Navarra Center for International Development

Working Paper nº 04/2011

LONG MEMORY, STRUCTURAL BREAKS AND MEAN SHIFTS IN THE INFLATION RATES IN NIGERIA

Luis Alberiko Gil-Alana
University of Navarra, Navarra Center for International Development, Pamplona, Spain

Olanrewaju L. Shittu
University of Ibadan, Nigeria

OlaOluwa S. Yaya
University of Ibadan, Nigeria

Navarra Center for International Development
WP-04/2011

Long memory, structural breaks, mean shifts in the inflation rates in Nigeria
Luis Alberiko Gil-Alana, Olanrewaju I. Shittu and OlaOluwa S. Yaya
Working Paper No. 04/2011
May 2011

ABSTRACT

This paper deals with the analysis of the inflation rate in Nigeria. We use long range dependence techniques based on fractional integration or I(d) models, incorporating structural breaks in the model. The results indicate that inflation in Nigeria displays long memory behaviour, with an order of integration of about 0.3 in spite of the existence of breaks at different periods. Including the growth rate of money (M1) as an exogenous term, the results indicate that this variable significantly affects inflation two and three periods (quarters) after the initial shock.

Keywords: Inflation rate, long memory, structural breaks, mean shifts, money supply.
JEL Classification: C22

Corresponding author: Prof. Luis A. Gil-Alana
University of Navarra
Navarra Center for International Development
E-31080 Pamplona, Spain

Phone: 00 34 948 425 625
Fax: 00 34 948 425 626
Email: alana@unav.es

1. Introduction

This paper deals with the analysis of the inflation rate in Nigeria. Modelling inflation rates is still a controversial issue. Thus, while many authors claim that this is an I(0) stationary process, based on the fact that the log-prices are in general I(1) processes, other authors argue that inflation itself is nonstationary I(1) and that it should be included in a system of cointegrated variables.[1] In another line of research, many authors claim that inflation is neither I(0) nor I(1) but I(d) where d is a value between 0 and 1. In this case, (when d is above 0) the process is said to be "*strongly autocorrelated*" as opposed to the case of "*weakly autocorrelated*" associated to the ARMA class of I(0) models. Contributions to this view are the papers of Backus and Zin (1993) for the US case; Hassler (1993) for the Swiss inflation rates, Delgado and Robinson (1994) for the Spanish case, and more recently, Gil-Alana (2011a, b) in the case of South Africa.[2]

In the context of fractional integration, some authors have suggested that the presence of fractional degrees of differentiation might be a spurious phenomenon caused by the existence of breaks in the data. Thus, for example, Bhattacharya et al. (1983), Teverovsky and Taqqu (1997), Diebold and Inoue (2001), Granger and Hyung (2004) and Ohanissian et al. (2008) among many others show that fractional integration may be caused by the existence of breaks in short-memory I(0) contexts. [3]

There are very few studies for the developing countries using I(d) models. Among them, we find Shittu and Yaya (2010), who examine inflation in Nigeria using a

[1] The results clearly vary from one country to another, but also depend heavily on the statistical methods employed. For example, Ng and Perron (2001) applied a battery of unit root tests to quarterly inflation data of the G7 countries but they could not reach firm conclusions, the results varying depending on the method used and the country examined.

[2] See also Hassler and Wolters (1995), Baillie, Chung and Tieslau (1996) and Baum, Barkoulas and Caglayan (1999) for the analysis of inflation in the context of multiple countries.

[3] In the reverse case, authors such as Kuan and Hsu (1998), Wright (1998) and Krämer and Sibbertsen (2002) showed that evidence of structural change might also be spurious since most commonly employed tests for breaks are biased towards an over-rejection of the null of no change when the process exhibits fractional degrees of differentiation.

fractionally integrated model in a non-linear framework. These authors conclude that the removal of the long memory in the series does not eliminate the non-linearity in the series.

The present paper is structured as follow: Section 2 briefly reviews the inflation rate in Nigeria, focusing on the most significant facts during the last fifty years that may suggest the existence of breaks in the data. Section 3 describes the methodology employed in the paper. Section 4 displays the empirical results, separating here the univariate work from the multivariate analysis. In the latter we use the growth rate of M1 as an exogenous variable that may directly have influenced the inflation rate in Nigeria. Section 5 contains some concluding comments.

2. The Inflation rate in Nigeria

Inflation depicts a general rise in the price of goods and services as measured by an index such as the consumer price index (CPI) or by an implicit price deflation for Gross National Product (GNP).

The effect of inflation in undermining the economy and its currency cannot be over estimated. Just as inflation could drastically erode the monetary well-being of a nation and drastically deteriorate a once buoyant economy, a nation with large domestic and foreign debt can utilize the inflationary trend to reduce the burden of its debt. The latter is the case when in 2006, Nigeria was granted an 18% write-off of her Paris Club debt, though high domestic inflation rate did not allow the Nigerian government to fully utilize the advantage of this debt reduction.

Average inflation during the period of the early 1960s up to the year 1972 was relatively low, Nigeria's historical average rate being 5.01 percent. When assessed on an annual basis, however, rising prices became a cause for concern for the then military

government when in 1969 the inflation rate hit double digits at 10.36 percent. The concern of the Nigeria government seems to have been justified by the fact that Nigeria was experiencing double-digit inflation for the first time, in the face of a raging civil war the end of which was not then in sight. As a reaction, government imposed a general wage freeze for a period of one year. Apparently aware of possible opposition by labor unions, price control measures were introduced with the official promulgation of the Price Control Decree in Nigeria from the early years of 1970 to 1975. In 1985, government was under pressure from debtor groups to reach an agreement with the International Monetary Fund and inflation was at the peak at that time. Based on this agreement, domestic currency was devalued and this fueled inflation as prices adjusted to the parallel exchange rate (Masha, 2000).

For instance, oil in the Nigerian economy has been factored as a hindrance to its economic progress as it created a booming mode of economic management. The oil boom of the 1970s concomitant of soaring international oil prices, resulted in substantial resources by way of government revenue and foreign exchange earnings along with an expansion of public sector expenditure in order to hastily develop productive capacity of the economy and to improve living standards. In the early 1980s there was near total collapse of international oil market. The dips in international oil prices aggravated the problems of the Nigerian economy in as much as foreign exchange earnings declined and credit was dishonored.

