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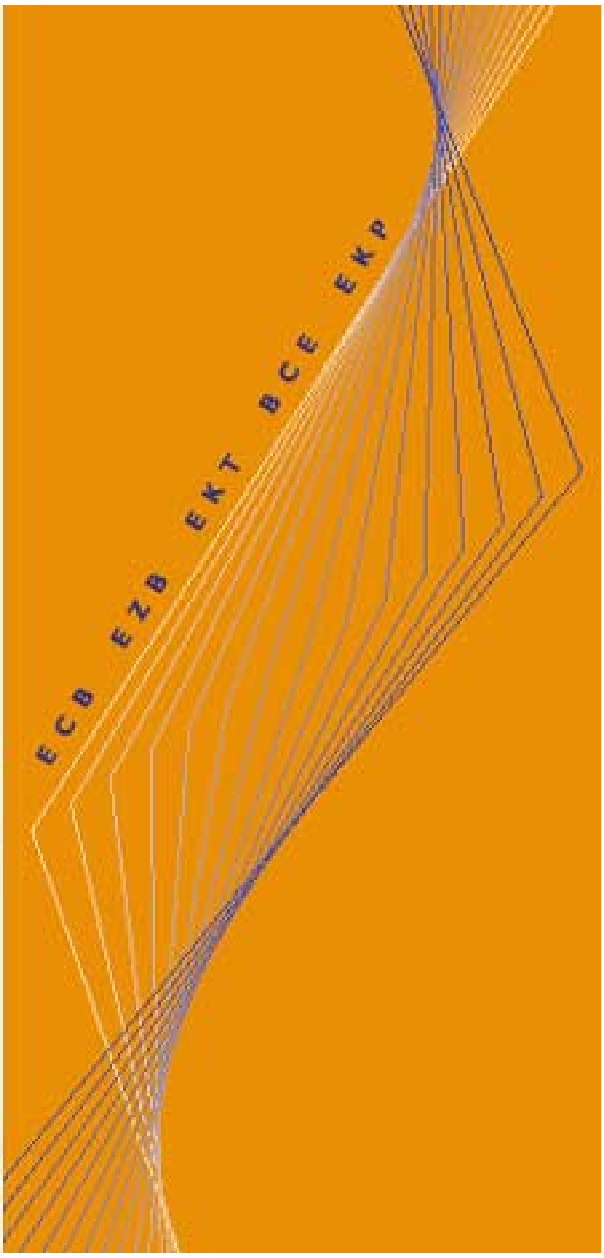

WORKING PAPER NO. 36

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BY CLAUDIO MORANA

November 2000

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Abstract

We propose a measure of core inflation which is derived from a Markov switching ARFIMA model. The Markov switching ARFIMA model generalises the standard ARFIMA model allowing mean reversion to take place with respect to a changing unconditional mean. By imposing a coswitching restriction for nominal money growth and HICP inflation we are able to identify three regimes and extablish a linkage between the long-run dynamics of inflation and money growth. The last regime has been found to be coherent with the objective of price stability and can be tentatively named EMU regime. The core inflation model has been contrasted with other models suggested in the literature and found to be superior in terms of forecasting power.

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Keywords: ARFIMA, core inflation, euro area, Markov switching.

1 Introduction

The concept of core inflation is not univocal and is theory dependent (see Wynne (1999) for a review). However, two main features help to define it. Firstly, core inflation is a long-run concept. Secondly, it can be interpreted as an expectational variable. Eckstein (1981) has suggested an interpretation which captures both these elements: "the core rate is the trend increase of the cost of the factors of production. It originates in the long-term expectations of inflation in the minds of households and business, in the contractual arrangements which sustain the wage-price momentum, and in the tax system." In equilibrium expectations are fulfilled and the real side-monetary side dichotomy applies. Therefore, core inflation is the rate of inflation prevailing in the long-run, when money is neutral and there are not any supply shocks. In this context inflation becomes a monetary phenomenon.

In statistical terms core inflation has in general been identified as that component of inflation that is permanent or highly persistent. Bryan and Cecchetti (1994), for instance, define core inflation as "the long-run, or persistent, component of the measured price index, which is tied in some way to money growth". Then, it becomes important to be able to separate the persistent inflation signal from the noisy dynamics.

In the paper we propose a measure of core inflation which is derived by taking into account the information contained in money growth, without modelling inflation as a non stationary process. This approach should be appropriate for the monetary policy framework at work in the euro area, given that, under successful price stabilisation, inflation necessarily becomes a mean reverting process. This is also coherent with some recent contributions that point towards the modelling of inflation as a fractionally integrated ARMA process (ARFIMA) (Hassler and Wolters, 1995; Baillie et al., 1996; Delgado and Robinson, 1994; Bos et al., 1999; Ooms and Doornik, 1999). A common finding in the studies above-mentioned is in fact a positive fractional differencing parameter below 0.5, suggesting that inflation can be modelled as a long memory process.

The measure of core inflation proposed is based on a Markov switching ARFIMA (MS-ARFIMA) model. The MS-ARFIMA model generalises the standard ARFIMA model allowing mean reversion to take place with respect to a changing equilibrium component. The advantage of the Markov switching mechanism is that the detection of regime shifting is made fully endogenous. Allowing for regime switching is of particular importance for the sample analysed (1980:1-1999:11), given that the monetary unification inaugurates a new regime for monetary policy in the euro area and should have a permanent impact on the mean of inflation. A multistate process can be rationalised in terms of a mixture of distributions. The observed data are realizations from the different distributions constituting the mixture and the unconditional mean of each component can be seen as a possible equilibrium state that can be assumed by the process. In the case of a Markov-switching process, when changes are permanent, i.e. the own transition probabilities have a unitary value, and the state is known, the long-run forecast of the process made at time t is equal to the unconditional mean of the component from which has been extracted the t-th observation. In this case the equilibrium state can also be seen as a long-run forecast. This suggests to identify persistent inflation over the medium run as the sum of its long-run forecast plus its persistent deviation. This latter component is captured by the ARFIMA component of the model. Allowing for switching regimes, we find a dramatic reduction in the persistence of inflation. Previous work carried out on the euro area by Cassola (1999) indicates the presence of two regimes in the GDP deflator and nominal M3 growth. The second regime is found to be coherent with the definition of price stability for the euro area. By imposing a coswitching restriction for nominal money growth and HICP inflation we are able to identify three regimes. The last regime, as in Cassola (1999), is found to be coherent with the definition of price stability for the euro area and can be tentatively named EMU regime, although its beginning is before the move to Stage Three in January 1999. The imposition of the coswitching restriction establishes a linkage between the long-run dynamics of inflation and money growth and Granger causality tests suggest the presence of unidirectional causality from core money growth to core inflation, confirming the economic content of the core inflation measure derived. The MS-ARFIMA model has been contrasted with other core inflation models, in particular a standard ARFIMA model, a common trends model and HICP less food and energy inflation. For the economic content and statistical properties, the MS-ARFIMA model and the common trends model constitute useful benchmarks to which a measure of core inflation can be compared. When the hypothesis of I(1) non stationarity can be rejected, then the MS-ARFIMA model provides a framework where a persistent-non persistent decomposition of inflation can be achieved and a measure of core inflation, that is suitable for monetary policy purposes, derived.

After this introduction the rest of the paper is organised as follows. In section two we overview the different approaches to core inflation estimation suggested in the literature. In section three we investigate the statistical properties of the series employed in the study. In section four we introduce the econometric methodology and present the results. In section five we compare the measure of core inflation derived from the MS-ARFIMA model to other measures suggested in the literature. Finally, in section six we conclude.

2 An overview of core inflation estimation methodologies

In the literature three main methodologies have been proposed. The first method is due to Bryan and Cecchetti (1994) and Bryan et al. (1997). In this approach a measure of underlying inflation is obtained by computing a trimmed mean of the cross-sectional distribution of individual price changes. The size of the trimming is decided optimally by minimising the mean square error of the aggregate inflation level, obtained by trimming, from the 3-year centered moving average of actual aggregate inflation. This approach can be considered as an improvement with respect to the practice of excluding some categories of goods as in the construction of ex food and energy measures. However, it is unclear whether the Bryan and Cecchetti approach allows to identify the permanent component of inflation (Bagliano and Morana, 1999b). A second approach useful to deal with the volatility of individual price components has been suggested by Diewert (1995) and Dow (1994). In their framework a measure of core inflation is obtained by computing a simple weighted average of individual price changes, with weights inversely proportional to the variance of price changes. Applications to euro area data of the two approaches discussed above can be found in Vega and Wynne (1999).

The second methodology is a panel approach. Two main contributions can be found in this line of research, namely the Dynamic Factor Index of Stock and Watson (1991) and the Diffusion Index of Stock and Watson (1998). In both approaches the multi product or multi country data dimension is exploited to determine a trend measure of inflation.

Finally, the third methodology is a time series approach. In this framework a measure of underlying inflation is obtained by computing a permanent-transitory decomposition of the inflation series. Starting with the seminal work of Beveridge and Nelson (1981), different approaches to the permanent-transitory decomposition have been proposed. Univariate techniques, such as simple moving averages calculated over a variable time span (from 3-6 months up to 36 months) or more sophisticated filters (e.g. unobserved component models estimated by the Kalman filter, the Hodrick-Prescott filter, the Beveridge-Nelson decomposition) have been used to smooth and reduce the noise component in the inflation pattern. Blanchard and Quah (1989) have shown how a trend-cycle decomposition may be attained for non cointegrated $I(1)$ variables in a multivariate framework by constraining their long-run responses to different shocks obtained from the VAR representation. Quah and Vahey (1995) applied this methodology to UK data to obtain an estimate of the core inflation component from a VAR model including only industrial production and inflation. In their framework, core inflation is identified as that component of inflation that is independent of output in the long-run. However, as shown by Stock and Watson (1988) and Gonzalo and Granger (1995), in a multivariate system also cointegration restrictions may be used to disentangle short-run and long-run components of a vector time-series. Bagliano and Morana (1999a,b,c) have derived a measure of core inflation from a common trends model including some of the economic determinants of inflation, in particular nominal money growth. Core inflation is then identified as the (Beveridge-Nelson-Stock-Watson) permanent component of inflation or the long-run inflation forecast. In Bagliano and Morana (1999a) this measure of core inflation has been found to outperform the Quah and Vahey (1995) core inflation measure in terms of robustness and economic and statistical interpretability.

3 Statistical properties of the inflation process

Over the span of time analysed (1980:1 to 1999:11[1]) monetary policy in the various EMU member countries has followed different principles. Only with the launch of the single monetary policy in 1999 a unique framework for monetary policy has been introduced. However, the convergence criteria set in the Maastricht Treaty have imposed an increasing harmonisation on the single member economic policies starting already in 1992. The policy changes connected to the increasing coordination of economic policies since 1992 should have left a permanent impact on the economies of the euro area. The aim of this section is therefore to investigate the presence of structural breaks in both inflation and nominal money growth. Some summary statistics are reported in Table 1 and Table 2, while in Figure 1 the harmonised CPI inflation (HICP) rate together with the rate of growth of M3 are plotted. During the period analysed annual inflation has averaged around a value of about 4.08% against an annual rate of nominal money growth of about 7.08%. Standard ADF tests reveal shock persistence, indicating the possible

[1]HICP figures before 1995 have been computed by extending backwards national CPI growth rates with GDP weights at ppp exchange rates in 1995. M3 figures are month-end stock from the ECB database in millions of euro.

presence of a unit root in the autoregressive representation of the processes. However, this result is not robust to the number of lags employed in the analysis and might reflect unaccounted changes in regime.

FIGURE 1
TABLES 1-2

As shown in Figure 1, the inflation rate seems to be characterised by structural change. Visual inspection allows one to clearly identify periods characterised by rather different dynamics. A first period span approximately from the beginning of the sample to the mid-eighties and is characterised by a steady and rapid decline of HICP inflation. A second period is characterised by a steady inflation rate and lasts until the mid-nineties. Finally, a third period is characterised by a further fall in the inflation rate. It is interesting to notice that a three regime process seems to characterise the rate of nominal money growth as well, although the downward trend in nominal money growth is much less pronounced. The coswitching dynamics in nominal money growth and inflation provide empirical evidence in favour of the existence of a long-run linkage between inflation and nominal money growth, as suggested by the view that inflation is a monetary phenomenon in the long-run. Visual inspection has been followed by tests for structural change and outliers based on Harvey and Koopman (1992).

