

# Estimation of pure-jump stable Cox-Ingersoll-Ross processes from high-frequency observations

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# Plan

- Parametric estimation of pure-jump stable CIR process : overview
- Moments estimates
- Joint estimation
- Implementation
- Python simulations



## Pure-jump stable CIR process

$$dX_t = (a - bX_t)dt + \delta X_t^{1/\alpha} dL_t^\alpha, \quad t \geq 0 \quad x_0 \geq 0$$

$(L_t^\alpha)$  non-symmetric pure-jump Lévy process, strictly  $\alpha$ -stable, with triplet  $(0, 0, F^\alpha)$  and representation

$$L_t^\alpha = \int_0^t \int z \tilde{\mu}(ds, dz),$$

where  $\tilde{\mu} = \mu - \bar{\mu}$  is a compensated Poisson random measure with compensator

$$\bar{\mu}(dt, dz) = dt F^\alpha(dz)$$

where the Lévy measure is given by

$$F^\alpha(dz) = \frac{c_\alpha}{z^{1+\alpha}} \mathbf{1}_{\mathbb{R}_+^*}(z) dz, \quad 1 < \alpha < 2.$$

Self similarity :  $L_t \stackrel{\mathcal{L}}{=} t^{1/\alpha} L_1$ .

The characteristic function is

$$\mathbb{E}(e^{izL_1^\alpha}) = \exp\left(-|z|^\alpha \left(1 - i \tan \frac{\pi\alpha}{2} \operatorname{sgn}(z)\right)\right).$$



$$dX_t = (a - bX_t)dt + \delta X_t^{1/\alpha} dL_t^\alpha, \quad t \geq 0 \quad x_0 \geq 0$$

- Existence and uniqueness of a strong solution such that

$$\mathbb{P}(X_t \geq 0, \forall t \geq 0) = 1$$

if  $a \geq 0, b \in \mathbb{R}, \delta \geq 0$ .

- The solution satisfies

$$\mathbb{P}(X_t > 0, \forall t \geq 0) = 1$$

if  $a > 0, b \in \mathbb{R}, \delta > 0$ .

*Kawazu-Watanabe (71), Fu-Li (10), Jiao-Ma-Scotti (18)*

## Parametric estimation : overview

- Small noise and pure-jump stable process

$$dX_t = (a - bX_t)dt + \varepsilon \delta X_{t-}^{1/\alpha} dL_t^\alpha, \quad t \geq 0, \quad x_0 > 0$$

$\alpha \in (1, 2)$  known

Estimation of  $(a, b, \delta)$

Observations :  $(X_{i\Delta_n})_{i \in \{1, \dots, n\}}$ ,  $\Delta_n \rightarrow 0$ ,  $n\Delta_n = T$  fixed,  $(T = 1)$

Maximising an approximation of the likelihood function (depends on  $\alpha$ )

Consistency and asymptotic normality of estimators as  $n \rightarrow \infty$  and  $\varepsilon \rightarrow 0$   
(with  $\liminf \varepsilon n^{1-1/\alpha} > 0$ )

Ma-Yang (14), Yang (17)



- Fixed step-size observations, long-time behavior

$$dX_t = (a - bX_t)dt + \delta X_{t-}^{1/\alpha} dL_t^\alpha, \quad t \geq 0, \quad x_0 > 0$$

Estimation of  $(a, b)$ , assuming  $b > 0$

Observations :  $(X_{i\Delta})_{i \in \{1, \dots, n\}}$ ,  $\Delta$  fixed and  $n \rightarrow \infty$

$(X_t)$  is geometrically ergodic. Explicit least squares estimators of  $(a, b)$  (independent of  $\alpha$  and  $\delta$ ) based on the equation satisfied by  $e^{bt} X_t$

Consistency if  $\alpha \in (1, 2)$  and rate of convergence  $n^{(\alpha-1)/\alpha^2}$  if

$$\alpha \in \left(1, \frac{1+\sqrt{5}}{2}\right)$$

*Li-Ma (15)*

## Moment estimates

We consider a pure-jump stable CIR process

$$dX_t = (a - bX_t)dt + \delta X_{t-}^{1/\alpha} dL_t^\alpha, \quad t \geq 0, \quad x_0 > 0$$

with  $a > 0$ ,  $b \in \mathbb{R}$ ,  $\delta > 0$ ,  $\alpha \in (1, 2)$

### Proposition (B. Clément (23))

We have

①  $\forall p \in (0, \alpha)$

$$\mathbb{E}_{|\mathcal{F}_s} \left( \sup_{s \leq u \leq t} X_u^p \right) \leq C_{p,t-s} (1 + X_s^p)$$

