UNIVERSITÀ DEGLI STUDI DI PADOVA

Dipartimento di Scienze Economiche "Marco Fanno"

LONG MEMORY AND NON-LINEARITIES IN INTERNATIONAL INFLATION

GIOVANNI CAGGIANO
Università di Padova

EFREM CASTELNUOVO
Università di Padova

May 2008

"MARCO FANNO" WORKING PAPER N.76

Long Memory and Non-Linearities in International Inflation*

Giovanni Caggiano
University of Padua

Efrem Castelnuovo
University of Padua

May 2008

Abstract

This paper investigates inflation dynamics in a panel of 20 OECD economies using an approach based on the sample autocorrelation function (ACF). We find that inflation is characterized by long-lasting fluctuations, which are similar across countries and that eventually revert to a potentially time-varying mean. The cyclical and persistent behavior of inflation does not belong to the class of linear autoregressive processes but rather to a more general class of nonlinear and long memory models. Recent theoretical contributions on heterogeneity in price setting and aggregation offer a rationale to our results. Finally, we draw the monetary policy implications of our findings.

JEL classification: E52, E58, C22.

Keywords: AutoCorrelation Function, long-memory, inflation persistence, inflation targeting, heavy tails.

*First draft: January 2007. We thank Viola Angelini, Roberto-Mario Billi, Nunzio Cappuccio, Riccardo DiCecio, Edward Knotek, Andrea Pescatori, Paolo Surico, Guglielmo Weber and seminar participants at the Midwest Macroeconomics Meetings 2007 (Cleveland), International Conference on Computing in Economics and Finance 2007 (Montreal), Annual Meeting of the European Economic Association 2007 (Budapest), BOMOPA Economics Meetings 2008 (Modena) and University of Padua for useful comments and suggestions. This paper is best viewed in colours. Castelnuovo thanks the Italian Ministry of University and Research for fundings (PRIN 2005-N. 2005132539). Authors' details: *Giovanni Caggiano*, Department of Economics, University of Padua, Via del Santo 33, I-35123 Padova (PD). Phone: +39 049 8273843; Fax: +39 049 8274211. E-mail: giovanni.caggiano@unipd.it. *Efrem Castelnuovo*, Department of Economics, University of Padua, Via del Santo 33, I-35123 Padova (PD). Phone: +39 049 8274257; Fax: +39 049 8274211. E-mail: efrem.castelnuovo@unipd.it.

1 INTRODUCTION

Inflation and its features have been the object of intense investigation for long time. In particular, the debate on how to model its dynamics has triggered big controversies over the last few years. This is due to the importance of inflation persistence as a measure of monetary policy effectiveness: given an inflationary shock, the faster inflation returns to the target (i.e. the less persistent the inflation process), the more effective monetary authorities are in dampening inflation fluctuations (all else being equal). As a consequence, the optimality of the timing and the magnitude of the intervention crucially depends on the knowledge of how shocks affect the dynamic path of future inflation.

Applied macroeconomists have typically measured inflation persistence by estimating autoregressive (AR) models, whose popularity is due to their good fit in the time domain (see e.g. Levin, Natalucci and Piger 2004; O'Reilly and Whelan 2005; Cogley and Sargent 2005; Pivetta and Reis 2007; Benati 2008, and the literature cited therein). The assessment of inflation persistence via AR models assumes that inflation is either a stationary process - I(0) - or a random walk - I(1): in the first case, the long-run persistence of shocks is zero and in the second case is infinite, and monetary authorities do not have any role in stabilizing inflation. However, this dichotomic view does not include all possible data generating processes (DGPs): macroeconomic variables can be fractionally integrated, and could be modeled as ARFIMA(p,d,q) processes (Abadir and Taylor 1999). In such a case, shocks, although very persistent, will eventually die out and inflation will revert to its possibly time-varying mean. The statistical foundation for this result is due to Granger (1980): under the assumptions of sufficient individual persistence and heterogeneity, the sum of a large number of stable and uncorrelated AR(1) processes is a long memory process. The result can be generalized to the case of a weighted sum (Chambers 1998) and to individual ARMA processes (Zaffaroni 2004). The economic rationale behind this finding is that macroeconomic variables are typically the result of aggregation over a large number of heterogenous units, such as households or firms, whose economic behavior, derived from models with inter-temporal optimization, is summarized by linear dynamic models. In the case of inflation, the individual heterogeneity can be traced back to firms' specific price-setting behavior, which are obtained as the solution of a cost-minimization problem and can be modeled as autoregressive processes (Rotemberg 1982). A number of recent works has provided empirical support to the hypothesis that inflation is fractionally integrated

(Hassler and Wolters 1995; Baillie, Chung and Tieslau 1996; Baum, Barkoulas and Caglayan 1999; Gadea and Mayoral 2005; Kumar and Okimoto 2007).

Two further circumstances, however, have often been neglected in the literature on aggregation and inflation persistence. First, price indices are constructed as the weighted average of log-linear sectoral prices: the aggregate price level is then the sum of multiplicative processes, and is a nonlinear function of its components even when they are added linearly. Second, there is a non-negligible degree of dependence between sectoral units. If both elements are correctly taken into account, then proper aggregation leads to a long memory process characterized by a *highly nonlinear* pattern, whose time series properties are summarized by an S-shaped autocorrelation function (Abadir and Talmain 2002, AT henceforth). Such a process may behave very differently from both linear AR and ARFIMA models, which are nested as special cases.

This paper investigates the dynamic properties of inflation in a group of 20 OECD countries by using an approach based on the autocorrelation function (ACF) to explicitly account for the above-mentioned potential long memory and nonlinearities. The importance of integrating long memory and nonlinearities in a time series framework has been advocated by Granger and Ding (1996). The economic foundation of nonlinearities to explain the dynamics of macroeconomic aggregates and inflation in particular has been shown in various papers by Caballero and Engel (1993, 2003, 2007) and Ratfai (2006). The usefulness of the sample ACF to detect nonlinearities has been highlighted by Davis and Mikosch (1998), who suggest that financial time series can be characterized by a complicated dependence structure that cannot be adequately modeled with a linear process. Abadir and Talmain (2002) and Abadir, Caggiano and Talmain (2005, ACT henceforth) provide a general framework, based on the autocorrelation function, to investigate persistence and nonlinearities jointly. Here, we extend such a framework to the analysis of inflation dynamics.

The main contributions to the debate on inflation persistence can be summarized as three main points. First, we define persistence in inflation in terms of the sample ACFs, which we estimate for 20 economies observed between 1960 and 2005, and find that inflation is characterized by long-lasting fluctuations around a potentially time-varying mean, which tend to slowly fade away. Such a cyclical and persistent behavior is common across countries, and represents a novel stylized fact. Second, we provide an inference and estimation set up which accounts for potential heavy-tailedness of inflation and find that the nonlinear and long memory model proposed by AT and extended by ACT outperforms a standard AR(p) process in replicating inflation dynamics: it does better in capturing both the slow rate of decay and the cyclical pattern displayed by the sample ACFs. Third, we investigate the robustness of our findings to the selection of different subsamples by looking at whether a monetary policy regime change, namely the official adoption of an inflation target (IT), has exerted a relevant impact on the properties of the inflation series. Interestingly, we find no change in the fundamental properties of the underlying DGP of inflation: the ACT model still represents a better characterization of the data.

The paper is structured as follows. Section 2 discusses the statistical and economic rationale of why a nonlinear and long memory process like that proposed by Abadir and Talmain (2002) and Abadir et al. (2005) may be more appropriate than a linear autoregressive framework to model inflation dynamics. In Section 3 we investigate inflation dynamics by estimating the sample ACFs and their empirical distributions for the 20 OECD countries under investigation. In Section 4 we compare the performance of a standard AR(p) model and of the nonlinear ACT process in the full sample and in different selected subsamples to account for monetary policy changes. Section 5 concludes by drawing some indications for monetary policy.

2 LONG MEMORY AND NONLINEARITIES IN AGGREGATE INFLATION

Aggregation over heterogeneous, correlated units

Suppose X_i is a time series process whose logarithm follows an AR(1) process:

$$x_i = \phi_i x_{t-1} + \varepsilon_{it}, \quad \varepsilon_{it} \sim i.i.d.N\left(0, \sigma_i^2\right) \tag{1}$$

where $x_i = \ln(X_i)$, $|\phi_i| \sim \beta eta\left(\bar{\phi}, \sigma_\phi^2\right)$, with $i = 1, \ldots, N$, and $t = 1, ..., T$. Then, its second-order moment properties are summarized by its autocorrelation function $\rho_{x_i}(\tau) \equiv \gamma(\tau)/\gamma(0)$, where $\gamma(\tau)$ is the lag-τ autocovariance of x_i. Under the assumption that $|\phi_i| < 1$, the autocorrelation function of x_i is strictly convex and decays to zero at an exponential rate, with speed of convergence inversely proportional to $|\phi_i|$.

