

A Nonparametric ANOVA-type Test for Regression Curves Based on Characteristic Functions

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Abstract

This article studies a new procedure to test for the equality of k regression curves in a fully nonparametric context. The test is based on the comparison of empirical estimators of the characteristic functions of the regression residuals in each population. The asymptotic behaviour of the test statistic is studied in detail. It is shown that under the null hypothesis the distribution of the test statistic converges to a finite combination of independent chi-squared random variables with one degree of freedom. The coefficients in this linear combination can be consistently estimated. The proposed test is able to detect contiguous alternatives converging to the null at the rate $n^{-1/2}$. The practical performance of the test based on the asymptotic null distribution is investigated by means of simulations.

Key Words: comparison of regression curves; empirical characteristic function; nonparametric regression, regression residuals.

Running title: An ANOVA-type test for regression curves

1 Introduction

Testing for the equality of the means of k populations ($k \geq 2$) is a classical problem in Statistics. When the populations are assumed to follow a normal distribution with equal variance, then the ANOVA F-test is the classical way to perform the test.

In this paper we consider a more general setting. We assume that in each population along with the response variable, Y , we observe another variable, X , the covariate, so that the mean and the variance of the response variable depend on the values of the covariate. More specifically, let (X_j, Y_j) , $1 \leq j \leq k$, be k independent random vectors satisfying general nonparametric regression models

$$Y_j = m_j(X_j) + \sigma_j(X_j)\varepsilon_j, \quad (1)$$

where $m_j(x) = E(Y_j | X_j = x)$ is the regression function, $\sigma_j^2(x) = Var(Y_j | X_j = x)$ is the conditional variance function and ε_j is the regression error, which is assumed to be independent of X_j . Note that, by construction, $E(\varepsilon_j) = 0$ and $Var(\varepsilon_j) = 1$. The covariate X_j is continuous with density function f_j . The regression functions, the variance functions, the distribution of the errors and the distribution of the covariates are unknown and no parametric models are assumed for them. Under this framework our approach is fully nonparametric.

In this conditional setting, the hypothesis of equality of means is stated in terms of the conditional means or regression functions

$$H_0 : m_1 = m_2 = \dots = m_k,$$

or, in other words, the mean effect of the covariates over the responses is equal in the k populations. Since the objective is to compare the regression curves, it is reasonable to assume that the covariates have common support. The alternative hypothesis is

$$H_1 : H_0 \text{ is not true.}$$

Note that this testing problem contains the simpler case described in the first paragraph as a particular case by only eliminating the covariates in the models.

The problem of testing for the equality of regression curves in nonparametric settings has been previously treated in the statistical literature. The majority of the available papers are either devoted to the comparison of only two curves or impose some restrictive assumptions like fixed design, equal sample sizes, identical design points or homoscedasticity of the residuals. Examples of such works include Delgado (1993), Kulasekera (1995), Munk & Dette (1998), Neumeyer & Pardo-Fernández (2009) and Srihera & Stute (2010), among many others. To the best of our knowledge, the most related works to ours are the papers of Neumeyer & Dette (2003) and of Pardo-Fernández *et al.* (2007). These papers proposed and studied a procedure to test the hypothesis of equality of k ($k \geq 2$) regression functions based on the comparison of marked empirical processes of the residuals for the former and the comparison of distribution functions of the residuals for the latter.

In this work, we investigate a new test procedure based on a weighted process generated by the characteristic functions of the residuals. Compared to the competitors, the main advantages of the proposed method are the following. First, the test is universally consistent for any fixed alternative without any restrictions on the weight function involved in the definition of the test statistic (except for the fact that it should be positive) and without any restrictions on the distribution of the regression errors. Thus, the method can be applied when the distributions of the errors are arbitrary: continuous, discrete or mixed. This is illustrated in the simulation study where an example with errors having a mixed distribution is given. Second, the test can be used to check the equality of any number of regression curves and can detect local alternatives converging to the null at the rate $n^{-1/2}$. Third, the critical values or the p -values can be obtained from the asymptotic null distribution of the proposed test statistic. This is not the case for most of the existing methods, which typically rely on bootstrap. In our case, although we study a bootstrap version of our test statistic in order to perform a comparison with other methods, the bootstrap is not needed because we are able to get the desired level and a good power even for moderate sample sizes by using the asymptotic null distribution. This is clearly shown for many scenarios considered in the simulation study.

Our approach is based on comparing the characteristic functions of the regression er-

rors. More specifically, let $\varepsilon_j = \{Y_j - m_j(X_j)\}/\sigma_j(X_j)$ be the regression error in population j . Let m_0 be the common regression curve under the null hypothesis, and define

$$\varepsilon_{0j} = \{Y_j - m_0(X_j)\}/\sigma_j(X_j) = \varepsilon_j + \{m_j(X_j) - m_0(X_j)\}/\sigma_j(X_j), \quad (2)$$

$1 \leq j \leq k$. It turns out that the null hypothesis H_0 is true if and only if, for all $1 \leq j \leq k$, the random variables ε_j and ε_{0j} have the same distribution (see Theorem 1 in Pardo-Fernández *et al.*, 2007). This assessment can be interpreted in terms of the cumulative distribution function (cdf) or in terms of any other function characterizing the probability law of the errors. Pardo-Fernández *et al.* (2007) restricted their attention to the cdf.

The probability law of any random variable X is also characterized by its characteristic function (cf), $\varphi(t) = E\{\exp(itX)\}$. Recent years have witnessed an increasing number of proposals for hypothesis testing whose test statistics measure deviations between the empirical characteristic function (ecf) of the available data and an estimator of the cf under the null hypothesis. In the line of the setting considered in this paper, that is, by assuming that the data are generated by regression models, are the papers by Jiménez-Gamero *et al.* (2005) and Hušková & Meintanis (2007, 2010), for testing goodness-of-fit for the errors, and Hušková & Meintanis (2009) for testing goodness-of-fit of the regression function to a parametric function. An advantage of the cf approach over the one based on the cdf, as observed in Hušková & Meintanis (2009), is that the former usually requires less stringent assumptions for its validity. In addition, from the simulation results that can be found in the literature (see, for example, Hušková & Meintanis, 2010) the tests based on the ecf compete very satisfactorily with those based on the empirical cdf (ecdf).

Having in mind the reasons above, the purpose of the present paper is to test H_0 by comparing consistent estimators of the cfs of the random variables ε_j and ε_{0j} , say $\hat{\varphi}_j(t)$ and $\hat{\varphi}_{0j}(t)$, respectively, $1 \leq j \leq k$. To measure deviations between these estimators, we consider a Cramér-von Mises type test statistic. In order to derive the asymptotic null distribution of the test statistic, we first give a stochastic expansion for the differences $\hat{\varphi}_j(t) - \hat{\varphi}_{0j}(t)$. As a consequence of this expansion, it is shown that the test statistic converges in law to a finite linear combination of independent chi-square variables. Moreover, under certain weak conditions on the distributions of the errors and the covariates,

the asymptotic null distribution is proportional to a χ_{k-1}^2 distribution. We provide consistent estimators of the coefficients appearing in this linear combination, which allow us to propose a consistent estimator of the asymptotic null distribution. The behaviour of the test under fixed and local alternatives is also studied. Specifically, it is shown that the proposed test is able to detect any fixed alternative and contiguous alternatives converging to the null at the rate $n^{-1/2}$, where n denotes the total sample size. In contrast to the procedure in Pardo-Fernández *et al.* (2007), to derive these properties we do not require further assumptions on the distribution on the errors, such as that they have a probability density. For finite sample, the quality of the proposed approximation of the null distribution of the test statistic as well as the power are investigated numerically. From this numerical study, we conclude that the proposed approximation of the null distribution works adequately for moderate sample sizes, and in terms of power the proposed test competes very satisfactorily with those based on the ecdf.

The paper is organized as follows. Section 2 introduces the test statistic and also provides an alternative expression, which is useful from a computational point of view. The asymptotic null distribution of the test statistic and the behaviour of the test under fixed and local alternatives are studied in Section 3. Section 4 reports a summary of a numerical study conducted to study the practical performance of the test and to compare it with other existing methods. Section 5 concludes the paper. All proofs of the theoretical results are deferred to the Supporting Information.

The following notation will be used along the paper: P_0 denotes probability assuming that H_0 is true; E_0 denotes expectation assuming that H_0 is true; P_* denotes the conditional probability law, given the data; all limits in this paper are taken when $n \rightarrow \infty$; $\xrightarrow{\mathcal{L}}$ denotes convergence in distribution; \xrightarrow{P} denotes convergence in probability; $\xrightarrow{a.s.}$ denotes the almost sure convergence; if $x \in \mathbb{R}^k$, with $x' = (x_1, \dots, x_k)$, then $diag(x)$ is the $k \times k$ diagonal matrix whose (i, i) entry is x_i , $1 \leq i \leq k$; for any complex number $z = a + ib$, $Re(z) = a$ is its real part, $\bar{z} = a - ib$ is its conjugate and $|z|$ is its modulus; $N_k(\mu, \Sigma)$ denotes the multivariate normal distribution with mean vector μ and variance-covariance matrix Σ ; an unspecified integral denotes integration over the whole real line \mathbb{R} ; for a given

non-negative real-valued function w and for any complex-valued measurable function g , we denote $\|g\|_w = (\int |g(t)|^2 w(t) dt)^{1/2}$ to the norm in the Hilbert space $L^2(\mathbb{R}, w)$.

2 The test statistic

Let (X_{jl}, Y_{jl}) , $1 \leq l \leq n_j$, be independent and identically distributed (iid) observations from (X_j, Y_j) , $1 \leq j \leq k$. Let $f_j(x)$ be the probability density function (pdf) of X_j , $n = \sum_{j=1}^k n_j$, and let $f_{mix}(x) = \sum_{j=1}^k p_j f_j(x)$ be the pdf of the mixture of covariates according to the weights p_1, \dots, p_k , where $p_j = \lim n_j/n$. In order to estimate the errors, we first need to estimate the regression functions, $m_j(x) = E(Y_j|X_j = x)$, the variance functions, $\sigma_j^2(x) = E\{[Y_j - m_j(x)]^2|X_j = x\}$, and the common regression function under H_0 , $m_0(x) = \sum_{j=1}^k p_j \{f_j(x)/f_{mix}(x)\} m_j(x)$. With this aim we use nonparametric estimators based on kernel smoothing techniques. Let K denote a nonnegative kernel function defined on \mathbb{R} , let $0 < h_n \equiv h \rightarrow 0$ be the bandwidth or smoothing parameter and $K_h(x) = h^{-1}K(x/h)$. We use the following estimators for the functions m_j , σ_j^2 and m_0 :

$$\hat{m}_j(x) = \sum_{l=1}^{n_j} w_{jl}(x) Y_{jl}, \quad \hat{\sigma}_j^2(x) = \sum_{l=1}^{n_j} w_{jl}(x) Y_{jl}^2 - \hat{m}_j^2(x), \quad \hat{m}_0(x) = \sum_{j=1}^k \frac{n_j}{n} \frac{\hat{f}_j(x)}{\hat{f}_{mix}(x)} \hat{m}_j(x),$$

where

$$\hat{f}_j(x) = n_j^{-1} \sum_{l=1}^{n_j} K_h(x - X_{jl}), \quad \hat{f}_{mix}(x) = \sum_{j=1}^k \frac{n_j}{n} \hat{f}_j(x),$$

$1 \leq j \leq k$. The quantities w_{jl} are, either the local-linear weights given by

$$w_{jl}(x) = \frac{K_h(X_{jl} - x) \{S_{2,n_j}(x) - (X_{jl} - x)S_{1,n_j}\}}{S_{0,n_j}(x)S_{2,n_j}(x) - S_{1,n_j}^2(x)},$$

with $S_{k,n_j}(x) = \sum_{l=1}^{n_j} (X_{jl} - x)^k K_h(X_{jl} - x)$, $k = 0, 1, 2$, or the Nadaraya-Watson weights

$$w_{jl}(x) = \frac{K_h(X_{jl} - x)}{\sum_{v=1}^{n_j} K_h(X_{jv} - x)},$$

Both are particular cases of local-polynomial weighting (see Fan & Gijbels, 1996). Under the model assumptions that will be stated in the next section, the results in this article are valid for local-linear and for Nadaraya-Watson (local-constant) estimators.

