PERSISTENCE IN INTERNATIONAL INFLATION RATES[1]

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Abstract

We test for fractional dynamics in CPI-based inflation rates for
twenty-seven countries and WPI-based inflation rates for twenty-two
countries. The fractional differencing parameter is estimated using
semiparametric and approximate maximum likelihood methods. Significant
evidence of fractional dynamics with long-memory features is found
in both CPI- and WPI-based inflation rates for industrial as well as
developing countries. Implications of the findings are considered and
sources of long memory are hypothesized.

1. Introduction

An understanding of the dynamic properties of the inflation rate is essential to policymakers' ability to keep inflation in check. Despite extensive research following the pioneering work of Nelson and Plosser (1982), disagreement remains in the literature on a key question: does the postwar inflation rate possess a unit root? Although there is considerable evidence in support of a unit root (e.g. Barsky 1987; MacDonald and Murphy 1989; Ball and Cecchetti 1990; Wickens and Tzavalis 1992; and Kim 1993), Rose (1988) provided evidence of stationarity in inflation rates. Mixed evidence has been provided by Kirchgassner and Wolters (1993). Brunner and Hess (1993) argue that the inflation rate was stationary before the 1960s, but that it possesses a unit root since that time.

A potential resolution to this debate should be of more than academic interest, as nonstationarity in the inflation process would have consequences for central banks' ratification of inflationary shocks and would affect macroeconomic policymakers' response to external pressures. An explanation for this conflicting evidence was recently provided by modeling inflation rates as fractionally integrated processes. Using the fractional differencing model developed by Granger and Joyeux (1980), Hosking (1981), and Geweke and Porter-Hudak (1983), Baillie, Chung, and

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Tieslau (1996) find strong evidence of long memory in the inflation rates for the Group of Seven (G7) countries (with the exception of Japan) and those of three high inflation countries: Argentina, Brazil, and Israel. Similar evidence of strong long-term persistence in the inflation rates of the U.S., U.K., Germany, France, and Italy is also provided by Hassler and Wolters (1995). Delgado and Robinson (1994) find evidence of persistent dependence in the Spanish inflation rate. The interpretation of this evidence suggests that inflation rates are mean-reverting processes, so that an inflationary shock will persist, but will eventually dissipate.

Since modeling the inflation rate as a fractionally integrated process appears to improve our understanding of inflationary dynamics, this study extends the existing long-memory evidence on inflation rates along two dimensions. First, it performs long-memory analysis on inflation rates for a number of countries not previously considered, both industrial and developing, in order to provide more comprehensive evidence regarding the low-frequency properties of international inflation rates and to determine whether long memory is a common feature. Second, the paper investigates the existence of long-memory properties of inflation rates based not only on the consumer price index (CPI), as exclusively considered in the literature, but also on the wholesale price index (WPI). The WPI is not as heavily influenced by the prices of nontraded goods as is the CPI, and it may therefore serve as a better indicator in tests

of the international arbitrage relationship between traded goods prices and exchange rates. WPI-based measures have been used extensively in empirical applications such as tests of purchasing power parity, empirical trade models, models of relative price responses, and models of the international transmission of inflation (e.g. Diebold, Husted and Rush 1991; Rogers and Wang 1993; Fukuda, Teruyama and Toda 1991). Therefore, we investigate and analyze the long-memory characteristics of WPI-based inflation rates, as well as their CPI-based counterparts, for developing as well as industrial countries.

Our data set consists of monthly CPI-based inflation rates for 27 countries and WPI-based inflation rates for 22 countries and covers the period 1971:1 to 1995:12. We estimate the fractional differencing parameter using both semiparametric (spectral regression and Gaussian semiparametric) and approximate maximum likelihood techniques. Evidence in the literature for long memory in major countries' CPI-based inflation rates is shown to generalize to both CPI- and WPI-based inflation rates for other industrial as well as developing countries. This evidence implies that policymakers may use fractionally integrated models of inflation to good advantage in modeling and forecasting the path of inflation rates. As potential sources of fractional dynamics in inflation rates, we hypothesize Granger's (1980) aggregation argument and the established presence of long memory in the growth rate of money.

The remainder of the paper is constructed as follows. Section 2

presents the methods employed for the estimation of the fractional
differencing parameter. Data and empirical results are discussed in
section 3. We conclude in section 4 with a summary and implications of
our results.

