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Convex Combinations of Long Memory Estimates from Different Sampling Rates

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Abstract: Convex combinations of long memory estimates using the same data observed at different sampling rates can decrease the standard deviation of the estimates, at the cost of inducing a slight bias. The convex combination of such estimates requires a preliminary correction for the bias observed at lower sampling rates, reported by Souza and Smith (2002). Through Monte Carlo simulations, we investigate the bias and the standard deviation of the combined estimates, as well as the root mean squared error (RMSE), which takes both into account. While comparing the results of standard methods and their combined versions, the latter achieve lower RMSE, for the two semi-parametric estimators under study (by about 30% on average for ARFIMA(0,d,0) series).

Keywords: Convex Combination, Long Memory, Sampling Rate.

JEL Codes: C13, C14, C63

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1 Introduction

Asymptotic self-similarity in long memory time series ensures that the memory parameter is constant even when changing the sampling rate. Tschernig (1995), Chambers (1998) and Souza (2003a,b) provide results on the issue. So, a convex combination of estimates from different sampling rates can reduce the estimation variance if the bias of the estimates from lower sampling rates is small and the correlation between the different estimates is not high. At a first glance this is likely to occur at least for values of d close to zero. However, Souza and Smith (2002) show that decreasing the sampling rate induces a substantial bias in some estimators (all that were under study) due to the aliasing effect[1]. To overcome such a problem a bias correction can be applied to the estimates obtained from lower sampling rates.

In this paper, we implement a procedure for combining convexly the estimates from different sampling rates taken from the same data. This procedure is a purely artificial construct to take advantage from asymptotic self-similarity, and to our knowledge no other computationally intensive method for enhancing the long memory estimation upon an existing estimator has been proposed so far. It is intended for small samples, where the root mean square error of some long memory estimators is high, even though most of them have been proved consistent. Correction for the bias in the memory parameter is applied to estimates from decreased sampling rates using the heuristic formula proposed by Souza and Smith (2002). The convex combination of the long memory estimates can decrease the standard deviation (and the root mean squared error – RMSE) by up to 50% in some cases, however a slight bias remains. The RMSE is reduced by about 30% on average if the process is an ARFIMA(0,d,0).

This paper is organised as follows. Section 2 briefly introduces long memory and the effect of changing the sampling rate on it. Section 3 explains how the convex combination is carried out and shows its results. Section 4 offers some concluding remarks.

[1] For details on the aliasing effect, see Priestley (1981, pp. 224, 506). The specific case where the original series comes from a discrete-time process is studied by Souza (2003a).

2 Long memory and the sampling rate

2.1 Long memory

Long memory models are receiving more attention in the econometrics literature these days, as many instances of apparently stationary time series with long-range dependence arise. Among alternative definitions of long memory in stationary time series available in the literature, we work with the following two.

The first definition refers to the asymptotic behaviour of the autocorrelations. Let X_t be a stationary process and let $\rho(k)$ be the k-th order serial correlation of the series X_t. If there exists a real number $d \in (0, 0.5)$ and a positive function $c_\rho(k)$ slowly varying as k tends to infinity such that

$$\rho(k) \sim c_\rho(k) k^{2d-1} \quad \text{as } k \to \infty \tag{1}$$

then X_t is said to have long memory or long range dependence. When $d \in (-0.5, 0)$ and $c_\rho(k)$ is no longer positive, the process X_t is said to be "antipersistent" (Mandelbrot, 1977, p.232).

The second definition considers the spectrum behaviour close to the zero frequency, as follows. If there exists a positive function $c_f(\lambda)$, $\lambda \in (-\pi, \pi]$, which varies slowly as the frequency λ tends to zero, such that $d \in (0, 0.5)$ and

$$f(\lambda) \sim c_f(\lambda) |\lambda|^{-2d} \text{ as } \lambda \to 0, \tag{1.A}$$

where $f(\lambda)$ is the spectral density function of the stationary process X_t, then X_t is a stationary process with long memory with (long-)memory parameter d. The behaviours defined by (1) and (1.A) are not equivalent, but arise together with the same parameter d in a number of long memory models, such as in the ARFIMA class of models, which is defined below, for a subset of the parametric space.

X_t is said to follow an autoregressive integrated moving average model (ARIMA) if

$$\Phi(B)(1-B)^d X_t = \Theta(B)\varepsilon_t \tag{2}$$

where ε_t is a mean zero constant variance white noise process, B is the backward shift operator, such that $BX_t = X_{t-1}$, and $\Phi(B) = 1-\phi_1 B-\ldots-\phi_p B^p$ and $\Theta(B)=1+\theta_1 B+\ldots+\theta_q B^q$ are the autoregressive and moving average polynomials, respectively. ARIMA models allowing for a non-integer value of the parameter d are called ARFIMA, and it can be shown (Granger and Joyeux, 1980, Hosking, 1981) that they display long memory dependence according to (1) and (1.A) while are still stationary when $d \in (0, 0.5)$ and the roots of $\Phi(B)$ are outside the unit circle. The fractional difference can be more easily understood by expanding the polynomial $(1-B)^d$ in a binomial series, yielding an infinite AR polynomial:

$$(1-B)^d = \sum_{j=0}^{\infty} \frac{\Gamma(j-d)B^j}{\Gamma(j+1)\Gamma(-d)} \qquad (3)$$

where $\Gamma(.)$ is the gamma function.