Consider now the aggregate process

$$x \equiv \sum_{i=1}^{N} h_i x_i, \tag{2}$$

obtained as a weighted sum of the individual units in (1). If the individual units are uncorrelated, sufficiently persistent and heterogeneous - i.e. there is a sufficiently large number of ϕ_i close to one and a large σ_ϕ^2 - Granger (1980) shows that, if $h_i = 1$ for all i, the aggregate series x is a long memory process whose autocorrelation function ρ_x is strictly convex and decays to zero at a hyperbolic rate. The result can be generalized to the case of $\sum_i h_i = 1$ (Chambers 1998) and to the case of individual ARMA processes (Zaffaroni 2004).

However, in a macroeconomic setting, two further circumstances must be taken into account. First, some form of cross-correlation among the individual units must be accounted for, i.e. $E(\varepsilon_{it}\varepsilon_{jt}) \neq 0$ for some $i \neq j$. Second, macroeconomic variables are constructed by summing up not the logarithms but the *levels* of the individual units X_i. The aggregate process is then given by

$$\tilde{x} \equiv \ln\left[\sum_{i=1}^{N} h_i \exp(x_i)\right] \neq x \equiv \sum_{i=1}^{N} h_i x_i. \tag{3}$$

Unlike (2), a process like (3) is a highly nonlinear function of the individual x_i and its dynamic properties can be substantially different from those of x (Attanasio and Weber 1993; Abadir and Talmain 2002).

To shed more light on the dynamic implications of aggregation-over-heterogenous units, Figure 1 shows the autocorrelations obtained by simulating the sectoral process (1) - $\bar{\rho}_{x_i}$, the geometric aggregate process (2) - ρ_x, and the multiplicative aggregate process (3) - $\rho_{\tilde{x}}$. As expected, in presence of sectoral heterogeneity and persistence, two effects are evident. First, the very fact of aggregating over sectoral units, as in the standard case of geometric averaging, is responsible of the hyperbolic rate of decay of the ACF. Second, aggregating according to (3) gives rise to an ACF with changing concavity, in line with the theoretical predictions of Abadir and Talmain (2002) and which is different from the slowly-decaying, strictly-convex ACF implied by a standard ARFIMA process, i.e. the result of aggregation as in eq. (2).

A model for aggregate inflation

Why aggregate inflation should display a slowly decaying autocorrelation function? Inflation is calculated as the annual rate of change of the Consumer Price Index. The CPI is constructed by aggregating over a large number of individual prices. Each individual price is set as the result of an optimization problem, and the resulting price-setting rule is usually approximated by a linear dynamic model. Hence, unless the degree of heterogeneity at the individual level is negligible, at the aggregate level Granger's result applies (see Altissimo, Mojon and Zaffaroni 2007 for a compelling theoretical and empirical argument).

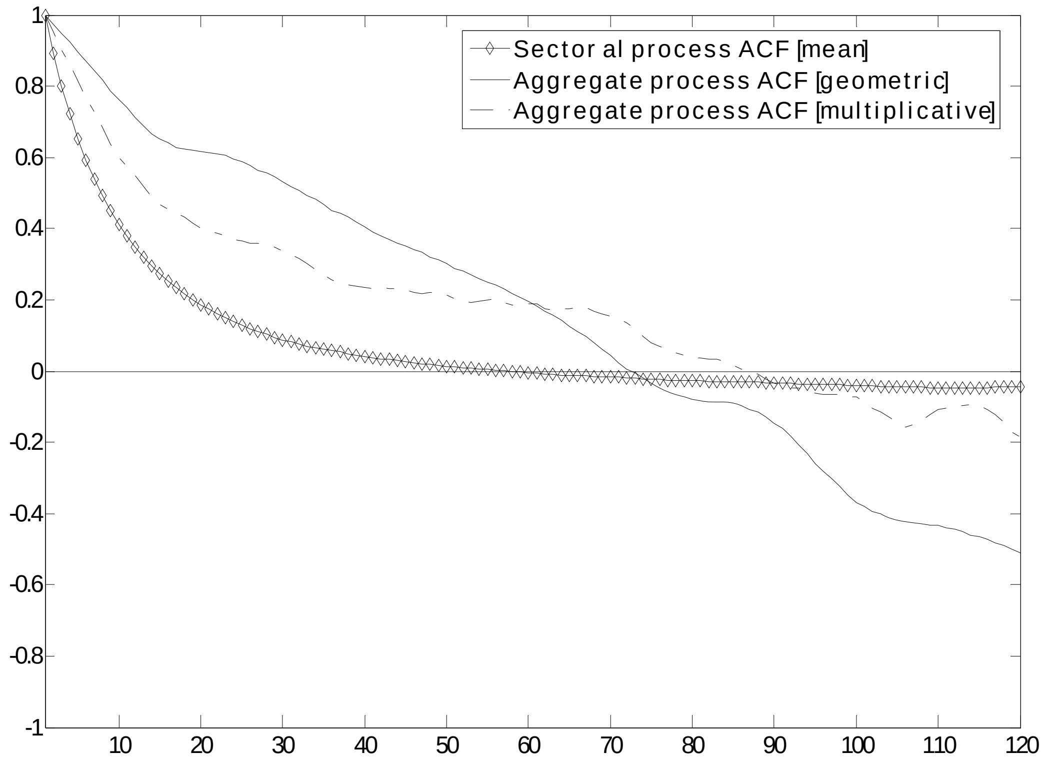

Figure 1: SECTORAL vs. AGGREGATE AUTOCORRELATION FUNCTION. Calibration of the simulated process: $N = 1,000$, $T = 600$, $\phi_i \sim \beta eta(0.91, 0.04)$, $\sigma_i^2 \sim Gamma(1.01, 1.14)$ (first and second moment of the distributions in brackets).

The statistical conditions required to characterize aggregate inflation as a long memory process may have several economic interpretations. One source of heterogeneity at the sectoral level that gives rise to persistence at the aggregate level is differences in firms' price-setting rules, as recently documented by Carvalho (2006). Gadea and Mayoral (2005) propose a model in which firms face quadratic costs in price setting, and have an idiosyncratic speed of price-correction. At a firm level, price changes display short memory. However, since at the aggregate level the price index is constructed as a weighted average of sectoral prices, aggregate inflation is characterized by long memory, as long as some (mild) conditions on the distribution of the speed of price correction are met. Another potential source of sectoral heterogeneity comes from the process of expectations formation. On the one hand, if individual inflation expectations adapt very slowly to changes in realized inflation, they will display some degree of sluggishness which will then propagate to aggregate inflation (Gagnon 1996). On the other hand, even though expectations adapt quickly, they may be very heterogenous across agents, as documented by Mankiw, Reis and Wolfers (2004), and this will directly affect the degree of inflation persistence through aggregation.

To highlight the importance of these results in this contest, we sketch a simple model to explain the dynamics of aggregate inflation. We consider Rotemberg (1982)'s model of sticky prices, where each firm faces quadratic costs of price adjustment. In presence of such costs, the dynamics of sectoral prices is given by:

$$p_{it} = \phi_i p_{it-1} + (1 - \phi_i) p_{it}^* \tag{4}$$

where $p_{it} \equiv \ln P_{it}$ and $p_{it}^* \equiv \ln P_{it}^*$ represent the actual and optimal price levels of firm i at time t in logs, and $|\phi_i| < 1$ is inversely related to the speed of adjustment of each firm to its optimal price level. Notice that we assume firm-specific speeds of adjustment: this choice may be rationalized on the basis of firm-specific adjustment costs. As in Rotemberg (1982), we assume that p_{it}^* follows a random walk, i.e.

$$p_{it}^* = \mu + p_{it-1}^* + \sigma_i u_t$$

where μ is a common drift capturing the long-term price level growth typically observed in industrialized countries, σ_i is the variance of idiosyncratic shocks to marginal costs, and u_t is a normally distributed inflationary shock.

The first difference of eq. (4) gives the sector-specific inflation rate, which reads as follows:

$$\pi_{it} \equiv \Delta p_{it} = \phi_i \Delta p_{it-1} + \xi_{it} \tag{5}$$

where $\xi_{it} \equiv (1-\phi_i)\Delta p_{it}^*$. Under the simplifying assumption of uniform distribution of the weight $h_i = 1/N$ for each i, the aggregate price index is given by

$$\begin{aligned} P_t &= \frac{1}{N}\sum_{i=1}^{N} P_{it} \\ &= \frac{1}{N}\sum_{i=1}^{N} \exp\left(p_{it}\right). \end{aligned}$$

Aggregate inflation is then given by:

$$\begin{aligned} \pi_t &\equiv \Delta p_t = \ln\left(\frac{1}{N}\sum_{i=1}^{N}\exp\left(p_{it}\right)\right) - \ln\left(\frac{1}{N}\sum_{i=1}^{N}\exp\left(p_{it-1}\right)\right) \\ &= \frac{1}{N}\sum_{i=1}^{N}\Delta p_{it} + R_t \neq \frac{1}{N}\sum_{i=1}^{N}\pi_{it}, \end{aligned} \tag{6}$$

where R_t is a residual which cannot be analytically derived in its exact form.