2. Fractional Integration Estimation Methods

The model of an autoregressive fractionally integrated moving average
process of order (p, d, q), denoted by ARFIMA (p, d, q), with mean μ, may be
written using operator notation as

$$\Phi(L)(1 - L)^d (y_t - \mu) = \Theta(L)u_t,\ u_t \sim i.i.d.(0, \sigma_u^2) \tag{1}$$

where L is the backward-shift operator, $\Phi(L)$ = 1 - $\phi_1 L$ - .. - $\phi_p L^p$,
$\Theta(L)$ = 1 + $\vartheta_1 L$ + ... + $\vartheta_q L^q$, and $(1 - L)^d$ is the fractional differencing
operator defined by

$$(1 - L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k - d)L^k}{\Gamma(-d)\Gamma(k + 1)}$$

with $\Gamma\ (\cdot)$ denoting the gamma function. The parameter d is allowed
to assume any real value. The arbitrary restriction of d to integer
values gives rise to the standard autoregressive integrated moving
average (ARIMA) model. The stochastic process y_t is both stationary
and invertible if all roots of $\Phi(L)$ and $\Theta(L)$ lie outside the unit
circle and $|d| < 0.5$. The process is nonstationary for $d \geq 0.5$, as

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it possesses infinite variance, i.e. see Granger and Joyeux (1980). Assuming that $d \in (0, 0.5)$ and $d \neq 0$, Hosking (1981) showed that the correlation function, $\rho(\cdot)$, of an ARFIMA process is proportional to k^{2d-1} as $k \to \infty$. Consequently, the autocorrelations of the ARFIMA process decay hyperbolically to zero as $k \to \infty$ in contrast to the faster, geometric decay of a stationary ARMA process. For $d \in (0, 0.5)$, $\sum_{j=-n}^{n} |\rho(j)|$ diverges as $n \to \infty$, and the ARFIMA process is said to exhibit long memory, or long-range positive dependence. The process is said to exhibit intermediate memory (anti-persistence), or long-range negative dependence, for $d \in (-0.5, 0)$. The process exhibits short memory for $d = 0$, corresponding to stationary and invertible ARMA modeling. For $d \in [0.5, 1)$ the process is mean reverting, even though it is not covariance stationary, as there is no long-run impact of an innovation on future values of the process.

The fractional differencing parameter is estimated using two semi-parametric methods, the spectral regression and Gaussian semiparametric approaches, and the frequency-domain approximate maximum likelihood method. A brief description of these estimation methods follows.

The Spectral Regression Method

Geweke and Porter-Hudak (1983) suggest a semiparametric procedure to obtain an estimate of the fractional differencing parameter d based on the slope of the spectral density function around the angular frequency

$\xi = 0$.

The spectral regression is defined by

$$\ln\{I(\xi_\lambda)\} = \beta_0 + \beta_1 \ln\left\{4\sin^2\left(\frac{\xi_\lambda}{2}\right)\right\} + \eta_\lambda, \ \lambda = 1, ..., \nu \tag{2}$$

where $I(\xi_\lambda)$ is the periodogram of the time series at the Fourier frequencies of the sample $\xi_\lambda = \frac{2\pi\lambda}{T}\left(\lambda = 1, ..., \frac{(T-1)}{2}\right)$, T is the number of observations, and $\nu = g(T) << T$ is the number of Fourier frequencies included in the spectral regression.

Assuming that $\lim_{T\to\infty} g(T) = \infty$, $\lim_{T\to\infty}\left\{\frac{g(T)}{T}\right\} = 0$, and $\lim_{T\to\infty}\left\{\frac{\ln(T)^2}{g(T)}\right\} = 0$, the negative of the OLS estimate of the slope coefficient in (2) provides an estimate of d. Geweke and Porter-Hudak (1983) prove consistency and asymptotic normality for $d < 0$, while Robinson (1995a) proves consistency and asymptotic normality for $d \in (0, 0.5)$ in the case of Gaussian ARMA innovations in (1).

Ooms and Hassler (1997) show that the spectral regression will contain singularities due to prior deseasonalization of the series through standard seasonal adjustment techniques (utilizing seasonal dummy variables). The singularity problem arises because the periodogram $I(\xi_\lambda)$ of a seasonally adjusted series is zero (and does not possess a finite logarithm) at frequencies $\xi_\lambda = \frac{2\pi\lambda}{s}, \lambda = 0, ..., s$, where s is the number of observations per year. In order to correct for this problem, Ooms and Hassler suggest extending the original data series to full calendar years via 'zero padding' and then omitting the periodogram ordinates corresponding to

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seasonal frequencies when estimating the log-periodogram regression in (2). We refer to this method, which yields more stable and reliable estimates than those generated by the standard spectral regression approach, as the adjusted spectral regression method.

