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Forecasting inflation in the European Monetary Union: A disaggregated approach by countries and by sectors

A. ESPASA, E. SENRA and R. ALBACETE*

Espasa, Dpto. de Estad¡stica y Econometr¡a, Universidad Carlos III de Madrid,
Senra, Dpto. de Estad¡stica, Estructura Económica y OEI, Universidad de Alcalá
Albacete, Dpto. de Estad¡stica y Econometr¡a, Universidad Carlos III de Madrid

Inflation in the European Monetary Union is measured by the Harmonized Indices of Consumer Prices (HICP) and it can be analysed by breaking down the aggregate index in two different ways. One refers to the breakdown into price indexes corresponding to big groups of markets throughout the European countries and another considers the HICP by countries. Both disaggregations are of interest because in each one, the component prices are not fully cointegrated, having more than one common factor in their trends. The paper shows that the breakdown by group of markets improves the European inflation forecasts and constitutes a framework in which general and specific indicators can be introduced for further improvements.

Keywords: core inflation, cointegration, common factor, univariate models, VeqCM, bottom-up approach

1. INTRODUCTION

Inflation in the European Monetary Union is directly measured by the Harmonized Indices of Consumer Prices (HICP). Other measures are available, such as the GDP or consumption deflators, but they are not based directly and exclusively on price data. Thus, even though they cover more of the economy than the HICP, they are not so widely used as relevant inflation measures. Besides, these alternative measures can only be broken down into a relatively small number of components, at least when they are originally published. Since an important aim of this paper is to study the question of whether prices in different markets follow a single common trend or not, a degree of detail on the disaggregation of the price indicator is important. Finally, macroeconomic deflators are available only on a quarterly basis and monthly updates are in high demand to forecast inflation. For all these reasons, the paper centres on the HICP.

* Please address correspondence to: Antoni Espasa, Universidad Carlos III, C/Madrid 126, 28903 Getafe, Madrid, Spain. Fax: 34 91 624 9849; Phone: 34 91 624 9803; E-mail: espasa@est-econ.uc3m.es

Inflation in the euro-zone can be analysed by breaking down the aggregate index in two different ways. One refers to the breakdown into price indexes corresponding to large groups of markets (sectors) throughout European countries and another considers the HICP by countries. Both disaggregations are of interest because in each one, as it is shown in the paper, thee different price components are restricted by some, but not by a possible maximum number (n-1) of cointegration relationships. In this respect, we say that the different price components are cointegrated but not fully cointegrated. The absence of full cointegration between the n elements of a vector time series implies that the n trends in the component time series are generated by more than one common factor (Escribano and Peña, 1994) and this indicates that there is no full convergence between the components, in this case between the different prices.

The lack of full cointegration between prices implies that the innovations in the aggregate will have different long-run effects depending on the common trend from which they mainly stem. Consequently, in this case disaggregation is important in order to understand the medium term behaviour of the aggregate price index. A disaggregated analysis can also be of interest if the impulse response functions of the components of a vector time series differ only in the short term, but then its results will only differ in the short run with respect to the results of an aggregate study. Certainly the practice of disaggregation has limits (Zellner and Tobias, 2000). In particular, if the quality of data deteriorates when disaggregating or the analyst does not succeed in modelling data properly, then the disaggregated models could be wrong and the forecasts derived from them for the aggregate could be much worse than the forecasts from an aggregate model. Modelling the vector of components becomes more complex than modelling the aggregate, not only because of the obvious question of dimensionality, but also because it is much more probable that, for some components at least, the linear approximation in modelling would not be supported by data, requiring non-linear structures which could be quite difficult to construct.

Forecasting inflation has been approached in different ways. Stock and Watson (1999) present and apply a number of conventional approaches and introduce a new approach based on a leading indicator constructed following the method presented in a related paper (Stock and Watson, 2002), and using a large number of macroeconomic time series. The model used by Stock and Watson (1999) to forecast the year-on-year inflation rate in the USA still has a unit root in the dynamic polynomial for inflation, implying that the long-term behaviour of the leading indicator does not fully explain the long-term behaviour of inflation. In other words, the innovations in this model, which are assumed to be independent of the leading indicator[1] have persistent effects in inflation. Therefore, if the components of the price index are not fully cointegrated, and this is indeed the case (Espasa *et al.*, 1999), the disaggregation and the use of a specific (leading indicator) model for each price index will

[1] Since the leading indicator is mainly obtained from nominal variables, we could expect feedback from inflation.

usually improve the forecast of the aggregate. The reason lies in the fact that, by disaggregating, the innovations of each price index are projected into the future with different persistent and short-term effects.

In order to improve inflation forecasting results, the approach in this paper is to make use of more information, and starts with increasing the amount of information on prices themselves. The idea is that the behaviour of prices through different markets and countries is sufficiently diverse in trend, seasonality, short-term oscillations and erraticity, that forecasting results can be considerably improved if all this information is taken into consideration. Having established the interest in increasing information by disaggregating the HICP, a subsequent paper could deal with the question of introducing general and specific leading indicators for each price component and consider if some components require a non-linear model.

The models in this paper are not structural models but final form models. Certainly, forecasting inflation with models which include causal relationships is much more helpful for policy analysis, provided the forecasts from these models are as accurate as those from final form models. One important reason for structural models not necessarily providing better forecasts is the fact that they require forecasts of the explanatory variables, and that variables like the unemployment rate, output gap, monetary variables, exchange rates, productivity, etc., are variables which are not forecast well and some of them are not available at a monthly level. As is the case when forecasting GDP, there is no doubt that forecasts from a full causal econometric model would be more helpful, provided that they do not lose much accuracy compared to non-causal models. But this is not the case. See, for instance, García-Ferrer *et al*. (1987) and Zellner and Hong (1989), and references mentioned in these papers.