Based on these estimators, for each population j , $1 \leq j \leq k$, we construct two samples of residuals:

$$\hat{\varepsilon}_{jl} = \frac{Y_{jl} - \hat{m}_j(X_{jl})}{\hat{\sigma}_j(X_{jl})} \quad \text{and} \quad \hat{\varepsilon}_{0jl} = \frac{Y_{jl} - \hat{m}_0(X_{jl})}{\hat{\sigma}_j(X_{jl})},$$

$1 \leq l \leq n_j$, whose ecfs are

$$\hat{\varphi}_j(t) = \frac{1}{n_j} \sum_{l=1}^{n_j} \exp(it\hat{\varepsilon}_{jl}) \quad \text{and} \quad \hat{\varphi}_{0j}(t) = \frac{1}{n_j} \sum_{l=1}^{n_j} \exp(it\hat{\varepsilon}_{0jl}),$$

respectively. These ecfs are nothing but (consistent) kernel based nonparametric estimators of the population cfs $\varphi_j(t) = E\{\exp(it\varepsilon_j)\}$ and $\varphi_{0j}(t) = E\{\exp(it\varepsilon_{0j})\}$, respectively, where ε_{0j} is as defined in (2). The testing procedure consists of comparing $\hat{\varphi}_j(t)$ and $\hat{\varphi}_{0j}(t)$, $1 \leq j \leq k$, using a weighted L_2 -distance. More precisely, following the work of Hušková & Meintanis (2007, 2009, 2010) we define the test statistic

$$T_{1n} \equiv T_{1n}(w) = \sum_{j=1}^k \frac{n_j}{n} \|\hat{\varphi}_j(t) - \hat{\varphi}_{0j}(t)\|_w^2,$$

where w is any given non-negative weight function with finite integral, $\int w(t)dt < \infty$. The presence of the weight function w in the integrals appearing in the expression of T_{1n} is necessary in order to ensure their finiteness, since $\|\hat{\varphi}_j(t) - \hat{\varphi}_{0j}(t)\|_w^2 \leq 4 \int w(t)dt$, for all j .

The motivation behind the test statistic T_{1n} is the following: T_{1n} converges in probability to (see Theorem 7 below)

$$T_1 \equiv T_1(w) = \sum_{j=1}^k p_j \|\varphi_j(t) - \varphi_{0j}(t)\|_w^2. \quad (3)$$

Under H_0 , $\varphi_j(t) = \varphi_{0j}(t)$ for all t and for $1 \leq j \leq k$, and thus T_1 vanishes. As a consequence, under H_0 , T_{1n} should be “very small”. We then conclude that, any value of T_{1n} which is “significantly large” should lead to the rejection of H_0 . In practice, given a significance level, a threshold value above which H_0 is rejected needs to be established. To this end we need to study the null distribution of T_{1n} . Since this distribution is unknown, as an approximation to it we derive the asymptotic null distribution. This will be done in the next section.

Remark 1 From Lemma 1 in Alba-Fernández et al. (2008), an alternative expression for T_{1n} , which is useful from a computational point of view, is given by

$$nT_{1n} = \sum_{j=1}^k \frac{1}{n_j} \left\{ \sum_{l,s=1}^{n_j} I_w(\hat{\varepsilon}_{jl} - \hat{\varepsilon}_{js}) + \sum_{l,s=1}^{n_j} I_w(\hat{\varepsilon}_{0jl} - \hat{\varepsilon}_{0js}) - 2 \sum_{l,s=1}^{n_j} I_w(\hat{\varepsilon}_{jl} - \hat{\varepsilon}_{0js}) \right\},$$

where $I_w(t) = \int \cos(tx)w(x)dx$. If w is a pdf with cf φ_w then $I_w(t) = \text{Re}\{\varphi_w(t)\}$, which clearly coincides with φ_w when w is a symmetric pdf.

3 Asymptotics

In order to study the limit behaviour of the test statistic T_{1n} we first need to introduce some assumptions on the models (1) and on the available data. Recall that we are assuming that $\{(X_{jl}, Y_{jl}), 1 \leq l \leq n_j\}$ are iid observations from (X_j, Y_j) and the sets $\{(X_{1l}, Y_{1l}), 1 \leq l \leq n_1\}, \dots, \{(X_{jk}, Y_{jk}), 1 \leq l \leq n_k\}$ are independent.

Assumption (A):

(A.1) For $1 \leq j \leq k$: (i) X_j has a compact support R . (ii) f_j , m_j and σ_j are two times continuously differentiable on R . (iii) $\inf_{x \in R} f_j(x) > 0$ and $\inf_{x \in R} \sigma_j(x) > 0$.

(A.2) For $1 \leq j \leq k$: the samples sizes satisfy $\lim n_j/n = p_j$, where $0 < p_j < 1$.

(A.3) K is a twice continuously differentiable symmetric pdf with compact support.

(A.4) The weight function satisfies $w(t) \geq 0$, for all $t \in \mathbb{R}$, and $\int t^4 w(t) dt < \infty$.

(A.5) $nh_n^4 \rightarrow 0$ and $nh_n^2/\ln n \rightarrow \infty$.

These assumptions are mainly needed to guarantee the uniform consistency of the kernel estimators \hat{f}_j , $\hat{\sigma}_j$, \hat{m}_j and \hat{m}_0 . Unlike the methods based on the ecdf, observe that we do not impose any restriction on the distribution of the errors, like the existence of a pdf. So the results in this paper could be used to compare two or more regression functions when the distributions of the errors are arbitrary: continuous, discrete or mixed. An example with errors having a mixed distribution is given in Section 4.

3.1 Asymptotic null distribution

The following theorem gives an asymptotic approximation for $\sqrt{n_j}\{\varphi_j(t) - \varphi_{0j}(t)\}$, $1 \leq j \leq n_j$, that will allow us to derive the asymptotic null distribution of the test statistic T_{1n} , given in the subsequent corollary. Let $\Sigma = (\sigma_{jv})_{1 \leq j, v \leq k}$ be the matrix whose elements are

$$\begin{aligned}\sigma_{jj} &= 1 - 2p_j E \left\{ \frac{f_j(X_j)}{f_{mix}(X_j)} \right\} + p_j \sum_{r=1}^k p_r E \left\{ \frac{\sigma_r^2(X_r)}{\sigma_j^2(X_r)} \frac{f_j^2(X_r)}{f_{mix}^2(X_r)} \right\}, \\ \sigma_{jv} &= \sqrt{p_j p_v} \sum_{r=1}^k p_r E \left\{ \frac{\sigma_r^2(X_r)}{\sigma_j(X_r) \sigma_v(X_r)} \frac{f_j(X_r) f_v(X_r)}{f_{mix}^2(X_r)} \right\} \\ &\quad - \sqrt{p_j p_v} E \left\{ \frac{\sigma_v(X_v)}{\sigma_j(X_v)} \frac{f_j(X_v)}{f_{mix}(X_v)} + \frac{\sigma_j(X_j)}{\sigma_v(X_j)} \frac{f_v(X_j)}{f_{mix}(X_j)} \right\}, \quad j \neq v.\end{aligned}\tag{4}$$

Theorem 2 *Under assumptions (A.1)-(A.3) and (A.5), if H_0 is true, then*

$$\sqrt{n_j} \{ \hat{\varphi}_j(t) - \hat{\varphi}_{0j}(t) \} = it\varphi_j(t)Z_j + tR_{1j}(t) + t^2R_{2j}(t),$$

where $\sup_t |R_{sj}(t)| = o_p(1)$, $s = 1, 2$, and $Z := (Z_1, \dots, Z_k)' \sim N_k(0, \Sigma)$.

Define the diagonal matrix $\mathcal{A} = \text{diag}(a_1, \dots, a_k)$, where $a_j = \|t\varphi_j(t)\|_w^2$, $1 \leq j \leq k$. The results in the theorems and the corollaries below will hold whenever $\text{trace}(\mathcal{A}\Sigma) > 0$. Before stating the results, we briefly discuss this condition. Observe that

$$\text{trace}(\mathcal{A}\Sigma) = \sum_{j=1}^k a_j \sigma_{jj} > 0 \quad \text{if and only if } a_j > 0 \text{ and } \sigma_{jj} > 0 \text{ for some } j, 1 \leq j \leq k.$$

The quantities σ_{jj} in (4) can be also expressed as

$$\sigma_{jj} = p_j \sum_{l=1}^k p_l E \left[\frac{\sigma_l^2(X_l)}{\sigma_j^2(X_l)} \left\{ \frac{f_j(X_l)}{f_{mix}(X_l)} - \frac{I(l=j)}{p_l} \right\}^2 \right],$$

where $I(A)$ denotes the indicator function of the set A . From Assumptions (A.1)(iii) and (A.2) it follows that $\sigma_{jj} > 0$ for all j . Thus, to ensure $\text{trace}(\mathcal{A}\Sigma) > 0$ we only need to ensure that $a_j > 0$ for some j . An easy way to get $a_j > 0$ is by taking $w(t) > 0$, for t in a neighborhood of the origin.

The following assumption will appear in the statement of some of the results below.

Assumption (B): $a_j > 0$ for some $1 \leq j \leq k$.

Corollary 3 Under Assumptions (A) and (B), if H_0 is true, then $nT_{1n} \xrightarrow{\mathcal{L}} W_1 = Z'AZ$, where Z is as in Theorem 2.

In other words, the limiting distribution of nT_{1n} under H_0 is a finite linear combination of independent chi-square variables, $\sum_{j=1}^k \beta_j \chi_{1,j}^2$, where $\chi_{1,1}^2, \dots, \chi_{1,k}^2$ are independent chi-square random variates with one degree of freedom and β_1, \dots, β_k are the eigenvalues of $A\Sigma$. Unfortunately, the quantities β_j in this linear combination are unknown. They depend on the distribution of the errors through the a_1, \dots, a_k , and on the distribution of the covariates through $\Sigma = (\sigma_{jv})_{1 \leq j, v \leq k}$. They also depend on the unknown design densities, f_j , and the conditional variance functions, σ_j^2 . So to use Theorem 2 in practice, one first need to find a consistent estimator, say $\hat{\beta}_j$, for every β_j , $1 \leq j \leq k$. This can be easily done via plug-in method using the estimators defined above instead of the unknown functions φ_j , f_j , f_{mix} and σ_j^2 . In order to perform the test we also need to approximate the distribution of $\sum_{j=1}^k \hat{\beta}_j \chi_{1,j}^2$ which can be done via Monte Carlo method or some numerical method (see for example Kotz *et al.*, 1967, Castaño-Martínez & López-Blázquez, 2005). With such a distribution, we can finally get the critical value and/or the p -value for the test based on T_{1n} . The next result states the validity of this procedure.