②  $\forall p > 0$

$$\sup_{t \in [0,1]} \mathbb{E} \left( \frac{1}{X_t^p} \right) < +\infty$$

2. Proof based on the expression of the Laplace transform of a CBI process.

## Approximation results

### Proposition (B. Clément (23))

①  $\forall p \in (0, \alpha)$

$$\mathbb{E}_{|\mathcal{F}_{\frac{i-1}{n}}} \left( \sup_{t \in [\frac{i-1}{n}, \frac{i}{n}]} \left| \int_{\frac{i-1}{n}}^t X_{s-}^{1/\alpha} dL_s^\alpha \right|^p \right) \leq \frac{C_p}{n^{p/\alpha}} (1 + X_{\frac{i-1}{n}}^{p/\alpha})$$

②  $\forall p \in (0, \alpha)$

$$\mathbb{E}_{|\mathcal{F}_{\frac{i-1}{n}}} \left( \sup_{t \in [\frac{i-1}{n}, \frac{i}{n}]} |X_t - X_{\frac{i-1}{n}}|^p \right) \leq \frac{C_p}{n^{p/\alpha}} (1 + X_{\frac{i-1}{n}}^p)$$

③  $\forall p \in (0, \alpha)$

$$\mathbb{E}_{|\mathcal{F}_{\frac{i-1}{n}}} \left( \left| \int_{\frac{i-1}{n}}^{\frac{i}{n}} (X_{s-}^{1/\alpha} - X_{\frac{i-1}{n}}^{1/\alpha}) dL_s^\alpha \right|^p \right) \leq \frac{C_p}{n^{2p/\alpha}} \left( 1 + X_{\frac{i-1}{n}}^p + \frac{1}{X_{\frac{i-1}{n}}^p} \right)$$



## Results of efficiency in high-frequency setting on a toy model

- Masuda (06), Brouste-Masuda (18) LAN property for  $(a, \delta, \alpha)$

$$X_t = x_0 + at + \delta S_t^\alpha$$

$S_t^\alpha$  : symmetric  $\alpha$ -stable process

- Diagonal rate in estimating  $\theta = (a, \delta, \alpha)$

$$u_n = \begin{pmatrix} \frac{1}{n^{1/\alpha-1/2}} & 0 & 0 \\ 0 & \frac{1}{\sqrt{n}} & 0 \\ 0 & 0 & \frac{1}{\sqrt{n} \log(n)} \end{pmatrix}$$

LAN property with **singular information matrix** (Masuda (06))

$$I(a, \delta, \alpha) = \begin{pmatrix} \mathbb{E}h_\alpha^2(S_1^\alpha)/\delta^2 & 0 & 0 \\ 0 & \mathbb{E}k_\alpha^2(S_1^\alpha)/\delta^2 & \mathbb{E}k_\alpha^2(S_1^\alpha)/\delta\alpha^2 \\ 0 & \mathbb{E}k_\alpha^2(S_1^\alpha)/\delta\alpha^2 & \mathbb{E}k_\alpha^2(S_1^\alpha)/\alpha^4 \end{pmatrix}$$

with  $h_\alpha = \varphi'_\alpha/\varphi_\alpha$  and  $k_\alpha(z) = 1 + zh_\alpha(z)$ .

(extension to  $L_t^\alpha : l_{2,1} = \mathbb{E}h_\alpha k_\alpha(L_1^\alpha)/\delta^2$ ,  $l_{3,1} = \mathbb{E}h_\alpha k_\alpha(L_1^\alpha)/\delta\alpha^2$ )

*Brouste-Masuda (18)*

- Non diagonal rate in estimating  $\theta = (a, \delta, \alpha)$

$$u_n = \begin{pmatrix} \frac{1}{n^{1/\alpha-1/2}} & 0 \\ 0 & \frac{1}{\sqrt{n}} v_n \end{pmatrix}, \quad v_n = \begin{pmatrix} v_n^{1,1} & v_n^{1,2} \\ v_n^{2,1} & v_n^{2,2} \end{pmatrix}$$

Assuming

$$\begin{pmatrix} \frac{1}{\delta} & \frac{\log n}{\alpha^2} \\ 0 & 1 \end{pmatrix} \times v_n \rightarrow \bar{v}$$

where  $\bar{v}$  is non singular.

