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PENALIZED CONTRAST ESTIMATION IN FUNCTIONAL LINEAR MODELS WITH CIRCULAR DATA

E. BRUNEL AND A. ROCHE *

ABSTRACT. Our aim is to estimate the unknown slope function in the functional linear model when the response Y is real and the random function X is a second order stationary and periodic process. We obtain our estimator by minimizing a standard (and very simple) mean-square contrast on linear finite dimensional spaces spanned by trigonometric bases. The novelty of our approach is to provide a penalization procedure which allows to automatically select the adequate dimension, in a non-asymptotic point of view. In fact, we can show that our penalized estimator reaches the optimal (minimax) rate of convergence in the sense of the prediction error. We complete the theoretical results by a simulation study which illustrates how the procedure works in practice.

AMS 2000 Subject Classifications. 62G05 - 62J05 - 62G08.

Keywords. Functional linear model, penalized contrast estimator, mean squared prediction error, minimax rate.

1. INTRODUCTION

Functional data analysis have known recent advances in the past two decades. In many practical situations, we aim to predict values of a scalar response by using functional predictors, or roughly speaking, curves. Many fields of applications are concerned with this kind of data, such as medicine, chemometrics or econometrics. This is especially the case when people have to predict electric consumption from a daily temperature curve, or in medicine when spectrometric signals are used to detect abnormality. We refer to Ferraty and Vieu (2006) and Ramsay and Silverman (2005) for detailed examples and to Preda and Saporta (2005) for application in econometrics. In this paper, we focus on the functional linear model, where the dependence between a scalar response Y and the functional random predictor X is given by:

$$(1) \quad Y = \int_0^1 \beta(t)X(t)dt + \sigma\varepsilon, \quad \sigma > 0,$$

where the random variable ε stands for a noise term. Our aim is to estimate the unknown slope function β from an independent and identically distributed (i.i.d.) sample (X_i, Y_i) , for $i = 1, \dots, n$. In the sequel, we suppose that the random function X takes value in $\mathbf{L}^2(A)$ with A a compact set and for sake of simplicity, we fix $A = [0, 1]$. We recall that the usual inner product $\langle \cdot, \cdot \rangle$ in $\mathbf{L}^2[0, 1]$ is defined by $\langle f, g \rangle = \int_0^1 f(u)g(u)du$ for all $f, g \in \mathbf{L}^2[0, 1]$. The random curve X will be supposed to be centred and periodic that is to say the function $s \mapsto \mathbf{E}[X(s)]$ is identically equal to zero and $X(0) = X(1)$. This context matches the description of circular data considered in Comte and Johannes (2010).

* I3M, UMR CNRS 5149, Montpellier 2 University, cc 051, place E. Bataillon, 34095 Montpellier cedex 5, France, e-mail: ebrunel@math.univ-montp2.fr ; angelina.roche@math.univ-montp2.fr.

By multiplying both sides of Equation (1) by $X(s)$ and by taking expectation, we easily obtain:

$$(2) \quad \mathbf{E}[YX(s)] = \int_0^1 \beta(t)\mathbf{E}[X(t)X(s)]dt =: \Gamma\beta(s), \text{ for all } s \in [0, 1],$$

where Γ is the covariance operator associated to the random function X . Then, the problem of the estimation of β is related to the inversion of the covariance operator Γ or of its empirical version:

$$\Gamma_n := \frac{1}{n} \sum_{i=1}^n \langle X_i, \cdot \rangle X_i.$$

Many authors have studied the functional linear model. Strategies using regression on functional principal components have been proposed by Bosq (2000), Cardot *et al.* (1999) or Cardot *et al.* (2007) among others. The mean squared estimator is usually obtained on the linear space spanned by the first eigenfunctions associated to the greatest eigenvalues of the empirical covariance operator Γ_n . Although the resulting estimator is shown to be convergent, its behaviour is often erratic in simulation studies, thus a smooth version by using splines has been proposed by Cardot *et al.* (2003). Smoothing splines estimator minimizing a standard least square criterion has been improved by Crambes *et al.* (2009) with a slight modification of the usual penalty. The authors have shown that rates of convergence for the risk defined by the mean squared prediction error depend on both the smoothness of the slope function and the structure of the covariance operator (in particular, the decreasing rate of the eigenvalues). They also prove that the obtained rates are minimax over large classes of slope functions. In a different way, Cardot and Johannes (2010) propose a thresholded projection estimator to circumvent instability problems, which can reach optimal convergence rate for the risk associated with the mean squared prediction error. Their techniques based on dimension reduction follow inverse problems ideas starting from Efromovich and Koltchinskii (2001) and covered more recently by Hoffmann and Reiss (2008). But all these procedures depend on one or more tuning parameters, which is a difficult problem to solve in practice.

Earlier, Goldenshluger and Tsybakov (2001, 2003) have considered the problem of optimal prediction under the canonical multiple linear regression model with a random design and infinitely many parameters. The performance is characterized by the mean square prediction error. They construct predictors based on a weighted regularized least square estimator. Moreover, under the normality of the random noise sequence, the predictor is asymptotically minimax over ellipsoids in ℓ_2 . However, in their setting, the regressors are uncorrelated and their common variance is supposed to be one, so that the application of their results requires to standardize the regressors. Consequently, one needs to fully know the covariance operator and this cannot be directly compared to our context.

Cai and Hall (2006) addressed the problem of prediction from an estimator of the slope function. Recently, Yuan and Cai (2010) have developed a smoothness regularization method for functional linear regression and provided a unified treatment for both the prediction and estimation problems. They obtain sharper results on the minimax rates of convergence and show that smoothness regularized estimators achieve the optimal rates of convergence for both prediction and estimation. Again, in the precedent works, the choice of the tuning parameter plays an important role in the performance of the regularized estimators. The usual practical strategy of empirically choosing the smoothing parameter value is performed through the generalized cross validation.

But nonasymptotic results providing adaptive data-driven estimators were missing up to the recent paper by Comte and Johannes (2010). They propose a model selection procedure for

the orthogonal series estimator introduced first by Cardot and Johannes (2010). The resulting estimator is completely data-driven and it is shown to achieve optimal minimax rates for general weighted \mathbf{L}^2 -risk (without including the mean squared prediction error).

In this paper, we propose an entirely data-driven procedure to select the adequate dimension of the functional space over which the standard mean square contrast is minimized. Though, our goal differs mainly from Comte and Johannes (2010) since we are interested in the mean squared prediction error. Our method is based on model selection tools developed in a general framework by Barron *et al.* (1999), recently outlined in Massart (2007) and in the particular multivariate regression model by Baraud (2002). The estimation procedure is presented in Section 3. Then, in Section 4, the resulting penalized estimator is proved to satisfy an oracle-type inequality for the risk associated to the prediction error and to reach optimal rates for slope functions belonging to Sobolev classes. Finally a simulation study is presented in Section 5.

Most of proofs are relegated to Appendix A.

2. THEORETICAL FRAMEWORK

2.1. Properties of the covariance operator. We give here some useful properties of the covariance operator Γ defined by (2).

First the operator Γ is a self-adjoint Hilbert-Schmidt operator and thus it is compact. By Theorem 6.11 of Brezis (2011), there exists an orthonormal basis $(\varphi_j)_{j \geq 1}$ of $\mathbf{L}^2([0, 1])$ where the φ_j 's are eigenfunctions of Γ . For $j \geq 1$, we denote by λ_j the eigenvalue associated to the eigenfunction φ_j .

We have $\lambda_j \geq 0$, for all $j \geq 1$. We suppose in addition that the λ_j 's are positive numbers: this condition ensures the model to be identifiable. Indeed, if there exists $j_0 \geq 1$ such that $\lambda_{j_0} = 0$, we have:

$$0 = \lambda_{j_0} \|\varphi_{j_0}\|^2 = \langle \Gamma \varphi_{j_0}, \varphi_{j_0} \rangle = \mathbf{E} [\langle X, \varphi_{j_0} \rangle^2],$$

and $\langle X, \varphi_{j_0} \rangle = 0$ almost surely. By consequence, if the slope function β satisfies Equation (1), then any slope function of the form $\beta + c\varphi_{j_0}$, with $c \in \mathbf{R}$, satisfies also Equation (1): it is clearly impossible to identify the slope function with our sample in that case.

As the curve X is supposed to be periodic and second-order stationary, the eigenfunctions of the covariance operator are the functions of the Fourier basis (see Comte and Johannes (2010)) and we can assume that:

$$(3) \quad \varphi_1 \equiv 1, \quad \varphi_{2j}(\cdot) = \sqrt{2} \cos(2\pi j \cdot) \quad \text{and} \quad \varphi_{2j+1}(\cdot) = \sqrt{2} \sin(2\pi j \cdot).$$

In this context, we only have to estimate the unknown eigenvalues of the covariance operator.

2.2. Risk—Prediction error. The quality of our estimator will be evaluated in terms of mean squared prediction error. The prediction error of an estimator $\hat{\beta}$ is the error made by predicting a new value Y_{n+1} , given a new curve X_{n+1} independent of the sample, by using the predictor $\hat{Y}_{n+1} := \langle \hat{\beta}, X_{n+1} \rangle$. This quantity can be written:

$$\mathbf{E} \left[\left(\hat{Y}_{n+1} - \mathbf{E}[Y_{n+1} | X_{n+1}] \right)^2 \mid X_1, \dots, X_n \right] = \langle \Gamma(\hat{\beta} - \beta), \hat{\beta} - \beta \rangle.$$

Then we define a new scalar product on $\mathbf{L}^2([0, 1])$ by:

$$\langle f, g \rangle_{\Gamma} := \langle \Gamma f, g \rangle = \sum_{j=1}^{\infty} \lambda_j \langle f, \varphi_j \rangle \langle g, \varphi_j \rangle, \quad \text{for all } f, g \in \mathbf{L}^2([0, 1]),$$

and its associated norm $\|\cdot\|_\Gamma$. With our assumption on the positivity of the eigenvalues λ_j , the form $\langle \cdot, \cdot \rangle_\Gamma$ satisfies the positive-definite property, otherwise we would only have a semi-norm $\|\cdot\|_\Gamma$ on $\mathbf{L}^2([0, 1])$.