2.2 Estimators

In this paper we consider two semiparametric estimators, the one proposed by Geweke and Porter-Hudak (1983), henceforth GPH, and its smoothed version, SMGPH, proposed by Hassler (1993). Choosing semiparametric long memory estimators (instead of parametric ones) implies that not all the spectrum will be considered, but only a band of it, discarding short memory components are known to bias the estimation. On the other hand, using a parametric estimator would require a prior specification for the model. The use of only a band of frequencies poses the question as to which bandwidth to choose, and there is a trade-off between bias and standard deviation implied by such choice. The wider the bandwidth, the more biased the estimator will be, but, on the other hand, the lower standard deviation it will achieve. It is well known that a positive autoregressive component bias upward and a negative moving average[2] component bias downward long memory estimation (Smith, Taylor and Yadav, 1997, Souza and Smith, 2002), the bias increasing with the parameter value. On the other hand,

[2] Note that the parameterisation of the MA polynomial differs in some works in the literature, in such a way that negative becomes positive and vice-versa.

negative autoregressive or positive moving average components do not bias considerably the estimation.

The GPH estimator, proposed by Geweke and Porter-Hudak (1983), estimates d from the spectrum behaviour close to the zero frequency. Taking the log of the both sides of (1.A) yields $\log f(\lambda) \approx \log c_f(\lambda) - 2d \log \lambda$ in the positive vicinity of the zero frequency. Replacing the spectral density function by the periodogram $I(\lambda_j)$ and rearranging gives way to:

$$\log I(\lambda_j) = \log c_f(\lambda) - 2d \log \lambda_j + \xi_j , \tag{2.A}$$

where $\lambda_j = 2\pi j/T$, j = 1, …, m, are the first Fourier frequencies and T is the sample size. Least-squares estimation applied to (2.A) yields an estimate for d. Hurvich, Deo and Brodsky (1998) prove that this estimator is consistent provided that the time series is Gaussian and $m \to \infty$ and $(m \log m)/T \to 0$ as $T \to \infty$. They also prove asymptotic normality:

$$\sqrt{m}\,(\hat{d} - d) \xrightarrow{D} N(0, \pi^2 / 24) . \tag{3.A}$$

Note that the variance of the asymptotic distribution depends only on the number of Fourier frequencies used in the estimation. It is usual to consider m as a function of the series length (m = g(T)). We use in this paper $g(T) = T^{0.5}$, a common choice in the literature, although Hurvich, Deo and Brodsky (1998) claim that the optimal rate would be $g(T) = O(T^{4/5})$. However, this is an asymptotic rate, and the bias can be particularly strong in small samples if a wide band is chosen. Results for different bandwidths are useful as a means of comparison, but are left for future research.

The smoothed version of the GPH, called here SMGPH, has a similar approach, using a smoothed estimator, instead of the raw periodogram, to estimate the spectrum. In this paper, the periodogram is smoothed by the Parzen lag window with degree of smoothness $\beta = 0.8$, such that the window size is $2l + 1$ and $l = T^{\beta}$ (for details on the Parzen window, refer to Priestley, 1981).

2.3 Invariance of the memory parameter to changes in the sampling rate

Using equation (1), it is easy to show the invariance of the long memory parameter, d, to changes in the sampling rate. Suppose the sampling rate is decreased n times, implying one samples every n^{th} observation. The autocorrelations, ρ_n, of the process X_{nt}, as the lag, k, tends to infinity behave like

$$\rho_n(k) = \rho(nk) \sim c_\rho(nk)(nk)^{2d-1} = n^{2d-1} c_\rho(nk) k^{2d-1} \quad \text{as } k \to \infty \qquad (4)$$

and the series X_{nt} has the same long memory parameter, d, as X_t, although its autocorrelations are lower and thus X_{nt} does not display exactly the same behaviour as X_t. The same result holds for $d \in (-0.5,0]$. For d = 0, if there is no short memory component, both X_t and X_{nt} are white noise processes. Souza and Smith (2002) show that there is a bias induced by decreasing the sampling rate, due to the aliasing effect, and propose a heuristic formula to account for this bias in some semi-parametric estimators, based on ARFIMA(0,d,0) processes. This bias is always towards zero. For d < 0 and n > 1 the average estimate of d is very close to zero, meaning that the bias has almost the same magnitude as the parameter itself. For d > 0 and n > 1 the bias is negative and U-shaped, being very small for d in the extremities of [0, 0.5] and reaching a maximum (in absolute value) for d around 0.25.

The reasons why not to use temporally aggregated series instead of sampling rate decreased series are twofold: first, there are less temporally aggregated series to be convexly combined than sampling rate decreased ones (one series for each n in the former case and n series for each n in the latter case); second, the estimates are highly correlated among themselves across levels of aggregation (Ohanissian, Russel and Tsay, 2003, and Souza, 2003b), which amounts to little or no gain when convexly combining them. One might argue that the bias of temporally aggregated series is lower (as shown, e.g., by Souza, 2003a, and Souza and Smith, 2003), as the "anti-aliasing" filter applied prior to sub-sampling would alleviate the bias induced by this sub-sampling. This would be particularly welcome in the case d < 0, as the bias has almost the same magnitude as d if the series is simply sub-sampled. However, small-scaled

simulations not shown here point to that little or no gain at all is obtained at convexly combining estimates from series with different levels of aggregation, probably because of the high correlation among estimates (as opposed to the low correlation observed in the estimates from different sampling rates). If d is negative, it is equivalent and simpler to use the conventional estimators. On the other hand, the computationally intensive methodology proposed here achieves gains in the RMSE over traditional estimates if d is non-negative, while not suffering much on accuracy otherwise.

