Persistence in Inflation: Long Memory, Aggregation, or Level Shifts?

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Abstract

This paper examines persistence in inflation rates using CPI and WPI based inflation series of the Turkish economy. The inflationary process in Turkey is believed to be inertial, which should lead to strongly persistent inflation series. Persistence of 84 inflation series at different aggregation levels are examined by estimating models that allow long memory through fractional integration. The order of fractional differencing is estimates using several semiparametric and approximate maximum likelihood methods. We find that the inflation series at the highest aggregation level show strong persistence. However, the data at lower aggregation levels show no significant persistence. Thus, paper finds evidence of spurious long memory due to aggregation. The paper also examines possibility of spurious long memory due to level shifts by estimating ARFIMA models that allow stochastic permanent breaks. We find that all inflation series are antipersistent, if the effects of stochastic level shifts are taken into account.

Key words: persistence, inflation, inertia, long memory models, aggregation, level shifts.

JEL Code: C14, C22, E31

1. Introduction

A number of countries have experienced very long periods of inflation. It is argued that inflationary processes in these countries are determined by their own inflationary experience and in the absence of new shocks the inflation reproduces itself. This implies that time series of inflation rates are highly persistent. Turkey is one of the very typical among these countries with a very long period of high inflation experience since late 1970s. Chronic inflation is the main feature of the Turkish economy. In the last 25 years the country has not faced a single year without two digit annual inflation rates.

If the inflationary process is inertial, then time series of inflation rates should have strong persistence. Persistence refers to an important statistical property of inflation, namely the current value of the inflation rate is strongly influenced by its past history. The major question is the following: Do one-time inflationary shocks give rise to long-term persistence? Long memory models are very commonly used to embody highly persistent time series data. In this paper, we examine

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The results presented in the empirical section of this paper are part of “reproducible research projects” and can be duplicated using the accompanying programs available at “http://rifle.manas.kg/persistence.html”.

persistence in inflation rates using several CPI and WPI based inflation measures of the Turkish economy. The inflationary process in Turkey is believed to be highly persistent. It is often argued that the feedback mechanism developed between inflation and wages was so strong that current supply shocks, such as the oil-price hikes, automatically translated into permanent increases in the rate of inflation. Further, because the inertia in inflation rendered inflation unresponsive to demand, monetary and fiscal policies were failed to curb inflation. Recently, Turkish government attempted to curb inflation using a controlled exchange rate policy and later turned to more orthodox policies after the failure of this policy. Inertial inflation was cited as the major reason for the failure of this policy. For instance, in the Letter of Intend submitted to IMF by the Undersecretariat of Treasury in March 2000, it was stated that "Inflation has remained high during December-February. This outcome reflected ... inflation inertia ..." This makes Turkey an interesting subject matter for a study on inflationary persistence.

There have been several papers analyzing the persistence in inflation rates. These papers can be classified into two major headings. The first group of papers test for the existence of unit roots in inflation rates. So, the main concern in these papers is the classification of inflation rates as stationary or nonstationary. Barsky (987), MacDonald and Murphy (1989), and Ball and Cecchetti (1990) found evidence in support of unit roots in inflation rates. On the other hand, Rose (1988) provided evidence against the existence of unit roots in inflation rates. Brunner and Hess (1993) claimed that the inflation rate was stationary before the 1980s, but it became nonstationary afterward.

In response to these conflicting evidences about the stationarity of inflation rates, following the influential paper Diebold and Rudebusch (1989), the second group papers used long memory models to examine the strength of persistence in inflation rates. Long memory implies that shocks have a long-lasting effect, but the underlying process is mean reversing. Furthermore, long memory is not the property of only nonstationary processes; the stationary processes may as well have long memory. Long memory can be captured by a fractionally integrated I(d) model, where the fractional order of differencing d is a real number. Baillie, Chung, and Tieslau (1996) used frictionally integrated ARMA (ARFIMA) models with GARCH errors to test for long memory in the inflation rates of the G7 countries and claim to have found significant evidence. Delgado and Robinson (1994) found significant evidence of long memory in the Spanish inflation rate. More recently, Baum, Barkoulas, and Caglayan (1999) found significant evidence of long memory in both CPI and WPI based inflation rates for industrial as well as developing countries.

The purpose of this paper is twofold. The first is to show whether the aggregate CPI and WPI based inflation series have long memory. Using several parametric and semiparametric estimators, we show that aggregate inflation rates show moderate to high persistence and have significant long memory parameter estimates. The estimators used include Geweke and Porter-Hudak's log periodogram regression estimator, Robinson's Gaussian semiparametric estimator, Whittle's approximate maximum likelihood estimator, and a wavelet based estimator. ARMA models are also estimated for comparison. For parametric models persistence is evaluated using the implied impulse response functions of the estimated models. Standard errors of the impulse response functions are obtained via bootstrap. For nine different inflation series at the highest aggregation level, all estimators gave significant long memory estimates. The implied impulse responses of the estimated parametric long memory models indicate strong long memory for all aggregate inflation series.

The second purpose of the paper is to investigate whether the finding of significant long memory in inflation series is intrinsic or due to other causes. For this purpose, the paper examines possible sources of long memory in inflation rates. Two causes of (spurious) long memory are regime switching and aggregation. Although long memory in inflation rates may be inertial, level shifts and aggregation can also create spurious long memory.

Aggregation over a large number of sectors each subject to white noise shocks may lead to long memory in aggregate inflation rates. The key idea is that aggregation of independent weakly dependent series may produce a series with strong dependence. A motivation for this can be found in Robinson (1978) and Granger (1980). In order to examine this possibility we estimate long memory models for 75 disaggregated inflation rates. Estimates show that disaggregated data display very weak memory. The hypothesis of no long memory cannot be rejected for the majority of sector specific inflation rates.

Alternatively, inflation series may show apparent long memory due to neglected occasional level shifts. Bos, Franses, and Ooms (1999) find evidence of spurious long memory due to neglected level shifts in inflation rates of the G7 countries. Bos, Franses, and Ooms (2001) argue that US CPI based inflation rates may have a long memory component because of occasional breaks. In order to examine the possibility of spurious long memory due to neglected occasional breaks the paper extends the STOPBREAK model of Engle and Smith (1999) to ARFIMA case and shows that when an ARFIMA model with occasional level shifts is estimated the long memory in aggregate inflation rates completely disappear.

The organization of the rest of the paper is the following. In section 2, we briefly review the long memory models and examine several estimation methods. How should the persistence of long memory models be evaluated is also discussed in this section. Section 3 discusses possible causes of long memory in economic time series. Section 4 briefly explains the dataset used in the paper. In section 5, we present our estimation results. In section 6, we briefly discuss our findings.

2. The theoretical framework

2.1. Long memory models

Granger (1966) first pointed out that power spectra of many economic variables suggest overwhelming contribution of the low frequency components. Autoregressive and moving average models (ARMA) cannot capture this phenomenon. In the last two decades, using integrated ARMA (ARIMA) models is the preferred approach to model this phenomenon. Overwhelming evidence of unit roots in most economic time series encouraged researchers to use ARIMA models. However, ARIMA models imply an extreme form of persistence since the impact of shocks on the level of time series does not die out even in the infinite horizon. It is usually impossible to justify this type of infinite persistence on theoretical grounds for many economic time series, such as inflation rates examined in this paper. Based on this observation, researchers looked for alternative ways of modeling strong persistence in economic time series data. Most recent work on persistence in economic time series data preferred long memory models as an alternative to ARIMA models. A good treatment of basic mathematical statistics related to long memory models can be found in Beran (1994). The econometric literature on long memory was reviewed by Robinson (1994a) and Baillie (1996). Here, we will only examine some salient features of long memory models relevant to our work. There are several different ways of defining long memory of which two most common ones will be given below. Let $y_t, t = 1, 2, \ldots, T$, be the time series of interest. For example, in the empirical section of this paper, y_t will represent rate of inflation. Assume that y_t is weakly stationary and let $f(\lambda)$ be the spectral density of y_t at frequency $\lambda \in (-\pi, \pi]$ satisfying

$$\rho_k = \operatorname{cov}(y_t, y_{t+k}) = \int_{-\pi}^{\pi} f(\lambda) \cos(k\lambda) d\lambda \qquad (1)$$

where $\rho_k, k = 0, \pm 1, \pm 2, \ldots$, are the autocovariances of y_t. Let spectral density of y_t satisfy

$$f(\lambda) \sim c\lambda^{-2d} \quad \text{as } \lambda \to 0^+ \qquad (2)$$

and autocovariances follow

$$\rho_k \sim ck^{2d-1} \quad \text{as } k \to \infty \qquad (3)$$

Then, y_t follows a long memory process with $-0.5 < d < 0.5$.

Parametric specifications of long memory models include fractional Gaussian noise (FGN) of Hurst (1951) and Mandelbrot (1963), an extension of the Bloomfield exponential model as in 3.19 of Robinson (1994a), and ARFIMA model of Granger and Joyeux (1980) and Hosking (1981). The FGN model with long memory parameter *d*, denoted FGN(*d*), can be described in terms of its spectral density as

$$f(\lambda) = 2c(1-\cos\lambda)\sum_{j=-\infty}^{\infty}\left|2\pi + \lambda\right|^{-2(d+1)} \tag{4}$$

where $c = \sigma^2(2\pi)^{-1}\sin\left(\pi(d+1/2)\right)\Gamma\left(2(d+1)\right)$. Here, $\sigma^2 = \mathrm{var}(y_t)$ and $\Gamma(\cdot)$ is the gamma function. Neither the FGN nor the Bloomfield exponential model has shared the empirical success of the ARFIMA model. The ARFIMA model with integration order *d*, autoregressive order *p*, and moving average order *q*, is denoted as ARFIMA(*p*,*d*,*q*) and satisfy the difference equations

$$\phi(L)(1-L)^d(y_t - \mu) = \theta(L)\varepsilon_t \tag{5}$$

where ε_t is a white noise and $\phi(L) = 1 - \sum_{j=1}^{p}\phi_j L^j, \theta(L) = 1 - \sum_{j=1}^{q}\theta_j L^j$ are polynomials in the lag operator *L* with degrees *p*, *q* respectively. We assume that $\phi(z)$ and $\theta(z)$ share no common roots and $\phi(z) \neq 0, \theta(z) \neq 0$ for $z \leq 1$. The order of integration *d* is not restricted to integer values and for any real number $d > -1$, we define the $(1-L)^d$ by means of binomial expansion (see Granger and Joyeux (1980), Hosking (1981), and Brockwell and Davis (1991)),

$$(1-L)^d = \sum_{j=-\infty}^{\infty} b_j L^j \tag{6}$$

where

$$b_j = \frac{\Gamma(j-d)}{\Gamma(j+d)\Gamma(-d)} = \prod_{0<k<j}\frac{k-1-d}{k}, \quad j = 0,1,2,\ldots \tag{7}$$

The time series y_t is denoted I(*d*) in reference to the degree of integration. The fundamental properties of y_t can be stated in terms of *d*. For $-0.5 < d < 0.5$ y_t is covariance stationary and invertible. When $d = 0$, the spectral density of y_t is finite and positive at $\lambda = 0$ and autocorrelations are summable. In this case, the ARFIMA model is reduced to a standard ARMA(*p*,*q*) model. The unit root case is obtained with $d = 1$. For $0 < d < 0.5$, y_t is said to have long memory with $\sum_{k=-\infty}^{\infty}\left|\rho_k\right| = \infty$. When $-0.5 < d < 0$, y_t is called antipersistent or intermediate memory. This case is characterized by $\sum_{k=-\infty}^{\infty}\left|\rho_k\right| < \infty$ with a shrinking spectral density at $\lambda = 0$ and it is empirically relevant to the extent that it describes the behavior of overdifferenced series that were mistakenly believed to have a unit root. When $d \leq -0.5$, y_t is covariance stationary but not invertible. For $d \geq .5$, y_t is nonstationary and has infinite variance. For macroeconomic applications a particularly interesting interval for *d* is $.5 < d < 1$, where the time series y_t has infinite variance and displays strong persistence as measured by (8), but mean reverts in the sense that impulse response function is slowly decaying.

2.2. Measuring persistence in long memory models

Although the presence of statistically significant *d* is commonly interpreted to mean that y_t is a persistent time series (see for instance Baum, Barkoulas, Caglayan (1999)), this is misleading. In this paper, impulse response function of an ARFIMA model will be used to measure persistence. An impulse response function a_k measures the effect of a unit shock at time *t* on y_{t+k}. Impulse responses of a stationary process are the coefficients of its infinite order moving average representation. For a stationary ARFIMA model the impulse responses are given by the coefficients a_k of

$$A(L) = (1-L)^{-d}\phi(L)^{-1}\theta(L) = 1 + a_1 L + a_2 L^2 + \cdots \tag{8}$$

where the impulse response a_k satisfy $\sum_{k=1}^{\infty} a_k^2 < \infty$. In this representation, the value taken by $a_k = \partial y_{t+k} / \partial \varepsilon_t$ certainly measures the effect of a unit shock at time *t* on y_{t+k}. In order to calculate impulse response function of an ARFIMA model first we obtain the impulse responses corresponding to ARMA part of the model. These impulse responses corresponds to ψ_k in $\psi(L) = \phi(L)^{-1}\theta(L)$ and obtained from

$$\psi_k = -\sum_{j=0}^{q} \theta_j \eta_{k+1-j}$$

with $\theta_0 = 1$, $\eta_l = 0$ for $l \le 0$, $\eta_1 = 1$, and $\eta_l = \sum_{j=1}^{p} \phi_j \eta_{l-j}$ for $l > 1$. There is a tendency in the literature on unit roots to classify models as stationary or nonstationary based on a_∞.

Usually, values of a_k for large *k* are reported and large values are interpreted to mean high persistence or existence of a unit root. Although $a_k \to a_\infty$ as $k \to \infty$, such an interpretation may be misleading for ARFIMA models. The persistence a_∞ calculated from an ARFIMA model satisfies

$$a_\infty = \begin{cases} \infty, & \text{if } d > 1 \\ \theta(1)/\phi(1), & \text{if } d = 1 \\ 0, & \text{if } d < 1 \end{cases} \tag{9}$$

Note that $0 \le \theta(1)/\phi(1) < \infty$ holds in view of our assumption on the impulse response coefficients a_k. For the purpose of measuring persistence implied by an ARFIMA model, the precise classification given in (1) is quite meaningless and undesirable. It is obvious from (9) that the estimated persistence $\hat{a}_\infty$ obtained from an estimated ARFIMA model for time series y_t will necessarily tend to 0 or ∞ whenever $d \ne 1$ (Hauser, Pötscher, and Reschenhofer (1999)). Furthermore, this result is true regardless of the sample size. Since finding estimates of *d* exactly equal to 1 will rarely be the case we will almost always find $\hat{a}_\infty$ to be 0 or ∞. In other words, assigning persistence implied by an estimated

ARFIMA model based on $\hat{a}_\infty$ is an untenable position, since a_∞ assumes a value of 0 or ∞ a priori and $\hat{a}_\infty \to a_\infty$ as $T \to \infty$. The measure $\hat{a}_k$ may also be misleading due to the fact that $a_k \to a_\infty$ and $\hat{a}_k \to \hat{a}_\infty$ as $k \to \infty$. Therefore, estimates $\hat{a}_k$ will be substantially distorted towards 0 or ∞. Another problem with persistence measure based on a_k is related to the very slow decay of a_k. Consider the following example: For an ARFIMA(0,0.4,0) processes, straightforward calculation shows that $a_{100} = 0.0286$ while $a_{1000} = 0.0071$ with $a_k / a_{10k} \simeq 4$. Indeed, for an ARFIMA(0,*d*,0), it is straightforward to show that

$$a_k = \frac{\Gamma(k+d)}{\Gamma(k+1)\Gamma(d)} \qquad (10)$$

Then, it follows that $a_k \sim \Gamma(d)^{-1} k^{d-1}$ as $k \to \infty$. For any $l > k$, we get $a_l / a_k = (l/k)^{d-1}$ as $k \to \infty$. The above example follows with $d = 0.4$ and $l = 10k$. In the special case of a unit root, we obtain the well known result $a_l / a_k = 1$. Thus, for an ARFIMA model, one gets no further information by calculating higher order persistence measures. The ratio a_l / a_k will always approach 1 in the limit. In such cases, a measure of persistence that is independent of the clear-cut classification in (1) is more appropriate. In this regard, a useful measure of persistence may be based on how fast the effects of shocks to y_t dissipate. In addition to a_k we use

$$\tau_\alpha = \sup_k \left| \partial y_{t+k} / \partial \varepsilon_t \right| \le 1 - \alpha, \quad 0 < \alpha < 1 \qquad (11)$$

as a measure of persistence. τ_α aims to capture the time required for a fraction α of the full effect of a unit shock to complete. For $\alpha = 0.5$, τ_α is the period beyond which $\left| \partial y_{t+k} / \partial \varepsilon_t \right|$ no longer exceed 0.5. The measure τ_α is independent of prior choice of *k*. *k* will be automatically determined once we decide on the value of α. Therefore, it is more appropriate for ARIMA models as a measure of persistence.

