A multi-country trend indicator for euro area inflation: computation and properties[1]

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1. Introduction

A crucial issue when analysing developments in the euro area is that of data availability, especially regarding the length of time series for the area as a whole. For example, the currently employed HICP - harmonised index of consumer prices - is available for the euro area only as of 1990 and the private consumption deflator only as of 1991. However, country data, although not available at the same frequency or with the same starting and ending date for all of the countries constituting the area,[2] offer a larger variety of data to pick from as well as a longer tradition of data collection. On the other hand, the need to deal with information collected for each individual country would significantly increase the size of the datasets to be employed. To the extent that new and ambitious techniques based on factor analysis (see, for example, Stock and Watson (1998) and Forni et al (1998)) are now available to extract summary information from very large datasets, it seems appropriate to use such techniques to analyse disaggregated multi-country data for the euro area. In this paper, we try to describe and analyse inflation on the basis of common factors underlying a large set of nominal variables for all the euro area countries.

One option to overcome the lack of long area-wide time series is to use explicit weighted-average formulas to aggregate country figures with a well defined weighting scheme, which requires having data on a homogenous and complete basis for all countries, a requirement not easily matched, if at all. Such an approach has a number of drawbacks, related in particular to interpolation and retropolation issues (as documented in Fagan et al (2001)) but also to the discussion of the respective relevance of various aggregation methods (see Winder (1997) or Fagan and Henry (1998)). In addition, such measures by construction ignore the information contained in cross-country variability.

Another option is to construct an "implicit" rather than an "explicit" average, in other words to employ statistical methods to derive the common trend in inflation for the euro area countries, using all of the information in the series for individual countries, without imposing ex ante some well defined weighting scheme. The objective is then to uncover the inflation common to a relatively large number of time series of inflation at the country level, with a view to identifying the latter as the underlying past trends for inflation in the countries now comprising the euro area.

Such an "implicit" approach is in fact very similar to that employed by Cecchetti (1997) (albeit using dynamic factors) in the case of the CPI in a single country, according to which some implicit trend is searched in the inflation numbers for the various sub-items entering the CPI. In both cases, be it multi-product or multi-country, the aim is to identify a summary statistic for inflation on the basis of a number of measures. The suggestion is to combine a multi-country approach with a multi-measure one, analysing a dataset comprising quarterly inflation measures based on national account deflators, consumer and producer price indices, and unit labour costs for all of the euro area countries over the period 1977 to 1999.

In one sense, such a multi-country-based indicator could, moreover, be viewed as an additional measure of underlying or "core" inflation in the euro area (see the review by Wynne (1999), on a

1 Opinions expressed in the paper are those of the authors and do not necessarily reflect those of the European Central Bank. We greatly benefited from discussions with J Stock at various stages of this work and from initial suggestions by S Cecchetti, as well as from input from colleagues at the ECB. Comments from participants in the CEPR European Summer Seminar on International Macroeconomics and in the BIS workshop on Empirical Studies of Structural Changes and Inflation are gratefully acknowledged, in particular from W Buiter, J Ihrig and L Reichlin, as well as from an anonymous referee. Remaining errors are the sole responsibility of the authors.

2 This paper refers to the euro area comprising those countries which adopted the euro on 1 January 1999.

number of standard alternative measures). Such an indicator should reflect some common level of inflation, filtered from the country-specific or measure-specific idiosyncratic component. In any event, it is worth checking the extent to which implicit aggregate inflation appears sensible in relation to simpler explicit measures, such as the weighted average of HICPs/CPIs and/or national account consumption deflators. Such investigation may eventually support an interpretation of the resulting trend inflation in terms of "underlying inflation". In turn, there is also a need to assess the forecasting properties of such implicit aggregate inflation measures in terms of predicting the more standard explicit aggregate measures.

Technically, a number of possibilities can be envisaged to find out what the implicit common inflationary trend has been for those countries now comprising the euro area. As already mentioned, the approach taken here is the factor analysis suggested by Stock and Watson (1998), which offers a number of clear advantages. First, alternative options based on multivariate cointegration analysis (see, for example, Warne (1993) on the basis of Johansen (1991)) are hardly feasible when dealing with a number of series as high as the one envisaged. Second, standard VARs deliver results on orders of integration that are very much lag-structure-dependent (as shown in Hall (1991)) whereas such techniques as factor analysis do not involve a specific lag structure. Third, the number of parameters to be estimated when taking such a statistical approach is much more parsimonious than within a VAR setting, which is hardly feasible when the number of series is large and the sample small (see also Forni and Reichlin (1996) on related issues). Fourth, issues of stationarity do not appear ex ante as crucial as when VAR techniques are employed, although such issues have not been clearly dealt with yet in the context of factor-based forecasting techniques. Ex post, the variance decomposition is expected to deliver some information on the non-stationary and therefore dominant components, as is the case, for instance, for standard principal component analysis (see Stock and Watson (1988) in the time domain or Phillips and Ouliaris (1988) in the frequency domain, at the zero frequency).

The technique employed can also outperform standard principal component analysis. First, the suggested approach goes beyond the principal component analysis to the extent that some time variability can be accommodated, first through additional factors and also through the loading terms; in other words, the extent to which any given series is affected by the common factors can vary slightly over time. Such a feature makes it easier to, for example, take due account of the structural change expected to have occurred prior to monetary union, when countries arguably converged towards a common level of inflation. The extent to which the latter could have changed can also be assessed by estimating the factors recursively. Second, the technique employed allows the econometrician to use series for which observations are only partially available over the sample (ie resorting to so-called "unbalanced" samples). This is clearly of interest in a situation where, as for the euro area, there is a lack of comprehensive back data. The robustness of results to non-available observations can be assessed by a straightforward comparison between factors computed with balanced and unbalanced samples, respectively.

Before going into further details, a summary view of the results can be provided. To begin with, the estimated factors appear to be fairly stable over time. Three to four factors appear to be sufficient to explain a large amount of the variability of the 100 or so series that are used. Moreover, standard "explicit" measures of euro area inflation, based on HICPs/CPIs and consumption deflators, are cointegrated with the first factor - which is clearly non-stationary - whereas further factors - the stationary ones - seem to account for dispersion of inflation across countries. Assuming further that the first factor is an implicit measure of common euro area inflation, it can be observed that that factor has remained extremely stable since the late 1980s, and slightly more stable than actual "explicit" standard measures of inflation. Moreover, on the basis of standard Granger (1988) causality tests in an ECM setting, "implicit" trend inflation seems to help to predict the more standard "explicit" measures, although results are not clear-cut in that respect.

The remainder of the paper is structured as follows. Section 2 describes the data collected. The third section documents the results of the dynamic factor analysis. Section 4 presents the causality analysis findings. Section 5 concludes and suggests further developments, mostly related to forecasting.

2. The data

The main criterion chosen for selecting among the different data sources was first of all to obtain the longest possible span of data for all of the countries considered; moreover, series were favoured that were readily available on a quarterly basis and seasonally adjusted directly by the corresponding source (see the table in Appendix 2 for the details). It was deemed appropriate to adjust the data as little as possible, with the exception of breaks clearly unrelated to economic factors, such as those arising from a change in methodology or coverage. However, for some countries all of these elements could not be fully satisfied. When non-seasonally adjusted series were the only ones available, we seasonally adjusted them applying the Seasonal Adjustment, Bell Labs method (SABL). Annual series (the only case is that of Ireland) were interpolated in order to recreate quarterly series using a simple linear interpolation filter. This procedure greatly simplified the calculations while not affecting the final results. Another exception, of course, was Germany, for which series for unified Germany exist only as of 1990 or 1991. In order to have historical data over a longer sample, series for West Germany prior to unification were used. The two series (pan-German and West German) were joined after the “old historical” data were rescaled to the “new” German series.[3]

For the national account deflators (for private consumption, exports, imports and GDP), the Quarterly National Accounts database published by the OECD was used. It is worth noting that trade deflators are inclusive of intra-area trade flows, to the extent that these trade series are not available on a consolidated basis. CPI, PPI and WPI series were taken from the OECD Main Economic Indicators database. Since PPI and WPI series were available only as monthly series, they were converted into quarterly ones.

In addition, due to the recent changeover to ESA95, it was necessary to backdate the national account series. The “old” series were rebased and joined to the “new” series, applying the same method used to overcome the German unification problem. Such a technique was used for all of the countries, the only exceptions being Belgium and the Netherlands - for which data were readily available over a large sample - and Ireland, for which, for the time being, only annual data are available, as already mentioned. In the latter case, we used the BIS annual data and interpolated the series in order to obtain quarterly data. The HICP and the consumer price deflator for the euro area as a whole were taken from the area-wide model database developed at the ECB (see Fagan et al (2001)).[4]

Once these data were compiled, the need for a “balanced panel” imposed restrictions on the series to be used and, as a consequence, on the countries covered, to the extent that series could be used only when they fully covered the preferred sample. In the case at hand, the balanced panel includes national account deflators for six of the ten countries considered and CPIs for all of the countries. The first analysis was run over the longest and most complete sample possible, ie starting in 1977 Q1 and ending in 1999 Q2. Therefore some countries were dropped altogether, either because their series ended too early or started too late (as in the case of Belgium and Portugal), or similarly some of the series were dropped for all countries, such as WPI (for which only recent data are available). Using an “unbalanced panel”, in turn, imposes no availability restriction, so that all countries and all variables can be taken into consideration, provided that at least any given series is partially available over the sample.[5]

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3 In practice, it is not strictly necessary to make such adjustments to the extent that one of the interests of Stock and Watson (1998) lies precisely in the ability to deal with series with breaks and missing observations. However, such manipulation allowed the so-called “balanced panel” - ie series without missing observations - to also include series for Germany over the longer horizon. The other option, namely excluding all series for Germany, would have somewhat limited the relevance of the “balanced panel” analysis for the euro area. At a later stage, however, some sensitivity analysis could be run on the basis of the “unbalanced panel” approach, where the availability constraint is not a binding one.

4 The euro area HICP series published by Eurostat starts in 1990. This series has been backdated using aggregated national CPIs going as far back as 1970.

5 In the case of the euro area countries, quite a high number of the series needed for the analysis are either not available for some countries or do not cover the whole sample - because of lack of sufficient back data or lesser frequency of the observations. All in all, if we compute an attrition ratio as the number of missing observations over TxNxS, where T is the size of the quarterly sample, N the number of countries and S the number of series, it appears that only two thirds of the data are available, which is markedly less than what happens, for example, for the United States.

Prior to factor analysis, all of the above-mentioned price series were differentiated to generate inflation measures, and univariate stationarity tests were systematically conducted on the various resulting inflation rates. Both the standard Dickey-Fuller (1981) tests and the Perron and Vogelsang (1992) tests were employed, the latter allowing for a structural break in the underlying process (recursive testing is conducted, whereby no specific assumption is made ex ante on the date at which the break, if any, could have occurred). Such tests were also carried out for a number of different lag lengths, to assess further the robustness of the findings.

A striking feature of the results, which holds irrespective of the number of lags employed (ranging from two to eight for the various series), is that the null of non-stationarity can never be rejected, even when the alternative considered incorporates breaks in the average inflation rate, a hypothesis which was tested for break points located between 1982q4 and 1993q4 (ie dropping the end and the beginning of the sample as potential break points).