The Gaussian Semiparametric Method

Robinson (1995b) proposes a Gaussian semiparametric estimator, GS hereafter, of the self-similarity parameter H, which is not defined in closed form. It is assumed that the spectral density of the time series, denoted by $f(\cdot)$, behaves as

$$f(\xi) \sim G\xi^{1-2H} \text{ as } \xi \to 0^+$$

for $G \in (0, \infty)$ and $H \in (0, 1)$. The self-similarity parameter H relates to the long-memory parameter d by $H = d + \frac{1}{2}$. The estimate for H, denoted $\widehat{H}$, is obtained through minimization of the function

$$R(H) = \ln \widehat{G}(H) - (2H - 1)\frac{1}{\nu} \sum_{\lambda=1}^{\nu} \ln \xi_\lambda$$

with respect to H, where $\widehat{G}(H) = \frac{1}{\nu} \sum_{\lambda=1}^{\nu} \xi_\lambda^{2H-1} I(\xi_\lambda)$. The discrete averaging is carried out over the neighborhood of zero frequency and, in asymptotic theory, ν is assumed to tend to infinity much more slowly than T. The GS estimator has several advantages over the spectral regression estimator and its variants. It is consistent under mild conditions and, under somewhat stronger conditions, it is asymptotically normal and more effi-

cient. Gaussianity is nowhere assumed in the asymptotic theory. The GS estimator is $\nu^{\frac{1}{2}}$-consistent with a variance of the limiting distribution free of nuisance parameters and equal to $\frac{1}{4\nu}$.

The Approximate Maximum Likelihood Method

Fox and Taqqu (1986) propose a frequency-domain approximate maximum likelihood (ML) method to simultaneously estimate both the short-memory and long-memory parameters of an ARFIMA model. It approximates the Gaussian likelihood in the frequency domain, which amounts to minimizing the logarithm of the spectral likelihood function

$$L\left(\gamma\right) = \frac{2\pi}{T} \sum_{\lambda=1}^{\frac{T}{2}} \left\{ \ln f\left(\xi_\lambda, \gamma\right) + \frac{I\left(\xi_\lambda\right)}{f\left(\xi_\lambda, \gamma\right)} \right\}$$

with respect to the parameter vector $\gamma = \left(d, \varphi_1, ..., \varphi_p, \vartheta_1, ..., \vartheta_q\right)$, where $I\left(\xi_\lambda\right)$ is defined as above and $f\left(\xi_\lambda, \gamma\right)$ is the spectrum of the ARFIMA model being estimated. The resulting ML estimates of γ are consistent and asymptotically normal. Cheung and Diebold (1994) suggest that the frequency-domain approximate ML estimator compares favorably, in terms of its finite-sample properties, to the much more computationally arduous time-domain exact ML estimator proposed by Sowell (1992) in the case that the mean of the process is unknown.

3. Data and Empirical Estimates

Data

We perform the analysis on CPI-based inflation rates for 27 countries
and WPI-based inflation rates for 22 countries. All data series are
seasonally unadjusted monthly observations beginning in 1971:1, roughly
corresponding to the end of the Bretton Woods exchange rate regime, and
ending in 1995:12 (for a total of 300 observations) and were obtained
from the IMF's International Financial Statistics database. For the CPI-
based inflation rate series, our sample countries are the U.S., Canada,
Germany, U.K., France, Italy, Japan, Austria, Belgium, Denmark, Mexico,
Netherlands, Norway, Sweden, Switzerland, Luxemburg, Finland, Greece,
Portugal, Spain, South Africa, Turkey, India, Indonesia, South Korea,
Philippines, and Pakistan. For the WPI-based inflation rate series,
our sample excludes France, Italy, Belgium, Switzerland, Luxemburg,
Portugal, and Turkey, for which WPI series are not available, and adds
Australia and Ireland, for which only WPI series are available. Unless
otherwise indicated, the estimation methods are applied to seasonally
adjusted series derived from the application of monthly seasonal dummies.
There is evidence of seasonality for all series except for the CPI-based
inflation rate series for Mexico and the WPI-based inflation rate series

for the U.S., Japan, Finland, Australia, South Africa, and Indonesia.[1]

Empirical Estimates for CPI-based Series

The evidence for the CPI-based inflation rates is presented first, followed by that for the WPI-based inflation rate series. The tables classify countries into three categories: G7 countries, other industrial countries, and developing countries.