2.3. *Estimation methods for long memory models*

In this paper, we will evaluate the persistence in inflation rates using the impulse response functions of the estimated ARFIMA models. In order to obtain impulse responses we first need to estimate the parameters of the models. The most important parameter is the long memory parameter *d*. The existing methods for estimating *d* may be grouped under four major headings: graphical, parametric, nonparametric, and semiparametric. Among many estimators in these groups, we will briefly examine four estimators, which are used in this paper.

Two well known parametric methods are the exact maximum likelihood estimator (Sowell (1992a)) and the approximate Whittle estimator (Whittle (1951), Fox and Taqqu (1986)). In this paper, only the Whittle estimator will be used. The Whittle estimator is obtained by maximizing an approximation of the likelihood function in the frequency domain. In this method, the parameter vector $\beta = \left(d, \phi_1, \ldots \phi_p, \theta_1, \ldots, \theta_q\right)'$ is estimated by minimizing the following approximate log likelihood function

$$\log L(\beta) = -\log m^{-1} \sum_{j=1}^{m} \frac{I(\lambda_j)}{g(\lambda_j, \beta)} - m^{-1} \sum_{j=1}^{m} \log g(\lambda_j, \beta) \tag{12}$$

where $I(\lambda_j)$ is the periodogram defined at the Fourier frequencies $\lambda_j = 2\pi j / T,\ j = 1, 2, \ldots m,$

$$I(\lambda_j) = \left| T^{-1} \sum_{t=1}^{T} (y_t - \overline{y}) e^{it\lambda_j} \right|^2 \tag{13}$$

$m = \left[(T-1)/2\right]$, $[\cdot]$ is the integer part, and $g(\lambda, \beta) = 2\pi f(\lambda, \beta) / \sigma^2$. Here, $f(\lambda_j, \beta)$ is the spectral density of an ARFIMA(*p*,*d*,*q*) model given by

$$f(\lambda, \beta) = \frac{\sigma^2}{2\pi} \left| \frac{\theta(e^{-i\lambda})}{\phi(e^{-i\lambda})} \right|^2 \left| 1 - e^{-i\lambda} \right|^{-2d} \tag{14}$$

The white noise variance σ^2 is estimated by

$$\hat{\sigma}^2 = m^{-1} \sum_{j=1}^{m} \frac{I(\lambda_j)}{g(\lambda_j, \hat{\beta})} \tag{15}$$

On the assumption that the order (*p*,*q*) of the ARFIMA model is known a priori, the model parameters β are estimated by maximizing the likelihood function in (12). The resulting estimates $\hat{\beta}$ are known to be asymptotically efficient, in the sense that, under suitable regularity conditions, $T^{1/2}(\hat{\beta} - \beta) \to_d N(0, \Omega)$ as $T \to \infty$, where Ω is the covariance matrix of β and $\to_d$ means convergence in distribution. Robinson (1994a) and Beran (1995) suggests a method to prove asymptotic efficiency and normality of the Whittle estimator. The asymptotic covariance matrix of the parameters (see Beran (1994, 1995)) is given by

$$\Omega(\beta) = (2\pi)^{-1} \int_{-\pi}^{\pi} \frac{\partial}{\partial \beta} \log f(\lambda, \beta) \frac{\partial}{\partial \beta'} \log f(\lambda, \beta) d\lambda \tag{16}$$

In the empirical section of this paper, the covariance matrix of parameter estimates $\hat{\beta}$ is calculated from (16) with $\beta = \hat{\beta}$.

One difficulty with the parametric estimators is their reliance on the correct specification of the orders (*p*,*q*). The simulation results in Taqqu and Teverovsky (1998) show that the parametric method may not be improved upon when the orders (*p*,*q*) is correctly specified, but it performs rather poorly when the order is misspecified. The semiparametric estimators of *d* advocated by Granger and Joyeux (1980) and Janacek (1982), and developed by Geweke and Porter-Hudak (1983) and Robinson (1194b, 1995a, 1995b) relies only on (2) and does not suffer from the problems of correct model specification. The modified log periodogram regression estimator (GPH) of Geweke and Porter-Hudak (1983) is based on the following relationship

$$\log I(\lambda_j) = \log f_u(0) - d\log\left|1-e^{i\lambda_j}\right| + \log I(\lambda_j)/f(\lambda_j) + \log f_u(\lambda_j)/f_u(0) \qquad (17)$$

where $\lambda_j = 2\pi j/T \in (0,\pi)$ and $f_u(\cdot)$ is the spectral density of $u_t = (1-L)^d y_t$ given by $f_u(\lambda) = (\sigma^2/2\pi)(|\theta(e^{i\lambda})|^2/|\phi(e^{i\lambda})|^2)$. If λ_j is near zero, say $\lambda_j \le \lambda_m$, where λ_m is small, the last term in (17) is small relative to others and (17) can be written as a simple linear regression

$$z_j = c - dx_j + \varepsilon_j, \qquad j = 1,2,\ldots,m \qquad (18)$$

where $z_j = \log I(\lambda_j)$, $x_j = \log\left|1-e^{i\lambda_j}\right|$, $\varepsilon_j = \log I(\lambda_j)/f(\lambda_j)$, and $c = f_u(0)$. *d* can be estimated by least squares regression of z_j on x_j, $j = 1,2,\ldots,m$, where *m* is a function of *T* such that $m/T \to 0$ as $T \to \infty$. Geweke and Porter-Hudak (1993) argue that there exists a sequence *m* such that $(\log n)^2/m \to 0$ as $T \to \infty$

$$\hat{d} \sim N\left(d, \pi^2\Big/\left[6\sum_{j=1}^{m}(x_j - \bar{x})\right]\right) \qquad (19)$$

Here $\pi^2/6$ is the asymptotic variance of ε_j. Ooms and Hasler (1997) showed that the GPH estimator will contain singularities when the data are deseasonalized by utilizing seasonal dummies. In order avoid this problem, following the suggestion by Ooms and Hassler (1997), we extend the data series to full calendar years via zero padding and then omit the periodogram ordinates corresponding to seasonal frequencies. For consistency, this method is also followed in other frequency domain estimators we use.

The Gaussian semiparametric estimator (GSP) suggested by Robinson (1995a) is also based on the periodogram and it only specifies the parametric form of spectral density via (2). Like the GPH estimator the GSP estimator involves the introduction of an additional parameter *m*, which can be taken less than or equal to $[(T-1)/2]$ and should satisfy $1/m + m/T \to 0$ as $T \to \infty$. The GSP estimator of d is obtained by minimizing the function

$$r(d) = q(\hat{g},d) - 1 = \log m^{-1}\sum_{j=1}^{m}\frac{I(\lambda_j)}{\lambda_j^{-2d}} - 2dm^{-1}\sum_{j=1}^{m}\log\lambda_j \qquad (20)$$

where

$$q(\hat{g},d) = m^{-1}\sum_{j=1}^{m}\left(\frac{I(\lambda_j)}{\hat{g}\lambda_j^{-2d}} + \log\hat{g}\lambda_j^{-2d}\right) \tag{21}$$

with $\hat{g} = m^{-1}\sum_{j=1}^{m}\lambda_j^{2d}I(\lambda_j)$. The value $\hat{d}$ which minimizes $r(d)$ converges in probability to the actual value of *d* as $T \to \infty$. Robinson (1995a) also shows that $m^{1/2}(\hat{d}-d) \to_d N(0,1/4)$ as $T \to \infty$. The asymptotic variance of $\hat{d}$ is then equal to $1/4m$.

For the GPH and GSP estimators the choice of the bandwidth parameter *m* may be quite important. For the GPH estimator the ad hoc $T^{1/2}$ order bandwidth suggested by Geweke and Porter-Hudak (1993) for the stationary region of *d* is commonly used. Hurvich, Deo, and Brodsky (1998) prove that the mean squared error minimizing bandwidth *m* is of order $T^{4/5}$. This is the upper rate for its class of estimators. However, this concerns the stationary region $d \in (0,.5)$ and most macroeconomic time series are found to be nonstationary. The larger the value of *m*, the faster $\hat{d}$ converges to *d*. On the other hand, if the time series is not ideal, e.g. if it is an ARFIMA(*p*,*d*,*q*) with not both $p=0$ and $q=0$, then we should use small values of *m*, since at higher frequencies the short run behavior of the series will affect the form of the spectral density. Sowell (1992b) argues that too large a choice of bandwidth *m* leads misspecification of the short run dynamics and this results in untrue strong mean reversion. In order to be robust against the choice of the bandwidth parameter *m* we will report the GPH and GSP estimates for $m = T^{\alpha}$ for various values of $\alpha \in [.5,1)$.

Another semiparametric estimator used in this study is the wavelet based maximum likelihood estimator of Jensen (2000). This estimator, called wavelet MLE, is invariant to unknown, means model specification, and contamination. In brief terms, a wavelet $\psi(t)$ is an oscillationg function that decreases rapidly to 0 as $t \to \pm\infty$ and satisfies the admissibility condition $\int t^r \psi(t)dt = 0$, $r = 0,1,\ldots,M-1$, (Mallat (1989), Daubechies (1992)). The wavelet $\psi(t)$ has *M* vanishing moments. By defining the dilated and translated wavelet as $\psi(t)_{m,n} = 2^{m/2}\psi(2^m t - n)$, where $m,n \in Z = \{0,\pm1,\pm2,\ldots\}$, we obtain a function well localized in time around *n*. For a time series $y(t)$ the wavelet $\psi(t)_{m,n}$ covers diverse frequencies and periods of time for different values of *m* and *n*. The wavelet MLE is based on the wavelet transform of $y(t)$ defined by

$$w_{m,n} = \int y(t)\psi(t)_{m,n}dt \tag{22}$$

By normalizing the time interval of $y(t)$ as $t \in [0,1]$, i.e., the unit interval, the support of $w_{m,n}$ can be thought of as $[n2^{-m},(n+1)2^{-m}]$. If we observe discrete realizations y_t at $t = 0,1,2,\ldots,2^J - 1$, then for

$m = J - 1$, $n = 0,1,2,\ldots,2^J - 1$ is needed. Therefore, for a given scale *m* the translation parameter need to take values only at $n = 0,1,2,\ldots,2^m - 1$.

As noted by Jensen (2000), the strength of wavelets lie in their ability to simultaneously localize a time series in time and scale. The recent book by Gençay, Selçuk, and Whitcher (2001) contains many practical wavelet examples from economics and finance. They also show that wavelets can successfully be used in wide variety of challenging research problems. Wavelets can zoom in on a time series behavior at a point in time at high frequencies (large *m*, $2^{-m}n$ is small). Alternatively, wavelets can also zoom out to reveal any long and smooth (low frequency or long run) features of a time series, such as trends and periodicity, at low frequencies (small *m*). The wavelet estimator of the long memory parameter *d* is obtained by maximizing the approximate log likelihood function

$$\log L(d) = -\frac{2^J - 1}{2}\log 2\pi - \frac{1}{2}\log|\Omega| - \frac{1}{2}W'\Omega^{-1}W \tag{23}$$

where $W = [w_{0,0}, w_{1,0}, w_{1,1}, w_{2,0}, \ldots, w_{J-1,2^{J-1}-2}, w_{J-1,2^{J-1}-1}]$ and $\Omega = E[WW']$ is the covariance matrix of *W*. In order to estimate *d* by wavelet MLE we need to specify *J* and the functional form of the wavelet function $\psi_{m,n}$ (wavelet filter). In the empirical section, we report estimates of *d* for several wavelets and two different choice of *J*. Simulations in Jensen (2000) show that wavelet MLE estimator is superior to the approximate frequency domain Whittle MLE when ARFIMA models are contaminated.

3. Causes of long memory in economic time series

Although long memory in natural time series data has been established in various fields, long memory in economic and other social time series data is at least an open question. Until now there has been a lack of theoretical explanations for the common existence of long memory in economic time series data (but see Haubrich and Lo (1989) for an account of long memory in the US business cycles). An immediate explanation for evidence of long memory in economic time series is the inheritance of climatological long memory through agricultural prices. In this way the long memory in geophysical time series, such as rainfall, riverflow, and climatic time series, spills over into the economic time series without any economic mechanism. Additionally, a real business cycle model with long memory shocks can explain the presence of long memory in aggregate income and output series. Although the inheritance of the long memory from the underlying geophysical process is not completely impossible, there are there more appealing explanation of long memory in economic time series. Nonstationarity of the underlying process may be a plausible explanation for long memory in the finite sample realized time series. This explanation will not be further pursued here, since inflation rates we examine are stationary time series.

One of the more appealing and one that is intrinsically rooted in the economic process is based on an aggregation result due to Robinson (1978) and Granger (1980). Backus and Zin (1993) argue that long memory in inflation rates are due to aggregation. More recently, Michelacci (1997) examines this possibility in the context of output fluctuations. Granger (1980) argued that if the economy is composed of a large number individual units each following an AR(*p*) process, whose coefficients are drawn from a beta distribution on (0,1), then the additive aggregation of these AR(*p*) processes will display long memory. Focusing on AR(1) for simplicity, let

$$y_t = n^{-1}\sum_{i=1}^{n} y_{i,t}, \quad i = 1,2,\ldots,n, t = 1,2,\ldots,T$$

be the result of aggregation of *n* cross sectional units

$$y_{i,t} = \alpha_i y_{i,t-1} + u_t + \varepsilon_{it}, \quad i = 1,2,\ldots,n, t = 1,2,\ldots,T$$

where u_t is a common shock, $\varepsilon_{i,t}$ is a idiosyncratic shock, and $E(\varepsilon_{i,t}\varepsilon_{j,t}) = 0, E(\alpha_i\varepsilon_{j,t}) = 0$ for all *i*, *j*, *t*. We assume that both shocks are i.i.d. white noise and α_i is drawn from a beta distribution on (γ,ν). As $n \to \infty$, the autocovariance of y_t is

$$\rho_k = \frac{2}{B(\gamma,v)}\int_0^1 \alpha^{2\gamma+k-1}(1-\alpha^2)^{v-2}\,d\alpha = ck^{1-v}$$

Therefore, $y_t \sim I(1-v/2)$. Lippi and Zaffaroni (1999) generalize this result by replacing assumed beta distribution with weaker semiparametric assumptions. Chambers (1998) examines temporal aggregation as well as cross sectional aggregation in both discrete and continuous time.

A second and more recent explanation is related to structural change and based on the stochastic permanent breaks (STOPBREAK) model of Engle and Smith (1999). The studies by Hidalgo and Robinson (1996), Lobato and Savin (1998), Granger and Hyung (1999), Liu (2000), and Diebold and Inoue (2001) suggested that occasional level shifts generates an illusion of apparent long memory in economic time series. Bos, Franses, and Ooms (1999) find that evidence about the spurious long memory due to level shifts in G7 inflation rates is weak. However, they note that long memory in some inflation series disappear when level shifts are taken into account.

The STOPBREAK model of Engle and Smith (1999) is formulated as follows:

$$\begin{aligned} y_t &= m_t + \varepsilon_t \\ m_t &= m_{t-1} + q_{t-1}\varepsilon_{t-1} \end{aligned} \tag{24}$$

where $q_t = q(|\varepsilon_t|)$ is a nondecreasing function in $|\varepsilon_t|$ and bounded by zero and one. The innovations ε_t are i.i.d. white noises. Engle and Smith (1999) use

$$q_t = \frac{\varepsilon_t^2}{\gamma + \varepsilon_t^2}, \quad \gamma > 0 \tag{25}$$

This model allows breaks (level shifts or regime switching) by allowing different innovations to have different degrees of persistence. The specification for q_t in (25) allows bigger innovations to have more permanent effect than small ones. The parameter γ for the specification of q_t in (25) controls the likelihood of persistent innovations, with more persistent innovations more likely when γ is small. Popular tests of long memory are substantially biased when applied to time series with occasional level shifts. This bias leads to incorrect conclusion that these time series have long memory. Diebold and Inoue (2001) replace γ in (25) with a time varying parameter $\gamma_T = O(T^{\delta})$, for some $\delta > 0$, and show that the STOPBREAK process with this modification is $I(d)$, where $d = 1 - \delta$. Thus, this process will appear fractionally integrated. When $\delta = 0$, we see that the standard STOPBRAK process is $I(1)$.

