

Martingale Transforms Goodness-Of-Fit tests in Regression Models ^{1,2}

by

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Abstract

This paper discusses two goodness-of-fit testing problems. The first problem pertains to fitting an error distribution to an assumed non-linear parametric regression model while the second pertains to fitting a parametric regression model when the error distribution is unknown. For the first problem, the paper contains tests based on a certain martingale type transform of residual empirical processes. The advantage of this transform is that the corresponding tests are asymptotically distribution free. For the second problem, the proposed asymptotically distribution free tests are based on innovation martingale transforms. A Monte Carlo study shows that the simulated level of the proposed tests is close to the asymptotic level for moderate sample sizes.

1 Introduction

This paper is concerned with developing asymptotically distribution free tests for two testing problems. The first problem pertains to testing a goodness-of-fit hypothesis about the error distribution in a class of non-linear regression models. The second problem pertains to fitting a regression model in the presence of the unknown error distribution. The tests are obtained via certain martingale transforms of some residual empirical processes for the first problem and partial sum residual empirical processes for the second problem.

To be more precise, let Θ be an open subset of the q -dimensional Euclidean space and let $\{\mu(\cdot, \vartheta); \vartheta \in \Theta\}$ be a parametric family of functions from \mathbb{R}^p to \mathbb{R} . For a pair (X, Y) of a p -dimensional random vector X with distribution function (d.f.) H and one-dimensional random variable (r.v.) Y with finite expectation let

$$m(x) := E[Y|X = x], \quad x \in \mathbb{R}^p,$$

denote the regression function of Y on X . In the first problem of interest, one assumes m is a member of a parametric family $\{\mu(\cdot, \vartheta); \vartheta \in \Theta\}$ and one observes a sequence $\{(X_i, Y_i), 1 \leq i \leq n\}$ such that for some $\theta \in \Theta$, the errors

$$(1.1) \quad \varepsilon_i(\theta) = Y_i - \mu(X_i, \theta), \quad 1 \leq i \leq n,$$

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are independent, identically distributed (i.i.d.) r.v.'s with expected value 0. Let F be a specified distribution function (d.f.) with mean 0 and finite Fisher information for location, i.e, F is absolutely continuous with a.e. derivative f' satisfying

$$(1.2) \quad 0 < \int \left(\frac{f'}{f} \right)^2 dF < \infty.$$

The problem of interest is to test the hypothesis

$$H_0 : \text{the d.f. of } \varepsilon_1(\theta) \text{ is } F,$$

against a class of all sequences of local (contiguous) alternatives where the error d.f.'s A_n are such that for some $a \in L_2(\mathbb{R}, F)$,

$$(1.3) \quad \left(\frac{dA_n}{dF} \right)^{1/2} = 1 + \frac{1}{2\sqrt{n}}a + r_n, \quad \int a dF = 0, \quad n \int r_n^2 dF = o(1).$$

Occasionally, we will also insist that a satisfy orthogonality assumption

$$(1.4) \quad \int a \frac{f'}{f} dF = 0.$$

In the second problem one is again given independent observations $\{(X_i, Y_i), 1 \leq i \leq n\}$ such that $Y_i - m(X_i)$ are i.i.d. according to some distribution, not necessarily known, and one wishes to test the hypothesis

$$(1.5) \quad \tilde{H}_0 : m(\cdot) = \mu(\cdot, \theta), \text{ for some } \theta \in \Theta.$$

The alternative to \tilde{H}_0 of interest here consists of all those sequences of functions $m_n(x)$, which ‘‘locally’’ deviate from one of $\mu(x, \theta)$, that is, for some $\theta \in \Theta$ and for some function $\ell_\theta \in L_2(\mathbb{R}^p, H)$,

$$(1.6) \quad \ell_\theta \perp \dot{\mu}_\theta, \quad m_n(x) = \mu(x, \theta) + \frac{1}{\sqrt{n}}\ell_\theta(x) + r_{n\theta}(x), \quad n \int r_{n\theta}^2(x) dH(x) \rightarrow 0,$$

while the errors $Y_i - m_n(X_i)$ are still i.i.d. Here, $\dot{\mu}_\theta(x)$ is a vector of L_2 -derivatives of $\mu(x, \theta)$ with respect to θ , assumed to exist, see the assumption (2.4) below.

Both of these testing problems are historically almost as old as the subject of statistics itself. The tests based on various residual empirical processes for H_0 have been discussed in the literature repeatedly, cf. Durbin (1972), Durbin, Knott, and Taylor (1975), Loynes (1980), D’Agostino and Stephens (1986), Koul (1992, 2002), among others. Several authors have addressed the problem of regression model fitting, i.e, testing for \tilde{H}_0 : see, e.g., Cox, Koh, Wahba and Yandell (1988), Eubank and Hart (1992, 1993), Eubank and Spiegelman (1990), Härdle and Mammen (1993), Koul and Ni (2002), An and Cheng (1991), Stute (1997), Stute, González Manteiga and Presedo Quindimil (1998), Stute, Thies and Zhu

(1998), Stute and Zhu (2002), among others. The last five references propose tests based on a certain marked empirical or partial sum processes while the former cited references base tests on nonparametric regression estimators. See also the review paper of MacKinnon (1992) for tests based on the least square methodology and the monograph of Hart (1997) and references therein for numerous other tests of \tilde{H}_0 based on smoothing methods in the case $p = 1$.

However, it is well known that most of these tests are not asymptotically distribution free. This is true even for the chi-square type of tests with the exception of modified chi-square statistic studied in Nikulin (1973) in the context of empirical processes. It is also well documented in the literature that chi-square type tests often have relatively low power against many alternatives of interest, see e.g., Moore (1986). Hence a larger supply of asymptotically distribution free (ADF) goodness of fit tests with relatively good power functions is needed.

The aim of this paper is to propose a large class of such tests. These will be the tests based on statistics of a certain ADF modification and extension (see, e.g., (5.3) and (5.4) below) of the (weighted) empirical process of residuals

$$\widehat{W}_\gamma(x) := n^{-1/2} \sum_{i=1}^n \gamma(X_i) [\mathbb{I}\{Y_i - \mu(X_i, \hat{\theta}) \leq y\} - F(y)], \quad -\infty \leq y \leq \infty,$$

where γ is a square integrable function with respect to H . The ADF versions of the Cramér-von Mises and the Kolmogorov-Smirnov tests will be particular cases of such tests. Write \widehat{W}_1 for \widehat{W}_γ whenever $\gamma \equiv 1$ - see Sections 3.2 and 5 below.

As far as the problem of estimation of θ is concerned, certain weighted residual empirical processes play an indispensable role (cf. Koul 1992, 1996). A part of the objective of the present paper is to clarify the role of these processes with regards to the above goodness-of-fit testing problem.

To begin with, we shall discuss the basic structure of the first problem from a geometric perspective. This perspective was explored in the context of empirical processes in Khmaladze (1979). We shall show that under H_0 , the asymptotic distribution of \widehat{W}_γ , and its general function-parametric form $\xi_n(\gamma, \varphi; \hat{\vartheta})$ (see (2.2)), is equivalent to that of the projection of (function-parametric) Brownian motion parallel to the tensor product $\dot{\mu}_\theta \cdot (f'/f)$. Since a “projection” is typically “smaller” than the original process we can intuitively understand why, at least for alternatives (1.3), it will lead to the increase in the asymptotic power if we substitute an estimator $\hat{\theta}$ even in the problems where the true value of the parameter is known. The distribution of this projection depends not only on the family of regression functions $\{\mu(\cdot, \vartheta); \vartheta \in \Theta\}$ and F but also on the estimator $\hat{\theta}$. Therefore, the limit distribution of any fixed statistic based on \widehat{W}_γ or on $\xi_n(\gamma, \varphi; \hat{\vartheta})$ will be very much model-dependent. However, using this “projection” point of view, we shall show in Sec.3.2 that the tests based on \widehat{W}_γ corresponding to a certain non-constant γ may be useful, because they may have simpler asymptotic behaviour, but at the cost of some loss of the asymptotic power, and the

tests based on \widehat{W}_1 , in general, will have higher asymptotic power.

But, as mentioned above, the asymptotic null distribution of \widehat{W}_1 is model dependent. Proposed martingale transforms of $\widehat{W}_\gamma(F^{-1})$ will be shown to converge in distribution to a standard Brownian motion on $[0, 1]$ under H_0 , and hence tests based on these transforms will be ADF for testing H_0 . It will also be shown that, for any γ this transform is one-to-one and therefore there is no loss of the asymptotic power associated with it.

The paper also provides ADF tests for the problem of testing

$$H_\sigma : \text{the d.f. of } \varepsilon_1(\theta) \text{ is } F(y/\sigma), \forall y \in \mathbb{R}, \text{ for some } \sigma > 0.$$

In the univariate design case, ADF tests for \widetilde{H}_0 based on certain partial sum processes and using ideas of Khmaladze (1981) have been discussed by Stute, Thies and Zhu (1998). An extension of this methodology to the general case of a higher dimensional design is far from trivial. The second important goal of this paper is to provide this extension. Here too we first discuss this problem from a general geometric perspective. It turns out that the weighted partial sum processes that are natural to this problem are

$$\xi_n(B; \widehat{\theta}) := n^{-1/2} \sum \mathbb{I}\{X_i \in B\} \varphi(Y_i - \mu(X_i, \widehat{\theta})),$$

for a fixed real valued function φ with $E\varphi^2(\varepsilon)$ finite, where B is a Borel measurable set in \mathbb{R}^p . Tests based on these processes and the innovation martingale transform ideas of Khmaladze (1993) (see, e.g., (6.4)) are shown to be ADF, i.e., their asymptotic null distribution is free of the model $\mu(\cdot, \theta)$ and the error distribution, but depends on the design distribution in the case $p > 1$. These tests include those proposed in Stute et al. (1998) where $p = 1$, $\varphi(y) \equiv y$, $B = (-\infty, x]$, $x \in \mathbb{R}$.

We mention that recently Stute and Zhu (2002) used the innovation approach of Khmaladze (1981) to derive ADF tests in a special case of the higher dimension design where the design vector appears in the null parametric regression function only in a linear form, e.g., as in generalized linear models, and where the sets B in $\xi_n(B; \widehat{\theta})$ are taken to be half spaces. This again reduces the technical nature of the problem to the univariate case.

In another recent paper Koenker and Xiao (2002) studied tests based on the transformations of a different process – regression quantile process to test the hypothesis that the effect of the covariate vector X on the location and/or on the location-scale of the conditional quantiles of Y , given X , is linear in X . They then used the Khmaladze approach to make these tests ADF. Based on several Monte Carlo experiments, Koenker and Xiao (2001) report that their tests have accurate size and respectable power.

The paper is organised as follows. Section 2 introduces some basic processes that are used to construct tests of the above hypotheses. It also discusses some asymptotics under H_0 of these processes. Section 3 discusses some geometric implications of the asymptotics of Section 2 while Section 4 gives the martingale transforms of these processes whose asymptotic distribution under H_0 is known and free from F . Section 5 contains some computational

formulas of these transformed processes. It also provides analogues of these ADF tests for non-random designs and when the underlying observations form a stationary autoregressive process. Section 6 contains the ADF processes for testing \tilde{H}_0 . Section 7 contains some simulation results to show how well the asymptotic level approximates the finite sample level for the proposed ADF tests. It is observed that even for the samples size 40, this approximation is quite good for the chosen simulation study. See section 7 for details.

2 Function-parametric regression processes with estimated parameter

2.1 Function parametric regression process.

Consider a regression process as is defined in Stute (1997):

$$(2.1) \quad \xi_n(B, y, \vartheta) := n^{-1/2} \sum_{i=1}^n \mathbb{I}\{X_i \in B\} [\mathbb{I}\{\varepsilon_i(\vartheta) \leq y\} - F(y)], \quad -\infty \leq y \leq \infty, \vartheta \in \Theta,$$

where B is a Borel measurable set in the p -dimensional Borel space $(\mathbb{R}^p, \mathcal{B}(\mathbb{R}^p))$, and

$$\varepsilon_i(\vartheta) := Y_i - \mu(X_i, \vartheta), \quad 1 \leq i \leq n.$$

We will use also notation $\mathbb{I}_B(X_i)$ for the indicator function $\mathbb{I}\{X_i \in B\}$ interchangeably. It is natural to consider an extension of the above process where the indicator weights are replaced by some weight function $\gamma(X_i)$. The function γ may be a scalar or a vector valued. The weak convergence of such processes in the y variable and for a fixed γ has been developed in Koul (1992, 1996) and Koul and Ossiander (1994).

It is not any less natural to consider an extension of these weighted empiricals to those processes where the second indicator involving the error random variable $\varepsilon_i(\vartheta)$ in (2.1) is also replaced by a function. Consider, therefore, a function-parametric version of (2.1) indexed by a pair of functions (γ, φ) :

$$(2.2) \quad \begin{aligned} \xi_n(\gamma, \varphi; \vartheta) &:= \int_{\mathbb{R}^{p+1}} \gamma(x) \varphi(y) \xi_n(dx, dy; \vartheta) \\ &= n^{-1/2} \sum_{i=1}^n \gamma(X_i) \left[\varphi(\varepsilon_i(\vartheta)) - \int \varphi(y) dF(y) \right]. \end{aligned}$$

We shall choose $\gamma \in L_2(\mathbb{R}^p, H)$ and $\varphi \in L_2(\mathbb{R}, F)$. In this way one can say that ξ_n is defined for the function $\alpha(x, y) = \gamma(x) \varphi(y)$, which is an element of $\mathbb{L} := L_2(\mathbb{R}^{p+1}, H \times F)$. For a general $\alpha \in \mathbb{L}$, we certainly have

$$\begin{aligned} \xi_n(\alpha; \vartheta) &:= \int_{\mathbb{R}^{p+1}} \alpha(x, y) \xi_n(dx, dy; \vartheta) \\ &= n^{-1/2} \sum_{i=1}^n \left(\alpha(X_i, \varepsilon_i(\vartheta)) - E \left[\alpha(X_i, \varepsilon_i(\vartheta)) \middle| X_i \right] \right). \end{aligned}$$

We will realize, however, that it is sufficient and natural for our present purpose to restrict α to be of the above product type. In the sequel, for any functional \mathcal{S} on \mathbb{L} , we will use the notation $\mathcal{S}(\alpha)$ or $\mathcal{S}(\gamma, \varphi)$ interchangeably, whenever $\alpha = \gamma \cdot \varphi$.

The processes defined at (2.1) and (2.2) are obviously closely related: (2.1) represents a regression process as a random measure on \mathbb{R}^{p+1} while (2.2) represents it as an integral from this random measure. Also, (2.2) defines a linear functional on \mathbb{L} .

The function-parametric version (2.2) will help to visualise in a natural way the geometric picture of what is involved when we estimate parameters and show why and when we need “martingale transformations” (Sections 4 and 6) to obtain asymptotically distribution free tests.

2.2 Asymptotic increments of ξ_n with respect to parameter.

Since θ is unknown, in order to base tests of H_0 on the process ξ_n , we will need to replace it by an estimator $\widehat{\theta}$ in this process. This estimator will be typically assumed to be $n^{1/2}$ -consistent, i.e.,

$$(2.3) \quad \|\widehat{\theta} - \theta\| = O_p(n^{-1/2}).$$

There is thus a need to understand the behaviour of $\xi_n(\alpha; \theta + n^{-1/2}v)$ as a process in $v \in \mathbb{R}^q$, $\|v\| \leq k < \infty$. The first thing certainly is to consider the Taylor expansion of this function in v .

To do this assume the following L_2 -differentiability condition of the regression function $\mu(x, \vartheta)$ with respect to ϑ : there exists a $q \times 1$ vector $\dot{\mu}_\theta$ of functions from $\mathbb{R}^p \times \Theta$ to \mathbb{R}^q , such that

$$(2.4) \quad \begin{aligned} \mu(x, \vartheta) - \mu(x, \theta) &= \dot{\mu}_\theta^T(x)(\vartheta - \theta) + \rho_\mu(x; \vartheta, \theta), \\ 0 &< \int \dot{\mu}_\theta^T(x) \dot{\mu}_\theta(x) dH(x) < \infty, \\ C_\theta &:= \int \dot{\mu}_\theta(x) \dot{\mu}_\theta^T(x) dH(x) \text{ is positive definite,} \\ \int \sup_{\|\vartheta - \theta\| \leq \epsilon} \rho_\mu^2(x; \vartheta, \theta) dH(x) &= o(\epsilon^2), \quad \text{as } \epsilon \rightarrow 0. \end{aligned}$$

Here, and in the sequel, for any Euclidean vector v , v^T denotes its transpose.

