

The $m(q, \Delta)$ estimator for fBM

Let $X_t = \sigma B_t^H$, and set $SS_n^{(q)} := \frac{1}{n} \sum_{i=1}^n |X_{i\Delta} - X_{(i-1)\Delta}|^q$. Then

$$\mathbb{E}(SS_n^{(q)}) = \frac{1}{n} \mathbb{E}\left(\sum_{i=1}^n |X_{i\Delta} - X_{(i-1)\Delta}|^q\right) = \Delta^{qH} \frac{1}{n} \sum_{i=1}^n \mathbb{E}(|X_i - X_{i-1}|^q) = \sigma^q \mathbb{E}(|Z|^q) \Delta^{qH} = \sigma^q K_q \Delta^{qH} \quad (1)$$

where $\Delta = \Delta_n = \frac{1}{n}$, $K_q = \mathbb{E}(|Z|^q) = \frac{2^{q/2}}{\sqrt{\pi}} \Gamma(\frac{q+1}{2})$, (for $q > -1$) and $Z \sim N(0, 1)$. This naturally leads to the estimates $(\hat{H}_n, \hat{\sigma}_n)$ for (H, σ) defined by

$$SS_n^{(q)} = \hat{\sigma}_n^q K_q \Delta^{q\hat{H}_n}$$

if we have computed $SS_n^{(q)}$ for at least two Δ -values. Taking logs we see that

$$\log SS_n^{(q)} = q \log \hat{\sigma}_n + \log K_q + q\hat{H}_n \log \Delta$$

so we can perform **linear regression** on $\log SS_n^{(q)}$ vs $\log \Delta = \log \frac{1}{n}$ for a range of Δ -values (i.e. using a log-log plot, see plot overleaf). Then for the line of best fit, the **slope** will equal $q\hat{H}_n$ (q is chosen by you, e.g. $q = 1, 2, 2.5, 3$ etc), and the **intercept** at $\log \Delta = 0$ is $q \log \hat{\sigma}_n + \log K_q$, from which we can compute $\hat{\sigma}_n$ since K_q has an explicit formula above. This is the $m(q, \Delta)$ estimator discussed in [GJR18]. One can then also compute the **R^2 -statistic** for the regression (which measures how close the data is to the line of best fit), and try to estimate the **sample variance** of \hat{H}_n and $\hat{\sigma}_n$.

To approximate the effect of using **realized variance** with m subwindows to estimate V_t (as in Part 2 of the project), we can use the Central Limit Theorem approximation from FM02:

$$V_{i\Delta} = V_0 e^{\sigma B_{i\Delta}^H} \left(1 + \sqrt{\frac{2}{m}} \varepsilon_i\right)$$

where the ε_i 's here are i.i.d. $N(0, 1)$ (and independent of B^H), so (using that $\log(1+x) = x + O(x^2)$), we see that $\log V_{i\Delta} = \log V_0 + \sigma B_{i\Delta}^H + \sqrt{\frac{2}{m}} \varepsilon_i + O(\frac{1}{m}) = \log V_0 + X_{i\Delta} + \sqrt{\frac{2}{m}} \varepsilon_i + O(\frac{1}{m})$.

For convenience we now define $\tilde{X}_{i\Delta} = X_{i\Delta} + \sqrt{\frac{2}{m}} \varepsilon_i$. Then $\tilde{X}_{i\Delta} - \tilde{X}_{(i-1)\Delta} = X_{i\Delta} - X_{(i-1)\Delta} + \sqrt{\frac{2}{m}} (\varepsilon_i - \varepsilon_{(i-1)}) \sim N(0, \sigma^2 \Delta^{2H} + \frac{4}{m})$, and setting $\widetilde{SS}_n^{(2)} := \frac{1}{n} \sum_{i=1}^n |\tilde{X}_{i\Delta} - \tilde{X}_{(i-1)\Delta}|^2$, adding the effect of ε into the computation above we find that

$$\mathbb{E}(\widetilde{SS}_n^{(2)}) = \sigma^2 \Delta^{2H} + \frac{4}{m}$$

(since $K_q = 1$ for $q = 2$) so we now regress $\log(\widetilde{SS}_n^{(2)} - \frac{4}{m})$ vs $\log \Delta$, which provides a smart adjustment to \hat{H}_n . (this adjustment is made in