In odder examine possibility of long memory in inflation rates due to aggregation this paper estimates long memory models at low aggregation levels. If the long memory in aggregate series is due to aggregation we should find weaker memory at lower aggregation levels. In order to guard against level shifts we modify the ARFIMA model to include a STOPBREAK component. This model simultaneously allows long memory and level shifts (shocks) that have permanent effects.

4. Data

The long memory properties of inflation rates are examined at different aggregation levels using both WPI and CPI based inflation rates of the Turkish economy. The literature on persistence in inflation rates exclusively considered CPI based inflation series except Baum, Barkoulas, and Caglayan (1999). Unlike CPI the prices of nontraded goods do not heavily influence WPI. Therefore, WPI based inflation series are better suited in tests of the international arbitrage. Inflation rates are constructed from the price indexes by taking 100 times the first differences of the natural logarithmic transformation of the indexes. All seasonal inflation series show moderate to high seasonal effects. The analyzed series are seasonally adjusted by discarding ordinates of the periodogram corresponding to seasonal frequencies when frequency domain estimation methods are used. When the estimation is carried out in the time domain, the data are deseasonalized by regressing the series on seasonal dummies. However, these two methods of deseasonalization are equivalent.

At the highest aggregation level, we examine 6 WPI based inflation and 3 CPI based inflation rates. First of these is an annual WPI based inflation series covering the period 1924-2001. The 1924-1990 period of this series is obtained from the WPI (1968=100) given in Pakdemirli (1991). The second part (1991-2001) is obtained from the State Institute of Statistics' (SIS) All Items WPI (1982=100) index. The second WPI based inflation series is a monthly inflation series, which is obtained by augmenting the Treasury Department's (1964:1-1988:1, 1963=100) WPI index by the SIS All Items WPI (1982=100) index and covers the period 1964:2-2002:6. The third WPI based inflation series is based on the Treasury Department's (1964:2-1988:1, 1963=100) monthly WPI index. The fourth aggregate WPI based inflation series we use is based on the SIS All Items WPI (1982=100) index. This monthly inflation series covers the period 982:2-2002:6. The fifth aggregate WPI inflation series is obtained from the Istanbul Chambers of Trade monthly WPI index and covers the period 1987:2-2002:6. The sixth WPI based inflation series is based on the SIS monthly WPI index (1994=100) and covers the period of 1994:2-2002:6. Among the three aggregate CPI based inflation rates, first one is an annual inflation series for 1951-2001. This series is obtained from the In IMF's International Financial Statistics database. The second and third CPI based inflation series are both monthly, which are obtained from the SIS's 1987=100 and 1994=100 CPI indexes, and cover the periods 1987:2-2002:6 and 1994:2-2002:6, respectively.

At lower aggregation levels we consider 3 major groups of monthly inflation series. The sector codes together with aggregation levels are for these series are given in the Appendix. All these data are obtained from the SIS. Several series included in the SIS database have many missing value and excluded from the analysis. First group contain WPI (1987=100) based inflation series for the period 1982:2-2002:6. There are 26 sectoral inflation series in this group. Four of these are at 1 digit aggregation level for agriculture, mining, manufacturing, and energy sectors. Remaining 22 series are at 2 digit aggregation level with 7 series in agriculture, 3 series in mining, 10 series in manufacturing, and 2 series in energy sectors. Total number of observations for each series in this group is 245. The second group of sectoral inflation series is based on the CPI (1987=100) indexes for the period 1987:2-2002:6 (185 observations for each series) and contain 9 series. The sectors in this group are about 1 digit aggregation level and include 7 sectors in addition to inflation series for Ankara and Istanbul. The third group of sectoral inflation series are also CPI (1994=100) based for the period 1994:2-2002:6 and contain 40 series. 10 of the series in this group are at 1 digit aggregation level and remaining 30 series are approximately at 3 digit aggregation level. Each series in this group has 101 observations.

5. Empirical estimates

Estimation results for the four different estimation methods are presented below. Results for the four groups of data sets are presented separately. Examination of the sample autocorrelation functions (available at the web site cited above) revealed that all monthly data examined in this paper show moderate to high seasonality. The available estimation methods for the long memory models unfortunately are not well suitable for the seasonal series. Although some progress is made in the literature for modeling seasonal long memory time series these methods at the moment are at their infancy and does not allow flexible modeling. Therefore, we decided to deseasonalize the data. For the frequency domain estimation methods, which are the Whittle, GPH, and GSP estimators, deseasonalization is performed by first extending the data into full calendar years and then discarding the periodogram ordinates corresponding to seasonal frequencies. For the wavelet MLE estimator this is not feasible and deseasonalization is carried in the time domain by subtracting the seasonal means, through a regression of the series on a set of seasonal dummies. All estimation is performed using the LONGMEM library for GAUSS written by the author.

For the parametric model estimates we present results for only FGN(*d*) and ARFIMA(*p*,*d*,*q*) models with $p,q \leq 1$. Thus, five parametric models are estimated. Estimation of ARFIMA models with $p,q > 1$ are also tried, in most cases, estimation of these models either failed and when estimation was successful they always had lower AIC value. Therefore, we do not report results for these higher order ARFIMA models. For brevity only the results of FGN(*d*) and ARFIMA(*p*,*d*,*q*) that has the minimum the Akaike information criterion (AIC) will be presented. We however report the AIC values for all FGN and ARFIMA models estimated with $p,q \leq 1$. The parameters of the FGN and ARFIMA models are estimated using the Whittle approximate maximum likelihood method. The ARFIMA models are also estimated by Sowell's exact maximum likelihood estimator. For brevity Sowell's exact maximum likelihood estimates are not reported here, but available at the web site cited above. Standard errors for the FGN and ARFIMA models are calculated using the asymptotic formula in Robinson (1994a) and Beran (1995). Persistence of these parametric models is evaluated using their impulse response functions. Inference is based on the 95 percent confidence intervals for the implied impulse responses. These 95 percent confidence intervals are obtained via a parametric bootstrap with 5000 replicates. For comparison, we also estimated ARMA models for each inflation series and constructed 95 percent confidence intervals for the models that have the minimum AIC values. In all cases, the best ARMA model selected by the AIC showed very weak persistence. The results for ARMA models are not reported for space requirements. Interested reader can obtain these results from the web site cited above.

In estimating the long memory parameter *d* with the semiparametric GPH and GSP methods, a choice has to be made with respect to the number of low order frequency ordinates (bandwidth). Inclusion of medium or high order periodogram ordinates will lead to bias in the estimates of *d*. On the other hand, inclusion of too few periodogram ordinates will increase the sampling variability of the estimates due to reduced sample size. In order to evaluate the robustness of the GPH and GSP estimates to the choice of bandwidth we report GPH and GSP estimates for several values of bandwidth choice *m*. These choices vary with sample size *T* and determined via $m = [T^{\alpha}]$ for $\alpha = \{0.50, 0.55.0.60, 0.70, 0.75, 0.80\}$.

The wavelet MLE estimator also requires a decision on two choices. First of all, there are different wavelet filters to use in the wavelet transform. Second, one should also determine the depth of the wavelet transform, *J*. The choice of wavelet depth determines number of scales used in the estimation. Thus, it is similar to bandwidth choice. To evaluate the sensitivity of estimates to the number of scales included, we use two different choices, $J = \log_2 T$ and $J = 4$. In regard to the choice of wavelet filter, we use 6 different wavelet families, compact Haar wavelet, Daubechies wavelet of order 8 and 16 (D8, D16), minimum-bandwidth discrete-time wavelet of length 8 and 16 (MB8, MB16), and Daubechies orthonormal compactly supported wavelet of length 8 (LA8).

5.1. Empirical results for aggregate inflation series

The GPH and GSP estimates of the long memory parameter *d* for the 9 aggregate inflation series are given in Table 1. For most series the results are quite robust to the choice of bandwidth. There are only two series that show some sensitivity to the bandwidth length. Both of these series are annual and have *d* greater than 0.50, .i.e., these series are nonstationary but mean reversing. Indeed, there is some evidence that these series may even not be mean reverting, since estimates of *d* for some bandwidths are close to or greater than 1. Although there is no theoretical result showing temporal aggregation creates long memory and the result in Chambers (1998) points to this direction, the estimates for the annual series have stronger memory than the estimates for the monthly series. However, this may be a sample issue. The annual series we use spans the longest history of the Turkish economy. One of the series (WPI based inflation series) spans the period of 1924-2002 and the other series (CPI based inflation series) covers the period of 1951-2002. The longest time span the monthly series cover is 1964-2002. We have no way of verifying whether this is a sample issue or not since we do not have monthly data that goes back to 1950s or 1920s. Estimates from other methods show that this maybe a sample size issue but the evidence in this direction is very weak. They also indicate that these two annual series are indeed mean reverting and probably stationary. For the first four and the sixth series in Table 1 estimates are all significant at the 5 percent level, except the fourth series for which some GPH estimates are not significant. At $\alpha = 0.50$ (a commonly used choice) two annual series and first four of the WPI based inflation series show significant long memory at the 5 percent level. When $\alpha = 0.80$, a choice possibly leading to biased estimates due to improper inclusion high frequency periodogram ordinates, all aggregate inflation series have significant long memory parameter estimates.

The wavelet based MLE estimates are displayed in Table 2. The estimates are very robust to the choices of scale and wavelet filter. Estimates closely match the estimates given in Table 1 for the GPH and GSP estimators, except for two annual series. For two annual series, the GPH and wavelet MLE estimates are below 0.50 across the choices of wavelet filter and scale. These two annual series seem to be either nonstationary or near nonstationary, and the GPH and GSP estimators may exaggerate the long memory parameter. Since wavelets strength lie in their ability to simultaneously localize a time series in time and scale wavelet estimates may be more reliable for nonstationary or near nonstationary time series.

The estimates for FGN and ARFIMA models are given in Table 3. The AIC values are always at the minimum for ARFIMA(0,*d*,0) among the ARFIMA(*p*,*d*,*q*), $p, q \leq 1$, class of models. A comparison of the AIC values between FGN and ARFIMA models show that the AIC is at the minimum for 6 series when the model is FGN. However, the FGN and ARFIMA models have different spectral densities, so a comparison is not completely correct across these models. Further, the FGN and ARFIMA(0,*d*,0) models are similar in terms of the behavior of the series they try to capture. They also give very close estimates of *d* for all series except two annual series. All parameter estimates for FGN and ARFIMA models are significant at the conventional 5 percent significance level. Estimates of the long memory parameter from the FGN and ARFIMA(0,*d*,0) models closely match each other for all series. These estimates are also very close to the estimates of *d* from the wavelet based MLE. When $\alpha \geq 0.65$, the FGN and ARFIMA model estimates are also close to the estimates by the semiparametric GPH and GSP methods. Thus, a value of α around 0.65 seems to be an optimal choice for these series.

For each series, the 95 percent confidence intervals for the impulse responses of the ARFIMA models that have the minimum AIC are given in Table 4. These confidence intervals are calculated via a parametric bootstrap with 5000 repetitions. None of the confidence intervals brackets zero even after 1200 periods, i.e., 100 years for monthly series and 1200 years for annual series. Long memory properties of these aggregate inflation series are profoundly reflected in the estimated impulse responses. As discussed in the second section, the impulse response function may not be a good mean for measuring persistence in long memory models. A more appropriate measure, the time required for α percent of a unit shock to dissipate, denoted τ_α, is proposed in the second section. Estimates of τ_α for each aggregate inflation series are displayed in Table 5. For the monthly series the longest time required for the 90 percent of the effect of shocks to disappear is 4 years. On the other hand, the annual WPI inflation series needs 666 years for the 90 percent of the effects of shocks to disappear, while the annual CPI inflation series requires even more than 1200 years. The shortest time required for the monthly inflation series for the 99 percent of the effect of a unit shock to disappear is about 13 years, while the longest time required is about 88 years.

5.2. Empirical results for sectoral WPI based inflation series

One of the reasons, which is examined in the third section, why evidence of long memory in the inflation series can be spurious is based on aggregation. The inflation series examined above are based on the aggregate WPI and CPI indexes. It may well happen that the specific shocks to inflationary process indeed do not exhibit strong persistence and the apparent long memory in the aggregate inflation series due to aggregation as argued by Robinson (1978) and Granger (1980). To examine this possibility, this subsection analyzes long memory properties of 26 sectoral WPI based inflation series. The next subsection will further examine 49 sectoral CPI based inflation series.

The GPH and GSP estimates of long memory parameter *d* are given in Table 6. There are several features of these estimates which should be noticed. First, the GPH estimates show evidence of long memory only for two series and the GSP estimates only for three series at the 5 percent significance level. Second, at the commonly used bandwidth choice $\alpha = 0.50$, there is only 1 GPH estimate and 5 GSP estimates significant at the 5 percent level. Third, five series have negative *d* estimates. Fourth, estimates are quite insensitive to the choice of bandwidth. Sixth, on average the estimates of *d* for these sectoral WPI based inflation series are lower than the *d* estimates of aggregate inflation series.

The wavelet MLE estimates are displayed in Table 7. Estimates of *d* are quite robust across the choices of wavelet filters and scales. For scale $J = \log_2 T$, 8 series are antipersistent and, for scale $J = 4$, 6 series are antipersistent. On average, the wavelet MLE estimates of *d* are lower than the GPH and GSP estimates. Like the GPH and GSP estimates, estimates of *d* for these sectoral WPI based inflation series are significantly less than the estimates of *d* for the aggregate inflation series.

The estimation results for the parametric FGN and ARFIMA models are given in Table 8. From the AIC values given in the left panel of Table 8, we see that among the family of ARFIMA(*p*,*d*,*q*) models we estimated ARFIMA(0,*d*,0) model has the minimum AIC value for all sectoral WPI based inflation series. For all series, the estimates of *d* for the FGN(*d*) ARFIMA(0,*d*,0) models are very close to each other. For the FGN model, estimates of *d* for 18 series are significant at 5 percent level. Likewise, estimates of *d* from the ARFIMA(0,*d*,0) model are significant at the five percent level for 19 series. In general, the estimates of the long memory parameter *d* are higher than the GPH, GSP, and wavelet MLE estimates. However, almost all of these estimates are still lower than the estimates for aggregate inflation series.

In order to evaluate the persistence sectoral WPI based inflation series we constructed the 95 percent confidence intervals for the impulse responses of the ARFIMA models with the minimum AIC values. These confidence intervals are shown in Table 9. For these series, it should be noted that estimates of *d* from the ARFIMA models were in general higher than the estimates obtained from other methods, so impulse responses are evaluated at the highest estimate of the long memory parameter and probably overstated. The confidence intervals given in Table 19 bracket zero for 22 series out of 26 at *k*=1200. At *k*=384, only confidence intervals for 6 series do not bracket zero. Compared to the confidence intervals for the impulse responses of the aggregate series, the much weaker persistence in the sectoral WPI based inflation series is very clearly evidenced by the confidence intervals given in Table 9. This claim is much strongly supported by the estimates of τ_α given in Table 10. These estimates show that only for 2 series a period of more than 2 years is required for 90 percent of the effects of shocks to dissipate. For 99 percent of the effect of a shock to dissipate, 20 series need less than 5 years and only 6 series need more than 10 years.

5.3. Empirical results for sectoral CPI based inflation series

In this section we will discuss the estimation results for two groups of sectoral monthly CPI based inflation series in the dataset we consider. The first group spans a longer time interval, 1987:2-2002:6, but is at 1 digit aggregation level, while the second group of inflation series contains 10 series at 1 digit aggregation level and 30 series at 2 digit aggregation level, but spans a shorter time period, 1994:2-2002:6.

The semiparametric GPH and GSP estimates for the first and second group of sectoral CPI based inflation series are given in Table 11 and Table 16, respectively. The GPH estimates of *d* given in the first panel of Table 11 show that only 1 series, A07, has significant long memory at the the 5 percent level across all choices of bandwidth. At the bandwidth choice of $\alpha = 0.50$ only two series have significant long memory. The GSP estimates given in the second panel of Table 11 confirm the significant long memory for series A07 and indicate that 3 more series have long memory when $\alpha = 0.50$. Both estimators show that 3 series are indeed antipersistent. In summary, for the first group of inflation series, there is evidence of significant long memory only for one series.

