NOTES D'ÉTUDES

ET DE RECHERCHE

FORECASTING INFLATION IN THE EURO AREA

Catherine Bruneau, Olivier De Bandt and Alexis Flageollet

May 2003

NER # 102

BANQUE DE FRANCE

DIRECTION GÉNÉRALE DES ÉTUDES ET DES RELATIONS INTERNATIONALES

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

FORECASTING INFLATION IN THE EURO AREA

Catherine Bruneau, Olivier De Bandt and Alexis Flageollet

May 2003

NER # 102

Forecasting Inflation in the Euro Area*

C. Bruneau†, O. De Bandt‡, A. Flageollet§

March 2003

*Comments on a earlier draft of the paper by A. Banerjee, E. Jondeau, L. Maurin and E. Michaux, as well as participants to the seminar "Modelling and forecasting price and wage developments in France, the euro area and the US" (Paris, Dec. 2002) are gratefully acknowledged. All errors remain ours. Views expressed in the paper are those of the authors and do not necessarily reflect those of the Banque de France or the Eurosystem.

†Banque de France and University of Paris X (Thema)

‡Banque de France, corresponding author. E-mail olivier.debandt@banque-france.fr

§Banque de France and University of Paris X (Thema)

Résumé:

De façon à obtenir des prévisions de moyen terme de l'inflation pour la zone euro, mesurée par l'IPCH total et sous-jacent, nous évaluons la performance des modèles factoriels dynamiques. Nous appliquons la méthodologie de Stock et Watson (1999) pour des prévisions hors échantillon sur la période 1988:1-2002:3, avec un panel de données soit cylindrées, soit non cylindrées. Nous mettons en évidence que les facteurs seuls ou combinés à des indicateurs permettent de prévoir mieux que le modèle autorégressif, à la fois pour l'inflation sous-jacente et l'inflation totale, sur la base du critère de "MSE relative" et en tenant compte de son écart-type. Cependant, s'agissant de l'IPCH total, nous ne produisons pas de prévisions totalement satisfaisantes, c'est-à-dire permettant de détecter suffisamment rapidement le redressement de l'inflation en 1999/2000. Mais nous élaborons un indicateur "synthétique" d'inflation sous-jacente qui possède de meilleures performances que le modèle auto-régressif pour des prévisions à 12 mois sur la dernière partie de l'échantillon. Nous montrons aussi que les résultats sont assez robustes au risque de "data snooping".

Mots clefs : inflation, prévisions hors échantillon, modèles à base d'indicateurs, modèles factoriels dynamiques, courbe de Phillips, zone euro, data snooping.

Abstract:

In order to provide medium run forecasts of headline and core HICP inflation for the euro area, we assess the usefulness of dynamic factor models. We use Stock and Watson's (1999) out-of-sample methodology for models estimated over the 1988:1-2002:3 period, with balanced and unbalanced panels. We provide evidence that factors alone or combined with indicators help improve upon the simple Autoregressive (AR) model for forecasting HICP core inflation as well total inflation, if one refers to the usual criterion of "Relative MSE" together with its standard deviation. However, regarding total HICP we do not produce forecasts that are totally satisfactory in the sense of being capable of recognizing the 1999-2000 upturn in inflation in a timely manner. But, from that point of view, the construction of a "synthetic core" indicator helps achieve significantly better forecasts over a 12-month horizon than the AR model for total inflation for the final part of the sample. We also show that the results are rather robust to potential data-snooping.

Key words : inflation, out-of-sample forecast, indicator models, dynamic factor models, Phillips curve, euro area, data snooping

JEL: C33, C53, E37.

Résumé non technique

Le papier étend au cas de la prévision d'inflation dans la zone euro la méthodologie développée par Stock et Watson (1998 et 1999) pour comparer les propriétés prédictives d'un grand nombre d'indicateurs macro-économiques, soit de façon isolée, soit simultanément. Dans notre étude, les indicateurs utilisés sont tirés pour l'essentiel des enquêtes de conjoncture menées au niveau national ou à l'échelle de l'ensemble de la zone euro, mais nous prenons aussi en compte les autres indicateurs conjoncturels disponibles ainsi que quelques variables financières. Pour l'essentiel, nous cherchons à prévoir à 12 mois l'inflation, mesurée en glissement annuel, à partir de l'inflation courante (et de ses retards) et d'indicateurs avancés disponibles à la période courante (et de leurs retards). Pour tester la performance d'un indicateur, nous réalisons des prévisions récursives en étendant progressivement l'échantillon.

En raison de contraintes de disponibilité de l'Indice des Prix de Consommation (IPCH) de la zone euro au niveau mensuel, l'analyse se limite à la période 1988:1-2002:12 (nous reconstruisons ces séries sur les années 1980), les prévisions commençant en 1996:1. Pour chaque indicateur, nous calculons l'erreur quadratique moyenne (RMSE), ainsi que son écart-type de façon à apprécier si la performance du modèle est meilleure que celle du modèle de référence, à savoir le modèle auto-régressif (AR). Dans ce dernier cas, l'inflation dans 12 mois n'est expliquée que par l'inflation actuelle. Il convient d'ailleurs de rappeler que le modèle AR est assez performant en prévision sur la période 1996-1998.