Univariate structural time series models have been fitted to the data in order to decompose the series in a trend component and a residual component. The trend component is modelled as a random walk process and its innovations are then employed to test for structural change. On the other hand, the residual component may be used to test for the presence of outlying observations. As suggested by the normality tests, both series show significant excess kurtosis, evidence that influential observations may well characterise the data.

After estimation, 95% envelope bounds have been computed via bootstrapping (1000 replications). The results are reported in Figures 2 and 3.

FIGURES 2-3

A number of features can be noticed from the graphs. First of all episodes of oil price turbulence seem to have left a clear impact on inflation. This is surely true for the break of 1986, the year of the oil countershock. As far as the Gulf War period is concerned, the residual components suggest that the episode should be interpreted more in terms of an additive outlier than as a structural break. Previous to 1986, in 1985 it is possible to identify a break point common to both the rate of money growth and inflation. Interestingly, the break point occurring around 1994 in nominal money growth appears to be an outlying observation for the inflation rate. Other outlying observations are located around 1981, 1990, 1991, 1992, 1993, and 1999. The latter is also a feature of the money growth process. Overall the results suggest the empirical relevance of breaks for the series considered and support a modelling framework where these features are fully taken in to account. Such econometric model is outlined below.

4 The econometric methodology

Two recent directions in time series econometrics have attempted to relax the assumption of a linear data generating process on the one hand, and of I(1) nonstationarity on the other. Both directions point towards the definition of statistical processes that are potentially better suited to model economic time series. Hamilton (1989), building on Goldfeld and Quandt (1973), has suggested to approximate a possibly nonlinear data generating process with a time switching autoregressive linear model, where the switching across regimes is governed by a Markov-chain process.

On the other hand, following the work of Granger (1980), Granger and Joyeux (1980) and Hosking (1981) several recent studies have focused on the estimation of fractionally integrated processes (ARFIMA) (see Baillie, 1996 for a survey). The concept of fractional integration has allowed researchers to better investigate the memory features of time series data. Fractional processes allow to model situations in which, differently from what is observed for I(1) processes, the effects of shocks do tend to decay, although according to a slow hyperbolic rate rather than to a quicker exponential rate as in the I(0) case. For $0 < d < 0.5$ the process is covariance stationary and long-memory, for $-0.5 < d < 0$ the process is covariance stationary and antipersistent, while for $0.5 < d < 1$ the process is non-stationary but still mean reverting. Relaxing the unit root assumption is also important in the light of the work of Perron (1989), where it is shown that allowing for occasional breaks in the deterministic components of a statistical model may affect significantly the persistence of innovations.

In this paper we employ a MS-ARFIMA model, where the two recent methodological contributions described above are integrated. The MS-ARFIMA process can be thought of as a statistical framework were a persistent-non persistent decomposition can be achieved for stationary processes. In this framework observations can be thought of as being realizations of a number of DGPs, which may differ in terms of unconditional means and variances. The switching across regimes is then modelled using a Markov chain mechanism. The MS component of the process is employed to model the equilibrium component of the series which is given by the unconditional means of the component of the mixture. When changes are permanent, and the state is known at the time the forecast is made, the equilibrium process can also be interpreted as long-run forecast. On the other hand, the ARFIMA component models the remaining zero mean cyclical component of the series that show some persistence.

The modelling framework suggested in this paper is conceptually similar to the model of stochastic segmented trends introduced by Engle and Hamilton (1990). However, the focus of this paper is on multivariate models. Two or more variables may be said to be coswitching when the switching in the unconditional mean and/or variance is perfectly correlated between the two series. Coswitching creates a framework in which economic theory can be employed to improve the estimation of the long-run component of the series by increasing the information set estimation is conditioned to. In fact, economic theory may be informative on the long-run linkages existing between economic variables. In this paper we exploit the view that inflation is a monetary phenomenon in the long-run. We therefore impose a coswitching restriction to derive a core inflation measure that is coherent with the mean dynamics of money growth. In particular, the contemporaneous switching allows the trend dynamics of inflation and money growth to be perfectly correlated, providing a statistical counterpart to the theoretical notion of long-run linkage between these two series. The MS-ARFIMA model is presented below.

4.1 The econometric model

Given the $I(d)$ series x_t subject to regime shift, its conditional probability density may be written as:

$$p(x_t \mid s_t) = \left\{ \begin{array}{cc} f(x_t \mid \boldsymbol{\theta}_1) & \text{if } \ s_t = 1 \\ \vdots & \\ f(x_t \mid \boldsymbol{\theta}_M) & \text{if } \ s_t = M, \end{array} \right\}$$

where $s_t \in \{1, ..., M\}$ indicates the feasible regimes, and $\boldsymbol{\theta}_m$ is the parameter vector in regime $m = 1, ..., M$.

The regime s_t can be modelled according to a discrete-state homogeneous Markov-chain generating mechanism:

$$\Pr\left(s_t \mid \{s_{t-j}\}_{j=1}^{\infty}\right) = \Pr\left(s_t \mid s_{t-1}; \boldsymbol{\rho}\right)$$

where $\boldsymbol{\rho}$ is the vector of parameters of the regime generating process.

The general econometric model can be written as

$$\Phi(L)\,(1-L)^{d}\,(x_t-\mu(s_t))=\Theta(L)\varepsilon_t$$

$$\varepsilon_t \sim NID\left(0,\sigma^2\right)$$

where $\Phi(L)=1-\phi_1 L-...-\phi_p L^p$, $\Theta(L)=1+\theta_1 L+...+\theta_q L^q$ and both lag polynomials have all the roots outside the unit circle, $\mu(s_t)$ is the switching unconditional mean. The long memory property of the series is governed by the part $(1-L)^{d}$, while the polynomials in the lag operator $\Theta(L)$ and $\Phi(L)$ determine the short memory behaviour. Estimation is carried out in two stages. In the first stage the switching unconditional mean is estimated via the Expectation-Maximization (EM) algorithm as indicated in Hamilton (1990) and the switching mean of the series is computed as

$$\sum_{k=1}^{M}\hat{p}_{ik}\hat{\mu}_k$$

where $\hat{p}_{ik}$ is the estimated probability that observation i belongs to state k and $\hat{\mu}_k$ is the estimated value of the unconditional mean in the kth state. In the second stage the demeaned time series is fitted by means of an ARFIMA(p,d,q) model estimated by Maximum Likelihood as shown by Sowell (1992). This modelling approach aims to decompose a covariance stationary series in two components. The first component is the persistent component of the series and is obtained by adding the fitted signal in the ARFIMA model from step 2 to the estimated break process from step 1. The second component is the residual component of the series and is characterised only by dynamics of short lived nature.[2] When changes are permanent, i.e. the own transition probabilities have a unitary value, and the state in t is known, the long-run forecast of the process made at time t is equal to the unconditional mean of the component of the mixture from which the t-th observation has been extracted . In this case the equilibrium state can be interpreted as long-run forecast. In fact, by rewriting the process as

$$x_t-\mu(s_t)=(1-L)^{-d}\,\Phi(L)^{-1}\Theta(L)\varepsilon_t$$

[2]Estimation has been carried out using the Ox routines MSVAR of H.M. Krolzig and ARFIMA of J.A Doornik and M. Ooms.

$$x_t = \mu(s_t) + z_t$$

where $z_t \equiv (1-L)^{-d}\,\Phi(L)^{-1}\Theta(L)\varepsilon_t$ follows an ARFIMA(p,d,q) process. We have then

$$\lim_{m\to\infty} E\left(x_{t+m}\right) = \lim_{m\to\infty} \mathbf{a}'\mathbf{P}^m\boldsymbol{\mu} + \lim_{m\to\infty} E\left[z_{t+m}\right]$$

where $\left[\ \mathbf{a}' = p\left(s_{t=1}|y_t\right) \ \ \ldots \ \ p\left(s_{t=k}|y_t\right)\ \right]$, $\mathbf{P}$ is the transition matrix, and $\boldsymbol{\mu}'= \left[\ \mu_1 \ \ \ldots \ \ \mu_k\ \right]$. When $\mathbf{P}$ is an identity matrix, i.e. the changes are permanent, and the state is known in t, $\lim_{m\to\infty} \mathbf{a}'\mathbf{P}^m\boldsymbol{\mu} = \mu_j$, where j indicates the state in which the system is at the time the forecast is made. We have therefore $\lim_{m\to\infty} E\left(x_{t+m}\right) = \mu_j$, since the second term converges to zero. For a two state model we have for instance

$$\lim_{m\to\infty} E\left(x_{t+m}\right) = \lim_{m\to\infty} \left[\ p\left(s_{t=1}|y_t\right) \ \ p\left(s_{t=2}|y_t\right)\ \right] \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}^m \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}$$

$$= \lim_{m\to\infty} \left[\ 1 \ \ 0\ \right] \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}^m \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} = \mu_1.$$

4.2 Empirical results

4.2.1 The estimation of the long-run

The selection of the regime switching process is complicated by the fact that under the null of linearity the elements of the transition matrix are not identified. As a consequence the likelihood ratio (LR) test does not have the usual χ^2 asymptotic distribution. Hansen (1992, 1996) has suggested a test for the null of linearity against a Markov switching alternative that provides a bound for the asymptotic distribution of the standardised LR test. In the paper we have implemented a less computationally intensive approach based on Davies (1987), which provides, as in Hansen (1992), an upper bound for the significance of the LR statistic.

The results are reported in Tables 3-5. Figure 4 plots the estimated smoothed probabilities.

FIGURE 4

TABLES 3-5

As shown in Table 3, the LR test rejects the null hypothesis of a single state or of a two state model for the unconditional mean. The three regimes are highly persistent, with the own transition probabilities very close to one. The first period (regime 3) goes from the beginning of the sample to 1983:12 and it may be related to the second oil shock of 1979-1981.The unconditional mean for the monthly inflation rate in the first regime is about 0.81% that is 9.72% on an annual basis. Inflation has been falling steadily since the second oil shock. The second regime captures an interim period that goes from 1984:1 to 1993:4. During this period monthly inflation averaged at 0.33% (3.99% on an annual basis). Finally, the third period (regime 1) starts in 1993:5 and continues till to the end of the sample. In this third period average inflation has been about 0.16% (1.99% on an annual basis). As far as nominal money growth is concerned, the figures are 0.79% (9.50%) in regime 3, 0.64% (7.71%) in regime 2 and 0.39% (4.73%) in regime 1. It is interesting to notice that the first regime is fully consistent with the price stability regime launched by EMU. In fact, the log-run forecasts for inflation and money growth are very close to the reference values set for these variables.

4.2.2 The estimation of the short-run

Once allowed for a switching mean, the demeaned series should show less persistence than the original ones. ADF tests carried out on the demeaned series indicate rejection of the unit root hypothesis for both series. However, inflation shows quite a strong persistence according to the Ljung- Box test (Table 6) and the estimated fractional differencing parameter.

TABLE 6

Both series appear to be covariance stationary, although only the rate of money growth is I(0). This suggests to model inflation without imposing the I(0) constraint, that is to employ an ARFIMA model for the residual inflation component. We estimated two different ARFIMA structures for the data at hand. The first model is a standard ARFIMA model for the actual inflation process that can be compared with an ARFIMA model with switching mean. The comparison should shade light on the consequences of ignoring regime switching for the estimation of the fractional integration parameter. The second model is therefore a MS-ARFIMA model, where changes in regime are fully taken into account. The fitted ARFIMA process on the demeaned inflation series can be interpreted in terms of deviations from long-run inflation that still belong to the inflation signal because of their shock persistence. On the other hand, the residuals of the MS-ARFIMA model should follow a white noise process.

In Table 7 the results of the estimation of the short-run structures of the models are reported.

