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A COMPARATIVE NOTE ABOUT ESTIMATION OF THE FRACTIONAL PARAMETER UNDER ADDITIVE OUTLIERS

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A Comparative Note about Estimation of the Fractional Parameter under Additive Outliers

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Abstract

In a recent paper, Fajardo et al. (2009) propose an alternative semiparametric estimator of the fractional parameter in ARFIMA models which is robust to the presence of additive outliers. The results are very interesting, however, they use samples of 300 or 800 observations which are rarely found in macroeconomics or economics. In order to perform a comparison, I use the procedure to detect for additive outliers based on the estimator τ_d suggested by Perron and Rodríguez (2003). Further, I use dummy variables associated to the location of the selected outliers to estimate the fractional parameter. I found better results for the mean and bias of this parameter when $T = 100$ and the results in terms of the standard deviation and the MSE are very similar. However, for higher sample sizes as 300 or 800, the robust procedure performs better, specially based on the standard deviation and MSE measures. Empirical applications for seven Latin American inflation series with very small sample sizes contaminated by additive outliers is discussed. What we find is that when no correction for additive outliers is performed, the fractional parameter is underestimated.
Keywords: Additive Outliers, ARFIMA Erros, Inflation, Semiparametric estimation. JEL: C2, C3, C5

Resumen

En un artículo reciente, Fajardo et al. (2009) proponen un estimador semiparamétrico alternativo del parámetro fraccional en modelos ARFIMA que es robusto a la presencia de valores atípicos aditivos. Los resultados son muy interesantes, sin embargo, utilizan muestras de 300 ó 800 observaciones que rara vez se encuentran en la macroeconomía o la economía. Para realizar una comparación, yo uso el procedimiento para la detección de valores atípicos aditivos basados en el estimador τ_d propuesto por Perron y Rodríguez (2003). Además, utilizo variables ficticias asociadas a la ubicación de los valores atípicos seleccionados para estimar el parámetro fraccional. Los resultados son mejores para la media y el sesgo de este parámetro cuando $T = 100$ y los resultados en términos de la desviación estándar y el MSE son muy similares. Sin embargo, para tamaños de muestra más altos como 300 ó 800, el procedimiento robusto tiene un mejor rendimiento, especialmente sobre la base de la desviación estándar y el MSE. Aplicaciones empíricas para siete series de inflación de América Latina, con muy pequeños tamaños de muestras contaminadas por los valores atípicos aditivos es discutida. Lo que encontramos es que cuando no se realiza ninguna corrección para los valores atípicos aditivos, se subestima el parámetro fraccional.
Palabras Claves: Outliers Aditivos, Errores ARFIMA, Inflación, Estimación Semiparamétrica. **Classificación JEL:** C2, C3, C5

A Comparative Note about Estimation of the Fractional Parameter under Additive Outliers[1]

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1 Introduction

In a recent paper, Fajardo et al. (2009) introduce an alternative semiparametric estimator of the fractional differencing parameter in ARFIMA models which is robust against additive outliers. The proposed estimator is a modification of the estimator proposed by Geweke and Porter-Hudak (1983) and they use the robust sample autocorrelations of Ma and Genton (2000). The numerical results show that the estimator proposed by Fajardo et al. (2009) is robust when data contain additive outliers.

Even when the simulation results of the robust method are encouraging, I observe that the estimator of the differencing parameter ($\widehat{d}$) is close to the true value of the parameter for $T = 300$ or more observations. When $T = 100$ and the true $d = 0.30$ and when there is no additive outliers, the method estimates a mean $\widehat{d}$ of 0.258; see Table 1 of Fajardo et al. (2009). When there are additive outliers of size $\omega = 10$ the mean value of $\widehat{d} = 0.245$. When the true value of the differencing parameter is 0.45, similar conclusions are obtained when $T = 100$. For higher sample sizes, the estimate parameter is closer to the true value (d); see $T = 300$ or $T = 800$. However, sample sizes like $T = 300$ or more observations are very difficult to find in macroeconomics and this issue is more delicate in developing countries.

Therefore, in this paper, I use the procedure τ_d proposed by Perron and Rodríguez (2003) for sample sizes $T = 100$ or smaller. I calculate the mean, standard deviation, bias and mean square error (MSE) of the differencing parameter. I compare the results obtained for $T = 100$ with those obtained by Fajardo et al. (2009).

