NOTES D'ÉTUDES

ET DE RECHERCHE

# AN INFLATION FORECASTING MODEL FOR THE EURO AREA

Valérie Chauvin and Antoine Devulder

January 2008

**NER - E # 192**

BANQUE DE FRANCE
EUROSYSTÈME

DIRECTION GÉNÉRALE DES ÉTUDES ET DES RELATIONS INTERNATIONALES

DIRECTION GÉNÉRALE DES ÉTUDES ET DES RELATIONS INTERNATIONALES
DIRECTION DE LA RECHERCHE

# AN INFLATION FORECASTING MODEL FOR THE EURO AREA

Valérie Chauvin and Antoine Devulder

January 2008

**NER - E # 192**

# AN INFLATION FORECASTING MODEL FOR THE EURO AREA[1]

*Valérie Chauvin and Antoine Devulder*
Banque de France[2]

[1] We thank Claudine Guibert and Laëtitia Francart for their precious help and Hervé Le Bihan for his most relevant comments.
Some of the results presented were published in French in the Bulletin de la Banque de France n°167, novembre 2007.

[2] Macroeconomic Analysis and Forecasting Division, Directorate Macroeconomic Analysis and Forecasting, Directorate General Economics and International Relations, E-mails: valerie.chauvin@banque-france.fr, antoine.devulder@banque-france.fr

ABSTRACT

An inflation forecasting model for the euro area

With the European economic integration, the understanding of inflation and inflationary pressures requires to analyse both the national level and the whole Euro area level. This is true in particular for the inflation forecasts that are carried out within the Eurosystem and published four times a year in the ECB Monthly Bulletin. For that purpose, the Banque de France is currently building tools for the Euro area in addition to those already in use for France. The present study puts forward a simple model of short-term developments (one year ahead) in inflation, as measured by the Harmonized Index of Consumer Prices (HICP) of the Euro area. This model does not take into account the feed-back effect of prices on activity, which should be considered in order to analyse medium-term price developments. It could hence be improved along these lines in the future.

The model includes seven equations, explaining the total HICP of the Euro area and some of its sector-based sub-indexes (services, manufacturing sector, unprocessed food, processed food, energy and underlying inflation, defined as HICP inflation excluding unprocessed food and energy prices). It uses exogenous variables such as unit labour cost, import deflator, indicators of tightening in the labour market, or in the goods market, and indirect tax indicators.

We have favoured an empirical approach rather than a strict compliance with theoretical models, paying particularly attention to the fit of the equations to the data. However, this model is able to provide relevant economic interpretations of recent price developments.

Finally, we assess the forecasting performance of the model in traditional in-sample and out-of-sample rolling event evaluations. To do so, the forecasts were compared to the ones obtained from simple autoregressive equations, which are also commonly used to forecast short-term price developments. On the whole, the model provides more accurate forecasts than those provided by the autoregressive model, and a sector-based disaggregated approach outperforms a single equation to forecast total HICP. Part of this result may come from dummy variables that correspond to well identified shocks that improve both the econometric characteristics and forecast performance of the equations of our model.



Keywords: inflation, economic modelling, forecast

JEL Codes: C52, C53, E37



Résumé

Maquette de prévision d’inflation dans la zone euro

Du fait de l’intégration économique européenne, la dynamique de l’inflation et des tensions inflationnistes ne peut se comprendre sans une analyse fine à la fois au niveau national et au niveau de la zone euro. Cela s’applique en particulier pour les prévisions d’inflation qui sont réalisées au sein de l’Eurosystème et publiées quatre fois par an dans le Bulletin Mensuel de la BCE. A cette fin, la Banque de France se dote d’outils pour la zone euro, en sus de ceux déjà utilisés pour la France. La présente étude propose une maquette simple des évolutions de court terme (à horizon d’un an) de l’inflation, telle que mesurée par l’indice des prix à la consommation harmonisé (IPCH) de la zone euro. Cette maquette ne prend pas en compte les effets de retour des prix sur l’activité, qui ne peuvent pas être négligés dans une analyse de moyen terme de l’évolution des prix. Elle pourrait donc être améliorée dans ce sens.

Nous avons privilégié l’approche empirique à une stricte application des modèles théoriques, en s’attachant à ce que les équations retracent le mieux possible les données. Cependant, cette maquette fournit une interprétation économique pertinente des évolutions récentes de l’inflation.

Enfin, nous évaluons la performance prédictive de la maquette par un exercice standard d'évaluation en et hors échantillon. A cette fin, les prévisions sont comparées à celles obtenues par de simples équations autorégressives, qui sont utilisées traditionnellement pour prévoir l'inflation à court terme. Dans l'ensemble, la maquette fournit des prévisions plus précises que celles du modèle autoregressif, et une approche agrégeant des équations par secteurs est plus pertinente qu'une seule équation pour l'IPCH d'ensemble. Ce résultat provient peut-être en partie de l'utilisation de variables muettes correspondant à des chocs bien identifiés, qui améliorent à la fois les caractéristiques économétriques et la performance prédictive des équations de notre maquette, alors que leur utilisation dans des équations autorégressives n'améliore pas significativement ces dernières.

Mots-clés : Inflation, modélisation économique, prévision

JEL number: C52, C53, E37

## Introduction

With the European economic integration and the Banque de France taking part to the Eurosystem, the fine understanding of inflation and inflationary pressures should not only focus on the national level, but should encompass the whole Euro area. This is true in particular for the inflation forecasts that are carried out within the Eurosystem. For that purpose, the Banque de France is currently building tools for the Euro area in addition to those already in use for France[3]. The present study puts forward a simple model of short-term developments (one year ahead) of the HICP of the Euro area. This model does not take into account the feed-back effect of prices on activity, which should be considered in order to analyse medium-term price developments.

Following Gallop and Heinz (2004), Benalal et alii (2004), Jondeau et alii (1999) for France, who model CPI or HICP sub-indexes by taking into account developments in costs, the model includes seven equations, explaining the total HICP of the Euro area, a decomposition in sector-based sub-indexes (services, manufacturing sector, unprocessed food, processed food, energy) and underlying inflation, defined as HICP inflation excluding unprocessed food and energy prices.

We have favoured an empirical approach rather than a strict compliance with theoretical models, paying particularly attention to the fit of the equations with the data. However, this model is able to provide relevant economic interpretations of recent price developments. It uses exogenous variables such as unit labour cost, import deflator, indicators of tightening in the labour market, or in the goods market, an indirect tax indicator and carefully identified dummy variables.

Finally, we tried to assess the forecasting performance of the model in traditional in-sample and out-of-sample rolling event evaluations; to do so, the forecasts were compared to the ones obtained from simple autoregressive equations, which are also commonly used to forecast short-term price developments. On the whole, the model provides more accurate forecasts than those provided by the autoregressive model, and a sector-based disaggregated approach outperforms a single equation to forecast total HICP.

In section 1 we will present our modelling strategy, detailing the underlying model, the data, the seasonal adjustment procedure, the stationarity tests and the estimation method we used. Section 2 presents the estimated equations as well as some comments about the way we dealt with autocorrelation, the dummy variables we used and the magnitude of the estimated coefficients. Finally in section 3 we assess the forecasting performance of the equations and compare the direct with the indirect approach.

## 1. Modelling strategy

### 1.1. Specification

This section describes the theoretical background that underlies our modelling strategy. In modelling directly total inflation, we follow the literature about the Phillips curve at the aggregate level, adopting the framework of Gordon (1982), also used by Stock and Watson (1999). Recent theoretical literature trying to found microeconomically the inflation process mostly leads to the New-Phillips curve where the current inflation rate depends on both past and expected inflation and a measure of output gap. We did not follow this stream because of the difficulties of such a theoretical framework to fit actual data, difficulties that were underlined in particular in Rudd and Whelan (2007). Besides, we have opted for an error correction model form, so we formalize separately the long term and the short term parts of the model.

[3] See also Adjemian et alii (2007) for the euro area DSGE model.

As regards the indirect approach, forecasting and aggregating the subcomponents of the HICP, the theoretical literature is much less developed. In addition, as we do not have enough sector-based explanatory variables for the euro area at our disposal, we introduce a general form for all of our equations (total HICP and sub-indexes), using the same aggregated exogenous variables. We follow here the practice of forecasters such as Gallop and Heinz (2004), Benalal et alii (2004), Jondeau et alii (1999) for France[4].

**Long-term specification**

Consumed goods and services in the Euro zone can have two origins: they are either imported or locally produced. If λ is the proportion of imported goods and services in consumption, considered constant over time, and τ the effective VAT rate, we have: $P = \left(\lambda P^M + (1-\lambda)P^{dom}\right)(1+\tau)$

Domestic products price, $P^{dom}$, is set as the sum of costs incurred by the firms to which is applied a mark-up. Let m denote the mark-up rate, Y domestic output, W the nominal compensation per employee, E employment, and θ1 and θ2 the ratios of firms' intermediate consumption and of oil expenses respectively to output, considered constant over time. Similarly to consumption prices, the price of intermediate consumption is modelled as a weighted average of import and domestic product prices:

$$P^{IC} = \mu P^M + (1-\mu)P^{dom}$$

We have:

$$P^{dom}Y = \left(WE + P^{IC}\theta_1 Y + P^{brent}\theta_2 Y\right)(1+m)$$

$$P^{dom} = \left(\frac{WE}{Y} + \left(\mu P^M + (1-\mu)P^{dom}\right)\theta_1 + P^{brent}\theta_2\right)(1+m)$$

$$P^{dom} = \frac{1+m}{1-(1-\mu)(1+m)\theta_1}\left(ULC + \mu\theta_1 P^M + \theta_2 P^{brent}\right)$$

With ULC being the unit labour cost. Replacing this second relation in the first one, we get:

$$P = \left(\lambda P^M + \frac{(1+m)(1-\lambda)}{1-(1-\mu)(1+m)\theta_1}\left(ULC + \mu\theta_1 P^M + \theta_2 P^{brent}\right)\right)(1+\tau)$$

And finally:

$$P = \frac{(1+m)(1-\lambda)(1+\tau)}{1-(1-\mu)(1+m)\theta_1}\left[ULC + \left(\lambda + \theta_1(1+m)(\mu-\lambda)\right)P^M + \theta_2 P^{brent}\right]$$

In the long term, we suppose that the mark-up rate m and the VAT rate τ are constant and, in practice, the log-linearized version of this equation will be estimated, that is:

$$\log P = \log(1+\tau) + \alpha_1 \log P^M + \alpha_2 \log ULC + \alpha_3 \log P^{brent} + \alpha_4$$

with α1, α2, α3 and α4 the parameters to be estimated.

No particular constraint will be imposed on the parameters during the estimation on the basis of this specification, although the specification of this equation should lead to $\alpha_1 + \alpha_2 + \alpha_3 = 1$ (see annex).

[4] Espasa et alii (2002) forecast euro area inflation but with a purely autoregressive approach.

However, we will discuss the estimated price-elasticities with respect to the major long term determinants in section 3. Moreover, the impact of the VAT rate did not appear significantly in the long run specification.

**Short-term specification**

Using the same approach, but considering that the VAT and mark-up rates are no longer constant in the short run, we have:

$$d\log P = \varphi_1 d\log P^M + \varphi_2 d\log ULC + \varphi_3 d\log P^{brent} + \varphi_4 dm + \varphi_5 d\log(1+\tau)$$
$$+\varphi_6\left[\log P - \left(\alpha_1 \log P^M + \alpha_2 \log ULC + \alpha_3 \log P^{brent}\right)\right]$$

Change in the mark-up rate is thus an element of price dynamics, but this variable is not observable. We suppose here that it depends on the firms' bargaining power in the goods and services market. A dynamic demand for goods and services relatively to the firms' production capacity would incite them to increase their profits. The capacity utilisation rate is a possible indicator for tightness of production facilities. In the same way, we can use the unemployment rate U: the higher it is or the faster it grows, the lower domestic demand will be, resulting in downward pressures on the mark-up rate.
We use the following modelling for changes in firms' mark-up rate:

$$dm = \rho \cdot dCUR - \upsilon \cdot dU - \xi \cdot (U - \overline{U})$$

This amounts to having two indicators explaining the mark-up behaviour, one for the developments in the goods and services market and another one for the labour market. Output gap measures are usual indicators that summarise this information. Nevertheless, we do not use them because the calculation of this variable is quite fragile (in particular, it is generally sensitive to revisions in the quarterly national accounts), *a fortiori* in projection, as shown in Orphanides, Van Norden (2005).

Finally, the equations that we have to estimate have the form:

$$d\log P = \beta_1 d\log P^M + \beta_2 d\log ULC + \beta_3 d\log P^{brent} + \beta_4 d\log CUR - \beta_5 dU - \beta_6 U + \beta_7 d\tau + \gamma$$
$$-\sigma\left(\log P - \alpha_1 \log P^M - \alpha_2 \log ULC - \alpha_3 \log P^{brent}\right)$$

Note that some explanatory variables introduced in the specification above may turn out to be not significant in the estimated equations. In addition, to minimize the impact of forecasted exogenous variables on the HICP projections that we will perform with our model, we favoured long lags (as long as the data accepted them) for the cointegrating relations. Last, we choose the number of lags for the short term variables in order to improve the fit of our model with the data. In addition, some shocks can be identified to have impacted the endogenous variable, without any link with their other determinants: in such cases dummy variables have been introduced.

## 1.2. Data

HICP data

The equations are estimated using HICP figures with 4 digits. As Kozicki Hoffmann (2004) showed, index data must be rebased very carefully to avoid distorsions that may affect variance properties, alter the lag distribution of time series models and cause a systematic bias in estimated coefficients. Although this may not be a very severe problem as our sample is not very long, the indexes based in 2005 were back-casted by the indexes based in 1996 with 4 digits.

Explanatory variables

Except for VAT indicators, the exogenous variables used in the model are taken from the Banque de France macroeconometric model for the euro area AMAZONE's database. These series are presented below with their sources and date ranges:

| *Label* | *Source* | *Range* |
|---|---|---|
| Import prices | Eurostat Quarterly National Accounts | 1995Q1-2007Q1 |
| Oil price in € | Market | 1978Q1-2007Q1 |
| Unemployment rate | Eurostat | 1993Q1-2007Q1 |
| Capacity Utilisation Rate | BIS | 1985Q1-2007Q1 |

Note that national accounts' series are seasonally and working-day adjusted.
The unit labour cost (ULC) is computed on the basis of Quarterly National Accounts data as follows:

$$ULC = \frac{compensation\,of\,employees}{employees} \times \frac{total\ \ employment}{real\_GDP}$$

The import price index represents import prices in euro. With oil price in euro, it accounts for shocks exogenous to the Euro zone economy (including real effective exchange rates, prices of oil and of foreign competitors in foreign currencies).

Eurostat series are back-casted until 1985Q1 using the ECB's Area Wide Model database (AWM)[5], in order to have a long enough estimation sample, after checking the consistency of AWM series and Amazone ones over their common period. AWM series that have been used are set out below:

| *Variable* | *AWM series* |
|---|---|
| Unit labour costs | ULC |
| Import prices | MTD |
| Unemployment rate | URX |

VAT rate
The European Commission publishes every year a document detailing the VAT rates applied in the different countries and giving backdata for reduced, standard and increased rates for each country[6]. The information on reduced and increased rates cannot be used because of changes in the tax base. However under the assumption that the standard rate is applied to every product[7], the evolution of the impact of changes in VAT rates on the consumption prices since the previous month of December is[8] :

$$\frac{P_t - P_{dec}}{P_{dec}} = \sum_i \pi_{t,i} * \frac{\left(1+\tau_t^i\right) - \left(1+\tau_{dec}^i\right)}{\left(1+\tau_{dec}^i\right)}$$

where $\pi_{i,t}$ is the weight of the country in the HICP component $P$, $\tau^i$ is the applied rate in country $i$. Thus, we compute the impact of VAT rate by chaining those changes, starting from the value in January 1987:

$$1+\tau_t = \left(1+\tau_{t-1}\right)\sum_i \pi_{t,i} * \frac{\left(1+\tau_t^i\right)}{\left(1+\tau_{t-1}^i\right)}$$

This computation differs slightly from the average standard rates weighted by the HICP country weights, because the latter changes with the weights every January, notwithstanding stable VAT rates.