2.4 Accounting for the bias

Let $\hat{d}_{nj}$, j = 1, …,n, be the estimate of d obtained from the j-th series with sampling rate 1/n, and $\bar{d}_n = \frac{1}{n}\sum_{j=1}^{n}\hat{d}_{nj}$ be the average estimate from all series with sampling rate 1/n. It is reasonable to assign equal weights to all series coming from the same original series and same sampling rate, as any of them must contain the same amount of information as each other. If the estimates from these series coming from the same sampling rate are highly correlated, there would be little or no gain in averaging them. But this is not the case and there are gains in so doing. However, as shown in Souza and Smith (2002), these estimates are biased if n > 1 and must be bias corrected. The correction is made using the heuristic formula[3] for the bias based on an ARFIMA (0,d,0) derived in Souza and Smith (2002), which is as follows:

$$HB(T,n,d) = \tag{5}$$

$$\frac{-d\left[2\left(\sum_{j=1}^{g(T)} z_j \ln(f_{nj}) - \bar{z}\sum_{j=1}^{g(T)}\ln(f_{nj})\right) + 4\left(\sum_{j=1}^{g(T)}(\ln(f_{nj}))^2 - \sum_{j=1}^{g(T)}(\overline{\ln(f_{nj})})^2\right)\right] - \sum_{j=1}^{g(T)}(z_{nj}-\bar{z}_n)\ln H(n,j,d)}{\left\{\sum_{j=1}^{g(T)} z_{nj}^{\;2} - \sum_{j=1}^{g(T)}\bar{z}_n^2\right\}}$$

[3] Although it is calculated having the GPH procedure in mind, for the SMGPH the phenomenon which leads to the bias is analogous and the approximation is still good.

where $z_j = \ln\{2\sin(\lambda_j/2)\}^2$; $\bar{z} = \dfrac{1}{g(T)}\sum_{j=1}^{g(T)} z_j$; $f_{nj} = \sum_{i=1}^{n}\left[\cos(\lambda_j/2)\right]^{i-1}\cos\left[(n-i)\lambda_j/2\right]$;

$z_{nj} = 2\ln(f_{nj}) + z_j$; $\bar{z}_n = \dfrac{1}{g(T)}\sum_{j=1}^{g(T)} z_{nj}$; and $\mathrm{H(j,n,d)} = \sum_{\mathrm{i=0}}^{\mathrm{n-1}}\left[\dfrac{\sin(\mathrm{i}\pi/\mathrm{n})}{\mathrm{tg}(\lambda_{\mathrm{j}}/2)} + \cos\left(\dfrac{\mathrm{i}\pi}{\mathrm{n}}\right)\right]^{-2\mathrm{d}}$.

$HB(T,n,d)$ is intended to approximate $E(\hat{d}_{nj}) - d = E(\bar{d}_n) - d$, the bias induced by decreasing the sampling rate. To use it as an estimate of the bias, (5) requires the actual value of d, which we replace by its best uncombined estimate $\bar{d}_1$. The upper limit g(T) in the summation is equivalent to the number of Fourier frequencies used in the GPH regression. For n>1, at first sight g(T/n) frequencies should be used. However, the j-th Fourier frequency regards the same sinusoidal component, having in mind the original series, no matter which sampling rate is applied (provided the sub-sampled series has length equal to or greater than 2j), even though the nominal frequency of this component changes across sampling rates. A component of the original process having frequency λ when n=1 has frequency nλ when n>1 and the j-th Fourier frequency is also increased n times (2jπ/T when n=1 and 2njπ/T for n>1). It is the high-frequency components that are discarded when one uses a lower sampling rate, as the ability to detect them disappears. When one chooses the bandwidth in the original series, it is a decision on those original sinusoidal components of the Fourier decomposition which amount to the whole series. For this reason, using always g(T) maintains the desired “effective bandwidth”, as in so doing the estimation on different sampling rates discards the same high-frequency components that may bias the results. As mentioned above, the estimators used here are semiparametric, and using the whole spectrum to estimate d makes the estimation more susceptible to bias due to the short memory components that may be present in the series. The convex combination is undertaken for the GPH and the SMGPH estimators, but this approach is extensible to other semiparametric estimation procedures not shown here, as long as the possible bias due to increasing n is accounted for.

3 Convex Combination

Yamamoto and Hughson (1991, 1993) have also used lower sampling rates applied to long-range dependent processes, in what they call "coarse graining". They aimed, however, at the separation between fractal properties and harmonic oscillations, in which they are successful. Here we aim at improving the precision of long memory estimates taking advantage of fractal properties and computational effort.

To study the influence of the maximum n used in the combination, we consider a convex combination of data from n = 1 to n = n*, where n* = 1, 2, …, 10 (ten different estimators). When n* = 1, this corresponds to the conventional estimator, as n = 1 corresponds to the original series. This case is useful as a benchmark, to measure the gain (or loss) obtained by the use of the technique introduced here. Since $\bar{d}_n$; n = 1, 2, …; are based on the same number of observations, it is not unreasonable to use equal weights in the convex combination, such that the proposed estimator becomes:

$$\hat{d}_{n*} = \frac{1}{n*}\sum_{i=1}^{n*}\bar{d}_i - HB(T,i,\bar{d}_1)\,, \qquad (??)$$

where HB(T,n,d) stands for the bias correction and is given by (5). A more refined weighting scheme would require further research, which is left for the future. In practice, one must regard the fact that the sub-sampled series have length T/n, and that series that are too short are inadequate to estimate long memory. For this reason, in this paper we use series with a minimum length of 50 observations (provided that 50 > T/n).