The fact that $\pi_t \neq N^{-1}\sum_i \pi_{it}$ implies that (6) is potentially different from a standard ARFIMA(p,d,q). A process like (6) has been studied by Abadir and Talmain (2002) and Abadir et al.(2005), who show that its dynamic properties can be summarized by the following autocorrelation function, whose characteristics will be discussed at length in the next section:

$$\rho_\tau^{ACT} = \frac{1 - a\left[1 - \cos\left(\omega\tau\right)\right]}{1 + b\tau^c}. \tag{7}$$

Figure 2 shows the ACFs of the sectoral inflation rate, π_{it}, and of aggregate inflation, π_t, which have been obtained by simulating (4) for $i = 1, \ldots, 1000$. The effect of heterogeneity and aggregation is evident when we move from the analysis of sectoral inflation to that of aggregate inflation: the ACF of simulated sectoral inflation is strictly convex and decays to zero exponentially, typical of AR processes with real roots as implied by models with representative agents, whereas the ACF of the implied aggregate process goes to zero at a slower rate and with changing concavity, typical of a process like (7) as implied by models with heterogenous and interdependent agents. The dynamic properties of sectoral inflation, which inherits the log-linearity properties of sectoral prices, are then substantially different from those of aggregate inflation, which instead inherits the nonlinearities and long memory behavior of the aggregate price index.

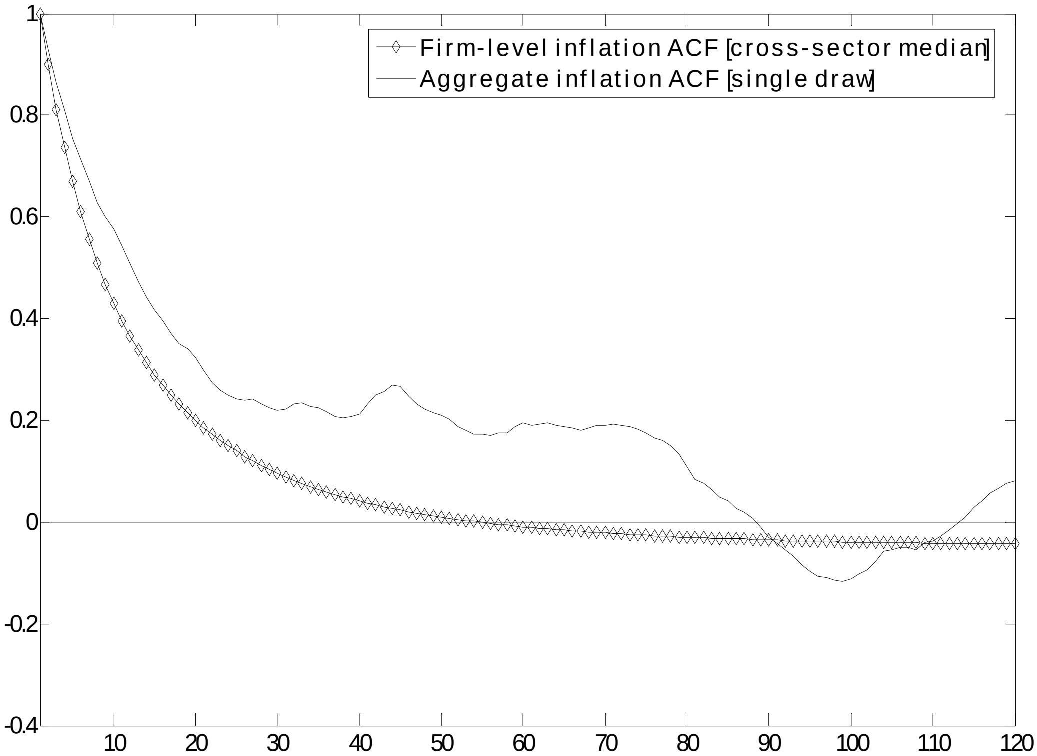

Figure 2: SECTORAL vs. AGGREGATE INFLATION ACFS. Model calibration: $N = 1,000$,$T = 600$, $\mu = 0.004$, $\phi_i \sim \beta eta(0.91, 0.04)$, $\sigma_i^2 \sim Gamma(1.01, 1.14)$. Simulated AR(1) sectoral inflation and aggregation processes detailed in the text.

To summarize, since the variable of interest for policy-makers is aggregate inflation, which under plausible assumptions may have a dynamic behavior very different from that of its sectoral components, researchers who aim at replicating its properties must account for the effects of cross-sectional aggregation: assumptions that hold at a sectoral level, i.e. log-linearity, may not hold at the aggregate level. Theoretical findings suggest that an aggregate series like inflation, constructed as a weighted average of heterogenous and persistent sectoral processes, will belong to a class of long memory and possibly nonlinear processes. The simulations of this section confirm the potential relevance of such findings. In the next section, we assess the empirical plausibility of these claims by looking at the sample ACF of aggregate inflation in a panel of 20 OECD economies.

3 INFLATION DYNAMICS IN OECD COUNTRIES: STYLIZED FACTS

The aim of this section is to identify stylized facts about inflation dynamics by estimating the sample ACF of annual inflation in a dataset of 20 OECD economies. The countries under investigation are Australia (acronym: AS), Austria (AT), Belgium (BE), Canada (CA), Switzerland (SZ), Germany (GE), Spain (SP), Finland (FI), France (FR), United Kingdom (UK), Greece (GR), Italy (IT), Japan (JP), Luxembourg (LX), the Netherlands (NL), Norway (NO), New Zealand (NZ), Portugal (PO), Sweden (SW), and the United States (US).

Our measure of inflation is the annualized inflation rate $\pi_{j,t} = 100\left[\left(P_{j,t} - P_{j,t-4}\right)/P_{j,t}\right]$ where j denotes the country and $P_{j,t}$ is quarterly seasonally adjusted Commodity Price Index for country j, obtained from the OECD Main Economic Indicators, with $t = 1960Q1, \ldots, 2006Q2$. We are aware that both the use of seasonally adjusted data and the use of a year-on-year, rather than a quarter-on-quarter, measure of inflation may introduce spurious persistence. However, on the one hand, such a measure is consistent with the one targeted by the central banks of the countries under investigation. On the other hand, the potential spurious persistence does not necessarily favor any of the competing models we consider.

The sample autocorrelation of $\pi_{j,t}$ at lag τ is given by:

$$\rho_j(\tau) = \frac{\sum_{t=\tau+1}^{T} (\pi_{j,t} - \overline{\pi}_{j,t})(\pi_{j,t-\tau} - \overline{\pi}_{j,t-\tau})}{\sqrt{\sum_{t=\tau+1}^{T} (\pi_{j,t} - \overline{\pi}_{j,t})^2 \sum_{t=1}^{T-\tau} (\pi_{j,t-\tau} - \overline{\pi}_{j,t-\tau})^2}} \tag{8}$$

where $\overline{\pi}_{j,t} = (T-\tau)^{-1} \sum_{t=\tau+1}^{T} \pi_{j,t}$, and $\overline{\pi}_{j,t-\tau} = (T-\tau)^{-1} \sum_{t=1}^{T-\tau} \pi_{j,t}$. Expression (8) accounts for the potential nonstationarity in the mean of the series. It differs from the standard textbook formula, which is designed for asymptotically stationary series and can exceed one for nonstationary series. We use eq. (8) to calculate the sample ACF for all countries and make inference to identify the cut-off lag at which the autocorrelation becomes insignificant. We identify the lag-τ autocorrelation coefficient $\rho_j(\tau)$ as statistically significant if $\tau < \tau^*$, where τ^* is such that, for every $\tau \in [\tau^*, T]$, $0 \in [\underline{CI\rho_j(\tau)}, \overline{CI\rho_j(\tau)}]$, where $\underline{CI\rho_j(\tau)}, \overline{CI\rho_j(\tau)}]$ denote the $(1-\alpha)\,\%$ lower and upper bounds for $\rho_j(\tau)$, respectively. Notice that, according to this definition, we may retain as informative also lags corresponding to - say - negative values of the ACF, if their confidence intervals do not include zero. Notice also that the number of significant lags may turn out to be somewhat large.

The sample ACF is a measure of dependence which must be interpreted with great care when the underlying series comes from a distribution with fat tails. It is a well known stylized fact in financial time series that log-returns of stock indices, share prices and exchange rates may have distribution with heavy tails. As shown by Wright (2002), in presence of fat tailedness estimates of the rate of decay of shocks may be severely biased. Indeed, inflation may fall into the same category.

More generally, suppose that we want to estimate and make inference on the ACF of a series X_t which comes from a jointly regularly varying distribution with index $\alpha > 0$. If $\alpha \in (0, 2)$, then X_t has infinite second moment and the sample ACF has a random limit. If $\alpha \in (2, 4)$, then X_t has finite second moment but infinite fourth moment: the sample ACF is a consistent estimate of the population ACF but the asymptotic rate of convergence is slower than $\sqrt{T}$, which means that the confidence bands are wider than the standard $\pm 2\sigma/\sqrt{T}$ (see Davis and Mikosch 1998; Mikosch and Starica 2000). It is therefore important to get an estimate of the tail index of a series X_t if we want to make inference on its ACF. The most popular tail index estimator is the Hill (1975) estimator.

