

# Semiparametric estimation in perturbed long memory series

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# Perturbed Long Memory Series

$$z_t = y_t + u_t$$

- $u_t$  is a weak dependent added noise with continuous, finite and positive spectral density (e.g. white noise).
- $y_t$  is a stationary long memory signal with spectral density satisfying as  $\lambda \rightarrow 0$

$$f_y(\lambda) = C\lambda^{-2d_0}(1 + O(\lambda^\alpha))$$

- $C$  a positive constant,
- $\alpha \in [1, 2]$  ( $\alpha = 2$  in standard fractional ARIMA),
- the memory parameter  $d_0$  satisfies  $0 < d_0 < 1/2$ .

# Examples:

- Measurement errors in economic series.
- Different factors for long run and short run behaviour.
- Rational expectation with persistent ex ante variable.
- Long Memory in Stochastic Volatility (LMSV) models for financial asset returns ( Harvey, 1998, Breidt, Crato and de Lima, 1998) satisfying:
  - Lack of temporal dependence in the returns (efficient market hypothesis).
  - High persistence or **long memory** in “proxies” of the volatility (squares or other powers of absolute values of returns).

# LMSV

$$x_t = \sigma \sigma_t \varepsilon_t \quad \sigma_t = \exp(y_t/2)$$

- $\sigma$  is a positive constant.
- $\varepsilon_t \sim iid(0, 1)$ .
- The **(log) volatility** process  $y_t$  is stationary long memory such that its spectral density satisfies as  $\lambda \rightarrow 0$

$$f_y(\lambda) = C \lambda^{-2d_0} (1 + O(\lambda^\alpha))$$

- If  $\varepsilon_t$  and  $y_t$  are independent  $x_t$  is zero mean stationary with zero autocovariances.

# LMSV

Taking logs of the squares

$$z_t = \log x_t^2 = \mu + y_t + u_t$$

- $\mu = \log \sigma^2 + E \log \varepsilon_t^2$
- $u_t = \log \varepsilon_t^2 - E \log \varepsilon_t^2$  is iid with zero mean and constant variance  $\sigma_u^2$ .

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$z_t$  is a long memory signal plus noise model

# Semiparametric estimation in perturbed LM

## Whittle based methods:

- Gaussian semiparametric or local Whittle estimation (GSE): Kunsch (1987), Robinson (1995), Arteche (2004).
- Modified Gaussian semiparametric (MGSE): Hurvich, Moulines and Soulier (2005).

## Log periodogram regression based methods:

- Log-periodogram regression estimation (LPE): Geweke and Porter-Hudak(1983), Robinson(1995), Deo and Hurvich(2001).
- Non linear log-periodogram (NLPE): Sun and Phillips (2003).
- **Augmented log-periodogram regression estimation (ALPE).**

# Periodogram and spectral density

As  $\lambda \rightarrow 0$

$$f_z(\lambda) = C\lambda^{-2d_0}(1+O(\lambda^\alpha)) + f_u(\lambda) = C\lambda^{-2d_0} \left( 1 + \frac{f_u(0)}{C}\lambda^{2d_0} + O(\lambda^\alpha) \right)$$

Define the periodogram of  $z_t$  at Fourier frequency  $\lambda_j = \frac{2\pi j}{n}$  as

$$I_{zj} = I_z(\lambda_j) = \frac{1}{2\pi n} \left| \sum_{t=1}^n z_t \exp(-i\lambda_j t) \right|^2$$



# Periodogram and spectral density

**Theorem 1:** *Let  $d < 0.5$  and define*

$$L_n(j) = E \left[ \frac{I_{zj}}{C \lambda_j^{-2d_0}} \right].$$

*Then, considering  $j$  fixed:*

$$L_n(j) = A_{1n}(j) + A_{2n}(j) + o(n^{-2d_0})$$

*where*

$$\lim_{n \rightarrow \infty} A_{1n}(j) = \int_{-\infty}^{\infty} \psi_j(\lambda) \left| \frac{\lambda}{2\pi j} \right|^{-2d_0} d\lambda, \quad \lim_{n \rightarrow \infty} n^{2d_0} A_{2n}(j) = \int_{-\infty}^{\infty} \psi_j(\lambda) \frac{f_u(0)}{C(2\pi j)^{-2d_0}} d\lambda$$

*where*

$$\psi_j(\lambda) = \frac{2}{\pi} \frac{\sin^2 \frac{\lambda}{2}}{(2\pi j - \lambda)^2}.$$

# Gaussian semiparametric estimation (GSE)

$$\hat{d}_{GSE} = \arg \min R(d)$$

$$R(d) = \log \left( \frac{1}{m} \sum_{j=1}^m \lambda_j^{2d} I_{zj} \right) - \frac{2d}{m} \sum_{j=1}^m \log \lambda_j$$

for the *bandwidth*  $m$  satisfying at least  $\frac{1}{m} + \frac{m}{n} \rightarrow 0$  as  $n \rightarrow \infty$ .

- Bias of  $\hat{d}_{GSE}$  is of order  $O(\lambda_m^{2d_0})$ .
- $\sqrt{m}(\hat{d}_{GSE} - d_0) \xrightarrow{d} N(0, \frac{1}{4})$  as long as  $m = \kappa n^\varsigma$  for  $\varsigma < 4d_0/(4d_0 + 1)$  (Arteche, 2004).

# Modified GSE (MGSE) (Hurvich, Moulines and Soulier, 2005)

$$(\hat{d}_{MGSE}, \hat{\beta}_{MGSE}) = \arg \min_{\Delta \times \Theta} R(d, \beta)$$

$$\Theta = [0, \Theta_1], 0 < \Theta_1 < \infty, \Delta = [\Delta_1, \Delta_2], 0 < \Delta_1 < \Delta_2 < 1/2,$$

$$R(d, \beta) = \log \left( \frac{1}{m} \sum_{j=1}^m \frac{\lambda_j^{2d} I_{zj}}{1 + \beta \lambda_j^{2d}} \right) + \frac{1}{m} \sum_{j=1}^m \log \{ \lambda_j^{-2d} (1 + \beta \lambda_j^{2d}) \}$$

for  $\beta_0 = f_u(0)/C$  the long run nsr.

- Bias of  $\hat{d}_{MGSE}$  is of order  $O(\lambda_m^\alpha)$ .
- $\sqrt{m}(\hat{d}_{MGSE} - d_0) \xrightarrow{d} N(0, \frac{1}{4}C_{d_0})$  for  $C_{d_0} = 1 + \frac{1+4d_0}{4d_0^2}$  as long as  $m = \kappa n^\varsigma$  for  $\varsigma < 2\alpha/(2\alpha + 1)$ .