Nous avons pour cela construit une base de données comprenant 310 variables, avec des données homogènes par pays. Nous utilisons ces variables soit directement, sous forme d'agrégats zone euro, soit en extrayant des facteurs dynamiques à partir d'analyses en composantes principales (ACP) récursives sur l'ensemble de la base de données ou sur des sous-ensembles de variables.

Ce type d'approche, qui compare un grand nombre de modèles et d'indicateurs différents (indicateurs simples ou multiples, facteurs, combinaison d'indicateurs et de facteurs) peut néanmoins courir le risque de "surexploitation des données" ("data snooping"), qui est souvent négligé dans ce type de littérature. En effet, en recherchant le meilleur modèle au sein d'un grand nombre de modèles, il est possible d'en trouver un qui dépasse le modèle de référence, mais cela peut résulter du simple hasard, au sens où le modèle sélectionné ne serait pas significativement meilleur si l'on prenait en compte l'information tirée des autres modèles disponibles. Pour se protéger contre ce type de risque, nous mettons en œuvre un test proposé par Hansen (2001). Il apparaît finalement que nos résultats sont robustes à ce biais potentiel.

Au total, les principales conclusions de l'étude sont les suivantes :

- Les meilleurs modèles confirment le rôle des indicateurs de pression de la demande pour la prévision de l'inflation à 12 mois, ce qui est cohérent avec l'approche en termes de "courbe de Phillips généralisée". Pour l'inflation "sous-jacente" (HICP, hors énergie et alimentation non transformée), les modèles "à facteurs" issus des variables d'enquête dans l'industrie ou sur les données d'emploi présentent de bonnes performances en prévision, qui sont proches de celles du meilleur modèle à deux indicateurs comprenant les carnets de commande dans le secteur de la construction et de l'industrie manufacturière. Pour l'inflation totale, les performances en prévision sont un peu moins bonnes en raison du choc pétrolier de 1999-2000. Les meilleurs modèles incluent deux indicateurs tirés parmi les variables suivantes : carnets de commande ou indicateur de confiance des industriels dans le secteur de la construction, perspectives futures de production

dans l'industrie, activité dans le secteur du commerce de détail, taux de chômage. Des modèles avec des performances quasiment équivalentes associent des indicateurs et des facteurs. Dans ce cas, les facteurs sont issus du sous-ensemble composé de toutes les variables de prix inclus dans la base, ou de la base composée des taux de chômage nationaux. Ils sont associés soit à l'indicateur de confiance des ménages (qui a un effet positif sur l'inflation dans 12 mois), soit aux carnets de commande dans l'industrie manufacturière.

- Les meilleures performances sont toutefois obtenues par l'indicateur d'inflation sous-jacente "synthétique" que nous construisons en projetant les indicateurs nationaux d'inflation sur deux facteurs représentant les prix les moins volatils de notre base de données. Ce nouvel indicateur possède de bonnes propriétés prédictives sur la période 1999-2002 au sens où il est capable de prédire le retournement à la hausse de l'inflation liée au choc pétrolier de façon plus précoce que les autres indicateurs.

Non technical summary

The paper investigates the information content of real and financial macro-economic variables for the forecast of euro area inflation in the short/medium run. It extends the methodology introduced by Stock and Watson (1998 and 1999) to compare the forecasting performance of a large number of macro-economic variables, either individually or jointly. We use data from business and consumer surveys available at the national or the euro area level, as well as other short term indicators, in particular financial indicators. We focus on the projection of the annual (year-on-year) inflation rate at the 12-month horizon, using inflation today (and possibly, lagged inflation) as well as one or several leading indicators known today (as well as possible lags). To test the performance of a given indicator, we produce recursive forecasts by extending progressively the sample period.

Due to data constraints, in particular regarding the availability of the euro area Harmonized Index of consumption Prices (HICP), at the monthly frequency, we limit ourselves to the 1988-2002 period (we provide backdata for the 1980s), with forecasts as from 1996:1. For each indicator we compute a synthetic measure of average prediction error, using the RMSE criterion, as well as its standard deviation in order to assess whether its performance is significantly different from the benchmark model, taken to be the simple AutoRegressive model (AR, i.e. where inflation 12 months ahead is only explained by inflation now and by its past values). One should recall that the AR model yields quite satisfactory results on the 1996-1998 period.

The whole panel of series that we consider amounts to 310 different variables, with homogeneous data across countries. These variables are used either directly on the basis of euro area aggregates, or as factors derived from dynamic factor models (i.e. a dynamic version of principal component analysis, PCA), applied to our panel or subsets of it.