In this paper, therefore, since accurate inflation forecasts represent important information for monetary policies, we develop final form models based exclusively on price data, but making use of the fact that different prices do not behave in a similar fashion. For instance, many analysts are forecasting a fall in the European annual inflation rate for 2002. Some forecasters, without presenting their models, try to justify their forecasts with the evolution of monetary variables, but this explanation is not very convincing because an econometric model between aggregate inflation and monetary variables is not stable. Others say that their forecasts expect a lower rate of economic growth for 2002 in the Euro-zone. But this is not very convincing either, because by mid-2000, when the expectations for economic growth in 2002 were higher, a greater fall in the inflation rate was forecast. As we will show in the last section of the paper, the fall in the inflation rate forecast for 2002 is mainly based on the fact that inflation rates in the non-processed food and energy markets are expected to decrease, whereas core inflation is forecast to remain stable. It is difficult to identify the factors behind a possibly stable core inflation rate. One is the GDP gap in 2002, which will possibly favour a fall in inflation. Another is the evolution of nominal salaries, which is quite uncertain for next year; the development of productivity, which is not necessarily going to increase; the recovery of the euro-dollar exchange rate, which could be very weak and depreciation is by no means impossible; etc. Given the uncertainty of all these explanatory variables, one-year-ahead forecasts with causal models are at least as uncertain, and usually more so, as forecasts from final form models. Confidence intervals for the expected values of the explanatory variables are not usually provided in forecasting reports and they generate the belief that those forecasts are firmly based on economic facts.

The models proposed in this paper are used for one-year-ahead forecasting. It could be argued that quarterly models would be a better choice for this horizon. Results that are not reported in this paper show that this is not the case, because before the end of one quarter, we have two very valuable monthly data points which improve next year's forecast in relation to forecasts made last quarter. This is why economic agents demand monthly updates of inflation forecasts.

After detecting the importance of the breaking down by markets into groups, and that disaggregation by countries is also required, one could use doubly indexed panel data and study aggregate inflation by considering a price index for each big group of markets in each country. But twelve countries and six or seven market groups represent a large number of components, and before facing such an approach, this paper starts by considering the two disaggregation possibilities separately. The fact is that modelling this type of panel data is not going to be easy, because the heterogeneous behaviour of each price index in the panel cannot be reduced to a fixed or random effect. This heterogeneity includes different responses to the cointegrated restrictions and different transitory dynamics. In any case, the most complex question will be derived from the fact that, as is shown in this paper, there are cointegrating relationships between sectors and countries and the cointegrating relationship in the panel could be very difficult to specify. Because of all this, we restrict ourselves to the aim of individually assessing the relevance of these two disaggregations for forecasting and policy analysis and at the same time, to obtain an indication of how to proceed in a further study when we work with a breakdown that joins both criteria.

In this paper, the breakdown of HICP by markets is approached taking into account theoretical considerations about differences in supply and demand, which could result in prices having different trends. This leads us to at least consider the following price indexes corresponding to: (1) Non-processed Food, (2) Energy, (3) Other Goods and (4) Other Services. For this vector of four elements, the number of cointegration relationships is less than three and, therefore, there is more than one common trend between them. Also, the seasonal factors and short-term dynamics are different in these price indexes. Based on this result, the paper studies if the forecast of the HICP is more accurate by forecasting the components and then aggregating the forecasts – bottom-up approach – than by aggregating first and forecasting the aggregate directly.

The above study by markets also shows that price indexes (1) and (2) are more volatile than (3) and (4). For the purpose of presenting results, then, it is useful to split HICP inflation in two, with the inflation coming from indexes (1) and (2) being denoted as residual, and the inflation coming from (3) and (4) being denoted as core inflation. The paper argues that the important question in the short-term analysis of inflation is to have good forecasts on which to base possible policy recommendations and the distinction between residual and core inflation is just an instrument for presenting results, which is occasionally of use. But since the price index from which residual inflation is obtained is not cointegrated with the price index used to calculate core inflation, the projections of the latter index are not always a good proxy for forecasts of overall HICP.

The analysis by countries covers only, France, Germany, Italy and Spain, the global weight of which in Euro-zone inflation is around 83%. With four countries, it is possible to analyse cointegration but, as in the case of studies by markets, there is no full cointegration between them. The lack of full cointegration appears as an indicator of convergence problems within MU.

The results in this paper are based on a sample from 1995 (or 1996), which is the date when Eurostat constructed an 'HICP'. We have tried to extend data before that date, but recursive estimations of the models presented in this paper show that models are unstable before 1995. Even cointegration relationships which appear after this date are not evident previously. These results force us to work with this relative small sample, which is, in any event, the only one available. Efforts to extend the sample before 1995 applying approximation procedures appear to be fruitless, because the specifications used in models explaining inflation changed at some time around 1995–1996.

The article is organized as follows. Section 2 describes the statistical integration and cointegration properties of Harmonized Indices of Consumer Prices and develops univariate and multivariate models for disaggregations by countries and by sectors, Section 3 analyses the proposed models' forecasting performance and, finally, Section 4 presents the conclusions and provides forecasts and a diagnosis for MU inflation in 2001 and 2002.