Before estimating the long memory of a time series, it is wise to study its characteristics and statistical properties, so that one really suspects the presence of long memory (d > 0) in the series. It includes visual inspecting the spectrum and the autocorrelation decay. Once the evidence is strong for long memory, the analyst carries on with the analysis and estimate its degree. If the evidence is weak, there may be a considerable cost in threat the series as having

the long memory property, due to the probability of misspecification. Ray (1993) and Man (2003) used respectively AR(p) and ARMA(2,2) to predict ARFIMA(0,d,0) processes, and these approximations proved useful for short-range predictions. Crato and Ray (1996) suggest that, in practice, only a long and strongly persistent time series justify using ARFIMA models for forecasting purposes. For this reason, we study only cases where $d \geq -0.2$.

The heuristic bias given by (5) is too high for negative values of d and n > 1 (almost the same absolute value as d, but with opposite sign), and in this case the high variation in $\bar{d}_1$ compared to $\bar{d}_n$ could destroy the precision obtained by $\bar{d}_n$ if the bias correction in (??) was applied. For this reason, we try three different approaches: bias correcting all $\bar{d}_n$; bias correcting $\bar{d}_n$ only if $\bar{d}_1 > 0$; and bias correcting $\bar{d}_n$ only if $\bar{d}_n > 0$. For cases where $d \geq 0$, little difference is noted among the results of these approaches, the second one performing slightly better and the first one slightly worse than the last one. The greatest differences are noted when $d < 0$ (or rather when the estimate is expected to be negative, like when there is a negative MA component), which correspond to the worst case and are briefly explained hereafter. In the first approach, there is the littlest bias induced by the technique, showing the bias given by (5) a good approximation, while on the other hand the standard deviation has the least decrease. In the second approach the bias in general has the greatest increase while achieving the least decrease in the standard deviation. The third and last approach has the best trade-off between bias increase and standard deviation reduction (also the best worst case), so that we choose this approach to show the results (and to use in practice). To sum up, we do not correct the bias when $\bar{d}_n$ is negative.

These differences in the precision of $\bar{d}_1$ and $\bar{d}_n$, n = 2, …, n*, are not shown in this paper, as they would require more tables and space to be displayed, but were observed in handling the results (statistics on this, however, are available from the authors under request).

3.1 Results

In order to verify the usefulness of the proposed method, a Monte Carlo simulation is carried out, with 500 replications of each case, where the series length takes the values of 200, 500, 1000 and 2000. We consider the following processes: ARFIMA(0,d,0); ARFIMA(1,d,0) with $\phi = 0.5$; and ARFIMA(0,d,1) with $\theta = -0.5$; all of them for d = -0.2, 0, 0.2 and 0.4. The method is applied on the GPH and SMGPH estimators, for n* = 1, 2, …, 10. Note that n* = 1 corresponds to the conventional, previously existing, estimator (GPH or SMGPH), as no bias correction is required and only the estimate from the original series (n = 1) is considered. By comparing the results of n* > 1 with those from n* = 1, a measure of the gain (or possibly loss) obtained by the convex combination method is assessed. The best results where achieved by the maximum n*, and so these will be outlined in the next paragraphs.

Table 1 displays bias, standard deviation and RMSE of the convex combination of GPH estimates for n* = 1, …, 10, where the series follow ARFIMA(0,d,0) processes. When $d \geq 0$, there very little bias, if any, induced by the convex combination, while the standard deviation is decreased by more than 40% if d = 0, by more than 25% if d = 0.2, and by about 30% if d = 0.4, considering n* = 10. For sample size T = 200, the maximum n* equals to 4 and the reduction is somewhat lower, although still considerable. The resulting RMSE gets reductions of same order as the standard deviation (around 30% on average), as the bias induced is negligible. For d = -0.2, however, the bias induced is considerable (around 0.1 for n* = 10), while the standard deviation is reduced by almost a half. The resulting RMSE suffers at most an increase of 3% (T = 2000), while can be reduced by about 30% for T = 200. In general, for negative values of d, the convex combination works better for smaller samples (differently from $d \geq 0$, where no great differences were observed across sample sizes), and as the sample increases the accuracy of the standard GPH can be no longer improved by the method.

Table 2 shows the same as Table 1, but refers to the SMGPH estimator, instead of the GPH. The results of the convex combination applied to the SMGPH are qualitatively

comparable, but quantitatively (in percentage points) slightly worse than those from the GPH if d ≥ 0. They are in general worse (especially when the sample size increases) if d < 0. For T = 2000 and d = -0.2, the RMSE is increased by about 37%, but sample sizes smaller than 1000 see reduction in the RMSE. However, note that the RMSE of the SMGPH is lower than that of GPH, so that is preferable to use the former in practical applications. Even in the worst case for the convex combination applied to the SMGPH (T = 2000, d = -0.2, commented above), the RMSE is pretty much the same as that from the convex combination applied to the GPH.

Table 3 shows the results of the convex combination applied to the GPH estimator, in the case the data generating process (DGP) is an ARFIMA(1,d,0), with $\phi = 0.5$. As commented in Section 2.2, the positive AR component biases the long memory estimation upward (in agreement with previous literature, see, for example, Bisaglia and Guégan, 1998). This bias tends to disappear as the sample size increases. The convex combination, on the other hand, makes this bias stronger, especially when d is negative. In addition to that, the reduction in the standard deviation is weaker than in the case of an ARFIMA(0,d,0), if d ≥ 0 (as opposed to the case d = -0.2, where it is decreased by more than a half for n* = 10). Even so, there are no losses (in the squared error sense) to the original estimator if the convex combination proposed here is applied. For d > 0, the RMSE is always decreased, but by no more than 10%. For d = 0, the reduction is greater than 20% for n* = 10, and is of order of 15% if T = 200 and n* = 4. For d = -0.2, the RMSE is reduced by about ¼ for T = 200 and n* = 4, but as the sample size increases, this reduction diminishes and even turns out to be an increase of 4% when T = 2000 and n* = 10.