Inflation as taken its bitter toll on the Nigerian economy and monetary and fiscal policies among others have been deployed to arrest it. The Central Bank of Nigeria has statutory responsibility for formulating and implementing monetary policy with the emphasis on price stability. The inflationary trend has been cyclical since mid the 1970s

peaking at various times, for example during 1975, 1990, 1996 and 2006 as the major factor which has been responsible for inflation in Nigeria has been poor fiscal management by the government. However, inflation since 2006 has fallen to a single digit of 8.4 percent on the average unlike the double digits experience since the 1980s. In addition, during 1970 broad money supply stood at N 949.9 million and rose to N23, 818.6 million during the year 1985. Then, near the end of 2006, money supply stood at N3 190.9 billion.

There are factors responsible for a certain amount of the growth in the monetary aggregates, monetization of foreign reserves is one, inadequate financial policy framework, and poor institutional frameworks are among the others. Besides, prior to the end of 2006 and up until early 2007, Nigeria was becoming one of highest indebted nations, owing huge sums of money to various international creditors. The exit from a certain group of countries was secured in 2006 and sealed in 2007 after the debt cancellations and subsequent pay-off of outstanding debts to the Paris Club among other creditors. The 2006 Nigerian Core Welfare Indication survey by the National Bureau of Statistics showed that the dependency ratio defined as the total number of household members aged 0 to 14 years and 65 years and above to the number of household members aged 15 to 64 years was 0.8 reflecting the high population growth rate of Nigeria.

However, although the Nigerian inflation rate has been fluctuating over time it has increased steadily from independence in 1960. Nigerian inflation rate was about equal to that of its trading partners (USA and the UK) between (1965-1975) in the decade (1975-1985), the respecting inflation rate diverged dramatically as Nigerians

average annual inflation nearly doubled to 18 percent while that of its trading partners increased by a marginal 4 percent (Moser, 1995).

A closer look at Nigeria's inflation rate data since 1970 to date reveals significant jumps/breaks at different points in time. These breaks can be found in 1981, 1984, 1988, 1994 and 2001. Each of these identified breaks will be investigated with a view to determining the significant ones using various statistical techniques thereafter we shall examine the potential mean shift level after the dates of breaks.

3. The Methodology

For the purpose of the present work we define an I(0) process as a covariance stationary process with spectral density function that is positive and bounded at the zero frequency. In this context we say that a process $\{x_t, t = 0, \pm 1, \ldots\}$ is I(d) if:

$$(1 - L)^d x_t = u_t, \qquad t = 0, \pm 1, \ldots, \tag{1}$$

with $x_t = 0$ for $t \leq 0$ and where L is the lag-operator ($Lx_t = x_{t-1}$) and u_t is I(0). Note that, for any real value d, the polynomial in the left hand side in (1) can be expressed in terms of its Binomial expansion such that:

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

implying that the higher the value of d is, the higher the degree of association is between observations distant in time. Thus, the parameter d plays a crucial role in determining the degree of persistence of the series. If $d = 0$ in (1), clearly $x_t = u_t$, the process is short memory, it is covariance stationary, and it may be weakly (ARMA) autocorrelated, with the values in the autocorrelation function decaying exponentially fast. If d belongs to the interval (0, 0.5), x_t is still covariance stationary though the autocorrelations will take longer to disappear than in the previous case of I(0)

behaviour; if d belongs to [0.5, 1) the process is no longer covariance stationary though is still mean reverting in the sense that shocks will tend to disappear in the long run. Finally, if $d \geq 1$, x_t is nonstationary and not mean reverting.

In the paper we also assume that x_t in (1) can be the errors in a regression model of the form:

$$y_t = \beta^T z_t + x_t, \quad (3)$$

where y_t is our series of interest, β is a (kx1) vector of unknown parameters, and z_t is a (kx1) vector of deterministic terms (or weakly exogenous variables) that might include, for example, an intercept ($z_t = 1$), an intercept with a linear trend ($z_t = (1, t)^T$), or any other type of deterministic terms like dummy variables to take into account potential breaks.

We will present in the empirical work in Section 4 estimates of d based on the frequency domain and using both parametric and semiparametric techniques. The difference between the two is that in the latter no functional form is imposed on the I(0) error term u_t. In the parametric methods we use a Whittle approximation to the likelihood function (Dahlhaus, 1989) along with a Lagrange Multiplier (LM) procedure developed by Robinson (1994) which is very suitable in the context of the present work. Several semiparametric methods (Robinson, 1995; Phillips and Shimotsu, 2005) will also be implemented in Section 4.

The presence of breaks in the context of I(d) models will also be examined in the paper. We will first assume that the break dates are known and we implement another version of Robinson's (1994) parametric tests, including dummy variables for the breaks in the regression model (3). Alternatively, we will also suppose that the break dates are unknown and will implement then a procedure developed by Gil-Alana (2008) along with other methods.

Finally, in the multivariate work conducted at the end of the paper, the growth rate of money (M1) (and lagged values of this variable) will be included as exogenous terms in the regression model (3) and here we will implement once more the tests of Robinson (1994), which are very appropriate in the context of the models employed in the paper. [4]

4. The Data and the Empirical Results

The data employed correspond to the inflation rate series in Nigeria, quarterly, from 1961q1 to 2008q4. A plot of the series is displayed in Figure 1. We observe that the data present significant peaks at certain periods especially in the middle of the sample. (See also the comments made in Section 2).

[Insert Figure 1 about here]

4.1 The Univariate framework

The first thing we do in this work is to consider a model of the form as the one given by the equations (3) and (1), with $z_t = (1, t)^T$, i.e.,

$$y_t = \beta_0 + \beta_1 t + x_t; \qquad (1 - L)^d x_t = u_t, \qquad t = 1, 2, ..., \tag{4}$$

where β_0 and β_1 are the coefficients corresponding to the intercept and a linear time trend respectively, and x_t are the regression errors that are supposed to be I(d). Initially, we suppose that u_t is a white noise process, though we will also consider different forms of weak autocorrelation. In particular, we will try with non-seasonal AR(1), Bloomfield (1973)[5], and seasonal (quarterly) AR(1) disturbances. Higher AR orders were also employed and the results were substantially the same as with the AR(1) cases. We

[4] See, for example, Gil-Alana and Robinson (1997) for an empirical application using this method.
[5] This is a non-parametric approach of modelling I(0) disturbances that produce autocorrelations decaying exponentially as in the AR(MA) case. See Gil-Alana (2004) for a study with Bloomfield disturbances in the context of Robinson's (1994) tests.

estimate d in all these cases using the Whittle function in the frequency domain, displaying also in Table 1 the 95% confidence band of the non-rejection values of d using Robinson's (1994) parametric approach.