TABLE 7

The estimates of the fractional differencing parameters are largely coherent with those reported in Hassler and Wolters (1995), Baillie et al. (1996), Delgado and Robinson (1994), Bos et al. (1999) and Ooms and Doornik, (1999). First of all, it can be noticed that the magnitude of the estimated fractional differencing parameter is dramatically reduced by the introduction of a limited number of switching regimes. Moving from the single state model (estimated after removing the sample mean from the series) to the 3-state model induces a reduction of about 30% in the fractional differencing parameter, from a value of about 0.40 to a value of about 0.28. The short-run structure for the two models is similar and parsimonious. Finally, both models pass diagnostic checking apart from the normality test.

In Figure 5 the impulse response functions for the two processes are plotted. The quicker decay of shocks to the MS-ARFIMA model relatively to the ARFIMA counterpart is noticeable. However, the effects of a unitary shock tend to fade away beyond a horizon of three years, suggesting that the ARFIMA component of the MS-ARFIMA model is still important for the determination of persistent inflation over the medium term. Figures 6 and 7 show the estimated persistent (core) inflation components, actual HICP (all-items) inflation and the estimated non persistent ("non-core") inflation components. Twelve-month lagged moving averages of all series are plotted.

FIGURES 6-7

As is shown in the plots, the main difference between the standard ARFIMA model and its Markov switching counterpart lies in the abrupt shift that the Markov switching model shows in correspondence of regime changes. On the other hand the ARFIMA model shows a smoother transition. This behaviour is clearly reflected in the estimated fractional differencing parameter that, as already noticed above, is lower for the Markov switching specification, indicating a lower shock persistence and therefore a more rapid adjustment.

As expected, persistent inflation displays less variability than measured inflation for both models. However, as can be noticed from the cyclical components as well, the ARFIMA model and the MS-ARFIMA model suggest a fairly different policy, particularly for the beginning of the sample. While the ARFIMA core inflation is indistinguishable from actual inflation up to 1986, the MS-ARFIMA core inflation follows closely the switch in nominal money growth and alternates a period in which it is above actual inflation (up to 1984) to a period in which it is below. As expected, both processes indicate that core inflation was above actual inflation during the period of the oil countershock. Since 1986 the two processes are rather similar apart from the inability of the ARFIMA process to track the switch in money growth in 1994. The final portion of the sample is of particular interest for policy purposes: both processes agree to locate core inflation on a falling trend, although on a higher level than actual inflation.

4.2.3 Core inflation and core money growth

In Figure 8 the MS-ARFIMA core inflation process and the core money growth process, obtained by fitting the money growth residuals from the switching regime analysis by an ARMA(6,0) model, are plotted. Diagnostic criteria and information criteria select this specification for the short-run component of M3 growth .

FIGURE 8

As shown in the figure, the coswitching restriction implies that the two processes are subject to switches in the unconditional mean occurring with the same timing. The correlation of the two series is high and about 0.80. The linkages existing between the two processes have also been investigated by means of Granger causality tests computed considering twelve lags of each variable. Interestingly, the null hypothesis of non Granger causality from core money growth to core inflation can be rejected at the 10% significance level, while the null of non Granger causality from core inflation to core money growth cannot be rejected. The p-value of the tests are 0.0915 and 0.1724, respectively. The results indicate therefore the presence of unidirectional causality from core money growth to core inflation, confirming the existence of a long-run linkage between the two series and the economic content of the MS-ARFIMA core inflation measure.

5 A comparison of core inflation measures

To yield reliable information for policy use, a core inflation measure must display some desirable properties. First, the estimated core inflation series should display lower variability and higher persistence than actual inflation.

In fact core inflation should be less sensitive to extreme observations, constituting a trend for actual inflation. Second, a measure of core inflation should be useful to forecast actual inflation, so as to be used to extrapolate trends in the actual inflation process or to be included as an additional explanatory variable in forecasting models for inflation. Finally, a measure of core inflation that is based on economic theory should perhaps be preferred to a purely statistical measure. Economic interpretability is an obvious asset for such a measure since it provides a theoretical framework where policy action can be grounded.

The MS-ARFIMA model allows to decompose the inflation series in three components. The first component is the break process that can be interpreted as the long-run inflation forecast when changes are permanent and the state is known. The second component is the fitted demeaned process. This component can be regarded still as inflation signal since it shows some persistence. Shocks to this component have effects that fade away over time as inflation goes back to its long-run value, but with a slow hyperbolic decay. Over the medium term it is the sum of these two components that gives a measure of underlying inflation. Finally, the third component is a white noise residual. As far as the properties of the MS-ARFIMA core inflation measure are concerned, it can be noticed that the coswitching restriction grants economic interpretability to the first component of the process. In particular, the coswitching restriction exploits the monetary nature of inflation, allowing the mean components of inflation and money growth to switch with the same timing. In other words the coswitching restriction allows the identification of inflation regimes that convey meaningful information for core inflation analysis. Moreover, as far as persistence is concerned, the ARFIMA component ensures that all of the persistent signal in inflation is contained in the measure proposed. Finally, as far as smoothness and forecasting power is concerned, further statistical investigation is required. In addition to the ARFIMA and MS-ARFIMA core inflation measures we consider two other alternative measures of core inflation proposed in the literature. The first one is the HICP less food and energy (HICPLFE) inflation[3]. The second one is the common trends core inflation proposed by Bagliano and Morana (1999a,b,c). The comparison with this measure is of particular interest since the latter is derived by assuming that inflation is an I(1) process. The common trends core inflation measure corresponds to the Beveridge-Nelson trend in a multivariate framework. Amongst the strength of this measure there is its interpretability in terms of long-run inflation forecast and the fact that its

[3]The index excludes electricity, gas, and other fuels, fuels and lubrificants, fish, fruit and vegetables.

derivation is grounded on economic theory. The common trends methodology yields a measure of core inflation which naturally has some of the features mentioned above. In particular, forecasting power for the actual inflation rate is warranted since core inflation is estimated as the long-run forecast of inflation conditional on an information set which includes a number of variables that are generally considered to be related to inflation. Such an information set should grant both economic interpretability and an effective decomposition of actual inflation in a permanent component and a transitory component. Moreover, the trend component of the series is modelled as a random walk, therefore exhibiting a high degree of persistence.

5.1 The common trends approach to core inflation estimation: empirical results

In the empirical analysis we have followed Coenen and Vega (1999) and Brand and Cassola (2000) and considered a five-variable system including price inflation measured by the monthly rate of change of the HICP all-items price index (π), the log of real money balances (M/P), the log of real GDP (y), the short term nominal interest rate (s) and the long term interest rate (l).[4] All of the variables apart from the long term interest rate and short term interest rate are seasonally adjusted.

The vector of endogenous variables is then $\mathbf{x}_t = (\ y_t\ M_t/P_t\ \pi_t\ s_t\ l_t)'$.

Cointegration analysis has been carried out using the Johansen (1988) Maximum Likelihood approach over the period 1980(1)-1999(9). The AIC criterion was employed to determine the lag length. According to this criterion four lags were selected. Diagnostic tests for autocorrelation show that the dynamic structure selected is appropriate apart from some residual serial correlation left in the real GDP equation.

In Tables 8-10 the results of the cointegration analysis are reported.

TABLES 8-10

The data suggest the existence of three cointegrating vectors at the 5% level of significance. From the estimated coefficients a money demand equation, a Fisher parity relation between inflation and the long term nominal

[4]Figures for GDP are national series on seasonally adjusted real GDP at market prices from BIS and AMECO. They are converted to euro via the irrevocable fixed conversion rates of 31 December 1998. The figures are adjusted for German unification. Monthly figures are derived via interpolation. Figures for the short term and long term interest rates are weighted averages of the corresponding euro 11 interest rates with GDP weights at ppp exchange rates in 1995. National figures are from BIS.

interest rate and a term structure relation between the short term interest rate and the long term interest rate are evident. A formal test does not reject this identifying structure: the likelihood-ratio test is $\chi^2(2) = 3.89$, with a p-value of 0.14. The addition of a homogeneity restriction between the long term rate and the short term rate or between the long term rate and inflation is not rejected by the data ($\chi^2(3) = 5.84$, with a p-value of 0.12 and $\chi^2(3) = 6.20$, with a p-value of 0.10, respectively). Finally, the imposition of both homogeneity constraints is not rejected by the data at the 1% significance level ($\chi^2(4) = 10.1$, with a p-value of 0.04). This final identifying structure has therefore been imposed in the rest of the analysis.

The permanent inflation component has been obtained following Proietti (1997). Starting from the p-th order vector autoregression

$$\mathbf{x}_t = \Pi_1 \mathbf{x}_{t-1} + ... + \Pi_p \mathbf{x}_{t-p} + \boldsymbol{\varepsilon}_t, \qquad t = 1, ..., T$$

where $\boldsymbol{\varepsilon}_t \sim NID(\mathbf{0}, \Sigma)$, the system can be rewritten as

$$\Delta\mathbf{x}_t = \Gamma_1 \Delta\mathbf{x}_{t-1} + ... + \Gamma_{p-1}\Delta\mathbf{x}_{t-p+1} + \Pi\mathbf{x}_{t-p} + \boldsymbol{\varepsilon}_t, \qquad t = 1, ..., T$$

where $\Pi = \sum_{j=1}^{p} \Pi_j - \mathbf{I}_n = -\Pi(1)$ and $\Gamma_j = -\mathbf{I}_n + \sum_{i=1}^{j} \Pi_i$, $j = 1, ..., p-1$.

If the variables are cointegrated, then $\Pi = \boldsymbol{\alpha}\boldsymbol{\beta}'$, where $\boldsymbol{\alpha}$ is the factor loading matrix and $\boldsymbol{\beta}$ is the matrix of the cointegrating vectors. The Beveridge-Nelson-Stock-Watson permanent-transitory decomposition can be written as

$$\mathbf{x}_t = \boldsymbol{\mu}_t + \boldsymbol{\psi}_t,$$

where $\boldsymbol{\mu}_t$ is a multivariate random walk and $\boldsymbol{\psi}_t$ is a vector of stationary components with

$$\boldsymbol{\mu}_t = (\mathbf{I}_n - \mathbf{P})(\Gamma(1) + \boldsymbol{\alpha}\boldsymbol{\beta}')^{-1}\Gamma^*(L)\mathbf{x}_t = \Phi_\mu \boldsymbol{\mu}_t^*,$$

$$\boldsymbol{\psi}_t = -(\mathbf{I}_n - \mathbf{P})(\Gamma(1) + \boldsymbol{\alpha}\boldsymbol{\beta}')^{-1}\Gamma^*(L)\Delta\mathbf{x}_t + \mathbf{P}\mathbf{x}_t,$$

where $\boldsymbol{\mu}_t^* = \boldsymbol{\alpha}_\perp'\Gamma(L)\mathbf{x}_t$ is the vector of $k = n - r$ common trends and $\Phi_\mu = (\mathbf{I}_n - \mathbf{P})(\Gamma(1) + \boldsymbol{\alpha}\boldsymbol{\beta}')^{-1}\boldsymbol{\alpha}_\perp(\boldsymbol{\alpha}_\perp'\boldsymbol{\alpha}_\perp)^{-1}$ is the factor loading matrix, with $\mathbf{P} = (\Gamma(1) + \boldsymbol{\alpha}\boldsymbol{\beta}')^{-1}\boldsymbol{\alpha}\left[\boldsymbol{\beta}'(\Gamma(1) + \boldsymbol{\alpha}\boldsymbol{\beta}')^{-1}\boldsymbol{\alpha}\right]^{-1}\boldsymbol{\beta}'$, $\Gamma^*(L) = \Gamma_0^* + \Gamma_1^* L +$

$... + \Gamma^*_{p-2} L^{p-2}$ and $\Gamma^*_i = \sum_{i=j+1}^{p-1} \Gamma_i$. Finally, $\boldsymbol{\alpha}_\perp$ is the orthogonal complement of $\boldsymbol{\alpha}$.

Figure 9 shows the estimated core inflation series, actual HICP (all-items) inflation and the estimated transitory ("non-core") inflation component. Twelve-month lagged moving averages of all series are plotted.