2. STATISTICAL DESCRIPTION OF HARMONIZED INDICES OF CONSUMER PRICES TIME SERIES: INTEGRATION AND COINTEGRATION ANALYSIS

The HICP is published by Eurostat by means of two different disaggregation patterns. The first one corresponds to disaggregation by countries and the second one to the breakdown into different markets of each country and the Monetary Union (MU) on the whole. This second group of data consists of approximately 130 subindexes, which cover twelve countries (Greece is included in the Euro-zone since the start of 2001) and total 1560 different time series to be analysed.

It is then necessary to simplify the information set including both the information relating to countries and the sectorial data. The approach taken in this study considers:

(1) The global HICP for each country.
(2) Five basic sectors for the Monetary Union (MU). These components come from the four mentioned in the previous section dividing component (3), 'Other goods', into food, classified as 'processed food', and the rest, classified as 'commodities'.

Eurostat is still improving the method used to calculate the HICP and reviewing current and historical data. For example, in the indexes corresponding to the prices of commodities and services these revisions have a magnitude up to four tenths of a percentage point at specific times for MU, Germany, France and Spain; they are less significant in the global HICP for each country. The sample used in this article are the revised figures from January 1995 to March 2001, published in April 2001. These revisions are a result of: (a) the extension of coverage, implemented with the January 2000 and 2001 indexes, to almost all consumers' expenditure items. In particular, the difficult areas of health, education and social protection services which are now covered more properly, as do insurance and financial services; (b) Greece's entry into the euro-zone from the beginning of 2001; (c) the inclusion of sales prices, starting with the January 2001 index. In spite of the annual revisions, the HICP presents no comparability problems because it is calculated as a Laspeyres chain index.

There are longer time series available since January 1990, but data for the 1990–1995 period is not reliable. The current sample for the MU and French HICP is available only since January 1996. Eurostat previously published some figures for 1995 which are now under revision. For the purpose of this paper, data for France was backdated with rates from the original CPI and they were used to construct a time series for MU. The data used in this paper are available from the authors upon request.

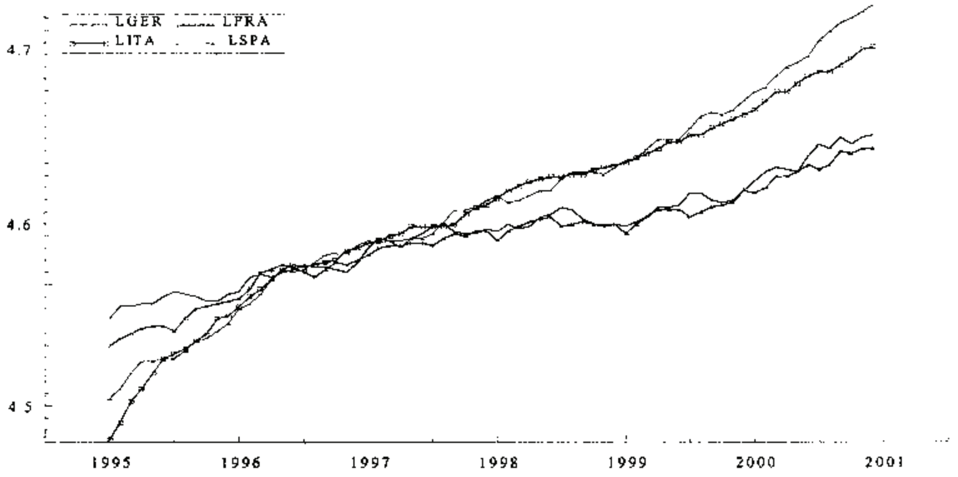
2.1 Analysis by countries

Table 1 shows the weights for different MU countries in the calculation of HICP, corresponding to the years 2000 and 2001. This table shows that four countries: Germany, France, Italy and Spain, sum up 82.95% of total MU weight in year 2000 and 80.6% in 2001. Given the scarce number of observations available, it has been necessary to further simplify the statistical analysis and these are the only four countries that we are going to take into consideration.

Table 1. Country weights in MU-HICP

Country	Weight (2000) (%)	Weight (2001) (%)
Austria	2.91	3.27
Belgium	3.99	3.35
Finland	1.51	1.59
France	20.91	20.55
Greece	0	2.43
Germany	34.65	30.91
Netherlands	5.65	5.25
Ireland	0.98	1.17
Italy	18.31	18.70
Luxembourg	0.20	0.25
Portugal	1.81	2.09
Spain	9.08	10.44
MU	100	100

Source: Eurostat



Source: Eurostat

Fig. 1. Harmonized Indices of Consumer Prices in different countries (in logs)

Graphs of the four indexes in logs can be found in Fig. 1. The sample available goes from January 1995 to March 2001, but there was some sort of instability at the beginning of the sample period and recursive estimations have been applied all along the paper. These estimations were performed with a sample that always ended in December 2000, from which one month was removed at the beginning, January 1995, and a total of 24 recursive estimations have been run in each case. Analysing the country data, there were no important changes in diagnosis for unit root hypothesis, but results on cointegration depend on the sample period used. Stability appears after April 1996 and this is the date that has been considered for estimation when using HICP data for countries.[2] Figure 2 shows the recursive estimates for the parameters of the only cointegration relationship found. Empirically, all variables appear to be intergrated of order 1, I(1) with the hypothesis of a second unit root being rejected. Therefore, in this study inflation is taken as stationary.[3]

Cointegration analysis helps to clarity the long-run relationships between integrated variables. Johansens' (1988, 1991) procedure for finite-order vector autoregressions (VAR) is applied. Given the low number of observations, the analysis began with a VAR model in levels of order 5 with a constant term and seasonal dummies, which was then reduced to a first-order VAR, able to capture all the dynamic structure.