[Insert Table 1 about here]

We see in this table that if the disturbances are uncorrelated, the estimates of *d* are above 1 in the three cases of no regressors, an intercept, and a linear trend; though the unit root null cannot be rejected at the 95% level in any of the three cases. If we permit weak autocorrelation, we obtain different results at each case. Thus, with Bloomfield disturbances, the estimated values of d are below 1 though statistically insignificantly different from 1. If u_t is seasonal AR(1), the estimated values of *d* are above 1 and the unit root null is rejected in favour of higher orders of integration. Finally, if u_t follows a non-seasonal AR(1) process, the non-rejection values of d range from 0.259 to 0.482, and the estimates are 0.378, 0.376 and 0.380 respectively for the three cases of no regressors, an intercept, and an intercept with a linear trend. Conducting several LR tests along with diagnostic tests on the residuals, we conclude that the best specification corresponds to the case of an intercept with AR(1) disturbances. Thus, the selected model is:

$$y_t = 13.214 + x_t; \quad (1-L)^{0.376}x_t = u_t; \quad u_t = 0.726u_{t-1} + \varepsilon_t \qquad (5)$$

(t-test: 3.064) (0.259, 0.479) (0.656, 0.796)

implying that the series is stationary long memory with mean reverting behavior. This result about the order of integration of the series is consistent with other empirical works on inflation in Nigeria that found an order of integration in the range (0, 0.5). (See, e.g., Shittu and Yaya, 2010).

[Insert Figure 2 about here]

Due in part to the disparity in the results depending on the specification for the error term we also tried with a semiparametric method (Robinson, 1995). This method is based on a "local" Whittle function, using a band of frequencies that degenerates to zero.[6] We display in Figure 2 the estimates of *d* along with the 95% confidence interval corresponding to the I(0) case. The horizontal axis refers to the bandwidth number while the vertical one represents the estimates of *d*. We observe that the estimates are in all cases above the I(0) interval, and using the bandwidth number $m = (T)^{0.5} \approx 14$ (which has been widely used in the empirical literature) the estimated value of *d* is 0.386, thus similar to the one obtained above with the parametric approach.

[Insert Figure 3 about here]

Focussing on the specification given by equation (5) we display in Figure 3 the first 40 impulse responses, observing that, after an initial increase, there is a slow (hyperbolic) decay in the responses, that is slightly significant even after 10 years.

The significant evidence of long memory obtained so far might be a consequence of the existence of breaks in the data that have not been taken into account. In what follows we wonder first about the stability of *d* across time. For this purpose we follow two strategies. First, we consider the model in (5) and re-estimate it for a sample size with the first 80 observations, thus corresponding to the first 20 years of data (1961q1 – 1980q4). Then, we add one observation each time till the end of the sample. The upper part in Figure 4 displays the estimates of *d* (along with its corresponding 95% confidence interval) while the lower part displays the estimates of the AR coefficient. We observe three clear points with unstable behavior, corresponding to the observations

[6] This method has been further examined and refined by Velasco (1999), Velasco and Robinson (2000), Phillips and Shimotsu (2004, 2005) and others. However, such refined methods require additional user-chosen parameters, and the estimates of d may be very sensitive to the choice of these parameters. In this respect, the method of Robinson (1995) seems computationally simpler.

94 (i.e., 1984q2), 110 (1988q2) and 136 (1994q4). Since 1995, the estimates remain stable across time till the end of the sample.

[Insert Figure 4 about here]

In Figure 5 we use a second approach, and estimate *d* moving forward the sample recursively one period ahead, and thus keeping the same sample size (80 observations) in all cases. In doing so, we avoid the potential bias that might occur in the previous case (in Figure 4) and due to the different sample sizes. The results are fairly similar to the previous case, noting the breaks at exactly the same periods of time as before.

Prior to 1984, Nigeria was operating a large scale fiscal deficit coupled with the excessive monetization of oil export revenue, which might have given inflation a monetary character. Also at this time the government was under pressure to reach agreement with the International Monetary Fund (IMF) to devaluate the domestic currency. The expectation that devaluation was imminently fuelled inflation as prices adjusted to the parallel rate of exchange. The government later agreed to the IMF conditions of Structural Adjustment Programme (SAP) in 1985.

[Insert Figure 5 about here]

The potential break in 1988 actually started in the last quarter of 1987. The inflationary trend was caused by the increase in oil revenue occasioned by oil price increase following the Gulf war. At this period of 1987 through 1989, there was a debt conversion exercise where the external debt was re-purchased with local currency.

1994, just like in the previous two periods, coincides with a period of fiscal deficit and money supply growth, which eventually pushed up the inflationary trend. According to Onwioduokit (CBN 37(2)) it takes about two years for fiscal deficit to impact on inflation in Nigeria.

Next we are concerned with the modelizations of the breaks still in the I(d) context. For this purpose we first fix the dates of the breaks in the periods above mentioned, in particular, in 1984q4, 1988q2 and 1994q4, and use four dummy variables to explain the potential mean shifts. Here, we consider the following model,

$$y_t = \gamma_1 D_{1t} + \gamma_2 D_{2t} + \gamma_3 D_{3t} + \gamma_4 D_{4t} + x_t; \qquad (1 - L)^d x_t = u_t, \qquad (6)$$

where D_{1t} = 1I(t in [1961q1 – 1984q2]); D_{2t} = 1I(t in [1984q3 – 1988q2]); D_{3t} = 1I(t in [1988q3 – 1994q4]); and finally, D_{4t} = 1I(t in [1995q1 – 2008q4]), and where I(x) is the indicator function.

Based on model (6) we estimate *d* for different types of I(0) disturbances. In fact, we use the same models as in Table 1, i.e., white noise, AR(1), Bloomfield, and seasonal AR(1) disturbances.

[Insert Table 2 about here]

We observe in Table 2 that the values of *d* are very similar to those reported in Table 1 (with no dummy variables). Thus, the unit root null cannot be rejected in the cases of white noise and Bloomfield disturbances; it is rejected in favour of d > 1 with seasonal AR, and *d* is significantly smaller than 1 in case of non-seasonal AR(1) u_t. If we look now at the dummy coefficients we observe that γ_3 and γ_4 are always significant. On the contrary, γ_1 is mostly insignificant, while the results for γ_2 are mixed: it is significant with seasonal and non-seasonal AR, but insignificant in the other two cases. It is also interesting to know that the coefficient increases across the subsamples in three of the four specifications (white noise, Bloomfield and seasonal AR) but this does not happen in case of AR(1) disturbances, which previously found to be the most realistic case. As expected, the highest coefficients for the intercept are obtained during the period [1988q3 – 1994q4], consistent with the data observed in Figure 1.