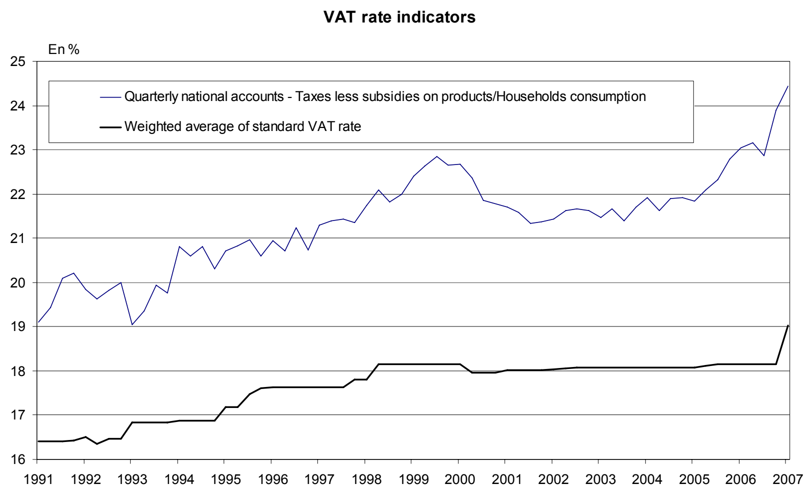
Another approach is to compute the implicit tax rate in the quarterly national accounts (ratio of indirect taxes _D21X31 that include VAT _over private consumption). But its profile is different from that of our computed rate, because this national accounts series includes indirect taxes other than VAT, the tax base consistent with this series is not limited to private consumption and, finally, one cannot identify the changes in marginal rates from the changes in the composition of the tax base that give rise to the observed fluctuations in this implicit tax rate. In addition, using this implicit tax rate did not appear significantly or appeared with the wrong sign in the equations, so that this latter measure was not introduced in the equations.

[5] Fagan et alii, 2001.

[6] "VAT Rates Applied in the Member States of the European Community" referenced DOC/2137/2007 for the one published on 1st May 2007.

[7] In fact, the standard rates applies to about 1/2 of the basket of HICP in France and 2/3 in Germany.

[8] This is coherent with the HICP methodology, as it is a chained Laspeyres index.




## 1.3. Reprocessing: seasonal adjustment and conversion into quarterly series

The price indexes are monthly and not seasonally adjusted whereas the explanatory variables are mostly quarterly and seasonally adjusted data (unit labour costs and import deflator among others). We hence have to derive a monthly forecast for the HICP as published by Eurostat from quarterly models. The steps are the following: first seasonally adjusting (if deemed necessary) and converting the HICP series into quarterly series, so that the endogenous variables are homogenous to exogenous ones, and second interpolating the quarterly forecast and adding a seasonal pattern. This will lead to losses in information and we investigated several approaches in order to reduce these losses.
To assess the accuracy of each method we proceed as follow. We first choose a way to convert the monthly series into quarterly series, with or without seasonal adjustment. Second, we assume that our model is perfect, that is this quarterly HICP series is perfectly projected with the models. Third, we perform the symmetric transformation of the first step in order to recover a monthly series, not seasonally adjusted. The difference between the results obtained this way with the original series allows to evaluate the method.[9]
Indeed, several methods can be envisaged. According to the level of integration of the series, the level of the series or its year-on-year growth can be modelled. The conversion method from one frequency to the other may use the last value of the quarter or the quarterly average. Finally, series can be seasonally adjusted or not. There are hence 8 combinations of all these possibilities. However this reduces to 6 different possibilities (Table 1): there is no direct conversion of the year-on-year growth rate from monthly to quarterly frequency (and vice versa) when data are averaged, so that the average level must be computed and then converted, which is equivalent to a method with quarterly average on the levels.

**Table 1: Potential methods for seasonal adjustment and convert series**

| *Criteria* | *Series* | *Conversion method* | *Seasonal adjustment* |
|---|---|---|---|
| Method 1 | Level | Last value of the quarter | None |
| Method 2 | Year-on-year growth | Quarterly average | Adjusted series |

The main result of table 2 is that it is fundamental to take the seasonality of the series into account, either by a procedure of seasonal adjustment or by the year-on-year growth. Indeed, the difference between the modified and the actual monthly series has the highest standard deviation with methods 5 and 6 (except for total HICP taken on the whole sample period and for both components of food). The methods using year-on-year growth are less efficient than methods with modelled seasonal adjustment but better than methods without. This result may come from 2 effects.

[9] In our exercise, we will have an additional step of projecting the quarterly series.

**Table 2: characteristics of the difference in percentage between the actual unadjusted series and the modified series (series converted to quarterly frequency and back to monthly frequency, non adjusted)**

| | *1* | *2* | *3* | *4* | *5* | *6* |
|---|---|---|---|---|---|---|
| *Series* | *Y-o-Y* | *Y-o-Y* | *Level* | *Level* | *Level* | *Level* |
| *Conversion method* | *Last value* | *Last value* | *Average* | *Last value* | *Average* | *Last value* |
| *Seasonal adjustment* | *Yes* | *No* | *yes* | *yes* | *no* | *no* |
| **Overall HICP** | | | | | | |
| All sample | | | | | | |
| Mean | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 |
| Standard deviation | 0.13 | 0.15 | 0.06 | 0.08 | 0.11 | 0.17 |
| 2002-2006 | | | | | | |
| Mean | 0.00 | 0.01 | 0.00 | 0.01 | 0.00 | 0.11 |
| Standard deviation | 0.12 | 0.13 | 0.05 | 0.07 | 0.15 | 0.24 |
| **HICP excl. unprocessed food and energy** | | | | | | |
| All sample | | | | | | |
| Mean | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.06 |
| Standard deviation | 0.05 | 0.07 | 0.02 | 0.03 | 0.10 | 0.18 |
| 2002-2006 | | | | | | |
| Mean | 0.00 | 0.01 | 0.00 | 0.01 | 0.00 | 0.16 |
| Standard deviation | 0.06 | 0.08 | 0.03 | 0.04 | 0.16 | 0.29 |
| **Unprocessed food** | | | | | | |
| All sample | | | | | | |
| Mean | -0.01 | 0.00 | 0.00 | -0.02 | 0.00 | -0.04 |
| Standard deviation | 0.46 | 0.47 | 0.26 | 0.30 | 0.34 | 0.45 |
| 2002-2006 | | | | | | |
| Mean | 0.05 | 0.06 | 0.00 | 0.09 | 0.00 | 0.09 |
| Standard deviation | 0.43 | 0.42 | 0.24 | 0.24 | 0.31 | 0.39 |
| **Processed food** | | | | | | |
| All sample | | | | | | |
| Mean | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | -0.02 |
| Standard deviation | 0.17 | 0.17 | 0.08 | 0.11 | 0.09 | 0.12 |
| 2002-2006 | | | | | | |
| Mean | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | -0.01 |
| Standard deviation | 0.29 | 0.29 | 0.13 | 0.18 | 0.13 | 0.18 |
| **Manufactured goods** | | | | | | |
| All sample | | | | | | |
| Mean | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.18 |
| Standard deviation | 0.06 | 0.11 | 0.03 | 0.04 | 0.24 | 0.52 |
| 2002-2006 | | | | | | |
| Mean | 0.01 | 0.04 | 0.00 | 0.00 | 0.00 | 0.38 |
| Standard deviation | 0.05 | 0.12 | 0.02 | 0.02 | 0.40 | 0.87 |
| **Services** | | | | | | |
| All sample | | | | | | |
| Mean | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | -0.02 |
| Standard deviation | 0.09 | 0.12 | 0.05 | 0.06 | 0.16 | 0.27 |
| 2002-2006 | | | | | | |
| Mean | -0.01 | -0.01 | 0.00 | 0.01 | 0.00 | 0.04 |
| Standard deviation | 0.08 | 0.11 | 0.04 | 0.05 | 0.21 | 0.34 |

Firstly, the year-on-year methods implicitly assume that the seasonal pattern did not change over time. As the method for compiling HICP has changed a lot over time (cf annex 1), the seasonal pattern of the series was modified, especially when the methodological issue dealt with taking into account end-of the-season sales period, which was enforced at different date according to the countries (from 1992 on, with a slow broadening of the components involved in France; from 2001 on in Germany, Spain and Italy). This issue is particularly obvious with the HICP for manufactured goods (cf graphs in annex 2). Moreover, seasonal patterns of prices may change over time further to any structural change in one country or the other.[10]

[10] See ECB (2004). The ECB computes seasonally adjusted HICP (see ECB 2000 for methodological details), but they are not coherent with the Eurostat data before 2000 and we do not have the forecasted coefficients.

Secondly, the year-on-year method cannot take into account base effects. Indeed the year-on-year growth depends on the monthly growth of the current month but also on that of the month one year before. Such information is lost by the year-on-year method but is taken into account by the modelled seasonal adjustment. However, in a real time projection exercise, the method using modelled adjustment may perform less advantageously as it appears here because the seasonal adjustment is fragile at the end of the sample.
Another result of table 2, less important, is that taking the last value of the quarter (methods 1, 2 and 6) possibly leads to a systematic bias (the average of the spread is not zero, so that the average of the modified series is not equal to the average of the actual series we started with). This may be due to the fact that averaging data over the quarters gives more robustness to the results, as the impact of exceptional growth is divided by 3 and may even be compensated for by the evolution observed in the months that are not the last one of a quarter. Moreover, data from the national accounts are averages over the quarter.
In conclusion, we use seasonally adjusted series and average them over the quarter.

## 1.4. Stationarity

The stationarity of all series (in logarithm, except for rates) have been tested over the estimation period (1988Q2-2007Q1) using both the Augmented Dickey-Fuller and the Kwiatkowski-Phillips-Schmidt-Shin tests. The following table summarizes the results[11]:

**Table 3: stationarity tests**

| | *DFA* | *KPSS* |
|---|---|---|
| ULC | I(0) + T | I(1) |
| Oil prices | I(0) + T | I(1) |
| Import prices | I(0) + T | I(0) |
| CUR | I(0) + T | I(0) |
| Unemployment rate | I(1) | I(0) |
| Indirect tax rate | I(1) | I(1) |
| VAT rate (HICP country weights) | I(1) + T | I(1) |
| Unprocessed food price | I(1) + T | I(0) |
| Processed food price | I(1) + T | I(1) |
| Manufactured goods price | I(2) | I(2) |
| Services prices | I(2) | I(2) |
| Energy prices | I(1) + T | I(1) |
| Underlying HICP | I(2) | I(2) |
| Total HICP | I(2) | I(2) |

*Note: I(x) means integrated to order x, and T deterministic trend*

Not all series are clearly integrated of order one, which seems an obstacle for building an error correction model as described above. However, considering the small size of the sample and the possible breaks in the data, the conclusions of these tests may be inaccurate. In particular, some HICP indexes may seem integrated of order 2 as a result of breaks related to the integration process into the Eurosystem and to changes in their computation methodology (Cf annex), but the stationarity of inflation in the recent past and in our forecasts is not questionable. Hence, and in order to be able to build a consistent and interpretable model, along the line of the structural ingredients presented above, we have considered that all series used in the model are integrated to order one.

## 1.5. Estimation method

The series we use are not stationary, so that three approaches were available: the VECM approach by Johansen (Johansen, 1988, Johansen and Juselius, 1990), the ECM approach in one step (Ericsson and

[11] See also graphs in annex 2.

Mackinnon, 2002) and the Engle and Granger approach in two steps (Engle and Granger, 1987). As our aim is to project the HICP indices and its components conditionally to the developments designed with the macro-model, we did not use the first approach that required that the full system should be well specified, including the wage equation and the import deflator equation. Both other approaches usually assume there is at most one cointegrating vector. The Engle and Granger approach assumes restriction on the common factor (for example, the short and long term elasticities are identical). As it is certainly untrue, the estimation of the coefficients of the cointegrating vector is biased. Thus, we followed Ericsson and Mackinnon (2002), who tabulated the *t-statistics* of the coefficients of the cointegrating vector. We estimated with the OLS the following equation:

$$\begin{aligned} dP = {} & \beta_1 d\log(P^M) + \beta_2 d\log(ULC) + \beta_3 d\log(P^{brent}) + \beta_4 d\log(CUR) - \beta_5 dU - \beta_6 U + \beta_7 d\tau + \gamma \\ & - \sigma\left(\log(P) - \alpha_1 \log(P^M) - \alpha_2 \log(ULC) - \alpha_3 \log(P^{brent})\right) \end{aligned}$$

As long as the residuals follow a white noise, the OLS estimators are not biased, but the *t-statistics* of $\sigma$, $\alpha 1$, $\alpha 2$, and $\alpha 3$ do not follow the Student distribution. The critical value of $\sigma$ at the 5 % threshold is not 1.96 but 3.5 in a sample of 69 observations, the equation having a constant, 3 variables in the cointegrating vector and 15 regressors. This method assumes that the explanatory variables are weakly exogenous.

## 2. The model

All equations have been estimated using ordinary least squares. The fit of each equation to the data is assessed on the basis of the t-statistics of the parameters, and to a lesser extent of the R-squared. In addition, we have tested for autocorrelation of residuals. The absence of autocorrelation to order 1 in the residuals is confirmed by the Durbin-Watson statistics being close to 2, and a serial correlation LM-test has been carried out to check the absence of autocorrelation to higher orders in the residuals (reported below).