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2 The Model of Fajardo et al. (2009)

Let $\{y_t\}$, $t \in \mathbb{Z}$ be a weakly stationary process. Let $\{z_t\}$, $t \in \mathbb{Z}$ be a process contaminated by additive outliers, which is described by

$$z_t = y_t + \sum_{j=1}^{m} \omega_j X_{j,t} \quad , \tag{1}$$

where m is the maximum number of outliers and the unknown parameter ω_j indicates the magnitude of the j_{th} outlier. The $X_{j,t}$ is a random variable with probability distribution $\Pr(X_j = -1) = \Pr(X_j = 1) = p_j/2$ and $\Pr(X_j = 0) = 1 - p_j$. Therefore, X_j is the product of a Bernouilli (p_j) and a Rademacher random variables; the latter equals 1 or -1, both with probability 1/2. Furthermore, y_t and X_j are independent random variables. The model (1) is based on the parametric models proposed by Fox (1972).

The principal results found by Fajardo et al. (2009) may be summarized as follows. First, the results indicate that the spectral density of $\{z_t\}$, $t \in \mathbb{Z}$ is characterized by a translation due to the contributions of ω_j and the probabilities p_j. A similar result was also discussed by Chan (1992, 1995) interpreting their results as a spurious memory loss in the autocorrelations.

The second result is a substantial increase in the sample autocovariance function and furthermore a bias in the periodogram. Therefore, the autocorrelation structure may be affected by the presence of additive outliers. Another result of Fajardo et al. (2009) is the fact that the information loss in the serial correlation dynamics of the process is translated into the parameter estimation process.

The solution proposed by Fajardo et al. (2009) is the use of a modified-robust version of the estimator proposed originally by Geweke and Porter-Hudak (1983). The basic idea is a robust sample estimator of the autocovariance function which allow to obtain a robust spectral estimator.

The Estimator of Geweke and Porter-Hudak (1983) is defined as

$$d = \frac{-\sum_{j=1}^{G(T)} (v_j - \widetilde{v}) \log I_y(\lambda_j)}{\sum_{j=1}^{G(T)} (v_j - \widetilde{v})^2} \tag{2}$$

where $v_j = \log\{2\sin(\lambda_j/2)\}^2$, $G(T)$ being the bandwidth which satisfies $G(T)/T \to 0$ when $G(T) \to \infty$. Furthermore, $\log I_y(\lambda_j) = \beta_0 - d \log\{2\sin(\lambda_j/2)\}^2 + \epsilon_j$ for $j = 1, 2, 3, ..., G(T)$; see more details in Fajardo et al. (2009)). The proposed estimator in Fajardo et al. (2009) is based on the robust autocorrelation coefficient due to Ma and Genton (2000) and is defined by

$$d_{GPHR} = \frac{-\sum_{j=1}^{G(T)}(v_j - \widetilde{v}) \log I_Q(\lambda_j)}{\sum_{j=1}^{G(T)}(v_j - \widetilde{v})^2} \tag{3}$$

where $v_j = \log\{2\sin(\lambda_j/2)\}^2$, $I_Q(\lambda_j) = \frac{1}{2\pi}\sum_{s=-(n-1)}^{n-1} k(s)\widehat{R}_Q(s)\cos(s\lambda)$. The term $\widehat{R}_Q(s) = (1/4)Q^2_{n-h}(\mathbf{u}+\mathbf{v}) - Q^2_{n-h}(\mathbf{u}-\mathbf{v})$ where $\mathbf{u}$ and $\mathbf{v}$ are vectors containing the initial $n-h$ and the final $n-h$ observations. Furthermore,

$$\begin{aligned} k(s) &= 1 \qquad s \leq M \\ &= 0 \qquad s > M, \end{aligned}$$

which is a particular case of kernel functions used in classical spectral theory. The M is the truncation parameter which is a function of T, that is, $M = G(T)$. In most of applications $G(T) = T^\beta$ where $\beta = 0.7, 0.8$, etc.

