

## PROCESSES

### Fractional Brownian Motion (FBM): mono-fractal

- Only Gaussian self-similar process with stationary increments
- $X(t) \stackrel{\text{fdd}}{=} a^H X(t/a)$  for all  $a > 0$
- $\zeta(q) = qH$  for  $q \in [0, \infty)$

### Multifractal Random Walk (MRW): multi-fractal

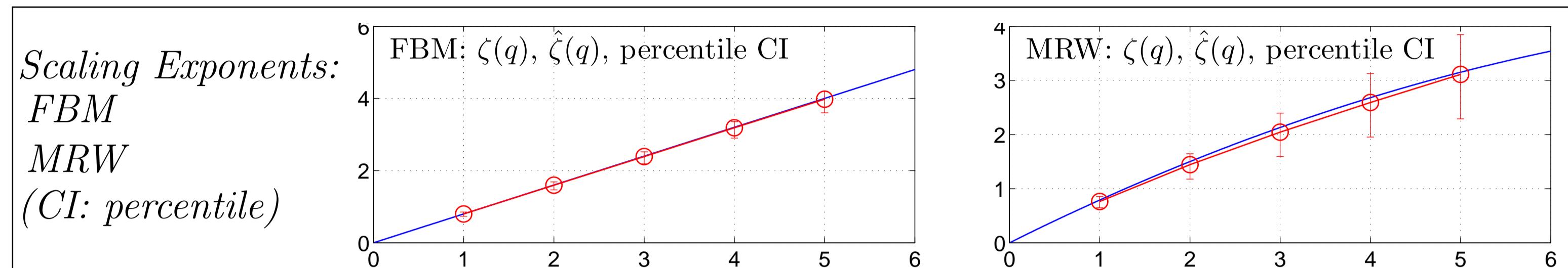
- Non Gaussian processes with stationary increments
- Multifractal properties mimic Mandelbrot's multiplicative log-normal cascades
- $X(k) = \sum_{k=1}^n G_H(k) e^{\omega(k)}$   
 $G_H(k)$ : increments of FBM with parameter  $H$ .

$\omega$ : independent of  $G_H$ , Gaussian, with non trivial covariance:

$$\text{cov}(\omega(k_1), \omega(k_2)) = c_2 \ln \left( \frac{L}{|k_1 - k_2| + 1} \right) \text{ for } |k_1 - k_2| < L; 0 \text{ otherwise}$$

$$-\zeta(q) = (H + c_2)q - c_2 q^2 / 2 \text{ for } q \in [0, \sqrt{2/c_2}]$$

⇒ departure from linear behavior in  $q$  fully controlled by  $c_2$



## ESTIMATORS AND CONFIDENCE LIMITS

### Estimators

$$\hat{\zeta}_X(q) = \sum_{j=1}^{j_2} w_j (\log_2 S(j, q) - \hat{g}_X(j, q))$$

X: A - Asymptotic

B - Bootstrap

### Confidence Intervals

#### 1. Asymptotic $(1 - \alpha)$ Confidence Intervals:

$$\text{CI}_{V_X}(q) = \left( \hat{\zeta}(q) - p\left(\frac{\alpha}{2}\right) \sqrt{V_X(q)}, \hat{\zeta}(q) + p\left(\frac{\alpha}{2}\right) \sqrt{V_X(q)} \right)$$

$$V_X(q) = \sum_{j=j_1}^{j_2} w_{j,q}^2 \hat{\sigma}_X^2(j, q)$$

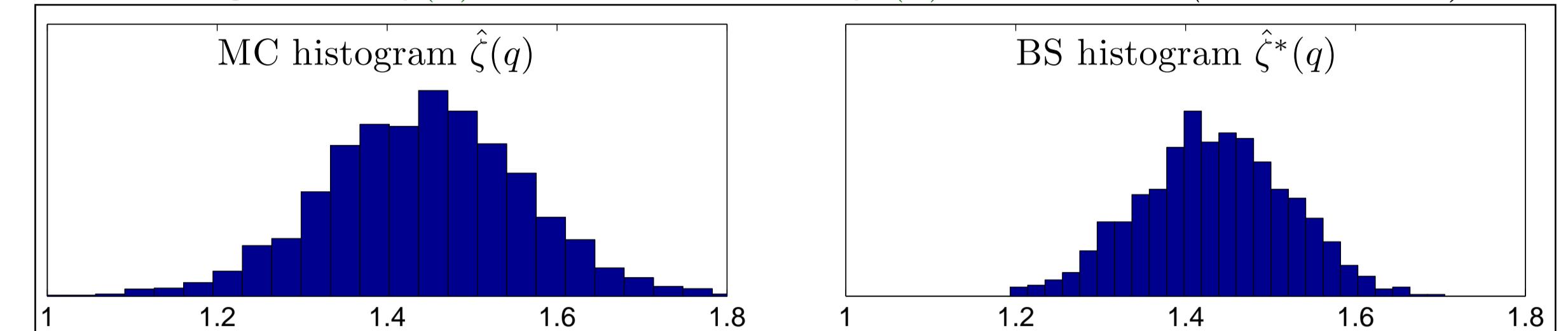
$p\left(\frac{\alpha}{2}\right)$ : Quantile of standard Normal distribution