<https://colab.research.google.com/drive/1jJGf4bVWETJqWRIMZ6STjsJ9jINgEaPd#scrollTo=e9fn6ABHNf52>

The $m(q, \Delta)$ estimator for the RL process

If $X_t = \sigma Z_t^H$ where $Z_t^H = \sqrt{2H} \int_0^t (t-s)^{H-\frac{1}{2}} dW_s$ is an RL process, then for $q = 2$ and $H \in (0, \frac{1}{2})$ one can show that

$$\mathbb{E}(SS_n^{(2)}) = \frac{1}{n} \mathbb{E}\left(\sum_{i=1}^n |X_{i\Delta} - X_{(i-1)\Delta}|^2\right) = \sigma^q \Delta^{2H} \frac{1}{n} \sum_{i=1}^n \mathbb{E}(|Z_i^H - Z_{i-1}^H|^2) \sim \sigma^2 c_H \Delta^{2H}$$

as $n \rightarrow \infty$ where $c_H = -\frac{4H\Gamma(\frac{1}{2}+H)\Gamma(-2H)}{\Gamma(\frac{1}{2}-H)} > 0$. Hence for the regression we now consider

$$\log(SS_n^{(2)}) = 2 \log \hat{\sigma}_n + \log c_{\hat{H}} + 2\hat{H}_n \log \Delta$$

so now the intercept is $2 \log \hat{\sigma}_n + \log c_{\hat{H}}$, which leads to an adjusted estimate for $\hat{\sigma}_n$. This can also be used for driftless rough Heston model below since (modulo an unimportant constant) both processes have the same covariance.

Convergence of \hat{H}_n to H for the first task in Part 2, and asymptotic normality

Above we considered sums of the form

$$SS_n^{(q)} := \frac{1}{n} \sum_{j=1}^n |B_j^H - B_{j-1}^H|^q. \quad (2)$$

We cannot apply the SLLN to this since the RVs in the sum here are not i.i.d. However, since the increments process $X_j = B_j^H - B_{j-1}^H \sim N(0, 1)$ is stationary (in particular $X_j \sim N(0, 1)$ for all j) and moreover is known to be **ergodic**, which means that for any measurable function g with $\mathbb{E}(|g(X_1)|) < \infty$

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{j=1}^n g(X_j) = \mathbb{E}(g(X_1)) \quad \text{a.s.} \quad (3)$$

In general, a stationary Gaussian process Y is ergodic if its covariance function $R(k) \rightarrow 0$ as $k \rightarrow \infty$, which we verified in the fBM.pdf document. Hence we can apply the general ergodic property in (3) to show that $SS_n^{(q)}$ in (2) tends to the **non-random** limit $K_q := \mathbb{E}(|Z|^q)$ a.s. (where $Z \sim N(0, 1)$, see Homework 3); hence from the self-similarity of fBM

$$SS_n^{(q)} \xrightarrow{w} \frac{1}{n} n^{qH} \sum_{j=1}^n |B_{j/n}^H - B_{(j-1)/n}^H|^q$$

i.e. the right hand side tends weakly to the constant K_q as $n \rightarrow \infty$, which also implies convergence in probability.

