Annales de l'Institut Henri Poincaré - Probabilités et Statistiques
2010, Vol. 46, No. 3, 595–617
DOI: 10.1214/09-AIHP323

ANNALES DE L'INSTITUT HENRI POINCARÉ
PROBABILITÉS ET STATISTIQUES
www.imstat.org/aihp

Nonparametric adaptive estimation for pure jump Lévy processes

F. Comte and V. Genon-Catalot

Université Paris Descartes, MAP5, UMR CNRS 8145, France.
E-mail: fabienne.comte@parisdescartes.fr; andvalentine.genon-catalot@parisdescartes.fr

Received 1 July 2008; revised 7 January 2009; accepted 2 June 2009

Abstract. This paper is concerned with nonparametric estimation of the Lévy density of a pure jump Lévy process. The sample path is observed at n discrete instants with fixed sampling interval. We construct a collection of estimators obtained by deconvolution methods and deduced from appropriate estimators of the characteristic function and its first derivative. We obtain a bound for the $\mathbb{L}^2$-risk, under general assumptions on the model. Then we propose a penalty function that allows to build an adaptive estimator. The risk bound for the adaptive estimator is obtained under additional assumptions on the Lévy density. Examples of models fitting in our framework are described and rates of convergence of the estimator are discussed.

Résumé. Ce travail étudie l'estimation non paramétrique de la densité d'un processus de Lévy de saut pur. Les trajectoires sont observées à n instants discrets de pas fixé. Nous construisons une collection d'estimateurs obtenus par des méthodes de type déconvolution, et s'appuyant sur des estimateurs pertinents de la fonction caractéristique et de ses dérivées. Sous des hypothèses assez générales sur le modèle, nous obtenons une borne pour le risque quadratique intégré. Nous proposons ensuite une pénalité permettant de construire un estimateur adaptatif. La borne de risque de l'estimateur adaptatatif est obtenue sous des hypothèses supplémentaires sur la densité de la mesure de Lévy. Nous donnons pour finir des exemples de modèles adaptés à notre contexte et nous calculons dans chaque cas la vitesse de convergence de l'estimateur.

MSC: 62G05; 62M05; 60G51

Keywords: Adaptive estimation; Deconvolution; Lévy process; Nonparametric projection estimator

1. Introduction

In recent years, the use of Lévy processes for modelling purposes has become very popular in many areas and especially in the field of finance (see e.g. Eberlein and Keller [9], Barndorff-Nielsen and Shephard [1], Cont and Tankov [7]; see also Bertoin [3] or Sato [21] for a comprehensive study for these processes). The distribution of a Lévy process is usually specified by its characteristic triple (drift, Gaussian component and Lévy measure) rather than by the distribution of its independent increments. Indeed, the exact distribution of these increments is most often intractable or even has no closed form formula. For this reason, the standard parametric approach by likelihood methods is a difficult task and many authors have rather considered nonparametric methods. For Lévy processes, estimating the Lévy measure is of crucial importance since this measure specifies the jumps behavior. Nonparametric estimation of the Lévy measure has been the subject of several recent contributions. The statistical approaches depend on the way observations are performed. For instance, Basawa and Brockwell [2] consider nondecreasing Lévy processes and observations of jumps with size larger than some positive ε, or discrete observations with fixed sampling interval. They build nonparametric estimators of a distribution function linked with the Lévy measure. More recently, Figueroa-López and Houdré [11] consider a continuous-time observation of a general Lévy process and study penalized projection estimators of the Lévy density based on integrals of functions with respect to the random Poisson measure associated with the jumps of the process. However, their approach remains theoretical since these Poisson integrals are hardly accessible.

In this paper, we consider nonparametric estimation of the Lévy measure for real-valued Lévy processes of pure jump type, i.e. without drift and Gaussian component. We rely on the common assumption that the Lévy measure admits a density $n(x)$ on $\mathbb{R}$ and assume that the process is discretely observed with fixed sampling interval Δ. Let (L_t) denote the underlying Lévy process and $(Z_k^\Delta = L_{k\Delta} - L_{(k-1)\Delta}, k = 1, \ldots, n)$ be the observed random variables which are independent and identically distributed. Under our assumption, the characteristic function of $L_\Delta = Z_1^\Delta$ is given by the following simple formula:

$$\psi_\Delta(u) = \mathbb{E}\big(\exp \mathrm{i}uZ_1^\Delta\big) = \exp\left(\Delta \int_{\mathbb{R}} \big(\mathrm{e}^{\mathrm{i}ux} - 1\big) n(x)\,\mathrm{d}x\right), \tag{1}$$

where the unknown function is the Lévy density $n(x)$. It is therefore natural to investigate the estimation of $n(x)$ using empirical estimators of the charasteristic functions. This approach is illustrated by Jongbloed and van der Meulen [12], Watteel and Kulperger [22] and Neumann and Reiss [20]. In the last two papers, the authors consider general Lévy processes, with drift and Gaussian component and use two derivatives of the characteristic function to reach the Lévy density. In our case, under the assumption that $\int_{\mathbb{R}} |x| n(x)\,\mathrm{d}x < \infty$, we get the simple relation:

$$g^*(u) = \int \mathrm{e}^{\mathrm{i}ux} g(x)\,\mathrm{d}x = -\mathrm{i}\frac{\psi'_\Delta(u)}{\Delta\psi_\Delta(u)} \tag{2}$$

with $g(x) = xn(x)$. This equation indicates that we can estimate $g^*(u)$ by using empirical counterparts of $\psi_\Delta(u)$ and $\psi'_\Delta(u)$ only. Then, the problem of recovering an estimator of g looks like a classical deconvolution problem. We have at hand the methods used for estimating unknown densities of random variables observed with additive independent noise. This requires the additional assumption that g belongs to $\mathbb{L}^2(\mathbb{R})$. However, the problem of deconvolution set by equation (2) is not standard and looks more like deconvolution in presence of unknown errors densities. This is due to the fact that both the numerator and the denominator are unknown and have to be estimated from the same data. This is why our estimator of $\psi_\Delta(u)$ is not a simple empirical counterpart. Instead, we use a truncated version analogous to the one used in Neumann [19] and Neumann and Reiss [20].

Below, we show how to adapt the deconvolution method described in Comte et al. [6]. We consider an adequate sequence $(S_m, m = 1, \ldots, m_n)$ of subspaces of $\mathbb{L}^2(\mathbb{R})$ and build a collection of projection estimators $(\hat{g}_m)$. Then using a penalization device, we select through a data-driven procedure the best estimator in the collection. We study the $\mathbb{L}^2$-risk of the resulting estimator under the asymptotic framework that n tends to infinity. Although the sampling interval Δ is fixed, we keep it as much as possible in all formulae since the distributions of the observed random variables highly depend on Δ.

In Section 2, we give assumptions and some preliminary properties. Section 3 contains examples of models included in our framework. Section 4 describes the statistical strategy. We present the projection spaces and define the collection of estimators. Proposition 4.1 gives the upper bound for the risk of a projection estimator on a fixed projection space. This proposition guides the choice of the penalty function and allows to discuss the rates of convergence of the projection estimators. Afterwards, we introduce a theoretical penalty (depending on the unknown characteristic function ψ_Δ) and study the risk bound of a false estimator (actually not an estimator) (Theorem 4.1). Then, we replace the theoretical penalty by an estimated counterpart and give the upper bound of the risk of the resulting penalized estimator (Theorem 4.2). Proofs are gathered in Section 5. In the Appendix, a fundamental result used in our proofs is recalled.

2. Framework and assumptions

Recall that we consider the discrete time observation with sample step Δ of a Lévy process L_t with Lévy density n and characteristic function given by (1). We assume that (L_t) is a pure jump process with finite variation on compacts. When the Lévy measure $n(x)\,\mathrm{d}x$ is concentrated on $(0, +\infty)$, then (L_t) has increasing paths and is called a subordinator. We focus on the estimation of the real valued function

$$g(x) = xn(x).$$

When the Lévy process is self-decomposable, this function is called the canonical function and is decreasing (see Barnforff-Nielsen and Shephard [1] and Jongbloed et al. [13]).

We introduce the following assumptions on the function g:

(H1) $\int_{\mathbb{R}} |x|n(x)\,\mathrm{d}x < \infty$.

(H2(p)) For p integer, $\int_{\mathbb{R}} |x|^{p-1}|g(x)|\,\mathrm{d}x < \infty$.

(H3) The function g belongs to $\mathbb{L}_2(\mathbb{R})$.

Note that the usual assumption is: $\int(|x| \wedge 1)n(x)\,\mathrm{d}x < +\infty$. Assumption (H1) is stronger and is also a moment assumption for L_t. Under the usual assumption, (H2(p)) for $p \geq 1$ implies (H1) and (H2(k)) for $k \leq p$.

Our estimation procedure is based on the random variables

$$Z_i^\Delta = L_{i\Delta} - L_{(i-1)\Delta}, \quad i = 1, \ldots, n, \tag{3}$$

which are independent, identically distributed, with common characteristic function $\psi_\Delta(u)$.

The moments of Z_1^Δ are linked with the function g. More precisely, we have:

Proposition 2.1. *Let $p \geq 1$ integer. Under* (H2(p)), $\mathbb{E}(|Z_1^\Delta|^p) < \infty$. *Moreover, setting, for $k = 1, \ldots p$, $M_k = \int_{\mathbb{R}} x^{k-1} g(x)\,\mathrm{d}x$, we have $\mathbb{E}(Z_1^\Delta) = \Delta M_1$, $\mathbb{E}[(Z_1^\Delta)^2] = \Delta M_2 + \Delta^2 M_1$, and more generally, $\mathbb{E}[(Z_1^\Delta)^l] = \Delta M_l + \mathrm{o}(\Delta)$ for all $l = 1, \ldots, p$.*

Proof. By the assumption, the exponent of the exponential in (1) is p times differentiable and, by derivating ψ_Δ, we get the result. □

Assumption (H1) together with (H3) are the basis of our estimation procedure. We complete with additional assumptions concerning ψ_Δ and g.

(H4) There exist constants c_ψ, C_ψ and $\beta \geq 0$ such that $\forall x \in \mathbb{R}$, we have

$$c_\psi\left(1+x^2\right)^{-\Delta\beta/2} \leq \left|\psi_\Delta(x)\right| \leq C_\psi\left(1+x^2\right)^{-\Delta\beta/2}.$$

(H5) There exists some positive a such that $\int |g^*(x)|^2(1+x^2)^a\,\mathrm{d}x < +\infty$.

(H6) $\int x^2 g^2(x)\,\mathrm{d}x < +\infty$.

Note that it is not possible to formulate all assumptions in terms of either ψ_Δ or g. Indeed, there may be no relation at all between these two functions (see the Examples).

Assumptions (H4)–(H6) are used to compute rates of convergence for $\mathbb{L}_2$-risks. Note that, from this point of view, exponential terms can also be considered (see examples in Section 4.5). But (H4)–(H6) are specifically required for the adaptive version of the estimator. In particular, precise control of ψ_Δ is needed. Assumption (H4) is also considered in Neumann and Reiss [20]. Due to Lemma 6.1 in the latter paper, (H4) implies that $\int_{[-1,1]} |x|^\alpha n(x)\,\mathrm{d}x < +\infty$ for $\alpha > 0$. Note that, in assumption (H5), which is a classical regularity assumption, the knowledge of a is not required. At last, (H6) is a technical assumption which, in view of (H1)–(H3), is rather weak.

3. Examples

3.1. *Compound Poisson processes*

Let $L_t = \sum_{i=1}^{N_t} Y_i$, where (N_t) is a Poisson process with constant intensity c and (Y_i) is a sequence of i.i.d. random variables with density f independent of the process (N_t). Then, (L_t) is a compound Poisson process with characteristic function

$$\psi_t(u) = \exp\left(ct\int_{\mathbb{R}}\left(\mathrm{e}^{\mathrm{i}ux} - 1\right)f(x)\,\mathrm{d}x\right). \tag{4}$$

Its Lévy density is $n(x) = cf(x)$ and thus $g(x) = cxf(x)$. Assumptions (H1)–(H2(p)) are equivalent to $\mathbb{E}(|Y_1|^p) < \infty$. Assumption (H3) is equivalent to $\int_{\mathbb{R}} x^2 f^2(x)\,\mathrm{d}x < \infty$, which holds for instance if $\sup_x f(x) < +\infty$ and $\mathbb{E}(Y_1^2) < +\infty$. We can compute the distribution of $Z_1^\Delta = L_\Delta$ as follows:

$$P_{Z_1^\Delta}(\mathrm{d}z) = \mathrm{e}^{-c\Delta}\left(\delta_0(\mathrm{d}z) + \sum_{n\geq 1} f^{\star n}(z)\frac{(c\Delta)^n}{n!}\,\mathrm{d}z\right). \tag{5}$$

We have the following bound:

$$1 \geq \left|\psi_\Delta(u)\right| \geq \mathrm{e}^{-2c\Delta}. \tag{6}$$

On this example, it appears clearly that we cannot link the regularity assumption on g and (H4) which holds with $\beta = 0$. Indeed, g can be here of any regularity, as f is any density.

