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Core Inflation in the Euro Area: An Application of the Generalized Dynamic Factor Model

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Core Inflation in the Euro Area: An Application of the Generalized Dynamic Factor Model

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Abstract:
Since the second half of the nineties the euro area has been subject to a considerable accumulation of temporary and idiosyncratic price shocks. Core inflation indicators for the euro area are thus of utmost interest. Based on euro area-wide data core inflation in this paper is analyzed by means of an indicator derived from the generalized dynamic factor model. This indicator reveals that HICP inflation strongly exaggerated both the decline as well as the increase in the price trend in 1999 and 2000/2001. Our results reinforce those achieved by Cristadoro, Forni, Reichlin and Versonese (2001) based on euro area country data which indicates the robustness of the indicator.

JEL Classification: C33, E31

Keywords: Core Inflation, Euro Area, Generalized Dynamic Factor Model, Principal Component Analysis

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1 Introduction

Since the second half of the nineties the euro area has been subject to a considerable accumulation of temporary and idiosyncratic price shocks. Substantial shocks to energy prices were accompanied by shocks to import prices reinforced by the protracted devaluation of the euro since the start of the European Monetary Union (EMU) in January 1999. These shocks were followed by large shocks to the prices of unprocessed food which originated from animal diseases like BSE and the food and mouth disease as well as bad weather conditions.[1]

Due to the long lags of the monetary policy transmission on prices, in the short run these unanticipated shocks are out of the control of monetary policy. Monetary policy should thus concentrate on medium to long run price developments and refrain from trying to counteract short-run fluctuations around the price trend. This idea is reflected in the monetary policy strategy of the European Central Bank (ECB) by restraining the definition of its primary objective, price stability, as a year-on-year increase of the Harmonized Index of Consumer Prices (HICP) of below two percent over the medium-term. The focus of monetary policy on the medium-term brings up the necessity of inflation indicators for the price analysis representing these medium to long run price developments i.e. the trend development of the price index. Such indicators are called core inflation indicators. To uncover the price trend core inflation indicators basically take care of two kind of distortions in the Consumer Price Index (CPI), the impact of idiosyncratic price developments and short-run price volatility. In the euro area the analysis of core inflation indicators is part of the second pillar of the ECB monetary policy strategy, the broadly based assessment of the outlook for price developments and risks to price stability.[2]

In the literature a large number of core inflation indicators have been developed. Usually the CPI provides the basis for the construction of these indicators. The different core inflation approaches may be divided into three main categories according to the

[1] For a review of price shocks that took place since the start of the EMU see *European Central Bank (2002)*.

[2] See *Issing, Gaspar, Angeloni and Tristani (2001)*.

information set they rely on. These are methods based on the cross sectional distribution of prices, time series methods, and panel methods.

The cross sectional approaches of core inflation address the problem of distortion in CPI inflation by reweighing the impact of the individual price data on the price index. Different cross sectional approaches are distinguished by the kind of reweighing that is applied. Important approaches of this category are the exclusion measures like e.g. the wide-spread "ex food and energy" approach, the limited influence estimators proposed by *Bryan and Cecchetti (1994)* and *Bryan, Cecchetti and WigginsII (1997)* and the Edgeworth or variance weighted index suggested by *Diewert (1995)* and *Dow (1994)*.

Among the time series approaches univariate measures are distinguished from multivariate methods. The univariate measures differ with respect to the smoothing techniques that are applied. Simple methods like taking moving averages as well as more sophisticated methods like the Hodrick Prescott filter and the Kalman filter are applied. The multivariate methods basically comprise the structural vector autoregression (VAR) approach suggested to the measurement of core inflation by *Quah and Vahey (1995)* and the common trends approach proposed by *Blix (1997)*.

As a third category the panel approaches combine information on the cross sectional and the time series dimension to identify the common element of the individual price changes. For the first time *Bryan and Cecchetti (1993)* applied the dynamic factor model of *Stock and Watson (1991)* to the measurement of core inflation. *Angelini, Henry and Mestre (2001)* used the diffusion index approach of *Stock and Watson (1998)* to estimate core inflation. Recently *Cristadoro, Forni, Reichlin and Veronese (2001)* have proposed an indicator of core inflation that is based on the generalized dynamic factor model (GDFM) developed by *Forni, Hallin, Lippi and Reichlin (2000)*, *Forni and Lippi (2000)* and *Forni, Hallin, Lippi and Reichlin (2001)*. This GDFM indicator features some properties that make it especially suited for the analysis of core inflation.

In view of the importance of temporary and idiosyncratic price shocks for euro area inflation core inflation indicators for the euro area are of utmost interest. This paper presents a core inflation indicator for the euro area that follows the approach suggested by *Cristadoro et al. (2001)* yet refers to a completely different data set. *Cristadoro et al. (2001)* base their analysis on a heterogenous data set of 450 series mainly referring to the six largest countries of the euro area. In contrast to their country data we put our focus on euro area-wide data. Our analysis thus encloses the information from all member countries of the EMU. Our heterogenous euro area data set comprises 181 time series. Special attention is given to price variables by making use of the disaggregated euro area HICP data provided by Eurostat. The maximum level of disaggregation available for the HICP which is the four digit level comprising 86 individual price series is used. To provide the most possible transparency, a detailed account of the data set is presented in Appendix A.

Our analysis gives a deeper insight into the inflation process in the euro area in several respects: First of all we provide evidence on euro area core inflation based on a large heterogenous panel of euro area-wide data covering all EMU member countries. The indicator reveals that HICP inflation strongly exaggerated both the decline as well as the increase in the price trend in 1999 and 2000/2001. Moreover reproducing similar results to those obtained by *Cristadoro et al. (2001)* by applying a different data set insights into the robustness of the indicator with respect to changes in the data set are obtained. The robustness of the indicator is of special importance for this kind of analysis since no fix ad hoc criteria in selecting the "correct" data set exists. At the same time insights into the correctness of the aggregation procedure from country to euro area data may be gained. Similar results based on country and area-wide data would indicate that the applied aggregation procedure works well in the sense that the relevant information are transmitted properly from country to euro area data. Finally the performance of the indicator is further analyzed by comparing it to the wide- spread "ex food and energy" core inflation indicator. The indicator seems to anticipate the general development of the less volatile components of the HICP very well.

The rest of the paper is organized as follows. In chapter 2 first the use of the GDFM core inflation indicator is motivated. Then the GDFM, its basic assumptions, and the estimation procedure are presented. Finally a formal representation of the GDFM core inflation indicator is derived. Chapter 3 presents the empirical results. First the data set is introduced. Thereafter the number of dynamic common factors is determined. In the main part of the chapter the results on core inflation in the euro area achieved by the GDFM indicator are presented and analyzed. The results are compared to those of *Cristadoro et al. (2001).* Additionally a comparison to "ex food and energy" inflation is drawn. Chapter 4 concludes.

