

# Long Memory

Taro Kanatani  
Graduate School of Economics, Kyoto University

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## Abstract

We survey the continuous and discrete time long memory SV models.

## 1 Long memory in continuous time SV

### 1.1 Fractional BM

$$x_t = \int_0^t a(t-s)dW_s \quad (1.1)$$

$$y_t = \int_{-\infty}^t a(t-s)dW_s \quad (1.2)$$

where (1.2) is the stationary process and  $\int_0^\infty a^2(t)dt < +\infty$ . Then  $x_t = y_t$  in quadratic mean.

**Definition 1** *If  $a(t) = t^\alpha \tilde{a}(t)/\Gamma(1+\alpha)$  for  $|\alpha| < 1/2$  where  $\tilde{a}$  is continuously differentiable on  $[0, T]$ , then (1.1) and (1.2) called fractional processes.*

Fractional processes can also written by

$$x_t = \int_0^t c(t-s)dW_{\alpha s}, \quad W_{\alpha s} = \int_0^s \frac{(s-u)^\alpha}{\Gamma(1+\alpha)} dW_u$$

where,  $W_\alpha$  is the so-called fractional BM of order  $\alpha$ .

- The relation between  $a$  and  $c$  is one to one.
- $W_\alpha$  is not semi-martingale (see e.g.[Rog97]) but stochastic integration w.r.t  $W_\alpha$  can be defined.
- The processes are long memory if

$$\lim_{t \rightarrow \infty} t\tilde{a}(t) = a(\infty), \quad 0 < \alpha < \frac{1}{2} \text{ and } 0 < a(\infty) < +\infty.$$

**Example 1**

$$dx_t = -kx_t dt + \sigma dW_{\alpha t}, \quad W_{\alpha t} = \int_0^t \frac{(t-s)^\alpha}{\Gamma(1+\alpha)} dW_s, \quad x_0 = 0, \quad 0 < \alpha < \frac{1}{2}$$

has a solution of

$$x_t = \int_0^t \frac{(t-s)^\alpha}{\Gamma(1+\alpha)} dx_s^{(\alpha)},$$

$$x_t^{(\alpha)} = \int_0^t e^{-k(t-s)} \sigma dW_s.$$

- $x_t^{(\alpha)}$  is the derivative of order  $\alpha$  of  $x_t$ . See the Appendix A.
- $x_t^{(\alpha)}$  is a solution of the linear SDE:  $dx_t^{(\alpha)} = -kx_t^{(\alpha)} dt + \sigma dW_t$ .<sup>1</sup>

**1.2 Fractional SV**

$$\frac{dS_t}{S_t} = \sigma_t dW_t \tag{1.3}$$

$$d \log \sigma_t = -k \log \sigma_t dt + \gamma dW_{\alpha t} \tag{1.4}$$

where  $k > 0$  and  $0 \leq \alpha < 1/2$ .

- The fractional exponent  $\alpha$  provides some degree of freedom in order of regularity of the volatility process; the greater  $\alpha$ , the smoother the path of volatility process.
- The volatility process itself (not only its logarithm) has hyperbolic decay of the correlogram.
- The persistence of volatility shocks yields leptokurtic features for returns. It vanishes with temporal aggregation at slow hyperbolic rate of decay.<sup>2</sup>

**1.3 Filtering and discrete time approximations**

By Example 1, the solution of (1.4) is given by

$$\log \sigma_t = \int_0^t \frac{(t-s)^\alpha}{\Gamma(1+\alpha)} d \log \sigma_s^{(\alpha)} \tag{1.5}$$

$$\log \sigma_s^{(\alpha)} = \int_0^s e^{-k(s-u)} \sigma dW_u \tag{1.6}$$

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<sup>1</sup>A linear SDE:

$$dz_t = -kz_t dt + \sigma dW_t$$

has a solution of

$$z_t = z_0 \int_0^t e^{-k(t-s)} \sigma dW_s.$$

<sup>2</sup>With usual CARCH or SV models, it vanish at an exponential rate (see [DN93] and [DW96] for these issues in short memory case).