Then the LAN property holds with **non-singular information** (extension to  $L_t^\alpha$ , the information is not bloc diagonal)

$$\bar{I}(a, \delta, \alpha) = \begin{pmatrix} \frac{1}{\delta^2} \mathbb{E} h_\alpha^2(S_1^\alpha) & 0 \\ 0 & \bar{v}^T \begin{pmatrix} \mathbb{E} k_\alpha^2(S_1^\alpha) & -\mathbb{E}(k_\alpha f_\alpha)(S_1^\alpha) \\ -\mathbb{E}(k_\alpha f_\alpha)(S_1^\alpha) & \mathbb{E} f_\alpha^2(S_1^\alpha) \end{pmatrix} \bar{v} \end{pmatrix}$$

with  $f_\alpha = \partial_\alpha \varphi_\alpha / \varphi_\alpha$ .

We lose  $\log(n)$  in estimating simultaneously  $(\delta, \alpha)$  :

Rate for  $\delta$  :  $\sqrt{n}/\log(n)$ , Rate for  $\alpha$  :  $\sqrt{n}$

## Joint estimation of $\theta = (a, b, \delta, \alpha)$ for the pure-jump stable CIR process

- Observations :  $(X_{\frac{i}{n}})_{i \in \{0, \dots, n\}}$  where  $(X_t)_{t \in [0, 1]}$  is a pure-jump stable CIR process for the parameter value  $\theta_0 \in (0, \infty) \times \mathbb{R} \times (0, \infty) \times (1, 2) = \Theta$
- Estimating functions method based on an approximation of the conditional distribution of  $X_{\frac{i}{n}}$  given  $X_{\frac{i-1}{n}}$

$$X_{\frac{i}{n}} \approx X_{\frac{i-1}{n}} + \frac{a_0}{n} - \frac{b_0}{n} X_{\frac{i-1}{n}} + \delta_0 X_{\frac{i-1}{n}}^{1/\alpha_0} (L_{\frac{i}{n}}^{\alpha_0} - L_{\frac{i-1}{n}}^{\alpha_0}).$$

$\hat{\theta}_n$  solution of  $G_n(\theta) = -\nabla_{\theta} L_n(\theta) = 0$  on  $\Theta$

$$L_n(\theta) = \sum_{i=1}^n \log \left[ \frac{n^{1/\alpha}}{\delta X_{\frac{i-1}{n}}^{1/\alpha}} \varphi_{\alpha} \left( n^{1/\alpha} \frac{X_{\frac{i}{n}} - X_{\frac{i-1}{n}} - \frac{a}{n} + \frac{b}{n} X_{\frac{i-1}{n}}}{\delta X_{\frac{i-1}{n}}^{1/\alpha}} \right) \right]$$

where  $\varphi_{\alpha}$  is the density of  $L_1^{\alpha}$ .

*Clément-Gloter (19) (20) : SDE with Lipschitz coefficients, driven by symmetric locally stable process*

## Existence of the estimator

### Theorem (B. Clément (23))

Let  $u_n$  be the previous non-diagonal rate (*Brouste-Masuda (18)*).

There exists a sequence  $(\hat{\theta}_n)$ , such that  $\lim_n \mathbb{P}(G_n(\hat{\theta}_n) = 0) = 1$ , that converges in probability to  $\theta_0$ .

Moreover we have the stable convergence in law with respect to  $\sigma(L_s^{\alpha_0}, s \leq 1)$

$$u_n^{-1} \left( \hat{\theta}_n - \theta_0 \right) \xrightarrow{\mathcal{L}_s} I(\theta_0)^{-1/2} \mathcal{N},$$

where  $\mathcal{N}$  is a standard Gaussian variable independent of  $I(\theta_0)$ , where  $I(\theta_0)$  is a symmetric non-negative and non-singular matrix.

- If  $\alpha_0$  is known (or  $\delta_0$  known), we obtain a similar result with the diagonal rate

$$u_n = \begin{pmatrix} \frac{1}{n^{1/\alpha-1/2}} & 0 \\ 0 & \frac{1}{\sqrt{n}} \end{pmatrix}, \quad u_n = \begin{pmatrix} \frac{1}{n^{1/\alpha-1/2}} & 0 \\ 0 & \frac{1}{\log n \sqrt{n}} \end{pmatrix}$$

and non-singular information.

