

INFLATION FORECASTING IN ANGOLA: A FRACTIONAL APPROACH

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Abstract / Resumo

This paper forecasts inflation in Angola with an ARFIMA (AutoRegressive Fractionally Integrated Moving Average) model. It is found that inflation in Angola is a highly persistent variable with an order of integration constrained between 0 and 1. Moreover, a structural break is found in August, 1996. Using the second sub-sample for forecasting purposes, the results reveal that inflation will remain low, assuming that prudent macroeconomic policies are maintained.

Keywords Angola; inflation, long memory

Jel Classification Numbers C22

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1. INTRODUCTION

Forecasting is a way to evaluate price evolution and therefore it is a macroeconomic management tool. There is a well-established tradition of research on price forecasting (Kallon, 1994; Stock and Watson, 1999; Hendry and Clements, 2003; Doornik and Ooms, 2004 and Duarte and Rua, 2007, Cancelo, Espasa and Grafe, 2008; Rueda and Rodriguez, 2010; Pedregal and Perez, 2010; Corberán-Vallet; Bermúdez and Vercher, 2011 among many others). This study analyses price forecasting in Angola using long memory techniques and ARFIMA (AutoRegressive Fractionally Integrated Moving Average) models. These models are an accepted reference in forecasting and are used extensively, due to the fact that they interpret the data with accuracy (Doornik and Ooms, 2004; Barkoulas and Baum, 2006). ARIMA models are found to dominate alternative approaches (Espasa et al., 2001; Fritzer et al., 2002). However, Doornik and Ooms (2004) found that the fractional ARIMA (ARFIMA) model better describes the inflation dynamics than non-fractional ARIMA models based on integer degrees of differentiation. Since then, inflation series have been examined in many countries by means of fractionally integrated or I(d) models. Examples are the papers by Hassler (1993), Delgado and Robinson (1994), Hassler and Wolters (1995), Baillie et al. (1996), Bos et al. (2001), Franses et al. (2006), Gil-Alana (2007), etc.

The present research applies an ARFIMA model for the first time to price forecasting in relation to the economy of Angola. The models are estimated using monthly data from 1991:1 to 2011:6. Inflation forecasts based on ARFIMA models suggest that inflationary pressures for the period 2011:7 to 2012:12 are expected to be relatively low.

This research is organised as follows. After the introduction, the contextual setting is presented in Section 2, followed by the literature survey in Section 3. The methodology is briefly presented in Section 4. Section 5 describes the data and displays the empirical results. Section 6 presents the forecasting results. Finally, Section 7 concludes the paper.

2. INFLATION IN ANGOLA

The macroeconomics of Angola's debt due to the civil war that ravaged the country from 1975 to 2002 generated a rampant inflation, which is depicted in Figure 1 below. Angola had attained its independence in 1975 after a long war of liberation against the former colonial ruler, Portugal. However, ideological and ethnic fractionalisation ensured that peace did not accompany independence, igniting instead a brutal, costly civil war that only came to an end in 2002 (Ferreira and Barros, 1998). Given its

exceptional potential wealth due to an abundance of raw materials, particularly oil and diamonds, present-day Angola, with a democratically-elected government, is well placed to experience a process of growth.

A restrictive monetary policy put into effect in 1996 resulted in a decreased rate of inflation. The world economic crisis in 2009 curbed oil demand and generated a terms-of-trade shock that resulted in Angola's negligible growth and a fiscal crisis, obliging the country to enter into a stand-by arrangement of US\$ 1.4 billion with the IMF, aiming to alleviate liquidity restrictions and the maintenance of a sustainable macroeconomic position. The more recent resurgence in global oil demand has brought about the recovery of Angola's oil production and exports which has combined with the IMF program and the tightening of monetary and fiscal policies.

An initial visual inspection of Figure 1 indicates a potential break in the data around mid-1996. Furthermore, the series decreases, revealing an erratic downward trend. The trend is dominated by multi-month swings. The inflation rate seems to be highly serially autocorrelated and each previous month's inflation rate contains much information about the current month's rate. However, there are still unexpected movements.

3. LITERATURE SURVEY

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4. METHODOLOGY

Denoting inflation by π_t we describe its behaviour throughout the following model:

$$\pi_t = \beta^T z_t + x_t, \quad t = 1, 2, \dots, \quad (1)$$

where z_t is a $(k \times 1)$ vector of deterministic terms that may be an intercept ($z_t = 1$) or an intercept with a linear trend (i.e., $z_t = (1, t)^T$), and x_t are the regression errors, which follow an I(d) model of the form:

$$(1 - L)^d x_t = u_t, \quad t = 1, 2, \dots, \quad (2)$$

where d can be any real number, and u_t is supposed to be I(0), defined for the purpose of the present work as a covariance stationary process with spectral density function that is positive and bounded at the zero frequency and therefore, it potentially allows for weak autocorrelation of the ARMA form:

$$\phi(L)u_t = \theta(L)\varepsilon_t, \quad t = 1, 2, \dots, \quad (3)$$

where $\phi(L)$ and $\theta(L)$ are the AR and MA polynomials and ε_t is a white noise process.

Note that this model is very general, in the sense, for example, that if we impose $d = 0$ and $z_t = (1, t)^T$, we obtain the classical “trend stationary” I(0) representation, while if $d = 1$, we obtain the “unit root” or I(1) model advocated by many authors (Nelson and Plosser, 1982). However, we also allow d to be a fractional number. Thus, the parameter d might be 0 or 1, but it may also take values between these two numbers or even above 1. Note that the polynomial $(1-L)^d$ in (2) can be expressed in terms of its Binomial expansion, such that, for all real d :

$$(1 - L)^d = \sum_{j=0}^{\infty} \psi_j L^j = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \dots$$

and thus:

$$(1 - L)^d x_t = x_t - d x_{t-1} + \frac{d(d-1)}{2} x_{t-2} - \dots$$

In this context, d plays a crucial role, since it will be an indicator of the degree of dependence of the series. Thus, the higher the value of d , the higher the level of association will be between the observations. Processes with $d > 0$ in (2) display the property of “*long memory*”, characterised because the autocorrelations decay hyperbolically slowly and the spectral density function is unbounded at the origin. The origin of these processes is found in the 1960s, when Granger (1966) and Adelman (1965) pointed out that most aggregate economic time series have a typical shape where the spectral density increases dramatically as the frequency approaches zero. However, differencing the data frequently leads to over-differencing at the zero frequency. Fifteen years later, Robinson (1978) and Granger (1980) showed that aggregation could be a source of fractional integration through the aggregation of heterogeneous autoregressive (AR) processes: data involving heterogeneous dynamic relationships at the individual level are then aggregated to form the time series.¹ Since then, fractional processes have been widely employed to describe the dynamics of many economic and financial time series (see, e.g. Diebold and Rudebusch, 1989; Sowell, 1992a; Baillie, 1996; Gil-Alana and Robinson, 1997; etc.).²