Now, if additionally φ is differentiable with derivative $\varphi' \in L_2(\mathbb{R}, F)$ satisfying

$$(2.5) \quad \lim_{\epsilon \rightarrow 0} \int \sup_{0 < \Delta < \epsilon} |\varphi'(y - \Delta) - \varphi'(y)|^2 dF(y) = 0,$$

then, with $\alpha(x, y) \equiv \gamma(x)\varphi(y)$, we have the following proposition.

Proposition 2.1 *Under assumptions (2.4) and (2.5), the following holds for every $0 < k < \infty$.*

(i) *For any $\gamma \in L_2(\mathbb{R}^p, H)$*

$$\sup_{\|v\| \leq k} |\xi_n(\alpha; \theta + n^{-1/2}v) - \xi_n(\alpha; \theta) - E\gamma(X_i)\dot{\mu}_\theta^T(X) E\varphi'(\varepsilon) v| = o_p(1).$$

(ii) *For $\gamma = \eta \mathbb{I}_B$, $B \in \mathcal{B}(\mathbb{R}^p)$, and a fixed $\eta \in L_2(\mathbb{R}^p, H)$,*

$$\sup_{B \in \mathcal{B}, \|v\| \leq k} |\xi_n(\alpha; \theta + n^{-1/2}v) - \xi_n(\alpha; \theta) - n^{-1} \sum_{i=1}^n \eta_i \mathbb{I}_B(X_i) \dot{\mu}_\theta^T(X_i) \varphi'(\varepsilon_i) v| = o_p(1).$$

Hence, under (2.3), one obtains

$$(2.6) \quad \xi_n(\alpha; \hat{\theta}) = \xi_n(\alpha; \theta) - n^{-1} \sum_{i=1}^n \eta_i \mathbb{I}_B(X_i) \dot{\mu}_\theta^T(X_i) \varphi'(\varepsilon_i) n^{1/2}(\hat{\theta} - \theta) + \rho_n(B),$$

where $\rho_n(B)$ is sequence of stochastic processes indexed by $B \in \mathcal{B}$, tending to zero, uniformly in $B \in \mathcal{B}$, in probability.

The representation in (i) or in (2.6) will be very convenient and appropriate when dealing with the fitting of a regression model in Section 6. But for testing H_0 pertaining to the error distribution, as we will see in the next section, the differentiability of φ is restrictive. We may wish, for example, to choose φ to be an indicator function as in (2.1). Thus it is desirable to obtain an analog of the above proposition for as general a φ as possible.

Towards this goal, let Φ denote the linear span of a class of nondecreasing real valued functions $\varphi(y)$, $y \in \mathbb{R}$, such that

$$(2.7) \quad \int \varphi^2(y) dF(y) < \infty, \\ \left(\int [\varphi(y-t) - \varphi(y-s)]^2 dF(y) \right)^{1/2} \leq \nu(|t-s|), \quad -\epsilon \leq s, t \leq \epsilon,$$

for some $\epsilon > 0$ and for some continuous function ν from $[0, \infty)$ to $[0, \infty)$, with $\nu(0) = 0$, $\int_0^\epsilon \log \nu^{-1}(t) dt < \infty$. This is a wide class of functions and will be a source of our φ in what follows.

For any two functions $\alpha, \beta \in \mathbb{L}$, let

$$\langle \alpha, \beta \rangle := \int_{\mathbb{R}^{p+1}} \alpha(x, y) \beta(x, y) dH(x) dF(y).$$

Note that if α or both α, β are vector functions, then $\langle \alpha, \beta \rangle$ or $\langle \alpha, \beta^T \rangle$ is a vector or a matrix of coordinate-wise inner products. Let $\|\alpha\| := \langle \alpha^T, \alpha \rangle^{1/2}$, for a vector function α . Finally, let

$$\psi_f(y) := \frac{f'(y)}{f(y)}, \quad m_\theta(x, y) := \dot{\mu}_\theta(x) \psi_f(y), \quad x \in \mathbb{R}^p, y \in \mathbb{R}.$$

Note that

$$\langle \dot{\mu}_\theta, \dot{\mu}_\theta^T \rangle = C_\theta, \quad \langle m_\theta, m_\theta^T \rangle = C_\theta \|\psi_f\|^2.$$

We are ready to state

Proposition 2.2 *Suppose that (1.2) and (2.4) hold. Then for $\alpha(x, y) = \gamma(x)\varphi(y)$ with $\gamma \in L_2(\mathbb{R}^p, H)$, $\varphi \in \Phi$,*

$$(2.8) \quad \xi_n(\alpha; \widehat{\theta}) = \xi_n(\alpha; \theta) + \langle \alpha, m_\theta^T \rangle \cdot n^{1/2}(\widehat{\theta} - \theta) + o_p(1).$$

To appreciate some implications of (2.8) we need to consider those estimators of θ that admit an asymptotic linear representation. For the purpose of the present paper it would be enough to assume this. However, for completeness of the presentation we give a relatively broad set of sufficient conditions under which a class of M-estimators is asymptotically linear. Let $\{\eta_\vartheta, \vartheta \in \Theta\}$ be a family of q -dimensional functions on \mathbb{R}^p with coordinates in $L_2(\mathbb{R}^p, H)$. Let $\beta_\vartheta := \eta_\vartheta \cdot \varphi$, $\varphi \in \Phi$. Define an M-estimator $\widetilde{\theta}$ to be a solution of the equation

$$(2.9) \quad \xi_n(\beta_\vartheta; \vartheta) = 0.$$

The following proposition gives a set of sufficient conditions for this estimator to be asymptotically linear.

Proposition 2.3 *Suppose that (1.2) and (2.4) hold. In addition, suppose $\varphi \in \Phi$ and $\{\eta_\vartheta, \vartheta \in \Theta\}$ are such that*

$$(2.10) \quad \int_{\mathbb{R}^p} \sup_{\|\vartheta - \theta\| < \epsilon} \|\eta_\vartheta - \eta_\theta\|^2 dH = o(1), \quad \text{as } \epsilon \longrightarrow 0,$$

and the matrix $\langle \beta_\theta, m_\theta^T \rangle$ is nonsingular. Then, $\widetilde{\theta}$ defined at (2.9) satisfies

$$(2.11) \quad n^{1/2}(\widetilde{\theta} - \theta) = -\langle \beta_\theta, m_\theta^T \rangle^{-1} \xi_n(\beta_\theta; \theta) + o_p(1).$$

In particular, if $\{\mu_\vartheta; \vartheta \in \Theta\}$ satisfies (2.10), then the solution $\widehat{\theta}$ of the likelihood equation

$$(2.12) \quad \xi_n(m_\vartheta; \vartheta) = 0,$$

has the asymptotic linear representation

$$(2.13) \quad n^{1/2}(\widehat{\theta} - \theta) = -\langle m_\theta, m_\theta^T \rangle^{-1} \xi_n(m_\theta; \theta) + o_p(1).$$

From now on $\widehat{\theta}$ will stand for the solution of (2.12), and we shall use the abbreviated notation $\xi_n(\alpha) = \xi_n(\alpha; \theta)$, $\widehat{\xi}_n(\alpha) = \xi_n(\alpha; \widehat{\theta})$ and $\widetilde{\xi}_n(\alpha) = \xi_n(\alpha; \widetilde{\theta})$. Combining (2.8) with (2.11) and (2.13) we see that the leading term of $\widehat{\xi}_n$ and of $\widetilde{\xi}_n$ in general can be represented as the linear transformation of ξ_n :

$$(2.14) \quad \widehat{\xi}_n(\alpha) = \xi_n(\alpha) - \langle \alpha, m_\theta^T \rangle \langle m_\theta, m_\theta^T \rangle^{-1} \xi_n(m_\theta) + o_p(1),$$

$$(2.15) \quad \widetilde{\xi}_n(\alpha) = \xi_n(\alpha) - \langle \alpha, m_\theta^T \rangle \langle \beta_\theta, m_\theta^T \rangle^{-1} \xi_n(\beta_\theta) + o_p(1).$$

These linear transformations have a remarkably simple and convenient structure as is described in the next subsection.

2.3 Processes $\widehat{\xi}_n$ and $\widetilde{\xi}_n$ as projections.

Let us use the notation 1 for the function in y identically equal to 1, so that, e.g. $\langle \varphi, 1 \rangle = \int \varphi(y) dF(y)$, and let $\varphi^1 = \varphi - \langle \varphi, 1 \rangle$ and for $\alpha = \gamma \cdot \varphi$, let $\alpha^1 = \gamma \cdot \varphi^1$. It is obvious that $\xi_n(\alpha) = \xi_n(\alpha^1)$.

For $\alpha \in \mathbb{L}$ and a vector-valued function β , with coordinates in \mathbb{L} , such that the matrix $\langle \beta, m_\theta^T \rangle$ is nonsingular (we require this for simplicity, although it is not necessary), let

$$(2.16) \quad \Pi\alpha = \alpha - \langle \alpha, m_\theta^T \rangle \langle m_\theta, m_\theta^T \rangle^{-1} m_\theta,$$

$$(2.17) \quad \Pi_\beta\alpha = \alpha - \langle \alpha, m_\theta^T \rangle \langle \beta, m_\theta^T \rangle^{-1} \beta.$$

Proposition 2.4 (i) *The linear transformation $\alpha \mapsto \alpha^1$ is an orthogonal projection in \mathbb{L} parallel to functions which are constant in y .*

(ii) *The linear transformation Π_{β_θ} (and therefore Π) is a projection. It projects parallel to β_θ on a subspace of functions orthogonal to m_θ . In particular Π is an orthogonal projection parallel to m_θ .*

(iii) *Adjoint projectors $\Pi_{\beta_\theta}^*$ (and therefore Π^*) project parallel to m_θ . For any two vector functions β, λ ,*

$$(2.18) \quad \Pi_\beta^* \Pi_\lambda^* = \Pi_\beta^*.$$

We can therefore say, that under the regularity conditions that guarantee the validity of the expansions at (2.8), (2.11) and (2.13), the substitution of the M-estimator $\widetilde{\theta}$ in $\xi_n(\alpha; \theta)$ for θ is asymptotically equivalent to projecting $\xi_n(\alpha; \theta)$ parallel to the linear functional m_θ generated by μ_θ and ψ_f . Similarly, the substitution of the MLE $\widehat{\theta}$ in $\xi_n(\alpha; \theta)$ for θ is asymptotically equivalent to projecting $\xi_n(\alpha; \theta)$ orthogonal to m_θ . Moreover, the property (2.18) shows that the leading terms of $\xi_n(\alpha; \widetilde{\theta}_1)$ and $\xi_n(\alpha; \widetilde{\theta}_2)$, for any two estimators $\widetilde{\theta}_1, \widetilde{\theta}_2$, admitting the asymptotic linear representation (2.11), are in one-to-one correspondence with each other. Even though one of the estimators may be asymptotically more efficient than the other, (2.18) shows that the stocks of test statistics based on each of these processes are asymptotically the same. Therefore the inference based on either $\xi_n(\alpha; \widetilde{\theta}_1)$ or $\xi_n(\alpha; \widetilde{\theta}_2)$ will be asymptotically indistinguishable.

We end this section by outlining the proofs for Propositions 2.2 and 2.4. Throughout, ε_i stands for $\varepsilon_i(\theta)$, $1 \leq i \leq n$.

2.4 Some Proofs.

Sketch of the proof of Proposition 2.1 We shall sketch details only for part (ii), while those for part (i) are similar and simpler. Let $\Delta_i(v) = \mu(X_i, \theta + n^{-1/2}v) - \mu(X_i, \theta)$. Rewrite

$$\begin{aligned} & \xi_n(\alpha; \theta + n^{-1/2}v) - \xi_n(\alpha; \theta) - n^{-1} \sum_{i=1}^n \eta_i \mathbb{I}_B(X_i) \dot{\mu}_\theta^T(X_i) \varphi'(\varepsilon_i) v \\ &= n^{-1} \sum_{i=1}^n \eta_i \mathbb{I}_B(X_i) [\varphi(\varepsilon_i + \Delta_i(v)) - \varphi(\varepsilon_i) - \Delta_i \varphi'(\varepsilon_i)] \\ & \quad + n^{-1/2} \sum_{i=1}^n \eta_i \mathbb{I}_B(X_i) [\Delta_i(v) - \dot{\mu}_\theta^T(X_i) n^{-1/2}v] \varphi'(\varepsilon_i) \end{aligned}$$

The condition (2.4) implies that for every $\epsilon > 0$, $\exists N_\epsilon < \infty$ such that with probability at least $1 - \epsilon$ the following holds for all $n > N_\epsilon$:

$$E \left\{ \sup_{\|v\| \leq k} \sum_{i=1}^n \left| \Delta_i(v) - n^{-1/2} \dot{\mu}_\theta^T(X_i) v \right|^2 \right\} \longrightarrow 0, \quad \sup_{1 \leq i \leq n; \|v\| \leq k} |\Delta_i(v)| = o_p(1).$$

This fact and (2.5) imply the conclusion (ii) in a routine fashion. \square

Before proving the next proposition, we recall from Hájek (1972) that (1.2) implies the mean-square differentiability of $f^{1/2}$:

$$\frac{f^{1/2}(y + \delta) - f^{1/2}(y)}{f^{1/2}(y)} = \frac{1}{2} \frac{f'}{f}(y) \delta + \rho_f(y; \delta), \quad \int \rho_f^2(y; \delta) dF(y) = o(\delta^2), \quad \delta \rightarrow 0.$$

This fact is used implicitly in the following proof and throughout the discussion in the paper without mentioning explicitly.

Proof of Proposition 2.2. Recall $\alpha(x, y) = \gamma(x)\varphi(y)$. Rewrite $\xi_n = \xi_{no} + \xi_n^*$, where

$$\begin{aligned} \xi_{no}(\alpha; \vartheta) &:= n^{-1/2} \sum_{i=1}^n \gamma(X_i) \left[\varphi(\varepsilon_i(\vartheta)) - E_\theta[\varphi(\varepsilon_i(\vartheta)) | X_i] \right], \\ \xi_n^*(\alpha; \vartheta) &:= n^{-1/2} \sum_{i=1}^n \gamma(X_i) \left[E_\theta \left[\varphi(\varepsilon_i(\vartheta)) | X_i \right] - E_\theta[\varphi(\varepsilon_i(\theta))] \right]. \end{aligned}$$

Note that $\xi_{no}(\alpha; \theta) = \xi_n(\alpha; \theta)$.

To prove the Proposition 2.2, it thus suffices to show that for every $0 < k < \infty$,

$$(2.19) \quad \sup_{\|v\| \leq k} \left| \xi_{no}(\alpha; \theta + n^{-1/2}v) - \xi_{no}(\alpha; \theta) \right| = o_p(1),$$

$$(2.20) \quad \sup_{\|v\| \leq k} \left| \xi_n^*(\alpha; \theta + n^{-1/2}v) - m^T(\alpha; \theta) n^{-1/2}v \right| = o_p(1),$$

But, (2.19) will follow from equicontinuity condition of the process $\xi_{no}(\alpha; \cdot)$:

$$\sup_{\|\vartheta - \theta\| \leq \epsilon} \left| \xi_{no}(\alpha; \vartheta) - \xi_{no}(\alpha; \theta) \right| = o_p(1),$$

as $n \rightarrow \infty$ and $\epsilon \rightarrow 0$. This in turn follows from the argument below.

