

Central limit theorems for partial sums of bounded functionals of infinite-variance moving averages

VLADAS PIPIRAS* and MURAD S. TAQQU**

Department of Mathematics, Boston University, 111 Cummington St., Boston MA 02215, USA.
E-mail: *pipiras@math.bu.edu; **murad@math.bu.edu

For $j = 1, \dots, J$, let $K_j : \mathbb{R} \rightarrow \mathbb{R}$ be measurable bounded functions and $X_{j,n} = \int_{\mathbb{R}} a_j(n - c_j x) M(dx)$, $n \geq 1$, be α -stable moving averages where $\alpha \in (0, 2)$, $c_j > 0$ for $j = 1, \dots, J$, and $M(dx)$ is an α -stable random measure on \mathbb{R} with the Lebesgue control measure and skewness intensity $\beta \in [-1, 1]$. We provide conditions on the functions a_j and K_j , $j = 1, \dots, J$, for the normalized partial sums vector $N_j^{-1/2} \sum_{n=1}^{N_j} (K_j(X_{j,n}) - \mathbb{E}K_j(X_{j,n}))$, $j = 1, \dots, J$, to be asymptotically normal as $N_j \rightarrow \infty$. This extends a result established by Tailen Hsing in the context of causal moving averages with discrete-time stable innovations. We also consider the case of moving averages with innovations that are in the stable domain of attraction.

Keywords: central limit theorem; moving averages; stable distributions

1. Introduction

Our goal is to extend Hsing's (1999) result on the convergence of bounded functionals of infinite-variance moving averages. This extension is used in Pipiras *et al.* (2003) to establish asymptotic normality of some wavelet-based estimators in linear fractional stable motion.

We first recall Hsing's result and then describe our extension. Hsing (1999) considered moving average sequences

$$X_n = \sum_{j=1}^{\infty} a_j \epsilon_{n-j}, \quad n \geq 1, \quad (1.1)$$

where $\{a_j\}_{j \geq 1}$ is a sequence of weights and $\{\epsilon_n\}_{n \in \mathbb{Z}}$ is a sequence of independent and identically distributed (i.i.d.) symmetric α -stable standard random variables with $\alpha \in (0, 2)$. Recall that a random variable ϵ is α -stable with $\alpha \in (0, 2)$ if its characteristic function has the form

$$\mathbb{E} \exp \{i\theta \epsilon\} = \begin{cases} \exp\{-\sigma^\alpha |\theta|^\alpha (1 - i\beta \text{sign}(\theta) \tan(\alpha\pi/2)) + i\mu\theta\} & \text{if } \alpha \neq 1, \\ \exp\{-\sigma |\theta| (1 + i\beta(2/\pi) \text{sign}(\theta) \ln |\theta|) + i\mu\theta\} & \text{if } \alpha = 1 \end{cases}$$

where $\theta \in \mathbb{R}$, $\sigma > 0$ is a scale parameter, $\mu \in \mathbb{R}$ is a shift parameter and $\beta \in [-1, 1]$ is a skewness parameter. It is called symmetric (SaS, in short) if $\beta = 0$ and $\mu = 0$, and standard

if $\sigma = 1$. Hsing (1999) obtained conditions on the weight sequence $\{a_j\}_{j \geq 1}$ for the normalized partial sums

$$\frac{S_N}{N^{1/2}} := \frac{1}{N^{1/2}} \sum_{n=1}^N (K(X_n) - \mathbb{E}K(X_n)), \quad (1.2)$$

where K is a bounded function, to converge in distribution to a Gaussian law, as $N \rightarrow \infty$. His result (Hsing 1999, Theorem 1) is stated below. The following notation is used:

$$X_{n,1,l} = \sum_{j=1}^l a_j \epsilon_{n-j}, \quad l \geq 1,$$

and

$$S_{N,l} = \sum_{n=1}^N (K(X_{n,1,l}) - \mathbb{E}K(X_{n,1,l})), \quad l \geq 1.$$

Theorem 1.1. *Let $\alpha \in (0, 2)$ and $\{X_n\}_{n \geq 1}$ be a SaS moving average sequence defined by (1.1). Suppose that K in (1.2) is a bounded function. Suppose also that*

$$\sum_{j=1}^{\infty} |a_j|^{\alpha/2} < \infty \quad (1.3)$$

and

$$\lim_{l \rightarrow \infty} \mathbb{E}(K(X_1) - K(X_{1,1,l}))^2 = 0. \quad (1.4)$$

Then

$$\lim_{l \rightarrow \infty} \limsup_{N \rightarrow \infty} N^{-1} \text{var}(S_N - S_{N,l}) = 0$$

and

$$N^{-1/2} S_N \xrightarrow{d} \mathcal{N}(0, \sigma^2),$$

where

$$\sigma^2 = \lim_{N \rightarrow \infty} N^{-1} \text{var}(S_N) = \lim_{l \rightarrow \infty} \lim_{N \rightarrow \infty} N^{-1} \text{var}(S_{N,l}).$$

We extend this result in the following ways:

- We drop condition (1.4).
- We replace the discrete noise ϵ_n by a (more general) continuous-time one.
- We consider both symmetric and skewed noise.
- We consider two-sided moving averages, since in the stable case, these are not equivalent to one-sided ones.

- We develop a multivariate extension which will be used in Pipiras *et al.* (2003) to prove the asymptotic normality of wavelet-based estimators.
- Assuming that K is smooth, we show that the result extends to discrete-time moving averages with innovations that are in the domain of attraction of an α -stable distribution.

These extensions of Theorem 1.1 are formulated and proved in Sections 2 and 3 below.

2. Results

Consider α -stable moving average sequences $\{X_{j,n}\}_{n \geq 1}, j = 1, \dots, J$, given by

$$X_{j,n} = \int_{\mathbb{R}} a_j(n - c_j x) M(dx), \tag{2.1}$$

where $\alpha \in (0, 2), c_j > 0, a_j \in L^\alpha(\mathbb{R}, dx)$ and, in addition, $a_j \ln |a_j| \in L^1(\mathbb{R}, dx)$ when $\alpha = 1$, and M is an α -stable random measure on \mathbb{R} with the Lebesgue control measure $m(dx) = dx$ and the skewness intensity $\beta(x) \equiv \beta \in [-1, 1]$. Heuristically, $M(dx), x \in \mathbb{R}$, can be viewed as a sequence of independent α -stable random variables with the scale parameter dx and the skewness parameter β . The representation (2.1) means that the characteristic function of $\{X_{j,n}, j = 1, \dots, J\}_{n \geq 1}$ can be expressed as

$$E \exp \left\{ i \sum_{p=1}^q \theta_p X_{j_p, n_p} \right\} = \exp \left\{ - \int_{\mathbb{R}} |f(\boldsymbol{\theta}, \mathbf{n}, \mathbf{j}, x)|^\alpha \left(1 - i\beta \operatorname{sign}(f(\boldsymbol{\theta}, \mathbf{n}, \mathbf{j}, x)) \tan \frac{\alpha\pi}{2} \right) dx \right\}$$

if $\alpha \neq 1$, and

$$E \exp \left\{ i \sum_{p=1}^q \theta_p X_{j_p, n_p} \right\} = \exp \left\{ - \int_{\mathbb{R}} |f(\boldsymbol{\theta}, \mathbf{n}, \mathbf{j}, x)| \left(1 + i\beta \frac{2}{\pi} \operatorname{sign}(f(\boldsymbol{\theta}, \mathbf{n}, \mathbf{j}, x)) \ln |f(\boldsymbol{\theta}, \mathbf{n}, \mathbf{j}, x)| \right) dx \right\}$$

if $\alpha = 1$, where $\boldsymbol{\theta} = (\theta_1, \dots, \theta_q) \in \mathbb{R}^q, \mathbf{n} = (n_1, \dots, n_q) \in \mathbb{N}^q, \mathbf{j} = (j_1, \dots, j_q) \in \{1, \dots, J\}^q$ and

$$f(\boldsymbol{\theta}, \mathbf{n}, \mathbf{j}, x) = \sum_{p=1}^q \theta_p a_{j_p}(n_p - c_{j_p} x), \quad x \in \mathbb{R}.$$

For more information on stable measures and stable processes, see Samorodnitsky and Taqqu (1994). In the wavelet setting considered in Pipiras *et al.* (2003), the indices c_j (usually taken equal to 2^{-j}) correspond to ‘scale’ and n to ‘shift’.

Definition 2.1. We will say that the moving average $\{X_{j,n}\}_{n \geq 1}$ is causal if $a_j(x) = 0$ for $x < x_0$, and non-causal if $a_j(x) = 0$ for $x > x_0$, where $x_0 \in \mathbb{R}$. When $\{X_{j,n}\}_{n \geq 1}$ is either causal or non-causal, we will say that it is one-sided. We will also call the moving average $\{X_{j,n}\}_{n \geq 1}$ two-sided if it is not one-sided.