The methodology employed in the paper to estimate the fractional differencing parameter is based on the Whittle function in the frequency domain (Dahlhaus, 1989). We also employ a testing procedure developed by Robinson (1994) that allows for the testing of any real value of d in $I(d)$ models. The latter is a Lagrange Multiplier (LM) procedure, and it is supposed to be the most efficient procedure in the context of fractional integration. It tests the null hypothesis $H_0: d = d_0$ for any real value d_0 in (1) and (2) and different types of $I(0)$ disturbances, and given the fact that the test statistic follows a standard (normal) limit distribution, it is possible to easily construct confidence bands for the non-rejection values.³ Other parametric methods, like Sowell’s (1992b) maximum likelihood estimation in the time domain, along with a semi-parametric Whittle method in the frequency domain (Robinson, 1995) where no functional form is imposed in u_t will also be implemented in the paper.

In a more general context, we also estimate the parameters in an ARFIMA(p, d, q) model of form:

$$\phi(L)(1 - L)^d (\pi_t - \alpha - \beta t) = \theta(L) \varepsilon_t, \quad \varepsilon_t \sim i.i.d.(0, \sigma_\varepsilon^2), \quad (4)$$

¹ Ciozbek-Georges and Mandelbrot (1995), Taqqu et al. (1997), and Chambers (1998) also use aggregation to motivate long memory processes, while Parke (1999) uses a closely related discrete time error duration model.

² See also Gil-Alana and Hualde (2009) for an updated review of fractional integration and its applications in economic time series.

³ The functional form of this method is specified in various empirical applications (Gil-Alana and Robinson, 1997; Gil-Alana, 2000; Gil-Alana and Henry, 2003; etc.).

where $\phi(L)$ and $\theta(L)$ are the AR and MA polynomials of orders p and q respectively, and that we suppose later in the empirical work that are equal to or smaller than 2.

If inflation is supposed to be nonstationary, the process has to be estimated in first differences. The parameters in (4) are estimated using MLE, assuming that the error term is white noise and follows a normal distribution. This simple ARFIMA structure—which needs only current and past inflation—has several advantages compared with the non-fractional ARIMA model. However, it is difficult to determine the specification of the model, since ARFIMA models are atheoretic. While economic theory suggests that money supply affects inflation, nominal appreciation reduces inflationary pressures and a widening output gap causes inflation, ARFIMA models cannot explicitly incorporate these insights. The absence of economic theory in ARFIMA models, therefore, requires other criteria to determine the specification of the model, in particular, the orders for the AR and MA polynomials. This paper adopts statistical measures to choose from among alternative ARFIMA models. Firstly we test for serial correlation in the residuals, using the Breusch-Godfrey LM test. Secondly, we test whether residuals follow the normal distribution, using the Jarque-Bera test. In addition, likelihood criteria are employed.⁴