3. ESTIMATION PROCEDURE

3.1. Definition of one estimator. Let $N_n \in \mathbf{N}^*$ and $\mathcal{M}_n := \{1, \dots, N_n\}$. For $m \in \mathcal{M}_n$ we denote by $S_m := \text{Vect}\{\varphi_1, \dots, \varphi_{2m+1}\}$, the linear space, called *model*, spanned by the trigonometric basis defined by (3), and of finite dimension $D_m := 2m + 1$.

Remark: Note that the models S_m are nested i.e. for $m \leq m'$, $S_m \subset S_{m'}$. Hence, the space $S_n := S_{N_n}$ contains all the models.

We define — in case that this definition makes sense — the least square estimator $\hat{\beta}_m$ of β in S_m by:

$$(4) \quad \hat{\beta}_m := \arg \min_{f \in S_m} \gamma_n(f),$$

where

$$\gamma_n(f) := \frac{1}{n} \sum_{i=1}^n (Y_i - \langle f, X_i \rangle)^2$$

is the least square contrast.

The function $f = \sum_{j=1}^{D_m} \alpha_j \varphi_j$ minimizes the contrast γ_n on S_m if and only if the vector $(\alpha_1, \dots, \alpha_{D_m}) \in \mathbf{R}^{D_m}$ minimizes the convex function

$$F(t_1, \dots, t_{D_m}) := \frac{1}{n} \sum_{i=1}^n \left(Y_i - \sum_{j=1}^{D_m} t_j \langle \varphi_j, X_i \rangle \right)^2$$

on \mathbf{R}^{D_m} . Let us define the matrix

$$(5) \quad \Phi_m := \left(\frac{1}{n} \sum_{i=1}^n \langle \varphi_j, X_i \rangle \langle \varphi_k, X_i \rangle \right)_{1 \leq j, k \leq D_m}$$

and the vector

$$b := \left(\frac{1}{n} \sum_{i=1}^n Y_i \langle \varphi_j, X_i \rangle \right)_{1 \leq j \leq D_m},$$

we have:

$$\nabla F(t) = -2b + 2\Phi_m t,$$

with $t = (t_1, \dots, t_{D_m})' \in \mathbf{R}^{D_m}$.

Therefore, we have existence and uniqueness of the least square estimator on S_m if and only if the matrix Φ_m is invertible. In that case, the estimator is given by:

$$\hat{\beta}_m = \sum_{j=1}^{D_m} \alpha_j \varphi_j,$$

with $\alpha = \Phi_m^{-1} b$.

3.2. Penalized estimator. Let $\hat{\lambda}_m$ be the minimal eigenvalue of Φ_m , we define for all $m \in \mathcal{M}_n$, the set

$$(6) \quad G_m := \{\hat{\lambda}_m \geq s_n\},$$

with $s_n := \frac{2}{n} \left(1 - \frac{1}{\sqrt{\ln n}}\right)$. We also define the set:

$$(7) \quad \bar{G} := \bigcap_{m \in \mathcal{M}_n} G_m.$$

For all m , on the set G_m , the matrix Φ_m is symmetric, positive and by consequence invertible. Then, by definition (7), we can compute on \bar{G} the least square estimator $\hat{\beta}_m$ of β on S_m for all $m \in \mathcal{M}_n$. Then we can define an integer

$$(8) \quad \hat{m} \in \arg \min_{m \in \mathcal{M}_n} \left(\gamma_n(\hat{\beta}_m) + \text{pen}(m) \right),$$

with

$$(9) \quad \text{pen}(m) := 4\theta(1 + 2\delta)D_m \frac{\sigma^2}{n}$$

where $\theta > 8$ and δ are two positive constants.

Finally the penalized estimator is defined by:

$$(10) \quad \tilde{\beta} := \begin{cases} \hat{\beta}_{\hat{m}} & \text{on } \bar{G} \\ 0 & \text{on } \bar{G}^c. \end{cases}$$

4. MAIN RESULT—RISK BOUND

4.1. Oracle inequality. We will denote by $(\mathcal{H}_{\text{Mom}})$ the following assumption:

$(\mathcal{H}_{\text{Mom}})$: *There exists two positive constants v and c such that for all $j = 1, \dots, D_{N_n}$ and for all $q \geq 2$:*

$$(11) \quad \mathbf{E} \left[\left| \frac{\langle \varphi_j, X \rangle}{\sqrt{\lambda_j}} \right|^{2q} \right] \leq \frac{q!}{2} v^2 c^{q-2}.$$

Under the assumption, we can bound the risk as follows:

Theorem 4.1. *Suppose that there exists $p > 6$ such that $\tau_p := \mathbf{E}[|\varepsilon|^p] < \infty$, moreover suppose that $\mathbf{E}[\langle \beta, X_1 \rangle^4] < +\infty$ and that Assumption $(\mathcal{H}_{\text{Mom}})$ is verified.*

If both conditions are satisfied:

$$(12) \quad \min_{1 \leq j \leq D_{N_n}} \lambda_j \geq 2/n \quad \text{and} \quad D_{N_n} \leq K \sqrt{\frac{n}{\ln^3 n}},$$

with K a numerical constant, we have, for all slope function $\beta \in \mathbf{L}^2([0, 1])$:

$$(13) \quad \mathbf{E}[\|\tilde{\beta} - \beta\|_{\Gamma}^2] \leq C \left(\min_{m \in \mathcal{M}_n} \left(\inf_{f \in S_m} \|\beta - f\|_{\Gamma}^2 + \text{pen}(m) \right) + \frac{1}{n} (1 + \|\beta\|_{\Gamma}^2 + \mathbf{E}[\langle \beta, X_1 \rangle^4]^{1/2}) \right),$$

with C depending only on $K, \Gamma, p, \tau_p, \sigma^2, c, v, \theta$ and δ .

Remark 1: the lower bound on $\min_{1 \leq j \leq D_{N_n}} \lambda_j$ in (12) can be expressed as a bound on the dimension D_{N_n} provided we give some explicit condition on the λ_j 's, see for instance the polynomial and exponential cases in Theorem 4.2 in the next paragraph.

Proof. Recall that $\mathcal{S}_n = S_{N_n}$. We define an empirical semi-norm naturally associated to our estimation problem by:

$$\|f\|_n^2 = \frac{1}{n} \sum_{i=1}^n \langle f, X_i \rangle^2, \text{ for all } f \in \mathbf{L}^2([0, 1]).$$

We define the set

$$(14) \quad \Delta_n := \{\forall f \in \mathcal{S}_n, \|f\|_\Gamma^2 \leq \rho_0 \|f\|_n^2\},$$

where $1 \leq \rho_0 \leq \theta/8$. The following inequality holds:

$$(15) \quad \mathbf{E}[\|\tilde{\beta} - \beta\|_\Gamma^2] \leq \mathbf{E}[\|\hat{\beta}_{\hat{m}} - \beta\|_\Gamma^2 \mathbf{1}_{\Delta_n \cap \bar{G}}] + \mathbf{E}[\|\tilde{\beta} - \beta\|_\Gamma^2 \mathbf{1}_{\Delta_n^c}] + \|\beta\|_\Gamma^2 \mathbf{P}(\bar{G}^c)$$

The second and the third terms of the inequality can be easily controlled by lemmas A.4 and A.5 deferred in Appendix A. Thus the end of the proof will be devoted to upper bound the first term in the right-hand-side of (15).

Let β_m be the orthogonal projection with respect to the scalar product $\langle \cdot, \cdot \rangle_\Gamma$, of β over S_m . By definition (4) of $\hat{\beta}_m$ we have $\gamma_n(\hat{\beta}_m) \leq \gamma_n(\beta_m)$, and by definition (8) of \hat{m} ,

$$(16) \quad \gamma_n(\hat{\beta}_{\hat{m}}) + \text{pen}(\hat{m}) \leq \gamma_n(\hat{\beta}_m) + \text{pen}(m).$$

We can write:

$$(17) \quad \gamma_n(\hat{\beta}_{\hat{m}}) - \gamma_n(\beta_m) = \|\hat{\beta}_{\hat{m}} - \beta\|_n^2 - \|\beta_m - \beta\|_n^2 - 2\nu_n(\hat{\beta}_{\hat{m}} - \beta_m),$$

with ν_n an empirical linear centred process defined by

$$(18) \quad \nu_n(f) := \frac{1}{n} \sum_{i=1}^n \varepsilon_i \langle f, X_i \rangle, \text{ for all } f \in S_m.$$

