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Long Memory in Turkish Inflation Rates

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Abstract:

Inflation in Turkey may have a highly persistent nature. To test whether inflation is stationary but exhibits long-memory, we first test for the presence of additive outliers (AO) in the inflation rates and, having identified the statistically significant ones, we apply the ADF test with AO dummies included in the regression and the modified Phillips-Perron test, as suggested by Vogelsang (1999). The results of these first-stage investigations indicate that the presence of a unit-root cannot be established unequivocally except for the public-sector wholesale price index (WPI) based inflation rates. We test long-memory in the inflation series using ARFIMA models and find a significant long memory component.

1. Introduction

Turkey is a high inflation country but, as opposed to other countries like Argentina, Brazil and Israel where periods of high inflation occurred, the inflation in Turkey is not hyper-inflation; in other words, it does not reach large three-digit levels annually but remains around a figure which is, consistently, greater than fifty percent but never goes beyond a hundred percent except for a couple of months in 1994. This observation implies that inflation in Turkey may have a highly persistent nature. The question is whether this persistence is due to the inflation rate being nonstationary, i.e., having a unit root, or whether it is stationary but exhibits long memory.

Investigations of this nature have been undertaken for developed countries like the U.S.A., the U.K., France, Germany and Italy, etc., by, e.g., Hassler and Wolter (1995), and Bos, Franses and Ooms (1999). Baillie, Chung and Tieslau (1996) have added high inflation countries like Argentina, Brazil and Israel to this list while Baum, Barkoulas and Caglayan (1999) also consider developing countries. The latter paper includes Turkey and investigates long-memory, via fractional integration, in CPI-based inflation using monthly series for the period 1971-1995. In the present study, we depart from Baum *et al*. (1999) (i) by considering the 1988.01-2000.01 period for which the 1987-based series exists, thereby avoiding spurious jumps in the data due to splicing different series and (ii) by investigating WPI-based inflation for the 1987.01-2000.01 period.

Our research consists of two stages. We *first* look for the presence of a unit-root in the CPI and WPI-based monthly inflation rates. The plots of these rates indicate that there may be one or more outliers, therefore we first test for the presence of additive outliers (AO), using a procedure developed by Vogelsang (1999). Based on the outcome of these tests, we utilise (i) the Augmented Dickey-Fuller (ADF) test with AO dummies introduced into the regression equation in the manner suggested by Franses and Haldrup (1994), and (ii) the modified Phillips-Perron test within the context of the Elliot, Rothenberg and Stock (1996)'s local-to-unity framework (Ng and Perron, 2000) which is shown by Vogelsang (1999) to be robust against the presence of AOs. Our objective in using several tests for the same purpose is to, unequivocally, establish the presence or absence of a unit root in the inflation rates. But, our findings do not indicate such a clear-cut result. Thus, in the *second* stage, we undertake Autoregressive Fractionally Integrated Moving Average (ARFIMA) modelling to find out the nature of the persistence component in the inflation rates.

Since the objective is not to simply estimate the fractional integration parameter, we utilise a predominantly parametric approach to estimation. We use two parametric estimation procedures; one, due to Sowell (1992), is the Exact Maximum Likelihood (EML) estimator, and the other is the nonlinear least squares (NLS) estimator by Ooms and Doornik (1999). We implement these procedures using the ARFIMA package for the Ox program (Doornik and Ooms, 1999). The initial estimates for the fractional integration parameter were obtained using the nonparametric Geweke and Porter-Hudak (1983) (GPH) estimator, so we provide these initial estimates as a third set of results. Again, the objective for using several estimators is to see if the results are robust to the use of alternative procedures.

The plan of the paper is as follows. In the next section, we introduce the data. The third section on empirical results contain descriptions of the unit root tests and ARFIMA modelling procedures and the empirical results based on these procedures. The final section gives our conclusions.

2. The Data

We measure monthly inflation as the first difference of the natural logs of price indexes. The price indexes we use are the Consumer (CPI) and Wholesale (WPI) Price Indexes. They are 1987 based and CPI covers the period 1988.01-2000.01 while WPI covers the period 1987.01-2000.01. The series were obtained from the State Institute of Statistics (SIS) database (where the 1987 figures for CPI were not available).