In estimating the fractional exponent using periodogram-based methods, a choice has to be made with respect to the number of low-frequency periodogram ordinates used. Improper inclusion of medium- or high-frequency periodogram ordinates will bias the estimate of d; at the same time too small an estimation sample will increase the sampling variability of the estimates. To evaluate the sensitivity of our results to the choice of estimation sample size ν, we report fractional differencing estimates for $\nu = 20, 30, 40, 50,$ and 60. We impose the known theoretical variance of the regression error $\frac{\pi^2}{6}$ in the construction of the standard error for the spectral regression d estimate.

Table 1 presents the spectral regression estimates of the fractional differencing parameter d for the CPI-based inflation rates.[2] The d estimates for the inflation rates for the G7, other industrial, and developing countries are significantly positive. They generally decline with the size of the spectral regression but they stabilize and remain significantly positive (with the exception of Switzerland).[3,4] Thus the

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presence of long-memory features in the CPI-based inflation rates for major industrial countries reported by Baillie, Chung and Tieslau. (1996) and Hassler and Wolters (1995) generalizes to other industrial countries as well as developing countries.

Table 2 reports the GS results for the CPI-based inflation rate series.[5] The GS fractional differencing estimates are generally similar in magnitude to the corresponding spectral regression estimates. Strong evidence of persistent dependence is obtained for all CPI-based inflation rates, with the possible exception of Indonesia for which the long-memory evidence is unstable across estimation sample sizes.

Table 3 reports the frequency-domain approximate ML estimates for the CPI-based inflation rate series. Contrary to the spectral regression and Gaussian semiparametric methods, the approximate ML method simultaneously estimates both the short-memory and long-memory parameters of the model. For simple models, such as fractional Gaussian noise, parameter estimates may be easily obtained. However, the computational problems associated with estimation of the model become more serious for higher-order short-memory (ARMA) structures (e.g. tradeoffs between the value of the long-memory parameter and those of the ARMA parameters, as well as possible stationarity and invertibility problems with the AR and MA polynomials, respectively). To minimize the effects of an overparameterized short-memory structure and preserve parsimony, we arrive at the final ARFIMA specification via the following strategy. We allow for a short-memory

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structure up to AR(2), use the Schwarz information criterion (SIC) to choose the best model, test the statistical significance of the AR coefficients, and ensure that the stationarity condition is met for the resulting AR polynomial.[6] As Table 3 reports, the ARFIMA specifications selected result in fractional-differencing parameter estimates broadly consistent with the semiparametric estimates. Significant evidence of long memory is obtained for all CPI-based inflation rate series, thus reinforcing the robustness of the evidence over alternative estimation methods.

Empirical Estimates for WPI-based Series

Spectral regression estimates of the fractional differencing parameter for the WPI-based inflation rate series are reported in Table 4. The spectral regression estimates are significantly greater than zero for all WPI-based inflation rate series except for Austria, the Netherlands, and Pakistan. This long-memory evidence is robust with respect to the number of harmonic ordinates used in the spectral regression. As in the case of the CPI-based series, long-term persistence appears to characterize the dynamic behavior of WPI-based inflation rate series for both industrial and developing countries.

   Strong evidence of persistence in the stochastic behavior of the WPI-based inflation rates is also provided by the GS results presented in Table 5. The GS fractional differencing estimates are broadly consistent

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with the corresponding spectral regression estimates. Evidence in support of long-memory dynamics is obtained for all WPI-based inflation rate series. For Austria, the Netherlands and Pakistan, for which the spectral regression method did not find evidence of long-term persistence, the GS method does find such evidence although it is rather mild for the Netherlands and Pakistan.

Approximate ML estimates of the long-memory parameter for the WPI-based inflation rate series, which are reported in Table 6, confirm the evidence obtained from the semiparametric estimation methods. There is evidence of fractional dynamics with long-memory features in the series for all countries except, possibly, for Pakistan, for which the long-memory parameter is only significant at the ten per cent level.

For several of the inflation rate series, the long-memory estimates are in the vicinity of the stationarity threshold of 0.5. In the majority of cases, the long-memory estimates are below 0.5 for both CPI- and WPI-based inflation rates, implying stationarity of the inflation rate series. Long memory indicates that the inflation rate exhibits strong positive dependence between distant observations. More specifically, positive persistent dependence suggests that countries experience long periods of generally upward-trending inflation rates as well as long periods of generally downward-trending inflation rates. The behavior of inflation rates is characterized by long yet nonperiodic cycles. In the time domain, a shock to the inflation rate series persists but it

eventually dissipates since the series is mean reverting.[7,8]

The robustness of the long-memory evidence across alternative estimation methods for most of these inflation series suggests that persistence is a common feature of these data, and that ARMA representations will generally be inadequate to capture their dynamic properties.[9] Additionally, the joint process of inflation rate series is no longer adequately characterized by a linear vector autoregression (VAR); the nonlinear relations arising in this context deserve further scrutiny. Care must be exercised in estimating any regression in which two or more fractionally integrated processes appear, as they would in virtually any model containing two or more of the series studied here. If their orders of integration sum to greater than 0.5, 'spurious regression' effects might appear (Tsay 1995).