3 The Model of Perron and Rodríguez (2003)

The data-generating process entertained is of the following general form:

$$y_t = d_t + \sum_{j=1}^{m} \delta_j D(T_{ao,j})_t + u_t \tag{4}$$

where $D(T_{ao,j})_t = 1$ if $t = T_{ao,j}$ and 0 otherwise. This permits the presence of m additive outliers occurring at dates $T_{ao,j}$ $(j = 1, ..., m)$. The term d_t specifies the deterministic components. In most cases, $d_t = \mu$ if the series is non-trending or $d_t = \mu + \beta t$ if the series is trending. The noise function is integrated of order one, i.e., $u_t = u_{t-1} + v_t$; where v_t is a stationary process.

Perron and Rodríguez (2003) have proposed a more powerful iterative strategy using tests based on first-differences of the data. Consider data generated by (4) with $d_t = \mu$, and a single outlier occurring at date T_{ao} with magnitude δ. Then,

$$\Delta y_t = \delta[D(T_{ao})_t - D(T_{ao})_{t-1}] + v_t, \tag{5}$$

where $D(T_{ao})_t = 1$, if $t = T_{ao}$ (0, otherwise) and $D(T_{ao})_{t-1} = 1$, if $t = T_{ao}-1$ (0, otherwise). If the data are trending a constant should be included.

We have that the least-squares estimate of δ is given by

$$\begin{aligned} \hat{\delta} &= \Delta y_t - \Delta y_{t-1} \\ &= u_t - u_{t-1} \end{aligned} \tag{6}$$

under the null hypothesis of no outlier. So the variance of $\hat{\delta}$ is given by

$$var(\hat{\delta}) = 2(R_u(0) - R_u(1)) \tag{7}$$

where $R_u(j)$ is the autocovariance function of u_t at delay j. Let $\hat{R}_u(j) = T^{-1}\sum_{t=1}^{T-j}\hat{v}_t\hat{v}_{t-j}$ with $\hat{v}_t$ the least-squares residuals obtained from regression (5). Then, $\hat{R}_u(j)$ is a consistent estimate of $R_u(j)$. We can then consider the following test statistic

$$\tau_d = \sup_{T_{ao}} |t_{\hat{\delta}}(T_{ao})| \tag{8}$$

where

$$t_{\hat{\delta}}(T_{ao}) = \hat{\delta}/(2(\hat{R}_u(0) - \hat{R}_u(1)). \tag{9}$$

To detect multiple outliers, we can follow a strategy similar to that suggested by Vogelsang (1999), by dropping the observation labelled as an outlier before proceeding to the next step. The important feature is that, unlike for the case of tests based on levels (as the τ statistic of Vogelsang), the limit distribution of the test τ_d is the same as each step of the iterations when dealing with multiple outliers. The reason is basically because at each steps the tests are now asymptotically independent

The disadvantage of this procedure, compared to that based on the levels of the data, is that the limiting distribution depends on the specific distribution of the errors u_t, though not on the presence of serial correlation and heteroskedasticity. This problem is exactly the same as that for finding outliers in stationary time series since by differencing we effectively work with a stationary series. Nevertheless, following standard practice in the literature, we shall simulate critical values assuming *i.i.d.* normal errors and assess the extent to which inference is affected when the data deviates from these specifications.

4 Monte Carlo Results

Fajardo et al. (2009) perform the following Monte-Carlo experiment considered in their Tables 1 and 2. In both Tables, an ARFIMA(0,d,0) model is simulate for $d = 0.30$ and $d = 0.45$. Furthermore $T = 100, 300$ and 800 observations are used with 10,000 replications. Furthermore, they use model (equation 1) with $m = 1$, $p = 0.05$ and magnitudes for the additive outliers $\omega = 3, 5$ and 10. The truncation parameter is fixed to be $\beta = 0.7$ (that is $T^{0.7}$). In order to compare with these results, I use the same model and values of the parameters.

Table 1 shows the results obtained for an ARFIMA (0,d,0) with $d = 0.3$ and $d = 0.45$ and $\omega = 0$ and 10. Fajardo et al. (2009) present results for $T = 100, 300$ and 800 observations. I perform the experiments for the same values but results are only presented for $T = 100$ and $T = 300$. The first column are the results of Fajardo et al. (2009) when $\omega = 0$, that is, when there is no additive outliers. Second column shows the results of applying the robust procedure of Fajardo et al. (2009). In the third column are the estimates of Geweke and Porter-Hudak (1983) when $\omega = 0$. Last column is similar to the previous one but outliers are selected using the procedure τ_d and the fractional parameter is estimated using dummies to control for the presence and number of additive outliers.