[2] A more detailed comment on stability can be found at the end of this section.
[3] These results could be due to the fact that we are working with a small sample. With longer time series it could appear that price indexes are I(2) or I(1) with segmented means (see Stock and Watson, 1999 for USA data and Lorenzo, 1997 for the Spanish case).

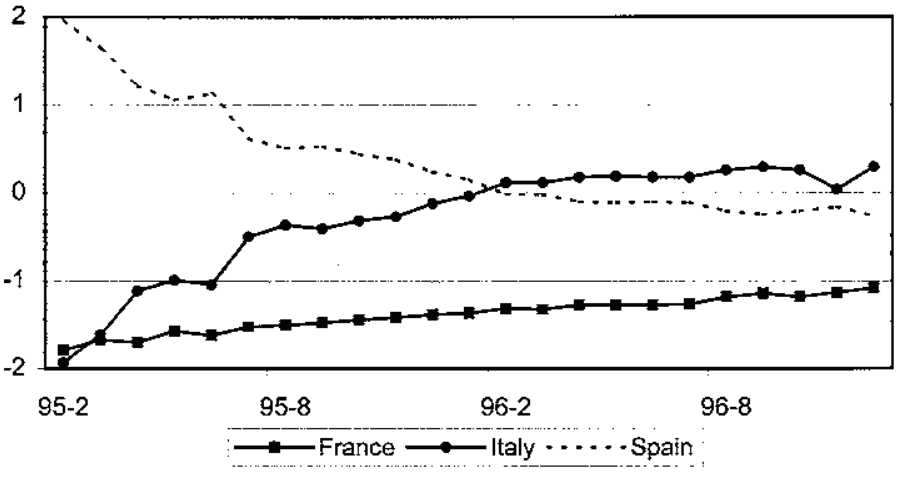


Fig. 2. Recursive estimation of the parameters in the conintegrating relationships (February 95 to December 96, Germany standardized at 1)

Table 2 reports the standard statistics and estimates for Johansen's procedure corresponding to this first-order VAR. The greatest eigenvalue and trace eigenvalue statistics (λ_{max} and λ_{trace}) reject the null of no cointegration in favour of one cointegrating relationship. This last hypothesis is not rejected in favour of a hypothesis with more than one cointegration relationship.

The estimated cointegration relationship could be expressed as:

$$\log(HCPI\ Germany) \underset{(0.11)}{-1.26} \log(HCPI\ France) +$$

$$+\underset{(0.09)}{0.19} \log(HCPI\ Italy) \underset{(0.08)}{-0.11} \log(HCPI\ Spain) \tag{1}$$

Table 2. A cointegration analysis of global HICP by countries

Eigenvalue	0.42	0.24	0.09	0.05
Null Hypothesis	$r=0$	$r \leq 1$	$r \leq 2$	$r \leq 3$
λ_{max}	30.96*	15.47	5.13	3.18
$\lambda_{max}{}^{a}$	28.79*	14.38	23.77	22.11
95% critical value	27.1	21.0	14.1	3.8
λ_{trace}	54.73**	23.77	8.30	3.18
$\lambda_{trace}{}^{a}$	50.89**	22.11	7.72	2.96
95% critical value	47.2	29.7	15.4	3.8
		Weak exogeneity test statistics		
Variable	*Germany*	*France*	*Italy*	*Spain*
$\chi^2(1)$	8.67**	0.09	4.50*	4.88*
p-value	0.0032	0.7686	0.0339	0.0272

Notes: * indicates rejection at 5%
** indicates rejection at 1%

where standard errors of estimates are in brackets. These results imply a restriction between some sort of weighted price differential between Germany and France and a weighted price differential between Italy and Spain. Two exercises have been performed to better understand this relationship. The first exercise is based on the hypothesis that prices in Italy and Spain could be excluded from the long-run relationship. The restricted analysis shows the following results:

$$\log(\mathit{HCPI\ France}) \underset{(0.016)}{-0.89470} \log(\mathit{HCPI\ Germany}) \tag{2}$$

and also exogeneity tests indicate that the speed of adjustment to the original cointegration relationship, equation (1), could be zero for France, Italy and Spain. With the restricted analysis the cointegration relationship, equation (2), only enters in the equations for short-run behaviour for Germany and Spain.

To further understand the long-run cointegration relationship and to decide between equations (1) and (2), we have also performed bivariate analysis of original CPIs for different countries. We have considered original CPIs because they provide longer samples and allow one to perform an analysis for different subsamples: from January 1991 to December 2000, from January 1991 to December 1995 and from January 1996 to December 2000. Results are summarized in Table 3.

Table 3. CPI bivariate cointegration analysis

	Germany–France	Italy–Spain
1991:02 to 2000:12	$r = 1$* log(*Germany*)–log(*France*)**	$r = 1$ log(*Italy*)–0.89log(*Spain*)
1991:02 to 1995:12	$r = 0$	$r = 0$
1996:01 to 2000:12	$r = 1$ log(*Germany*)–log(*France*)	$r = 0$ or 1* log(*Italy*)–0.89log(*Spain*)

* *r* is the number of estimated cointegration relationships.

** Estimated cointegration relationship.

* this relation could be rejected at 99% significance level.

Note: There is no cointegration relationship between any other pair of countries.

Table 3 confirms the results previously stated:

(1) Estimations based on the whole sample period can be misleading.
(2) There are no cointegration relationships prior to 1996. It seems that it is as a result of the European convergence process that prices in different countries begin to cointegrate.
(3) There are no cointegration relationships between any other pair of countries other than those mentioned above.
(4) Weighted differentials between Germany and France and between Italy and Spain, cointegrate as equation (1) suggested.