In Turkey, the WPI series are formed as a weighted average of two series; one for the private sector (WPIPRIV) and the other for the public sector (WPIPUB). While WPIPRIV-based inflation is regarded as the more important indicator, we decided to carry out our calculations for both aggregated WPI-based inflation (IWPI) and inflation based on its components (IWPIPRIV and IWPIPUB).

Examination of raw data plots of these inflation series (which are not provided to conserve on space but can be requested from the author) show that (a) all four series fluctuate around a nonzero constant, (b) there may be a significant seasonal component in some or all of them, and (c) there appears to be significant additive outliers that need to be dealt with. The implication of (a) is that all regressions used to test for a unit root will contain an intercept but no linear trend. To deal with (b), we ran regressions for each inflation series using centred seasonal dummies and found that for the CPI (ICPI), WPI and WPIPRIV-based series there was significant seasonality while IWPIPUB did not appear to have any significant seasonality. Thus, in what follows, we use the deseasonalised series based on these regressions, for ICPI, IWPI and IWPIPRIV (denoting them by ICPISA, IWPISA and IWPIPRIVSA, respectively) and the unadjusted series for IWPIPUB.

Raw data plots also show one unmistakable outlier in 1994.04, as well as others. Thus, our empirical applications in the next section will start by testing for the presence of outliers, since the statistical tools to be utilised need to be appropriately adjusted when they exist.

3. Empirical Results

a. *Testing For a Unit Root*

Since we expect additive outliers to be present in the data, we shall first apply a systematic testing procedure to the data by which they can be determined and then apply two unit root tests which take the presence of outliers into account. This procedure is due to Vogelsang (1999) and is based on estimating

$$y_t = \alpha_0 + \alpha_1 D(T_{ao}) + u_t \tag{1}$$

where $D(T_{ao})$ is an AO dummy that takes on the value 1 if $t = T_{ao}$ and is zero otherwise. The statistic to test for an additive outlier will simply be based on the t-ratio to test for $\alpha_1 = 0$, namely, $t_{\alpha_1}(T_{ao})$ and will be obtained as $\tau = \max_{T_{ao}} |t_{\alpha_1}(T_{ao})|$ The null distribution of t is established under the assumption that y_t contains a unit root and is non-standard. Its asymptotic critical values have been tabulated by Vogelsang (1999).

The procedure is applied as follows: First, t is calculated for the entire series and if a statistically significant value for t is found at, say $\hat{T}_{w}$, then the outlier and the corresponding row of the regressors are dropped from (1) and the equation is reestimated sequentially to test for a new outlier. These steps are repeated until an outlier is not found.

Table 1 - Outlier Detection Test Results

	$\hat{T}_{w}$	t
ICPI	1994.04	13.373
	1994.05	5.211
	1992.01	3.242
IWPI	1994.04	13.017
	1987.06	4.263
	1987.12	3.864
	1994.05	3.751
IWPIPRIV	1994.04	9.325
	1987.06	4.667
	1994.05	4.828
IWPIPUB	1994.04	13.157
	1987.12	5.818
	1992.01	3.808
Significance levels : 0.05 0.01		
Critical Values : 3.13 3.55		

The results of this procedure, as applied to the four inflation series, are given in Table 1. We note that, as expected, there is a highly significant outlier in 1994.04 for all series. This is a period of exchange rate crises and its effects appear to have spilled over to the following month because 1994.05 also appears as an outlier in all but the IWPIPUB series.

In any event, all outliers are found to be significant at the 1% level except for the one in ICPI at 1992.01 which is significant at the 5% level.

We take account of outliers in testing for a unit root using two different procedures. The first one is the ADF statistic with AO dummies added to the test equation in such a way that the asymptotic null distribution is not changed. The second procedure is to use the Modified Phillips-Perron GLS statistic (MZ_tGLS), as suggested by Vogelsang (1999), since it is robust against the presence of outliers.