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Taking the log of  $f_z(\lambda)$

$$\log I_{zj} = a + d_0(-2 \log \lambda_j) + \log \left( 1 + \frac{f_u(\lambda)}{C} \lambda_j^{2d_0} + O(\lambda_j^\alpha) \right) + U_{zj}$$

•  $a = \log C - c$ ,  $c = 0.577216\dots$  is Euler's constant.

•  $U_{zj} = \log \left( \frac{I_{zj}}{f_z(\lambda_j)} \right) + c$ .

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for  $j = 1, 2, \dots, m$ .

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- $U_{zj} = \log \left( \frac{I_{zj}}{f_z(\lambda_j)} \right) + c$ .
- $m$  is the *bandwidth* satisfying at least  $\frac{1}{m} + \frac{m}{n} \rightarrow 0$  as  $n \rightarrow \infty$ .

# Log-periodogram regression estimator (LPE)

$\hat{d}_{LPE}$  (Robinson, 1995) is obtained by least squares to

$$\log I_{zj} = a + d(-2 \log \lambda_j) + v_j \quad j = 1, 2, \dots, m$$

- Bias of  $\hat{d}_{LPE}$  is of order  $O(\lambda_m^{2d_0})$ .
- $\sqrt{m}(\hat{d}_{LPE} - d_0) \xrightarrow{d} N(0, \frac{\pi^2}{24})$  as long as  $m = \kappa n^\varsigma$  for  $\varsigma < 4d_0/(4d_0 + 1)$  (Deo and Hurvich, 2001).

$\hat{d}_{LPE}$  and  $\hat{d}_{GSE}$  have a large downward bias caused by the added noise.

## Non linear LPE (NLPE) (Sun and Phillips, 2003)

$$\begin{aligned}\log I_{zj} &= a + d_0(-2 \log \lambda_j) + \log \left( 1 + \frac{f_u(\lambda_j)}{C} \lambda_j^{2d_0} + O(\lambda_j^\alpha) \right) + U_{zj} \\ &= a + d_0(-2 \log \lambda_j) + \log \left( 1 + \frac{f_u(0)}{C} \lambda_j^{2d_0} \right) + O(\lambda_j^\alpha) + U_{zj} \\ &= a + d_0(-2 \log \lambda_j) + \frac{f_u(0)}{C} \lambda_j^{2d_0} + O(\lambda_j^{\alpha^*}) + U_{zj}\end{aligned}$$

where  $\alpha^* = \min(4d_0, \alpha)$ .



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where  $\alpha^* = \min(4d_0, \alpha)$ .

# Non linear LPE (NLPE) (Sun and Phillips, 2003)

$$(\hat{d}_{NLPE}, \hat{\beta}_{NLPE}) = \arg \min_{\Delta \times \Theta} \sum_{j=1}^m (\log^* I_{zj} + d(2 \log \lambda_j)^* - \beta(\lambda_j^{2d})^*)^2$$

where for a general  $\xi_t$ ,  $\xi_t^* = \xi_t - \bar{\xi}$  for  $\bar{\xi} = \sum \xi_t / n$ .

- Bias of  $\hat{d}_{NLPE}$  is of order  $O(\lambda_m^{\alpha^*})$ .
- $\sqrt{m}(\hat{d}_{NLPE} - d_0) \xrightarrow{d} N(0, \frac{\pi^2}{24} C_{d_0})$  as long as  $m = \kappa n^\varsigma$  for  $\varsigma < 2\alpha^* / (2\alpha^* + 1)$ .

For  $\alpha > 4d_0$  (e.g. in ARFIMA  $\alpha = 2$ )  $\alpha^* = 4d_0$ .

# Augmented log-periodogram estimation (ALPE)

$$\begin{aligned}\log I_{zj} &= a + d_0(-2 \log \lambda_j) + \log \left( 1 + \frac{f_u(\lambda_j)}{C} \lambda_j^{2d_0} + O(\lambda_j^\alpha) \right) + U_{zj} \\ &= a + d_0(-2 \log \lambda_j) + \log \left( 1 + \frac{f_u(0)}{C} \lambda_j^{2d_0} \right) + O(\lambda_j^\alpha) + U_{zj} \\ &= a + d_0(-2 \log \lambda_j) + \frac{f_u(0)}{C} \lambda_j^{2d_0} + O(\lambda_j^{\alpha^*}) + U_{zj}\end{aligned}$$

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# Augmented log-periodogram estimation (ALPE)

$$(\hat{d}_{ALPE}, \hat{\beta}_{ALPE}) = \arg \min_{\Delta \times \Theta} Q(d, \beta)$$

under the constraint  $\beta \geq 0$ , where

$$Q(d, \beta) = \sum_{j=1}^m (\log^* I_{zj} + d(2 \log \lambda_j)^* - \log^*(1 + \beta \lambda_j^{2d}))^2$$

- Bias of  $\hat{d}_{ALPE}$  is of order  $O(\lambda_m^\alpha)$ .
- $\sqrt{m}(\hat{d}_{ALPE} - d_0) \xrightarrow{d} N(0, \frac{\pi^2}{24} C_{d_0})$  as long as  $m = \kappa n^\varsigma$  for  $\varsigma < 2\alpha/(2\alpha + 1)$ .

# Assumptions

- **B.1:**  $y_t$  and  $u_t$  are independent Gaussian processes.
- **B.2:** When  $\sigma_u^2 > 0$ ,  $f_u(\lambda)$  is continuous on  $[-\pi, \pi]$ , bounded above and away from zero with bounded first derivative in a neighbourhood of zero.
- **B.3:** The spectral density of  $y_t$  satisfies as  $\lambda \rightarrow 0$ ,

$$f_y(\lambda) = C\lambda^{-2d_0}(1 + G\lambda^\alpha + O(\lambda^{\alpha+\iota}))$$

for some  $\iota > 0$ , finite positive  $C$ , finite  $G$ ,  $0 < d_0 < 0.5$  and  $\alpha \in (4d_0, 2] \cap [1, 2]$ .