FIGURE 9

As shown in the graph the estimated core inflation process displays less variability than actual inflation. This feature is also shared with the core inflation measures estimated in the previous section. Interestingly, three different regimes can be noticed in the data. In a first period which lasts until the beginning of 1986 core inflation is very close to actual inflation. Starting with the oil countershock and until 1995 core inflation is above actual inflation. Finally, from 1995 onwards core inflation is again close to actual inflation, although noticeably below at the end of the sample. It is interesting to notice that the MS-ARFIMA core inflation and the common trends core inflation suggest very different policies at the end of the sample and during the period 1989-1993, while for the remaining time span the two processes provide with similar indications. As shown in the figure, starting from 1996 the two estimated processes suggest opposite policies since, while the MS-ARFIMA model suggests that core inflation is above actual inflation, the common trends model indicates that core inflation is below actual inflation. The two processes therefore only share a similar downward trend for the last portion of the sample.

5.2 Assessment of the core inflation measures

The estimated core inflation measures have been compared under a number of dimensions over the period 1995:2-1999:9. The selection of the sample period has been forced by data availability[5]. Table 13 reports a battery of statistics, namely the root mean square forecast error ($RMSFE$), the Theil (1961) inequality coefficient (U), the decomposition of the $MSFE$ in the mean (U_M), variance (U_V) and covariance (U_C) components, and the test for the prediction of direction (*Sign test*). The decomposition of the $MSFE$ is informative regarding the nature of the prediction error, in particular about which proportion is due to biased predictions and which one is due to a different degree of variability in the forecasted and actual series. Moreover,

[5] The HICP less food and energy for the euro area is in fact available only for this short sub sample.

the covariance component is informative regarding the randomness of the prediction error. Finally, the *Sign test* quantifies the ability of a model to correctly predict the sign of changes in the predicted variable. In the comparison we are particularly interested in the decomposition of the inequality coefficient and in the test for the prediction of direction. As mentioned already, a measure of core inflation should behave like a trend for realised inflation. Unbiasedness is therefore an important characteristic, as it is the ability of tracking turning points. Smoothness is also an important feature since a core inflation measure should be less affected by temporary disturbances than realised inflation. The degree of smoothness is captured by the variance component. We therefore expect a core inflation measure to show a low bias component, a variance component significantly different from zero and a value higher than 0.5 for the test of the prediction of direction.

TABLES 11-12

As shown in Table 11, the ARFIMA core inflation measure achieves the lowest U coefficient and the lowest $RMSFE$, although the statistics are not significantly different from those of the common trends model and the MS-ARFIMA model. On the contrary, HICP less food and energy (HICPLFE) inflation shows significantly higher statistics. As far as the bias component is concerned, all of the models show values that are not statistically different from zero, while the variance component indicates significant smoothing for all of the models apart from HICPLFE inflation. Finally, according to the *Sign test* all of the models accurately predict the sign of inflation changes about 8 times out of ten, with the common trends core inflation faring worst. In table 12 the correlation matrix is reported. It is interesting to notice that the ARFIMA core inflation measure is highly correlated with its Markov switching counterpart and the common trends core inflation measure. On the other hand, the correlation with HICP inflation and HICPLFE inflation is low and does not achieve a value higher than 0.60. Interestingly, the correlation between these two latter measures is fairly low as well (about 0.36). Overall, the correlation patterns suggest that the estimated core inflation measures have very different properties from actual inflation and HICPLFE inflation, while sharing some common structure among them. This can also be noticed from Figure 10, where the twelve lags moving averages of the different core inflation measures and actual inflation are plotted over the sub period considered.

FIGURE 10

It is important to notice the very different policy implications that the

HICPLFE core inflation measure has relatively to the MS-ARFIMA and ARFIMA core inflation measures for the last portion of the data. While in fact all of the measures suggest that core inflation is currently rising, only HICPLFE inflation and the common trends core inflation are located below actual inflation.

While the smoothness property allows one to rank last HICPLFE inflation, no clear discrimination is possible for the other three processes. We then repeated the comparison excluding HICPLFE inflation from the sample, using all of the data available, that is the period 1981:2-1999:9. The results are reported in Tables 13 and 14.

TABLES 13-14

As shown in Table 13, the common trends model minimises the $RMSFE$ and the U inequality coefficient, followed by the ARFIMA and MS-ARFIMA models, although the statistics are not significantly different for these two latter models. All of the models achieve a bias component which is not statistically different from zero. In addition, the MS-ARFIMA model shows a higher smoothing than the other two models, faring best according to this criterion. Finally, all of the models show forecasting power and correctly predict the sign of inflation changes about 7 times out of ten. As far as correlations are concerned, from Table 14 it can be noticed that the core inflation measures are strongly correlated among them and with inflation as well.

As a final comparison, the sensitivity of the different core inflation measures to the addition of new information has been examined. In particular, the impact on the estimated processes, over the period 1981:2-1997:9, of the addition of 24 observations (from 1997:10 to 1999:9) has been assessed by means of the $RMSFE$ and U inequality coefficient. The results are reported in Table 15.

TABLE 15

As reported in the Table, while the common trends model shows the most robust estimates on the basis of the $RMSFE$ and U criteria, the MS-ARFIMA model achieves the best decomposition of the U coefficient. The deviations of the two estimated MS-ARFIMA core inflation processes appear to be almost entirely due to random factors, being the two series indistinguishable according to the bias and variance criteria. On the contrary the common trends model and the ARFIMA model show some bias. Finally, for all of the models the correlation is very high. Overall the exercise allows to rank the ARFIMA model last as far as robustness to information updating is concerned.

From our comparison it appears that the core inflation processes derived from the MS-ARFIMA model, the ARFIMA model and the common trends model show similar properties. In addition the MS-ARFIMA model and the common trends model appear to be superior to the ARFIMA measure in terms of economic content and robustness. The issue concerning the stationarity of inflation is also relevant for the appraisal of the various core inflation measures. Over the sample period considered a number of structural breaks seems to have left a permanent influence on inflation. In fact, the Markov switching analysis has allowed to separate the sample analysed in three separate regimes, and the ARFIMA models have shown that acounting for structural change is important for persistence analysis. Since the inflation process appears to be long memory, the MS-ARFIMA model should perhaps be preferred to the common trends model.

5.3 Forecasting analysis

An important additional requirement for a core inflation measure is the ability to forecast future inflation. Hence, we have evaluated the forecasting performance of the different core inflation models by computing a sequence of multi step ahead out of sample forecasts. The models have been estimated recursively and forecasts generated starting from 1990:1 up to 1999:9. We have therefore a sequence of 117 1-step ahead forecasts, 106 12-step ahead forecasts and 94 24-step ahead forecasts. The results are reported in Tables 17-22 and Figures 11-13.

TABLES 17-22
FIGURES 11-13

As shown in the Tables the results of the forecasting exercise are fairly clear cut. Firstly, the ARFIMA and MS-ARFIMA models show a similar forecasting performance at the one month horizon. Predictions are substantially unbiased and about 70% of the forecast error is due to randomness. The *Sign test* confirms the good forecasting performance of the two models: the sign of the changes in inflation is accurately predicted about 7 times out of ten. On the other hand, the $RMSFE$, the U coefficient and the *Sign test* suggest a slightly worse performance of the common trends model. Secondly, increasing the forecast horizon to one year and two years allows more discrimination among the models. While the three models show a similar value for the U statistic, the Markow switching ARFIMA model clearly outperforms the other two models in terms of bias, with the common trends model following in the ranking. The MS-ARFIMA model fares best also according to the *Sign test*. In fact, it is the only model that, according to this criterion, does not show a deterioration of the forecasting performance relatively to the performance at the one month horizon. Thirdly, from the comparison of the ARFIMA models it can be noticed the importance of allowing for regime switching for unbiased forecasting. Although all of the models show some bias at the two year horizon, the bias component in the ARFIMA model is threefold larger than that of the MS-ARFIMA model. On the other hand, according to the variance component the MS-ARFIMA model tends to generate forecasts that are smoother than actual inflation. This finding is coherent with the fact that the model should predict the underlying dynamics of inflation. Smoothing is also achieved to some extent by the ARFIMA model and the common trends model. Overall, the forecasting exercise favours the MS-ARFIMA model as forecasting model for inflation.

6 Conclusions

In this paper we employed a MS-ARFIMA model to derive a persistent-non persistent decomposition of the inflation process in the euro area. The persistent component is suitable of economic interpretation, having been derived by imposing a coswitching restriction with nominal money growth and being Granger caused by core money growth. The measure is composed of the inflation long-run forecast plus a persistent component estimated by the ARFIMA part of the model. For the horizon of interest for monetary policy, say up to three years, it is the sum of these two components which provides a measure of core inflation. This measure of underlying inflation has been contrasted with other measures of core inflation, in particular a standard ARFIMA model, the HICP less food and energy inflation and a measure of core inflation derived from a common trends model. In the latter model core inflation may be interpreted as the long-run forecast of inflation conditional to the information contained in real money balances, output fluctuations and movements in the short and long term interest rates.

The comparison has considered a number of dimensions. Although a clear cut discrimination is difficult on the basis of the unbiasedness and smoothness properties, the MS-ARFIMA model results to be preferred on the basis of the out of sample forecasting exercise, particularly at horizons higher than one month. A tentative ranking can also be made on the basis of the statistical properties of the inflation process. While the common trends core inflation process is derived starting from the assumption of I(1) non stationarity, the MS-ARFIMA model is derived starting from the assumption of weak stationarity of inflation subject to a switching unconditional mean. Looking ahead, under successful price stabilisation, it is this latter model that should provide a better description of inflation in the euro area. Of course, a core inflation rate estimated from a statistical model will depend on the modelling choices. Yet, the core inflation series derived in the paper, for their economic interpretability and statistical properties, constitute a valid benchmark to evaluate the other measures of core inflation currently used in the monetary policy debate.

References

[1] Bagliano, F. and C. Morana (1999a). A common Trends Model of UK Core Inflation, Department of Economics, Aberdeen University, Working Paper Series, 99/2.

[2] Bagliano, F. and C. Morana (1999b). Measuring US Core Inflation, ICER Working Papers, 13/99.

[3] Bagliano, F. and C. Morana (1999c). Measuring Core Inflation in Italy, *Giornale degli Economisti*, 58, 301-28.

[4] Baillie, R.T. (1996). Long Memory Processes and Fractional Integration in Econometrics, *Journal of Econometrics*, 73, 5-99.

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

[6] Beveridge, S. and C.R. Nelson (1981). A New Approach to Decomposition of Economic Time Series into a Permanent and Transitory Components with Particular Attention to Measurement of the "Business Cycle", *Journal of Monetary Economics*, 7, 151-74.

[7] Blanchard, O. and D. Quah (1989). The Dynamic Effects of Aggregate Supply and Demand Disturbances, *American Economic Review*, 79, 655-73.

[8] Bos, C.S., P.H. Franses and M. Ooms (1999). Long Memory and Level Shifts: Re-Analyzing Inflation Rates, *Empirical Economics*, 24, 427-49.

[9] Brand, C. and N. Cassola (2000). A Money Demand System for Euro Area M3, mimeo, ECB, Monetary Policy Strategy Division.

[10] Bryan, M.F. and S.G. Cecchetti (1994). Measuring Core Inflation, in N.G. Mankiw (ed.), *Monetary Policy*, 195-215, NBER, University if Chicago Press.

[11] Bryan, M.F, S.G. Cecchetti and R.L. Wiggins II (1997). Efficient Inflation Estimation, NBER Working Paper Series, no. 6183.

[12] Cassola, N. (1999). Inflation and M3 Growth in the Euro Area as Regime Switching Processes, mimeo, ECB, Monetary Policy Strategy Division.

[13] Coenen, G. and J.-L.Vega (1999). The Demand for M3 in the Euro Area, ECB, Working Paper Series, no. 6.

[14] Crowder, W. and D. Hoffman (1992). The Long-Run Relationship between Nominal Interest Rates and Inflation: the Fisher Equation Revisited, *Journal of Money Credit and Banking, 28(1), 102-18.*

[15] Davies, R.B., 1987, Hypothesis testing when a nuisance parameter is present only under the alternative, Biometrika, 74, 33-43.

[16] Delgado, M.A. and P.M. Robinson (1994). New Methods for the Analysis of Long Memory Time Series: Application to Spanish Inflation, *Journal of Forecasting*, 13, 97-107.

[17] Diewert, W.E. (1995). On the Stochastic Approach to Index Numbers, Discussion Paper, no. DP 95-31, Department of Economics, University of British Columbia.

