Ann. Statist.* 42 (4) (2014) 1564–1597. [MR3262461](#)
6. V. Chernozhukov, D. Chetverikov, K. Kato, Empirical and multiplier bootstraps for suprema of empirical processes of increasing complexity, and related Gaussian couplings, *Stochastic Process. Appl.* 126 (12) (2016) 3632–3651. [MR3565470](#)
7. F. Comte, J. Kappus, Density deconvolution from repeated measurements without symmetry assumption on the errors, *J. Multivariate Anal.* 140 (2015) 31–46. [MR3372551](#)
8. A. Delaigle, P. Hall, A. Meister, On deconvolution with repeated measurements, *Ann. Statist.* 36 (2) (2008) 665–685. [MR2396811](#)
9. K. Kato, Y. Sasaki, Uniform confidence bands in deconvolution with unknown error distribution, *J. Econometrics* 207 (1) (2018) 129–161. [MR3856764](#)
10. K. Kato, Y. Sasaki, Uniform confidence bands for nonparametric errors-in-variables regression, *J. Econometrics* 213 (2) (2019) 516–555. [MR4023921](#)
11. K. Kato, Y. Sasaki, T. Ura, Robust inference in deconvolution, *Quant. Econ.* 12 (1) (2021) 109–142. [MR4220375](#)
12. I. Kotlarski, On characterizing the gamma and the normal distribution, *Pacific J. Math.* 20 (1) (1967) 69–76. [MR0203769](#)
13. E. Krasnokutskaya, Identification and estimation of auction models with unobserved heterogeneity, *Rev. Econom. Stud.* 78 (1) (2011) 293–327. [MR2807728](#)
14. D. Kurisu, T. Otsu, On the uniform convergence of deconvolution estimators from repeated measurements, *Econom. Theory* (2021) 1–22. [MR4376499](#)
15. T. Li, I. Perrigne, Q. Vuong, Conditionally independent private information in OCS wildcat auctions, *J. Econometrics* 98 (1) (2000) 129–161. [MR1790650](#)
16. T. Li, Q. Vuong, Nonparametric estimation of the measurement error model using multiple indicators, *J. Multivariate Anal.* 65 (2) (1998) 139–165. [MR1625869](#)
17. T.L. McMurry, D.N. Politis, Nonparametric regression with infinite order flat-top kernels, *J. Nonparametr. Stat.* 16 (3–4) (2004) 549–562. [MR2073041](#)
18. A. Meister, *Deconvolution Problems in Nonparametric Statistics*, Springer, Berlin, 2009. [MR2768576](#)
19. M.H. Neumann, Deconvolution from panel data with unknown error distribution, *J. Multivariate Anal.* 98 (10) (2007) 1955–1968. [MR2396948](#)
20. A. Pakes, D. Pollard, Simulation and the asymptotics of optimization estimators, *Econometrica* (1989) 1027–1057. [MR1014540](#)

21. S.M. Schennach, Nonparametric regression in the presence of measurement error, *Econom. Theory* 20 (6) (2004) 1046–1093. [MR2101951](#)
22. A. van der Vaart, J. Wellner, *Weak Convergence and Empirical Processes: With Applications to Statistics*, Springer, New York, 1996. [MR1385671](#)

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