#### 2. Bootstrap $(1 - \alpha)$ Percentile Confidence Interval:

$$\text{CI}_B(q) = \left( \hat{\zeta}^{*(b_1)}(q), \hat{\zeta}^{*(b_2)}(q) \right) \quad \hat{\zeta}^*(q): \text{bootstrap distribution}$$

$b_1 = \frac{B\alpha}{2}, \quad b_2 = \frac{B(1-\alpha)}{2}$ : Quantiles of bootstrap distribution

Histograms:  $\hat{\zeta}(q)$  Monte Carlo     $\hat{\zeta}^*(q)$  Bootstrap (MRW,  $q=2$ )



## PERFORMANCE ASSESSMENT

### Monte Carlo Simulation:

Estimation procedures applied to  $N_{MC}$  realizations of FBM and MRW of length  $n$ :

Biases

$$\hat{\beta}(q) = \frac{\mathbb{E}\hat{\zeta}(q) - \zeta(q)}{q}$$

Standard deviations

$$\hat{s}(q) = \sqrt{\text{Var}\hat{\zeta}(q)/q}$$

Mean-square errors

$$\text{MSE}(q) = \sqrt{\hat{s}(q)^2 + \hat{\beta}(q)^2}$$

Empirical coverages

$$\text{Cemp}(q) = \frac{\sum_{i=1}^{N_{MC}} \varepsilon(\zeta(q), \text{CI}_i(q))}{N_{MC}}$$

$$\varepsilon(\zeta(q), \text{CI}(q)) = 1 \text{ if } \zeta(q) \in \text{CI}(q) \text{ and } 0 \text{ otherwise}$$