The proof is based on the following convergences :

- ① For  $\eta > 0$ , we set  $W_n^{(\eta)} = \left\{ (\delta, \alpha); \left\| w_n^{-1} \begin{pmatrix} \delta - \delta_0 \\ \alpha - \alpha_0 \end{pmatrix} \right\| \leq \eta \right\}$  with  $\forall q > 0, \ln(n)^q w_n \rightarrow 0$ .

For smooth functions  $f$  and  $h_\alpha$  and  $K \subset \mathbb{R}_+^* \times \mathbb{R}$  a compact set, we have  $\forall q > 0$

$$\sup_{A \times W_n^{(\eta)}} \ln(n)^q \left| \frac{1}{n} \sum_{i=1}^n f(X_{\frac{i-1}{n}}, \delta, \alpha) h_\alpha(z_n^i(\theta)) - \int_0^1 f(X_t, \delta_0, \alpha_0) dt \mathbb{E} h_{\alpha_0}(L_1^{\alpha_0}) \right| \xrightarrow{\mathbb{P}} 0$$

where 
$$z_n^i(\theta) = n^{1/\alpha} \frac{X_i - X_{\frac{i-1}{n}} - \frac{a}{n} + \frac{b}{n} X_{\frac{i-1}{n}}}{\delta X_{\frac{i-1}{n}}^{1/\alpha}} \approx L_1^{\alpha_0}.$$

- ② For  $F = (f_{i,j})$  and  $H = (h_i)$ , we have the stable convergence in law

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n F(X_{\frac{i-1}{n}}) H(z_n^i(\theta_0)) \rightarrow \Sigma^{1/2} \mathcal{N}$$

with  $\mathcal{N}$  standard gaussian independent of  $\Sigma$

$$\Sigma_{i,j} = \int_0^1 F(X_t) \tilde{\Sigma} F(X_t)^T ds, \quad \tilde{\Sigma}_{i,j} = \mathbb{E}(h_i h_j)(L_1^{\alpha_0}).$$

## Sketch of proof

We define  $J_n(\theta) = \nabla_{\theta} G_n(\theta)$  ( $G_n$  is an approximation of the score function).

We can prove uniform local convergence in probability and stable convergence in law

- 1 For all compact  $A \subset (0, +\infty) \times (1, 2)$

$$\sup_{(a,b) \in A, (\delta, \alpha) \in W_n^{(\eta)}} \|u_n^T J_n(\theta) u_n - I(\theta_0)\| \rightarrow 0$$

- 2  $u_n^T G_n(\theta_0)$  stably converges in law to  $I(\theta_0)^{1/2} \mathcal{N}$

where  $I(\theta_0)$  is a symmetric non-negative and **non-singular** matrix depending on  $(X_t)_{t \in [0,1]}$  and  $\mathcal{N}$  is a standard Gaussian variable independent of  $I(\theta_0)$ .

Information for the estimation of  $(a, \delta, \alpha)$

$$I(a, \delta, \alpha) = \begin{pmatrix} \frac{1}{\delta^2} \mathbb{E} h_\alpha^2(L_1^\alpha) \int_0^1 \frac{ds}{X_s^{1/\alpha}} & \text{Sym.} \\ \bar{\mathbf{v}}^T I^{2,1} & \bar{\mathbf{v}}^T I^{2,2} \bar{\mathbf{v}} \end{pmatrix}$$

$$I^{2,1} = \begin{pmatrix} \frac{1}{\delta} \mathbb{E}(h_\alpha k_\alpha)(L_1^\alpha) \int_0^1 \frac{ds}{X_s^{1/\alpha}} \\ -\frac{1}{\delta \alpha^2} \mathbb{E}(h_\alpha k_\alpha)(L_1^\alpha) \int_0^1 \frac{\log(X_s)}{X_s^{1/\alpha}} ds - \frac{1}{\delta} \mathbb{E}(f_\alpha h_\alpha)(L_1^\alpha) \int_0^1 \frac{ds}{X_s^{1/\alpha}} \end{pmatrix}$$