Although the Hill estimator is asymptotically unbiased for at least an ARFIMA(p,d,q) process with fraction difference $d \in [0, 1)$, it is biased in small samples (for a proof of weak consistency of the Hill estimator for ARFIMA(p,d,q) processes, see Hill 2007). To overcome the severe small-sample bias, we adopt the approach proposed by Huisman, Koedijk, Kool and Palm (2001). Results are reported in Table 1.

Country	$\widehat{\alpha}$	$\underline{CI}$	$\overline{CI}$	Country	$\widehat{\alpha}$	$\underline{CI}$	$\overline{CI}$
Australia	4.83	3.89	5.78	Greece	6.23	5.89	6.67
Austria	4.80	4.42	5.17	Italy	4.14	2.89	5.40
Belgium	3.39	2.94	3.84	Japan	3.25	2.61	3.89
Canada	5.13	4.75	5.51	Luxembourg	4.36	3.97	4.75
Switzerland	4.44	3.88	5.00	Netherlands	5.31	4.95	5.66
Germany	5.98	5.45	6.51	Norway	5.74	5.34	6.14
Spain	4.61	4.16	5.06	New Zealand	7.20	6.80	7.60
Finland	4.39	3.80	4.98	Portugal	4.43	3.83	5.04
France	5.51	5.10	5.91	Sweden	6.50	5.95	7.05
U.K.	2.83	1.79	3.88	U.S.	3.25	2.51	4.00

Table 1: INFLATION RATES: TAIL INDEX ESTIMATES. Tail index estimated following the approach by Huisman et al. (2001).

The point estimates show that we can exclude for all countries the case of infinite variance $\alpha \in (0, 2)$, that is, the case where the sample ACF would converge to a random limit (only for the U.K. the 95% confidence interval contains 2). For a limited number of countries, namely Australia, Belgium, U.K., Japan and the U.S., the estimated tail index belongs to the interval $(2, 4)$, which corresponds to the region where the variance is finite but the fourth moment is infinite. We take into account the implied higher degree of uncertainty surrounding the sample ACF of a series with potential fat tails by bootstrapping the empirical distribution of inflation.

To estimate the empirical distribution of the autocorrelations we use the stationary bootstrap. The stationary bootstrap is a resampling scheme introduced by Politis and Romano (1994). The idea is to generate a large number of pseudo sequences by sampling from the observed data blocks of random length. Unlike other block bootstrap techniques, the stationary bootstrap pseudo-series keep the same stationarity properties as the original series. Simulations available from the authors show that the stationary bootstrap confidence bands for the first k autocorrelations of a possibly non-stationary time series are more accurate than those constructed by other resampling techniques for dependent data (for a similar use of block bootstrap techniques to make inference on the sample ACF, see Caggiano and Leonida 2007; 2008).

The bootstrapped series have been used to calculate the distribution of the Fisher's z transform of the autocorrelation coefficient. The confidence limits have then been transformed back using the hyperbolic tangent operator, tanh, that is, the inverse of the z transform. The lag-τ Fisher's z transform for country j, defined as

$$z_j(\tau) \equiv \tanh^{-1}\left[\rho_j(\tau)\right] = \frac{1}{2}\ln\frac{1+\rho_j(\tau)}{1-\rho_j(\tau)},$$

has two main advantages over the autocorrelation coefficient, $\rho_j(\tau)$. One is a symmetric distribution over the entire range of values $\rho \in (-1, 1)$ (see Hall 1988 for a discussion on the advantages of bootstrap symmetric confidence intervals compared to equal-tailed percentile-t confidence intervals). Second, it ensures boundedness in the interval $[-1, 1]$ of the confidence bands for the ACF.

More formally, the confidence bands have been calculated as:

$$\underline{CI\rho_j(\tau)} = \tanh\left[z_j(\tau) - c_{\|\cdot\|}(1-\alpha/2) \times \sigma_z\right]$$

and

$$\overline{CI\rho_j(\tau)} = \tanh\left[z_j(\tau) + c_{\|\cdot\|}(1-\alpha/2) \times \sigma_z\right]$$

where $c_{\|\cdot\|}(1-\alpha/2)$ is the bootstrapped $(1-\alpha/2)$ quantile of the distribution of the studentized z, and σ_z is its standard deviation.

Figure 3 plots the sample ACFs and the 90% confidence bands for all countries included in our dataset. Most of the correlograms display a slow rate of decay, with frequent and long-lasting oscillations around a time-varying mean: they cross the zero-line, displaying statistically significant positive and negative values, but show the tendency to revert back to it. Moreover, most of the countries have similar inflation dynamics. This is confirmed by the fact that number of statistically significant lags is high in all but two countries, i.e. Germany and the Netherlands (interestingly, Germany is ranked first and the Netherlands fifth in a ranking built on the "Index of Central Bank Independence" provided by Grilli, Masciandaro, and Tabellini 1991). The computation of the cross-correlations among all the computed ACFs gives a minimum value of 0.48, and a mean value of 91% (we computed the cross-correlations over the first 69 lags, those of Japan that has the minimum number of significant lags excluding the "outliers" Germany and the Netherlands). Overall, these values confirm that there are strong comovements across the sample ACFs.

4 MODELING INFLATION PERSISTENCE

Is there any model capable to replicate the sample ACFs estimated in the previous Section? To address this question, we run a horserace between an autoregressive process with p lags, widely employed by macroeconomists to measure the persistence of inflation, and the non-linear process recently proposed by AT and extended by ACT. Formally, the first model reads as

$$\pi_t = a_0 + a_1\pi_{t-1} + ... + a_p\pi_{t-p} + \varepsilon_t \tag{9}$$

where $\{\varepsilon_t\}$ is a sequence of $i.i.d.$ $N(0,\sigma_\varepsilon^2)$ residuals. The ACF of (9) is denoted by ρ_τ^{AR}, and its first p values are given by the Yule-Walker equations (see Granger and Newbold 1986):

$$\begin{bmatrix} 1 & \rho_1^{AR} & \rho_2^{AR} & \cdots & \rho_{p-1}^{AR} \\ \rho_1^{AR} & 1 & \rho_1^{AR} & \ddots & \vdots \\ \rho_2^{AR} & \rho_1^{AR} & 1 & \ddots & \rho_2^{AR} \\ \vdots & \ddots & \ddots & \ddots & \rho_1^{AR} \\ \rho_{p-1}^{AR} & \cdots & \rho_2^{AR} & \rho_1^{AR} & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_p \end{bmatrix} = \begin{bmatrix} \rho_1^{AR} \\ \rho_2^{AR} \\ \rho_3^{AR} \\ \vdots \\ \rho_p^{AR} \end{bmatrix} \tag{10}$$

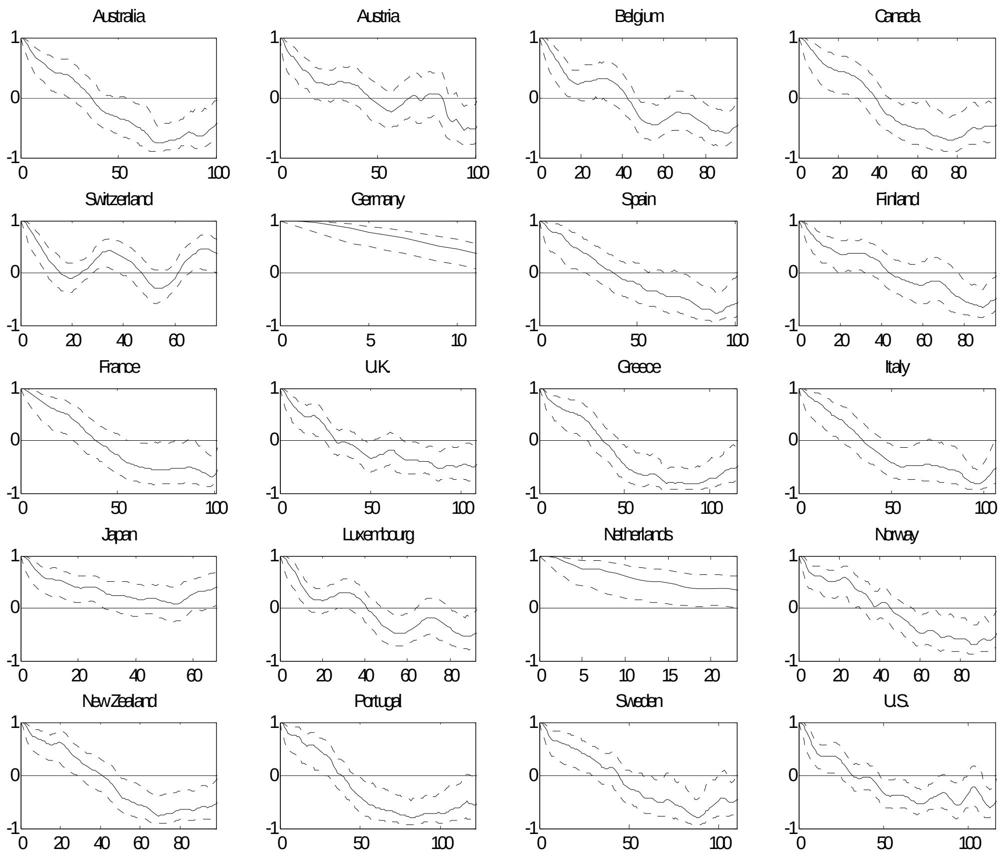

Figure 3: SAMPLE AUTOCORRELATION FUNCTIONS. Lags selected according to the criterion explained in the text. 90% confidence bands computed using the stationary bootstrap a la Politis and Romano (1994).