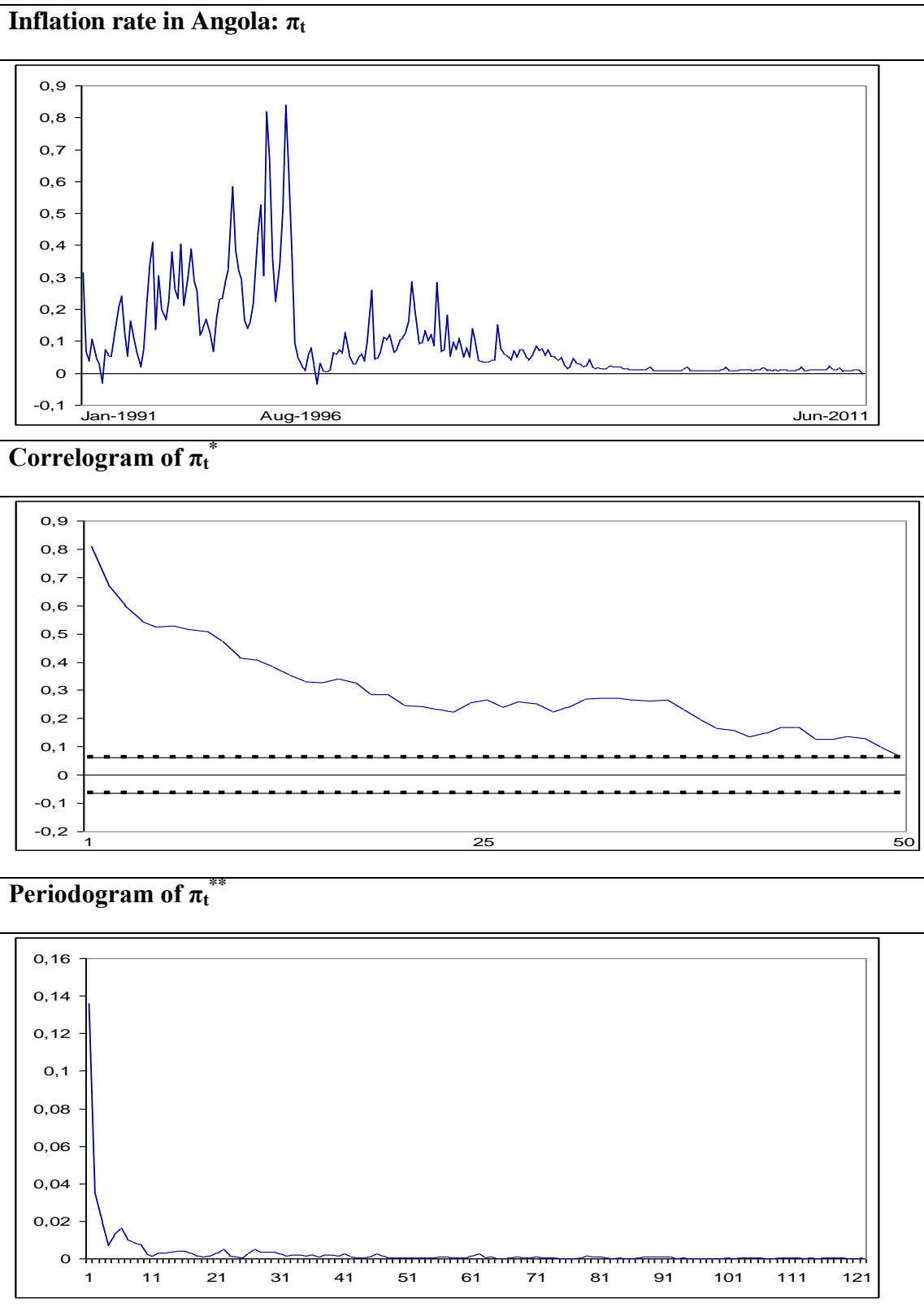
5. DATA AND EMPIRICAL RESULTS

The dataset refers to Angola's CPI – Consumer Price Index - and covers the period from January 1991 to June 2011, comprising 204 observations. During this period, Angola's CPI underwent several changes that were briefly discussed earlier in the contextual setting. Inflation rates were computed as the first differences of the log-transformed data.

Figure 1 displays the time series plot of the inflation rate in Angola, along with its sample correlogram and periodogram. An initial visual inspection indicates a potential break in the data around mid-1996. The sample correlogram values are all significant and decay very slowly, which indicates a relevant degree of persistence, while the periodogram indicates a large value at the smallest frequency. Both are indicators of potential unit roots.

⁴ We use AIC and BIC though these criteria may not necessarily be optimal for applications involving fractional differences, as these criteria focus on the short-term forecasting ability of the fitted model and may not give sufficient attention to the long-run properties of the ARFIMA models (see, e.g. Hosking, 1981, 1984).

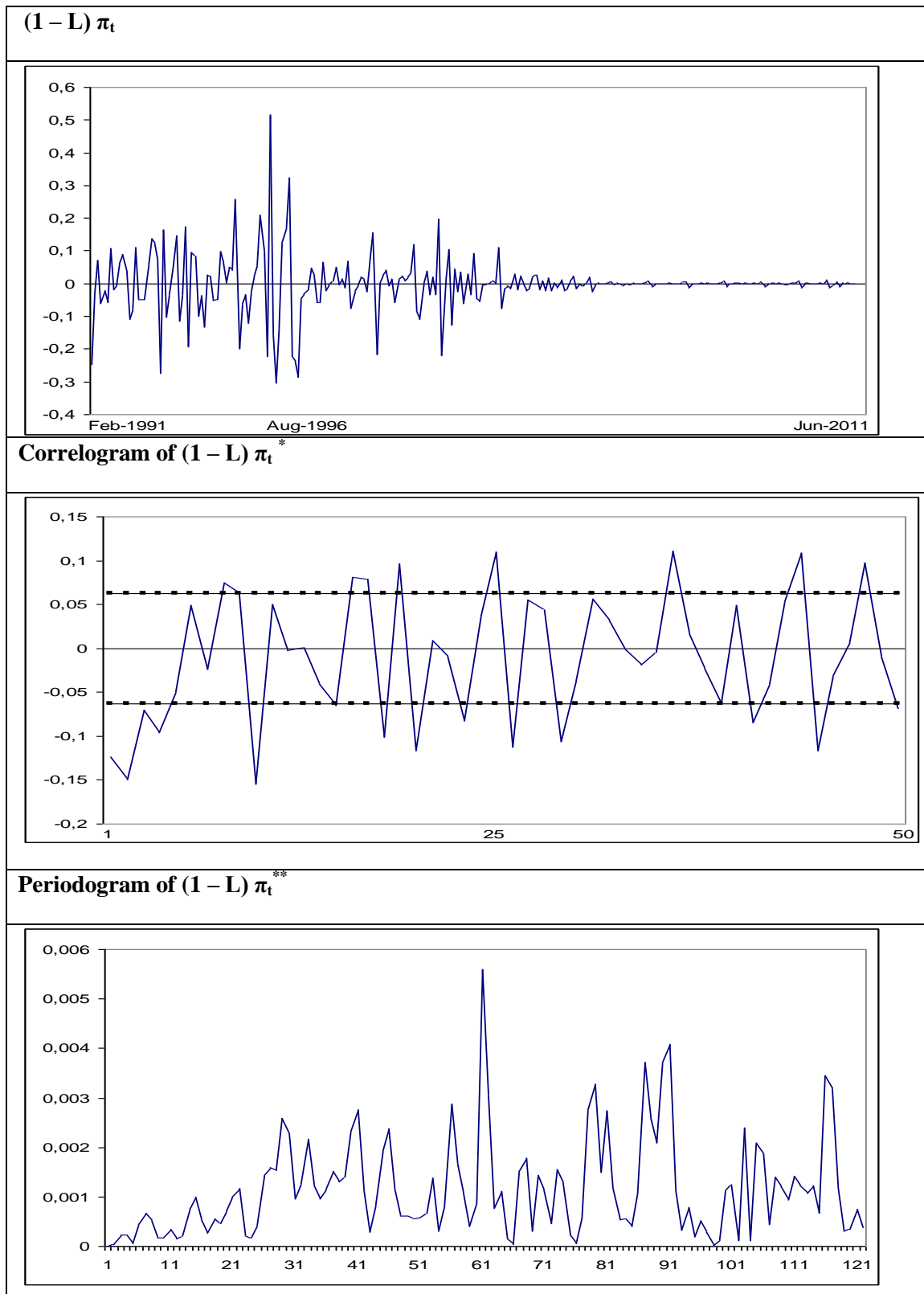
Figure 1: Original time series data



*: The thick lines refer to the 95% confidence band for the null hypothesis of no autocorrelation.

** : The periodogram refers to the discrete Fourier frequencies $\lambda_j = 2\pi j/T, j = 1, \dots, T/2$.

Figure 2: First differenced data, correlogram and periodogram



*: The thick lines refer to the 95% confidence band for the null hypothesis of no autocorrelation.

***: The periodogram refers to the discrete Fourier frequencies $\lambda_j = 2\pi j/T$, $j = 1, \dots, T/2$.

In Figure 2, we present similar plots, but based on the first differenced data. We notice here that there is higher volatility during the first half of the sample.⁵ The correlogram and the periodogram of the first differences seem to indicate now that the series is over-differencing, noting the significant negative first value in the correlogram, and the value close to zero in the periodogram at the smallest frequency. Therefore, the plots in these two figures suggest that the series is I(d) with d higher than 0 (persistent), but smaller than 1 (mean reverting).