The evidence from Table 1 suggests the following comments. When $T = 100$ and there are no additive outliers ($\omega = 0$), the procedure of Fajardo et al. (2009) has a tendency to distortion the true value of the parameter. When the true value of $d = 0.30$, the mean of the robust procedure is 0.258. When $T = 300$ or more, the robust procedure appears to fix this distortion. Our procedure (based on τ_d) has a mean very close to the true value and consequently the bias is very small. When there are additive outliers ($\omega = 10$) things are very similar. That is, the robust procedure is 0.245 showing an important level of bias. It does not happen with our procedure. However, even when mean and bias are adequate, our procedure show slight high levels of standard deviation and MSE. When $T = 300$ the advantage of our procedure in terms of the mean and bias of d disappears.

Table 2 shows results for $d = 0.45$ and different sample sizes and different sizes of the additive outlier. The message is the same as in the previous Table. When $T = 100$ our procedure has a mean value very close to the true fractional parameter and consequently bias is smaller. However, the standard deviation and the MSE are slightly higher in our procedure. The advantages disappear when T is higher.

It appears to be clear that the robust procedure works well for high sample sizes. It is a nice characteristic but $T = 800$ or even $T = 300$ are sample sizes very difficult to find in macroeconomics or economics in general and for developing countries the situation is more delicate. Another issue which could be an advantage for our procedure is that the method allows to find the location of the outliers before the estimation of the fractional parameter[3].

In order to proportionate more evidence in favor of our procedure, we

[3] In some cases, empirical researcher could be interested in find the dates of the additive outliers. In other cases, this finding is not an issue.

present Table 3 which show same specifications as in Table 1 but for small sample sizes. Table 4 use similar experiment as Table 2. Some comments appear clear from Table 3. The method of GPH is good when no additive outliers are in the time series. However, when $\omega = 10$, the method GPH gives higher standard deviations, very high bias and large MSE. On the hand, when no additive outliers are in the series ($\omega = 0$), the approach of Perron and Rodríguez (2003) gives close results to the case where we use the GPH with $\omega = 0$. Further, when $\omega = 10$, Perron and Rodríguez (2003) allows to obtain similar standard deviation compared to the case where $\omega = 0$. When $\omega = 10$, we have very short bias and shorter MSE compared to the other columns. The bias and specially the MSE are smaller when sample size increases. Similar conclusions are obtained when $d = 0.45$.

Table 4 (when there are always additive outliers) offers the following comments. When $\omega = 3, 5$, and 10,the mean of d using Perron and Rodríguez (2003) is close to 0.45. The standard deviations are very similar. The same thing is observed for the bias. The MSE is smaller when sample is higher. However, MSE is relatively higher when size of additive outliers increase.

In conclusion, Tables 3 and 4, offer similar results as those obtained from Tables 1 and 2. That is, for very small sample sizes, the procedure based on τ_d works well.

5 Empirical Applications

In order to continue with the comparison with Fajardo et al. (2009), I also use the annual minimum water levels of the Nile river measure at Roda Gorge near Cairo. Some reference that used this data set are Beran (1992) and Robinson (1995). The period ranges from 622 to 1284 A.D. (663 observations). Figure 1 shows the series. As I explained before, some researcher may be interested in the detection of additive outliers. I find two additive outliers which are located in same dates as Chareka et al. (2006), that is, observations 646 and 809 A.D.

This data set has been extensively used to show evidence of long-range dependence. The semiparametric method of Geweke and Porter-Hudak (1983) reveals that the values of the fractional parameter (d) range from 0.386 to 0.503 using a truncation parameter of 0.5 to 0.8, respectively. Using similar truncation values, Fajardo et al. (2009) show estimates relatively more stable ranging from 0.416 to 0.475. They argue that these values are close to values obtained in other references using other robust estimator. Using the τ_d procedure, I find different results. Firstly, I simulate critical values at 1%, 5% and 10% for $T = 663$ which is the sample size of the data. After it, I detected two outliers above mentioned. Using truncation values of 0.7, 0.8 and $T/2$ my estimates are very stable among the different set of critical values used for the τ_d statistic ranging from 0.160 to 0.277.