To estimate a_j we replace $\varphi_j(t)$ by $\hat{\varphi}_j(t)$ in its expression obtaining,

$$\tilde{a}_j = \int t^2 |\hat{\varphi}_j(t)|^2 w(t) dt = \frac{1}{n_j^2} \sum_{r,s=1}^{n_j} \int t^2 \cos\{t(\hat{\varepsilon}_{jr} - \hat{\varepsilon}_{js})\} w(t) dt = \frac{n_j - 1}{n_j} \hat{a}_j + \frac{1}{n_j} \int t^2 w(t) dt,$$

where

$$\hat{a}_j = \frac{-1}{\binom{n_j}{2}} \sum_{1 \leq r < s \leq n_j} D_2 I_w(\hat{\varepsilon}_{jr} - \hat{\varepsilon}_{js}), \quad 1 \leq j \leq k, \quad (5)$$

$D_2 I_w(t) = \frac{\partial^2}{\partial t^2} I_w(t) = -\int t^2 \cos(tu) w(u) du$ and I_w is as defined in Remark 1. Since $\int t^2 w(t) dt$ is a constant term, we estimate a_j by \hat{a}_j , which resembles a U-statistic. Let $\hat{A} = \text{diag}(\hat{a}_1, \dots, \hat{a}_k)$ and $\hat{\Sigma} = (\hat{\sigma}_{jv})_{1 \leq j, v \leq k}$, with $\hat{\sigma}_{jj} = 1 - 2\hat{p}_j \hat{\mu}_j + \hat{p}_j \sum_{r=1}^k \hat{p}_r \hat{\mu}_{jrr}$,

$$\hat{\sigma}_{jv} = \sqrt{\hat{p}_j \hat{p}_v} \sum_{r=1}^k \hat{p}_r \hat{\mu}_{jvr} - \sqrt{\hat{p}_j \hat{p}_v} (\hat{\mu}_{jv} + \hat{\mu}_{vj}), \quad j \neq v,$$

$$\hat{p}_j = \frac{n_j}{n}, \quad \hat{\mu}_j = \frac{1}{n_j} \sum_{l=1}^{n_j} \frac{\hat{f}_j(X_{jl})}{\hat{f}_{mix}(X_{jl})}, \quad \hat{\mu}_{jv} = \frac{1}{n_v} \sum_{l=1}^{n_v} \frac{\hat{\sigma}_v(X_{vl})}{\hat{\sigma}_j(X_{vl})} \frac{\hat{f}_j(X_{vl})}{\hat{f}_{mix}(X_{vl})},$$

$$\hat{\mu}_{jvr} = \frac{1}{n_r} \sum_{l=1}^{n_r} \frac{\hat{\sigma}_r^2(X_{rl})}{\hat{\sigma}_j(X_{rl}) \hat{\sigma}_v(X_{rl})} \frac{\hat{f}_j(X_{rl}) \hat{f}_v(X_{rl})}{\hat{f}_{mix}^2(X_{rl})},$$

$$1 \leq j, v, r \leq k.$$

Let $W_{1n} = \sum_{j=1}^k \hat{\beta}_j \chi_{1j}^2$, where $\chi_{11}^2, \dots, \chi_{1k}^2$ are independent chi-square variables with one degree of freedom and $\hat{\beta}_1, \dots, \hat{\beta}_k$ are the eigenvalues of $\hat{A}\hat{\Sigma}$.

Theorem 4 *Under Assumptions (A) and (B),*

$$\sup_x |P_0\{nT_{1n} \leq x\} - P_*(W_{1n} \leq x)| \xrightarrow{P} 0.$$

Remark 5 *If all the covariates have the same distribution, $f_1 = \dots = f_k$, and all variance functions are equal, $\sigma_1 = \dots = \sigma_k$, then*

$$\Sigma = I_k - pp', \quad p' = (\sqrt{p_1}, \dots, \sqrt{p_k}). \quad (6)$$

In this case, it is easy to see that Σ has two different eigenvalues: 0, with multiplicity 1, and 1, with multiplicity $k - 1$. Therefore, if it is also assumed that the laws of the errors are such that $a = a_1 = \dots = a_k$ (for instance, if they also have the same distribution), then $a^{-1}nT_{1n}(w) \xrightarrow{\mathcal{L}} \sum_{j=1}^{k-1} \chi_{1j}^2 = \chi_{k-1}^2$, which coincides with the null distribution of the classical ANOVA test for comparing means. To get a consistent null distribution estimator of $nT_{1n}(w)$ in this case, it suffices to have a consistent estimator of a .

Corollary 6 *Suppose that Assumptions (A) and (B) hold. If all covariates have the same distribution, all variance functions are equal and the laws of the errors are such that $a = a_1 = \dots = a_k$, then*

$$\sup_x |P_0\{nT_{1n} \leq x\} - P_*(W_{01n} \leq x)| \xrightarrow{P} 0,$$

where $W_{01n} = \hat{a}\chi_{k-1}^2$, with $\hat{a} = \sum_{j=1}^k \hat{p}_j \hat{a}_j$, and \hat{a}_j is as defined by (5).

The result in Corollary 3 tells us that $nT_{1n} = O_P(1)$. As a decision rule for testing H_0 against H_1 we propose to use $\Psi_{1,\alpha} = I(nT_{1n} > t_{1,\alpha})$, where $t_{1,\alpha}$ is the $1 - \alpha$ percentile of the null distribution of nT_{1n} or any consistent estimator of it.

3.2 Consistency

In this section we study the test statistic T_{1n} when the alternative hypothesis is fixed. The following theorem shows that, with probability tending to 1, T_{1n} behaves (asymptotically) like T_1 , see (3). This will allow us to derive the consistency of the test $\Psi_{1,\alpha}$.

Theorem 7 *Suppose that Assumption (A) hold. Then, $T_{1n} = T_1 + o_p(1)$, where T_1 is as defined in (3).*

As an immediate consequence of the above theorem and Corollary 3, we conclude that the test $\Psi_{1,\alpha}$ is consistent against all fixed alternatives. This property is formally stated in the following corollary.

Corollary 8 *Suppose that Assumption (A) and the alternative hypothesis H_1 hold. If $w(t) > 0$, for all $t \in \mathbb{R}$, then $\lim_{n \rightarrow \infty} P(\Psi_{1,\alpha} = 1) = 1$, for any $0 < \alpha < 1$.*

It is known that two distinct characteristic functions can be equal in a finite interval (see, for example, Feller, 1971, p. 479). In order to ensure that $T_1 > 0$ whenever $m_r \neq m_s$, for some $1 \leq r, s \leq k$, $r \neq s$, we made the assumption that $w > 0$. It is important to note that this assumption does not involve any characteristic of the underlying data generating procedure. For instance, taking w to be the pdf of, for example, a normal law guarantees the universal consistency of our test. In opposition, some existing works made rather restrictive assumptions that exclude certain type of alternatives. For example, the test of Srihera & Stute (2010) may not be able to detect a difference between two crossing curves.

3.3 Local alternatives

In this section, we study the limiting behaviour of the test statistic under local alternatives converging to the null hypothesis at the rate $n^{-1/2}$. Specifically, let us consider the following local alternative hypothesis

$$H_{1,n} : m_j = m_{00} + n^{-1/2}r_j, \quad 1 \leq j \leq k,$$

where m_{00} is assumed to be two times continuously differentiable, and the functions r_j satisfy

$$E\{r_j^2(X_l)\} < \infty, \quad 1 \leq j, l \leq k. \quad (7)$$

Theorem 9 *Under Assumption (A) and the alternative hypothesis $H_{1,n}$, if (7) holds, then*

$$\sqrt{n_j} \{\hat{\varphi}_j(t) - \hat{\varphi}_{0j}(t)\} = it\varphi_j(t)(Z_j + \sqrt{p_j}\mu_j) + R_j(t),$$

where $\|R_j\|_w = o_p(1)$, $Z = (Z_1, \dots, Z_k)'$ is as in Theorem (2) and

$$\mu_j = \sum_{v=1}^k p_v E \left\{ \frac{f_v(X_j)r_v(X_j)}{f_{mix}(X_j)\sigma_j(X_j)} \right\} - E \left\{ \frac{r_j(X_j)}{\sigma_j(X_j)} \right\}, \quad 1 \leq j \leq k.$$

Corollary 10 *Under Assumption (A) and the alternative hypothesis $H_{1,n}$, if (7) holds, then $nT_{1n} \xrightarrow{\mathcal{L}} (Z + \mu)' \mathcal{A}(Z + \mu)$, where Z is as defined in Theorem 2 and $\mu' = (\sqrt{p_1}\mu_1, \dots, \sqrt{p_k}\mu_k)$.*

We conclude that, although the test based on the rule $\Psi_{1,\alpha}$ is fully nonparametric, it is able to detect local alternatives converging to the null hypothesis at the rate $n^{-1/2}$ whenever $\mu' \mathcal{A} \neq 0$.

3.4 A second test statistic

The paper by Pardo-Fernández *et al.* (2007) studies two Kolmogorov-Smirnov and two Cramér-von Mises type statistics for testing H_0 based on the ecdf of the residuals. Our

test statistic T_{1n} can be seen as the cf analogue of their first Cramér-von Mises type statistic. An ecf version of their second Cramér-von Mises type statistic is

$$T_{2n} = \|\hat{\varphi}(t) - \hat{\varphi}_0(t)\|_w^2,$$

where $\hat{\varphi}(t) = \sum_{j=1}^k \frac{n_j}{n} \hat{\varphi}_j(t)$ and $\hat{\varphi}_0(t) = \sum_{j=1}^k \frac{n_j}{n} \hat{\varphi}_{0j}(t)$, which are consistent estimators of $\varphi(t) = \sum_{j=1}^k p_j \varphi_j(t)$ and $\varphi_0(t) = \sum_{j=1}^k p_j \varphi_{0j}(t)$, respectively. The motivation of this statistic is that the equality of $\varphi(t)$ and $\varphi_0(t)$ also characterizes the null hypothesis.

The same steps followed in the analysis of T_{1n} can be used to study T_{2n} . In particular, T_{2n} can be computed as (see Remark 1)

$$n^2 T_{2n} = \sum_{j,v=1}^k \sum_{l=1}^{n_j} \sum_{s=1}^{n_v} \{I_w(\hat{\varepsilon}_{jl} - \hat{\varepsilon}_{vs}) + I_w(\hat{\varepsilon}_{0jl} - \hat{\varepsilon}_{0vs}) - 2I_w(\hat{\varepsilon}_{jl} - \hat{\varepsilon}_{0vs})\}.$$

The asymptotic null distribution of T_{2n} is given in the following result, which is analogous to Corollary 2.

Corollary 11 *Let $\mathcal{B} = \text{diag}(p)\mathcal{C}\text{diag}(p)$, where p is as defined in (6) and $\mathcal{C} = (c_{jv})_{1 \leq j,v \leq k}$ is the matrix with elements*

$$c_{jv} = \int t^2 \text{Re}\{\varphi_j(t)\overline{\varphi_v(t)}\}w(t)dt, \quad 1 \leq j, v, \leq k.$$

Under Assumption (A), if H_0 is true and $\text{trace}(\mathcal{B}\Sigma) > 0$, then $nT_{2n} \xrightarrow{\mathcal{L}} W_2 = Z'\mathcal{B}Z$, where Z is as in Theorem 2.

In contrast to the case of T_{1n} , there is no easy way of ensuring that $\text{trace}(\mathcal{B}\Sigma) > 0$. To see this fact, consider for example the case with $f_1 = \dots = f_k$ and $\sigma_1 = \dots = \sigma_k$. In this situation we saw that Σ has the expression (6); if in addition the errors are such that $c = c_{jv}$, $1 \leq j, v \leq k$, then $\text{trace}(\mathcal{B}\Sigma) = 0$, and thus the distribution of nT_{2n} is degenerate for any choice of the weight function w .