Table 4 shows the results of the convex combination applied to the GPH estimator, in the case the DGP is an ARFIMA(0,d,1), with $\theta = -0.5$. The negative MA, as previously commented, biases the long memory estimation downward, this bias tending to vanish as the sample size increases. That is because a negative MA component reduces the memory of long memory processes (see Andersson, 2000) and makes the estimates for n>1 very close to zero (see Souza and Smith, 2002). The convex combination induces a bias in the estimation, increasing with n*,

and of opposite sign as d (negligible when d = 0), of order of 0.1 when n* = 10. On the other hand, the standard deviation is decreased to almost a half in general when n* = 10, and decreased to about 2/3 of its original value when T = 200 and n* = 4. The resulting RMSE is decreased to almost a half when d = 0; while when d > 0 the result is ambiguous. When d = 0.2, the reduction can be of 20%, decreasing with sample size until an increase of 1% when T = 2000. When d = 0.4, there is a 10% reduction for T = 200 and n* = 4, but for longer series and n* = 10 there is an increase in the RMSE, varying from 5% to 18%, increasing with sample size. For d = -0.2, the reduction in the RMSE decreases with sample size, going from about 30%, if T = 200 and n* = 4, to 11% when T = 1000 and n* = 10. For the longest series, T = 2000, there is actually a 5% increase in the RMSE.

The RMSE reduction achieved by the method on the SMGPH for ARFIMA(1,d,0) and ARFIMA(0,d,1) is not shown here, but is in general slightly worse than that obtained for the GPH in percentage points. On the other hand, the RMSE of the SMGPH is originally lower than that of the GPH, such that the RMSE resulting from the convex combination frequently favours the SMGPH. It is important to point out that the technique proposed here achieves considerable reduction in the RMSE when the DGP is an ARFIMA(0,d,0), and a smaller reduction in general when a positive AR or negative MA (the most likely to bias the long memory estimation) of magnitude 0.5 is present. It is noted that the greater n* used, the better result is achieved in general, but the greater n* are likely to worsen the few unfavourable cases.

5 Concluding Remarks

In this paper, we propose a convex combination of long memory estimates taken from the same data using different sampling rates. The Geweke and Porter-Hudak (1983) estimator and its smoothed version are used, and the estimates from lower sampling rates must be bias corrected. We use for this purpose the heuristic bias formula in Souza and Smith (2002), proposed for an ARFIMA(0,d,0) DGP. Convexly combining the estimates decreases the standard deviation,

while introducing some bias, and the best results are in general obtained for positive values of d (long memory). The resulting RMSE of the estimation is considerably reduced if the DGP is an ARFIMA(0,d,0), by about 30% on average, and is in general slightly reduced when the process is an ARFIMA (1,d,0) with $\phi = 0.5$, or an ARFIMA (0,d,1) with $\theta = -0.5$. The few cases were the RMSE is only slightly increased do not justify abandoning this approach in face of the gains it can offer.

The RMSE reduction for the ARFIMA (0,d,0) case makes it advantageous to use the convex combination to estimate the degree of fractional integration, even taking into account the risk of the misspecification in the bias formula.

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Table 1: Bias, standard deviation and RMSE obtained by the method upon the GPH estimator for ARFIMA(0,d,0) processes (n*=1 corresponds to the GPH alone).

		d=-0.2				d=0				d=0.2				d=0.4			
		T=200	500	1000	2000	T=200	500	1000	2000	T=200	500	1000	2000	T=200	500	1000	2000
BIAS	n*=1	0.005	0.021	0.013	0.010	-0.007	-0.004	0.002	0.000	0.012	0.001	0.009	-0.004	0.003	0.002	0.014	0.005
	2	0.041	0.063	0.059	0.059	-0.005	-0.002	0.003	-0.002	-0.004	-0.007	0.002	-0.007	0.001	0.000	0.013	0.005
	3	0.062	0.081	0.077	0.076	-0.005	-0.001	0.003	0.001	-0.017	-0.012	-0.002	-0.009	-0.004	-0.001	0.011	0.005
	4	0.070	0.090	0.084	0.085	-0.003	0.000	0.003	0.002	-0.020	-0.017	-0.006	-0.010	-0.008	-0.004	0.010	0.004
	5		0.095	0.089	0.092		0.000	0.003	0.002		-0.021	-0.010	-0.012		-0.005	0.009	0.003
	6		0.098	0.093	0.095		0.001	0.003	0.002		-0.024	-0.012	-0.014		-0.008	0.007	0.003
	7		0.101	0.095	0.097		0.000	0.003	0.002		-0.026	-0.014	-0.015		-0.009	0.005	0.002
	8		0.104	0.098	0.099		0.000	0.002	0.002		-0.029	-0.015	-0.016		-0.011	0.004	0.001
	9		0.105	0.100	0.101		0.000	0.003	0.002		-0.030	-0.017	-0.017		-0.012	0.002	0.001
	10		0.106	0.101	0.102		-0.001	0.003	0.002		-0.032	-0.018	-0.018		-0.014	0.001	0.000
STD	n*=1	0.236	0.170	0.141	0.116	0.234	0.177	0.135	0.108	0.227	0.167	0.138	0.111	0.239	0.165	0.139	0.109
	2	0.189	0.135	0.109	0.092	0.187	0.142	0.111	0.089	0.207	0.151	0.122	0.100	0.222	0.151	0.129	0.102
	3	0.163	0.115	0.096	0.080	0.167	0.124	0.098	0.081	0.191	0.139	0.114	0.093	0.209	0.143	0.121	0.095
	4	0.146	0.108	0.090	0.075	0.157	0.116	0.093	0.075	0.183	0.134	0.111	0.089	0.201	0.136	0.114	0.091
	5		0.102	0.086	0.070		0.110	0.088	0.071		0.129	0.107	0.088		0.131	0.109	0.087
	6		0.098	0.083	0.068		0.107	0.086	0.069		0.126	0.105	0.086		0.128	0.105	0.083
	7		0.093	0.082	0.066		0.103	0.082	0.066		0.124	0.103	0.085		0.125	0.102	0.081
	8		0.091	0.080	0.064		0.101	0.080	0.065		0.122	0.102	0.084		0.122	0.099	0.078
	9		0.090	0.078	0.062		0.099	0.078	0.063		0.122	0.102	0.083		0.121	0.097	0.076
	10		0.089	0.076	0.062		0.098	0.076	0.062		0.121	0.102	0.083		0.120	0.096	0.075
RMSE	n*=1	0.236	0.172	0.141	0.116	0.235	0.177	0.135	0.108	0.227	0.167	0.138	0.111	0.239	0.165	0.140	0.109
	2	0.193	0.149	0.124	0.109	0.187	0.142	0.111	0.089	0.207	0.151	0.122	0.100	0.222	0.151	0.130	0.102
	3	0.174	0.141	0.123	0.111	0.167	0.124	0.098	0.081	0.192	0.140	0.114	0.093	0.209	0.143	0.121	0.096
	4	0.162	0.140	0.124	0.114	0.157	0.116	0.093	0.075	0.184	0.135	0.111	0.090	0.201	0.136	0.114	0.091
	5		0.139	0.124	0.115		0.110	0.088	0.071		0.131	0.108	0.089		0.131	0.110	0.087
	6		0.139	0.125	0.117		0.107	0.086	0.069		0.129	0.106	0.087		0.128	0.105	0.083
	7		0.138	0.125	0.117		0.103	0.082	0.066		0.127	0.104	0.086		0.125	0.102	0.081
	8		0.138	0.126	0.118		0.101	0.080	0.065		0.126	0.104	0.085		0.123	0.099	0.078
	9		0.138	0.127	0.119		0.099	0.078	0.063		0.125	0.103	0.085		0.122	0.097	0.076
	10		0.138	0.126	0.120		0.098	0.076	0.062		0.125	0.103	0.085		0.121	0.096	0.075