$$I^{2,2} = \begin{pmatrix} \mathbb{E} k_\alpha^2(L_1^\alpha) & -\frac{1}{\alpha^2} \mathbb{E} k_\alpha^2(L_1^\alpha) \int_0^1 \log(X_s) ds - \mathbb{E}(k_\alpha f_\alpha)(L_1^\alpha) \\ \text{Sym.} & \mathbb{E} f_\alpha^2(L_1^\alpha) + \frac{1}{\alpha^4} \mathbb{E} k_\alpha^2(L_1^\alpha) \int_0^1 \log(X_s)^2 ds + \frac{2}{\alpha^2} \mathbb{E}(f_\alpha k_\alpha)(L_1^\alpha) \int_0^1 \log(X_s) ds \end{pmatrix}$$

$$(x \ z \ t) I \begin{pmatrix} x \\ z \\ t \end{pmatrix} = \int_0^1 \int ds \phi(u) du \left( \frac{1}{\delta} \frac{1}{X_s^{1/\alpha}} h_\alpha(u) x + k_\alpha(u) z - \left( f_\alpha(u) + \frac{\ln(X_s)}{\alpha} k_\alpha(u) \right) t \right)^2$$

## Implementation

- The previous result states existence of a consistent estimator with optimal rate of convergence but there might be other sequences that solve the estimating equation that are not consistent.
- Uniqueness of the drift estimator is obtained if  $\delta_0$  and  $\alpha_0$  are known or if we have preliminary estimators  $\tilde{\delta}_n$  and  $\tilde{\alpha}_n$ .
- We will give preliminary estimators  $\tilde{\delta}_n$  and  $\tilde{\alpha}_n$ .
- Using these estimators, we obtain a preliminary estimator  $(\tilde{a}_n, \tilde{b}_n, \tilde{\delta}_n, \tilde{\alpha}_n)$  that we will correct using a one-step procedure.



## Drift estimator

### Theorem (B. Clément (23))

Let  $G_{n,d}$  be the approximation of the score function restricted to the drift parameters  $(a, b)$

$$G_{n,d}(a, b) = -\nabla_{(a,b)} L_n(a, b, \tilde{\delta}_n, \tilde{\alpha}_n).$$

We assume that  $(a_0, b_0) \in \text{Int}(\Theta)$  for a compact set  $\Theta \subset (0, +\infty) \times \mathbb{R}$  and that  $\frac{\sqrt{n}}{\log(n)}(\tilde{\delta}_n - \delta_0)$  and  $\frac{\sqrt{n}}{\log(n)}(\tilde{\alpha}_n - \alpha_0)$  are tight.

Then any sequence  $(\tilde{a}_n, \tilde{b}_n)$  that solves  $G_{n,d}(\tilde{a}_n, \tilde{b}_n) = 0$  converges in probability to  $(a_0, b_0)$  and this sequence is unique.

Moreover the sequence  $\frac{n^{1/\alpha_0}}{\sqrt{n} \log(n)^2}(\tilde{a}_n - a_0, \tilde{b}_n - b_0)$  is tight.

## Estimators $\tilde{\delta}_n$ and $\tilde{\alpha}_n$

### Preliminary estimators $\tilde{\alpha}_n$

Non parametric methods for semimartingales based on  $p$ -order power variation  
(*Todorov-Tauchen (11)*, *Todorov (13)*, *Todorov (15)*)

The first and two order power variation are defined by

$$V_n^1(p, X) = \sum_{i=2}^n |\Delta_i^n X - \Delta_{i-1}^n X|^p \quad \text{where } \Delta_i^n X = X_{\frac{i}{n}} - X_{\frac{i-1}{n}},$$

$$V_n^2(p, X) = \sum_{i=4}^n |\Delta_i^n X - \Delta_{i-1}^n X + \Delta_{i-2}^n X - \Delta_{i-3}^n X|^p.$$

## Limit theorems (Todorov (13))

- ① For  $p \in (0, \alpha)$ , we have the convergences in probability

$$\frac{n^{p/\alpha}}{n} V_n^1(p, X) \rightarrow \int_0^1 \delta^p X_{t-}^{p/\alpha} dt \mathbb{E} |L_1 - \bar{L}_1|^p,$$

$$\frac{n^{p/\alpha}}{n} V_n^2(p, X) \rightarrow 2^{p/\alpha} \int_0^1 \delta^p X_{t-}^{p/\alpha} dt \mathbb{E} |L_1 - \bar{L}_1|^p$$

where  $\bar{L}_1$  is an independent copy of  $L_1$ .