Note, however, that the approach employed above and based on equation (6) imposes the same degree of integration at all subsamples. Due to this limitation, we also employ another method (Gil-Alana, 2008) that permits a more flexible specification of the model, with different orders of integration, different intercepts and different short run parameters at each subsample. We briefly describe this approach which is based on minimizing the residuals sum squares across the different subsamples. Gil-Alana (2008) considers the following model,

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

where nb is the number of breaks (i.e., nb = 0, 1, 2, 3), 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 subsample, and the T_b^i's correspond to the times of the unknown breaks. The method is based on minimizing the residuals sum squares for a grid of values of the fractional differencing parameters and the time breaks.

The results using this approach indicate that there are at most two breaks in the series, one at 1988q3 and the other at 1994q4, which are values that appeared in previous parts of the paper. However, given the reduced number of observations that should be included in the second of the three subsamples, we simply consider the case of a single break at 1994q4. We try with different short run specifications for the disturbances, and it was found that an AR(1) was again sufficient to describe the short run dynamics of the series. Table 3 displays the results of the two specifications based on white noise and AR(1) errors.

[Insert Table 3 about here]

We notice that if the error term is white noise the estimates of d are above 1 in the two subsamples, though in the first period the unit root cannot be rejected. Using the AR(1) specification, which is the most realistic case according to the diagnostic tests,

the values of d are respectively 0.119 and 0.135 for the first and second subsamples and the AR coefficients are very close to 1 in the two cases (0.842 for the first subsample, and 0.929 for the second one). Thus, though the orders of integration are relatively small (and the two subseries are stationary) they are highly persistent throughout the AR short memory part, observing also a slight increase in the degree of dependence after the break in the two cases.

[Insert Figure 6 about here]

Finally, in Figure 6 we display the first 40 impulse responses in the two subsamples. We clearly observe a higher degree of persistence during the second subsample.

4.2 A Multivariate approach

A series of articles have considered modeling inflation in a multivariate framework because of the belief that monetary policy affects the movements in inflation. Authors in this school of thought are, among others, Bernanke, Laubach, Mishkin and Posen (1999), and in particular, dealing with Nigerian data, Adebiyi (2009) who applied a vector autoregressive (VAR) model to predict the relationship between money supply (M1) and consumer price index (CPI) in Nigeria. It was found in that study that the two variables are not cointegrated. He considered an unrestricted VAR model in levels using two lags of each variable, finding that M1 had little predictive power on the price level. The period examined in the paper (1960 – 1985) was characterized by price regulation and thus money supply did not have any significantly effect on the price level within the period.

The approach considered in Adebiyi (2009) used yearly data and the possibility of structural breaks was not taken into account. We present our multivariate approach using the model below:

$$y_t = \alpha + \beta^T z_{t-k} + x_t; \qquad (1-L)^d x_t = u_t, \qquad u_t = \phi u_{t-1} + \varepsilon_t , \qquad (8)$$

where y_t is the inflation rate (quarterly) in Nigeria and z_t is the growth rate of money (M1), measured as the first differences of the log-values of the monetary aggregate. Note that though there are some economists that argue that money growth and inflation are unrelated (Mandel, 1999) it is a general accepted view that changes in the nominal quantity of money and the price level are closely related. Authors in this line include Lucas (1980), Dwyer and Hafer (1988), Friedman (1992), Barro (1993), McCandless and Weber (1995), Dewald (1998), Rolnick and Weber (1997) and Dwyer (1998) among many others.

For Nigeria, Chimobi and Igwe (2010) investigated the long run relationship between budget deficit, money growth and inflation. They found a single relationship between inflation and money supply, with a causal link running from money to inflation.

[Insert Figure 7 about here]

Figure 7 displays the values of the monetary aggregate M1 and its corresponiding growth rate. It is observed that the values of M1 remain stable till the mid 90s (1995) when they start increasing sharply.

[Insert Table 4 about here]

Table 4 displays the estimated coefficients in the model given by equation (8) for values k = 0, 1, 2, 3, 4 and 5. It is observed that for k = 0 and 1 the coefficients corresponding to the money growth are positive though statistically insignificant. The same happens with k = 4 and 5; however, for k = 2 and 3 the coefficients are

significantly positive implying a positive relation between the growth rate of M1 and inflation two and three periods after. The last two columns in Table 4 display the estimates of β and the AR coefficient under the (erroneous) presumption that the regression error x_t in (8) is I(0). We first notice here that the coefficients related with the money growth are now statistically significant in all cases, with the AR coefficient being higher than in the case of d being estimated. We should note however that these significantly positive slope coefficients are invalid since the I(0) assumption was decisively rejected with the procedures based on fractional integration.

5. Conclusion

This paper has explored the inherent properties in the Nigerian inflation rates using both univariate and multivariate approaches. The results revealed some structural breaks in the series, which may be responsible for the long memory detected in the series based on the estimated fractional differencing parameter. This value is found to be about 0.3, implying covariance stationarity and mean reverting behavior.

The break dates are identified at 1984q2, 1988q2 and 1994q4. The literature reveals that these breaks are the result of excess money supply in the economy during these periods. We then re-considered in a multivariate framework the relationship between inflation and money supply (M1) as a variable for growth rate of money. The results indicate that this variable significantly affects inflation two and three periods (quarters) after the initial shock, an effect that is substantially smaller than the one obtained if we were supposing stationarity I(0) errors and lack of long memory.

References

Adebiyi, M. A. (2009). Inflation Targeting: Can we establish a Stable and Predictable Relationship between Inflation and monetary Policy instruments in Nigeria and Ghana? In: Applied Econometrics and Macroeconometric Modeling in Nigeria. Ibadan University Press, Nigeria.

Backus, D. and S. Zin (1993) Long memory inflation uncertainty. Evidence from the term structure of interest rates. Journal of Money, Credit and Banking 25, 681-700.

Baillie, R.T., C.F. Chung and M.A. Tieslau (1996) Analyzing inflation by the fractionally integrated ARFIMA-GARCH model, Journal of Applied Econometrics 11, 23-40.

Barro, R. (1993) Macroeconomics, 4th Edition, New York, Willey.

Baum, C.F., J. Barkoulas and M. Caglayan (1999) Persistence in the international inflation rates, Southern Economic Journal 65, 900-913.