A $\varphi \in \Phi$ may be written as $\varphi = \varphi_1 - \varphi_2$, where nondecreasing φ_1, φ_2 both satisfy (2.7). Let $I_i := \text{sign}(\gamma(X_i))$, $i = 1, \dots, n$. Then for any $\delta > 0$, and for all $i = 1, \dots, n$,

$$\begin{aligned} \gamma(X_i)[\varphi_1(Y_i - \Delta - \delta I_i) - \varphi_2(Y_i - \Delta + \delta I_i)] \\ \leq \gamma(X_i)\varphi(Y_i - \Delta) \\ \leq \gamma(X_i)[\varphi_1(Y_i - \Delta + \delta I_i) - \varphi_2(Y_i - \Delta - \delta I_i)]. \end{aligned}$$

The expected value of the square of the above upper and lower bounds is bounded from above by

$$\int \gamma^2 dH 2\nu^2(2\delta).$$

Therefore the bracketing entropy (log of covering number) does not exceed

$$\log \nu^{-1} \left(t / \left[2 \int \gamma^2 dH \right]^{1/2} \right),$$

and hence is integrable by the definition of ν . Therefore, by a result in van der Vaart and Wellner (1996; sections 2.5.2, 2.7), (2.19) follows.

To prove (2.20), let, as above, $\Delta_i(v) = \mu(X_i, \theta + n^{-1/2}v) - \mu(X_i, \theta)$. Then one has

$$\begin{aligned} \xi_n^*(\alpha; \theta + n^{-1/2}v) &= n^{-1/2} \sum_{i=1}^n \gamma(X_i) \int \varphi(y)[f(y + \Delta_i(v)) - f(y)] dy \\ &= n^{-1} \sum_{i=1}^n \gamma(X_i) \dot{\mu}^T(X_i) \int \varphi(y) \psi_f(y) dF(y) v + \rho_n(v) \\ &= \langle \alpha, m_\theta^T \rangle v + \rho_n^*(v), \end{aligned}$$

where under the assumed conditions, and using an argument similar to one used, e.g., in Hájek and Šidák (1967) one can show that $\sup_{\|v\| \leq k} |\rho_n^*(v)| = o_p(1)$. \square

Proof of Proposition 2.4. Let us prove part (iii) only. We need to show that $\Pi_\beta^* \Pi_\lambda^* \mathcal{S}(\alpha) = \Pi_\beta^* \mathcal{S}(\alpha)$. We have

$$\Pi_\beta^* \Pi_\lambda^* \mathcal{S}(\alpha) = \Pi_\beta^* \mathcal{S}(\alpha) - \Pi_\beta^* \langle \alpha, m_\theta^T \rangle \langle \lambda, m_\theta^T \rangle^{-1} \mathcal{S}(\lambda).$$

But, by definition,

$$\Pi_\beta^* \langle \alpha, m_\theta^T \rangle = \langle \alpha, m_\theta^T \rangle - \langle \alpha, m_\theta^T \rangle \langle \beta, m_\theta^T \rangle^{-1} \langle \beta, m_\theta^T \rangle = 0.$$

Hence the last claim. It implies that $\Pi_\beta^* \Pi_\beta^* = \Pi_\beta^*$, i.e., Π_β^* is a projection. The remainder of the proof is obvious. \square

3 Limiting process and asymptotic power

3.1 The limiting process

Let $b(x, y)$, $x \in \mathbb{R}^p$, $y \in \mathbb{R}$, be a Brownian motion with the covariance function $H(x \wedge x')F(y \wedge y')$, where $x \wedge x'$ is the vector with coordinates $\min(x_i, x'_i)$, $i = 1, \dots, p$. In the discussion below, all γ 's and φ 's are in $L_2(\mathbb{R}^p, H)$ and $L_2(\mathbb{R}, F)$, respectively, i.e., $(\gamma, \varphi) \in \mathbb{L}$. Define, for $\alpha(x, y) = \gamma(x)\varphi(y)$, the function parametric Brownian motion

$$b(\alpha) := b(\gamma, \varphi) := \int_{\mathbb{R}^{p+1}} \gamma(x)\varphi(y)b(dx, dy).$$

Clearly the class $\{b(\alpha) : \alpha \in \mathbb{L}\}$ is a family of zero mean Gaussian random variables with the covariance given by

$$Eb(\alpha_1)b(\alpha_2) = \langle \alpha_1, \alpha_2 \rangle.$$

Let

$$\xi(\alpha) := b(\gamma, \varphi) - \langle \varphi, 1 \rangle b(\gamma, 1) = b(\gamma, \varphi^1) = b(\alpha^1).$$

The family $\{\xi(\alpha) : \alpha \in \mathbb{L}\}$ is also a family of zero mean Gaussian random variables with the covariance

$$E\xi(\alpha_1)\xi(\alpha_2) = \langle \gamma_1, \gamma_2 \rangle \left[\langle \varphi_1, \varphi_2 \rangle - \langle \varphi_1, 1 \rangle \langle \varphi_2, 1 \rangle \right] = \langle \alpha_1^1, \alpha_2^1 \rangle.$$

Thus, $\xi(\alpha)$ is a function parametric Kiefer process in α and simply a Brownian motion in α^1 . Finally, define

$$\widehat{\xi}(\alpha) := \xi(\alpha) - \langle \alpha, m_\theta^T \rangle \langle m_\theta, m_\theta^T \rangle^{-1} \xi(m_\theta) = \Pi \xi(\alpha).$$

Since $\langle \psi_f, 1 \rangle = \int f'(y)dy = 0$, we have $\xi(m_\theta) = b(m_\theta)$. Hence, $\widehat{\xi}$ can be rewritten as

$$(3.1) \quad \widehat{\xi}(\alpha) = b(\alpha^1) - \langle \alpha^1, m_\theta^T \rangle \langle m_\theta, m_\theta^T \rangle^{-1} b(m_\theta) = \Pi b(\alpha^1) = b(\Pi \alpha^1).$$

It seems easier to use below the notation α_\perp for $\Pi \alpha^1$:

$$\alpha_\perp = \alpha^1 - \langle \alpha^1, m_\theta \rangle \langle m_\theta, m_\theta^T \rangle^{-1} m_\theta$$

which is the part of α orthogonal to 1 and m_θ .

Here and everywhere below we will consider only the case of orthogonal projectors, which asymptotically correspond to the substitution of the MLE. As our comment after Proposition 2.4 shows, we can do this without loss of generality.

In view of (2.14), the reason for introducing the processes ξ and $\widehat{\xi}$ is clear and is given by the following statement.

Proposition 3.1 *Suppose that the conclusion (2.14) holds. Then, the following holds for every $\alpha \in \mathbb{L}$:*

Under H_0 ,

$$(3.2) \quad \xi_n(\alpha) \longrightarrow_d \xi(\alpha), \quad \widehat{\xi}_n(\alpha) \longrightarrow_d \widehat{\xi}(\alpha).$$

Under the alternatives (1.3),

$$(3.3) \quad \begin{aligned} \xi_n(\alpha) &\longrightarrow_d \xi(\alpha) + \langle \alpha, a \rangle, \\ \widehat{\xi}_n(\alpha) &\longrightarrow_d \widehat{\xi}(\alpha) + \langle \alpha, a \rangle - \langle \alpha, m_\theta^T \rangle \langle m_\theta, m_\theta^T \rangle^{-1} \langle m_\theta, a \rangle. \end{aligned}$$

Because both ξ_n and $\widehat{\xi}_n$ are linear in α , the above proposition is equivalent to the weak convergence of any finite dimensional distributions of these processes. Hence, the possible weak limits of these processes are uniquely determined.

From (3.2)-(3.3), we see that the asymptotic shift of $\widehat{\xi}_n$ under the alternatives (1.3) and (1.4) is simply $\langle \alpha, a \rangle$, if $\alpha \perp m_\theta$, i.e., if either $\gamma \perp \dot{\mu}_\theta$ or $\varphi \perp \psi_f$.

3.2 The case of $\gamma \perp \dot{\mu}_\theta$

In this case there exists an optimal choice of γ which will maximise the asymptotic “signal to noise” ratio Δ of $\widehat{\xi}_n(\gamma, \varphi)$ uniformly in a , that is, uniformly in alternatives (1.3), where

$$\Delta := \frac{|\langle \alpha, a \rangle|}{\|\alpha\|} = \frac{|\langle \gamma, 1 \rangle|}{\|\gamma\|} \frac{|\langle \varphi, a \rangle|}{\|\varphi\|}.$$

Here too we use the notation 1 for the function in x identically equal to 1. Clearly, the γ that maximises Δ , uniformly in a , is the γ that maximises the ratio

$$(3.4) \quad \frac{|\langle \gamma, 1 \rangle|}{\|\gamma\|},$$

subject to the condition that $\gamma \perp \dot{\mu}_\theta$, and is given by

$$1_\perp := 1 - \int \dot{\mu}_\theta^T dHC_\theta^{-1} \dot{\mu}_\theta = 1 - \langle \dot{\mu}_\theta^T, 1 \rangle C_\theta^{-1} \dot{\mu}_\theta.$$

On the other hand the γ that maximises Δ or (3.4) among all $\gamma \in L_2(\mathbb{R}^p, H)$ is 1. Then 1_\perp is simply part of the identity function 1 orthogonal to $\dot{\mu}_\theta$. It thus follows that $1_\perp(x) \equiv 0$ when $\mu(x, \vartheta)$ is linear in ϑ and has a non-zero intercept.

Now, consider $\widehat{\xi}(1_\perp, \varphi)$ as a process in φ , assuming that $\|1_\perp\| \neq 0$. Since $1_\perp \cdot \varphi$ is orthogonal to $\dot{\mu}_\theta$, from (3.1) we obtain

$$\widehat{\xi}(1_\perp, \varphi) = \xi(1_\perp, \varphi) = b(1_\perp, \varphi^1).$$

It thus follows that $\widehat{\xi}(1_{\perp}, \varphi)$ is a Brownian bridge in φ . If, e.g., we choose $\varphi(y) = \varphi_t(y) = \mathbb{I}(y \leq F^{-1}(t))$, $0 \leq t \leq 1$, then along the family of functions $\{\varphi_t(\cdot), 0 \leq t \leq 1\}$, the process

$$u(t) := \widehat{\xi}\left(\frac{1_{\perp}}{\|1_{\perp}\|}, \varphi_t\right)$$

is a standard Brownian bridge with $Eu(s)u(t) = s \wedge t - st$.

A prelimiting form of the process u is

$$\begin{aligned} \widehat{u}_n(t) &= \widehat{\xi}_n\left(\frac{1_{\perp,n}}{\|1_{\perp,n}\|_n}, \varphi_t\right) = n^{-1/2} \sum_{i=1}^n \frac{1_{\perp,n}(X_i)}{\|1_{\perp,n}\|_n} \left[\mathbb{I}\left\{\varepsilon_i(\widehat{\theta}) \leq F^{-1}(t)\right\} - t \right], \\ 1_{\perp,n}(x) &:= \left[1 - \langle \dot{\mu}_{\widehat{\theta}}^T, 1 \rangle_n C_{\widehat{\theta},n}^{-1} \dot{\mu}_{\widehat{\theta}}(x) \right], \quad x \in \mathbb{R}^p; \end{aligned}$$

where

$$\begin{aligned} C_{\widehat{\theta},n} &:= \int \dot{\mu}_{\widehat{\theta}} \dot{\mu}_{\widehat{\theta}}^T dH_n, \quad \langle \dot{\mu}_{\widehat{\theta}}^T, 1 \rangle_n = \int \dot{\mu}_{\widehat{\theta}}^T dH_n, \\ \|1_{\perp,n}\|_n &:= \left(1 - \langle \dot{\mu}_{\widehat{\theta}}^T, 1 \rangle_n C_{\widehat{\theta},n}^{-1} \langle \dot{\mu}_{\widehat{\theta}}, 1 \rangle_n \right)^{1/2}, \end{aligned}$$

and where H_n is the empirical d.f. of the design variables $\{X_i, 1 \leq i \leq n\}$. One can verify, using, e.g., the results from Koul (1996), that under the present set up, \widehat{u}_n converges weakly to a Brownian bridge. Hence, for instance, tests based on

$$\sup_t |\widehat{u}_n(t)| \quad \text{or} \quad \int_0^1 |\widehat{u}_n(t)|^2 dt$$

will have asymptotically the well known Kolmogorov and Cramér - von Mises distributions, respectively.

Now, suppose that the design d.f. H and the regression function μ_{θ} are such that

$$(3.5) \quad \langle \dot{\mu}_{\theta}, 1 \rangle = \int \dot{\mu}_{\theta} dH = 0.$$

Then $1_{\perp} \equiv 1$, and $\widehat{u}_n \equiv \widehat{W}_1(F^{-1})$, the ordinary empirical process of the residuals whose weak convergence to Brownian bridge can also be derived from Koul (1996) under the present set up.

There is, however, a draw back in the choice of $\gamma \perp \dot{\mu}_{\theta}$: although, as we see, this choice of γ makes the asymptotic behaviour of $\widehat{\xi}_n$ in φ simple, the tests based on the process $\widehat{\xi}_n(\|1_{\perp}\|^{-1} 1_{\perp}, \varphi)$ will in general have some loss of the asymptotic power. Consider for the moment the problem of testing H_0 vs. the alternative (1.3) for given a , when θ is known. Then the shift function that will appear in the asymptotic power for $\xi_n(\gamma, \varphi)$ is $|\langle \gamma, 1 \rangle \langle \varphi, a \rangle| / \|\gamma\| \|\varphi\|$. This will attain its maximum in γ when $\gamma \equiv 1$. However, for the process $\widehat{\xi}_n(1_{\perp}, \varphi)$ the corresponding shift is uniformly smaller in absolute value:

$$\left| \frac{\langle 1_{\perp}, 1 \rangle}{\|1_{\perp}\|} \langle \varphi, a \rangle \right| < |\langle \varphi, a \rangle|$$

and, in particular, the statistic $\widehat{\xi}_n(1_\perp, a)$ will have smaller asymptotic power against the alternative a than the statistic $\xi_n(1, a)$. The actual loss may be quite small, depending on the quantity

$$\|1_\perp\|^2 = 1 - \langle \dot{\mu}_\theta^T, 1 \rangle C_\theta^{-1} \langle \dot{\mu}_\theta^T, 1 \rangle,$$

and may actually equal to 0, if (3.5) holds. But, in general there is some loss.

We shall see in Section 6 below that the choice of $\gamma \perp \dot{\mu}_\theta$ will become most natural when fitting a regression model. However, one should not think that the loss of power associated with this choice in testing the hypothesis H_0 is unavoidable due to the estimation of the nuisance parameters. On the contrary, estimation of the parameter may lead to an *increase of power* against “most” alternatives. We will see this better in the next subsection.

Finally, we remark that the geometric picture similar to the one depicted by Propositions 2.4 and 3.1 and also in this and the next subsections was developed in the context of the parametric empirical processes in Khmaladze (1979). See also the monograph by Bickel, Klaassen, Ritov and Wellner (1998) describing the related geometry in connection with efficient and adaptive estimation in semiparametric models.

3.3 The case of $\varphi \perp \psi_f$

This case is important for two reasons. The first is that in this case again $\widehat{\xi}(\gamma, \varphi) = \xi(\gamma, \varphi)$, i.e., the asymptotic behaviour of the processes $\widehat{\xi}_n(\alpha)$ and $\xi_n(\alpha)$ under H_0 is the same. The second is that if we assume that a of (1.3) also satisfies (1.4), then there is in general a gain in the signal to noise ratio if we choose φ orthogonal to ψ_f . Indeed, let φ_\perp denote the part of φ orthogonal to ψ_f and 1. The signal to noise ratio for $\widehat{\xi}_n(\gamma, \varphi_\perp)$ is *asymptotically larger* than that for $\xi_n(\gamma, \varphi)$ as is seen from the following elementary argument:

$$\frac{\langle \gamma, 1 \rangle \langle \varphi, a \rangle}{\|\gamma\| \|\varphi^1\|} = \frac{\langle \gamma, 1 \rangle \langle \varphi_\perp, a \rangle}{\|\gamma\| \|\varphi^1\|} \leq \frac{\langle \gamma, 1 \rangle \langle \varphi_\perp, a \rangle}{\|\gamma\| \|\varphi_\perp\|},$$

because $\|\varphi^1\| \geq \|\varphi_\perp\|$.