2 The GDFM Core Inflation Indicator

This chapter provides the idea and the background on the construction of the GDFM core inflation indicator. In the first section the use of the indicator is motivated. Thereafter a short introduction to the GDFM and to the underlying basic assumptions is given. Moreover the estimation procedure is presented. In the final section the derivation of the core inflation indicator on the basis of the GDFM is explained.

2.1 The Motivation

In this section the use of the GDFM core inflation indicator is motivated by referring to two of its particularly favorable properties making it especially suited for the assessment of the general price trend.

The first property concerns the kind and amount of information that may be handled by the indicator. A huge number of heterogenous variables contain information about inflation. Ideally an indicator of the price trend should be derived on the basis of the entirety of these information. Most core inflation indicators however consider only a very limited fraction of these information. The univariate time series approaches solely refer to the aggregated CPI, while the multivariate approaches use the CPI in conjunction with one or a few other variables. The cross sectional approaches on the other hand usually consider the information enclosed in the homogenous data set of the more or less disaggregated CPI. By contrast the panel approaches are able to take into account the information on the cross sectional as well as the time series dimension contained in a huge heterogenous panel data set. The GDFM core inflation indicator thus opposed to the majority of other core inflation indicators shows the preferred property of providing a picture of the general price trend based on all information considered as relevant. Using this approach the multitude of information about inflation analyzed within the two pillars of the ECB's monetary policy strategy may be properly summarized to one single indicator of the price trend.

The second preferred property of the indicator refers to the kind of distortions in the CPI that are taken into account. As was already noted in short above two major kind of distortions in CPI inflation cover the underlying price trend. These are the impacts of idiosyncratic price developments on the CPI and short-run volatility in prices. Idiosyncratic price shocks at times may have a considerable impact on CPI inflation. Yet monetary policy cannot react to price developments in specific sectors, but has to focus on the general price development. Eliminating these idiosyncratic effects from the CPI should thus give a more reliable picture of the price trend. Due to the long lags of the monetary policy transmission on prices also short-run volatility in prices is out of the control of monetary policy and should thus additionally be neglected by an indicator of the price trend.

The three categories of core inflation indicators approach these problems in different ways. Most of them focus on one of the two kinds of distortions. As these distortions often are interdependent the other kind of distortion may then be partially captured indirectly. The time series approaches mainly focus on eliminating short-run volatility in prices, while the cross sectional and most of the panel approaches basically exclude the impact of idiosyncratic prices on the CPI. The only approach that directly addresses both kind of distortions is the GDFM indicator. In a first step by smoothing over the cross sectional dimension this indicator cleans CPI inflation from idiosyncratic noise to unveil the "common" price development. In a subsequent second step by smoothing over the time series dimension short-run price volatility is removed to get an indicator of the medium to long run common price movements representing the price trend.

To sum up, the GDFM indicator features two particularly favorable properties for a core inflation indicator: Based on the information contained in a large heterogenous panel of data and directly addressing both kind of major distortions in CPI inflation the indicator seems to be tailored for the analysis of the price trend. A formal representation of the GDFM core inflation indicator will be given in section 2.5 below.

2.2 The Model

Dynamic Factor Models (DFM) are designed to handle large panels of data, where the cross sectional units are subject to strong co-movements. In contrast to other models by exploiting these co-movements DFMs permit a strong reduction of the dimension of the model. Hence they ensure a parsimonious parameterization despite the large cross sectional dimension.

In this paper the GDFM of *Forni et al. (2000)*, *Forni and Lippi (2000)*, and *Forni et al. (2001)* is applied, which combines the advantages of two strands of factor models. On the one hand, as the name already indicates, the GDFM is a dynamic model following the tradition of the DFM of *Sargent and Sims (1977)* and *Geweke (1977)*.[3] Using a dynamic model is essential since the question at hand, like many macroeconomic issues, is dynamic. On the other hand it extends or "generalizes" the traditional DFM by allowing for a limited amount of cross correlation among the so called idiosyncratic components.[4] This aspect is adopted from the approximate factor models proposed by *Chamberlain (1983)* and *Chamberlain and Rothschild (1983)* which are however static in nature. The assumption of some cross-correlation among the idiosyncratic components seems to be more realistic in our application than that of orthogonality. By abandoning the assumption of mutual orthogonality among the idiosyncratic components, the assumption of an infinite cross section n is crucial for the identification of the model (see *Forni et al. (2000)*).[5]

[3] In contrast to a static factor model, where all factors are loaded contemporaneously, a DFM is characterized by dynamic factor loadings, i.e. the factors may enter the equations contemporaneously and delayed.

[4] In the traditional DFMs the idiosyncratic components are supposed to be orthogonal.

[5] Opposed to traditional factor models where usually the time series dimension T is large compared to the cross sectional dimension n, the GDFM allows for a large cross sectional dimension n. It therefore is subject to the nonstandard asymptotic theory, where n and T go to infinity.

The basic idea underlying the GDFM is that each variable x_{jt} of the panel is decomposed into two mutually orthogonal unobservable components, a so called common component χ_{jt} and the above mentioned idiosyncratic component ξ_{jt}. Here $j = 1, \dots, n$ denotes the cross sectional dimension and $t = 1, \dots, T$ indicates the time series dimension. The common component captures the co-movements of the data and is therefore characterized by its strong correlation with all series in the panel. The co-movements are represented by a small number of say q common factors u_{ht}, $h = 1, 2, \dots, q$, (where q is much smaller than n) that enter all cross sectional units n and possibly are loaded with different coefficients and lag structures. The idiosyncratic component on the other hand reflecting the individual shocks to the variables is only weekly correlated with the panel.

If the four assumptions that will be presented in the next section hold, the GDFM can be represented as in equation (1)

$$x_{jt} = \chi_{jt} + \xi_{jt} = b_j(L)u_t + \xi_{jt} = \sum_{h=1}^{q} b_{jh}(L)u_{ht} + \xi_{jt} \tag{1}$$

where b_{jh} is a $s-$order polynomial in the lag operator L.

2.3 The Assumptions

In this section the four basic assumptions of the GDFM introduced by *Forni et al. (2000)* are shortly summarized.[6]

Assumption 1 ensures that the n-dimensional vector process $x_n = \{(x_{1t}\, x_{2t}\, \dots\, x_{nt})', t \in Z\}$ is zero-mean and stationary for any n (see *Forni et al. (2000)*). To that aim it is assumed that the q-dimensional vector process $u_q = \{(u_{1t}\ u_{2t}\ \dots\ u_{qt})', t \in \mathrm{Z}\}$ is orthonormal white noise, i.e. $E(u_{jt}) = 0$, $Var(u_{jt}) = 1$ for any j and t, $u_{jt} \perp u_{jt-k}$ for any j,t, and $k \neq 0$, $u_{jt} \perp u_{st-k}$, for any $s \neq j, t$, and k. Suppose further that $\xi_n = \{(\xi_{1t}\, \xi_{2t}\, \dots\, \xi_{nt})', t \in Z\}$ is a zero-mean stationary vector process for any n and that $\xi_{it} \perp u_{jt-k}$ for any i, j, t, and k. Moreover the filters $b_{jh}(L)$ are one-sided in L and their coefficients are square summable.