- **B.4:** As  $n \rightarrow \infty$ , for some positive constant  $K$ ,

$$\frac{m^{2\alpha+1}}{n^{2\alpha}} \rightarrow K$$

# Main result: Properties of $\hat{d}_{ALPE}$

When  $var(u_t) > 0$ ,  $\hat{d}_{ALPE}$  is asymptotically normal and

- $ABias(\hat{d}_{ALPE}) = K_0 \left(\frac{m}{n}\right)^\alpha$ ,  $K_0 = \frac{(2\pi)^\alpha \alpha (2d_0 + 1)(\alpha - 2d_0)G}{4d_0(1+\alpha)^2(2d_0 + \alpha + 1)}$

- $AVar(\hat{d}_{ALPE}) = \frac{\pi^2}{24m} C_{d_0}$  where  $C_{d_0} = 1 + \frac{1+4d_0}{4d_0^2}$

- $AMSE(\hat{d}_{ALPE}) = \frac{\pi^2}{24m} C_{d_0} + \left(\frac{m}{n}\right)^{2\alpha} K_0^2$ .

- The optimal bandwidth, in an AMSE sense, is

$$m_{opt} = \left( \frac{\pi^2 C_{d_0}}{48\alpha K_0^2} \right)^{\frac{1}{2\alpha+1}} n^{\frac{2\alpha}{2\alpha+1}}.$$

# Comparing estimators

	GSE	MGSE	LPE	NLPE	ALPE
$ABias$	$O\left(\left(\frac{m}{n}\right)^{2d_0}\right)$	$O\left(\left(\frac{m}{n}\right)^\alpha\right)$	$O\left(\left(\frac{m}{n}\right)^{2d_0}\right)$	$O\left(\left(\frac{m}{n}\right)^{4d_0}\right)$	$O\left(\left(\frac{m}{n}\right)^\alpha\right)$
$m_{opt}$	$O\left(n^{\frac{4d_0}{4d_0+1}}\right)$	$O\left(n^{\frac{2\alpha}{2\alpha+1}}\right)$	$O\left(n^{\frac{4d_0}{4d_0+1}}\right)$	$O\left(n^{\frac{8d_0}{8d_0+1}}\right)$	$O\left(n^{\frac{2\alpha}{2\alpha+1}}\right)$
$AMSE(m_{opt})$	$O\left(n^{-\frac{4d_0}{4d_0+1}}\right)$	$O\left(n^{-\frac{2\alpha}{2\alpha+1}}\right)$	$O\left(n^{-\frac{4d_0}{4d_0+1}}\right)$	$O\left(n^{-\frac{8d_0}{8d_0+1}}\right)$	$O\left(n^{-\frac{2\alpha}{2\alpha+1}}\right)$



# Finite sample behaviour

- $z_t = y_t + u_t$ .
- $u_t = \log \varepsilon_t^2$ , for  $\varepsilon_t \sim N(0, 1)$ .
- $(1 - L)^{d_0} y_t = w_t$  with  $w_t \sim N(0, \sigma_w^2)$ ,  
 $d_0 = 0.2, 0.45, 0.8$ .
- $\sigma_w^2 = 0.5, 0.1$ , correspond to long run noise to  
signal ratios  $f_u(0)/f_w(0) = \pi^2, 5\pi^2$ .
- $w_t$  and  $\varepsilon_t$  independent.
- $n = 1024, 4096, 8192$ .
- $m = n^{0.4}, n^{0.6}, n^{0.8}, m^{opt}$ , 1000 replications.

# “Optimal” bandwidths

Table 1: “Optimal” bandwidths

		$\sigma_w^2 = 0.5$					$\sigma_w^2 = 0.1$				
$n$	$d_0$	LPE	GSE	NLPE	ALPE	MGSE	LPE	GSE	NLPE	ALPE	MGSE
1024	0.2	6	5	12	511	511	5	5	5	511	511
	0.45	13	11	29	511	502	5	5	7	511	502
	0.8	27	24	53	511	511	12	11	22	511	511
4096	0.2	12	9	29	1895	1715	5	5	5	1895	1715
	0.45	32	27	87	1681	1522	10	8	21	1681	1522
	0.8	79	70	177	2047	1936	36	32	74	2047	1936
8192	0.2	16	12	45	3299	2987	5	5	5	3299	2987
	0.45	51	42	149	2927	2650	16	13	36	2927	2650
	0.8	134	119	323	3723	3370	62	55	135	3723	3370