It is also obvious that the optimal choice of γ that maximises Δ uniformly in a is $\gamma \equiv 1$. Therefore, consider the process

$$(3.6) \quad \widehat{\xi}(1, \varphi) = \xi(1, \varphi) = b(1, \varphi)$$

as a process in φ , for φ satisfying $\varphi \perp \psi_f$ and $\varphi \perp 1$. From (3.6), it is clear that if we had a family of functions $\{\varphi_t, 0 \leq t \leq 1\}$ from $L_2(\mathbb{R}, F)$ such that

$$(3.7) \quad \langle \varphi_t, 1 \rangle = \langle \varphi_t, \psi_f \rangle = 0.$$

$$(3.8) \quad \langle \varphi_t, \varphi_t \rangle = t, \quad 0 \leq t \leq 1.$$

$$(3.9) \quad \langle \varphi_{t_2} - \varphi_{t_1}, \varphi_{t_1} \rangle = 0, \quad t_2 \geq t_1.$$

then the process $\xi(1, \varphi_t)$, $0 \leq t \leq 1$, would be a Brownian motion in $0 \leq t \leq 1$. Hence, all tests based on

$$n^{-1/2} \sum_{i=1}^n \varphi_t(\varepsilon_i(\hat{\theta})), \quad 0 \leq t \leq 1,$$

will be ADF.

It is straightforward to construct a family of functions satisfying (3.8) and (3.9). For example, take any function φ from $L_2(\mathbb{R}, F)$ such that $L(y) := \int_{-\infty}^y \varphi^2 dF$ is a continuous distribution function on \mathbb{R} , and $\varphi^2 f > 0$, a.e. Then the family

$$(3.10) \quad \varphi_t(y) := \varphi(y) \mathbb{I}\{y \leq L^{-1}(t)\}, \quad L^{-1}(t) := \inf\{y \in \mathbb{R} : L(y) \geq t\}, \quad 0 \leq t \leq 1,$$

satisfies these conditions. However, finding a family $\{\varphi_t, 0 \leq t \leq 1\}$ that satisfies (3.7) as well becomes far less straightforward. It is here we will exploit the ‘‘martingale transform’’ ideas of Khmaladze (1981, 1993) in the next section.

4 A martingale transform

Let $h(y) := (1, \psi_f(y))^T$ be an extended score function of the error distribution and set

$$\Gamma_t := \int_{z \geq y} h(z) h^T(z) dF(z) = \begin{pmatrix} 1 - F(y) & -f(y) \\ -f(y) & \int_y^\infty \psi_f^2(z) dF(z) \end{pmatrix}, \quad t = F(y).$$

The matrix Γ_t will be assumed to be nonsingular for every $0 \leq t < 1$. This indeed is true if and only if 1 and $\psi_f(y)$ are linearly independent on the set $y > c$, for all sufficiently large c . This, in turn, is true if ψ_f is not a constant in the right tail of the support of f . Then the unique inverse Γ_t^{-1} exists for every $0 \leq t < 1$. (The case when Γ_t is not uniquely invertible does not create, however, much of a problem for the transformation (4.1) below, as is shown in Tsigroshvili (1998).)

Now, observe that the condition (3.7) above is equivalent to requiring that φ be orthogonal to the vector h . For a function $\varphi \in L_2(\mathbb{R}, F)$, consider the transformation

$$(4.1) \quad \mathcal{L}\varphi(y) := \varphi(y) - \int_{z \leq y} \varphi(z) h^T(z) \Gamma_{F(z)}^{-1} dF(z) h(y), \quad y \in \mathbb{R}.$$

Let, for a $(\gamma, \varphi) \in \mathbb{L}$,

$$w(\alpha) := \hat{\xi}(\gamma, \mathcal{L}\varphi), \quad \alpha = \gamma \cdot \varphi.$$

We have the following

Proposition 4.1 *Let $\mathcal{H} := \{\varphi \in L_2(\mathbb{R}, F) : \langle \varphi, h \rangle = 0\}$. The transformation \mathcal{L} of (4.1) is a norm preserving transformation from $L_2(\mathbb{R}, F)$ to \mathcal{H} :*

$$\mathcal{L}\varphi \perp h, \quad \|\mathcal{L}\varphi\| = \|\varphi\|.$$

Consequently the process $w(\alpha)$ is a (function parametric) Brownian motion on \mathbb{L} .

A consequence of this proposition is the following

Corollary 4.1 *Suppose $\{\varphi_t, 0 \leq t \leq 1\}$ is a family of functions satisfying the conditions (3.8) and (3.9). Then $\{\mathcal{L}\varphi_t, 0 \leq t \leq 1\}$ is a family of functions satisfying all three conditions (3.7) - (3.9). Consequently, $\{\widehat{\xi}(\gamma, \mathcal{L}\varphi_t), 0 \leq t \leq 1\}$ for any fixed γ with $\|\gamma\| = 1$ is a standard Brownian motion in t .*

Now, if $\{\widehat{\xi}_n(\gamma, \mathcal{L}\varphi_t), 0 \leq t \leq 1\}$ converges weakly to $\{\widehat{\xi}(\gamma, \mathcal{L}\varphi_t), 0 \leq t \leq 1\}$, then tests based on any continuous functionals of $\widehat{\xi}_n(\gamma, \mathcal{L}\varphi_t)$ will be ADF for testing H_0 . Some general sufficient conditions for the weak convergence of $\{\widehat{\xi}_n(\gamma, \varphi_t), 0 \leq t \leq 1\}$ can be drawn from Proposition 6.2 below. Others can be inferred from, e.g., van der Vaart and Wellner (1996). In particular, these claims hold for the family $\{\varphi_t, 0 \leq t \leq 1\}$ given at (3.10).

It is also important to note that the transformation \mathcal{L} is free from γ and hence the statement concerning the asymptotic distribution of $\{\widehat{\xi}_n(\gamma, \mathcal{L}\varphi_t), 0 \leq t \leq 1\}$, is valid for any $\gamma \in L_2(\mathbb{R}^p, H)$.

Another consequence of Proposition 4.1 is worth formulating separately.

Proposition 4.2 *Let $\widetilde{\theta}$ be any estimator which satisfies (2.3) (and does not necessarily have a linear representation (2.11)) and let ψ_f be a function of bounded variation. If, additionally, (1.2) and (2.4) hold, then for every $\alpha = \gamma \cdot \varphi$ with $\gamma \in L_2(\mathbb{R}^p, H)$ and $\varphi \in \Phi$, under H_0 ,*

$$\widetilde{\xi}_n(\gamma, \mathcal{L}\varphi) \rightarrow_d w(\alpha),$$

while under alternatives (1.3),

$$\widetilde{\xi}_n(\gamma, \mathcal{L}\varphi) \rightarrow_d w(\alpha) + \langle \mathcal{L}\alpha, a \rangle.$$

This proposition shows that although we used asymptotically linear representations (2.11) and (2.13) of $\widehat{\theta}$ and $\widetilde{\theta}$ to develop the previous theory, for the asymptotic behaviour of the transformed processes $\widehat{\xi}_n(\gamma, \mathcal{L}\varphi)$ and $\widetilde{\xi}_n(\gamma, \mathcal{L}\varphi)$, the behaviour of $\widehat{\theta}$ and $\widetilde{\theta}$ plays only a minor role.

It is instructive to consider informally a probabilistic connection between the processes $\widehat{\xi}(\gamma, \varphi_t)$ and $\widehat{\xi}(\gamma, \mathcal{L}\varphi_t)$. Let us associate with $\{\widehat{\xi}(\gamma, \varphi_t), 0 \leq t \leq 1\}$ its natural filtration $\{\mathcal{F}_t, 0 \leq t \leq 1\}$, where each σ -field is

$$\widehat{\mathcal{F}}_t = \sigma\{\widehat{\xi}(\gamma, \varphi_s), s \leq t\}, \quad 0 \leq t \leq 1,$$

and consider the filtered process $\{\widehat{\xi}(\gamma, \varphi_t), \widehat{\mathcal{F}}_t, 0 \leq t \leq 1\}$. This is in t a Gaussian semimartingale and it can be shown that the process $\{\widehat{\xi}(\gamma, \mathcal{L}\varphi_t), \widehat{\mathcal{F}}_t, 0 \leq t \leq 1\}$ is actually its martingale part. In other words, if \mathcal{V} denotes the Volterra operator defined by the integral on the right hand side of (4.1), then the identity

$$(4.2) \quad \widehat{\xi}(\gamma, \varphi_t) = \widehat{\xi}(\gamma, \mathcal{V}\varphi_t) + \widehat{\xi}(\gamma, \mathcal{L}\varphi_t), \quad 0 \leq t \leq 1,$$

is simply the Doob-Meyer decomposition of the process $\{\widehat{\xi}(\gamma, \varphi_t), \widehat{\mathcal{F}}_t, 0 \leq t \leq 1\}$.

Details of this decomposition can be found in Khmaladze (1993) where the general construction of this form for a function-parametric process was introduced and studied. The notion of Doob-Meyer decomposition for a semimartingale can be found, e.g., in Liptser and Shiriyayev (1978).

Remark 4.1 Since $\mathcal{L}\varphi$ is orthogonal to 1 and to ψ_f , the equality (4.2) can be rewritten in terms of the process b :

$$(4.3) \quad b(\gamma, \varphi_t) = b(\gamma, \mathcal{V}\varphi_t) + b(\gamma, \mathcal{L}\varphi_t).$$

To some extent this is an unusual equation because both processes $b(\gamma, \varphi_t)$ and $b(\gamma, \mathcal{L}\varphi_t)$, taken separately, are Brownian motions. However, the nature of (4.3) can be more clearly understood as follows: let $\{\mathcal{F}_t^b, 0 \leq t \leq 1\}$ be the natural filtration of the process $b(\gamma, \varphi_t)$ in t and let us enrich it with the σ -field $\sigma\{b(\gamma, h)\}$. Then the process $\{b(\gamma, \varphi_t), \mathcal{F}_t^b \vee \sigma\{b(\gamma, h)\}, 0 \leq t \leq 1\}$ is a Gaussian semimartingale (and not a martingale) and (4.3) is its Doob-Meyer decomposition. See, e.g., Liptser and Shiriyayev (1989) for more details on this.

Remark 4.2 Another consequence of the orthogonality of $\mathcal{L}\varphi_t$ to 1 and to ψ_f is this: although the process $\xi(\gamma, \varphi_t)$, with φ_t chosen according to (3.10) with a non-constant φ , is not a Brownian bridge (because in this case $\|\varphi_t^1\|^2 < \|\varphi_t\|^2 = t$) and hence even the process $\xi_n(\gamma, \varphi_t)$ with known value of parameter and statistics based on it may have an inconvenient limiting distribution, the transformed process $\xi(\gamma, \mathcal{L}\varphi_t)$ is the *standard Brownian motion* for any such choice of φ_t .

We shall now describe an analog of the above transformation suitable for testing the hypothesis $H_\sigma : G(y) = F(y/\sigma), \forall y \in \mathbb{R}$, and for some $\sigma > 0$. Let $\widehat{\sigma}$ be an estimate of σ based on $\{(X_i, Y_i), 1 \leq i \leq n\}$ satisfying

$$(4.4) \quad \|n^{1/2}(\widehat{\sigma} - \sigma)\| = o_p(1).$$

The analog of the processes $\widehat{\xi}_n$ here is

$$\widehat{\xi}_{n\sigma}(\gamma, \varphi) := n^{-1/2} \sum_{i=1}^n \gamma(X_i) \left[\varphi \left(\frac{Y_i - \mu(X_i, \widehat{\theta})}{\widehat{\sigma}} \right) - \int \varphi dF \right].$$

To transform its weak limit $\widehat{\xi}_\sigma$ under H_σ , again define an extended score function of $F((y - \mu)/\sigma)$ with respect to both parameters μ and σ , which is $h_\sigma(y) = (1, \psi_{f\mu}(y/\sigma), \psi_{f\sigma}(y/\sigma))^T$ where obviously

$$\psi_{f\mu}\left(\frac{y}{\sigma}\right) = \frac{1}{\sigma}\psi_f\left(\frac{y}{\sigma}\right), \quad \psi_{f\sigma}\left(\frac{y}{\sigma}\right) = \frac{1}{\sigma}\left[1 + \frac{y}{\sigma}\psi_f\left(\frac{y}{\sigma}\right)\right]$$

With notation

$$q(t) = \frac{1}{\sigma}f\left(\frac{y}{\sigma}\right), \quad q_\sigma(t) = \frac{y}{\sigma^2}f\left(\frac{y}{\sigma}\right), \quad t = F\left(\frac{y}{\sigma}\right).$$

the analog of the Γ_t matrix is

$$\Gamma_{\sigma,t} := \begin{pmatrix} 1-t & -q(t) & -q_\sigma(t) \\ -q(t) & \int_t^1 \dot{q}^2(s)ds & \int_t^1 \dot{q}(s)\dot{q}_\sigma(s)ds \\ -q_\sigma(t) & \int_t^1 \dot{q}(s)\dot{q}_\sigma(s)ds & \int_t^1 \dot{q}_\sigma^2(s)ds \end{pmatrix}.$$

Again, assume that $\Gamma_{\sigma,t}^{-1}$ exists for all $0 \leq t < 1$. Then, as above, let

$$(4.5) \quad \mathcal{L}_\sigma\varphi(y) := \varphi(y) - \int_{-\infty}^y \varphi(z)h_\sigma^T(z)\Gamma_{\sigma,F(z)}^{-1}dF(z) h_\sigma(y), \quad y \in \mathbb{R}.$$

One can show that \mathcal{L}_σ is a norm preserving transformation from $L_2(\mathbb{R}, F)$ to the subspace $\mathcal{H}_\sigma = \{\varphi \in L_2(\mathbb{R}, F) : \langle \varphi, h_\sigma \rangle = 0\}$ and hence $\widehat{\xi}(\gamma, \mathcal{L}_\sigma\varphi)$ is Brownian motion on \mathbb{L} .

Proof of Proposition 4.1. Though we could refer to the proof of Proposition 6.1, for presentational purposes it seems more convenient to give it here separately. Let, within this proof only, $\psi(t) := \varphi(F^{-1}(t))$ and $g(t) = h(F^{-1}(t))$ for $0 \leq t \leq 1$. Then

$$\begin{aligned} \int \mathcal{L}\varphi(y) h(y)^T dF(y) &= \int_0^1 \psi(t) g(t)^T dt - \int_0^1 \int_0^t \psi(s) g(s)^T \Gamma_s^{-1} ds g(t) g^T(t) dt \\ &= \int_0^1 \psi(t) g(t)^T dt - \int_0^1 \psi(s) g(s)^T \Gamma_s^{-1} \int_s^1 g(t) g^T(t) dt ds \\ &= \int_0^1 \psi(t) g(t)^T dt - \int_0^1 \psi(s) g(s)^T ds \\ &= 0. \end{aligned}$$

For the technical justification of the interchange of integration in the second equation above see the proof of Proposition 6.1 below or Khmaladze (1993). Similarly, we also have

$$\begin{aligned} \int [\mathcal{L}\varphi]^2 dF &= \int_0^1 \psi^2(s) ds - 2 \int_0^1 \psi(s) g^T(s) \Gamma_s^{-1} \int_s^1 \psi(t) g(t) ds dt \\ &\quad + \int_0^1 \int_0^1 \psi(s) g^T(s) \Gamma_{s \vee t}^{-1} \Gamma_{s \vee t} h(t) \psi(t) ds dt \\ &= \int \varphi^2 dF. \end{aligned} \quad \square$$

Proof of Proposition 4.2. If ψ_f is the function of bounded variation and $\varphi \in \Phi$ then $\mathcal{L}\varphi \in \Phi$ and therefore we can use (2.8). Together with the orthogonality property $\mathcal{L}\varphi \perp \psi_f$ which implies that $\langle \mathcal{L}\alpha, m_\theta \rangle = 0$ we obtain that

$$\widehat{\xi}_n(\mathcal{L}\alpha) = \xi_n(\mathcal{L}\alpha) + o_p(1)$$

and the rest follows from Proposition 4.1, the CLT for $\xi_n(\mathcal{L}\alpha)$ and the standard contiguity argument. \square

5 Some Explicit Formulas and Remarks

5.1 Transformation of the processes \widehat{W}_1 and $\widehat{\xi}_n(1, \varphi_t)$

In this section we shall apply the above transformation to residual empirical processes and give computational formulae of the transformed processes for testing H_0 and H_σ .