Assumption 2 refers to the spectral density matrix $\Sigma_n(\theta)$ of the vector process x_{nt}, where θ indicates the frequency. It is assumed that for any $i \in N$, there exists a real $c_i > 0$

[6] See *Forni et al. (2000)* for a comprehensive, formal representation of these assumptions.

such that the elements $\sigma_{ii}(\theta)$ of the spectral density matrix are bounded, i.e. $\sigma_{ii}(\theta) \leq c_i$ for any $\theta \in [-\pi, \pi]$.

Assumptions 3 and 4 make use of the dynamic eigenvalues $\lambda^{\chi}_{nj}(\theta)$ and $\lambda^{\xi}_{nj}(\theta)$ of the spectral density matrices of the common components $\Sigma^{\chi}_n(\theta)$ and of the idiosyncratic components $\Sigma^{\xi}_n(\theta)$ respectively.[7] Assumption 3 states that the first "idiosyncratic" dynamic eigenvalue $\lambda^{\xi}_{n1}(\theta)$ is uniformly bounded, i.e. there exists a real Λ such that $\lambda_{n1}(\theta)^{\xi} \leq \Lambda$ for any $\theta \in [-\pi, \pi]$ and any $n \in N$. Assumption 4 states that the first q "common" dynamic eigenvalues diverge almost everywhere in $[-\pi, \pi]$, i.e. $\lim_{n \to \infty} \lambda^{\chi}_{nj} = \infty$ for $j \leq q$ almost everywhere in $[-\pi, \pi]$. *Forni et al. (2000)* illustrate that the assumption 3 introduces the possibility of a limited amount of cross correlation among the idiosyncratic components, while the assumption 4 guarantees a minimum amount of cross correlation between the common components.

Further important points to note for the practical implementation of the model are the following: *Forni et al. (2000)* prove that the statements on the dynamic eigenvalues of the unobserved common and idiosyncratic spectral density matrices given in the assumptions 3 and 4 can be equivalently represented by statements on the dynamic eigenvalues of the observed spectral density matrix of the x_n: "Under assumptions 1 through 4, the first q eigenvalues of $\Sigma_n(\theta)$ diverge, as $n \to \infty$, almost everywhere in $[-\pi, \pi]$, whereas the $(q+1)$-th one is uniformly bounded, i.e. there exists a real M such that $\lambda_{nq+1}(\theta) \leq M$ for any $\theta \in [-\pi, \pi]$ and any $n \in N$." This statement derives conclusions about the asymptotic behavior of the dynamic eigenvalues from a given GDFM with q dynamic factors. *Forni and Lippi (2000)* prove that also the converse holds, i.e. the asymptotic behavior of the dynamic eigenvalues of the observed spectral density matrix $\Sigma_n(\theta)$ provides information on the number q of dynamic factors of the GDFM: "If the first q eigenvalues of $\Sigma_n(\theta)$ diverge, as $n \to \infty$, almost everywhere in $[-\pi, \pi]$, whereas the $(q+1)$-th one is uniformly bounded, then the x's can be represented as in (1)."

[7] The dynamic eigenvalues $\lambda_{nj}(\theta)$ are defined as the eigenvalues of the spectral density matrix $\Sigma_n(\theta)$ as functions of the frequency θ, with $\theta \in [-\pi, \pi]$. $\lambda_{nj}(\theta)$ represents the real non-negative j-th eigenvalue of $\Sigma_n(\theta)$ in descending order of magnitude.

2.4 The Estimation Procedure

The core inflation indicator is derived in three steps.[8]

The objective of the first step is the determination of the covariance matrices of the common and idiosyncratic components and of the medium to long-run common components. These matrices are employed in the subsequent estimation steps.

A prerequisite to divide the covariance matrix of the data into a covariance matrix of the common and one of the idiosyncratic component is the knowledge of the number of dynamic common factors. The number of dynamic common factors q is however unknown and has to be estimated. Starting from the spectral density matrices of the data calculated for a grid of frequencies in $[-\pi, \pi]$ the number of these factors is determined by performing a dynamic principal component analysis.[9] *Forni et al. (2000)* show that the first q dynamic principal components converge to the factor space of the q dynamic common factors as $n \to \infty$. The results of *Forni et al. (2000)* presented in section 2.3 showed that there exists a linkage between the number of factors q and the eigenvalues of the spectral density matrix $\Sigma_n(\theta)$. In praxis however no formal testing procedure to distinguish between a slowly diverging eigenvalue and a bounded one is available (see *Forni et al. (2000)*). Therefore in determining the number of dynamic factors one has to resort to a heuristic procedure. In this paper we orientate at the procedure applied by *Cristadoro et al. (2001)*: The derived dynamic eigenvalues represent the variances of the respective dynamic principal components at each frequency. Imposing the criteria that the dynamic common factors should account for a certain percentage of the total variability in the data across all frequencies, the number of dynamic common factors q equals the number of the largest dynamic eigenvalues that together capture this variance ratio.

Multiplying the diagonal matrix of the ordered[10] q largest dynamic eigenvalues with

[8]A formal representation of the estimation procedure is given in Appendix B of *Cristadoro et al. (2001)*. The first two steps of the estimation procedure were first introduced by *Forni et al. (2001)*, the third step was added by *Cristadoro et al. (2001)*.

[9]A principal component analysis conducted on a series of spectral density matrices referring to different frequencies is called a dynamic principal component analysis. Following *Forni et al. (2000)* dynamic eigenvalues and dynamic eigenvectors are the eigenvalues and eigenvectors of the spectral density matrix as functions of the frequency.

[10]The dynamic eigenvalues are ordered decreasingly with respect to their size.

the matrix of the corresponding q dynamic eigenvectors from the left and the conjugate transposed eigenvector matrix from the right, for each frequency the spectral density matrix of the common components is derived. By subtracting these matrices from the corresponding spectral density matrices of the data the spectral density matrices of the idiosyncratic components are obtained. As *Cristadoro et al. (2001)* state if q is determined correctly these matrices are consistently estimated as both the cross sectional dimension n and the time dimension T go to infinity.

By applying the inverse Fourier transform to these spectral density matrices the covariance matrices of the common and idiosyncratic components at all leads and lags are derived. Furthermore by restraining the inverse Fourier transform on the frequency band of interest (fluctuations with a periodicity corresponding to the medium to long run) we get the covariance matrices of the medium to long-run common component at all leads and lags.

The second step of the estimation procedure is concerned with the estimation of the common components. Following *Forni et al. (2001)*, as n and T go to infinity, the best linear estimate of the common components in a minimum squared error sense is the projection of the common components on the space spanned by the common components. This space however is unknown and has to be estimated. *Forni et al. (2001)* show that the space spanned by a predetermined number r of the first generalized principal components of the covariance matrix of the common components with respect to the covariance matrix of the idiosyncratic components approaches the space spanned by the common components as $n \to \infty$.[11] They prove that, as both n and T go to infinity, the projection onto this estimated space converges in probability to the common components.