Next, we focus on the estimation of d, and consider the following model:

$$\pi_t = \alpha + \beta t + x_t, \quad t = 1, 2, \dots, \quad (5)$$

$$(1 - L)^d x_t = u_t, \quad t = 1, 2, \dots, \quad (6)$$

assuming that u_t in (6) is first a white noise process; then we assume an AR(1) structure for u_t ; also the model of Bloomfield (1973) (which is a nonparametric approximation to ARMA models) is employed and, given the monthly nature of the data examined, a seasonal monthly AR(1) process is finally considered.

We estimate the fractional differencing parameter d for the three standard cases examined in the literature, i.e., the case of no regressors (i.e., $\alpha = \beta = 0$ *a priori* in equation (5)), an intercept (α unknown, and $\beta = 0$ *a priori*), and an intercept with a linear time trend (α and β unknown). Together with the estimates, we also present the 95% confidence band of the non-rejection values of d, using Robinson's (1994) parametric tests. The results are displayed in Table 1.

Table 1: Estimates of d based on the Whittle parametric approach

	No regressors	An intercept	A linear time trend
White noise	0.642 (0.557, 0.760)	0.639 (0.541, 0.782)	0.639 (0.535, 0.783)
AR (1)	0.465 (0.329, 0.622)	0.411 (0.282, 0.569)	0.248 (0.198, 0.543)
Bloomfield	0.502 (0.401, 0.632)	0.449 (0.360, 0.591)	0.399 (0.259, 0.581)
Monthly AR (1)	0.642 (0.557, 0.760)	0.639 (0.542, 0.782)	0.639 (0.534, 0.783)

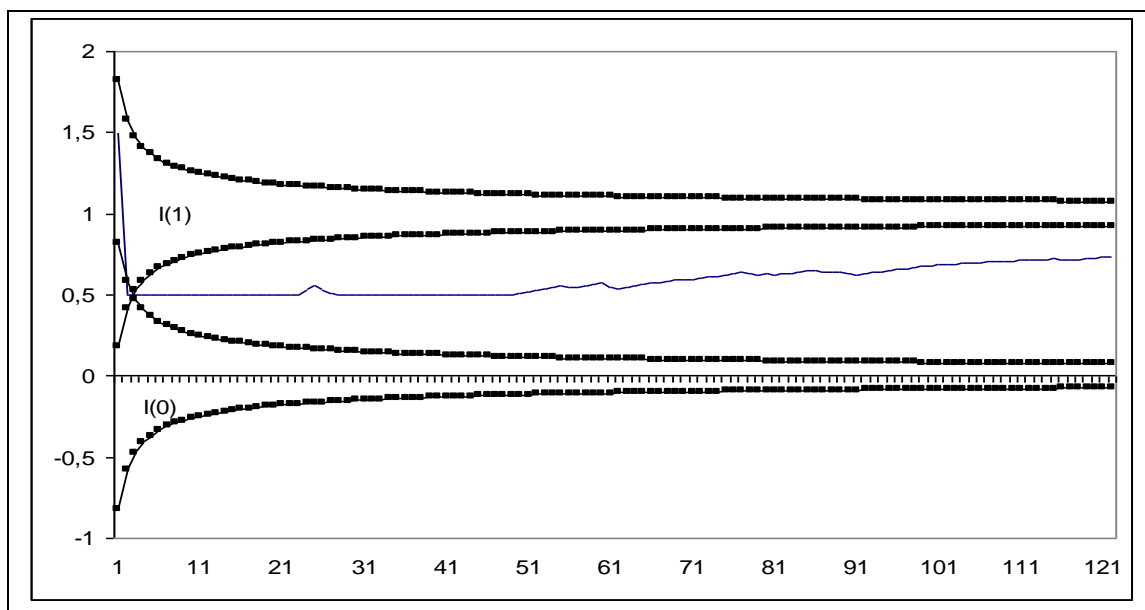
The values in parenthesis refer to the 95% confidence band of the non-rejection values of d using Robinson's (1994) parametric tests.

⁵ This is not a matter of concern in our work, since the methods employed in this paper seem to be robust against conditional heteroskedastic errors.

As expected, the results indicate that the value of d is in the interval $(0, 1)$, rejecting thus the null hypothesis of $d = 0$ (trend stationarity) and also that of $d = 1$ (a unit root). Note that if the disturbances are white noise or monthly AR, the values are strictly above 0.5 (implying non-stationarity), while in the other two cases (AR(1) and Bloomfield), the estimated values of d are smaller than 0.5 (implying then stationary behaviour). In any case, since d is smaller than 1 in all cases, the series is clearly mean-reverting.

Based on the sensitivity of our results to the specification of the error term, next we use another approach to estimate d (Robinson, 1995), which is semi-parametric in the sense that we do not impose any structure for the error term u_t in (2).

Figure 3: Estimates of d based on the Whittle semiparametric estimate (Robinson, 1995)



The horizontal axis refers to the bandwidth parameter while the vertical axis corresponds to the estimated values of d . We report the estimates of d along with the 95% confidence band of the $I(0)$ and $I(1)$ hypotheses.

In Figure 3, we display the estimates of d (the thin line) along the horizontal axis that corresponds to the bandwidth number required in this procedure. We also display in the figure the 95% confidence bands for the $I(0)$ and $I(1)$ hypotheses. We clearly see that the estimates are away from the two intervals, supporting the view that the inflation rate in Angola is integrated of order d or $I(d, 0 < d < 1)$.

Based on the strong evidence in favour of $I(d)$ models with d different from 0 and 1, we focus next on the selection of the most adequate specification for this series.

For this purpose, we employ different ARFIMA(p, d, q) models, first including only an intercept, and then with an intercept and a linear trend. We choose the orders p and q equal to or smaller than 2, and the results are displayed in Table 2 (for the model with an intercept) and in Table 3 (for the model with a linear time trend).