The GPH and GSP estimates of *d* for the second group of CPI based inflation series given in Table 16 show that 19 out of 40 series are antipersistent when $\alpha = 0.50$. Only for two series are the GPH estimates for most of α choices significant at the 5 percent level. Likewise, the GSP estimates indicate that only 5 series have significant long memory at the 5 percent level for all choices of α. When $\alpha = 0.50$, only two GPH estimates are significant, while for the same value of α, 11 of the GSP estimates are significant. For this group of inflation series, the GPH and GSP estimates are somewhat differ both in magnitude and number of significant estimates. This, however, most likely due to small sample size, since the inflation series in this group have the smallest number of observations with a sample size of 101.

The wavelet MLE estimates are given in Table 12 and Table 17 for the first and second groups of inflation series, respectively. Estimates are quite insensitive to the choices of wavelet filter and scale for both groups. For the majority of wavelet filter and scale choices, 3 series in the first group and 10 series in the second group are antipersistent. Similar to the GPH and GSP estimates the wavelet MLE estimates of *d* for the majority of sectoral CPI based inflation rates are lower than the estimates of *d* for the aggregate series.

The estimation results for the FGN and ARFIMA models are given in Table 13 and Table 18, for the first and second group of sectoral CPI based inflation series, respectively. The first panels of these tables display the AIC values for FGN and ARFIMA models. Within the class of ARFIMA models, the AIC values are always at minimum for the ARFIMA(0,*d*,0) model. Like the estimates for other inflation series the estimates of *d* for the FGN and ARFIMA(0,*d*,0) models are very close to each other. Only half of the estimates are significant at the 5 percent significance level for both FGN and

ARFIMA(0,*d*,0) models. Magnitudes of *d* estimates are in most cases lower compared to the estimates for aggregate series. Last feature of these estimates we notice is the similarity with the estimates from wavelet MLE.

As we did for the other inflation series, we will evaluate persistence of sectoral CPI based inflation series using the impulse responses of the ARFIMA models that has the minimum AIC values and time required for α percent of the effect of a unit shock to dissipate. The 95 percent bootstrap confidence intervals for the longer inflation series are given in Table 14. Confidence intervals bracket zero for all series when impulse responses are evaluated at $k = 1200$ (100 years). When $k = 384$, the confidence intervals do not bracket zero only for 2 series. The weaker persistence in these sectoral inflation series can be followed by narrower confidence intervals at all values of *k*. In Table 15, we display estimates of τ_α for the longer CPI based inflation series. Estimates for τ_α point out that a period of less than 6 months is required for 90 percent of the effects of shocks to dissipate for all series. Moreover, only 2 series require more than 10 years an only 3 series requires more than 5 years for 99 percent of the effects of shocks to die out.

In Table 19, we display the 95 percent confidence intervals for the shorter sectoral CPI based inflation series. When evaluated at $k = 1200$, the 95 percent confidence intervals of 33 out of 40 series bracket zero. At a much shorter horizon, $k = 384$, the 95 percent confidence intervals do not bracket zero only for 9 series. Although estimates of *d* for the ARFIMA(0,*d*,0) model indicate that half the series have significant long memory, it seems that this is not fully supported by the bootstrap estimates of impulse responses. This result suggests that there may be a small sample issue that biases the estimates of *d* upward. Bootstrap is a method that reduces bias due to small sample and this is probably why we do not observe strong persistence in the bootstrap impulse responses.

The estimates of τ_α for the shorter sectoral CPI based inflation series are given in Table 20. We observe that only 1 series require more than 3 years for 90 percent of the effect of shocks to fade away, while only 7 series require more than 1 year. Indeed, for 28 series, time required for 90 percent of the effects of shocks to dissipate is less than 6 months. The last column of Table 20 reveals that the estimates of τ_α are greater than 10 years for 99 percent of the effects of shocks to dissipate for 16 series, while they are less than 5 years for 21 series.

It should be noted that small sample bias will also be reflected in the estimates of τ_α. A better approach would be to consider bootstrap estimates of τ_α. Even though these estimates may be upward biased, we see that the disaggregate CPI based inflation series do not display persistence as strong as the aggregate inflation series.

5.4. Long memory and regime shifts

In this subsection, we examine the possibility of spurious long memory due to neglected structural breaks. The studies by Hidalgo and Robinson (1996), Lobato and Savin (1998), Granger and Hyung (1999), Liu (2000), and Diebold and Inoue (2001) showed that apparent long memory may also be caused by neglected stochastic level shifts. The stochastic permanent level shifts mimic the effect of a persistent shock. Therefore, the long memory models fitted to the data that has occasional level shifts may incorrectly find evidence of long memory.

Several studies examined this possibility using models that allow level shifts. Bos, Franses, and Ooms (1999) attempt to capture the effect of level shifts by inclusion of dummy variables. This approach is subject known critics of pretesting, since the locations of the level shifts are predetermined. A more flexible model is the STOPBREAK model examined above (see Smith (2000) for further details), which models the level shifts as a component with stochastic permanent shifts. Hence, a model that can capture both long memory and occasional level shifts seems to be highly desirable. A version of such model is studied in Hyung and Franses (2002). We consider the following extension of an ARFIMA model

$$\begin{aligned} y_t &= m_t + u_t \\ m_t &= m_{t-t} + q_{t-1}\varepsilon_{t-1} \\ (1-L)^d \phi(L) u_t &= \theta(L)\varepsilon_t \\ q_t &= \frac{\left(\varepsilon_t + \varepsilon_{t-1} + \cdots + \varepsilon_{t-s}\right)^2}{\gamma + \left(\varepsilon_t + \varepsilon_{t-1} + \cdots + \varepsilon_{t-s}\right)^2} \end{aligned} \qquad (26)$$

where ε_t is a white noise and $\phi(L) = 1 - \sum_{j=1}^{p} \phi_j L^j, \theta(L) = 1 - \sum_{j=1}^{q} \theta_j L^j$ are polynomials in the lag operator L with degrees p, q respectively. We assume that $\phi(z)$ and $\theta(z)$ share no common roots and $\phi(z) \neq 0, \theta(z) \neq 0$ for $z \leq 1$. The operator $(1-L)^d$ is defined in (6) and (7). We will call this model the ARFIMA-BREAK model. This model can be written as

$$\phi(L)(1-L)^d (\Delta y_t - q_{t-1}\varepsilon_{t-1}) = \theta(L)\varepsilon_t \qquad (27)$$

where $\Delta = 1 - L$. The model examined in Hyung and Franses (2002) is a variant of this model and given by

$$\phi(L)(1-L)^d \Delta y_t = \varepsilon_t - \theta_{t-1}\varepsilon_{t-1}$$

where $\theta_{t-1} = 1 - q_{t-1}$.

In this susection, we will fit the ARFIMA-BREAK model given in (26) to aggregate inflation series. Parameters of this model can be estimated using the approximate likelihood method (AML) of

Beran (1995). Under the regularity conditions given in Engle and Smith (1999) the AML estimator is consistent and asymptotically normal.

We already established that disaggregated inflation series do not show significant persistence. Therefore, we will examine the possible spurious long memory due to level shifts only for the aggregate inflation series. In order to estimate the parameters of the ARFIMA-BREAK model one needs to determine the orders *p*, *q*, and *s*. We tried to estimate models with $p, q \in \{0,1\}$ and $s \in \{1,2\}$. For $q = 1$, estimation often either failed or did not converge. Therefore, we estimated all models with $q = 0$.

Estimation results for the ARFIMA-BREAK model are given in Table 21. Several features of these estimates should be noted. First, the estimates of γ for 6 series are significant at the 5 percent significance level. Second, five inflation series have estimate of γ below 1 and all series have no γ estimate above 6. Hence, all inflation series have high likelihood of occasional level shifts. Third, estimates of *d* are all less than zero and significant at the 5 percent level except the last one. That is, all series become antipersistent once the effects of level shifts are taken into account. All persistence in these inflation series are then due to level shifts. Therefore, the evidence of long memory in the aggregate inflation series we found in the previous section is spurious.

6. Discussion

Inflation has been a major problem of many economies. In order to keep inflation in check the policymakers need to have good knowledge about the dynamic properties of the inflation. Despite extensive research on the dynamic properties of inflation rates, there is still no agreement about the key question of persistence in inflation. Since the early eighties the inertial inflation approach has become very influential. The inertial inflation implies highly persistent inflation rates. Turkey is one of the countries believed to have a highly inertial inflationary process. Thus, an examination of the long lasting inflation in Turkey should provide a valuable contribution to the literature on the dynamics of inflation.

The purpose of this paper has been to evaluate the persistent inflation hypothesis using an extensive dataset on the CPI and WPI based inflation rates of the Turkish economy. The paper used several parametric and semiparametric estimators of long memory models. All estimators gave similar results. Thus, the findings of the paper are quite robust. The persistence in inflation series are evaluated using the impulse responses of the estimated models. We found significant evidence of strong persistence for the inflation series at the highest aggregation level.

The paper also examined the causes of long memory in inflation series. We considered two reasonable explanations. The first one is due to Robinson (1978) and Granger (1980), which states that aggregation over a large number of sectors each subject to white noise shocks may lead to long memory in aggregate inflation rates. The key idea is that aggregation of independent weakly dependent series may produce a series with strong dependence. In order to examine this possibility we estimated long memory models for 75 disaggregated CPI and WPI based inflation rates. Estimates show that disaggregated data display very weak memory. The hypothesis of no long memory cannot be rejected for the majority of sector specific CPI and WPI based inflation rates.

Neglected level shifts can also cause long memory. In order to examine the possibility of spurious long memory in inflation rates due to level shifts we extended the ARFIMA model by incorporating a component with occasional stochastic level shifts. With this extension the effect of level shifts are removed, and the long memory is captured by the ARFIMA component. This model is estimated for 9 inflation series at the highest aggregation level. The standard ARFIMA model estimates indicated significant long memory for these series. After taking into account the effect of occasional level shifts, we showed that all these series have indeed intermediate memory (antipersistent).

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Appendix: Sector Codes for Inflation Series

Code	Description	Aggregation
Monthly Wholesale Prices Index (1987=100)		
E01	Agriculture Sector Price Index	1
E02	Mining Sector Price Index	1
E03	Manufacturing Sector Price Index	1
E04	Energy Sector Price Index	1
E05	Cereals	2
E06	Pulses	2
E07	Other Field Products	2
E08	Vegetables and Fruits	2
E09	Live Animals	2
E10	Animal Products	2
E11	Fishery Products	2
E12	Coal Mining	2
E13	Crude Petroleum	2
E14	Metallic Mining	2
E15	Non-Metallic Mining	2
E16	Food, Beverages, Tobacco	2
E17	Textiles	2
E18	Wood Products	2
E19	Paper Products and Printing	2
E20	Chemicals, Petroleum Products	2
E21	Non-Metallic Minerals	2
E22	Metals	2
E23	Metals and Machinery	2
E24	Other Industries	2
E25	Water (Energy Sector)	2
E26	Electricity (Energy Sector)	2
Monthly Consumer Price Index (1987=100)		
A01	Food-Stuffs	1
A02	Clothing	1
A03	House Appliances and Furniture	1
A04	Medical Health and Personal Care	1
A05	Transportation and Communication	1
A06	Culture, Training and Entertainment	1
A07	Housing	1
A08	Consumer Prices Index of Ankara	1
A09	Consumer Prices Index of Istanbul	1
Monthly Consumer Price Index (1994=100)		
T01	Food, Beverages and Tobacco	1
T02	Clothing and Shoes	1
T03	Housing	1
T04	Houseware	1
T05	Health	1
T06	Transportation	1
T07	Entertainment and culture	1
T08	Education	1
T09	Restaurant, Cafe and Hotels	1
T10	Miscelaneous	1
T11	Food	3

T12	Beverages	3
T13	Clothing	3
T14	Shoes	3
T15	House rent	3
T16	Housing maintenance	3
T17	Other housing expenditures	3
T18	Elektricity, gas and other fuels	3
T19	Furniture and floor	3
T20	Fabric furnishings	3
T21	Electric and non-eletric houseware	3
T22	Kitchenware	3
T23	Tools	3
T24	Housekeeping and services	3
T25	Medicine and medical goods	3
T26	Medical services	3
T27	Hospital services	3
T28	Private transportation vehicles	3
T29	Maintenance	3
T30	Transportation services	3
T31	Goods	3
T32	Services	3
T33	Newspapers, books and stationery	3
T34	Services	3
T35	Goods	3
T36	Dining	3
T37	Hotel services	3
T38	Personal care	3
T39	Jewelary	3
T40	Other services	3

Table 1: GPH and GSP Estimates of d for Aggregate Inflation Series

Inflation Series		a =0.50	a =0.55	a =0.60	a =0.65	a =0.70	a =0.75	a =0.80
					GPH Estimates			
WPI (1923-2001)	d	1.151	0.936	0.636	0.663	0.656	0.701	0.673
	s.e.	0.347	0.295	0.246	0.215	0.182	0.162	0.147
WPI (1964:2−2002:6)	d	0.373	0.568	0.558	0.420	0.384	0.342	0.308
	s.e.	0.176	0.143	0.120	0.100	0.084	0.071	0.061
WPI (1964:2−1988:1)	d	0.477	0.633	0.507	0.306	0.282	0.274	0.205
	s.e.	0.210	0.171	0.146	0.121	0.103	0.088	0.076
WPI (1982:2−2002:6)	d	0.320	0.419	0.283	0.215	0.202	0.282	0.346
	s.e.	0.220	0.182	0.150	0.129	0.109	0.094	0.082
WPI (1987:2−2002:6)	d	0.505	0.529	0.307	0.206	0.277	0.353	0.446
	s.e.	0.243	0.202	0.171	0.145	0.124	0.107	0.094
WPI (1994:2−2002:6)	d	-0.059	-0.107	0.098	0.263	0.308	0.369	0.410
	s.e.	0.294	0.258	0.222	0.185	0.162	0.144	0.127
CPI (1951−2001)	d	0.965	1.107	0.928	0.885	0.895	0.845	0.835
	s.e.	0.388	0.351	0.299	0.265	0.231	0.203	0.185
CPI (1987:2−2002:6)	d	0.243	0.313	0.193	0.178	0.141	0.319	0.376
	s.e.	0.243	0.202	0.171	0.145	0.124	0.107	0.094
CPI (1994:2−2002:6)	d	0.107	-0.002	0.088	0.242	0.335	0.396	0.421
	s.e.	0.294	0.258	0.222	0.185	0.162	0.144	0.127
					GSP Estimates			
WPI (1923-2001)	d	0.984	0.754	0.572	0.601	0.647	0.681	0.616
	s.e.	0.177	0.158	0.139	0.125	0.109	0.098	0.088
WPI (1964:2−2002:6)	d	0.476	0.534	0.565	0.409	0.355	0.345	0.333
	s.e.	0.109	0.093	0.080	0.069	0.059	0.050	0.043
WPI (1964:2−1988:1)	d	0.580	0.689	0.487	0.366	0.363	0.328	0.272
	s.e.	0.125	0.107	0.094	0.081	0.071	0.061	0.053
WPI (1982:2−2002:6)	d	0.277	0.323	0.247	0.178	0.192	0.250	0.328
	s.e.	0.129	0.112	0.096	0.085	0.073	0.064	0.056
WPI (1987:2−2002:6)	d	0.219	0.365	0.168	0.163	0.217	0.287	0.400
	s.e.	0.139	0.121	0.107	0.093	0.081	0.071	0.062
WPI (1994:2−2002:6)	d	-0.031	-0.060	0.025	0.188	0.317	0.403	0.451
	s.e.	0.158	0.144	0.129	0.112	0.100	0.090	0.079
CPI (1951−2001)	d	0.962	1.050	0.830	0.760	0.770	0.751	0.734
	s.e.	0.189	0.177	0.158	0.144	0.129	0.115	0.104
CPI (1987:2−2002:6)	d	0.269	0.332	0.178	0.176	0.152	0.242	0.336
	s.e.	0.139	0.121	0.107	0.093	0.081	0.071	0.062
CPI (1994:2−2002:6)	d	0.137	0.036	0.075	0.204	0.306	0.405	0.398
	s.e.	0.158	0.144	0.129	0.112	0.100	0.090	0.079

Notes: GSP and GPH estimates are the Geweke and Porter-Hudak (1983) log periodogram and Robison (1995a) gaussian semiparametric estimates, respectively. s.e. is the standard error of the estimate above it. a determines the number of periodogram ordinates (sample size), m, used in the estimation by $m = [T^a]$. For the GSP estimates the known theoretical variance $p^2/6$ of innovations is imposed in the calculation of the s.e. of d. Similarly, the known innovation variance of $1/4m$ is imposed in the calculation of the s.e. of the GSP estimates. Data are seasonally adjusted by discarding the periodogram ordinates corresponding to seasonal frequencies.