We can remark that $\mathbf{E}[\|\beta_m - \beta\|_n^2] = \mathbf{E}[\langle \beta_m - \beta, X \rangle^2] = \|\beta_m - \beta\|_\Gamma^2$. To control the random term $\|\hat{\beta}_{\hat{m}} - \beta\|_n^2$ we can see that, on the set Δ_n , for all $f \in \mathcal{S}_n$ we have $\|f\|_\Gamma^2 \leq \rho_0 \|f\|_n^2$. To deal with the last term we remark that, by the linearity of ν_n , we have, as $\theta > 0$:

$$(19) \quad \begin{aligned} 2\nu_n(\hat{\beta}_{\hat{m}} - \beta_m) &\leq 2\|\hat{\beta}_{\hat{m}} - \beta_m\|_\Gamma \sup_{f \in \mathbf{S}_{m \vee \hat{m}}^\Gamma} (\nu_n(f)) \\ &\leq \frac{1}{\theta} \|\hat{\beta}_{\hat{m}} - \beta_m\|_\Gamma^2 + \theta \sup_{f \in \mathbf{S}_{m \vee \hat{m}}^\Gamma} (\nu_n(f))^2, \end{aligned}$$

with $\mathbf{S}_{m \vee \hat{m}}^\Gamma := \{f \in S_{m \vee \hat{m}}, \|f\|_\Gamma = 1\}$. Gathering (16), (17) and (19) and taking the expectation, we obtain after several use of the triangular inequality:

$$\begin{aligned} \mathbf{E} \left[\left\| \hat{\beta}_{\hat{m}} - \beta \right\|_\Gamma^2 \mathbf{1}_{\Delta_n \cap \bar{G}} \right] &\leq \frac{4\theta\rho_0}{\theta - 8\rho_0} \mathbf{E}[\text{pen}(m) - \text{pen}(\hat{m})] \\ &+ \frac{8\rho_0 + 8\theta\rho_0 + 2\theta}{\theta - 8\rho_0} \|\beta_m - \beta\|_\Gamma^2 + \frac{4\theta^2\rho_0}{\theta - 8\rho_0} \mathbf{E} \left[\sup_{f \in \mathbf{S}_{m \vee \hat{m}}^\Gamma} (\nu_n(f))^2 \right] \\ &\leq \frac{8\rho_0 + 8\theta\rho_0 + 2\theta}{\theta - 8\rho_0} \|\beta_m - \beta\|_\Gamma^2 + \frac{8\theta\rho_0}{\theta - 8\rho_0} \text{pen}(m) \\ &+ \frac{4\theta^2\rho_0}{\theta - 8\rho_0} \sum_{m' \in \mathcal{M}_n} \mathbf{E} \left[\left(\sup_{f \in \mathbf{S}_{m \vee m'}^\Gamma} (\nu_n(f))^2 - p(m, m') \right)_+ \right], \end{aligned}$$

with $p(m, m') := 4(1 + 2\delta)D_{m \vee m'} \frac{\sigma^2}{n}$. The following lemma allows us to control the last term of the bound which completes the proof:

Lemma 4.1. *Suppose that there exists $p > 6$ such that $\tau_p := \mathbf{E}[|\varepsilon|^p] < \infty$. Let ν_n be the process defined by Equation (18) and $p(m, m') = 4(1 + 2\delta)D_{m \vee m'} \frac{\sigma^2}{n}$, then under Assumption (\mathcal{H}_{mom}) , there exists a constant C depending only on p , τ_p , σ^2 and δ such that:*

$$\sum_{m' \in \mathcal{M}_n} \mathbf{E} \left[\left(\sup_{f \in \mathbf{S}_{m \vee m'}^\Gamma} (\nu_n(f))^2 - p(m, m') \right)_+ \right] \leq \frac{C}{n}.$$

The proof of this lemma is presented in Appendix A and relies on Talagrand's Inequality. \square

4.2. Convergence rates over Sobolev spaces. Given an integer k and a positive real number L , we define the periodic Sobolev space $W^{per}(k, L)$ as follows:

$$(20) \quad W^{per}(k, L) := \{f \in W_2^k(L), \forall j = 0, \dots, k-1, f^{(j)}(0) = f^{(j)}(1)\},$$

with

$$W_2^k(L) := \{f : [0, 1] \rightarrow \mathbf{R}, f^{(k-1)} \text{ is absolutely continuous and } \|f\| \leq L\}.$$

Theorem 4.1 allows us to derive a uniform risk bound over $W^{per}(k, L)$. We consider here as in Comte and Johannes (2010) or Cardot and Johannes (2010) two types of rate of decrease of the sequence $(\lambda_j)_{j \geq 1}$.

Theorem 4.2. *Assume that the assumptions of Theorem 4.1 are verified. For all $k \in \mathbf{N}^*$ and $L > 0$:*

Polynomial case. : *If there exists two constants $c > 0$ and $a > 1/2$ such that, for all $j \geq 1$, $j^{-2a}/c \leq \lambda_j \leq cj^{-2a}$, we have:*

$$(21) \quad \sup_{\beta \in W^{per}(k, L)} \mathbf{E} \|\tilde{\beta} - \beta\|_\Gamma^2 \leq C_P n^{-(2k+2a)/(2k+2a+1)},$$

Exponential case. : *If there exists two constants $c > 0$ and $a > 0$ such that, for all $j \geq 1$, $\exp(-j^{2a})/c \leq \lambda_j \leq c \exp(-j^{2a})$, we have:*

$$(22) \quad \sup_{\beta \in W^{per}(k, L)} \mathbf{E} \|\tilde{\beta} - \beta\|_\Gamma^2 \leq C_E n^{-1} (\ln n)^{1/2a},$$

with C_P and C_E independent of n .

Remark 2: those bounds coincide with the minimal bounds which can be found in Cardot and Johannes (2010) under the assumption that the noise ε is Gaussian. Hence, in that case, the rate of convergence is optimal.

Remark 3: the bounds (21) and (22) are the same to those obtained in Cardot and Johannes (2010) and are very similar to those presented in Crambes *et al.* (2009).

Proof. First we suppose that we are in the polynomial case, we have:

$$(23) \quad \|\beta - \beta_m\|_{\Gamma}^2 = \sum_{j \geq D_m+1} \lambda_j < \beta, \varphi_j >^2 \leq c \sum_{j \geq D_m+1} j^{-2a} < \beta, \varphi_j >^2.$$

By lemma A.3 of Tsybakov (2004) we have that $f \in W^{per}(k, L)$ if and only if

$$\sum_{j \geq 1} c_j^2 < f, \varphi_j >^2 \leq \frac{L^2}{\pi^{2k}},$$

with $c_j = j^k$ if j is an even number and $c_j = (j-1)^k$ otherwise. Then, by equation (23), we obtain:

$$\|\beta - \beta_m\|_{\Gamma}^2 \leq c' D_m^{-2a-2k},$$

with $c' = 2^{-2a} L^2 / \pi^{2k}$ and by theorem 4.1:

$$\begin{aligned} \mathbf{E}[\|\tilde{\beta} - \beta\|_{\Gamma}^2] &\leq C \left(\min_{m \in \mathcal{M}_n} \left(c' D_m^{-2a-2k} + 4\theta(1+2\delta) D_m \frac{\sigma^2}{n} \right) \right. \\ &\quad \left. + \frac{1}{n} (1 + \|\beta\|_{\Gamma}^2 + \mathbf{E}[< \beta, X_1 >^4]^{1/2}) \right). \end{aligned}$$

The minimum is reached for $D_m \sim n^{1/(2a+2k+1)}$ and is of order $n^{-(2a+2k)/(2a+2k+1)}$.

The proof in the exponential case is quite similar and thus omitted. \square

5. SIMULATION STUDY

5.1. Sample simulation. In the sequel, we generate samples $(X_i, Y_i)_{i=1}^n$ from model (1) and we consider the following slope functions:

$$\begin{aligned} \beta_1(t) &= \log(15t^2 + 10) + \cos(4\pi t), & \beta_2(t) &= 12 \sin(\sqrt{2}\pi t) + 7 \cos(13\pi t), \\ \beta_3(t) &= t(t-1), & \beta_4(t) &= \mathbf{1}_{t \in [1/2, 3/4]}. \end{aligned}$$

The function β_1 is the same as the one used in the simulation study presented in Cardot *et al.* (2003). The function β_3 is in $W^{per}(1, 1)$.

For the simulation of the curve X we can remark that, as $(\varphi_j)_{j \geq 1}$ is an orthonormal basis of $\mathbf{L}^2([0, 1])$,

$$(24) \quad X = \sum_{j \geq 1} < X, \varphi_j > \varphi_j \text{ in } \mathbf{L}^2([0, 1]),$$

and, for all $j \geq 1$, $< X, \varphi_j >$ is a centred random variable of variance λ_j ; this decomposition is called the *Karhunen-Loeve decomposition* of X . For the simulations, as Hall and Horowitz (2007) and Hall *et al.* (2006), we have truncated the sum of Equation (24):

$$X(t) = \sum_{j=1}^{2J+1} \xi_j \varphi_j(t), \text{ for all } t \in [0, 1],$$

with $\{\xi_1, \dots, \xi_{2J+1}\}$ a sequence of independent centred random variables such that, for all $j = 1, \dots, 2J+1$, $\text{Var}(\xi_j) = \lambda_j$. We choose here $J = 500$ and $\xi_j \sim \mathcal{N}(0, \lambda_j)$.

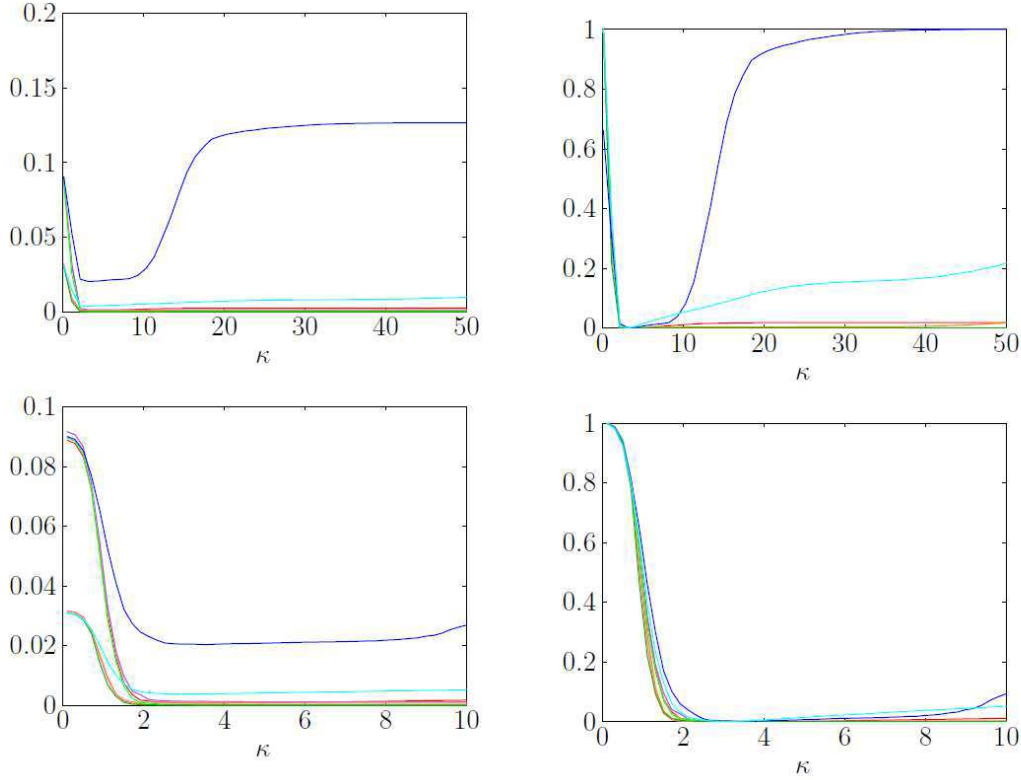


FIGURE 1. Evolution of $\hat{E}_{n_{est}}$ versus κ for β_i , $i = 1, \dots, 4$ and $\lambda \in \{\lambda^{(P)}, \lambda^{(E)}\}$. On the right-hand-side each plot is linearly transformed. ($n = 2000$)