Now, fix $n_j, j = 1, \dots, J$, and let N_j be positive integers such that

$$N_j \sim \frac{N}{n_j}, \tag{2.2}$$

as $N \rightarrow \infty$. For $j = 1, \dots, J$, set

$$\frac{S_{j,N_j}}{N_j^{1/2}} = \frac{1}{N_j^{1/2}} \sum_{n=1}^{N_j} (K_j(X_{j,n}) - \mathbb{E}K_j(X_{j,n})), \tag{2.3}$$

where K_j is some measurable function. For $j = 1, \dots, J$ and $n \geq 1$, define also the truncated integrals

$$X_{j,n,l_1,l_2} = \int_{c_j^{-1}(n-l_2)}^{c_j^{-1}(n-l_1+1)} a_j(n - c_j x) M(dx), \quad -\infty \leq l_1 \leq l_2 \leq \infty, \tag{2.4}$$

and $X_{j,n,l_1,l_2} = 0$ for $l_1 > l_2$. This ordering of the indices is motivated by the fact that, after a change of variables,

$$X_{j,n,l_1,l_2} = \int_{l_1-1}^{l_2} a_j(z) M(d(c_j^{-1}(n-z))), \tag{2.5}$$

so the indices $l_1 - 1$ and l_2 refer to the range of the weights $a_j(z)$. It is best henceforth to view X_{j,n,l_1,l_2} as represented by (2.5); for example, one has

$$X_{j,n} = X_{j,n,-\infty,m-1} + X_{j,n,m,\infty}, \quad \text{for all } m \in \mathbb{Z}. \tag{2.6}$$

Define also the corresponding partial sums

$$S_{j,N_j,l_1,l_2} = \sum_{n=1}^{N_j} (K_j(X_{j,n,l_1,l_2}) - \mathbb{E}K_j(X_{j,n,l_1,l_2})), \quad -\infty \leq l_1 \leq l_2 \leq \infty.$$

The following result is our first extension of Hsing’s Theorem 1.1. It is proved in Section 3 below.

Theorem 2.1. *Let $\alpha \in (0, 2)$ and $\{X_{j,n}\}_{n \geq 1}, j = 1, \dots, J$, be α -stable moving averages defined by (2.1). Suppose that, for each $j = 1, \dots, J$, the kernel a_j in (2.1) satisfies the condition*

$$\sum_{m=-\infty}^{\infty} \left(\int_{m-1}^m |a_j(x)|^\alpha dx \right)^{1/2} < \infty. \tag{2.7}$$

Suppose also that, for each $j = 1, \dots, J$, the function K_j in (2.3) is bounded if $\{X_{j,n}\}_{n \geq 1}$ is one-sided, and is bounded and twice differentiable with bounded derivatives if $\{X_{j,n}\}_{n \geq 1}$ is two-sided. Then, for $j = 1, \dots, J$,

$$\lim_{(l_1,l_2) \rightarrow (-\infty,\infty)} \limsup_{N \rightarrow \infty} N_j^{-1} \text{var}(S_{j,N_j} - S_{j,N_j,l_1,l_2}) = 0 \tag{2.8}$$

and

$$\left(N_j^{-1/2} S_{j,N_j} \right)_{j=1}^J \xrightarrow{d} \mathcal{N}(\mathbf{0}, \boldsymbol{\sigma}). \tag{2.9}$$

The entries of the covariance matrix $\boldsymbol{\sigma} = (\sigma_{jk})_{j,k=1,\dots,J}$ can be obtained as

$$\sigma_{jk} = \lim_{N \rightarrow \infty} E \frac{S_{j,N_j} S_{k,N_k}}{N_j^{1/2} N_k^{1/2}} \tag{2.10}$$

$$= \lim_{(l_1, l_2) \rightarrow (-\infty, \infty)} \lim_{N \rightarrow \infty} E \frac{S_{j,N_j, l_1, l_2} S_{k,N_k, l_1, l_2}}{N_j^{1/2} N_k^{1/2}} < \infty. \tag{2.11}$$

If $J = 1$, $c_1 = 1$, $\beta = 0$ and $a_1(x) = \sum_{k=1}^{\infty} a_k 1_{[k-1, k)}(x)$, $x \in \mathbb{R}$, $a_k \in \mathbb{R}$ in (2.1), then $X_{1,n} = \int_{\mathbb{R}} a(n-x)M(dx) = \sum_{k=1}^{\infty} a_k \epsilon_{n-k}$ for some sequence $\{a_k\}$ of i.i.d. SaS random variables. Condition (2.7) becomes $\sum_{k=1}^{\infty} |a_k|^{\alpha/2} < \infty$, which is (1.3) in Hsing’s Theorem 1.1 above. Observe, however, that Theorem 1.1 also requires condition (1.4). This condition is missing in Theorem 2.1 because, in fact, it *always* holds (and it can therefore be removed from Theorem 1.1). This is shown by the following results which are also used in the proof of Theorem 2.1.

Lemma 2.1. For $\alpha \in (0, 2)$, let X_n , $n \geq 0$, be α -stable random variables such that $X_n \rightarrow X_0$ almost surely. Then, for any bounded measurable function K ,

$$\lim_{n \rightarrow \infty} E(K(X_0) - K(X_n))^2 = 0. \tag{2.12}$$

Proof. Let f_n and ϕ_n , $n \geq 0$, be the density and characteristic functions of X_n , respectively. For any $\epsilon > 0$, there is a bounded and continuous function \tilde{K} such that

$$E(K(X_0) - \tilde{K}(X_0))^2 = \int_{\mathbb{R}} (K(x) - \tilde{K}(x))^2 f_0(x) dx < \epsilon.$$

Indeed, $K(x)$ can be approximated uniformly by a continuous function on a compact interval, and this interval can be chosen large enough so that the measure of its complement is arbitrarily small. By using the Fourier inversion formula, we have

$$f_n(x) = \frac{1}{2\pi} \int_{\mathbb{R}} e^{-itx} \phi_n(t) dt, \quad x \in \mathbb{R}, n = 0, 1, \dots \tag{2.13}$$

Since $X_n \rightarrow X_0$ a.s., we have $X_n \rightarrow X_0$ in distribution. Hence, $\phi_n(t) \rightarrow \phi_0(t)$, $t \in \mathbb{R}$, and $\gamma_n \rightarrow \gamma_0$, $\beta_n \rightarrow \beta_0$ and $\sigma_n \rightarrow \sigma_0$, where γ_n , β_n and σ_n , $n \geq 0$, are shift, skewness and scale parameters of X_n . Since $\sup_{n \geq 0} |\phi_n(t)| \leq \exp\{-C|t|^\alpha\}$, where C depends on γ_0 , β_0 and σ_0 only, it follows from (2.13) that $f_n(x) \rightarrow f_0(x)$ for $x \in \mathbb{R}$. Then, by Scheffé’s theorem (see, for example, Billingsley 1995),

$$\int_{\mathbb{R}} |f_0(x) - f_n(x)| dx \rightarrow 0. \tag{2.14}$$

By using (2.14) and since K and \tilde{K} are bounded functions, we have that, for large enough n ,

$$\begin{aligned} E(K(X_n) - \tilde{K}(X_n))^2 &= \int_{\mathbb{R}} (K(x) - \tilde{K}(x))^2 f_n(x) dx \\ &\leq C \int_{\mathbb{R}} |f_0(x) - f_n(x)| dx + \int_{\mathbb{R}} (K(x) - \tilde{K}(x))^2 f_0(x) dx < \epsilon. \end{aligned}$$

Then, by using the inequality $(a + b + c)^2 \leq 3a^2 + 3b^2 + 3c^2$ and the decomposition $K(X_0) - K(X_n) = K(X_0) - \tilde{K}(X_0) + (\tilde{K}(X_0) - \tilde{K}(X_n)) + \tilde{K}(X_n) - K(X_n)$, we obtain that, for large enough n ,

$$E(K(X_0) - K(X_n))^2 \leq 6\epsilon + 3E(\tilde{K}(X_0) - \tilde{K}(X_n))^2.$$

Since $X_n \rightarrow X_0$ a.s. and the function \tilde{K} is bounded and continuous, the dominated convergence theorem implies that $E(\tilde{K}(X_0) - \tilde{K}(X_n))^2 \rightarrow 0$. The conclusion follows because $\epsilon > 0$ is arbitrarily small. □

Corollary 2.1. *Condition (1.4) in Theorem 1.1 always holds.*

Proof. This follows from Lemma 2.1 since, by Kolmogorov’s three-series theorem, $X_{1,l} \rightarrow X_1$ a.s. as $l \rightarrow \infty$. □

In the following result, we extend Theorem 1.1 to two-sided moving averages with innovations that are in the domain of attraction of an α -stable distribution, $\alpha \in (0, 2)$, if K is bounded and is twice differentiable with bounded derivatives. We will assume that the innovations ϵ_j satisfy the assumption

$$L_1(z) := z^\alpha P(\epsilon_j \leq -z) \sim c_- L(z), \tag{2.15}$$

$$L_2(z) := z^\alpha P(\epsilon_j \geq z) \sim c_+ L(z), \tag{2.16}$$

as $z \rightarrow \infty$, where $c_-, c_+ \geq 0, c_- + c_+ > 0$ and L is a slowly varying function at infinity (for definition, see, for example, Bingham *et al.* 1987). The function L , for example, can behave like a constant or a logarithm for large z . When $1 < \alpha < 2$, we will suppose that $E\epsilon_j = 0$. We will also use the notation

$$X_{n,l_1,l_2} = \sum_{j=l_1}^{l_2} a_j \epsilon_{n-j}, \quad l_1 \leq l_2,$$

$$S_{N,l_1,l_2} = \sum_{n=1}^N (K(X_{n,l_1,l_2}) - EK(X_{n,l_1,l_2})), \quad l_1 \leq l_2.$$