Recall this also suggests the estimator of $\hat{H} = \hat{H}_n$ for H defined by the relation

$$K_q = \frac{1}{n} n^{q\hat{H}} \sum_{j=1}^n |B_{j/n}^H - B_{(j-1)/n}^H|^q = \frac{1}{n} n^{qH} \sum_{j=1}^n |B_{j/n}^H - B_{(j-1)/n}^H|^q \cdot n^{q(\hat{H}-H)}.$$

But from the discussion immediately before this, we know that $\frac{1}{n} n^{qH} \sum_{j=1}^n |B_{j/n}^H - B_{(j-1)/n}^H|^q$ tends to K_q in probability as $n \rightarrow \infty$, hence we must have that $n^{q(\hat{H}-H)} \rightarrow 1$ in probability as well, which implies that

$$q(\hat{H}_n - H) \log n \rightarrow 0$$

in probability (where we are now emphasizing the dependence of \hat{H} on n), which can only be true if $\hat{H}_n - H \rightarrow 0$ in probability (recall that \hat{H} depends on n).

Moreover, it can be shown that $\sqrt{n} \log n (\hat{H}_n - H)$ is asymptotically $N(0, 2\gamma)$ as $n \rightarrow \infty$, where

$$\gamma = \sum_{r=-\infty}^{\infty} (|r+1|^{2H} - 2|r|^{2H} + |r-1|^{2H})$$

(see code and histogram numerically verifying this at <https://colab.research.google.com/drive/18ISGhNSN9ybbcpJ1P0-0je>)

If a function X_t is $\frac{1}{q}$ Hölder continuous on $[0, T]$ i.e. $|X_t - X_s| \leq c|t - s|^{1/q}$ for some constant c , then it has finite q -variation. To see this, we just note that

$$\sup_{\mathcal{P}} \sum_{t_k} |X_{t_k} - X_{t_{k-1}}|^q \leq \sum_{t_k} |c(t_k - t_{k-1})^{\frac{1}{q}}|^q = c^q \sum_{t_k} |t_k - t_{k-1}| = c^q T < \infty \quad (4)$$

where \mathcal{P} is the set of partitions of $[0, T]$.

The Han-Schied [HS21] estimator for fBM

Let $X_t = \sigma B_t^H$ and let

$$\theta_{m,k} = 2^{\frac{m}{2}} (2X_{\frac{2k+1}{2^m}} - X_{\frac{k}{2^m}} - X_{\frac{k+1}{2^m}}) = -2^{\frac{m}{2}} (X_{\frac{2(k+1)}{2^m}} - 2X_{\frac{2k+1}{2^m}} + X_{\frac{2k}{2^m}})$$

(note the similarity of the second expression to a 2nd order finite difference estimate). Then (with some tedious algebra) using the formula for $R(s, t) = \mathbb{E}(B_s^H B_t^H)$, one can check that

$$\mathbb{E}(\theta_{m,k}^2) = \sigma^2 2^{m-2H(1+m)} (4 - 4^H). \quad (5)$$

Then setting $s_n^2 = \sum_{m=0}^{n-1} \sum_{k=0}^{2^m-1} \theta_{m,k}^2$, we see that $\mathbb{E}(s_n^2) = \sum_{m=0}^{n-1} 2^m \mathbb{E}(\theta_{m,k}^2)$ (since (5) does not depend on k) which simplifies to

$$\mathbb{E}(s_n^2) = \sigma^2 (4^{n(1-H)} - 1) \sim \sigma^2 4^{n(1-H)} = \sigma^2 2^{2n(1-H)} \quad (6)$$