An important issue that may arise from such an exercise is that we consider a very large set of indicators, as well as models (models with a single indicator, with several indicators, with factors, or mixing indicator models). One potential problem is that, by searching for a better model over a very large set of alternative models, one may be forced to find a model better than the benchmark, but maybe by pure luck, in the sense that the selected model may actually not be significantly better if one would take into account all the information available from the other models. Such a problem is commonly known as "data-snooping". Using a test suggested by Hansen (2001), it turns out that our results appear to be robust to that problem.

In the end, our findings are the following:

- The best models confirm the role of demand pressure on inflation at the 12 month horizon, in line with the "generalised Phillips curve". For "core" inflation (i.e. inflation excluding energy and unprocessed food), factor models related to business surveys in the manufacturing sector or to employment exhibit forecasting performance that are quite close to our preferred model which relies on two indicators, namely order books in the manufacturing industry as well as in the construction sectors. For total inflation, the forecasting properties of the models are more unstable due to the 1999-2000 oil shock. The best models include two leading indicators taken among the indicator of order book position or confidence in the construction sector, production expectations in the manufacturing industry, current business situation in the retail sector, or the unemployment rate. Almost equivalent models mix factors from the price block in our database or the employment block with the household confidence indicator or the order book position in the manufacturing industry.

- The best results are however available from the "synthetic core inflation indicator", which is constructed by projecting the national inflation indicators in our database on factors representing the least volatile prices in our database. This indicator exhibits very good forecasting properties on the 1999-2002 period et is able to predict the inflation upturn following the 1999-2000 oil shock in a more timely fashion than other indicators.

1 Introduction

The advent of European Monetary Union and the choice of price stability as the main objective of the European Central Bank have increased the importance of inflation forecasts. Not surprisingly, a flurry of models have been put forward to forecast euro area inflation. In particular, the availability of large databases of economic indicators has prompted analysis based on dynamic factor models in the line of Stock and Watson (1998) as well as Forni et al. (2000).

Inflation forecasts are usually based on a Phillips curve, where past values of the unemployment rate gap (difference between the unemployment rate and the NAIRU), as well as of the inflation rate itself, are related to the current change in inflation. This is the underlying theoretical model used in the paper to empirically compare the predictive performance of different single-equation models, obtained by replacing the unemployment rate by various economic indicators, as well as factors extracted from dynamic factor analysis.[1] From that respect, we follow the tradition of a few recent papers.

For the US, Stock and Watson (1999) used monthly data from 1960:1 to 1997:9. and produced forecasts over 1986-1994. Their preferred factor model had a Mean Square Error equal to 0.75 (i.e.75%) that of the Autoregressive (AR) model with a standard error of 0.08. However the model did not outperform the benchmark over 1984-1996.[2]

More recently, Artis et al. (2002) have provided interesting results for the UK, using quarterly observations over 1970:01-1988:03 and monthly data over 1985:01-1998:03. The best model is a factor model estimated from an unbalanced panel (i.e. where missing data are interpolated using factor methods), with intercept correction, which provides a MSE equal to 0.43 (i.e. 43%) that of the AR model, with a standard error equal to 0.19.[3] For France, a companion paper (Bruneau, De Bandt, Flageollet and Michaux, 2002, hereafter referred to as Bruneau et al., 2002) also reports encouraging results, in particular regarding"core" HICP. However, when referring to the charts which display actual and simulated inflation, there is no definite conclusion regarding the usefulness of factor models for the euro area, except when one focuses on core inflation.

In an extensive study by Marcellino et al. (2001), country-specific factor models are estimated but their predictive performance is not satisfactory when national rate of inflation are forecast at the annual horizon (except for Portugal).[4] Indeed, the analysis is performed over a period which is more limited (1982-1997) than in the previous studies. However, surprisingly, their factor model, based on country-specific factor, yields a MSE

[1] Our approach is empirical, since economic theory indicates that there is no garantee that such a model is stable over time. See in particular Atkeson and Ohanian (2001). It turns out however, as shown in our paper, that such a model has reasonable forecasting properties.

[2] In Stock and Watson (1999), predictive performances are measured by the relative MSE, with a Phillips curve as benchmark. Note that the AR model has similar performances: a RMSE level of 1.26 (resp. 0.98) with a standard error of 0.19 and 0.98 (resp. 0.15) for the two different sub-periods considered.

[3] Note that the model using the first two factors of the same analysis, with the regression performed with the same options, only provides a MSE of 1.09 that of the AR model with a standard error of 0.25.

[4] The levels of their MSE compared to the AR model are: Austria (1.02), Belgium (1.27), Finland (1.07), France (1.02), Germany (0.82), Ireland (1.41), Italy (0.90), Luxembourg (2.65), the Netherlands (1.25), Portugal (0.73) and 1.27 for Spain.

of 0.57 that of the AR model, which has to be compared with a rel MSE of 1.20 for a factor model using European factors.

Angelini et al (2001) forecast European inflation using quarterly data over a longer period 1977-1999, for forecasts performed from 1995. The best model has a MSE equal to 0.80 that of the AR model, but no standard errors are reported and there is no chart to illustrate the out-of-sample performance.

