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Research Article

Least Squares Estimation for α -Fractional Bridge with Discrete Observations

Guangjun Shen and Xiuwei Yin

Department of Mathematics, Anhui Normal University, Wuhu 241000, China

Correspondence should be addressed to Guangjun Shen; gjshen@163.com

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We consider a fractional bridge defined as $dX_t = -\alpha(X_t/(T-t))dt + dB_t^H$, $0 \le t < T$, where B^H is a fractional Brownian motion of Hurst parameter H > 1/2 and parameter $\alpha > 0$ is unknown. We are interested in the problem of estimating the unknown parameter $\alpha > 0$. Assume that the process is observed at discrete time $t_i = i\Delta_n$, $i = 0, \ldots, n$, and $T_n = n\Delta_n$ denotes the length of the "observation window." We construct a least squares estimator $\widehat{\alpha}_n$ of α which is consistent; namely, $\widehat{\alpha}_n$ converges to α in probability as $n \to \infty$.

1. Introduction

Self-similar stochastic processes with long range dependence are of practical interest in various applications, including econometrics, internet traffic, and hydrology. These are processes $X=\{X_t:t\geq 0\}$ whose dependence on the time parameter t is self-similar, in the sense that there exists a (self-similarity) parameter $H\in(0,1)$ such that, for any constant $c\geq 0$, $\{X_{ct}:t\geq 0\}$ and $\{c^HX_t:t\geq 0\}$ have the same distribution. These processes are often endowed with other distinctive properties.

The fractional Brownian motion (fBm) is the usual candidate to model phenomena in which the self-similarity property can be observed from the empirical data. The fBm is a suitable generalization of the standard Brownian motion, which exhibits long-range dependence and self-similarity and has stationary increments. Some surveys and complete literatures could be found in Biagini et al. [1], Hu [2], Mishura [3], and Nualart [4].

Recently, Es-Sebaiy and Nourdin [5] study the asymptotic properties of a least squares estimator for the parameter α of a fractional bridge defined as

$$X_0 = 0,$$
 $dX_t = -\alpha \frac{X_t}{T - t} dt + dB_t^H, \quad 0 \le t < T,$ (1)

where B^H is a fBm with Hurst parameter H > 1/2 and the process X was observed continuously. In particular,

when H=1/2, Barczy and Pap [6, 7] study the various problems related to the α -Wiener bridge. The parametric estimation problems for fractional diffusion processes based on continuous-time observations have been studied, for example, in Tudor and Viens [8], Hu and Nualart [9], and Belfadli et al. [10].

In applications usually the process cannot be observed continuously. Only discrete-time observations are available. There exists a rich literature on the parameter estimation problem for diffusion processes driven by fBm based on discrete observations (see, e.g., Hu and Song [11], Es-Sebaiy [12]).

Motivated by all these results, in this paper, we will consider the α fractional bridge (1). Assume that the process X is observed equidistantly in time with the step size $t_i=i\Delta_n, i=0,\ldots,n$, and $T_n=n\Delta_n$ denotes the length of the "observation window." We also assume that $T_n+\Delta_n=T$ and $\Delta_n\to 0$ when $n\to\infty$. Our goal is to study the asymptotic behavior of the least squares estimator (LSE for short) $\widehat{\alpha}_n$ of α based on the sampling data $X_{t_i}, i=0,\ldots,n$. Our technics used in this work are inspired from Es-Sebaiy [12].

The least squares estimator $\hat{\alpha}_n$ aims to minimize

$$\alpha \longmapsto \sum_{i=1}^{n} \int_{t_{i-1}}^{t_{i}} \left| \dot{X}_{t} + \alpha \frac{X_{t_{i-1}}}{T - t_{i-1}} \right|^{2} dt. \tag{2}$$

This is a quadratic function of α . The minimum is achieved when

$$\widehat{\alpha}_{n} = -\frac{\sum_{i=1}^{n} \int_{t_{i-1}}^{t_{i}} \left(X_{t_{i-1}} / \left(T - t_{i-1} \right) \right) \delta^{H} X_{t}}{\Delta_{n} \sum_{i=1}^{n} \left(X_{t_{i-1}}^{2} / \left(T - t_{i-1} \right)^{2} \right)}.$$
 (3)

By (1), we can get the following result

$$\widehat{\alpha}_n - \alpha = -\frac{\sum_{i=1}^n M_i}{\Delta_n \sum_{i=1}^n \left(X_{t_{i-1}}^2 / (T - t_{i-1})^2 \right)},\tag{4}$$

where
$$M_i = \alpha(X_{t_{i-1}}/(T-t_{i-1})\int_{t_{i-1}}^{t_i}((X_{t_{i-1}}/(T-t_{i-1}))-(X_s/(T-s)))ds + \int_{t_{i-1}}^{t_i}(X_{t_{i-1}}/(T-t_{i-1})\delta^H B_t^H, i=1,\ldots,n.$$
 The paper is organized as follows. In Section 2 some

The paper is organized as follows. In Section 2 some known results that we will use are recalled. The consistency of estimator is proved in Section 3.