Table 2: Bias, standard deviation and RMSE obtained by the method upon the SMGPH estimator for ARFIMA(0,d,0) processes (n*=1 corresponds to the SMGPH alone).

		d=-0.2				d=0				d=0.2				d=0.4			
		T=200	500	1000	2000	T=200	500	1000	2000	T=200	500	1000	2000	T=200	500	1000	2000
	n*=1	-0.026	-0.005	0.000	0.005	-0.030	-0.019	-0.014	-0.012	-0.003	-0.015	-0.007	-0.009	0.001	0.002	0.008	0.013
	2	0.025	0.049	0.053	0.058	-0.025	-0.016	-0.010	-0.011	-0.013	-0.020	-0.011	-0.011	-0.003	0.001	0.007	0.012
	3	0.047	0.069	0.074	0.078	-0.023	-0.015	-0.011	-0.010	-0.022	-0.023	-0.014	-0.014	-0.007	-0.001	0.006	0.011
	4	0.059	0.079	0.085	0.088	-0.019	-0.013	-0.010	-0.009	-0.025	-0.026	-0.017	-0.015	-0.012	-0.003	0.004	0.010
BIAS	5		0.084	0.091	0.096		-0.012	-0.010	-0.008		-0.030	-0.020	-0.017		-0.005	0.003	0.009
	6		0.088	0.097	0.101		-0.012	-0.010	-0.008		-0.032	-0.022	-0.018		-0.007	0.001	0.008
	7		0.092	0.099	0.105		-0.013	-0.009	-0.007		-0.035	-0.023	-0.019		-0.009	0.000	0.007
	8		0.094	0.102	0.108		-0.013	-0.009	-0.007		-0.037	-0.025	-0.020		-0.010	-0.001	0.006
	9		0.096	0.104	0.110		-0.012	-0.009	-0.007		-0.038	-0.026	-0.021		-0.012	-0.003	0.005
	10		0.098	0.106	0.112		-0.012	-0.008	-0.007		-0.040	-0.027	-0.022		-0.013	-0.004	0.004
	n*=1	0.183	0.134	0.111	0.087	0.193	0.141	0.110	0.093	0.193	0.136	0.113	0.090	0.190	0.138	0.122	0.096
	2	0.139	0.104	0.082	0.066	0.163	0.116	0.093	0.079	0.179	0.129	0.105	0.084	0.179	0.128	0.115	0.090
	3	0.117	0.088	0.070	0.056	0.146	0.106	0.083	0.072	0.170	0.123	0.101	0.079	0.170	0.122	0.108	0.085
	4	0.104	0.083	0.063	0.052	0.136	0.099	0.078	0.068	0.164	0.121	0.098	0.078	0.164	0.117	0.103	0.081
STD	5		0.077	0.058	0.048		0.092	0.074	0.063		0.118	0.096	0.076		0.113	0.099	0.077
	6		0.074	0.055	0.045		0.090	0.070	0.061		0.117	0.095	0.076		0.110	0.095	0.074
	7		0.069	0.053	0.043		0.085	0.067	0.058		0.115	0.094	0.075		0.108	0.092	0.071
	8		0.067	0.052	0.041		0.083	0.066	0.057		0.114	0.094	0.075		0.106	0.090	0.069
	9		0.065	0.050	0.041		0.080	0.064	0.055		0.114	0.094	0.074		0.105	0.089	0.067
	10		0.064	0.048	0.040		0.078	0.063	0.054		0.114	0.094	0.074		0.104	0.087	0.065
	n*=1	0.185	0.134	0.111	0.087	0.196	0.142	0.111	0.093	0.193	0.136	0.113	0.090	0.190	0.138	0.123	0.097
	2	0.141	0.115	0.097	0.088	0.165	0.117	0.094	0.080	0.180	0.130	0.105	0.085	0.179	0.128	0.115	0.091
	3	0.126	0.112	0.102	0.096	0.148	0.107	0.083	0.072	0.171	0.125	0.102	0.081	0.170	0.122	0.108	0.086
	4	0.119	0.114	0.106	0.103	0.137	0.100	0.079	0.068	0.166	0.123	0.099	0.079	0.164	0.117	0.103	0.081
RMSE	5		0.114	0.108	0.107		0.093	0.074	0.064		0.121	0.098	0.078		0.113	0.099	0.077
	6		0.115	0.111	0.111		0.091	0.071	0.062		0.121	0.098	0.078		0.110	0.095	0.074
	7		0.115	0.113	0.113		0.086	0.068	0.059		0.120	0.097	0.077		0.108	0.092	0.071
	8		0.116	0.114	0.116		0.084	0.067	0.057		0.120	0.097	0.077		0.106	0.090	0.069
	9		0.116	0.116	0.118		0.081	0.064	0.055		0.120	0.097	0.077		0.106	0.089	0.067
	10		0.117	0.117	0.119		0.079	0.063	0.054		0.121	0.098	0.078		0.105	0.087	0.065