Table 1

Tests for the null of non-stationarity of two measures of euro area inflation

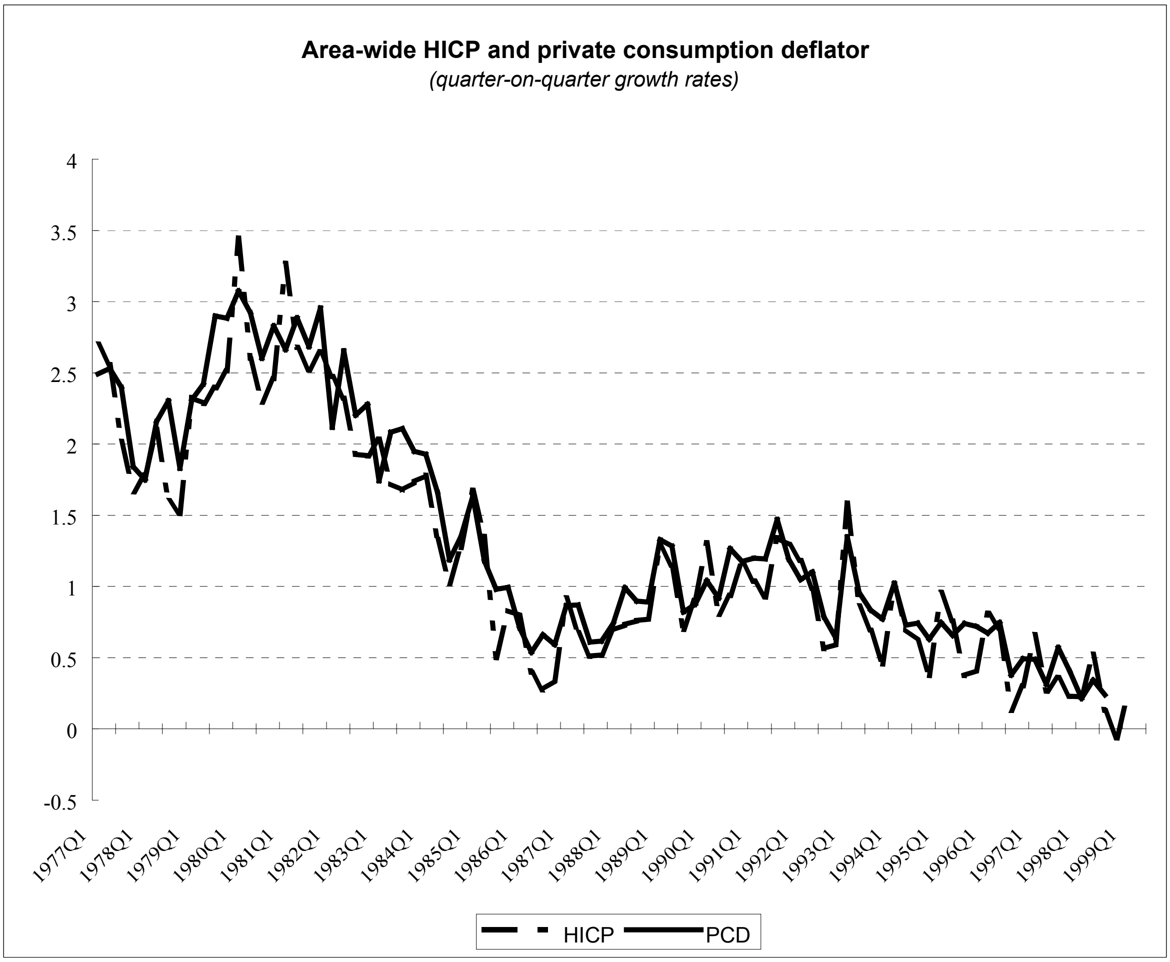
HICP 1977 Q1 – 1999 Q1 shift in mean model, break in 1986 Q4, DF(4) = –2.2
HICP 1977 Q1 – 1999 Q1 breaking trend model, break in 1985 Q4, DF(4) = –3.2
PCD 1977 Q1 – 1998 Q3 shift in mean model, break in 1986 Q4, DF(4) = –2.1
PCD 1977 Q1 – 1998 Q3 breaking trend model, break in 1985 Q4, DF(4) = –3.8
HICP: harmonised index of consumer prices
PCD: private consumption deflator

The results in Table 1 are provided for illustration. In all cases, the resulting *t*-stat for the Dickey-Fuller test never goes beyond –2.2, ie far from any sensible threshold of significance. The statistics are, however, much higher - beyond –3 - for models involving a breaking trend, but still quite far from the relevant critical values, ie under the ex ante assumption of an unknown break point.[6]

On strictly statistical grounds, inflation in the various euro area countries appears therefore as a non-stationary process (see Graph 1), albeit with a structural break in the mean or in the trend most likely in the mid-1980s, which may be related to the effect of the counter oil price shock or to the (then) EEC-wide convergence process. The resulting feature - namely an ever growing variance for inflation around its deterministic components - does not, however, seem to be a wholly acceptable picture, as opposed to the idea of inflation being brought progressively under control, with the successful convergence observed prior to monetary union taking place. Such considerations are to some extent related to the never-ending debate on the stationarity of interest rates (see Watson (1999) for a recent related methodological contribution). Irrespective of such issues, the major conclusion is that at least some of the factors should appear as non-stationary too, more specifically those explaining the largest share of the multi-country and temporal variance. It would then be appropriate in such a case to also investigate the cointegration properties of the estimated factors in relation to both the country and "explicit" aggregate measures of inflation. Although the factor technique allows in principle for non-stationary analysis, this in turn raises a number of questions not directly dealt with in this paper or in the literature, ie in connection with the asymptotic nature of implicit distributions. The approach followed here is a pragmatic one: although nothing explicit is stated on asymptotic distributional behaviour from a theoretical viewpoint, it is empirically the case that non-stationary variables will, as the sample increases in the time and cross-section dimensions, dominate the cross-moment matrix. There is therefore an increasing probability that the first factors will be linked to stochastic trends as N and T increase, provided that the number of trends is relatively small and stable as N increases.

[6] This is not the case for the private consumption deflator PCD (see Table 1), but this conclusion would hold only under the less conservative assumption of an exogenously given break point, which is not really an appropriate hypothesis.

Graph 1



3. An "implicit" measure of trend inflation for the euro area

The framework employed is one where factor analysis is carried out to uncover the common "driving forces" underlying the joint behaviour of the above-mentioned time series of inflation for the countries constituting the euro area. In the fully-fledged Stock and Watson (1999) approach, an additional element is used, whereby some time-varying combination of the above-mentioned factors is a predictor of some variable of interest. In the case at hand, one might for example at a later stage envisage applying the full analysis to predict euro area inflation, but in such a case the coverage of the dataset should be extended to variables measuring not only inflation.

3.1 Specification and estimation of the model

The model proposed by Stock and Watson (1998) is a specification in terms of dynamic factors. At each point in time some "driving forces" - namely the *r* factors summarising the variance of the panel - affect the *N* various series in the panel of time dimension *T* with weights that can vary over time, albeit asymptotically constant (the so-called "loadings"). More specifically, the model reads as follows:

$X_t = \Lambda_t F_t + e_t$ with dimensions $[N \times 1] = [N \times r]\ [r \times 1] + [N \times 1]$

where X_t is at each point in time the vector comprising the observations for all of the *N* series, F_t the *r* common factors driving the process, each of the *N* series being generated by the *r* factors, Λ_t the time-varying loadings, and e_t a stochastic disturbance, assumed to be stationary, with room for some correlation across series and over time (see Stock and Watson (1998) for the specific technical requirements).

The rank of the matrix F is r, ie the true number of factors driving the system (namely the data generating process or DGP). In the estimated model, however, since r is not known, k factors are estimated, and this number may of course differ from that driving the DGP.

Stock and Watson (1998) suggest using a least-squares approach to estimate the factors, in the simpler case where the loadings are constant over time.[7] The programme to be solved is then the following:

$$\mathrm{Min}_F\, E(F) \text{ where } E(F) = Min_{\lambda_i} \frac{1}{NT}\sum_{i=1}^{i=N}(\overline{X}_i - F\lambda_i)'(\overline{X}_i - F\lambda_i)$$

where $\overline{X}_i$ is the $[T \times 1]$ vector comprising stacked observations for the i-th of the N variables, F the stacked $[T \times k]$ matrix with all observations for the k factors (stacking and transposing F_t) *and* λ_i the $[k \times 1]$ vector of loadings for the i-th of the N variables (similar to a row in Λ_t).

There are two possible ways of solving the above-mentioned optimisation problem. First, it can be shown that the loadings will coincide in a balanced panel - ie without any missing observations - with the eigenvectors associated with the k-th largest eigenvalues of the $[N\text{x}N]$ variance-covariance matrix of the stacked observations, namely:

$$\frac{1}{\sqrt{N}}X'X$$

where X corresponds to the $T\text{x}N$ matrix collecting all data information, pooling together the various $\overline{X}_i$. This result is standard, based on principal component analysis (see, for example, Anderson (1984)), and the approach is moreover similar to what is found when resorting to rank reduction techniques, such as the one employed in the Johansen (1991) multivariate cointegration framework. Factors can then be estimated by a simple projection (ie $\hat{F} = X\Lambda$ under the appropriate normalisation). Alternatively, the problem can be solved directly in terms of the F matrix. The time-varying factors would then correspond to the eigenvectors associated with the k largest eigenvalues of the matrix:

$$\frac{1}{\sqrt{T}}XX'$$

This second approach entails solving for the eigenvalues of a $T\text{x}T$ matrix, yielding the same results as the previous one - up to a rotation factor - but numerically more efficient when $N>T$. The latter approach is the one followed in this paper. To complete the computation, an identification scheme is also needed, namely a normalisation of the factors whereby $F'F/T$ equals the identity matrix of order k.

In the case of an unbalanced panel, however, an iterative procedure has to be employed, for which initial estimates of the factors are taken from a balanced panel of series covering the same sample. The intuition underlying each iteration is simple, ie series with missing observations are first projected over the initial set of factors so as to obtain the appropriate loadings, then artificial data are computed to fill the missing observations, and finally factors are recomputed on this artificially obtained balanced sample. The procedure should then converge, delivering the non-linear least-squares (NLLS) estimate for the factors.

In fact, experiments conducted with unbalanced panels suggest a relatively high degree of distortion in the final calculation of the factors in those observations for which a large portion of the variables are missing. The initial fitted values of the out-of-sample portion of some of the variables with missing observations were found to be poor enough to very probably downgrade the quality of the subsequently estimated factors. This problem in all likelihood arose because of the relatively large number of missing variables for some observations, a feature inherent in the very different data collecting procedures of the 11 countries. The problem was mitigated when the number of factors at

[7] The proposed methodology is robust, under assumptions specified in Stock and Watson (1998), to mild levels of time variation in the loadings, as expressed, for example, in the following specification: $\Lambda_t = \Lambda_{t-1} + \frac{h}{T}\varepsilon_t$ where h is a scalar and ε_t a wide-sense stationary disturbance, the contribution of which disappears asymptotically.

each iteration was kept low, in which case the convergence of the algorithm was fairly quick and the number of iterations correspondingly low. This problem compounds any interpretation of the unbalanced-panel factors, and in particular blurs the impact of the unbalanced-panel variables. An example of this impact, particularly relevant for the purpose in question, is the appearance of further non-stationary factors linked to trends present in the unbalanced-panel dataset but not in the balanced-panel one.