The ADF statistic with impulse dummies for additive outliers is based on the OLS estimation of

(2) $$\Delta y_t = \beta_0 + \beta_1 y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta y_{t-i} + \sum_{r-1}^{m}\sum_{i=0}^{p} \delta_{ri} D(T_{aor})_{t-i} + \varepsilon_t$$

Thus, for each outlier, p+2 dummy variables are added to the regression so that their effect on the Δy_{t-i} terms are removed and the distribution of the ADF statistic remains unchanged (Franses and Haldrup, 1994). In practice, of course, some AO dummies may be redundant and some may yield lagged values which consist of all zeroes if $\hat{T}_{aor}$ is close to the beginning of the period and p is large. These dummies, of course, need to be dropped from (2).

In choosing the lag length for (2) we use the Akaike Information Criterion (AIC), the Schwartz Information Criterion (SIC) and the sequential testing of the coefficient of the last lag. We, initially, see if at least two of them agree upon a lag length. If there is no agreement, then we use the outcome of that criterion which provides us with the longest lag length since the whole purpose of this exercise is to remove any autocorrelation that may exist in the residuals. Finally, after choosing the lag length, we test for autocorrelation in the residuals and add more lags if we find that there is still some autocorrelation left over. Testing for autocorrelation is done by using the Ljung-Box portmanteau statistic. All through this procedure, we start by choosing a maximal lag length, p_{max}, set the sample size at T-p_{max} and keep it fixed as we reduce the lag length one at a time.

The results of the ADF test are given in Table 2. They contain the outcomes of the tests with and without AO dummies. The ADF tests without dummies imply that ICPISA has a unit root, while a unit root is strongly rejected for IWPISA and

Table 2: ADF Test Results

	Without AO Dummies				
	T	**p**	**ADF**	**LB(24)**	**AO Dummies**
ICPISA	144	8	-2.503	7.716 (0.999)	
IWPISA	156	7	-3.632***	9.352 (0.997)	
IWPIPRIVSA	156	8	-2.781*	21.492 (0.610)	
IWPIPUB	156	0	-11.045***	10.985 (0.989)	
	With AO Dummies				
ICPISA	144	8	-2.291	17.633 (0.820)	D(94.04)
	144	8	-2.915**	14.253 (0.941)	D(94.04), D(92.01)
IWPISA	156	7	-4.281***	13.844 (0.950)	D(94.04)
	156	7	-3.535***	10.130 (0.994)	D(94.04), D(87.12)
IWPIPRIVSA	156	8	-3.737***	19.802 (0.708)	D(94.04)
IWPIPUB	156	8	-9.615***	15.299 (0.912)	D(94.04)
	156	8	-9.059***	17.849 (0.810)	D(94.04), D(87.12)
	156	8	-8.560***	19.976 (0.698)	D(94.04), D(87.12) D(92.01)

Notes

1. LB stands for the Ljung-Box statistic which has an asymptotic chi-square distribution with k-p degrees of freedom under the null, with k = number of autocorrelations. In the present case, k = 24. The figure in parentheses next to the LB statistic is its p-value.

2. The critical values for the ADF statistic are based on the response surface results due to Cheung and Lai (1995a) where both the sample size, T-p-1, and the lag length, p, are taken into account. They are:

T	p	T-p-1	0.10	0.05	0.01
144	8	135	-2.5394	-2.8376	-3.4281
156	8	147	-2.5413	-2.8388	-3.4274
156	7	148	-2.5453	-2.8432	-3.4317
156	0	155	-2.5751	-2.8752	-3.4650

3. "*" : significant at the 10% level.

"**" : significant at the 5% level.

"***": significant at the 1% level.

IWPIPUB but weakly rejected for IWPIPRIVSA. We added the AO dummies in a cumulative fashion to the regressions but only for IWPIPUB were we able to add all dummies and their lags. In any event, when AO dummies are added, we find that all WPI-based inflation series strongly reject a unit root in every case. For ICPISA, on the other hand, the null of a unit root is not rejected when only D(94.04) and its lags are added to the regression, but it is rejected when D(92.01) and its lags are also added. Thus, even though we may, quite safely, say that the WPI-based inflation series do not have a unit root when outliers are accounted for using dummies, the result is not as clear-cut in the case of ICPISA.