Bernanke, B. S., Laubach, T., Mishkin, F. S., Posen, A. S. (1999). Inflation Targeting. Lessons from the International Experience. Princeton University Press.

Bhattacharya, R.N. and V.K. Gupta and E. Waymire (1983) The Hurst effect under trends, Journal of Applied Probability 20, 649-662.

Bloomfield, P. (1973) An exponential model in the spectrum of a scalar time series, Biometrika 60, 217-226.

Chimobi, O.P. and O.L. Igwe (2010) Budget deficit, money supply and inflation in Nigeria, European Journal of Economics, Finance and Administrative Sciences, 19.

Dahlhaus, R. (1989) Efficient parameter estimation for self-similar process. Annals of Statistics 17, 1749-1766.

Delgado, M. and P.M. Robinson (1994) New methods for the analysis of long memory time series. Application to Spanish inflation. Journal of Forecasting 13, 97-107.

Dewald, W. (1998) Money still matters, Federal Reserve Bank of St. Louis Review 80, 13-24.

Diebold, F.X. and Inoue, A. (2001) Long memory and regime switching. Journal of Econometrics 105, 131-159.

Dwyer, G.P. (1998) Is money a leading indicator of inflation. Unpublished manuscript, Federal Reserve Bank of Atlanta.

Dwyer, G.P. and R.W. Hafer (1988) Is money irrelevant? Federal Reserve Bank of St. Louis Review 3-17.

Friedman, M. (1992) Money Mischief. Episodes in Monetary History. New York, Harcourt Brace Jovanovich.

Gil-Alana, L.A (2004) The use of the model of Bloomfield as an approximation to ARMA processes in the context of fractional integration, Mathematical and Computer Modelling 39, 429-436.

Gil-Alana, L.A. (2008) Fractional integration and structural breaks at unknown periods of time, Journal of Time Series Analysis 29, 163-185.

Gil-Alana, L.A. (2011a) Inflation in South Africa. A long memory approach, Economics Letters 11, 3, 207-209.

Gil-Alana, L.A. (2011b) Inflation in South Africa. A time series view across sectors using long range dependence, South African Journal of Economics, forthcoming.

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

Granger, C.W.J. and N. Hyung (2004) Occasional structural breaks and long memory with an application to the S&P 500 absolute stock returns. 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 J. Wolters (1995) Long memory in inflation rates. Interantional evidence, Journal of Business and Economic Statistics 13, 37-45.

Kramer, W. And P. Sibbertsen (2002) Testing for structural changes in the presence of long memory, International Journal of Business and Economics 1, 235-242.

Kuan, C.M. and C.C. Hsu (1998) Change point estimation of fractionally integrated processes, Journal of Time Series Analysis 19, 693-708.

Lucas, R.E., (1980) Two illustration of the Quantity Theory of Money, American Economic Review 70, 1005-1014.

Mandel, M.J. (1999) "Rivers of Cash Won't Swamp th Economy", Business Week 8, 34.

Masha I. (2000) New perspectives on inflation in Nigeria" Central Bank of Nigeria, CBN, Economic and Financial Review, Vol. 38, 2, 34-56.

McCandless G.T. and W.E. Weber (1995) Some monetary facts, Federal Reserve Bank of Minneapolis Quarterly Review 19, 3, 2-11.

Moser G.G. (1995) The main determinants of inflation in Nigeria. IMF Working Paper 94/76

Ng, S. and P. Perron (2001) lag length selection and the construction of unit root tests with good size and power, Econometrica 69, 1519-1554.

Ohanissian, A., J.R. Russell and R.S. Tsay (2008) True or spurious long memory? A new test, Journal of Business Economics and Statistics 26, 161-175.

Onwioduokit E.A (2002) Fiscal Deficits and Inflation dynamics in Nigeria: An Empirical Investigation of Causal Relationship, Central Bank of Nigeria, CBN, Economic and Financial Review, Vol. 37, 2, 1-16.

Phillips, P.C.B. and Shimotsu, K., 2004, Local Whittle estimation in nonstationary and unit root cases, Annals of Statistics 32, 656-692.

Phillips, P.C.B. and Shimotsu, K., 2005, Exact local Whittle estimation of fractional integration, Annals of Statistics 33, 1890-1933.

Robinson, P.M., 1994, Efficient tests of nonstationary hypotheses, Journal of the American Statistical Association 89, 1420-1437.

Robinson, P.M., 1995, Gaussian semiparametric estimation of long range dependence, Annals of Statistics 23, 1630-1661.

Rolnick, A.J. and W.E. Weber (1995) Inflation, money and output under alternative monetary standards, Federal Reserve Bank of Minneapolis Research Department.

Sherwin, M. (2000). Institutional Frameworks for Inflation Targeting: In: Practical Journal Experience in Inflation Targeting. Bank of Thailand Symposium.

Shittu, O.I. and O.S. Yaya (2010) On fractionally integrated logistic smooth transitions in time series, American Journal of Scientific and Industrial Research 1, 439-447

Teverovski, V. and M.S. Taqqu (1997) Testing for long range dependence in the presence of shifting means or a slow declining trend using a variance-type estimator, Journal of Time Series Analysis 18, 279-304.

Velasco, C. (1999) Gaussian semiparametric estimation of nonstationary time series, Journal of Time Series Analysis 20, 87-127.

Velasco, C. and P.M. Robinson (2000) Whitle pseudo maximum likelihood estimation for nonstationary time series, Journal of the American Statistical Association 95, 1229-1243.

Wright, J.H. (1998. Testing for a structural break at unknown date with long memory disturbances, Journal of Time Series Analysis19, 369-376.