4. Conclusions and Implications

This paper tests for the existence of long memory, or persistence, in international inflation rates for a number of industrial and developing countries using semiparametric and maximum likelihood estimation methods. The analysis employs both CPI-based and WPI-based inflation rates for twenty-seven and twenty-two countries, respectively, over the post-Bretton Woods (1971-1995) period. Extending previous research on CPI-based inflation rates for major industrial countries, we provide evidence

that long memory in the CPI-based inflation rate is a general phenomenon
for other industrial countries as well as for a number of developing
countries. In addition, we provide the first evidence that WPI-based
inflation rates also exhibit long-memory features for both developed
and developing economies. This evidence is substantial and robust in
support of persistence in both CPI- and WPI-based inflation rates. In
general, the estimate of the fractional-differencing parameter for
either series is similar when we apply adjusted spectral regression,
Gaussian semiparametric, and approximate maximum likelihood techniques.
In that respect, we demonstrate that an ARFIMA model is an appropriate
representation of the stochastic behavior of international inflation
rates and that long memory is a common feature for the countries studied.
Contrary to the popular belief arising from unit-root tests in many
empirical applications, inflation rates, however defined and for the vast
majority of countries, do not possess a unit root.

It should be noted that the ability to adequately represent infla-
tion series as ARFIMA processes, which allow for richer dynamics in the
stochastic behavior of the series, should be of particular interest to
policymakers. Policymakers utilizing the properties of ARFIMA represen-
tations may be able to make more accurate short- and long-term forecasts
of the future path of inflation rates, which are instrumental to the
successful implementation of deflationary policies based on inflation
targeting. Since forecasting performance improves significantly when

the correct stochastic process is utilized for the series under scrutiny, generating forecasts of CPI-based and WPI-based inflation rates using ARFIMA models should be a fruitful approach. However, performance of forecasting experiments is beyond the scope of this paper and warrants further research.

A likely explanation of the significant persistence in these inflation rate series is the aggregation argument put forth by Granger (1980), which states that persistence can arise from the aggregation of constituent processes, each of which has short memory.[10,11] Granger and Ding (1996) show that the long-memory property could also arise from time-varying coefficient models or nonlinear models. An alternative conjecture is that inflation inherits the long-memory property from money growth. Porter-Hudak (1990) and Barkoulas, Baum, and Caglayan (1998) have shown that the U.S. monetary aggregates exhibit the long-memory property, which will be transmitted to inflation, given the dependence of long-run inflation on the growth rate of money. Further analysis of the monetary policy mechanism that gives rise to this persistence in the monetary aggregates--and thus in inflation and other macroeconomic variables--will be one focus of our future research.

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Notes

[1]For those inflation rate series in which no seasonality was detected, the spectral regression method (Geweke and Porter-Hudak 1983) is applied. For those series exhibiting seasonality, the adjusted spectral regression method of Ooms and Hassler (1997) is applied to the original series, since that method utilizes only non-seasonal frequencies in the log-periodogram regression.

[2]We also applied the Phillips-Perron (PP, 1988) and Kwiatkowski et al. (KPSS, 1992) unit-root tests to both CPI- and WPI-based inflation rate series. The combined use of these unit-root tests offers contradictory inference regarding the low-frequency behavior of the vast majority of the inflation rate series, thus providing motivation for testing for fractional roots in the series. The long-memory evidence to follow reconciles the conflicting inference derived from the PP and KPSS tests. To conserve space, these results are not reported but they are available upon request.

[3]For small spectral regression sample sizes, especially for $\nu = 20$, the variance of the spectral regression estimator is rather large and we do not therefore rely on the corresponding estimates in interpreting our evidence. We proceed similarly for the evidence obtained from the GS method.

[4]It must be noted that in most cases the spectral regression d estimates lie within the 95% confidence intervals ($d(\nu) \pm 2$ SE) around $d(\nu)$

for $\nu = 20,\ 30,\ 40,\ 50,\ 60$, where SE denotes the corresponding estimated standard error for the d estimates across the sample sizes considered. The same holds true for the GS estimates of the long-memory parameter.