2. Preliminaries

Recall that fBm B^H with index $H \in (0,1)$ is a mean zero Gaussian process $B^H = \{B_t^H, t \ge 0\}$ with $B_0^H = 0$ and the covariance

$$R^{H}(t,s) := E(B_{t}B_{s}) = \frac{1}{2}(t^{2H} + s^{2H} - |t-s|^{2H})$$
 (5)

for all $s,t \geq 0$. For H=1/2, B^H coincides with the standard Brownian motion B. B^H is neither a semimartingale nor a Markov process unless H=1/2, so many of the powerful techniques from stochastic analysis are not available when dealing with B^H . It is possible to construct a stochastic calculus of variations with respect to the Gaussian process B^H , which will be related to the Malliavin calculus. Some surveys and complete literatures could be found in Alòs et al. [13], Nualart [4] and the reference. We recall here the basic definitions and results of this calculus. The crucial ingredient is the canonical Hilbert space $\mathcal H$ (it is also said to be reproducing kernel Hilbert space) associated with the fBm which is defined as the closure of the linear space $\mathcal E$ generated by the indicator functions $\{1_{[0,t]},t\in[0,T]\}$ with respect to the scalar product

$$\langle 1_{[0,t]}, 1_{[0,s]} \rangle_{\mathcal{H}} = R_H(t,s) = \frac{1}{2} \left(t^{2H} + s^{2H} - |t-s|^{2H} \right).$$
 (6)

The mapping $1_{[0,s]} \to B_s^H$ can be extended to a linear isometry between $\mathcal H$ and the Gaussian space associated with B^H . We will denote the isometry by $\varphi \to B^H(\varphi)$. For 1/2 < H < 1 we denote by $\mathcal S$ the set of smooth functionals of the form

$$F = f\left(B^{H}\left(\varphi_{1}\right), \dots, B^{H}\left(\varphi_{n}\right)\right),\tag{7}$$

where $f \in C_b^{\infty}(\mathbb{R}^n)$ and $\varphi_i \in \mathcal{H}$. The Malliavin derivative of a functional F as above is given by

$$D^{H}F = \sum_{i=1}^{n} \frac{\partial f}{\partial x_{i}} \left(B^{H} \left(\varphi_{1} \right), \dots, B^{H} \left(\varphi_{n} \right) \right) \varphi_{i}, \tag{8}$$

and this operator can be extended to the closure $\mathbb{D}^{m,2}$ $(m \ge 1)$ of \mathcal{S} with respect to the norm

$$||F||_{m,2}^2 \equiv E|F|^2 + E||D^H F||_{\mathcal{H}}^2 + \dots + E||D^{H,m} F||_{\mathcal{H}^{\hat{\otimes}_m}}^2,$$
 (9)

where $\mathcal{H}^{\otimes m}$ denotes the m fold symmetric tensor product and the mth derivative $D^{H,m}$ is defined by iteration. The divergence integral δ^H is the adjoint operator of D^H . Concretely, a random variable $u \in L^2(\Omega, \mathcal{H})$ belongs to the domain of the divergence operator δ^H (in symbol $\mathrm{Dom}(\delta^H)$) if

$$E\left|\left\langle D^{H}F,u\right\rangle _{\mathcal{H}}\right|\leq c\|F\|_{L^{2}}$$
 (10)

for every $F \in \mathcal{S}$. In this case $\delta^H(u)$ is given by the duality relationship

$$E(F\delta^{H}(u)) = E\langle D^{H}F, u \rangle_{\mathscr{H}}$$
 (11)

for any $F \in \mathbb{D}^{1,2}$, and we have the following integration by parts:

$$F\delta^{H}(u) = \delta^{H}(Fu) + \langle D^{H}F, u \rangle_{\mathscr{L}}$$
 (12)

for any $u \in \text{Dom}(\delta^H)$, $F \in \mathbb{D}^{1,2}$ such that $Fu \in L^2(\Omega, \mathcal{H})$. It follows that

$$E\left[\delta^{H}(u)^{2}\right] = E\|u\|_{\mathcal{H}}^{2} + E\left\langle D^{H}u, \left(D^{H}u\right)^{*}\right\rangle_{\mathcal{H}\otimes\mathcal{H}}, \quad (13)$$

where $(D^H u)^*$ is the adjoint of $D^H u$ in the Hilbert space $\mathcal{H} \otimes \mathcal{H}$, and

$$\|u\|_{\mathscr{H}}^{2} = \iint_{0}^{T} u_{s} u_{r} \phi_{H}(s, r) \, ds \, dr,$$
 (14)

where

$$\phi_H(s,r) = \frac{\partial^2 R_H}{\partial s \partial r}(s,r) = H(2H-1)|s-r|^{2H-2} \ge 0,$$
 (15)

and, for $\varphi : [0, T]^2 \to \mathbb{R}$, we have

$$\|\varphi\|_{\mathcal{H}\otimes\mathcal{H}}^{2}$$

$$= \int_{[0,T]^{4}} \varphi(t,s) \varphi(t',s') \phi_{H}(t,t') \phi_{H}(s,s') dt ds dt' ds'.$$
(16)