For both types of panel, the cross-country and cross-indicator dimension will be summarised at each point in time by the value of the factors for this given observation (the whole set of NT observations is taken into account in the maximisation programme solved). The approach can therefore be viewed as a proxy to the dynamic factor one, to the extent that finite lag structure in the process underlying the factors would indeed be captured by some of the k factors. Although infinite lag structure - such as that resulting from a factor following an AR(1) - will then necessitate an infinite number of factors, it may be equivalent from an observational viewpoint to truncate the lag distribution so that the variance explained would be comparable to that given by a dynamic factor model.

In addition, contrary to the dynamic factor approach, where some restrictions such as stationarity are generally imposed on the factors, factors estimated using this procedure will capture the dominant dynamic properties of the initial series, including non-stationarity. For example, in the event that some strong autocorrelation or even unit roots are empirically present in the panel, these features would also be reflected in the estimated factors (as in Stock and Watson (1989)). Presumably, if some of the variables in X were non-stationary, the first factors - ie those corresponding to the largest eigenvalues - would by construction end up sharing the same integration properties; moreover, they would be cointegrated with those X components that are non-stationary.

3.2 The estimated factors: time-series properties

Factors were first estimated on a sample covering the period 1977 Q1 to 1999 Q2. Both balanced and unbalanced panels were used, the latter also including data for Belgium, Ireland and Portugal, all countries for which series have missing observations either prior to 1985 Q2, 1988 Q2 or after 1997 Q4. On the basis of the variance decomposition, irrespective of the type of panel employed, two or three factors seem to be enough to capture most of the common variation in the cross-country and cross-indicator dimensions of the various inflation measures employed. Thereafter, further factors contribute only marginally to the variance of the panel (see Table 2). Some work could be envisaged with a view to employing a selection criterion for the number of factors instead of using such a heuristic approach. Furthermore, the proportion of the variance explained by the most important factors is fairly robust to changes in the sample size.

The high proportion of variance explained by the first few factors is a clear indication that the number of forces underlying movements in prices is relatively small.

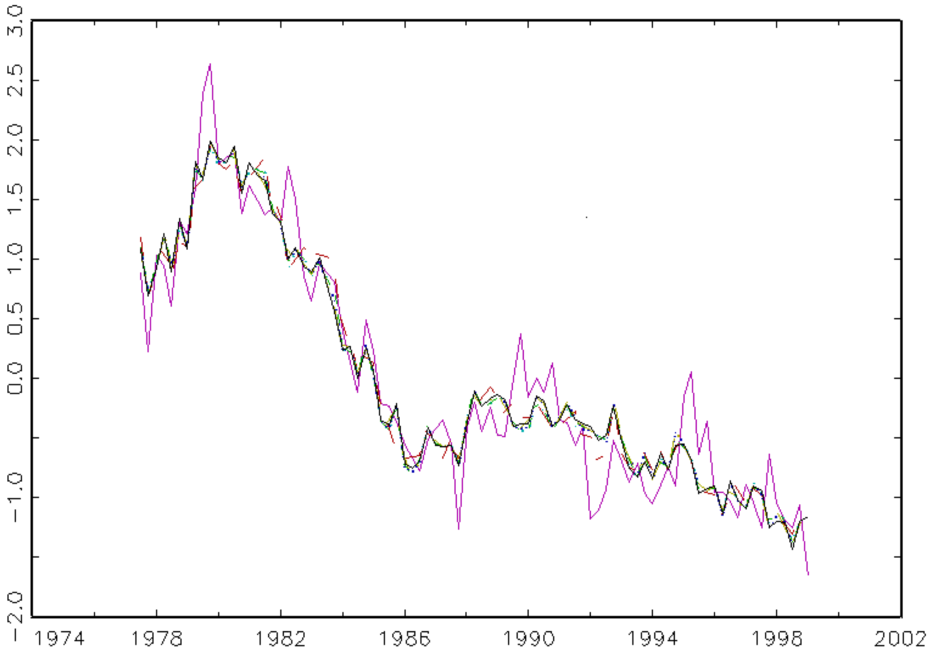
Table 2

Contributions to the explanation of the panel variance, marginal and cumulated

	Marginal	Cumulated
Eigenvalue 1	59%	59%
Eigenvalue 2	10%	69%
Eigenvalue 3	5%	72%
Eigenvalue 4	3%	75%
Eigenvalue 5	3%	78%

Graph 2

Variable 40 across iters., balanced panel

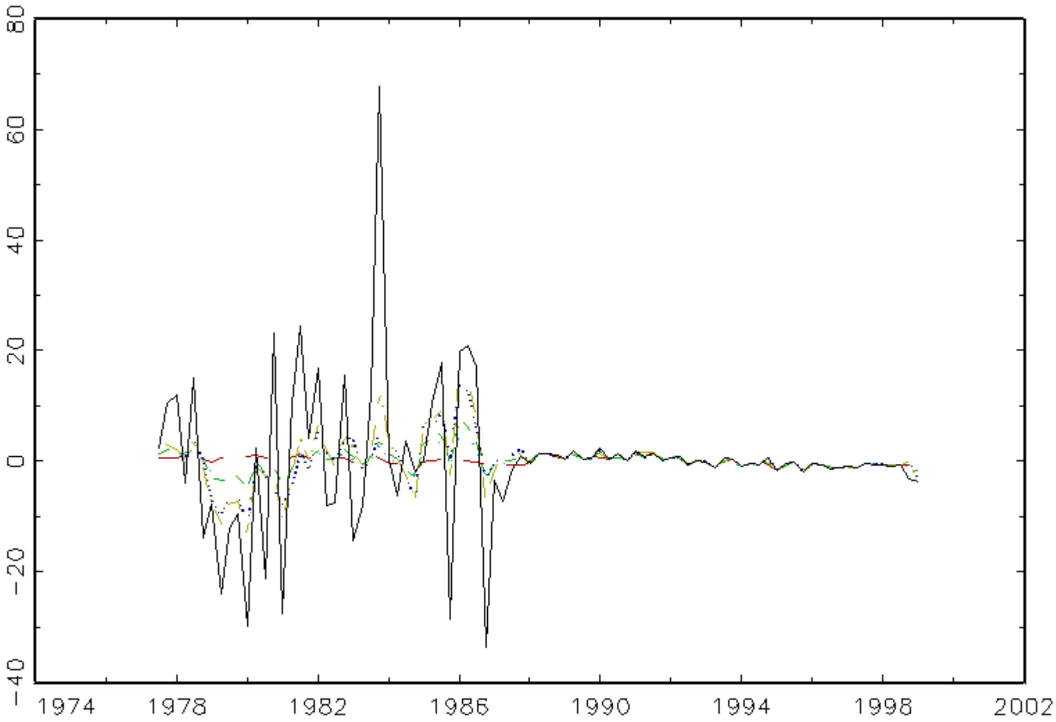


It is worth remembering that the results with the unbalanced panel are slightly puzzling, which calls for cautiousness when interpreting them. As already mentioned, the estimates drift away as the number of iterations increases, although eventually they do not differ drastically from the balanced-panel results. For illustration, Graphs 2 and 3 show estimated series (ie projections of the estimated series on the computed factors) as obtained at successive iterations of the unbalanced-panel procedure.[8] For series belonging to the balanced panel, iterations do not change the estimated value by much, whereas for series with missing values the backdated values do change a lot across iterations before convergence is reached, thereby reflecting the growing importance of the new series in the estimated factors.

[8] In the given case, the number of factors extracted at each iteration was relatively high (5), in order to better illustrate the distortion.

Graph 3

Variable 30 across iters., unbalanced panel



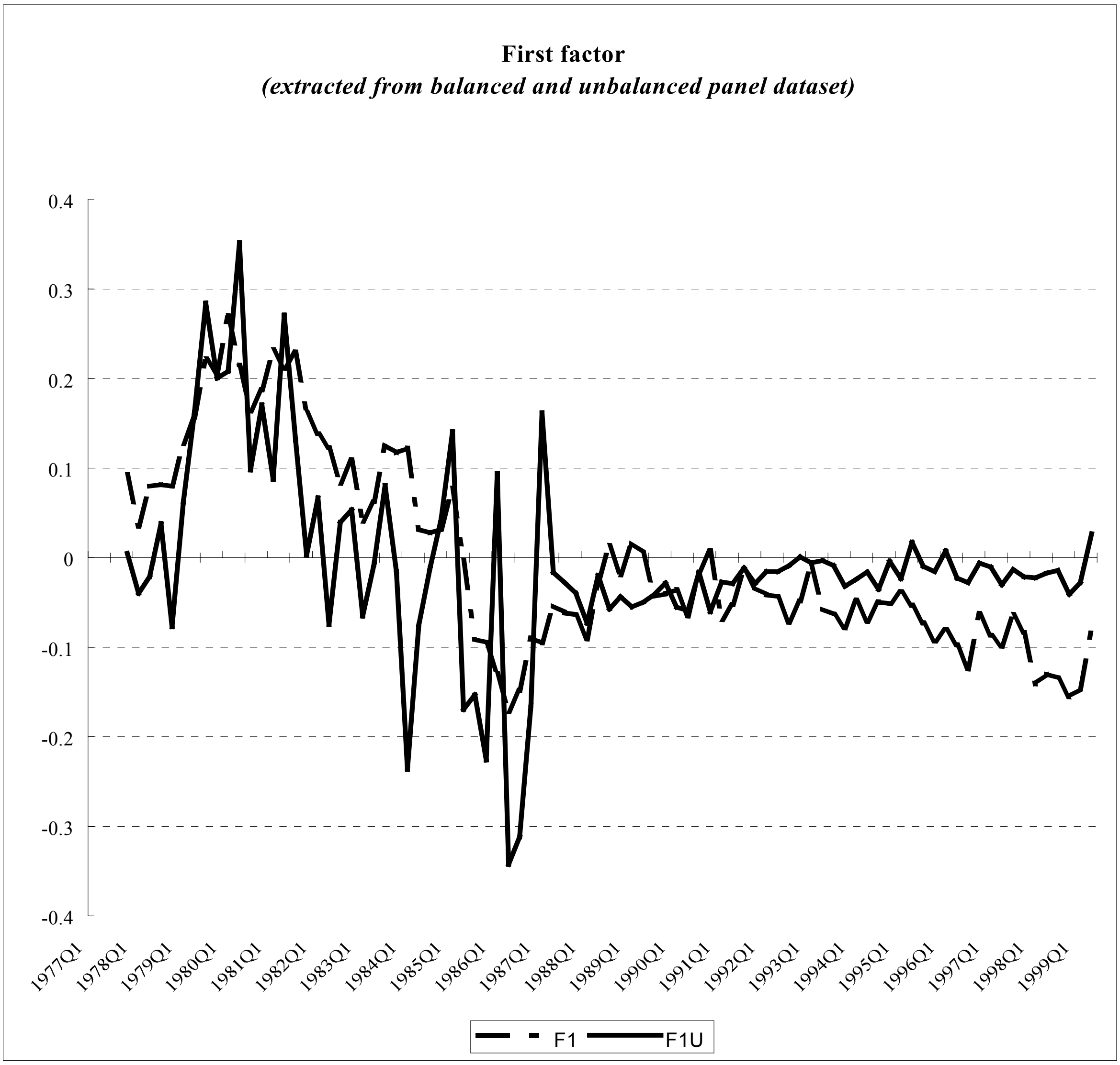
Furthermore, where the new series introduced also contain a seemingly non-stationary or highly volatile factor, the end result could be that the variance would be spread over a larger number of factors. In other words, extending the sample to variables with missing observations may lead to the introduction of a new and independent stochastic trend in the dataset, which would probably be reflected in an additional non-stationary factor. In such a case, the comparison across the two types of panels would not be relevant on a factor by factor basis but should focus on the space spanned by whatever number of factors is deemed relevant.