We also take two sequences of covariance operator eigenvalues, corresponding respectively to the polynomial and exponential cases of Theorem 4.2: $\lambda^{(P)} := (1/j^2)_{j \geq 1}$ and $\lambda^{(E)} := (\exp(-\sqrt{j}))_{j \geq 1}$. The sequence $\lambda^{(P)}$ decreases with the same rate as the eigenvalues of the covariance operator of the Brownian motion (see Ash and Gardner (1975)), then the corresponding curve X should have the same regularity. To our knowledge, the case where the sequence $(\lambda_j)_{j \geq 1}$ decreases exponentially has never been treated by simulations. The parameter a appearing in Theorem 4.2 should not be too large otherwise the sequence $(\exp(-j^{2a}))_{j \geq 1}$ is quickly too small to be treated numerically, the choice $(a = 1/4)$ seems to be reasonable.

The noise ε has been chosen Gaussian with variance $\sigma^2 = 0.01$.

5.2. Rough calibration of the constant appearing in the penalty. Recall that the constant $\kappa = 4\theta(1 + 2\delta)$ is a (unknown) numerical constant involved in the penalty term defined by (9). In practice, we have to fix the value of κ for any slope function and any rate of decrease of the covariance operator eigenvalues. Our strategy consists in choosing κ so as to minimize the risk $\mathbf{E}[\|\hat{\beta} - \beta\|_{\Gamma}^2]$ for our choice of slope functions and rates of decrease of the eigenvalues defined in Paragraph 5.1. As it cannot be calculated, we have to approach it by a Monte-Carlo method: we simulate $n_{est} = 1000$ independent samples $\{(X_i^{(j)}, Y_i^{(j)}), i = 1, \dots, n\}$ and we calculate, for all $j = 1, \dots, n_{est}$, $\tilde{\beta}^{(j)}$ the corresponding estimator. For all $j \geq 1$, according to Paragraph 2.2,

the quantity $\|\tilde{\beta}^{(j)} - \beta\|_{\Gamma}^2$ can be approached by:

$$\hat{e}(\tilde{\beta}^{(j)}) := \sum_{j=1}^{2J+1} \lambda_j \langle \tilde{\beta}^{(j)} - \beta, \varphi_j \rangle^2.$$

Then the mean squared error of prediction can be approximated by:

$$\hat{E}_{n_{est}} := \frac{1}{n_{est}} \sum_{j=1}^{n_{est}} \hat{e}(\tilde{\beta}^{(j)}).$$

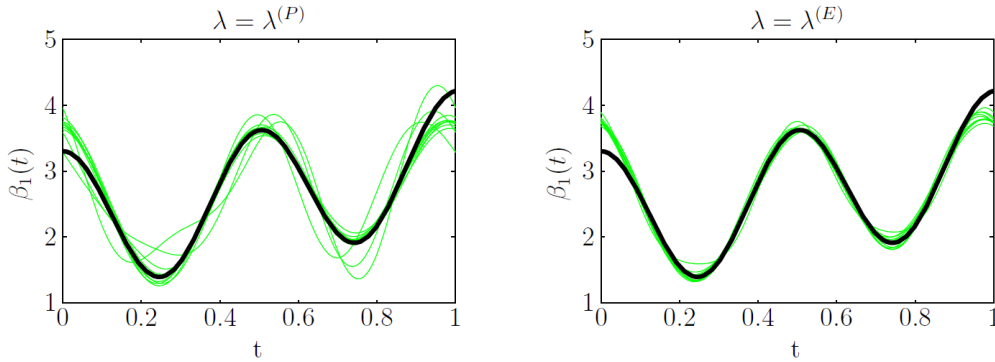


FIGURE 2. Plot of β_1 (bold) and $\tilde{\beta}_1$ computed for 10 independent samples of size $n = 2000$.

On Figure 1-left, we plot eight (approximated) risk curves $\hat{E}_{n_{est}}$ versus κ , corresponding to $\beta_1, \beta_2, \beta_3, \beta_4$ and the eigenvalues $\lambda^{(P)}, \lambda^{(E)}$. We also present Figure 1-right, the risk curves linearly transformed to avoid the scale effect. We can see the optimal value of κ seems to be around 2.5, this is the value used hereafter in the simulations. It is not in accordance with the theoretical lower bound on κ , induced by the condition $\theta > 8$. The methodology we used here for the calibration should be improved with sharper tools, but this is out of the scope of the paper.

5.3. Results. On Figures 2 and 3, we can see that the estimators of β_2 and β_3 are reasonably close to the estimated function. Figures 4 and 5 show that the quality of the estimation is not as good for β_3 and β_4 . This is due to the difficulty to approximate polynomials and piecewise continuously differentiable functions (Gibbs phenomenon) with the Fourier basis. On all figures, the quality of the estimation seems to be better when $\lambda = \lambda^{(E)}$, which is coherent with the theoretical results given in Theorem 4.2. Moreover, we observe in Table 1 a decreasing of the empirical version of the mean squared error of prediction when the size n of the sample increase in all cases. Note that it is difficult to compare the rate of decrease on Table 1 for the different curves since the approximated mean squared prediction error $\hat{E}_{n_{est}}$ depends on the value of λ which is taking successively value $\lambda^{(E)}$ or $\lambda^{(P)}$. Moreover, there is also a size effect due to the

TABLE 1. Mean and median for 1000 Monte-Carlo replications of $\hat{e}(\tilde{\beta}^{(j)})$

		β_1			β_2		
		$n = 100$	$n = 1000$	$n = 5000$	$n = 100$	$n = 1000$	$n = 5000$
$\lambda^{(P)}$	mean	0.0084	0.0018	0.0011	0.13	0.03	0.01
	median	0.0054	0.0013	0.00098	0.13	0.028	0.011
$\lambda^{(E)}$	mean	0.0045	0.0011	0.0005	0.54	0.021	0.083
	median	0.0036	0.00096	0.00044	0.54	0.021	0.080

		β_3			β_4		
		$n = 100$	$n = 1000$	$n = 5000$	$n = 100$	$n = 1000$	$n = 5000$
$\lambda^{(P)}$	mean ($\times 10^{-4}$)	29	3.7	0.66	17	9.8	7.5
	median ($\times 10^{-4}$)	10	1.1	0.26	9.2	5.4	4.8
$\lambda^{(E)}$	mean ($\times 10^{-4}$)	18	2	0.52	14	8.8	7.2
	median ($\times 10^{-4}$)	11	1.2	3.4	11	6.7	5.5

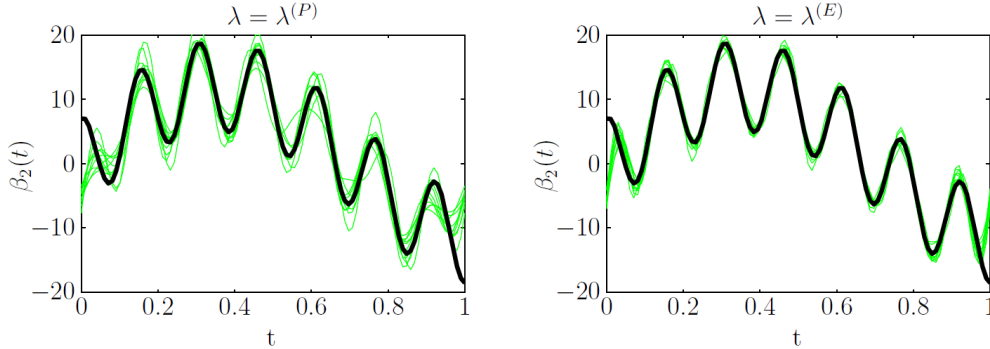


FIGURE 3. Plot of β_2 (bold) and $\tilde{\beta}_2$ computed for 10 independent samples of size $n = 2000$.

range of the functions β we have chosen. This makes the comparison between the different curves β difficult.