Theorem 2.2. *Let*

$$X_n = \sum_{j=-\infty}^{\infty} a_j \epsilon_{n-j}, \quad n \geq 1,$$

be a moving average with a sequence of i.i.d. innovations $\{\epsilon_j\}$ satisfying assumptions above with $\alpha \in (0, 2)$, and let S_N , $N \geq 1$, be the partial sums defined by (1.2). Suppose that

$$\sum_{j=-\infty}^{\infty} |a_j|^{\alpha/2} \left(L\left(\frac{1}{|a_j|}\right) \right)^{1/2} < \infty, \quad \text{when } \alpha \neq 1, \tag{2.17}$$

and

$$\sum_{j=-\infty}^{\infty} |a_j|^{1/2} \left(L\left(\frac{1}{|a_j|}\right) \right)^{1/2} + \sum_{j=-\infty}^{\infty} |a_j|^{1/2} \left| \gamma + H\left(\frac{1}{|a_j|}\right) \right|^{1/2} < \infty, \quad \text{when } \alpha = 1, \tag{2.18}$$

where H and γ are defined in (2.20) and (2.21) below, and that K in (1.2) is a bounded function with its first two derivatives bounded. Then

$$\lim_{(l_1, l_2) \rightarrow (-\infty, \infty)} \limsup_{N \rightarrow \infty} N^{-1} \text{var}(S_N - S_{N, l_1, l_2}) = 0 \tag{2.19}$$

and

$$N^{-1/2} S_N \xrightarrow{d} \mathcal{N}(0, \sigma^2),$$

where

$$\sigma^2 = \lim_{N \rightarrow \infty} N^{-1} \text{var}(S_N) = \lim_{(l_1, l_2) \rightarrow (-\infty, \infty)} \lim_{N \rightarrow \infty} N^{-1} \text{var}(S_{N, l_1, l_2}).$$

The function H and the constant γ in (2.18) of Theorem 2.2 are defined as

$$H(z) = \int_0^z \frac{xL_1(x)}{1+x^2} dx - \int_0^z \frac{xL_2(x)}{1+x^2} dx \tag{2.20}$$

and

$$\gamma = \int_{\mathbb{R}} \left(\frac{x}{1+x^2} + \text{sign}(x) \int_0^{|x|} \frac{2u^2}{(1+u^2)^2} du \right) G(dx), \tag{2.21}$$

where G denotes the distribution function of ϵ_j . They appear in the representation of a characteristic function of a random variable in the domain of attraction of a 1-stable random variable (see Aaronson and Denker 1998). Observe also that $H \equiv 0$ and $\gamma = 0$ when ϵ_j (or its distribution function G) is symmetric.

Remark 2.1. Conditions (2.17) and (2.18) are equivalent to

$$\sum_{j=-\infty}^{\infty} |a_j|^{\alpha/2} \left(\tilde{L}(1/|a_j|) \right)^{1/2} < \infty,$$

where

$$\tilde{L}(z) = \begin{cases} L(z) & \text{if } \alpha \neq 1, \\ L(z) + |H(z) + \gamma| & \text{if } \alpha = 1. \end{cases} \tag{2.22}$$

The function \tilde{L} is slowly varying at infinity because the functions H (see Lemma 3 in Aaronson and Denker 1998) and L are slowly varying at infinity.

Remark 2.2. When $1 < \alpha < 2$, suppose $\mu = E\epsilon_j \neq 0$ and $\sum_j |a_j| < \infty$ so that the process X_n is well defined. Theorem 2.2 continues to hold since one can replace $K(x)$ by $K_1(x) = K(x - \mu \sum_j a_j)$.

3. Proofs

The following three elementary lemmas play an important role. The first lemma is implicit in Hsing (1999) and the second and third lemmas amplify Lemma 3 in Hsing (1999). We will use the notation $f^{(j)} = d^j f / dx^j$ for the j th derivative of a function f .

Lemma 3.1. *Let X, Y be two random variables such that $EX^2 < \infty$ and $EY^2 < \infty$. Also let $\{\mathcal{F}_n\}_{n \in \mathbb{Z}}$ be a monotone sequence of σ -algebras, that is, for $n_1 \leq n_2$, either $\mathcal{F}_{n_1} \subset \mathcal{F}_{n_2}$ or $\mathcal{F}_{n_1} \supset \mathcal{F}_{n_2}$. Then, for all $n, m \in \mathbb{Z}$ such that $n \neq m$, we have*

$$E\{(E(X|\mathcal{F}_n) - E(X|\mathcal{F}_{n-1}))(E(Y|\mathcal{F}_m) - E(Y|\mathcal{F}_{m-1}))\} = 0. \tag{3.1}$$

Proof. Consider the case when $\mathcal{F}_{n_1} \subset \mathcal{F}_{n_2}$ for $n_1 \leq n_2$ and take, for example, $n < m$. Denote the left-hand side of (3.1) by I . Since the random variable $E(X|\mathcal{F}_n) - E(X|\mathcal{F}_{n-1})$ is \mathcal{F}_n -measurable and $n < m$, it is also measurable with respect to \mathcal{F}_{m-1} and \mathcal{F}_m . Then, by the definition of conditional expectation,

$$\begin{aligned} I &= E\{(E(X|\mathcal{F}_n) - E(X|\mathcal{F}_{n-1}))E(Y|\mathcal{F}_m)\} - E\{(E(X|\mathcal{F}_n) - E(X|\mathcal{F}_{n-1}))E(Y|\mathcal{F}_{m-1})\} \\ &= E\{(E(X|\mathcal{F}_n) - E(X|\mathcal{F}_{n-1}))Y\} - E\{(E(X|\mathcal{F}_n) - E(X|\mathcal{F}_{n-1}))Y\} = 0. \quad \square \end{aligned}$$

Lemma 3.2. *Let $g(x) = EG(x + X)$, where $x \in \mathbb{R}$ and X is an α -stable standard random variable with $\alpha \in (0, 2)$, scale parameter $\sigma > 0$, skewness parameter $\beta \in [-1, 1]$ and shift parameter $\mu = 0$. If G is a bounded function, then g is infinitely differentiable and, for all $x \in \mathbb{R}$ and $j = 0, 1, \dots$,*

$$|g^{(j)}(x)| \leq \begin{cases} C_j \sigma^{-j} & \text{if } \alpha \neq 1, \\ C_j \sigma^{-j} (1 + |\ln \sigma| + |\ln \sigma|^2) & \text{if } \alpha = 1, \end{cases} \tag{3.2}$$

where the constant C_j does not depend on σ and β .

Proof. Relation (3.2) holds for $j = 0$ since G is bounded. Now suppose $j \geq 1$. We have $X = \sigma Z$, where Z is an α -stable random variable with scale parameter 1, skewness parameter β and shift parameter $\mu = 0$ when $\alpha \neq 1$, and $\mu = \beta(2/\pi)\ln \sigma$ when $\alpha = 1$. Let $f(z)$ and $\phi(z)$ be the density and characteristic functions of Z , respectively. By using the

Fourier inversion formula and the integration by parts formula twice, we can express $f^{(j)}$ as in Hsing (1999):

$$f^{(j)}(z) = \frac{(-i)^j}{2\pi} \int_{\mathbb{R}} e^{-itz} \phi_j(t) dt, \tag{3.3a}$$

$$f^{(j)}(z) = -\frac{(-i)^j}{2\pi z^2} \int_{\mathbb{R}} e^{-itz} \phi_j^{(2)}(t) dt, \tag{3.3b}$$

where $\phi_j(t) = t^j \phi(t)$, $t \in \mathbb{R}$.

When $\alpha = 1$, relation (3.3a) implies that $|f^{(j)}(z)| \leq \tilde{C}_j$ for all z , where \tilde{C}_j does not depend on σ and β . By computing $\phi_j^{(2)}$ and using relation (3.3b), we can conclude that $|f^{(j)}(z)| \leq \tilde{C}_j(1 + |\ln \sigma| + |\ln \sigma|^2)z^{-2}$. Hence, when $\alpha = 1$,

$$|f^{(j)}(z)| \leq \frac{C_j(1 + |\ln \sigma| + |\ln \sigma|^2)}{1 + z^2}, \quad z \in \mathbb{R}. \tag{3.4}$$

Similarly, in the case $\alpha \neq 1$, one obtains

$$|f^{(j)}(z)| \leq \frac{C_j}{1 + z^2}, \quad z \in \mathbb{R}, \tag{3.5}$$

where the constant C_j does not depend on β .

Since, by (3.4) and (3.5), $f^{(j)} \in L^1(\mathbb{R})$, we conclude as in Lemma 3 of Hsing (1999) that

$$\begin{aligned} g^{(j)}(x) &= \frac{d^j}{dx^j} \int_{\mathbb{R}} G(x + \sigma z) f(z) dz \\ &= \frac{d^j}{dx^j} \int_{\mathbb{R}} G(y) f(\sigma^{-1}(y - x)) dy \\ &= \int_{\mathbb{R}} G(y) \frac{d^j}{dx^j} (f(\sigma^{-1}(y - x))) dy \\ &= (-1)^j \sigma^{-j} \int_{\mathbb{R}} G(x + \sigma z) f^{(j)}(z) dz, \end{aligned} \tag{3.6}$$

where in the last step we used the fact that

$$\frac{d^j}{dx^j} (f(\sigma^{-1}(y - x))) = (-1)^j \sigma^{-j} f^{(j)}(\sigma^{-1}(y - x))$$

and a change of variables. Inequality (3.2) follows from (3.6) by using (3.4) when $\alpha = 1$ and (3.5) when $\alpha \neq 1$, since G is bounded. □

Lemma 3.3. *Let $h(x) = \mathbb{E}H(x + X)$, where $x \in \mathbb{R}$ and X is a random variable. If H is bounded and differentiable up to order r with its derivatives bounded, then for all $x \in \mathbb{R}$, all random variables X and $j = 0, 1, 2, \dots, r$,*

$$|h^{(j)}(x)| \leq C_j, \tag{3.7}$$

where $C_j = \sup_{x \in \mathbb{R}} |H^{(j)}(x)|$.