3.2. *The Lévy Gamma process*

Let $\alpha > 0$, $\beta > 0$. The Lévy Gamma process (L_t) with parameters (β, α) is a subordinator such that, for all $t > 0$, L_t has distribution Gamma with parameters $(\beta t, \alpha)$, i.e. has density:

$$\frac{\alpha^{\beta t}}{\Gamma(\beta t)} x^{\beta t - 1} \mathrm{e}^{-\alpha x} \mathbb{1}_{x\geq 0}. \tag{7}$$

The characteristic function of Z_1^Δ is equal to:

$$\psi_\Delta(u) = \left(\frac{\alpha}{\alpha - \mathrm{i}u}\right)^{\beta\Delta}. \tag{8}$$

The Lévy density is $n(x) = \beta x^{-1}\mathrm{e}^{-\alpha x}\mathbb{1}_{\{x>0\}}$ so that $g(x) = \beta \mathrm{e}^{-\alpha x}\mathbb{1}_{\{x>0\}}$ satisfies our assumptions. We have:

$$\frac{\psi'_\Delta(u)}{\psi_\Delta(u)} = \mathrm{i}\Delta\frac{\beta}{\alpha - \mathrm{i}u}, \qquad \left|\psi_\Delta(u)\right| = \frac{\alpha^{\beta\Delta}}{(\alpha^2 + u^2)^{\beta\Delta/2}}. \tag{9}$$

3.3. *A general class of subordinators*

Consider the Lévy process (L_t) with Lévy density

$$n(x) = cx^{\delta - 1/2}x^{-1}\mathrm{e}^{-\beta x}\mathbb{1}_{x>0},$$

where (δ, β, c) are positive parameters. If $\delta > 1/2$, $\int_0^{+\infty} n(x)\,\mathrm{d}x < +\infty$, and we recover compound Poisson processes. If $0 < \delta \leq 1/2$, $\int_0^{+\infty} n(x)\,\mathrm{d}x = +\infty$ and $g(x) = xn(x)$ belongs to $\mathbb{L}^2(\mathbb{R}) \cap \mathbb{L}^1(\mathbb{R})$. The case $\delta = 0$, which corresponds to the Lévy inverse Gaussian process does not fit in our framework. For $0 < \delta < 1/2$, we find

$$g^*(x) = c\frac{\Gamma(\delta + 1/2)}{(\beta - \mathrm{i}x)^{\delta + 1/2}}$$

and

$$\left|\psi_\Delta(x)\right| = \exp\left(-c\frac{\Delta\Gamma(\delta + 1/2)}{1/2 - \delta}\left[\left(\beta^2 + x^2\right)^{-(\delta - 1/2)/2} - \beta^{-(\delta - 1/2)}\right]\right).$$

Note that

$$\left|\psi_\Delta(x)\right| \sim_{x\to+\infty} K(\beta, \delta)\exp\left(-c\Delta\frac{\Gamma(\delta + 1/2)}{1/2 - \delta}x^{-\delta + 1/2}\right), \tag{10}$$

where $K(\beta, \delta) = \exp(c\frac{\Delta\Gamma(\delta + 1/2)}{1/2 - \delta}\beta^{-(\delta - 1/2)})$. Consequently, it has an exponential rate of decrease and does not satisfy assumption (H4). Thus, only the nonadaptive part applies to this class of examples.

3.4. *The bilateral Gamma process*

This process has been recently introduced by Küchler and Tappe [15]. Consider X, Y two independent random variables, X with distribution $\Gamma(\beta,\alpha)$ and Y with distribution $\Gamma(\beta',\alpha')$. Then, $Z = X - Y$ has distribution bilateral Gamma with parameters $(\beta,\alpha,\beta',\alpha')$, that we denote by $\Gamma(\beta,\alpha;\beta',\alpha')$. The characteristic function of Z is equal to:

$$\psi(u) = \left(\frac{\alpha}{\alpha - \mathrm{i}u}\right)^{\beta}\left(\frac{\alpha'}{\alpha' + \mathrm{i}u}\right)^{\beta'} = \exp\left(\int_{\mathbb{R}} (\mathrm{e}^{\mathrm{i}ux} - 1) n(x)\,\mathrm{d}x\right) \tag{11}$$

with

$$n(x) = x^{-1} g(x)$$

and, for $x \in \mathbb{R}$,

$$g(x) = \beta \mathrm{e}^{-\alpha x}\mathbb{1}_{(0,+\infty)}(x) - \beta' \mathrm{e}^{-\alpha'|x|}\mathbb{1}_{(-\infty,0)}(x).$$

The bilateral Gamma process (L_t) has characteristic function $\psi_t(u) = \psi(u)^t$.

The method can be generalized and we may consider Lévy processes on $\mathbb{R}$ obtained by bilateralisation of two subordinators.

3.5. *Subordinated processes*

Let (W_t) be a Brownian motion, and let (Z_t) be an increasing Lévy process (subordinator), independent of (W_t). Assume that the observed process is

$$L_t = W_{Z_t}.$$

We have

$$\psi_\Delta(u) = \mathbb{E}\big(\mathrm{e}^{\mathrm{i}uL_\Delta}\big) = \mathbb{E}\big(\mathrm{e}^{-(u^2/2)Z_\Delta}\big).$$

As Z_t is positive, we consider, for $\lambda \geq 0$,

$$\vartheta_\Delta(\lambda) = \mathbb{E}\big(\mathrm{e}^{-\lambda Z_\Delta}\big) = \exp\left(-\Delta\int_0^{+\infty}\big(1 - \mathrm{e}^{-\lambda x}\big) n_Z(x)\,\mathrm{d}x\right),$$

where n_Z denotes the Lévy density of (Z_t). Now let us assume that $g_Z(x) = x n_Z(x)$ is integrable over $(0,+\infty)$. We have:

$$\begin{aligned}\log\big(\vartheta_\Delta(\lambda)\big) &= -\Delta\int_0^{+\infty}\frac{1-\mathrm{e}^{-\lambda x}}{x} x n_Z(x)\,\mathrm{d}x = -\Delta\int_0^{+\infty}\left(\int_0^{\lambda}\mathrm{e}^{-sx}\,\mathrm{d}s\right) x n_Z(x)\,\mathrm{d}x \\ &= -\Delta\int_0^{\lambda}\left(\int_0^{+\infty}\mathrm{e}^{-sx} x n_Z(x)\,\mathrm{d}x\right)\mathrm{d}s.\end{aligned}$$

Hence,

$$\psi_\Delta(u) = \exp\left(-\Delta\int_0^{u^2/2}\left(\int_0^{+\infty}\mathrm{e}^{-sx} g_Z(x)\,\mathrm{d}x\right)\mathrm{d}s\right).$$

Moreover, it is possible to relate the Lévy density n_L of (L_t) with the Lévy density n_Z of (Z_t) as follows. Consider f a nonnegative function on $\mathbb{R}$, with $f(0) = 0$. Given the whole path (Z_t), the jumps $\delta L_s = W_{Z_s} - W_{Z_{s-}}$ are centered

Gaussian with variance $\delta Z_s := Z_s - Z_{s^-}$. Hence,

$$\mathbb{E}\biggl(\sum_{s\le t} f(\delta L_s)\biggr) = \sum_{s\le t}\mathbb{E}\biggl(\int_{\mathbb{R}} f(u)\exp\bigl(-u^2/2\delta Z_s\bigr)\frac{\mathrm{d}u}{\sqrt{2\pi\delta Z_s}}\biggr)$$
$$= t\int_{\mathbb{R}} f(u)\,\mathrm{d}u\biggl(\int_0^{+\infty}\exp\bigl(-u^2/2x\bigr)\frac{n_Z(x)\,\mathrm{d}x}{\sqrt{2\pi x}}\biggr).$$

This gives $n_L(u) = \int_0^{+\infty}\exp(-u^2/2x)\frac{n_Z(x)\,\mathrm{d}x}{\sqrt{2\pi x}}$. By the same tools, we see that

$$\mathbb{E}\biggl(\sum_{s\le t}|\delta L_s|\biggr) = \sqrt{2/\pi}\,\mathbb{E}\biggl(\sum_{s\le t}\sqrt{\delta Z_s}\biggr) = t\int_0^{+\infty}\sqrt{x}\,n_Z(x)\,\mathrm{d}x.$$

Therefore, if the above integral is finite, the process (L_t) has finite variation on compact sets and it holds that $\int_{\mathbb{R}}|u|n_L(u)\,\mathrm{d}u < \infty$.

With (Z_t) a Lévy Gamma process, $g_Z(x) = \beta \mathrm{e}^{-\alpha x}\mathbb{1}_{x>0}$. Then $\int_0^{+\infty}\mathrm{e}^{-sx}\beta\mathrm{e}^{-\alpha x}\,\mathrm{d}x = \beta/(\alpha+s)$, and

$$\psi_\Delta(u) = \biggl(\frac{\alpha}{\alpha+(u^2/2)}\biggr)^{\Delta\beta}.$$

This model is the Variance Gamma stochastic volatility model described by Madan and Seneta [17]. As noted in Küchler and Tappe [15], the Variance Gamma distributions are special cases of bilateral Gamma distributions. We can compute the Lévy density:

$$n_L(u) = \int_0^{+\infty}\exp\biggl(-\frac{1}{2}\biggl(\frac{u^2}{x}+2\alpha x\biggr)\biggr)\frac{\beta x^{-3/2}\,\mathrm{d}x}{\sqrt{2\pi}} = \beta(2\alpha)^{1/4}|u|^{-1}\exp\bigl(-(2\alpha)^{1/2}|u|\bigr).$$

4. Statistical strategy

4.1. *Notations*

Subsequently we denote by u^* the Fourier transform of the function u defined as $u^*(y) = \int \mathrm{e}^{\mathrm{i}yx}u(x)\,\mathrm{d}x$, and by $\|u\|$, $\langle u, v\rangle$, $u * v$ the quantities

$$\|u\|^2 = \int \bigl|u(x)\bigr|^2\,\mathrm{d}x,$$
$$\langle u, v\rangle = \int u(x)\overline{v}(x)\,\mathrm{d}x \quad \text{with } z\overline{z} = |z|^2 \quad \text{and} \quad u\star v(x) = \int u(y)\bar{v}(x-y)\,\mathrm{d}y.$$

Moreover, we recall that for any integrable and square-integrable functions u, u_1, u_2,

$$\bigl(u^*\bigr)^*(x) = 2\pi u(-x) \quad \text{and} \quad \langle u_1, u_2\rangle = (2\pi)^{-1}\bigl\langle u_1^*, u_2^*\bigr\rangle. \tag{12}$$

4.2. *Estimation strategy*

We want to estimate g such that

$$g^*(x) = -\mathrm{i}\frac{\psi'_\Delta(x)}{\Delta\psi_\Delta(x)} = \frac{\theta_\Delta(x)}{\Delta\psi_\Delta(x)} \tag{13}$$

with

$$\psi_\Delta(x) = \mathbb{E}\bigl(\mathrm{e}^{\mathrm{i}xZ_1^\Delta}\bigr), \qquad \theta_\Delta(x) = -\mathrm{i}\psi'_\Delta(x) = \mathbb{E}\bigl(Z_1^\Delta\mathrm{e}^{\mathrm{i}xZ_1^\Delta}\bigr).$$

We have at hand the empirical versions of ψ_Δ and θ_Δ:

$$\hat{\psi}_\Delta(x) = \frac{1}{n}\sum_{k=1}^{n} \mathrm{e}^{\mathrm{i}xZ_k^\Delta}, \qquad \hat{\theta}_\Delta(x) = \frac{1}{n}\sum_{k=1}^{n} Z_k^\Delta \mathrm{e}^{\mathrm{i}xZ_k^\Delta}.$$

Although $|\psi_\Delta(x)| > 0$ for all x, this is not true for $\hat{\psi}_\Delta$. Following Neumann [19] and Neumann and Reiss [20], we truncate $1/\hat{\psi}_\Delta$ and set, for κ_ψ a constant (that can be taken equal to one):

$$\frac{1}{\tilde{\psi}_\Delta(x)} = \frac{1}{\hat{\psi}_\Delta(x)}\mathbb{1}_{|\hat{\psi}_\Delta(x)|>\kappa_\psi n^{-1/2}}. \tag{14}$$

This provides an estimator of g^* given by $\hat{\theta}_\Delta/(\Delta\tilde{\psi}_\Delta)$. The natural idea is to take the Fourier inverse of the latter function. Since this function may be not integrable, we use a positive cutoff parameter m and introduce

$$\hat{g}_m(x) = \frac{1}{2\pi}\int_{-\pi m}^{\pi m} \mathrm{e}^{-\mathrm{i}xu}\frac{\hat{\theta}_\Delta(u)}{\Delta\tilde{\psi}_\Delta(u)}\,\mathrm{d}u. \tag{15}$$

The difficulty is to find an adequate and possibly optimal choice of m that should be data driven. To this end, we need another formulation of the family of estimators $(\hat{g}_m)$ using projection spaces and contrast minimization devices.