Figure 1: Time Plot of Inflation Rate in Nigeria

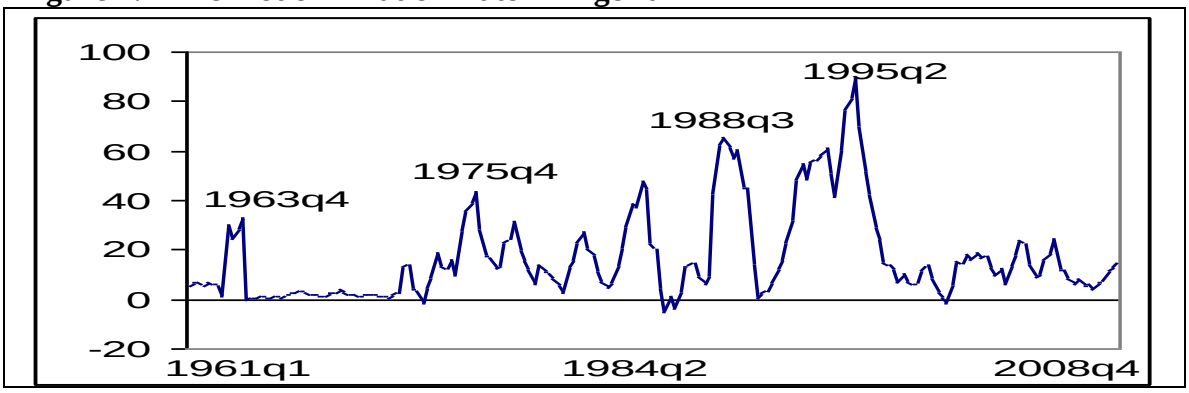
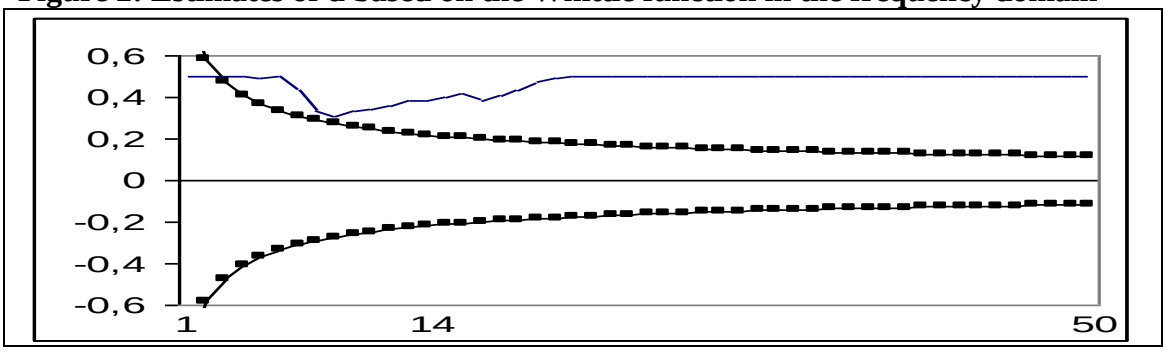
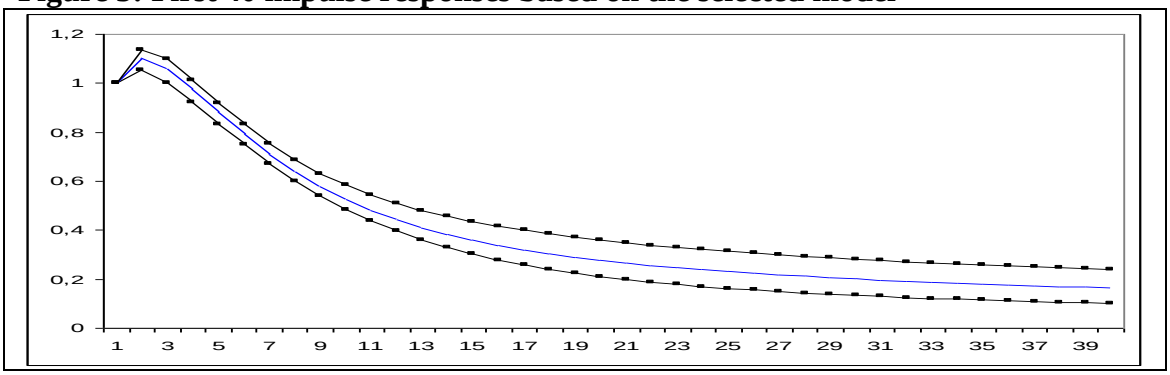


Figure 2: Estimates of d based on the Whittle function in the frequency domain



The thick lines refer to the 95% confidence interval of the I(0) hypothesis

Figure 3: First 40 impulse responses based on the selected model



The dotted line refers to the 95% confidence interval.

Figure 4: Estimates of d and the AR coefficient starting with a sample of 80 observations (1961q1-1980q4), adding 1 observation each time

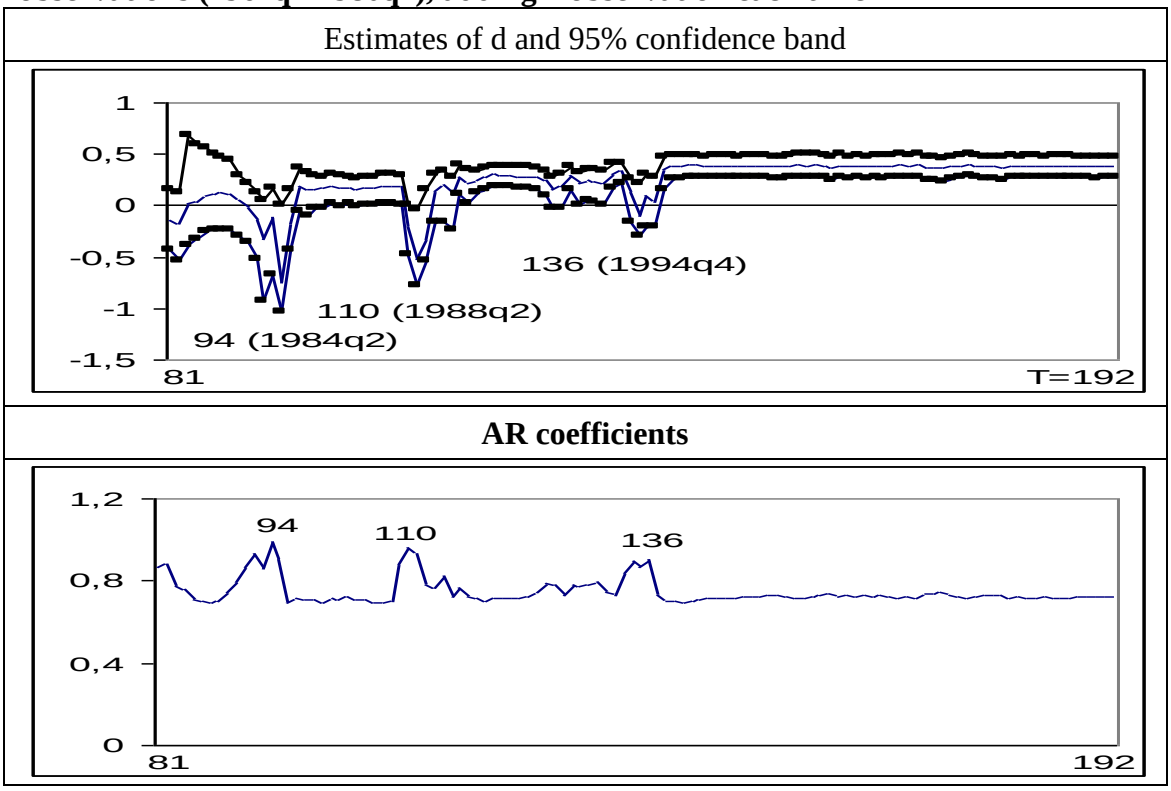


Figure 5: Estimates of d and the AR coefficient starting with the sample 1961q1-1980q4, moving recursively one observation each time till the end of the sample (1989q1-2008q4)