The asymptotic distribution of T_{2n} under H_0 depends on certain properties of the populations, which are typically unknown, and it can be summarized as

$$nT_{2n} = \begin{cases} O_p(1) & \text{if } \text{trace}(\mathcal{B}\Sigma) > 0, \\ o_p(1) & \text{if } \text{trace}(\mathcal{B}\Sigma) = 0. \end{cases}$$

In the first case ($\text{trace}(\mathcal{B}\Sigma) > 0$), the asymptotic null distribution of T_{2n} is analogous to the distribution of T_{1n} , that is, a combination of chi-square random variables multiplied by the eigenvalues of $\mathcal{B}\Sigma$, which can be estimated as in Theorem 4. In the second case ($\text{trace}(\mathcal{B}\Sigma) = 0$), a deeper analysis of the asymptotic distribution is required. However, from a practical point of view, this analysis is somehow useless since the practitioner would not know which one of the two situations apply for a given data set. Because of these reasons, we have focused on the test statistic T_{1n} .

4 Numerical results

In this section we report the results of an experiment carried out to study the practical behaviour of the proposed testing procedure by means of simulations. We investigate the approximation given in Theorem 4 and also the bootstrap approximation used in Pardo-Fernández *et al.* (2007) in order to compare their tests with ours. In all cases, the tables display the observed proportion of rejections in 1000 simulated data sets.

Firstly, in a two-population ($k = 2$) framework, the following regression models are considered:

(i) $m_1(x) = m_2(x) = 1$

(ii) $m_1(x) = m_2(x) = x$

(iii) $m_1(x) = m_2(x) = \sin(2\pi x)$

(iv) $m_1(x) = m_2(x) = \exp(x)$

(v) $m_1(x) = x, m_2(x) = 1 + x$

(vi) $m_1(x) = \exp(x), m_2(x) = \exp(x) + x$

(vii) $m_1(x) = \sin(2\pi x), m_2(x) = \sin(2\pi x) + x$

(viii) $m_1(x) = 1, m_2(x) = 1 + \sin(2\pi x)$

Models (i)-(iv) are under the null hypothesis, and models (v)-(viii) are under the alternative. For the scale functions, in each case we study a homoscedastic and a heteroscedastic scenario:

Homoscedastic models (S1): $\sigma_1(x) = 0.50$; $\sigma_2(x) = \sqrt{0.50}$.

Heteroscedastic models (S2): $\sigma_1(x) = \frac{7}{6}0.50x + \frac{1}{2}0.50$; $\sigma_2(x) = \frac{7}{8}\sqrt{0.50}x + \frac{1}{2}\sqrt{0.50}$.

The covariates X_1 and X_2 have distributions $Beta(1.5, 2)$ and $Beta(2, 1.5)$, respectively. This choice of the distributions of the covariates motivates the models of the scale functions in the heteroscedastic case, as they verify that $E[\sigma_1(X_1)] = 0.50$ and $E[\sigma_2(X_2)] = \sqrt{0.50}$, so the homoscedastic case and the heteroscedastic case are somehow comparable. If not mentioned otherwise, the regression errors ε_1 and ε_2 are $N(0, 1)$, although other distributions will also be considered in Section 4.3.

Nonparametric estimation of the regression functions is performed by the local-linear estimator. For the estimation of the variance functions, we prefer the local-constant estimator (Nadaraya-Watson), since the local-linear may produce negative values. In both cases the kernel function is the kernel of Epanechnikov $K(u) = 0.75(1-u^2)I(-1 < u < 1)$, which have some optimal properties. In the next section we will discuss the choice of the smoothing parameter.

4.1 The choice of the smoothing parameter

The choice of the smoothing parameter or bandwidth is certainly a delicate issue in any non-parametric procedure. For estimation purposes, it is well known that the bandwidth controls the trade-off between bias and variance of the estimator. In the context of testing, this problem has not been studied in detail yet. González-Manteiga & Crujeiras (2013) gave a very recent review about goodness-of-fit problems in nonparametric regression, including the comparison of regression curves. In the discussion of the paper, the authors say that the bandwidth selection for tests based on smoothing is a “really tough problem” and “it is far from being solved”. This conclusion was also raised by several discussants of

the paper (see, for example, the discussions of Sperlich (2013) and de Uña-Álvarez (2013) to the aforementioned article). We also share that opinion.

Although a detailed study on this topic is still missing, in the context of comparing regression curves several practical proposals have been made, sometimes explicitly, something implicitly. We will review here three of relatively recent and relevant papers on the topic: (a) In Neumeyer & Dette (2003) the proposed methodology allows for the use of the optimal bandwidth for estimation (of order $n^{-1/5}$) and bandwidths based on the classical rule of the thumb are employed. (b) In Pardo-Fernández *et al.* (2007), the theory does not allow for the use of the optimal bandwidth in estimation (which is also the case in the current piece of research), but some practical recommendations are suggested: first, when estimating the regression curves to be compared it is recommended to use a common bandwidth; second, in practical applications, the test can be performed for a reasonable range of bandwidths and the obtained p-values can be analysed. (c) In Sriheda & Stute (2010) nearest-neighbor estimators are used and the optimal smoothing parameters for estimation are also excluded by the theory; in simulations fixed values are used.

In a recent paper about testing for the distribution of the regression error, Heuchenne & Van Keilegom (2010) suggested several possibilities for the choice of the smoothing parameter based on cross-validation techniques. We have checked the practical performance of one of their proposal in our context (the one referred as method f, which is the one recommended by the authors). A summary of the obtained results is given in Table 1, which shows the approximation of the level of the test based on T_{1n} for models (i)-(iv) with sample sizes $n_1 = n_2 = 100$. The weight function, w , is the pdf of a standard normal (see the discussion about the role of the weight function in the next section). The critical values are obtained from the approximation of the asymptotic distribution given in Theorem 4. The level approximation is good for model (iv) but not correct for models (i) and (iii). Besides, we have observed that the proposed cross-validation procedure tends to pick very large bandwidths (often, the largest value in the allowed interval). Although the use of cross-validation bandwidths might be a reasonable choice in some cases, we are not sure that they offer a global solution to the problem since their practical performance

is not always satisfactory.

[Table 1 to be placed here]

In the simulations contained in the rest of this section, we essay to study the general behaviour of the proposed test and therefore we prefer to consider non-data dependent bandwidths. We take a bandwidth depending on the sample size of the form $h_n = Cn^a$. According to assumption (A.5), the allowed values for a are $-0.5 < a < -0.25$. We choose to take the exponent in the middle of the interval of allowed values, $a = -0.375$, and then several values of the constant C are taken into account.

4.2 The weight function

In the present section we discuss the role of the weight function w . For our test to be consistent, it is only needed a positive w satisfying $\int t^4 w(t) dt < \infty$. However, from the results in Section 3, it is clear that the choice of the weight function affects the power. In fact, from Corollary 10, the asymptotic power of the test $\Psi_{1,\alpha}$ is given by

$$P((Z + \mu)' \mathcal{A}(Z + \mu) > t_{1,\alpha}). \quad (8)$$

This probability depends on w through $\mathcal{A} = \text{diag}(a_1, \dots, a_k)$, where $a_j = \int t^2 |\varphi_j(t)|^2 w(t) dt$, $1 \leq j \leq k$. Clearly, the optimal weight (the one that maximizes the power) depends on the characteristic functions $\varphi_1, \dots, \varphi_k$ and on μ_1, \dots, μ_k . Because all these quantities are unknown and involve the unobservable residuals, formula (8) is of little help in practice.

An alternative approach is to use different weight functions w_1, \dots, w_k for the different populations. This leads to the following test statistic

$$\sum_{j=1}^k \frac{n_j}{n} \|\hat{\varphi}_j(t) - \hat{\varphi}_{0j}(t)\|_{w_j}^2.$$

By Theorem 2, this quantity has the same asymptotic properties as T_{1n} . In fact, one only needs to replace $a_j = \|t\varphi_j(t)\|_w^2$ by $\bar{a}_j = \|t\varphi_j(t)\|_{w_j}^2$ for the results given in Section 3 to continue to hold. Following the guidelines in Epps & Pulley (1983) (see also Epps, 2005, Jiménez-Gamero *et al.*, 2009, and Hušková & Meintanis, 2010), a reasonable choice

for $w_j(t)$ is $|\varphi_j(t)|^2$. This choice attempts to give high weight where the statistic $\hat{\varphi}_j(t)$ is a relatively precise estimator of $\varphi_j(t)$. The problem is that $\varphi_j(t)$ is unknown and needs to be estimated. Taking $w_j(t) \propto |\hat{\varphi}_j(t)|^2$ is not possible because $\int |\hat{\varphi}_j(t)|^2 dt = \infty$, since $\hat{\varphi}_j(t)$ is a periodic function. To overcome this difficulty we could consider a kernel smoothing estimator, but its application requires to assume rather strong assumptions on the distribution of the errors.

A more practical method avoiding the above difficulties is to use a parametric density function as a weight. The density function should put most of the weight near the origin, because the ecf estimates more accurately the population cf around $t = 0$. This approach is connected with the comparison of kernel density estimators as follows. Let S be a pdf symmetric around the origin and let w be such that $w^{1/2}(x) = (2\pi)^{-1/2} \int \exp(itx)S(t)dt$. Lemma 2.1 in Fan (1998) (see also Anderson *et al.*, 1994, Henze *et al.*, 2005, Hušková & Meintanis, 2012, and Meintanis, 2013) shows that

$$\int |\hat{\varphi}_j(t) - \hat{\varphi}_{0j}(t)|^2 w_j(t) dt = \int \left\{ \hat{f}_j(t) - \hat{f}_{0j}(t) \right\}^2 dt,$$

where

$$\hat{f}_j(t) = \frac{1}{n} \sum_{l=1}^{n_j} S(t - \hat{\varepsilon}_{jl}), \quad \hat{f}_{0j}(t) = \frac{1}{n} \sum_{l=1}^{n_j} S(t - \hat{\varepsilon}_{0jl}),$$

that is to say, for adequate choices of the weight function w_j , the quantity $\|\hat{\varphi}_j - \hat{\varphi}_{0j}\|_w^2$ coincides with the integral of the squared of the difference between kernel estimators of the pdf of the errors, both estimated with bandwidth $\eta = 1$. This bandwidth can be taken arbitrary by considering $S_\eta(x) = \eta^{-1}S(x/\eta)$ instead of $S = S_1$.