4.3. *The projection spaces*

We describe the projection spaces used in the deconvolution setting (see e.g. Comte et al. [6], Comte and Lacour [5]). Let us define

$$\varphi(x) = \frac{\sin(\pi x)}{\pi x} \quad \text{and} \quad \varphi_{m,j}(x) = \sqrt{m}\varphi(mx - j),$$

where m is an integer, that can be taken equal to 2^ℓ. It is well known (see Meyer [18], p. 22) that $\{\varphi_{m,j}\}_{j\in\mathbb{Z}}$ is an orthonormal basis of the space of square integrable functions having Fourier transforms with compact support included into $[-\pi m, \pi m]$. Indeed an elementary computation yields

$$\varphi_{m,j}^*(x) = \frac{\mathrm{e}^{\mathrm{i}xj/m}}{\sqrt{m}}\mathbb{1}_{[-\pi m,\pi m]}(x). \tag{16}$$

We denote by S_m such a space:

$$S_m = \operatorname{Span}\{\varphi_{m,j}, j \in \mathbb{Z}\} = \{h \in \mathbb{L}_2(\mathbb{R}), \operatorname{supp}(h^*) \subset [-m\pi, m\pi]\}.$$

For any function $h \in \mathbb{L}_2(\mathbb{R})$, let h_m denote the orthogonal projection of h on S_m, given by

$$h_m = \sum_{j\in\mathbb{Z}} a_{m,j}(h)\varphi_{m,j} \quad \text{with } a_{m,j}(h) = \int_{\mathbb{R}} \varphi_{m,j}(x)h(x)\,\mathrm{d}x = \langle\varphi_{m,j}, h\rangle. \tag{17}$$

Using (16), and $a_{m,j}(h) = (1/2\pi)\langle\varphi_{m,j}^*, h^*\rangle$, we obtain

$$h_m^* = h^*\mathbb{1}_{[-\pi m,\pi m]}.$$

Thus, it turns out that

$$\hat{g}_m = \sum_{j\in\mathbb{Z}} \hat{a}_{m,j}\varphi_{m,j} \quad \text{with } \hat{a}_{m,j} = \frac{1}{2\pi\Delta}\int \hat{\theta}_\Delta(x)\frac{\varphi_{m,j}^*(-x)}{\tilde{\psi}_\Delta(x)}\,\mathrm{d}x. \tag{18}$$

For model selection, we need a third presentation of $\hat{g}_m$. Let t belong to a space S_m and define

$$\gamma_n(t) = \|t\|^2 - \frac{1}{\pi}\left\langle \frac{\hat{\theta}_\Delta}{\Delta\tilde{\psi}_\Delta}, t^* \right\rangle. \tag{19}$$

Expanding t on the basis $\varphi_{m,j}$, we find that:

$$\hat{g}_m = \arg\min_{t\in S_m} \gamma_n(t). \tag{20}$$

Therefore, $\hat{g}_m$ appears also as a minimum contrast estimator. Actually, $\gamma_n(t)$ can be viewed as an approximation of the theoretical contrast

$$\gamma_n^{th}(t) = \|t\|^2 - \frac{1}{\pi}\left\langle \frac{\hat{\theta}_\Delta}{\Delta\psi_\Delta}, t^* \right\rangle.$$

The following sequence of equalities, relying on (12), explains also the relevance of using the constrast (19) for estimating g:

$$\mathbb{E}\left(\frac{1}{2\pi\Delta} Z_k^\Delta \int e^{ixZ_k^\Delta} \frac{t^*(-x)}{\psi_\Delta(x)}\,dx\right) = \frac{1}{2\pi\Delta}\int \theta_\Delta(x)\frac{t^*(-x)}{\psi_\Delta(x)}\,dx = \frac{1}{2\pi}\langle t^*, g^*\rangle = \langle t, g\rangle.$$

Therefore, we find that $\mathbb{E}(\gamma_n^{th}(t)) = \|t\|^2 - 2\langle g, t\rangle = \|t-g\|^2 - \|g\|^2$ is minimal when $t = g$.

We denote by $(S_m)_{m\in\mathcal{M}_n}$ the collection of linear spaces, where

$$\mathcal{M}_n = \{1, \ldots, m_n\}$$

and $m_n \le n$ is the maximal admissible value of m, subject to constraints to be precised later.

In practice, we should consider the truncated spaces $S_m^{(n)} = \mathrm{Span}\{\varphi_{m,j}, j \in \mathbb{Z}, |j| \le K_n\}$, where K_n is an integer depending on n, and the associated estimators. Under assumption (H6), it is possible and does not change the main part of the study (see Comte et al. [6]). For the sake of simplicity, we consider here sums over $\mathbb{Z}$.

4.4. *Risk bound of the collection of estimators*

First, we recall a key Lemma, borrowed from Neumann [19] (see his Lemma 2.1):

Lemma 4.1. *It holds that, for any $p \ge 1$,*

$$\mathbb{E}\left(\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^{2p}\right) \le C\left(\frac{1}{|\psi_\Delta(x)|^{2p}} \wedge \frac{n^{-p}}{|\psi_\Delta(x)|^{4p}}\right),$$

where $1/\tilde{\psi}_\Delta$ is defined by (14).

Neumann's result is for $p = 1$ but the extension to any p is straighforward. See also Neumann and Reiss [20]. This lemma allows to prove the following risk bound.

Proposition 4.1. *Under assumptions* (H1)–(H2(4))–(H3), *then for all m*:

$$\mathbb{E}(\|g - \hat{g}_m\|^2) \le \|g - g_m\|^2 + K\frac{\mathbb{E}^{1/2}[(Z_1^\Delta)^4]\int_{-\pi m}^{\pi m} dx/|\psi_\Delta(x)|^2}{n\Delta^2}, \tag{21}$$

where K is a constant.

It is worth stressing that (H4)–(H5) are not required for the above result. Therefore, it holds even for exponential decay of ψ_Δ or g^*.

Proof of Proposition 4.1. First with Pythagoras Theorem, we have

$$\|g-\hat{g}_m\|^2 = \|g-g_m\|^2 + \|\hat{g}_m - g_m\|^2. \tag{22}$$

Let

$$a_{m,j}(g) = \frac{1}{2\pi\Delta}\int \theta_\Delta(x)\frac{\varphi^*_{m,j}(-x)}{\psi_\Delta(x)}\,\mathrm{d}x.$$

Then, using Parseval's formula and (16), we obtain

$$\|\hat{g}_m - g_m\|^2 = \sum_{j\in\mathbb{Z}}\bigl|\hat{a}_{m,j} - a_{m,j}(g)\bigr|^2 = \frac{1}{2\pi\Delta^2}\int_{-\pi m}^{\pi m}\left|\frac{\hat{\theta}_\Delta(x)}{\tilde{\psi}_\Delta(x)} - \frac{\theta_\Delta(x)}{\psi_\Delta(x)}\right|^2\mathrm{d}x.$$

It follows that

$$\begin{aligned}
\mathbb{E}\bigl(\|\hat{g}_m - g_m\|^2\bigr) &\le \frac{1}{\pi\Delta^2}\left\{\int_{-\pi m}^{\pi m}\mathbb{E}\left|\hat{\theta}_\Delta(x)\left(\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right)\right|^2\mathrm{d}x + \int_{-\pi m}^{\pi m}\frac{\mathbb{E}|\hat{\theta}_\Delta(x) - \theta_\Delta(x)|^2}{|\psi_\Delta(x)|^2}\,\mathrm{d}x\right\}\\
&\le \frac{2}{\pi\Delta^2}\left\{\int_{-\pi m}^{\pi m}\mathbb{E}\left(\bigl|\hat{\theta}_\Delta(x) - \theta_\Delta(x)\bigr|^2\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^2\right)\mathrm{d}x\right.\\
&\quad\left.+\int_{-\pi m}^{\pi m}\left(\Delta^2\bigl|g^*(x)\psi_\Delta(x)\bigr|^2\mathbb{E}\left(\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^2\right) + \frac{1}{n}\frac{\mathbb{E}[(Z_1^\Delta)^2]}{|\psi_\Delta(x)|^2}\right)\mathrm{d}x\right\}.
\end{aligned} \tag{23}$$

The Schwarz inequality yields

$$\mathbb{E}\left(\bigl|\hat{\theta}_\Delta(x) - \theta_\Delta(x)\bigr|^2\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^2\right) \le \mathbb{E}^{1/2}\bigl(\bigl|\hat{\theta}_\Delta(x) - \theta_\Delta(x)\bigr|^4\bigr)\mathbb{E}^{1/2}\left(\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^4\right).$$

Then, with the Rosenthal inequality $\mathbb{E}(|\hat{\theta}_\Delta(x) - \theta_\Delta(x)|^4) \le c\mathbb{E}[(Z_1^\Delta)^4]/n^2$ and by using Lemma 4.1,

$$\mathbb{E}\left(\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^4\right) \le \frac{C}{|\psi_\Delta(x)|^4}$$

so that

$$\int_{-\pi m}^{\pi m}\left(\mathbb{E}^{1/2}\bigl(\bigl|\hat{\theta}_\Delta(x) - \theta_\Delta(x)\bigr|^4\bigr)\mathbb{E}^{1/2}\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^4\right)\mathrm{d}x \le \frac{\sqrt{cC}\,\mathbb{E}^{1/2}[(Z_1^\Delta)^4]}{n}\int_{-\pi m}^{\pi m}\frac{\mathrm{d}x}{|\psi_\Delta(x)|^2}.$$

For the second term, we use Lemma 4.1, to get

$$\mathbb{E}\left(\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^2\right) \le \frac{Cn^{-1}}{|\psi_\Delta(x)|^4}.$$

We obtain

$$\mathbb{E}\bigl(\|\hat{g}_m - g_m\|^2\bigr) \le \frac{K}{n\Delta^2}\bigl(\mathbb{E}^{1/2}\bigl[\bigl(Z_1^\Delta\bigr)^4\bigr] + \Delta^2\|g\|_1^2 + \mathbb{E}\bigl[\bigl(Z_1^\Delta\bigr)^2\bigr]\bigr)\int_{-\pi m}^{\pi m}\frac{\mathrm{d}x}{|\psi_\Delta(x)|^2}, \tag{24}$$

where $\|g\|_1 = \int|g(x)|\,\mathrm{d}x$. Therefore, gathering (22) and (24) implies the result. □

Remark 4.1. *In papers concerned with deconvolution in presence of unknown error densities, the error characteristic function is estimated using a preliminary and independent set of data. This solution is possible here: we may split the sample and use the first half to obtain a preliminary and independent estimator of ψ_Δ, and then estimate g from the second half. This would simplify the above proof, but not the study of the adaptive case.*

4.5. *Discussion about the rates*

Let us study some examples and use (21) to get a relevant choice of m. Suppose that g belongs to the Sobolev class

$$\mathcal{S}(a,L)=\left\{f,\int\left|f^*(x)\right|^2\left(x^2+1\right)^a\,\mathrm{d}x\le L\right\}.$$

We have $\|g-g_m\|^2=\int_{|x|\ge\pi m}|g^*(x)|^2\,\mathrm{d}x$. Then, the bias term satisfies

$$\|g-g_m\|^2=\int_{|x|\ge\pi m}\left[\left|g^*(x)\right|^2\left(1+x^2\right)^a\right]\left(1+x^2\right)^{-a}\,\mathrm{d}x\le\frac{L}{(1+\pi^2m^2)^a}=\mathrm{O}\left(m^{-2a}\right).$$

Under (H4), the bound of the variance term satisfies

$$\frac{\int_{-\pi m}^{\pi m}\mathrm{d}x/|\psi_\Delta(x)|^2}{n\Delta}=\mathrm{O}\left(\frac{m^{2\beta\Delta+1}}{n\Delta}\right).$$

The optimal choice for m is $\mathrm{O}((n\Delta)^{1/(2\beta\Delta+2a+1)})$ and the resulting rate for the risk is $(n\Delta)^{-2a/(2\beta\Delta+2a+1)}$. It is worth noting that the sampling interval Δ explicitely appears in the exponent of the rate. Therefore, for positive β, the rate is worse for large Δ than for small Δ. Thus we can state the following corollary of Proposition 4.1:

Corollary 4.1. *Under assumptions* (H1)–(H2(4))–(H3)–(H5), *then*

$$\mathbb{E}\left(\|\hat g_m-g\|^2\right)=\mathrm{O}\left((n\Delta)^{-2a/(2\beta\Delta+2a+1)}\right)\quad\textit{when } m=\mathrm{O}\left((n\Delta)^{1/(2\beta\Delta+2a+1)}\right).$$

- Let us consider the example of the compound process. In this case $\beta=0$ and, if g belongs to the Sobolev class $\mathcal{S}(a,L)$, the upper bound of the mean integrated squared error is of order $\mathrm{O}((n\Delta)^{-2a/(2a+1)})$.
  If g is analytic, i.e. belongs to a class
  $$\mathcal{A}(\gamma,Q)=\left\{f,\int\left(\mathrm{e}^{\gamma x}+\mathrm{e}^{-\gamma x}\right)^2\left|f^*(x)\right|^2\mathrm{d}x\le Q\right\},$$
  then the bias satisfies $\|g-g_m\|^2=\mathrm{O}(\mathrm{e}^{-2\gamma\pi m})$. Choosing $m=\ln(n\Delta)/(2\pi\gamma)$, we obtain that the risk is of order $\mathrm{O}(\ln(n\Delta)/(n\Delta))$.
- For the Lévy Gamma process, we have a more precise result since we have
  $$\left|\psi_\Delta(u)\right|=\frac{\alpha^{\beta\Delta}}{(\alpha^2+u^2)^{\beta\Delta/2}},\qquad g^*(x)=\frac{\beta}{\alpha-\mathrm{i}x}.$$
  Therefore $\int_{|x|\ge\pi m}|g^*(x)|^2\,\mathrm{d}x=\mathrm{O}(m^{-1})$ and $\int_{[-\pi m,\pi m]}\mathrm{d}x/|\psi_\Delta(x)|^2=\mathrm{O}(m^{2\beta\Delta+1})$. The resulting rate is of order $(n\Delta)^{-1/(2\beta\Delta+2)}$ for a choice of m of order $\mathrm{O}((n\Delta)^{1/(2\beta\Delta+2)})$.
- For the bilateral Gamma process with $(\beta,\alpha)=(\beta',\alpha')$, we have
  $$\psi_\Delta(u)=\frac{\alpha^{\beta\Delta}}{(\alpha^2+u^2)^{\beta\Delta}},\qquad g^*(x)=\frac{2\mathrm{i}\beta\alpha x}{\alpha^2+x^2}.$$
  Therefore $\int_{|x|\ge\pi m}|g^*(x)|^2\,\mathrm{d}x=\mathrm{O}(m^{-1})$ and $\int_{[-\pi m,\pi m]}\mathrm{d}x/|\psi_\Delta(x)|^2=\mathrm{O}(m^{4\beta\Delta+1})$. The resulting rate is of order $(n\Delta)^{-1/(4\beta\Delta+2)}$ for a choice of m of order $\mathrm{O}((n\Delta)^{1/(4\beta\Delta+2)})$.

These examples illustrate that the relevant choice of m depends on the unknown function, in particular on its smoothness. The model selection procedure proposes a data driven criterion to select m.

- Consider now the process described in Section 3.3. In that case, it follows from (10) that $\int_{[-\pi m,\pi m]} \mathrm{d}x/|\psi_\Delta(x)|^2 = \mathrm{O}(m^{\delta+1/2}\exp(\kappa m^{1/2-\delta}))$ and $\int_{|x|\geq \pi m} |g^*(x)|^2\,\mathrm{d}x = \mathrm{O}(m^{-2\delta})$. In this case, choosing $\kappa m^{1/2-\delta} = \ln(n\Delta)/2$ gives the rate $[\ln(n\Delta)]^{-2\delta}$ which is thus very slow, but known to be optimal in the usual deconvolution setting (see Fan [10]). This case is not considered in the following for the adaptative strategy since it does not satisfy (H4).

4.6. *Study of the adaptive estimator*

We have to select an adequate value of m. For this, we start by defining the term

$$\Phi_\psi(m) = \int_{-\pi m}^{\pi m} \frac{\mathrm{d}x}{|\psi_\Delta(x)|^2}, \tag{25}$$

and the following theoretical penalty

$$\mathrm{pen}(m) = \kappa\big(1 + \mathbb{E}\big[\big(Z_1^\Delta\big)^2\big]/\Delta\big)\frac{\Phi_\psi(m)}{n\Delta}. \tag{26}$$

We set

$$\hat{m} = \underset{m\in\mathcal{M}_n}{\arg\min}\big\{\gamma_n(\hat{g}_m) + \mathrm{pen}(m)\big\},$$

and study first the "risk" of $\hat{g}_{\hat{m}}$.

Moreover we need the following assumption on the collection of models $\mathcal{M}_n = \{1,\dots,m_n\}$, $m_n \leq n$:

(H7) $\exists\varepsilon, 0<\varepsilon<1, m_n^{2\beta\Delta} \leq Cn^{1-\varepsilon}$,

where C is a fixed constant and β is defined by (H4).

For instance, assumption (H7) is fulfilled if:

(1) $\mathrm{pen}(m_n) \leq C$. In such a case, we have $m_n \leq C(n\Delta)^{1/(2\beta\Delta+1)}$.
(2) Δ is small enough to ensure $2\beta\Delta < 1$. In such a case we can take $\mathcal{M}_n = \{1,\dots,n\}$.

Remark 4.2. *Assumption* (H7) *raises a problem since it depends on the unknown β and concrete implementation requires the knowledge of m_n. It is worth stressing that the analogous difficulty arises in deconvolution with unknown error density* (*see Comte and Lacour* [5]). *In the compound Poisson model, $\beta = 0$ and nothing is needed. Otherwise one should at least know if ψ_Δ is in a class of polynomial decay. The estimator $\hat{\psi}_\Delta$ may be used to that purpose and to provide an estimator of β* (*see e.g. Diggle and Hall* [8]).

Let us define

$$\theta_\Delta^{(1)}(x) = \mathbb{E}\big(Z_1^\Delta \mathbb{1}_{|Z_1^\Delta|\leq k_n\sqrt{\Delta}} \mathrm{e}^{\mathrm{i}xZ_1^\Delta}\big), \qquad \theta_\Delta^{(2)}(x) = \mathbb{E}\big(Z_1^\Delta \mathbb{1}_{|Z_1^\Delta|> k_n\sqrt{\Delta}} \mathrm{e}^{\mathrm{i}xZ_1^\Delta}\big)$$

so that $\theta_\Delta = \theta_\Delta^{(1)} + \theta_\Delta^{(2)}$ and analogously $\hat{\theta}_\Delta = \hat{\theta}_\Delta^{(1)} + \hat{\theta}_\Delta^{(2)}$. For any two functions t, s in S_m, the contrast γ_n satisfies:

$$\gamma_n(t) - \gamma_n(s) = \|t-g\|^2 - \|s-g\|^2 - 2\nu_n^{(1)}(t-s) - 2\nu_n^{(2)}(t-s) - 2\sum_{i=1}^4 R_n^{(i)}(t-s) \tag{27}$$

with

$$\nu_n^{(1)}(t) = \frac{1}{2\pi\Delta}\int t^*(-x)\frac{\hat{\theta}_\Delta^{(1)}(x) - \theta_\Delta^{(1)}(x)}{\psi_\Delta(x)}\,\mathrm{d}x,$$

$$\nu_n^{(2)}(t) = \frac{1}{2\pi\Delta}\int t^*(-x)\frac{\theta_\Delta(x)}{[\psi_\Delta(x)]^2}\big(\psi_\Delta(x) - \hat{\psi}_\Delta(x)\big)\,\mathrm{d}x,$$

$$R_n^{(1)}(t) = \frac{1}{2\pi\Delta}\int t^*(-x)\big(\hat{\theta}_\Delta(x) - \theta_\Delta(x)\big)\left(\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right)\mathrm{d}x,$$

$$R_n^{(2)}(t) = \frac{1}{2\pi\Delta}\int t^*(-x)\frac{\theta_\Delta(x)}{\psi_\Delta(x)}\big(\psi_\Delta(x) - \hat{\psi}_\Delta(x)\big)\left(\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right)\mathrm{d}x,$$

$$R_n^{(3)}(t) = \frac{1}{2\pi\Delta}\int t^*(-x)\frac{\hat{\theta}_\Delta^{(2)}(x) - \theta_\Delta^{(2)}(x)}{\psi_\Delta(x)}\,\mathrm{d}x,$$

$$R_n^{(4)}(t) = -\frac{1}{2\pi\Delta}\int t^*(-x)\frac{\theta_\Delta(x)}{\psi_\Delta(x)}\mathbb{1}_{|\hat{\psi}_\Delta(x)|\le\kappa_\psi/\sqrt{n}}\,\mathrm{d}x.$$

We want to stress that the above very precise decomposition is needed to obtain Theorem 4.2. The specific problem treated here raises unusual difficulties when compared with standard model selection problems. Of course, the terms $\nu_n^{(1)}$, $\nu_n^{(2)}$ are centered empirical processes which can be studied using Talagrand's inequality (see the Appendix). The remainder terms $R_n^{(3)}$, $R_n^{(4)}$ are found to be negligible as could be expected. But the study of $R_n^{(1)}$, $R_n^{(2)}$ is surprisingly difficult.

We prove successively the two theorems below.

Theorem 4.1. *Assume that assumptions* (H1)–(H2(8))–(H3)–(H7) *hold. Then*

$$\mathbb{E}\big(\|\hat{g}_{\hat{m}} - g\|^2\big) \le C \inf_{m\in\mathcal{M}_n}\big(\|g - g_m\|^2 + \mathrm{pen}(m)\big) + K\frac{\ln^2(n)}{n\Delta},$$

where K is a constant.

Remark 4.3. *Assumption* (H6) *is satisfied for the Lévy Gamma process. For the compound Poisson process, it is equivalent to $\int x^4 f^2(x)\,\mathrm{d}x < +\infty$, where f denotes the density of Y_i* (*see Section* 3).

To get an estimator, we replace the theoretical penalty by:

$$\widehat{\mathrm{pen}}(m) = \kappa'\left(1 + \frac{1}{n\Delta^2}\sum_{i=1}^n \big(Z_i^\Delta\big)^2\right)\frac{\int_{-\pi m}^{\pi m}\mathrm{d}x/|\tilde{\psi}_\Delta(x)|^2}{n}.$$

In that case we can prove:

Theorem 4.2. *Assume that assumptions* (H1)–(H2(8))–(H3)–(H7) *hold and let $\tilde{g} = \hat{g}_{\hat{\hat{m}}}$ be the estimator defined with $\hat{\hat{m}} = \arg\min_{m\in\mathcal{M}_n}(\gamma_n(\hat{g}_m) + \widehat{\mathrm{pen}}(m))$. Then*

$$\mathbb{E}\big(\|\tilde{g} - g\|^2\big) \le C \inf_{m\in\mathcal{M}_n}\big(\|g - g_m\|^2 + \mathrm{pen}(m)\big) + K'_\Delta\frac{\ln^2(n)}{n},$$

where K'_Δ is a constant depending on Δ (*and on fixed quantities but not on n*).

Theorem 4.2 shows that the adaptive estimator automatically achieves the best rate that can be hoped. If g belongs to the Sobolev ball $\mathcal{S}(a, L)$, and under (H4), the rate is automatically of order $\mathrm{O}((n\Delta)^{-2a/(2\beta\Delta+2a+1)})$ (see Section 4.5).

Remark 4.4. (1) *It may be possible to extend our study of the adaptive estimator to the case ψ_Δ having exponential decay. This would imply a change of both* (H4) *and* (H7) (*see Comte and Lacour* [5]). *Note that the faster $|\psi_\Delta|$ decays, the more difficult it will be to estimate g.*

(2) *Few results on rates of convergence are available in the literature for this problem. The results of Neumann and Reiss* [20] *are difficult to compare with ours since the point of view is different.*

5. Proofs

5.1. *Proof of Theorem 4.1*

Writing that $\gamma_n(\hat{g}_{\hat{m}}) + \mathrm{pen}(\hat{m}) \le \gamma_n(g_m) + \mathrm{pen}(m)$ in view of (27) implies that

$$\|\hat{g}_{\hat{m}} - g\|^2 \le \|g_m - g\|^2 + 2\nu_n^{(1)}(\hat{g}_{\hat{m}} - g_m) + 2\nu_n^{(2)}(\hat{g}_{\hat{m}} - g_m) + 2\sum_{i=1}^{4} R_n^{(i)}(\hat{g}_{\hat{m}} - g_m) + \mathrm{pen}(m) - \mathrm{pen}(\hat{m}).$$

We have to take expectations of both sides and bound each r.h.s. term. This will be obtained through the following propositions.