Recall from the previous sections that, for $0 \leq t \leq 1$,

$$(5.1) \quad \widehat{U}_1(t) := \widehat{W}_1(F^{-1}(t)) = n^{-1/2} \sum_{i=1}^n \left[\mathbb{I}\{\varepsilon_i(\widehat{\theta}) \leq F^{-1}(t)\} - t \right],$$

$$(5.2) \quad \widehat{\xi}_n(1, \varphi_t) = n^{-1/2} \sum_{i=1}^n \left[\varphi(\varepsilon_i(\widehat{\theta})) \mathbb{I}\{\varepsilon_i(\widehat{\theta}) \leq F^{-1}(t)\} - \int_{y \leq F^{-1}(t)} \varphi(y) dF(y) \right],$$

where in (5.2), $\varphi_t(y) = \varphi(y) \mathbb{I}(y \leq F^{-1}(t))$. Note that $\widehat{U}_1(t)$ also corresponds to the $\widehat{\xi}_n(1, \varphi_t)$ with $\varphi_t(y) = \mathbb{I}\{y \leq F^{-1}(t)\}$. As another practically useful consequence of orthogonality of $\mathcal{L}\varphi$ to 1 we have the following equality:

$$\widehat{\xi}_n(\gamma, \mathcal{L}\varphi) = n^{-\frac{1}{2}} \sum_{i=1}^n \gamma(X_i) \mathcal{L}\varphi(\varepsilon_i(\widehat{\theta})) + o_p(1).$$

It means that we only need to construct transformations of random summands in (5.1) and (5.2). Introduce vector-functions

$$G(z) = \int_{y \leq z} \Gamma_{F(y)}^{-1} h(y) dF(y) \quad J(z) = \int_{y \leq z} \varphi(y) \Gamma_{F(y)}^{-1} h(y) dF(y), \quad z \in \mathbb{R}.$$

Then the transformation \mathcal{L} of (4.1) applied to \widehat{U}_1 of (5.1) gives

$$(5.3) \quad \widehat{w}_{n1}(t) = n^{-1/2} \sum_{P_i=1}^n \left[\mathbb{I}\{\varepsilon_i(\widehat{\theta}) \leq z\} - [1, \psi_f(\varepsilon_i(\widehat{\theta}))] G(z \wedge \varepsilon_i(\widehat{\theta})) \right], \quad t = F(z),$$

while the transformation of (5.2) is

$$(5.4) \quad \widehat{w}_{n2}(t) = n^{-1/2} \sum_{i=1}^n \left[\varphi(\varepsilon_i(\widehat{\theta})) \mathbb{I}\{\varepsilon_i(\widehat{\theta}) \leq z\} - [1, \psi_f(\varepsilon_i(\widehat{\theta}))] J(z \wedge \varepsilon_i(\widehat{\theta})) \right], \quad t = F(z).$$

Similarly, to describe ADF tests for H_σ based on the analog of \widehat{w}_1 , let now $\widehat{r}_i \equiv \varepsilon_i(\widehat{\theta})/\widehat{\sigma}$, and let us consider the processes

$$\begin{aligned} & n^{-1/2} \sum_{i=1}^n [\mathbb{I}(\widehat{r}_i \leq z) - F(z)], \\ & n^{-1/2} \sum_{i=1}^n \left[\varphi(\widehat{r}_i) \mathbb{I}\{\widehat{r}_i \leq z\} - \int_{y \leq z} \varphi(y) dF(y) \right], \quad t = F(z), \quad z \in \mathbb{R}. \end{aligned}$$

Then arguing as above we are led to the following respective computational formulae:

$$\begin{aligned} w_{n1}(t) &= n^{-1/2} \sum_{i=1}^n \left[\mathbb{I}\{\widehat{r}_i \leq z\} - h_{\widehat{\sigma}}^T(\varepsilon_i(\widehat{\theta})) G_{\widehat{\sigma}}(z \wedge \varepsilon_i(\widehat{\theta})) \right] \\ w_{n2}(t) &= n^{-1/2} \sum_{i=1}^n \left[\varphi(\widehat{r}_i) \mathbb{I}\{\widehat{r}_i \leq z\} - h_{\widehat{\sigma}}^T(\varepsilon_i(\widehat{\theta})) J_{\widehat{\sigma}}(z \wedge \varepsilon_i(\widehat{\theta})) \right], \quad t = F(z), \quad z \in \mathbb{R}, \end{aligned}$$

where $h_\sigma(y)$ is as in the previous section while G_σ and J_σ are defined as above with h replaced by h_σ and Γ replaced by Γ_σ .

These formulae may be used in the computation of any test statistic based on continuous functionals of w_{n1} , w_{n2} . From the theory developed above, if these functionals are invariant under usual time transformation $t = F(y)$, they will be ADF!

5.2 Non-random design

We now state some analogous facts for the case of non-random design where now the design vectors are denoted by x_{ni} . An analog of the condition (2.4) here is as follows: There exists a q -vector $\dot{\mu}$ on $\mathbb{R}^p \times \Theta$ and a $q \times q$ positive definite symmetric matrix Σ such that

$$(5.5) \quad \begin{aligned} \Sigma_n &:= n^{-1} \sum_{i=1}^n \dot{\mu}(x_{ni}, \theta) \dot{\mu}^T(x_{ni}, \theta) \longrightarrow \Sigma, \quad \max_{1 \leq i \leq n} n^{-1/2} \|\dot{\mu}(x_{ni}, \theta)\| = o(1). \\ &\sup_{1 \leq i \leq n, n^{1/2} \|\vartheta - \theta\| \leq k} n^{1/2} |\mu(x_{ni}, \vartheta) - \mu(x_{ni}, \theta) - (\vartheta - \theta)^T \dot{\mu}(x_{ni}, \theta)| = o(1). \end{aligned}$$

Under these conditions on the regression function and the rest of the conditions as before, the analogs of the above results with $\mu(X_i, \cdot)$ replaced by $\mu(x_{ni}, \cdot)$ remain valid in the present case. Using the results from Koul (1996), it is possible to obtain the analog of the expansions (2.14) and (2.15) under more general conditions on the function μ than given in (5.5), but we refrain from doing this for the sake of not obscuring main ideas and for the sake of brevity.

A similar remark applies to the linear regression model. In particular, in the case of non-random and general designs, but having the $n \times p$ design matrix \mathbf{X} of rank p , just replace $n^{-1/2} X_i$ in the above formulas by $(\mathbf{X}'\mathbf{X})^{-1/2} x_{ni}$, $1 \leq i \leq n$, everywhere. Then, tests based on the analogues of \widehat{w}_{n1} and \widehat{w}_{n2} are ADF for H_0 , provided $\max_{1 \leq i \leq n} n^{1/2} \|(\mathbf{X}'\mathbf{X})^{-1/2} x_{ni}\| = O(1)$.

5.3 Autoregressive time series

Because of the close connection between regression and autoregressive models, analogues of the above ADF tests pertaining to the error distribution are easy to see in this case. Accordingly, suppose $Y_i, i \in \mathbb{Z} := \{0, \pm 1, \pm 2, \dots\}$, is now an observable stationary and ergodic time series. Let μ be as before satisfying (1.1) with $X_i := (Y_{i-1}, \dots, Y_{i-p})^T$, where $p \geq 1$ is a known integer. Then the above tests with this X_i will be again ADF for testing H_0 . A rigorous proof of this claim is similar to that appearing above, with the proviso that one uses the ergodic theorem in place of the law of the large numbers, and the CLT for martingale differences in place of the Lindeberg-Feller CLT. Note that now H is the d.f. of the random vector X_0 .

In the case of a stationary and ergodic *linear* AR(p) model, i.e., when $\mu(x, \vartheta) = x'\vartheta$, if the null error d.f. F has mean zero and finite variance, then $EX_0 = 0$, i.e., (3.5) is automatically satisfied, and hence tests based on the analog of \widehat{U}_1 of (5.1) will be *a priori* ADF for H_0 . This was first proved in Boldin (1982), assuming F has bounded second derivative, and in Koul (1991) when F has only uniformly continuous density. Thus, in linear autoregressive models, the above transformation is useful only when there is a non-zero mean present in these models.

6 Fitting a regression model

In this section we shall develop some tests based on innovation processes that will be asymptotically distribution free for fitting a parametric model to the regression function $m(x) := E(Y|X = x)$. Actually we consider a bit more general problem where we fit a parametric model to a general regression function defined as follows.

For a real valued measurable function φ on \mathbb{R} , let \mathcal{F}_φ denote a class of distribution functions F on \mathbb{R} such that $\varphi \in L_2(\mathbb{R}, F)$ and $\int |\varphi(y+t)|F(dy) < \infty$, for all $|t| \leq k < \infty$. Let $m_\varphi(x)$ be defined by the relation

$$(6.1) \quad E \left[\varphi \left(Y - m_\varphi(x) \right) \middle| X = x \right] = 0.$$

Note that if $\varphi(y) = y$, then $m_\varphi(x) = m(x)$, while if $\varphi(y) \equiv \mathbb{I}\{y > 0\} - (1 - \alpha)$ for an $0 < \alpha < 1$, then $m_\varphi(x)$ is the α -th quantile of the conditional distribution of Y , given $X = x$. The choice of φ is up to the practitioner. The d.f. F of the error $Y - m_\varphi(X)$ will be assumed to be an unknown member of \mathcal{F}_φ , for a given φ .

The problem of testing \widetilde{H}_0 is now extended to testing the hypothesis that $H_\varphi : m_\varphi(x) = \mu(x, \theta)$ for some $\theta \in \Theta$, against the alternatives described in (1.6). Consider again the function-parametric regression process

$$\xi_n(\gamma, \varphi; \vartheta) := n^{-1/2} \sum_{i=1}^n \gamma(X_i) \varphi \left(Y_i - \mu(X_i, \vartheta) \right).$$

Note that because of (6.1), under H_φ , $E\xi_n(\gamma, \varphi; \theta) = 0$.

Let $\tilde{\theta}$ be an M-estimator of θ satisfying (2.9) corresponding to $\eta_\theta \equiv \dot{\mu}_\theta$. Suppose, additionally, $F \in \mathcal{F}_\varphi$ is such that the function $t \mapsto \int \varphi(y+t)F(dy)$, $t \in \mathbb{R}$ is strictly monotonic and differentiable in a neighbourhood of 0. Now, if we consider problems where $\varphi(y)$ is differentiable, such as $\varphi(y) = y$ which is a most interesting case, then we need to assume regularity condition (2.4) on the regression function $\mu(\cdot, \vartheta)$. While in the case of a non-differentiable φ , as in for example, $\varphi(y) = \mathbb{I}\{y > 0\} - (1 - \alpha)$, we need to assume as well that F , although unknown, satisfies also (1.2). In both cases, under (2.4) and (2.10), $\tilde{\theta}$ satisfies (2.11) and we obtain

$$\begin{aligned} \tilde{\xi}_n(\gamma, \varphi) &= \xi_n(\gamma, \varphi) - \langle \gamma, \dot{\mu}_\theta^T \rangle C_\theta^{-1} \xi_n(\dot{\mu}_\theta, \varphi) + o_p(1) \\ &= \xi_n(\gamma_\perp, \varphi) + o_p(1), \end{aligned}$$

where

$$\gamma_\perp(x) = \gamma(x) - \langle \gamma, \dot{\mu}_\theta^T \rangle C_\theta^{-1} \dot{\mu}_\theta(x), \quad x \in \mathbb{R}^p,$$

is the part of γ orthogonal to $\dot{\mu}_\theta$ and no transformation of φ is involved.

We emphasise that it is only for the motivational purpose we are confining the attention here to M-estimators. As we shall see later, any $n^{1/2}$ -consistent estimator may be used to construct ADF tests for H_φ .

Now one can show that under H_φ , for each γ, φ of the given type,

$$(6.2) \quad \tilde{\xi}_n(\gamma, \varphi) \longrightarrow_d b(\gamma_\perp, \varphi),$$

while, under any sequence of alternatives (1.6),

$$\tilde{\xi}_n(\gamma, \varphi) \longrightarrow_d b(\gamma_\perp, \varphi) + \lambda \langle \gamma_\perp, \ell_\theta \rangle$$

where λ is either $\langle \varphi', 1 \rangle$ or $-\langle \varphi, \psi_f \rangle$ depending on whether we assume (2.4) and (2.5) or (1.2).

As this last result shows, the asymptotic shift of the regression process $\tilde{\xi}_n(\gamma, \varphi)$, under the alternatives (1.6), is the linear functional of ℓ_θ defined by the function γ_\perp . Therefore, to be able to detect all alternatives of the assumed type, we need to have a substantial supply of γ_\perp , i.e., we need to consider $\tilde{\xi}_n(\gamma, \varphi)$ as a process in γ , and there is no need to vary φ just in the same way as we had to vary φ when testing our previous hypothesis H_0 and keep γ fixed. We do not try to choose in any sense ‘‘optimal’’ φ because the result will depend on F while we prefer to work under assumption that we do not know this d.f. Thus we can and will assume that φ in the rest of this section is fixed.

From (6.2) we note that the limiting process as a function in γ is again a projection of Brownian motion, but as a function in γ_\perp , it is just a Brownian motion.

Now, we may have a convenient and customary way to parametrise $b(\gamma, \varphi)$ in $\gamma \in L_2(\mathbb{R}^p, H)$ to obtain processes with standard and convenient distribution, and if we had

similar ways to do this in sub-spaces of $L_2(\mathbb{R}^p, H)$, we could have the same convenient limiting processes in our problem. This, however, is not a straightforward task, as we have said earlier, especially because these subspaces, being orthogonal to $\dot{\mu}_\theta$, change from one regression function to another, and may even well change, for the same regression function, along the changes in the parameter θ .

Nevertheless, we will see below that given a ‘‘convenient’’ indexing class $\mathcal{G}_0 \subset L_2(\mathbb{R}^p, H)$, in a sense that $\{b(\gamma, \varphi), \gamma \in \mathcal{G}_0\}$ forms a ‘‘convenient’’ asymptotic process - say, we can find distribution of statistics based on $\{b(\gamma, \varphi), \gamma \in \mathcal{G}_0\}$ easily, and so on - we can map it isometrically into the subspace of functions orthogonal to $\dot{\mu}_\theta$. Thus, we obtain the process $\{b(\gamma, \varphi), \gamma \in \mathcal{G}'_0\}$, where \mathcal{G}'_0 is the image of this isometry, which on the one hand has exactly the same distribution and therefore carries the same ‘‘convenience’’ as the process $\{b(\gamma, \varphi), \gamma \in \mathcal{G}_0\}$, and on the other hand, is the limiting process for $\tilde{\xi}_n(\gamma, \varphi)$ if we index it by $\gamma \in \mathcal{G}'_0$.

To achieve this goal, first introduce the so called scanning family of measurable subsets $\mathcal{A} := \{A_z : z \in \mathbb{R}\}$ of \mathbb{R}^p such that $A_z \subseteq A_{z'}$, for all $z \leq z'$, $H(A_{-\infty}) = 0$, $H(A_\infty) = 1$, and $H(A_z)$ is strictly increasing absolutely continuous function of $z \in \mathbb{R}$.

To give examples, let X^j denote the j th coordinate of the p -dimensional design variable X , $j = 1, \dots, p$. Suppose that the marginal distribution of X^1 is absolutely continuous. Then we can take the family $A_z = \{x \in \mathbb{R}^p : x^1 \leq z\}$ as a scanning family. Or, if the sum $X^1 + \dots + X^p$ is absolutely continuous, then one can take the family of half spaces $A_z = \{x \in \mathbb{R}^p : x^1 + x^2 + \dots + x^p \leq z\}$.