Results obtained using Daubechies wavelets with  $N = 3$  vanishing moments

FBM:  $H = 0.8$

$n = 2^{15}$

Resamples  $B = 200$

MRW:  $(H, c_2) = (0.75, 0.08)$

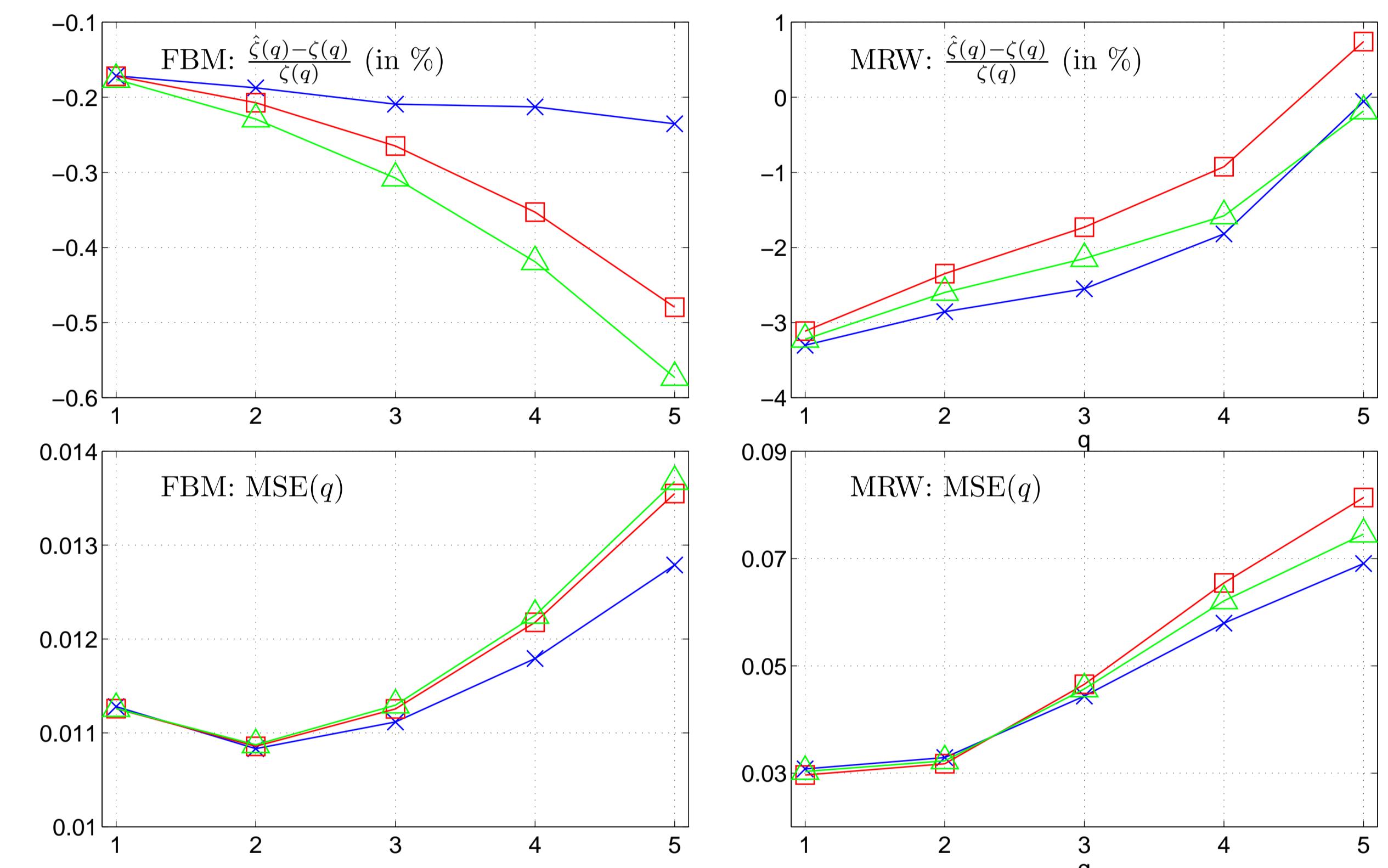
$N_{MC} = 3000$

Blocklength  $L = 6$

## COVERAGE OF CONFIDENCE INTERVALS

$n = 2^{15}$ : Empirical Coverage (in %): Nominal 95%									
		FBM				MRW			
q	X	CI <sub>B</sub>	CI <sub>V_G</sub>	CI <sub>V_B</sub>	CI <sub>V_A</sub>	CI <sub>B</sub>	CI <sub>V_G</sub>	CI <sub>V_B</sub>	CI <sub>V_A</sub>
1	<i>G</i>	89.9	88.2	<b>90.9</b>	88.0	72.5	<b>30.0</b>	<b>80.6</b>	52.0
	<i>B</i>	89.9	88.5	<b>91.0</b>	88.2	74.6	<b>32.7</b>	<b>82.2</b>	55.8
	<i>A</i>	89.9	88.3	<b>91.1</b>	88.1	73.4	<b>31.0</b>	<b>81.3</b>	53.8
2	<i>G</i>	88.1	86.8	<b>90.6</b>	85.9	82.2	<b>35.2</b>	<b>89.8</b>	74.1
	<i>B</i>	87.9	86.8	<b>90.3</b>	86.0	84.9	<b>38.7</b>	<b>90.9</b>	76.3
	<i>A</i>	87.9	86.9	<b>90.4</b>	86.0	83.6	<b>37.3</b>	<b>90.4</b>	75.5
3	<i>G</i>	86.7	87.7	<b>90.0</b>	86.0	88.9	<b>32.7</b>	<b>92.7</b>	82.4
	<i>B</i>	86.0	87.6	<b>89.4</b>	85.5	89.5	<b>32.2</b>	<b>91.5</b>	81.6
	<i>A</i>	85.7	87.6	<b>89.4</b>	85.4	89.0	<b>32.7</b>	<b>91.9</b>	81.8
4	<i>G</i>	86.3	89.2	<b>89.3</b>	86.3	<b>92.6</b>	<b>28.4</b>	91.4	80.5
	<i>B</i>	83.9	87.9	<b>88.4</b>	85.0	<b>91.4</b>	<b>26.1</b>	87.4	76.3
	<i>A</i>	83.4	87.5	<b>88.0</b>	84.2	<b>91.6</b>	<b>26.6</b>	89.3	78.1
5	<i>G</i>	84.6	<b>90.4</b>	89.4	85.8	<b>92.1</b>	<b>26.2</b>	86.3	73.9
	<i>B</i>	79.9	<b>88.3</b>	87.1	83.6	<b>88.9</b>	<b>24.2</b>	81.2	67.1
	<i>A</i>	79.1	<b>88.0</b>	86.8	82.8	<b>90.9</b>	<b>24.3</b>	84.1	70.9

## PERFORMANCE OF ESTIMATORS



## CONCLUSIONS

### Estimators

$g_B(j, q)$  has smallest bias and MSE for both Gaussian mono-fractal and non Gaussian multi-fractal process