This is a linear system of p equations in the p values $\left\{\rho_1^{AR}, ..., \rho_p^{AR}\right\}$, which can be determined uniquely. The remaining values ρ_τ^{AR} are given by the recursive expression:

$$\rho_\tau^{AR} = a_1\rho_{\tau-1}^{AR} + ... + a_p\rho_{\tau-p}^{AR}$$

for all $\tau > p$.

The competing model to the AR is the functional form (7), which directly models the ACF of a potentially nonstationary time series process:

$$\rho_\tau^{ACT} = \frac{1 - a[1 - \cos(\omega\tau)]}{1 + b\tau^c}. \tag{11}$$

This functional form is an extension of the 1-term asymptotic approximation of the ACF function proposed by AT. The extension includes higher-order terms that account for cycles in addition to the "plateau plus drop-off" form induced by the original AT. Eq. (11) models the ACF with just four key-parameters a, b, c, ω. The denominator controls the decay of memory, with the parameter c being the rate-of-decay parameter. The parameter b regulates the "on impact" slope of the ACF. The numerator is responsible for the oscillations of the ACF. In particular, the parameter a regulates the impact of the oscillations implied by the presence of the cosine function in the numerator, while ω drives the frequency of such oscillations. Notice that a special case of (11) is that of a unit root process, whose ACF is $(1 + \tau/t)^{-1/2} \approx 1 - kt$ where $k \equiv 1/(2t)$. It can also be noticed that if the data-generating process is an ARFIMA(p,d,q), the parameter c of the ACT function is proportional to the order of integration d - $d \approx\ 1 - c/2$ (see Hassler 1994, 1997 for a theoretical analysis of the properties of the sample ACF of nonstationary I(d) and I(1)).

It is important to point out that this paper does not explicitly deal with ARFIMA models. Gadea and Mayoral (2005) have showed that inflation in the OECD countries is better represented by I(d) processes than by I(0) or I(1) processes when the time domain is considered. For the purpose of this paper we notice that, as stressed by Abadir et al. (2005), ARFIMA(p,d,q) processes imply convex hyperbolic decay rates for the ACFs, therefore giving good indications on the decay rate regarding the tails of the ACF, but not in the interim. The reason is that an ARFIMA model has a spectrum with a peak at the origin and cannot therefore account for long cycles (See Giraitis, Hidalgo and Robinson 2001; Hidalgo 2005 for recent developments on modelling long cycles within an ARFIMA framework).

We now turn to the formal comparison of the two competing models (9) and (11).

First, we estimate both models by Nonlinear Least Squares. To select the order of the autoregressive process, we employ the Schwarz Criterion (SC). Given its consistency, the same criterion is used to compare the two competing models. The use of an information criterion allows us to compare two models not necessarily having the same degrees of freedom. The alternatives are the Akaike and the Hannan-Quinn criteria. The former has been shown to be inconsistent by Nishii (1988). The latter is designed to pin down the orders p and q of an ARMA(p,q) process. Given that the ACT function does not belong to the ARMA class, we employ the Schwarz criterion. We also follow the suggestion of Ng and Perron (2005) and hold the effective sample size fixed across models to be compared.

4.1 Results

Figure 4 shows the sample and fitted ACFs. First, in all cases the ACT function fits the empirical ACF much better than the competing AR model. A result not shown, but available upon request, is that the AR-fitted ACFs are not included in the 90% bands displayed in Figure 2 for most of the countries. Viceversa, all the ACT-induced ACFs are statistically equivalent to the empirical ones. Second, in several occasions the AR model is forced to deliver the wrong sign of the concavity of the ACF (initial lags) to get as close as possible to the sample ACF in the middle of the sample. As a consequence, it tends to overestimate the ACF at low lags, and hence the rate of decay of shocks. It is worth stressing that the computation of the implied Sum of the Autoregressive Coefficients returns an average value equal to 0.99, with a minimum of 0.935 for Austria and a maximum of 0.999 for Switzerland. This would suggest that, *if* the true DGP is a linear autoregressive process, aggregate inflation is a unit root, or a near unit root process. Third, in some cases the estimated autoregressive processes (typically, AR(3) processes) deliver implausible high-frequency oscillations.

The superior goodness of fit of the ACT model is confirmed by the Schwarz criterion values, which are reported in Table 2: in all cases, the SC is minimized when the sample ACF is fitted by the ACT functional form. Table 2 reports also another measure of goodness of fit, the Q-ratio, which is based on the sum of squared residuals. Let

$$Q_k^j = \frac{1}{\tau^*} \sum\nolimits_{\tau=1}^{\tau^*} \left(\widehat{\rho}_{k,\tau}^j - \widehat{\rho}_\tau^j\right)^2, \quad k = \{AR, ACT\} \tag{12}$$

be the Q-statistic for model k and country j, where $\widehat{\rho}^j$ is the sample ACF for country j, $\widehat{\rho}_k^j$ is the model-k fitted ACF, and τ^* is defined as in Section 3. The Q-ratio for country

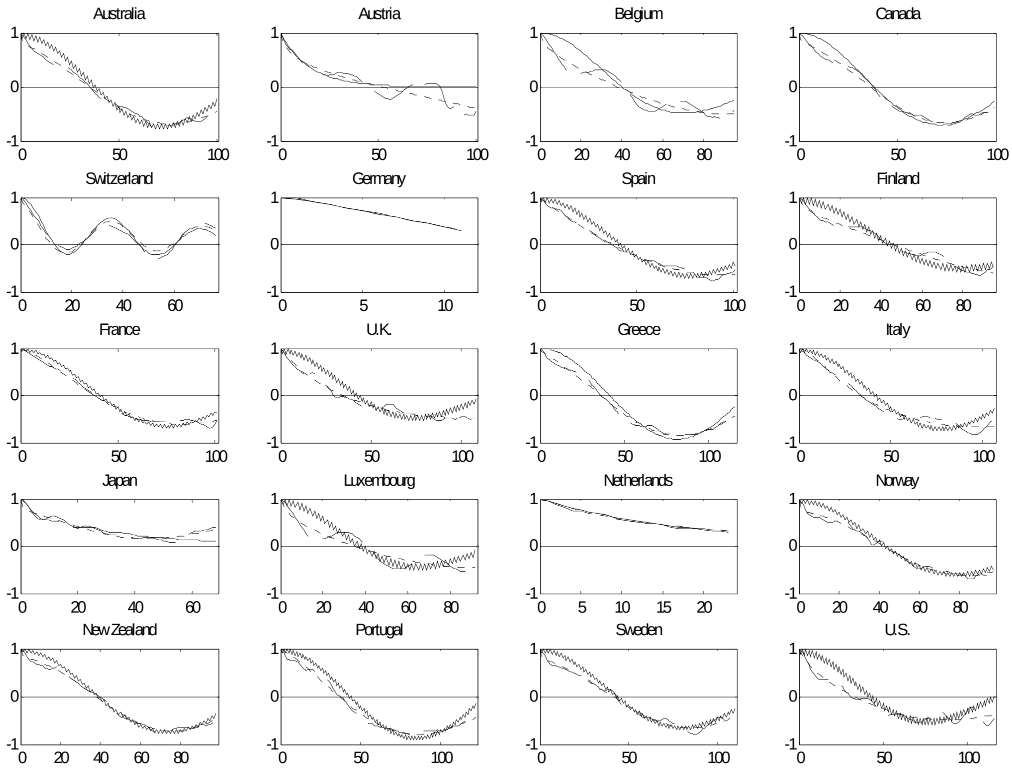

Figure 4: SAMPLE AND FITTED ACFs: FULL SAMPLE. Dashed line: Sample ACF. Dotted line: ACT-fitted ACF. Solid line: AR-fitted ACF. Lags selected according to the criterion explained in the text.

j is then given by:

$$Q_r^j = Q_{AR}^j / Q_{ACT}^j. \tag{13}$$

A value of Q_r larger than one indicates a better fit of the ACT model relative to the AR process, and can be interpreted as a measure of distance from linearity (for an example on the use of such a statistical criterion to compare sample and model-induced ACFs, see Cogley and Nason 1995).