Now, let B^c denote the complement of a set B ,

$$z(x) := \inf\{z : A_z \ni x\}, \quad \mathcal{C}_{\vartheta, z} := \int_{A_z^c} \dot{\mu}_\vartheta(y) \dot{\mu}_\vartheta^T(y) dH(y), \quad z \in \mathbb{R},$$

$$\mathcal{T}_\vartheta \gamma(x) = \int_{A_z(x)} \gamma(y) \dot{\mu}_\vartheta^T(y) \mathcal{C}_{z(y)}^{-1} dH(y) \dot{\mu}_\vartheta(x), \quad x \in \mathbb{R}^p, \vartheta \in \Theta.$$

We shall often write \mathcal{C}_z , \mathcal{T} for $\mathcal{C}_{\theta, z}$, \mathcal{T}_θ , respectively. Now, define the operator

$$\mathcal{K}\gamma(x) := \gamma(x) - \mathcal{T}\gamma(x), \quad x \in \mathbb{R}^p.$$

Proposition 6.1 *Let $\mathcal{G} := \{\gamma \in L_2(\mathbb{R}^p, H) : \langle \gamma, \dot{\mu}_\theta \rangle = 0\}$. Assume \mathcal{C}_z is non-singular for all $-\infty < z < \infty$. Then the transformation \mathcal{K} is a norm preserving transformation from $L_2(\mathbb{R}^p, H)$ to \mathcal{G} :*

$$\mathcal{K}\gamma \perp \dot{\mu}_\theta, \quad \|\mathcal{K}\gamma\| = \|\gamma\|.$$

Consequently, for any fixed φ , the process $w(\gamma, \varphi) = \tilde{\xi}(\mathcal{K}\gamma, \varphi)$ is (function parametric) Brownian motion in γ .

Similarly to Proposition 4.2 the following corollary shows that much less is required from an estimator $\tilde{\theta}$ than its asymptotic linearity. The random vector Z below can be thought of as the limit in distribution of $\sqrt{n}(\tilde{\theta} - \theta)$.

Corollary 6.1 *Let $\tilde{\xi}$ be any process of the form*

$$\tilde{\xi}(\gamma, \varphi) = b(\gamma, \varphi) - \langle \gamma, \dot{\mu}_\theta^T \rangle Z,$$

where Z is a random vector (not necessarily Gaussian) in \mathbb{R}^q . Then for any fixed $\varphi \in L_2(\mathbb{R}, F)$, the process

$$w(\gamma, \varphi) = \tilde{\xi}(\mathcal{K}\gamma, \varphi)$$

is Brownian motion in $\gamma \in L_2(\mathbb{R}^p, H)$.

Now we shall, as an example, focus on the case $\gamma = \mathbb{I}_B$, for B a Borel set in \mathbb{R}^p . Then

$$\mathcal{K}\mathbb{I}_B(x) = \mathbb{I}_B(x) - \int_{A_z(x)} \mathbb{I}_B(y) \dot{\mu}_\theta^T(y) \mathcal{C}_{z(y)}^{-1} dH(y) \dot{\mu}_\theta(x).$$

In view of the above discussion, our transformation is the process

$$(6.3) \quad w_n(B) := \tilde{\xi}_n(\mathcal{K}\mathbb{I}_B, \varphi) \\ = n^{-1/2} \sum_{i=1}^n \left[\mathbb{I}_B(X_i) - \int_{A_z(X_i)} \mathbb{I}_B(y) \dot{\mu}_\theta^T(y) \mathcal{C}_{z(y)}^{-1} dH(y) \dot{\mu}_\theta(X_i) \right] \varphi(Y_i - \mu(X_i, \tilde{\theta})).$$

We do not consider in this paper the problem of weak convergence of transformed processes $\{\tilde{\xi}_n(\gamma, \mathcal{L}\varphi), \varphi \in \Phi_0\}$ or $\{\tilde{\xi}_n(\mathcal{K}\gamma, \varphi), \gamma \in \mathcal{G}_0\}$ to corresponding Brownian motions for appropriate indexing classes Φ_0 and \mathcal{G}_0 in full generality. Nevertheless we shall now state a sufficient condition under which the process (6.3) converges weakly to a set-parametric Brownian motion on the practically important class of sets - a sub-class \mathcal{B}_0 of all right closed rectangles in \mathbb{R}^p , i.e. $\mathcal{B}_0 \subset \{(-\infty, v], v \in \mathbb{R}^p\}$. Our assumption is the following:

$$(6.4) \quad \text{There exists a } \tau > 0 \text{ such that } B \subseteq A_{1-\tau}, \text{ for all } B \in \mathcal{B}_0.$$

This condition is not necessary, but simplifies the proof substantially. See Khmaladze (1993) for the version without this condition.

Let $\{w(B), B \in \mathcal{B}_0\}$ be set-parametric Brownian motion on \mathcal{B}_0 with covariance function

$$Ew(B)w(B') = cH(B \cap B'),$$

where, without loss of generality we can assume the constant c to be 1, cf. Remark 6.1 below.

The space in which we will consider weak convergence of w_n will be $\ell^\infty(\mathcal{G}_0)$, where $\mathcal{G}_0 = \{\mathbb{I}_B(\cdot), B \in \mathcal{B}_0\}$ is equipped with the L_2 -norm. (See, e.g., page 34 in van der Vaart and Wellner (1996)). Now, write $\hat{\varepsilon}_i, \tilde{\varepsilon}_i$, for $\varepsilon_i(\hat{\theta}), \varepsilon_i(\tilde{\theta})$, respectively. Also, let ε denote a r.v. having the same distribution as $\varepsilon_1(\theta)$.

Proposition 6.2 *Suppose regularity conditions (2.4) and (2.5) are satisfied. Suppose also $E\varphi^2(\varepsilon) = 1$ and $\tilde{\theta}$ is any estimator such that $\sqrt{n}(\tilde{\theta} - \theta) = O_p(1)$. If \mathcal{B}_0 is such that (6.4) is satisfied then, under H_φ ,*

$$w_n \longrightarrow_d w, \quad \text{in } l^\infty(\mathcal{G}_0).$$

Remark 6.1 In the definition (6.3) of the process w_n we assumed that $E\varphi^2(\varepsilon) = 1$ without loss of generality. Indeed, we can always replace $\varphi(\hat{\varepsilon}_i)$ by $\varphi(\hat{\varepsilon}_i)/\hat{\sigma}$ in w_n , where $\hat{\sigma}^2 = n^{-1} \sum_{i=1}^n \varphi^2(\hat{\varepsilon}_i)$ is an estimator of $\sigma^2 = E\varphi^2(\varepsilon)$. Then it is obvious that the processes which incorporate $\varphi(\hat{\varepsilon}_i)/\hat{\sigma}$ and $\varphi(\hat{\varepsilon}_i)/\sigma$, respectively, will converge to each other, uniformly in B , in probability.

Since the kernel of the transformation \mathcal{T} depends on θ we will certainly need to replace it with an estimator. It seems the simplest to use the same estimator $\tilde{\theta}$ as is used in $\tilde{\xi}_n$, although it is not necessary and in principle any consistent estimator can be used: small perturbation of θ in \mathcal{T}_θ will only slightly perturb the process $\tilde{\xi}_n(\mathcal{T}_\theta\gamma, \varphi)$. To prove this latter statement formally we need to compliment (2.4) by the following two mild assumptions.

Let

$$\begin{aligned} d^2(\vartheta_1, \vartheta_2) &:= E\|\dot{\mu}_{\vartheta_1}(X) - \dot{\mu}_{\vartheta_2}(X)\|^2 E\varphi^2(\tilde{\varepsilon}), & \tilde{\varepsilon} &:= \varepsilon(\tilde{\theta}), \quad \vartheta \in \Theta, \\ \rho(\delta) &:= \sup_{\|\vartheta_1 - \vartheta_2\| \leq \delta} d(\vartheta_1, \vartheta_2), & \delta &> 0. \end{aligned}$$

Suppose that $E\varphi^2(\varepsilon) = 1$, and that for some $\epsilon > 0$,

$$(6.5) \quad \sup_{\|\vartheta_1 - \vartheta_2\| \leq \epsilon} \left| \frac{1}{n} \sum_{i=1}^n \|\dot{\mu}_{\vartheta_1}(X_i) - \dot{\mu}_{\vartheta_2}(X_i)\|^2 - d^2(\vartheta_1, \vartheta_2) \right| = o_p(1), \quad \text{as } n \rightarrow \infty.$$

$$(6.6) \quad \sum_{k=0}^{\infty} k\rho(\epsilon 2^{-k}) < \infty.$$

Define the estimated transformed process:

$$\tilde{w}_n(B) := \tilde{\xi}_n(\mathbb{I}_B, \varphi) - \tilde{\xi}_n(\mathcal{T}_{\tilde{\theta}}\mathbb{I}_B, \varphi).$$

We have the following statement.

Proposition 6.3 *Let $\{\mathbb{I}_B, B \in \mathcal{B}_0\}$ be any collection of indicator functions such that \mathcal{B}_0 satisfies (6.4). Then, under the assumptions (6.5) and (6.6),*

$$\sup_{B \in \mathcal{B}_0} |\tilde{w}_n(B) - w_n(B)| = o_p(1).$$

To prove this last proposition we will use the following lemma, which is of independent interest. Let, for a $c > 0$,

$$D_n = \left\{ \sup_{\|\vartheta_1 - \vartheta_2\| \leq \delta} \frac{1}{n} \sum_{i=1}^n \|\dot{\mu}_{\vartheta_1}(X_i) - \dot{\mu}_{\vartheta_2}(X_i)\|^2 \varphi^2(\tilde{\varepsilon}_i) \leq (1+c)d^2(\delta), \text{ for all } 0 < \delta < c \right\}.$$

Lemma 6.1 *Let $\{\mathbb{I}_A, A \in \mathcal{A}\}$ be any collection of indicator functions. Then, under the assumptions (6.5) and (6.6),*

$$P\left(\sup_{\|\vartheta-\theta\|\leq\epsilon} |\tilde{\xi}_n(\mathbb{I}_A\dot{\mu}_\vartheta, \varphi) - \xi_n(\mathbb{I}_A\dot{\mu}_\theta, \varphi)| > x | D_n\right) \leq \exp\left\{-\frac{x}{2}C \sum_{k=0}^{\infty} k\rho(\epsilon 2^{-k})\right\},$$

$$E\left\{\sup_{\|\vartheta-\theta\|\leq\epsilon} |\tilde{\xi}_n(\mathbb{I}_A\dot{\mu}_\vartheta, \varphi) - \tilde{\xi}_n(\mathbb{I}_A\dot{\mu}_\theta, \varphi)|^2 \middle| D_n\right\} \leq C \sum_{k=0}^{\infty} k\rho(\epsilon 2^{-k}) \rightarrow 0,$$

as $\epsilon \rightarrow 0$, where C is a positive universal constant.

Now we prove all three propositions and the lemma.

Proof of Proposition 6.1. Fix a $k < \infty$ and consider $\gamma_k := \gamma\mathbb{I}_{A_k}$. We shall first show that $\langle \mathcal{K}\gamma_k, \dot{\mu}_\theta^T \rangle = 0$. Note that $y \in A_{z(x)}$ is equivalent to $x \in A_{z(y)}^c$ for almost all x, y with respect to the measure H . This fact together with changing the order of integration, yields

$$\begin{aligned} & \langle \mathcal{K}\gamma_k, \dot{\mu}_\theta^T \rangle \\ &= \int_{\mathbb{R}^p} \gamma_k(x) \dot{\mu}_\theta^T(x) dH(x) - \int_{\mathbb{R}^p} \int_{A_{z(x)}} \gamma_k(y) \dot{\mu}_\theta^T(y) \mathcal{C}_{z(y)}^{-1} dH(y) \dot{\mu}_\theta(x) \dot{\mu}_\theta^T(x) dH(x) \\ &= \langle \gamma_k, \dot{\mu}_\theta^T \rangle - \int_{\mathbb{R}^p} \gamma_k(y) \dot{\mu}_\theta^T(y) \mathcal{C}_{z(y)}^{-1} dH(y) \int_{A_{z(y)}^c} \dot{\mu}_\theta(x) \dot{\mu}_\theta^T(x) dH(x) \\ &= \langle \gamma_k, \dot{\mu}_\theta^T \rangle - \langle \gamma_k, \dot{\mu}_\theta^T \rangle = 0. \end{aligned}$$

Now we shall show that

$$(6.7) \quad \langle \mathcal{K}\gamma_k, \mathcal{K}\gamma_k \rangle = \langle \gamma_k, \gamma_k \rangle.$$

Using the notation

$$\rho_k^T(z) := \int_{A_z} \gamma_k(y) \dot{\mu}_\theta^T(y) \mathcal{C}_{z(y)}^{-1} dH(y), \quad z \in \bar{\mathbb{R}},$$

rewrite

$$\begin{aligned} & \langle \mathcal{K}\gamma_k, \mathcal{K}\gamma_k \rangle \\ &= \langle \gamma_k, \gamma_k \rangle - 2 \int_{\mathbb{R}^p} \rho_k^T(z(x)) \dot{\mu}_\theta(x) \gamma_k(x) dH(x) + \int_{\mathbb{R}^p} \rho_k^T(z(x)) \dot{\mu}_\theta(x) \dot{\mu}_\theta^T(x) \rho_k(z(x)) dH(x) \\ &= \langle \gamma_k, \gamma_k \rangle - 2 \int_{z \leq z_0} \rho_k^T(z) \mathcal{C}_z d\rho_k(z) + \int_{-\infty}^{\infty} \rho_k^T(z) d\mathcal{C}_z \rho_k(z) \\ &= \langle \gamma_k, \gamma_k \rangle - \rho_k^T(z) \mathcal{C}_z \rho_k(z) \Big|_{-\infty}^{\infty}. \end{aligned}$$

Because $\gamma_k = \gamma\mathbb{I}_{A_k}$, the function ρ_k remains bounded as $z \rightarrow \infty$ and hence the substitution in the above equals zero, thereby proving (6.7).