Table 2: Estimates of ARFIMA models in a model with an intercept

ARMA (p, q)	d	Autoregression			Moving Average			Lik. Criteria	
		AR1	AR2	AR3	MA1	MA2	MA3	AIC	BIC
(0, 0)	0.642 (0.021)	xxx	xxx	xxx	xxx	xxx	xxx	12.12	4.3
(1, 0)	0.734 (0.015)	0.382 (0.126)	xxx	xxx	xxx	xxx	xxx	13.03	4.2
(0, 1)	0.814 (0.026)	xxx	xxx	xxx	0.298 (0.027)	xxx	xxx	13.13	4.1
(1, 1)	0.821 (0.037)	0.298 (0.218)	xxx	xxx	0.294 (0.014)	xxx	xxx	13.24	4.5
(2, 0)	0.892 (0.016)	0.310 (0.223)	-0.321 (0.132)	xxx	xxx	xxx	xxx	13.38	4.4
(2, 1)	0.895 (0.057)	0.315 (0.136)	-0.331 (0.117)	xxx	0.285 (0.018)	xxx	xxx	14.45	4.2
(0, 2)	0.867 (0.025)	xxx	xxx	xxx	0.280 (0.019)	0.153 (0.024)	xxx	14.34	4.1
(1, 2)	0.910 (0.027)	0.317 (0.334)	xxx	xxx	0.278 (0.017)	0.146 (0.018)	xxx	14.38	4.4
(2, 2)	0.945 (0.018)	0.321 (0.221)	-0.218 (0.114)	xxx	0.286 (0.005)	0.158 (0.017)	xxx	14.12	4.2

In parenthesis, standard errors.

Table 3: Estimates of ARFIMA models in a model with a linear time trend

ARMA (p, q)	d	Autoregression			Moving Average			Lik. Criteria	
		AR1	AR2	AR3	MA1	MA2	MA3	AIC	BIC
(0, 0)	0.615 (0.014)	xxx	xxx	xxx	xxx	xxx	xxx	16.8	8.6
(1, 0)	0.534 (0.006)	0.418 (0.015)	xxx	xxx	xxx	xxx	xxx	16.7	8.7
(0, 1)	0.318 (0.008)	xxx	xxx	xxx	0.332 (0.015)	xxx	xxx	16.4	8.8
(1, 1)	0.525 (0.003)	0.410 (0.018)	xxx	xxx	0.396 (0.007)	xxx	xxx	16.6	8.5

(2, 0)	0.572 (0.001)	0.389 (0.007)	-0.167 (0.007)	xxx	Xxx	xxx	xxx	16.1	9.4
(2, 1)	0.543 (0.004)	0.371 (0.017)	-0.218 (0.025)	xxx	0.326 (0.007)	xxx	xxx	17.2	9.6
(0, 2)	0.560 (0.003)	xxx	xxx	xxx	0.319 (0.004)	0.153 (0.011)	xxx	17.3	9.7
(1, 2)	0.631 (0.013)	0.415 (0.022)	xxx	xxx	0.307 (0.031)	0.142 (0.001)	xxx	17.4	9.7
(2, 2)	0.610 (0.016)	0.410 (0.013)	-0.145 (0.012)	xxx	0.354 (0.023)	0.124 (0.036)	xxx	17.1	9.6

In parenthesis, standard errors.

In bold the selected models based on the AIC and BIC.

Starting with the model with an intercept, we observe that the estimated values of d range from 0.642 to 0.945; the AR coefficients are statistically insignificant in all cases, while the MA terms are all significant. However, comparing this model with the one with a linear time trend, the latter presents a better fit. We observe here that the estimated values of d range between 0.318 and 0.631 and all the AR and MA coefficients remain statistically significant at conventional statistical levels. According to the AIC, the best fit seems to be the ARFIMA(1, d , 2), with an estimated value of d equal to 0.631; however, using the BIC, the ARFIMA(0, d , 2) seems to be preferred, with an estimate of d of 0.560. Once more here, the two hypotheses of $I(0)$ and $I(1)$ specifications are decisively rejected in the two cases in favour of fractional integration.

Based on the above evidence, we could conclude that the inflation rate in Angola can be well described in terms of an $I(d)$ process. Nevertheless, several authors have argued that fractional integration may be a simple artifact generated by the presence of non-linear structures or structural breaks in the data. Therefore, in what follows, we examine the possibility of breaks in the data (Diebold and Inoue, 2001; Granger and Hyung, 2004). For this purpose, we employed a procedure that endogenously determines the number of breaks and the break dates in the series, allowing for different fractional differencing parameters at each sub-sample. This method, due to Gil-Alana (2008), is based on minimising the residuals' sum squares at different break dates and different (possibly fractional) differencing parameters. In particular, the following model is considered:

$$y_t = \beta_i^T z_t + x_t; \quad (1-L)^{d_i} x_t = u_t, \quad t = 1, \dots, T_b^i, \quad i = 1, \dots, nb, \quad (7)$$

where nb is the number of breaks, y_t is the observed time series, the β_i 's are the coefficients corresponding to the deterministic terms; the d_i 's are the orders of integration for each sub-sample, and the T_b^i 's correspond to the times of the unknown breaks. Note that given the difficulties in distinguishing between models with fractional

orders of integration and those with broken deterministic trends, it is important to consider estimation procedures that deal with fractional unit roots in the presence of broken deterministic terms.

Table 4: Estimates of d based on Gil-Alana (2008)

	α	β	D
1st sub-sample	0.08201 (1.101)	0.00567 (3.033)	0.342 (0.119, 0.821)
Number of breaks = 1; Break date = August, 1996			
2nd sub-sample	0.07702 (4.447)	-0.000421 (-2.509)	0.355 (0.289, 0.451)

In parenthesis, in the second and third column, t-values. In the fourth column, the 95% confidence interval of the non-rejection values of d.

Using the above approach, the results indicate that there is evidence of a single break in the data. The estimated coefficients are displayed in Table 4. We see that the break date is found to be in August 1996, consistent with the plots presented in Figures 1 and 2. We also see, however, that there is not much difference in the order of integration in the two sub-samples (0.342 and 0.355 respectively for the first and second sub-samples), but the slope coefficient is significantly positive in the first sub-sample and significantly negative in the second sub-sample. (See Figure 3)

Given the presence of a structural break and based on the forecasting approach employed in the following section, we consider now the estimation procedure exclusively based on the second sub-sample, with data starting from August 1996. Next, we repeat the ARFIMA method for the two cases of an intercept and a linear time trend. Taking into account the short data span, a bootstrap approach was adopted (5000 simulations were used) here.