Proposition 5.1. *Under the assumptions of Theorem 4.1, define*

$$p_1(m, m') = \left(4\mathbb{E}\left[\left(Z_1^{\Delta}\right)^2\right] \int_{-\pi(m\vee m')}^{\pi(m\vee m')} \left|\psi_\Delta(x)\right|^{-2} \mathrm{d}x\right) / \left(\pi n \Delta^2\right),$$

then

$$\sum_{m'\in\mathcal{M}_n} \mathbb{E}\Big(\sup_{t\in S_{m\vee m'}, \|t\|=1} \left|\nu_n^{(1)}(t)\right|^2 - p_1(m, m')\Big)_+ \le \frac{c}{n}. \tag{28}$$

Next we have:

Proposition 5.2. *Under the assumptions of Theorem 4.1, define $p_2(m, m') = 0$ if $-a + \beta\Delta \le 0$ and $p_2(m, m') = (\int_{-\pi(m\vee m')}^{\pi(m\vee m')} |\psi_\Delta(x)|^{-2}\,\mathrm{d}x)/n$ otherwise. Then*

$$\mathbb{E}\Big(\sup_{t\in S_{m\vee \hat{m}}, \|t\|=1} \left|\nu_n^{(2)}(t)\right|^2 - p_2(m, \hat{m})\Big)_+ \le \frac{c}{n}. \tag{29}$$

For the residual terms, two types of results can be obtained.

Proposition 5.3. *Under the assumptions of Theorem 4.1, for $i = 1, 2$,*

$$\mathbb{E}\Big(\sup_{t\in S_{m\vee \hat{m}}, \|t\|=1} \left[R_n^{(i)}(t)\right]^2 - p_1(m, \hat{m})\Big) \le \frac{C}{n\Delta}.$$

Proposition 5.4. *Under the assumptions of Theorem 4.1, for $i = 3, 4$,*

$$\mathbb{E}\Big(\sup_{t\in S_{m_n}, \|t\|=1} \left[R_n^{(i)}(t)\right]^2\Big) \le c\frac{\ln^2(n)}{n\Delta}.$$

Relying on Proposition 5.1, and using $2xy \le 16x^2 + (1/16)y^2$ for nonnegative x, y, we obtain

$$\begin{aligned}
2\left|\mathbb{E}\left(\nu_n^{(1)}(\hat{g}_{\hat{m}} - g_m)\right)\right| &\le 2\mathbb{E}\Big(\|\hat{g}_{\hat{m}} - g_m\| \sup_{t\in S_m + S_{\hat{m}}, \|t\|=1} \left|\nu_n^{(1)}(t)\right|\Big) \\
&\le \frac{1}{16}\mathbb{E}\left(\|g_m - \hat{g}_{\hat{m}}\|^2\right) + 16\mathbb{E}\Big[\sup_{t\in S_m + S_{\hat{m}}, \|t\|=1} \left|\nu_n^{(1)}(t)\right|^2\Big] \\
&\le \frac{1}{8}\mathbb{E}\left(\|g - \hat{g}_{\hat{m}}\|^2\right) + \frac{1}{8}\|g - g_m\|^2 \\
&\quad + 16\mathbb{E}\Big(\sup_{t\in S_{m\vee \hat{m}}, \|t\|=1} \left|\nu_n^{(1)}(t)\right|^2 - p_1(m, \hat{m})\Big)_+ + 16\mathbb{E}\left(p_1(m, \hat{m})\right).
\end{aligned}$$

The same kind of bounds are obtained for $\nu_n^{(2)}$ and the residuals. Gathering all terms $\|\hat{g}_{\hat{m}}-g\|^2$ on the left-hand-side and all terms $\|g-g_m\|^2$ on the right-hand-side leads to

$$\begin{aligned}\left(1-\frac{6}{8}\right)\mathbb{E}\big(\|\hat{g}_{\hat{m}}-g\|^2\big) \le{}& \left(1+\frac{6}{8}\right)\|g-g_m\|^2 \\ &+16\sum_{m'\in\mathcal{M}_n}\mathbb{E}\Big(\sup_{t\in S_{m\vee m'},\|t\|=1}\big|\nu_n^{(1)}(t)\big|^2-p_1\big(m,m'\big)\Big)_+ \\ &+16\mathbb{E}\Big(\sup_{t\in S_{m\vee\hat{m}},\|t\|=1}\big|\nu_n^{(2)}(t)\big|^2-p_2(m,\hat{m})\Big)_+ \\ &+16\sum_{i=1}^{2}\mathbb{E}\Big(\sup_{t\in S_{m\vee\hat{m}},\|t\|=1}\big|R_n^{(i)}(t)\big|^2-p_1(m,\hat{m})\Big) \\ &+16\sum_{i=3}^{4}\mathbb{E}\Big(\sup_{t\in S_{m_n},\|t\|=1}\big|R_n^{(i)}(t)\big|^2\Big) \\ &+\operatorname{pen}(m)+\mathbb{E}\big(48p_1(m,\hat{m})+16p_2(m,\hat{m})-\operatorname{pen}(\hat{m})\big). \end{aligned}\tag{30}$$

Next, definition of $\operatorname{pen}(\cdot)$ comes from the following constraint:

$$48p_1\big(m,m'\big)+16p_2\big(m,m'\big)\le\operatorname{pen}\big(m'\big)+\operatorname{pen}(m).\tag{31}$$

This leads to

$$\operatorname{pen}(m)+\mathbb{E}\big(48p_1(m,\hat{m})+16p_2(m,\hat{m})-\operatorname{pen}(\hat{m})\big)\le 2\operatorname{pen}(m).$$

Then the choice $\operatorname{pen}(m)$ given by (26) gives, following (30) and (31),

$$\frac{1}{4}\mathbb{E}\big(\|\hat{g}_{\hat{m}}-g\|^2\big)\le\frac{7}{4}\|g-g_m\|^2+2\operatorname{pen}(m)+C\frac{\ln^2(n)}{n\Delta},$$

which is the result.

5.2. *Proof of Proposition* 5.1

We apply Talagrand's inequality recalled in Lemma A.1 to prove the result.

Let

$$\omega_t(z)=\frac{z\mathbb{1}_{\{|z|\le k_n\sqrt{\Delta}\}}}{2\pi\Delta}\int e^{izx}\frac{t^*(-x)}{\psi_\Delta(x)}\,dx$$

and notice that

$$\nu_n^{(1)}(t)=\frac{1}{n}\sum_{k=1}^{n}\big[\omega_t\big(Z_k^\Delta\big)-\mathbb{E}\big(\omega_t\big(Z_k^\Delta\big)\big)\big].$$

To apply Lemma A.1, we compute M_1, H_1 and v_1 defined therein. First, we have

$$\begin{aligned}\mathbb{E}\Big(\sup_{t\in S_m,\|t\|=1}\big|\nu_n^{(1)}(t)\big|^2\Big)&\le\mathbb{E}\bigg(\sum_{j\in\mathbb{Z}}\big|\nu_n^{(1)}(\varphi_{m,j})\big|^2\bigg) \\ &=\mathbb{E}\bigg(\frac{1}{2\pi\Delta^2}\int_{-\pi m}^{\pi m}\bigg|\frac{\hat{\theta}_\Delta^{(1)}(x)-\theta_\Delta^{(1)}(x)}{\psi_\Delta(x)}\bigg|^2\,dx\bigg)\le\frac{\mathbb{E}[(Z_1^\Delta)^2]}{2\pi n\Delta^2}\Phi_\psi(m),\end{aligned}$$

where $\Phi_\psi(m)$ is defined in (25). We can take, for $m^\star = m \vee m'$,

$$H_1^2 = \frac{\mathbb{E}[(Z_1^\Delta)^2]}{2\pi n\Delta^2}\Phi_\psi(m^\star).$$

Then it is easy to see that if $\|t\| = 1$ and $t \in S_{m^\star}$,

$$\left|\omega_t(z)\right| \le \frac{k_n}{2\pi\sqrt{\Delta}}\int\left|\frac{t^*(-x)}{\psi_\Delta(x)}\right|\mathrm{d}x \le \frac{k_n}{2\pi\sqrt{\Delta}}\sqrt{\Phi_\psi\left(m^\star\right)} := M_1.$$

Lastly, for $t \in S_m$, $\|t\| = 1$, $t = \sum_{j\in\mathbb{Z}} t_{m,j}\varphi_{m,j}$,

$$\begin{aligned}\operatorname{Var}\left(\omega_t\left(Z_1^\Delta\right)\right) &\le \frac{1}{(2\pi)^2\Delta^2}\iint \mathbb{E}\left(\mathrm{e}^{\mathrm{i}(u-v)Z_1^\Delta}\left(Z_1^\Delta\mathbb{1}_{|Z_1^\Delta|\le k_n\sqrt{\Delta}}\right)^2\right)\frac{t^*(-u)t^*(v)}{\psi_\Delta(u)\psi_\Delta(-v)}\,\mathrm{d}u\,\mathrm{d}v\\ &= \frac{1}{(2\pi\Delta)^2}\sum_{j,k} t_{m,j}t_{m,k}\iint \mathbb{E}\left(\mathrm{e}^{\mathrm{i}(u-v)Z_1^\Delta}\left(Z_1^\Delta\mathbb{1}_{|Z_1^\Delta|\le k_n\sqrt{\Delta}}\right)^2\right)\frac{\varphi_{m,j}^*(-u)\varphi_{m,k}^*(v)}{\psi_\Delta(u)\psi_\Delta(-v)}\,\mathrm{d}u\,\mathrm{d}v.\end{aligned}$$

Denoting by

$$h_\Delta^*(u) = \mathbb{E}\left[\mathrm{e}^{\mathrm{i}uZ_1^\Delta}\left(Z_1^\Delta\mathbb{1}_{|Z_1^\Delta|\le k_n\sqrt{\Delta}}\right)^2\right], \tag{32}$$

we obtain:

$$\begin{aligned}\operatorname{Var}\left(\omega_t\left(Z_1^\Delta\right)\right) &\le \frac{1}{(2\pi\Delta)^2}\left(\sum_{j,k}\left|\iint h_\Delta^*(u-v)\frac{\varphi_{m,j}^*(-u)\varphi_{m,k}^*(v)}{\psi_\Delta(u)\psi_\Delta(-v)}\,\mathrm{d}u\,\mathrm{d}v\right|^2\right)^{1/2}\\ &= \frac{1}{2\pi\Delta^2}\left(\iint_{[-\pi m,\pi m]^2}\left|\frac{h_\Delta^*(u-v)}{\psi_\Delta(u)\psi_\Delta(-v)}\right|^2\mathrm{d}u\,\mathrm{d}v\right)^{1/2},\end{aligned}$$

where the last equality follows from the Parseval equality. Next with the Schwarz inequality and the Fubini theorem, we obtain

$$\begin{aligned}\operatorname{Var}\left(\omega_t\left(Z_1^\Delta\right)\right) &\le \frac{1}{2\pi\Delta^2}\left(\iint_{[-\pi m,\pi m]^2}\frac{|h_\Delta^*(u-v)|^2}{|\psi_\Delta(u)|^4}\,\mathrm{d}u\,\mathrm{d}v\right)^{1/2}\\ &= \frac{1}{2\pi\Delta^2}\left(\int_{[-\pi m,\pi m]}\left|\frac{\mathrm{d}u}{\psi_\Delta(u)}\right|^4\mathrm{d}u\int\left|h_\Delta^*(z)\right|^2\mathrm{d}z\right)^{1/2} \le \frac{\sqrt{\int_{-\pi m}^{\pi m}\mathrm{d}x/|\psi_\Delta(x)|^4}}{2\pi\Delta}\frac{\|h_\Delta^*\|}{\Delta}.\end{aligned}$$

Now we use the following lemma:

Lemma 5.1. *Under the assumptions of Theorem 4.1*,

$$\left\|h_\Delta^*\right\|/\Delta \le 2\sqrt{\pi}\left(\int x^2g^2(x)\,\mathrm{d}x + \mathbb{E}\left[\left(Z_1^\Delta\right)^2\right]\|g\|^2\right)^{1/2} := \xi.$$

Thus, under (H5), ξ is finite. We set

$$v_1 = \frac{\xi\sqrt{\int_{-\pi m^\star}^{\pi m^\star}\mathrm{d}x/|\psi_\Delta(x)|^4}}{2\pi\Delta}.$$

Therefore, setting $\epsilon^2 = 1/2$,

$$p_1\left(m,m'\right) = 4\mathbb{E}\left[\left(Z_1^\Delta\right)^2/\Delta\right]\frac{\Phi_\psi(m^\star)}{2\pi n\Delta}\quad\left(=2\left(1+2\epsilon^2\right)H_1^2\right).$$