The above observation does not narrow down the spectrum of possibilities. So further criteria must taken into account. From a practical point of view, the ease of computation of T_{1n} (also T_{2n}) is closely related to the choice of w . This is specially appealing if instead of using the approximation given in Theorem 4, one wishes to employ a bootstrap approximation, which requires to evaluate the test statistic in a high number of artificial samples. In this sense, a good choice is $w(t) \propto \exp\{-t^2/2\sigma_w^2\}$, which is tantamount to estimate the pdf of the errors by using the normal kernel and bandwidth σ_w . Nevertheless, at this point we must say that the choice of σ_w cannot be guided by standard results on

kernel density estimation, because in such a case the asymptotic results in this paper are no longer true. A theoretical study of the optimal choice of σ_w in terms of Bahadur slopes can be found in Tenreiro (2009) for the problem of testing goodness-of-fit for the normal distribution. The results in the cited paper show that the optimal choice of σ_w depends on the alternative, which is unknown in practice. Because of this reason, we did not pursue this line. Neither too large, nor too small values of σ_w are appropriate because, proceeding as in Henze *et al.* (2005), we get

$$\lim_{\sigma_w \rightarrow 0} \sigma_w^{-2} T_{1n} = \sum_{j=1}^k \frac{n_j}{n} (\bar{\hat{\varepsilon}}_j - \bar{\hat{\varepsilon}}_{0j})^2, \quad (9)$$

with $\bar{\hat{\varepsilon}}_j = \frac{1}{n_j} \sum_{l=1}^{n_j} \hat{\varepsilon}_{jl}$, $\bar{\hat{\varepsilon}}_{0j} = \frac{1}{n_j} \sum_{l=1}^{n_j} \hat{\varepsilon}_{0jl}$, $1 \leq j \leq k$. The right-side of (9) estimates $\theta = \sum_{j=1}^k p_j \{E(\varepsilon_j) - E(\varepsilon_{0j})\}^2$. In certain situations θ might be zero, even when H_0 is not true and therefore the resulting test based on small σ_w would not be consistent against all fixed alternatives. A similar phenomenon occurs when $\sigma_w \rightarrow \infty$.

In the context of testing goodness-of-fit for the distribution of the errors in nonparametric regression models, the simulations in Hušková & Meintanis (2010) reveal that taking $\sigma_w = 1$ gives good results. We have also investigated numerically the effect of changing the parameter σ_w in models (iv) (level approximation) and (vi) (power) when the critical values are approximated from the asymptotic distribution of T_{1n} as explained in Theorem 4. Table 2 (which is just a part of a larger simulation study) summarizes the obtained results. It can be seen that the results are quite homogeneous with slightly better level with $\sigma_w = 1$, which is the value that we will consider in the rest of the simulations.

[Table 2 to be placed here]

4.3 Results of the test based on the asymptotic null distribution

In this section we present the results of the test based on the approximation of the asymptotic null distribution of T_{1n} as given in Theorem 4. Tables 3 (homoscedastic models; see supporting information) and 4 (heteroscedastic models; see supporting information) display the results for bandwidths of the form $h = Cn^{-0.375}$, with $C = 1, 1.5, 2$, which

provide reasonable values for the considered setups. The level –models (i)-(iv)– is slightly overestimated for small sample sizes, but the approximation improves as the sample sizes increase, reaching a good approximation for $(n_1, n_2) = (100, 100)$. The test also reaches good power, both in the homoscedastic case and in the heteroscedastic case.

We have also run simulations with error distributions different from the normal distribution. In particular, we have considered two cases: (a) errors with mixed distribution of the form

$$\varepsilon_j = \begin{cases} 0 & \text{with probability } 0.5 \\ N(0, \sqrt{2}) & \text{with probability } 0.5, \end{cases}$$

$j = 1, 2$, which in practice could model a case where the observations come from two devices, one of them with no measurement error; and (b) errors with a recentered Exponential distribution, i.e., $\varepsilon_j + 1 \sim Exponential(1)$, for $j = 1, 2$. Table 5 displays a brief summary of the obtained results for models (ii), (iv), (vi) and (viii) under heteroscedasticity and sample sizes $n_1 = n_2 = 100$. In the case of the mixed distribution, the approximation of the level is very good. In the case on the exponential distribution, we observe an overestimation of the level, probably cause by a bad approximation of the asymptotic null distribution due to the asymmetry of the error distribution (although not shown in the table, better approximations are achieved for larger sample sizes). Both cases show good power. The same kind of conclusions can be established for the rest of the models, which are not shown here.

[Table 3 to be placed here]

[Table 4 to be placed here]

[Table 5 to be placed here]

4.4 Results based on a bootstrap approximation

The aim of this subsection is to compare the power of the test proposed in this paper with those in Pardo-Fernández *et al.* (2007). To approximate the null distribution

of their test statistics, Pardo-Fernández *et al.* (2007) employed a bootstrap procedure based on smoothed residuals (see also Neumeyer, 2009, for a theoretical justification). Of course, the same bootstrap procedure could be used to approximate the null distribution of nT_{1n} . Nevertheless, from a computational point of view, the estimators in Theorem 4 and Corollary 6 are less time consuming. In order to establish a fair comparison, we have also estimated the null distribution of the test proposed in this paper by using the bootstrap algorithm defined in the above-mentioned paper. Besides, we have also incorporated here the test statistic T_{2n} , for which the asymptotic null distribution is difficult to approximate. Table 6 (see supporting information) shows the results of the tests based on T_{1n} and T_{2n} and the four tests proposed in Pardo-Fernández *et al.* (2007), which are denoted by T_{KS}^1 , T_{KS}^2 , T_{CM}^1 and T_{CM}^2 . For the sake of brevity of the presentation of the table, we restrict ourselves to the significance level $\alpha = 0.05$ and bandwidth with $C = 1$ (similar results have been obtained for other significance levels and other specifications of the bandwidth). In terms of level approximation, we can see that it is good for all test statistics, except for T_{KS}^2 . Compared to the asymptotic approximation, the bootstrap approximation improves the behaviour of the test statistic T_{1n} for small sample sizes. For models (v)-(vii), the highest power is achieved by the test based on the ecf, T_{1n} . For model (viii), the highest power is achieved by T_{2n} , which is also based on the ecf. Note that in this model T_{1n} reaches reasonable power and it is much better than its ecdf-based analog T_{CM}^1 . Summarizing, for the models considered, the test based on T_{1n} presents, as a whole, the best behaviour.

[Table 6 to be placed here]

4.5 The case of three populations

We have also investigated the test based on the estimated asymptotic null distribution of T_{1n} in the case of three populations ($k = 3$). Now the regression models are:

$$(ix) \quad m_1(x) = m_2(x) = m_3(x) = 1.$$

$$(x) \quad m_1(x) = m_2(x) = m_3(x) = x.$$

$$(xi) m_1(x) = x, m_2(x) = x + 0.2, m_3(x) = x + 0.4.$$

$$(xii) m_1(x) = x, m_2(x) = x, m_3(x) = x + 0.25.$$

$$(xiii) m_1(x) = 0.5, m_2(x) = x, m_3(x) = 1 - x.$$

$$(xiv) m_1(x) = 0, m_2(x) = \sin(2\pi x), m_3(x) = -\sin(2\pi x).$$

Models (ix)-(x) are under the null hypothesis, models (xi)-(xiv) are under the alternative. We only consider homoscedastic models with scale functions $\sigma_1(x) = \sqrt{0.25}$, $\sigma_2(x) = \sqrt{0.25}$ and $\sigma_3(x) = \sqrt{0.50}$. The covariates X_1 , X_2 and X_3 are $Beta(1.5, 2)$, $Beta(2, 1.5)$ and $Beta(2, 2)$, respectively, and all regression errors are $N(0, 1)$. As in the previous cases, a bandwidth of the form $h = Cn^{-0.375}$ is chosen, but now the $C = 2, 2.5, 3$ are displayed. Other choices for C were also tried, but better results were obtained for these values. The results are shown in Table 7 (see supporting information). As in Tables 3 and 4, the level is well approximated for large sample sizes and the behaviour in terms of power is correct.

[Table 7 to be placed here]

5 Conclusions

A test for the comparison of k regression functions has been proposed and studied under a totally nonparametric setting. The test statistic compares the ecf of the residuals in each population with the ecf of the residuals under the null hypothesis. For adequate choices of the weight function involved in the definition of the test statistic, the resulting test is consistent against any fixed alternative and is able to detect contiguous alternatives converging to the null at a rate $n^{-1/2}$. To derive these properties we have assumed certain assumptions, which are weaker than those required by those based on the ecdf. Specifically, no requirement is imposed on the distributions of the errors. An estimation of the asymptotic null distribution has been proposed as an estimator of the null distribution

of the test statistic. In the cases tried in our numerical experiments it is observed that this approximation works, in the sense of providing type I errors close to the nominal values, specially when the sample sizes are at least 100. For smaller sample sizes it is recommended to approximate the null distribution through a bootstrap mechanism.

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Supporting information

Additional information for this article is available online, including:

- Appendix: Proofs of the asymptotic results
- Table 3. Observed rejection proportions of the test based on the asymptotic distribution of T_{1n} under models (i)-(viii). The models are homoscedastic.
- Table 4. Observed rejection proportions of the test based on the asymptotic distribution of T_{1n} under models (i)-(viii). The models are heteroscedastic.
- Table 6. Observed rejection proportions of the tests based on the bootstrap approximation of T_{1n} and T_{2n} , T_{KS}^1 , T_{KS}^2 , T_{CM}^1 and T_{CM}^2 under models (i)-(viii). The

significance level is $\alpha = 0.05$ and the bandwidth is constructed with $C = 1.0$.

- Table 7. Observed rejection proportions of the tests based on the asymptotic distribution of T_{1n} under models (ix)-(xiv).

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Table 1: Empirical level of the test based on the asymptotic distribution of T_{1n} for homoscedastic and heteroscedastic models and smoothing parameters chosen by cross-validation with $n_1 = n_2 = 100$.

model	$\alpha :$	homoscedastic models			heteroscedastic models		
		0.100	0.050	0.010	0.100	0.050	0.010
(i)		0.154	0.064	0.018	0.148	0.062	0.012
(ii)		0.136	0.052	0.012	0.124	0.052	0.010
(iii)		0.152	0.088	0.016	0.152	0.086	0.012
(iv)		0.106	0.048	0.010	0.106	0.046	0.010

Table 2: Observed rejection proportions of the test based on the asymptotic distribution of T_{1n} for homoscedastic models (iv) and (vi) and for different choices of the parameter σ_w with $n_1 = n_2 = 100$.

model	σ_w	$\alpha :$	0.100			0.050			0.010		
			$C:$	1.0	1.5	2.0	1.0	1.5	2.0	1.0	1.5
(iv)	0.50		0.100	0.082	0.078	0.046	0.041	0.039	0.012	0.009	0.007
	0.75		0.111	0.090	0.083	0.049	0.043	0.039	0.012	0.009	0.008
	1.00		0.122	0.097	0.084	0.052	0.046	0.041	0.012	0.009	0.008
	1.25		0.133	0.100	0.086	0.056	0.047	0.042	0.012	0.010	0.008
	1.50		0.138	0.109	0.093	0.065	0.051	0.044	0.013	0.010	0.008
(vi)	0.50		1.000	1.000	1.000	1.000	1.000	1.000	0.996	0.997	0.996
	0.75		1.000	1.000	1.000	1.000	1.000	1.000	0.996	0.997	0.997
	1.00		1.000	1.000	1.000	1.000	1.000	1.000	0.996	0.997	0.997
	1.25		1.000	1.000	1.000	1.000	1.000	1.000	0.997	0.997	0.997
	1.50		1.000	1.000	1.000	1.000	1.000	1.000	0.999	0.997	0.997

Table 3: See the supplementary material available from the journal website.

Table 4: See the supplementary material available from the journal website.

Table 5: Observed rejection proportions of the test based on the asymptotic distribution of T_{1n} for different error distribution with $n_1 = n_2 = 100$. The models are for heteroscedastic.

error distribution	model	α :	0.100	0.100	0.100	0.050	0.050	0.050	0.010	0.010	0.010
		C :	1.0	1.5	2.0	1.0	1.5	2.0	1.0	1.5	2.0
mixed	(ii)		0.104	0.094	0.093	0.051	0.050	0.047	0.010	0.007	0.008
	(iv)		0.105	0.090	0.083	0.049	0.046	0.044	0.011	0.008	0.007
	(vi)		0.996	1.000	0.999	0.992	0.998	0.998	0.985	0.993	0.990
	(viii)		0.989	0.997	0.994	0.987	0.992	0.985	0.950	0.917	0.836
exponential	(ii)		0.149	0.125	0.115	0.076	0.063	0.055	0.015	0.014	0.010
	(iv)		0.146	0.115	0.105	0.077	0.061	0.046	0.015	0.012	0.008
	(vi)		0.997	0.999	0.999	0.997	0.999	0.998	0.992	0.990	0.988
	(viii)		0.998	1.000	0.995	0.995	0.990	0.981	0.948	0.904	0.812

Table 6: See the supplementary material available from the journal website.