[5]The GS and approximate ML estimation methods are applied to the seasonally adjusted series if seasonality is detected. These methods are not subject to the Ooms-Hassler critique discussed above.

[6]We allowed for short-memory dynamics up to ARMA(2,2) but in several cases parameter redundancies, nonstationarity of the AR polynomial, or noninvertibility of the MA polynomial resulted. After some experimentation, we opted for a short-memory structure up to AR(2). The reported long-memory evidence (estimates of d) is not materially sensitive to the specific AR (or ARMA) structure considered.

[7]The cumulative impulse response at an infinite horizon of future values of the inflation rate series to a unit innovation is zero for $0 < d < 1$.

[8]In the frequency domain, long memory is characterized by an unbounded spectral density at zero frequency.

[9]The integration properties of cross-country data have been tested, in recent literature, with panel data methods (e.g. Pedroni 1995; Canzoneri, Cumby and Diba 1996; Oh 1996). These pooling methods allow stronger inferences to be drawn from the data. In our case, the robust evidence available from univariate tests would not be qualitatively affected by multivariate test findings.

[10]Granger (1980) showed that if a time series y_t is the sum of many independent AR(1) processes which have equal variances and whose autoregressive parameters are drawn independently from a beta distribution, then it has the same correlation structure as an ARFIMA process with an appropriately defined fractional differencing parameter.

[11]Ooms (1997), analyzing disaggregated components of the U.S. CPI-based inflation rate, finds that Granger's aggregation hypothesis may be important in explaining long memory.

Table 1: Spectral Regression Estimates of the
Fractional-Differencing Parameter d for CPI-based Inflation Rates

	Number of Harmonic Ordinates in Spectral Regression				
Inflation Series	$\nu = 20$	$\nu = 30$	$\nu = 40$	$\nu = 50$	$\nu = 60$
G7 Countries					
U.S.	0.811	0.568	0.457	0.598	0.458
Canada	0.711	0.585	0.547	0.523	0.474
Germany	0.541	0.355	0.353	0.257	0.303
U.K.	0.624	0.572	0.608	0.452	0.400
France	0.661	0.535	0.460	0.390	0.390
Italy	0.596	0.768	0.590	0.522	0.488
Japan	1.151	0.644	0.493	0.504	0.461
Other Industrial Countries					
Austria	0.602	0.226	0.304	0.196	0.212
Belgium	0.661	0.437	0.513	0.420	0.374
Denmark	0.480	0.347	0.282	0.209	0.260
Netherlands	0.678	0.418	0.391	0.250	0.283
Norway	0.860	0.547	0.400	0.343	0.357
Sweden	0.565	0.374	0.292	0.188	0.240
Switzerland	0.607	0.172	0.138	0.143	0.166
Luxemburg	0.639	0.373	0.290	0.277	0.234
Finland	0.989	0.616	0.576	0.373	0.301
Greece	0.511	0.394	0.311	0.307	0.302
Portugal	0.498	0.463	0.305	0.186	0.156
Spain	0.692	0.308	0.151	0.229	0.133
Developing Countries					
South Africa	0.640	0.228	0.176	0.156	0.147
Mexico	0.516	0.314	0.278	0.167	0.137
Turkey	0.627	0.460	0.358	0.297	0.306
India	0.401	0.479	0.474	0.454	0.386
Indonesia	0.728	0.459	0.251	0.197	0.289
South Korea	0.542	0.532	0.442	0.382	0.397
Philippines	0.419	0.569	0.451	0.311	0.321
Pakistan	0.375	0.201	0.224	0.208	0.229
Standard Errors	0.181	0.140	0.117	0.103	0.093

Notes: The adjusted spectral regression method of Ooms and Hassler (1997) is applied to all series except Mexico, for which no seasonality is detected. The spectral regression method of

Geweke and Porter-Hudak (1983) is used for Mexico. The number of harmonic ordinates indicate the sample size of the spectral regression. The known theoretical error variance of $\frac{\pi^2}{6}$ is imposed in the calculation of the standard error of the fractional differencing parameter d .