The idea behind the use of the generalized principal component analysis is the following: In the dynamic factor model the common components are driven by q dynamic common factors which enter the equation both contemporaneously and with up to s lags. In the estimation procedure the q dynamic common factors and their lags are treated

[11] More precisely, the generalized principal component analysis is conducted with respect to the diagonal matrix having on the diagonal the variances of the idiosyncratic components. The diagonalized covariance matrix of the idiosyncratic components is used as simulation results of *Forni et al. (2001)* showed that this produces better results in the case of large n compared to T.

as $q(s+1)$ separate static factors. These unknown static factors are estimated by the first $r = q(s+1)$ generalized principal components, where the number of static factors r is determined by applying the panel criteria of *Bai and Ng (2001)*. The above defined generalized principal component procedure ensures that the selected generalized principal components are the linear combinations of the data with the largest common-idiosyncratic variance ratio. Using the covariance matrices of the common components derived in the first estimation step, estimates of the common components are derived by projecting the common components on the space spanned by the first r generalized principal components.

Finally in the third step the medium to long-run common components are estimated. The procedure used in this step closely follows the approach underlying the second estimation step. Here using the covariance matrices of the medium to long-run common components derived in step one, the medium to long-run common components again are estimated by projecting on the space spanned by the first r generalized principal components.

2.5 The Indicator

The basic idea underlying the GDFM core inflation indicator has already been illustrated in section 2.1. Building on the GDFM introduced in the previous sections this section now derives in short the corresponding formal representation of the GDFM core inflation indicator.

In the first step the indicator cleans inflation from idiosyncratic noise. Thus the common components χ_{jt} indicated in equation (1) that correspond to the m price series entering the HICP are the series of interest, where $j = 1 \ldots m$ (without loss of generality it is assumed that the price series of the HICP are ordered first in the panel).

In the second step the indicator additionally eliminates the high frequency noise. To that aim in equation (2) the common components are split up into the common components that capture the medium to long run developments χ_{jt}^L and those referring to the high frequencies χ_{jt}^S. The relevant series for the indicator are then given by χ_{jt}^L.

$$\chi_{jt} = \chi_{jt}^L + \chi_{jt}^S \tag{2}$$

Finally reversing the data transformations that have to be conducted prior to the analysis (the data have to be demeaned and divided by their standard deviation) and taking care of their respective HICP weights the GDFM core inflation indicator, $Core_t$, is derived as the weighted sum of the medium to long run common components χ_{jt}^L corresponding to the HICP

$$Core_t = \sum_{j=1}^{m} w_j(\chi_{jt}^L \sigma_j + \mu_j) \tag{3}$$

where μ_j, σ_j, and w_j indicate the mean, the standard deviation, and the weights of the j-th HICP series respectively.

3 The Empirical Results

In this chapter the empirical results are presented. First the data set is introduced. Thereafter the number of dynamic common factors is determined. In the main section the GDFM core inflation indicator is presented. The development of core inflation in the euro area in the two years prior to the EMU and the first three years thereafter is analyzed. The results are compared to those of *Cristadoro et al. (2001)* who use euro area country data to construct their indicator. Finally the performance of the indicator is examined by comparing it to the widely used ex food and energy core inflation indicator.

3.1 The Data

The empirical analysis is based on data of the euro area mainly provided by Eurostat.[12] To capture the common factors of the economy a heterogenous data set of 181 monthly time series is applied. The data set comprises consumer prices, producer prices, monetary aggregates, interest rates, exchange rates, industrial production, retail sales, confidence indicators, and unemployment data. The choice of these variables was also determined by the availability of euro area data.

[12] An overview of the data sources and a detailed account of the data series is provided in the Tables 1 to 6 in Appendix A. Most of the variables refer to the twelve countries participating in the EMU. Deviations are indicated in Table 1.

In view of the aim of this study special importance is attached to price variables. About two third of the data refer to consumer and producer prices. Consumer prices are represented by a large set of disaggregated HICP data. We use the maximum level of disaggregation available for the HICP which is the four digit level of the classification of individual consumption by purpose (coicop) comprising 86 price series.[13] Producer prices encompass 27 time series derived from the general classification for economic activities in the European Community (NACE Rev.1) referring to the home market.[14]

Monetary and financial variables cover about twenty percent of the data set. Nominal as well as real monetary aggregates M1, M2, and M3 are included.[15] Furthermore a set of ten nominal interest rates ranging from overnight deposits to government bonds with maturities up to ten years as well as the respective real series deflated with the HICP are inclosed. Additionally interest rate spreads are computed. Moreover a number of nominal and real effective exchange rates as provided by the ECB are considered.

The remaining ten percent of the data set refer to variables capturing economic activity. Industrial production is represented by 18 time series of the NACE Rev.1 classification. Retail sales, confidence indicators, and unemployment data complete the data set by four series each.

Prior to the analysis some data transformations are in order. Unfortunately not all data were available non-seasonally adjusted. For reasons of consistency we therefore decided to use seasonally adjusted series throughout with two exceptions. Since they usually don't show seasonal patterns we use non-seasonal adjusted interest rate and exchange rate series. We furthermore took care of the stationarity properties of the data. Due to the large data set the application of tailored unit root tests for individual series was not practicable yet. In our data transformations we therefore assumed that the series of each category feature the stationarity properties usually assigned to them.[16] Additionally the

[13]Some price series of the four digit level that were missing completely or over large time periods had to be dropped and replaced by less disaggregated price series.

[14]We use data of the home market since concerning to Eurostat the producer price data of the member countries for the foreign market at the present time are not sufficient to construct euro area aggregates. Eurostat defines the home market as the market where the clients are located in the same national territory as the observed unit. See *Lipp-Lingua (2001)*, p. 7.

[15]Real monetary aggregates are derived by deflating the nominal series with the HICP.

[16]Compare the transformations indicated in Table 7 in Appendix A.

series were standardized by subtracting their mean and dividing them by their standard deviation. This standardization is important to avoid that series with a high variance dominate and distort the results. By visual inspection and by applying standardized unit root tests we finally checked whether the non-stationarity in the data has been properly removed. From these results we conclude that for the majority of series the applied procedure worked well (compare the results on the Augmented Dickey Fuller (ADF) Tests and the Phillips Perron (PP) Tests in Table 7 in Appendix A).

Unfortunately, for many of the euro area data only a relatively short history exists. For example the four digit level HICP data or the producer price data basically are available from 1995(1) onwards. An almost complete set of these data however starts only in 1996(1). Taking also into account the necessity to difference some of the variables the analysis refers to the time period 1996(2) to 2001(11).

3.2 The Determination of the Number of Dynamic Common Factors

As was explained in detail in section 2.4 the estimation of the covariance matrices of interest in the first step of the estimation procedure requires the determination of the number of dynamic common factors. To that aim a dynamic principal component analysis is conducted on the basis of the spectral density matrices of the data calculated over a grid of frequencies in $[-\pi, \pi]$.[17] We orientate at the heuristic procedure suggested by *Cristadoro et al. (2001)* that claims that the dynamic common factors should account for at least fifty percent of the total variability across all frequencies.