We denote by $|\mathcal{H}|$ the subspace of \mathcal{H} , which is defined as the set of measurable functions f on [0, T] with

$$||f||_{|\mathcal{H}|}^2 := \iint_0^T |f(s)| |f(r)| \phi_H(s,r) \, ds \, dr < \infty.$$
 (17)

Note that, if $\varphi, \psi \in |\mathcal{H}|$, then

$$EB^{H}(\varphi)B^{H}(\psi) = \iint_{0}^{T} \varphi(s)\psi(r)\phi_{H}(s,r)\,ds\,dr. \tag{18}$$

It follows actually from Pipiras and Taqqu [14] that the space $|\mathcal{H}| \subset \mathcal{H}$ is a Banach space for the norm $\|\cdot\|_{|\mathcal{H}|}$. Moreover,

$$L^{2}([0,T]) \subset L^{1/H}([0,T]) \subset |\mathcal{H}| \subset \mathcal{H}. \tag{19}$$

If $u \in \mathbb{D}^{1,2}(|\mathcal{H}|)$, $u \in \text{Dom}(\delta^H)$, then we have (Nualart [4])

$$E\left(\delta^{H}\left(u\right)\right)^{2} \leq C_{H}\left(E\left\|u\right\|_{\left|\mathcal{H}\right|}^{2} + E\left\|D^{H}\left(u\right)\right\|_{\left|\mathcal{H}\left|\otimes\right|\mathcal{H}\right|}^{2}\right) \tag{20}$$

and if $\varphi : [0, T]^2 \to \mathbb{R}$, then

 $\|\varphi\|_{|\mathscr{H}|\otimes|\mathscr{H}|}^2$

$$= \int_{\left[0,T\right]^{4}} \left| \varphi\left(t,s\right) \right| \left| \varphi\left(t',s'\right) \right| \phi_{H}\left(t,t'\right) \phi_{H}\left(s,s'\right) dt ds dt' ds'. \tag{21}$$

As a consequence, we have

$$E(\delta^{H}(u))^{2} \leq C_{H}\left(E\|u\|_{L^{1/H}([0,T])}^{2} + E\|D^{H}(u)\|_{L^{1/H}([0,T]^{2})}^{2}\right). \tag{22}$$

For every $n \geq 1$, let \mathcal{H}_n be the nth Wiener chaos of B^H , that is, the closed linear subspace of $L^2(\Omega)$ generated by the random variables $\{H_n(B^H(h)), h \in \mathcal{H}, \|h\|_{\mathcal{H}} = 1\}$, where H_n is the nth Hermite polynomial. The mapping $I_n(h^{\otimes n}) = n!H_n(B^H(h))$ provides a linear isometry between the symmetric tensor product $\mathcal{H}^{\otimes n}$ (equipped with the modified norm $\|\cdot\|_{\mathcal{H}^{\otimes n}} = (1/\sqrt{n!})\|\cdot\|_{\mathcal{H}^{\otimes n}})$ and \mathcal{H}_n . For every $f,g\in\mathcal{H}^{\otimes n}$ the following multiplication formula holds

$$E(I_n(f)I_n(g)) = n!\langle f, g \rangle_{\mathscr{H}^{\otimes n}}.$$
 (23)

Let $f,g:[0,T]\to\mathbb{R}$ be Hölder continuous functions of orders $\alpha\in(0,1)$ and $\beta\in(0,1)$ with $\alpha+\beta>1$. Young proved that the Riemann-Stieltjes integral (so-called Young integral) $\int_0^T f_s dg_s$ exists. Moreover, if $\alpha=\beta\in(1/2,1)$ and $F:\mathbb{R}^2\to\mathbb{R}$ is a function of class \mathscr{C}^1 , the integrals $\int_0^1 (\partial F/\partial f)(f_u,g_u)df_u$ and $\int_0^1 (\partial F/\partial g)(f_u,g_u)dg_u$ exist in the Young sense and the following change of variables formula holds:

$$F(f_t, g_t) = F(f_0, g_0) + \int_0^t \frac{\partial F}{\partial f}(f_u, g_u) df_u + \int_0^t \frac{\partial F}{\partial g}(f_u, g_u) dg_u, \quad t \in [0, T].$$
(24)

As a consequence, if $H \in (1/2,1)$ and $(u_t,t\in[0,T])$ is a process with Hölder paths of order $\alpha<(1-H,1)$, the integral $\int_0^T u_s dB_s^H$ is well defined as Young integral. Suppose that, for any $t\in[0,T]$, $u_t\in\mathbb{D}^{1,2}(|\mathcal{H}|)$, and

$$\iint_{0}^{T} |D_{s}u_{t}| |t-s|^{2H-2} ds dt < \infty \quad \text{a.s.}$$
 (25)