Table 2: Gaussian Semiparametric Estimates of the
Fractional-Differencing Parameter d for CPI-based Inflation Rates

| | Number of Harmonic Ordinates | | | | |
Inflation Series	$\nu = 20$	$\nu = 30$	$\nu = 40$	$\nu = 50$	$\nu = 60$
G7 Countries					
U. S.	0.840	0.584	0.528	0.539	0.510
Canada	0.667	0.512	0.486	0.483	0.427
Germany	0.643	0.497	0.444	0.432	0.397
U. K.	0.513	0.469	0.521	0.373	0.362
France	0.803	0.687	0.594	0.549	0.563
Italy	0.647	0.696	0.488	0.503	0.470
Japan	0.939	0.565	0.487	0.461	0.415
Other Industrial Countries					
Austria	0.480	0.239	0.293	0.210	0.215
Belgium	0.660	0.511	0.571	0.509	0.459
Denmark	0.569	0.469	0.386	0.319	0.318
Netherlands	0.811	0.500	0.458	0.353	0.297
Norway	0.640	0.541	0.408	0.292	0.281
Sweden	0.517	0.341	0.223	0.190	0.198
Switzerland	0.645	0.243	0.236	0.222	0.224
Luxemburg	0.581	0.438	0.380	0.364	0.361
Finland	0.846	0.545	0.527	0.358	0.310
Greece	0.538	0.426	0.399	0.354	0.336
Portugal	0.551	0.579	0.404	0.315	0.304
Spain	0.709	0.436	0.331	0.346	0.295
Developing Countries					
South Africa	0.554	0.331	0.291	0.272	0.265
Mexico	0.289	0.215	0.219	0.167	0.163
Turkey	0 586	0.409	0.337	0.314	0.278
India	0.650	0.681	0.605	0.536	0.462
lndonesia	0.286	0.095	0.096	0.125	0.203
South Korea	0.454	0.488	0.364	0.337	0.326
Philippines	0.338	0.766	0.549	0.388	0.340
Pakistan	0.573	0.404	0.380	0.343	0.330
Standard Errors	0.111	0.091	0.079	0.070	0.064

Notes: The number of harmonic ordinates indicates the number of low-frequency periodogram
ordinates used in the estimation.

Table 3: Approximate Maximum Likelihood Estimates of the Fractional-Differencing Parameter d for CPI-based Inflation Rates

Inflation Series	$AR(p)$ Order	Long Memory Parameter d	Standard Error for d Estimate	t-statistic for $H_0 : d = 0$
G7 Countries				
U.S.	0	0.497	0.046	10.779
Canada	1	0.597	0.057	10.304
Germany	2	0.475	0.075	6.327
U.K.	2	0.632	0.081	7.791
France	2	0.651	0.058	11.085
Italy	2	0.638	0.080	7.940
Japan	2	0.587	0.074	7.939
Other Industrial Countries				
Austria	2	0.387	0.067	5.753
Belgium	1	0.552	0.057	9.599
Denmark	2	0.441	0.061	7.156
Netherlands	1	0.450	0.048	9.368
Norway	0	0.387	0.043	8.888
Sweden	2	0.355	0.069	5.166
Switzerland	2	0.434	0.074	5.806
Luxemburg	1	0.477	0.061	7.803
Finland	1	0.464	0.048	9.620
Greece	0	0.262	0.047	5.467
Portugal	2	0.440	0.068	6.400
Spain	2	0.479	0.058	8.229
Developing Countries				
South Africa	0	0.206	0.044	4.648
Mexico	1	0.234	0.067	3.493
Turkey	0	0.314	0.043	7.171
India	0	0.417	0.049	8.514
Indonesia	0	0.226	0.047	4.779
South Korea	0	0.401	0.047	8.511
Philippines	0	0.428	0.052	8.219
Pakistan	0	0.265	0.049	5.408

Note: The ML method is the frequency-domain approximate ML method proposed by Fox and Taqqu (1986).

Table 4: Spectral Regression Estimates of the
Fractional-Differencing Parameter d for WPI-based Inflation Rates

	Number of Harmonic Ordinates in Spectral Regression				
Inflation Series	$\nu = 20$	$\nu = 30$	$\nu = 40$	$\nu = 50$	$\nu = 60$
G7 Countries					
U.S.	0.517	0.385	0.305	0.274	0.286
Canada	0.369	0.319	0.388	0.358	0.355
Germany	0.445	0.340	0.370	0.401	0.449
U.K.	0.713	0.621	0.646	0.513	0.471
Japan	0.474	0.467	0.545	0.496	0.467
Other Industrial Countries					
Austria	0.157	0.207	0.263	0.186	0.198
Denmark	0.443	0.224	0.170	0.152	0.277
Netherlands	0.369	0.132	0.157	0.074	0.058
Norway	0.661	0.468	0.339	0.269	0.296
Sweden	0.338	0.250	0.253	0.269	0.370
Finland	0.901	0.705	0.542	0.394	0.465
Greece	0.251	0.275	0.362	0.293	0.342
Spain	0.510	0.293	0.308	0.162	0.181
Ireland	0.616	0.303	0.364	0.321	0.280
Australia	0.695	0.431	0.286	0.253	0.332
Developing Countries					
South Africa	0.200	0.387	0.305	0.325	0.316
Mexico	0.908	0.852	0.639	0.597	0.493
India	0.354	0.406	0.293	0.291	0.250
Indonesia	0.312	0.261	0.167	0.217	0.265
South Korea	0.515	0.405	0.310	0.349	0.347
Philippines	0.486	0.456	0.427	0.395	0.355
Pakistan	0.349	0.211	0.104	0.150	0.069
Standard Errors	0.181	0.139	0.117	0.103	0.093