Table 4. VEqCM model for counties

$$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & -0.28L \\ 0 & 0 & 0 & 1-0.44L \end{pmatrix} \begin{pmatrix} \Delta \log(Germany)_t \\ \Delta \log(France)_t \\ \Delta \log(Italy)_t \\ \Delta \log(Spain)_t \end{pmatrix} - \begin{pmatrix} -0.0055 \\ 0.0009 \\ 0.0012 \\ -0.0018 \end{pmatrix} - \begin{pmatrix} -0.65 \\ 0 \\ 0 \\ -0.26 \end{pmatrix} (CI_{t-1} + 0.93) = \begin{pmatrix} a_{1t} \\ a_{2t} \\ a_{3t} \\ a_{4t} \end{pmatrix}$$

Table 5. Correlation matrix of residuals

	Δ log(*Germany*)	Δ log(*France*)	Δ log(*Italy*)	Δ log(*Spain*)
Δ log(*Germany*)	1			
Δ log(*France*)	0.75	1		
Δ log(*Italy*)	0.17	0.08	1	
Δ log(*Spain*)	0.37	0.27	0.28	1

Table 6. Standard residual deviations

	VEqCM (%)	Univariate ARIMA (%)
Germany	0.20	0.21
France	0.17	0.17
Italy	0.10	0.11
Spain	0.13	0.14

Since the bivariate analysis shows a cointegration relationship between Italy and Spain, we take equation (1) for the cointegrated relationship present in the vector of four countries.

A Vector Autoregression Model with Equilibrium-correction Mechanism for the four countries has been estimated and results are shown in Table 4. The model also includes seasonal dummies and CI_t represents the cointegration relationship. The residual standard deviation for each equation is shown later in Table 6 and the contemporaneous correlation matrix for the residuals is given in Table 5.

This model shows:

(1) the cointegration relationship only enters into the equations for Germany and Spain;
(2) there is not much dependence between the variables in the short run, and only the contemporaneous correlation between HICP in Germany and France seems important.

This VEqCM model shows that a disaggregating analysis of HICP by countries could be carried out without too much distortion – except, perhaps, for

Germany – by separate single-equation models. For forecasting purposes, then, ARIMA models or ARIMA models with leading indicators for each country could be entertained.

Table 6 shows the standard residual deviations with degrees of freedom correction from the VEqCM and ARIMA models[4].

2.2 Analysis by sectors

The breakdown of HICP by markets has been approached considering the price indexes corresponding to: (1) Processed Food (PF), (2) Non-energy Commodities excluding food (COM), (3) Non-energy Services (SER), (4) Non-processed Food (NPF) and (5) Energy (ENE). Espasa *et al*. (1987) proposed to calculate core inflation for Spain from PF, COM and SER and this practice has also been adopted later for MU. With the NPF and ENE we can calculate an inflation measure denoted as 'residual inflation'.

Table 7 shows the weights for different MU sectors in the calculation of HICP, corresponding to the years 2000 and 2001. The weights corresponding to the services and energy HICP have increased in 2001 respect to 2000. Graphs of the five indexes in logs can be found in Fig. 3. Eurostat has published time series for the five mentioned sectors since January 1995, but for 1995 the aggregate cannot be precisely recovered using these components from the information published by Eurostat. This means that data for 1995 is not very reliable. Running iterative estimations for the presence and parameter values of the cointegration relationships along sectors, it is observed that they become stable after June 1995, but not before. Consequently, the models in this section have been estimated with a sample from June 1995 till December 2000.

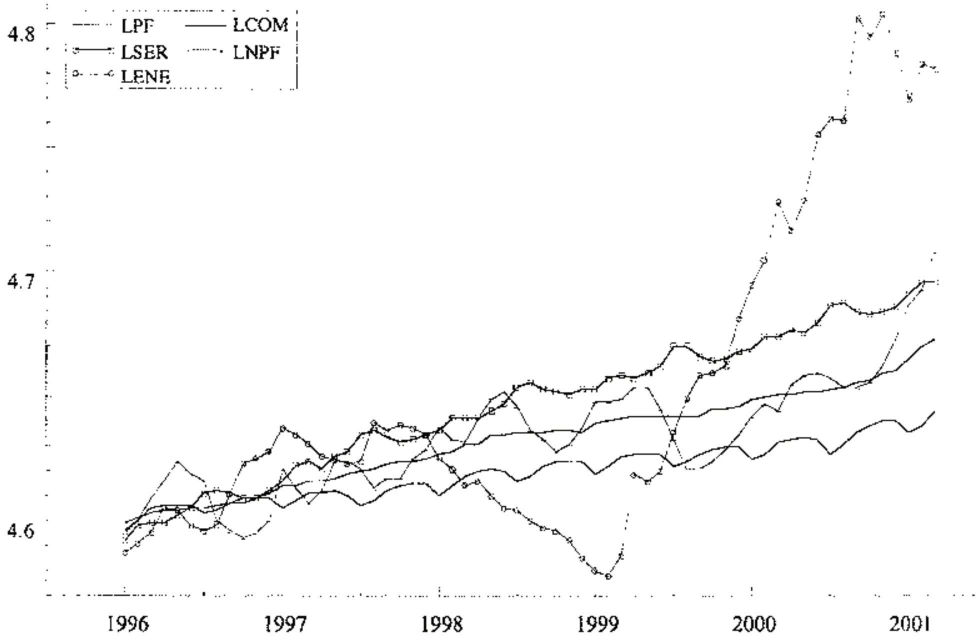
Empirically, all variables appear to be integrated of order 1 - I(1) - and the hypothesis of a second unit root is rejected. The cointegration analysis began with a VAR model in levels of order 5 with a constant term and seasonal dummies which then has been reduced to a first-order VAR, able to capture residual correlation.