- ② For  $p \in (\frac{\alpha-1}{2}, \frac{\alpha}{2})$

$$\sqrt{n} \left( \begin{array}{c} \frac{n^{p/\alpha}}{n} V_n^1(p, X) - \int_0^1 \delta^p X_{t-}^{p/\alpha} dt \mathbb{E} |L_1 - \bar{L}_1|^p \\ \frac{n^{p/\alpha}}{n} V_n^2(p, X) - 2^{p/\alpha} \int_0^1 \delta^p X_{t-}^{p/\alpha} dt \mathbb{E} |L_1 - \bar{L}_1|^p \end{array} \right)$$

stably converges in law.

- ③ Considering  $p = 1/2$

$$\tilde{\alpha}_n = \frac{\log 2}{2 \log(V_n^2(1/2, X)/V_n^1(1/2, X))} \mathbf{1}_{V_n^1(1/2, X) \neq V_n^2(1/2, X)}$$

$\sqrt{n}(\tilde{\alpha}_n - \alpha)$  stably converges in law.

## Preliminary estimators $\tilde{\delta}_n$

We define a non parametric estimator of  $\delta$  based on p-order power variation

$$\tilde{\delta}_n = \left( \frac{1}{m(\tilde{\alpha}_n)} \frac{n^{1/2\tilde{\alpha}_n}}{n} \sum_{i=2}^n \left| \frac{\Delta_i^n X - \Delta_{i-1}^n X}{X_{\frac{i-1}{n}}^{1/\tilde{\alpha}_n}} \right|^{1/2} \right)^2$$

where  $m(\alpha) = \mathbb{E}|L_1^\alpha - \bar{L}_1^\alpha|^{1/2} = 2^{p/\alpha} \mathbb{E}|S_1^\alpha|^{1/2}$  where  $S_1^\alpha$  is symmetric  $\alpha$ -stable.

### Theorem (B. Clément (23))

Then  $\tilde{\delta}_n$  converges in probability to  $\delta_0$  and  $\frac{\sqrt{n}}{\log(n)}(\tilde{\delta}_n - \delta_0)$  is tight.

## One-step improvement

- There exists a joint estimator  $\hat{\theta}_n = (\hat{a}_n, \hat{b}_n, \hat{\delta}_n, \hat{\alpha}_n)$  consistent, rate optimal and probably efficient that solves  $G_n(\hat{\theta}_n) = 0$ .
- We have explicit (easy to implement) preliminary estimators  $\tilde{\delta}_n$  and  $\tilde{\alpha}_n$ . By plugging, we obtain consistent estimators of the drift  $\tilde{a}_n$  and  $\tilde{b}_n$  (not rate optimal).  
Finally we have a first step estimator  $\tilde{\theta}_n = (\tilde{a}_n, \tilde{b}_n, \tilde{\delta}_n, \tilde{\alpha}_n)$ .
- One-step improvement : define

$$\hat{\theta}'_n = \tilde{\theta}_n - J_n(\tilde{\theta}_n)^{-1} G_n(\tilde{\theta}_n)$$

We prove that  $\hat{\theta}'_n$  inherits the asymptotic properties of  $\hat{\theta}_n$  ie

$$u_n^{-1} \left( \hat{\theta}'_n - \theta_0 \right) \xrightarrow{\mathcal{L}_s} I(\theta_0)^{-1/2} \mathcal{N} \text{ for } u_n = \begin{pmatrix} \frac{1}{n^{1/\alpha-1/2}} Id_2 & 0 \\ 0 & \begin{pmatrix} \frac{\delta}{\sqrt{n}} & \frac{-\log n}{\alpha^2 \sqrt{n}} \\ 0 & \frac{1}{\sqrt{n}} \end{pmatrix} \end{pmatrix}.$$

Simulating  $(X_t)$  solution of  $dX_t = (a - bX_t)dt + \delta X_t^{1/\alpha} dL_t^\alpha$

We use the an implicit discretisation scheme which preserves the positivity proposed by *Li-Taguchi* (19) . For  $h(x) = \min\{|x|^{1/\alpha_0}, H\}$ , we set  $X_0^{H,n} = x_0$  and for  $i \geq 0$

$$X_{\frac{i+1}{n}}^{H,n} = \frac{|X_{\frac{i}{n}}^{H,n} + \frac{a}{n} + \delta h(X_{\frac{i}{n}}^{H,n}) \Delta_i^n L^\alpha|}{(1 + \frac{b}{n})}.$$

We know that  $\Delta_i^n L^\alpha = L_{\frac{i}{n}}^\alpha - L_{\frac{i-1}{n}}^\alpha \stackrel{\mathcal{L}}{=} L_{1/n}^\alpha \stackrel{\mathcal{L}}{=} n^{-1/\alpha} L_1^\alpha$ .