Next, by definition, $\gamma_k \rightarrow \gamma$, as $k \rightarrow \infty$. Let $k \rightarrow \infty$ in (6.7) to conclude that it remains true for a general $\gamma \in L_2(\mathbb{R}^p, H)$. \square

Proof of Proposition 6.2. Using the definition of the operator \mathcal{K} one can write

$$\begin{aligned} & \sup_{B \in \mathcal{B}_0} |w_n(B) - \xi_n(\mathcal{K}\mathbb{I}_B, \varphi)| \\ & \leq \sup_{B \in \mathcal{B}_0} |\tilde{\xi}_n(\mathbb{I}_B, \varphi) - \xi_n(\mathbb{I}_B, \varphi) - E\varphi' E(\mathbb{I}_B \dot{\mu}_\theta^T) n^{1/2}(\tilde{\theta} - \theta)| \\ & \quad + \sup_{B \in \mathcal{B}_0} |\tilde{\xi}_n(\mathcal{T}\mathbb{I}_B, \varphi) - \xi_n(\mathcal{T}\mathbb{I}_B, \varphi) + E\varphi' E(\mathbb{I}_B \dot{\mu}_\theta^T) n^{1/2}(\tilde{\theta} - \theta)|. \end{aligned}$$

However, Proposition 2.1 implies that the first supremum on the right hand side is $o_p(1)$. To deal with the second supremum, let us use the fact that $\mathbb{I}_{A_{z(x)}}(y) = \mathbb{I}_{A_{z(y)}}(x)$ a.e. and change the order of summation and integration:

$$\begin{aligned} \xi_n(\mathcal{T}\gamma, \varphi) &= n^{-1/2} \sum_{i=1}^n \int_{A_i(X_i)} \gamma(y) \dot{\mu}_\theta^T(y) C_{z(y)}^{-1} dH(y) \dot{\mu}_\theta(X_i) \varphi(e_i) \\ &= \int \gamma(y) \dot{\mu}_\theta^T(y) C_{z(y)}^{-1} \xi_n(\mathbb{I}_{A_z^c(y)} \dot{\mu}_\theta, \varphi) dH(y). \end{aligned}$$

Similar equality is certainly true for $\tilde{\xi}_n$. Therefore, using Proposition 2.1 once again we obtain

$$\sup_{B \in \mathcal{B}_0} |\tilde{\xi}_n(\mathcal{T}\mathbb{I}_B, \varphi) - \xi_n(\mathcal{T}\mathbb{I}_B, \varphi) - E\varphi' E(\mathbb{I}_B \dot{\mu}_\theta^T) n^{1/2}(\tilde{\theta} - \theta)| = o_p(1). \quad \square$$

Proof of Proposition 6.3. First note that from the previous proof we have

$$\tilde{w}_n(B) - w_n(B) = \tilde{\xi}_n(\mathcal{T}_{\tilde{\theta}}\mathbb{I}_B, \varphi) - \tilde{\xi}_n(\mathcal{T}_\theta\mathbb{I}_B, \varphi).$$

Now, let $\eta^T(y, \vartheta) = \dot{\mu}_\vartheta^T(y) C_{\vartheta, z(y)}^{-1}$ and $\tilde{\xi}_n(z, \vartheta) = \tilde{\xi}_n(\mathbb{I}_{A_{z(y)}^c} \dot{\mu}_\vartheta, \varphi)$. Then we can rewrite

$$\begin{aligned} \tilde{\xi}_n(\mathcal{T}_\vartheta\mathbb{I}_B, \varphi) &= \int \mathbb{I}_B(y) \dot{\mu}_\vartheta^T(y) C_{\vartheta, z(y)}^{-1} \tilde{\xi}_n(\mathbb{I}_{A_{z(y)}^c} \dot{\mu}_\vartheta, \varphi) dH(y) \\ &= \int \mathbb{I}_B(y) \eta^T(y, \vartheta) \tilde{\xi}_n(z(y), \vartheta) dH(y). \end{aligned}$$

Since

$$\begin{aligned} |\tilde{\xi}_n(\mathcal{T}_{\tilde{\theta}}\mathbb{I}_B, \varphi) - \tilde{\xi}_n(\mathcal{T}_\theta\mathbb{I}_B, \varphi)| &\leq \mathbb{I}_{\{\|\tilde{\theta} - \theta\| \leq \epsilon\}} \sup_{\|\vartheta - \theta\| \leq \epsilon} |\tilde{\xi}_n(\mathcal{T}_\vartheta\mathbb{I}_B, \varphi) - \tilde{\xi}_n(\mathcal{T}_\theta\mathbb{I}_B, \varphi)| \\ &\quad + \mathbb{I}_{\{\|\tilde{\theta} - \theta\| > \epsilon\}} |\tilde{\xi}_n(\mathcal{T}_{\tilde{\theta}}\mathbb{I}_B, \varphi) - \tilde{\xi}_n(\mathcal{T}_\theta\mathbb{I}_B, \varphi)| \end{aligned}$$

and $\tilde{\theta}$ is consistent estimator, it is enough to prove that

$$\sup_{B \in \mathcal{B}_0, \|\vartheta - \theta\| \leq \epsilon} \int \mathbb{I}_B(y) |\eta^T(y, \vartheta) \tilde{\xi}_n(z(y), \vartheta) - \eta^T(y, \theta) \tilde{\xi}_n(z(y), \theta)| dH(y) = o_p(1),$$

as $\epsilon \rightarrow 0$ and $n \rightarrow \infty$. Using the Cauchy - Schwarz inequality and the fact that $B \subset A_{1-\tau}$ we find that the left hand side of the above equality is bounded above by

$$\sup_{\|\vartheta - \theta\| \leq \epsilon} \|\eta(\cdot, \vartheta) - \eta(\cdot, \theta)\|_H \|\tilde{\xi}_n(\cdot, \vartheta)\|_H + \|\eta(\cdot, \theta)\|_H \sup_{\|\vartheta - \theta\| \leq \epsilon} \|\tilde{\xi}_n(\cdot, \vartheta) - \tilde{\xi}_n(\cdot, \theta)\|_H,$$

where $\|\cdot\|_H$ is the L_2 norm with respect to H .

Since C_z is non-singular for $z < 1 - \tau$, we have $\|\eta(\cdot, \theta)\|_H < \infty$. Moreover, $\dot{\mu}_\vartheta$ being continuous in ϑ in mean square sense (condition (2.4)), it follows that for all sufficiently small ϵ , $C_{\vartheta, z}$ is non-singular for all $\|\vartheta - \theta\| \leq \epsilon$, $z < 1 - \tau$, and that $\sup_{\|\vartheta - \theta\| \leq \epsilon} \|\eta(\cdot, \vartheta) - \eta(\cdot, \theta)\|_H$ is small. What remains therefore to show is that $\sup_{B \in \mathcal{B}_0, \|\vartheta - \theta\| \leq \epsilon} \|\tilde{\xi}_n(\cdot, \vartheta)\|_H = o_p(1)$, and that $\sup_{B \in \mathcal{B}_0, \|\vartheta - \theta\| \leq \epsilon} \|\tilde{\xi}_n(\cdot, \vartheta) - \tilde{\xi}_n(\cdot, \theta)\| = o_p(1)$ as $n \rightarrow \infty$ and $\epsilon \rightarrow 0$. These properties are proved in Lemma 6.1 below. \square

Proof of Lemma 6.1. First note that Symmetrisation Lemma (see, e.g., van der Vaart and Wellner (1996), Sec.2.3.2) can be used to imply that

$$\|\tilde{\xi}_n(z, \vartheta_1) - \tilde{\xi}_n(z, \vartheta_2)\| \leq 2\|\tilde{\xi}_n^0(z, \vartheta_1) - \tilde{\xi}_n^0(z, \vartheta_2)\|,$$

where

$$\tilde{\xi}_n^0(z, \vartheta) = n^{-1/2} \sum_{i=1}^n e_i \mathbb{I}_{A_z} \dot{\mu}_\vartheta(X_i) \varphi(\tilde{\varepsilon}_i),$$

and $\{e_i\}_{i=1}^n$ are Rademacher random variables independent of $\{(X_i, Y_i)\}_{i=1}^n$. Averaging first over $\{e_i\}_{i=1}^n$ we obtain, for all $t > 0$,

$$\begin{aligned} & E \left[\exp \left\{ t^{-1} \|\tilde{\xi}_n^0(z, \vartheta_1) - \tilde{\xi}_n^0(z, \vartheta_2)\| \right\} \middle| D_n \right] \\ & \leq E \left[\exp \left\{ 2t^{-2} n^{-1} \sum_{i=1}^n \|\dot{\mu}_{\vartheta_1}(X_i) - \dot{\mu}_{\vartheta_2}(X_i)\|^2 \varphi^2(\tilde{\varepsilon}_i) \right\} \middle| D_n \right] \\ & \leq \exp \{ 2t^{-2} (1+c) \rho^2 (\|\vartheta_1 - \vartheta_2\|) \}. \end{aligned}$$

Following van der Vaart and Wellner (1996), Sec.2.2, denote $\|X\|_{\psi, D_n}$ the Orlicz norm of the random variable X induced by the function $\psi(x) = e^x - 1$ - this is the smallest constant t , such that $E[\exp(|X|/t) - 1 | D_n] \leq 1$. Then the previous inequality implies that

$$\|\tilde{\xi}_n^0(z, \vartheta_1) - \tilde{\xi}_n^0(z, \vartheta_2)\|_{\psi, D_n} \leq C \rho (\|\vartheta_1 - \vartheta_2\|).$$

Since $e^{x/t} - 1 > (x/t)^2/2!$, it immediately follows that

$$E \sup_{\|\vartheta - \theta\| \leq \epsilon} \|\tilde{\xi}_n(y, \vartheta) - \tilde{\xi}_n(y, \theta)\|^2 \leq 2 \left\| \sup_{\|\vartheta - \theta\| \leq \epsilon} \|\tilde{\xi}_n(y, \vartheta) - \tilde{\xi}_n(y, \theta)\| \right\|_{\psi, D_n}.$$

We now show that the Orlicz norm on the right hand side is small for small ϵ . We will do this slightly adjusting the chaining argument. Let $N(\delta)$ be the covering number (the cardinality of the minimal δ -net $\mathcal{N}(\delta)$) of the unit ball in \mathbb{R}^q . Let each $\zeta_{k+1} \in \mathcal{N}(2^{-k-1})$ be linked to

unique $\zeta_k \in \mathcal{N}(2^{-k})$ in such a way that $\|\zeta_{k+1} - \zeta_k\| \leq 2^{-k}$. Then using the Fundamental Lemma 2.2 of van der Vaart and Wellner (1996), Sec.2.2, one can write (with $\vartheta = \epsilon\zeta$)

$$\left\| \max_{\vartheta_k, \vartheta_{k+1}} \|\tilde{\xi}_n(y, \vartheta_k) - \tilde{\xi}_n(y, \vartheta_{k+1})\| \right\|_{\psi, D_n} \leq C \ln N(2^{-k}) \rho(\epsilon 2^{-k}).$$

Hence,

$$\begin{aligned} (6.8) \quad & \left\| \sup_{\|\vartheta - \theta\| \leq \epsilon} \|\tilde{\xi}_n^0(y, \vartheta) - \tilde{\xi}_n^0(y, \theta)\| \right\|_{\psi, D_n} \\ & \leq \sum_{k=1}^{\infty} \left\| \max_{\vartheta_k, \vartheta_{k+1}} \|\tilde{\xi}_n(y, \vartheta_k) - \tilde{\xi}_n(y, \vartheta_{k+1})\| \right\|_{\psi, D_n} \\ & \leq C \sum_{k=1}^{\infty} \ln N(2^{-k}) \rho(\epsilon 2^{-k}) \leq C q \sum_{k=1}^{\infty} k \rho(\epsilon 2^{-k}), \end{aligned}$$

where the last inequality follows from obvious estimation from above $N(\delta) \leq C \delta^{-q}$. Since $\rho(\epsilon 2^{-k}) \rightarrow 0$ as $\epsilon \rightarrow 0$ and the series converges for some $\epsilon > 0$ it tends to 0 as $\epsilon \rightarrow 0$.

Finally combine the symmetrisation and Markov inequalities to obtain

$$\begin{aligned} & P\left(\sup_{\|\vartheta - \theta\| \leq \epsilon} \|\tilde{\xi}_n(y, \vartheta) - \tilde{\xi}_n(y, \theta)\| > x \mid D_n \right) \\ & \leq P\left(\sup_{\|\vartheta - \theta\| \leq \epsilon} \|\tilde{\xi}_n^0(y, \vartheta) - \tilde{\xi}_n^0(y, \theta)\| > \frac{x}{2} \mid D_n \right) \\ & \leq E\left[\exp\left\{ t^{-1} \sup_{\|\vartheta - \theta\| \leq \epsilon} \|\tilde{\xi}_n^0(y, \vartheta) - \tilde{\xi}_n^0(y, \theta)\| \right\} \mid D_n \right] \exp\left(-\frac{x}{4t}\right). \end{aligned}$$

From the definition of Orlicz norm $\left\| \sup_{\|\vartheta - \theta\| \leq \epsilon} \|\tilde{\xi}_n^0(y, \vartheta) - \tilde{\xi}_n^0(y, \theta)\| \right\|_{\psi, D_n}$ and the inequality (6.8) it follows that the expectation above does not exceed 2 for $t = q \sum_{k=1}^{\infty} k \rho(\epsilon 2^{-k})$. Hence the inequality of the lemma. \square

We end this section by pointing out that the conditions (6.5) and (6.6) are trivially satisfied in the case $\mu(x, \vartheta) \equiv \vartheta' S(x)$, where $S(x)$ is a vector of functions of x with finite second moment $E\|S(X)\|^2$.

7 Some simulations

This section presents some simulations to see how well the finite sample level of significance is approximated by the asymptotic level for the supremum of the absolute values of the transformed processes defined at (5.3) and (6.3). It is noted that when fitting a standard normal distribution to the errors with a rapidly changing regression function, or when fitting a 2-variable linear regression model with standard normal errors and using the least square residuals, this approximation is very good even for the sample size 40, especially in the right tail.

The lack of an analytical form of the distribution of the supremum of the Brownian motion on $[0, 1]^2$ created an extra difficulty here. We had to first obtain simulated approximation to this distribution. This was done by simulating an appropriate two time parameter Poisson process of the sample of size $5K, 20K$ times. Selected quantiles based on this simulation are presented in Tables 2 - 4 of the sub-section 7.2. This should be of independent interest also.

7.1 $\sup_z |\widehat{w}_{n1}(z)|$ of (5.3)

This sub-section presents some selected empirical percentiles of the transformed statistic $D_n := \sup_z |\widehat{w}_{n1}(z)|$ of (5.3) for testing $H_0 : F$ is the standard normal d.f. The regression function is taken to be $\mu(x, \vartheta) = e^{\vartheta x}$, with true $\theta = 0.25$, the regressors $X_i, i = 1, \dots, n$, are chosen to be uniformly distributed on $[2, 4]$, and the errors $\varepsilon_i \equiv \varepsilon_i(\theta), i = 1, \dots, n$ are standard Gaussian. In this case the Γ function of section 5.3 becomes

$$\Gamma_{F(y)}^{-1} = \frac{1}{[1 - F(y)][ya(y) + 1 - a^2(y)]} \begin{pmatrix} 1 + ya(y) & a(y) \\ a(y) & 1 \end{pmatrix},$$

where $a(y) = f(y)/(1 - F(y))$ with f and F denoting standard normal density and d.f., respectively. Consequently, the vector-function G of (5.3) is now equal to

$$G^T(z) = \int_{-\infty}^z (1, -y)\Gamma_{F(y)}^{-1}f(y)dy = \int_{-\infty}^z \frac{1}{ya(y) + 1 - a^2(y)}(1, a(y) - y)a(y)dy.$$

and, eventually, the transformed process of (5.3) has the form

$$(7.1) \quad \widehat{w}_{n1}(t) = n^{-1/2} \sum_{i=1}^n \left[\mathbb{I}\{\varepsilon_i(\widehat{\theta}) \leq z\} - \int_{-\infty}^{z \wedge \varepsilon_i(\widehat{\theta})} \frac{1 + \varepsilon_i(\widehat{\theta})(a(y) - y)}{ya(y) + 1 - a^2(y)} a(y)dy \right], \quad t = F(z)$$

Although the form of the regression function does not participate in the martingale transformation \mathcal{L} it still may affect the finite sample behavior of the transformed process as far as it affects $\varepsilon_i(\widehat{\theta}), i = 1, \dots, n$, where $\widehat{\theta}$ is the MLE under the null hypothesis. It was thus of interest to see whether the estimation of θ will not affect the values of $\varepsilon_i(\widehat{\theta}), i = 1, \dots, n$, too much and worsen the convergence of the transformed process to its limit. For this reason we chose a more or less rapidly changing regression function. On the other hand there was no point in choosing multidimensional regressors X_i here, since the transformed process depends solely on $\varepsilon_i(\widehat{\theta}), i = 1, \dots, n$.