[18] Dow, J.P., Jr. (1994). Measuring Inflation Using Multiple Price Indexes, mimeo, Department of Economics, University of California Riverside.

[19] Eckstein, O. (1981). *Core Inflation,* Englewood Cliffs, Prentice Hall.

[20] Engle, C. and J.D. Hamilton (1990). Long Swings in the Dollar: Are they in the Data and Do Markets know it?, *The American Economic Review,* 80(4), 689-713.

[21] Goldfeld, S. M. and R.M. Quandt (1973). A Markov Model for Switching Regressions, *Journal of Econometrics*, 1, 3-16.

[22] Gonzalo, J. and C.W.J. Granger (1995). Estimation of Common Long-Memory Components in Cointegrated Systems, *Journal of Business and Economic Statistics*, 13, 27-35.

[23] Granger, C.W. J. (1980). Long Memory Relationships and the Aggregation of Dynamic Models, *Journal of Econometrics*, 14, 227-38.

[24] Granger, C.W.J. and R. Joyeux (1980). An Introduction to Long Memory Time Series Models and Fractional Differencing, *Journal of Time Series Analysis*, 1, 15-39.

[25] Hamilton, J.D. (1989). A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle, *Econometrica*, 57, 357-84.

[26] Hamilton, J.D. (1990). Analysis of Time Series Subject to Changes in Regime, *Journal of Econometrics*, 45, 39-70.

[27] Hansen, B.E., 1992, The likelihood ratio test under non standard conditions: testing the Markov switching model of GNP, Journal of Applied Econometrics, 7, S61-S82.

[28] Hansen, B.E., 1992, Erratum: The likelihood ratio test under non standard conditions: testing the Markov switching model of GNP, Journal of Applied Econometrics, 11, 195-98.

[29] Harvey, A.C. and S.J. Koopman (1992). Diagnostic Checking of Unobserved Component Time Series Models, *Journal of Business and Economic Statistics,* 10, 377-389.

[30] Hassler, U. and J. Wolters (1995). Long Memory in Inflation Rates: International Evidence, *Journal of Business and Economic Statistics*, 13, 1.

[31] Hosking, J.R.M. (1981). Fractional Differencing, *Biometrika*, 68, 165-76.

[32] Johansen, S. (1988). Statistical Analysis of Cointegrating Vectors, *Journal of Economic Dynamics and Control*, 12, 231-54.

[33] King R.J., C. Plosser, J. Stock and M. Watson (1991). Stochastic Trends and Economic Fluctuations, *American Economic Review*, 81.

[34] Mellander, E., A. Vredin and A. Warne (1992). Stochastic Trends and Economic Fluctuations in a Small Open Economy, *Journal of Applied Econometrics*, 7, 369-94.

[35] Ooms, M and J. Doornik (1999). Inference and Forecasting for Fractionally Autoregressive Integrated Moving Average Models, with an Application to US and UK inflation, mimeo, Econometric Institute, Erasmus University Rotterdam.

[36] Perron, P. (1989). The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis, *Econometrica*, 57, 1361-1401.

[37] Proietti, T. (1997). Short-Run Dynamics in Cointegrated Systems, Oxford Bulletin in Economics and Statistics, 59(3), 405-22.

[38] Quah, D. and S.P. Vahey (1995). Measuring Core Inflation, *Economic Journal*, 105, 1130-1144.

[39] Sowell, F. (1992). Maximum Likelihood Estimation of Stationary Univariate Fractionally Integrated Time Series Models, *Journal of Econometrics*, 53, 165-88.

[40] Stock, J.H. and M.W. Watson (1988). Testing for Common Trends, *Journal of the American Statistical Association*, 83, 1097-107.

[41] Stock, J.H. and M.W. Watson (1991). A Probability Model of the Coincident Economic Indicator, In *Leading Economic Indicators New Approaches and Forecasting Records*, K. Lahiri and G. Moore eds., Cambridge University Press, 63-89.

[42] Stock, J.H. and M.W. Watson (1998). Diffusion Indexes, NBER Working Paper, no. W 7023.

[43] Vega, J.L. and M.A. Wynne (1999). Measures of Core Inflation for the Euro Area, mimeo, DG Research, European Central Bank.

[44] Warne, A. (1993). A Common Trends Model: Identification, Estimation and Inference, Seminar Paper, no. 555, IIES, Stockholm University.

[45] Wynne, M.A. (1999). Core Inflation: A Review of Some Conceptual Issues. ECB Working Paper Series, no. 5.

Table 1

Summary statistics (levels): 1980:1–1999:11

	m	π
Maximum	0.0189	0.0121
Minimum	-0.0021	-0.0009
Mean	0.0059	0.0037
Std. Devn.	0.0029	0.0027
Skewness	0.2319	0.9452
Kurtosis	4.5020	3.2466
Normality $\chi^2(2)$	18 [.0000]	77 [.0000]
ADF	-3.1089	-2.1854

The table reports summary statistics for the rate of growth of nominal M3 (m) and the harmonised CPI inflation rate (π). ADF is the augmented Dickey-Fuller test for stationarity. The ADF test regression includes both a costant and a time trend. The critical value for the ADF unit root test are -3.431 (5%) and -4.002 (1%).

Table 2

Summary statistics (first diferences): 1980:1–1999:11

	Δm	$\Delta \pi$
Maximum	0.0211	0.0069
Minimum	-0.0165	-0.0074
Mean	5e-6	-4.5e-4
Std. Devn.	0.0038	0.0017
Skewness	0.0986	-0.0856
Kurtosis	8.3624	5.9614
Normality $\chi^2(2)$	126 [.0000]	55 [.0000]
ADF	-12.215	-9.9812

The table reports summary statistics for the first differences of the rate of growth of nominal M3 (m) and the harmonised CPI inflation rate (π). ADF is the augmented Dickey-Fuller test for stationarity. The ADF test regression includes a costant. The critical value for the ADF unit root test are -2.875 (5%) and -3.461 (1%).

Table 3

Transition matrix of mean switching: 3-regimes model

	Regime 1	Regime 2	Regime 3
Regime 1	1	0.0084	0
Regime 2	0	0.9916	0.0208
Regime 3	0	0	0.9792
Number of observations	78	113	47

The table reports the transition matrix for the bivariate (m, π) coswitching model. The element i, j of the table is the probability that in time t there is a switch to regime i, given that in period $t-1$ the system was in regime j.

Table 4

Coefficients: switching unconditional means

	m	π
μ_1	0.0039 (0.0003)	0.0017 (0.0002)
μ_2	0.0064 (0.0002)	0.0033 (0.0001)
μ_3	0.0079 (0.0004)	0.0081 (0.0002)

The table reports the switching unconditional means for the bivariate coswitching model (m, π).

Table 5

Regime switching: LR tests

H_0	H_1	LR
linear	2 regimes	233.7 [.0000]
linear	3 regimes	309.7 [.0000]
2 regimes	3 regimes	75.97 [.0000]

The table reports LR tests for model selection with upper bound con puted as in Davies (1987). P-values are in brackets.

Table 6

Persistence analysis: Ljung-Box test

Lags	m	π
1	[.244]	[.000]
6	[.159]	[.000]
12	[.454]	[.000]
24	[.576]	[.000]
36	[.757]	[.000]
60	[.829]	[.000]
120	[.798]	[.000]
d	-0.0205 (0.0526)	0.2760 (0.0531)
ADF*	-3.6723	-3.6514

The table reports p-values for the Ljung-Box test for the demeaned seri using the switching model. d is the fractional differencing coefficient. ADI is the augmented Dickey-Fuller test for stationarity carried out on the d meaned series obtained from the regime switching analysis. The ADF* te regression includes only a constant. The critical value for the ADF* unit ro test are -2.874 (5%) and -3.461 (1%).

Table 7

Short-run structure

	ARFIMA	MS-ARFIMA
d	0.4155 (0.0466)	0.2760 (0.0531)
π_{t-4}	0.1407 (0.0684)	–
π_{t-10}	0.2285 (0.0720)	0.1296 (0.0667)
μ	0.0040 (0.0020)	–
Normality	34 [0.0000]	21 [0.0000]
ARCH-1	3.6 [0.0584]	3.1 [0.0819]
Box-Pierce	34 [0.3710]	31 [0.6307]

The table reportd ML estimates with standard errors in the brackets. Normality is the Bera-Jarque normality test, ARCH-1 is the LM test for ARCH effects of the first order, Box-Pierce is the Box-Pierce Portmanteau test for serial correlation up to 36 lags.

Table 8

Cointegration tests: 1981(2) 1999(9)

Eigenvalue:	0.1599	0.1413	0.0779	0.0522	0.0004
Hypothesis:	$r = 0$	$r \leq 1$	$r \leq 2$	$r \leq 3$	$r \leq 4$
λ_{MAX}	39.71**	34.72**	18.48	12.22	0.0873
95% crit. value	33.5	27.1	21.0	14.1	3.8
λ_{TRACE}	105.2**	65.51**	30.79*	12.31	0.0873
95% crit. value	68.5	47.2	29.7	15.4	3.8

The table reports the maximum eigenvalue (λ_{MAX}) and the trace statistics (λ_{TRACE}) for the multivariate system $(y\ m\ \pi\ s\ l)$. r denotes the number of valid cointegrating vectors. * denotes significance at the 5% level; ** denotes significance at the 1% level.

Table 9

Unrestricted cointegrating vectors

	y	M/P	π	s	l
β_1'	-1.2593	1	0.5790	-0.5894	1.0190
β_2'	1	-0.7616	1.7343	0.0096	-1.8212
β_3'	1.8655	-1.2094	1	-2.7689	3.5666

The table reports the unconstrained cointegrating vectors normalised on real money balances, output and inflation, respectively.

Table 10

Restricted cointegrating vectors

	y	M/P	π	s	l	χ^2test	[p-value]
β_1'	-1.3144	1	0	0.4136	0		
	(0.0270)	(−)	(−)	(0.1254)	(−)		
β_2'	0	0	-1.2462	0	1	3.8907	[0.1429]
	(−)	(−)	(0.1017)	(−)	(−)		
β_3'	0	0	0	-0.8117	1		
	(−)	(−)	(−)	(0.0662)	(−)		
β_1'	-1.2862	1	0	0.4253	0		
	(0.0279)	(−)	(−)	(0.1315)	(−)		
β_2'	0	0	-1	0	1	6.2046	[0.1021]
	(−)	(−)	(−)	(−)	(−)		
β_3'	0	0	0	-0.7378	1		
	(−)	(−)	(−)	(0.0641)	(−)		
β_1'	-1.2757	1	0	0.7907	0		
	(0.0286)	(−)	(−)	(0.1230)	(−)		
β_2'	0	0	-1.278	0	1	5.8426	[0.1195]
	(−)	(−)	(0.1027)	(−)	(−)		
β_3'	0	0	0	-1	1		
	(−)	(−)	(−)	(−)	(−)		
β_1'	-1.2696	1	0	0.8266	0		
	(0.0295)	(−)	(−)	(0.1267)	(−)		
β_2'	0	0	-1	0	1	10.097	[0.0388]
	(−)	(−)	(−)	(−)	(−)		
β_3'	0	0	0	-1	1		
	(−)	(−)	(−)	(−)	(−)		

The table reports the constrained cointegrating vectors normalised on real money balances and the long term interest rate, respectively, with the test for overidentifying restrictions.

Table 11

Goodnes of fit analysis (levels): 1995:2–1999:9

	π^c_A	π^c_{MS-A}	π^c_{CT}	π^c_{LFE}
$RMSFE$	0.0010 $(9.03E-05)$	$9.9E-04$ $(9.57E-05)$	0.0010 $(9.18E-05)$	0.0014 $(1.5E-04)$
U	0.2825 (0.0275)	0.2835 (0.0263)	0.3007 (0.0312)	0.3702 (0.0340)
U_M	0.0292 (0.0446)	0.0153 (0.0379)	0.0399 (0.0576)	0.0002 (0.0202)
U_V	0.3100 (0.0670)	0.3521 (0.0636)	0.3016 (0.0717)	0.0418 (0.0418)
U_C	0.6608 (0.0763)	0.6325 (0.0755)	0.6584 (0.0850)	0.9580 (0.0462)
Sign test	0.7222	0.7407	0.7000	0.7593

The table reports summary statistics for the goodness of fit analysis. The inflation benchmark is realised inflation.The sample period is 1995:2-1999:9 for a total of 56 observations. π^c_A is the ARFIMA core inflation measure, π^c_{MS-A} is the Markov switching core inflation measure, π^c_{CT} is the common trends core inflation measure, π^c_{LFE} is the HICP less food and energy inflation. RMSFE is the root mean square forecast error, U is the Theil (1961) inequality coefficient, mean (U_M), variance (U_V) and covariance (U_C) refer to the decomposition of the $MSFE$. For all the statistics standard errors have been computed via bootstrapping and are reported in brackets. *Sign test* is the test for the prediction of direction.