Finally Cristadoro et al. (2001) develop an analysis in the line of Forni et al. (2000). They focus on the period 1987-2001 using monthly data, but there is no indication of the precision of the forecasts e.g. through the introduction of standard errors.

In this paper, we extend our previous study to the euro area and focus on the same period (1988:1-2002:3). There are two types of conclusions, first regarding the results, then from a methodological point of view.

On the first point, we provide evidence that some indicators -related to consumer surveys- combined with factors -linked to industrial activity or employment- help improve upon the simple Autoregressive (AR) model for forecasting HICP core inflation. Moreover, regarding total HICP, even if we produce significantly better forecasts than what is already available in the literature for the whole period, according to the relative MSE criterion, we must keep in mind that the corresponding charts qualify such a claim. Nevertheless, the construction of a "synthetic core" indicator helps achieve significantly improved 12-month ahead forecasts than the AR model for total inflation for the final part of the sample.

From the methodological point of view, we stress that factor models become more useful for extracting common features from national data, especially when euro area data are lacking. Second, the extension of the Phillips curve to the euro area level, following Stock and Watson (1999) yields interesting results -especially for total inflation when combining one factor and one indicator- but they are less robust than at the national level. The segmentation of labor markets across euro area countries, as well as the absence of full synchronization of business cycles (Angeloni and Dedola, 1999), might be an explanation for such a finding. In addition, the averaging effect of aggregate euro area variables is partly offset by other types of shocks affecting notably indirect taxes. Third, the finally better results for core inflation underline the sensitivity of the results to the sample period, as the period under study was characterized by major shocks in the unprocessed food (BSE crisis) and energy sectors in 1999-2000. Satisfactory forecasts of core inflation are therefore only a first step towards forecasting total inflation by combining it with energy and unprocessed food inflation forecasts (see Bruneau et al., 2002, for details). Fourth, the comparison of our results to the literature points to the sensitivity of the findings to a certain number of necessary choices: transformation of the series, measure of forecast performance (standard errors around Mean Square Error, as well as charts in order to assess possible lags between forecasts and realizations).

In addition, since we consider here a large number of alternative models there might be a risk that one increase the likelihood of finding better models. For that reason, we investigate the issue of possible data snooping bias. It turns out that our results are significatly affected by this problem.

All in all, since long time series are not yet available at the euro area level, the purpose of our study is to provide a reference against which future studies could be compared, when additional data become available.

The paper is set out as follows. Section 2 briefly presents the methodology and the benchmark model against which the other models are compared. Section 3 discusses the models based on single and multiple indicators. Factor models using the Stock and Watson's (1998) methodology are presented in section 4. Section 5 introduces a "synthetic core" indicator. Some sensitivity analysis is presented in section 6. Section 7 the implementation of these models in real time, while section 8 investigates the robustness of the paper to potential data snooping. Section 9 concludes and suggests directions for future research.

2 Forecasting methods

2.1 Forecasting equations

The methodology is similar to that used in Bruneau et al. (2002), following Stock and Watson (1998) . In order to forecast inflation in the euro area, we rely on various specifications of the Phillips curve and introduce various indicators of the business cycle x_t.

The model used is:

$$\pi_{t+h}^{12} - 12.\pi_t = \phi + \beta(L)x_t + \gamma(L)\Delta\pi_t + e_{t+h} \tag{1}$$

where $\pi_t^{12} = ln(P_t/P_{t-h})$ is the 12-month inflation rate at date t with P_t the price index. π_{t+h}^{12} is the 12-period inflation rate at date $t+h$. $\pi_t^1 \equiv \pi_t = ln(P_t/P_{t-1})$ is the one-month inflation rate. By multiplying by 12, one gets a consistent definition of the change in the inflation rate on the left-hand side. P_t is either the Harmonized Index of Consumer prices (hereafter labelled "Total" HICP), or the HICP excluding unprocessed food and energy (hereafter labelled "Core").[5] The 12-month inflation rate is forecast h-months ahead using current and past inflation and various lags of x_t.

Such a specification is based on the assumption that π_t^{12} is non stationary. Indeed, stationarity tests indicate that for total and core HICP, 12 month inflation rates are quite persistent and therefore taken as I(1). We run alternative specifications yielding similar results.[6]

[5] As indicated in Annex 2, we used data from Eurostat for HICP, as well as HICP excluding energy and unprocessed food. We used country data and aggregated them to obtain euro area data for the period before 1995, using Eurostat country weights for 1995. This implied using Eurostat data for most countries, save France and Spain where national CPI data were used. We are grateful to Banco d'Espana for providing the data for Spain. Data for France are identical to those used in Bruneau et al. (2002). HICP has been available since 1986 in DE, ES, FR, IT, AT, PT, FI and October 1987 for NL. The other countries were integrated progressively as data became available.