The previous example appears contradictory with results obtained from simulations. When there are additive outliers and no correction or robustness is performed, the fractional parameters is smaller compared to the alternative situation when a robust procedure is used or when additive outliers are taken into account. I proceed to illustrate these issues using monthly inflation series in some Latin American countries where additive outliers are clearly evident and also they have a big size. Figure 2 shows monthly inflation series for seven Latin American series where I am considering only short periods of $T = 50$ or $T = 60$ where additive outliers are evident and caused by the different stabilization programs to stop high inflation in all these countries. All pictures show presence of additive outliers although it is more clear in the cases of Argentina, Bolivia, Chile, and Peru. On the other hand, Colombia and Paraguay do not show clear presence of additive outliers; see also Rodríguez (2004) for an earlier treatment.

Table 5 shows results when no correction for the presence of additive outliers is performed or when no robust procedure is used. Following comment may be extracted from this Table. Argentina shows high estimates of the fractional parameter and all are statistically significant. Similar evidence is show for Bolivia but magnitudes of the estimate are shorter. Chile presents very short estimates and the null hypothesis that $d = 0$ can not be rejected. Colombia is very similar. Ecuador shows estimates in the range 0.40-0.50 and all are statistically significant. The estimates of Paraguay are very stable around 0.14 and statistically significant. Peru shows very short estimates and the null hypothesis can not be rejected.

Table 6 presents the results obtained using the statistic τ_d (at 5.0%). In both cases, I use truncation of 0.7, 0.8 and T/2. In all cases estimates of the fractional parameter in Table 6 are higher than those corresponding to the Table 5 which is the principal message of Fajardo et al. (2009) and the current paper. As an example note the case of Peru where now the estimates are very higher and all are statistically significant.

6 Conclusions

In a recent paper, Fajardo et al. (2009) propose an alternative semiparametric estimator of the estimate the fractional parameter in ARFIMA models which is robust to the presence of additive outliers when there are additive outliers. The results are very interesting, however, they use samples of 300 or 800 observations which are rarely found in macroeconomics or economics in general. In order to perform a comparison, I use the procedure to detect for additive outliers based on the estimator τ_d suggested by Perron and Rodríguez (2003). I use dummy variables associated to the location of the selected outliers to estimate the fractional parameter. I found better results for the mean and bias of this parameter when $T = 100$ and the results in terms of the standard deviation and the MSE are very similar. However, for higher sample size as 300 or 800, the robust procedure performs better. As in Fajardo et al. (2009), I illustrate the procedure using the annual minimum levels of the Nile river. In order to present more robust empirical evidence, I applied the procedure to seven Latin American inflation series with very small sample sizes contaminated by additive outliers.

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Table 1. ARFIMA(0,d,0) with $\beta = 0.7$ and $\omega = 0, 10$.

d	T		Fajardo et al. (2009)		Perron and Rodríguez (2003)	
			$\omega = 0$	$\omega = 10$	$\omega = 0$	$\omega = 10$
			d_{GPHR}	d_{GPHR_c}	$d_{GPH\tau_d}$	$d_{GPH\tau_d}$
0.3	100	Mean	0.2584	0.2449	0.302	0.272
		S.D.	0.1558	0.1556	0.164	0.171
		Bias	-0.0416	-0.0551	0.002	-0.028
		MSE	0.0260	0.0272	0.027	0.030
	300	Mean	0.2907	0.2837	0.304	0.271
		S.D.	0.0926	0.0960	0.101	0.117
		Bias	-0.0093	-0.0163	0.004	-0.029
		MSE	0.0087	0.0095	0.010	0.015
	800	Mean	0.2949	0.2869	0.302	0.252
		S.D	0.0573	0.0610	0.068	0.101
		Bias	-0.0051	-0.0131	0.002	-0.048
		MSE	0.0033	0.0039	0.005	0.013
0.45	100	Mean	0.3975	0.3778	0.457	0.411
		S.D.	0.1506	0.1433	0.163	0.179
		Bias	-0.0525	-0.0722	0.007	-0.039
		MSE	0.0254	0.0258	0.026	0.033
	300	Mean	0.4329	0.4233	0.458	0.414
		S.D.	0.1041	0.1013	0.102	0.126
		Bias	-0.0171	-0.0267	0.008	-0.036
		MSE	0.0111	0.0110	0.010	0.017
	800	Mean	0.4457	0.4349	0.455	0.393
		S.D.	0.0562	0.0576	0.068	0.113
		Bias	-0.0043	-0.0151	0.005	-0.057
		MSE	0.0032	0.0035	0.005	0.016