Figure 1 depicts the cumulated variance shares captured by the first six dynamic principal components in the frequency interval $[0, \pi]$, i.e the lowest line refers to the variance share explained by the first dynamic principal component, the second line from the bottom captures the sum of the variance shares accounted for by the first two principal

[17]For the construction of the spectral density matrices the following settings were selected: To get consistent estimates of the spectral density matrices a Bartlett lag window of size $M = 4$ was chosen. The weights were computed as $w_k = 1 - \frac{|k|}{M+1}$, where $k = -M, -(M-1), \ldots, (M-1), M$. The spectral density matrices were calculated at the frequencies $\theta_j = \frac{2\pi j}{T}$ with $j = -35, \ldots, 35$ in the interval $[-\pi, \pi]$.

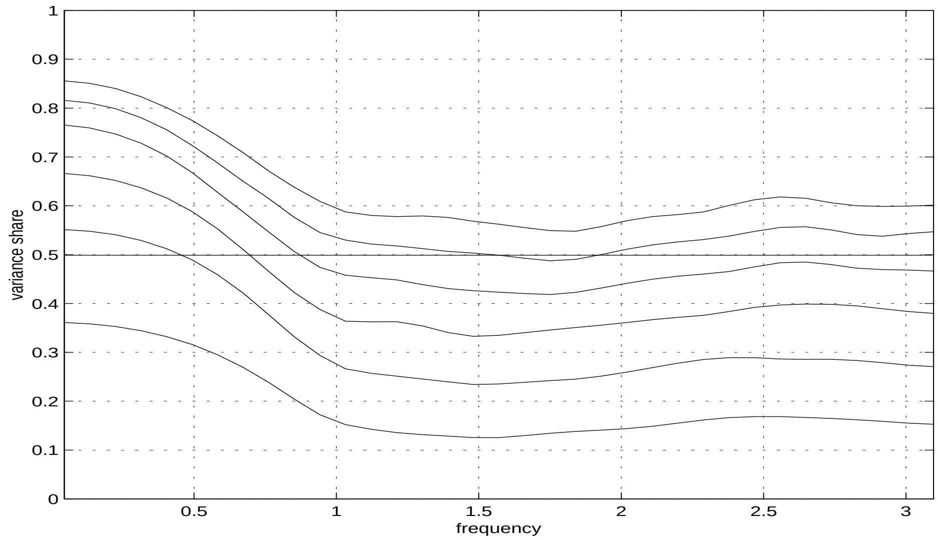

Figure 1: Cumulated Variance Shares Explained by the First Six Dynamic Principal Components in the Frequency Interval $[0, \pi]$

components and so on. Figure 1 shows that the first five dynamic principal components account for at least fifty percent of the variance over almost all frequencies and a much larger fraction of up to more than eighty percent of the variance at the lower frequencies that are of most interest for our analysis. According to the procedure of *Cristadoro et al. (2001)* these five principal components should thus be selected as dynamic common factors.

To get a better insight into the variability accounted for by individual principal components in figure 2 the first ten eigenvalues representing the variances of the first ten dynamic principal components are shown in the frequency interval $[0, \pi]$. As can be seen the first four eigenvalues are considerably larger than the others especially at lower frequencies. This is an indication that the common movements in the data is captured by these first four dynamic principal components, while the smaller variances of the remaining principal components may be interpreted as idiosyncratic developments. This view is reinforced by the fact that the first four factors explain very large fractions of the variability at lower

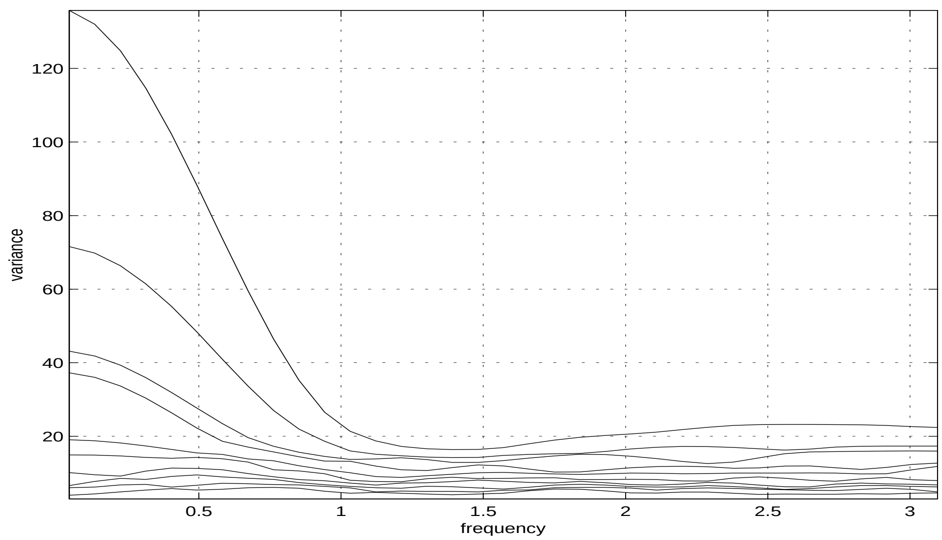

Figure 2: First Ten Eigenvalues of the Spectral Density Matrix of the Data in the Frequency Interval $[0, \pi]$

frequencies, i.e. of the medium to long-run developments in the data, while the majority of the variability at higher frequencies is accounted for by the multitude of remaining principal components. We consider it therefore as more convincing to interpret the first four principal components as the dynamic common factors. By doing so we deviate only slightly from the heuristic criteria suggested by *Cristadoro et al. (2001)*, since these first four common factors almost fulfill their criteria (compare figure 1).[18]

Before turning to the presentation of core inflation in the euro area in the next section a final note on the selection of the static factors of step two of the estimation procedure is in order. By applying the panel criteria of *Bai and Ng (2001)* the number of static factors was set to 68, i.e. sixteen lags of the dynamic common factors are used.

[18]Indeed the deviation between core inflation derived on the basis of four or five dynamic principal components is negligible.

3.3 Core Inflation in the Euro Area

In this section core inflation in the euro area derived by means of the GDFM core inflation indicator is presented. This indicator aims at cleaning CPI inflation in two steps from both idiosyncratic and high frequency noise. The step of distinguishing between common and idiosyncratic impacts was described in the previous section. Restraining the indicator on the medium to long-run price developments in the final step the inverse Fourier transform was applied to frequencies corresponding to a periodicity as of one and a half years.[19]

In order to receive an impression of the smoothing performance of the core inflation indicator, figure 3 gives a comparison between the monthly changes of the HICP and the core indicator. Figure 3 illustrates that the two step smoothing procedure achieves an enormous reduction of the monthly volatility of the HICP.