Proof. Let X be any random variable and F_X denote its distribution function. If H is a bounded and twice differentiable function with its first r derivatives bounded, then one can show by using relation (16) in Lemma 3 of Hsing (1999) that, for $j = 0, 1, \dots, r$,

$$h^{(j)}(x) = \int_{\mathbb{R}} H^{(j)}(x+z) dF_X(z).$$

Inequality (3.7) follows, since the functions $H^{(j)}$ are bounded. □

Proof of Theorem 2.1. We will consider the case $J = 2$ only. To show (2.9) with (2.10) and (2.11), it is then enough to verify that, for all fixed $b_1, b_2 \in \mathbb{R}$, the random variables $b_1 N_1^{-1/2} S_{1,N_1} + b_2 N_2^{-1/2} S_{2,N_2}$ converge in distribution to a Gaussian law as $N \rightarrow \infty$, whose variance can be expressed as

$$\lim_{N \rightarrow \infty} E \left(b_1 \frac{S_{1,N_1}}{N_1^{1/2}} + b_2 \frac{S_{2,N_2}}{N_2^{1/2}} \right)^2 = \lim_{(l_1, l_2) \rightarrow (-\infty, \infty)} \lim_{N \rightarrow \infty} E \left(b_1 \frac{S_{1,N_1, l_1, l_2}}{N_1^{1/2}} + b_2 \frac{S_{2,N_2, l_1, l_2}}{N_2^{1/2}} \right)^2.$$

We will do this as in the proof of Theorem 1 in Hsing (1999), by arguing first that, for all $-\infty \leq l_1 \leq l_2 \leq \infty$,

$$b_1 \frac{S_{1,N_1, l_1, l_2}}{N_1^{1/2}} + b_2 \frac{S_{2,N_2, l_1, l_2}}{N_2^{1/2}} \xrightarrow{d} \mathcal{N}(0, \sigma_{l_1, l_2}^2) \tag{3.8}$$

with

$$\sigma_{l_1, l_2}^2 = \lim_{N \rightarrow \infty} E \left(b_1 \frac{S_{1,N_1, l_1, l_2}}{N_1^{1/2}} + b_2 \frac{S_{2,N_2, l_1, l_2}}{N_2^{1/2}} \right)^2, \tag{3.9}$$

and then verifying that, for $j = 1, 2$, the limit relation (2.8) holds.

To prove (3.8) with (3.9), suppose that $n_1 \leq n_2$ in (2.2) and assume for simplicity that $N_j = N/n_j$ and $EK_j(X_{j,1,l_1,l_2}) = 0$ for $j = 1, 2$. Since $N_2 \leq N_1$, the sequence in (3.8) can be written as

$$N_2^{-1/2} \sum_{n=1}^{N_2} \left(\frac{b_1 n_1^{1/2}}{n_2^{1/2}} K_1(X_{1,n,l_1,l_2}) + b_2 K_2(X_{2,n,l_1,l_2}) \right) + N_1^{-1/2} \sum_{n=N_2+1}^{N_1} b_1 K_1(X_{1,n,l_1,l_2}). \tag{3.10}$$

Now consider the random variables X_{j_1, n, l_1, l_2} and X_{j_2, n', l_1, l_2} in (2.4), where $j_1, j_2 = 1, \dots, J$. These are independent when $n - n' > n_0$ for some fixed large enough n_0 because the corresponding kernel functions $a_{j_1}(n - c_{j_1} x)$ for $c_{j_1}^{-1}(n - l_2) \leq x < c_{j_1}^{-1}(n - l_1 + 1)$ and $a_{j_2}(n' - c_{j_2} x)$ for $c_{j_2}^{-1}(n' - l_2) \leq x < c_{j_2}^{-1}(n' - l_1 + 1)$ have disjoint supports (see Samorodnitsky and Taqqu 1994, Theorem 3.5.3). It follows, using the so-called ‘ m -dependent central limit theorem’, that each of the two terms in (3.10) converges in distribution to a Gaussian law with the corresponding limiting variances. By summing the second term from

N'_2 to N_1 where the difference $N'_2 - N_2$ is large enough but of fixed length, we observe that these two terms are also asymptotically independent. This then implies the convergence (3.8) with (3.9).

We show (2.8) with, for example, $j = 1$. The proof below involves the random sequence X_{1,n,m_1,m_2} , $n \geq 1$, $-\infty \leq m_1 \leq m_2 \leq \infty$. Since

$$\{X_{1,n,m_1,m_2}\}_{n,m_1,m_2} \stackrel{d}{=} \left\{ c_1^{-1/\alpha} \int_{n-m_2}^{n-m_1+1} a_1(n-x)M(dx) \right\}_{n,m_1,m_2}, \tag{3.11}$$

after a change of variables, we can suppose without loss of generality that $c_1 = 1$ in (2.4). We will also assume for simplicity that $n_1 = 1$, $N_1 = N$ and use the notation $a_1 = a$, $K_1 = K$, $S_{1,N} = S_N$, $X_{1,n} = X_n$,

$$X_{1,n,m_1,m_2} = X_{n,m_1,m_2} = \int_{n-m_2}^{n-m_1+1} a(n-x)M(dx)$$

and

$$S_{1,N,l_1,l_2} = S_{N,l_1,l_2} = \sum_{n=1}^N (K(X_{n,l_1,l_2}) - EK(X_{n,l_1,l_2})), \quad -\infty \leq l_1 \leq l_2 \leq \infty.$$

Recall that our goal is to establish

$$\lim_{(l_1,l_2) \rightarrow (-\infty,\infty)} \limsup_{N \rightarrow \infty} N^{-1} \text{var}(S_N - S_{N,l_1,l_2}) = 0. \tag{3.12}$$

We will prove (3.12) for causal moving averages, non-causal moving averages and two-sided moving averages separately.

Causal moving averages. We assume for simplicity that $x_0 = 0$ in Definition 2.1 of a causal moving average X_n , that is, $a(x) = 0$ for $x < 0$. We may also suppose without loss of generality that $\int_0^1 |a(x)|^\alpha dx \neq 0$. We need to establish (3.12), which now becomes

$$\lim_{l \rightarrow \infty} \limsup_{N \rightarrow \infty} N^{-1} \text{var}(S_{N,1,\infty} - S_{N,1,l}) = 0. \tag{3.13}$$

The proof uses ideas due to Hsing (1999). Let \mathcal{F}_{k-1} , $k \in \mathbb{Z}$, be σ -algebras generated by the ‘causal’ random variables $\int_{-\infty}^k f(x)M(dx)$, $f \in L^\alpha(\mathbb{R}, dx)$. Then, for instance, $X_{n,1,l} = \int_{n-l}^n a(n-x)M(dx)$, $l \geq 1$, is measurable with respect \mathcal{F}_{n-1} . Using the relations

$$E(K(X_{n,1,\infty})|\mathcal{F}_{n-1}) = K(X_{n,1,\infty}),$$

$$E(K(X_{n,1,\infty})|\mathcal{F}_{-\infty}) = EK(X_{n,1,\infty})$$

and, for any $l \geq 1$,

$$E(K(X_{n,1,l})|\mathcal{F}_{n-1}) = K(X_{n,1,l}),$$

$$E(K(X_{n,1,l})|\mathcal{F}_{n-(l+1)}) = EK(X_{n,1,l}),$$

we can express

$$S_{N,1,\infty} = \sum_{n=1}^N (K(X_{n,1,\infty}) - \mathbb{E}K(X_{n,1,\infty}))$$

and

$$S_{N,1,l} = \sum_{n=1}^N (K(X_{n,1,l}) - \mathbb{E}K(X_{n,1,l}))$$

as telescoping sums,

$$S_{N,1,\infty} = \sum_{n=1}^N \sum_{m=1}^{\infty} (\mathbb{E}(K(X_{n,1,\infty})|\mathcal{F}_{n-m}) - \mathbb{E}(K(X_{n,1,\infty})|\mathcal{F}_{n-(m+1)})),$$

$$S_{N,1,l} = \sum_{n=1}^N \sum_{m=1}^l (\mathbb{E}(K(X_{n,1,l})|\mathcal{F}_{n-m}) - \mathbb{E}(K(X_{n,1,l})|\mathcal{F}_{n-(m+1)})).$$

We obtain

$$S_{N,1,\infty} - S_{N,1,l} = \sum_{n=1}^N \sum_{m=1}^{\infty} U_{n,m,l},$$

where

$$U_{n,m,l} = (\mathbb{E}(K(X_{n,1,\infty})|\mathcal{F}_{n-m}) - \mathbb{E}(K(X_{n,1,\infty})|\mathcal{F}_{n-(m+1)})) - (\mathbb{E}(K(X_{n,1,l})|\mathcal{F}_{n-m}) - \mathbb{E}(K(X_{n,1,l})|\mathcal{F}_{n-(m+1)})) 1_{\{1 \leq m \leq l\}}. \tag{3.14}$$