### 2.1. Equations and autocorrelation tests

<u>Overall HICP</u>
Estimation sample: 1990Q2-2007Q1

$$\begin{aligned} \Delta\log(P_t) = {} & \underset{[5.28]}{0.0065}\,\Delta\log(P_t^{brent}) + \underset{[2.06]}{0.0005}\,\Delta CUR_{t-2} + \underset{[3.08]}{0.0546}\,\Delta\log(P_{t-1}^M) - \underset{[-10.3]}{0.0470}\,\log(P_{t-2}) \\ & + \underset{[4.52]}{0.0374}\,\log(ULC_{t-2}) + \underset{[2.24]}{0.0117}\,\log(P_{t-2}^M) - \underset{[-6.68]}{0.0012}\,U_{t-3} + \underset{[3.35]}{0.0032}\,(Dum\,1991\,q3 - Dum\,1991\,q4) \\ & - \underset{[-3.30]}{0.0033}\,(Dum\,2001\,q1 - Dum\,2001\,q2) - \underset{[-3.40]}{0.0049}\,Dum\,2000\,q2 + \varepsilon_t \end{aligned}$$

*$R^2$ = 0.7812* *DW = 2.08*

<u>Underlying HICP</u>
Estimation sample: 1988Q3-2007Q1

$$\begin{aligned} \Delta\log(P_t) = {} & \underset{[2.64]}{0.2373}\,\Delta\log(P_{t-1}) + \underset{[3.61]}{0.0025}\,\Delta VAT_t - \underset{[-6.01]}{0.0512}\,\log(P_{t-3}) + \underset{[5.41]}{0.0449}\,\log(ULC_{t-3}) + \underset{[2.58]}{0.0131}\,\log(P_{t-3}^M) \\ & - \underset{[-4.37]}{0.0006}\,U_{t-3} - \underset{[-1.61]}{0.0293} - \underset{[-2.55]}{0.0020}\,Dum2000q2 - \underset{[-1.86]}{0.0010}(Dum2001q1 - Dum2001q2) \\ & - \underset{[-2.74]}{0.0022}\,Dum1993q4 + \underset{[2.27]}{0.0018}\,Dum2004q1 + \varepsilon_t \end{aligned}$$

*$R^2$ = 0.929* *DW = 2.16*

Services prices
Estimation sample: 1988Q3-2007Q1

$$\Delta\log(P_t) = \underset{[3.15]}{0.3111}\,\Delta\log(P_{t-1}) + \underset{[1.88]}{0.0004}\,\Delta CUR_{t-1} + \underset{[1.96]}{0.0019}\,\Delta VAT_t - \underset{[-5.53]}{0.0465}\log(P_{t-3}) + \underset{[5.13]}{0.0561}\log(ULC_{t-3})$$
$$+ \underset{[2.45]}{0.0164}\log(P^M_{t-3}) - \underset{[-3.47]}{0.0006}\,U_{t-3} - \underset{[-3.48]}{0.1171} + \underset{[2.75]}{0.0030}\,Dum1990q4 + \underset{[4.66]}{0.0036}(Dum1991q3 - Dum1991q4) + \varepsilon_t$$

*R² = 0.9127* *DW = 1.80*

Manufactured goods prices
Estimation sample: 1988Q3-2007Q1

$$\Delta\log(P_t) = \underset{[1.83]}{0.0016}\,\Delta VAT_t - \underset{[-10.85]}{0.0788}\log(P_{t-3}) + \underset{[6.82]}{0.0416}\log(ULC_{t-3}) + \underset{[3.28]}{0.0123}\log(P^M_{t-3}) + \underset{[12.64]}{0.1120} + \varepsilon_t$$

*R² = 0.8573* *DW = 0.38*

Processed food prices
Estimation sample: 1989Q1-2007Q1

$$\Delta\log(P_t) = \underset{[4.84]}{0.3886}\,\Delta\log(P_{t-1}) + \underset{[2.00]}{0.0813}\,\Delta\log(ULC_{t-2}) - \underset{[-3.85]}{0.04001}\log(P_{t-2}) + \underset{[2.85]}{0.0319}\log(ULC_{t-2})$$
$$+ \underset{[3.50]}{0.0323}\log(P^M_{t-2}) - \underset{[-3.19]}{0.1156} + \underset{[4.38]}{0.0077}\,Dum2003q1 + \underset{[3.66]}{0.0065}\,Dum2003q4 + \underset{[3.14]}{0.0059}\,Dum2004q2 + \varepsilon_t$$

*R² = 0.6710* *DW = 2.25*

Unprocessed food prices
Estimation sample: 1990Q3-2007Q1

$$\Delta\log(P_t) = \underset{[3.09]}{0.0029}\,\Delta CUR_{t-2} - \underset{[-4.16]}{0.1507}\log(P_{t-2}) + \underset{[4.84]}{0.0112}\log(P^{brent}_{t-2}) + \underset{[4.06]}{0.6186} + \underset{[2.98]}{0.0006}\,trend$$
$$+ \underset{[2.91]}{0.0153}\,Dum1991q3 + \underset{[3.83]}{0.0200}\,Dum2001q2 + \underset{[4.53]}{0.0234}\,Dum2002q1 + \underset{[3.02]}{0.0155}\,Dum2003q3 - \underset{[-1.90]}{0.0103}\,Dum2007q1 + \varepsilon_t$$

*R² = 0.6691* *DW = 2.09*

Energy prices
Estimation sample: 1990Q4-2007Q1

$$\Delta\log(P_t) = \underset{[10.06]}{0.0989}\,\Delta\log(P^{brent}_t) + \underset{[5.82]}{0.0518}\,\Delta\log(P^{brent}_{t-1}) - \underset{[-2.63]}{0.0454}\log(P_{t-3}) + \underset{[3.35]}{0.0205}\log(P^{brent}_{t-3}) + \underset{[2.39]}{0.1410}$$
$$+ \underset{[2.17]}{0.0213}\,Dum1994q1 + \underset{[3.59]}{0.0252}(Dum2003q1 - Dum2003q2) + \varepsilon_t$$

*R² = 0.7605* *DW = 2.30*

Table 3 summarizes the results of the LM testing for autocorrelation in the residuals of the equations above. The null hypothesis is no serial correlation. The lags have been chosen on the basis of residuals' autocorrelograms.

**Table 3: some characteristics of the equations**

| *Equation* | *lag* | *LM test statistic* | *p-value* |
|---|---|---|---|
| Overall HICP | 4 | 3.24 | 0.519 |
| Underlying HICP | 5 | 8.61 | 0.126 |
| Manufactured goods | 2 | 57.7 | 0.000 |
| Services | 4 | 6.36 | 0.174 |
| Unprocessed food | 4 | 9.27 | 0.055 |
| Processed food | 3 | 5.65 | 0.130 |
| Energy | 1 | 1.84 | 0.175 |

Apart from the manufactured goods HICP equation, these results confirm the absence of autocorrelation in the residuals of our model's equations. Hence, there is no bias in the estimation and the statistical tests that have been performed are valid, in particular concerning the significance of estimated parameters.

We find that the residuals of the manufactured goods equation are autocorrelated to order 2, but this equation is not autoregressive, and we conclude that the estimation is even so unbiaised.

To complete the check, we have also estimated the equations of the model following the method of Newey-West: the estimated coefficients are unchanged but the variances calculations are adjusted to take into account both the autocorrelation and heteroskedasticity of residuals. The results are presented in annex 5. Finally, although the adjusted *t-statistics* of the estimated coefficients of the equations of the model are lower, they are still significant.

## 2.2. Elasticities

No constraint has been imposed on the estimation of price elasticities with respect to their major long-term determinants. However, for the aggregates, we expect the sum of elasticities of the import deflator (external source of price changes) and of unit labour costs (internal source) to be close to one for homogeneity reasons. Nevertheless, in case of a specification error which would omit an explanatory variable, positively (resp. negatively) correlated with a variable present in the equation, this error would lead to an upward (resp. downward) bias of the estimated coefficient affecting the later variable. This way, the biased coefficient, in giving more (resp. less) weight to the variable present in the equation, would capture partly the effect of the omitted variable. For forecasting purposes, such a bias would help upon using the "true" coefficient. In our equations for example, the unemployment rate may be correlated with unit labour costs, which would impact the estimated elasticity but not the forecast. These elasticities, as they are implied by our equations, are nevertheless presented below for both total and underlying HICP:

**Table 4:Long term elasticities**

| | Underlying (through aggregation) | Overall (through aggregation) | Underlying (directly) | Overall (directly) |
|---|---|---|---|---|
| Unit labour costs | 0.88 | 0.74 | 0.88 | 0.80 |
| Import deflator | 0.37 | 0.34 | 0.26 | 0.25 |
| Total | 1.25 | 1.08 | 1.13 | 1.05 |

The sum of elasticities is slightly above 1 when components are aggregated and for the equation modelling directly the overall and underlying HICP. In the first case, there is also a trend in the equation for unprocessed food, which implies a trend inflation rate by 1.6 % per year for the unprocessed food sector, which contributes by 0.1 pp per year on the overall consumption inflation. In the direct approach as well as in the indirect approach, the restriction that the sum is equal to 1 is accepted by the data.

The relative weight of ULC in total costs lies between 0.7 and 0.8, which is near the usual estimate of 2/3 for the part of labour costs in total costs incurred by the firm. Another way to assess the elasticities to import prices computed through our model is to compare them with the content of imports of household consumption expenditures which can be computed with the input-output tables of the national accounts. We assume the import content is the same in one sector, whether the products or goods are aimed at final consumption, investment, export or intermediate consumption but the import content of household consumption takes into account the fact that some of the final products are produced thanks to imported intermediate consumptions. The table reports the overall import content of household consumption and the contribution of the consumption of some categories of goods to this content. This figure is comparable to the elasticities of the overall prices to import deflator estimated in our equations. One main difference is that the coverage of household consumption and the basket considered for the computation of HICP is not exactly the same, as the deflator includes imputed rents, contrary to the HICP. Thus, the import content of consumption expenditures is lower than that of the basket of HICP. Overall, the magnitude of the effect of import prices obtained in our equations is in line with those computations:

**Table 5: Import content of the household consumption in the national accounts and elasticities of HICP components to import prices**

| | computation with the model Amazone* for 1999 | model – direct approach | model – approach by aggregation |
|---|---|---|---|
| goods and services | 0.23 | 0.26 | 0.34 |
| goods excl. energy | 0.17 | | 0.17 |
| Services | 0.04 | | 0.14 |
| Energy | 0.02 | | 0.09 |

** Amazone is the macroeconometric model for the Euro area developed at the Banque de France.*

Elasticities for each equation at different horizon are shown in annex 4. These equations are not structural and we are not able to simulate the impact of a shock that would, for instance, lead first a rise in employment, a subsequent fall in the unemployment rate, and, in the short run at least, a rise in unit labour cost. As a consequence, we just report independently the effects of a change in unit labour cost and of a change in the unemployment rate.

As regards the impact on total HICP, across the various ways of recovering the results, the effects are pretty similar, especially as regards the effects of a change in ULC, import prices, oil prices and CUR. The only marked difference comes from the effects of a change in the unemployment rate, for which modelling directly the overall HICP implies a greater sensitivity of inflation to the unemployment rate, compared with the disaggregated approaches. The same holds as regards underlying inflation. Indeed, at the disaggregated level, only the service component of HICP depends on the unemployment rate in our model, process food and manufactured goods HICP do not.

The impact of the standard VAT rate never appeared significant in level (in the cointegrating vector). However its first difference appeared in the equations of manufactured goods and services HICP, as well as in the underlying inflation equation, but it did not in the other ones. The subcomponents where the VAT rate proved to have significant explanatory power are indeed those where the goods and services consumed are mostly taxed with the standard rate. The impact on the price level of a rise in 1 pp of the tax rate lies between 0.15 and 0.26% in the first quarter of the government measure, reaches its maximum in the third quarter of the tax hike, around 0.3 pp and then weakens slowly. The impact, even at its peak, is lower than 1% because not all products and goods are submitted to the standard rate (about half the basket in France, 2/3 in Germany). Moreover, retail traders do squeeze their margin after a tax hike. On the whole, the impact at the horizon we consider (one year) seems coherent with other evaluations.

### 2.3. Dummy variables used in the model

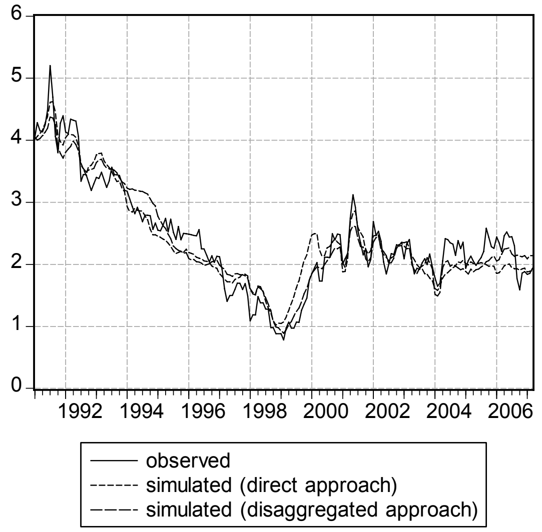
Several dummies have been used in the model, primarily in order to take into account well identified shocks, not related to changes in the explanatory variables. They are described below:

| | |
|---|---|
| Sep-oct 1990 | Increase in the Germany HICP data, not present in the CPI data |
| July 1991 | Increase of telecom prices in Germany |
| 1991q3 | Widespread increase of unprocessed food prices in the Euro zone due to unfavourable weather conditions |
| 1993q4 | Small increases in tobacco prices and change in the seasonality in Italy |
| Jan 1994 | Increase of excise taxes on oil products in Germany |
| April 2000 | Increase in the VAT standard rate in France and service prices in Germany |
| 2001q1-2001q2 | Change in the seasonality in Italy and Spain |
| 2001q2 | Price increase due to food emergencies (bovine spongiform encephalopathy and foot-and-mouth disease) and a rigorous winter |
| 2002q1 | Increase of unprocessed food prices due to a rigorous winter |
| 2003q1 | Increase in tobacco prices in France |
| 2003q1 | Increase in gas and electricity prices in the Euro zone |
| 2003q3 | Impact of heat wave on unprocessed food prices |
| March 2004 | Increase in tobacco prices in Germany |
| 2007q1 | Decrease of unprocessed food prices due to a mild winter |

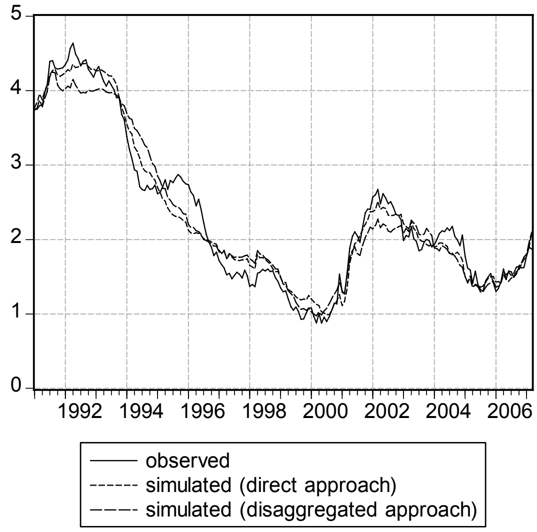
## 2.4. Dynamic simulations

The following graphs present dynamic simulations of the equations of our model over the period 1991Q1-2007Q1, converted into monthly series and including their seasonal component, together with actual HICP figures:

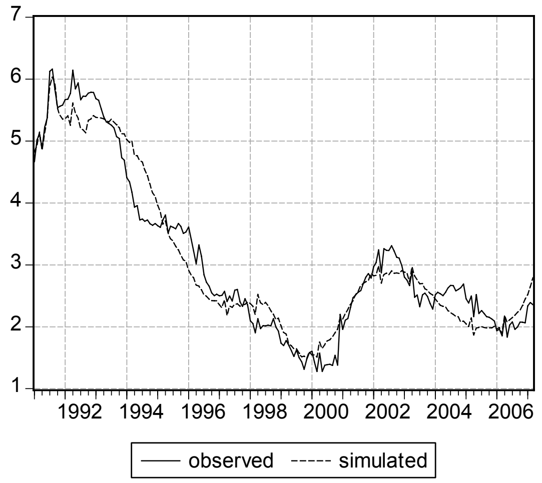
**total HICP y-o-y growth rate (in %)**



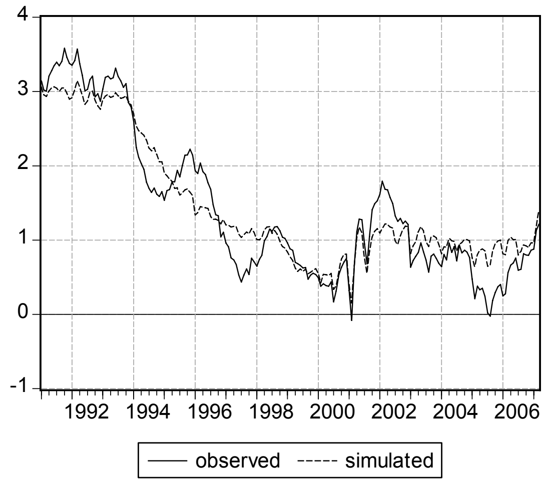

**underlying HICP y-o-y growth rate (in %)**



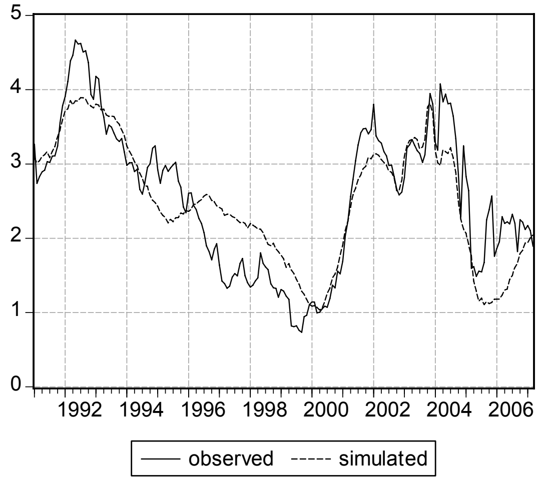

**services HICP y-o-y growth rate (in %)**



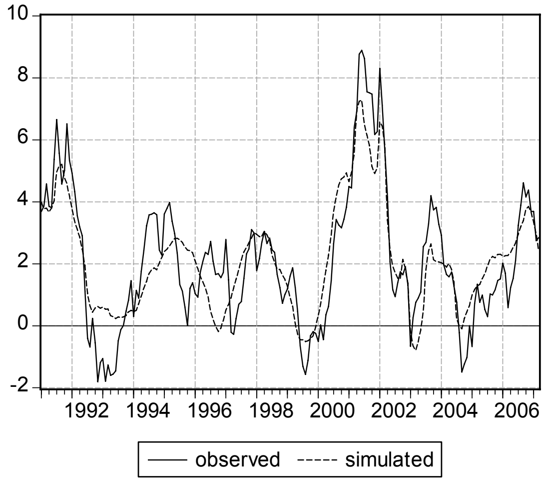

**manufactured goods HICP y-o-y growth rate (in %)**



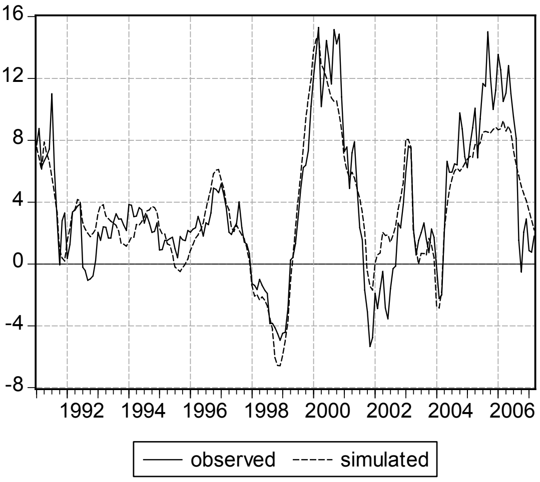
**processed food HICP y-o-y growth rate (in %)**