In the case concerned, although far more volatile in the earlier part of the sample, the first factor for the unbalanced sample - denoted F1U - is pretty similar to the one based on a balanced panel - denoted F1 - as can be seen in Graph 4a. The second factors - F2 and F2U - seem to differ basically only because of the arbitrary normalisation, so that essentially they are opposites (see Graph 4b).

Additional computations were carried out over the balanced sample, based on a recursive approach. All samples start in 1977 Q1. Graph 5 shows on the same plot the superimposition of the various estimates for each of the four factors, thereby providing a sort of visual illustration of the stability interval surrounding the various estimated factors. The interpretation is straightforward for each of the factors: the thicker the distribution of lines, the less constancy over time. This exercise therefore demonstrates that at least the first four factors seem to be quite robust and very stable over time, although some slight instability can be observed over the period prior to the mid-1980s. A quick overview seems also to indicate that the first two factors have a non-constant mean, some structural break taking place presumably at some point in the late 1980s.

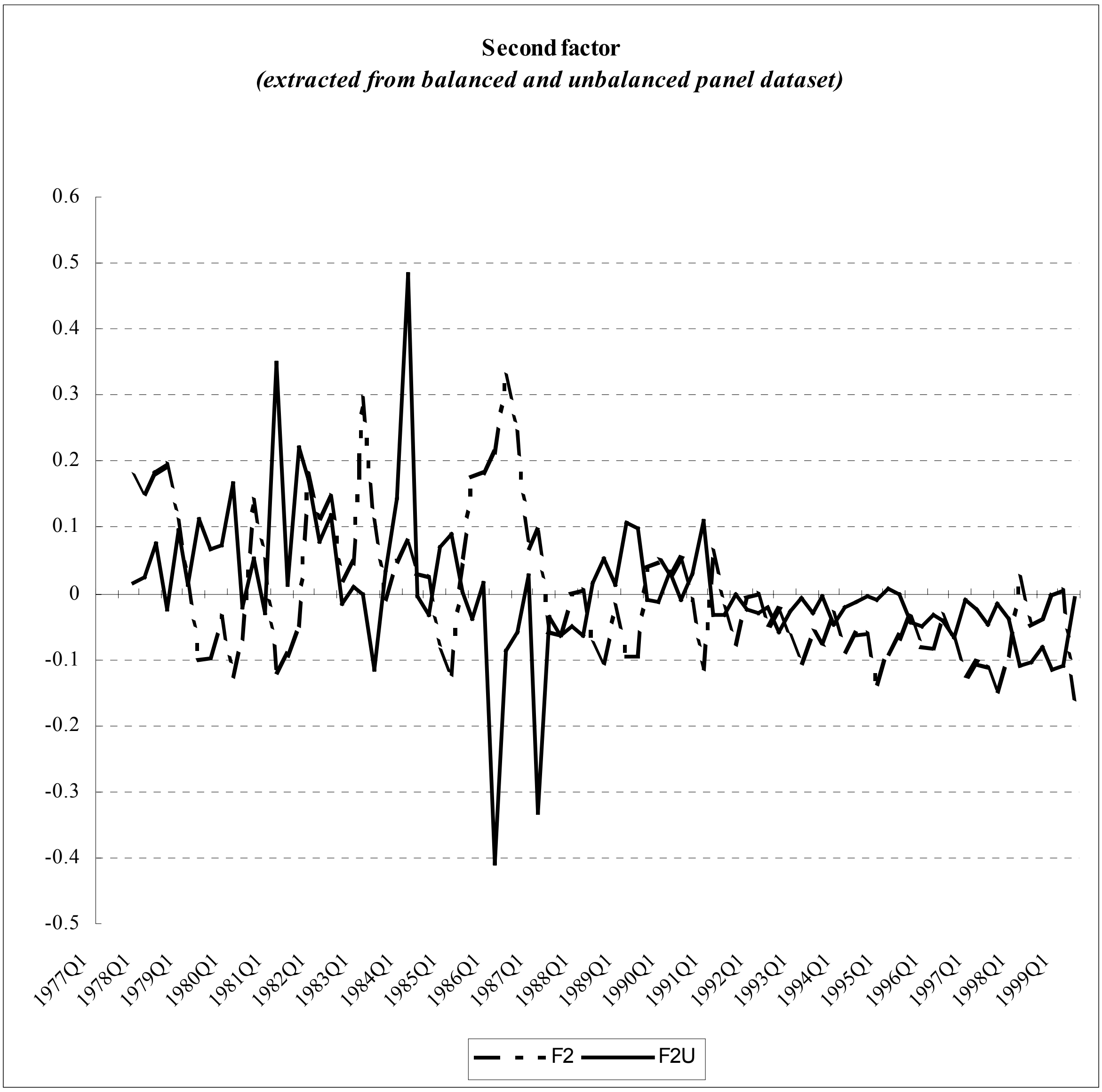
Graph 4a

Balanced and unbalanced panel, first factor



Graph 4b

Balanced and unbalanced panel, second factor



As a matter of fact, standard Dickey-Fuller (1981) and also Perron and Vogelsang (1992) stationarity tests confirm the “eyeball econometrics” intuition, namely that only the first factor is found to be I(1), whereas all subsequent factors - tested up to rank 4 - appear to be stationary (see Table 3). Such findings are consistent with the ranking of the factor not being neutral, with, for example, the first factor corresponding to the highest eigenvalues of the analysed variance-covariance matrix, thus capturing the component that has the strongest volatility. A by-product of this basic stationarity analysis is that the various indicators of country inflation analysed share one single common stochastic trend, which could be viewed as some underlying measure of euro area inflation. It should be noted in this respect that the first factor appears smoother than the otherwise standard measures of inflation for the euro area, thus coming closer to a “core” or “trend” indicator of underlying inflation.

Graph 5

Recursive estimates of the first four factors extracted from balanced panel

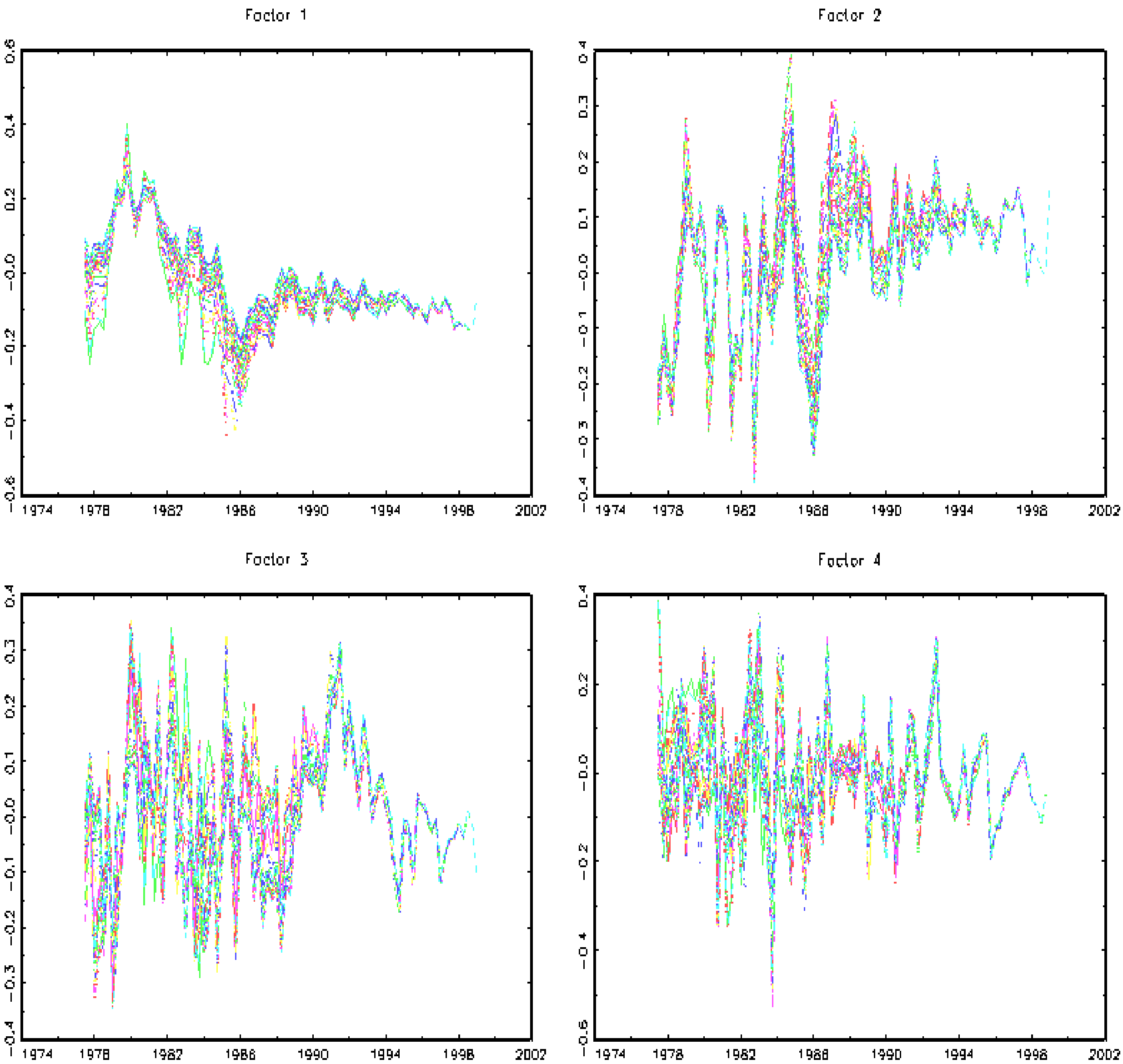


Table 3

Testing for the null of non-stationarity for the first three factors

F1	1977 Q1 – 1999 Q2 shift in mean model, break in 1986 Q4, DF(4) = –2.5
F1	1977 Q1 – 1999 Q2 break in trend model, break in 1985 Q4, DF(4) = –4.0
F2	1977 Q1 – 1999 Q2 standard DF model with an intercept, DF(4) = –3.7
F3	1977 Q1 – 1999 Q2 standard DF model with an intercept, DF(4) = –3.0

3.3 The estimated factors: interpretation

As to the interpretation of the various estimated factors, the properties of the factors and hence of these underlying forces may be gauged by the relationship between the factors and the variables on an individual basis. The interpretation therefore has to be factor-dependent, starting with the standard approach analysing the loadings, which we complement with an econometric time-series analysis of the factors.