Table 12

Correlations (levels): 1995:2–1999:9

	π^c_A	π^c_{MS-A}	π^c_{CT}	π^c_{LFE}	π
π^c_A	1 (–)				
π^c_{MS-A}	0.9694 (0.0072)	1 (–)			
π^c_{CT}	0.7380 (0.0555)	0.7291 (0.0574)	1 (–)		
π^c_{LFE}	0.4167 (0.1318)	0.3997 (0.1401)	0.5229 (0.1073)	1 (–)	
π	0.4436 (0.1052)	0.4504 (0.1027)	0.4990 (0.1028)	0.3616 (0.1422)	1 (–)

The table reports the matrix of linear correlations with bootstrapped standard errors. The inflation benchmark is realised inflation. The sample period is 1995:2-1999:9 for a total of 56 observations. π^c_A is the ARFIMA core inflation measure, π^c_{MS-A} is the Markov switching core inflation measure, π^c_{CT} is the common trends core inflation measure, π^c_{LFE} is the HICP less food and energy inflation and π is actual inflation.

Table 13

Goodness of fit analysis (levels): 1981:2–1999:9

	π^c_A	π^c_{MS-A}	π^c_{CT}
$RMSFE$	0.0013 $(9.46E-05)$	0.0013 $(8.65E-05)$	0.0012 $(8.72E-05)$
U	0.1561 (0.0126)	0.1593 (0.0116)	0.1489 (0.0107)
U_M	$8.78E-06$ (0.0060)	0.0023 (0.0095)	0.0017 (0.0075)
U_V	0.0986 (0.0325)	0.0367 (0.0213)	0.0938 (0.0347)
U_C	0.9014 (0.0326)	0.9609 (0.0217)	0.9045 (0.0352)
Sign test	0.7315	0.7315	0.7721

The table reports summary statistics for the goodness of fit analysis. The inflation benchmark is realised inflation. The sample period is 1981:2-1999:9 for a total of 224 observations. π^c_A is the ARFIMA core inflation measure, π^c_{MS-A} is the Markov switching core inflation measure, π^c_{CT} is the common trends core inflation measure. RMSFE is the root mean square forecast error, U is the Theil (1961) inequality coefficient, mean (U_M), variance (U_V) and covariance (U_C) refer to the decomposition of the $MSFE$. For all the statistics standard errors have been computed via bootstrapping and are reported in brackets. *Sign test* is the test for the prediction of direction.

Table 14

Correlations (levels): 1981:2–1999:9

	π^c_A	π^c_{MS-A}	π^c_{CT}	π
π^c_A	1 (–)			
π^c_{MS-A}	0.9743 (0.0063)	1 (–)		
π^c_{CT}	0.9294 (0.0095)	0.9267 (0.0096)	1 (–)	
π	0.8540 (0.0208)	0.8437 (0.0230)	0.8659 (0.0211)	1 (–)

The table reports the matrix of linear correlations with bootstrapped standard errors. The inflation benchmark is realised inflation. The sample period is 1981:2-1999:9 for a total of 224 observations. π^c_A is the ARFIMA core inflation measure, π^c_{MS-A} is the Markov switching core inflation measure, π^c_{CT} is the common trends core inflation measure.

Table 15

Robustness analysis: 1981:2–1997:9

	π^c_A	π^c_{MS-A}	π^c_{CT}
$RMSFE$	0.0005	0.0002	$9.37E-05$
	$(2.10E-05)$	$(2.24E-05)$	$(3.88E-06)$
U	0.0542	0.0227	0.0109
	(0.0030)	(0.0029)	(0.0006)
U_M	0.4815	0.0093	0.4491
	(0.0423)	(0.0202)	(0.0573)
U_V	0.0608	0.0225	0.1476
	(0.0218)	(0.0174)	(0.0430)
U_C	0.4576	0.9682	0.4034
	(0.0398)	(0.0326)	(0.0356)
Correlation	0.9881	0.9960	0.9995
	(0.0018)	(0.0011)	$(6.24E-05)$

The table reports summary statistics for the robustness analysis. The sample period is 1981:2-1997:9 for a total of 191 observations. π^c_A is the ARFIMA core inflation measure, π^c_{MS-A} is the Markov switching core inflation measure, π^c_{CT} is the common trends core inflation measure. RMSFE is the root mean square forecast error, U is the Theil (1961) inequality coefficient, mean (U_M), variance (U_V) and covariance (U_C) refer to the decomposition of the $MSFE$. For all the statistics standard errors have been computed via bootstrapping and are reported in brackets.

Table 16

Forecasting analysis (1-step ahead): 1990:1–1999:9

	π^c_A	π^c_{MS-A}	π^c_{CT}
$RMSFE$	$1.52E-03$	$1.52E-03$	$1.90E-03$
	$(1.62E-04)$	$(1.31E-04)$	$(1.40E-04)$
U	0.2716	0.2672	0.3024
	(0.0227)	(0.0189)	(0.0211)
U_M	0.0194	0.0719	0.1285
	(0.0283)	(0.0529)	(0.0594)
U_V	0.1058	0.2168	0.0030
	(0.0667)	(0.0919)	(0.0184)
U_C	0.8746	0.7113	0.8685
	(0.0569)	(0.0662)	(0.0649)
Sign test	0.7117	0.7027	0.6486

The table reports summary statistics for the 1-step ahead forecast analysis. The benchmark is realised HICP inflation. The sample period is 1990:1-1999:9 for a total of 117 observations. π^c_A is the ARFIMA core inflation measure, π^c_{MS-A} is the Markov switching core inflation measure, π^c_{CT} is the common trends core inflation measure. RMSFE is the root mean square forecast error, U is the Theil (1961) inequality coefficient, mean (U_M), variance (U_V) and covariance (U_C) refer to the decomposition of the $MSFE$. For all the statistics standard errors have been computed via bootstrapping and are reported in brackets. *Sign test* is the test for the prediction of direction.

Table 17

Correlations (1-step ahead forecasts): 1990:1–1999:9

	π^c_A	π^c_{MS-A}	π^c_{CT}	π
π^c_A	1			
	$(-)$			
π^c_{MS-A}	0.9559	1		
	(0.0090)	$(-)$		
π^c_{CT}	0.7019	0.7089	1	
	(0.0568)	(0.0628)	$(-)$	
π	0.4912	0.4934	0.4736	1
	(0.0771)	(0.0732)	(0.0641)	$(-)$

The table reports the matrix of linear correlations with bootstrapped standard errors. The sample period is 1990:1-1999:9 for a total of 117 observations. π^c_A is the ARFIMA core inflation measure, π^c_{MS-A} is the Markov switching core inflation measure, π^c_{CT} is the common trends core inflation measure.

Table 18

Forecasting analysis (12-step ahead): 1990:12–1999:9

	π^c_A	π^c_{MS-A}	π^c_{CT}
$RMSFE$	0.0016 (0.0001)	0.0014 (0.0001)	0.0020 (0.0001)
U	0.2736 (0.0175)	0.2640 (0.0186)	0.3154 (0.0217)
U_M	0.3454 (0.0945)	0.1465 (0.0780)	0.2817 (0.0746)
U_V	0.2205 (0.0842)	0.3135 (0.0993)	0.0066 (0.0246)
U_C	0.4341 (0.0553)	0.5400 (0.0653)	0.7117 (0.0795)
Sign test	0.6100	0.7100	0.6600

The table reports summary statistics for the 12-step ahead forecast analysis. The sample period is 1990:12-1999:9 for a total of 106 observations. The benchmark is realised HICP inflation. π^c_A is the ARFIMA core inflation measure, π^c_{MS-A} is the Markov switching core inflation measure, π^c_{CT} is the common trends core inflation measure. RMSFE is the root mean square forecast error, U is the Theil (1961) inequality coefficient, mean (U_M), variance (U_V) and covariance (U_C) refer to the decomposition of the $MSFE$. For all the statistics standard errors have been computed via bootstrapping and are reported in brackets. *Sign test* is the test for the prediction of direction.

Table 19

Correlations (12-step ahead forecasts): 1990:12–1999:9

	π^c_A	π^c_{MS-A}	π^c_{CT}	π
π^c_A	1 (–)			
π^c_{MS-A}	0.9355 (0.0146)	1 (–)		
π^c_{CT}	0.7340 (0.0784)	0.7819 (0.0784)	1 (–)	
π	0.5601 (0.0616)	0.5237 (0.0688)	0.4789 (0.0580)	1 (–)

The table reports the matrix of linear correlations with bootstrapped standard errors. The sample period is 1990:12-1999:9 for a total of 106 observations. π^c_A is the ARFIMA core inflation measure, π^c_{MS-A} is the Markov switching core inflation measure, π^c_{CT} is the common trends core inflation measure.

Table 20

Forecasting analysis (24-step ahead): 1990:12–1999:9

	π^c_A	π^c_{MS-A}	π^c_{CT}
$RMSFE$	0.0020	0.0014	0.0021
	(0.0001)	(0.0001)	(0.0001)
U	0.3339	0.2805	0.3503
	(0.0207)	(0.0218)	(0.0252)
U_M	0.5942	0.2063	0.4339
	(0.1038)	(0.0986)	(0.0986)
U_V	0.1670	0.2982	0.0047
	(0.0750)	(0.1096)	(0.0234)
U_C	0.2388	0.4955	0.5613
	(0.0471)	(0.0658)	(0.0951)
Sign test	0.5340	0.7045	0.5227

The table reports summary statistics for the 24-step ahead forecast analysis. The benchmark is realised HICP inflation. The sample period is 1991:12-1999:9 for a total of 94 observations. π^c_A is the ARFIMA core inflation measure, π^c_{MS-A} is the Markov switching core inflation measure, π^c_{CT} is the common trends core inflation measure. RMSFE is the root mean square forecast error, U is the Theil (1961) inequality coefficient, mean (U_M), variance (U_V) and covariance (U_C) refer to the decomposition of the $MSFE$. For all the statistics standard errors have been computed via bootstrapping and are reported in brackets. *Sign test* is the test for the prediction of direction.

Table 21

Correlations (24-step ahead forecasts): 1991:12–1999:9

	π^c_A	π^c_{MS-A}	π^c_{CT}	π
π^c_A	1			
	$(-)$			
π^c_{MS-A}	0.8880	1		
	(0.0226)	$(-)$		
π^c_{CT}	0.8217	0.8518	1	
	(0.0504)	(0.0484)	$(-)$	
π	0.4747	0.4638	0.4308	1
	(0.0814)	(0.0760)	(0.0793)	$(-)$

The table reports the matrix of linear correlations with bootstrapped standard errors. The sample period is 1991:12-1999:9 for a total of 94 observations. π^c_A is the ARFIMA core inflation measure, π^c_{MS-A} is the Markov switching core inflation measure, π^c_{CT} is the common trends core inflation measure.