We also try to quantify the rate of decrease of the prediction risk as shown on Figure 6 and 7. For all the curves, except for β_2 , we observe quite the same behaviour: this is why we only show the results for β_1 and β_2 on Figure 6 and 7. On Figure 6, we can notice the rapid decrease of the prediction error (mean, median and deciles computed over the 1000 independent replications) both for the sequences $\lambda^{(P)}$ (at top) or $\lambda^{(E)}$ (at bottom). The logarithmic transformation of the mean prediction error on Figure 6-right makes appear a linear trend (red line). This corresponds to the theoretical rate of convergence in Theorem 4.2. As we can see on Figure 7, the behaviour of the mean squared error of prediction for β_2 is less obvious: there is a stable period for small samples before starting to decrease. This can be explained by the fact that β_2 has a

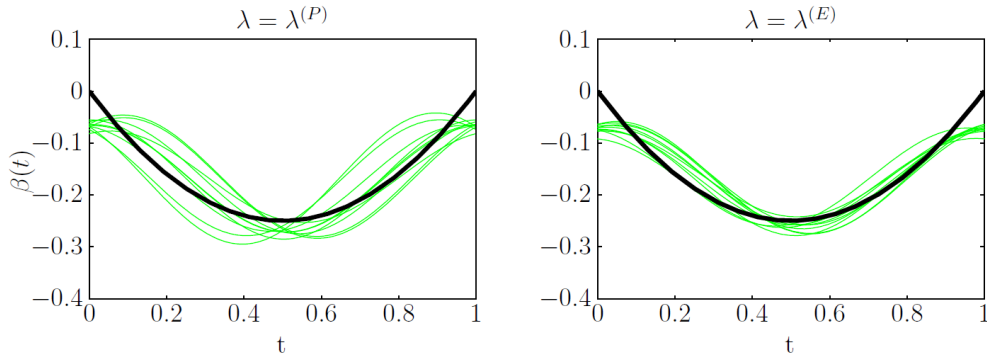


FIGURE 4. Plot of β_3 (bold) and $\tilde{\beta}_3$ computed for 10 independent samples of size $n = 2000$.

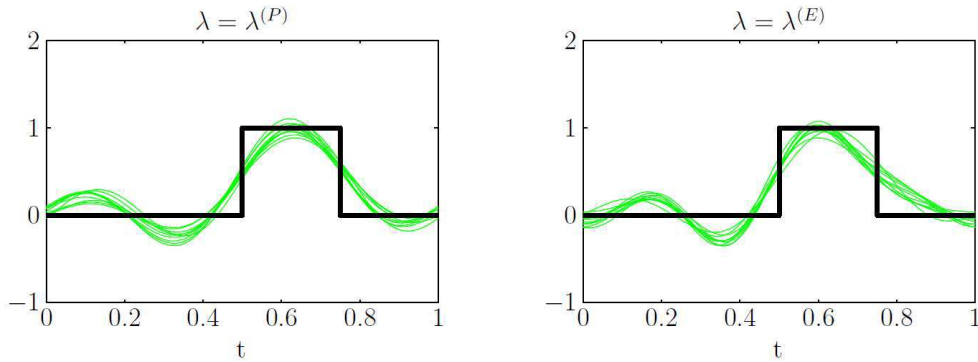


FIGURE 5. Plot of β_4 (bold) and $\tilde{\beta}_4$ computed for 10 independent samples of size $n = 2000$.

non-homogeneous behaviour (multiple monotonicity changing) and hence can be approximated accurately only by functions belonging to a space of sufficiently high dimension. Though, the adequate dimension can be achieved only if the size of the sample is sufficiently large.

APPENDIX A. TECHNICAL LEMMAS AND PROOFS

Proof of Lemma 4.1. The proof relies on the following integrated version of Talagrand's Inequality which can be found in Comte *et al.* (2006):

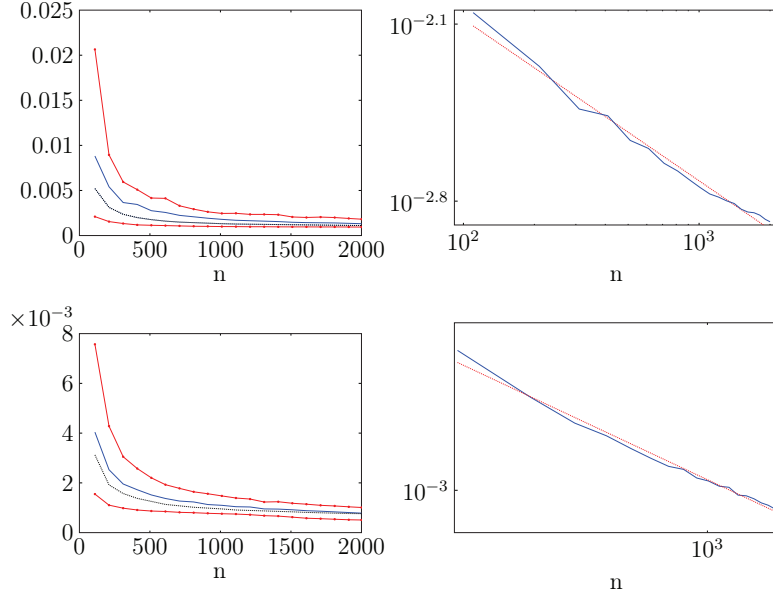


FIGURE 6. On the left-side : Plots of the empirical mean (blue line), median (black dotted line) and first and last deciles (red lines) of the mean square prediction error $\hat{E}_{n_{est}}$ versus n , for the curve β_1 ; on the right-side : logarithmic transformation of the mean of $\hat{E}_{n_{est}}$ (in blue) and linear mean-square approximation (in red); for both choices of $\lambda^{(P)}$ (left-top) and $\lambda^{(E)}$ (left-bottom).

Lemma A.1. *Let T_1, \dots, T_n be i.i.d random variables and \mathcal{F} a denombrable class of measurable functions. For all $f \in \mathcal{F}$ we define $r_n(f) := \frac{1}{n} \sum_{i=1}^n (f(T_i) - \mathbf{E}[f(T_i)])$. We have, for all $\delta > 0$:*

$$\mathbf{E} \left[\sup_{f \in \mathcal{F}} |r_n(f)|^2 - 2(1 + 2\delta)H^2 \right]_+ \leq \frac{6}{K_1} \frac{V}{n} \exp \left(-K_1 \delta \frac{nH^2}{V} \right) + \frac{8M_1^2}{K_1 n^2 C^2(\delta)} \exp \left(-\frac{K_1 C(\sqrt{\delta}) \sqrt{\delta} nH}{\sqrt{2} M_1} \right),$$

where $C(\delta) = \sqrt{1 + \delta^2} - 1$, K_1 is a universal constant and with

$$\sup_{f \in \mathcal{F}} \|f\|_\infty \leq M_1, \quad \mathbf{E} \left[\sup_{f \in \mathcal{F}} |r_n(f)| \right] \leq H \quad \text{and} \quad \sup_{f \in \mathcal{F}} \text{Var}(f(T_1)) \leq V.$$

We can write $\nu_n = \nu_n^{(1)} + \nu_n^{(2)}$ with:

$$\begin{aligned} \nu_n^{(1)}(f) &:= \frac{1}{n} \sum_{i=1}^n \varepsilon_i \langle f, X_i \rangle \mathbf{1}_{\Omega_{\varepsilon_i, X_i}} - \mathbf{E} \left[\varepsilon_1 \langle f, X_1 \rangle \mathbf{1}_{\Omega_{\varepsilon_1, X_1}} \right], \\ \nu_n^{(2)}(f) &:= \frac{1}{n} \sum_{i=1}^n \varepsilon_i \langle f, X_i \rangle \mathbf{1}_{\Omega_{\varepsilon_i, X_i}^c} - \mathbf{E} \left[\varepsilon_1 \langle f, X_1 \rangle \mathbf{1}_{\Omega_{\varepsilon_1, X_1}^c} \right], \end{aligned}$$

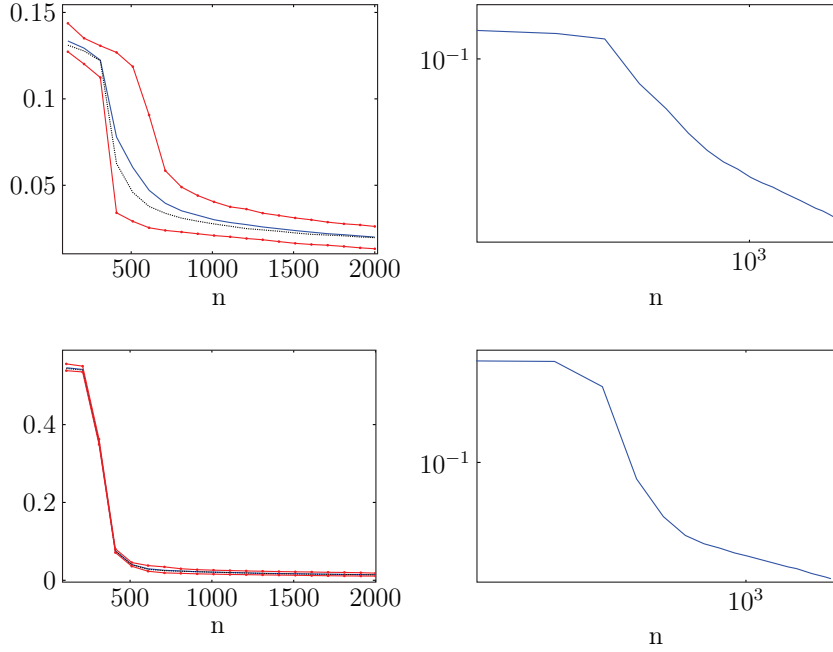


FIGURE 7. On the left-side : Plots of the empirical mean (blue line), median (black dotted line) and first and last deciles (red lines) of the mean square prediction error $\hat{E}_{n_{est}}$ versus n , for the curve β_2 ; on the right-side : logarithmic transformation of the mean of $\hat{E}_{n_{est}}$ (in blue) and linear mean-square approximation (in red); for both choices of $\lambda^{(P)}$ (left-top) and $\lambda^{(E)}$ (left-bottom).

and:

$$\Omega_{\varepsilon, X} := \left\{ |\varepsilon| \leq \kappa_n, \left| \frac{\langle X, \varphi_j \rangle}{\sqrt{\lambda_j}} \right| \leq b_n \right\};$$

where $\kappa_n := n^{2/(p-2)}$ and $b_n := K_1 \frac{C(\sqrt{\delta})\sqrt{\delta}}{2\sqrt{2}} \frac{\sqrt{n}/\ln n}{n^{2/(p-2)}}$. For all $m' \in \mathcal{M}_n$, we have:

$$(25) \quad \mathbf{E} \left[\left(\sup_{t \in \mathbf{S}_{m \vee m'}^\Gamma} (\nu_n(f))^2 - p(m, m') \right)_+ \right] \leq 2\mathbf{E} \left[\left(\sup_{f \in \mathbf{S}_{m \vee m'}^\Gamma} (\nu_n^{(1)}(f))^2 - \frac{p(m, m')}{2} \right)_+ \right] + 2\mathbf{E} \left[\left(\sup_{f \in \mathbf{S}_{m \vee m'}^\Gamma} (\nu_n^{(2)}(f)) \right)_+^2 \right]$$