where  $\log \sigma_s^{(\alpha)}$  follows the O-U process:  $d \log \sigma_s^{(\alpha)} = -k \log \sigma_s^{(\alpha)} dt + \gamma dW_t$ . To discretize (1.5), divide  $[0, t]$  at time points  $j/n$ ,  $j = 0, 1, \dots, [nt]$ . First discretize (1.6) as

$$(1 - \rho L) \log \sigma_{j/n}^{(\alpha)} = u_{i/n}$$

where  $\rho = \exp(-k/n)$  and  $u_{i/n}$  is the associated innovations process.

$$\begin{aligned} \log \sigma_{j/n} &\approx \sum_{i=1}^j \frac{(j - (i - 1))^\alpha}{n^\alpha \Gamma(1 + \alpha)} \Delta \log \sigma_{i/n}^{(\alpha)} \\ &= \left[ \sum_{i=0}^{j-1} \frac{(i + 1)^\alpha - i^\alpha}{n^\alpha \Gamma(1 + \alpha)} L^i \right] \log \sigma_{i/n}^{(\alpha)} \\ &= \left[ \sum_{i=0}^{j-1} \frac{(i + 1)^\alpha - i^\alpha}{n^\alpha \Gamma(1 + \alpha)} L^i \right] (1 - \rho L)^{-1} u_{i/n} \end{aligned}$$

**long memory filter**  $\left[ \sum_{i=0}^{j-1} \frac{(i+1)^\alpha - i^\alpha}{n^\alpha \Gamma(1+\alpha)} L^i \right]$

**short memory filter**  $(1 - \rho L)^{-1}$

## 2 Long memory in discrete time models

(1) FIGARCH (2) FIEGARCH (3) Long-memory SV

### 2.0.1 Long-memory SV

$$h_t = (1 - L)^{-d} \eta_t, \quad \eta_t \sim NID(0, \sigma_\eta^2)$$

where  $h_t \equiv \log \sigma_t^2$ .

$d = 0$	white noise
$-1 < d < 0$	stationary intermediate-memory process
$0 < d < 1/2$	stationary long-memory process
$d = 1$	random walk

## 3 Stylized facts about long memory

### A Fractional Calculus

Denote the  $n$ th derivative  $D^n$  and the  $n$ -fold integral  $D^{-n}$ . Then

$$D^{-1} f(t) = \int_0^t f(x) dx$$

Now if

$$D^{-n} f(t) = \frac{1}{(n-1)!} \int_0^t (t-x)^{n-1} f(x) dx \quad (\text{A.1})$$

is true for  $n$ , then

$$\begin{aligned} D^{-(n+1)} f(t) &= D^{-1} \left[ \frac{1}{(n-1)!} \int_0^t (t-x)^{n-1} f(x) dx \right] \\ &= \int_0^t \left[ \frac{1}{(n-1)!} \int_0^s (s-x)^{n-1} f(x) dx \right] ds \\ &= \frac{1}{(n-1)!} \int_0^t \int_0^s (s-x)^{n-1} f(x) dx ds \\ &= \frac{1}{(n-1)!} \int_0^t \int_0^x (s-x)^{n-1} f(x) ds dx \\ &= \frac{1}{n!} \int_0^t (t-x)^n f(x) dx \end{aligned}$$

But (A.1) is true for  $n = 1$ , so it is also true for all  $n$  by induction. The fractional integration can be defined by

$$D^{-\alpha} f(t) = \frac{1}{\Gamma(\alpha)} \int_0^t (t-x)^{\alpha-1} f(x) dx.$$

## References

- [DN93] Feike C. Drost and Theo E. Nijman, *Temporal aggregation of GARCH processes*, *Econometrica* **61** (1993), 909–927.
- [DW96] Feike C. Drost and Bas J.M. Werker, *Closing the GARCH gaps: Continuous time GARCH modeling*, *Journal of Econometrics* **74** (1996), 31–57.
- [Rog97] L. C. G. Rogers, *Arbitrage with fractional brownian motion*, *Mathematical Finance* **7** (1997), 95–105.