Our second statistic, $MZ_t GLS$, is obtained by applying the modified Phillips-Perron statistic (MZ_t), as discussed by Perron and Ng (1996), to the framework introduced by Elliot *et al.* (1996). The Elliot *et al* (1996) framework involves expressing y_t as

(3) $$y_t = \beta_0 + \eta_t, \qquad \eta_t = \rho\eta_{t-1} + u_t$$

where r is assumed to take on values local to unity, $\rho = 1 + (c/T)$. Then, (3) is first estimated by GLS, taking $\bar{\rho} = 1 + (-7/T)$ and regressing $\{y_1, y_2 - \bar{\rho}y_1, \ldots, y_T - \bar{\rho}y_{T-1}\}$ on $\{1, 1-\bar{\rho}, \ldots, 1-\bar{\rho}\}$. Subsequently, using the residuals, $\tilde{y}_t = y_t - \hat{\beta}_0$, we consider estimating

(4a) $$\Delta\tilde{y}_t = \beta_1\tilde{y}_{t-1} + e_t$$

(4b) $$\Delta\tilde{y}_t = b_1\tilde{y}_{t-1} + \sum_{i=1}^{p}\gamma_i\Delta\tilde{y}_{t-i} + v_t$$

The DFGLS statistic of Elliot *et al.* (1996) is simply the t-ratio of $\hat{b}_1$ obtained from (4b). MZ_tGLS, on the other hand, is obtained by using the estimates from (4a) and (4b), to yield

(5) $$MZ_tGLS = \left(\frac{\hat{\sigma}_e}{\hat{\sigma}_{vR}}\right)t_{\hat{\beta}_1} - \frac{1}{2}\frac{\hat{\sigma}_{vR}^2 - \hat{\sigma}_e^2}{\left[\hat{\sigma}_{vR}^2(T-1)^{-2}\sum_{t=2}^{T}\tilde{y}_{t-1}^2\right]^{1/2}} + \frac{1}{2}\left[\sum_{t=2}^{T}\frac{\tilde{y}_{t-1}^2}{\hat{\sigma}_{vR}^2}\right]^{1/2}(\hat{\beta}_1 - 1)^2$$

where $\hat{\sigma}_e^2 = \sum_{t=2}^{T}\hat{e}_t^2/(T-1)$ and $\hat{\sigma}_{vR}^2 = \sum_{t=p+2}^{T}\hat{v}_t^2/(T-p-1)(1-\sum_{i=1}^{p}\hat{\gamma}_i)^2$.

Now, Ng and Perron (2000), where the MZ_tGLS statistic is developed, show that its nominal size approximates its finite sample size much better than the DFGLS statistic, which has better power properties. This improvement in size is particularly relevant when the disturbances in the unit root test equations contain a moving average component with a root close to -1. On the other hand, Franses and Haldrup (1994) show that systematic additive outliers induce such a MA component in the disturbances. Hence its suggestion by

Vogelsang (1999) as a test robust to the presence of additive outliers.

Note that we again face the problem of choosing the lag length, now in (4b). In this case, however, we use the Modified AIC and SIC (MAIC and MSIC) criteria, due to Ng and Perron (2000), together with the sequential testing procedure. The modified information criteria may be expressed as,

$$MIC(p) = \ln \hat{\sigma}_p^2 + \frac{C_T(\varphi_T(p)+p)}{T-p_{max}} \qquad (6)$$

where $\hat{\sigma}_p^2 = \sum_{t=p_{max}-1}^{T} \hat{v}_{tp}^2 / (T-p_{max})$ and $\varphi_T = \hat{b}_1^2 \sum_{t=p_{max}+1}^{T} \tilde{y}_{t-1}^2 / \hat{\sigma}_p^2$. We obtain MAIC when C_T = 2 and MSIC when $C_T = \ln(T-p_{max})$.