[6] Among the alternative specifications, we ran, for h=12:

$$\pi_{t+h}^{12} - \pi_t^{12} = \phi + \beta(L)x_t + \gamma(L)\Delta\pi_t^1 + e_{t+h}$$

Most of our results are based on $h = 12$, so that equation (1) is actually:

$$\pi_{t+12}^{12} - 12.\pi_t = \phi + \beta(L)x_t + \gamma(L)\Delta\pi_t + e_{t+h}$$

The different indicators are compared according to out-of-sample simulation exercises. We recursively estimate our equations and produce rolling forecasts. For example, let us focus on the forecast of the 12-month inflation rate, 12 months ahead, *i. e.* between 1995:12 and 1996:12. In this case, the Phillips curve is estimated, information criteria are computed and lag lengths are selected using data on annual inflation from 1989:1 through 1995:12.[7] Next, moving forward one month, the model is reestimated using data from 1989:1 until 1996:1 and forecasts are made for 12-month inflation until the 1997:01 period. At each step, one forecast of the 12-period inflation rate, 12 periods ahead, is produced. The performance of all indicators is assessed on the basis of their Root Mean-Squared Error, defined as $RMSE = \sqrt{\frac{1}{N-h}\sum_{t=1}^{N-h}(\widehat{\pi}_{t+h}^{12} - \pi_{t+h}^{12})^2}$,with N the number of periods (months) until the end of the sample, for forecasts over the h months ahead.[8] It is also useful to compare the performance of the different indicators to a benchmark model which we define as the AR model. It is well known that it is actually difficult to out-perform the AR model.

In order to assess the accuracy of the alternative models, we compute the standard deviation of the ratio of the Mean Square Error (MSE) of the various models to the MSE of the AR model (namely MSE of the model divided by MSE of the AR model). We note this indicator the "Rel. MSE". The lower the "Rel. MSE", the more stable the performance of the alternative model as compared to the AR model. More precisely, we use a one-sided test H_0: Rel MSE = 1 against H_1: Rel MSE < 1. The p-values measure the type I error associated with the test. A Heteroskedasticity-Autocorrelation Consistent (HAC) standard error of the "Rel. MSE" is also reported (West, 1996).

In comparison to the previous literature, we also combine different indicators in order to improve upon the single indicator approach, the intuition being that several indicators that are uncorrelated may provide- when taken separately- comparable RMSE so that it might be better to combine two (or more) indicators $x_{i,t}$. For p indicators, we run:

---

as well as:

$$\pi_{t+h}^{12} - \pi_t^{12} = \phi + \beta(L)x_t + \gamma(L)\Delta\pi_t^{12} + e_{t+h}$$

both providing either equivalent or slightly worse forecasts than equ. (2). This may explain the dominant role of equ. (2) in the literature.

[7] Actually, to produce forecasts from 1995:12 to 1996:12, only inflation data are used for estimation until 1995:12: the x_t variable is used up till 1994:12 since it is introduced with a 12-month lag. Data on x_t in 1995:12 is only used to get a forecast of inflation in 1996:12, assuming the estimated relationship is still valid for this extended period.

[8] Of course, for h smaller than 12, the RMSE is likely to be smaller since the price level is already known for $12 - h$ months. Indeed, for $h = 3$, $\sqrt{\frac{1}{N-12}\sum_{t=1}^{N-12}(\widehat{\pi}_{t+3}^{12} - \pi_{t+3}^{12})^2} \leq \sqrt{\frac{1}{N-12}\sum_{t=1}^{N-12}(\widehat{\pi}_{t+12}^{12} - \pi_{t+12}^{12})^2}$

$$\pi^{12}_{t+12} - 12.\pi_t = \phi + \sum_{i=1}^{p} \beta_i(L) x_{i,t} + \gamma(L)\Delta\pi_t + e_{t+h} \quad (2)$$

2.2 Forecasting performance of the Autoregressive (AR) model

The main results are based on the 12-month horizon, which is an horizon that becomes relevant for monetary policy. Obviously, at a shorter horizon, the AR model would perform much better and, indeed, at the 3 month horizon, the AR model cannot be improved upon.[9]

Regarding the performance of the benchmark, the out-of-sample Root Mean Square Error (RMSE) of the AR model for the period January 1996 to March 2002 amounts to half a percentage point of annual inflation (as in Bruneau et al., 2002, the AR model is defined as equation (2), without the lagged component in x_t).

An alternative benchmark could have been the Random Walk (RW) as in Cristadoro et al. (2001) who indicate that such a model is more difficult to out-perform than the AR model. In that case the best predictor of future inflation would have been current inflation.[10]

However, we will see that the two models are actually indistinguishable from a statistical point of view. We find that the RMSE of the RW model on core HICP (0.571) is higher than for the AR model (0.508). Whereas the RMSE of the RW model on total HICP (0.672) is lower than for the AR model (0.712).

These statistics have to be compared to a higher RMSE for the AR model for France, reaching 0.81 and 0.60, respectively, for Total and Core inflation (Bruneau et al., 2002). The explanation of the lower volatility of inflation in the euro area is the "averaging effect" of euro area aggregates as compared to national developments that are more erratic (see Fagan, Henry and Mestre, 1999).