Table 7. Sectors weights in MU-HICP

Sectors	Weight (2000) (%)	Weight (2001) (%)
Core inflation	82.82	82.54
Processed Food (PF)	12.64	12.31
Non-energy Commodities (COM)	32.66	32.10
Non-energy Services (SER)	37.52	38.13
Residual inflation	17.18	17.46
Non-processed Food (NPF)	8.21	7.98
Energy (ENE)	8.97	9.48
Global	100	100

Source: Eurostat

[4] Univariate ARIMA models are available from the authors upon request.



Source: Eurostat

Fig. 3. Different MU HICP for sectors (in logs)

Table 8 reports the standard statistics and estimates for Johansen's procedure applied to this first-order VAR. The greatest eigenvalue and trace

Table 8. A cointegration analysis of global HICP by sectors

Eigenvalue	0.55	0.35	0.14	0.09	0.006
Null Hypothesis	$r = 0$	$r \leq 1$	$r \leq 2$	$r \leq 3$	$r \leq 4$
λ_{max}	53.03**	29.25*	10.45	6.35	0.37
λ_{max}^{a}	49.07**	27.06	9.67	5.87	0.34
95% critical value	33.5	27.1	21.0	14.1	3.8
λ_{trace}	99.44**	46.41	17.16	6.72	0.37
λ_{trace}^{a}	92.02**	42.95	15.88	6.22	0.34
95% critical value	68.5	47.2	29.7	15.4	3.8
		Weak exogeneity test statistics			
Variable	*PF*	*COM*	*SER*	*NPF*	*ENE*
$\chi^2(1)$	0.12583	5.69*	22.06**	10.75**	0.03
p-value	0.7228	0.0171	0.0000	0.0010	0.8528

Notes: * indicates rejection at 5%
** indicates rejection at 1%

Table 9. VEqCM model for sectors

$$\begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0.5L & 0 & 1 & 0 & 0 \\ -1.86L & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \Delta\log(PF) \\ \Delta\log(COM) \\ \Delta\log(SER) \\ \Delta\log(NPF) \\ \Delta\log(ENE) \end{pmatrix} - \begin{pmatrix} -0.00016 \\ -0.0041 \\ -0.0047 \\ -0.0070 \\ -0.0030 \end{pmatrix} - \begin{pmatrix} 0 \\ -0.16 \\ -0.52 \\ 0 \\ 0 \end{pmatrix} (CL_{t-1} - 1.34) = \begin{pmatrix} a_{1t} \\ a_{2t} \\ a_{3t} \\ a_{4t} \\ a_{5t} \end{pmatrix}$$

Table 10. Correlation matrix of residuals

	Δ log(*PF*)	Δ log(*COM*)	Δ log(*SER*)	Δ log(*NPF*)	Δ log(*ENE*)
Δ log(*PF*)	1				
Δ log(*COM*)	0.36	1			
Δ log(*SER*)	0.24	0.03	1		
Δ log(*NPE*)	0.24	0.06	0.009	1	
Δ log(*ENE*)	0.005	0.03	–0.08	–0.009	1

eigenvalue statistics (λ_{max} and λ_{trace}) reject the null of no cointegration in favour of at least one cointegrating relationship.

The previous analysis indicates the lack of full cointegration between HICP sectors and, therefore, the existence of more than one single common trend between them. These type of results also appear for specific countries (Espasa *et al.*, 1999), and favour the argument that monetary policy is not the single most important factor determining long-run price behaviour. The results show that there are other factors affecting price trends in the different sectors of the economy, which could possibly be different ways and degrees of incorporating technical innovations, different ways of improving the quality of the goods and services produced, etc. This last factor could be important, because qualitative improvements generate an upward bias in the usual measures of prices employed in the construction of consumer price indexes, and this bias could have very different profiles across sectors.

The estimated cointegration relationship can be written as:

$$-\underset{(0.096)}{1.84}\log(PF) + \underset{(0.145)}{0.44}\log(COM) + \log(SER) + \underset{(0.037)}{0.14}\log(NPF) - \underset{(0.006)}{0.03}\log(ENE)$$

and it can be interpreted in the sense that the consumer price index for services can be expressed as an algebraic sum of the price indexes for goods.

A Vector Autoregression Model with Equilibrium-correction Mechanism for the five sectors has been estimated and results are shown in Table 9. The model also includes seasonal dummies and CI_t represents the cointegration relationship.

The residual standard deviation for each equation is shown in Table 11 and the contemporaneous correlation matrix for the residuals is shown in Table 10.

Table 11. Standard residual deviations

	VeqCM (%)	Univariate ARIMA (%)
PF	0.10	0.12
COM	0.09	0.08
SER	0.09	0.11
NPF	0.36	0.39
ENE	1.08	1.02

This model shows: (1) that the long run equilibrium equation only enters in the Non-energy Commodities and Services equations; (2) that there is less contemporaneous correlation between the sector residuals than in the breakdown by countries; and (3) that there is not much dependency among the variables in the short-run. The presence of the equilibrium mechanism in two equations indicates that the analysis by single-equation models for each sector is not efficient. Nevertheless, for forecasting purposes we have also estimated univariate ARIMA models for each price sector.