Table 3: Bias, standard deviation and RMSE obtained by the method upon the GPH estimator for ARFIMA(1,d,0) processes, ϕ = 0.5 (n*=1 corresponds to the GPH alone).

		d=-0.2				d=0				d=0.2				d=0.4			
		T=200	500	1000	2000	T=200	500	1000	2000	T=200	500	1000	2000	T=200	500	1000	2000
BIAS	n*=1	0.066	0.043	0.024	0.015	0.053	0.020	0.012	0.006	0.072	0.024	0.020	0.002	0.063	0.025	0.025	0.010
	2	0.081	0.064	0.053	0.048	0.060	0.027	0.017	0.010	0.081	0.036	0.032	0.014	0.077	0.036	0.034	0.017
	3	0.093	0.078	0.071	0.070	0.061	0.029	0.021	0.014	0.086	0.044	0.040	0.022	0.087	0.047	0.042	0.025
	4	0.100	0.089	0.083	0.085	0.062	0.032	0.022	0.015	0.089	0.048	0.045	0.028	0.095	0.054	0.049	0.031
	5		0.096	0.092	0.095		0.033	0.023	0.016		0.051	0.048	0.032		0.060	0.055	0.036
	6		0.101	0.099	0.101		0.032	0.024	0.017		0.052	0.050	0.034		0.065	0.059	0.041
	7		0.104	0.103	0.105		0.032	0.024	0.017		0.051	0.050	0.036		0.068	0.063	0.045
	8		0.108	0.107	0.109		0.032	0.024	0.017		0.051	0.051	0.037		0.071	0.066	0.048
	9		0.110	0.109	0.111		0.032	0.024	0.017		0.050	0.050	0.038		0.072	0.068	0.051
	10		0.112	0.111	0.113		0.032	0.024	0.017		0.049	0.050	0.038		0.073	0.069	0.053
STD	n*=1	0.233	0.168	0.140	0.115	0.236	0.175	0.136	0.109	0.227	0.167	0.138	0.110	0.236	0.165	0.140	0.109
	2	0.202	0.139	0.109	0.086	0.221	0.168	0.132	0.105	0.223	0.166	0.134	0.107	0.230	0.159	0.134	0.105
	3	0.174	0.118	0.092	0.070	0.212	0.162	0.127	0.101	0.219	0.164	0.132	0.107	0.224	0.154	0.130	0.101
	4	0.154	0.107	0.080	0.061	0.202	0.155	0.122	0.098	0.216	0.162	0.131	0.106	0.220	0.150	0.125	0.098
	5		0.099	0.071	0.054		0.150	0.118	0.095		0.160	0.130	0.105		0.147	0.122	0.095
	6		0.093	0.066	0.051		0.146	0.114	0.092		0.158	0.129	0.105		0.145	0.119	0.093
	7		0.088	0.062	0.048		0.141	0.112	0.090		0.157	0.128	0.104		0.143	0.116	0.090
	8		0.085	0.060	0.046		0.138	0.109	0.087		0.155	0.128	0.104		0.141	0.114	0.088
	9		0.082	0.059	0.045		0.134	0.106	0.085		0.155	0.127	0.104		0.140	0.112	0.087
	10		0.080	0.058	0.044		0.132	0.104	0.083		0.155	0.126	0.103		0.139	0.111	0.086
RMSE	n*=1	0.242	0.174	0.142	0.116	0.242	0.176	0.137	0.109	0.238	0.169	0.139	0.110	0.244	0.167	0.142	0.110
	2	0.217	0.153	0.121	0.099	0.229	0.170	0.133	0.105	0.238	0.170	0.138	0.108	0.243	0.163	0.138	0.106
	3	0.197	0.141	0.116	0.099	0.220	0.165	0.129	0.102	0.235	0.169	0.138	0.109	0.240	0.161	0.136	0.104
	4	0.183	0.139	0.115	0.104	0.211	0.158	0.124	0.099	0.233	0.169	0.139	0.109	0.240	0.160	0.135	0.102
	5		0.138	0.117	0.109		0.153	0.120	0.096		0.167	0.139	0.110		0.159	0.134	0.102
	6		0.137	0.119	0.113		0.149	0.117	0.093		0.167	0.138	0.110		0.159	0.133	0.101
	7		0.136	0.121	0.116		0.144	0.114	0.091		0.165	0.138	0.110		0.158	0.132	0.101
	8		0.137	0.123	0.118		0.141	0.112	0.089		0.164	0.138	0.110		0.158	0.132	0.101
	9		0.137	0.124	0.120		0.138	0.109	0.087		0.163	0.137	0.110		0.157	0.131	0.101
	10		0.138	0.126	0.121		0.136	0.107	0.085		0.162	0.136	0.110		0.157	0.131	0.101