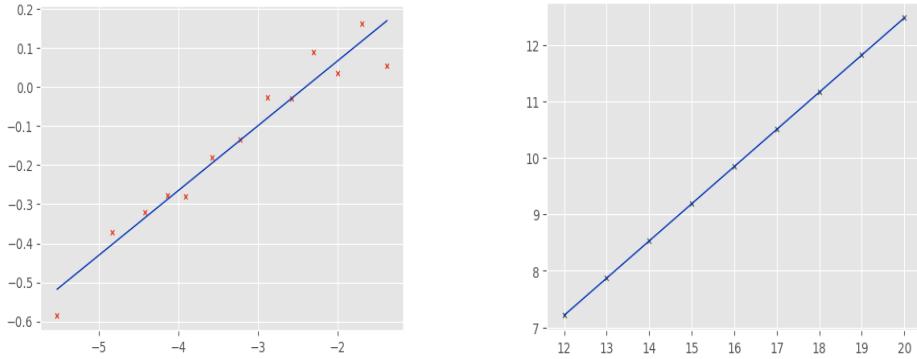


Figure 1: On the left, we see estimates of H for the SPX using the $m(q, \Delta)$ method for the SPX from 3rdJan22-15thJul24 for $q = 2$ for which $\hat{H} = 0.0830$ and $\hat{\sigma} = 1.221$ (see similar plots in [GJR18]). On the right we see the linear regression in (7) for the Han-Schied method ($\log s_n$ vs n) for a true fBM path with 2^{20} time points, for which $\hat{H} = 0.0508$, and $\hat{\sigma} = 1.010$.

as $n \rightarrow \infty$, which suggests an estimator \hat{H}_n defined by $s_n = \hat{\sigma}_n 2^{n(1-\hat{H}_n)}$ which (assuming $\hat{\sigma}_n = O(1)$ as $n \rightarrow \infty$) we can re-arrange as

$$\hat{H}_n = 1 - \frac{1}{n} \log_2 \left(\frac{s_n}{\hat{\sigma}_n} \right) = 1 - \frac{1}{n} \log_2 s_n + O\left(\frac{1}{n}\right)$$

where \log_2 denotes the base-2 logarithm, so (ignoring the $O(\frac{1}{n})$ remainder term), we recover the Han-Schied[HS21] estimator $\hat{H}_n = 1 - \frac{1}{n} \log_2 s_n$. Then

$$\begin{aligned} \mathbb{E}(\hat{H}_n) &= 1 - \frac{1}{n} \mathbb{E}(\log_2(s_n)) = 1 - \frac{1}{2n} \mathbb{E}(\log_2(s_n^2)) \geq 1 - \frac{1}{2n} \log_2 \mathbb{E}(s_n^2) = 1 - \frac{1}{2n} \log_2(\sigma^2(4^{n(1-H)} - 1)) \\ &\geq 1 - \frac{1}{2n} \log_2(\sigma^2(4^{n(1-H)})) \\ &= 1 - \frac{1}{2n} \log_2(\sigma^2) - \frac{1}{2n} \log_2(4^{n(1-H)}) \\ &= H - \frac{1}{n} \log_2 \sigma \end{aligned}$$

and the final line is $> H$ if $\sigma < 1$, so $\mathbb{E}(\hat{H}_n) > H$ if $\sigma < 1$.

Jointly estimating H and σ using [HS21]

If $X_t = \sigma B_t^H$, we can jointly estimate H and σ by performing linear regression since

$$\log s_n = \log \hat{\sigma}_n + n(1 - \hat{H}_n) \log 2 \tag{7}$$

but we now have to compute $\log s_n$ for a range of different n -values to get a line of best fit, for which the slope is $(1 - \hat{H}_n) \log 2$ and the intercept is $\log \hat{\sigma}_n$.

Proof of scale-invariance of the [HS21] SSE

Recall Definition 8.1 in [HS21]:

$$\lambda_n^s(x) := \operatorname{argmin}_{\lambda > 0} \sum_{k=n-m}^n \alpha_{n-k} (\hat{R}_k(\lambda x) - \hat{R}_{k-1}(\lambda x))^2 \tag{8}$$

¹ where $\hat{R}_n(x)$ is the basic [HS21] estimator at order n . Then we see that $\lambda_n^s(cx) = \frac{\lambda_n^s(x)}{c}$, so

$$\hat{R}_n(\lambda_n^s(cx) cx) = \hat{R}_n(\lambda_n^s(x) x).$$

But the right hand side here is the SSE $R_n^s(x) := \hat{R}_n(\lambda_n^s(x)x)$ applied to the path x , and the left hand side is the SSE applied to the scaled path cx . Hence the SSE is **scale-invariant**.