Then, following from Alòs and Nualart [15], we have

$$\int_{0}^{t} u_{s} dB_{s}^{H} = \int_{0}^{t} u_{s} \delta^{H} B_{s}^{H} + H (2H - 1)$$

$$\times \iint_{0}^{t} D_{s} u_{r} |r - s|^{2H - 2} dr ds.$$
(26)

In particular, when φ is a nonrandom Hölder continuous function of order $\alpha \in (1 - H, 1)$, we have

$$\int_{0}^{t} \varphi_{s} dB_{s}^{H} = \int_{0}^{t} \varphi_{s} \delta^{H} B_{s}^{H} = B^{H} (\varphi). \tag{27}$$

In addition, for all $\varphi, \psi \in |\mathcal{H}|$,

$$E\left(\int_0^T \varphi_s dB_s^H \int_0^T \psi_s dB_s^H\right)$$

$$= H\left(2H - 1\right) \iint_0^T \varphi_u \psi_v |u - v|^{2H - 2} du \, dv.$$
(28)

3. Asymptotic Behavior of the Least Squares Estimator

Throughout this paper we assume $H \in (1/2, 1)$. We will study (1) driven by a fractional Brownian motion B^H with Hurst parameter H and $\alpha > 0$ being the unknown parameter to be estimated for discretely observed X. It is readily checked that we have the following explicit expression for X_t :

$$X_t = (T - t)^{\alpha} \int_0^t (T - s)^{-\alpha} dB_s^H, \quad 0 \le t < T,$$
 (29)

where the integral can be understood as Young integral. In order to study the asymptotic behavior of the least squares estimator, let us introduce the following processes:

$$A_t := \int_0^t (T - s)^{-\alpha} dB_s^H, \quad 0 \le t < T.$$
 (30)

Hence, we have

$$X_t = (T - t)^{\alpha} A_t, \quad 0 \le t < T.$$
 (31)

For simplicity, we assume that the notation $a_n \ge b_n$ means that there exists positive constants $C = C_{H,\alpha} > 0$ (depending only on H, α and its value may differ from line to line) so that

$$\sup_{n\geq 1} \frac{|a_n|}{|b_n|} < C < \infty. \tag{32}$$

We firstly give the following lemmas.

Lemma 1. Let $\alpha > 0$, 1/2 < H < 1. Then

$$\int_{0}^{T_{n}} \frac{X_{s}}{T - s} dB_{s}^{H} = \int_{0}^{T_{n}} \frac{X_{s}}{T - s} \delta^{H} B_{s}^{H} + \beta_{n}, \tag{33}$$

where

$$\beta_n = H (2H - 1) \int_0^{T_n} \int_0^r (T - r)^{\alpha - 1} (T - s)^{-\alpha} (r - s)^{2H - 2} ds dr,$$

$$\lim_{n\to\infty}\beta_n = HB(\alpha, 2H-1)T^{2H-1}.$$
(34)

Proof. By (26), we have

$$\int_{0}^{T_{n}} \frac{X_{s}}{T-s} dB_{s}^{H} = \int_{0}^{T_{n}} \frac{X_{s}}{T-s} \delta^{H} B_{s}^{H} + H (2H-1)$$

$$\times \iint_{0}^{T_{n}} D_{s}^{H} \frac{X_{r}}{T-r} |s-r|^{2H-2} dr ds$$

$$= \int_{0}^{T_{n}} \frac{X_{s}}{T-s} \delta^{H} B_{s}^{H} + H (2H-1)$$

$$\times \int_{0}^{T_{n}} \int_{0}^{r} (T-r)^{\alpha-1} (T-s)^{-\alpha} (r-s)^{2H-2} ds dr$$

$$= \int_{0}^{T_{n}} \frac{X_{s}}{T-s} \delta^{H} B_{s}^{H} + \beta_{n}.$$
(35)

On the other hand,

$$\lim_{n \to \infty} \beta_{n}$$

$$= H (2H - 1)$$

$$\times \lim_{n \to \infty} \int_{0}^{T_{n}} \int_{0}^{r} (T - r)^{\alpha - 1} (T - s)^{-\alpha} (r - s)^{2H - 2} ds dr$$

$$= H (2H - 1) \lim_{n \to \infty} \int_{T - T_{n}}^{T} \int_{r}^{T} r^{\alpha - 1} s^{-\alpha} (s - r)^{2H - 2} ds dr$$

$$= H (2H - 1) \lim_{n \to \infty} \int_{0}^{T_{n}} \int_{r}^{T_{n}} (T - T_{n} + r)^{\alpha - 1}$$

$$\times (T - T_{n} + s)^{-\alpha} (s - r)^{2H - 2} ds dr$$

$$= H (2H - 1) \int_{0}^{T} \int_{r}^{T} r^{\alpha - 1} s^{-\alpha} (s - r)^{2H - 2} ds dr$$

$$= H (2H - 1) \int_{0}^{T} s^{-\alpha} \int_{0}^{s} r^{\alpha - 1} (s - r)^{2H - 2} dr ds$$

$$= HB(\alpha, 2H - 1) T^{2H - 1}.$$
(36)

This completes the proof.