Using (H4) and the fact that $\mathbb{E}[(Z_1^\Delta)^2/\Delta]$ is bounded, we find

$$\mathbb{E}\Big(\sup_{t\in S_{m^\star},\|t\|=1}\big|\nu_n^{(1)}(t)\big|^2 - p_1\big(m,m'\big)\Big)_+ \le C\bigg(\frac{(m^\star)^{2\beta\Delta+1/2}}{n\Delta}\mathrm{e}^{-K\sqrt{m^\star}} + \frac{k_n^2\Phi_\psi(m^\star)}{n^2\Delta}\mathrm{e}^{-K'\sqrt{n}/k_n}\bigg).$$

Here $K = K(c_\psi, C_\psi)$. Moreover, we take

$$k_n = K'\sqrt{n}/\big((2\beta\Delta+3)\ln(n)\big) \tag{33}$$

and we obtain

$$\sum_{m'\in\mathcal{M}_n}\mathbb{E}\Big(\sup_{t\in S_{m^\star},\|t\|=1}\big[\nu_n^{(1)}(t)\big]^2 - p_1\big(m,m'\big)\Big)_+ \le \frac{K''}{n\Delta}.$$

5.3. *Proof of Proposition* 5.2

The study of $\nu_n^{(2)}$ is slightly different.

$$\mathbb{E}\Big(\sup_{t\in S_m,\|t\|=1}\big|\nu_n^{(2)}(t)\big|^2\Big) \le \frac{1}{2\pi n\Delta^2}\int_{-\pi m}^{\pi m}\frac{|\theta_\Delta(x)|^2}{|\psi_\Delta(x)|^4}\,\mathrm{d}x = \frac{1}{2\pi n}\int_{-\pi m}^{\pi m}\frac{|g^*(x)|^2}{|\psi_\Delta(x)|^2}\,\mathrm{d}x.$$

With assumptions (H4) and (H5), we can see that if $-a+\beta\Delta\le 0$, then

$$\int_{-\pi m}^{\pi m}\frac{|g^*(x)|^2}{|\psi_\Delta(x)|^2}\,\mathrm{d}x \le \int_{-\pi m}^{\pi m}\big|g^*(x)\big|^2\big(1+x^2\big)^a\frac{(1+x^2)^{-a+\beta\Delta}}{c_\psi^2}\,\mathrm{d}x \le \frac{1}{c_\psi^2}\int\big|g^*(x)\big|^2\big(1+x^2\big)^a\,\mathrm{d}x \le \frac{L}{c_\psi^2}.$$

In that case, we simply take $p_2(m,m') = 0$ and write

$$\mathbb{E}\Big(\sup_{t\in S_{m\vee\hat{m}},\|t\|=1}\big[\nu_n^{(2)}\big]^2(t)\Big) \le \mathbb{E}\Big(\sup_{t\in S_{m_n},\|t\|=1}\big[\nu_n^{(2)}\big]^2(t)\Big) \le \frac{L}{nc_\psi^2}.$$

Now we study the case $-a+\beta\Delta>0$ and find the constants $H = H_2$, $v = v_2$, $\epsilon = \epsilon_2$ to apply Lemma A.1. Consider

$$\tilde{\omega}_t(z) = (1/2\pi\Delta)\int \mathrm{e}^{\mathrm{i}zu}t^*(-u)\big\{\theta_\Delta(u)/\big[\psi_\Delta(u)\big]^2\big\}\,\mathrm{d}u.$$

As

$$\int_{-\pi m}^{\pi m}\frac{|g^*(x)|^2}{|\psi_\Delta(x)|^2}\,\mathrm{d}x \le \frac{L}{c_\psi^2}m^{-2a+2\beta\Delta},$$

we take

$$H_2^2 = \frac{L}{2\pi c_\psi^2}\frac{(m^\star)^{-2a+2\beta\Delta}}{n}.$$

Next, we have

$$M_2 = \sqrt{n}H_2$$

and we use the rough bound $v_2 = nH_2^2$. Moreover, we take $\epsilon_2^2 = (-2a+2\beta\Delta+2)\ln(m^\star)/K_1$. There exists m_0, such that for $m^\star \ge m_0$,

$$2\big(1+2\epsilon_2^2\big)H_2^2 \le \Phi_\psi\big(m^\star\big)/n.$$

We set $p_2(m,m') = \Phi_\psi(m^\star)/n$. Introducing

$$W_n(m,m') = \Big[\sup_{t\in S_{m\vee m'},\|t\|=1} \big|\nu_n^{(2)}\big|^2(t) - p_2(m,m')\Big]_+,$$

we find that

$$\begin{aligned}\sum_{m'\in\mathcal{M}_n} \mathbb{E}\big(W_n(m,m')\big) &= \sum_{m'|m^\star\le m_0} \mathbb{E}\big(W_n(m,m')\big) + \sum_{m'|m^\star> m_0} \mathbb{E}\big(W_n(m,m')\big)\\ &\le \sum_{m'|m^\star\le m_0} \mathbb{E}\Big(\Big[\sup_{t\in S_{m^\star},\|t\|=1} \big|\nu_n^{(2)}(t)\big|^2 - 2\big(1+2\epsilon_2^2\big)H_2^2\Big]_+\Big)\\ &\quad + \sum_{m'|m^\star\le m_0} \big|p_2(m,m') - 2\big(1+2\epsilon_2^2\big)H_2^2\big|\\ &\quad + \sum_{m'|m^\star> m_0} \mathbb{E}\Big(\Big[\sup_{t\in S_{m^\star},\|t\|=1} \big|\nu_n^{(2)}(t)\big|^2 - 2\big(1+2\epsilon_2^2\big)H_2^2\Big]_+\Big).\end{aligned}$$

Therefore

$$\begin{aligned}\sum_{m'\in\mathcal{M}_n} \mathbb{E}\big(W_n(m,m')\big) &\le 2\sum_{m'\in\mathcal{M}_n} \mathbb{E}\Big(\Big[\sup_{t\in S_{m^\star},\|t\|=1} \big|\nu_n^{(2)}(t)\big|^2 - 2\big(1+2\epsilon_2^2\big)H_2^2\Big]_+\Big)\\ &\quad + \sum_{m'|m^\star\le m_0} \big|p_2(m,m') - 2\big(1+2\epsilon_2^2\big)H_2^2\big|\\ &\le 2\sum_{m'\in\mathcal{M}_n} \mathbb{E}\Big(\Big[\sup_{t\in S_{m^\star},\|t\|=1} \big|\nu_n^{(2)}(t)\big|^2 - 2\big(1+2\epsilon_2^2\big)H_2^2\Big]_+\Big) + \frac{C(m_0)}{n}.\end{aligned}$$

Talagrand's inequality again can be then applied and gives that

$$\sum_{m'\in\mathcal{M}_n} \mathbb{E}\Big(\Big[\sup_{t\in S_{m^\star},\|t\|=1} \big|\nu_n^{(2)}(t)\big|^2 - 2\big(1+2\epsilon_2^2\big)H_2^2\Big]_+\Big) \le \frac{C}{n}.$$

The result for $\nu_n^{(2)}$ in this case follows then by saying as for $\nu_n^{(1)}$ that

$$\mathbb{E}\big(W_n(m,\hat m)\big) \le \sum_{m'\in\mathcal{M}_n} \mathbb{E}\big(W_n(m,m')\big).$$

5.4. *Proof of Proposition* 5.3

First define $\Omega(x) = \Omega_1(x)\cap\Omega_2(x)$ with

$$\begin{aligned}\Omega_1(x) &= \big\{\big|\hat\theta_\Delta(x) - \theta_\Delta(x)\big| \le 8\mathbb{E}^{1/2}\big[\big(Z_1^\Delta\big)^2\big]\log^{1/2}(n)n^{-1/2}\big\},\\ \Omega_2(x) &= \left\{\left|\frac{1}{\tilde\psi_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right| \le 1/\big(\log^{1/2}(n)n^\omega\big|\psi_\Delta(x)\big|^2\big)\right\}.\end{aligned}$$

Then split: $R_n^{(1)}(t) = R_n^{(1,1)}(t) + R_n^{(1,2)}(t)$ where

$$R_n^{(1,1)}(t) = \frac{1}{2\pi\Delta}\int t^*(-x)(\hat\theta_\Delta - \theta_\Delta)(x)\left(\frac{1}{\tilde\psi_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right)\mathbb{1}_{\Omega(x)}\,\mathrm{d}x$$

and $R_n^{(1,2)}(t)$ the integral on the complement of $\Omega(x)$.

$$\mathbb{E}\Big(\sup_{t\in S_{m\vee\hat m},\|t\|=1}\big|R_n^{(1)}(t)\big|^2\Big)\le 2\mathbb{E}\Big(\sup_{t\in S_{m\vee\hat m},\|t\|=1}\big|R_n^{(1,1)}(t)\big|^2\Big)+2\mathbb{E}\Big(\sup_{t\in S_{m_n},\|t\|=1}\big|R_n^{(1,2)}(t)\big|^2\Big),$$

$$\begin{aligned}
&\mathbb{E}\Big(\sup_{t\in S_{m\vee\hat m},\|t\|=1}\big|R_n^{(1,1)}(t)\big|^2\Big)\\
&\quad\le\frac{1}{2\pi\Delta^2}\mathbb{E}\bigg(\int_{-\pi(m\vee\hat m)}^{\pi(m\vee\hat m)}\big|\hat\theta_\Delta(x)-\theta_\Delta(x)\big|^2\bigg|\frac{1}{\tilde\psi_\Delta(x)}-\frac{1}{\psi_\Delta(x)}\bigg|^2\mathbb{1}_{\Omega(x)}\,\mathrm{d}x\bigg)\\
&\quad\le\frac{8(\mathbb{E}[(Z_1^\Delta)^2]/\Delta)}{2\pi n\Delta}\mathbb{E}\bigg(\int_{-\pi(m\vee\hat m)}^{\pi(m\vee\hat m)}n^{-2\omega}\frac{\mathrm{d}x}{|\psi_\Delta(x)|^4}\bigg)\le\frac{4\mathbb{E}[(Z_1^\Delta)^2]}{\pi\Delta}\mathbb{E}\bigg(\frac{\Phi_\psi(m\vee\hat m)}{n\Delta}\bigg)\le\mathbb{E}\big(p_1(m,\hat m)\big),
\end{aligned}$$

under the condition $-2\omega+(1-\varepsilon)\le 0$. Therefore we choose $\omega=(1-\varepsilon)/2$. Note that if $\beta=0$ the decomposition is useless and the residual is straightforwardly negligible.

On the other hand, Lemma 4.1 yields:

$$\mathbb{E}^{1/4}\bigg[\bigg|\frac{1}{\tilde\psi_\Delta(x)}-\frac{1}{\psi_\Delta(x)}\bigg|^8\bigg]\le\frac{C_\Delta}{n|\psi_\Delta(x)|^4}.$$

Now, we find

$$\begin{aligned}
&\mathbb{E}\Big(\sup_{t\in S_{m_n},\|t\|=1}\big|R_n^{(1,2)}(t)\big|^2\Big)\\
&\quad\le\frac{1}{2\pi\Delta^2}\int_{-\pi m_n}^{\pi m_n}\mathbb{P}^{1/2}\big(\Omega(x)^c\big)\mathbb{E}^{1/4}\big[\big(\hat\theta_\Delta(x)-\theta_\Delta(x)\big)^8\big]\mathbb{E}^{1/4}\bigg[\bigg|\frac{1}{\tilde\psi_\Delta(x)}-\frac{1}{\psi_\Delta(x)}\bigg|^8\bigg]\mathrm{d}x\\
&\quad\le\frac{C\mathbb{E}^{1/4}[(Z_1^\Delta)^8]}{2\pi n^2}\int_{-\pi m_n}^{\pi m_n}\frac{\mathbb{P}^{1/2}(\Omega(x)^c)}{|\psi_\Delta(x)|^4}\,\mathrm{d}x\\
&\quad\le\frac{C\mathbb{E}^{1/4}[(Z_1^\Delta)^8]n^{2(1-\varepsilon)+1-b}}{n^2}\le\frac{C'_\Delta}{n}\quad\text{if }\mathbb{P}\big(\Omega(x)^c\big)\le n^{-2b}\text{ and }2(1-\varepsilon)-b\le 0.
\end{aligned}$$

We take $b=2(1-\varepsilon)$. In fact,

$$\mathbb{P}\big(\Omega(x)^c\big)\le\mathbb{P}\big(\Omega_1(x)^c\big)+\mathbb{P}\big(\Omega_2(x)^c\big).$$

We use the Markov inequality to bound $\mathbb{P}(\Omega_2(x)^c)$:

$$\begin{aligned}
\mathbb{P}\big(\Omega_2(x)^c\big)&\le\log^p(n)n^{2p\omega}\big|\psi_\Delta(x)\big|^{4p}\mathbb{E}\bigg(\bigg|\frac{1}{\tilde\psi_\Delta(x)}-\frac{1}{\psi_\Delta(x)}\bigg|^{2p}\bigg)\\
&\le\log^p(n)n^{2p\omega-p}.
\end{aligned}$$

The choice of p is thus constrained by $2p\omega-p=-p(1-2\omega)<-4(1-\varepsilon)$ that is $p>4(1-\varepsilon)/\varepsilon$, e.g. $p=5(1-\varepsilon)/\varepsilon$.