¹one can check the minimizer is unique here since the objective function is strictly convex

Corollary 8.4 in [HS21] shows if $X = \sigma B^H$, then all of their three SSEs (R_n^s , R_n^t and R_n^r) have error

$$|R_n^p - H| = O(2^{-n/2} \sqrt{\log n}) = O\left(\frac{1}{\sqrt{N}} \sqrt{\log_2 \log_2 N}\right) \quad (9)$$

since $N = 2^n$ so $2^{-n/2} = 2^{-\log_2 N/2} = \frac{1}{\sqrt{N}}$. Note this is slightly slower convergence than $O(\frac{1}{\sqrt{N}})$ because $\sqrt{\log_2 \log_2 N}$ tends to infinity (very slowly). The intuition behind the SSE is that we are trying to find the λ -value that minimizes the difference between consecutive iterates: $|\hat{R}_k(\lambda x) - \hat{R}_{k-1}(\lambda x)|$, since (loosely speaking) this difference being smaller implies that the sequence $R_k(\lambda x)$ is converging quicker. Note if $m = 0$ and $\alpha_0 = 1$, then (8) simplifies to

$$\lambda_n^s(x) := \operatorname{argmin}_{\lambda > 0} (\hat{R}_k(\lambda x) - \hat{R}_{k-1}(\lambda x))^2.$$

The driftless rough Heston model as a non-Gaussian process with the same covariance as the RL process

The driftless rough Heston model satisfies

$$V_t = V_0 + \nu \int_0^t (t-u)^{H-\frac{1}{2}} \sqrt{V_u} dW_u.$$

Then $\mathbb{E}(V_t) = V_0$, and V has covariance function:

$$\begin{aligned} \mathbb{E}((V_s - V_0)(V_t - V_0)) &= \nu^2 \mathbb{E}\left(\int_0^s (s-u)^{H-\frac{1}{2}} \sqrt{V_u} dW_u \cdot \int_0^t (t-r)^{H-\frac{1}{2}} \sqrt{V_r} dW_r\right) \\ &= \nu^2 \int_0^s (s-u)^{H-\frac{1}{2}} (t-u)^{H-\frac{1}{2}} \mathbb{E}(V_u) du \\ &= V_0 \nu^2 \int_0^s (s-u)^{H-\frac{1}{2}} (t-u)^{H-\frac{1}{2}} du = V_0 \nu^2 \bar{R}(s, t) \end{aligned}$$

for $0 \leq s \leq t$, where $\bar{R}(s, t)$ is the covariance function for the Riemann-Liouville (RL) process $Z_t = \int_0^t (t-u)^{H-\frac{1}{2}} dW_u$ used for the rough Bergomi model (note Z is a Gaussian process but V is not), but the explicit formula for $\bar{R}(s, t)$ is more complicated than the $R(s, t)$ formula for fBM.

The Mandelbrot-van Ness representation for fBM and relation to the RL process

We also have the **Mandelbrot-van Ness** representation for fBM:

$$W_t^H = c_H \left(\int_{-\infty}^0 ((t-s)^{H-\frac{1}{2}} - (-s)^{H-\frac{1}{2}}) dW_s + \int_0^t (t-s)^{H-\frac{1}{2}} dW_s \right) = c_H (A_t + Z_t)$$

for $t \geq 0$, in terms of an RL process Z (and note that A_t is known at time zero for all $t \geq 0$), and $c_H = \left(\frac{2H\Gamma(\frac{3}{2}-H)}{\Gamma(H+\frac{1}{2})\Gamma(2-2H)}\right)^{\frac{1}{2}}$. Note also that A_t and Z_t are independent.

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