By Lemma 3.1, the random variables $U_{n,m,l}$ satisfy

$$\text{cov}(U_{n,m,l}, U_{n',m',l}) = 0 \quad \text{unless } n - m = n' - m'.$$

By writing

$$\mathbb{E}(S_{N,1,\infty} - S_{N,1,l})^2 \leq 3\mathbb{E}\left(\sum_{n=1}^N U_{n,1,l}\right)^2 + 3\mathbb{E}\left(\sum_{n=1}^N \sum_{m=2}^l U_{n,m,l}\right)^2 + 3\mathbb{E}\left(\sum_{n=1}^N \sum_{m=l+1}^{\infty} U_{n,m,l}\right)^2,$$

and then using the decorrelation of $\{U_{n,m,l}\}$ and the Cauchy–Schwarz inequality, we obtain

$$\mathbb{E}(S_{N,1,\infty} - S_{N,1,l})^2 \leq 3Q_{N,1,l} + 3Q_{N,2,l} + 3Q_{N,3,l},$$

where

$$\begin{aligned}
 Q_{N,1,l} &= \sum_{n=1}^N \mathbb{E}U_{n,1,l}^2, \\
 Q_{N,2,l} &= \sum_{n=1}^N \sum_{m=2}^l \sum_{m'=2}^l (\mathbb{E}U_{n,m,l}^2)^{1/2} (\mathbb{E}U_{n',m',l}^2)^{1/2}, \\
 Q_{N,3,l} &= \sum_{n=1}^N \sum_{m=l+1}^{\infty} \sum_{m'=l+1}^{\infty} (\mathbb{E}U_{n,m,l}^2)^{1/2} (\mathbb{E}U_{n',m',l}^2)^{1/2},
 \end{aligned}$$

with $n' = n - m + m'$. One then needs to show that

$$\lim_{l \rightarrow \infty} \limsup_{N \rightarrow \infty} N^{-1} Q_{N,i,l} = 0, \quad \text{for } i = 1, 2, 3. \tag{3.15}$$

We first prove (3.15) for $i = 1$. We have

$$\begin{aligned}
 \mathbb{E}(\mathbb{E}(X|\mathcal{G}) - \mathbb{E}(Y|\mathcal{F}))^2 &\leq 2\mathbb{E}(\mathbb{E}(X|\mathcal{G}))^2 + 2\mathbb{E}(\mathbb{E}(Y|\mathcal{F}))^2 \leq 2\mathbb{E}(\mathbb{E}(X^2|\mathcal{G})) + 2\mathbb{E}(\mathbb{E}(Y^2|\mathcal{F})) \\
 &= 2(\mathbb{E}X^2 + \mathbb{E}Y^2).
 \end{aligned}$$

Applying this inequality to (3.14) gives

$$N^{-1} Q_{N,1,l} \leq 4N^{-1} \sum_{n=1}^N \mathbb{E}(K(X_{n,1,\infty}) - K(X_{n,1,l}))^2 = 4\mathbb{E}(K(X_{1,1,\infty}) - K(X_{1,1,l}))^2.$$

Since, by Kolmogorov's three-series theorem, $X_{1,1,l} \rightarrow X_{1,1,\infty}$ a.s. as $l \rightarrow \infty$, it follows from Lemma 2.1 that $\mathbb{E}(K(X_{1,1,\infty}) - K(X_{1,1,l}))^2 \rightarrow 0$ and hence that (3.15) holds with $i = 1$.

We now prove (3.15) for $i = 2, 3$. Since the function a satisfies (2.7), it is enough to show that

$$\mathbb{E}U_{n,m,l}^2 \leq C \left(\int_{m-1}^m |a(x)|^\alpha dx \right) \left(\int_l^\infty |a(x)|^\alpha dx \right), \quad \text{for } 2 \leq m \leq l, \tag{3.16}$$

$$\mathbb{E}U_{n,m,l}^2 \leq C \left(\int_{m-1}^m |a(x)|^\alpha dx \right), \quad \text{for } m \geq l + 1. \tag{3.17}$$

We will first establish (3.16). As in (2.6), we have $X_{n,1,\infty} = X_{n,1,m-1} + X_{n,m,\infty}$ and $X_{n,1,l} = X_{n,1,m-1} + X_{n,m,l}$. Observe that in the decomposition of $X_{n,1,\infty}$, for example, the terms $X_{n,1,m-1}$ and $X_{n,m,\infty}$ are respectively independent and measurable with respect to the σ -algebra \mathcal{F}_{n-m} . Hence setting

$$k_m(x) = \mathbb{E}K(x + X_{n,1,m-1}), \tag{3.18}$$

we obtain $\mathbb{E}(K(X_{n,1,\infty})|\mathcal{F}_{n-m}) = k_m(X_{n,m,\infty})$ and $\mathbb{E}(K(X_{n,1,l})|\mathcal{F}_{n-m}) = k_m(X_{n,m,l})$. In view of (3.14), we can then write

$$U_{n,m,l} = k_m(X_{n,m,\infty}) - k_{m+1}(X_{n,m+1,\infty}) - (k_m(X_{n,m,l}) - k_{m+1}(X_{n,m+1,l})). \tag{3.19}$$

Now denote the distribution functions corresponding to X_{n,m_1,m_2} and $X_{n,m,m}$ by F_{m_1,m_2} and F_m , respectively. Since

$$\begin{aligned} X_{n,m,\infty} &= X_{n,m,m} + X_{n,m+1,l} + X_{n,l+1,\infty}, \\ X_{n,m+1,\infty} &= X_{n,m+1,l} + X_{n,l+1,\infty}, \\ X_{n,m,l} &= X_{n,m,m} + X_{n,m+1,l}, \end{aligned}$$

we obtain from (3.19) that

$$\begin{aligned} EU_{n,m,l}^2 &= \int_{\mathbb{R}} \int_{\mathbb{R}} \int_{\mathbb{R}} \{ (k_m(u+v+w) - k_{m+1}(v+w)) \\ &\quad - (k_m(u+v) - k_{m+1}(v)) \}^2 dF_m(u) dF_{m+1,l}(v) dF_{l+1,\infty}(w). \end{aligned}$$

By using the relation $k_{m+1}(z) = EK(z + X_{n,1,m}) = EK(z + X_{n,1,m-1} + X_{n,m,m}) = \int k_m(z + x) dF_m(x)$, we obtain further that

$$\begin{aligned} EU_{n,m,l}^2 &= \int_{\mathbb{R}} \int_{\mathbb{R}} \int_{\mathbb{R}} \left\{ \int_{\mathbb{R}} D(u, v, w, x) dF_m(x) \right\}^2 dF_m(u) dF_{m+1,l}(v) dF_{l+1,\infty}(w) \\ &\leq \int_{\mathbb{R}} \int_{\mathbb{R}} \int_{\mathbb{R}} \int_{\mathbb{R}} D(u, v, w, x)^2 dF_m(u) dF_{m+1,l}(v) dF_{l+1,\infty}(w) dF_m(x), \end{aligned} \tag{3.20}$$

where

$$D(u, v, w, x) = k_m(u + v + w) - k_m(v + w + x) - (k_m(u + v) - k_m(v + x)).$$

Observe now that $\lambda_{1,m-1} = (\int_0^{m-1} |a(x)|^\alpha dx)^{1/\alpha}$ is the scale parameter of the α -stable random variables $X_{n,1,m-1}$. Since $\lambda_{1,m-1}$, $m \geq 2$, is uniformly bounded away from 0 and from infinity, relation (3.2) of Lemma 3.2 implies that the functions $k_m(x)$ have their first two derivatives bounded uniformly for $m \geq 2$ and $x \in \mathbb{R}$. Then, by the mean value theorem,

$$D(u, v, w, x)^2 \leq C \min\{1, w^2, (u-x)^2, (u-x)^2 w^2\}. \tag{3.21}$$

To show, for example, that $D(u, v, w, x)^2 \leq Cw^2$, write $D(u, v, w, x) = g_2(w) - g_2(0)$ with $g_2(w) = k_m(u + v + w) - k_m(v + w + x)$ and apply the mean value theorem using the uniform boundedness of the derivatives $k_m^{(1)}(x)$. To obtain $D(u, v, w, x)^2 \leq C(u-x)^2$, write $D(u, v, w, x) = g_1(u) - g_1(x)$ with $g_1(z) = k_m(z + v + w) - k_m(z + v)$ and apply the mean value theorem, and to obtain $D(u, v, w, x)^2 \leq C(u-x)^2 w^2$, use the previous mean value relationship $D(u, v, w, x) = g_1^{(1)}(z^*)(u-x)$ and again apply the mean value theorem to $g_1^{(1)}(z^*) = k_m^{(1)}(z^* + v + w) - k_m^{(1)}(z^* + v)$. Then, by using (3.20) and (3.21), we obtain that

$$\begin{aligned}
 EU_{n,m,l}^2 \leq & C \left(\iint_{|u-x| \leq 1} (u-x)^2 dF_m(u) dF_m(x) \right) \left(\int_{|w| \leq 1} w^2 dF_{l+1,\infty}(w) \right) \\
 & + C \left(\iint_{|u-x| > 1} dF_m(u) dF_m(x) \right) \left(\int_{|w| \leq 1} w^2 dF_{l+1,\infty}(w) \right) \\
 & + C \left(\iint_{|u-x| \leq 1} (u-x)^2 dF_m(u) dF_m(x) \right) \left(\int_{|w| > 1} dF_{l+1,\infty}(w) \right) \\
 & + C \left(\iint_{|u-x| > 1} dF_m(u) dF_m(x) \right) \left(\int_{|w| > 1} dF_{l+1,\infty}(w) \right). \tag{3.22}
 \end{aligned}$$

We will now use the fact that, for an α -stable standard random variable Z , $P(\lambda|Z| > 1) \leq C\lambda^\alpha$ and $E((\lambda Z)^2 1_{\{\lambda|Z| \leq 1\}}) \leq C\lambda^\alpha$ for any $\lambda > 0$, where the constant C does not depend on the skewness parameter of Z . These bounds follow from the asymptotic behaviour of the tails $P(|Z| > z) \sim cz^{-\alpha}$ as $z \rightarrow \infty$ (see, for example, Samorodnitsky and Taqqu 1994, p. 16) and the relation $E X^2 1_{\{|X| \leq x_0\}} \leq \int_0^{x_0} 2xP(|X| > x)dx$ which yields $E((\lambda Z)^2 1_{\{\lambda|Z| \leq 1\}}) = \lambda^2 E Z^2 1_{\{|Z| \leq 1/\lambda\}} \leq \lambda^2 C \lambda^{\alpha-2} = C \lambda^\alpha$. Since $\lambda_m Z_1$ has the distribution F_m with $\lambda_m^\alpha = \int_{m-1}^m |a(x)|^\alpha dx$ and $\lambda_{l+1,\infty} Z_2$ has the distribution $F_{l+1,\infty}$ with $\lambda_{l+1,\infty}^\alpha = \int_l^\infty |a(x)|^\alpha dx$, where Z_1 and Z_2 are α -stable standard random variables (with perhaps different skewness parameters), we conclude that each of the four terms in (3.22) is bounded by $C \lambda_m^\alpha \lambda_{l+1,\infty}^\alpha$ and hence that the bound (3.16) holds. One may prove the bound (3.17) in a similar (in fact, simpler) manner.