Figure 1

Actual series: monthly HICP inflation (HICP) and monthly nominal M3 growth (M3)

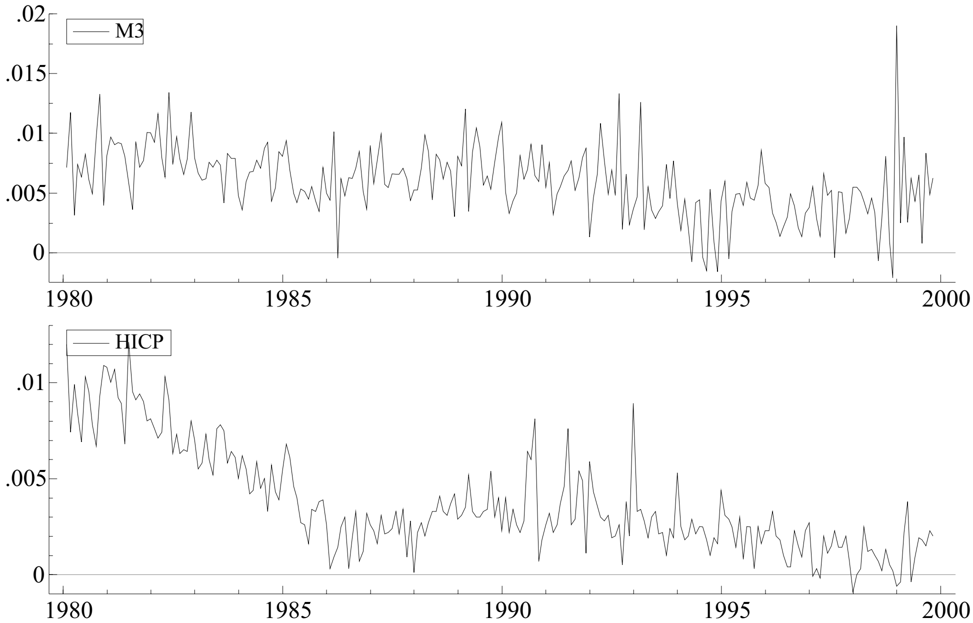


Figure 2

Structural break analysis: nominal M3 growth (M3), HICP inflation (HICP), with 90% confidence bound.

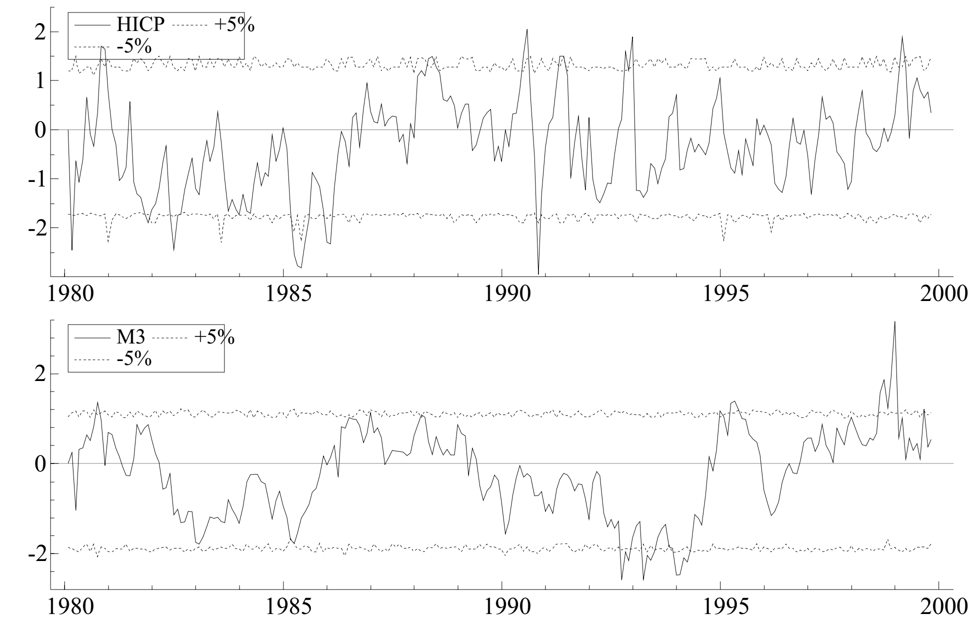


Figure 3

Outlier analysis: nominal M3 growth (M3), HICP inflation (HICP), with 90% confidence bound

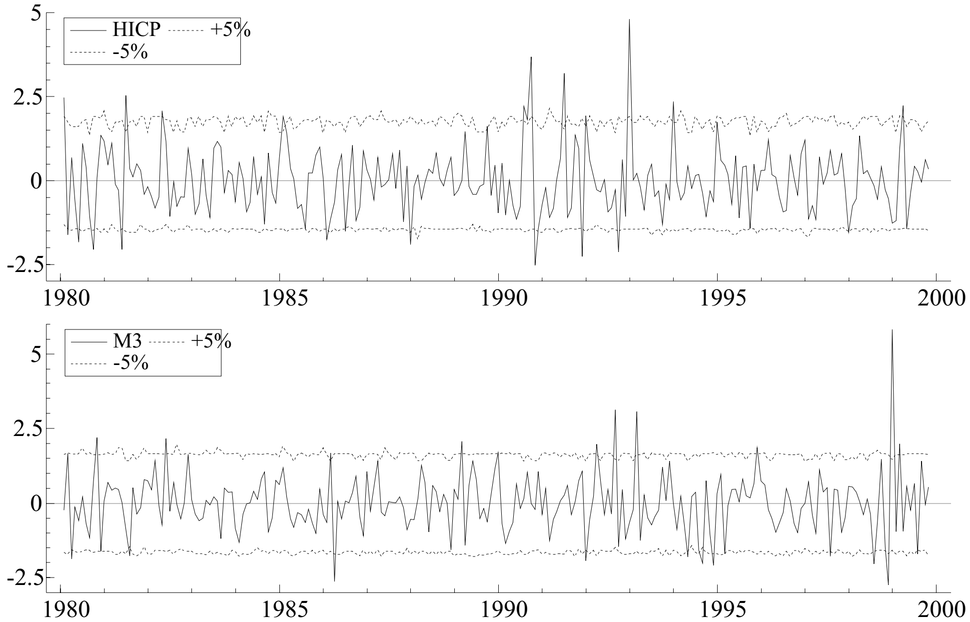


Figure 4

Regime analysis: smoothed probabilities

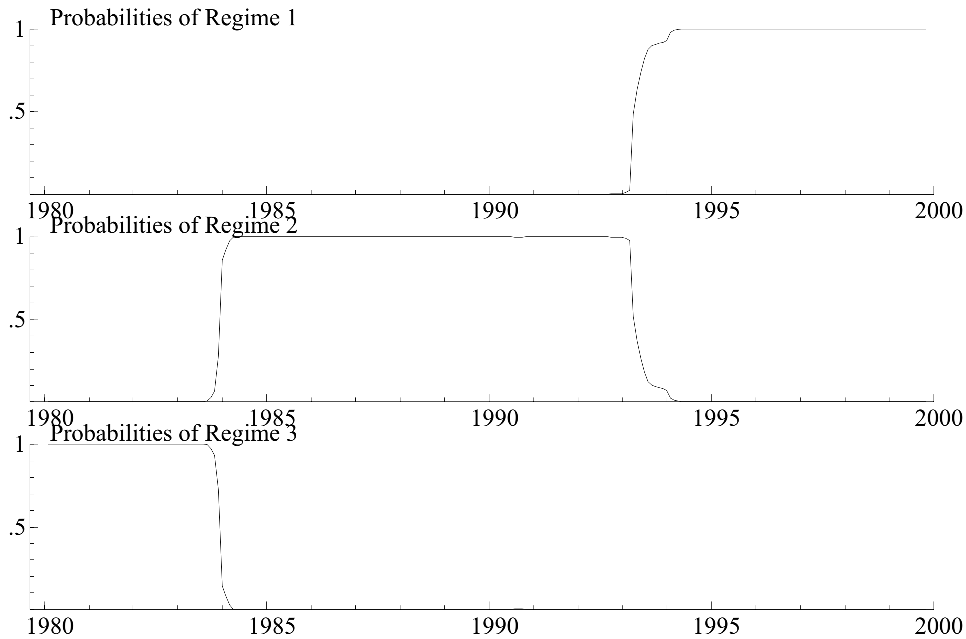


Figure 5

Impulse response function: ARFIMA model (A); Markov switching ARFIMA model (MS-A).

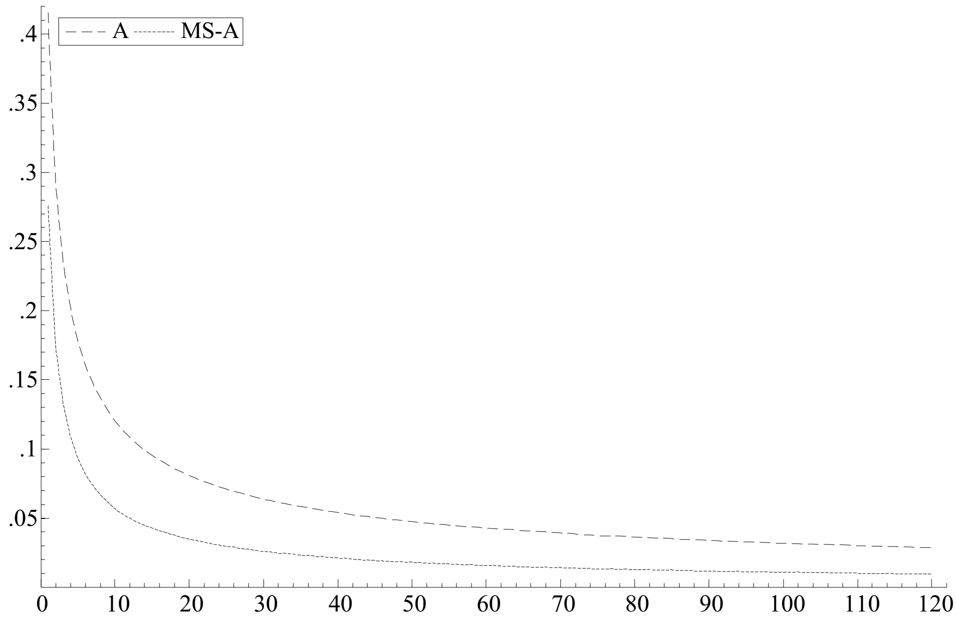


Figure 6

Actual inflation (ACTUAL) and estimated core inflation (12-months mooving average): ARFIMA model (A)

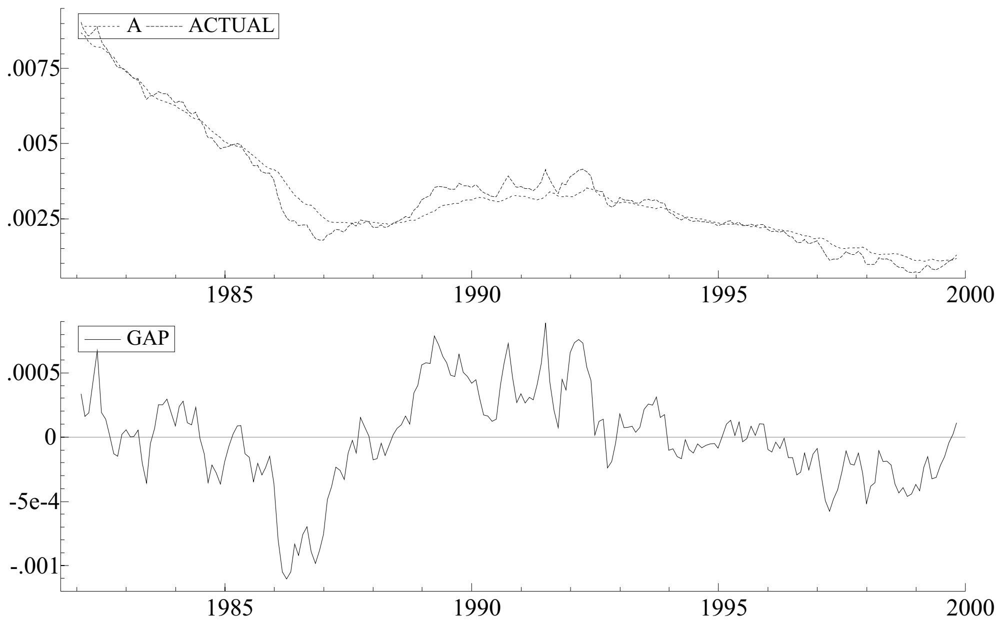


Figure 7

Actual inflation (ACTUAL) and estimated core inflation (12-months mooving average): Markov switching ARFIMA model (MS-A)