The following Lemma 2 comes from Lemma 3.2 of Es-Sebaiy and Nourdin [5].

Lemma 2. *Letting* $0 < \alpha < H$, 1/2 < H < 1, *one has*

$$E\left(\frac{X_{t}}{T-t}\right)^{2} \le \frac{H(2H-1)}{H-\alpha}B(1-\alpha,2H-1)(T-t)^{2\alpha-2}T^{2H-2\alpha},$$

$$0 \le t < T.$$
(37)

Lemma 3. Assume $1 - H < \alpha < H$, 1/2 < H < 1, and let $F_{T_n} = \int_0^{T_n} (X_t/(T-t)) \delta^H B_t^H$. Then

$$\lim_{n \to \infty} E\left(F_{T_n}^2\right)$$

$$= \frac{H^2(2H-1)^2 B(\alpha, 2H-1) B(1-\alpha, 2H-1)}{2(H+\alpha-1)(H-\alpha)} T^{4H-2}.$$
(38)

Proof. By the isometry property of the double stochastic integral I_2 , the variance of F_{T_n} is given by

$$E(F_{T_n}^2) = \frac{H^2(2H-1)^2}{2} I_{T_n},$$
(39)

where

$$I_{T_n} = \int_{[0,T_n]^4} (T - t_1)^{\alpha - 1} (T - s_1)^{-\alpha} (T - t_2)^{\alpha - 1} (T - s_2)^{-\alpha}$$

$$\times |s_1 - s_2|^{2H - 2} |t_1 - t_2|^{2H - 2} ds_1 ds_2 dt_1 dt_2.$$
(40)

Now, we study I_{T_n} , by setting

$$I_{1} = \int_{[0,T_{n}]^{2}} (T - s_{1})^{-\alpha} (T - s_{2})^{-\alpha} |s_{1} - s_{2}|^{2H-2} ds_{1} ds_{2},$$

$$I_{2} = \int_{[0,T_{n}]^{2}} (T - t_{1})^{\alpha-1} (T - t_{2})^{\alpha-1} |t_{1} - t_{2}|^{2H-2} dt_{1} dt_{2}.$$
(41)

We have $I_{T_n} = I_1 I_2$. By (17.40) of Es-Sebaiy and Nourdin [5], we have

$$I_{1} = \int_{[0,T_{n}]^{2}} (T - s_{1})^{-\alpha} (T - s_{2})^{-\alpha} |s_{1} - s_{2}|^{2H-2} ds_{1} ds_{2}$$

$$= \frac{B(1 - \alpha, 2H - 1)}{H - \alpha} T_{n}^{2H-2\alpha}$$

$$\longrightarrow \frac{B(1 - \alpha, 2H - 1)}{H - \alpha} T^{2H-2\alpha}, \quad n \longrightarrow \infty.$$
(42)

Similarly

$$I_2 \longrightarrow \frac{B(\alpha, 2H-1)}{H+\alpha-1} T^{2H+2\alpha-2}$$
. (43)

Thus, the proof is finished.

The following theorem gives the consistency of the least squares estimator $\widehat{\alpha}_n$ of α .

Theorem 4. Let $1/2 < \alpha < H < 1$. If $\Delta_n \to 0$, $T_n = n\Delta_n \to T$ as $n \to \infty$, and $T_n + \Delta_n = T$, then, one has

$$\widehat{\alpha}_n \stackrel{P}{\longrightarrow} \alpha, \quad n \longrightarrow \infty,$$
 (44)

where \xrightarrow{P} means convergence in probability.

Proof. By (4), we have

$$\widehat{\alpha}_{n} - \alpha = -\frac{(\alpha/n) \sum_{i=1}^{n} M_{i}}{(\alpha \Delta_{n}/n) \sum_{i=1}^{n} (X_{t_{i-1}}^{2}/(T - t_{i-1})^{2})}.$$
 (45)

Letting $0 < \varepsilon < 1$, we obtain

$$P\left(\left|\widehat{\alpha}_{n} - \alpha\right| > \varepsilon\right)$$

$$= P\left(\left|\frac{(\alpha/n)\sum_{i=1}^{n} M_{i}}{(\alpha\Delta_{n}/n)\sum_{i=1}^{n} \left(X_{t_{i-1}}^{2}/(T - t_{i-1})^{2}\right)}\right| > \varepsilon\right)$$

$$\leq P\left(\left|\frac{\alpha}{n}\sum_{i=1}^{n} M_{i}\right| > \varepsilon\left(1 - \varepsilon\right)\right)$$

$$+ P\left(\left|\frac{\alpha\Delta_{n}}{n}\sum_{i=1}^{n} \frac{X_{t_{i-1}}^{2}}{(T - t_{i-1})^{2}} - 1\right| > \varepsilon\right)$$

$$:= B_{1}\left(n\right) + B_{2}\left(n\right).$$
(46)