We simulated $\{(X_i, Y_i = e^{0.25X_i} + \varepsilon_i), 1 \leq i \leq n\}$ for sample sizes $n = 40, 100$ and for each sample calculated the value of Kolmogorov-Smirnov statistic $D_n := \sup\{|\widehat{w}_{n1}(t)|; 0 \leq t \leq 1\}$, with $\widehat{w}_{n1}(t)$ as in (7.1). This was done $m = 10K$ times. In the Table 1, d_α is the $100(1 - \alpha)\%$ percentile of the limiting distribution of D_n . They are obtained by approximating the d.f. of the supremum of the Brownian motion over $[0, 1]$ by $\mathcal{G}(z) := P(\sup_{0 \leq t \leq 1} |\xi_n(t) - nt|/\sqrt{n} \leq z)$,

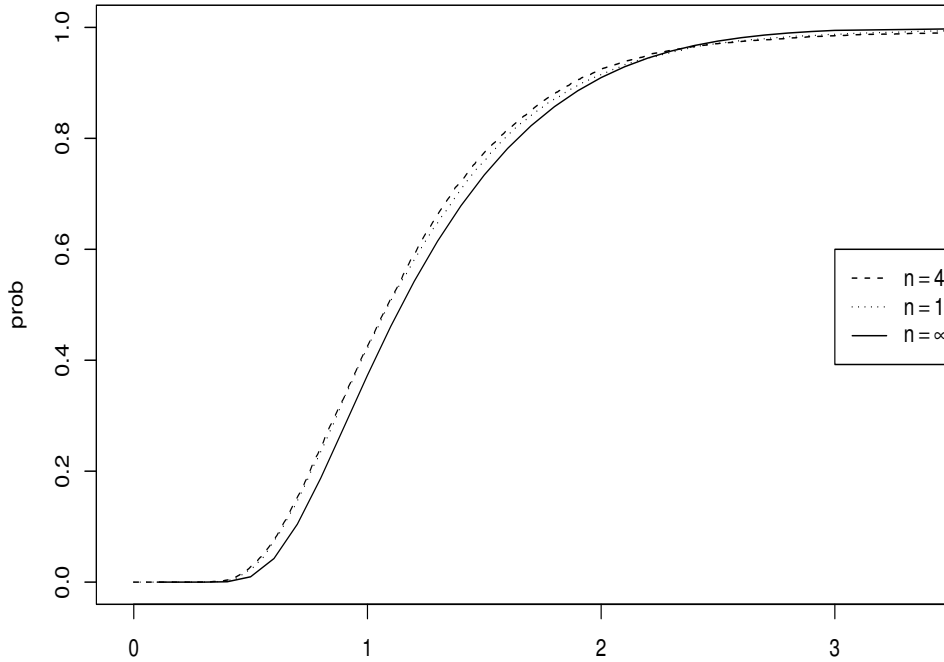


Figure 1: *Edf of D_n for $n = 40, 100, m = 10K$ and \mathcal{G} .*

with $n = 5K$, where $\xi_n(t)$, $t \in [0, 1]$ is a Poisson process with intensity n . The d.f. \mathcal{G} was calculated using the exact recurrent formulas and code given in Khmaladze and Shinjikashvili (2001). The values obtained are accurate to 5×10^{-3} .

Table 1 also gives the Monte Carlo estimates of $P(D_n > d_\alpha)$ for $n = 40$ and $n = 100$ based on $m = 10K$ replications. The resulting (simulated) distribution functions of D_n along with \mathcal{G} as solid line are shown in Figure 1. The quality of approximation appears to be quite close to what one has in the classical case of empirical process and the limiting Brownian bridge. Especially, in the upper tail where we need it the most.

Table 1: *Selected quantiles of $P(D_n > d_\alpha)$*

α	0.2	0.1	0.05	0.025	0.01
$n \setminus d_\alpha$	1.64	1.96	2.24	2.50	2.81
40	0.168	0.084	0.046	0.029	0.019
100	0.178	0.093	0.052	0.029	0.014

7.2 $\sup_B |w_n(B)|$ of (6.3)

Here the regressors $X_i, i = 1, \dots, n$ are two-dimensional Gaussian random vectors with standard normal marginal distributions and correlation r . The regression function being fitted is chosen to be linear:

$$(7.2) \quad \mu(x, \vartheta) = \vartheta_1 x_1 + \vartheta_2 x_2,$$

with the true parameter $\theta' = (1, 1)$, while the scanning family $\mathcal{A} = \{A_z : z \in \mathbb{R}\}$ is just one of the examples mentioned in section 6: $A_z = \{x \in \mathbb{R}^2 : x^1 \leq z\}$. Let w_n, w_H be as in section 6.

For the above regression function and the scanning family the matrix \mathcal{C}^{-1} has the form

$$\mathcal{C}_z^{-1} = \frac{1}{[1-r^2][1-F(z)]} \begin{pmatrix} r^2 & -r \\ -r & 1 \end{pmatrix} + \frac{1}{1-F(z)} \begin{pmatrix} (za(z)+1)^{-1} & 0 \\ 0 & 0 \end{pmatrix}$$

and the integral in (6.3) becomes

$$\int_{-\infty}^{x_1 \wedge X_{i1}} \frac{ya(y)}{ya(y)+1} F\left(\frac{x_2 - ry}{\sqrt{1-r^2}}\right) dy X_{1i} - \int_{-\infty}^{x_1 \wedge X_{i1}} a(y) \frac{1}{\sqrt{1-r^2}} dy (X_{i2} - rX_{i1})$$

Here, as above, f and F denote the standard normal density and distribution function, respectively. In our simulations the class of sets B were chosen to be $(-\infty, x]$, $x \in \mathbb{R}^2$. Write $w_n(x), w_H(x)$ for $w_n(B), w_H(B)$, whenever $B = (-\infty, x]$, $x \in \mathbb{R}^2$, respectively. Choosing $\varphi(y) = y$ and $\tilde{\theta}$ to be the least square estimator, the transformed process (6.3) becomes

$$\begin{aligned} w_n(x) &= n^{-1/2} \sum_{i=1}^n \left[\mathbb{I}(X_i \leq x) - \int_{-\infty}^{x_1 \wedge X_{i1}} \frac{ya(y)}{ya(y)+1} F\left(\frac{x_2 - ry}{\sqrt{1-r^2}}\right) dy X_{1i} \right. \\ &\quad \left. - \int_{-\infty}^{x_1 \wedge X_{i1}} a(y) \frac{1}{\sqrt{1-r^2}} dy (X_{i2} - rX_{i1}) \right] \left(Y_i - \mu(X_i, \tilde{\theta}) \right). \end{aligned}$$

Let $\mathcal{V}_n := \sup_x |w_n(x)|$, $\mathcal{V}_H := \sup_x |w_H(x)|$.

In order to demonstrate how well the null distribution of \mathcal{V}_n is approximated by the distribution of \mathcal{V}_H , we had to first understand the form of the latter distribution. We thus first obtained an approximation for the distribution of this r.v. as follows.

Let $H(x_1, x_2; r)$, $x = (x_1, x_2)' \in \mathbb{R}^2$, denote the d.f. of the bivariate normal distribution with standard marginals and correlation r . Let

$$(7.3) \quad H_r(s, t) := H(F^{-1}(s), F^{-1}(t); r), \quad 0 \leq s, t \leq 1,$$

be the corresponding copula function, and let $w(s, t) := w_H(F^{-1}(s), F^{-1}(t))$. The d.f. $P(\sup_{0 \leq s, t \leq 1} |w(s, t)| \leq v)$, is the limit as n tends to infinity of, and is approximated by

$$L_r(v) := P\left(\sup_{0 \leq s, t \leq 1} |\xi_{nH_r}(s, t) - nH_r(s, t)| / \sqrt{n} \leq v\right),$$

where $\xi_{nH_r}(s, t)$ is a Poisson process on $[0, 1]^2$ with expected value $nH_r(s, t)$. Tables 2 - 4 give the simulated values of these probabilities for $r = -0.5, 0, 0.5$ and $n = 5K$ with $m = 20K$ replications. All these tables are based on the tables and graphs of the distribution function L_r and percentile points, prepared by Dr R. Brownrigg, at the address <http://www.mcs.vuw.ac.nz/~ray/Brownian>.

Table 2: *Selected values of $(v, L_r(v))$ for $r = -0.5$*

x	0.71	0.88	1.00	1.25	1.50	1.75	2.00	2.25	2.50	2.75	3.00	3.25
$L_r(x)$	0.00	0.01	0.05	0.25	0.50	0.69	0.82	0.91	0.95	0.98	0.99	0.995

Table 3: *Selected values of $(v, L_r(v))$ for $r = 0$*

x	0.66	0.84	1.00	1.25	1.50	1.75	2.00	2.25	2.50	2.75	3.00	3.25
$L_r(x)$	0.00	0.01	0.07	0.30	0.53	0.72	0.84	0.91	0.95	0.98	0.99	0.995

Table 4: *Selected values of $(v, L_r(v))$ for $r = 0.5$*

x	0.59	0.79	1.00	1.25	1.50	1.75	2.00	2.25	2.50	2.75	3.00	3.25
$L_r(x)$	0.00	0.01	0.11	0.35	0.57	0.74	0.85	0.92	0.96	0.98	0.99	0.996

Although the distribution of \mathcal{V}_H depends on the copula function H_r the first useful observation is that relatively sharp changes in H_r do not appear to change the distribution of this r.v. by much. Table 5 summarizes a few selected percentiles to readily assess the effect of r on them. It contains the values of v_α defined by the relation $1 - L_r(v_\alpha) = \alpha$. One readily sees that these values are very stable across the three chosen values of r , especially for $\alpha \leq 0.1$.

Table 5: *Selected values of v_α for $r = -0.5, 0, 0.5$*

$r \setminus \alpha$	0.5	0.25	0.20	0.10	0.05	0.025	0.01
-0.5	1.50	1.86	1.95	2.23	2.50	2.74	3.03
0.0	1.46	1.81	1.91	2.21	2.46	2.70	3.03
0.5	1.42	1.77	1.88	2.17	2.43	2.70	2.98

We illustrate the closeness of the distribution of \mathcal{V}_n for finite n to the limiting distribution with the graphs of edfs for $n = 40, 100$, with $m = 10K$ replications. Figures 2-4 show the (simulated) d.f.'s of \mathcal{V}_n for $n = 40, 100$; $m = 10K$, and the approximating d.f. L_r (solid line) for H_r as in (7.3) above with $r = -0.5, 0$ and 0.5 . One readily notes the remarkable closeness of these d.f.'s, especially in the right tail.

Table 6 gives the simulated values of $P(\mathcal{V}_n > v_\alpha)$ for several values of α and sample sizes $n = 40$ and $n = 100$, based on $m = 10K$ replications. From this table one also sees that

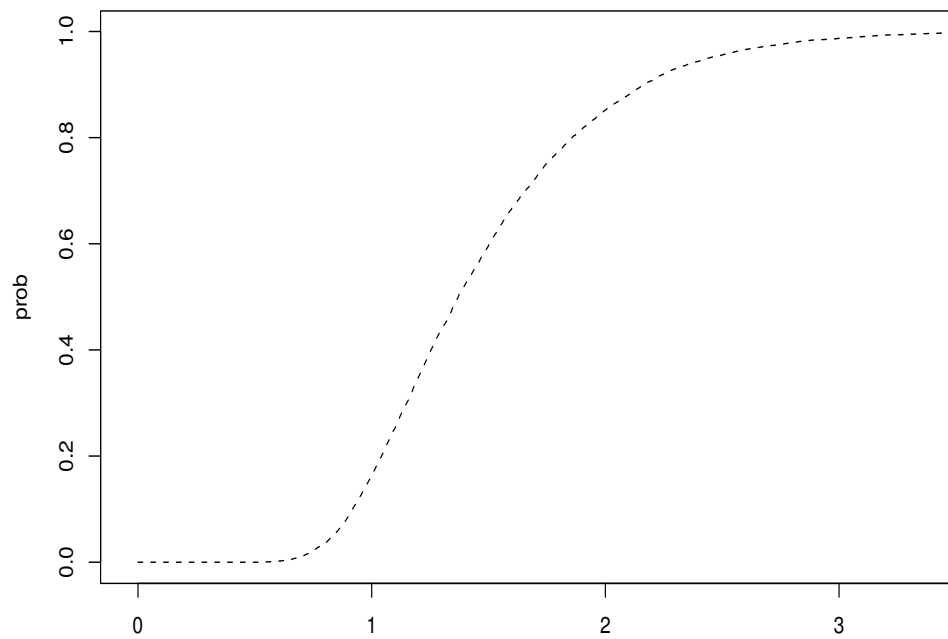


Figure 2: *Edf of \mathcal{V}_n , $n = 40, 100$, with $m = 10K$, and d.f. L_r , $r = -0.5$*

the large sample approximation is reasonably good for even the sample size of 40 and fairly stable across the chosen values of r .

Table 6: $P(\mathcal{V}_n > v_\alpha)$, $m = 20K$

n	r \ α	0.2	0.1	0.05	0.01
40	-0.5	0.166	0.084	0.045	0.012
40	0.0	0.166	0.085	0.045	0.011
40	0.5	0.162	0.084	0.042	0.008
100	-0.5	0.179	0.092	0.046	0.009
100	0.0	0.183	0.092	0.048	0.008
100	0.5	0.178	0.093	0.046	0.009

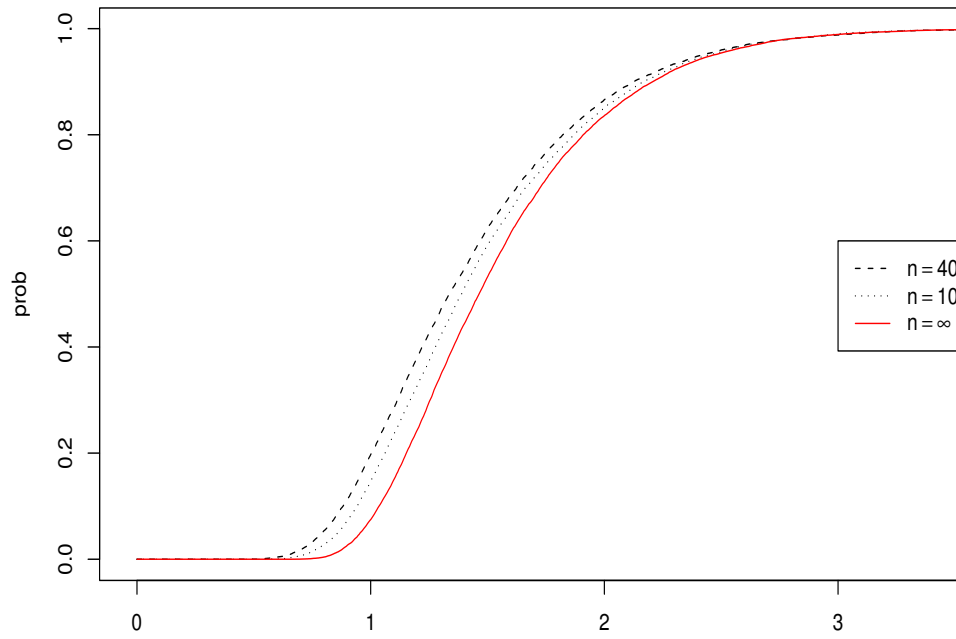


Figure 3: Edf of \mathcal{V}_n , $n = 40, 100$, with $m = 10K$, and d.f. L_r , $r = 0$

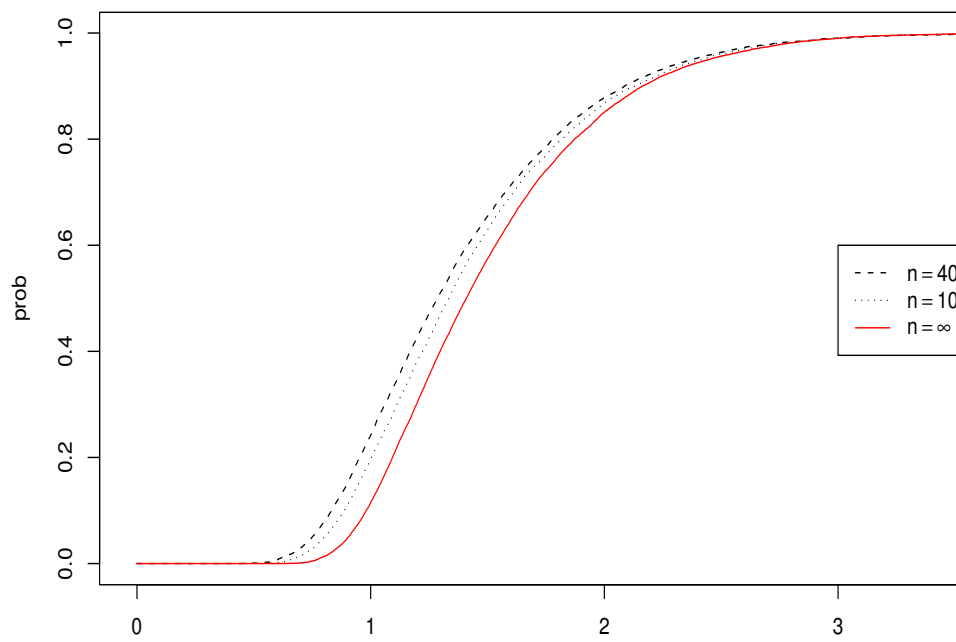


Figure 4: Edf of \mathcal{V}_n , $n = 40, 100$, with $m = 10K$, and d.f. L_r , $r = 0.5$

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