The d_{GPHR} and d_{GPHR_c} are the fractional parameters estimated by Fajardo et al. (2009) without and with additive outliers, respectively. The $d_{GPH_{\tau_d}}$ and $d_{GPHc_{\tau_d}}$ are the fractional parameters estimated using the procedure τ_d suggested by Perron and Rodríguez (2003).

Table 2. ARFIMA(0,d,0) with $\beta = 0.7$, $\omega = 3, 5, 10$ and $d = 0.45$

ω	T		Fajardo et al. (2009)	Perron and Rodríguez (2003)
			d_{GPHR_c}	$d_{GPH\tau_d}$
3	100	Mean	0.3799	0.408
		S.D.	0.1513	0.165
		Bias	-0.0701	-0.042
		MSE	0.0278	-0.029
	800	Mean	0.4309	0.412
		S.D.	0.0576	0.067
		Bias	-0.0191	-0.038
		MSE	0.0037	0.006
5	100	Mean	0.3741	0.408
		S.D.	0.1452	0.169
		Bias	-0.0759	-0.042
		MSE	0.0268	0.030
	800	Mean	0.4270	0.375
		S.D.	0.0568	0.075
		Bias	-0.0229	-0.075
		MSE	0.0038	0.011
10	100	Mean	0.3778	0.411
		S.D.	0.1433	0.179
		Bias	-0.0722	-0.039
		MSE	0.0258	0.033
	800	Mean	0.4349	0.393
		S.D.	0.0576	0.067
		Bias	-0.0151	-0.057
		MSE	0.0035	0.016

The d_{GPHR_c} is the fractional parameters estimated by Fajardo et al. (2009) with additive outliers. The $d_{GPHc_{\tau_d}}$ is the fractional parameters estimated using the procedure τ_d suggested by Perron and Rodríguez (2003).

Table 3. ARFIMA(0,d,0) with $\beta = 0.7$ and $\omega = 0; 10$.

d	T		GPH		Perron and Rodríguez (2003)	
			$\omega = 0$	$\omega = 10$	$\omega = 0$	$\omega = 10$
			d_{GPH}	d_{GPH}	$d_{GPH\tau_d}$	$d_{GPH_{\tau_d}}$
0.3	50	Mean	0.304	0.079	0.364	0.274
		S.D.	0.231	0.236	0.221	0.239
		Bias	0.004	-0.221	0.064	-0.026
		MSE	0.054	0.105	0.053	0.058
	70	Mean	0.304	0.081	0.322	0.274
		S.D.	0.195	0.197	0.210	0.202
		Bias	0.004	-0.219	0.022	-0.026
		MSE	0.038	0.087	0.045	0.041
	80	Mean	0.303	0.083	0.327	0.271
		S.D.	0.185	0.184	0.181	0.193
		Bias	0.003	-0.217	0.027	-0.029
		MSE	0.034	0.081	0.034	0.038
	90	Mean	0.301	0.082	0.326	0.270
		S.D.	0.173	0.174	0.181	0.182
		Bias	0.001	-0.218	0.026	-0.030
		MSE	0.030	0.078	0.033	-0.034
0.45	50	Mean	0.461	0.145	0.513	0.402
		S.D.	0.233	0.245	0.233	0.253
		Bias	0.011	-0.305	0.063	-0.048
		MSE	0.054	0.153	0.058	0.066
	70	Mean	0.460	0.151	0.478	0.409
		S.D.	0.196	0.205	0.206	0.210
		Bias	0.010	-0.299	0.028	-0.041
		MSE	0.039	0.131	0.043	0.046
	80	Mean	0.459	0.157	0.476	0.408
		S.D.	0.185	0.190	0.183	0.201
		Bias	0.009	-0.293	0.026	-0.042
		MSE	0.034	0.122	0.034	0.042
	90	Mean	0.475	0.158	0.476	0.407
		S.D.	0.173	0.177	0.184	0.190
		Bias	0.007	-0.292	0.026	-0.043
		MSE	0.030	0.117	0.035	0.038