The standard and natural way to measure these links is by analysing the loadings, which are the parameters measuring the projection of the factors on each variable. As the variables have been normalised, loadings are such that they lie between 1 and –1 and can thus be understood as correlations between each factor and each variable, while their value squared can be understood as the R^2 of the corresponding regression. Loadings for the balanced panel are collected in the table in Appendix 1, together with their value squared. It is not simple to extract robust conclusions from these numbers because factors and loadings can be rotated without affecting the variance decomposition of the principal-components analysis, but some outstanding facts nevertheless deserve some mention. First and foremost, loadings for the first factor are appreciably higher than the rest of the loadings for *all* variables. Only for variables such as import deflators and the GDP deflator are the loadings for the other factors close to those for the first one. The second outstanding fact is the clearer relationship between factors and variables *across* countries, rather than with countries *across* variables. Although the loadings for some variables show some country-specific behaviour (as, for instance, the relatively high loadings for the second factor for many Spanish series), the variable-specific behaviour is much more widespread and marked (such as the strong loading for the second factor for import deflators, irrespective of the country). This would point to area-wide specific factors as important elements in the description of inflation; on the other hand, the distribution of loadings for most variables across countries appears to be much more dispersed for factors two and three than for the first factor.

The univariate results reported in Table 3 seem to indicate that the first factor has to be treated in a somewhat specific manner with respect to the other ones, to the extent that it is only for that first variance component that cointegration analysis is meaningful. As regards subsequent factors, a correlation analysis with the first differences of the inflation rates should be preferred.

Cointegration analysis in effect supports the hypothesis that the first variance component reflects a common inflation trend for all of the euro area countries. Applying a residual-based test, ie Engle and Granger (1987), both the inflation rate for the consumption expenditure deflator and the HICP for the euro area appear cointegrated with the first factor, albeit at a relatively low level of confidence. The respective test statistics are DF(1) = –4.0 for PCD and DF(8) = –3.4 for CPI.[9] As a matter of fact, and quite consistently with the expectations, the HICP measure and the consumption deflator measure are also cointegrated with each other (DF(5) = –4.3 for CPI and PCD); this result is in line with the ECM specification linking the two prices, which is reported in the euro area model developed by Fagan et al (2001).

The projection of the euro area inflation rates on the first factor would suggest some increase in the inflation rate out-of-sample for the consumption deflator, as observed already for the HICP measure (see Graphs 6 and 7). In addition, the gap between the three indicators seems limited, as can be seen

[9] In the latter case, the sample is 1977 Q1-1999 Q1 with 1977 Q1-1998 Q3 for the deflator. The discrepancy comes from the fact that the data for the consumption deflator are not the Eurostat ones - for which no longer span of back data exists - but those constructed for modelling purposes; see Fagan et al (2001).

in fact from the residual plots in Graph 8. Although the HICP measure fluctuates more, in particular for seasonality reasons, the cycles remaining once the inflation rates have been filtered out from their common trend component seem to be pretty similar. Of course, further analysis should be conducted to take account of the role of subsequent factors F2 and F3 in explaining the behaviour of both the HICP and the consumption deflator for the euro area before according too much significance to such a conclusion.

In terms of the relationship between inflation for specific countries and the first factor, cointegration regressions supplemented with ADF(4) residual-based tests show that not all countries have inflation rates that are cointegrated with this factor (see Table 4 for the resulting *t*-stats). Interestingly enough, taking a critical value at 10% with 100 observations of –3.0, only four countries have an inflation rate not cointegrated with the common trend; in particular, two low-inflation countries, Germany and the Netherlands, depart somewhat from the average.[10] This is not surprising inasmuch as convergence took place towards such countries, so that the common trend may differ from the one specific to these countries, at least viewed from a relatively long-run perspective using historical data. As to the other countries, namely Finland and Portugal, this may indicate that convergence has been even quicker than in the average euro area country or that the historical inflation pattern is too specific to be close to the "implicit" average just computed. In the case of Germany and Portugal, the lack of cointegration could be related to the relatively weak loadings for the first factor.

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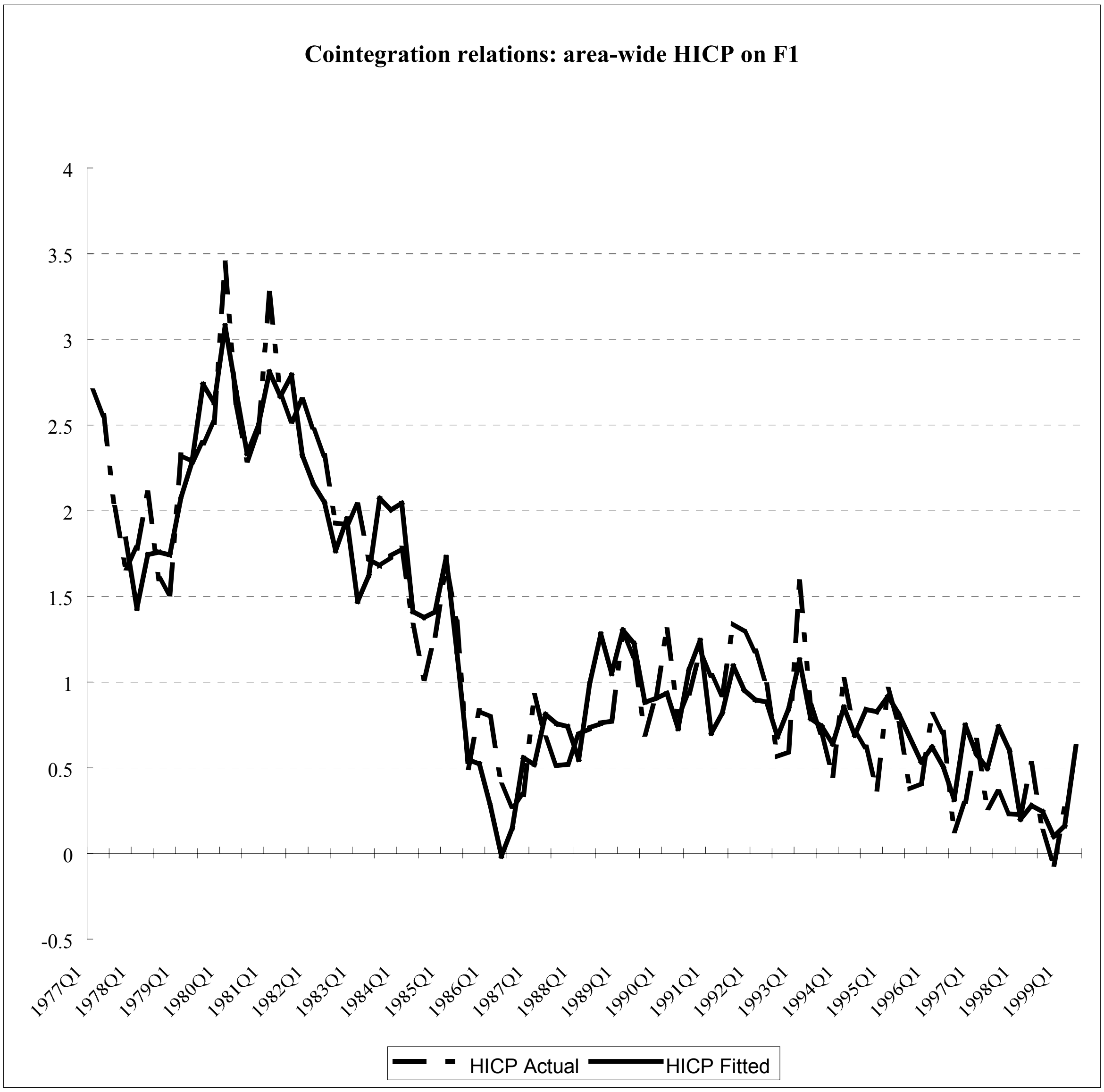
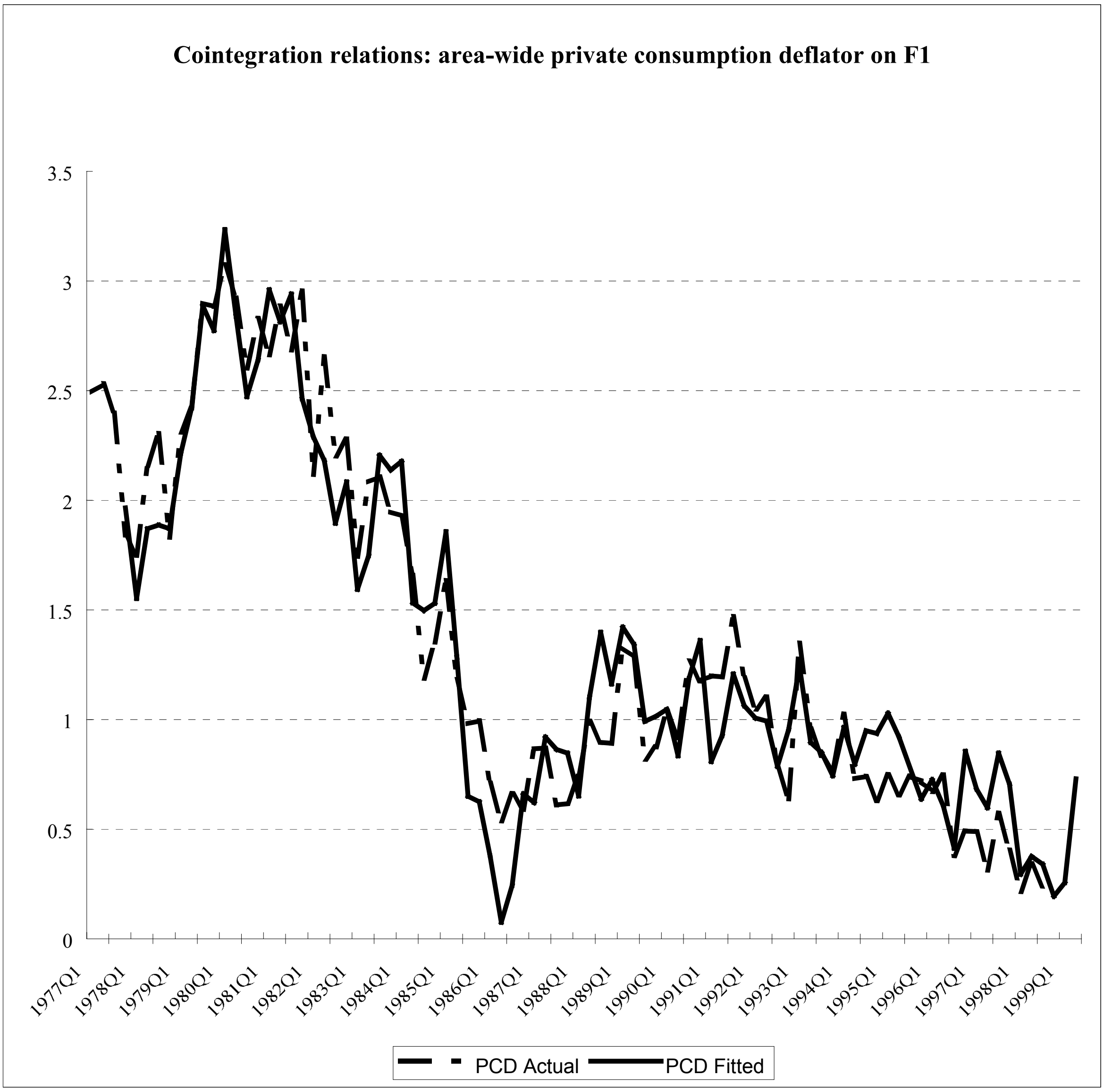
[10] A second - and less rigorous, given the integration properties of the series - exercise was to run stepwise OLS regressions, projecting the factors on all countries' CPI and PC inflation. On that basis, the first factor seems to be more correlated with inflation in Germany, Italy, Portugal and Ireland. For factors beyond the first one, on the other hand, a similar regression approach does not seem to indicate that factors can be associated with specific groups of countries, to the extent that results are highly sensitive to whether the CPI or the private consumption deflator is employed.