Table 5: Estimates of ARFIMA models in a model with an intercept with data starting from August 1996

ARMA (p, q)	d	Autoregression			Moving Average			Lik. Criteria	
		AR1	AR2	AR3	MA1	MA2	MA3	AIC	BIC
(0, 0)	0.315 (0.012)	xxx	xxx	xxx	xxx	xxx	xxx	22.16	10.12
(1, 0)	0.322 (0.007)	0.372 (0.117)	xxx	xxx	xxx	xxx	xxx	21.18	10.38

(0, 1)	0.314 (0.008)	xxx	xxx	xxx	0.190 (0.017)	xxx	xxx	29.64	10.31
(1, 1)	0.332 (0.021)	0.124 (0.019)	xxx	xxx	0.014 (0.004)	xxx	xxx	20.41	10.18
(2, 0)	0.335 (0.034)	0.132 (0.056)	0.126 (0.057)	xxx	xxx	xxx	xxx	19.37	10.24
(2, 1)	0.316 (0.015)	0.128 (0.041)	0.132 (0.065)	xxx	0.162 (0.004)	xxx	xxx	24.54	10.28
(0, 2)	0.334 (0.008)	xxx	xxx	xxx	0.131 (0.015)	0.142 (0.027)	xxx	22.18	10.18
(1, 2)	0.313 (0.014)	0.141 (0.057)	xxx	xxx	0.132 (0.007)	0.107 (0.005)	xxx	29.53	10.11
(2, 2)	0.312 (0.032)	0.133 (0.056)	0.135 (0.018)	xxx	0.146 (0.034)	0.126 (0.063)	xxx	22.06	10.29

In parenthesis, standard errors.

Table 6: Estimates of ARFIMA models in a model with a linear time trend with data starting from August 1996

ARMA		Autoregression			Moving Average			Lik. Criteria	
(p, q)	d	AR1	AR2	AR3	MA1	MA2	MA3	AIC	BIC
(0, 0)	0.312 (0.007)	xxx	xxx	xxx	xxx	xxx	xxx	31.16	10.14
(1, 0)	0.314 (0.008)	0.118 (0.016)	xxx	xxx	xxx	xxx	xxx	31.18	10.10
(0, 1)	0.317 (0.001)	xxx	xxx	xxx	0.138 (0.001)	xxx	xxx	31.17	10.12
(1, 1)	0.321 (0.006)	0.137 (0.021)	xxx	xxx	0.148 (0.005)	xxx	xxx	31.89	10.28
(2, 0)	0.320 (0.004)	0.137 (0.003)	0.115 (0.005)	xxx	xxx	xxx	xxx	31.34	10.54
(2, 1)	0.325 (0.002)	0.127 (0.017)	0.138 (0.003)	xxx	0.137 (0.017)	xxx	xxx	31.65	10.32
(0, 2)	0.322 (0.002)	xxx	xxx	xxx	0.129 (0.013)	0.118 (0.014)	xxx	31.62	10.37
(1, 2)	0.323 (0.017)	0.138 (0.013)	xxx	xxx	0.131 (0.015)	0.154 (0.015)	xxx	31.28	10.33
(2, 2)	0.327 (0.015)	0.143 (0.002)	0.127 (0.017)	xxx	0.142 (0.014)	0.137 (0.021)	xxx	31.87	10.18

In parenthesis, standard errors.

In bold the selected models based on the AIC and BIC.

In the model with the intercept, the estimated value of d ranges from 0.312 to 0.334. However, as in the previous case, the model with an intercept presents a better fit. Here, the estimates of d range between 0.312 and 0.327 and the selected models are the ARFIMA(1, 0.321, 1) with the AIC and the ARFIMA(2, 0.320, 0) with the BIC. Diagnostic checking based on the analysis of the residuals indicates that the latter model is preferred.

6. OUT-OF-SAMPLE FORECAST EVALUATION

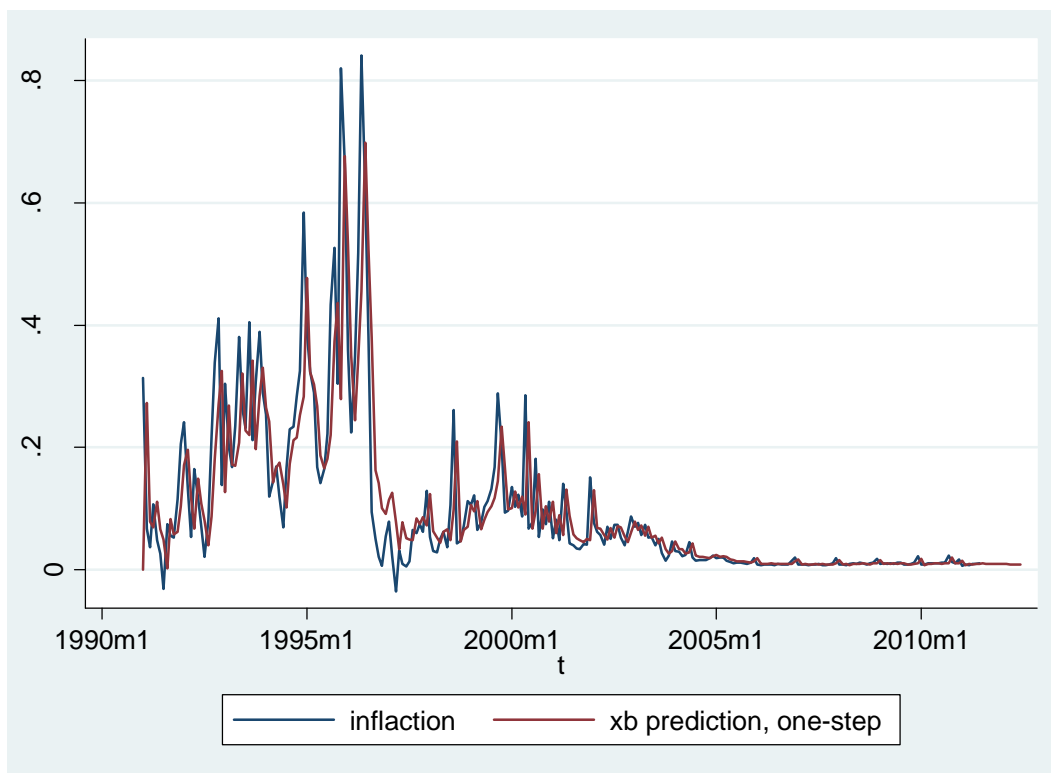
Forecasting performance is evaluated through an out-of-sample forecast exercise. For the time series examined and the model selected, a recursive estimation process is implemented. Starting from the estimation period (1991:1 to 2011:6) each round a new observation is added to the sample, and forecasts are computed for the period 2011:7 - 2012:12. The forecasting values based on the ARFIMA (2, 0.320, 0) model for the two cases of an intercept and an intercept with a linear trend are presented in Table 7

Table 7: Angola forecasting with ARFIMA model.