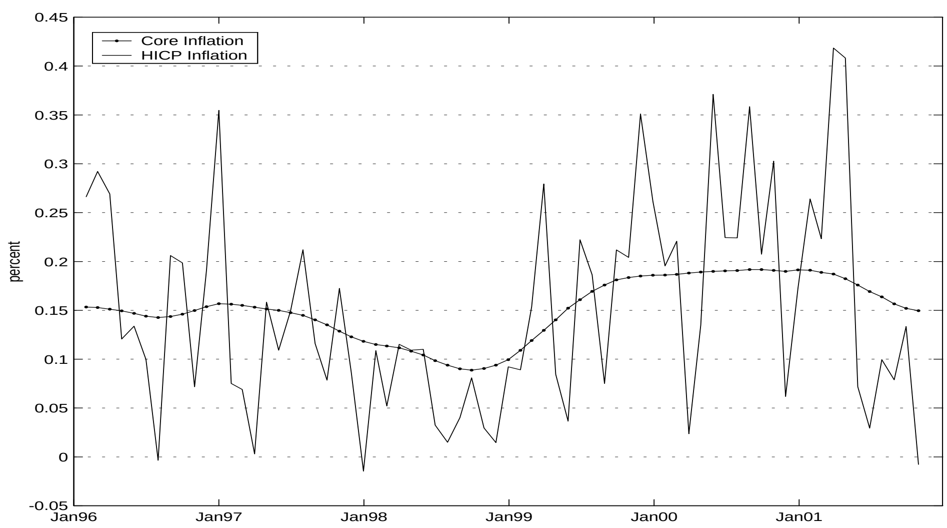

Figure 3: Month-on-Month Change in HICP and Core Inflation

Figure 4 depicts year-on-year core inflation together with HICP inflation over the time period 1997 to 2001. These five years cover the interesting period of the final years of the

[19]More precisely, a concession on the grid of calculated frequencies, frequencies corresponding to a periodicity as of 17.5 month are taken into consideration.

convergence process towards the EMU and the first three years thereafter. Within this time period basically four periods have to be distinguished. While core inflation evolved very stable at 1.8 percent in 1997, over the year 1998 it steadily decreased reaching a bottom level of about 1.2 percent in spring 1999. In the course of 1999 this development reversed and core inflation continually rose to stabilize at the midyear of 2000 for about a year at 2.3 percent. The development in the last months of 2001 finally points towards a renewed decline in core inflation.

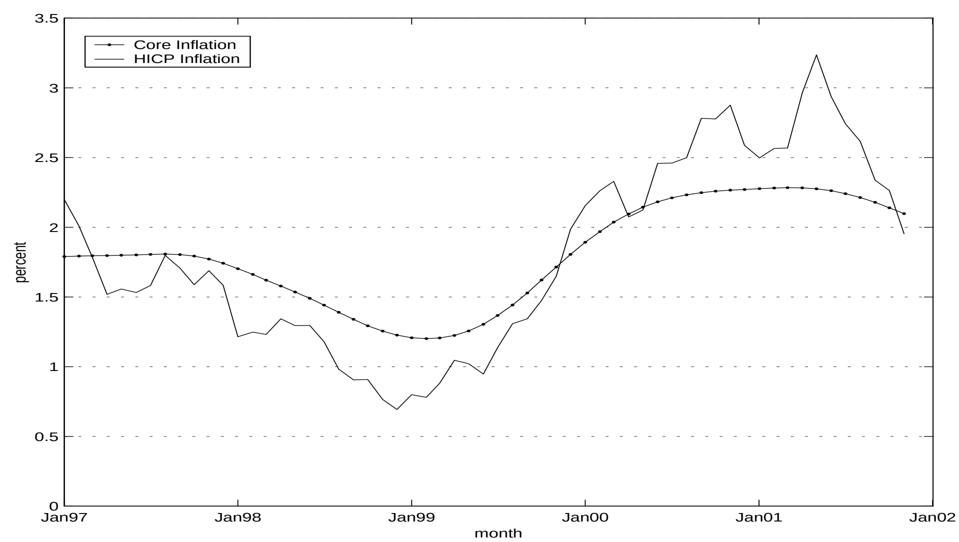

Figure 4: Year-on-Year Change in HICP and Core Inflation

In contrast to core inflation year-on-year HICP inflation was much more volatile and showed much pronounced highs and lows. The comparison between core and HICP inflation points up that both the period of very low HICP inflation in 1999 as well as the period of strongly exceeding the ECB's medium term HICP target of two percent in 2000 and 2001 were induced by idiosyncratic price developments and high frequency noise. In the year prior to the EMU HICP inflation exaggerated the decline in the price trend. This seems to be mainly caused by the strong fall in energy prices. In contrast in the second and third year of the EMU a number of adverse shocks e.g. to energy and unprocessed food prices seem to have induced HICP inflation to overstate the price trend.

Comparing our results to those of *Cristadoro et al. (2001)* we conclude that except for minor differences the two indicators display a very similar development of core inflation over the years under consideration. This refers to both the basic development of core inflation as well as the indicated level of core inflation. The indicator of *Cristadoro et al. (2001)* seems to be a bit more volatile than ours. This feature may be due to the fact that *Cristadoro et al. (2001)* restrain their indicator to a periodicity of longer than one year (14 month) while we prefer to define the medium to long run as corresponding to a periodicity as of one and a half years (17.5 month).

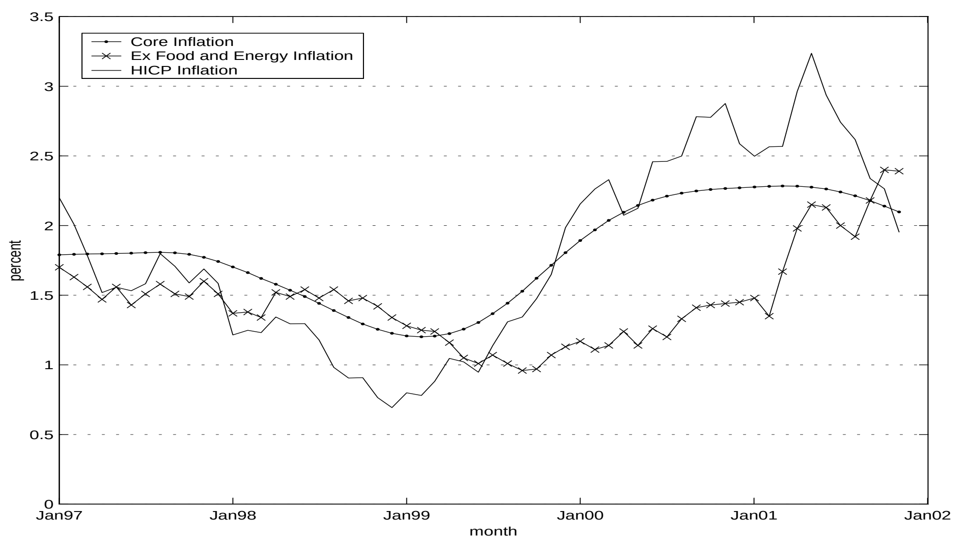

Figure 5: Year-on-Year Change in Core Inflation, Ex Food and Energy Inflation, and HICP Inflation

Finally a comparison of the GDFM core inflation indicator to the widely used ex food and energy core inflation indicator is of interest. Having in mind the construction of the two indicators, the comparison gives a deeper insight into the performance of the GDFM indicator. It is thus important to recall that the GDFM indicator is based on the dynamic common factors reflecting the co-movements in the economy, while the ex food and energy indicator is derived by excluding the direct impact of the historically very volatile components, unprocessed food and energy, from the HICP.