The d_{GPH} is the fractional parameter estimated by Geweke and Porter-Hudak (1983) without and with additive outliers, respectively. The $d_{GPH_{\tau_d}}$ is the fractional parameter estimated using the procedure τ_d suggested by Perron and Rodríguez (2003).

Table 4. ARFIMA(0,d,0) with $\beta = 0.7$, $\omega = 3, 5, 10$ and $d = 0.45$

ω	T		GPH	Perron and Rodríguez (2003)
			d_{GPH_c}	$d_{GPH\tau_d}$
3	50	Mean	0.365	0.423
		S.D.	0.236	0.236
		Bias	-0.085	-0.027
		MSE	0.063	0.057
	70	Mean	0.370	0.417
		S.D.	0.200	0.195
		Bias	-0.080	-0.033
		MSE	0.047	0.039
	90	Mean	0.376	0.409
		S.D.	0.175	0.175
		Bias	-0.074	-0.041
		MSE	0.036	0.032
5	50	Mean	0.279	0.419
		S.D.	0.240	0.238
		Bias	-0.171	-0.031
		MSE	0.087	0.057
	70	Mean	0.288	0.415
		S.D.	0.202	0.202
		Bias	-0.162	-0.035
		MSE	0.067	0.042
	90	Mean	0.294	0.407
		S.D.	0.179	0.182
		Bias	-0.156	-0.043
		MSE	0.056	0.035
10	50	Mean	0.145	0.402
		S.D.	0.245	0.253
		Bias	-0.305	-0.048
		MSE	0.153	0.066
	70	Mean	0.151	0.409
		S.D.	0.205	0.210
		Bias	-0.299	-0.041
		MSE	0.131	0.046
	90	Mean	0.158	0.407
		S.D.	0.177	0.190
		Bias	-0.292	-0.043
		MSE	0.117	0.038

Table 5. Monthly Inflation in Latin America: Estimation of the Fractional Parameter without Correction for Additive Outliers
(t-statistics in parentheses)

	Sample	Truncation Value		
		0.7	0.8	T/2
Argentina	1987:06 - 1991:07	0.556	0.656	0.632
		(3.277)	(4.201)	(4.306)
Bolivia	1983:04 - 1987:05	0.258	0.476	0.450
		(1.602)	(2.963)	(3.012)
Chile	1972:03 - 1976:04	0.119	0.075	0.070
		(0.825)	(0.752)	(0.758)
Colombia	1972:03 - 1976:04	0.187	0.193	0.078
		(1.429)	(1.545)	(0.534)
Ecuador	1996:12 - 2001:01	0.416	0.504	0.494
		(4.530)	(4.728)	(4.782)
Paraguay	2004:10 - 2008:11	0.149	0.149	0.141
		(1.688)	(2.476)	(2.519)
Peru	1988:11 - 1992:12	0.057	0.091	0.040
		(0.224)	(0.449)	(0.203)

Table 6. Monthly Inflation in Latin America: Estimation of the Fractional Parameter using τ_d at 5.0%
(t-statistics in parentheses)

	Sample	Truncation Value		
		0.7	0.8	T/2
Argentina	1987:06 - 1991:07	0.563	0.736	0.730
		(2.292)	(3.877)	(3.877)
Bolivia	1983:04 - 1987:05	0.723	0.692	0.703
		(3.341)	(3.122)	(3.406)
Chile	1972:03 - 1976:04	0.339	0.475	0.459
		(1.576)	(2.885)	(2.912)
Colombia	1972:03 - 1976:04	0.261	0.280	0.162
		(1.127)	(2.252)	(1.105)
Ecuador	1996:12 - 2001:01	1.089	0.845	0.792
		(4.070)	(3.817)	(3.785)
Paraguay	2004:10 - 2008:11	0.350	0.286	0.227
		(1.514)	(1.177)	(0.971)
Peru	1988:11 - 1992:12	0.770	0.681	0.671
		(3.285)	(3.586)	(3.949)