**unprocessed food HICP y-o-y growth rate (in %)**




**energy HICP y-o-y growth rate (in %)**




These graphs show the ability of equations to capture in sample properly and on time trend reversals in price developments, beyond very short term fluctuations. This property would have been also true out of sample over the most recent period as the coefficient stability is obtained in most cases (see annex), at least as of the beginning of the 2000s. With respect to this property, which is crucial for the quality of forecasts, our model seems satisfactory.

# 3. Forecasting performance

## 3.1. Forecast evaluation

As it is commonly done in the literature, the forecasting performance of our model is assessed in comparison to a benchmark model. This benchmark model here is made of single 4-lag autoregressive equations. Their major drawback in practice is that they do not convey any economic interpretation of price developments, besides inflation persistence. Nevertheless, and although not based on the same information sets as the structural models, since no exogenous variable is used, such non-informative models are frequently used by central banks to forecast short term inflation, and are known to have satisfactory forecasting accuracy. They hence are good benchmark models to compete with. Though no exogenous explanatory variable is taken into account, we have nevertheless added all the dummy variables used in the estimation of our structural model, in order to have a fair comparison in terms of

forecasting performance. We will refer to this specification of the AR models as "augmented AR" models.
This exercise consists in traditional in-sample and out-of-sample rolling event evaluations and the comparison is based on the computation of two statistical indicators:

- The root mean square error (RMSE), which is the standard deviation of forecast errors;
- The Diebold-Mariano statistic: $DM = \frac{\overline{d}}{\sqrt{V(\overline{d})}}$ with $\overline{d} = \frac{1}{N}\sum_{i=1}^{N}(\varepsilon_{A,i}^2 - \varepsilon_{B,i}^2)$ where $\varepsilon_{m,i}$ is the forecast error at horizon i of the model m, N is the number of forecasts and *V(d)* is the variance of squared errors differences *d* adjusted for the autocorrelations of the series as advocated in Newey West (1987). This test statistic compares the average difference between the forecast errors obtained from the two models to their variance, in order to conclude whether or not the forecasting errors of a model are significantly lower than those of the other one. Under the null hypothesis that the variances of the forecast errors obtained from the two models are the same, this test statistic must be distributed as $\mathcal{N}(0,1)$. So the critical value associated with the level 5% is 1.96.

As regards our structural model, the exogenous variables over the forecast period are taken to the value in the database, i.e. the value available ex-post. This is a favourable hypothesis for the structural model.

For each equation, 29 forecasts are computed at horizons of 5 quarters (i.e. 15 months): the first is 1999Q1-2000Q2 and the last is 2006Q1-2007Q1, both for in-sample and out-of-sample forecasts. Note that, for the estimation, only the end of the sample changes: in all cases, the starting point is fixed, set at the beginning of our estimation sample (between 1988Q3 and 1990Q4, depending on the equation). The statistics are calculated on the basis of the forecasted HICP series converted into monthly frequency and including seasonal components.
The comparison aims at deciding between:

- the seven equations of the model versus their corresponding autoregressive equations;
- the seven equations of the model with or without dummies. We also assess their relative impact on autoregressive equations;
- the forecasts of overall and underlying HICP obtained by aggregating HICP subcomponents' forecasts (the "indirect" approach with full decomposition or the decomposition for underlying HICP and volatile components) versus the forecasts obtained directly from the overall and underlying HICP equations of our model (the "direct" approach).

## 3.2. Single equations performance

We present the forecasting performance of our equations compared to autoregressive equations where we included the dummy variables we used, both in sample and out of sample.
Table 6 presents the ratio in % of the in-sample root mean squared error (RMSE) of the equations of the model to the RMSE of the standard autoregressive ones.

**Table 6:RMSE of the equations of the model in % of the RMSE of the autoregressive model (for horizons from 1 to 15 months) – in sample**

| Equation | Average* | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Services | **57** | 78 | 100 | 85 | 69 | 82 | 72 | 59 | 68 | 60 | 50 | 57 | 50 | 41 | 47 | 48 |
| Manufactured goods | **77** | 145 | 124 | 121 | 130 | 120 | 105 | 104 | 100 | 88 | 83 | 79 | 73 | 67 | 68 | 66 |
| Processed food | **62** | 84 | 68 | 95 | 74 | 66 | 80 | 63 | 57 | 67 | 55 | 51 | 61 | 52 | 49 | 59 |
| Unprocessed food | **45** | 94 | 63 | 66 | 67 | 49 | 52 | 54 | 40 | 46 | 48 | 37 | 42 | 42 | 35 | 42 |
| Energy | **45** | 72 | 64 | 65 | 57 | 51 | 52 | 52 | 46 | 45 | 45 | 41 | 40 | 40 | 38 | 35 |
| Total HICP | **55** | 87 | 78 | 78 | 82 | 75 | 69 | 71 | 66 | 55 | 56 | 54 | 42 | 45 | 46 | 38 |
| Underlying HICP | **34** | 81 | 71 | 59 | 52 | 52 | 46 | 37 | 36 | 35 | 30 | 28 | 26 | 21 | 22 | 23 |

* The average is the ratio of the average RMSE over all horizons.

The RMSE of our model is lower than the ones of the autoregressive model for all equations and almost all horizons, except for short term forecasts using the equation of manufactured goods HICP. In addition, the difference seems to increase with the horizon. The Diebold-Mariano statistic test has been implemented to confirm whether the difference between the forecasting errors of the two models is statistically significant or not.

**Table 7: Diebold-Mariano statistic for each forecast horizon (in months) – in sample**

| Equation | Average | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Services | **2.1** | 7.3 | 0.0 | 1.1 | 2.6 | 1.5 | 1.8 | 2.3 | 1.8 | 1.8 | 2.2 | 1.8 | 1.8 | 2.0 | 1.8 | 1.7 |
| Manufactured goods | **0.4** | -1.4 | -1.1 | -0.8 | -1.1 | -0.8 | -0.2 | -0.2 | 0.0 | 0.8 | 1.2 | 1.3 | 1.9 | 2.0 | 1.9 | 2.1 |
| Processed food | **1.6** | 0.9 | 1.7 | 0.4 | 1.4 | 1.6 | 1.2 | 1.7 | 1.9 | 1.6 | 1.8 | 1.9 | 1.7 | 2.0 | 2.1 | 2.0 |
| Unprocessed food | **4.3** | 0.3 | 3.4 | 3.2 | 3.3 | 4.8 | 4.0 | 5.6 | 5.4 | 5.1 | 6.0 | 4.8 | 4.6 | 4.0 | 4.7 | 5.0 |
| Energy | **3.8** | 2.8 | 4.0 | 3.0 | 3.5 | 5.0 | 3.5 | 4.0 | 4.9 | 3.5 | 4.1 | 4.5 | 3.5 | 3.5 | 3.6 | 3.2 |
| Total HICP | **1.9** | 0.9 | 1.9 | 1.9 | 2.0 | 2.6 | 1.9 | 2.1 | 2.2 | 1.9 | 2.1 | 2.1 | 1.9 | 1.9 | 1.8 | 1.8 |
| Underlying HICP | **2.4** | 1.5 | 1.7 | 2.1 | 2.6 | 2.7 | 2.4 | 2.6 | 2.8 | 2.5 | 2.6 | 2.6 | 2.5 | 2.6 | 2.7 | 2.6 |

*Note : shaded cells correspond to Diebold-Mariano statistics that are significantly different from zero, i.e. above 1.9.*

For the unprocessed food, energy, total and underlying HICP, the Diebold-Mariano test confirms that, within the estimation sample, our model's forecasting errors are significantly smaller than those of the benchmark model at nearly any horizon. The results are mixed concerning services, manufactured goods and processed food HICP. The processed food and manufactured goods HICP equations seem to allow for comparable forecasting errors than an augmented AR(4) in average and, more precisely, for horizons up to about 10-12 months. Their performances are significantly better for longer horizons. In addition, the services price equation of our model generates forecasts slightly better but statistically comparable in quality to those of an augmented AR(4) for almost all horizons.

The forecasting performance of our model is also assessed through an out-of-sample rolling event evaluation, which corresponds more to the conditions in which the model is meant to be used in actual practice. As above, we set out below the ratios of RMSE:

**Table 8: RMSE of the equations of the model in % of the RMSE of the autoregressive model (for horizons from 1 to 15 months) – out of sample**

| Equation | Average* | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Services | **67** | 82 | 99 | 88 | 76 | 88 | 80 | 69 | 78 | 70 | 61 | 67 | 59 | 52 | 57 | 59 |
| Manufactured goods | **109** | 153 | 138 | 137 | 147 | 142 | 125 | 122 | 122 | 109 | 102 | 101 | 95 | 89 | 91 | 92 |
| Processed food | **84** | 91 | 75 | 97 | 87 | 78 | 90 | 82 | 75 | 84 | 79 | 73 | 81 | 76 | 72 | 79 |
| Unprocessed food | **59** | 93 | 64 | 67 | 76 | 60 | 61 | 70 | 57 | 58 | 64 | 54 | 54 | 59 | 52 | 52 |
| Energy | **57** | 71 | 61 | 62 | 62 | 55 | 56 | 63 | 59 | 58 | 61 | 58 | 58 | 62 | 61 | 58 |
| Total HICP | **64** | 88 | 75 | 81 | 80 | 69 | 71 | 70 | 62 | 61 | 59 | 55 | 54 | 53 | 52 | 51 |
| Underlying HICP | **38** | 83 | 75 | 61 | 59 | 58 | 51 | 45 | 44 | 41 | 37 | 34 | 34 | 30 | 29 | 31 |

* The average is the ratio of the average RMSE over all horizons.

Except for the manufactured goods HICP equation, the forecasting performances of our equations, as measured by the RMSE, are also better than those of the benchmark model, in average and for all horizons. This better performance is confirmed as the projection horizon increases. As done previously, we present the Diebold-Mariano statistics for that exercise:

**Table 9: Diebold-Mariano statistic for each forecast horizon (in months) – out of sample**

| Equation | Average | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Services | **1.1** | 2.1 | 0.1 | 0.6 | 1.3 | 0.7 | 1.0 | 1.4 | 1.0 | 1.1 | 1.4 | 1.2 | 1.2 | 1.4 | 1.2 | 1.2 |
| Manufactured goods | **-0.9** | -6.7 | -1.6 | -1.0 | -1.2 | -1.2 | -0.7 | -0.6 | -0.7 | -0.3 | -0.1 | 0.0 | 0.2 | 0.4 | 0.3 | 0.3 |
| Processed food | **1.1** | 0.6 | 1.3 | 0.3 | 0.8 | 1.2 | 0.9 | 1.2 | 1.3 | 1.2 | 1.3 | 1.4 | 1.2 | 1.4 | 1.5 | 1.6 |
| Unprocessed food | **2.5** | 0.4 | 3.2 | 2.4 | 2.5 | 3.2 | 2.3 | 2.7 | 2.8 | 2.4 | 2.6 | 2.6 | 2.3 | 2.5 | 2.8 | 2.7 |
| Energy | **2.9** | 2.9 | 4.3 | 3.5 | 3.6 | 4.4 | 3.0 | 2.8 | 2.9 | 2.2 | 2.6 | 2.8 | 2.3 | 2.1 | 2.0 | 2.0 |
| Total HICP | **1.5** | 0.7 | 1.9 | 1.8 | 1.5 | 2.2 | 1.7 | 1.4 | 1.6 | 1.5 | 1.4 | 1.6 | 1.4 | 1.3 | 1.4 | 1.4 |
| Underlying HICP | **2.2** | 1.4 | 1.6 | 1.8 | 2.2 | 2.4 | 2.2 | 2.3 | 2.4 | 2.3 | 2.3 | 2.3 | 2.3 | 2.3 | 2.3 | 2.3 |

The fact that the forecasting errors of our model are significantly lower than those obtained by an atheoretical approach is clearly evidenced for the unprocessed food, energy (the two most volatile HICP components) and underlying HICP equations. However, this exercise reveals the relative fragility in terms of forecasting performance of our services, processed food, manufactured goods and total HICP equations, although the forecasting errors are in average lower than those of the benchmark model.
To complete this exercise, we have assessed in section 3.3 the relevance of using dummies in order to improve forecasts. Finally, as the overall HICP equation is not very good, we have compared its forecasting performance with that of the aggregation of all the detailed subcomponents or of the aggregation of underlying HICP with other volatile components, i.e. unprocessed food and energy HICP, in section 3.4.

## 3.3. Assessment of the dummies in the forecasting performance

Including dummy variables in our equations for econometric reasons raised two questions: (i) what is their impact on the model's forecasting performance ? and (ii) should performance be assessed in comparison with simply autoregressive equations or with augmented AR equations as defined above ? We have thus computed RMSE to evaluate the in and out-of-sample performance of equations with or without dummy variables (the Diebold-Mariano test is not suitable in order to assess the significance of the difference because the specification without dummy is nested in the other).