Notes: For the inflation series of the U.S., Japan, Finland, Australia, South Africa, and Indonesia, the spectral regression method of Geweke and Porter-Hudak (1983) is applied as no seasonality is present in these series. For the remaining series, seasonality is present and the spectral regression method of Ooms and Hassler (1997) is applied. The number of harmonic ordinates indicate the sample size of the spectral regression. The known theoretical error variance of $\frac{\pi^2}{6}$ is imposed in the calculation of the standard error of the fractional differencing parameter d.

Table 5. Gaussian Semiparametric Estimates of the
Fractional-Differencing Parameter d for WPI-based Inflation Rates

	Number of Harmonic Ordinates				
Inflation Series	$\nu = 20$	$\nu = 30$	$\nu = 40$	$\nu = 50$	$\nu = 60$
G7 Countries					
U.S.	0.310	0.292	0.267	0.213	0.227
Canada	0.812	0.551	0.545	0.531	0.494
Germany	0.636	0.467	0.459	0.504	0.521
U K.	0.609	0.565	0.552	0.459	0.447
Japan	0.592	0.525	0.547	0.538	0.514
Other Industrial Countries					
Austria	0.411	0.408	0.360	0.387	0.368
Denmark	0.639	0.499	0.387	0.375	0.404
Netherlands	0.333	0.223	0.267	0.177	0.172
Norway	0.555	0.506	0.349	0.296	0.293
Sweden	0.589	0.507	0.420	0.431	0.469
Finland	0.655	0.573	0.426	0.317	0.330
Greece	0.538	0.433	0.418	0.362	0.317
Spain	0.688	0.430	0.282	0.202	0.165
Ireland	0.488	0.235	0.294	0.341	0.299
Australia	0.372	0.294	0.144	0.131	0.187
Developing Countries					
South Africa	0.200	0.387	0.305	0.325	0.316
Mexico	0.722	0.722	0.537	0.576	0.459
India	0.713	0.667	0.473	0.492	0.447
Indonesia	0.390	0.350	0.271	0.266	0.265
South Korea	0.650	0.446	0.401	0.420	0.364
Philippines	0.479	0.434	0.415	0.462	0.330
Pakistan	0.390	0.249	0.218	0.246	0.185
Standard Errors	0.111	0.091	0.079	0.070	0.064

See notes in Table 2 for explanation of table.

Table 6: Approximate Maximum Likelihood Estimates of the
Fractional-Differencing Parameter d for WPI-based Inflation Rates

Inflation Series	$AR(p)$ Order	Long Memory Parameter d	Standard Error for d Estimate	t-statistic for $H_0 : d = 0$
G7 Countries				
U.S.	0	0.331	0.045	7.253
Canada	1	0.560	0.066	8.451
Germany	0	0.550	0.050	10.822
U.K.	0	0.479	0.044	10.898
Japan	1	0.436	0.120	3.607
Other Industrial Countries				
Austria	0	0.135	0.044	3.028
Denmark	2	0.410	0.080	5.083
Netherlands	1	0.315	0.061	5.149
Norway	1	0.362	0.062	5.812
Sweden	1	0.255	0.098	2.603
Finland	1	0.516	0.061	8.456
Greece	0	0.300	0.051	5.839
Spain	2	0.446	0.070	6.328
Ireland	0	0.363	0.045	7.917
Australia	2	0.403	0.064	6.254
Developing Countries				
South Africa	0	0.231	0.045	5.054
Mexico	0	0.465	0.043	10.610
India	0	0.361	0.052	6.918
Indonesia	0	0.209	0.048	4.306
South Korea	0	0.355	0.048	7.350
Philippines	0	0.322	0.049	6.504
Pakistan	0	0.079	0.044	1.786

Note: The ML method is the frequency-domain approximate ML method proposed by Fox and Taqqu
(1986).