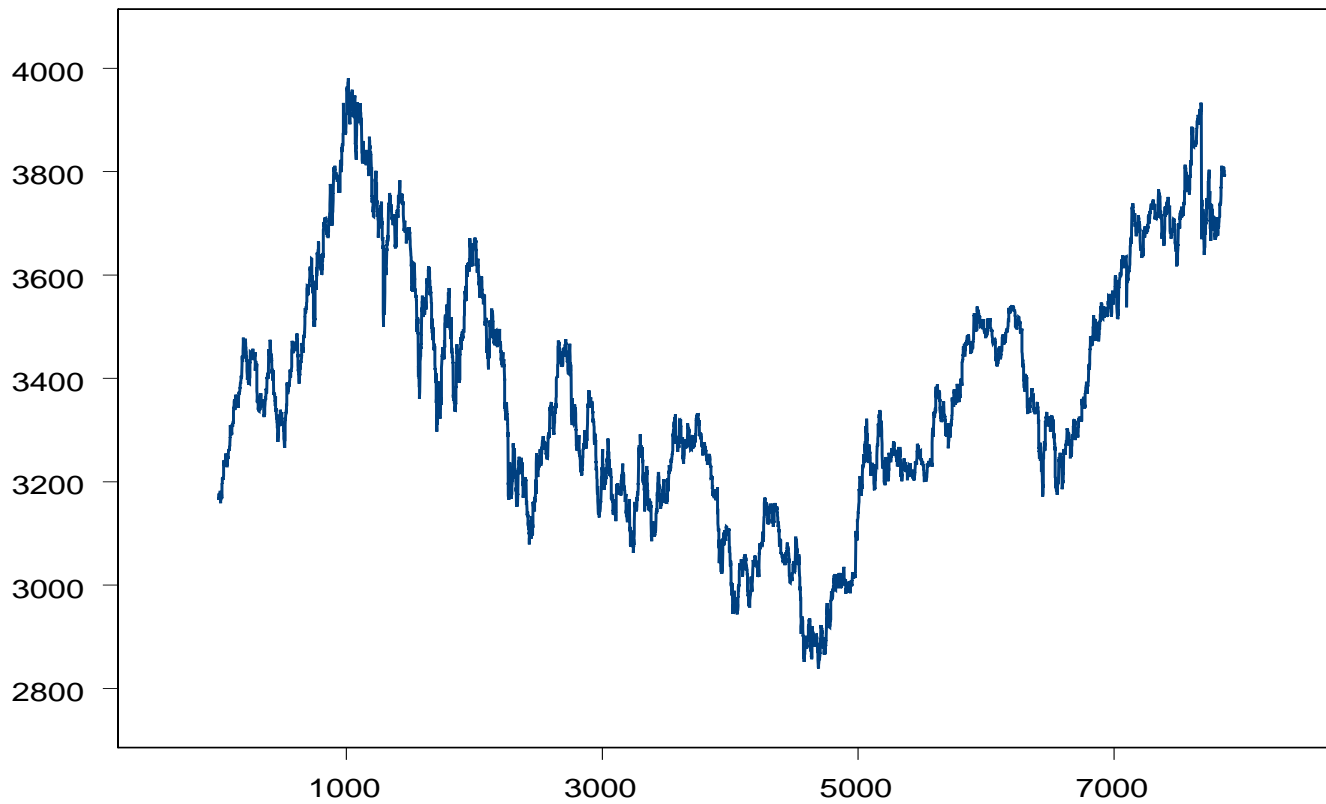






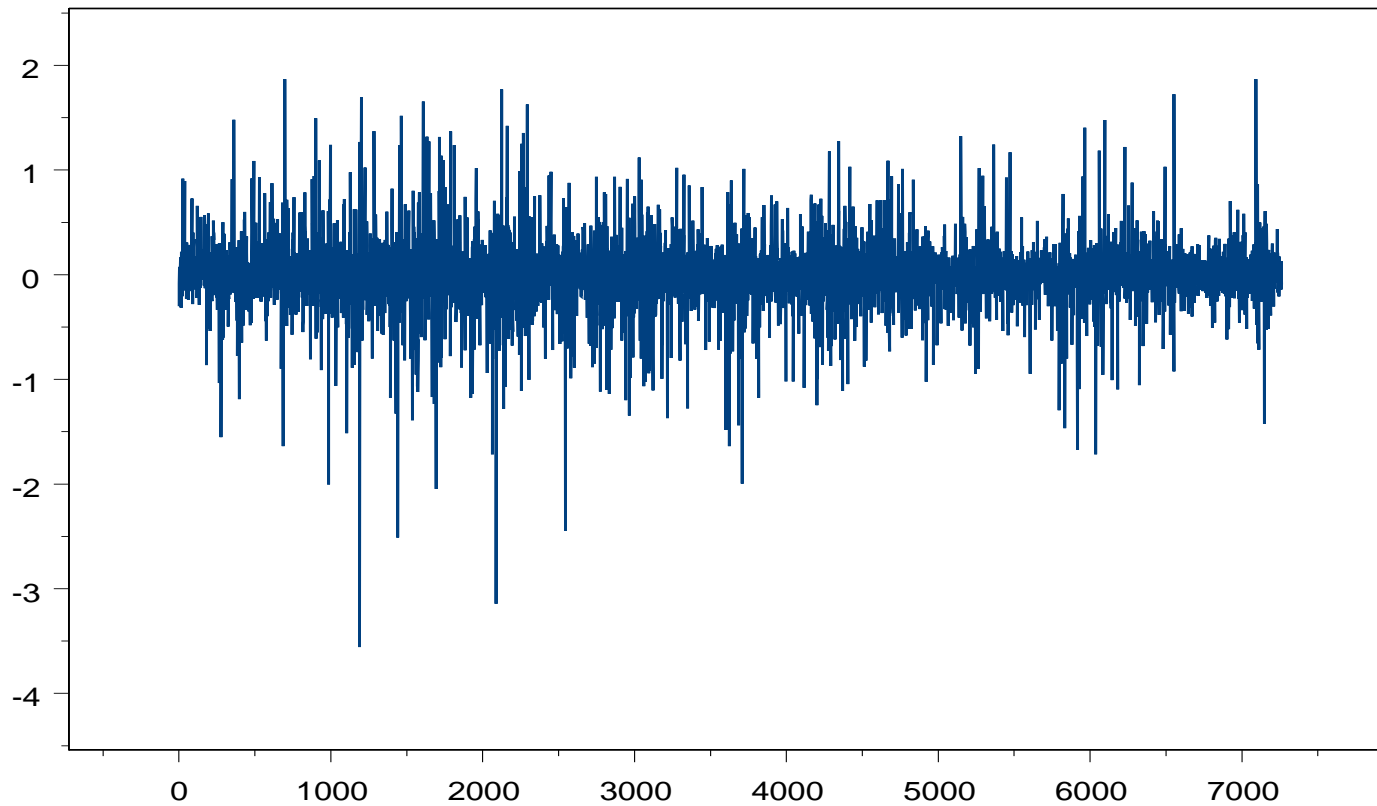
# Ibex35

The series of returns covers the period 1-10-93 to 22-3-96 half-hourly.