**Table 10 : RMSE of the equations of the model in % of the RMSE of the same equations without dummies, for each forecast horizon (in months) – in sample**

| Equation | | Average | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Services | Model | **56** | 76 | 93 | 82 | 66 | 78 | 71 | 58 | 67 | 60 | 49 | 56 | 50 | 41 | 46 | 47 |
| | AR | **98** | 97 | 93 | 96 | 96 | 95 | 98 | 98 | 99 | 99 | 98 | 99 | 99 | 98 | 99 | 99 |
| Processed food | Model | **59** | 63 | 52 | 84 | 63 | 59 | 70 | 56 | 53 | 61 | 51 | 48 | 59 | 51 | 50 | 55 |
| | AR | **95** | 75 | 77 | 88 | 85 | 89 | 87 | 89 | 93 | 91 | 93 | 95 | 97 | 100 | 102 | 94 |
| Unprocessed food | Model | **40** | 70 | 47 | 53 | 54 | 41 | 45 | 45 | 35 | 40 | 39 | 32 | 37 | 34 | 29 | 35 |
| | AR | **88** | 75 | 75 | 80 | 80 | 83 | 87 | 84 | 87 | 88 | 82 | 85 | 87 | 80 | 82 | 85 |
| Energy | Model | **42** | 69 | 54 | 57 | 53 | 47 | 48 | 50 | 44 | 43 | 44 | 40 | 39 | 40 | 38 | 35 |
| | AR | **95** | 95 | 84 | 89 | 93 | 93 | 94 | 96 | 95 | 96 | 98 | 97 | 98 | 99 | 100 | 99 |
| Total HICP | Model | **63** | 79 | 71 | 77 | 83 | 79 | 77 | 80 | 76 | 64 | 63 | 61 | 49 | 54 | 56 | 45 |
| | AR | **114** | 91 | 91 | 99 | 102 | 106 | 111 | 112 | 115 | 116 | 111 | 114 | 115 | 121 | 122 | 119 |
| Underlying HICP | Model | **38** | 78 | 63 | 56 | 52 | 52 | 46 | 38 | 37 | 37 | 32 | 30 | 29 | 24 | 25 | 26 |
| | AR | **112** | 96 | 89 | 94 | 99 | 101 | 101 | 102 | 103 | 107 | 107 | 109 | 111 | 114 | 115 | 115 |

**Table 11 : RMSE of the equations of the model in % of the RMSE of the same equations without dummies, for each forecast horizon (in months) – out of sample**

| Equation | | Average | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Services | Model | **89** | 96 | 88 | 95 | 94 | 91 | 94 | 92 | 93 | 93 | 91 | 90 | 88 | 87 | 87 | 88 |
| | AR | **101** | 97 | 94 | 97 | 98 | 97 | 100 | 100 | 101 | 102 | 101 | 102 | 102 | 102 | 102 | 102 |
| Processed food | Model | **80** | 66 | 59 | 84 | 72 | 71 | 77 | 73 | 72 | 73 | 72 | 71 | 76 | 76 | 75 | 75 |
| | AR | **122** | 75 | 80 | 95 | 93 | 99 | 101 | 106 | 111 | 109 | 114 | 118 | 122 | 127 | 131 | 122 |
| Unprocessed food | Model | **59** | 70 | 58 | 64 | 63 | 58 | 62 | 62 | 59 | 62 | 60 | 57 | 59 | 58 | 54 | 55 |
| | AR | **100** | 74 | 78 | 83 | 87 | 92 | 98 | 95 | 99 | 100 | 95 | 101 | 105 | 100 | 105 | 111 |
| Energy | Model | **94** | 98 | 81 | 85 | 90 | 85 | 86 | 94 | 90 | 90 | 96 | 93 | 93 | 96 | 95 | 91 |
| | AR | **97** | 96 | 89 | 92 | 95 | 95 | 96 | 97 | 97 | 98 | 98 | 98 | 99 | 100 | 101 | 100 |
| Total HICP | Model | **84** | 83 | 74 | 85 | 88 | 84 | 90 | 86 | 84 | 86 | 80 | 80 | 83 | 81 | 83 | 85 |
| | AR | **134** | 92 | 92 | 104 | 111 | 117 | 126 | 128 | 133 | 134 | 129 | 132 | 134 | 142 | 145 | 141 |
| Underlying HICP | Model | **81** | 91 | 76 | 75 | 80 | 81 | 76 | 74 | 72 | 76 | 73 | 70 | 74 | 75 | 72 | 74 |
| | AR | **119** | 97 | 90 | 94 | 100 | 103 | 102 | 104 | 105 | 109 | 110 | 112 | 114 | 117 | 118 | 118 |

The relative RMSE show that the dummy variables improve the forecasting performance of the equations of the model both in-sample and out-of-sample. Their impact on the performance of autoregressive equations is, to say the least, less favourable: they may improve the forecasts of the autoregressive equations until one quarter ahead but it is less true for longer horizon and they may even worsen them significantly. Thus, the chosen dummy variables may contribute to the observed stability of the equations.

## 3.4. Direct versus indirect approach

Our model performs total and underlying HICP forecasts in two ways: either directly with a single equation for each index as presented supra, or indirectly by aggregating sub-indexes forecasts with the corresponding weights provided by Eurostat, forecasts based either on the equations of our model or on the autoregressive equations formerly presented. From an economic perspective, this dual approach is likely to enrich our analysis of price developments projections. However, it is useful to compare their forecasting performance, using the same test statistics as in the previous sections.
Note that this exercise is carried out only on the basis of out-of-sample projections. The results (RMSE ratios and Diebold-Mariano statistics) are presented below for both underlying and total HICP:

**Table 12: RMSE of the indirect approach in % of the RMSE of the "direct" approach (for horizons from 1 to 15 months)**

| Equation | Average* | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Underlying HICP– | | | | | | | | | | | | | | | | |
| equations of the model vs direct | **106** | 79 | 80 | 111 | 102 | 90 | 98 | 101 | 105 | 98 | 98 | 107 | 98 | 94 | 102 | 113 |
| equations of the model vs direct autoregressive (AR) forecast | **40** | 65 | 60 | 68 | 60 | 53 | 50 | 46 | 46 | 40 | 36 | 36 | 33 | 28 | 30 | 35 |
| Total HICP – | | | | | | | | | | | | | | | | |
| equations of the model – full decomposition vs direct | **62** | 83 | 69 | 65 | 67 | 64 | 57 | 60 | 64 | 56 | 64 | 65 | 62 | 62 | 63 | 67 |
| equations of the model - underlying and volatile components vs direct | **82** | 156 | 139 | 108 | 99 | 95 | 86 | 84 | 87 | 80 | 74 | 76 | 76 | 67 | 69 | 75 |
| equations of the model (full decomp.) vs direct AR forecast | **39** | 73 | 52 | 53 | 54 | 44 | 40 | 42 | 40 | 35 | 38 | 35 | 33 | 33 | 33 | 34 |

* The average is the ratio of the average RMSE over all horizons.

**Table 13: Diebold-Mariano statistic for each forecast horizon (in months)**

| Equation | Average | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Underlying HICP equations of the model | | | | | | | | | | | | | | | | |
| Indirect vs direct | **0.2** | 2.1 | 1.1 | -0.8 | -0.2 | 0.7 | 0.1 | -0.1 | -0.4 | 0.1 | 0.1 | -0.5 | 0.1 | 0.3 | -0.1 | -0.4 |
| Indirect vs AR | **2.0** | 2.1 | 1.6 | 1.4 | 1.9 | 2.2 | 1.8 | 2.1 | 2.1 | 2.0 | 2.1 | 2.2 | 2.0 | 2.2 | 2.2 | 2.0 |
| Total HICP equations of the model | | | | | | | | | | | | | | | | |
| full decomp. vs direct | **3.5** | 1.0 | 1.8 | 2.9 | 2.4 | 2.7 | 6.2 | 3.8 | 3.4 | 4.3 | 4.4 | 4.0 | 3.7 | 5.6 | 4.5 | 2.5 |
| underlying and volatile comp. vs direct | **1.7** | -6.9 | -2.1 | -0.6 | 0.1 | 0.3 | 1.4 | 1.4 | 1.1 | 3.4 | 3.2 | 3.4 | 5.0 | 5.9 | 6.1 | 3.7 |
| full decomp. vs AR | **2.5** | 1.5 | 2.2 | 3.0 | 4.4 | 5.1 | 2.7 | 2.7 | 2.5 | 2.0 | 2.0 | 2.0 | 1.7 | 1.7 | 1.7 | 1.6 |

As regards underlying HICP projections, although the indirect approach significantly outperforms the autoregressive equation, it generates forecasting errors close in average to those of the equation of our model. This is confirmed by the Diebold-Mariano test, which cannot reject the null hypothesis that the two approaches are equivalent in terms of forecasting performance, for all horizons except one month ahead.
For total HICP, the conclusion is different: the indirect approach by aggregation provides significantly better forecasts than a single equation, for both our model and the AR specification and for almost all horizons. For horizons over 8 months, the decomposition of total HICP in underlying HICP on the one hand and volatiles components on the other performs better than the direct approach.

The different findings obtained for underlying HICP and for total HICP with that respect are consistent with (i) the good performance of the unprocessed food and energy HICP equations, which are the most volatile components of inflation and are excluded from underlying HICP, (ii) the good performance of the underlying inflation equation and (iii) the relatively lower performance of the total HICP equation, as emphasized in the previous section.

Regarding the comparison of direct vs indirect approach, Hubrich (2005) reminds that theoretical evidence is mixed upon this issue. Indeed, aggregating individual forecasts might prove the best solution if the individual dynamic properties of each series can be better taken into account in well-specified models so that the forecasts errors of disaggregated components might cancel partly. However, the conclusion depends heavily on possible misspecification in the equations and on the data generating process of the series used. Even in the absence of misspecification, Hendry and Hubrich (2007) show that uncertainty of estimates is also an issue.

In practical terms, there is no consensus either about the superiority of the direct or indirect approach at the Euro area level, as well as at the country level. For example in France, Bruneau et alii (2007) find that the indirect approach leads to forecasts with lower RMSE than the direct one for overall HICP, in particular because of separate modelling of energy prices. Espasa et alii (2002) also find that the indirect approach improves the forecasting performance. However, Hubrich (2005) and Benalal et alii (2004) find that the direct approach is better for total HICP whereas it is inferior for underlying inflation.

Besides the fact that different datasets may lead to different conclusions, our approach is different from that of the previously cited papers. In the first place, we want to assess the coherence of HICP projections with the macroeconomic projections given by other forecasting tools. Thus, our projection is conditional to a selected set of other factors that have an impact on inflation in the short run, such as wages and import deflator developments. In the second place, professional forecasters have sometimes some information about future price developments at the time they produce their forecast that is not properly taken into account by most studies, when the recursive projections are performed mechanically *ex-post* (even using real time data). For instance, the VAT hike in Germany, which was implemented 1 January 2007, was known 8 months in advance. Such events are usually ignored in most statistical studies, whereas they have been accounted for here through dummy variables, and were also included in the autoregressive equations. Ignoring these shocks with a mechanical approach, when they are known and properly taken into account in real time, can lead to biased estimators and autocorrelation problems of different kinds in the different competing models and hence to wrong inference, as was shown in the previous section.

In order to further understand our findings with regards to the comparison between direct and indirect approaches, we have computed, for horizons of 1, 6 and 15 months, the correlation matrix of the sub-indexes equations' forecasting errors. Uncorrelated or negatively correlated forecasting errors suggest that they may compensate for each others to some extent when the sub-indexes forecasts are aggregated, giving an advantage to the indirect approach versus the direct one. On the opposite, strongly correlated errors would probably mean that a large part of them would add up, which would deteriorate the forecasting performance of the indirect approach in case of misspecification:

**horizon 1 month**

| | unprocessed food | processed food | manufactured goods | energy | services | Total | underlying |
|---|---|---|---|---|---|---|---|
| unprocessed food | 1.00 | 0.06 | -0.10 | -0.25 | 0.12 | 0.24 | 0.17 |
| processed food | 0.06 | 1.00 | -0.05 | -0.19 | 0.17 | -0.03 | 0.18 |
| manufactured goods | -0.10 | -0.05 | 1.00 | -0.11 | 0.24 | 0.12 | 0.53 |
| energy | -0.25 | -0.19 | -0.11 | 1.00 | 0.02 | 0.47 | -0.33 |
| services | 0.12 | 0.17 | 0.24 | 0.02 | 1.00 | 0.26 | 0.57 |
| total | 0.24 | -0.03 | 0.12 | 0.47 | 0.26 | 1.00 | 0.26 |
| underlying | 0.17 | 0.18 | 0.53 | -0.33 | 0.57 | 0.26 | 1.00 |

**horizon 6 months**

| | unprocessed food | processed food | manufactured goods | energy | services | Total | underlying |
|---|---|---|---|---|---|---|---|
| unprocessed food | 1.00 | 0.23 | -0.13 | -0.46 | 0.02 | -0.18 | -0.23 |
| processed food | 0.23 | 1.00 | -0.36 | -0.01 | 0.26 | 0.14 | -0.10 |
| manufactured goods | -0.13 | -0.36 | 1.00 | -0.35 | -0.06 | -0.13 | 0.37 |
| energy | -0.46 | -0.01 | -0.35 | 1.00 | 0.04 | 0.57 | -0.02 |
| services | 0.02 | 0.26 | -0.06 | 0.04 | 1.00 | 0.14 | 0.51 |
| Total | -0.18 | 0.14 | -0.13 | 0.57 | 0.14 | 1.00 | 0.32 |
| Underlying | -0.23 | -0.10 | 0.37 | -0.02 | 0.51 | 0.32 | 1.00 |

**horizon 15 months**

| | unprocessed food | processed food | manufactured goods | energy | services | Total | underlying |
|---|---|---|---|---|---|---|---|
| unprocessed food | 1.00 | 0.19 | 0.03 | -0.65 | 0.03 | -0.07 | -0.31 |
| processed food | 0.19 | 1.00 | -0.30 | -0.05 | 0.56 | 0.16 | 0.13 |
| manufactured goods | 0.03 | -0.30 | 1.00 | -0.31 | -0.11 | 0.06 | 0.57 |
| Energy | -0.65 | -0.05 | -0.31 | 1.00 | 0.26 | 0.28 | 0.12 |
| Services | 0.03 | 0.56 | -0.11 | 0.26 | 1.00 | 0.29 | 0.31 |
| Total | -0.07 | 0.16 | 0.06 | 0.28 | 0.29 | 1.00 | 0.51 |
| underlying | -0.31 | 0.13 | 0.57 | 0.12 | 0.31 | 0.51 | 1.00 |

For a 1-month horizon, the sub-indexes forecasting errors are not significantly positively correlated with each others. Thus, the performance of an aggregation of sector-based forecasts would not largely deteriorate for underlying HICP as compared to a single equation. For total HICP, the negative correlation between the forecasting errors of unprocessed food equation and (i) the energy equation on the one hand and (ii) the manufactured goods equations on the other hand are expected to allow the indirect approach to achieve quite good results, which is indeed the case according to the RMSE analysis.

For a 6-month horizon, there are only small correlations between the error forecasts of the subindices of the underlying inflation. Moreover, the negative correlation between the forecasting errors of the manufactured goods and processed food equations may be compensated for by the positive correlation between those of the services and processed food equations. Conversely, in the case of total HICP, the strong negative correlation between the unprocessed food and energy equations' forecasting errors, and to a lesser extent between those of the manufactured goods and energy equations, suggest that the errors of the disaggregated forecasts would compensate at the aggregate level.

The same interpretation can be done for a horizon of 15 months, with even more contrasted results between total and underlying HICP, on account of stronger positive correlation between forecasting errors for services and processed food HICP, and stronger negative correlation between forecasting errors for energy and unprocessed food HICP. These findings seem thus consistent with the relative higher forecasting performance in terms of RMSE of the disaggregated approach for total HICP as compared to underlying HICP.

On the whole, the fact that the disaggregated approach provides better forecasts for total HICP than for underlying HICP seems thus mainly related to:

– the relative good performances of the direct underlying HICP equation of our model, as compared to the total HICP equation;
– the quality of the energy and unprocessed food equations of our model;
– the positive correlations between forecast errors of services and processed food equations (in the sample under review);
– the negative correlations between forecast errors of energy and unprocessed food equations (in the sample under review).

## 4. Conclusion

Modelling inflation in the euro area is particularly challenging. Many papers document that inflation volatility has declined so that it has become more difficult to forecast (Cogley and Sargent 2005, Stock and Watson 2007, Cecchetti et alii 2007). Data is being slowly harmonized so that the characteristics of the series themselves change. Moreover, the monetary union is an institutional change that is added to all the world-wide shocks that influence inflation: globalisation, structural changes on the goods and labour markets, etc. Thus, there is a trade-off between the length of the sample used to estimate equations and the homogeneity of the period covered. We chose to start the estimations with the start of the HICP data for the euro zone, ie in the late 1980s. At that period, an important part of the members of the present euro area had already experienced low inflation (Germany, Austria, the Netherlands, France, Belgium), but this was not fully the case for some other countries of the euro area.