The results for the DFGLS and MZ_tGLS tests are presented in Table 3. They appear to be quite similar. Both indicate that ICPISA and IWPIPRIVSA have unit roots while IWPISA and IWPIPUB do not. Thus, there is no conflict with the ADF results for the latter two series; the ADF results, however, are stronger for IWPISA. The IWPIPRISA results are definitely in conflict with the ADF results while the conflict is not so strong for ICPISA.

Thus, the results in Tables 2 and 3 cast a great deal of doubt about the presence of a unit root in the inflation series considered; the evidence appears to favour the hypothesis that they, in fact, are stationary. Hence, looking for evidence of long-memory becomes even more important.

Table 3 - DFGLS and MZ_tGLS Test Results

	T	P	DFGLS[2]	MZ_tGLS[3]	LB(24)[1]
ICPISA	144	8	-1.418	-1.171	8.699 (0.998)
IWPISA	156	8	-2.011**	-1.739*	9.590 (0.996)

IWPIPRIVSA	156	8	-1.409	-1.265	21.979 (0.581)
IWPIPUB	156	11	-3.749**	-7.173***	9.230 (0.997)

Notes:

1. See Notes to Table 2.

2. The critical values for the DFGLS statistic are based on the response surface results due to Cheung and Lai (1995b) where both the sample size, T-p-1, and the lag length, p, are taken into account. They are:

T	-p-	T-p-1	0.10	0.05
144	8	135	-1.7049	-2.0112
156	8	147	-1.6999	-2.0074
156	11	144	-1.6756	-1.9813

3. Vogelsang (1999) points out that the MZ_tGLS statistic will have the same asymptotic null distribution as the ADF statistic obtained from a regression with no deterministic terms. Hence, the critical values are based on the response surface results due to Cheung and Lai (1995a). They are:

T	-p-	T-p-1	0.10	0.05	0.01
144	8	135	-1.5942	-1.9209	-2.5572
156	8	147	-1.5952	-1.9215	-2.5572
156	11	144	-1.5897	-1.9154	-2.5491

4. "*" : significant at the 10% level.
"**" : significant at the 5% level.
"***": significant at the 1% level.

B. *ARFIMA Modelling*

Our final set of results are based on estimating the ARFIMA(p,d,q) model

$$\Phi(L)(1-L)^d(y_t - x_t'\beta) = \Theta(L)\varepsilon_t \tag{7}$$

where F(L) and Q(L) are polynomials in the lag operator L of degrees p and q, respectively,

x_t is an mx1 vector of regressors that explain the mean of y_t which, in the present case, will consist of an intercept, AO dummies and, in three cases, seasonal dummies. We will be interested in values of d less than unity. Now, if all roots of $\Phi(L)$ and Q(L) lie outside the unit circle and -0.5 <d< 0.5, then y_t is stationary and invertible. On the other hand, if 0.5 $\leq d < 1$, then y_t is nonstationary because it has infinite variance (Granger and Joyeux, 1980). However, since d is still less than one, the process is mean reverting. As to the values lying between -0.5 and 0.5, if 0< d< 0.5 then y_t is said to exhibit long-memory , if -0.5< d <0, y_t is said to have intermediate memory. Of course, for d = 0, the process exhibits short-memory. Thus, in our empirical work we shall try to find out if d lies in the interval (0, 0.5).

We assume that $y_t \sim N(x_t' \beta, \Sigma)$ and, based on this assumption, we use two parametric Maximum Likelihood (ML) methods to estimate (7), and a nonparametric procedure. The *first* one is the EML method due to Sowell (1992). Let z = y - Xb where y and z are Tx1, X is Txm and S = s^2R. Then, the loglikelihood function, concentrated with respect to $\hat{\beta} = (X' R^{-1} X)^{-1} X' R^{-1} y$ and $\hat{\sigma}^2 = z' R^{-1} z / T$,

$$\ell_c = c - \tfrac{1}{2} \ln|R| - \tfrac{T}{2} \ln\left(\frac{\hat{z}' R^{-1} \hat{z}}{T}\right) \qquad (8)$$

is maximised with respect to the elements of R, which include d and the parameters of the polynomials F(L) and Q(L). In the *second* method, which we call NLS following Ooms and Doornik (1999), the concentrated loglikelihood function is approximated by

$$f = -\tfrac{1}{2} \ln\left(\frac{1}{T-m} \sum_{t=2}^{T} e_t^2\right) \qquad (9)$$

where $e_t = z_t - \sum_{i=1}^{t-1} \pi_i z_{t-i}, \quad t = 2, \ldots, T$ and the p_i are obtained from $\Pi(L) = \Theta(L)^{-1} \Phi(L)(1-L)^d$.