Forecast Horizon	ARFIMA (2, 0.320, 0) with and intercept	ARFIMA (2, 0.320, 0) with a linear trend
2011m7	0.0123141	0.0101678
2011m8	0.0142345	0.0099932
2011m9	0.0167413	0.0097893
2011m10	0.0195719	0.0095719
2011m11	0.020112	0.0094674
2011m12	0.0202114	0.0093895
2012m1	0.0202732	0.0092543
2012m2	0.0202818	0.0091783
2012m3	0.0208356	0.0090453
2012m4	0.02086479	0.0089134

2012m5	0.0209186	0.0088563
2012m6	0.02097798	0.0087174
2012m7	0.02099698	0.0086436
2012m8	0.02186178	0.0086235
2012m9	0.02185386	0.0085143
2012m10	0.02184602	0.0084645
2012m11	0.02183827	0.0083887
2012m12	0.02183061	0.008467

Figure 4: Forecasted values from ARFIMA model



The values are smaller in the second case, which is more realistic according to the RMSFEs (not displayed). Figure 4 displays the time series plots, including the one-and-a-half-years predictions. It is observed that inflation will remain relatively stable and low, assuming that prudent macroeconomic policies are maintained.

7. CONCLUSION

In this paper, we have examined the monthly inflation rate in Angola from January 1991 to June 2011 by means of long range dependence techniques. In particular, we have employed I(d) models and the results support the view that inflation in Angola is long memory, with an order of integration constrained between 0 and 1. Thus, the series present long memory and mean reverting behavior. Moreover, we noticed the existence of a structural break around August 1996. Including such a break in the data, the order of integration is about 0.3, implying stationary long memory behaviour. Using the second sub-sample for forecasting purposes, the results reveal that Angola's inflation is low and will remain so, as long as the present sound monetary policy is maintained.

REFERENCES

- Adelman, I. 1965. Long cycles: Fact or artifacts, *American Economic Review* 55, 444-463.
- Almoussor, A. 2010. Inflation Dynamics in Yemen: An Empirical Analysis. IMF Working Paper WP/10/144.
- Aron, J. and Muellbauer, J. 2011. Improving forecasting in an emerging economy, South Africa: Changing trends, long run restrictions and disaggregation. *International Journal of Forecasting* (forthcoming).
- Backus, D. and Zin, S. 1993. Long memory inflation uncertainty: Evidence of term structure of interest rate, *Journal of Money, Credit and Banking* 25, 687-700.
- Baillie, R.T. 1996. Long memory processes and fractional integration in econometrics, *Journal of Econometrics* 73, 5-59.
- Baillie, R.T. and Chung, C.F. 1996. Analyzing inflation by the fractionally integrated ARFIMA-GARCH model, *Journal of Applied Econometrics* 11, 23-40.

- Baillie, R.T., C.F. Chung and Tieslau, M.A. 1996. Analyzing inflation by the fractionally integrated ARFIMA-GARCH Model, *Journal of Applied Econometrics* 11, 23-40.
- Baillie, R.T., Y.W. Han and Kwon, T.G. 2002. Further long memory properties of inflationary shocks, *Southern Economic Journal* 68, 496-510.
- Barkoulas, J.T. and Baum, C.F. 2006. Long memory forecasting of US monetary indices, *Journal of Forecasting* 25, 291-302.
- Baum, C.F., J. Barkoulas and Caglayan, M. 1999. Persistence in the international inflation rates, *Southern Economic Journal* 65, 900-913.
- Bloomfield, P. 1973. An exponential model in the spectrum of a scalar time series, *Biometrika* 60, 217-226.
- Bos, C., P.H. Franses and Ooms, M. 1999. Long memory and level shifts: Reanalyzing inflation rates, *Empirical Economics* 24, 427-450.
- Bos, C., P.H. Franses and Ooms, M. 2001. Inflation, forecast intervals and long memory regression models, *International Journal of Forecasting* 18, 243-264.
- Cancelo, J.R.; Espasa, A. and Grafe, R. 2008. Forecasting the electricity load from one day to one week ahead for the Spanish system operator. *International Journal of Forecasting*, 24, 4, 588-602.
- Corberán-Vallet, A.; Bermúdez, J.D. and Vercher. E. 2011. Forecasting correlated time series with exponential smoothing models. *International Journal of Forecasting*. 27, 2, 252-265.
- Chambers, M. 1998. Long memory and aggregation in macroeconomic time series, *International Economic Review* 39, 1053-1072.
- Chhibber, A., Cottani, J., Firuzabadi, D. and Walton, M. 1989. Inflation, Price Controls and Fiscal Adjustment in Zimbabwe. *World Bank Working Paper WPS 192*, World Bank, Washington DC.
- Chhibber, A. And Shafik, N. 1990. Exchange Reform, Parallel Markets and Inflation in Africa: The Case of Ghana. *World Bank Working Paper WPS 427*, World Bank, Washington DC.
- Cioczek-George, R. and Mandelbrot, B.B. 1995. A class of micropulses and antipersitent fractional Brownian motion, *Stochastic Processes and Their Applications* 60, 1-18.
- Dahlhaus, R. 1989. Efficient parameter estimation for self-similar process, *Annals of Statistics*, 17, 1749-1766.