From an econometric point of point, data is not homogenous and breaks occurred. Moreover, the inflation in the euro area process is characterised by its persistence, so that series are very much autocorrelated. Thus, we have favoured simple robust estimation techniques (OLS). From a forecasting point of view, we have considered that some information was available at the time of the forecast and that major shocks such as oil shocks were perfectly taken into account in the forecasts. In order to benchmark the forecasts, we have considered the projections of overall and underlying inflation both directly and by aggregating forecasts for subindexes. We found that aggregation may be fruitful to forecast overall inflation, because of parameters uncertainty and negatively correlated shocks.

This work could be furthered along two directions: checking whether the dynamics of the different components of price and that of wage brings more information on the inflation process, and using synthetic indicators coming from large datasets in the forecast process such as dynamic factors.

## Bibliography

Stéphane Adjemian, Christophe Cahn, Antoine Devulder and Nicolas Maggiar (2007) “Variantes en univers incertain” Economie et prévision forthcoming

Nicholai Benalal, Juan Luiz Diaz del Hoyo, Bettina Landau, Moreno Roma, Frauke Skudelny (2004) “To aggregate or not to aggregate? Euro area inflation forecasting” ECB working paper n°374 July

Catherine Bruneau, Olivier de Bandt, Alexis Flageollet and Emmanuel Michaux (2007), "Forecasting Inflation Using Economic Indicators: the Case of France" Journal of Forecasting, January.

Timothy Cogley and Thomas Sargent (2007) “Inflation gap persistence in the US” Presented at 8th EABCN workshop on changes in inflation dynamics and implication for forecasting hosted by Banque de France, September

Stephen G. Cecchetti, Peter Hooper, Brunce C. Kasman, Kermit L. Schoenholtz, Mark W. Watson (2007) “Understanding the evolving inflationj process” Presented at the Fed US monetary policy forum

ECB (2000), “Seasonal Adjustments of Monetary Aggregates and HICP for the Euro Area”, August.

ECB (2001), "A guide to Eurosystem Staff Macroeconomic Projection Exercices", June.

ECB (2004) “Seasonal patterns and volatility in the euro area HICP”, ECB Monthly Bulletin, box 5 June .

Antoni Espasa, Eva Senra and Rebecca Albacete (2002) “Forecasting inflation in the European Monetary Union : a disaggregated approach by countries and sectors” The European journal of Finance n°8, pp 402-421.

Neil. R Ericsson, James G. Mackinnon (2002) “Distributions of error correction tests for cointegration” Econometrics Journal), volume 5, pp. 285–318.

Gabriel Fagan, Jérôme Henry and Ricardo Mestre (2001)"An area-wide model (AWM) for the euro area," Working Paper Series 42, European Central Bank.

Philippe Gallot, Benoît Heitz (2004) « L’inflation en France et en zone euro : une approche macro sectorielle » Note de conjoncture INSEE de mars 2004

Robert J. Gordon (1982) « Price inertia and ineffectiveness in the United States » Journal of Political Economy n°90, pp 1087-1117

David F. Hendry, Kirstin Hubrich, (2007), “Combining disaggregate forecasts or combining disaggregate information to forecast an aggregate”, *mimeo*, May

Kirstin Hubrich, (2005), “Forecasting euro area inflation: Does aggregating forecasts by HICP component improve forecast accuracy?”, International Journal of Forecasting n°21, pp. 119– 136

Sharon Kozicki, Hoffmann Barak, (2004), “Rounding Error: A Distorting Influence on Index Data” Journal of Money, Credit and Banking Vol. 36, No. 3 (June 2004, Part 1) pp 319-338

Eric Jondeau, Hervé Le Bihan and Franck Sédillot (1999) « Modélisation et prévision des indices de prix sectoriels » Note d'études et de recherche Banque de France n°68

Gilles Moec, (2003), « Les écarts d'inflation dans la zone euro : éléments de quantification et d'analyse », Bulletin de la Banque de France n°115, juillet

Athanasios Orphanides, Simon Van Norden, (2005) « The Reliability of Inflation Forecasts Based on Output Gap Estimates in Real Time" Journal of Money, Credit and Banking vol 37 issue 3 pp583-601

Jeremy Rudd, Karl Whelan (2007) "Modeling inflation dynamics: a critical review of recent research" Money, credit and banking vol 39, n°1

James H. Stock, Mark W. Watson (1999) "Forecasting inflation" Journal of monetary economics n°44 pp293-335

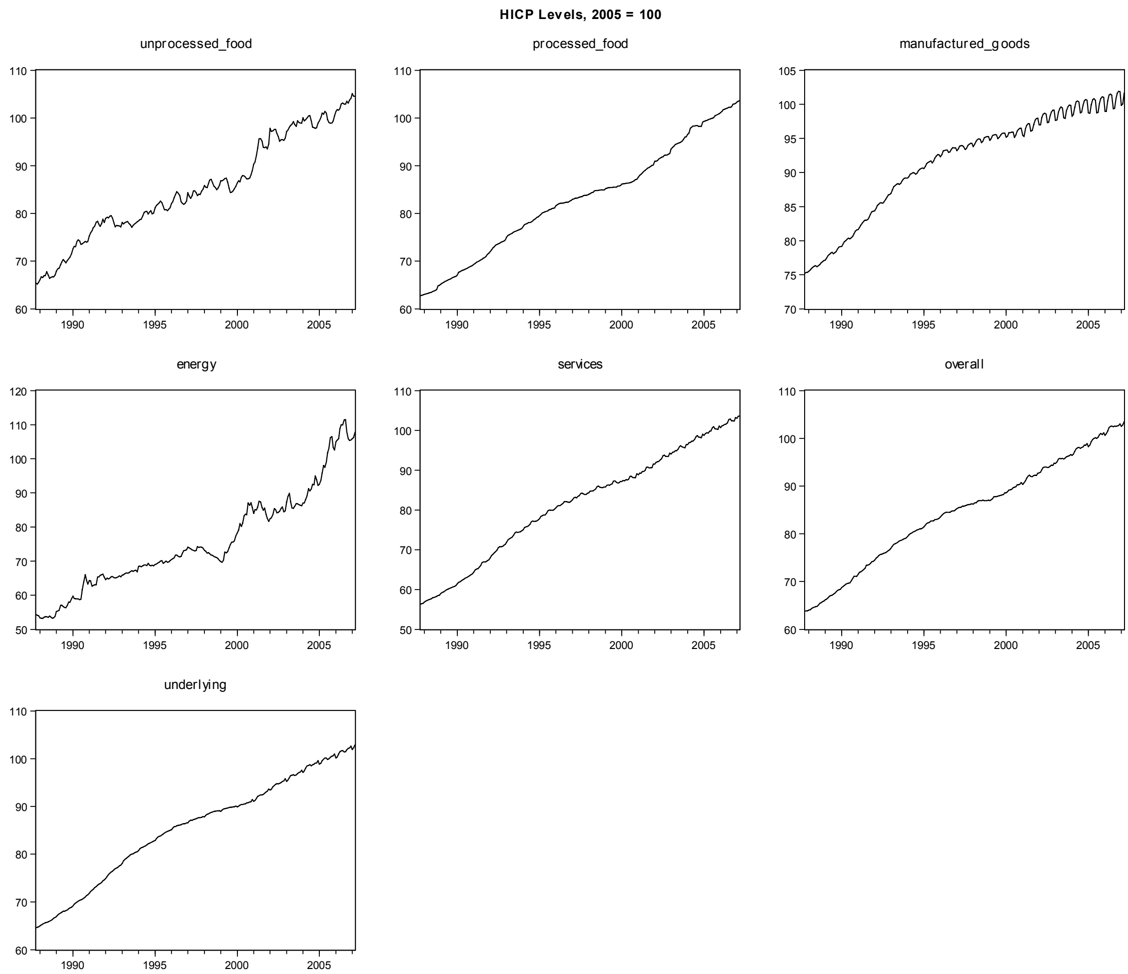
James H. Stock, Mark W. Watson (2007) "Why has inflation become harder to forecast?" Journal of Money, credit and banking, supplement to Vol. 39, n°1pp 3-33

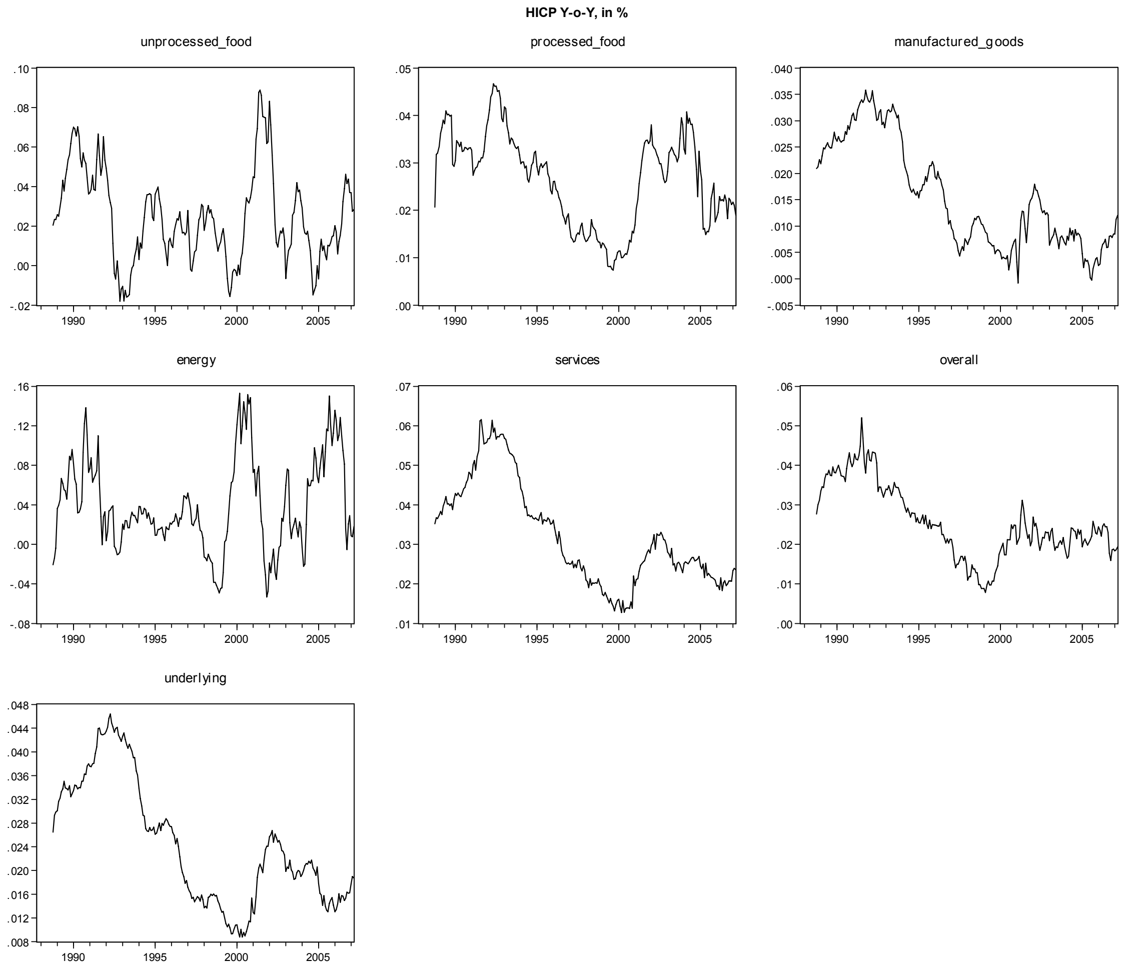
# Annexes

## Annex 1: Development of HICP methodology

| Year | UE legislation | Harmonisation measures | Implementation |
|---|---|---|---|
| 1992 | Treaty establishing the UE, protocol No. 6 | Criterion on price stability | |
| 1995 | Council Regulation No. 2494/95, 23 October 1995 | Set framework for harmonisation and required provision of HICPs | Jan 1997 |
| 1996 | Commission Regulations No. 1749/96, 9 September 1996 No. 2214/96, 20 November 1996 | - Initial common coverage of HICPs<br>- Classification and publication of sub-indices<br>- Minimum standards for quality adjustment<br>- Comparable formulae for compiling elementary aggregates<br>- Minimum standards for the treatment of missing observations<br>- Standard for the inclusion of new goods | Jan 1997 |
| 1997 | Commission Regulation No. 2454/97, 10 December 1997 | - Standard item weight update frequency | 1998 |
| | Guideline | - Standard practice for revisions of HICP results | 1998 |
| 1998 | Council Regulation | - Extension of coverage to health, education and social services<br>- geographic and population coverage | Déc 1999, dec. 2000, dec. 2001 |
| | Commission Regulation No. 2646/98, 9 December 1998 | - Standard treatment of tariff prices | Dec 1998 |
| 1999 | Commission Regulation No. 1617/1999, 23 July 1999 | - Standard treatment of insurance services | 1999 |
| | Council Regulation No. 2166/1999, 8 October 1999 | - Minimum standards for the treatment of products in the health, education and social protection sectors | Dec 1999, dec 2000 |
| | Guidelines | - Treatment of price reductions (sales period)<br>- Treatment of rejected price observations<br>- Coverage of personal computers | Dec 1998 |
| 2000 | Commission Regulations No. 2601/2000, 17 November 2000 No. 2602/2000, 17 November 2000 | - Minimum standard for the treatment of price reductions<br>- Timing of entry of purchasers prices | Dec 2000 |
| 2001 | Commission Regulations No.1920/2001, 28 September 2001 No. 1921/2001, 28 September 2001 | - Minimum standards for the treatment of services charges proportional to transactions values<br>- Minimum standards for revisions | Dec 2001 |
| 2005 | Commission Regulation No. 1708/2005, 19 October 2005 | - Common reference period for the index (2005 = 100) | |
| | Recommandation Commission 8 December 2005 (2005/881/EC) | - Questions linked to health care reform (following the reform in the Netherlands) | |
| 2006 | Council Regulation No. 701/2006, 25 April 2006 | - Temporal coverage of the price collection | Dec 2007 |

# Annex 2: HICP series: graphs






## Annex 3: Specification of the estimated price equation

$$P = \frac{(1+m)(1-\lambda)(1+\tau)}{1-(1-\mu)(1+m)\theta_1}\left[ULC + \left(\lambda + \theta_1(1+m)(\mu-\lambda)\right)P^M + \theta_2 P^{brent}\right]$$

Taking the log of this expression leads to:

$$\log P = \log(1+\tau) + \log\left[\frac{(1+m)(1-\lambda)}{1-(1-\mu)(1+m)\theta_1}\right] + \log\left[ULC + \left(\lambda + \theta_1(1+m)(\mu-\lambda)\right)P^M + \theta_2 P^{brent}\right]$$

The last term can be log-linearized:

$$
\begin{aligned}
\log\left[ULC+\left(\lambda+\theta_1(1+m)(\mu-\lambda)\right)P^M+\theta_2 P^{brent}\right] \approx{} & \log\left[ULC_0+\left(\lambda+\theta_1(1+m)(\mu-\lambda)\right)P_0^M+\theta_2 P_0^{brent}\right] \\
& +\frac{ULC_0}{\left[ULC_0+\left(\lambda+\theta_1(1+m)(\mu-\lambda)\right)P_0^M+\theta_2 P_0^{brent}\right]}\cdot\bigl(\log ULC-\log ULC \\
& +\frac{\left(\lambda+\theta_1(1+m)(\mu-\lambda)\right)P_0^M}{\left[ULC_0+\left(\lambda+\theta_1(1+m)(\mu-\lambda)\right)P_0^M+\theta_2 P_0^{brent}\right]}\cdot\left(\log P^M-\log P_0^M\right) \\
& +\frac{\theta_2 P_0^{brent}}{\left[ULC_0+\left(\lambda+\theta_1(1+m)(\mu-\lambda)\right)P_0^M+\theta_2 P_0^{brent}\right]}\cdot\bigl(\log P^{brent}-\log P_0^{bre}
\end{aligned}
$$