Table 2: Wavelet Based Estimates of d for Aggregate Inflation Series

	$J = \log_2 T$					
Inflation Series	Haar	D8	D16	MB8	MB16	LA8
WPI (1923-2001)	0.459	0.460	0.429	0.448	0.451	0.480
WPI (1964:2−2002:6)	0.289	0.251	0.230	0.316	0.313	0.327
WPI (1964:2−1988:1)	0.277	0.275	0.246	0.205	0.283	0.299
WPI (1982:2−2002:6)	0.298	0.269	0.264	0.305	0.320	0.382
WPI (1987:2−2002:6)	0.311	0.313	0.317	0.380	0.389	0.393
WPI (1994:2−2002:6)	0.360	0.346	0.356	0.396	0.414	0.450
CPI (1951−2001)	0.484	0.456	0.485	0.476	0.487	0.483
CPI (1987:2−2002:6)	0.336	0.242	0.282	0.329	0.334	0.355
CPI (1994:2−2002:6)	0.373	0.299	0.330	0.377	0.390	0.438
	$J = 4$					
	Haar	D8	D16	MB8	MB16	LA8
WPI (1923-2001)	0.433	0.413	0.423	0.418	0.423	0.431
WPI (1964:2−2002:6)	0.328	0.340	0.340	0.338	0.346	0.359
WPI (1964:2−1988:1)	0.289	0.294	0.307	0.287	0.297	0.307
WPI (1982:2−2002:6)	0.286	0.284	0.286	0.312	0.318	0.338
WPI (1987:2−2002:6)	0.283	0.297	0.282	0.318	0.330	0.344
WPI (1994:2−2002:6)	0.305	0.305	0.302	0.333	0.344	0.376
CPI (1951−2001)	0.444	0.449	0.453	0.452	0.455	0.446
CPI (1987:2−2002:6)	0.293	0.263	0.264	0.284	0.293	0.319
CPI (1994:2−2002:6)	0.326	0.298	0.301	0.334	0.341	0.373

Notes: The wavelet MLE estimates are obtained from the discrete wavelet transform with depth J of the inflation series. Six different wavelet filters, compact Haar wavelet, Daubechies wavelet of order 8 and 16 (D8, D16), minimum-bandwidth discrete-time wavelet of length 8 and 16 (MB8, MB16), and Daubechies orthonormal compactly supported wavelet of length 8 (LA8), are used. Data are seasonally adjusted prior to estimation using a set of seasonal dummies.

Table 3: Parameter Estimates and Model Selection Criteria of FGN and ARFIMA Models for Aggregate Inflation Series

	AIC for FGN and ARFIMA Models				
Inflation Series	FGN(*d*)	ARFIMA(0,*d*,0)	ARFIMA(1,*d*,0)	ARFIMA(0,*d*,1)	ARFIMA(1,*d*,1)
WPI (1923-2001)	3.023	2.971	4.971	4.939	6.939
WPI (1964:2−2002:6)	3.324	3.331	5.329	5.328	7.326
WPI (1964:2−1988:1)	3.537	3.525	5.524	5.518	7.518
WPI (1982:2−2002:6)	3.581	3.614	5.578	5.589	7.566
WPI (1987:2−2002:6)	3.558	3.598	5.556	5.542	7.529
WPI (1994:2−2002:6)	3.580	3.634	5.577	5.488	7.484
CPI (1951−2001)	2.741	2.706	4.703	4.681	6.674
CPI (1987:2−2002:6)	3.638	3.676	5.631	5.639	7.612
CPI (1994:2−2002:6)	3.586	3.635	5.585	5.520	7.520
	Estimates for FGN and Best ARFIMA Models Selected by AIC				
	FGN(*d*)			ARFIMA(0,*d*,0)	
	d	s.e.		*d*	s.e.
WPI (1923-2001)	0.433	0.077		0.600	0.089
WPI (1964:2−2002:6)	0.308	0.031		0.358	0.037
WPI (1964:2−1988:1)	0.260	0.039		0.304	0.046
WPI (1982:2−2002:6)	0.307	0.043		0.355	0.050
WPI (1987:2−2002:6)	0.335	0.049		0.392	0.058
WPI (1994:2−2002:6)	0.366	0.067		0.439	0.078
CPI (1951−2001)	0.472	0.095		0.702	0.110
CPI (1987:2−2002:6)	0.297	0.049		0.337	0.058
CPI (1994:2−2002:6)	0.350	0.067		0.413	0.078

Notes: First panel of the Table reports the Akaike Information Criterion ($-2 \ln L + 2k$) for each model, where L is the likelihood and k is the number of parameters. Both the FGN and ARFIMA models are estimated using the Whittle frequency domain approximate maximum likelihood method. The second panel shows the estimates for the FGN and ARFIMA models that have the minimum AIC. Standard errors (s.e.) are calculated using the asymptotic formula in Robinson (1994a) and Beran (1995). For an ARFIMA(0,*d*,0) process the asymptotic variance is independent of d and difference in s.e. estimates in the bottom right panel of the Table is only due to sample size differences. Data are seasonally adjusted by discarding the periodogram ordinates corresponding to seasonal frequencies.

Table 4: Bootstrap Confidence Intervals of the Impulse Response Functions of the Best ARFIMA Models for Aggregate Inflation Series

Inflation Series	*Pct.*	k=1	k=3	k=6	k=12	k=24	k=48	k=96	k=192	k=384	k=504	k=744	k=984	k=1200
WPI (1923-2001)	2.5	0.336	0.175	0.112	0.072	0.045	0.029	0.018	0.011	0.007	0.006	0.005	0.004	0.003
	97.5	0.781	0.645	0.562	0.486	0.419	0.361	0.310	0.267	0.229	0.216	0.198	0.187	0.179
WPI (1964:2−2002:6)	2.5	0.270	0.130	0.080	0.048	0.029	0.018	0.011	0.006	0.004	0.003	0.002	0.002	0.002
	97.5	0.426	0.246	0.168	0.114	0.077	0.052	0.035	0.023	0.016	0.014	0.011	0.009	0.008
WPI (1964:2−1988:1)	2.5	0.187	0.081	0.047	0.027	0.015	0.009	0.005	0.003	0.002	0.001	0.001	0.001	0.001
	97.5	0.386	0.213	0.142	0.094	0.061	0.040	0.026	0.017	0.011	0.010	0.007	0.006	0.006
WPI (1982:2−2002:6)	2.5	0.224	0.102	0.060	0.035	0.021	0.012	0.007	0.004	0.002	0.002	0.001	0.001	0.001
	97.5	0.444	0.261	0.181	0.124	0.085	0.058	0.039	0.027	0.018	0.016	0.013	0.011	0.010
WPI (1987:2−2002:6)	2.5	0.233	0.107	0.064	0.038	0.022	0.013	0.008	0.005	0.003	0.002	0.002	0.001	0.001
	97.5	0.494	0.307	0.220	0.157	0.111	0.078	0.055	0.039	0.027	0.024	0.020	0.017	0.015
WPI (1994:2−2002:6)	2.5	0.198	0.087	0.051	0.029	0.017	0.010	0.006	0.003	0.002	0.001	0.001	0.001	0.001
	97.5	0.573	0.387	0.294	0.221	0.165	0.123	0.092	0.068	0.051	0.045	0.038	0.034	0.031
CPI (1951−2001)	2.5	0.321	0.164	0.105	0.066	0.041	0.026	0.016	0.010	0.006	0.005	0.004	0.003	0.003
	97.5	0.909	0.842	0.795	0.749	0.705	0.662	0.622	0.584	0.549	0.535	0.517	0.504	0.495
CPI (1987:2−2002:6)	2.5	0.177	0.076	0.043	0.025	0.014	0.008	0.004	0.003	0.001	0.001	0.001	0.001	0.001
	97.5	0.433	0.251	0.173	0.118	0.080	0.054	0.037	0.025	0.017	0.014	0.011	0.010	0.009
CPI (1994:2−2002:6)	2.5	0.175	0.074	0.043	0.024	0.014	0.008	0.004	0.002	0.001	0.001	0.001	0.001	0.001
	97.5	0.549	0.361	0.269	0.199	0.146	0.107	0.079	0.057	0.042	0.037	0.031	0.028	0.025

Notes: For each series, we report the 95 percent (1-2a , a =0.025) confidence intervals of the impulse response function, a_k, of the ARFIMA model that has the minimum AIC. k is measured in the frequency of corresponding inflation series, i.e., months for monthly series and years for annual series. The confidence intervals are calculated using 5000 bootstrap replicates from the ARFIMA models that have the minimum AICs.

Table 5: Estimates of t_a for Aggregate Inflation Series

Inflation Series	a =0.30	a =0.50	a =0.80	a =0.90	a =0.95	a =0.99
WPI (1923-2001)	1	2	21	118	666	>1200
WPI (1964:2−2002:6)	1	1	3	9	26	315
WPI (1964:2−1988:1)	1	1	2	6	16	159
WPI (1982:2−2002:6)	1	1	3	9	25	305
WPI (1987:2−2002:6)	1	1	4	12	36	508
WPI (1994:2−2002:6)	1	1	5	18	60	1054
CPI (1951−2001)	2	4	93	947	>1200	>1200
CPI (1987:2−2002:6)	1	1	3	8	21	240
CPI (1994:2−2002:6)	1	1	5	14	45	695

Notes: For each series, we report the time required for a percent of the effect of a unit shock to dissipate, t_a. t_a is calculated from the impulse response function of the ARFIMA model that has the minimum AIC. Time is measured in the frequency of the corresponding series, i.e., months for monthly series and years for annual series.

Table 6: GPH and GSP Estimates for Sectoral WPI Based Inflation Series

	GPH Estimates							*GSP Estimates*						
Code	*a* =0.50	*a* =0.55	*a* =0.60	*a* =0.65	*a* =0.70	*a* =0.75	*a* =0.80	*a* =0.50	*a* =0.55	*a* =0.60	*a* =0.65	*a* =0.70	*a* =0.75	*a* =0.80
E01	0.371	0.361	0.116	0.233	0.092	0.224	0.161	0.328	0.297	0.107	0.105	0.063	0.104	0.107
E02	-0.121	-0.035	-0.051	0.024	0.037	0.140	0.193	0.161	0.168	0.113	0.114	0.130	0.167	0.219
E03	0.249	0.401	0.230	0.136	0.131	0.206	0.273	0.172	0.238	0.199	0.129	0.170	0.233	0.312
E04	0.162	0.270	0.338	0.239	0.205	0.112	0.094	0.120	0.250	0.263	0.158	0.041	-0.005	0.011
E05	0.286	0.347	0.182	0.254	0.153	0.144	0.241	0.218	0.235	0.182	0.208	0.151	0.146	0.221
E06	0.275	0.341	0.279	0.259	0.110	0.224	0.172	0.385	0.434	0.290	0.260	0.156	0.197	0.193
E07	0.154	0.274	0.115	0.144	0.224	0.219	0.210	0.157	0.244	0.086	0.087	0.145	0.129	0.144
E08	0.036	-0.129	-0.362	-0.190	-0.265	-0.167	-0.149	-0.022	-0.099	-0.220	-0.189	-0.197	-0.124	-0.077
E09	0.061	0.070	0.131	0.079	0.038	-0.045	-0.024	0.165	0.149	0.136	0.097	0.041	-0.067	-0.056
E10	0.105	0.166	0.083	-0.060	-0.048	0.019	0.029	0.084	0.087	0.103	-0.027	-0.029	0.020	0.053
E11	-0.094	-0.349	-0.399	-0.424	-0.275	-0.241	-0.185	-0.190	-0.337	-0.376	-0.399	-0.342	-0.244	-0.140
E12	0.472	0.266	0.133	0.111	0.115	0.115	0.109	0.296	0.233	0.146	0.121	0.114	0.123	0.122
E13	0.021	0.237	-0.064	0.026	0.081	0.103	0.132	-0.069	-0.008	-0.139	-0.055	0.066	0.116	0.129
E14	-0.170	-0.102	0.083	-0.035	-0.061	-0.011	-0.034	0.060	0.105	0.161	0.029	0.001	0.004	0.001
E15	0.097	0.298	0.127	0.081	0.058	0.073	0.159	0.049	0.174	0.147	0.108	0.120	0.143	0.209
E16	0.015	0.077	0.074	0.013	0.057	0.165	0.158	0.173	0.203	0.192	0.088	0.098	0.156	0.172
E17	0.224	0.360	0.335	0.264	0.245	0.312	0.403	0.190	0.297	0.275	0.246	0.233	0.309	0.414
E18	0.421	0.207	0.154	0.150	0.090	0.152	0.147	0.258	0.129	0.140	0.130	0.101	0.102	0.115
E19	0.362	0.119	0.273	0.211	0.103	0.059	0.067	0.250	0.137	0.111	0.096	0.108	0.112	0.098
E20	-0.045	0.028	-0.035	-0.032	0.070	0.127	0.165	0.058	0.125	0.056	0.060	0.144	0.173	0.215
E21	-0.212	-0.138	-0.132	-0.193	-0.083	0.029	0.136	-0.017	-0.004	0.020	-0.053	0.001	0.076	0.179
E22	0.238	0.245	0.179	0.130	0.180	0.314	0.330	0.174	0.222	0.169	0.092	0.154	0.221	0.256
E23	0.396	0.492	0.392	0.310	0.285	0.317	0.464	0.298	0.421	0.321	0.260	0.254	0.291	0.384
E24	0.125	-0.012	-0.015	-0.013	0.055	0.135	0.210	0.220	0.057	0.049	0.054	0.070	0.136	0.165
E25	0.387	0.097	-0.005	0.147	-0.023	0.017	-0.013	0.216	-0.057	-0.066	0.016	-0.079	-0.088	-0.078
E26	0.357	0.466	0.304	0.151	0.060	-0.029	-0.127	0.155	0.382	0.229	0.101	-0.023	-0.085	-0.113
s.e	0.220	0.182	0.150	0.129	0.109	0.094	0.082	0.129	0.112	0.096	0.085	0.073	0.064	0.056

Notes: See notes to Table 1.

Table 7: Wavelet Based Estimates of *d* for Sectoral WPI Based Inflation Series

	$J = \log_2 T$						$J = 4$					
Code	Haar	D8	D16	MB8	MB16	LA8	Haar	D8	D16	MB8	MB16	LA8
E01	0.089	0.137	0.257	0.088	0.139	0.098	0.162	0.160	0.203	0.190	0.188	0.171
E02	0.249	0.285	0.248	0.269	0.246	0.250	0.234	0.244	0.226	0.259	0.241	0.247
E03	0.272	0.308	0.276	0.320	0.324	0.395	0.270	0.266	0.268	0.291	0.301	0.328
E04	-0.048	-0.013	-0.014	-0.063	-0.035	-0.021	-0.011	-0.009	-0.023	-0.009	-0.014	0.003
E05	0.172	0.250	0.265	0.191	0.208	0.158	0.197	0.238	0.227	0.230	0.227	0.205
E06	0.126	0.148	0.204	0.057	0.157	0.143	0.156	0.165	0.168	0.162	0.173	0.191
E07	0.111	0.128	0.173	0.099	0.131	0.140	0.145	0.148	0.159	0.151	0.156	0.160
E08	-0.131	-0.029	0.100	-0.047	-0.001	-0.045	-0.021	-0.016	0.057	0.009	0.021	-0.014
E09	-0.094	-0.075	-0.036	-0.122	-0.120	-0.115	-0.063	-0.020	-0.032	-0.024	-0.047	-0.075
E10	-0.003	-0.046	0.014	-0.101	-0.025	-0.122	0.021	0.016	0.027	0.019	0.028	0.039
E11	-0.049	-0.065	-0.019	-0.012	-0.024	-0.059	-0.037	-0.060	-0.047	0.002	-0.020	-0.037
E12	0.097	0.095	0.123	0.056	0.076	0.080	0.141	0.124	0.124	0.145	0.132	0.124
E13	0.131	0.197	0.161	0.130	0.144	0.143	0.126	0.165	0.140	0.140	0.146	0.160
E14	-0.026	0.071	0.016	0.027	0.009	-0.019	0.008	0.069	0.046	0.067	0.043	0.025
E15	0.189	0.166	0.172	0.195	0.212	0.232	0.198	0.168	0.195	0.197	0.204	0.218
E16	0.160	0.168	0.203	0.148	0.162	0.263	0.190	0.174	0.191	0.192	0.204	0.252
E17	0.369	0.372	0.367	0.405	0.406	0.401	0.333	0.314	0.323	0.349	0.346	0.348
E18	0.132	0.111	0.119	0.112	0.133	0.181	0.164	0.150	0.141	0.161	0.147	0.185
E19	0.093	0.043	0.080	0.060	0.079	0.077	0.135	0.097	0.097	0.112	0.113	0.093
E20	0.157	0.227	0.192	0.207	0.193	0.253	0.167	0.191	0.185	0.206	0.210	0.239
E21	0.106	0.109	0.105	0.167	0.144	0.145	0.126	0.106	0.119	0.159	0.155	0.139
E22	0.170	0.282	0.212	0.275	0.288	0.260	0.193	0.252	0.242	0.248	0.257	0.234
E23	0.405	0.370	0.364	0.405	0.410	0.430	0.352	0.319	0.327	0.355	0.350	0.365
E24	0.125	0.086	0.109	0.058	0.095	0.118	0.143	0.117	0.104	0.128	0.125	0.144
E25	-0.050	-0.074	-0.151	-0.101	-0.119	-0.083	-0.059	-0.092	-0.093	-0.073	-0.105	-0.110
E26	-0.254	-0.181	-0.167	-0.225	-0.219	-0.212	-0.202	-0.146	-0.206	-0.187	-0.193	-0.162

Notes: See notes to Table 2.