The estimators for all the parameters are obtained by minimising f. The *third* method is the nonparametric GPH procedure, which is also used to start off the previous two nonlinear methods by providing an initial estimate for d.

Table 4 contains the results of the full ARFIMA(p,d,q) modelling effort together with the GPH results. We note the following points from this table:

Table 4 - Estimates of ARFIMA(p,d,q) Models			
ICPISA[1]			
	EML	NLS	GPH
d	0.2519 (0.000)***[2]	0.2512 (0.000)***	0.2713 (0.000)***
AR(9)[3]	0.1918 (0.032)**	0.1983 (0.027)**	-
Constant	0.0444 (0.000)***	0.0461 (0.000)***	0.0702 (0.000)***
D(92.01)	0.0342 (0.000)***	0.0342 (0.000)***	0.0360 (0.000)***
D(94.04)	0.1559 (0.000)***	0.1561 (0.000)***	0.1631 (0.000)***
D(94.05)	0.0629 (0.000)***	0.0634 (0.000)***	0.0619 (0.000)***
Normality [chi(2)][4]	3.0920 (0.213)	4.0519 (0.132)	2.4924 (0.288)
ARCH(1,1) [F(1,125)] [F(1,126)][4]	0.0135 (0.908)	0.0195 (0.889)	0.0515 (0.821)
LB(36) [chi(19)] [chi(20)][4]	29.4398 (0.059)*	31.4749 (0.036)**	34.8503 (0.021)**
IWPISA[1]			
d	0.4437 (0.000)***	-	0.4224 (0.000)***
AR(7)	0.1972 (0.017)**	-	-
AR(12)	0.4819 (0.000)***	-	-

MA(12)[3]	-1.0000 (0.000)***	-	-
Constant	0.0417 (0.000)***	-	0.0452 (0.000)***
D(87.06)	-0.0646 (0.000)***	-	-0.0626 (0.000)***
D(87.12)	0.0591 (0.000)***	-	0.0707 (0.000)***
D(94.04)	0.2186 (0.000)***	-	0.2404 (0.000)***
D(94.05)	0.0391 (0.000)***	-	0.0554 (0.000)***
Normality [chi(2)]	4.9473 (0.084)*	-	13.7764 (0.001)***
ARCH(1,1) [F(1,134)] [F(1,137)]	0.9318 (0.336)	-	0.0006 (0.981)
LB(36) [chi(16)] [chi(19)]	51.9703 (0.000)***	-	68.5472 (0.000)***
<u>IWPIPRIVSA</u>[1]			
d	0.4350 (0.000)***	0.5261 (0.000)***	0.4192 (0.000)***
AR(2)	-0.2081 (0.016)**	-0.1403 (0.110)	-
AR(7)	0.2380 (0.005)***	0.2362 (0.001)***	-
Constant	0.0411 (0.009)***	0.0377 (0.022)**	0.0421 (0.000)***
D(87.06)	-0.0818 (0.000)***	-0.0964 (0.025)**	-0.0778 (0.000)***
D(94.04)	0.1648 (0.000)***	0.1601 (0.000)***	0.1743 (0.000)***
D(94.05)	0.0660 (0.000)***	0.0667 (0.000)***	0.0591 (0.000)***
Normality [chi(2)]	10.9870 (0.004)***	10.5741 (0.005)***	18.228 (0.001)***
ARCH(1,1) [F(1,136)]	0.4846 (0.488)	0.1945 (0.660)	1.0167 (0.315)