First, we considering the term $B_1(n)$, we have

$$B_{1}(n)$$

$$= P\left(\left|\frac{\alpha}{n}\sum_{i=1}^{n}M_{i}\right| > \varepsilon\left(1 - \varepsilon\right)\right)$$

$$\leq P\left(\left|\frac{\alpha}{n}\sum_{i=1}^{n}\left[M_{i} - \int_{t_{i-1}}^{t_{i}}\frac{X_{t_{i-1}}}{T - t_{i-1}}\delta^{H}B_{t}^{H}\right]\right| > \frac{1}{3}\varepsilon\left(1 - \varepsilon\right)\right)$$

$$+ P\left(\left|\frac{\alpha}{n}\sum_{i=1}^{n}\int_{t_{i-1}}^{t_{i}}\left(\frac{X_{t_{i-1}}}{T - t_{i-1}} - \frac{X_{t}}{T - t}\right)\delta^{H}B_{t}^{H}\right| > \frac{1}{3}\varepsilon\left(1 - \varepsilon\right)\right)$$

$$+ P\left(\left|\frac{\alpha}{n}\int_{0}^{T_{n}}\frac{X_{t}}{T - t}\delta^{H}B_{t}^{H}\right| > \frac{1}{3}\varepsilon\left(1 - \varepsilon\right)\right)$$

$$:= B_{1,1}(n) + B_{1,2}(n) + B_{1,3}(n). \tag{47}$$

For the term $B_{1,1}(n)$, using Lemma 2, we obtain

$$\begin{split} \sum_{i=1}^{n} E \left| \left[M_{i} - \int_{t_{i-1}}^{t_{i}} \frac{X_{t_{i-1}}}{T - t_{i-1}} \delta^{H} B_{t}^{H} \right] \right| \\ &\leq \alpha \sum_{i=1}^{n} \left(E \left(\frac{X_{t_{i-1}}}{T - t_{i-1}} \right)^{2} \right)^{1/2} \\ &\times \int_{t_{i-1}}^{t_{i}} \left(E \left(\frac{X_{t_{i-1}}}{T - t_{i-1}} - \frac{X_{t}}{T - t} \right)^{2} \right)^{1/2} dt \end{split}$$

So, we get

$$\frac{\alpha}{n} \sum_{i=1}^{n} E \left| \left[M_i - \int_{t_{i-1}}^{t_i} \frac{X_{t_{i-1}}}{T - t_{i-1}} \delta^H B_t^H \right] \right| \ge \Delta_n^{2\alpha - 1}. \tag{49}$$

Hence,

$$B_{1,1}(n) \ge \frac{\Delta_n^{2\alpha - 1}}{\varepsilon (1 - \varepsilon)}.$$
 (50)

For the term $B_{1,2}(n)$, it follows the fact that, for $0 \le t < T$,

$$\frac{X_{t_{i-1}}}{T - t_{i-1}} - \frac{X_t}{T - t} = -\left[\left((T - t)^{\alpha - 1} - (T - t_{i-1})^{\alpha - 1}\right)A_{t_{i-1}} + (T - t)^{\alpha - 1}\left(A_t - A_{t_{i-1}}\right)\right].$$
(51)

We have

$$E\left|\sum_{i=1}^{n} \int_{t_{i-1}}^{t_{i}} \left(\frac{X_{t_{i-1}}}{T - t_{i-1}} - \frac{X_{t}}{T - t}\right) \delta^{H} B_{t}^{H}\right|$$

$$\leq E\left|\sum_{i=1}^{n} \int_{t_{i-1}}^{t_{i}} \left((T - t)^{\alpha - 1} - \left(T - t_{i-1}\right)^{\alpha - 1}\right) A_{t_{i-1}} \delta^{H} B_{t}^{H}\right|$$

$$+ E\left|\sum_{i=1}^{n} \int_{t_{i-1}}^{t_{i}} (T - t)^{\alpha - 1} \left(A_{t} - A_{t_{i-1}}\right) \delta^{H} B_{t}^{H}\right|.$$
(52)