Table 8: Parameter Estimates and Model Selection Criteria of FGN and ARFIMA Models for Sectoral WPI Based Inflation Series

	AIC for FGN and ARFIMA Models					*Estimates for FGN and Best ARFIMA Models Selected by AIC*			
						FGN(*d*)		ARFIMA(0,*d*,0)	
Code	FGN(*d*)	ARFIMA(0,*d*,0)	ARFIMA(1,*d*,0)	ARFIMA(0,*d*,1)	ARFIMA(1,*d*,1)	*d*	s.e.	*d*	s.e.
E01	3.837	3.872	5.762	5.853	7.762	0.210	0.042	0.209	0.050
E02	3.744	3.782	5.701	5.711	7.701	0.260	0.042	0.285	0.050
E03	3.647	3.679	5.643	5.646	7.626	0.291	0.043	0.338	0.050
E04	4.015	3.999	5.993	5.995	6.000	-0.009	0.040	-0.017	0.050
E05	3.763	3.786	5.752	5.764	6.000	0.231	0.042	0.257	0.050
E06	3.899	3.897	5.897	5.897	7.869	0.148	0.042	0.172	0.050
E07	3.903	3.910	5.895	5.893	7.892	0.155	0.042	0.173	0.050
E08	3.993	3.997	5.845	5.860	7.835	0.088	0.041	0.038	0.050
E09	4.012	3.994	5.994	5.994	7.986	-0.026	0.039	-0.043	0.050
E10	4.013	4.000	6.000	6.000	7.981	0.018	0.040	0.009	0.050
E11	4.006	4.000	5.836	5.818	7.796	0.057	0.041	-0.011	0.050
E12	3.932	3.932	5.926	5.919	6.000	0.125	0.041	0.136	0.050
E13	3.924	3.937	5.885	5.877	7.861	0.154	0.042	0.163	0.050
E14	3.999	3.993	5.966	5.972	7.965	0.061	0.041	0.049	0.050
E15	3.868	3.878	5.865	5.860	7.855	0.177	0.042	0.202	0.050
E16	3.847	3.864	5.833	5.846	7.831	0.189	0.042	0.207	0.050
E17	3.464	3.495	5.469	5.459	7.449	0.353	0.043	0.421	0.050
E18	3.887	3.903	5.849	5.865	6.000	0.168	0.042	0.174	0.050
E19	3.959	3.956	5.951	5.952	6.000	0.105	0.041	0.113	0.050
E20	3.854	3.866	5.850	5.842	7.832	0.188	0.042	0.216	0.050
E21	3.933	3.941	5.921	5.900	7.890	0.139	0.041	0.151	0.050
E22	3.724	3.754	5.714	5.712	7.700	0.262	0.042	0.300	0.050
E23	3.430	3.469	5.426	5.434	7.410	0.366	0.043	0.427	0.050
E24	3.955	3.951	5.950	5.949	7.939	0.108	0.041	0.124	0.050
E25	4.002	3.981	5.981	5.981	7.968	-0.053	0.039	-0.080	0.050
E26	3.915	3.906	5.843	5.865	7.842	-0.136	0.037	-0.170	0.050

Notes: See notes to Table 3.

Table 9: Bootstrap Confidence Intervals of the Impulse Response Functions of the Best ARFIMA Models for Sectoral WPI Based Inflation Series

Code	*Pct.*	*k* =1	*k* =3	*k* =6	*k* =12	*k* =24	*k* =48	*k* =96	*k* =192	*k* =384	*k* =504	*k* =744	*k* =984	*k* =1200
E01	2.5	0.075	0.028	0.015	0.008	0.004	0.002	0.001	0.001	0.000	0.000	0.000	0.000	0.000
	97.5	0.293	0.145	0.090	0.056	0.034	0.021	0.013	0.008	0.005	0.004	0.003	0.003	0.002
E02	2.5	0.156	0.065	0.037	0.020	0.011	0.006	0.004	0.002	0.001	0.001	0.001	0.000	0.000
	97.5	0.371	0.201	0.133	0.087	0.056	0.037	0.024	0.015	0.010	0.008	0.007	0.005	0.005
E03	2.5	0.205	0.091	0.053	0.031	0.018	0.010	0.006	0.003	0.002	0.002	0.001	0.001	0.001
	97.5	0.425	0.245	0.168	0.114	0.077	0.052	0.035	0.023	0.016	0.013	0.011	0.009	0.008
E04	2.5	-0.152	-0.040	-0.018	-0.008	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.067	0.025	0.013	0.007	0.004	0.002	0.001	0.001	0.000	0.000	0.000	0.000	0.000
E05	2.5	0.126	0.050	0.028	0.015	0.008	0.005	0.002	0.001	0.001	0.001	0.000	0.000	0.000
	97.5	0.340	0.177	0.114	0.073	0.046	0.029	0.019	0.012	0.007	0.006	0.005	0.004	0.004
E06	2.5	0.037	0.013	0.007	0.003	0.002	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.256	0.121	0.073	0.044	0.026	0.016	0.009	0.006	0.003	0.003	0.002	0.002	0.001
E07	2.5	0.044	0.015	0.008	0.004	0.002	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.258	0.122	0.074	0.045	0.027	0.016	0.010	0.006	0.003	0.003	0.002	0.002	0.001
E08	2.5	-0.095	-0.027	-0.013	-0.006	-0.003	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.121	0.048	0.026	0.014	0.008	0.004	0.002	0.001	0.001	0.001	0.000	0.000	0.000
E09	2.5	-0.177	-0.044	-0.019	-0.008	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.042	0.015	0.008	0.004	0.002	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000
E10	2.5	-0.123	-0.034	-0.015	-0.007	-0.003	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.098	0.038	0.020	0.011	0.006	0.003	0.002	0.001	0.000	0.000	0.000	0.000	0.000
E11	2.5	-0.146	-0.039	-0.017	-0.008	-0.003	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.074	0.027	0.014	0.008	0.004	0.002	0.001	0.001	0.000	0.000	0.000	0.000	0.000
E12	2.5	0.004	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.220	0.099	0.059	0.034	0.020	0.012	0.007	0.004	0.002	0.002	0.001	0.001	0.001
E13	2.5	0.030	0.011	0.005	0.003	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.250	0.117	0.071	0.042	0.025	0.015	0.009	0.005	0.003	0.003	0.002	0.002	0.001
E14	2.5	-0.086	-0.025	-0.012	-0.005	-0.003	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.132	0.053	0.029	0.016	0.009	0.005	0.003	0.001	0.001	0.001	0.000	0.000	0.000
E15	2.5	0.069	0.026	0.013	0.007	0.004	0.002	0.001	0.001	0.000	0.000	0.000	0.000	0.000
	97.5	0.284	0.139	0.086	0.053	0.032	0.020	0.012	0.007	0.004	0.004	0.003	0.002	0.002
E16	2.5	0.071	0.026	0.014	0.007	0.004	0.002	0.001	0.001	0.000	0.000	0.000	0.000	0.000
	97.5	0.292	0.144	0.090	0.055	0.034	0.021	0.013	0.008	0.005	0.004	0.003	0.002	0.002
E17	2.5	0.287	0.141	0.088	0.054	0.033	0.020	0.012	0.008	0.005	0.004	0.003	0.002	0.002
	97.5	0.513	0.325	0.237	0.171	0.122	0.088	0.063	0.045	0.032	0.028	0.023	0.020	0.018
E18	2.5	0.040	0.014	0.007	0.004	0.002	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.258	0.122	0.074	0.045	0.027	0.016	0.010	0.006	0.003	0.003	0.002	0.002	0.001
E19	2.5	-0.017	-0.006	-0.003	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.195	0.085	0.050	0.029	0.016	0.009	0.005	0.003	0.002	0.001	0.001	0.001	0.001
E20	2.5	0.079	0.029	0.016	0.008	0.004	0.002	0.001	0.001	0.000	0.000	0.000	0.000	0.000
	97.5	0.301	0.150	0.094	0.058	0.036	0.022	0.014	0.008	0.005	0.004	0.003	0.003	0.002
E21	2.5	0.015	0.005	0.002	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.237	0.109	0.065	0.039	0.023	0.014	0.008	0.005	0.003	0.002	0.002	0.001	0.001
E22	2.5	0.169	0.071	0.041	0.023	0.013	0.007	0.004	0.002	0.001	0.001	0.001	0.001	0.001
	97.5	0.389	0.215	0.144	0.095	0.063	0.041	0.027	0.018	0.012	0.010	0.008	0.007	0.006
E23	2.5	0.300	0.150	0.094	0.058	0.036	0.022	0.014	0.008	0.005	0.004	0.003	0.003	0.002
	97.5	0.518	0.330	0.241	0.175	0.126	0.090	0.065	0.046	0.033	0.029	0.024	0.021	0.019
E24	2.5	-0.009	-0.003	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.205	0.091	0.053	0.031	0.018	0.010	0.006	0.003	0.002	0.002	0.001	0.001	0.001
E25	2.5	-0.212	-0.050	-0.021	-0.009	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.003	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
E26	2.5	-0.303	-0.060	-0.023	-0.009	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	-0.086	-0.025	-0.012	-0.006	-0.003	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000

Notes: See notes to Table 4.

Table 10: Estimates of t_a for Sectoral WPI Based Inflation Seri

Code	a =0.30	a =0.50	a =0.80	a =0.90	a =0.95	a =0.99
E01	1	1	2	3	7	53
E02	1	1	2	5	14	126
E03	1	1	3	8	22	241
E04	1	1	1	1	1	2
E05	1	1	2	4	11	91
E06	1	1	1	3	5	34
E07	1	1	1	3	5	35
E08	1	1	1	1	1	5
E09	1	1	1	1	1	4
E10	1	1	1	1	1	1
E11	1	1	1	1	1	2
E12	1	1	1	2	4	23
E13	1	1	1	2	5	31
E14	1	1	1	1	1	6
E15	1	1	2	3	7	48
E16	1	1	2	3	7	52
E17	1	1	5	15	49	783
E18	1	1	1	3	5	35
E19	1	1	1	2	3	17
E20	1	1	2	3	8	57
E21	1	1	1	2	4	27
E22	1	1	2	6	15	150
E23	1	1	5	16	52	867
E24	1	1	1	2	3	19
E25	1	1	1	1	2	7
E26	1	1	1	2	3	11

Notes: See notes to Table 5.

Table 11: GPH and GSP Estimates of *d* for Sectoral CPI Based Inflation Series (1987-2002)

Code	*a* =0.50	*a* =0.55	*a* =0.60	*a* =0.65	*a* =0.70	*a* =0.75	*a* =0.80
				GPH Estimates			
A01	0.138	0.326	0.177	0.150	0.098	0.155	0.194
A02	-0.061	-0.103	-0.026	-0.087	-0.129	-0.034	0.023
A03	0.059	0.047	0.198	0.200	0.187	0.302	0.339
A04	0.455	0.229	0.260	0.226	0.172	0.083	0.180
A05	-0.009	0.000	-0.134	-0.101	-0.049	-0.020	0.015
A06	0.045	-0.202	-0.160	-0.140	-0.048	-0.038	-0.026
A07	0.486	0.426	0.392	0.296	0.290	0.243	0.246
A08	0.466	0.323	0.130	0.135	0.095	0.166	0.266
A09	0.398	0.427	0.254	0.246	0.168	0.176	0.094
s.e.	0.243	0.202	0.171	0.145	0.124	0.107	0.094
				GSP Estimates			
A01	0.160	0.218	0.043	0.033	0.034	0.113	0.181
A02	0.007	-0.018	0.035	-0.044	-0.082	-0.010	0.063
A03	0.160	0.158	0.186	0.205	0.199	0.257	0.288
A04	0.295	0.180	0.168	0.191	0.181	0.128	0.180
A05	-0.038	-0.037	-0.129	-0.108	-0.048	-0.004	0.067
A06	0.228	0.050	0.037	0.068	0.087	0.088	0.059
A07	0.519	0.500	0.440	0.394	0.344	0.309	0.297
A08	0.317	0.282	0.121	0.144	0.113	0.164	0.212
A09	0.286	0.348	0.165	0.137	0.096	0.108	0.064
s.e.	0.139	0.121	0.107	0.093	0.081	0.071	0.062

Notes: See notes to Table 1.

Table 12: Wavelet Based Estimates of *d* for Sectoral CPI Based Inflation Series (1987-2002)

	$J = \log_2 T$					
Code	Haar	D8	D16	MB8	MB16	LA8
A01	0.083	0.110	0.131	0.050	0.070	0.024
A02	-0.065	0.063	0.066	-0.015	0.014	-0.047
A03	0.226	0.296	0.285	0.249	0.253	0.213
A04	0.054	0.083	0.115	0.043	0.040	0.018
A05	0.028	0.022	0.042	0.028	0.049	0.047
A06	-0.017	-0.001	0.042	-0.064	-0.065	-0.068
A07	0.242	0.146	0.315	0.247	0.263	0.229
A08	0.234	0.122	0.190	0.076	0.153	0.146
A09	-0.054	-0.040	0.013	-0.192	-0.077	-0.170
	$J = 4$					
	Haar	D8	D16	MB8	MB16	LA8
A01	0.094	0.124	0.123	0.133	0.134	0.115
A02	-0.054	0.076	0.061	0.068	0.059	0.022
A03	0.214	0.272	0.243	0.265	0.255	0.241
A04	0.079	0.116	0.098	0.108	0.104	0.097
A05	0.027	0.075	0.023	0.081	0.068	0.093
A06	-0.002	0.057	0.011	0.027	0.010	0.026
A07	0.257	0.290	0.267	0.288	0.280	0.275
A08	0.237	0.190	0.177	0.187	0.208	0.230
A09	-0.024	0.048	-0.011	0.006	0.018	0.032

Notes: See notes to Table 2.

Table 13: Parameter Estimates and Model Selection Criteria of FGN and ARFIMA Models for Sectoral CPI Inflation Series (1987-2002)

	AIC for FGN and ARFIMA Models				
Code	FGN(*d*)	ARFIMA(0,*d*,0)	ARFIMA(1,*d*,0)	ARFIMA(0,*d*,1)	ARFIMA(1,*d*,1)
A01	3.932	3.937	5.921	5.912	7.908
A02	3.997	3.992	5.955	5.952	7.931
A03	3.701	3.726	5.699	5.683	7.673
A04	3.959	3.947	5.944	5.944	7.942
A05	3.991	3.989	5.943	5.929	7.928
A06	4.011	3.995	5.994	5.994	7.994
A07	3.564	3.555	5.548	5.546	7.537
A08	3.822	3.841	5.809	5.810	7.808
A09	4.017	3.997	5.976	5.979	6.000

	Estimates for FGN and Best ARFIMA Models Selected by AIC			
	FGN(*d*)		ARFIMA(0,*d*,0)	
	d	s.e.	*d*	s.e.
A01	0.139	0.048	0.148	0.058
A02	0.076	0.047	0.058	0.058
A03	0.268	0.049	0.308	0.058
A04	0.103	0.047	0.120	0.058
A05	0.087	0.047	0.068	0.058
A06	0.040	0.046	0.038	0.058
A07	0.248	0.049	0.292	0.058
A08	0.205	0.048	0.223	0.058
A09	0.023	0.046	0.025	0.058

Notes: See notes to Table 3.