- De-Brouwer, G., and Ericsson, N. R. 1998. Modelling inflation in Australia. *Journal of Business and Economic Statistics*, 16, 433–449.
- Delgado, M. and Robinson, P.M. 1994. New methods for the analysis of long memory time series. Application to Spanish inflation, *Journal of Forecasting* 13, 97-107.
- Diebold, F.X. and Inoue, A. 2001. Long memory and regime switching. *Journal of Econometrics* 105: 131-59.
- Diebold, F.X. and Rudebusch, G.D. 1989. Long memory and persistence in aggregate output, *Journal of Monetary Economics* 24, 189-209.
- Doornik, J.A. and Ooms, M. 2004. Inference and Forecasting for ARFIMA Models With an Application to US and UK Inflation. *Studies in Non-Linear Dynamics and Econometrics*. 8,2, article 14, 1-23.
- Duarte, C. E and Rua, A. 2007. Forecasting inflation through a Bottom-up approach. The portuguese case, *Economic Modelling* 24, 6, 941-953.
- Espasa, A., Senra, E., Albacete, R. 2001. Forecasting Inflation in the European Monetary Union: A Disaggregated Approach by Countries and by Sectors. Univ. Carlos III de Madrid Working Paper no 37.
- Ferreira M.E. and Barros C.P. 1988. From war to economic recovery: peace as a public good in Angola. *Defence Peace Economics* 9:283–297
- Franses, N. Hyung and Penn, J. 2006. Structural breaks and long memory in US inflation rates. Do they matter for forecasting, *Research in International Business and Finance* 20, 95-110.
- Franses, P.H. and Ooms. M. 1997. A periodic long memory model for quarterly UK inflation, *International Journal of Forecasting* 13, 117-126.
- Fritzer, F., Moser, G., and Scharler, J. 2002. Forecasting Austrian HICP and Its Components Using VAR and ARIMA Models. Oesterreichische Nationalbank Working Paper no 73.
- Gadea, M.D., M. Sabate and Serrano, J.M. 2004. Structural breaks and their trace in the memory_ Inflation rate series in the long run, *Journal of International Financial Markets, Institutions and Money* 14, 117-134.
- Gaomah II, M. 1998. Modelling inflation in Namibia, Occasional Paper n.1, Bank of Namibia.

Gil-Alana, Luis A. 2000. Mean reversion in the real exchange rates, *Economics Letters* 69, 285-288.

Gil-Alana, L.A., 2008. Fractional integration and structural breaks at unknown periods of time. *Journal of Time Series Analysis* 29: 163-85.

Gil-Alana, L.A. and Henry, B. 2003. Fractional integration and the dynamics of UK unemployment, *Oxford Bulletin of Economics and Statistics* 65, 221-240.

Gil-Alana, L.A. and Hualde, J. 2009. Fractional integration and cointegration. An overview with an empirical application. The Palgrave Handbook of Applied Econometrics, Volume 2. Edited by Terence C. Mills and Kerry Patterson, MacMillan Publishers, pp. 434-472.

Gil-Alana, L.A. and Robinson, P.M. 1997. Testing of unit roots and other nonstationary hypotheses in macroeconomic time series, *Journal of Econometrics* 80, 241-268.

Gottschalk, J.; Kalonji, K. and Miyajima, K. 2008. Analyzing Determinants of Inflation When There Are Data Limitation: The Case of Sierra Leone. IMF Working Paper WP/08/271.

Granger, C.W.J 1966. The Typical Spectral Shape of an Economic Variable. *Econometrica*, 34, 150-161.

Granger, C.W.J. 1980. Long memory relationships and the aggregation of dynamic models, *Journal of Econometrics* 14, 227-238.

Granger, C.W. and Hyung, N. 2004. Occasional structural breaks and long memory with an application to the S&P 500 absolute stock return. *Journal of Empirical Finance* 11: 399-421.

Hassler, U., 1993. Regression of spectral estimators with fractionally integrated time series, *Journal of Time Series Analysis* 14, 369-380.

Hassler, U. and Wolters, J. 1995. Long memory in inflation rates. International evidence, *Journal of Business and Economic Statistics* 13, 37-45.

Hosking, J.R.M., 1981, Fractional differencing, *Biometrika* 68, 165-176.

Hosking, J.R.M., 1984, Modelling persistence in hydrological time series using fractional differencing, *Water Resources Research* 20, 1898-1908.

Hubrich, K., 2005. Forecasting euro area inflation: Does aggregating forecasts by HICP component improve forecast accuracy? *International Journal of Forecasting* 21, 1, 119-136.

- Hendry, D. and Clements, M. 2003. Economic Forecasting: Some Lessons from Recent Research, *Economic Modelling* 20, 2, 301-329.
- Kallon, K. M. 1994. An Econometric Analysis of Inflation in Sierra Leone, *Journal of African Economies*, Vol. 3 (2), pp. 199–230.
- Masale, S.M., 1993. *Inflation and Exchange Rate Policy in Botswana (1976-1992): an Exploratory Study*. MA dissertation (unpublished), University of Sussex.
- Moriyama, K. and Naseer, A. 2009. Forecasting Inflation in Sudan. IMF Working Paper WP/09/132.
- Nelson, C.R. and Plosser, C.I. 1982. Trends and Random Walks in Macroeconomic Time Series. *Journal of Monetary Economics*, 10, 139-162.
- Parke, W.R. 1999. What is fractional integration? *The Review of Economics and Statistics* 81, 632-638.
- Pedregal, D.J. and Perez, J. 2010. Should quarterly government finance statistics be used for fiscal surveillance in Europe? *International Journal of Forecasting*, 26,4, 794-807.
- Robinson, P.M. 1978. Statistical inference for a random coefficient autoregressive model, *Scandinavian Journal of Statistics* 5, 163-168.
- Robinson, P. M. 1994. Efficient tests of nonstationary hypotheses. *Journal of the American Statistical Association*, 89, 1420-1437.
- Robinson, P.M. 1995. Gaussian semi-parametric estimation of long range dependence, *Annals of Statistics* 23, 1630-1661.
- Rossi, B. and Sekhposyan, T. 2010. Have economic models' forecasting performance for US output growth and inflation changed over time, and when? *International Journal of Forecasting*, 26, 4, 808-835
- Rueda, C. and Rodriguez, P. 2010. State space models for estimating and forecasting fertility. *International Journal of Forecasting*, 26, 4, 712-724.
- Sinclair, T.M.; Gamber, E.N.; Stekler, H. and Reid, E. 2011. Jointly evaluating the Federal Reserve's forecasts of GDP growth and inflation. *International Journal of Forecasting* (forthcoming).
- Sowa, N.K. and Kwakye, J.K. 1991. Inflationary Trends and Control in Ghana. *AERC Research Report No 22*, African Economic Research Consortium, Nairobi, Kenya.

Sowell, F. 1992a. Modelling long run behaviour with the fractional ARIMA model, *Journal of Monetary Economics* 29, 277-302.

Sowell, F. 1992b. Maximum likelihood estimation of stationary univariate fractionally integrated time series models, *Journal of Econometrics* 53, 165-188.

Stock, J.H. and Watson. M.W. 1999. Forecasting inflation. *Journal of Monetary Economics* 44: 293-335.

Taqqu, M.S., W. Willinger and Sherman, R. 1997. Proof of a fundamental result in self-similar traffic modeling, *Computer Communication Review* 27, 5-23.