Table 2 reports both the Q_{ACT} statistic - multiplied by 100 - and the Q_r. The reported values confirm the that the ACT functional form, which is derived from a long memory and nonlinear process, replicates the sample ACFs much better than an autoregressive model, which is based on the assumption of log-linearity. The relative performance summarized by the Q_r shows that this is true for all countries included in the dataset, but with a remarkable variability: gains are relatively small in the case of Switzerland and Netherlands, and relatively larger in all other cases, with the largest gains obtained for Spain and the UK. Overall, these results are in line with the claim by Caballero and Engel (2003), i.e. estimates of persistence based on partial-adjustment ARMA models are likely to be incorrect.

j	τ^*	$\frac{SC}{ACT}$	$\frac{SC}{AR(p)}$	Q_{ACT}	Q_r	j	τ^*	$\frac{SC}{ACT}$	$\frac{SC}{AR(p)}$	Q_{ACT}	Q_r
AS	101	-5.79	-3.69(3)	0.25	8.55	GR	117	-5.72	-3.66(2)	0.28	8.51
AT	101	-3.94	-3.04(1)	1.59	2.84	IT	107	-4.95	-3.10(3)	0.59	6.64
BE	96	-3.97	-2.84(2)	1.53	3.44	JP	69	-5.73	-4.30(3)	0.25	4.47
CA	100	-5.62	-4.01(2)	0.30	5.44	LX	93	-3.69	-2.65(3)	2.04	2.93
SZ	77	-4.57	-4.50(3)	0.81	1.14	NL	24	-7.59	-7.20(1)	0.03	2.18
GE	12	-10.44	-8.76(4)	0.00	4.38	NO	98	-5.39	-3.85(3)	0.37	4.88
SP	102	-5.94	-3.56(3)	0.22	11.35	NZ	99	-5.91	-4.39(3)	0.22	4.81
FI	96	-4.79	-3.24(3)	0.68	4.91	PO	123	-5.54	-3.52(3)	0.33	7.73
FR	102	-5.73	-4.23(3)	0.27	4.68	SW	111	-5.50	-3.82(3)	0.34	5.60
UK	109	-5.30	-2.91(3)	0.42	11.32	US	117	-4.62	-2.72(3)	0.82	7.05

Table 2: SAMPLE AND FITTED ACFs - FULL SAMPLE: GOODNESS OF FIT. 'j' stands for 'Country'. 'SC' denotes Schwarz Criterion. The number of lags p of the AR(p) processes is reported in brackets. 'QACT' is the Q-statistic for the ACT model. 'Qr' is the ratio between QAR and QACT.

4.2 Inflation persistence and Inflation Targeting: Subsample analysis

In light of the Lucas critique, changes in monetary policy may determine changes in the data generating process of inflation. During the 1990s, many countries experienced a potentially significant change in policy due to the official adoption of the inflation targeting monetary policy strategy (for a detailed presentation of the inflation targeting monetary policy strategy, see Svensson 2006). Several articles have been written on the impact of IT in dampening inflation and its fluctuations (see e.g. Bernanke, Laubach, Mishkin and Posen1999; Castelnuovo, Nicoletti-Altimari and Rodríguez Palenzuela 2003; Ball and Sheridan 2005; Dueker and Fischer 2006; Mishkin and Schmidt-Hebbel 2007). In our context, the choice of adopting an explicit inflation target is of particular relevance: had the inflation targeting announcement in a given country exerted a noticeable effect on inflation expectations, in terms of reducing their heterogeneity, one should have observed a change in the dynamics of aggregate inflation. In particular, one might expect a decrease of persistence, a signal witnessing the enhanced ability of the central bank to quickly return inflation to its target after an inflationary shock. This implies a faster decay rate of shocks, i.e. a sharper and quicker drop of the autocorrelations, which in turn means that the properties of the individual dynamic models would not be substantially different from those of the aggregate. Furthermore, if such a change is due to the adoption of an inflation targeting policy rather than other determinants, one should find that both results - a faster decay rate of shocks and a change in the underlying DGP of aggregate inflation - do not hold, or at the very least are less clear-cut, for non inflation targeting (NIT). Alternatively, a change in persistence and in aggregate inflation DGP may be driven by a change in the fundamental properties of the inflation process.

To investigate these issues, we split the group of countries into two subgroups, i.e. IT countries and NIT countries. The IT countries are those whose central bank has publicly announced the adoption of the IT strategy framework. Following Ball and Sheridan (2005), for each IT country we identify its IT adoption date (break-date for our stability analysis) as the first full quarter in which a specific inflation target or target range was in effect, and the target had been announced publicly as some earlier time. The break dates for the IT we consider are the following: Australia 1994Q4, Sweden 1995Q1, New Zealand 1990Q3, U.K. 1993Q1. Notice that we do not distinguish between Inflation Targeters and Constant Inflation Targeters. For a discussion on this and on the discrepancies between announcement and implementation of the IT strategy, see Ball and Sheridan (2005). Following Svensson (2003), we treat Euro Area countries as non-targeters. For the NIT countries, we adopt the break-date proposed by Ball and Sheridan (2005), i.e. 1993Q3 (the average of the IT break-dates).

We exclude Canada, Japan, Luxembourg, Greece, Norway, Switzerland, Finland, and Spain from our analysis. Canada, and Japan are excluded by the Schwarz information Criterion, which returns a number of significant lags in the second subsamples that is too low to estimate the competing models. Luxembourg (being part of a monetary union with Belgium) lacked an independent currency before the Euro, so it does not allow us to link its monetary policy to the persistence of its inflation rate. Greece appears to be an outlier when considering the convergence of the OECD countries's inflation in the '90s (it is the only country with an inflation over 20% in 1990, and over 10% in 1995). Norway and Switzerland adopted inflation target very recently (respectively in 2001 and 2000), so offering a too short post-break subsample to perform meaningful estimate of the ACFs. Finland and Spain adopted inflation targeting in 1994 (according to Ball and Sheridan 2005, the break-date is 1994Q1 for Finland and 1995Q2 for Spain), but joined the Euro area in 1999Q1 therefore moving from IT to NIT. We are then left with 4 countries that officially adopted IT and 8 NIT countries.

Figures 5 and 6 show the sample and the fitted ACFs in the pre- and in the post-break period, respectively. As before, the better performance of the ACT model is evident in both subsamples, and is confirmed by the Schwarz criterion values reported in Table 3: it does regularly better than the AR competitor, the only exception being the case of Italy in the second subsample. Moreover, the drawbacks of the AR process already underlined in the full sample analysis (wrong sign of the concavity and overestimation of the ACF values in the initial lags, counterfactual high-frequency oscillations) are also present in both subsample analysis. As regards the US, we also investigated subsamples identified by breaks either in 1979Q3 - the quarter in which Paul Volcker was appointed as new chairman of the Federal Reserve Board - or in 1985Q1 - the beginning of the so called Great Moderation. Our results - unreported but available upon request - turn out to be robust to this further check. We conclude that the explicit adoption of IT has not changed the main features of the underlying DGP of inflation: long memory and nonlinearities still play an important role. This does not necessarily imply that persistence is unchanged, but a rigorous analysis of time-varying persistence is beyond the scope of this paper.

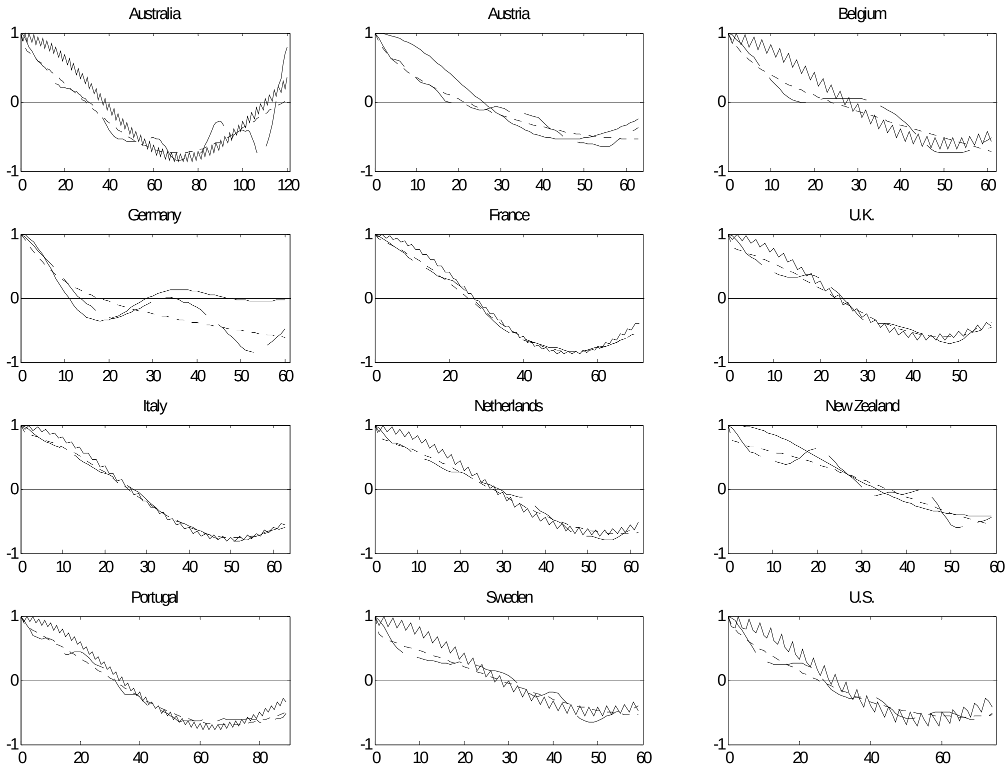

Figure 5: SAMPLE AND FITTED ACFs: FIRST SUBSAMPLE. Dashed line: Sample ACF. Dotted line: ACT-fitted ACF. Solid line: AR-fitted ACF. Lags selected according to the criterion explained in the text.