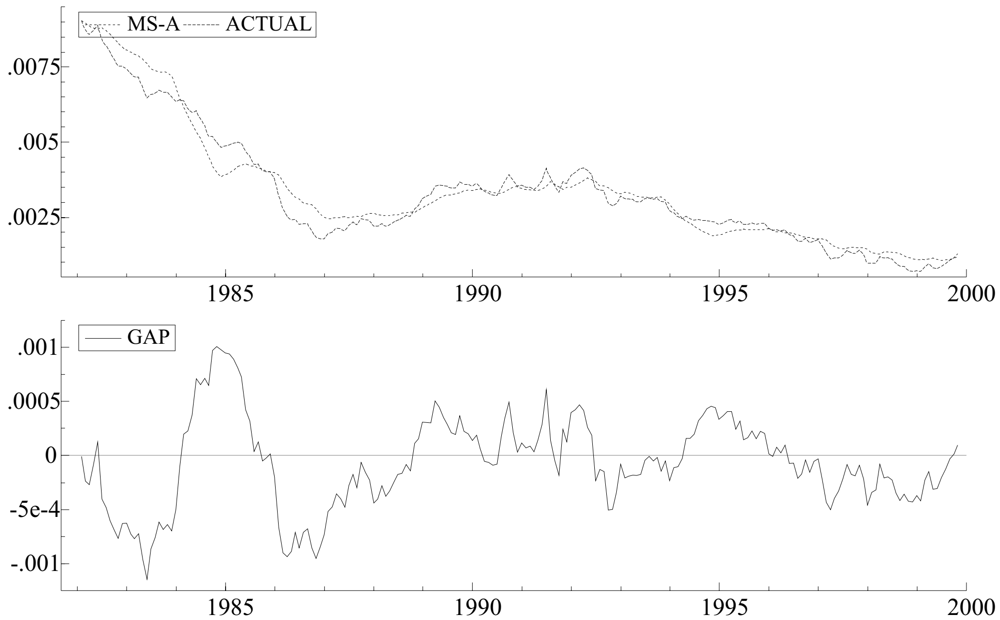


Figure 8

MS-ARFIMA model: core inflation (MS-A_HICP) and core money growth (MS-A_M3).

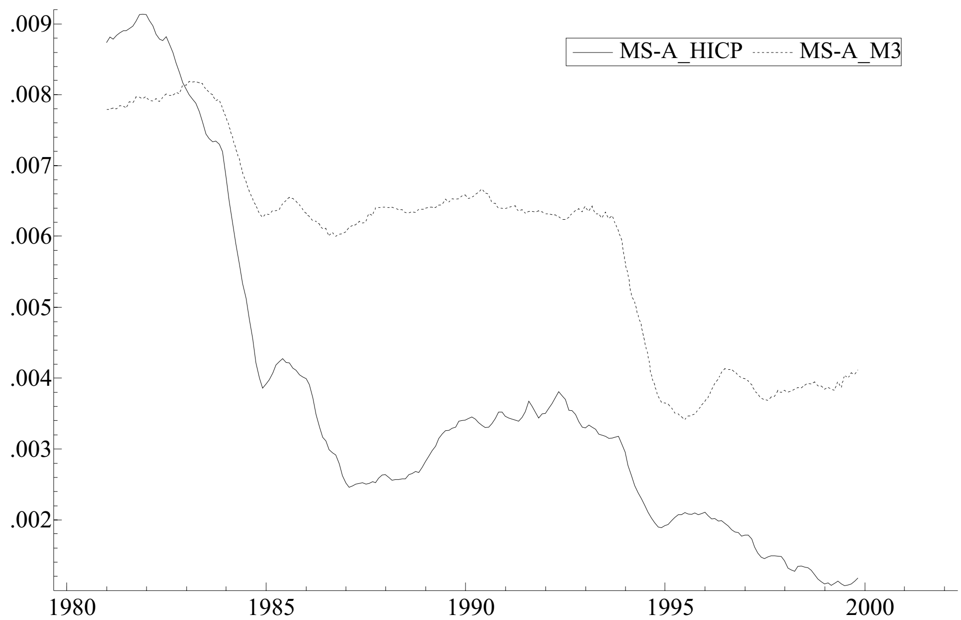


Figure 9

Actual inflation (ACTUAL) and estimated core inflation (12-months mooving average): common trends model (CT)

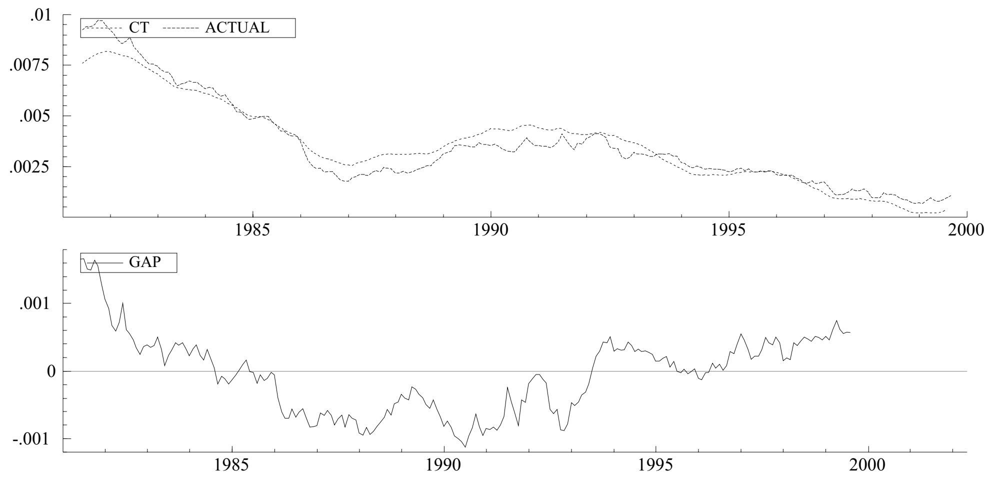


Figure 10

Actual inflation (ACTUAL) and estimated core inflations (12-months mooving average): ARFIMA model (A), Markov switching ARFIMA model (MS-A), common trends model (CT), HICP less food and energy series (LFE)

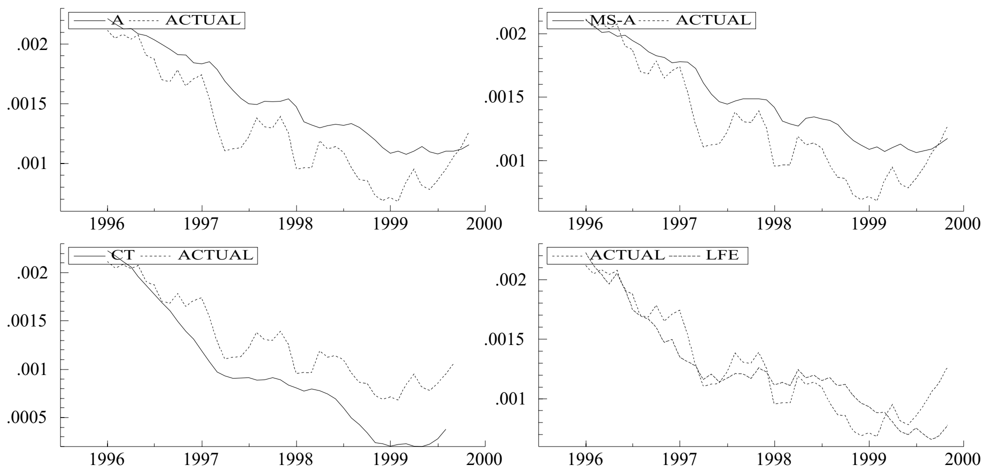


Figure 11

One step ahead forecasts: ARFIMA model (A), MS-ARFIMA (MS-A), common trends model (CT)

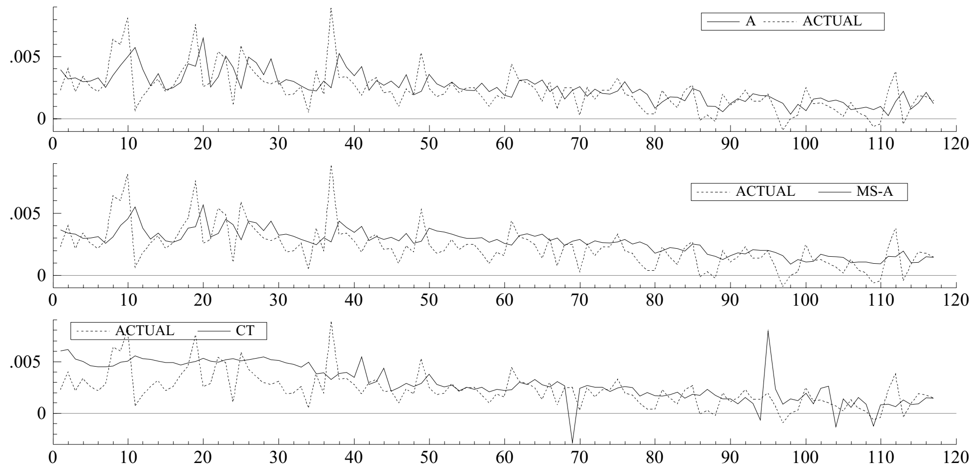


Figure 12

Twelve step ahead forecasts: ARFIMA model (A), MS-ARFIMA (MS-A), common trends model (CT)

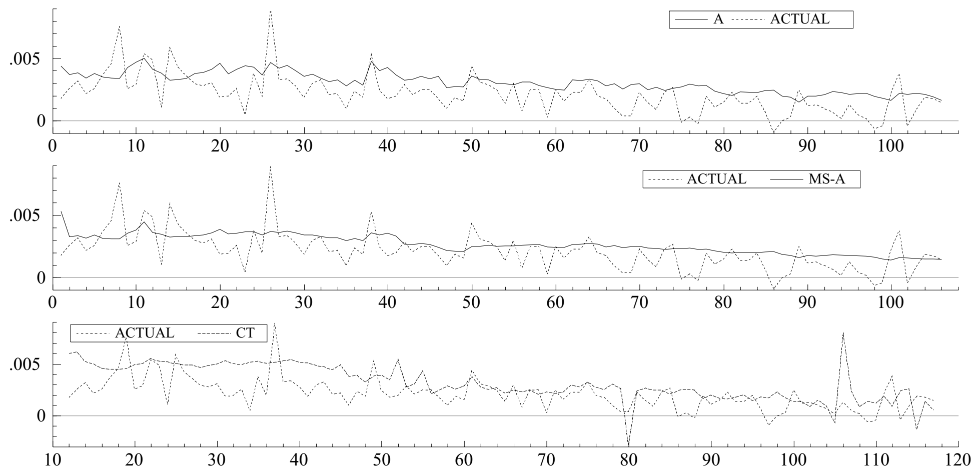
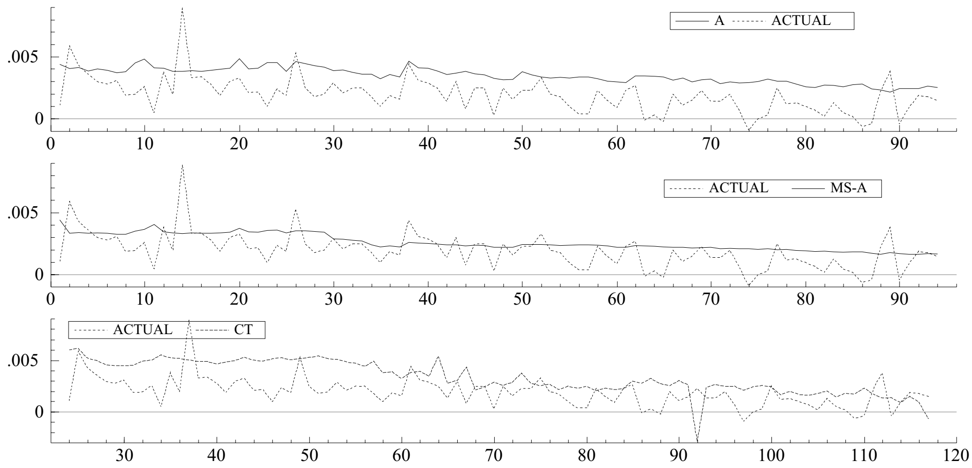


Figure 13

Twenty-four step ahead forecasts: ARFIMA model (A), MS-ARFIMA (MS-A), common trends model (CT)



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