We simulate  $L_1^\alpha$  according to *Weron-Weron* (05) with  $V$  a uniform random variable on  $(-\frac{\pi}{2}, \frac{\pi}{2})$  and an independent exponential variable  $W$  with mean 1.

$$L_1^\alpha = S_\alpha \times \frac{\sin(\alpha(V + B_\alpha))}{(\cos(V))^{1/\alpha}} \times \left( \frac{\cos(V - \alpha(V + B_\alpha))}{W} \right)^{(1-\alpha)/\alpha},$$

where

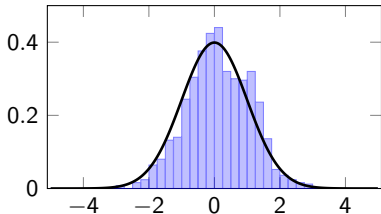
$$B_\alpha = \frac{\arctan(\tan \frac{\alpha\pi}{2})}{\alpha}, \quad S_\alpha = \left( 1 + \tan^2 \frac{\alpha\pi}{2} \right)^{1/(2\alpha)}.$$

## Estimating (a,b) for $\delta_0$ and $\alpha_0$ known

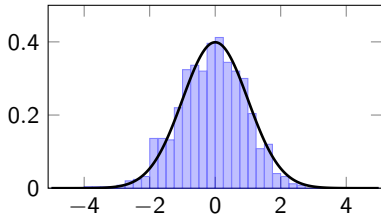
Theoretical limit :

$$u_n^{-1}(\hat{\theta}_n - \theta_0) \xrightarrow[n \rightarrow \infty]{\mathcal{L}-s} \Sigma^{1/2} \mathcal{N}$$

where  $\mathcal{N}$  is a standard Gaussian variable independent of  $\Sigma = I^{11}(\theta_0)^{-1}$ .



$$((\Sigma_n)_{11})^{-1/2} n^{1/\alpha_0 - 1/2} (\hat{a}_n - a_0)$$



$$((\Sigma_n)_{22})^{-1/2} n^{1/\alpha_0 - 1/2} (\hat{b}_n - b_0)$$

**Figure** - Distribution of the rescaled errors of estimation and comparison with  $\mathcal{N}(0, 1)$  ( $a_0 = 3$ ,  $b_0 = 5$ ,  $\delta_0 = 1$ ,  $\alpha_0 = 1.3$ ,  $n=4096$ ,  $n_{dis} = (1000n)^{-1}$ ,  $n_{MC} = 1000$ )

## One-step improvement of $a, \delta, \alpha$

We correct our preliminary estimator  $\tilde{\theta}_n = (\tilde{a}_n, \tilde{\delta}_n, \tilde{\alpha}_n)$  which is consistent but not rate optimal to the one-step estimator  $\hat{\theta}'_n = (\hat{a}_{1,n}, \hat{\delta}_{1,n}, \hat{\alpha}_{1,n})$ .

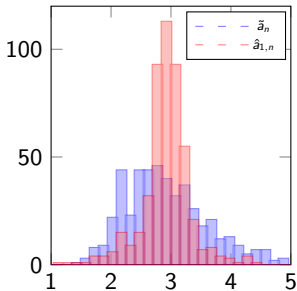


Figure – Estimation of  $a$

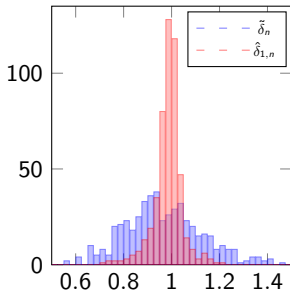


Figure – Estimation of  $\delta$

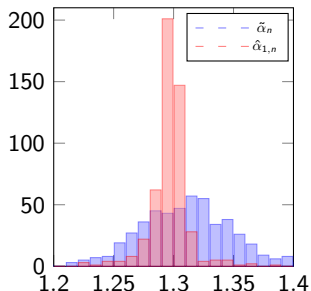


Figure – Estimation of  $\alpha$



## Estimating (a,b) for $\delta_0$ and $\alpha_0$ known

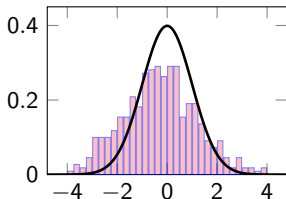
Theoretical limit :

$$((\bar{\Sigma}_n)_{11})^{-1/2} n^{1/\alpha_0 - 1/2} (\hat{a}_{1,n} - a_0) \xrightarrow[n \rightarrow \infty]{\mathcal{L}-s} \mathcal{N}$$