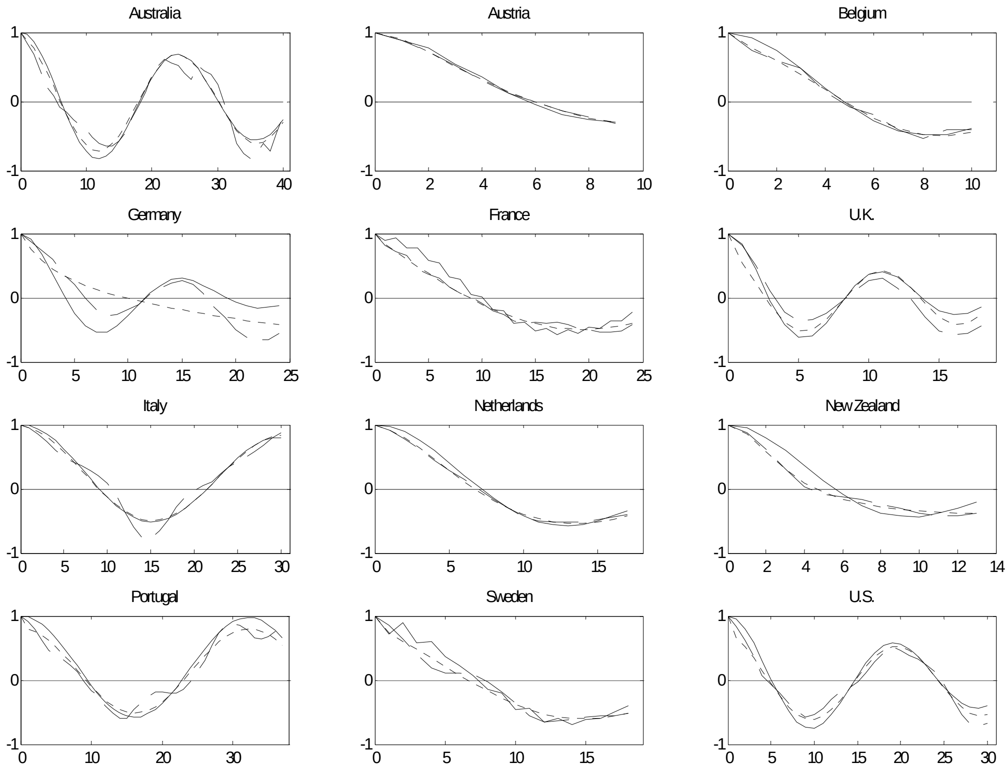

Figure 6: SAMPLE AND FITTED ACFs: SECOND SUBSAMPLE. Dashed line: Sample ACF. Dotted line: ACT-fitted ACF. Solid line: AR-fitted ACF. Lags selected according to the criterion explained in the text.

$j(S)$	τ^*	$\frac{SC}{ACT}$	$\frac{SC}{AR(p)}$	Q_{ACT}	Q_r	$j(S)$	τ^*	$\frac{SC}{ACT}$	$\frac{SC}{AR(p)}$	Q_{ACT}	Q_r
AS(1)	122	-3.00	-2.35(3)	4.19	1.99	IT(1)	65	-6.27	-4.64(3)	0.14	5.45
AS(2)	40	-3.43	-3.26(2)	2.19	1.42	IT(2)	34	-3.69	-3.80(3)	1.54	1.00
AT(1)	63	-4.61	-2.64(2)	0.75	8.16	NL(1)	64	-4.81	-3.59(3)	0.61	3.62
AT(2)	11	-8.51	-5.98(3)	0.01	15.69	NL(2)	19	-6.80	-4.68(2)	0.05	11.43
BE(1)	63	-3.63	-2.42(3)	1.99	3.57	NZ(1)	61	-3.82	-3.05(2)	1.64	2.48
BE(2)	12	-5.24	-4.51(2)	0.20	3.22	NZ(2)	15	-5.64	-3.18(2)	0.16	16.95
GE(1)	62	-3.10	-1.87(2)	3.39	3.89	PO(1)	91	-5.39	-3.62(3)	0.37	6.11
GE(2)	26	-2.33	-2.21(2)	5.60	1.46	PO(2)	39	-3.91	-3.32(3)	1.33	1.98
FR(1)	73	-6.41	-4.40(3)	0.13	7.87	SW(1)	61	-4.20	-2.87(3)	1.12	4.03
FR(2)	26	-5.67	-3.44(3)	0.20	10.58	SW(2)	20	-4.28	-3.09(3)	0.71	3.28
UK(1)	59	-4.61	-3.58(3)	0.74	2.99	US(1)	76	-4.03	-2.98(4)	0.56	7.08
UK(2)	20	-2.82	-2.80(2)	3.05	1.39	US(2)	32	-4.37	-3.44(2)	0.79	3.16

Table 3: SAMPLE AND FITTED ACFs - SUBSAMPLES: GOODNESS OF FIT. 'j(S)' stands for 'Country(Subsample)'. 'SC' denotes Schwarz Criterion. The number of lags p of the AR(p) processes is reported in brackets. 'QACT' is the Q-statistic for the ACT model. 'Qr' is the ratio between QAR and QACT.

5 CONCLUSIONS

The autocorrelation function domain, which is very informative about the cyclical and persistence properties of a time-series process, has been surprisingly understudied compared to the time-domain. In this paper we have proposed a set up based on the sample ACFs to investigate inflation dynamics in a dataset of 20 OECD countries. Our empirical findings can be summarized as three main points. First, we find that inflation is characterized by long-lasting fluctuations around a potentially time-varying mean, which are common across economies and tend to slowly fade away. This seems to be a novel stylized fact which should be taken into account by researchers aiming at replicating the dynamics of aggregate inflation both with reduced-form and with micro-founded models.

Second, we find that a nonlinear and long memory model proposed by Abadir et al. (2005) outperforms a standard autoregressive process (very popular in the macroeconomic literature) in replicating the cyclical and persistent dynamics of inflation for all countries. This holds true both in the full sample and in selected subsamples, which account for institutional changes in monetary policy occurred in the time period under analysis. This finding is in line with the theoretical implications of the literature on heterogeneity and aggregation: in presence of cross-sectional adjustment discontinuities, as is the case of sectoral price setting, macroeconomic aggregates would not behave like autoregressive processes (see Caballero and Engel 2007; Abadir and Talmain 2002).

Third, further analysis based on subsamples shows that results are robust to changes in monetary policy regimes. In particular, we examine the effects on inflation dynamics of the adoption of an inflation target and find that the data generating process is unchanged.

These results are surely of interest for monetary policy-making, since they imply that central banks willing to dampen the effects of a supply shock should i) move quickly and aggressively enough in order to impart a sufficient stimulus to achieve their target, and ii) return to a neutral stance well before the policy objective is achieved. In this sense, our results corroborate the following recent statement by Ben S. Bernanke, chairman of the Federal Reserve Bank:

> "Financial and economic conditions can change quickly. Consequently, the Committee must remain exceptionally alert and flexible, prepared to act in a decisive and timely manner and, in particular, to counter any adverse dynamics that might threaten economic or financial stability." (Ben S. Bernanke, "Financial Markets, the Economic Outlook, and Monetary Policy", speech held at the Women in Housing and Finance and Exchequer Club Joint Luncheon, Washington D.C. on January 10, 2008).

Further research on the distributional properties of the estimated ACT functional form and on its use to testing for breaks and to the analysis of time-varying persistence is in our agenda.

References

Abadir, K. M., and Talmain, G. (2002) "Aggregation, Persistence and Volatility in a Macro Model", *Review of Economic Studies,* 69, 749-779.

Abadir, K. M., and Taylor A. M. R. (1999) "On the definitions of (co)-integration", *Journal of Time Series Analysis,* 20, 129-137.

Abadir, K. M., Caggiano, G., and Talmain, G. (2005) "Nelson-Plosser Revisited: The ACF Approach", Discussion Paper 2005-07, Dept. of Economics, University of Glasgow.