Graph 6



Cointegration relations: area-wide HICP on F1
4
3.5
3
2.5
2
1.5
1
0.5
0
-0.5
1977Q1
1978Q1
1979Q1
1980Q1
1981Q1
1982Q1
1983Q1
1984Q1
1985Q1
1986Q1
1987Q1
1988Q1
1989Q1
1990Q1
1991Q1
1992Q1
1993Q1
1994Q1
1995Q1
1996Q1
1997Q1
1998Q1
1999Q1
HICP Actual
HICP Fitted

Graph 7


Cointegration relations: area-wide private consumption deflator on F1
3.5
3
2.5
2
1.5
1
0.5
0
1977Q1
1978Q1
1979Q1
1980Q1
1981Q1
1982Q1
1983Q1
1984Q1
1985Q1
1986Q1
1987Q1
1988Q1
1989Q1
1990Q1
1991Q1
1992Q1
1993Q1
1994Q1
1995Q1
1996Q1
1997Q1
1998Q1
1999Q1
PCD Actual
PCD Fitted

Graph 8

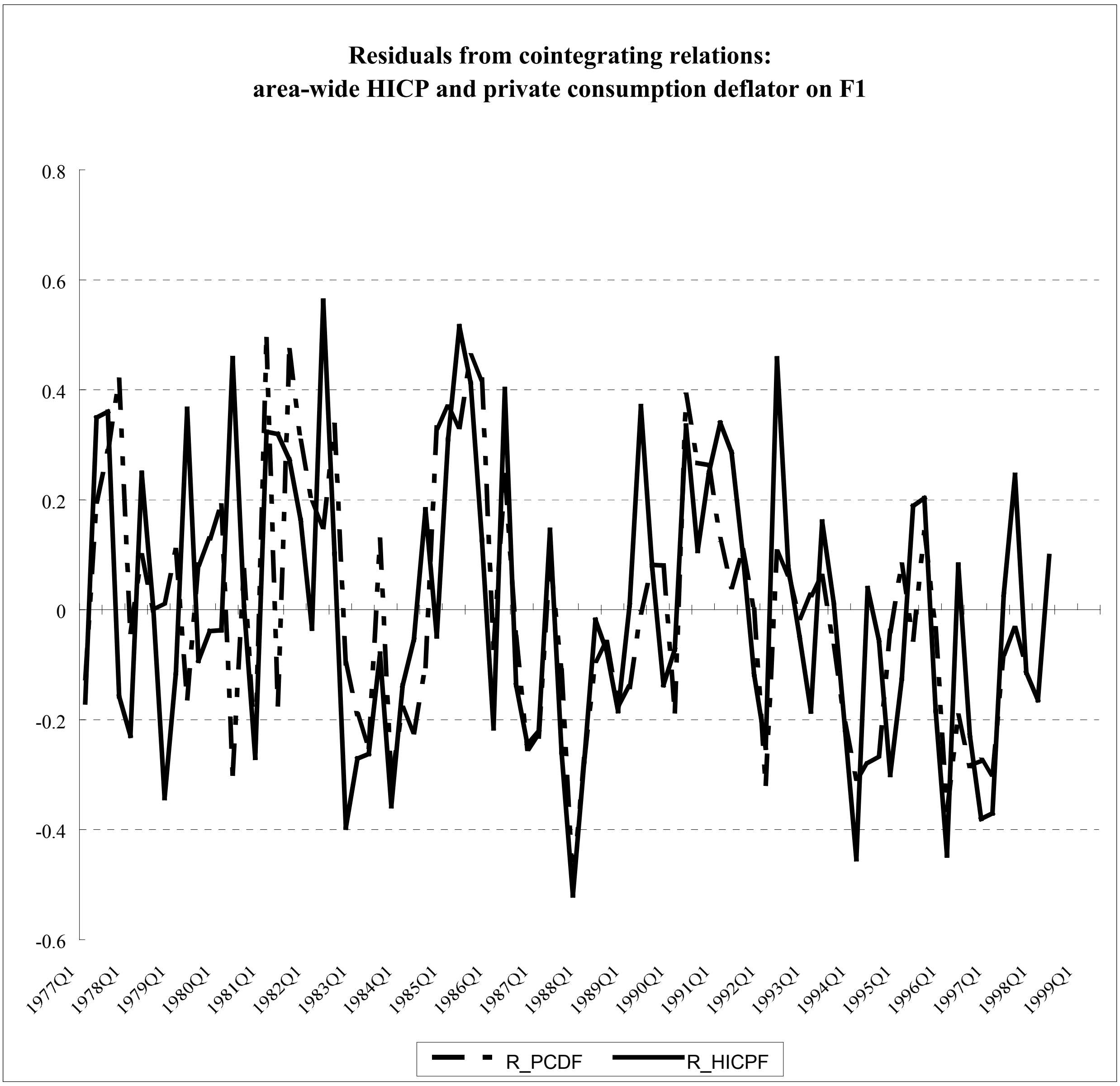

Residuals from cointegrating relations:
area-wide HICP and private consumption deflator on F1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
1977Q1
1978Q1
1979Q1
1980Q1
1981Q1
1982Q1
1983Q1
1984Q1
1985Q1
1986Q1
1987Q1
1988Q1
1989Q1
1990Q1
1991Q1
1992Q1
1993Q1
1994Q1
1995Q1
1996Q1
1997Q1
1998Q1
1999Q1
R_PCDF
R_HICPF

Table 4

ADF(4) cointegration tests for CPI / PCD regressed on F1

(1979 Q1–1999 Q2)[11]

AT –3.1 / –3.5	BE –3.0 / –1.9	DE –2.2 / –2.0	ES –3.9 / –4.0	FI –2.1 / –2.8
FR –3.0 / –2.9	IE –3.2 / –3.7	IT –4.2 / –4.1	NL –2.5 / –2.4	PT –2.7 / –2.8

As to the relationship between changes in inflation and the other factors, no clear conclusion can be elicited from the correlation analysis. Although the second factor appears significantly correlated with changes in inflation in two countries (Germany and the Netherlands) when the full sample and CPIs are used, it seems on the other hand to reflect more the pattern for Italy when consumption deflators are considered over the shorter period. In turn, the third factor is not significantly correlated with any of the country inflation measures, based on the two available consumer prices.

A complementary exercise that was conducted to help interpret the factors was to simply regress factors on the two main measures of inflation for all of the euro area countries, which is tantamount to computing the "implicit" weighting schemes associated with any given factor.[12] The suggested analysis was carried out for F1, which captures most of the non-stationarity in the country data, but not for the other factors, the contribution of which appears less important. When compared to the explicit weights used in the computation of the two standard measures of average euro area inflation, it appears - see Table 5 - that the implicit weighting scheme leads to less emphasis being put on countries such as Spain, whereas Austria, for example, is given more prominence. All in all, however, the first three weights are attributed to the largest countries in the euro area, which is broadly in line with the idea that the first factor was a proxy for the common average trend in the data.

Table 5

Implicit and explicit weights for the first factor, in CPI terms

(1977 Q1-1999 Q2)

Countries	Implicit	Explicit	Countries	Implicit	Explicit
AT	14.1	3.0	FR	23.1	21.1
BE	0.5	3.9	IE	2.7	1.1
DE	23.7	30.6	IT	15.6	20.4
ES	0.5	10.2	NL	10.4	5.6
FI	6.9	1.7	PT	2.5	2.4

To the extent that, quite clearly, the first factor seems to summarise the non-stationary or stochastic trend component underlying the data employed, a final hypothesis worth checking with reference in turn to the stationary factors is whether they capture the cross-sectional dimension of the data. It is in fact the case that both standard deviations of the CPI and the PCD across countries are significantly correlated over time in particular with the second factor. Regressing the cross-country standard error for both inflation measures on factors two and three gives *t*-stats equal to 4.1 for F2 and 2.2 for F3 in the CPI equation (sample 1977 Q1 to 1999 Q1), with 3.0 and 0.3 respectively for the PCD (sample 1988 Q2 to 1998 Q3).

[11] Some data are missing for the deflators; for Belgium and Portugal, for example, data are available only starting in 1985 and 1988, whereas for Ireland (interpolated from annual frequency) data stops in 1997.

[12] Not to be confused with the factor loadings themselves, which are computed via an OLS regression of each variable on the factors as documented above. Treating the first factor as a specific one appears warranted in view of its particularly persistent behaviour, in comparison with that of the other two factors.

3.4 The estimated factors: potential links with "core" inflation

On the basis of the above-mentioned results, the derived factors might bear some relationship to stable underlying forces of inflation. The first factor could, for example, be a convenient measure of "trend" inflation. A natural and further interpretation of this factor may relate it to "core" inflation indicators.

It is thus worth assessing the degree of potential usefulness of the derived first factor in the light of its potential links with measures of "core" inflation. One possible source for a list of criteria to be met by potential measures of this kind is to be found in Wynne (1999), as already mentioned. The table below gives a brief overview of the extent to which the trend inflation indicator delivered by the first estimated factor could qualify as a "core" inflation measure, on the basis of each of these criteria. The set of criteria is wide enough to cover the analysis of measures of "core" inflation that are very different in nature. Obviously, some ranking is needed to take into account the specific nature of the proposed measure. For instance, dynamic factors extracted from a large panel of data will in all likelihood never be an important element in the communication strategy of central banks vis-à-vis the public. From this point of view, the timeliness and leading-indicator properties of the proposed measure are, in our view, clearly more relevant than its technical simplicity.

Table 6

Factor-based trend inflation as a measure of core inflation

	Relative importance of criteria	**Compliance with criteria**
Computable in real time	High	Yes
Forward-looking	High	Still to be assessed
Track record	Intermediate	No
Understandable to public	Low	No
History does not change	Low	No
Theoretical basis	Intermediate	No

In most cases, the factor-based trend indicator for inflation quite obviously does not comply with the requirements. In spite of this somewhat negative assessment, two elements should be emphasised. In the first place, the dismal overall performance of the factor-based trend indicator is partially balanced by the relative strength of the measure in criteria that are deemed more important. It is an evident feature of dynamic factors that they can be estimated in real time, and even before the variables entering the initial panel have all been released. Also, there could be grounds in the literature to expect good forecasting properties of the indicator (see Stock and Watson (1999)), a feature that deserves to be explored. Last but not least, factors extracted in the context of this paper have shown a remarkable degree of stability over time, as shown in the first panel in Graph 5.