Or, in a more compact way:

$$\log\left[ULC+\left(\lambda+\theta_1(1+m)(\mu-\lambda)\right)P^M+\theta_2 P^{brent}\right]\approx\alpha_1\log P^M+\alpha_2\log ULC++\alpha_3\log P^{brent}+\beta$$

with:

$$
\begin{aligned}
\alpha_1 &= \frac{\left(\lambda+\theta_1(1+m)(\mu-\lambda)\right)P_0^M}{\left[ULC_0+\left(\lambda+\theta_1(1+m)(\mu-\lambda)\right)P_0^M+\theta_2 P_0^{brent}\right]} \\
\alpha_2 &= \frac{ULC_0}{\left[ULC_0+\left(\lambda+\theta_1(1+m)(\mu-\lambda)\right)P_0^M+\theta_2 P_0^{brent}\right]} \\
\alpha_3 &= \frac{\theta_2 P_0^{brent}}{\left[ULC_0+\left(\lambda+\theta_1(1+m)(\mu-\lambda)\right)P_0^M+\theta_2 P_0^{brent}\right]} \\
\beta &= \log\left[ULC_0+\left(\lambda+\theta_1(1+m)(\mu-\lambda)\right)P_0^M+\theta_2 P_0^{brent}\right]-\frac{ULC_0}{\left[ULC_0+\left(\lambda+\theta_1(1+m)(\mu-\lambda)\right)P_0^M+\theta_2 P_0^{brent}\right]}\log ULC_0 \\
&\quad-\frac{\left(\lambda+\theta_1(1+m)(\mu-\lambda)\right)P_0^M}{\left[ULC_0+\left(\lambda+\theta_1(1+m)(\mu-\lambda)\right)P_0^M+\theta_2 P_0^{brent}\right]}\cdot\log P_0^M \\
&\quad-\frac{\theta_2 P_0^{brent}}{\left[ULC_0+\left(\lambda+\theta_1(1+m)(\mu-\lambda)\right)P_0^M+\theta_2 P_0^{brent}\right]}\log P_0^{brent}
\end{aligned}
$$

Finally the price equation in logs becomes:

$$\log P=\log(1+\tau)+\alpha_1\log P^M+\alpha_2\log ULC+\alpha_3\log P^{brent}+\alpha_4$$

with: $\alpha_4=\log\left[\frac{(1+m)(1-\lambda)}{1-(1-\mu)(1+m)\theta_1}\right]+\beta$

and, by construction $\alpha_1+\alpha_2+\alpha_3=1$.

## Annex 4: Impulse responses

The shocks are permanent and implemented in the following way, by types of variables:

- ULC, import deflator excluding energy, import deflator, trend: +1 %
- Brent prices denominated in Euro, +10 %, total import prices or import prices excluding energy + 1% (the elasticity of the import deflator to the price of the brent denominated in euro being assumed to be 10 %)
- CUR, Unemployment rate, standard VAT rate, residuals: + 1 pp

We report the dynamic impact of a permanent change in the level of the residual by 0.01. This shock is not meaningful in economic terms but represents for the forecaster the impact of such a change in the add-factor for the forecast.

The tables report the deviation in % of the level of the indexes with respect to the baseline.

| | 1st quarter | 4th quarter | 8th quarter | 20th quarter |
|---|---|---|---|---|
| **HICP overall- direct** | | | | |
| ULC | 0.00 | 0.08 | 0.22 | 0.50 |
| Import deflator excl. energy | 0.00 | 0.06 | 0.08 | 0.12 |
| Brent price in € | 0.06 | 0.12 | 0.15 | 0.19 |
| CUR | 0.00 | 0.05 | 0.04 | 0.02 |
| Unemployment rate | 0.00 | -0.12 | -0.58 | -1.51 |
| Residuals | 0.01 | 0.04 | 0.07 | 0.14 |
| **HICP overall - indirect** | | | | |
| ULC | 0.00 | 0.06 | 0.24 | 0.55 |
| Import deflator excl. energy | 0.00 | 0.02 | 0.08 | 0.19 |
| Brent price in € | 0.09 | 0.12 | 0.19 | 0.32 |
| CUR | 0.00 | 0.04 | 0.03 | 0.01 |
| Unemp. rate | 0.00 | -0.02 | -0.15 | -0.37 |
| VAT | 0.02 | 0.15 | 0.11 | 0.04 |
| Residuals | 0.00 | 0.05 | 0.09 | 0.16 |
| **HICP overall - underlying & volatile components** | | | | |
| ULC | 0.00 | 0.04 | 0.23 | 0.55 |
| Import deflator excluding energy | 0.00 | 0.01 | 0.06 | 0.15 |
| Brent price in € | 0.09 | 0.12 | 0.17 | 0.27 |
| CUR | 0.00 | 0.02 | 0.01 | 0.00 |
| Unemp. rate | 0.00 | -0.05 | -0.27 | -0.64 |
| VAT | 0.02 | 0.18 | 0.13 | 0.05 |
| Residuals | 0.00 | 0.05 | 0.09 | 0.15 |
| **HICP underlying- direct** | | | | |
| ULC | 0.00 | 0.05 | 0.27 | 0.66 |
| Import deflator | 0.00 | 0.01 | 0.08 | 0.20 |
| Unemp. rate | 0.00 | -0.06 | -0.32 | -0.78 |
| VAT | 0.19 | 0.22 | 0.16 | 0.06 |
| Residuals | 0.01 | 0.05 | 0.09 | 0.15 |
| **HICP underlying - indirect** | | | | |
| ULC | 0.00 | 0.07 | 0.29 | 0.67 |
| Import deflator excluding energy | 0.00 | 0.02 | 0.10 | 0.23 |
| Brent price in € | 0.00 | 0.02 | 0.11 | 0.26 |
| CUR | 0.00 | 0.02 | 0.02 | 0.01 |
| Unemp. rate | 0.00 | -0.03 | -0.18 | -0.44 |
| VAT | 0.02 | 0.18 | 0.13 | 0.05 |
| Residuals | 0.00 | 0.05 | 0.09 | 0.15 |
| **HICP processed food** | | | | |
| ULC | 0.00 | 0.19 | 0.37 | 0.63 |
| Import deflator | 0.00 | 0.08 | 0.26 | 0.58 |
| Residuals | 0.01 | 0.05 | 0.10 | 0.19 |

| | 1st quarter | 4th quarter | 8th quarter | 20th quarter |
|---|---|---|---|---|
| **HICP manufactured goods** | | | | |
| ULC | 0.00 | 0.04 | 0.19 | 0.43 |
| Import deflator | 0.00 | 0.01 | 0.06 | 0.13 |
| VAT | 0.16 | 0.15 | 0.10 | 0.03 |
| Residuals | 0.01 | 0.04 | 0.07 | 0.11 |
| **HICP services** | | | | |
| ULC | 0.00 | 0.06 | 0.36 | 0.90 |
| Import deflator | 0.00 | 0.02 | 0.10 | 0.26 |
| CUR | 0.00 | 0.05 | 0.04 | 0.01 |
| Unemp. rate | 0.00 | -0.06 | -0.40 | -1.00 |
| VAT | 0.20 | 0.28 | 0.21 | 0.08 |
| Residuals | 0.01 | 0.05 | 0.10 | 0.17 |
| **HICP unprocessed food** | | | | |
| Brent price in € | 0.00 | 0.22 | 0.50 | 0.69 |
| CUR | 0.00 | 0.29 | 0.13 | 0.01 |
| Trend | 0.00 | 0.01 | 0.03 | 0.07 |
| Residuals | 0.00 | 0.00 | 0.00 | 0.00 |
| **HICP energy** | | | | |
| Brent price in € | 1.13 | 1.72 | 2.26 | 3.29 |
| Residuals | 0.00 | 0.00 | 0.00 | 0.00 |

## Annex 5: Estimations corrected for heteroskedasticity and autocorrelation of residuals (Newey-West)

Overall HICP

$$\begin{aligned}\Delta \log(P_t) &= \underset{[4.33]}{0.0065}\ \Delta \log(P_t^{brent}) + \underset{[2.24]}{0.0005}\ \Delta CUR_{t-2} + \underset{[2.88]}{0.0546}\ \Delta \log(P_{t-1}^M) - \underset{[-11.6]}{0.0470}\ \log(P_{t-2}) \\ &+ \underset{[5.64]}{0.0374}\ \log(ULC_{t-2}) + \underset{[3.11]}{0.0117}\ \log(P_{t-2}^M) - \underset{[-7.82]}{0.0012}\ U_{t-3} + \underset{[9.29]}{0.0032}\ (Dum\,1991\,q3 - Dum\,1991\,q4) \\ &- \underset{[-7.73]}{0.0033}\ (Dum\,2001\,q1 - Dum\,2001\,q2) - \underset{[-8.11]}{0.0049}\ Dum\,2000\,q2 + \varepsilon_t\end{aligned}$$

Underlying HICP

$$\begin{aligned}\Delta \log(P_t) &= \underset{[1.92]}{0.2373}\Delta \log(P_{t-1}) + \underset{[4.00]}{0.0025}\Delta VAT_t - \underset{[-4.52]}{0.0512}\log(P_{t-3}) + \underset{[4.10]}{0.0449}\log(ULC_{t-3}) + \underset{[2.80]}{0.0131}\log(P_{t-3}^M) \\ &- \underset{[-3.66]}{0.0006}U_{t-3} - \underset{[-1.68]}{0.0293} - \underset{[-8.03]}{0.0020}Dum2000q2 - \underset{[-11.69]}{0.0010}(Dum2001q1 - Dum2001q2) \\ &- \underset{[-8.10]}{0.0022}Dum1993q4 + \underset{[8.91]}{0.0018}Dum2004q1 + \varepsilon_t\end{aligned}$$

Services prices

$$\begin{aligned}\Delta \log(P_t) &= \underset{[2.45]}{0.3111}\Delta \log(P_{t-1}) + \underset{[2.57]}{0.0004}\Delta CUR_{t-1} + \underset{[1.89]}{0.0019}\Delta VAT_t - \underset{[-3.52]}{0.0465}\log(P_{t-3}) + \underset{[3.11]}{0.0561}\log(ULC_{t-3}) \\ &+ \underset{[2.34]}{0.0164}\log(P_{t-3}^M) - \underset{[-3.26]}{0.0006}U_{t-3} - \underset{[-2.68]}{0.1171} + \underset{[7.14]}{0.0030}Dum1990q4 + \underset{[11.17]}{0.0036}(Dum1991q3 - Dum1991q4) + \varepsilon_t\end{aligned}$$

Manufactured goods prices

$$\Delta \log(P_t) = \underset{[1.40]}{0.0016}\Delta VAT_t - \underset{[-8.13]}{0.0788}\log(P_{t-3}) + \underset{[4.62]}{0.0416}\log(ULC_{t-3}) + \underset{[1.99]}{0.0123}\log(P_{t-3}^M) + \underset{[6.60]}{0.1120} + \varepsilon_t$$

Processed food prices

$$\Delta\log(P_t) = \underset{[4.68]}{0.3886}\,\Delta\log(P_{t-1}) + \underset{[2.00]}{0.0813}\,\Delta\log(ULC_{t-2}) - \underset{[-4.40]}{0.04001}\log(P_{t-2}) + \underset{[3.66]}{0.0319}\log(ULC_{t-2})$$
$$+\underset{[4.70]}{0.0323}\log(P^{M}_{t-2}) - \underset{[-4.48]}{0.1156} + \underset{[24.7]}{0.0077}\,Dum2003q1 + \underset{[13.1]}{0.0065}\,Dum2003q4 + \underset{[8.70]}{0.0059}\,Dum2004q2 + \varepsilon_t$$

Unprocessed food prices

$$\Delta\log(P_t) = \underset{[2.55]}{0.0029}\,\Delta CUR_{t-2} - \underset{[-3.68]}{0.1507}\log(P_{t-2}) + \underset{[5.93]}{0.0112}\log(P^{brent}_{t-2}) + \underset{[3.57]}{0.6186} + \underset{[2.51]}{0.0006}\,trend$$
$$+\underset{[10.1]}{0.0153}\,Dum1991q3 + \underset{[15.2]}{0.0200}\,Dum2001q2 + \underset{[20.0]}{0.0234}\,Dum2002q1 + \underset{[15.7]}{0.0155}\,Dum2003q3 - \underset{[-5.57]}{0.0103}Dum2007q1 + \varepsilon_t$$

Energy prices

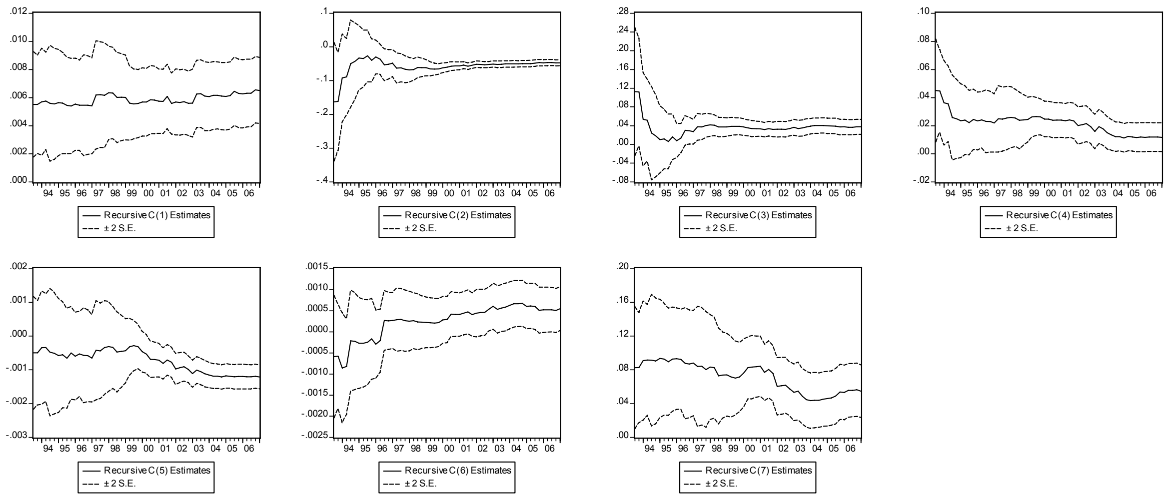
$$\Delta\log(P_t) = \underset{[8.84]}{0.0989}\,\Delta\log(P^{brent}_{t}) + \underset{[6.67]}{0.0518}\,\Delta\log(P^{brent}_{t-1}) - \underset{[-3.12]}{0.0454}\log(P_{t-3}) + \underset{[3.67]}{0.0205}\log(P^{brent}_{t-3}) + \underset{[2.84]}{0.1410}$$
$$+\underset{[13.4]}{0.0213}\,Dum1994q1 + \underset{[13.1]}{0.0252}(Dum2003q1 - Dum2003q2) + \varepsilon_t$$

## Annex 6: Coefficient estimation stability

In order to check to robustness of our estimates, we set out below graphs representing the estimated values and confidence ranges of our equations' coefficients as the estimation sample varies (the starting point is fixed and the ending point moves forward):