We use the decomposition of $\theta_\Delta(x)=\theta_\Delta^{(1)}(x)+\theta_\Delta^{(2)}(x)$ with

$$k_n\sqrt{\Delta}=\frac{\sqrt{n\mathbb{E}[(Z_1^\Delta)^2]}}{8\sqrt{\log(n)}}.$$

We use the Bernstein inequality to bound $\mathbb{P}(\Omega_1(x)^c)$. If $X_1,\dots,X_n$ are i.i.d. variables with variance less than v^2 and such that $|X_i|\le c$, then for $S_n=\sum_{i=1}^n X_i$, we have:

$$\mathbb{P}\big(\big|S_n-\mathbb{E}(S_n)\big|\ge n\epsilon\big)\le 2\exp\bigg(-\frac{n\epsilon^2/2}{v^2+c\epsilon}\bigg).$$

This yields

$$
\begin{aligned}
\mathbb{P}\big(\Omega_1(x)^c\big) &\le \mathbb{P}\Big(\big|\hat{\theta}_\Delta^{(1)}(x)-\theta_\Delta^{(1)}(x)\big| \ge 4\sqrt{\mathbb{E}\big[\big(Z_1^\Delta\big)^2\big]\log(n)/n}\Big) \\
&\quad + \mathbb{P}\Big(\big|\hat{\theta}_\Delta^{(2)}(x)-\theta_\Delta^{(2)}(x)\big| \ge 4\sqrt{\mathbb{E}\big[\big(Z_1^\Delta\big)^2\big]\log(n)/n}\Big) \\
&\le n^{-16/3} + \frac{n}{16\mathbb{E}[(Z_1^\Delta)^2]\log(n)}\mathbb{E}\big(\big|\hat{\theta}_\Delta^{(2)}(x)-\theta_\Delta^{(2)}(x)\big|^2\big) \\
&\le n^{-16/3} + \frac{\mathbb{E}[(Z_1^\Delta)^2\mathbb{1}_{|Z_1^\Delta|\ge k_n\sqrt{\Delta}}]}{16\mathbb{E}[(Z_1^\Delta)^2]\log(n)} \\
&\le n^{-16/3} + \frac{8^4\mathbb{E}[(Z_1^\Delta)^6]\log^2(n)}{16\mathbb{E}^3[(Z_1^\Delta)^2]n^2} \\
&\le n^{-16/3} + \frac{c}{n^2\Delta^2}.
\end{aligned}
$$

This gives the result of Proposition 5.3 for $R_n^{(1)}$. The study of $R_n^{(2)}$ follows the same line and is omitted.

5.5. *Proof of Proposition* 5.4

First we study $R_n^{(3)}$.

$$
\begin{aligned}
\mathbb{E}\Big(\sup_{t\in S_{m_n},\|t\|=1}\big|R_n^{(3)}(t)\big|^2\Big) &\le \frac{1}{4\pi^2\Delta^2}\mathbb{E}\Big[\sup_{t\in S_{m_n},\|t\|=1}\Big|\int\big(\hat{\theta}_\Delta^{(2)}(x)-\theta_\Delta^{(2)}(x)\big)\frac{t^*(-x)}{\psi_\Delta(x)}\,\mathrm{d}x\Big|^2\Big] \\
&\le \frac{1}{2\pi\Delta^2}\int_{-\pi m_n}^{\pi m_n}\mathbb{E}\big[\big|\hat{\theta}_\Delta^{(2)}(x)-\theta_\Delta^{(2)}(x)\big|^2\big]\frac{\mathrm{d}x}{|\psi_\Delta(x)|^2} \\
&= \frac{1}{2\pi\Delta^2}\int_{-\pi m_n}^{\pi m_n}\frac{\operatorname{Var}(Z_1^\Delta\mathbb{1}_{|Z_1^\Delta|\ge k_n\sqrt{\Delta}})}{n}\frac{\mathrm{d}x}{|\psi_\Delta(x)|^2} \\
&\le \frac{\mathbb{E}[(Z_1^\Delta)^8]\Phi_\psi(m_n)}{2\pi n k_n^6\Delta^4} \\
&\le \frac{K\mathbb{E}[(Z_1^\Delta)^8]\ln^6(n)}{n^{2+\varepsilon}\Delta^4},
\end{aligned}
$$

using the choice of k_n given by (33).

Next,

$$
\mathbb{E}\Big(\sup_{t\in S_{m_n},\|t\|=1}\big|R_n^{(4)}(t)\big|^2\Big) \le \frac{1}{2\pi\Delta}\int_{-\pi m_n}^{\pi m_n}\big|g^*(x)\big|^2\mathbb{P}\big(\big|\hat{\psi}_\Delta(x)\big|\le\kappa_\psi/\sqrt{n}\big)\,\mathrm{d}x \le \frac{c}{n\Delta}.
$$

If $|\psi_\Delta(x)|\ge 2\kappa_\psi/\sqrt{n}$, then

$$
\begin{aligned}
\mathbb{P}\big(\big|\hat{\psi}_\Delta(u)\big|\le\kappa_\psi n^{-1/2}\big) &\le \mathbb{P}\big(\big|\hat{\psi}_\Delta(u)-\psi_\Delta(u)\big|\le\big|\psi_\Delta(u)\big|-\kappa_\psi n^{-1/2}\big) \\
&\le \mathbb{P}\Big(\big|\hat{\psi}_\Delta(u)-\psi_\Delta(u)\big|\ge\frac{1}{2}\big|\psi_\Delta(u)\big|\Big) \\
&\le \exp\big(-cn\big|\psi_\Delta(u)\big|^2\big)
\end{aligned}
$$

for some $c>0$, where the last inequality follows from Bernstein's inequality.

Now, it follows from (H4) that $|\psi_\Delta(u)| \geq c_\psi(1+u^2)^{-\Delta\beta/2}$. Therefore, for $|u| \leq \pi m_n$ with $m_n^{2\beta\Delta} \leq Cn^{1-\varepsilon}$ by (H7),

$$\left|\psi_\Delta(u)\right| \geq c' m_n^{-\beta\Delta} \geq 2\kappa_\psi n^{-1/2}.$$

Moreover, with the previous remarks, $\exp(-cn|\psi_\Delta(u)|^2) \leq \exp(-cn^\varepsilon)$ and thus

$$\int_{-\pi m_n}^{\pi m_n} \left|g^*(x)\right|^2 \mathbb{P}\left(\left|\hat{\psi}_\Delta(x)\right| \leq \kappa/\sqrt{n}\right) \mathrm{d}x \leq \left\|g^*\right\|^2 \exp\left(-cn^\varepsilon\right).$$

Therefore

$$\mathbb{E}\Big(\sup_{t \in S_{m_n}, \|t\|=1} \left|R_n^{(4)}(t)\right|^2\Big) \leq \frac{c}{n\Delta}.$$

5.6. *Proof of Lemma* 5.1

Let us denote by P_Δ the distribution of Z_1^Δ and define $\mu_\Delta(\mathrm{d}z) = \Delta^{-1} z P_\Delta(\mathrm{d}z)$. Let us set $\mu(\mathrm{d}x) = g(x)\,\mathrm{d}x$. Equation (13) states that

$$\mu_\Delta^* = \mu^* P_\Delta^*.$$

Hence, $\mu_\Delta = \mu \star P_\Delta$. Therefore, μ_Δ has a density given by

$$\int g(z-y) P_\Delta(\mathrm{d}y) = \mathbb{E}g\left(z - Z_1^\Delta\right).$$

Moreover, we have, for any compactly supported function t:

$$\frac{1}{\Delta}\mathbb{E}\left(Z_1^\Delta t\left(Z_1^\Delta\right)\right) = \int t(z)\mathbb{E}g\left(z - Z_1^\Delta\right) \mathrm{d}z = \int \mathbb{E}\left(t\left(x + Z_1^\Delta\right)\right) g(x)\,\mathrm{d}x.$$

Hence, we apply first Parseval formula:

$$\begin{aligned}
\left\|h_\Delta^*\right\|^2 &= \int \left|h_\Delta^*(x)\right|^2 \mathrm{d}x = 2\pi \int h_\Delta^2(x)\,\mathrm{d}x = 2\pi\Delta \int z^2 \mathbb{1}_{|z| \leq k_n\sqrt{\Delta}} \mathbb{E}^2\left(g\left(z - Z_1^\Delta\right)\right) \mathrm{d}z \\
&\leq 2\pi\Delta\mathbb{E}\left(\int z^2 \mathbb{1}_{|z| \leq k_n\sqrt{\Delta}} g^2\left(z - Z_1^\Delta\right) \mathrm{d}z\right) \\
&\leq 2\pi\Delta\mathbb{E}\left(\int \left(x + Z_1^\Delta\right)^2 g^2(x)\,\mathrm{d}x\right) \leq 4\pi\Delta\mathbb{E}\left(\int \left(x^2 + \left(Z_1^\Delta\right)^2\right) g^2(z)\,\mathrm{d}z\right) \\
&\leq 4\pi\Delta\left(\int x^2 g^2(x) + \mathbb{E}\left[\left(Z_1^\Delta\right)^2\right]\|g\|^2\right).
\end{aligned}$$

This ends the proof.

5.7. *Proof of Theorem* 4.2

Let us define the sets

$$\Omega_1 = \left\{\forall m \in \mathcal{M}_n, \int_{-\pi m}^{\pi m} \left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^2 \mathrm{d}x \leq k_1 \int_{-\pi m}^{\pi m} \frac{\mathrm{d}x}{|\psi_\Delta(x)|^2}\right\}$$

and

$$\Omega_2 = \left\{\left|\frac{(1/n)\sum_{i=1}^n [Z_i^\Delta]^2}{\mathbb{E}[(Z_i^\Delta)^2]} - 1\right| \leq k_2\right\}.$$

Take $0 < k_1 < 1/2$ and $0 < k_2 < 1$. On Ω_1, we have, $\forall m \in \mathcal{M}_n$,

$$\int_{-\pi m}^{\pi m} \frac{\mathrm{d}x}{|\tilde{\psi}_\Delta(x)|^2} \le (2k_1+2)\int_{-\pi m}^{\pi m} \frac{\mathrm{d}x}{|\psi_\Delta(x)|^2}$$

and

$$\int_{-\pi m}^{\pi m} \frac{\mathrm{d}x}{|\psi_\Delta(x)|^2} \le \frac{2}{1-2k_1}\int_{-\pi m}^{\pi m} \frac{\mathrm{d}x}{|\tilde{\psi}_\Delta(x)|^2}$$

and on Ω_2, we find

$$\frac{1}{n}\sum_{i=1}^{n}\left[Z_i^\Delta\right]^2 \le (1+k_2)\mathbb{E}\left[\left(Z_1^\Delta\right)^2\right] \quad \text{and} \quad \mathbb{E}\left[\left(Z_1^\Delta\right)^2\right] \le \frac{1}{1-k_2}\frac{1}{n}\sum_{i=1}^{n}\left[Z_i^\Delta\right]^2.$$

Il follows that, on $\Omega_1 \cap \Omega_2 := \Omega_{1,2}$, we can choose κ' large enough to ensure

$$48p_1(m,\widehat{\widehat{m}}) + 16p_2(m,\widehat{\widehat{m}}) + \widehat{\mathrm{pen}}(m) - \widehat{\mathrm{pen}}(\widehat{\widehat{m}}) \le C(a,b)\,\mathrm{pen}(m).$$

This allows to extend the result of Theorem 4.1 as follows: $\forall m \in \mathcal{M}_n$,

$$\mathbb{E}\left(\|\tilde{g}-g\|^2 \mathbb{1}_{\Omega_{1,2}}\right) \le C\left(\|g-g_m\|^2 + \mathrm{pen}(m)\right) + \frac{K\ln^2(n)}{n\Delta}.$$

Next we need to prove that

$$\mathbb{E}\left(\|\tilde{g}-g\|^2 \mathbb{1}_{\Omega_{1,2}^c}\right) \le \frac{K'}{n}. \tag{34}$$