A fully-fledged analysis of out-of-sample forecasts of inflation using the factor approach is beyond the scope of this paper, and is not developed further. The next section attempts to gauge the in-sample properties of the first factor in relation to observed inflation, with a view to obtaining a better assessment of the performance as to the second most important criterion, ie the amount of forward looking behaviour.

4. The "implicit" inflation Granger-causes the "explicit" inflation

The above-mentioned results suggest that the first factor already possesses a number of interesting properties, namely its relative smoothness, its robustness to changes in the sample, its apparent non-stationarity, its cointegration properties with standard measures of euro area inflation, and finally its seemingly acceptable "implicit" weighting scheme. It therefore seems tempting to pursue the analysis further, extending it to causality considerations. The issue there is to check whether the trend indicator thus found can be used in forecasting average inflation in the euro area, bearing in mind of course that the interpretation is more in terms of forecasting properties than indicator properties as such.[13]

4.1 Causality analysis: the setting

The framework to be employed for the analysis is a bivariate ECM comprising the first factor with euro area inflation, measured alternatively by either the consumption deflator or the HICP. As pointed out in Granger (1988), the standard causality framework has to be adapted in the case where there are some cointegration properties linking the series to be analysed.

In the case of a bivariate cointegrated VAR process, the general framework is the following:

$$\begin{cases} \Delta X = \Phi_{xy}(L)\Delta Y + \Phi_{xx}(L)\Delta X - \gamma_x L(X - \beta Y) + \varepsilon_x \\ \Delta Y = \Phi_{yy}(L)\Delta Y + \Phi_{yx}(L)\Delta X - \gamma_y L(\beta Y - X) + \varepsilon_y \end{cases}$$

where X and Y are I(1) processes, stationary in first difference, $\Phi_{xy}, \Phi_{yy}, \Phi_{xx}$, and Φ_{yx} finite-lag polynomials of degree higher than 1, all roots outside the unit circle, and ε_x and ε_y serially uncorrelated perturbations of zero mean (possibly cross-correlated).

In such a setting, a number of causality tests can be implemented, each of them with a different interpretation in economic and/or econometric terms.[14]

A first test is that for the null of an ECM term equal to zero, namely either γ_x and γ_y can be equal to zero. When holding, this non-causality property, which can be termed "ECM causality", implies that the concerned variable is weakly exogenous with respect to the long-run parameters β. As is well known, the representation theorem in Engle and Granger (1987) implies that causality exists through at least one of the two ECMs in the VAR.

A second test is that of the null of the parameters entering either Φ_{xy} or Φ_{yx} being jointly zero, namely a so-called short-run causality linking the two variables. Combining the two restrictions under a composite hypothesis corresponds to the causality aspects of the strong exogeneity concept. The interpretation in economic terms is that no past information from the other variable can be valuably incorporated to improve a univariate forecast for the other variable (which brings causality results in line with a forecasting approach).

A final remark regards the estimation procedure prior to the test itself. In the reduced form, single equation OLS is suitable since both variables are explained by exactly the same series. However, in the event that some contemporaneous correlation exists across the two perturbation terms (in other words, bidirectional instantaneous causality) entering the equations contained in the above-mentioned system, a structural model has to be estimated, allowing for some term of degree equal to 0 in the lag polynomial involved. In such a case, the estimation process has also to be changed slightly, to the extent that the list of explanatory variables is now variable-specific, and therefore a SURE method is appropriate for estimating and testing further for the various causal links.

4.2 Causality analysis: results

The results of the causality analysis are quite clear as to weak exogeneity of the first factor with respect to the long-run parameters, whereas the causality pattern is somewhat mixed and depends on the inflation measure considered in the analysis.[15]

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[13] A similar approach has been taken, for example, in Davis and Fagan (1997). As a matter of fact, the interesting aspect of this indicator is clearly in terms of providing a measure of trend inflation and some view on longer-run prospects rather than using it as an "indicator" in the context of the lagging-coincident-leading indicator, in particular to the extent that some of the series entering the computation are indeed available *after*, for example, the CPIs - HICPs nowadays - are released.

[14] The results have to be considered as a preliminary investigation, to the extent that the standard critical values to be used may be affected by a "generated regressor" issue; see Pagan (1984). A full and accurate treatment of this issue would, however, go beyond the scope of the present paper and will therefore be left for future work.

Table 7

Causality test results (p-value)

Null of non-causality	Joint hypothesis	ECM non-significant	F1 does not cause inflation
(F1 = X)	$\gamma_x = \Phi_{xy} = 0$	$\gamma_x = 0$	$\Phi_{xy} = 0$
HICP	22%	56%	18%
PCD	4%	38%	7%

First, as regards the relationship between the HICP and the first factor, assessed over the sample 1980 Q1 to 1999 Q1, the latter appears as weakly exogenous with respect to the parameters involved in the long-run relation between the factor and euro area inflation (at a level of 56%). In addition, the null of no short-term causality from the HICP to the first factor can also be accepted (at a level of 18%). Taking both hypotheses jointly, which is equivalent to the null of non-causality, the restriction is also accepted (at a level of 22%), thereby implying that the first factor incorporates specific information which is useful for forecasting euro area inflation, as measured by the headline CPI growth rates. However, this is not to be considered as a leading indicator analysis, to the extent that no out-of-sample tests have been carried out.

The results are somewhat different for the private consumption deflator, computed over the sample 1980 Q1 to 1998 Q3. In that case, weak exogeneity of the first factor is also accepted at the 38% level; however, short-run non-causality is marginally significant at the 7% level, and the p-value at only 4% for the corresponding joint restriction of non-causality leads to the rejection of the latter.

On the basis of such results, it seems fair to advance that the first factor, as computed in the balanced panel, does provide some additional information on future euro area inflation for consumer prices, with respect to the information already embedded in the past values of inflation itself. To some extent, the combination of such properties with the relatively smooth behaviour of the corresponding factor in comparison with standard "explicit" weight measures of inflation could signal that underlying trends and also longer-run prospects of euro area inflation could be assessed valuably by looking at such an indicator.

It is the case, however, as rightly pointed out by Wynne (1999) when discussing criteria for measuring "core" inflation, that such an econometrically computed indicator suffers from two major drawbacks from a policy viewpoint. First, the relative intricacy which would render communication to the public difficult and, second, the fact that additional observations would lead to re-estimation of the whole history of the factor although such a drawback would probably be less pressing than with, for example, dynamic factors.

On the other hand, mention has already been made of the forecasting properties of the factors, and the out-of-sample approach necessary for analysing them. Such an approach is clearly worth pursuing, as is done in the seminal paper by Stock and Watson (1998) and subsequently in Stock and Watson (1999), but is left for further work. The focus in the current paper has indeed been on detecting potential common trends in nominal variables for a number of countries and their link to inflation itself for the area as a whole. In contrast, the focus on the leading-indicator properties pertains to the second step of the factor analysis, by which they are fitted against a number of alternative indicators to test their predictive power as regards, for example, inflation. In this sense, the analysis is

[15] Such results are information-set-dependent, so that, for example, adding or removing lags could lead to different results. For the time being, no particular care has been taken regarding lag selections (eight lags have been employed in all cases), so that results should be viewed with caution. In addition, when a SURE method is employed, some significant contemporaneous correlation is found among the three series, so that causality results become less clear-cut than in the reduced form.

fundamentally different from the one undertaken here, as the goal is to find the links between the calculated factors and data not used beforehand in their derivation.[16]

5. Conclusions

The first step of the "diffusion indices" approach proposed by Stock and Watson (1998), namely factor analysis, has been applied to a panel comprising time series for a number of price and cost indicators for all of the member countries. This approach allows the econometrician to capture both the time and the cross-country dimension of the information available, with a view in particular to computing summary indicators of the path for inflation in the euro area, without imposing ex ante any given weighting scheme. It was also intended to better understand the cross-country dimension of past inflation developments.

A number of interesting, albeit provisional, results have been obtained, as described below.

First, some summary indicator of inflation trends in the euro area has been derived, through the first estimated factor. The resulting indicator is non-stationary, and also cointegrated with standard measures of euro area inflation that are otherwise available, such as the HICP and the private consumption deflator, ie the indicator seems to represent a "common trend" in the inflation measures.

Second, this "implicit" measure of inflation appears moreover to be quite stable, to the extent that recursive estimates show low dependence of the factor on the sample used. It remains to be checked, however, whether the inclusion of series with missing observations would greatly disturb that picture.

Third, a by-product of the analysis is that the dispersion of inflation across countries seems to be captured by the subsequent factors, which are stationary. Nevertheless, it appears quite difficult to associate any given set of countries with those lower-order factors, which may in fact be deemed an interesting property.

Fourth, an assessment of the causality properties of the "implicit" measure of inflation with respect to explicit measure(s) shows that there is evidence of unilateral causality from the factor to especially the CPI inflation indicator, so that the factor could possibly be valuably employed in forecasting aggregate inflation.

Such an assessment should of course trigger further research, part of it being quite straightforward, namely a comparison exercise with standard indicators of "core" inflation, for example the trimmed mean, for which data are available only as of 1996, or some ex-food and ex-energy measures in order to cover a larger sample. Further work could pave the way for a further paper, involving the extended version of the dataset, with a view to carrying out the second step of the analysis in Stock and Watson (1999), namely running the forecasting routines.

[16] True out-of-sample analysis also implies that the variable to be forecast should *by definition* not belong to the dataset from which factors were derived. Whether observed realisations of the variable to be forecast (ie contemporaneous and past values) are used to extract factors, on the other hand, is a matter of choice. It is thus possible to use the same variables to extract factors as done in this paper, or alternatively to conduct a similar analysis after having dropped variables that are too close to the one to be forecast, such as country CPIs with respect to the euro area HICP.

Appendix 1: Loadings

The table below contains the loadings of the balanced panel (and their squared value), in order to help illustrate the basic properties of the factors.