Altissimo, F., Mojon, B., and Zaffaroni P. (2007), "Fast Micro and Slow Macro: Can Aggregation Explain the Persistence of Inflation", Working Paper No. 729, European Central Bank.

Attanasio, O., and Weber G. (1993), "Consumption Growth, the Interest Rate and Aggregation", *Review of Economic Studies*, 60, 631-649.

Baillie, R. T, Chung, C.-F., and Tieslau M. A. (1996) "Analysing Inflation by the Fractionally Integrated ARFIMA-GARCH Model", *Journal of Applied Econometrics,* 11, 23-40.

Ball, L., and Sheridan, N. (2005) "Does Inflation Targeting Matter?", in : Bernanke B., and Woodford M. (eds), The Inflation Targeting Debate, NBER.

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

Benati, L. (2008), "Investigating Inflation Persistence across Monetary Regimes", Working Paper 851, European Central Bank.

Bernanke, B. S. (2008), "Financial Markets, the Economic Outlook, and Monetary Policy",. http//www.federalreserve.gov/newsevents/speech.

Bernanke, B. S., Laubach, T. Mishkin, F., and Posen A. (1999), Inflation Targeting, Priceton University Press, Princeton.

Caballero, R. J., and Engel E. M. R. A. (1993), "Microeconomic Rigidities and Aggregate Price Dynamics", *European Economic Review,* 37, 697-717.

Caballero, R. J., and Engel E. M. R. A. (2003), "Adjustment Is Much Slower Than You Think", NBER Working Paper No. 9898.

Caballero, R. J., and Engel E. M. R. A. (2007), "Price Stickiness in Ss Models: New Interpretations of Old Results", *Journal of Monetary Economics,* 54, 100-121.

Caggiano, G., and Leonida L. (2007), "A Note on the Empirics of the Neoclassical Growth Model", *Economics Letters*, 94, 170-176.

Caggiano, G., and Leonida L. (2008), "International Output Convergence: Evidence from an Autocorrelation Function Approach", *Journal of Applied Econometrics,* forthcoming.

Carvalho, C. (2006), "Heterogeneity in Price Stickiness and the Real Effects of Monetary Shocks", *The BE Journal of Macroeconomics,* Vol. 2, Issue 1, (Frontiers).

Castelnuovo, E., Nicoletti-Altimari S., and Rodríguez Palenzuela D. (2003), "Definition of Price Stability, Range and Point Inflation Targets: The Anchoring of Long-term Inflation Expectations", 43-66, in O. Issing (ed.): Background Studies for the ECB's Evaluation of Its Monetary Policy Strategy, Frankfurt-am-Main, Germany: European Central Bank.

Chambers, M. J. (1998), "Long Memory and Aggregation in Macroeconomic Time Series", *International Economic Review*, 39, 1053-1072.

Cogley, T., and Nason J. (1995), "Output Dynamics in Real-Business-Cycle Models", *American Economic Review*, 85, 492-511.

Cogley, T., and Sargent T.J. (2005), "Drifts and Volatilities: Monetary Policies and Outcomes in the Post WWII U.S.", *Review of Economic Dynamics*, 8, 262-302.

Davis, R. A., and Mikosch T. (1998), "The Sample Autocorrelations of Heavy-Tailed Processes with Applications to ARCH", *Annals of Statistics*, 26, 2049-2080.

Dueker, M.J. and Fischer A.M. (2006), "Do Inflation Targeters Outperform Non-Targeters", *Federal Reserve Bank of St.Louis Review*, 88, 431-450.

Gadea, M.D. and Mayoral L. (2005), "The Persistence of Inflation in OECD Countries: A Fractionally Integrated Approach", *The International Journal of Central Banking*, 2, 51-104.

Gagnon, J. E. (1996), "Long Memory in Inflation Expectations: Evidence from International Financial Markets", International Finance Discussion Papers, No. 538, Board of Governors of the Federal Reserve System.

Giraitis, L., Hidalgo J. and Robinson P. M. (2001), "Gaussian Estimation of Parametric Spectral Density with Unknown Pole", *Annals of Statistics,* 29, 987-1023.

Granger, C. W. J. (1980), "Long Memory Relationships and the Aggregation of Dynamic Models", *Journal of Econometrics*, 14, 227-238.

Granger, C. W. J., and Ding Z. (1996), "Varieties of Long Memory Models", *Journal of Econometrics*, 73, 61-77.

Granger, C.W.J., and Newbold P. (1986), Forecasting Economic Time Series, San Diego: Academic Press.

Grilli, V., Masciandaro D., and Tabellini G. (1991), "Political and Monetary Institutions and Public Finance Policies in the Industrial Countries", *Economic Policy*, 13, 341-392.

Hall, P. (1988), "On Symmetric Bootstrap Confidence Intervals", *Journal of the Royal Statistic Society, Series B (Methodological),* 50, 35-45.

Hassler, U. (1994), "The Sample Autocorrelation Function of I(1) Processes", *Statistical Papers,* 35, 1-16.

Hassler, U. (1997), "Sample Autocorrelations of Nonstationary Fractionally Integrated Series", *Statistical Papers,* 38, 43-62.

Hassler, U., and Demetrescu M. (2005), "Spurious Persistence and Unit Roots due to Seasonal Differencing: The Case of Inflation Rates", *Journal of Economics and Statistics*, 225, 413-426.

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

Hidalgo, J. (2005), "Semiparametric Estimation for Stationary Processes whose Spectra have an Unknown Pole", *Annals of Statistics,* 33, 1843-1889.

Hill, B. M. (1975), "A Simple General Approach to Inference about the Tail of a Distribution", *Annals of Mathematical Statistics,* 3, 1163-1174.

Hill, J. B. (2007), "On Tail Index Estimation for Dependent, Heterogeneous Data", unpublished manuscript, University of North Carolina, Dept. of Economics.

Huisman, R, Koedijk, K. G., Kool, C. J. M., and Palm F. (2001), "Tail-Index Estimates in Small Samples", *Journal of Business and Economic Statistics*, 19, 208-216.

Johnson, D.R. (2002), "The Effect of Inflation Targeting on the Behavior of Expected Inflation: Evidence from an 11 Country Panel", *Journal of Monetary Economics*, 49, 1521-38.

Kumar, M. S., and Okimoto T. (2007), "Dynamics of Persistence in International Inflation Rates", *Journal of Money, Credit and Banking* 39, 1457-1479.

Levin, A.T., Natalucci, F.M., and Piger J.M. (2004), "The Macroeconomic Effects of Inflation Targeting", *Federal Reserve Bank of St.Louis Review*, 86, 51-80.

Mankiw, N. G., Reis, R. and Wolfers, J. (2004), "Disagreement about Inflation Expectations", *NBER Macroeconomics Annual 2003*, MIT Press, 18, 209-248.

Mikosch, T., and Starica, C. (2000), "Limit Theory for the Sample Autocorrelations and Extremes of a GARCH(1,1) Process", *The Annals of Statistics*, 28, 1427-1451.

Mishkin, F.S., and Schmidt-Hebbel K. (2007), "Does Inflation Targeting Make a Difference?", NBER Working Paper No. 12876.

Ng, S. and Perron, P. (2005), "A Note on the Selection of Time Series Models", *Oxford Bulletin of Economics and Statistics*, 67, 115-134.

Nishii, R. (1988), "Maximum Likelihood Principle and Model Selection when the True Model is Unspecified", *Journal of Multivariate Analysis*, 27, 392-403.

O'Reilly, G. and Whelan, K. (2005), "Has Euro-Area Inflation Persistence Changed over Time?", *Review of Economics and Statistics*, 87, 709-720.

Paya, I., Duarte, A., and Holden, K. (2007), "On the Relationship between Inflation Persistence and Temporal Aggregation", *Journal of Money, Credit and Banking*, 39, 1521-1531.

Pivetta, F. and Reis, R. (2007), "The Persistence of Inflation in the United States", *Journal of Economic Dynamics and Control*, 31, 1326-1358.

Politis, D.N. and Romano, J.P. (1994), "The Stationary Bootstrap", *Journal of the American Statistical Association*, 89, 1303-1313.

Ratfai, A. (2006), "Linking Individual and Aggregate Price Changes", *Journal of Money, Credit and Banking*, 38, 2199-2224.

Rotemberg, J. (1982), "Mopolistic Price Adjustment and Aggregate Output", *The Review of Economic Studies*, 49, 517-531.

Svensson, L.E.O. (2003), "In the Right Direction, but not Enough: The Modification of the Monetary-Policy Strategy of the ECB", unpublished manuscript, Princeton University, Dept. of Economics.

Svensson, L.E.O. (2006), "Inflation Targeting", The New Palgrave Dictionary of Economics, 2nd Edition, forthcoming.

Wright, J. H. (2002), "Log-Periodogram Estimation of Long Memory Volatility Dependencies with Heavy Tailed Returns", *Econometric Reviews*, 21, 397-417.

Zaffaroni, P. (2004), "Contemporaneous Aggregation of Linear Dynamic Models in Large Economies", *Journal of Econometrics*, 120, 75-102.