Table 7: See the supplementary material available from the journal website.

Supplementary material for “A Nonparametric ANOVA-type Test for Regression Curves Based on Characteristic Functions”

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This supplementary material contains the proofs of the theoretical results of the article and some tables of Section 4.

Appendix: Proofs of the asymptotic results

We now sketch the proofs of the results stated in Section 3. With this aim, we first observe that under the considered assumptions, for $1 \leq j \leq k$,

$$\sup_t |\hat{m}_j(t) - m_j(t)| = o_p(n_j^{-1/4}),$$

$$\sup_t |\hat{\sigma}_j(t) - \sigma_j(t)| = o_p(n_j^{-1/4}),$$

$$\sup_t |\hat{f}_j(t) - f_j(t)| = o_p(n_j^{-1/4}).$$

Proof of Theorem 1 By Taylor’s Theorem,

$$\begin{aligned} \sqrt{n_j} \{ \hat{\varphi}_j(t) - \hat{\varphi}_{0j}(t) \} &= \sqrt{n_j} \left\{ \frac{1}{n_j} \sum_l \exp(it\hat{\varepsilon}_{jl}) - \frac{1}{n_j} \sum_l \exp(it\hat{\varepsilon}_{0jl}) \right\} \\ &= it \frac{1}{\sqrt{n_j}} \sum_l (\hat{\varepsilon}_{jl} - \hat{\varepsilon}_{0jl}) \exp(it\hat{\varepsilon}_{0jl}) + t^2 R_{1n_j}(t), \end{aligned}$$

where

$$\sup_t |R_{1n_j}(t)| \leq \sqrt{n_j} O_p(1) \{ \sup_t |\hat{m}_j(t) - \hat{m}_0(t)| \}^2 = o_p(1).$$

Again by Taylor's Theorem,

$$it \frac{1}{\sqrt{n_j}} \sum_l (\hat{\varepsilon}_{jl} - \hat{\varepsilon}_{0jl}) \exp(it\hat{\varepsilon}_{0jl}) = it \frac{1}{\sqrt{n_j}} \sum_l (\hat{\varepsilon}_{jl} - \hat{\varepsilon}_{0jl}) \exp(it\varepsilon_{jl}) + t^2 R_{2n_j}(t),$$

with

$$\begin{aligned} \sup_t |R_{2n_j}(t)| &\leq O_p(1) \sup_t |\hat{m}_j(t) - \hat{m}_0(t)| \left\{ \sqrt{n_j} \sup_t |m_0(t) - \hat{m}_0(t)| + \right. \\ &\quad \left. + \sup_t |\hat{\sigma}_j(t) - \sigma_j(t)| \frac{1}{\sqrt{n_j}} \sum_l |\varepsilon_{jl}| \right\} = o_p(1). \end{aligned}$$

From the definition of the residuals,

$$it \frac{1}{\sqrt{n_j}} \sum_l (\hat{\varepsilon}_{jl} - \hat{\varepsilon}_{0jl}) \exp(it\varepsilon_{jl}) = \hat{A}_j(t) + tR_{3n_j}(t),$$

where

$$\hat{A}_j(t) = it \frac{1}{\sqrt{n_j}} \sum_l \frac{\hat{m}_0(X_{jl}) - \hat{m}_j(X_{jl})}{\sigma_j(X_{jl})} \exp(it\varepsilon_{jl}), \quad (1)$$

and

$$\sup_t |R_{3n_j}(t)| \leq O_p(1) \sqrt{n_j} \sup_t |\hat{m}_j(t) - \hat{m}_0(t)| \sup_t |\hat{\sigma}_j(t) - \sigma_j(t)| = o_p(1).$$

Under H_0 ,

$$\hat{m}_0(x) - m_0(x) = \sum_{v=1}^k w_v(x) \{\hat{m}_v(x) - m_v(x)\} + o_p(n^{-1/2}),$$

uniformly in x , where $w_v(x) = (n_v/n) f_v(x) / f_{mix}(x)$. Therefore, $\hat{A}_j(t) = \hat{A}_{2j}(t) - \hat{A}_{1j}(t) + tR_{4n_j}(t)$, with $\sup_t |R_{4n_j}(t)| = o_p(1)$,

$$\hat{A}_{1j}(t) = \frac{it}{\sqrt{n_j}} \sum_{l=1}^{n_j} \frac{1}{\sigma_j(X_{jl})} \{\hat{m}_j(X_{jl}) - m_j(X_{jl})\} \exp(it\varepsilon_{jl}), \quad (2)$$

and

$$\hat{A}_{2j}(t) = \sum_{v=1}^k \frac{it}{\sqrt{n_j}} \sum_{l=1}^{n_j} \frac{w_v(X_{jl})}{\sigma_j(X_{jl})} \{\hat{m}_v(X_{jl}) - m_v(X_{jl})\} \exp(it\varepsilon_{jl}). \quad (3)$$

Standard arguments (see e.g. Masry, 1996) show that, under the assumed conditions,

$$\hat{m}_v(x) - m_v(x) = \frac{1}{n_v f_v(x)} \sum_{s=1}^{n_v} K_h(x - X_{vs}) \sigma_v(X_{vs}) \varepsilon_{vs} + o_p(n_v^{-1/2}),$$

uniformly in x . Thus,

$$\hat{A}_{2j}(t) = it \frac{1}{n \sqrt{n_j}} \sum_{v=1}^k n_j n_v U_{v,j}(t) + tR_{5n_j}(t),$$

where $\sup_t |R_{5n_j}(t)| = o_p(1)$ and

$$U_{v,j}(t) = \frac{1}{n_j n_v} \sum_{l=1}^{n_j} \sum_{s=1}^{n_v} S_n(X_{jl}, \varepsilon_{jl}; X_{vs}, \varepsilon_{vs}; t),$$

with

$$S_n(X_{jl}, \varepsilon_{jl}; X_{vs}, \varepsilon_{vs}; t) = \frac{\sigma_v(X_{vs})}{f_{mix}(X_{jl})\sigma_j(X_{jl})} K_h(X_{jl} - X_{vs}) \varepsilon_{vs} \exp(it\varepsilon_{jl}).$$

If $j \neq v$, then, for every t , $U_{v,j}(t)$ is a two sample U-statistic of degree (1, 1) with kernel $S_n(X_{jl}, \varepsilon_{jl}; X_{vs}, \varepsilon_{vs}; t)$. Its Hájek projection is given by

$$\hat{U}_{v,j}(t) = \varphi_j(t) \frac{1}{n_v} \sum_{s=1}^{n_v} \varepsilon_{vs} \sigma_v(X_{vs}) \tilde{h}_n(X_{vs}),$$

where $\tilde{h}_n(x) = E[K_h(X_j - x)/(f_{mix}(X_j)\sigma_j(X_j))]$. We have (see e.g. Theorem 11.1 and the proof of Theorem 12.6 in van der Vaart, 1998)

$$E[\{U_{v,j}(t) - \hat{U}_{v,j}(t)\}^2] = Var\{U_{v,j}(t)\} - Var\{\hat{U}_{v,j}(t)\} = \frac{1}{n_v n_j} E\{S_n^2(X_j, \varepsilon_j; X_v, \varepsilon_v; t)\}.$$

Because $E\{S_n^2(X_j, \varepsilon_j; X_v, \varepsilon_v; t)\} = O(1/h) = o(n)$, uniformly in t , we obtain $E[\{U_{v,j}(t) - \hat{U}_{v,j}(t)\}^2] = o(n^{-1})$, uniformly in t . This together with the fact that

$$\tilde{h}_n(x) = \frac{f_j(x)}{f_{mix}(x)\sigma_j(x)} + O(h^2),$$

uniformly in x , implies

$$U_{v,j}(t) = \varphi_j(t) \frac{1}{n_v} \sum_{s=1}^{n_v} \frac{f_j(X_{vs})\sigma_v(X_{vs})}{f_{mix}(X_{vs})\sigma_j(X_{vs})} \varepsilon_{vs} + R_{v,j}(t), \quad \text{with} \quad \sup_t |R_{v,j}(t)| = o_p(n^{-1/2}). \quad (4)$$

If $j = v$, then $U_{j,j}(t)$ can be written as

$$U_{j,j}(t) = \frac{K(0)}{n_j^2 h} \sum_{s=1}^{n_j} \frac{\varepsilon_{js} \exp(it\varepsilon_{js})}{f_{mix}(X_{js})} + \frac{n_j - 1}{2n_j} U_j(t),$$

where, for every t , $U_j(t)$ is a one sample U-statistic of degree 2 with kernel

$$S_n(X_{jl}, \varepsilon_{jl}; X_{js}, \varepsilon_{js}; t) + S_n(X_{js}, \varepsilon_{js}; X_{jl}, \varepsilon_{jl}; t).$$

Arguments very similar to those employed for the case $j \neq v$ can be used to show that $U_j(t) = 2\hat{U}_{j,j}(t) + R_j(t)$, with $\sup_t |R_j(t)| = o_p(n^{-1/2})$. Since

$$\sqrt{n} \frac{K(0)}{n_j^2 h} \left| \sum_{s=1}^{n_j} \frac{\varepsilon_{js} \exp(it\varepsilon_{js})}{f_{mix}(X_{js})} \right| \leq \frac{M}{\sqrt{nh^2}} \frac{1}{n_j} \sum_{l=1}^{n_j} |\varepsilon_{jl}| = o_p(1), \quad \text{for all } t,$$

for some constant $M > 0$, we get that $U_{j,j}(t)$ also satisfies (4) with $j = v$, and thus

$$\hat{A}_{2j}(t) = it \frac{p_j}{\sqrt{n_j}} \varphi_j(t) \sum_{v=1}^k \sum_{s=1}^{n_v} \frac{f_j(X_{vs})}{f_{mix}(X_{vs})} \frac{\sigma_v(X_{vs})}{\sigma_j(X_{vs})} \varepsilon_{vs} + tR_{2j}(t), \quad \text{with} \quad \sup_t |R_{2j}(t)| = o_p(1). \quad (5)$$

Similarly, it can be proved that

$$\hat{A}_{1j}(t) = it \frac{1}{\sqrt{n_j}} \varphi_j(t) \sum_{s=1}^{n_j} \varepsilon_{js} + tR_{1j}(t), \quad \text{with} \quad \sup_t |R_{1j}(t)| = o_p(1). \quad (6)$$

We conclude that, under H_0 ,

$$\sqrt{n_j} \{ \hat{\varphi}_j(t) - \hat{\varphi}_{0j}(t) \} = it \varphi_j(t) Z_{n,j} + tR_1(t) + t^2 R_2(t),$$

with $\sup_t |R_s(t)| = o_p(1)$, $s = 1, 2$, with

$$Z_{n,j} = \frac{\sqrt{p_j}}{\sqrt{n}} \sum_{v=1}^k \sum_{s=1}^{n_v} \frac{f_j(X_{vs})}{f_{mix}(X_{vs})} \frac{\sigma_v(X_{vs})}{\sigma_j(X_{vs})} \varepsilon_{vs} - \frac{1}{\sqrt{n_j}} \sum_{s=1}^{n_j} \varepsilon_{js}. \quad (7)$$