Table 11 shows the standard residual deviations with degrees of freedom correction in both approaches.

2.3 Conclusions

The results obtained for countries and for sectors suggest that if in a particular month the innovation in the HICP comes mainly from a given country or sector it will have a long-run effect which will differ from the one produced by a similar innovation in another month referring primarily to a different country or sector. The question is that aggregating *n* non-stationary time series, the resulting ARIMA model for the aggregate can have a quite complex structure with important restrictions and it turns out to be almost impossible to discover such a specification from the analysis of only the aggregate data. Consequently, a usually parsimonious unrestricted univariate model, say ARIMA, will not be adequate for the aggregate. On the other hand, simple ARIMA models for the components could imply a complex model for the aggregate. Evidence for this can be found in the fact that for a huge number of macroeconomic time series after estimating univariate ARIMA models, a certain number of outliers appear (see, for instance, Balke and Fomby, 1994). This evidence also points out that the linearity hypothesis could not be appropriate. In that respect Senra (1998) shows that an ARIMA model with innovative outliers can be represented as a model with stochastic unit roots and in those models the innovation response functions change with time. In this paper we restrict ourselves to linear formulations, but the need for non-linear models is more clear at the disaggregate level, for instance, in modelling certain energy consumer prices.

The previous discussion shows that when the *n* time series which compound a given aggregate are not fully cointegrated, it is advisable to work with the components, provided we have good disaggregated data and it is possible to obtain reasonably acceptable models for the components. In this section, it has been shown that European inflation does not show full cointegration by countries, nor by sectors and that it will pay to analyse this inflation in a disaggregated way.

Certainly this breakdown of a vector variable like HICP, when there is not full cointegration, is also important for diagnosis purposes, because, for instance, an innovation from services prices, properly weighted, does not have the same implications as from non-processed food prices. In fact, institutions which perform monthly inflation analyses occasionally alert readers by claiming that unexpected inflation in a given month is particularly worrying because it comes from prices included in the core inflation index. In other cases, these institutions could refer to an innovation of the same magnitude in the CPI as not being particularly important because it comes from the set of prices corresponding to residual inflation.

3. FORECASTING MU INFLATION

3.1 Forecasting the MU aggregate

This section evaluates the forecast performance of the ARIMA and VEqCM models proposed in section 2, and compares them with an aggregate univariate ARIMA model for the Monetary Union HICP. All the models were re-estimated with information up to December 1999. The univariate ARIMA model for the Monetary Union HICP has been estimated with information from January 1996 to December 1999. The model in first differences shows a constant value of 0.0012, centred seasonal dummies, no dynamic structure and a standard residual deviation of 0.11%.

Table 12 shows the statistics related to the errors in forecasting MU inflation rate for one, three, six and nine periods ahead from January 2000 to March 2001.

The *MSE(i)/MSE(univ)* ratio compares the forecast accuracy of the different models with respect to the aggregate univariate formulation. A less than unit value indicates an improvement with respect to the aggregate univariate model. Results in Table 12 show that for one-period ahead forecasts, disaggregating by countries slightly improves the accuracy, with respect to the reference model and for this horizon the breakdown by sectors shows no improvement on the aggregate results. But for all other horizons, the forecasts made by modelling the sectors improve results consistently. For short horizons, one to six months, univariate sector models provide better forecasts than the VEqCM, but for longer horizons the opposite is the case. We can conclude that disaggregating by sectors seems to be a useful way of obtaining better European inflation forecasts. On the other hand, only using a country disaggregation improves the results in the very short run, one to three periods, but for longer horizons forecasting performance deteriorates considerably with respect to an aggregate univariate model. It has been mentioned before that in order to improve forecast accuracy by disaggregating, we must be able to construct good models for all components. The models used have a unit root with a constant, which implies constant means for inflation rates. Better specifications can be obtained substituting the means by segmented means, but this is not very useful for forecasting. In any case, the data requires segmented means and the approximations by global means are much worse for country inflation than for MU inflation. This bad specification at country level is responsible for the worst forecasting performance. This shows that ARIMA models are not complex enough when disaggregating by countries. In particular, we need to construct time series or econometric models capable of explaining the segmented evolution of the country inflation means.

Table 13 gives measures of the forecasting errors for each of the sector prices for the same period as Table 12. It can be seen in Table 13 that the forecasting performance of prices of non-processed food and energy had been much worse than expected from the fits reported in Section 2. In fact, during the forecasting period, (Fig. 2.) energy prices have registered a period of high and fast growth, which is very different from their behaviour in the five previous years contained in the sample for estimation. In these circumstances, reasonable forecasts cannot be expected without including more information that helps to explain this surge in energy prices. One possibility is to take spot international oil prices as a leading indicator. This indicator is known immediately and the HICP appears one month after the reference month. Therefore, the indicator is available for one-period ahead forecasts. For longer horizons the indicator can be forecast using future market prices. *Bulletin EU and US Inflation and*