First, we prove that $\mathbb{P}(\Omega_{1,2}^c) \le c/n^2$ by proving that $\mathbb{P}(\Omega_1^c) \le c/n^2$ and $\mathbb{P}(\Omega_2^c) \le c/n$.

$$\begin{aligned}
\mathbb{P}\left((\Omega_1)^c\right) &\le \sum_{m\in\mathcal{M}_n} \mathbb{P}\left(\int_{-\pi m}^{\pi m}\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^2 \mathrm{d}x > k_1 \int_{-\pi m}^{\pi m}\frac{\mathrm{d}x}{|\psi_\Delta(x)|^2}\right) \\
&\le \sum_{m\in\mathcal{M}_n} \mathbb{E}\left[\left(\left(\int_{-\pi m}^{\pi m}\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^2 \mathrm{d}x \Big/ \left(k_1\Phi_\psi(m)\right)\right)^p\right] \\
&\le \sum_{m\in\mathcal{M}_n} \frac{(2\pi m)^{p-1}}{(k_1\Phi_\psi(m))^p}\mathbb{E}\left(\int_{-\pi m}^{\pi m}\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^{2p} \mathrm{d}x\right) \\
&\le \sum_{m\in\mathcal{M}_n} C_p m^{p-1} n^{-p} \frac{\int_{-\pi m}^{\pi m}\mathrm{d}x/|\psi_\Delta(x)|^{4p}}{(\Phi_\psi(m))^p} \\
&\le \sum_{m\in\mathcal{M}_n} C'_p n^{-p} m^{(p-1)-p(2\beta\Delta+1)+4p\beta\Delta+1} = \sum_{m\in\mathcal{M}_n} C'_p m^{2p\beta\Delta} n^{-p} \\
&\le C'' n^{1-p+p(1-\varepsilon)} \le C'' n^{1-p\varepsilon}, \quad \varepsilon = \frac{1}{(2\beta\Delta+1)}.
\end{aligned}$$

As $m^{2\beta\Delta+1}/(n\Delta)$ is bounded $m^{2p\beta\Delta}n^{-p} = \mathrm{O}(n^{2p\beta\Delta/(2\beta\Delta+1)-p}) = \mathrm{O}(n^{-p/(2\beta\Delta+1)})$. Therefore, choosing $p = 3/\varepsilon$ ensures that $n^{1-p\varepsilon} = n^{-2}$ and $\mathbb{P}(\Omega_1^c) \le C/n^2$.

On the other hand,

$$\mathbb{P}\left[\Omega_2^c\right] \le \frac{1}{k_2^p \mathbb{E}^p[(Z_1^\Delta)^2]}\mathbb{E}\left(\left|\frac{1}{n}\sum_{i=1}^{n}\left[\left(Z_i^\Delta\right)^2 - \mathbb{E}\left[\left(Z_1^\Delta\right)^2\right]\right]\right|^p\right).$$

Here the choice $p=4$ gives $\mathbb{P}[\Omega_2^c]=\mathrm{O}(1/n^2)$ with a simple variance inequality, provided that $\mathbb{E}[(Z_1^\Delta)^8]<+\infty$. Next, we write that

$$\|g-\tilde g\|^2=\|g-g_{\widehat{\widehat{m}}}\|^2+\|g_{\widehat{\widehat{m}}}-\hat g_{\widehat{\widehat{m}}}\|^2\le\|g\|^2+\sum_{j\in\mathbb{Z}}\bigl|\hat a_{\widehat{\widehat{m}},j}-a_{\widehat{\widehat{m}},j}(g)\bigr|^2$$

and

$$\begin{aligned}
&\sum_{j\in\mathbb{Z}}\bigl|\hat a_{\widehat{\widehat{m}},j}-a_{\widehat{\widehat{m}},j}(g)\bigr|^2\\
&\quad=\sum_{j\in\mathbb{Z}}\left|\nu_n^{(1)}(\varphi_{\widehat{\widehat{m}},j})+\nu_n^{(2)}(\varphi_{\widehat{\widehat{m}},j})+\sum_{k=1}^4 R_n^{(k)}(\varphi_{\widehat{\widehat{m}},j})\right|^2\\
&\quad\le C\sum_{j\in\mathbb{Z}}\left\{\bigl|\nu_n^{(1)}(\varphi_{\widehat{\widehat{m}},j})\bigr|^2+\bigl|\nu_n^{(2)}(\varphi_{\widehat{\widehat{m}},j})\bigr|^2+\sum_{k=1}^4\bigl|R_n^{(k)}(\varphi_{\widehat{\widehat{m}},j})\bigr|^2\right\}\\
&\quad=C\left\{\sup_{t\in S_{\widehat{\widehat{m}}},\|t\|=1}\bigl|\nu_n^{(1)}(t)\bigr|^2+\sup_{t\in S_{\widehat{\widehat{m}}},\|t\|=1}\bigl|\nu_n^{(2)}(t)\bigr|^2+\sum_{k=1}^4\sup_{t\in S_{\widehat{\widehat{m}}},\|t\|=1}\bigl|R_n^{(k)}(t)\bigr|^2\right\}.
\end{aligned}$$

It follows that, $\mathbb{E}(\|g\|^2\mathbb{1}_{\Omega_{1,2}^c})=\|g\|^2\mathbb{P}(\Omega_{1,2}^c)\le c/n$, and for $k=3,4$,

$$\mathbb{E}\Bigl(\sup_{t\in S_{\widehat{\widehat{m}}},\|t\|=1}\bigl|R_n^{(k)}(t)\bigr|^2\mathbb{1}_{\Omega_{1,2}^c}\Bigr)\le\mathbb{E}\Bigl(\sup_{t\in S_{m_n},\|t\|=1}\bigl|R_n^{(k)}(t)\bigr|^2\Bigr)\le C/n$$

as it has been proved previously. Lastly,

$$\begin{aligned}
\mathbb{E}\Bigl(\sup_{t\in S_{\widehat{\widehat{m}}},\|t\|=1}\bigl|\nu_n^{(1)}(t)\bigr|^2\mathbb{1}_{\Omega_{1,2}^c}\Bigr)&\le\mathbb{E}\Bigl(\sup_{t\in S_{\widehat{\widehat{m}}},\|t\|=1}\bigl\{\bigl|\nu_n^{(1)}(t)\bigr|^2-\mathrm{pen}(\widehat{\widehat{m}})\bigr\}\Bigr)_+ +\mathbb{E}\bigl(\mathrm{pen}(\widehat{\widehat{m}})\mathbb{1}_{\Omega_{1,2}^c}\bigr)\\
&\le c\left(\frac{1}{n\Delta}+n\mathbb{P}\bigl(\Omega_{1,2}^c\bigr)\right)\le\frac{c'}{n}
\end{aligned}$$

using the proof of Theorem 4.1 and the fact that $\mathrm{pen}(\cdot)$ is less than $\mathrm{O}(n)$. The same line can be followed for the other terms.

Appendix

Lemma A.1 (Talagrand inequality). *Let $Y_1,\dots,Y_n$ be independent random variables, let $\nu_{n,Y}(f)=(1/n)\times\sum_{i=1}^n[f(Y_i)-\mathbb{E}(f(Y_i))]$ and let $\mathcal{F}$ be a countable class of uniformly bounded measurable functions. Then for $\epsilon^2>0$*

$$\mathbb{E}\Bigl[\sup_{f\in\mathcal{F}}\bigl|\nu_{n,Y}(f)\bigr|^2-2\bigl(1+2\epsilon^2\bigr)H^2\Bigr]_+\le\frac{4}{K_1}\left(\frac{v}{n}\mathrm{e}^{-K_1\epsilon^2(nH^2/v)}+\frac{98M^2}{K_1n^2C^2(\epsilon^2)}\mathrm{e}^{-(2K_1C(\epsilon^2)\epsilon/(7\sqrt{2}))(nH/M)}\right)$$

with $C(\epsilon^2)=\sqrt{1+\epsilon^2}-1$, $K_1=1/6$, and

$$\sup_{f\in\mathcal{F}}\|f\|_\infty\le M,\qquad\mathbb{E}\Bigl[\sup_{f\in\mathcal{F}}\bigl|\nu_{n,Y}(f)\bigr|\Bigr]\le H,\qquad\sup_{f\in\mathcal{F}}\frac{1}{n}\sum_{k=1}^n\mathrm{Var}\bigl(f(Y_k)\bigr)\le v.$$

This result follows from Ledoux and Talagrand [16], the concentration inequality given in Klein and Rio [14] and arguments in Birgé and Massart [4] (see the proof of their Corollary 2, p. 354). It can be extended to the case where $\mathcal{F}$ is a unit ball of a linear space.

References

[1] O. E. Barndorff-Nielsen and N. Shephard. Modelling by Lévy processes for financial econometrics. In *Lévy Processes. Theory and Applications* 283–318. O. E. Barndorff-Nielsen, T. Mikosch and S. L. Resnick (Eds). Birkhauser, Boston, 2001. MR1833702

[2] I. V. Basawa and P. J. Brockwell. Nonparametric estimation for nondecreasing Lévy processes. *J. Roy. Statist. Soc. Ser. B* **44** (1982) 262–269. MR0676217

[3] J. Bertoin. *Lévy Processes*. Cambridge Univ. Press, Cambridge, 1996. MR1406564

[4] L. Birgé and P. Massart. Minimum contrast estimators on sieves: Exponential bounds and rates of convergence. *Bernoulli* **4** (1998) 329–375. MR1653272

[5] F. Comte and C. Lacour. Deconvolution with estimated error. Preprint MAP5 2008-15, 2008. Available at http://www.math-info.univ-paris5.fr/map5/Prepublications-2008.

[6] F. Comte, Y. Rozenholc and M.-L. Taupin. Penalized contrast estimator for adaptive density deconvolution. *Canad. J. Statist.* **34** (2006) 431–452. MR2328553

[7] R. Cont and P. Tankov. Financial modelling with jump processes. In *Financial Mathematics Series*. Chapman & Hall/CRC, Boca Raton, 2004. MR2042661

[8] P. J. Diggle and P. Hall. A Fourier approach to nonparametric deconvolution of a density estimate. *J. Roy. Statist. Soc. Ser. B* **55** (1993) 523–531. MR1224414

[9] E. Eberlein and U. Keller. Hyperbolic distributions in finance. *Bernoulli* **1** (1995) 281–299.

[10] J. Fan. On the optimal rates of convergence for nonparametric deconvolution problems. *Ann. Statist.* **19** (1991) 1257–1272. MR1126324

[11] J. E. Figueroa-López and C. Houdré. Risk bounds for the nonparametric estimation of Lévy processes. *IMS Lecture Notes Monogr. Ser.* **51** (2006) 96–116. MR2387763

[12] G. Jongbloed and F. H. van der Meulen. Parametric estimation for subordinators and induced OU processes. *Scand. J. Statist.* **33** (2006) 825–847. MR2300918

[13] G. Jongbloed, F. H. van der Meulen and A. W. van der Vaart. Nonparametric inference for Lévy-driven Ornstein–Uhlenbeck processes. *Bernoulli* **11** (2005) 759–791. MR2172840

[14] T. Klein and E. Rio. Concentration around the mean for maxima of empirical processes. *Ann. Probab.* **33** (2005) 1060–1077. MR2135312

[15] U. Küchler and S. Tappe. Bilateral Gamma distributions and processes in financial mathematics. *Stochastic Processes Appl.* **118** (2008) 261–283. MR2376902

[16] M. Ledoux and M. Talagrand. *Probability in Banach Spaces. Isoperimetry and Processes*. *Ergebnisse der Mathematik und ihrer Grenzgebiete* **3**. Folge 23. Springer, Berlin, 1991. MR1102015

[17] D. B. Madan and E. Seneta. The Variance Gamma (V. G.) model for share market returns. *The Journal of Business* **63** (1990) 511–524.

[18] Y. Meyer. *Ondelettes et opérateurs* **I**. Hermann, Paris, 1990. MR1085487

[19] M. Neumann. On the effect of estimating the error density in nonparametric deconvolution. *J. Nonparametr. Stat.* **7** (1997) 307–330. MR1460203

[20] M. Neumann and M. Reiss. Nonparametric estimation for Lévy processes from low-frequency observations. *Bernoulli* **15** (2009) 223–248. MR2546805

[21] K. I. Sato. *Lévy Processes and Infinitely Divisible Distributions*. *Cambridge Studies in Advanced Mathematics* **68**. Cambridge Univ. Press, Cambridge, 1999. MR1739520

[22] R. N. Watteel and R. J. Kulperger. Nonparametric estimation of the canonical measure for infinitely divisible distributions. *J. Stat. Comput. Simul.* **73** (2003) 525–542. MR1986343