Table 14: Bootstrap Confidence Intervals of the Impulse Response Functions of the Best ARFIMA Models for Sectoral CPI Based Inflation Series (1987-2002)

Code	*Pct.*	$k=1$	$k=3$	$k=6$	$k=12$	$k=24$	$k=48$	$k=96$	$k=192$	$k=384$	$k=504$	$k=744$	$k=984$	$k=1200$
A01	2.5	-0.016	-0.005	-0.003	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.246	0.115	0.069	0.041	0.025	0.015	0.009	0.005	0.003	0.002	0.002	0.002	0.001
A02	2.5	-0.114	-0.032	-0.015	-0.007	-0.003	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.153	0.063	0.036	0.020	0.011	0.006	0.003	0.002	0.001	0.001	0.001	0.000	0.000
A03	2.5	0.154	0.064	0.036	0.020	0.011	0.006	0.003	0.002	0.001	0.001	0.001	0.000	0.000
	97.5	0.406	0.229	0.155	0.104	0.069	0.046	0.030	0.020	0.013	0.011	0.009	0.008	0.007
A04	2.5	-0.045	-0.014	-0.007	-0.003	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.214	0.096	0.057	0.033	0.019	0.011	0.006	0.004	0.002	0.002	0.001	0.001	0.001
A05	2.5	-0.093	-0.027	-0.012	-0.006	-0.003	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.161	0.067	0.038	0.021	0.012	0.007	0.004	0.002	0.001	0.001	0.001	0.001	0.000
A06	2.5	-0.123	-0.034	-0.015	-0.007	-0.003	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.129	0.052	0.029	0.016	0.009	0.005	0.003	0.001	0.001	0.001	0.000	0.000	0.000
A07	2.5	0.135	0.054	0.030	0.017	0.009	0.005	0.003	0.002	0.001	0.001	0.000	0.000	0.000
	97.5	0.390	0.216	0.144	0.095	0.063	0.041	0.027	0.018	0.012	0.010	0.008	0.007	0.006
A08	2.5	0.063	0.023	0.012	0.006	0.003	0.002	0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.320	0.163	0.104	0.065	0.041	0.026	0.016	0.010	0.006	0.005	0.004	0.003	0.003
A09	2.5	-0.137	-0.037	-0.016	-0.007	-0.003	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.123	0.049	0.027	0.015	0.008	0.004	0.002	0.001	0.001	0.001	0.000	0.000	0.000

Notes: See notes to Table 4.

Table 15: Estimates of t_a for Sectoral CPI Based Inflation Series (1987-2002)

Code	a =0.30	a =0.50	a =0.80	a =0.90	a =0.95	a =0.99
A01	1	1	1	2	4	26
A02	1	1	1	1	2	7
A03	1	1	3	6	17	166
A04	1	1	1	2	3	18
A05	1	1	1	1	2	9
A06	1	1	1	1	1	5
A07	1	1	2	6	14	137
A08	1	1	2	4	8	62
A09	1	1	1	1	1	3

Notes: See notes to Table 5.

Table 16: GPH and GSP Estimates for Sectoral CPI Based Inflation Series (1994-2002)

	GPH Estimates							*GSP Estimates*						
Code	*a* =0.50	*a* =0.55	*a* =0.60	*a* =0.65	*a* =0.70	*a* =0.75	*a* =0.80	*a* =0.50	*a* =0.55	*a* =0.60	*a* =0.65	*a* =0.70	*a* =0.75	*a* =0.80
T01	0.265	0.054	0.059	0.195	0.342	0.493	0.503	0.184	-0.034	-0.039	0.077	0.232	0.427	0.356
T02	0.637	0.461	0.373	0.356	0.588	0.504	0.450	0.449	0.378	0.349	0.337	0.357	0.381	0.396
T03	0.336	0.241	0.661	0.604	0.499	0.433	0.385	0.344	0.297	0.427	0.389	0.381	0.399	0.409
T04	-0.015	-0.086	0.040	0.293	0.341	0.360	0.434	-0.062	-0.092	0.016	0.246	0.376	0.397	0.493
T05	0.036	0.059	0.187	0.288	0.271	0.255	0.147	0.152	0.177	0.257	0.146	0.189	0.160	0.108
T06	-0.200	-0.202	-0.138	0.029	0.075	0.093	0.142	-0.103	-0.093	-0.068	0.039	0.060	0.092	0.159
T07	0.252	0.360	0.245	0.304	0.196	0.174	0.289	0.163	0.179	0.218	0.215	0.193	0.211	0.318
T08	-0.041	-0.011	-0.149	-0.109	-0.077	-0.206	-0.252	-0.077	-0.048	-0.119	-0.179	-0.178	-0.223	-0.216
T09	0.339	0.202	0.139	0.228	0.260	0.326	0.292	0.349	0.250	0.226	0.244	0.288	0.243	0.221
T10	-0.193	-0.200	-0.131	0.206	0.199	0.203	0.190	-0.213	-0.199	-0.145	0.017	0.053	0.079	0.112
T11	0.176	-0.022	0.088	0.227	0.326	0.437	0.514	0.154	-0.055	-0.036	0.086	0.219	0.365	0.357
T12	-0.221	-0.166	-0.133	0.029	0.068	0.040	0.030	-0.155	-0.190	-0.122	-0.033	0.069	0.070	0.073
T13	0.558	0.399	0.343	0.344	0.515	0.453	0.456	0.454	0.366	0.356	0.343	0.367	0.380	0.413
T14	0.424	0.412	0.306	0.328	0.427	0.461	0.384	0.411	0.406	0.310	0.266	0.284	0.314	0.264
T15	1.052	0.894	0.743	0.618	0.464	0.372	0.428	0.961	0.761	0.680	0.569	0.425	0.370	0.382
T16	-0.031	-0.088	0.097	0.294	0.249	0.252	0.203	0.008	0.003	0.130	0.358	0.340	0.338	0.268
T17	0.023	0.062	0.026	-0.056	-0.175	-0.242	-0.096	-0.023	0.068	0.080	0.021	-0.087	-0.137	-0.053
T18	-0.246	-0.273	-0.111	0.075	0.052	0.086	0.086	-0.310	-0.247	-0.066	0.091	0.086	0.116	0.147
T19	0.176	0.042	0.231	0.273	0.253	0.363	0.343	0.146	0.025	0.142	0.170	0.187	0.209	0.182
T20	-0.010	-0.037	0.134	0.318	0.442	0.443	0.522	-0.007	0.006	0.138	0.297	0.416	0.411	0.524
T21	0.089	0.021	0.001	0.301	0.250	0.140	0.151	-0.064	-0.041	-0.020	0.222	0.230	0.141	0.153
T22	-0.031	-0.136	0.123	0.271	0.355	0.408	0.488	-0.084	-0.180	-0.047	0.083	0.243	0.334	0.482
T23	-0.485	-0.512	-0.342	-0.098	0.011	0.080	0.235	-0.431	-0.404	-0.235	0.010	0.197	0.291	0.445
T24	-0.152	-0.242	-0.178	-0.053	0.139	0.191	0.273	-0.235	-0.276	-0.203	-0.041	0.188	0.312	0.393
T25	-0.312	-0.243	-0.046	0.128	0.206	0.094	-0.009	-0.337	-0.234	-0.065	0.130	0.074	-0.031	-0.142
T26	0.540	0.355	0.277	0.221	0.188	0.225	0.173	0.449	0.396	0.381	0.093	0.142	0.189	0.161
T27	0.372	0.297	0.233	0.118	0.227	0.175	0.142	0.344	0.303	0.262	0.094	0.143	0.144	0.111
T28	0.486	0.251	0.009	0.131	0.153	0.042	0.048	0.501	0.259	0.095	0.115	0.114	0.020	0.036
T29	-0.315	-0.280	0.020	0.126	0.094	0.126	0.090	-0.329	-0.246	-0.153	-0.020	0.016	0.085	0.078
T30	-0.496	-0.405	-0.384	-0.278	-0.155	-0.155	-0.033	-0.181	-0.155	-0.132	-0.102	-0.033	-0.010	0.086
T31	-0.062	-0.127	-0.177	0.121	0.044	0.121	0.345	-0.108	-0.131	-0.147	0.015	-0.033	0.076	0.262
T32	0.200	0.316	0.229	0.202	0.210	0.128	0.168	0.205	0.330	0.217	0.190	0.124	0.095	0.120
T33	0.412	0.257	0.291	0.361	0.331	0.295	0.340	0.294	0.228	0.242	0.214	0.286	0.220	0.269
T34	-0.137	-0.113	-0.242	-0.268	-0.239	-0.344	-0.382	-0.146	-0.131	-0.177	-0.251	-0.241	-0.289	-0.292
T35	-0.023	0.023	-0.065	-0.044	-0.081	-0.063	-0.049	0.069	0.117	0.052	0.010	-0.030	-0.019	-0.016
T36	0.342	0.190	0.153	0.208	0.216	0.262	0.274	0.325	0.226	0.228	0.232	0.259	0.212	0.207
T37	0.278	0.184	0.040	0.215	0.209	0.198	0.160	0.255	0.192	0.074	0.099	0.132	0.062	0.077
T38	-0.176	-0.184	-0.039	0.090	0.286	0.354	0.489	-0.140	-0.125	-0.042	0.069	0.252	0.391	0.596
T39	-0.234	-0.239	-0.045	0.179	0.097	0.060	0.084	-0.288	-0.215	-0.016	0.096	0.132	0.114	0.196
T40	0.554	0.291	0.128	-0.143	-0.075	-0.141	-0.235	0.395	0.138	-0.019	-0.141	-0.073	-0.104	-0.160
s.e.	0.294	0.258	0.222	0.185	0.162	0.144	0.127	0.158	0.144	0.129	0.112	0.1	0.09	0.079

Notes: See notes to Table 1.

Table 17: Wavelet Based Estimates of *d* for Sectoral CPI Based Inflation Series (1994-2002)

	$J=\log_2 T$						$J=4$					
Code	Haar	D8	D16	MB8	MB16	LA8	Haar	D8	D16	MB8	MB16	LA8
T01	0.380	0.255	0.354	0.378	0.385	0.394	0.320	0.272	0.282	0.331	0.340	0.341
T02	0.301	0.256	0.332	0.192	0.295	0.288	0.308	0.308	0.300	0.303	0.316	0.325
T03	0.233	0.361	0.281	0.256	0.181	0.166	0.275	0.322	0.286	0.293	0.301	0.308
T04	0.425	0.329	0.352	0.405	0.329	0.403	0.341	0.301	0.305	0.338	0.323	0.356
T05	-0.006	-0.031	0.097	0.066	-0.157	-0.054	0.073	0.071	0.079	0.102	0.085	0.096
T06	0.159	0.092	0.184	0.115	0.123	0.215	0.146	0.114	0.134	0.166	0.180	0.240
T07	0.397	0.177	0.373	0.317	0.287	0.342	0.327	0.225	0.296	0.293	0.305	0.315
T08	-0.370	-0.343	-0.237	-0.291	-0.392	-0.494	-0.344	-0.247	-0.263	-0.272	-0.262	-0.296
T09	0.183	0.157	0.272	0.212	0.104	0.213	0.262	0.217	0.234	0.252	0.250	0.303
T10	0.036	0.032	0.096	0.094	0.039	0.097	0.052	0.074	0.074	0.127	0.129	0.143
T11	0.357	0.233	0.322	0.365	0.371	0.405	0.307	0.262	0.263	0.325	0.329	0.346
T12	0.080	0.006	0.096	0.062	0.010	0.123	0.079	0.067	0.058	0.079	0.117	0.165
T13	0.278	0.250	0.325	0.186	0.281	0.252	0.300	0.304	0.289	0.295	0.305	0.313
T14	0.292	0.184	0.273	0.111	0.245	0.284	0.282	0.255	0.273	0.262	0.289	0.299
T15	0.226	0.338	0.281	0.292	0.222	0.141	0.298	0.323	0.304	0.297	0.305	0.298
T16	0.191	0.194	0.263	0.201	0.136	0.220	0.186	0.203	0.203	0.229	0.227	0.245
T17	-0.019	-0.110	-0.065	-0.302	-0.252	-0.276	-0.021	-0.131	-0.064	-0.113	-0.118	-0.105
T18	0.116	0.134	0.118	0.131	0.119	0.249	0.107	0.148	0.111	0.134	0.157	0.205
T19	0.173	0.059	0.153	0.099	0.032	0.034	0.185	0.137	0.134	0.157	0.157	0.158
T20	0.447	0.352	0.373	0.430	0.384	0.431	0.357	0.311	0.331	0.354	0.349	0.377
T21	0.110	0.033	0.036	0.012	-0.021	0.006	0.116	0.071	0.061	0.072	0.073	0.119
T22	0.428	0.349	0.404	0.447	0.436	0.463	0.330	0.298	0.331	0.356	0.353	0.386
T23	0.441	0.311	0.419	0.437	0.344	0.473	0.329	0.278	0.319	0.343	0.336	0.386
T24	0.454	0.275	0.354	0.418	0.362	0.456	0.355	0.258	0.301	0.333	0.332	0.371
T25	-0.059	-0.197	-0.070	-0.129	-0.340	-0.181	-0.044	-0.112	-0.084	-0.058	-0.068	-0.060
T26	-0.011	0.021	0.116	0.104	-0.118	-0.082	0.094	0.118	0.110	0.131	0.116	0.102
T27	-0.092	-0.082	0.026	0.003	-0.155	-0.111	0.007	-0.001	0.021	0.043	0.034	0.039
T28	0.089	-0.045	0.062	-0.201	-0.037	-0.009	0.098	0.061	0.065	0.049	0.055	0.069
T29	0.038	-0.001	0.078	0.029	0.047	0.086	0.038	0.019	0.037	0.089	0.096	0.143
T30	0.075	0.032	0.120	0.093	-0.021	0.213	0.079	0.072	0.083	0.115	0.124	0.215
T31	0.411	0.133	0.259	0.313	0.281	0.356	0.308	0.163	0.232	0.258	0.280	0.300
T32	-0.031	0.109	0.110	-0.021	-0.226	-0.110	0.064	0.117	0.116	0.087	0.086	0.098
T33	0.221	0.198	0.335	0.215	0.218	0.265	0.235	0.239	0.258	0.233	0.246	0.263
T34	-0.456	-0.496	-0.307	-0.363	-0.500	-0.500	-0.457	-0.364	-0.370	-0.386	-0.384	-0.421
T35	-0.161	-0.056	-0.119	-0.165	-0.134	-0.175	-0.125	-0.018	-0.062	-0.067	-0.043	-0.051
T36	0.154	0.143	0.254	0.198	0.089	0.207	0.242	0.204	0.220	0.236	0.236	0.293
T37	0.044	-0.024	0.107	-0.042	-0.099	-0.148	0.112	0.070	0.078	0.072	0.090	0.109
T38	0.446	0.416	0.466	0.468	0.433	0.477	0.353	0.347	0.373	0.388	0.378	0.410
T39	0.031	0.205	0.113	0.071	0.060	0.112	0.028	0.186	0.094	0.099	0.129	0.122
T40	-0.192	-0.213	-0.290	-0.218	-0.266	-0.231	-0.195	-0.131	-0.158	-0.139	-0.166	-0.187

Notes: See notes to Table 2.