Table 12. Forecast errors for MU aggregate

Periods ahead	Statistics	UNIV	Sectors UNIV	Sectors VEqCM	Countries UNIV	Countries VeqCM
1	Mean error %	0.1535	0.0953	0.1443	0.0533	0.0004
	RMSE %	0.1940	0.1997	0.2425	0.1906	0.1898
	$\frac{MSE(i)}{MSE(univ)}$	1.00	1.06	1.56	0.97	0.96
3	Mean error %	0.2616	0.2188	0.2706	0.2480	0.1976
	RMSE %	0.3224	0.3140	0.3715	0.3113	0.3512
	$\frac{MSE(i)}{MSE(univ)}$	1.00	0.95	1.33	0.93	1.19
6	Mean error %	0.6096	0.4986	0.5023	0.6829	0.7707
	RMSE %	0.6417	0.5544	0.5600	0.7070	0.8159
	$\frac{MSE(i)}{MSE(univ)}$	1.00	0.75	0.76	1.21	1.62
9	Mean error %	0.9346	0.8119	0.6784	1.2556	1.5928
	RMSE %	0.9437	0.8229	0.6965	1.3102	1.6425
	$\frac{MSE(i)}{MSE(univ)}$	1.00	0.76	0.54	1.93	3.03

Notes: RMSE stands for root mean squared error
MSE stands for mean squared error

Table 13. Forecast errors for sectors

Periods ahead		PF		COM		SERV		NPF		ENE	
		Univ.	VEC	Univ.	VEC	Univ.	VEC	Univ.	VEC	Univ.	VEC
1	Mean error %	0.0394	0.0472	0.0088	0.0705	–0.0165	0.1167	0.2444	0.2395	0.3078	0.0877
	RMSE %	0.1277	0.1176	0.1422	0.1764	0.1841	0.2275	0.5741	0.6597	2.0040	1.9874
3	Mean error %	0.1082	0.1300	0.0302	0.1423	–0.0108	0.2304	0.7703	0.7207	1.0705	0.3175
	RMSE %	0.2719	0.2699	0.2263	0.2761	0.1927	0.3573	1.0462	1.1608	2.9957	2.7255
6	Mean error %	0.1952	0.2196	0.1425	0.2661	–0.0698	0.2959	1.7193	1.2901	3.0473	1.5302
	RMSE %	0.4321	0.4217	0.2706	0.3825	0.2205	0.4210	1.9238	1.5866	4.9217	3.7700

Note: RMSE stands for root mean squared error

Macroeconomic Analysis gives forecasts for inflation in the euro-zone using a disaggregated approach along the lines mentioned in this paper. This publication uses the international oil prices as a leading indicator for the HICP for energy and the improvements in forecasting during the January 2000–March 2001 period have been significant. The RMSE for one, three and six periods ahead has been 0.1384, 0.2572 and 0.5935. This shows that the approach based on disaggregating by sectors is even more promising than indicated by the results in Table 12, since this framework allows us to include specific indicators for each particular price index.

4. CONCLUDING REMARKS: DIAGNOSIS AND FORECASTS FOR MU INFLATION

The analysis of European inflation by countries and by sectors shows that there is not full cointegration in either case, therefore disaggregation is significant. From a forecasting perspective, the breakdown by sectors generates forecasts with smaller bias and variance for all horizons greater than one month, showing that disaggregating is also of interest to forecast the European aggregate.

The above results and the fact that HICP by countries are not fully cointegrated suggest that a breakdown of the European HICP applying both sector and country criteria will produce further improvements in forecasting.

In this paper it has been mentioned that Eurostat revisions of HICP data by sector are more significant and take place more often than the revisions of the aggregated HICP for individual countries. The results of this paper show how important it is for the study of European inflation that Eurostat improves the quality of consumer prices by sectors.

Table 14, taken from the monthly publication *Bulletin EU & US Inflation and Macroeconomic Analysis* (2001), can be used as an example of how disaggregated forecasts can be employed for diagnosis purposes. The forecasts for 2001 and 2002 include Greece in the HICP for the Monetary Union.

These results show that it is highly probable that the European Central Bank's target of 2% inflation for the euro-zone will not be reached in 2001 and that the

Table 14. Average annual rates of growth

	Observed		Forecasts	
	1998	2000	2001	2002
HICP Germany	0.64	2.1	2.4	1.7
HICP France	0.56	1.8	1.7	1.7
HICP Italy	1.65	2.6	2.6	2.1
HICP Spain	2.23	3.5	3.9	3.2
Core inflation	1.11	1.3	2.2	2.3
Residual inflation	1.16	7.6	5.1	0.8
HICP Monetary Union	1.12	2.3	2.7	2.0

* Year on year rate of growth

Source: Eurostat & IFL, University Carlos III.

probability of reaching it in 2002 is around 50%. The disaggregation also shows that the point forecasts for annual average core inflation in 2001 and 2002 are over 2% and, therefore, that targeted inflation relies too much on the behaviour of the most volatile prices included in the calculation of residual inflation, non-processed food and energy.

Using a further disaggregated forecast by countries and sectors taken from the mentioned publication, it can be observed that inflation differences among countries are important and are not only due to the evolution of energy prices. In fact, in France, Germany, Italy, Spain and the MU, energy prices showed annual figures not lower than 13%, and the inflation differential among these countries in the non-energy HICP is high. While France and Germany will register mean values around 2% in this index throughout 2001 and 2002, Italy will come closer to 3% and Spain will reach average growth rates of 4% in 2001 and 2002.

It seems, then, that once the objectives established in the Maastricht Treaty as criteria for entering the Monetary Union have been achieved, a certain price convergence may have started within the Union. This convergence may be such that countries with higher price levels are registering much less inflation than countries where prices are lower, which have consequently reached a target of less than 2% inflation in 1999 (almost achieved in the case of Spain), but not in 2000. This may mean a change in relative prices between the European economies, which could threaten the greater economic growth that, in general, the Monetary Union countries with greater inflation are showing with respect to those with lower inflation levels. These changes in relative prices will also bring about national specialization in those sectors in which comparative advantages are evident.

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