Using inequality (22) and $EA_t = 0$, $D_s^H A_t = (T - s)^{-\alpha} 1_{[0,t]}(s)$, we have

$$E\left|\sum_{i=1}^{n}\int_{t_{i-1}}^{t_{i}}\left((T-t)^{\alpha-1}-(T-t_{i-1})^{\alpha-1}\right)A_{t_{i-1}}\delta^{H}B_{t}^{H}\right|$$

$$=E\left|\int_{0}^{T_{n}}\sum_{i=1}^{n}\left((T-t)^{\alpha-1}-(T-t_{i-1})^{\alpha-1}\right)A_{t_{i-1}}1_{(t_{i-1},t_{i}]}(t)\delta^{H}B_{t}^{H}\right|$$

$$\leq \left(E\left|\int_{0}^{T_{n}}\sum_{i=1}^{n}\left((T-t)^{\alpha-1}-(T-t_{i-1})^{\alpha-1}\right)A_{t_{i-1}}1_{(t_{i-1},t_{i}]}(t)\delta^{H}B_{t}^{H}\right|^{2}\right)^{1/2}$$

$$\leq C_{H}\left(\int\int_{0}^{T_{n}}\left|\sum_{i=1}^{n}\left((T-t)^{\alpha-1}-(T-t_{i-1})^{\alpha-1}\right)A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}}A_{t_{i-1}$$

On the other hand,

$$\begin{split} E \left| \sum_{i=1}^{n} \int_{t_{i-1}}^{t_{i}} \left(T - t \right)^{\alpha - 1} \left(A_{t} - A_{t_{i-1}} \right) \delta^{H} B_{t}^{H} \right| \\ &= E \left| \int_{0}^{T_{n}} \sum_{i=1}^{n} \left(T - t \right)^{\alpha - 1} \left(A_{t} - A_{t_{i-1}} \right) 1_{(t_{i-1}, t_{i}]} \left(t \right) \delta^{H} B_{t}^{H} \right| \\ &\leq C_{H} \left(\iint_{0}^{T_{n}} \left| \sum_{i=1}^{n} \left(T - t \right)^{\alpha - 1} D_{s}^{H} \left(A_{t} - A_{t_{i-1}} \right) \right. \\ & \left. \times 1_{(t_{i-1}, t_{i}]} \left(t \right) \right|^{1/H} ds \, dt \right)^{H} \end{split}$$

$$\leq C_{H} \left(\iint_{0}^{T_{n}} \sum_{i=1}^{n} \left| (T-t)^{\alpha-1} D_{s}^{H} \left(A_{t} - A_{t_{i-1}} \right) \right|^{1/H} \right) \\
\times 1_{(t_{i-1},t_{i}]} (t) ds dt \right)^{H} \\
= C_{H} \left(\iint_{0}^{T_{n}} \sum_{i=1}^{n} \left((T-t)^{\alpha-1} (T-s)^{-\alpha} \right)^{H} 1_{[t_{i-1},t]} (s) \right) \\
\times 1_{(t_{i-1},t_{i}]} (t) ds dt \right)^{H} \\
= C_{H} \left(\sum_{i=1}^{n} \int_{t_{i-1}}^{t_{i}} (T-t)^{(\alpha-1)/H} dt \int_{t_{i-1}}^{t} (T-s)^{-\alpha/H} ds \right)^{H} \\
\leq C_{H} \left(\sum_{i=1}^{n} \int_{t_{i-1}}^{t_{i}} (T-t)^{(\alpha-1)/H} dt \int_{t_{i-1}}^{t} (T-t_{n})^{-\alpha/H} ds \right)^{H} \\
\leq C_{H} \left(n \Delta_{n}^{(2H-1)/H} \right)^{H} \leq C_{H} n \Delta_{n}^{2H-1}. \tag{54}$$

So, we get

$$E\left|\sum_{i=1}^{n} \int_{t_{i-1}}^{t_{i}} \left(\frac{X_{t_{i-1}}}{T - t_{i-1}} - \frac{X_{t}}{T - t}\right) \delta^{H} B_{t}^{H}\right| \ge n \Delta_{n}^{H + \alpha - 1}.$$
 (55)

Thus,

$$\frac{\alpha}{n}E\left|\sum_{i=1}^{n}\int_{t_{i-1}}^{t_{i}} \left(\frac{X_{t_{i-1}}}{T-t_{i-1}} - \frac{X_{t}}{T-t}\right) \delta^{H} B_{t}^{H}\right| \ge \Delta_{n}^{H+\alpha-1}.$$
 (56)

Hence

$$B_{1,2}(n) \trianglerighteq \frac{\Delta_n^{H+\alpha-1}}{\varepsilon(1-\varepsilon)}.$$
 (57)

For the term $B_{1,3}(n)$, by setting $F_{T_n} = \int_0^{T_n} (X_t/(T-t)) \delta^H B_t^H$ and by using Lemma 3, we get

$$B_{1,3}(n) = P\left(\left|\frac{\alpha}{n}\int_{0}^{T_{n}} \frac{X_{t}}{T - t} \delta^{H} B_{t}^{H}\right| > \frac{1}{3}\varepsilon(1 - \varepsilon)\right)$$

$$\leq \left[\frac{3\alpha}{\varepsilon(1 - \varepsilon)n}\right]^{2} E\left(F_{T_{n}}^{2}\right) \geq \frac{1}{\varepsilon^{2}(1 - \varepsilon)^{2}n^{2}}.$$
(58)