Table 4: Bias, standard deviation and RMSE obtained by the method upon the GPH estimator for ARFIMA(0,d,1) processes, θ = -0.5 (n*=1 corresponds to the GPH alone).

		d=-0.2				d=0				d=0.2				d=0.4			
		T=200	500	1000	2000	T=200	500	1000	2000	T=200	500	1000	2000	T=200	500	1000	2000
BIAS	n*=1	-0.053	0.000	0.005	0.006	-0.070	-0.027	-0.008	-0.005	-0.051	-0.021	-0.002	-0.008	-0.056	-0.020	0.003	0.000
	2	0.008	0.054	0.058	0.056	-0.053	-0.027	-0.007	-0.011	-0.102	-0.074	-0.056	-0.056	-0.119	-0.079	-0.049	-0.044
	3	0.031	0.070	0.076	0.072	-0.050	-0.025	-0.010	-0.009	-0.122	-0.094	-0.076	-0.073	-0.144	-0.107	-0.078	-0.067
	4	0.041	0.078	0.083	0.082	-0.047	-0.023	-0.010	-0.009	-0.125	-0.103	-0.087	-0.081	-0.159	-0.123	-0.094	-0.082
	5		0.084	0.088	0.087		-0.024	-0.010	-0.009		-0.108	-0.094	-0.086		-0.133	-0.104	-0.093
	6		0.087	0.092	0.090		-0.023	-0.010	-0.009		-0.111	-0.097	-0.089		-0.140	-0.112	-0.100
	7		0.090	0.092	0.093		-0.023	-0.010	-0.008		-0.113	-0.101	-0.090		-0.144	-0.118	-0.106
	8		0.092	0.094	0.096		-0.022	-0.010	-0.008		-0.114	-0.101	-0.091		-0.148	-0.123	-0.110
	9		0.094	0.096	0.097		-0.021	-0.009	-0.008		-0.115	-0.102	-0.092		-0.150	-0.126	-0.114
	10		0.095	0.097	0.098		-0.021	-0.009	-0.008		-0.116	-0.103	-0.093		-0.152	-0.128	-0.117
STD	n*=1	0.243	0.173	0.143	0.114	0.232	0.175	0.134	0.109	0.229	0.169	0.136	0.110	0.241	0.164	0.139	0.109
	2	0.202	0.145	0.115	0.099	0.182	0.138	0.109	0.085	0.180	0.130	0.102	0.086	0.199	0.132	0.113	0.091
	3	0.179	0.126	0.101	0.089	0.158	0.118	0.091	0.072	0.154	0.109	0.089	0.073	0.171	0.117	0.100	0.080
	4	0.167	0.123	0.095	0.084	0.148	0.109	0.086	0.068	0.142	0.104	0.084	0.069	0.158	0.107	0.091	0.073
	5		0.115	0.092	0.077		0.101	0.080	0.063		0.096	0.077	0.065		0.102	0.085	0.068
	6		0.111	0.088	0.076		0.099	0.078	0.062		0.095	0.076	0.064		0.099	0.080	0.064
	7		0.105	0.087	0.073		0.094	0.074	0.060		0.090	0.071	0.062		0.094	0.076	0.060
	8		0.102	0.085	0.070		0.092	0.072	0.058		0.088	0.071	0.061		0.091	0.073	0.058
	9		0.100	0.084	0.070		0.091	0.071	0.057		0.087	0.070	0.060		0.090	0.071	0.056
	10		0.098	0.083	0.070		0.089	0.070	0.056		0.086	0.070	0.060		0.089	0.069	0.054
RMSE	n*=1	0.249	0.173	0.143	0.114	0.243	0.177	0.134	0.109	0.235	0.170	0.136	0.110	0.247	0.166	0.139	0.109
	2	0.202	0.155	0.129	0.114	0.190	0.141	0.109	0.085	0.207	0.150	0.117	0.102	0.232	0.154	0.124	0.101
	3	0.181	0.145	0.126	0.115	0.166	0.121	0.091	0.072	0.197	0.144	0.117	0.103	0.223	0.158	0.127	0.104
	4	0.172	0.145	0.126	0.117	0.155	0.112	0.086	0.069	0.190	0.146	0.121	0.106	0.224	0.163	0.131	0.110
	5		0.142	0.127	0.117		0.104	0.080	0.064		0.144	0.121	0.108		0.167	0.134	0.115
	6		0.141	0.127	0.118		0.102	0.079	0.063		0.146	0.123	0.109		0.171	0.138	0.119
	7		0.138	0.127	0.118		0.097	0.074	0.060		0.145	0.123	0.109		0.173	0.141	0.122
	8		0.138	0.127	0.119		0.095	0.073	0.059		0.144	0.124	0.110		0.174	0.143	0.124
	9		0.137	0.127	0.119		0.094	0.071	0.058		0.144	0.124	0.110		0.175	0.145	0.126
	10		0.137	0.128	0.120		0.092	0.071	0.057		0.144	0.124	0.111		0.177	0.146	0.128

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