Non-causal moving averages. Assuming for simplicity that $x_0 = 0$ in Definition 2.1 for a non-causal moving average X_n , we have $X_n = \int_n^\infty a(n-x)M(dx)$. We need to prove that

$$\lim_{l \rightarrow -\infty} \limsup_{N \rightarrow \infty} N^{-1} \text{var}(S_{N,-\infty,0} - S_{N,l,0}) = 0, \tag{3.23}$$

where

$$\begin{aligned}
 S_{N,-\infty,0} &= \sum_{n=1}^N (K(X_{n,-\infty,0}) - EK(X_{n,-\infty,0})) \\
 S_{N,l,0} &= \sum_{n=1}^N (K(X_{n,l,0}) - EK(X_{n,l,0})).
 \end{aligned}$$

We will show that the proof of (3.23) can be reduced to that of (3.13). While $(X_{n,-\infty,0}, X_{n,l,0}, l \leq 0)_{n=1,\dots,N}$ does not have the same distribution as $(X_{N-n+1,-\infty,0}, X_{N-n+1,l,0}, l \leq 0)_{n=1,\dots,N}$, one has, for fixed N ,

$$S_{N,-\infty,0} = \sum_{n=1}^N (K(X_{N-n+1,-\infty,0}) - \mathbb{E}K(X_{N-n+1,-\infty,0})) \tag{3.24}$$

and

$$S_{N,l,0} = \sum_{n=1}^N (K(X_{N-n+1,l,0}) - \mathbb{E}K(X_{N-n+1,l,0})). \tag{3.25}$$

Now, for fixed N , by making the change of variables $N + 1 - x = y$ below,

$$\begin{aligned} & (X_{N-n+1,-\infty,0}, X_{N-n+1,l,0}, l \leq 0)_{n=1,\dots,N} \\ &= \left(\int_{N-n+1}^{\infty} a(N-n+1-x)M(dx), \int_{N-n+1}^{N-n+2-l} a(N-n+1-x)M(dx), l \leq 0 \right)_{n=1,\dots,N} \\ &= \left(-\int_{-\infty}^n a(y-n)M(d(N+1-y)), -\int_{n+l-1}^n a(y-n)M(d(N+1-y)), l \leq 0 \right)_{n=1,\dots,N} \\ &\stackrel{d}{=} \left(\int_{-\infty}^n \tilde{a}(n-y)\tilde{M}(dy), \int_{n+l-1}^n \tilde{a}(n-y)\tilde{M}(dy), l \leq 0 \right)_{n=1,\dots,N} \\ &= (\tilde{X}_{n,1,\infty}, \tilde{X}_{n,1,-l+1}, l \leq 0)_{n=1,\dots,N}, \end{aligned}$$

where \tilde{M} is an α -stable random measure with the Lebesgue control measure and the skewness intensity β , $\tilde{a}(z) = a(-z)$ for $z \in \mathbb{R}$ and $\tilde{X}_{n,m_1,m_2} = \int_{n-m_2}^{n-m_1+1} \tilde{a}(n-y)\tilde{M}(dy)$, $-\infty \leq m_1 \leq m_2 \leq \infty$. Then, by using (3.24) and (3.25), we obtain that, for fixed N , $(S_{N,-\infty,0}, S_{N,l,0}) =_d (\tilde{S}_{N,1,\infty}, \tilde{S}_{N,1,-l+1})$ with $\tilde{S}_{N,m_1,m_2} = \sum_{n=1}^N (K(\tilde{X}_{n,m_1,m_2}) - \mathbb{E}K(\tilde{X}_{n,m_1,m_2}))$ and hence

$$N^{-1} \text{var}(S_{N,-\infty,0} - S_{N,l,0}) = N^{-1} \text{var}(\tilde{S}_{N,1,\infty} - \tilde{S}_{N,1,-l+1}).$$

The convergence (3.23) then follows from (3.13) since \tilde{a} satisfies condition (2.7) and \tilde{X} is causal.

Two-sided moving averages. We need to prove (3.12) for $X_n = \int_{-\infty}^{\infty} a(n-x)M(dx)$ and for a function K which is twice differentiable with bounded derivatives. As in the case of causal moving averages, we can write

$$\begin{aligned} S_N &= \sum_{n=1}^N \sum_{m=-\infty}^{\infty} (\mathbb{E}(K(X_n)|\mathcal{F}_{n-m}) - \mathbb{E}(K(X_n)|\mathcal{F}_{n-(m+1)})), \\ S_{N,l_1,l_2} &= \sum_{n=1}^N \sum_{m=l_1}^{l_2} (\mathbb{E}(K(X_{n,l_1,l_2})|\mathcal{F}_{n-m}) - \mathbb{E}(K(X_{n,l_1,l_2})|\mathcal{F}_{n-(m+1)})) \end{aligned}$$

and hence $S_N - S_{N,l_1,l_2} = \sum_{n=1}^N \sum_{m=-\infty}^{\infty} U_{n,m,l_1,l_2}$, where the random variables

$$\begin{aligned}
 U_{n,m,l_1,l_2} &= (\mathbb{E}(K(X_n)|\mathcal{F}_{n-m}) - \mathbb{E}(K(X_n)|\mathcal{F}_{n-(m+1)})) \\
 &\quad - (\mathbb{E}(K(X_{n,l_1,l_2})|\mathcal{F}_{n-m}) - \mathbb{E}(K(X_{n,l_1,l_2})|\mathcal{F}_{n-(m+1)})) \mathbf{1}_{\{l_1 \leq m \leq l_2\}} \quad (3.26)
 \end{aligned}$$

satisfy $\text{cov}(U_{n,m,l_1,l_2}, U_{n',m',l_1,l_2}) = 0$ unless $n - m = n' - m'$. Then $\mathbb{E}(S_N - S_{N,l_1,l_2})^2 \leq 3Q_{N,1,l_1,l_2} + 3Q_{N,2,l_1,l_2}$, where

$$\begin{aligned}
 Q_{N,1,l_1,l_2} &= \sum_{n=1}^N \sum_{m=l_1}^{l_2} \sum_{m'=l_1}^{l_2} (\mathbb{E}U_{n,m,l_1,l_2}^2)^{1/2} (\mathbb{E}U_{n',m',l_1,l_2}^2)^{1/2}, \\
 Q_{N,2,l_1,l_2} &= \sum_{n=1}^N \left(\sum_{m=-\infty}^{l_1-1} \sum_{m'=-\infty}^{l_1-1} + \sum_{m=l_2+1}^{\infty} \sum_{m'=l_2+1}^{\infty} \right) (\mathbb{E}U_{n,m,l_1,l_2}^2)^{1/2} (\mathbb{E}U_{n',m',l_1,l_2}^2)^{1/2}
 \end{aligned}$$

with $n' = n - m + m'$, and one needs to show that

$$\lim_{(l_1,l_2) \rightarrow (-\infty,\infty)} \limsup_{N \rightarrow \infty} N^{-1} Q_{N,i,l_1,l_2} = 0, \quad \text{for } i = 1, 2. \quad (3.27)$$

The convergence (3.27) will follow from the bounds

$$\mathbb{E}U_{n,m,l_1,l_2}^2 \leq C \left(\int_{m-1}^m |a(x)|^\alpha dx \right) \left(\int_{-\infty}^{l_1-1} |a(x)|^\alpha dx + \int_{l_2}^{\infty} |a(x)|^\alpha dx \right), \quad \text{for } l_1 \leq m \leq l_2, \quad (3.28)$$

$$\mathbb{E}U_{n,m,l_1,l_2}^2 \leq C \left(\int_{m-1}^m |a(x)|^\alpha dx \right), \quad \text{for } m \leq l_1 - 1 \text{ or } m \geq l_2 + 1. \quad (3.29)$$

We will first prove (3.28). Setting

$$k_{m,l_1}(z) = \mathbb{E}K(z + X_{n,l_1,m-1}), \quad (3.30)$$

we can write $\mathbb{E}(K(X_{n,l_1,l_2})|\mathcal{F}_{n-m}) = k_{m,l_1}(X_{n,m,l_2})$ and

$$\begin{aligned}
 \mathbb{E}(K(X_n)|\mathcal{F}_{n-m}) &= \mathbb{E}K(z + X_{n,-\infty,m-1})|_{z=X_{n,m,\infty}} \\
 &= \mathbb{E}K(z + X_{n,-\infty,l_1-1} + X_{n,l_1,m-1})|_{z=X_{n,m,\infty}} \\
 &= \int_{\mathbb{R}} k_{m,l_1}(z + y) dF_{-\infty,l_1-1}(y)|_{z=X_{n,m,\infty}}
 \end{aligned}$$

and hence, in view of (3.26),

$$\begin{aligned}
 U_{n,m,l_1,l_2} &= \int_{\mathbb{R}} k_{m,l_1}(z + y) dF_{-\infty,l_1-1}(y)|_{z=X_{n,m,\infty}} - \int_{\mathbb{R}} k_{m+1,l_1}(z + y) dF_{-\infty,l_1-1}(y)|_{z=X_{n,m+1,\infty}} \\
 &\quad - (k_{m,l_1}(X_{n,m,l_2}) - k_{m+1,l_1}(X_{n,m+1,l_2})).
 \end{aligned}$$