It is also interesting to report RMSEs for the two subperiods considered here for out-of-sample forecasting: the disinflationary period (1996:1-1998:12) and the inflation upturn (1999:1-2002:3).

Samples :	Jan.1996-Dec.1998	Jan.1999-March 2002	Jan.1996-March 2002
Total inflation	0.280	0.950	0.712
Core inflation	0.381	0.603	0.509

Table 1: Level of RMSE of *AR* model for total and core HICP on subperiods

[9] Variant analysis -available from the authors upon request- indicate that interest rates have a more significant effect at the 6 and 9 month-horizon. In addition, at 18 month-horizon, factor models perform much better than the autoregressive (AR) model.

[10] $\widehat{\pi}^{12}_{t+h} = \pi^{12}_t$. On our sample both models have equivalent forecasting properties. Note that for the random walk model, the RMSE is just $\sqrt{\frac{1}{N-12}\sum_{t=1}^{N-12}(\pi^{12}_{t+h} - \pi^{12}_t)^2}$.

The forecasting performance of the AR model appears to be much higher for the first period characterized by the "convergence play" in the transition to EMU. Indeed, as we will see, it is quite difficult to improve upon the AR model during that period. Conversely, during the second period, the AR fails to recognize immediately the sharp upturn in inflation in 1999-2000 from the low reached by oil prices in January 1999. Actually it took around a year for the AR model to acknowledge the surge in inflation.

One should also mention that RMSE may be insufficient to assess the ability of the different models to anticipate upturns or downturns in inflation. For that reason, we complement our analysis with a concordance index in the line of Artis et al. (2002), as well as charts of the forecast inflation.

3 Phillips curve type models

In the following, we refer to the Phillips curve as the model of reference which is extended so as to include several economic indicators in the lines of Stock and Watson (1999). However, one cannot, strictly speaking, refer to the economic argument underlying this approach.

3.1 Description of the data

Our database is mainly composed of disaggregated series at the national level. Data sources include Eurostat, as well as OECD and the Bank for International Settlements' database. We use the total HICP, as well as its five main subcomponents (manufacturing, services, processed food, unprocessed food and energy) for all countries when available.[11] Only a limited number of series are aggregates for the euro area. In some cases, the euro area series we constructed, backdating the series available by Eurostat for HICP as well as for unemployment (see below). All in all the sample is made up of 310 series. Series are first transformed to obtain stationary variables. Then they are subsequently seasonally adjusted using TRAMO-SEATS in DEMETRA (2000).

Regarding the results, it appears difficult to reproduce at the euro area level, the analysis conducted by Stock and Watson (1999) for the US, Artis et al. (2001) for the UK, or Bruneau et al. (2002) for France.

The use of individual indicators available at the national level is also not straightforward either. Two cases are possible: either an indicator represents a large country, e.g. Germany, and has an impact on the euro area due to the sheer size of the country; or some countries have leading-indicator properties. The latter is the case for Belgium. Indeed, Vanhaelen et al. (2000) indicate that turning points in Belgium lead turning points in the euro area from 1993 onwards, although they cannot validate the three hypotheses that may explain such a result: Belgium's specialization in intermediate goods, its high degree of openness and the high proportion of small and medium-sized entreprises.

However, due to the absence of full synchronization of the business cycle across countries in the euro area, especially at a monthly frequency, it sometimes appears difficult to

[11] See note 5 above for details.

use euro area activity indicators to forecast euro area inflation. It might be preferable, from that point of view, to forecast inflation at the national level using national activity indicators, then to aggregate the national inflation forecasts to obtain a forecast of euro area inflation (Marcellino et al., 2000). Due to the lack of data for a certain number of countries, such a study was not pursued in this paper. Note that Marcellino et al. (2000) claim that aggregating national forecasts based on factor models yields better results than directly providing euro area forecasts, but, no indication is provided on the associated standard errors on RMSE, and the sample period (1982-1997) does not include the 1999 inflation upturn. Moreover the results obtained by these authors for each of the countries of the panel are sometimes puzzling.

Before presenting results from factor models in section 3, we consider results from the generalized Phillips curve where single as well as multiple indicators are introduced in the forecasting equation.

3.2 Models with a single indicator

About 30 (stationary) indicators x_t were (successively) introduced in equation (2) in order to forecast core and total inflation. Most of these indicators come from business survey data published by Eurostat as well as National Statistical Institutes. Other types of indicators were also introduced, namely a monthly euro area unemployment rate (reconstructed before 1992 using Eurostat Labor Force Survey and national data). We also used financial variables, a euro area index of industrial production, as well as oil prices.

Tables 2 and 3 exhibit, for Total and Core HICP respectively, the RMSE and the Relative MSE ("Rel. MSE") of the five best models of equation (2) using a single indicator (the mnemonics of the variable used in each of these models are explained in Annex A1). Note that the "Rel. MSE" of the RW model for total inflation is not significantly below 1 (p-value of 0.29 for total inflation), indicating that the AR and RW models are statistically indistinguishable.[12]

Among our indicators, survey data exhibit the best forecasting performance, in particular those associated with the construction sector. In addition, "activity compared to the previous month" (LI_2) and "order books in the construction sector" (LI_3), are the best indicators to forecast total and core inflation at the 12-month horizon. The unemployment rate (LI_{12}) provides some relevant information for total inflation in the lines of Stock and Watson (1999) for the US.