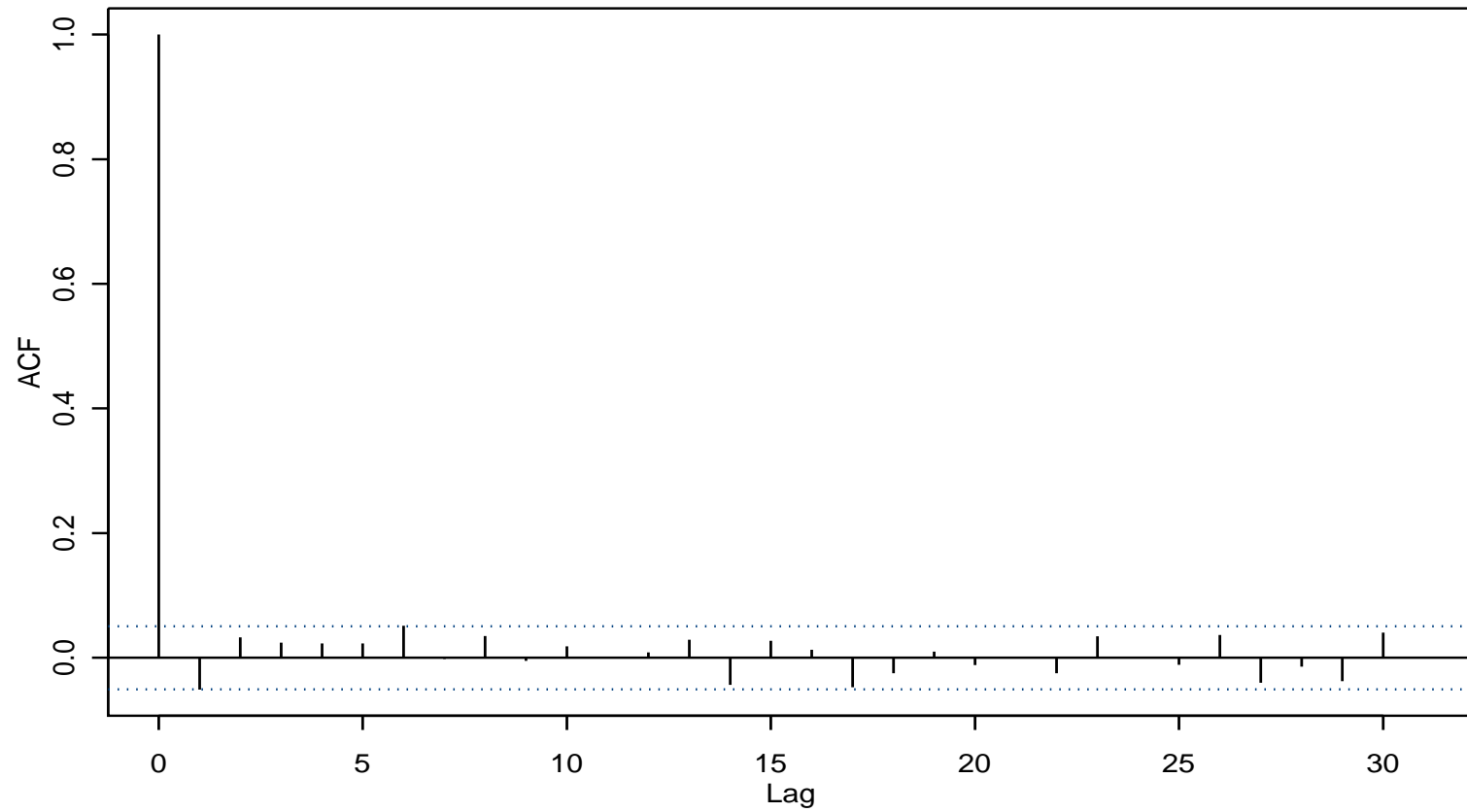
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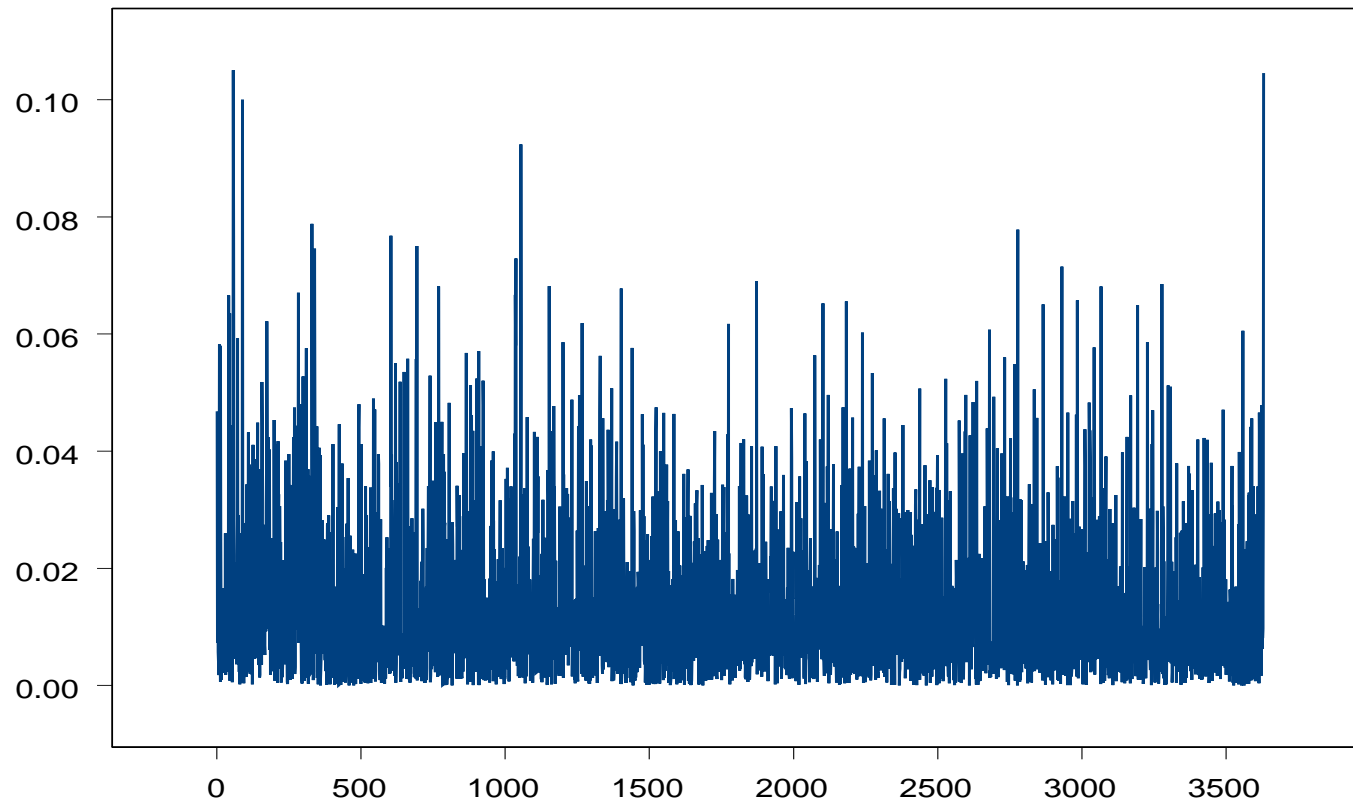