Then, by writing, as in the causal case,

$$\begin{aligned} X_{n,m,\infty} &= X_{n,m,m} + X_{n,m+1,l_2} + X_{n,l_2+1,\infty}, \\ X_{n,m+1,\infty} &= X_{n,m+1,l_2} + X_{n,l_2+1,\infty}, \\ X_{n,m,l_2} &= X_{n,m,m} + X_{n,m+1,l_2}, \end{aligned}$$

and by using the relation $k_{m+1,l_1}(z) = \int k_{m,l_1}(z+x)dF_m(x)$ and the Cauchy–Schwarz inequality, we obtain that

$$\begin{aligned} EU_{n,m,l_1,l_2}^2 &= \int_{\mathbb{R}} \int_{\mathbb{R}} \int_{\mathbb{R}} \left\{ \int_{\mathbb{R}} \int_{\mathbb{R}} D(u, v, w, x, y) dF_{-\infty,l_1-1}(y) dF_m(x) \right\}^2 \\ &\quad \times dF_m(u) dF_{m+1,l_2}(v) dF_{l_2+1,\infty}(w) \\ &\leq \int_{\mathbb{R}} \dots \int_{\mathbb{R}} D(u, v, w, x, y)^2 dF_m(u) dF_{m+1,l_2}(v) dF_{l_2+1,\infty}(w) dF_m(x) dF_{-\infty,l_1-1}(y), \end{aligned} \tag{3.31}$$

where

$$\begin{aligned} D(u, v, w, x, y) &= k_{m,l_1}(u + v + w + y) - k_{m,l_1}(v + w + x + y) \\ &\quad - (k_{m,l_1}(u + v) - k_{m,l_1}(v + x)). \end{aligned}$$

By assumption on K and by using (3.7) in Lemma 3.3, we obtain that the functions $k_{m,l_1}(x)$ have their first two derivatives bounded uniformly for $m, l_1 \in \mathbb{Z}$ and $x \in \mathbb{R}$. Then, as in (3.21) with w replaced by $w + y$, we obtain that

$$D(u, v, w, x, y)^2 \leq C \min\{1, (w + y)^2, (u - x)^2, (u - x)^2(w + y)^2\}$$

and hence, by (3.31),

$$\begin{aligned} EU_{n,m,l_1,l_2}^2 &\leq C \left(\iint_{|u-x|\leq 1} (u - x)^2 dF_m(u) dF_m(x) \right) \\ &\quad \times \left(\iint_{|w+y|\leq 1} (w + y)^2 dF_{l_2+1,\infty}(w) dF_{-\infty,l_1-1}(y) \right) \\ &\quad + C \left(\iint_{|u-x|>1} dF_m(u) dF_m(x) \right) \left(\iint_{|w+y|\leq 1} (w + y)^2 dF_{l_2+1,\infty}(w) dF_{-\infty,l_1-1}(y) \right) \\ &\quad + C \left(\iint_{|u-x|\leq 1} (u - x)^2 dF_m(u) dF_m(x) \right) \left(\iint_{|w+y|>1} dF_{l_2+1,\infty}(w) dF_{-\infty,l_1-1}(y) \right) \\ &\quad + C \left(\iint_{|u-x|>1} dF_m(u) dF_m(x) \right) \left(\iint_{|w+y|>1} dF_{l_2+1,\infty}(w) dF_{-\infty,l_1-1}(y) \right). \end{aligned} \tag{3.32}$$

Since $\lambda_{-\infty, l_1-1} Z_1$ has the distribution $F_{-\infty, l_1-1}$ with $\lambda_{-\infty, l_1-1}^\alpha = \int_{-\infty}^{l_1-1} |a(x)|^\alpha dx$, $\lambda_{l_2+1, \infty} Z_2$ has the distribution $F_{l_2+1, \infty}$ with $\lambda_{l_2+1, \infty}^\alpha = \int_{l_2}^\infty |a(x)|^\alpha dx$ and $\lambda_m Z_3$ has the distribution F_m with $\lambda_m^\alpha = \int_{m-1}^m |a(x)|^\alpha dx$, where Z_1, Z_2 and Z_3 are α -stable standard random variables (with perhaps different skewness parameters), we conclude as in the case of (3.22) that each of the four terms in (3.32) is bounded by $C\lambda_m^\alpha(\lambda_{-\infty, l_1-1}^\alpha + \lambda_{l_2+1, \infty}^\alpha)$ and hence that the bound (3.28) holds. One can prove the bound (3.29) in a similar way. \square

Remark 3.1. The proof for two-sided moving averages does not apply to partial sums with any bounded function K because the scale parameters of α -stable random variables

$$X_{n, l_1, m-1} = \int_{n-m+1}^{n-l_1+1} a(n-x)M(dx),$$

namely, $\lambda_{l_1, m-1} = (\int_{l_1-1}^{m-1} |a(x)|^\alpha dx)^{1/\alpha}$, are not bounded away from zero uniformly in m and l_1 , since $\lambda_{l_1, m-1} \rightarrow 0$ as $l_1 \rightarrow -\infty$ and $m \rightarrow -\infty$. Hence, the first and second derivatives of the functions $k_{m, l_1}(x)$ in (3.30) are not necessarily bounded uniformly in m and l_1 (see Lemma 3.2, which involves a scale parameter $\sigma > 0$). Whether Theorem 2.1 is valid for two-sided moving averages with any bounded functions K_j is still an open question.

Proof of Theorem 2.2. Observe first that the moving average X_n is well defined since, by assumptions (2.17) and (2.18), $\sum_j |a_j|^\delta < \infty$ for some $0 < \delta < \min\{1, \alpha\}$ and hence $E|X_n|^\delta \leq \sum_j |c_j|^\delta E|\epsilon_{n-j}|^\delta = E|\epsilon_1|^\delta \sum_j |c_j|^\delta < \infty$. As in the proof of Theorem 2.1, it is enough to show the convergence (2.19). Let $\mathcal{F}_k, k \in \mathbb{Z}$, be σ -algebras generated by innovations $\epsilon_i, i \leq k$. (This notation corresponds to that used in the continuous case with $\epsilon_i = \int_i^{i+1} M(dx)$.) We set $X_{n, m_1, m_2} = \sum_{m_1 \leq j \leq m_2} a_j \epsilon_{n-j}$. Then, by proceeding as in the proof of Theorem 2.1 for two-sided moving averages, it is enough to prove (3.27), which will follow here (compare with (3.28) and (3.29)) from the bounds

$$EU_{n, m, l_1, l_2}^2 \leq C|a_m|^\alpha \tilde{L}\left(\frac{1}{|a_m|}\right) \left(\sum_{j=-\infty}^{l_1-1} + \sum_{j=l_2+1}^\infty \right) |a_j|^\alpha \tilde{L}\left(\frac{1}{|a_j|}\right), \quad \text{for } l_1 \leq m \leq l_2, \quad (3.33)$$

$$EU_{n, m, l_1, l_2}^2 \leq C|a_m|^\alpha \tilde{L}\left(\frac{1}{|a_m|}\right), \quad \text{for } m \leq l_1 - 1 \text{ or } m \geq l_2 + 1, \quad (3.34)$$

where \tilde{L} is defined in (2.22).

To show (3.33), observe that we can bound EU_{n, m, l_1, l_2}^2 as in (3.32) and hence it is enough to prove that there is a constant C such that, for every $-\infty \leq m_1 \leq m_2 \leq \infty$,

$$P\left(\left|\sum_{j=m_1}^{m_2} b_j \epsilon_j\right| > 1\right) \leq C \sum_{j=m_1}^{m_2} |b_j|^\alpha \tilde{L}\left(\frac{1}{|b_j|}\right), \quad (3.35)$$

$$E\left(\left|\sum_{j=m_1}^{m_2} b_j \epsilon_j\right|^2 1_{\{|\sum_{j=m_1}^{m_2} b_j \epsilon_j| < 1\}}\right) \leq C \sum_{j=m_1}^{m_2} |b_j|^\alpha \tilde{L}\left(\frac{1}{|b_j|}\right), \quad (3.36)$$

where $\{b_j\}$ satisfies $\sum_j |b_j|^\alpha \tilde{L}(1/|b_j|) < \infty$. For example,

$$\begin{aligned} \iint_{|w+y|>1} dF_{l_2+1,\infty}(w)dF_{-\infty,l_1-1}(y) &= P\left(\left|\sum_{j=-\infty}^{l_1-1} a_j\epsilon'_{n-j} + \sum_{j=l_2+1}^{\infty} a_j\epsilon''_{n-j}\right| > 1\right) \\ &= P\left(\left|\sum_{j=-\infty}^{\infty} b_j\epsilon_j\right| > 1\right), \end{aligned}$$

where ϵ', ϵ'' are independent copies of the sequence ϵ , and $b_j = a_j$ for $-\infty < j \leq l_1 - 1$ and $l_2 + 1 \leq j < \infty$ and 0 otherwise.