Control of $\nu_n^{(1)}$: For all $f \in \mathbf{S}_{m \vee m'}^\Gamma$, we define a function $g_f : \mathbf{R} \times \mathbf{L}^2([0, 1]) \rightarrow \mathbf{R}$ by $g_f(x, \mathcal{X}) = x \langle f, \mathcal{X} \rangle \mathbf{1}_{\Omega_{x, \mathcal{X}}}$, we denote by $\mathcal{F} = \{g_f, f \in \mathbf{S}_{m \vee m'}^\Gamma\}$. Usual density arguments allows us to apply Lemma A.1 to the non denombrable family of functions \mathcal{F} , by taking $T = (\varepsilon, X)$, $r_n(g_f) = \nu_n^{(1)}(f)$ and provided that we can find the quantities M_1, H and V such that:

$$\sup_{g \in \mathcal{F}} \|g\|_\infty \leq M_1, \quad \mathbf{E} \left[\sup_{g \in \mathcal{F}} |r_n(g)| \right] \leq H \quad \text{and} \quad \sup_{g \in \mathcal{F}} \text{Var}(g(T_1)) \leq V.$$

For all $f \in \mathbf{S}_{m \vee m'}^\Gamma$, for all $\mathcal{X} \in \mathbf{L}^2([0, 1])$, we have that:

$$\langle f, \mathcal{X} \rangle = \sum_{j=1}^{D_{m \vee m'}} \sqrt{\lambda_j} \langle f, \varphi_j \rangle \frac{\langle \varphi_j, \mathcal{X} \rangle}{\sqrt{\lambda_j}}.$$

Then by Cauchy-Schwarz Inequality, for all $x \in \mathbf{R}$:

$$|x \langle f, \mathcal{X} \rangle| \mathbf{1}_{\Omega_{x, \mathcal{X}}} \leq \kappa_n \sqrt{D_{m \vee m'} b_n^2} \|f\|_\Gamma.$$

Hence, as $\|f\|_\Gamma = 1$ and by definition of $g \in \mathcal{F}$:

$$\sup_{g \in \mathcal{F}} \|g\|_\infty \leq \kappa_n b_n \sqrt{D_{m \vee m'}} =: M_1.$$

By linearity of $\nu_n^{(1)}$, for all $f \in \mathbf{S}_{m \vee m'}^\Gamma$:

$$\begin{aligned} \left(\nu_n^{(1)}(f) \right)^2 &= \left(\sum_{j=1}^{D_{m \vee m'}} \sqrt{\lambda_j} \langle f, \varphi_j \rangle \nu_n^{(1)} \left(\frac{\varphi_j}{\sqrt{\lambda_j}} \right) \right)^2 \\ &\leq \sum_{j=1}^{D_{m \vee m'}} \left(\nu_n^{(1)} \left(\frac{\varphi_j}{\sqrt{\lambda_j}} \right) \right)^2, \end{aligned}$$

and

$$\begin{aligned} \mathbf{E} \left[\left(\nu_n^{(1)} \left(\frac{\varphi_j}{\sqrt{\lambda_j}} \right) \right)^2 \right] &= \text{Var} \left(\frac{1}{n} \sum_{i=1}^n \varepsilon_i \frac{\langle \varphi_j, X_i \rangle}{\sqrt{\lambda_j}} \mathbf{1}_{\Omega_{\varepsilon_i, X_i}} \right) \\ &\leq \frac{\sigma^2}{n} \mathbf{E} \left[\frac{\langle \varphi_j, X_1 \rangle^2}{\lambda_j} \right], \end{aligned}$$

as $\mathbf{E}[\langle \varphi_j, X_1 \rangle^2] = \langle \Gamma \varphi_j, \varphi_j \rangle = \lambda_j$, we obtain:

$$\mathbf{E} \left[\sup_{g \in \mathcal{F}} |r_n(g)| \right]^2 = \mathbf{E} \left[\sup_{f \in \mathbf{S}_{m \vee m'}^\Gamma} \left| \nu_n^{(1)}(f) \right| \right]^2 \leq D_{m \vee m'} \frac{\sigma^2}{n} =: H^2.$$

Finally, for all $f \in \mathbf{S}_{m \vee m'}^\Gamma$, $\mathbf{E}[\langle f, X_1 \rangle^2] = \|f\|_\Gamma^2 = 1$, then we have:

$$\sup_{g \in \mathcal{F}} \text{Var}(g(\varepsilon_1, X_1)) \leq \sup_{f \in \mathbf{S}_{m \vee m'}^\Gamma} \mathbf{E}[\varepsilon_1^2 \langle f, X_1 \rangle^2] = \sigma^2 =: V.$$

Then by Lemma A.1, we have, for all $\delta > 0$ and with $p(m, m') = 4(1 + 2\delta)\sigma^2 D_{m \vee m'}/n$:

$$\begin{aligned} \mathbf{E} \left[\left(\sup_{f \in \mathbf{S}_{m \vee m'}^\Gamma} \left| \nu_n^{(1)}(f) \right|^2 - \frac{p(m, m')}{2} \right)_+ \right] &\leq \frac{6\sigma^2}{K_1 n} \exp(-K_1 \delta D_{m \vee m'}) \\ &\quad + C_1 D_{m \vee m'} \frac{\kappa_n^2 b_n^2}{n^2} \exp\left(-C_2 \frac{\sqrt{n}}{\kappa_n b_n}\right), \end{aligned}$$

with $C_1 := 8/(K_1 C^2(\delta))$, $C_2 := (K_1 \sigma C(\sqrt{\delta}) \sqrt{\delta})/\sqrt{2}$. This leads to the following bound:

$$\sum_{m' \in \mathcal{M}_n} \mathbf{E} \left[\left(\sup_{f \in \mathbf{S}_{m \vee m'}^\Gamma} \left| \nu_n^{(1)}(f) \right|^2 - \frac{p(m, m')}{2} \right)_+ \right] \leq \frac{\tilde{C}}{n},$$

with \tilde{C} depending exclusively on σ^2 and δ .

Control of $\nu_n^{(2)}$. By Cauchy-Schwarz Inequality we have, for all $f \in \mathbf{S}_{m \vee m'}^\Gamma$:

$$|\nu_n^{(2)}(f)|^2 \leq \sum_{j=1}^{D_{m \vee m'}} \nu_n^{(2)} \left(\frac{\varphi_j}{\sqrt{\lambda_j}} \right)^2 \|f\|_\Gamma^2,$$

then:

$$\mathbf{E} \left[\sup_{f \in \mathbf{S}_{m \vee m'}} |\nu_n^{(2)}(f)|^2 \right] \leq \sum_{j=1}^{D_{m \vee m'}} \mathbf{E} \left[\nu_n^{(2)} \left(\frac{\varphi_j}{\sqrt{\lambda_j}} \right)^2 \right].$$

By independence of X and ε :

$$\begin{aligned} \mathbf{E} \left[\nu_n^{(2)} \left(\frac{\varphi_j}{\sqrt{\lambda_j}} \right)^2 \right] &= \frac{1}{n} \text{Var} \left(\varepsilon \frac{\langle \varphi_j, X \rangle}{\sqrt{\lambda_j}} \mathbf{1}_{\Omega_{\varepsilon, X}^c} \right) \\ &\leq \frac{1}{n} \mathbf{E} [\varepsilon^2 \mathbf{1}_{\{|\varepsilon| > \kappa_n\}}] \mathbf{E} \left[\frac{\langle \varphi_j, X \rangle^2}{\lambda_j} \right] \\ &\quad + \frac{1}{n} \mathbf{E}[\varepsilon^2] \mathbf{E} \left[\frac{\langle \varphi_j, X \rangle^2}{\lambda_j} \mathbf{1}_{\left\{ \left| \frac{\langle X, \varphi_j \rangle}{\sqrt{\lambda_j}} \right| > b_n \right\}} \right] \\ &\leq \frac{1}{n} \left(\frac{\tau_p}{\kappa_n^{p-2}} + \frac{\sigma^2/2}{b_n^{2q-2}} q! v^2 c^{q-2} \right), \end{aligned}$$

by using Assumption $(\mathcal{H}_{\text{mom}})$ with q an integer greater than $\frac{2(p-2)}{p-6} + 1$. We obtain then:

$$\sum_{m' \in \mathcal{M}_n} \mathbf{E} \left[\sup_{f \in \mathbf{S}_{m \vee m'}} |\nu_n^{(2)}(f)|^2 \right] \leq N_n \frac{D_{m \vee m'}}{n} \left(\frac{\tau_p}{\kappa_n^{p-2}} + \frac{\sigma^2}{b_n^{2q-2}} q! v^2 c^{q-2} \right) \leq \frac{\check{C}}{n},$$

with \check{C} depending exclusively on p , τ_p , v , c and δ . Inequality (25) allows to conclude the proof. \square

The demonstration of lemmas A.4 and A.5 requires some technical results about the eigenvalues of Gram matrices given in the following lemma:

Lemma A.2. *For $m \in \mathcal{M}_n$, let $\hat{\lambda}_m$ be the smallest eigenvalue of the matrix Φ_m defined by (5) and $\hat{\mu}_m$ be the smallest eigenvalue of the matrix*

$$(26) \quad \Psi_m := \left(\frac{1}{n} \sum_{i=1}^n \frac{\langle \varphi_j, X_i \rangle \langle \varphi_k, X_i \rangle}{\sqrt{\lambda_j} \sqrt{\lambda_k}} \right)_{1 \leq j, k \leq D_m}.$$

Then:

(1)

$$\frac{\hat{\lambda}_m}{\rho(\Gamma)} \leq \hat{\mu}_m \leq \hat{\lambda}_m \left(\min_{1 \leq j \leq D_m} \lambda_j \right)^{-1},$$

with $\rho(\Gamma)$ the spectral radius of the operator Γ .