As a consequence,

$$B_{1}(n) \ge \frac{\Delta_{n}^{2\alpha-1}}{\varepsilon(1-\varepsilon)} + \frac{\Delta_{n}^{H+\alpha-1}}{\varepsilon(1-\varepsilon)} + \frac{1}{\varepsilon^{2}(1-\varepsilon)^{2}n^{2}}.$$
 (59)

Second, we estimate the term $B_2(n)$:

$$B_{2}(n)$$

$$= P\left(\left|\frac{\alpha\Delta_{n}}{n}\sum_{i=1}^{n}\left(\frac{X_{t_{i-1}}}{T - t_{i-1}}\right)^{2} - 1\right| > \varepsilon\right)$$

$$\leq P\left(\left|\frac{\alpha}{n}\sum_{i=1}^{n}\int_{t_{i-1}}^{t_{i}}\left[\left(\frac{X_{t_{i-1}}}{T - t_{i-1}}\right)^{2} - \left(\frac{X_{t}}{T - t}\right)^{2}\right]dt\right| > \varepsilon/2\right)$$

$$+ P\left(\left|\frac{\alpha}{n}\int_{0}^{T_{n}}\left(\frac{X_{t}}{T - t}\right)^{2}dt - 1\right| > \varepsilon/2\right)$$

$$:= B_{2,1}(n) + B_{2,2}(n). \tag{60}$$

We firstly consider $B_{2,1}(n)$, since

$$\begin{split} E\left|\frac{\alpha}{n}\sum_{i=1}^{n}\int_{t_{i-1}}^{t_{i}}\left[\left(\frac{X_{t_{i-1}}}{T-t_{i-1}}\right)^{2}-\left(\frac{X_{t}}{T-t}\right)^{2}\right]\right|dt \\ &\leq \frac{\alpha}{n}\sum_{i=1}^{n}\int_{t_{i-1}}^{t_{i}}E\left|\left(\frac{X_{t_{i-1}}}{T-t_{i-1}}\right)^{2}-\left(\frac{X_{t}}{T-t}\right)^{2}\right|dt \\ &\leq \frac{\alpha}{n}\sum_{i=1}^{n}\int_{t_{i-1}}^{t_{i}}\left(E\left(\frac{X_{t_{i-1}}}{T-t_{i-1}}\right)^{2}+E\left(\frac{X_{t}}{T-t}\right)^{2}\right)dt \\ &\leq \frac{\alpha}{n}\sum_{i=1}^{n}\int_{t_{i-1}}^{t_{i}}\left(E\left(\frac{X_{t_{i-1}}}{T-t_{i-1}}\right)^{2}+E\left(\frac{X_{t_{i}}}{T-t_{i}}\right)^{2}\right)dt \\ &\leq \frac{2\alpha}{n}\sum_{i=1}^{n}\Delta_{n}^{2\alpha-1} \trianglerighteq \Delta_{n}^{2\alpha-1}. \end{split}$$

By Markov inequality, we obtain

$$B_{2,1}(n) \ge \frac{\Delta_n^{2\alpha - 1}}{\varepsilon}.$$
 (62)

Now, we estimate the term $B_{2,2}(n)$. Applying the change of variable formula (24), we get

$$\frac{\alpha}{n} \int_0^{T_n} \left(\frac{X_t}{T-t}\right)^2 dt - 1 = \frac{1}{n(\alpha - (1/2))} \times \left(\frac{X_{T_n}}{2\Delta_n} - \int_0^{T_n} \frac{X_t}{T-t} \delta^H B_t^H - \beta_n\right).$$
(63)

Hence,

$$B_{2,2}(n) \le P\left(\left|\frac{X_{T_n}}{T_n(2\alpha - 1)}\right| > \frac{\varepsilon}{6}\right) + P\left(\left|\frac{1}{n(\alpha - (1/2))}\int_0^{T_n} \frac{X_t}{T - t}\delta B_t^H\right| > \frac{\varepsilon}{6}\right)$$

$$+ P\left(\left|\frac{\beta_n}{n(\alpha - (1/2))}\right| > \frac{\varepsilon}{6}\right).$$
(64)

By Markov inequality and Lemma 2, we obtain

$$B_{2,2}(n) \ge \frac{\Delta_n^{2\alpha}}{\varepsilon^2 T_n^2} + \frac{1}{\varepsilon n^2} + \frac{1}{\varepsilon n}.$$
 (65)

Therefore

$$B_{2}(n) \ge \frac{\Delta_{n}^{2\alpha-1}}{\varepsilon} + \frac{\Delta_{n}^{2\alpha}}{\varepsilon^{2}T_{n}^{2}} + \frac{1}{\varepsilon n^{2}} + \frac{1}{\varepsilon n} \le \frac{\Delta_{n}^{2\alpha-1}}{\varepsilon} + \frac{\Delta_{n}^{2\alpha}}{\varepsilon^{2}T_{n}^{2}} + \frac{1}{\varepsilon n}.$$
(66)

Combining (59) and (66), this completes the proof.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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