The result follows by applying the CLT to $Z_n = (Z_{n,1}, \dots, Z_{n,k})'$. \square

Proof of Corollary 1 From the definition of T_{1n} and the result in Theorem 2 we get, $nT_{1n} = \sum_{j=1}^k Z_j^2 \int t^2 |\varphi_j(t)|^2 w(t) dt + o_p(1) = Z^t \mathbf{A} Z + o_p(1) \xrightarrow{\mathcal{L}} W_1$. \square

Proof of Theorem 2 Since asymptotically, under H_0 , $T_{1n}(w)$ is a continuous function of the quantities a_j , p_j and σ_{rj}^2 , $1 \leq r, j \leq k$, to prove the result it suffices to prove the consistency of the estimators of these quantities. From assumption (A.2), $\hat{p}_j \rightarrow p_j$, $1 \leq j \leq k$. Next, to prove the consistency of \hat{a}_j we will consider the following equivalent expression

$$\hat{a}_j = \frac{n_j}{n_j - 1} \left\{ \int t^2 |\hat{\varphi}_j(t)|^2 w(t) dt \right\} - \frac{1}{n_j - 1} \int t^2 w(t) dt.$$

Observe that for $1 \leq j \leq k$ and $l = 1, \dots, n_j$,

$$\hat{\varepsilon}_{jl} - \varepsilon_{jl} = \left(\frac{\sigma_j(X_{jl})}{\hat{\sigma}_j(X_{jl})} - 1 \right) \varepsilon_{jl} - \frac{\hat{m}_j(X_{jl}) - m_j(X_{jl})}{\hat{\sigma}_j(X_{jl})}.$$

By Taylor's Theorem,

$$n_j^{-1} \sum_l \exp(it \hat{\varepsilon}_{jl}) = n_j^{-1} \sum_l \exp(it \varepsilon_{jl}) + tR_{1n_j}(t), \quad \text{with} \quad \sup_t |R_{1n_j}(t)| = o_p(1), \quad (8)$$

and thus,

$$\hat{a}_j = U_j + o_p(1), \quad 1 \leq j \leq k, \quad (9)$$

with

$$U_j = \frac{-1}{\binom{n_j}{2}} \sum_{1 \leq r < s \leq n_j} D_2 I_w(\varepsilon_{jr} - \varepsilon_{js}), \quad 1 \leq j \leq k,$$

which is a degree-2 U -statistic and therefore (see Serfling, 1980)

$$U_j = a_j + o_p(1), \quad 1 \leq j \leq k. \quad (10)$$

Now, from (9) and (10), we get $\hat{a}_j = a_j + o_p(1)$, $1 \leq j \leq k$.

From the assumed conditions and the SLLN, we get

$$\hat{\mu}_j = \frac{1}{n_j} \sum_{l=1}^{n_j} \frac{\hat{f}_j(X_{jl})}{\hat{f}_{mix}(X_{jl})} = \frac{1}{n_j} \sum_{l=1}^{n_j} \frac{f_j(X_{jl})}{f_{mix}(X_{jl})} + o_p(n^{-1/4}) = E \left\{ \frac{f_j(X_j)}{f_{mix}(X_j)} \right\} + o_p(1),$$

$1 \leq j \leq k$. The consistency of $\hat{\mu}_{jv}$ and $\hat{\mu}_{jvu}$ can be analogously dealt with, $1 \leq j, v, u \leq k$.
□

Proof of Corollary 2 The proof follows from the proof of Theorem 4, so we omit it. □

Proof of Theorem 3 Under the assumed conditions, (8) holds. Similarly,

$$\frac{1}{n_j} \sum_l \exp(it\hat{\varepsilon}_{0jl}) = \frac{1}{n_j} \sum_l \exp(it\varepsilon_{0jl}) + tR_{2n_j}(t),$$

with $\sup_t |R_{2n_j}(t)| = o_p(1)$, where $\varepsilon_{0jl} = \{Y_{jl} - m_0(X_{jl})\}/\sigma_j(X_{jl})$. Let $\tilde{\varphi}_j(t) = n_j^{-1} \sum_l \exp(it\varepsilon_{jl})$ and $\tilde{\varphi}_{0j}(t) = n_j^{-1} \sum_l \exp(it\varepsilon_{0jl})$. We conclude that

$$T_{1n} = \sum_{j=1}^k \frac{n_j}{n} \int |\tilde{\varphi}_j(t) - \tilde{\varphi}_{0j}(t)|^2 w(t) dt + o_p(1) = \sum_{j=1}^k \frac{n_j}{n} V_j + o_p(1),$$

where $V_j = \frac{1}{n_j^2} \sum_{r,s=1}^{n_j} \{I_w(\varepsilon_{jr} - \varepsilon_{js}) + I_w(\varepsilon_{0jr} - \varepsilon_{0js}) - 2I_w(\varepsilon_{jr} - \varepsilon_{0js})\}$, with I_w as defined in Remark 1. For $1 \leq j \leq k$, V_j is a V -statistic of degree 2 with a bounded kernel and thus (see Serfling, 1980) it converges to its expected value which is $\|\varphi_j(t) - \varphi_{0j}(t)\|_w^2$. This concludes the proof. □

Proof of Theorem 4 We first note that under $H_{1,n}$,

$$m_0 = m_{00} + \frac{1}{\sqrt{n}} r_0, \quad \text{with} \quad r_0(t) = \sum_{v=1}^k p_v \frac{f_v(t)}{f_{mix}(t)} r_v(t).$$

Thus from (10),

$$\frac{1}{\sqrt{n_j}} \sum_l \{m_j(X_{jl}) - m_0(X_{jl})\}^2 = \frac{1}{n\sqrt{n_j}} \sum_l \{r_j(X_{jl}) - r_0(X_{jl})\}^2 = O_P(n^{-1/2}), \quad 1 \leq j \leq k. \quad (11)$$

Now, taking into account (11) and following the same steps as those given in the proof of Theorem 2, we get

$$\sqrt{n_j} \{\hat{\varphi}_j(t) - \hat{\varphi}_{0j}(t)\} = \hat{A}_j(t) + tR_{1n_j}(t) + t^2R_{2n_j}(t),$$

with $\hat{A}_j(t)$ as defined in (1) and $\sup_t |R_{sn_j}(t)| = o_p(1)$, $s = 1, 2$. Under $H_{1,n}$,

$$\begin{aligned} \hat{m}_0(x) - m_0(x) &= \sum_{v=1}^k \frac{n_v}{n} \frac{f_v(x)}{f_{mix}(x)} \{\hat{m}_v(x) - m_v(x)\} + \\ &\quad \frac{1}{\sqrt{n}} \sum_{v=1}^k \left\{ \frac{n_v}{n} \frac{\hat{f}_v(x)}{\hat{f}_{mix}(x)} - p_v \frac{f_v(x)}{f_{mix}(x)} \right\} r_v(x) + o_p(n^{-1/2}), \end{aligned}$$

uniformly in x . Therefore, $\hat{A}_j(t) = \tilde{A}_{2j}(t) - \hat{A}_{1j}(t) + \hat{A}_{3j}(t) + tR_{3n_j}(t)$, with $\sup_t |R_{3n_j}(t)| = o_p(1)$, $\hat{A}_{1j}(t)$ as in (2) $\tilde{A}_{2j}(t) = \hat{A}_{2j}(t) + it\hat{A}_{22j}(t)$, $\hat{A}_{2j}(t)$ as in (3),

$$\begin{aligned} \hat{A}_{22j}(t) &= \frac{1}{\sqrt{nn_j}} \sum_{v=1}^k \sum_l \left\{ \frac{n_v}{n} \frac{\hat{f}_v(X_{jl})}{\hat{f}_{mix}(X_{jl})} - p_v \frac{f_v(X_{jl})}{f_{mix}(X_{jl})} \right\} r_v(X_{jl}) \exp(it\varepsilon_{jl}), \\ \hat{A}_{3j}(t) &= it \frac{1}{\sqrt{n_j}} \sum_l \frac{m_j(X_{jl}) - m_0(X_{jl})}{\sigma_j(X_{jl})} \exp(it\varepsilon_{jl}). \end{aligned}$$

From (10), $\sup_t |\hat{A}_{22j}(t)| = o_p(1)$. Now, by the SLLN in Hilbert spaces,

$$\hat{A}_{3j}(t) = it\varphi_j(t)\sqrt{p_j}\mu_j + R_{3j}(t),$$

with $\|R_{3j}(t)\|_w = o_p(1)$. Finally, taking into account (5) and (6), we conclude that under $H_{1,n}$

$$\sqrt{n_j} \{\hat{\varphi}_j(t) - \hat{\varphi}_{0j}(t)\} = it\varphi_j(t)(Z_{n,j} + \sqrt{p_j}\mu_j) + R_j(t), \quad \text{with } \|R_j(t)\|_w = o_p(1),$$

with $Z_{n,j}$ as defined in (7). The result follows from the CLT. \square

Proof of Corollary 5 Analogously to the proof of Corollary 3, from the definition of T_{2n} and the result in Theorem 2, we get

$$nT_{2n} = \int \left| \sum_{j=1}^k \sqrt{p_j} t \varphi_j(t) Z_j \right|^2 w(t) dt + o_p(1) =$$

$$\int \left\{ \sum_{j=1}^k \sqrt{p_j} t \varphi_j(t) Z_j \right\} \left\{ \sum_{v=1}^k \sqrt{p_v} t \overline{\varphi_v(t)} Z_v \right\} w(t) dt + o_p(1) =$$

$$\sum_{j,v=1}^k \sqrt{p_j p_v} Z_j Z_v \int t^2 \varphi_j(t) \overline{\varphi_v(t)} w(t) dt + o_p(1).$$

Note that the coefficient of $Z_j Z_v$ in the non-negligible term in the above expression is

$$\sqrt{p_j p_v} \left\{ \int t^2 \varphi_j(t) \overline{\varphi_v(t)} w(t) dt + \int t^2 \varphi_v(t) \overline{\varphi_j(t)} w(t) dt \right\} =$$

$$2\sqrt{p_j p_v} \operatorname{Re} \left\{ \int t^2 \varphi_j(t) \overline{\varphi_v(t)} w(t) dt \right\} = 2\sqrt{p_j p_v} \operatorname{Re} \left\{ \int t^2 \varphi_v(t) \overline{\varphi_j(t)} w(t) dt \right\}.$$

Thus,

$$nT_{2n} = Z^t \mathcal{B} Z + o_p(1) \xrightarrow{\mathcal{L}} W_2. \quad \square$$

References

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Table S1: Observed rejection proportions of the test based on the asymptotic distribution of T_{1n} under models (i)-(viii). The models are homoscedastic.