Consider inequality (3.35) first. By using

$$P(|Z| \geq x) \leq \frac{x}{2} \int_{-2/x}^{2/x} (1 - \text{E}e^{i\theta Z})d\theta, \quad x > 0,$$

(Billingsley 1995, p. 350), we obtain that

$$\begin{aligned} P\left(\left|\sum_{j=m_1}^{m_2} b_j\epsilon_j\right| > 1\right) &\leq C \int_{-2}^2 \left|1 - \text{E}e^{i\theta \sum_{j=m_1}^{m_2} b_j\epsilon_j}\right| d\theta \\ &= C \int_{-2}^2 \left|1 - \prod_{j=m_1}^{m_2} \text{E}e^{i\theta b_j\epsilon_j}\right| d\theta \leq C \sum_{j=m_1}^{m_2} \int_{-2}^2 \left|1 - \text{E}e^{i\theta b_j\epsilon_j}\right| d\theta, \end{aligned} \tag{3.37}$$

by applying the inequality $|1 - \prod_{j=m_1}^{m_2} c_j| \leq \sum_{j=m_1}^{m_2} |1 - c_j|$ valid for $|c_j| \leq 1$.

Consider first the case $\alpha \neq 1$. By using (2.15), (2.16) and Ibragimov and Linnik (1971, Theorem 2.6.5), there exist $c > 0$, $\beta \in [-1, 1]$ and a function $h(u) = h_1(u) + ih_2(u)$ with $h(u) \rightarrow 1$, as $u \rightarrow 0$, such that

$$\begin{aligned} \text{E} \exp\{iu\epsilon_1\} &= \exp\left\{-c|u|^\alpha \tilde{L}\left(\frac{1}{|u|}\right) \left(1 - i\beta \text{sign}(u) \tan \frac{\alpha\pi}{2}\right) h(u)\right\} \\ &= \exp\left\{-c|u|^\alpha \tilde{L}\left(\frac{1}{|u|}\right) \left(h_1(u) + \beta \text{sign}(u) \tan \frac{\alpha\pi}{2} h_2(u)\right)\right. \\ &\quad \left.+ ic|u|^\alpha \tilde{L}\left(\frac{1}{|u|}\right) \left(\beta \text{sign}(u) \tan \frac{\alpha\pi}{2} h_1(u) - h_2(u)\right)\right\}, \end{aligned}$$

where $\tilde{L}(z) = L(z)$. Then, by using the fact that $h_1(u) + \beta \text{sign}(u) \tan(\alpha\pi/2)h_2(u) \rightarrow 1$, as $u \rightarrow 0$, and the inequalities $|1 - c_1c_2| \leq |1 - c_1| + |1 - c_2|$ for $|c_1|, |c_2| \leq 1$, $|1 - e^{-x}| \leq x$ for $x > 0$, and $|1 - e^{ix}| \leq |x|$ for $x \in \mathbb{R}$, we conclude that

$$\left|1 - \text{E}e^{iu\epsilon_1}\right| \leq C|u|^\alpha \tilde{L}\left(\frac{1}{|u|}\right), \tag{3.38}$$

for small enough u . We may suppose without loss of generality that (3.38) holds for all u . Indeed, since the function $\tilde{L}(z) = L(z)$ need not be defined around $z = 0$ (see (2.15) and (2.16)), we can define it as

$$z^{-\alpha} \tilde{L}(z) \sim 1, \tag{3.39}$$

as $z \rightarrow 0$. With this non-restricting assumption in mind, by observing that the the left-hand side of (3.38) is bounded by 2 and by increasing C , we obtain that the bound (3.38) holds for all u .

For $\alpha = 1$, by using Aaronson and Denker (1998, Theorem 2), we can write

$$\begin{aligned} E \exp\{iu\epsilon_1\} &= \exp\left\{-c|u|L\left(\frac{1}{|u|}\right)\left(1 - i\frac{2\beta}{c}C \operatorname{sign}(u)\right)h(u) + iu\left(\gamma + H\left(\frac{1}{|u|}\right)\right)\right\} \\ &= \exp\left\{-c|u|L\left(\frac{1}{|u|}\right)\left(h_1(u) + \frac{2\beta}{c}C \operatorname{sign}(u)h_2(u)\right)\right. \\ &\quad \left.+ ic|u|L\left(\frac{1}{|u|}\right)\left(\frac{2\beta}{c}C \operatorname{sign}(u)h_1(u) - h_2(u)\right) + iu\left(\gamma + H\left(\frac{1}{|u|}\right)\right)\right\}, \end{aligned}$$

where c, C, β are constants, $h(u) = h_1(u) + ih_2(u) \rightarrow 1$ as $u \rightarrow 0$, and the function H and the constant γ are defined by (2.20) and (2.21). Then, by arguing as in the case $\alpha \neq 1$, we can conclude that (3.38) holds for small enough u with $\tilde{L}(z) = L(z) + |\gamma + H(z)|$. Recall from Remark 2.1 that \tilde{L} is a slowly varying function at infinity. By choosing $L(z)$ such that $z^{-1}L(z) \sim 1 - |\gamma + H(z)|z^{-1}$ as $z \rightarrow 0$, we can suppose without loss of generality that (3.39) holds and hence that (3.38) holds for all u .

By using (3.38), we obtain from (3.37) that

$$P\left(\left|\sum_{j=m_1}^{m_2} b_j \epsilon_j\right| > 1\right) \leq C \sum_{j=m_1}^{m_2} |b_j|^\alpha \int_{-2}^2 |\theta|^\alpha \tilde{L}\left(\frac{1}{|b_j \theta|}\right) d\theta.$$

The bound (3.35) follows since, by Potter’s bounds (see, for example, Bingham *et al.* 1987), $\tilde{L}(1/|\theta b_j|)(\tilde{L}(1/|b_j|))^{-1}$ is bounded by $C|\theta|^{-\epsilon}$ with any $\epsilon > 0$, uniformly for j and $|\theta| \leq 2$.

To prove inequality (3.36), observe that $EX^2 1_{\{0 < |X| < 1\}} \leq \int_0^1 2xP(|X| > x)dx$ and hence that

$$E\left(\left|\sum_{j=m_1}^{m_2} b_j \epsilon_j\right|^2 1_{\{|\sum_{j=m_1}^{m_2} b_j \epsilon_j| < 1\}}\right) \leq \int_0^1 2xP\left(\left|\sum_{j=m_1}^{m_2} b_j \epsilon_j\right| > x\right)dx. \tag{3.40}$$

By arguing as above, we can conclude that

$$\begin{aligned} P\left(\left|\sum_{j=m_1}^{m_2} b_j \epsilon_j\right| > x\right) &\leq Cx \sum_{j=m_1}^{m_2} |b_j|^\alpha \int_{-2/x}^{2/x} |\theta|^\alpha \tilde{L}\left(\frac{1}{|b_j \theta|}\right) d\theta \\ &\leq Cx \sum_{j=m_1}^{m_2} |b_j|^{-1} \int_{-2|b_j|/x}^{2|b_j|/x} |\nu|^\alpha \tilde{L}\left(\frac{1}{|\nu|}\right) d\nu. \end{aligned}$$

Then, by using Karamata’s theorem for the case $2|b_j| < x$ and by making the change of variables $z = 1/\nu$, we obtain that

$$\begin{aligned}
 P\left(\left|\sum_{j=m_1}^{m_2} b_j \epsilon_j\right| > x\right) &\leq Cx \sum_{j=m_1}^{m_2} |b_j|^{-1} \left(\frac{|b_j|}{x}\right)^{\alpha+1} \tilde{L}\left(\frac{x}{|b_j|}\right) 1_{\{2|b_j| < x\}} \\
 &\quad + Cx \sum_{j=m_1}^{m_2} |b_j|^{-1} \int_{x/(2|b_j|)}^{\infty} z^{-2} z^{-\alpha} \tilde{L}(z) dz 1_{\{2|b_j| \geq x\}} \\
 &\leq C' \sum_{j=m_1}^{m_2} |b_j|^\alpha x^{-\alpha} \tilde{L}\left(\frac{x}{|b_j|}\right) 1_{\{2|b_j| < x\}} + C' \sum_{j=m_1}^{m_2} 1_{\{2|b_j| \geq x\}}. \tag{3.41}
 \end{aligned}$$

The last term in (3.41) follows from (3.39), yielding the bound

$$\int_{x/(2|b_j|)}^{\infty} z^{-2} z^{-\alpha} \tilde{L}(z) dz \leq C_1 \int_{x/(2|b_j|)}^{\infty} z^{-2} dz \leq C_2 \frac{|b_j|}{x}.$$

By substituting the bound (3.41) into (3.40) and by using Karamata’s theorem with a change of variables as above, we obtain that

$$\begin{aligned}
 E\left(\left|\sum_{j=m_1}^{m_2} b_j \epsilon_j\right|^2 1_{\{|\sum_{j=m_1}^{m_2} b_j \epsilon_j| < 1\}}\right) &\leq C \sum_{j=m_1}^{m_2} \left\{ \int_0^{2|b_j|} x dx + |b_j|^\alpha \int_{2|b_j|}^1 x^{1-\alpha} \tilde{L}\left(\frac{x}{|b_j|}\right) dx \right\} \\
 &\leq C' \sum_{j=m_1}^{m_2} \left\{ |b_j|^2 + |b_j|^2 \int_2^{1/|b_j|} y^{1-\alpha} \tilde{L}(y) dy \right\} \\
 &\leq C'' \sum_{j=m_1}^{m_2} \left\{ |b_j|^2 + |b_j|^\alpha \tilde{L}\left(\frac{1}{|b_j|}\right) \right\} \\
 &\leq C \sum_{j=m_1}^{m_2} |b_j|^\alpha \tilde{L}\left(\frac{1}{|b_j|}\right).
 \end{aligned}$$

Finally, the bound (3.34) can be proved in a similar way by using (3.35) and (3.36). □

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