Table 18: Parameter Estimates and Model Selection Criteria of FGN and ARFIMA Models for Sectoral CPI Based Inflation Series (1994-2002)

	AIC for FGN and ARFIMA Models					*Estimates for FGN and Best ARFIMA Models Selected by AI(*			
						FGN(*d*)		ARFIMA(0,*d*,0)	
Code	FGN(*d*)	ARFIMA(0,*d*,0)	ARFIMA(1,*d*,0)	ARFIMA(0,*d*,1)	ARFIMA(1,*d*,1)	*d*	s.e.	*d*	s.e.
T01	3.612	3.678	5.580	5.519	7.512	0.362	0.067	0.419	0.078
T02	3.563	3.570	5.570	5.538	7.538	0.291	0.066	0.344	0.078
T03	3.641	3.641	5.641	5.594	7.586	0.274	0.066	0.334	0.078
T04	3.621	3.663	5.628	5.521	7.519	0.342	0.067	0.413	0.078
T05	4.019	3.989	5.978	5.973	7.966	0.055	0.063	0.056	0.078
T06	3.938	3.950	5.874	5.834	7.817	0.169	0.065	0.154	0.078
T07	3.693	3.744	5.652	5.644	7.604	0.308	0.066	0.332	0.078
T08	3.901	3.833	5.831	5.831	7.832	-0.182	0.056	-0.262	0.078
T09	3.748	3.766	5.741	5.749	6.000	0.242	0.066	0.263	0.078
T10	4.002	3.988	5.956	5.880	7.879	0.096	0.064	0.073	0.078
T11	3.663	3.721	5.640	5.575	7.573	0.333	0.067	0.378	0.078
T12	4.005	3.990	5.957	5.892	7.890	0.092	0.064	0.067	0.078
T13	3.589	3.590	5.589	5.558	7.556	0.279	0.066	0.332	0.078
T14	3.683	3.693	5.690	5.661	6.000	0.255	0.066	0.290	0.078
T15	3.574	3.547	5.478	5.525	7.444	0.254	0.066	0.309	0.078
T16	3.855	3.858	5.855	5.760	7.755	0.204	0.065	0.237	0.078
T17	4.018	3.964	5.964	5.964	7.963	-0.067	0.060	-0.117	0.078
T18	3.946	3.952	5.900	5.800	7.793	0.160	0.065	0.153	0.078
T19	3.967	3.953	5.952	5.897	7.895	0.121	0.064	0.127	0.078
T20	3.528	3.569	5.539	5.447	7.446	0.371	0.067	0.455	0.078
T21	4.022	3.994	5.994	5.916	7.904	0.055	0.063	0.046	0.078
T22	3.534	3.617	5.482	5.428	7.378	0.412	0.067	0.493	0.078
T23	3.593	3.678	5.510	5.463	7.379	0.402	0.067	0.472	0.078
T24	3.640	3.717	5.584	5.506	7.461	0.376	0.067	0.436	0.078
T25	4.001	3.944	5.942	5.865	7.845	-0.090	0.059	-0.155	0.078
T26	3.975	3.952	5.947	5.947	7.927	0.100	0.064	0.108	0.078
T27	4.036	4.000	5.937	5.915	7.852	0.007	0.062	0.005	0.078
T28	4.009	3.989	5.945	5.975	6.000	0.079	0.064	0.058	0.078
T29	4.017	3.996	5.975	5.866	7.866	0.072	0.063	0.045	0.078
T30	3.972	3.981	5.833	5.840	7.792	0.146	0.065	0.101	0.078
T31	3.789	3.865	5.619	5.655	7.553	0.309	0.066	0.291	0.078
T32	3.994	3.974	5.973	5.973	7.972	0.092	0.064	0.090	0.078
T33	3.753	3.780	5.742	5.712	7.697	0.260	0.066	0.285	0.078
T34	3.776	3.711	5.694	5.700	6.000	-0.253	0.052	-0.353	0.078
T35	4.028	3.981	5.980	5.980	7.920	-0.043	0.061	-0.083	0.078
T36	3.779	3.798	5.758	5.776	7.736	0.233	0.066	0.247	0.078
T37	4.005	3.983	5.981	5.981	7.979	0.080	0.064	0.071	0.078
T38	3.336	3.429	5.218	5.222	7.123	0.470	0.068	0.683	0.078
T39	3.933	3.941	5.894	5.800	7.797	0.170	0.065	0.169	0.078
T40	3.983	3.924	5.923	5.886	7.883	-0.111	0.059	-0.171	0.078

Notes: See notes to Table 3.

Table 19: Bootstrap Confidence Intervals of the Impulse Response Functions of the Best ARFIMA Models for Sectoral CPI Based Inflation Series (1994-2002)

Code	*Pct.*	*k* =1	*k* =3	*k* =6	*k* =12	*k* =24	*k* =48	*k* =96	*k* =192	*k* =384	*k* =504	*k* =744	*k* =984	*k* =1200
T01	2.5	0.190	0.083	0.048	0.027	0.016	0.009	0.005	0.003	0.002	0.001	0.001	0.001	0.001
	97.5	0.559	0.371	0.279	0.208	0.154	0.113	0.084	0.062	0.045	0.040	0.034	0.030	0.027
T02	2.5	0.105	0.041	0.022	0.012	0.006	0.003	0.002	0.001	0.001	0.000	0.000	0.000	0.000
	97.5	0.473	0.287	0.203	0.142	0.099	0.069	0.048	0.033	0.023	0.020	0.016	0.014	0.013
T03	2.5	0.090	0.034	0.018	0.010	0.005	0.003	0.001	0.001	0.000	0.000	0.000	0.000	0.000
	97.5	0.470	0.284	0.201	0.140	0.098	0.068	0.047	0.033	0.023	0.020	0.016	0.014	0.012
T04	2.5	0.175	0.074	0.042	0.024	0.014	0.008	0.004	0.002	0.001	0.001	0.001	0.001	0.001
	97.5	0.551	0.364	0.272	0.201	0.148	0.109	0.080	0.059	0.043	0.038	0.032	0.028	0.026
T05	2.5	-0.194	-0.047	-0.020	-0.009	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.180	0.077	0.044	0.025	0.014	0.008	0.005	0.003	0.001	0.001	0.001	0.001	0.001
T06	2.5	-0.091	-0.026	-0.012	-0.006	-0.003	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.280	0.136	0.084	0.051	0.031	0.019	0.012	0.007	0.004	0.004	0.003	0.002	0.002
T07	2.5	0.094	0.036	0.019	0.010	0.006	0.003	0.002	0.001	0.000	0.000	0.000	0.000	0.000
	97.5	0.464	0.279	0.196	0.137	0.095	0.065	0.045	0.031	0.022	0.019	0.015	0.013	0.012
T08	2.5	-0.508	-0.064	-0.023	-0.009	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	-0.129	-0.035	-0.016	-0.006	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
T09	2.5	0.015	0.005	0.003	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.395	0.220	0.147	0.098	0.065	0.043	0.028	0.018	0.012	0.010	0.008	0.007	0.006
T10	2.5	-0.175	-0.044	-0.019	-0.008	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.204	0.090	0.053	0.031	0.018	0.010	0.006	0.003	0.002	0.002	0.001	0.001	0.001
T11	2.5	0.140	0.057	0.032	0.018	0.010	0.005	0.003	0.002	0.001	0.001	0.001	0.000	0.000
	97.5	0.515	0.328	0.239	0.173	0.124	0.089	0.064	0.045	0.033	0.028	0.024	0.021	0.019
T12	2.5	-0.177	-0.044	-0.019	-0.008	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.195	0.085	0.049	0.028	0.016	0.009	0.005	0.003	0.002	0.001	0.001	0.001	0.001
T13	2.5	0.084	0.031	0.017	0.009	0.005	0.003	0.001	0.001	0.000	0.000	0.000	0.000	0.000
	97.5	0.466	0.280	0.198	0.138	0.096	0.066	0.046	0.032	0.022	0.019	0.015	0.013	0.012
T14	2.5	0.040	0.014	0.007	0.004	0.002	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.422	0.242	0.166	0.112	0.076	0.051	0.034	0.023	0.015	0.013	0.010	0.009	0.008
T15	2.5	0.064	0.024	0.012	0.006	0.003	0.002	0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.440	0.258	0.178	0.122	0.083	0.057	0.038	0.026	0.018	0.015	0.012	0.010	0.009
T16	2.5	-0.009	-0.003	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.361	0.193	0.127	0.082	0.053	0.034	0.022	0.014	0.009	0.008	0.006	0.005	0.004
T17	2.5	-0.359	-0.063	-0.023	-0.009	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.008	0.003	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
T18	2.5	-0.094	-0.027	-0.013	-0.006	-0.003	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.281	0.137	0.085	0.052	0.032	0.019	0.012	0.007	0.004	0.004	0.003	0.002	0.002
T19	2.5	-0.111	-0.031	-0.014	-0.007	-0.003	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.253	0.119	0.072	0.043	0.026	0.016	0.009	0.006	0.003	0.003	0.002	0.002	0.001
T20	2.5	0.216	0.097	0.057	0.034	0.020	0.011	0.007	0.004	0.002	0.002	0.001	0.001	0.001
	97.5	0.592	0.407	0.313	0.238	0.181	0.136	0.103	0.078	0.059	0.052	0.045	0.040	0.037
T21	2.5	-0.192	-0.047	-0.020	-0.009	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.173	0.073	0.042	0.024	0.013	0.008	0.004	0.002	0.001	0.001	0.001	0.001	0.001
T22	2.5	0.252	0.119	0.072	0.043	0.026	0.015	0.009	0.005	0.003	0.003	0.002	0.002	0.001
	97.5	0.635	0.456	0.361	0.283	0.221	0.172	0.133	0.104	0.081	0.073	0.063	0.057	0.053
T23	2.5	0.236	0.109	0.065	0.039	0.023	0.013	0.008	0.005	0.003	0.002	0.002	0.001	0.001
	97.5	0.609	0.426	0.331	0.255	0.196	0.150	0.114	0.087	0.066	0.060	0.051	0.046	0.043
T24	2.5	0.196	0.086	0.050	0.029	0.016	0.009	0.005	0.003	0.002	0.001	0.001	0.001	0.001
	97.5	0.570	0.383	0.290	0.218	0.162	0.121	0.090	0.067	0.050	0.044	0.037	0.033	0.030
T25	2.5	-0.394	-0.064	-0.023	-0.009	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	-0.026	-0.008	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
T26	2.5	-0.139	-0.037	-0.017	-0.007	-0.003	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.229	0.105	0.062	0.037	0.022	0.013	0.007	0.004	0.003	0.002	0.002	0.001	0.001

T27	2.5	-0.238	-0.053	-0.022	-0.009	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.133	0.054	0.030	0.016	0.009	0.005	0.003	0.001	0.001	0.001	0.000	0.000	0.000
T28	2.5	-0.184	-0.045	-0.020	-0.009	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.183	0.079	0.045	0.026	0.015	0.008	0.005	0.003	0.002	0.001	0.001	0.001	0.001
T29	2.5	-0.200	-0.048	-0.020	-0.009	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.170	0.072	0.041	0.023	0.013	0.007	0.004	0.002	0.001	0.001	0.001	0.001	0.001
T30	2.5	-0.143	-0.038	-0.017	-0.008	-0.003	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.224	0.102	0.060	0.035	0.021	0.012	0.007	0.004	0.002	0.002	0.001	0.001	0.001
T31	2.5	0.045	0.016	0.008	0.004	0.002	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.416	0.237	0.162	0.109	0.073	0.049	0.033	0.022	0.015	0.012	0.010	0.008	0.007
T32	2.5	-0.152	-0.040	-0.018	-0.008	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.212	0.095	0.056	0.032	0.019	0.011	0.006	0.004	0.002	0.002	0.001	0.001	0.001
T33	2.5	0.042	0.015	0.008	0.004	0.002	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.418	0.239	0.163	0.110	0.074	0.050	0.033	0.022	0.015	0.013	0.010	0.009	0.008
T34	2.5	-0.596	-0.064	-0.023	-0.009	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	-0.221	-0.050	-0.017	-0.005	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
T35	2.5	-0.322	-0.061	-0.023	-0.009	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.043	0.015	0.008	0.004	0.002	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000
T36	2.5	0.005	0.002	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.378	0.207	0.137	0.090	0.059	0.038	0.025	0.016	0.011	0.009	0.007	0.006	0.005
T37	2.5	-0.177	-0.044	-0.019	-0.008	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.195	0.085	0.049	0.028	0.016	0.009	0.005	0.003	0.002	0.001	0.001	0.001	0.001
T38	2.5	0.455	0.271	0.189	0.131	0.090	0.062	0.043	0.029	0.020	0.017	0.014	0.012	0.011
	97.5	0.839	0.730	0.660	0.594	0.533	0.477	0.427	0.382	0.342	0.327	0.307	0.294	0.285
T39	2.5	-0.080	-0.023	-0.011	-0.005	-0.002	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	0.295	0.146	0.091	0.056	0.035	0.021	0.013	0.008	0.005	0.004	0.003	0.003	0.002
T40	2.5	-0.410	-0.064	-0.023	-0.009	-0.004	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	97.5	-0.042	-0.013	-0.006	-0.003	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: See notes to Table 4.

Table 20: Estimates of t_a for Sectoral CPI Based Inflation Series (1994-2002)

Code	a =0.30	a =0.50	a =0.80	a =0.90	a =0.95	a =0.99
T01	1	1	5	15	48	766
T02	1	1	3	8	23	262
T03	1	1	3	8	21	229
T04	1	1	4	14	45	691
T05	1	1	1	1	2	7
T06	1	1	1	2	5	28
T07	1	1	3	7	20	223
T08	1	1	2	2	4	12
T09	1	1	2	5	11	97
T10	1	1	1	1	2	9
T11	1	1	4	11	32	418
T12	1	1	1	1	2	8
T13	1	1	3	7	20	223
T14	1	1	2	6	14	133
T15	1	1	3	6	17	167
T16	1	1	2	4	9	72
T17	1	1	1	2	3	9
T18	1	1	1	2	4	28
T19	1	1	1	2	4	20
T20	1	1	6	20	72	>1200
T21	1	1	1	1	1	6
T22	1	1	8	30	116	>1200
T23	1	1	7	24	89	>1200
T24	1	1	5	17	58	995
T25	1	1	1	2	3	10
T26	1	1	1	2	3	16
T27	1	1	1	1	1	1
T28	1	1	1	1	2	7
T29	1	1	1	1	1	5
T30	1	1	1	2	3	14
T31	1	1	2	6	14	135
T32	1	1	1	1	2	12
T33	1	1	2	5	14	126
T34	1	1	2	3	4	12
T35	1	1	1	1	2	7
T36	1	1	2	4	10	81
T37	1	1	1	1	2	9
T38	1	4	66	582	>1200	>1200
T39	1	1	1	2	5	33
T40	1	1	1	2	3	11

Notes: See notes to Table 5.

Table 21: Parameter Estimates and Model Selection Criteria of ARFIMA-BREAK Models for Aggregate Inflation Series

		AIC for ARFIMA-BREAK Models			
Inflation Series	*p,q,s*	0,0,1	1,0,1	0,0,2	1,0,2
WPI (1923-2001)		565.163	566.050	558.293	559.321
WPI (1964:2−2002:6)		1568.063	1903.738	1567.141	1756.581
WPI (1964:2−1988:1)		932.742	930.237	1068.706	1059.603
WPI (1982:2−2002:6)		834.759	836.639	844.394	833.697
WPI (1987:2−2002:6)		602.782	602.230	665.820	684.735
WPI (1994:2−2002:6)		285.473	286.603	300.401	302.376
CPI (1951−2001)		337.776	336.965	330.969	328.103
CPI (1987:2−2002:6)		577.562	578.538	574.401	575.137
CPI (1994:2−2002:6)		226.140	246.350	224.699	224.491

Estimates for ARFIMA-BREAK Models with Minimum AIC

	g	s.e.	*d*	s.e.	ϕ_1	s.e.
	0.150	0.113	-0.356	0.089	-	-
WPI (1923-2001)	0.000	0.000	-0.476	0.037	-	-
WPI (1964:2−2002:6)	0.487	0.024	-0.538	0.105	0.338	0.127
WPI (1964:2−1988:1)	3.071	0.125	-0.472	0.099	0.218	0.123
WPI (1982:2−2002:6)	2.877	0.109	-0.624	0.134	0.353	0.160
WPI (1987:2−2002:6)	0.000	0.001	-0.593	0.078	-	-
WPI (1994:2−2002:6)	5.458	1.700	-0.426	0.189	0.070	0.240
CPI (1951−2001)	2.268	0.077	-0.407	0.058	-	-
CPI (1987:2−2002:6)	0.809	0.025	-0.389	0.226	0.491	0.252
CPI (1994:2−2002:6)						

Notes: First panel of the Table reports the Akaike Information Criterion (-2 ln L + 2k) for ecah model, where L is the likelihood and k is the number of paremters. The models are estimated using the approximate maximum likelihood function. The second panel shows the estimates for the ARFIMA-BREAK model that has the minimum AIC. Data are seasonally adjusted by subtracting the seasonal means.