[12] Since we have a one-sided test H_0 : Relative MSE $= 1$ vs H_a : Relative MSE < 1, the values of Student statistics are $t = 1.28$ (10%), $t = 1.64$ (5%), or $t = 2.33$ (1%). Note that we also introduce the concordance index in the tables, labelled as "Conc". Let us define $z_{t+12} = \pi^{12}_{t+12} - \pi^{12}_t$ and $\widehat{z}_{t+12} = \widehat{\pi}^{12}_{t+12} - \pi^{12}_t$, as well as $i_{t+12} = I(z_{t+12} > 0)$ and $\widehat{i}_{t+12} = I(\widehat{z}_{t+12} > 0)$. For N out-of-sample forecasts, the concordance indicator is defined as:

$$C = \frac{1}{N}\left[\sum_{t=1}^{t=N} i_t \widehat{i}_t + \sum_{t=1}^{t=N}(1-i_t)(1-\widehat{i}_t)\right]$$

with $0 \leq C \leq 1$, where unity indicating maximum concordance.

One should note, that -at the 12-month horizon- there is no reduction in RMSE when using financial variables (interest rates, yield spreads, stock market indices, real and nominal exchange rates, monetary aggregates). This is not exactly in line with the results of Forni et al (2001), who, however, do not report any precision indication. Nevertheless, there is evidence -not reported in the paper- of the role of factor models for interest rates at the 18-month horizon.

Concerning total inflation, the Table 2 reports "Rel MSEs" which are significantly below one, indicating that on average the alternative models perform better than the AR model, with low p-values due to small standard errors. In the case of core inflation (Table 3), the results are quite similar to the ones obtained for France in Bruneau et al. (2002), where a large number of indicators exhibit low p-values. From that point of view, inflation in the euro area does not seem to be more difficult to predict. Moreover, one should keep in mind that in the case of France, HICP is corrected for VAT tax changes, while there is no correction at the euro area level[13]. All models improve upon the AR model in term of the concordance index.

	LI_1	LI_2	LI_3	LI_4	LI_{12}	RW	AR
RMSE	0.621	0.604	0.625	0.617	0.637	0.672	0.712
Rel.MSE	0.76	0.72	0.77	0.75	0.80	0.89	1.00
Std.dev	0.05	0.06	0.05	0.09	0.05	0.20	-
p-Value	0.00	0.00	0.00	0.00	0.00	0.29	-
Conc.	0.76	0.76	0.76	0.76	0.72	0.71	0.69

Table 2: RMSE on leading indicators for total HICP

	LI_1	LI_2	LI_3	LI_5	LI_{15}	RW	AR
RMSE	0.400	0.400	0.397	0.413	0.384	0.571	0.509
Rel.MSE	0.62	0.62	0.61	0.66	0.57	1.26	1.00
Std.dev	0.24	0.15	0.21	0.14	0.16	-	-
p-Value	0.06	0.00	0.03	0.00	0.00	-	-
Conc.	0.76	0.71	0.76	0.69	0.69	0.67	0.68

Table 3: RMSE on leading indicators for core inflation.

In the next section, we examine the performances obtained when one introduces multiple indicators.

[13] In the case of France, we managed to filter the noise created by changes in VAT rates. Such a correction at the euro area level was beyond the scope of the paper.

3.3 Models with multiple economic indicators

We introduce two indicators and test the following equation, where x_{1t} and x_{2t} are stationary euro area aggregate:

$$\pi^{12}_{t+h} - 12.\pi^1_t = \phi + \beta_1(L)x_{1t} + \beta_2(L)x_{2t} + \gamma(L)\Delta\pi^1_t + \varepsilon_{t+h} \tag{3}$$

Tables 4 and 5 display the RMSE and the "Rel. MSE" of the three best models and their relative performances in comparison to the AR model.

Regarding total inflation, RMSE decreases as compared to the model with one indicator, with a 0.05-percentage point average reduction in RMSE with respect to the AR model. As expected, standard errors are also quite low. Although we do not report the information for all models, the sign of the elasticity of inflation to the various indicators is consistent with standard macroeconomic theory as well as fairly stable over time. As example, figure 21 in Annex D provides for the model $DLI_{3,8}$, the elasticity of inflation to order book positions, which appears to be significantly positive and quite stable. It can therefore be interpreted as an indicator of demand shocks. At the same time, the negative elasticity of the future business situation can be interpreted as a supply shock: when controlled for demand shocks, an improvement in the future business situation leads to lower inflation. Although productivity shocks are a possible explanation of such a link, further analysis should investigate the possible effect of oil price shocks.