(2) If, in addition, $\hat{\mu}_{N_n} > 0$:

$$\hat{\mu}_{N_n} = \inf_{f \in \mathcal{S}_n \setminus \{0\}} \frac{\|f\|_n^2}{\|f\|_\Gamma^2}.$$

Proof of Assertion 1. Let $m \in \mathcal{M}_n$, and:

$$\Lambda_m := \begin{pmatrix} \sqrt{\lambda_1} & & \\ & \ddots & \\ & & \sqrt{\lambda_{D_m}} \end{pmatrix}.$$

We have:

$$\Phi_m = \Lambda_m \Psi_m \Lambda_m.$$

Hence, $\hat{\mu}_m = 0$ if and only if $\hat{\lambda}_m = 0$, and in case $\hat{\mu}_m = 0$, the assertion is true. On the other hand, if $\hat{\mu}_m > 0$ then both Φ_m and Ψ_m are invertible and we have:

$$\hat{\mu}_m = \rho(\Psi_m^{-1})^{-1} \quad \text{and} \quad \hat{\lambda}_m = \rho(\Phi_m^{-1})^{-1}.$$

Denote by $|||\cdot|||$ the matrix norm induced by the usual euclidean norm on \mathbf{R}^{D_m} denoted by $|\cdot|_2$. We recall that:

$$|||A||| = \sup_{|a|_2=1} |Aa|_2, \text{ for all square matrix } A.$$

If A is symmetric, $\rho(A) = |||A|||$, then we have:

$$\begin{aligned} \rho(\Phi_m^{-1}) &= |||\Phi_m^{-1}||| = |||\Lambda_m^{-1} \Psi_m^{-1} \Lambda_m^{-1}||| \\ &\leq |||\Lambda_m^{-1}|||^2 |||\Psi_m^{-1}||| = \rho(\Lambda_m^{-1})^2 \rho(\Psi_m^{-1}). \end{aligned}$$

Hence:

$$\hat{\lambda}_m \geq \min_{1 \leq j \leq D_m} \lambda_j \hat{\mu}_m.$$

In the same way, as $\Psi_m^{-1} = \Lambda_m \Phi_m^{-1} \Lambda_m$, we have that:

$$\hat{\mu}_m^{-1} \leq \max_{1 \leq j \leq D_m} \lambda_j \hat{\lambda}_m^{-1} \leq \rho(\Gamma) \hat{\lambda}_m^{-1},$$

which gives the result.

Proof of Assertion 2.

Let $f = \sum_{j=1}^{D_{N_n}} \alpha_j \varphi_j \in \mathcal{S}_n \setminus \{0\}$:

$$\begin{aligned} \|f\|_n^2 &= \sum_{j,k=1}^{D_{N_n}} \alpha_j \alpha_k \frac{1}{n} \sum_{i=1}^n \langle \varphi_j, X_i \rangle \langle \varphi_k, X_i \rangle \\ &= \sum_{j,k=1}^{D_{N_n}} \sqrt{\lambda_j} \sqrt{\lambda_k} \alpha_j \alpha_k \frac{1}{n} \sum_{i=1}^n \frac{\langle \varphi_j, X_i \rangle}{\sqrt{\lambda_j}} \frac{\langle \varphi_k, X_i \rangle}{\sqrt{\lambda_k}} = {}^t(\Lambda_m \alpha) \Psi_{N_n} \Lambda_m \alpha. \end{aligned}$$

We have:

$$\|f\|_\Gamma^2 = \sum_{j=1}^{D_{N_n}} \lambda_j \alpha_j^2 = |\Lambda_m \alpha|_2^2.$$

Consequently:

$$\inf_{\mathcal{S}_n \setminus \{0\}} \frac{\|f\|_n^2}{\|f\|_\Gamma^2} = \inf_{a \in \mathbf{R}^{D_{N_n}}, |a|_2=1} {}^t a \Psi_{N_n} a.$$

On the condition $\hat{\mu}_{N_n} = \min \text{Sp}(\Psi_{N_n}) > 0$ the symmetric matrix Ψ_{N_n} is also positive. Then there exists an orthogonal matrix U such that ${}^t U \Psi_{N_n} U$ is a diagonal matrix whose main diagonal entries are the eigenvalues of Ψ_{N_n} . Then we have:

$$\inf_{a \in \mathbf{R}^{D_{N_n}}, |a|_2=1} {}^t a \Psi_{N_n} a = \inf_{a \in \mathbf{R}^{D_{N_n}}, |a|_2=1} {}^t a {}^t U \Psi_{N_n} U a = \hat{\mu}_{N_n}.$$

□

The following lemma allows us to control the minimal eigenvalue of Ψ_m :

Lemma A.3. *Let τ be a real number such that $0 < \tau < 1$. For $m \in \mathcal{M}_n$, consider the smallest eigenvalue $\hat{\mu}_m$ of the matrix Ψ_m defined by (26), then, under Assumption (\mathcal{H}_{mom}) :*

$$\mathbf{P}(\hat{\mu}_m < \tau) \leq 2D_m^2 \exp\left(-n \frac{(1-\tau)^2}{4D_m^2 \max(2v^2, c)}\right).$$

Proof. We have:

$$\{\hat{\mu}_m < \tau\} = \{1 - \hat{\mu}_m > 1 - \tau\}.$$

As $1 - \tau > 0$,

$$\{1 - \hat{\mu}_m > 1 - \tau\} \subset \{|1 - \hat{\mu}_m| > 1 - \tau\} \subset \{\rho(\Psi_m - I) > 1 - \tau\}.$$

We know that the trace of a matrix is equal to the sum of its eigenvalues (counted according to their algebraic multiplicities), then:

$$(27) \quad \rho(\Psi_m - I)^2 \leq \text{tr}((\Psi_m - I)^2) = \text{tr}({}^t(\Psi_m - I)(\Psi_m - I)),$$

as $\Psi_m - I$ is symmetric. The last term of the inequality being equal to the sum of the squared coefficient of $\Psi_m - I$.

Define, for $j, k = 1, \dots, D_m$:

$$Z_i^{(j,k)} = \frac{\langle \varphi_j, X_i \rangle}{\sqrt{\lambda_j}} \frac{\langle \varphi_k, X_i \rangle}{\sqrt{\lambda_k}},$$

we have, for all, j, k , $\mathbf{E} [Z_i^{(j,k)}] = \delta_{j,k}$. Hence, by (27) :

$$\rho(\Psi_m - I)^2 \leq \sum_{1 \leq j, k \leq D_m} \left(\frac{1}{n} \sum_{i=1}^n Z_i^{(j,k)} - \mathbf{E} [Z_i^{(j,k)}] \right)^2.$$

This gives:

$$\begin{aligned}
 \mathbf{P}(\hat{\mu}_m < \tau) &\leq \mathbf{P}\left(\sum_{1 \leq j, k \leq D_m} \left(\frac{1}{n} \sum_{i=1}^n Z_i^{(j,k)} - \mathbf{E}[Z_i^{(j,k)}]\right)^2 > (1-\tau)^2\right) \\
 &\leq \mathbf{P}\left(\bigcup_{1 \leq i, j \leq D_m} \left\{ \left(\frac{1}{n} \sum_{i=1}^n Z_i^{(j,k)} - \mathbf{E}[Z_i^{(j,k)}]\right)^2 > \frac{(1-\tau)^2}{D_m^2} \right\}\right) \\
 &\leq \sum_{1 \leq j, k \leq D_m} \mathbf{P}\left(\left(\frac{1}{n} \sum_{i=1}^n Z_i^{(j,k)} - \mathbf{E}[Z_i^{(j,k)}]\right)^2 > \frac{(1-\tau)^2}{D_m^2}\right) \\
 &\leq \sum_{1 \leq j, k \leq D_m} \mathbf{P}\left(\left|\frac{1}{n} \sum_{i=1}^n Z_i^{(j,k)} - \mathbf{E}[Z_i^{(j,k)}]\right| > \frac{1-\tau}{D_m}\right) \\
 &\leq \sum_{1 \leq j, k \leq D_m} \mathbf{P}\left(\frac{1}{n} \sum_{i=1}^n Z_i^{(j,k)} - \mathbf{E}[Z_i^{(j,k)}] > \frac{1-\tau}{D_m}\right) \\
 (28) \quad &+ \mathbf{P}\left(-\frac{1}{n} \sum_{i=1}^n Z_i^{(j,k)} + \mathbf{E}[Z_i^{(j,k)}] > \frac{1-\tau}{D_m}\right).
 \end{aligned}$$

Assumption $(\mathcal{H}_{\text{mom}})$ allows us to apply Bernstein's Inequality (we use here the particular form which can be found in Birgé and Massart (1998)) to the sequence $Z_1^{(j,k)}, \dots, Z_n^{(j,k)}$, for all $j, k = 1, \dots, D_m$. We obtain, for all $x > 0$:

$$\mathbf{P}\left(\frac{1}{n} \sum_{i=1}^n Z_i^{(j,k)} - \mathbf{E}[Z_i^{(j,k)}] > v\sqrt{2x} + cx\right) \leq \exp(-nx),$$

and in the same way, for all $x > 0$:

$$\mathbf{P}\left(-\frac{1}{n} \sum_{i=1}^n Z_i^{(j,k)} + \mathbf{E}[Z_i^{(j,k)}] > v\sqrt{2x} + cx\right) \leq \exp(-nx),$$

by applying Bernstein's Inequality to the sequence $-Z_1^{(j,k)}, \dots, -Z_n^{(j,k)}$.