model	(n_1, n_2)	$\alpha:$	0.100	0.100	0.100	0.050	0.050	0.050	0.010	0.010	0.010
		$C:$	1.0	1.5	2.0	1.0	1.5	2.0	1.0	1.5	2.0
(i)	(50,50)		0.148	0.135	0.133	0.081	0.070	0.072	0.015	0.013	0.011
	(100,50)		0.143	0.118	0.114	0.069	0.058	0.058	0.014	0.010	0.012
	(100,100)		0.126	0.107	0.105	0.056	0.048	0.045	0.012	0.011	0.013
(ii)	(50,50)		0.146	0.132	0.126	0.078	0.069	0.061	0.012	0.012	0.009
	(100,50)		0.139	0.112	0.111	0.071	0.054	0.053	0.013	0.010	0.012
	(100,100)		0.124	0.104	0.095	0.053	0.047	0.044	0.012	0.011	0.010
(iii)	(50,50)		0.109	0.097	0.118	0.059	0.046	0.061	0.007	0.007	0.012
	(100,50)		0.111	0.078	0.089	0.054	0.034	0.040	0.007	0.004	0.007
	(100,100)		0.086	0.067	0.085	0.039	0.032	0.036	0.009	0.006	0.004
(iv)	(50,50)		0.140	0.123	0.111	0.074	0.064	0.049	0.013	0.012	0.008
	(100,50)		0.137	0.102	0.102	0.067	0.051	0.042	0.013	0.009	0.011
	(100,100)		0.122	0.097	0.084	0.052	0.046	0.041	0.012	0.009	0.008
(v)	(50,50)		0.999	1.000	1.000	0.999	1.000	1.000	0.999	1.000	1.000
	(100,50)		1.000	1.000	1.000	0.999	1.000	1.000	0.999	1.000	1.000
	(100,100)		1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
(vi)	(50,50)		0.974	0.976	0.970	0.953	0.949	0.936	0.839	0.831	0.803
	(100,50)		0.994	0.997	0.997	0.986	0.994	0.990	0.962	0.957	0.939
	(100,100)		1.000	1.000	1.000	1.000	1.000	1.000	0.996	0.997	0.997
(vii)	(50,50)		0.976	0.979	0.976	0.947	0.955	0.953	0.817	0.835	0.851
	(100,50)		0.993	0.998	0.998	0.987	0.995	0.992	0.957	0.953	0.955
	(100,100)		1.000	1.000	1.000	1.000	1.000	1.000	0.994	0.996	0.996
(viii)	(50,50)		0.838	0.688	0.567	0.659	0.484	0.367	0.318	0.179	0.117
	(100,50)		0.922	0.826	0.712	0.777	0.625	0.502	0.450	0.270	0.165
	(100,100)		0.982	0.953	0.907	0.937	0.859	0.767	0.705	0.519	0.368

Table S2: Observed rejection proportions of the test based on the asymptotic distribution of T_{1n} under models (i)-(viii). The models are heteroscedastic.

model	(n_1, n_2)	α :	0.100	0.100	0.100	0.050	0.050	0.050	0.010	0.010	0.010
		C :	1.0	1.5	2.0	1.0	1.5	2.0	1.0	1.5	2.0
(i)	(50,50)		0.147	0.127	0.122	0.075	0.072	0.065	0.014	0.010	0.009
	(100,50)		0.146	0.116	0.106	0.072	0.054	0.052	0.017	0.011	0.010
	(100,100)		0.129	0.104	0.097	0.060	0.048	0.046	0.012	0.010	0.009
(ii)	(50,50)		0.145	0.120	0.111	0.071	0.065	0.055	0.014	0.009	0.006
	(100,50)		0.142	0.110	0.102	0.070	0.052	0.048	0.017	0.009	0.010
	(100,100)		0.130	0.101	0.092	0.059	0.049	0.047	0.012	0.009	0.008
(iii)	(50,50)		0.099	0.089	0.122	0.055	0.045	0.056	0.006	0.005	0.013
	(100,50)		0.109	0.071	0.084	0.052	0.034	0.044	0.010	0.005	0.005
	(100,100)		0.091	0.068	0.081	0.038	0.029	0.034	0.009	0.006	0.005
(iv)	(50,50)		0.141	0.111	0.100	0.072	0.060	0.050	0.011	0.009	0.005
	(100,50)		0.140	0.104	0.090	0.067	0.049	0.040	0.015	0.008	0.008
	(100,100)		0.127	0.094	0.082	0.059	0.045	0.043	0.012	0.008	0.006
(v)	(50,50)		0.999	1.000	1.000	0.999	1.000	1.000	0.999	1.000	1.000
	(100,50)		0.999	1.000	1.000	0.998	1.000	1.000	0.998	1.000	1.000
	(100,100)		1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
(vi)	(50,50)		0.961	0.964	0.944	0.932	0.927	0.904	0.801	0.787	0.746
	(100,50)		0.992	0.997	0.994	0.984	0.985	0.980	0.945	0.926	0.904
	(100,100)		0.999	1.000	1.000	0.998	1.000	1.000	0.992	0.994	0.991
(vii)	(50,50)		0.965	0.966	0.964	0.931	0.928	0.938	0.771	0.788	0.807
	(100,50)		0.994	0.998	0.996	0.983	0.988	0.987	0.932	0.927	0.920
	(100,100)		1.000	1.000	1.000	0.999	1.000	1.000	0.992	0.992	0.991
(viii)	(50,50)		0.917	0.837	0.800	0.807	0.673	0.597	0.453	0.316	0.249
	(100,50)		0.939	0.902	0.828	0.884	0.758	0.665	0.583	0.405	0.291
	(100,100)		0.991	0.990	0.975	0.979	0.955	0.921	0.864	0.763	0.661

Table S3: Observed rejection proportions of the tests based on the bootstrap approximation of T_{1n} and T_{2n} , T_{KS}^1 , T_{KS}^2 , T_{CM}^1 and T_{CM}^2 under models (i)-(viii). The significance level is $\alpha = 0.05$ and the bandwidth is constructed with $C = 1.0$.

model	(n_1, n_2)	Homoscedastic models						Heteroscedastic models					
		T_{1n}	T_{2n}	T_{KS}^1	T_{KS}^2	T_{CM}^1	T_{CM}^2	T_{1n}	T_{2n}	T_{KS}^1	T_{KS}^2	T_{CM}^1	T_{CM}^2
(i)	(50,50)	0.051	0.043	0.046	0.024	0.052	0.041	0.047	0.047	0.043	0.021	0.048	0.041
	(100,50)	0.047	0.048	0.052	0.036	0.047	0.041	0.040	0.048	0.052	0.037	0.045	0.045
	(100,100)	0.042	0.043	0.041	0.033	0.038	0.037	0.042	0.042	0.041	0.027	0.041	0.040
(ii)	(50,50)	0.052	0.049	0.048	0.029	0.055	0.042	0.049	0.050	0.045	0.028	0.047	0.045
	(100,50)	0.046	0.045	0.052	0.037	0.048	0.042	0.042	0.048	0.030	0.046	0.046	0.046
	(100,100)	0.042	0.042	0.041	0.031	0.043	0.043	0.043	0.047	0.038	0.027	0.041	0.041
(iii)	(50,50)	0.057	0.051	0.052	0.042	0.059	0.049	0.057	0.059	0.045	0.040	0.055	0.054
	(100,50)	0.047	0.050	0.047	0.044	0.048	0.049	0.045	0.055	0.048	0.036	0.050	0.054
	(100,100)	0.042	0.049	0.033	0.031	0.043	0.046	0.042	0.047	0.034	0.033	0.035	0.044
(iv)	(50,50)	0.055	0.053	0.052	0.033	0.055	0.042	0.054	0.053	0.045	0.029	0.048	0.041
	(100,50)	0.047	0.046	0.052	0.037	0.045	0.050	0.043	0.049	0.049	0.032	0.048	0.046
	(100,100)	0.042	0.044	0.039	0.029	0.042	0.041	0.043	0.044	0.040	0.027	0.042	0.042
(v)	(50,50)	1.000	1.000	1.000	0.979	1.000	0.998	1.000	1.000	1.000	0.979	1.000	0.996
	(100,50)	1.000	1.000	1.000	0.995	1.000	1.000	1.000	1.000	1.000	0.995	1.000	1.000
	(100,100)	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
(vi)	(50,50)	0.937	0.784	0.895	0.438	0.924	0.678	0.912	0.639	0.868	0.348	0.911	0.548
	(100,50)	0.988	0.913	0.980	0.652	0.989	0.871	0.981	0.791	0.968	0.479	0.981	0.734
	(100,100)	1.000	0.986	0.999	0.843	1.000	0.969	0.999	0.935	0.998	0.685	0.999	0.892
(vii)	(50,50)	0.950	0.776	0.912	0.431	0.942	0.649	0.926	0.619	0.891	0.326	0.930	0.532
	(100,50)	0.991	0.916	0.986	0.640	0.992	0.872	0.985	0.813	0.975	0.500	0.987	0.739
	(100,100)	1.000	0.987	1.000	0.838	1.000	0.970	1.000	0.937	1.000	0.680	1.000	0.889
(viii)	(50,50)	0.584	0.936	0.188	0.586	0.164	0.822	0.726	0.963	0.324	0.692	0.299	0.891
	(100,50)	0.712	0.971	0.307	0.688	0.250	0.891	0.804	0.984	0.380	0.766	0.341	0.932
	(100,100)	0.898	1.000	0.418	0.935	0.386	0.992	0.957	1.000	0.688	0.962	0.648	0.998

Table S4: Observed rejection proportions of the tests based on the asymptotic distribution of T_{1n} under models (ix)-(xiv).

model	(n_1, n_2, n_3)	α :	0.100	0.100	0.100	0.050	0.050	0.050	0.010	0.010	0.010
		C :	2.00	2.50	3.00	2.00	2.50	3.00	2.00	2.50	3.00
(ix)	(50,50,50)		0.132	0.128	0.137	0.068	0.071	0.074	0.009	0.011	0.011
	(100,50,50)		0.128	0.126	0.124	0.078	0.075	0.071	0.012	0.014	0.013
	(100,100,50)		0.138	0.131	0.130	0.080	0.081	0.085	0.021	0.020	0.019
	(100,100,100)		0.122	0.124	0.121	0.057	0.057	0.061	0.013	0.011	0.010
(x)	(50,50,50)		0.125	0.114	0.112	0.062	0.059	0.062	0.008	0.008	0.007
	(100,50,50)		0.116	0.116	0.113	0.065	0.069	0.068	0.008	0.012	0.011
	(100,100,50)		0.127	0.123	0.121	0.076	0.072	0.070	0.018	0.017	0.016
	(100,100,100)		0.109	0.105	0.099	0.055	0.054	0.054	0.012	0.010	0.009
(xi)	(50,50,50)		0.909	0.899	0.899	0.839	0.830	0.815	0.620	0.608	0.588
	(100,50,50)		0.971	0.966	0.960	0.925	0.923	0.918	0.782	0.764	0.757
	(100,100,50)		0.975	0.970	0.968	0.952	0.949	0.946	0.837	0.832	0.818
	(100,100,100)		0.996	0.996	0.996	0.995	0.991	0.990	0.956	0.953	0.953
(xii)	(50,50,50)		0.657	0.635	0.622	0.528	0.507	0.496	0.269	0.249	0.244
	(100,50,50)		0.647	0.638	0.624	0.535	0.518	0.517	0.306	0.294	0.289
	(100,100,50)		0.694	0.676	0.669	0.590	0.568	0.558	0.350	0.329	0.322
	(100,100,100)		0.889	0.883	0.885	0.823	0.813	0.804	0.643	0.630	0.619
(xiii)	(50,50,50)		0.393	0.378	0.364	0.248	0.241	0.220	0.078	0.070	0.063
	(100,50,50)		0.416	0.390	0.374	0.264	0.252	0.238	0.087	0.081	0.069
	(100,100,50)		0.391	0.366	0.350	0.234	0.221	0.215	0.071	0.067	0.062
	(100,100,100)		0.552	0.534	0.511	0.374	0.353	0.355	0.153	0.140	0.130
(xiv)	(50,50,50)		1.000	1.000	0.999	1.000	0.999	0.997	0.996	0.986	0.972
	(100,50,50)		1.000	1.000	1.000	1.000	1.000	0.999	0.995	0.992	0.981
	(100,100,50)		1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	(100,100,100)		1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000