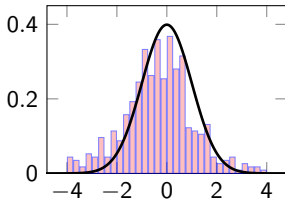
$$((\bar{\Sigma}_n)_{33})^{-1/2} \frac{\sqrt{n}}{\ln(n)} \frac{\alpha_0^2}{\delta_0} (\hat{\delta}_{1,n} - \delta_0) \xrightarrow[n \rightarrow \infty]{\mathcal{L}-s} \mathcal{N}$$

$$((\bar{\Sigma}_n)_{33})^{-1/2} \sqrt{n} (\hat{\alpha}_{1,n} - \alpha_0) \xrightarrow[n \rightarrow \infty]{\mathcal{L}-s} \mathcal{N}.$$

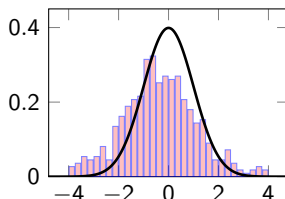
where  $\mathcal{N}$  is a standard Gaussian variable independent of  $\bar{\Sigma} = \bar{I}(\theta_0)^{-1}$ .



$$((\bar{\Sigma}_n)_{11})^{-1/2} n^{1/\alpha_0 - 1/2} (\hat{a}_{1,n} - a_0)$$



$$((\bar{\Sigma}_n)_{33})^{-1/2} \frac{\alpha_0^2}{\delta_0} \frac{\sqrt{n}}{\ln(n)} (\hat{\delta}_{1,n} - \delta_0)$$



$$((\bar{\Sigma}_n)_{33})^{-1/2} \sqrt{n} (\hat{\alpha}_{1,n} - \alpha_0)$$

**Figure** - Distribution of the rescaled errors of estimation and comparison with  $\mathcal{N}(0,1)$  ( $a_0 = 3$ ,  $b_0 = 5$ ,  $\delta_0 = 1$ ,  $\alpha_0 = 1.3$ ,  $n=5000$ ,  $n_{dis} = (1000n)^{-1}$ ,  $n_{MC} = 1000$ )

## Futur work : Stable CIR process

We will try to estimate all parameters in presence of a Brownian motion.

$$dX_t = (a - bX_t)dt + \sigma\sqrt{X_t}dB_t + \delta X_t^{1/\alpha} dL_t^\alpha, \quad t \geq 0 \quad x_0 \geq 0$$

- $(B_t)$  standard Brownian motion independent of  $(L_t^\alpha)$
- Existence and uniqueness of a strong solution such that

$$\mathbb{P}(X_t > 0, \forall t \geq 0) = 1$$

if  $x_0 > 0$ ,  $a \geq \frac{\sigma^2}{2} > 0$ ,  $b \in \mathbb{R}$ ,  $\delta \geq 0$

*Kawazu-Watanabe (71), Fu-Li (10), Jiao-Ma-Scotti (18)*

- Continuous time observations with  $\sigma > 0$

$$dX_t = (a - bX_t)dt + \sigma\sqrt{X_t}dB_t + \delta X_t^{1/\alpha}dL_t^\alpha, \quad t \geq 0, \quad x_0 > 0$$

$a \geq 0$ ,  $\sigma > 0$ ,  $\delta > 0$  and  $\alpha \in (1, 2)$  are known

### Estimation of $b$

Observations :  $(X_t)_{t \in [0, T]}$ ,  $T \rightarrow \infty$

Explicit expression of the maximum likelihood estimator  $\hat{b}$  from Girsanov's Theorem (depends on  $a \geq 0$ ,  $\delta > 0$  and  $\alpha$ )

- $b > 0$  : consistency and asymptotic normality with rate  $\sqrt{T}$
- $b = 0$  : consistency
- $b < 0$  : consistency and asymptotic mixed normality with rate  $e^{-bT}$

*Barczy-Ben Alaya-Kebaier-Pap (19)*

Overview



Moment estimates



Toy model



Joint estimation



Implementation



Simulations



Futur work



Thank you for your attention