Taking $x = \frac{(1-\tau)^2}{4D_m^2 \max(2v^2, c)}$, we have that:

$$v\sqrt{2x} + cx \leq \frac{1-\tau}{D_m} \left(\frac{\sqrt{2}v/2}{\sqrt{\max(2v^2, c)}} + \frac{1-\tau}{4D_m} \frac{c}{\max(2v^2, c)} \right) \leq \frac{1-\tau}{D_m},$$

and by (28):

$$\mathbf{P}(\hat{\mu}_m < \tau) \leq 2 \sum_{1 \leq j, k \leq D_m} \exp(-nx) \leq 2D_m^2 \exp(-nx).$$

This concludes the proof. \square

Lemma A.4. *Under Assumption $(\mathcal{H}_{\text{Mom}})$, if $D_{N_n} \leq K\sqrt{n/\ln^3 n}$ and if $\mathbf{E}[\langle \beta, X_1 \rangle^4] < +\infty$, there exists a constant C' depending only on ρ_0, K, c and v such that:*

$$\mathbf{E}[\|\tilde{\beta} - \beta\|_{\Gamma}^2 \mathbf{1}_{\Delta_n^c}] \leq \frac{C'}{n} (\mathbf{E}[\langle \beta, X_1 \rangle^4]^{1/2} + \|\beta\|_{\Gamma}^2 + 1).$$

Proof. First, by triangular inequality,

$$\begin{aligned}
\mathbf{E}[\|\tilde{\beta} - \beta\|_{\Gamma}^2 \mathbf{1}_{\Delta_n^c}] &\leq 2\mathbf{E}\left[\left(\|\tilde{\beta}\|_{\Gamma}^2 + \|\beta\|_{\Gamma}^2\right) \mathbf{1}_{\Delta_n^c}\right] \\
(29) \qquad \qquad \qquad &= 2\mathbf{E}\left[\|\hat{\beta}_{\hat{m}}\|_{\Gamma}^2 \mathbf{1}_{\Delta_n^c \cap \bar{G}}\right] + 2\|\beta\|_{\Gamma}^2 \mathbf{P}(\Delta_n^c).
\end{aligned}$$

With Lemma A.2, it is easy to see that $\bar{G} \subset \{\hat{\lambda}_{N_n} > s_n\} \subset \{\hat{\mu}_{N_n} > s_n/\rho(\Gamma)\}$ and that for any function $f \in \mathcal{S}_n \setminus \{0\}$, on the set \bar{G} , we have:

$$\|f\|_{\Gamma}^2 < \frac{\rho(\Gamma)\|f\|_n^2}{s_n}.$$

By taking $f = \hat{\beta}_{\hat{m}}$, we obtain:

$$(30) \qquad \mathbf{E}\left[\|\hat{\beta}_{\hat{m}}\|_{\Gamma}^2 \mathbf{1}_{\Delta_n^c \cap \bar{G}}\right] \leq \frac{\rho(\Gamma)}{s_n} \mathbf{E}\left[\|\hat{\beta}_{\hat{m}}\|_n^2 \mathbf{1}_{\Delta_n^c \cap \bar{G}}\right]$$

Now, since $\hat{\beta}_m$ is a mean-square-type estimator, the vector $(\langle \hat{\beta}_m, X_1 \rangle, \dots, \langle \hat{\beta}_m, X_n \rangle)'$ can be seen as the orthogonal projection (w.r.t the Euclidean scalar product on \mathbf{R}^n) of the vector $(Y_1, \dots, Y_n)'$ on the subspace $\{(\langle f, X_1 \rangle, \dots, \langle f, X_n \rangle)', f \in S_m\}$. Since the squared empirical norm $\|\cdot\|_n^2$ corresponds to the Euclidean norm up to the multiplicative factor $1/n$, we deduce that:

$$n\|\hat{\beta}_m\|_n^2 \leq \sum_{i=1}^n Y_i^2, \text{ for all } m,$$

as the norm of the vector $(Y_1, \dots, Y_n)'$ is larger than the norm of its projection. Then, we can use that $Y_i = \langle \beta, X_i \rangle + \varepsilon_i$ and have:

$$\|\hat{\beta}_{\hat{m}}\|_n^2 \leq 2\|\beta\|_n^2 + \frac{2}{n} \sum_{i=1}^n \varepsilon_i^2.$$

By gathering the last inequality and inequalities (29) and (30), we obtain:

$$\mathbf{E}[\|\tilde{\beta} - \beta\|_{\Gamma}^2 \mathbf{1}_{\Delta_n^c}] \leq \frac{4\rho(\Gamma)}{s_n} \mathbf{E}\left[\left(\|\beta\|_n^2 + \frac{1}{n} \sum_{i=1}^n \varepsilon_i^2\right) \mathbf{1}_{\Delta_n^c \cap \bar{G}}\right] + 2\|\beta\|_{\Gamma}^2 \mathbf{P}(\Delta_n^c).$$

The ε_i 's are independent of the X_i 's, and the set Δ_n^c depends only on the X_i 's so that:

$$\mathbf{E}\left[\frac{1}{n} \left(\sum_{i=1}^n \varepsilon_i^2\right) \mathbf{1}_{\Delta_n^c}\right] = \sigma^2 \mathbf{P}(\Delta_n^c)$$

On the other hand, by Cauchy-Schwarz Inequality, we have:

$$\begin{aligned}
\mathbf{E}\left[\|\beta\|_n^2 \mathbf{1}_{\Delta_n^c \cap \bar{G}}\right] &\leq \mathbf{E}[\|\beta\|_n^4]^{1/2} \sqrt{\mathbf{P}(\Delta_n^c)} \\
&= \left(\frac{1}{n} \mathbf{E}[\langle \beta, X_1 \rangle^4] + \frac{n-1}{n} \|\beta\|_{\Gamma}^4\right)^{1/2} \sqrt{\mathbf{P}(\Delta_n^c)} \\
&\leq \left(\frac{1}{\sqrt{n}} [E\langle \beta, X_1 \rangle^4]^{1/2} + \|\beta\|_{\Gamma}^2\right) \sqrt{\mathbf{P}(\Delta_n^c)}
\end{aligned}$$

As $\mathbf{P}(\Delta_n^c) \leq \sqrt{\mathbf{P}(\Delta_n^c)}$ and $s_n \leq 2$, we get:

$$\mathbf{E}[\|\tilde{\beta} - \beta\|_{\Gamma}^2 \mathbf{1}_{\Delta_n^c}] \leq \frac{4\sqrt{\mathbf{P}(\Delta_n^c)}}{s_n} \left(\rho(\Gamma) \left[\frac{1}{\sqrt{n}} [E\langle \beta, X_1 \rangle^4]^{1/2} + \|\beta\|_{\Gamma}^2 + \sigma^2\right] + \|\beta\|_{\Gamma}^2\right).$$

To end the proof, we study the term $\sqrt{\mathbf{P}(\Delta_n^c)}/s_n$. The definition of Δ_n and the Assertion 2 of Lemma A.2 gives us the following inclusions:

$$\Delta_n^c \subset \left\{ \inf_{f \in \mathcal{S}_n \setminus \{0\}} \frac{\|f\|_n^2}{\|f\|_T^2} < \rho_0^{-1} \right\} \subset \{\hat{\mu}_{N_n} < \rho_0^{-1}\}.$$

Then by Lemma A.3 and by the assumption $D_{N_n} \leq K\sqrt{n/\ln^3(n)}$, we can easily see that:

$$\begin{aligned} \frac{\sqrt{\mathbf{P}(\Delta_n^c)}}{s_n} &\leq \frac{K/\sqrt{2}}{1 - 1/\sqrt{\ln n}} (\ln n)^{-3/2} n^{3/2} \exp\left(-\frac{(1 - \rho_0^{-1})^2 \ln^3 n}{8K^2 \max\{2v^2, c\}}\right) \\ &\leq C \exp\left(\frac{3}{2} \ln n - C' \ln^3 n\right) \leq \frac{C''}{n}. \end{aligned}$$

with C , C' and C'' depending only on K , ρ_0 , v and c . □

Lemma A.5. *Under Assumption (\mathcal{H}_{Mom}) and if $\min_{1 \leq j \leq D_{N_n}} \lambda_j \geq 2/n$ we have:*

$$\mathbf{P}(\bar{G}^c) \leq D_{N_n}^3 \exp\left(-\frac{n}{2 \ln n D_{N_n}^2 \max\{2v^2, c\}}\right).$$

Proof.

$$(31) \quad \mathbf{P}(\bar{G}^c) = \mathbf{P}\left(\bigcup_{m \in \mathcal{M}_n} G_m^c\right) \leq \sum_{m \in \mathcal{M}_n} \mathbf{P}\left(\hat{\lambda}_m < s_n\right).$$

By Assertion 1 of Lemma A.2 we have that:

$$\mathbf{P}\left(\hat{\lambda}_m < s_n\right) \leq \mathbf{P}\left(\hat{\mu}_m < \frac{s_n}{\min_{1 \leq j \leq D_m} \lambda_j}\right).$$

Since $\min_{1 \leq j \leq D_{N_n}} \lambda_j \geq 2/n$ and by definition of s_n , we have:

$$\frac{s_n}{\min_{1 \leq j \leq D_m} \lambda_j} \leq \frac{ns_n}{2} = 1 - \frac{1}{\sqrt{\ln n}},$$

by applying Lemma A.3 with $\tau = 1 - 1/\sqrt{\ln n}$, we obtain:

$$\mathbf{P}\left(\hat{\lambda}_m < s_n\right) \leq 2D_m^2 \exp\left(-n \frac{1}{4 \ln n D_m^2 \max(2v^2, c)}\right).$$

As $D_m \leq D_{N_n}$ and $N_n \leq \frac{D_{N_n}}{2}$,

$$\sum_{m \in \mathcal{M}_n} \mathbf{P}\left(\hat{\lambda}_m < s_n\right) \leq D_{N_n}^3 \exp\left(-n \frac{1}{4 \ln n D_{N_n}^2 \max(2v^2, c)}\right).$$

Then Inequality (31) allows us to complete the proof. □

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