[F(1,138)]			
LB(36) [chi(18)] [chi(20)]	76.0253 (0.000)***	68.8577 (0.000)***	83.0054 (0.000)***
IWPIPUB			
d	0.2504 (0.001)***	0.2236 (0.003)***	0.2492 (0.001)***
AR(7)	-0.1528 (0.065)*	-0.1591 (0.054)*	-
AR(12)	-0.1416 (0.093)*	-0.1441 (0.083)*	-
Constant	0.0408 (0.00)***	0.0429 (0.000)**	0.0408 (0.000)***
D(87.12)	0.1585 (0.000)***	0.1335 (0.184)	0.1599 (0.000)***
D(92.01)	0.1116 (0.000)***	0.1105 (0.000)***	0.0999 (0.000)***
D(94.04)	0.3944 (0.000)***	0.3941 (0.000)***	0.3984 (0.000)***
Normality [chi(2)]	39.8354 (0.000)***	36.6963 (0.000)***	40.755 (0.001)***
ARCH(1,1) [F(1,147)] [F(1,149)]	0.0171 (0.896)	0.1482 (0.701)	0.2291 (0.633)
LB(36) [chi(29)] [chi(31)]	33.7681 (0.247)	31.9007 (0.324)	40.6755 (0.115)***

Notes:

1. Instead of using the deseasonalised series, as we did when testing for unit roots, we added eleven centred seasonal dummies to the model, but the actual coefficient estimates are not provided to conserve on space. However, their coefficients are found to be highly significant in every case. The test results are available upon request.

2. The figures in parentheses are p-values.

3. AR(p) stands for the pth autoregressive lag of the dependent variable and MA(q) stands for the qth moving average lag.

4. "Normality" is the test for normality in the residuals due to Doornik and Hansen (1994), ARCH(1,1) is the F-version of the Lagrange Multiplier test for first-order Autoregressive Conditional Heteroscedasticity, and LB(36) is the Ljung-Box test for autocorrelation based on 36 sample autocorrelations. The second bracketed figures in

front of ARCH(1,1) and LB(36) are the degrees of freedom for the GPH estimates.

5. "*" : significant at the 10% level. "**" : significant at the 5% level. "***": significant at the 1% level.

i. All estimates of d, except the NLS estimate for IWPIPRIVSA, lie between 0 and 0.50, indicating that the majority of the inflation rates are stationary and exhibit long memory. The fact that the NLS estimate of d for IWPIPRIVSA is greater than 0.5 implies that the EML estimate may be misleading since the estimation procedure constrains the estimate of d to lie within the (0, 0.5) interval [Doornik and Ooms (1999: 23)] while NLS does not.

ii. The estimates of d for ICPISA and IWPIPUB are smaller than those for IWPISA and IWPRIVSA. This result is not surprising for IWPIPUB, in view of the

unit root results, where stationarity evidence is quite strong. But the results for the remaining series, ICPISA and IWPIPRIVSA in particular, appear to be in conflict. The diagnostics for ICPISA appear to be acceptable except for LB which indicates the presence of some autocorrelation in the residuals; this is less significant in the EML case than the NLS case. For IWPIPUB, on the other hand, the diagnostic test which is significant is Normality.

iii. Turning to the IWPISA and IWPIPRIVSA results, we first note that the NLS estimates for IWPISA are not available because of the presence of a negative unit root at MA(12) which makes the polynomial Q(L) of equation (7) noninvertible. Secondly, we find that the estimates of d are closer to 0.50 than those obtained for ICPISA and IWPIPUB, indicating that they have stronger long memory components than ICPISA and IWPIPUB.

5. Conclusions

In this study we investigated the nature of persistence in Turkish monthly inflation rates. We first carried out unit root tests in order to see if the persistence was due to the presence of a unit root. We did this by using tests which took additive outliers into account. We found that the evidence favoured the absence of a unit root in IWPIPUB and a possible presence of one in ICPISA. For IWPISA one, probably, could argue for the absence of a unit root, but for IWPIPRIVSA, the evidence is mixed. Hence, we may conclude that unit root tests do not provide us with clear-cut evidence, one way or the other, but they do lean towards implying that the WPI-based series may be stationary.