### Confidence Intervals

FBM: -  $CI_{V_B}$  very good

-  $CI_{V_G}$  and  $CI_B$  good

MRW: -  $CI_B$  and  $CI_{V_B}$  good

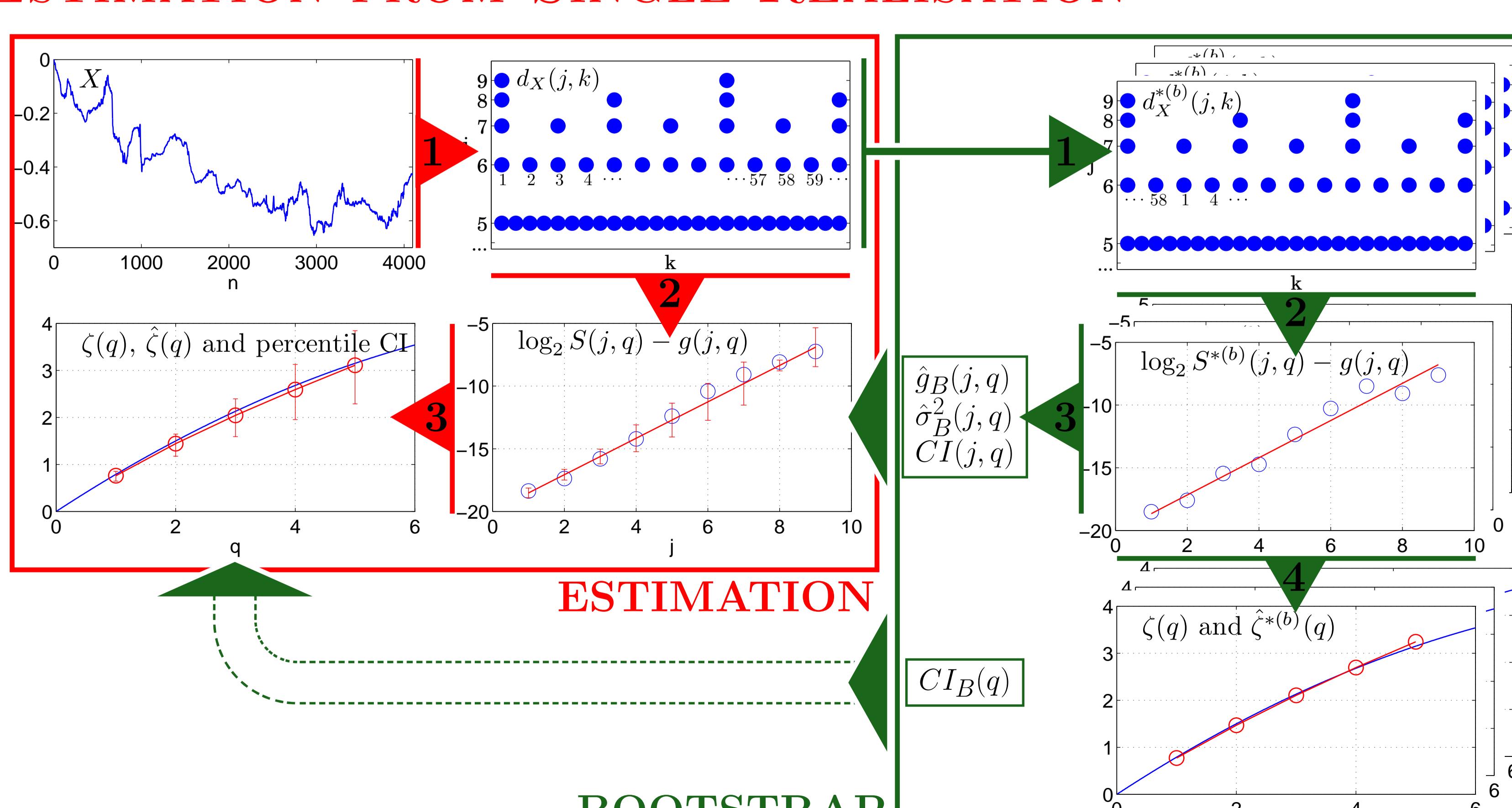
-  $CI_{V_G}$  has empirical coverage below 45%!

- Confidence intervals are the main benefit of bootstrap in Multifractal Analysis
- Bootstrap  $CI_B$  and  $CI_{V_B}$  highly relevant for both Gaussian mono-fractal and non Gaussian multi-fractal process
- "Optimal" block length is  $L = 2N$  (wavelet time support)

### Perspectives

- Double Bootstrap Techniques ?
- Time-Scale Bootstrap ?
- Bootstrap Hypothesis Test (mono- vs. multi.fractal) ?

## ESTIMATION FROM SINGLE REALISATION



## REFERENCES:

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- D.B. Percival, S. Sardy, and A.C. Davison, "Wavestrapping time series: Adaptive wavelet-based bootstrapping," in *Nonlinear and Nonstationary Signal Processing*, W.J. Fitzgerald et al., Eds., 2000, pp. 442–471, Cambridge University Press.
- A.M. Zoubir, *On confidence intervals for the coherence function*, in *Proc. of the 30th ICASSP*, Philadelphia, 2005.
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