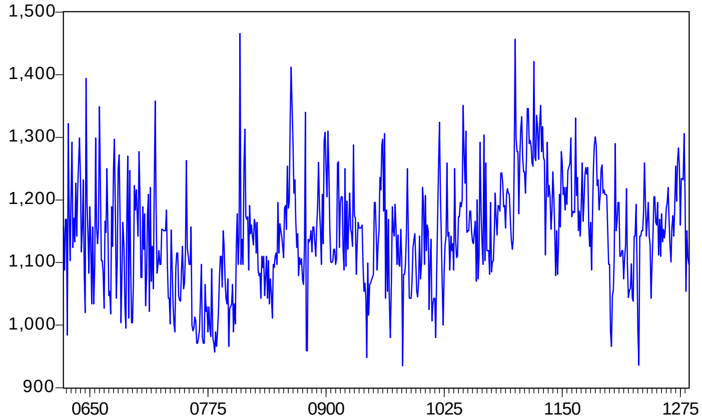

Figure 1. Annual Minimum Levels of the Nile River

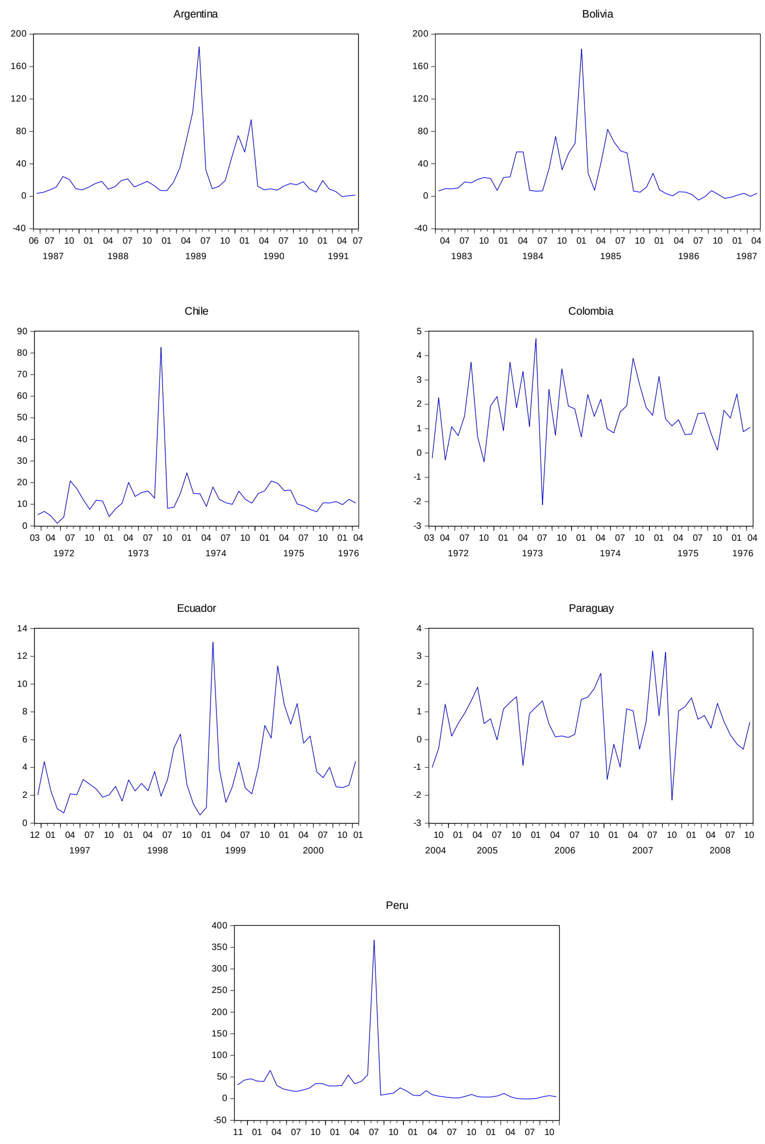

Figure 2. Latin-American Inflation Series

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