# Ibex35: autocorrelations of returns

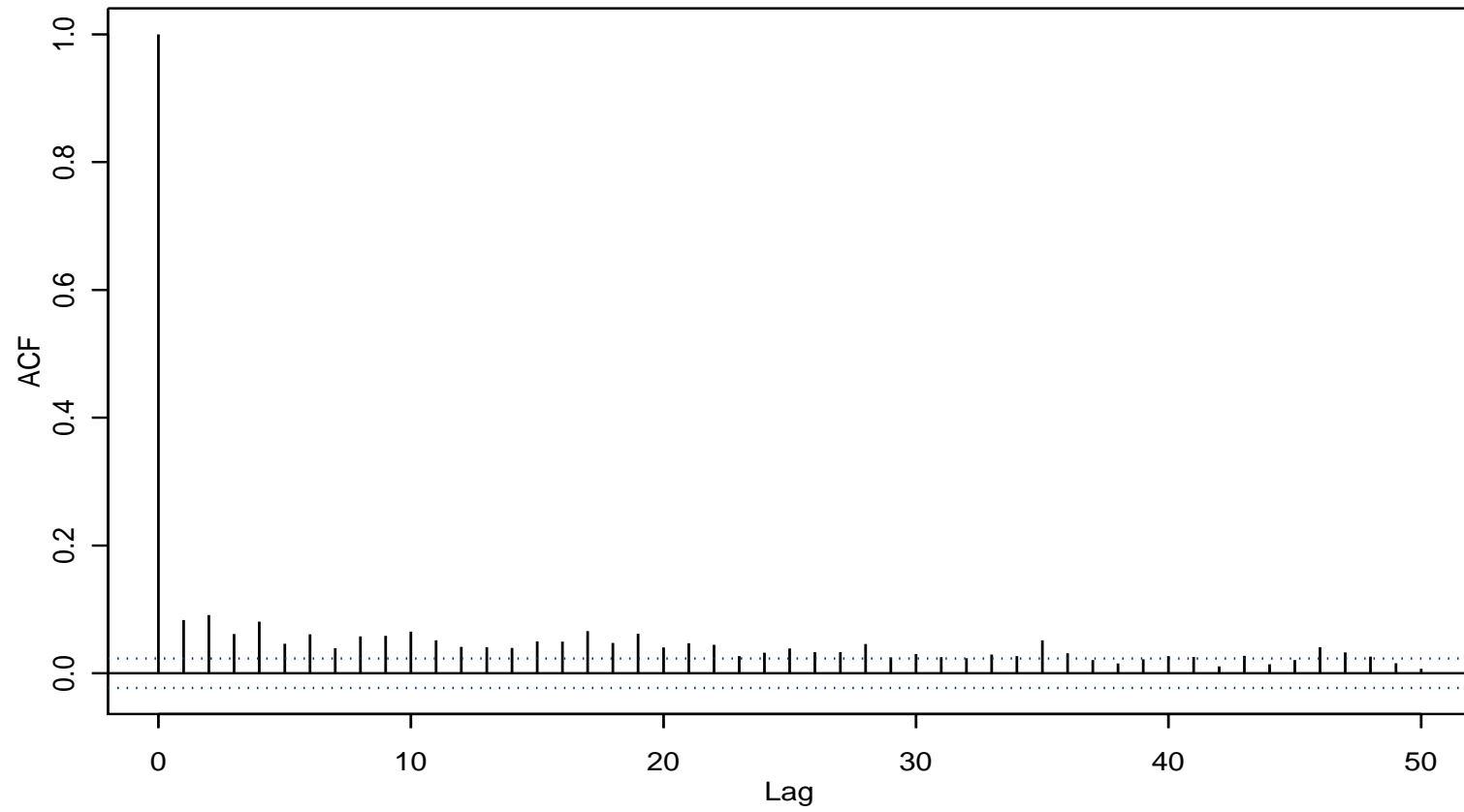


# Ibex35: periodogram of returns

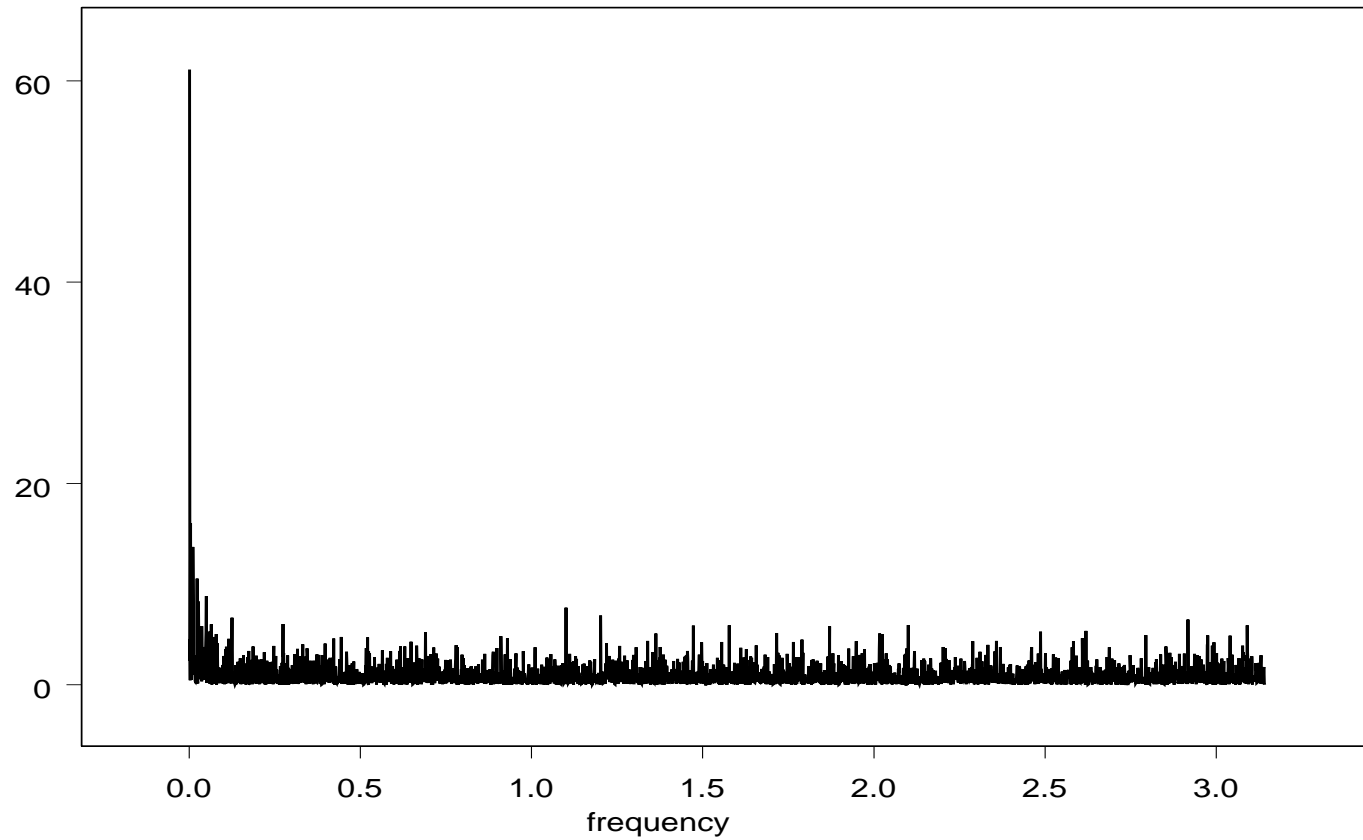
Periodogram Ibex35 returns



# Ibex35: autocorrelations of volatility

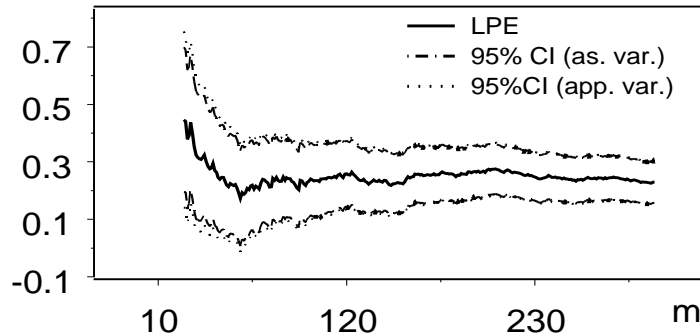


# Ibex35: periodogram of volatility

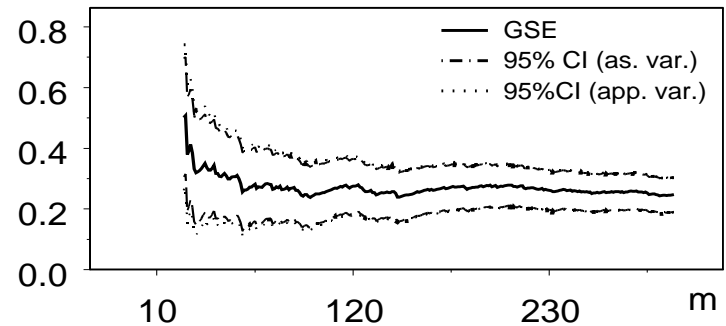


# Ibex35: estimates of memory parameter of volatility

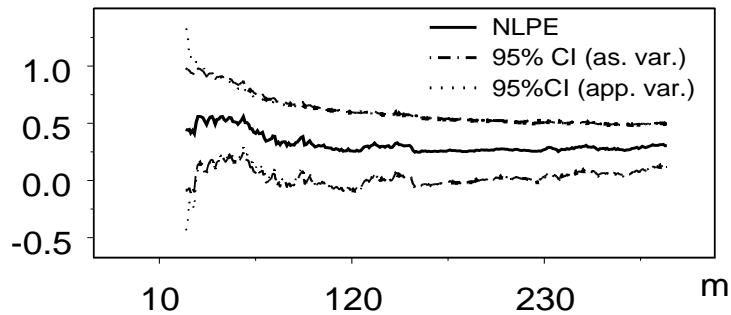
a) LPE and 95% confidence intervals



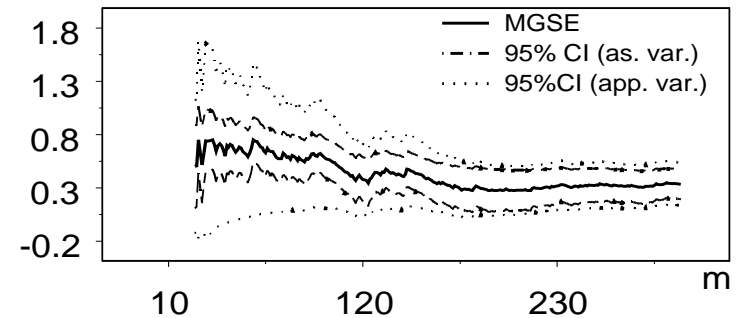
b) GSE and 95% confidence intervals



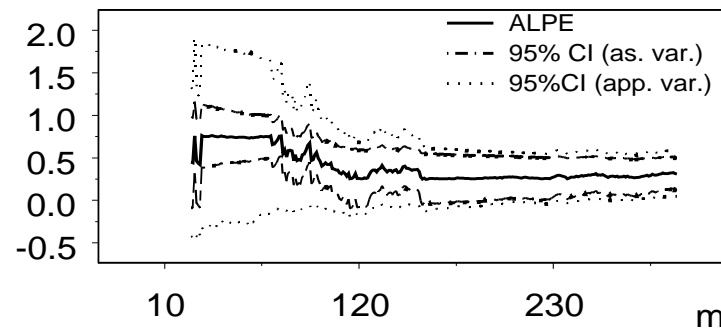
c) NLPE and 95% confidence intervals