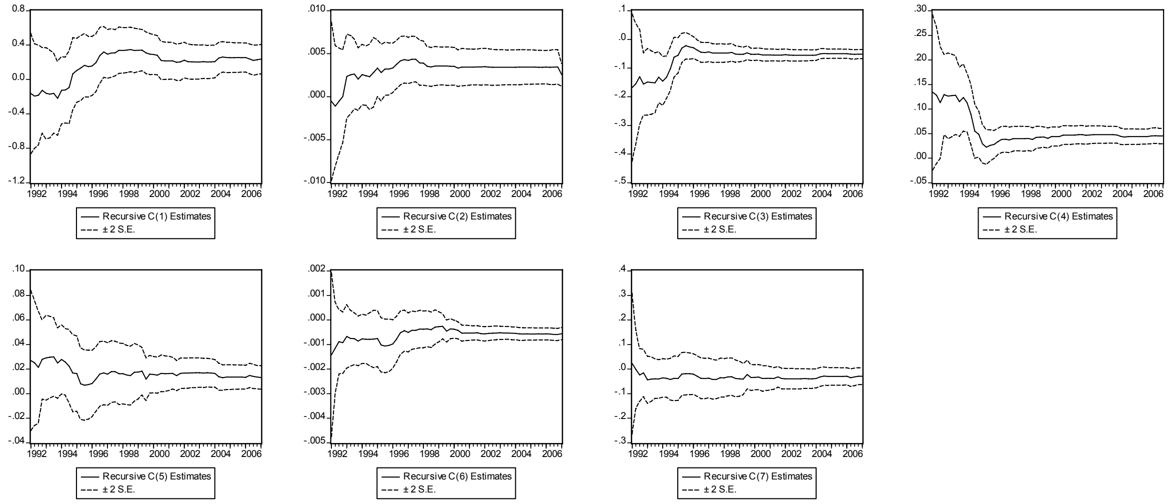
Total HICP

| parameter | corresponding variable |
|---|---|
| C(1) | dlog(brenteuro) |
| C(2) | log(P(-2)) |
| C(3) | log(ULC)) |
| C(4) | log(Pm(-2)) |
| C(5) | U(-3) |
| C(6) | d(CUR(-2)) |
| C(7) | dlog(Pm(-1)) |



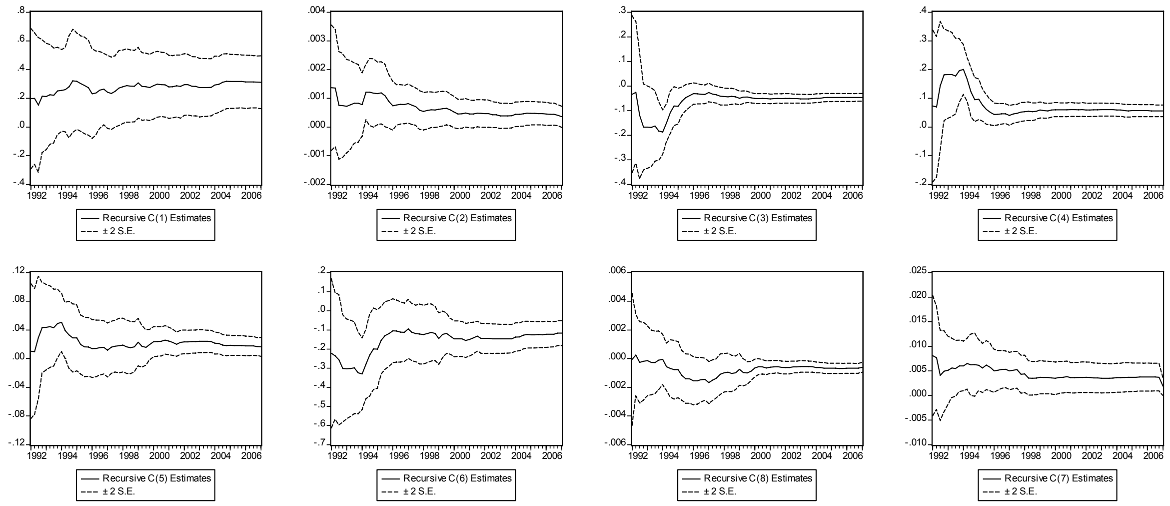
## Underlying HICP

| parameter | corresponding variable |
|---|---|
| C(1) | dlog(P(-1)) |
| C(2) | d(VAT) |
| C(3) | log(P(-3)) |
| C(4) | log(ULC(-3)) |
| C(5) | log(Pm(-3)) |
| C(6) | U(-3) |
| C(7) | C |



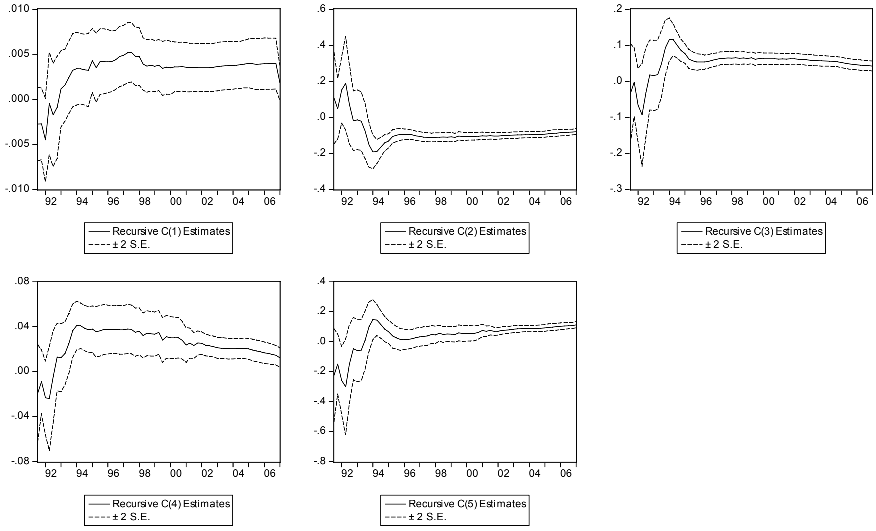

## Services

| parameter | corresponding variable |
|---|---|
| C(1) | dlog(P(-1)) |
| C(2) | d(CUR(-1)) |
| C(3) | log(P(-3)) |
| C(4) | log(ULC(-3)) |
| C(5) | log(Pm(-3)) |
| C(6) | C |
| C(7) | U(-3) |
| C(8) | d(VAT) |



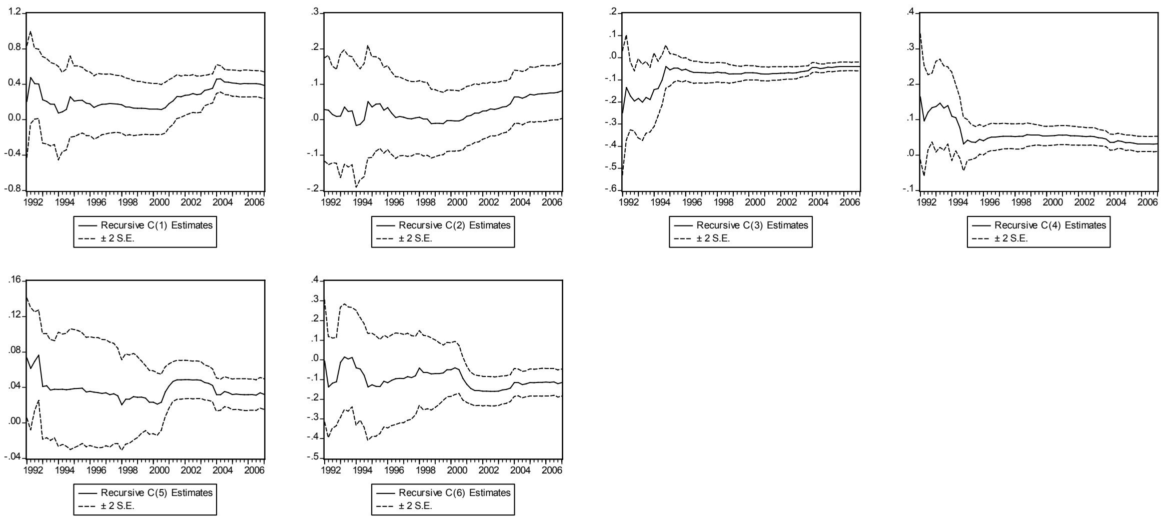
## Manufactured goods

| parameter | corresponding variable |
|---|---|
| C(1) | d(VAT) |
| C(2) | log(P(-3)) |
| C(3) | log(ULC(-3)) |
| C(4) | log(Pm(-3)) |
| C(5) | C |



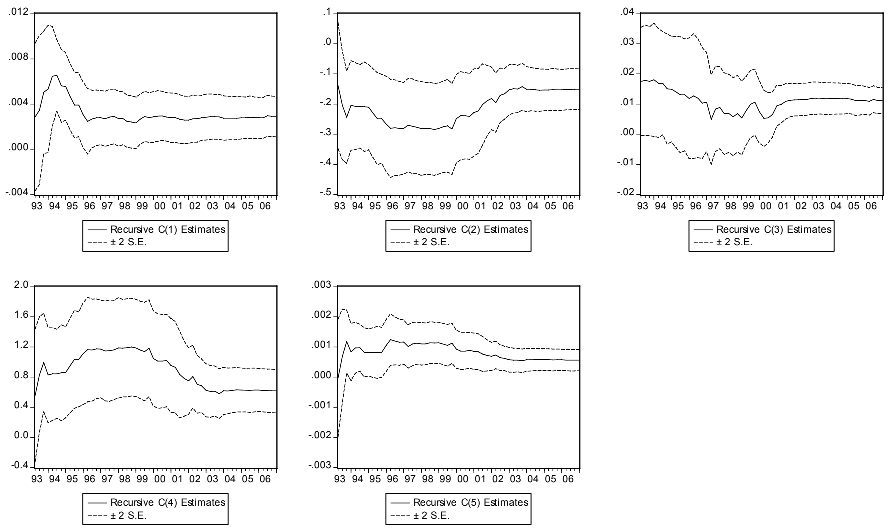

## Processed food

| parameter | corresponding variable |
|---|---|
| C(1) | dlog(P(-1)) |
| C(2) | dlog(ULC(-2)) |
| C(3) | log(P(-2)) |
| C(4) | log(ULC(-2)) |
| C(5) | log(Pm(-2)) |
| C(6) | C |



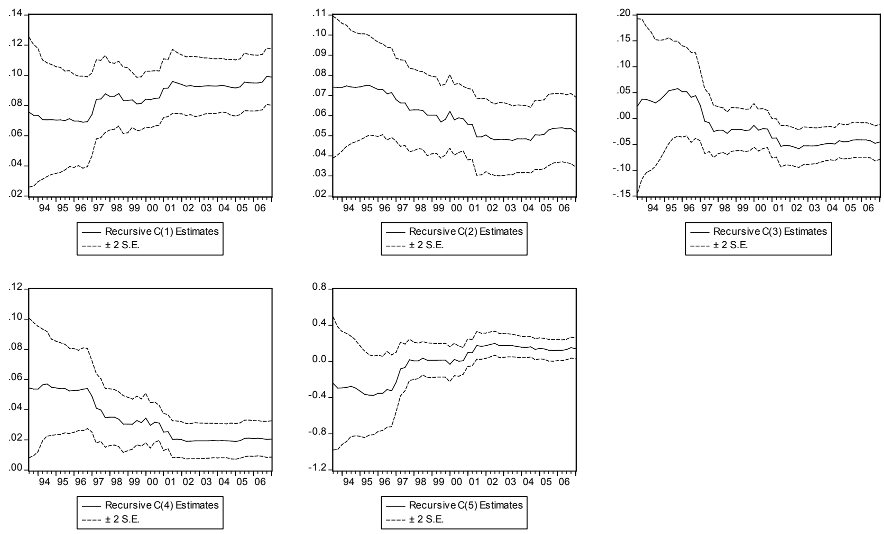
## Unprocessed food

| parameter | corresponding variable |
|---|---|
| C(1) | d(TUC(-2)) |
| C(2) | log(P(-2)) |
| C(3) | log(brenteuro(-2)) |
| C(4) | C |
| C(5) | trend |




## Energy

| parameter | corresponding variable |
|---|---|
| C(1) | dlog(brenteuro) |
| C(2) | dlog(brenteuro(-1)) |
| C(3) | log(P(-3)) |
| C(4) | log(brenteuro(-3)) |
| C(5) | C |



## Notes d'Études et de Recherche

171. O. Darné et V. Brunhes-Lesage, « L'Indicateur Synthétique Mensuel d'Activité (ISMA) : une révision », Juillet 2007.

172. R. Kierzenkowski et V. Oung, « L'évolution des crédits à l'habitat en France : une grille d'analyse en termes de cycles », Juillet 2007.

173. O. de Bandt, A. Banerjee and T. Koźluk, "Measuring Long-Run Exchange Rate Pass-Through," July 2007.

174. J. Alho and V. Borgy, "Global Ageing and Macroeconomic Consequences of Demographic Uncertainty in a Multi-regional Model," July 2007.

175. J.-S. Mésonnier and J.-P. Renne, "Does uncertainty make a time-varying natural rate of interest irrelevant for the conduct of monetary policy?," September 2007.

176. J. Idier and S. Nardelli, "Probability of informed trading: an empirical application to the euro overnight market rate," September 2007.

177. H. Partouche, "Time-Varying Coefficients in a GMM Framework: Estimation of a Forward Looking Taylor Rule for the Federal Reserve," September 2007.

178. C. Ewerhart and N. Valla, "Financial Market Liquidity and the Lender of Last Resort," September 2007.

179. C. Ewerhart and N. Valla, "Forced Portfolio Liquidation," September 2007.

180. P.-A. Beretti and G. Cette, "Indirect ICT Investment," September 2007.

181. E. Jondeau and J.-G. Sahuc, "Testing heterogeneity within the euro area," September 2007.

182. J.-G. Sahuc and Frank Smets, "Differences in Interest Rate Policy at the ECB and the Fed: An Investigation with a Medium-Scale DSGE Model," September 2007.

183. J. Coffinet and S. Gouteron, "Euro Area Market Reactions to the Monetary Developments Press Release," October 2007.

184. C. Poilly, "Does Money Matter for the Identification of Monetary Policy Shocks: A DSGE Perspective," October 2007.

185. E. Dhyne, C. Fuss, H. Pesaran and P. Sevestre, "Lumpy Price Adjustments: a Microeconometric Analysis," October 2007.

186. R. Cooper, H. Kempf and D. Peled, "Regional Debt in Monetary Unions: Is it Inflationary?," November 2007.

187. M. Adanero-Donderis, O. Darné and L. Ferrara, « Deux indicateurs probabilistes de retournement cyclique pour l'économie française », Novembre 2007.

188. H. Bertholon, A. Monfort and F. Pegoraro, "Pricing and Inference with Mixtures of Conditionally Normal Processes," November 2007.

189. A. Monfort and F. Pegoraro, "Multi-Lag Term Structure Models with Stochastic Risk Premia," November 2007.

190. F. Collard, P. Fève and J. Matheron, “The Dynamic Effects of Disinflation Policies,” November 2007.

191. A. Monfort and F. Pegoraro, “Switching VARMA Term Structure Models - Extended Version,” December 2007.

192. V. Chauvin and A. Devulder, “An Inflation Forecasting Model For The Euro Area,” January 2008.

Pour accéder à la liste complète des Notes d’Études et de Recherche publiées par la Banque de France veuillez consulter le site : http://www.banque-france.fr/fr/publications/ner/ner.htm

For a complete list of Working Papers published by the Banque de France, please visit the website: http://www.banque-france.fr/gb/publications/ner/ner.htm

Pour tous commentaires ou demandes sur les Notes d'Études et de Recherche, contacter la bibliothèque de la direction de la recherche à l'adresse suivante :

For any comment or enquiries on the Working Papers, contact the library of the Research Directorate at the following address :

BANQUE DE FRANCE
41- 1404 Labolog
75049 Paris Cedex 01
tél : 0033 (0)1 42 92 49 55 ou 62 65
fax :0033 (0)1 42 92 62 92
email : thierry.demoulin@banque-france.fr
jeannine.agoutin@banque-france.fr