Balanced panel

Variable	Loadings			Loadings squared		
	F1	F2	F3	F1	F2	F3
CPIAT	0.73	-0.04	0.33	0.54	0.00	0.11
CPIBE	0.82	0.09	0.09	0.68	0.01	0.01
CPIDE	0.69	-0.31	0.49	0.47	0.10	0.24
CPIES	0.81	0.42	-0.08	0.66	0.17	0.01
CPIFI	0.82	0.25	-0.07	0.68	0.06	0.00
CPIFR	0.93	0.25	-0.05	0.87	0.06	0.00
CPIIE	0.84	0.16	0.06	0.70	0.03	0.00
CPIIT	0.92	0.21	0.02	0.85	0.05	0.00
CPINL	0.76	-0.15	0.33	0.58	0.02	0.11
CPIPT	0.69	0.37	-0.20	0.48	0.14	0.04
PCDAT	0.73	-0.04	0.34	0.54	0.00	0.12
PCDDE	0.66	-0.29	0.42	0.44	0.09	0.17
PCDES	0.77	0.48	-0.03	0.60	0.23	0.00
PCDFR	0.92	0.26	-0.07	0.84	0.07	0.00
PCDIT	0.93	0.22	-0.01	0.87	0.05	0.00
PCDFI	0.79	0.25	0.15	0.63	0.06	0.02
YEDAT	0.51	0.34	0.43	0.26	0.11	0.18
YEDDE	0.40	0.23	0.61	0.16	0.05	0.37
YEDES	0.70	0.54	-0.02	0.49	0.29	0.00
YEDFI	0.59	0.31	-0.18	0.35	0.10	0.03
YEDFR	0.80	0.44	-0.16	0.64	0.20	0.03
YEDIT	0.91	0.26	-0.01	0.82	0.07	0.00
PPIAT	0.68	-0.32	-0.01	0.47	0.10	0.00
PPIDE	0.82	-0.41	-0.01	0.67	0.17	0.00
PPIES	0.88	0.15	-0.16	0.77	0.02	0.03
PPIFI	0.85	-0.23	-0.13	0.72	0.05	0.02
PPIFR	0.80	0.07	-0.34	0.63	0.01	0.12
PPINL	0.75	-0.45	0.02	0.56	0.20	0.00
MTDAT	0.54	-0.50	-0.18	0.29	0.25	0.03
MTDDE	0.67	-0.59	-0.08	0.45	0.35	0.01
MTDES	0.78	-0.23	-0.02	0.61	0.05	0.00
MTDFI	0.59	-0.27	0.05	0.35	0.07	0.00
MTDFR	0.75	-0.38	-0.08	0.57	0.15	0.01
MTDIT	0.71	-0.48	-0.07	0.51	0.23	0.00
XTDAT	0.74	-0.36	-0.10	0.55	0.13	0.01
XTDDE	0.82	-0.34	-0.17	0.67	0.11	0.03
XTDES	0.87	0.08	-0.07	0.76	0.01	0.00
XTDFI	0.59	-0.09	-0.13	0.35	0.01	0.02
XTDFR	0.82	-0.09	-0.29	0.68	0.01	0.08
XTDIT	0.80	-0.22	-0.07	0.63	0.05	0.01

Variables are those entering the balanced panel, and their label includes the concept in the first three characters of each variable's name, and the country in the remaining two characters. Thus, concepts are:

CPI: consumer price index, national concept

PCD: private consumption deflator

YED: GDP deflator

PPI: producer price index

MTD: import deflator

XTD: export deflator

Countries are:

AT: Austria

BE: Belgium

DE: Germany

ES: Spain

FI: Finland

FR: France

IE: Ireland

IT: Italy

NL: Netherlands

PT: Portugal

Appendix 2:
Data description and coverage ratios

A total of 35 series per country were considered for the creation of the dataset; only the price variables (10 per country) have been used in this paper. The dataset comprises: real variables, national account deflators, and different prices, monetary and credit variables, interest rates, labour statistics, and inventories of finished and ordered manufactured goods. Only 65% of the total data are available for the 10 countries analysed (see the following table). Going beyond this overall picture, the following points can be made:

1. The countries for which severe problems arise in terms of availability are Germany, Ireland, Austria and Portugal, countries for which almost half of the series are not available. For Germany the problem arises from the lack of data for "Germany as a whole" prior to 1991 for most series (the total share of available data is only 43%). Data for Ireland are mostly annual, while for Austria and Portugal the starting dates for many series are only 1985 and 1988. Also worth mentioning is Belgium, for which some series start only in 1985.
2. Some series are not available for all countries; for example WPI (33.4%) is available only for Germany, Ireland, Italy, Austria and Finland. Unit labour costs are covered by only 40% (no data are available for Ireland, Austria or Portugal, and German data start in 1991 Q1).
3. Finally, there is also a timeliness problem, ie, not all countries have yet published data for all series for 1999 Q2; also some series are drawn from annual data, and therefore the latest observation is 1998.

Series	Countries								
	Belgium			Germany			Spain		
	Availability	Observations	Coverage[(a)]	Availability	Observations	Coverage[(a)]	Availability	Observations	Coverage[(a)]
PPI Finished goods (OECD, MEI, and ECB database*)	80q1-99q2	**80**	**68%**	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**
WPI (ECB database* and BIS)**			**0%**	91q1-99q2*	**34**	**29%**			**0%**
CPI (OECD, MEI)	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**
Private Cons.Deflator (OECD, QNA)	85q1-99q2	**58**	**49%**	91q1-99q2(b)	**34**	**29%**	70q1-99q2	**118**	**100%**
GDP deflator (OECD, QNA)	85q1-99q2	**58**	**49%**	91q1-99q2(b)	**34**	**29%**	70q1-99q2	**118**	**100%**
Government Consumption Deflator (OECD, QNA)	85q1-99q2	**58**	**49%**	91q1-99q2	**34**	**29%**	70q1-99q2	**118**	**100%**
Gross fixed capital formation Deflator (OECD, QNA)	85q1-99q2	**58**	**49%**	91q1-99q2	**34**	**29%**	70q1-99q2	**118**	**100%**
Exports Deflator (OECD, QNA)	85q1-99q2	**58**	**49%**	91q1-99q2(b)	**34**	**29%**	70q1-99q2	**118**	**100%**
Imports Deflator (OECD, QNA)	85q1-99q2	**58**	**49%**	91q1-99q2(b)	**34**	**29%**	70q1-99q2	**118**	**100%**
ULC	85q1-99q2	**58**	**49%**	91q1-99q2(b)	**34**	**29%**	70q1-99q1	**117**	**99%**
TOTAL 10 Series		**604**	**51%**		**508**	**43%**		**1061**	**90%**

Series	Countries								
	France			Ireland			Italy		
	Availability	Observations	Coverage[(a)]	Availability	Observations	Coverage[(a)]	Availability	Observations	Coverage[(a)]
PPI Finished goods (OECD, MEI, and ECB database*)	70q1-99q2	**118**	**100%**	85q1-99q2*	**58**	**49%**	81q1-99q2	**74**	**63%**
WPI (ECB database and BIS*)			**0%**	70q1-99q1*	**117**	**99%**	70q1-97q4**	**112**	**95%**
CPI (OECD, MEI)	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**
Private Cons.Deflator (OECD, QNA)	70q1-99q2	**118**	**100%**	75q1-97q4*	**23**	**19%**	70q1-99q2	**118**	**100%**
GDP deflator (OECD, QNA)	70q1-99q2	**118**	**100%**	75q1-97q4*	**23**	**19%**	70q1-99q2	**118**	**100%**
Government Consumption Deflator (OECD, QNA)	70q1-99q2	**118**	**100%**	75q1-97q4*	**23**	**19%**	70q1-99q2	**118**	**100%**
Gross fixed capital formation Deflator (OECD, QNA)	70q1-99q2	**118**	**100%**	75q1-97q4*	**23**	**19%**	70q1-99q2	**118**	**100%**
Exports Deflator (OECD, QNA)	70q1-99q2	**118**	**100%**	75q1-97q4*	**23**	**19%**	70q1-99q2	**118**	**100%**
Imports Deflator (OECD, QNA)	70q1-99q2	**118**	**100%**	75q1-97q4*	**23**	**19%**	70q1-99q2	**118**	**100%**
ULC (BIS)	78q1-99q2	**118**	**100%**				82q1-99q2	**70**	**59%**
TOTAL 10 Series		**1062**	**90%**		**431**	**37%**		**1082**	**92%**

(a) Coverage stands for the ratio between available data and total number of observations.

(b) Data for Germany is available in most cases only as of 1991, however it is possible to obtain longer series by rescaling them to the Western Germany series.

Series	Countries								
	Netherlands			Austria			Portugal		
	Availability	Observations	Coverage[a]	Availability	Observations	Coverage[a]	Availability	Observations	Coverage[a]
PPI Finished goods (OECD, MEI, and ECB database*)	76q1-99q2*	**94**	**80%**	70q1-99q2	**118**	**100%**			**0%**
WPI (ECB database and BIS*)			**0%**	96q1-99q2**	**14**	**12%**			**0%**
CPI (OECD, MEI)	70q1-99q2	**118**	**100%**	76q1-99q2	**94**	**80%**	88q1-99q2	**46**	**39%**
Private Cons.Deflator (OECD, QNA)	77q1-99q1	**89**	**75%**	76q1-99q2	**94**	**80%**	88q1-98q4	**44**	**37%**
GDP deflator (OECD, QNA)	77q1-99q1	**89**	**75%**	76q1-99q2	**94**	**80%**	88q1-98q4	**44**	**37%**
Government Consumption Deflator (OECD, QNA)	77q1-99q1	**89**	**75%**	76q1-99q2	**94**	**80%**	88q1-98q4	**44**	**37%**
Gross fixed capital formation Deflator (OECD, QNA)	77q1-99q1	**89**	**75%**	76q1-99q2	**94**	**80%**	88q1-98q4	**44**	**37%**
Exports Deflator (OECD, QNA)	77q1-99q1	**89**	**75%**	76q1-99q2	**94**	**80%**	88q1-98q4	**44**	**37%**
Imports Deflator (OECD, QNA)	77q1-99q1	**89**	**75%**	76q1-99q2	**94**	**80%**	88q1-98q4	**44**	**37%**
ULC (BIS)	84q1-99q1	**61**	**52%**			**0%**			**0%**
TOTAL 10 Series		**807**	**68%**		**790**	**67%**		**310**	**26%**

Series	Countries		
	Finland		
	Availability	Observations	Coverage[a]
PPI Finished goods (OECD, MEI, and ECB database*)	70q1-99q2	**118**	**100%**
WPI (ECB database and BIS*)	70q1-99q2**	**118**	**100%**
CPI (OECD, MEI)	70q1-99q2	**118**	**100%**
Private Cons.Deflator (OECD, QNA)	75q1-99q2	**98**	**83%**
GDP deflator (OECD, QNA)	75q1-99q2	**98**	**83%**
Government Consumption Deflator (OECD, QNA)	75q1-99q2	**98**	**83%**
Gross fixed capital formation Deflator (OECD, QNA)	75q1-99q2	**98**	**83%**
Exports Deflator (OECD, QNA)	75q1-99q2	**98**	**83%**
Imports Deflator (OECD, QNA)	75q1-99q2	**98**	**83%**
ULC (BIS)	89q1-99q2	**42**	**36%**
TOTAL 10 Series		**984**	**83%**

Series	Total Coverage[a] For Each Variable
PPI Finished goods (OECD, MEI, and ECB database*)	**75.93%**
WPI (ECB database and BIS*)	**33.47%**
CPI (OECD, MEI)	**91.86%**
Private Cons.Deflator (OECD, QNA)	**67.29%**
GDP deflator (OECD, QNA)	**67.29%**
Government Consumption Deflator (OECD, QNA)	**67.29%**
Gross fixed capital formation Deflator (OECD, QNA)	**67.29%**
Exports Deflator (OECD, QNA)	**67.29%**
Imports Deflator (OECD, QNA)	**67.29%**
ULC (BIS)	**42.37%**
TOTAL (Coverage of the 10 Series)	**65%**

(a) Coverage stands for the ratio between available data and total number of observations.

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