In figure 5 both indicators display a rather constant price trend in 1997, followed by a decline in core inflation in the course of 1998, which however starts about half a year later according to the ex food and energy indicator. Major differences arise also with respect to the subsequent increase in core inflation. While the GDFM indicator shows a fast increase in core inflation reaching its hight already in the midyear of 2000, ex food and energy inflation rises only slowly over the year 2000 surging strongly in spring 2001.

The comparison between HICP and ex food and energy inflation in 1998 confirms our presumption that the strong decline in HICP inflation was at first induced solely by the shock to energy prices (the prices of unprocessed food remained comparatively stable over that period). Only since the midyear of 1998 also the ex food and energy inflation indicator, i.e. the rates of change in the prices of less volatile components of the HICP, started to decline, presumably also due to an impact of the energy shock on these prices. The earlier decline in the GDFM core indicator may be seen as an indication that the indicator anticipated the development in the less volatile components of the HICP.

Since the beginning of the year 1999 HICP inflation increased enormously, while ex food and energy inflation rose only very slowly over the year 2000 followed by strong upward jumps in 2001. The large deviation between HICP and ex food and energy inflation since the mid of 1999 indicates the size of the direct impact of upward shocks to energy and unprocessed food on HICP inflation that took place during that period. At times almost half of the increase in the HICP was due to these shocks. The increase in ex food and energy inflation may represent pass through effects of these shocks as well as other effects on the general price trend. The GDFM indicator again seems to have anticipated those effects as well as their size very early (already about one year before they showed up in ex food and energy inflation). A further factor explaining the higher rates of change in GDFM core inflation compared to ex food and energy inflation is that the latter opposed to the former considers only shocks to the above mentioned two categories of goods thus neglecting the idiosyncratic shock to communication services that induced these prices to strongly decline since 1999.

4 Conclusions

Idiosyncratic price developments and high frequency noise in prices may induce large deviations of CPI inflation from the price trend. Due to the long lags of the monetary policy transmission on prices these shocks are out of the control of monetary policy. Monetary policy should thus focus on medium to long-run price developments. Core inflation indicators aim at capturing exactly these price developments.

Since the second half of the nineties the euro area has been subject to a noticeable accumulation of idiosyncratic and short-run shocks. The analysis of core inflation in the euro area seems thus of utmost interest. In this paper euro area core inflation is analyzed by means of the GDFM core inflation indicator of *Cristadoro et al. (2001).* This indicator combines two particularly favorable properties which make it especially suited for the analysis of the price trend. First since the indicator is based on a DFM it is capable of properly summarizing information about inflation from a large number of heterogenous variables to one single indicator. Second this indicator opposed to all other core inflation indicators directly addresses both essential kinds of distortions in CPI inflation, idiosyncratic price developments and short-run volatility.

In contrast to *Cristadoro et al. (2001)* who use country data mainly of the six largest countries forming the EMU, our indicator is based on euro area-wide data thus covering the information of all EMU member countries. Comparable to the United States euro area data as opposed to euro area country data should become the predominant source for empirical analysis of the EMU at least in the future. Today by using these data one has to accept the challenge of relying on much shorter historical time series than in the case of country data.

As was shown the two step smoothing procedure achieves an enormous reduction of the volatility in the HICP. The GDFM core inflation indicator reveals that HICP inflation strongly exaggerated both the decline in the price trend in 1999 as well as the increase in the price trend in 2000 and 2001. The comparison of the GDFM core inflation indicator with the wide-spread ex food and energy core inflation indicator discloses further that by eliminating idiosyncratic and short-run developments in prices the GDFM indicator seems to anticipate the general development of the less volatile components of the HICP very well.

The indicator based on euro area-wide data displays a very similar development of core inflation over the years under consideration as was presented by *Cristadoro et al. (2001)* by using euro area country data. This applies to both the general development of core inflation as well as its level. As these analyses refer to different data not only with respect to the aggregation level but also with regard to the exact setup of the data base these results seem to be quite promising regarding the robustness of the indicator. As no unique ad hoc "correct" data set exists the feature of a robust indicator with respect to data variations is of utmost importance for this kind of analyses. Finally the results also provide a strong corroboration for the aggregation procedure underlying the construction of the euro area data. Obviously the relevant information contained in country data are properly transformed to euro area data.

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A Tables Appendix

Table 1: Data Sources

Variable	Number of series	Source
HICP*	86	Eurostat
Producer prices*	27	Eurostat
Nominal interest rates	10	ECB
Real interest rates	10	own computations
Interest rate spreads	9	own computations
Nominal M1, M2, M3	3	ECB
Real M1, M2, M3	3	own computations
Exchange rates	5	ECB
Industrial production	16	Eurostat
Retail sales	4	Eurostat
Confidence indicators	4	Eurostat
Unemployment data	4	Eurostat

* Until 31.12.2000 the data refer to the 11 starting member countries of the EMU, as from 01.01.2001 the data comprise the 12 member countries of the EMU.

Table 2: Data Series (1)

Category	No.	Series
HICP	1	Bread and cereals
	2	Meat
	3	Fish
	4	Milk, cheese, and eggs
	5	Oils and fats
	6	Fruit
	7	Vegetables including potatoes and other tubers
	8	Sugar, jam, honey, syrups, chocolate and confectionary
	9	Food products n.e.c.
	10	Coffee, tea and cocoa
	11	Mineral waters, soft drinks, and juices
	12	Spirits
	13	Wine
	14	Beer
	15	Tobacco
	16	Clothing materials
	17	Garments
	18	Other articles of clothing and clothing accessoires
	19	Dry-cleaning, repair and hire of clothing
	20	Footwear, incl. repairs
	21	Actual rentals for housing
	22	Products for the regular maintenance and repair of the dwelling
	23	Services for the regular maintenance and repair of the dwelling
	24	Water supply
	25	Garbage collection
	26	Effluent disposal
	27	Other services related to the dwelling
	28	Electricity
	29	Gas
	30	Liquid fuels
	31	Solid fuels
	32	Heat energy
	33	Furniture and furnishings
	34	Carpets and other floor coverings
	35	Repair of furniture, furnishings and floor covering
	36	Household textiles
	37	Major household appliances whether electronic or not and small electronic household appliances
	38	Repair of household appliances
	39	Glassware, tableware and household utensils
	40	Tools and equipment for house and garden

Table 3: Data Series (2)