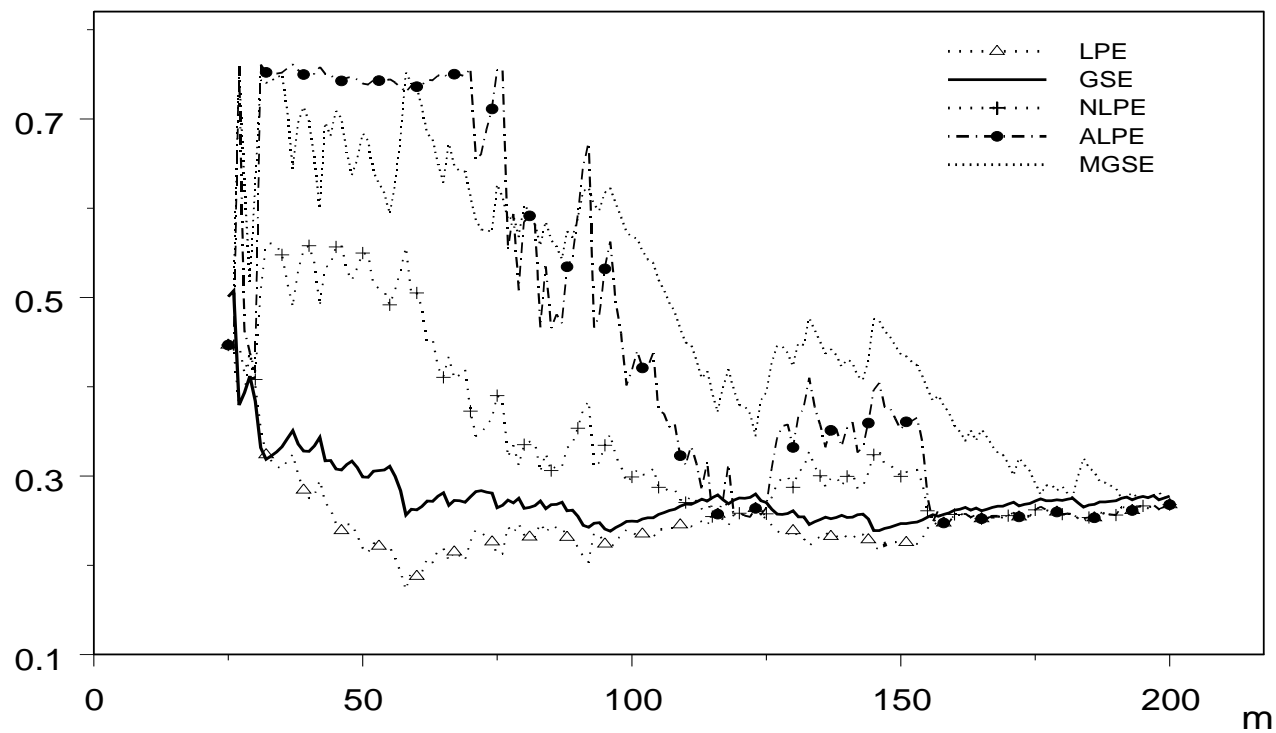
d) MGSE and 95% confidence intervals



e) ALPE and 95% confidence intervals

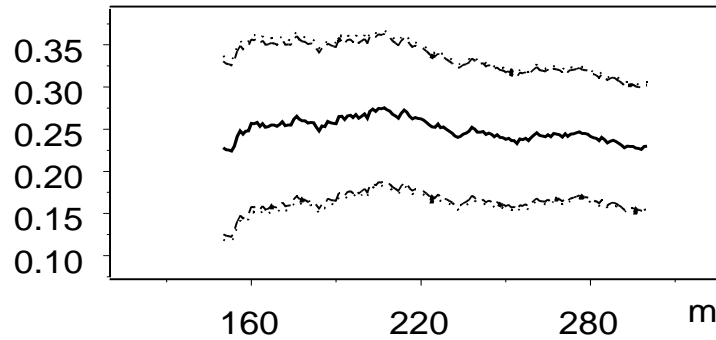


# Ibex35: estimates of memory parameter of volatility

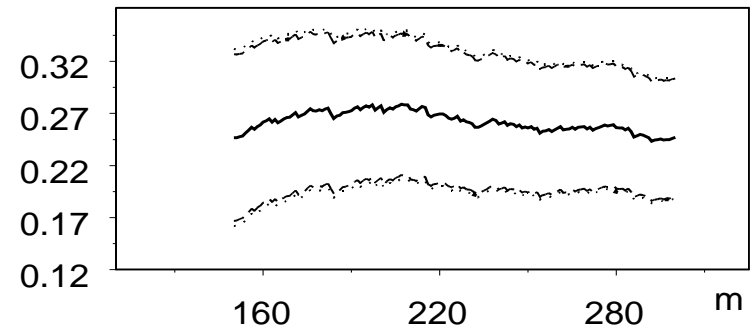


# Ibex35: estimates of memory parameter of volatility

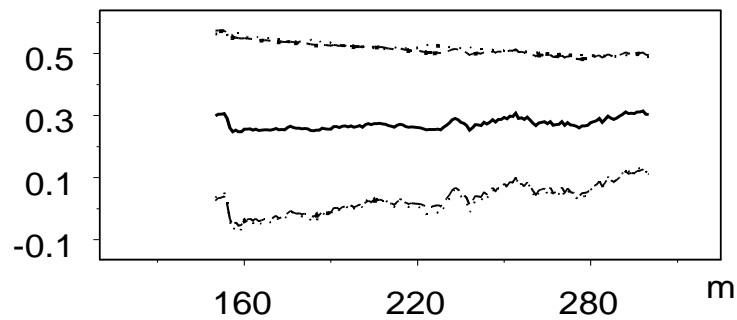
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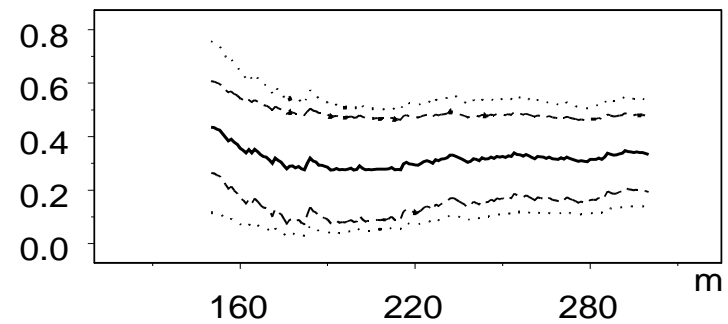
b) GSE and 95% confidence intervals



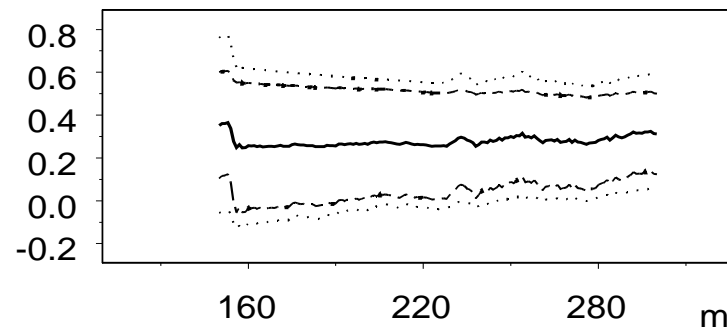
c) NLPE and 95% confidence intervals



d) MGSE and 95% confidence intervals



e) ALPE and 95% confidence intervals



# Conclusions

- If the added noise is not considered explicitly in the estimation the LPE and GSE can render meaningless estimates.
- More reliable are the NLPE (with low  $n$  and  $m$ ) and the ALPE and MGSE.



# Conclusions and extensions

- If the added noise is not considered explicitly in the estimation the LPE and GSE can render meaningless estimates.
- More reliable are the NLPE (with low  $n$  and  $m$ ) and the ALPE and MGSE.
- To be proved: properties of ALPE when  $u_t, y_t$  are not Gaussian and/or  $d \geq 0.5$
- Proposal of feasible versions of  $m^{opt}$ .
- Extensions for correlated signal and noise.