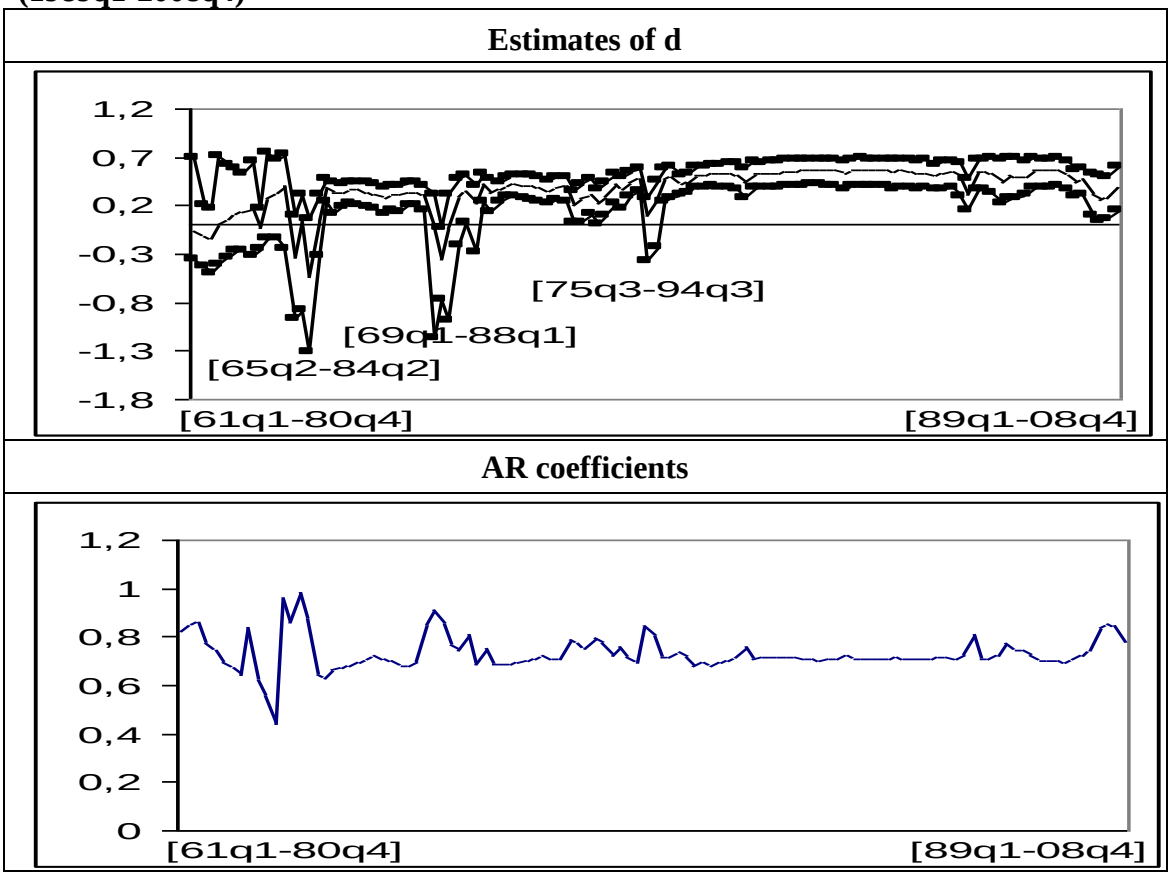
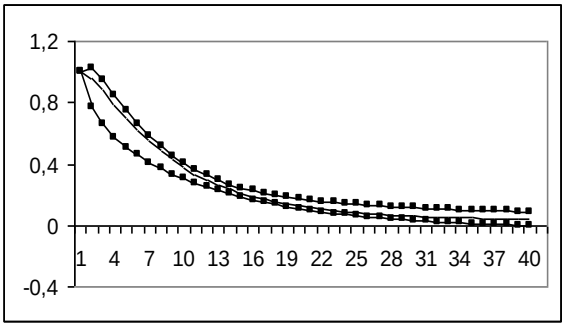
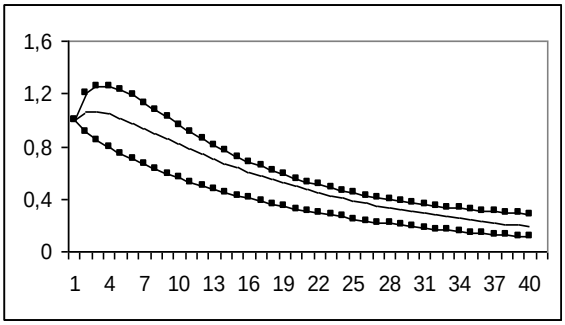


Figure 6: First 40 impulse responses based on the selected model for each subsample

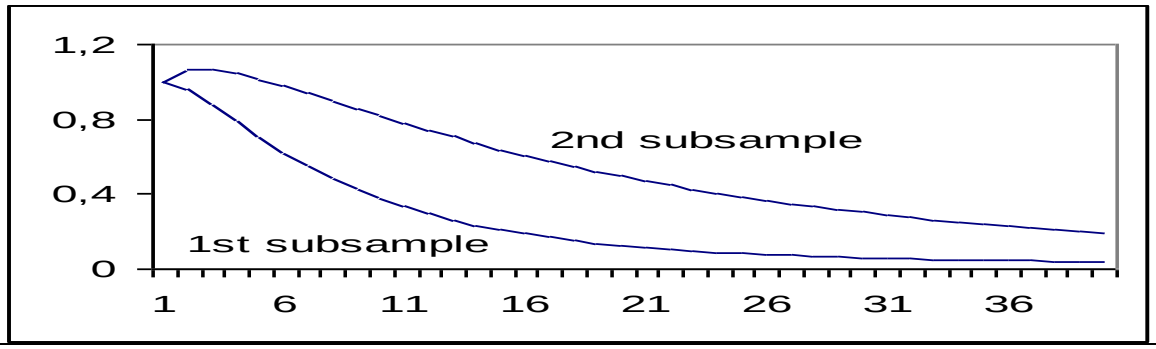
First subsample (1961q1-1994q4)



Second subsample (1995q1 – 2008q4)



First and second subsamples



The dotted line refers to the 95% confidence interval.