Category	No.	Series
HICP	41	Non-durable household goods
	42	Domestic services and home care services
	43	Health - goods paid by the consumer and not reimbursed
	44	Motor cycles and bicycles
	45	New and second-hand motorcars
	46	Spares parts and accessoires
	47	Fuels and lubricants
	48	Maintenance and repairs
	49	Other services in respect of personal transport equipment
	50	Passenger transport by railway
	51	Passenger transport by road
	52	Passenger transport by air
	53	Passenger transport by sea and inland waterway
	54	Combined tickets
	55	Other purchased transport services
	56	Postal services
	57	Telephone and telefax equipment
	58	Telephone and telefax services
	59	Equipment for reception, recording and reproduction of sound and pictures
	60	Photographic and cinematographic equipment and reproduction of sound and pictures
	61	Data processing equipment
	62	Recording media for pictures and sound
	63	Games, toys and hobbies, equipment for sport, camping and open-air recreation
	64	Major durables for recreation including music instruments
	65	Maintenance and repair of other important durables of recreation and culture
	66	Equipment for games and hobbies
	67	Equipment for sports, camping, and open-air recreation
	68	Plants
	69	Pets, equipments for pets, and veterinary and other services for pets
	70	Services for recreation and sports
	71	Cultural services
	72	Books
	73	Newspapers and magazines
	74	Other print products and stationary
	75	Package holidays
	76	Education
	77	Restaurants and cafes
	78	Canteens

Table 4: Data Series (3)

Category	No.	Series
HICP	79	Accommodation services
	80	Hairdressing saloons and personal grooming establishments
	81	Appliances and other products for personal care
	82	Jewellery and watches
	83	Other personal durables
	84	Insurances
	85	Financial services
	86	Other services
Producer prices	87	Mining of coal and lignite, extraction of peat
	88	Extraction of crude petroleum and natural gas, service activities
	89	Mining of ore and quarrying
	90	Manufacture of food products and beverages
	91	Manufacture of tobacco products
	92	Manufacture of textiles
	93	Manufacture of wearing apparel
	94	Manufacture of leather and leather products
	95	Manufacture of wood and wood products
	96	Manufacture of pulp, paper, and paper products
	97	Publishing, printing, and reproduction of recorded media
	98	Manufacture of coke, refined petroleum products, and nuclear fuel
	99	Manufacture of chemicals, chemical products, and man-made fibres
	100	Manufacture of rubber and plastic products
	101	Manufacture of non-metallic mineral products
	102	Manufacture of basic metals
	103	Manufacture of fabricated metal products, except machinery, and equipment
	104	Manufacture of machinery and equipment n.e.c.
	105	Manufacture of office machinery and computers
	106	Manufacture of electrical machinery and apparatus n.e.c.
	107	Manufacture of radio, television, and communication equipment and apparatus
	108	Manufacture of medical, precision and optical instrument, watches and clocks
	109	Manufacture of motor vehicles, trailers, and semi-trailers
	110	Manufacture of other transport equipment
	111	Manufacture n.e.c.
	112	Electricity, gas, steam, and hot water supply
	113	Collection, purification, and distribution of water
Nominal interest rates	114	Overnight deposits
	115	1-month deposits
	116	3-month deposits

Table 5: Data Series (4)

Category	No.	Series
Nominal interest rates	117	6-month deposits
	118	12-month deposits
	119	Gov. bond yields 2 years
	120	Gov. bond yields 3 years
	121	Gov. bond yields 5 years
	122	Gov. bond yields 7 years
	123	Gov. bond yields 10 years
Real interest rates	124	overnight deposits
	125	1-month deposits
	126	3-month deposits
	127	6-month deposits
	128	12-month deposits
	129	Gov. bond yields 2 years
	130	Gov. bond yields 3 years
	131	Gov. bond yields 5 years
	132	Gov. bond yields 7 years
	133	Gov. bond yields 10 years
Interest rate spreads	134	Gov. bond yields 10 years - overnight deposits
	135	Gov. bond yields 10 years - 1-month deposits
	136	Gov. bond yields 10 years - 3-month deposits
	137	Gov. bond yields 10 years - 6-month deposits
	138	Gov. bond yields 10 years - 12-month deposits
	139	Gov. bond yields 10 years - Gov. bond yields 2 years
	140	Gov. bond yields 10 years - Gov. bond yields 3 years
	141	Gov. bond yields 10 years - Gov. bond yields 5 years
	142	Gov. bond yields 10 years - Gov. bond yields 7 years
Nominal money supply	143	M1
	144	M2
	145	M3
Real money supply	146	M1
	147	M2
	148	M3
Effective exchange rates	149	Narrow group, nominal
of the Euro	150	Narrow group, real CPI
	151	Narrow group, real PPI
	152	Broad group, nominal
	153	Broad group, real CPI
Industrial production	154	Mining and quarrying
	155	Manufacture of food products, beverages, and tobacco
	156	Manufacture of textiles
	157	Manufacture of leather and leather products

Table 6: Data Series (5)

Category	No.	Series
Industrial production	158	Manufacture of wood and wood products
	159	Manufacture of pulp, paper and paper products; publishing and printing
	160	Manufacture of coke, refined petroleum products and nuclear fule
	161	Manufacture of chemicals, chemical products and man-made fibres
	162	Manufacture of rubber and plastic products
	163	Manufacture of other non-metallic mineral products
	164	Manufacture of basic metals and fabricated metal products
	165	Manufacture of machinery and equipment n.e.c.
	166	Manufacture of electrical and optical equipment
	167	Manufacture of transport equipment
	168	Manufacturing n.e.c.
	169	Electricity, gas, water supply
Retail sales	170	Food, beverages, tobacco
	171	Textiles, clothing, footwear
	172	Household equipment
	173	Books, magazines, newspapers
Confidence indicators	174	Industry
	175	Construction
	176	Retail sales
	177	Consumers
Unemployment data	178	Men, younger than 25 years
	179	Men, 25 years and older
	180	Women, younger than 25 years
	181	Women, 25 years and older

Table 7: Unit Root Tests^{+}

Variable	Transformation	Number of series	Unit Root Tests^{++}	
			ADF Test^{+++}	PP Test^{++++}
HICP	$(1-L)ln$	86	9	2
Producer prices	$(1-L)ln$	27	4	0
Nominal interest rates	$(1-L)ln$	10	0	0
Real interest rates	none	10	0	7
Interest rate spreads	none	9	0	8
Nominal M1, M2, M3	$(1-L)ln$	3	0	0
Real M1, M2, M3	$(1-L)ln$	3	0	0
Exchange rates	$(1-L)ln$	5	0	0
Industrial production	$(1-L)ln$	16	0	0
Retail sales	$(1-L)ln$	4	0	0
Confidence indicators	$(1-L)$	4	0	0
Unemployment data	$(1-L)ln$	4	2	0

$^{+}$ Sample period: 1997(2) - 2001(11); five percent significance level and critical values of *MacKinnon (1991)* are used.

$^{++}$ The figures indicate the number of series of this category for which the respective tests could not reject the null hypothesis of a unit root.

$^{+++}$ The ADF tests were in general specified with 12 lags of differenced dependent variables. When problems in rejecting the null hypothesis occurred we individually specified the test equation to make sure that these were not due to a loss in power induced by an unnecessary large number of lags.

$^{++++}$ The PP tests were specified with three truncation lags.

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