Given this state of affairs, we undertook the task of modelling each series as ARFIMA(p,d,q). The results clearly show that the estimated value of d, which is highly significant in every case, lies in the interval (0, 0.5), implying that the series are stationary but exhibit long-memory. This long-memory component is smaller in the case of ICPISA and IWPIPUB, which is in contrast with the unit root test results for ICPISA but is in accordance with the same test results for IWPIPUB. On the other hand, the estimate of d is closer to 0.5 in the case of IWPISA and IWPIPRIVSA, which contrasts with, at least, the ADF results for these two inflation rates.

These results indicate that the two recent, IMF-backed attempts by the government to reduce inflation has to deal with a process which, essentially, is stationary but has a strong long-memory component and will exhibit a great deal of resistance initially, but if the anti-inflationary policy is successful, would yield long-lived results.

References

Baillie, R.T., Chung, C.F. and Tieslau, M.A., “Analysing Inflation by the Fractionally Integrated ARFIMA-GARCH Model’, Journal of Applied Econometrics, 1996, 11, 23-40.

Baum, C.F., Barkoulas, J.T. and Caglayan, M., “Persistence in International Inflation Rates”, Southern Economic Journal, 1999, 65, 900-913.

Bos, C.S., Franses, P.H. and Ooms, M, “Long Memory and Level Shifts: Re-analysing Inflation Rates”, Empirical Economics, 1999, 24, 427-449.

Cheung, Y.W. and Lai, K.S., “Lag Order and Critical Values of the Augmented Dickey-Fuller Test”, Journal of Business and Economic Statistics, 1995a, 13, 277-288.

Cheung, Y.W. and Lai, K.S., “Lag Order and Critical Values of a Modified Dickey-Fuller

Test", Oxford Bulletin of Economics and Statistics, 1995b, 57, 411-419.

Doornik, J.A. and Hansen, H., "An Omnibus Test for Univariate and Multivariate Normality", Working Paper, Nuffield College, University of Oxford, 1994.

Doornik, J. and Ooms, M., "A Package for Estimating, Forecasting and Simulating Arfima Models: Arfima Package 1.0 for Ox", Working Paper, Nuffield College, University of Oxford, 1999.

Elliot, G., Rothenberg, T.J. and Stock, J.H., "Efficient Tests for an Autoregressive Unit Root", Econometrica, 64, 1992, 813-836.

Franses, P.H. and Haldrup, N., "The Effects of Additive Outliers on Tests of Unit Roots and Cointegration", Journal of Business and Economic Statistics, 1994, 12. 471-478.

Geweke, J.F. and Porter-Hudak, S., "The Estimation and Application of Long Memory Time Series Models", Journal of Time Series Analysis, 1983, 4, 221-238.

Granger, C.W.J. and Joyeux, R., "An Introduction to Long-Memory Time Series and Fractional Differencing", Journal of Time Series Analysis, 1980, 1, 15-39.

Hassler, U. and Wolters, J., "Long Memory in Inflation Rates: International Evidence", Journal of Business and Economic Statistics, 1995, 13, 37-45.

Ng, S. and Perron, P., "Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power", Working Paper, Department of Economics, Boston College, 2000.

Ooms, M, and Doornik, J., "Inference and Forecasting for Fractional Autoregressive Integrated Moving Average Models, with an Application to US and UK Inflation", Report 9947/A, Econometric Institute, Erasmus University Rotterdam, 1999.

Perron, P. and Ng, S., "Useful Modifications to Some Unit Root Tests with Dependent Errors and Their Local Asymptotic Properties", Review of Economic Studies, 1996, 63, 435-463.

Sowell, F., "Maximum Likelihood Estimation of Stationary Univariate Fractionally Integrated Time Series Models", Journal of Econometrics, 1992, 53, 165-188.

Vogelsang, T.J., "Two Simple Procedures for Testing for a Unit Root When There are Additive Outliers", Journal of Time Series Analysis, 1999, 20, 237-252.