Figure 7: Time Plots of the Monetary Aggregate, M1 and its corresponding growth rate

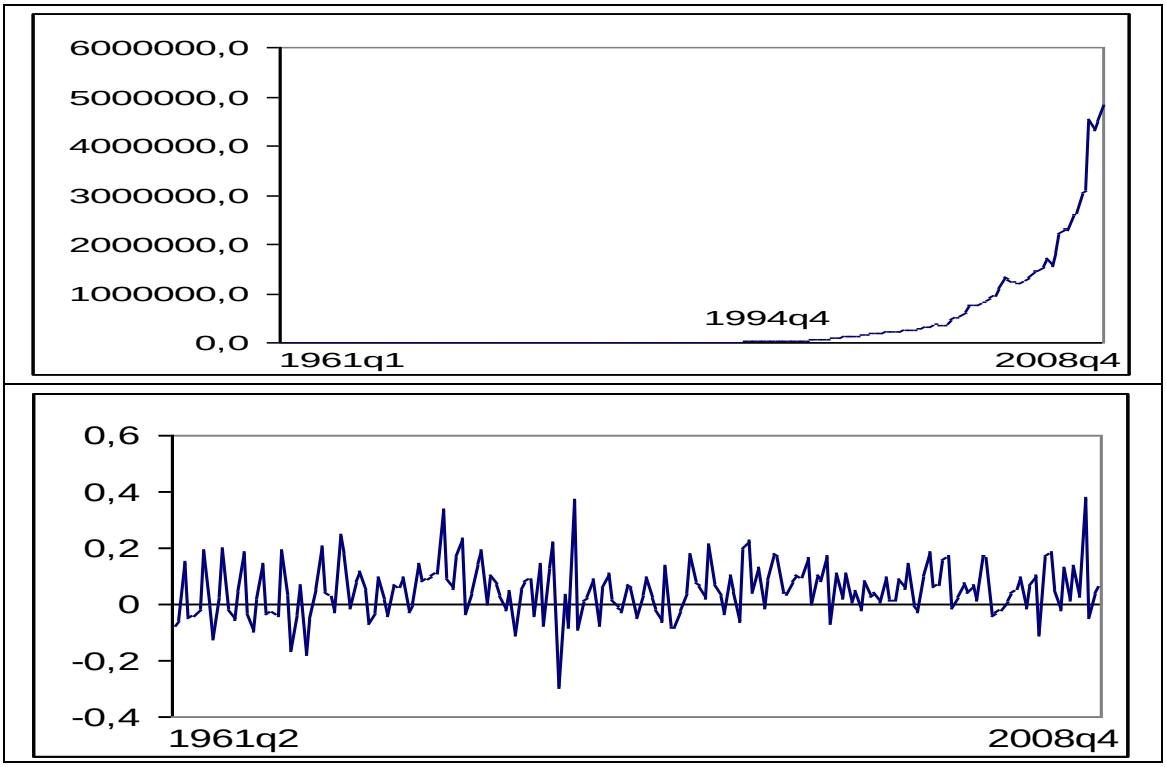


Table 1: Estimates of d and 95% Confidence bands

Disturbances /	No regresors	An intercept	A linear time trend
White noise	[0.987 (1.134)	[0.986 (1.133)	[0.986 (1.133)
AR (1)	[0.267 (0.378)	**[0.259 (0.376)**	[0.267 (0.380)
Bloomfield	[0.464 (0.707)	[0.477 (0.705)	[0.478 (0.706)
Monthly AR(1)	[1.075 (1.201)	[1.073 (1.200)	[1.073 (1.199)

In bold the most adequate specification.

Table 2: Estimates of d including dummy variables for the breaks

Disturbances	γ_1	γ_2	γ_3	γ_4	d
White noise	5.517 (0.728)	16.376 (1.528)	**33.356** **(2.538)**	**49.199** **(3.241)**	1.086 (0.948, 1.262)
AR(1)	**9.233** **(3.514)**	**8.645** **(2.127)**	**32.256** **(8.466)**	**21.239** **(6.288)**	0.309 (0.047, 0.640)
Bloomfield	5.800 (0.791)	13.290 (1.278)	**36.302** **(2.905)**	**52.084** **(3.634)**	0.827 (0.512, 1.194)
Seas. AR(1)	5.425 (0.776)	**16.811** **(1.702)**	**31.568** **(2.606)**	**46.364** **(3.313)**	1.171 (1.047, 1.320)

Table 3: Estimates in the context of a single structural break (Gil-Alana, 2008)

	First Subsample (1961q1-1994q4)				Second subsample (1995q1 – 2008q4)			
	d	β_0	AR *p*.	RSS	*D*	β_0	AR *p*.	RSS
Wh. N.	1.068 (0.889, 1,286)	5.513 (1.659)	---	9518.95	1.237 (1.054, 1,513)	76.961 (13.712)	---	1929.03
AR (1)	**0.119 (-0.166, 0.263)**	**17.466 (7.898)**	**0.842**	**8926.97**	**0.135 (-0.047, 0.345)**	**20.051 (5.794)**	**0.929**	**1797.23**

Table 4: Estimates of d and 95% Confidence bands

k	d	β	AR	Imposing d = 0	
				β	AR
0	0.388 (0.274, 0.489)	4.2689 (0.833)	0.720	20.908 (3.561)	0.899
1	0.373 (0.236, 0.481)	2.6993 (0.518)	0.725	24.042 (3.738)	0.887
2	**0.349** **(0.180, 0.465)**	**9.961** **(1.877)**	**0.735**	32.533 (4.968)	0.880
3	**0.351** **(0.171, 0.466)**	**11.951** **(2.222)**	**0.730**	35.186 (5.292)	0.877
4	0.368 (0.217, 0.479)	7.718 (1.406)	0.724	33.672 (4.862)	0.876
5	0325 (0.145, 0.434)	4.141 (0.745)	0.753	27.373 (4.036)	0.882

In parenthesis in the 2nd column the 95% confidence band.
In parenthesis in the 3rd column the t-values of the coefficient.