An improvement in forecasting performance with two indicators is also visible for core inflation. The two indicators "order books in construction" (LI_3) and "order books in manufacturing industry" (LI_{10}) lead, at the 5% confidence level, to an average forecast error (measured in terms of RMSE) of one third of a percentage point at the 12-month horizon, against half a percentage point for the AR model. As indicated in figure 20, the elasticity of inflation to both indicators is positive and stable. We also notice that the industrial production index (manufacturing, LI_{14}[14]) -which is affected by second-round effects of oil price shocks-as well as the price of Brent oil (LI_{15}) have extra forecasting power when added to survey indicators in the construction sector: respectively "order book position" (LI_3) and "activity compared to the previous month" (LI_2).

	$DLI_{1,12}$	$DLI_{2,11}$	$DLI_{3,8}$	RW	AR
RMSE	0.583	0.722	0.547	0.672	0.712
Rel.MSE	0.67	0.72	0.59	0.89	1
Std.dev	0.06	0.04	0.13	0.20	-
p-value	0.00	0.00	0.00	0.29	-
Conc.	0.81	0.79	0.87	0.71	0.69

Table 4: RMSE on double leading indicator for total HICP

[14] Industrial production excluding energy is also a valid predictor.

	$DLI_{3,10}$	$DLI_{2,15}$	$DLI_{3,14}$	RW	AR
RMSE	0.356	0.358	0.367	0.571	0.509
Rel.MSE	0.49	0.50	0.52	1.26	1
Std.dev	0.12	0.18	0.19	-	-
p-value	0.00	0.00	0.01	-	-
Conc.	0.76	0.71	0.77	0.67	0.68

Table 5: RMSE on double leading indicator on core HICP

In the next section, we consider factors extracted from (quasi) dynamic factor analysis, which are included in the forecasting equation either individually, or associated with indicators.

4 Factor Analysis

Dynamic factor analysis (DFA) is able to summarize information from a large number of variables. It is assumed that the large panel of time series X_t that we possess at date t has the following structure:

$$X_t = \Lambda F_t + e_t \tag{4}$$

where F_t is of dimension $(T \times k)$, with k smaller than the total number of variables. These are (a relatively small number of) unobserved factors that summarize the systematic information in the data set (see Annex D for details). In a second step F_t, derived from (4), is directly introduced as indicator in equation (2). The main drawback of DFA is that factors are often difficult to interpret from an economic point of view. A principal component analysis (PCA) is potentially useful if the variables possess a high degree of correlation: factors usually summarize the correlation structure. In the case of the euro area, one observes that many variables are correlated but sometimes with lags. But at this stage, DFA is not fully dynamic: it summarizes the instantaneous correlation structure since the variables are included contemporaneously so that the factors are linear combinations of contemporaneous variables. Doz (1999) provided the proof that factor analysis applied to a small number of time series yields a good estimator of dynamic factors when maximizing the quasi-log likelihood of the static model, with asymptotic time dimension. The proof has not yet been extended to the case where the number of series is large. However, when the number of series is large, the space spanned by the axis of the PCA is proved to be the same as the space spanned by the eigenvectors from the DFA (Doz, 1999). It is therefore likely that asymptotically (N and T large), the static estimator may take care of the inter-temporal correlation between the series.

In finite samples, no result is available and one should, at least, run a truly dynamic analysis by extending the vector of series: each series should be introduced as well as its lags. In the literature, such an extension is not often mentioned although it is a priori crucial, from a forecasting perspective, to take into account the inter-temporal correlation structure of the series.

In our database, this feature may be illustrated by the fact that one factor can satisfactorily summarize the instantaneous correlation structure without being very useful in forecasting, when one refers to the corresponding graphs. This is the case, in particular, for survey data which are relatively well-represented on the first axis derived from the complete set of series. At the same time, this factor does not produce satisfactory forecasts and even less the aggregate euro area business survey, as we will see in the subsection dealing with model mixing indicators and factors.

When running PCA on the complete panel, the first ten factors account for 50.5% of the variance (20% for the first one, 9% for the second and 5% for the third). Survey data (especially in the manufacturing industry) and unemployment rates contribute to the first factor. The least volatile HICP variables (services, manufacturing industry and processed food) which represent 27% of the series in the panel, are mostly represented on the second factor together with non-volatile series in services sector, manufacturing as well as retail sales in Germany and some wage series.[15]

Due to the mixed results from DFA on the complete panel, when forecasting is at hand, we decided to run it on blocks of variables, corresponding to countries or sets of homogeneous variables (survey, industrial production, etc.-subsection 4.1). Better results are obtained when factors and indicators are combined (subsection 4.2).

4.1 Models using exclusively factors from DFA

Here, we present models using only factors from DFA, either derived from the complete panel, or from selected blocks, the latter factors exhibiting higher forecasting performance. Two dimensions are possible: countries or blocks of homogeneous variables. From country blocks, one obtains country factors that may be used either to forecast euro area inflation directly or to provide forecasts of national inflation developments which can then be aggregated at the euro area level. We focus here on the first approach, the second has already been investigated by Marcellino et al. (2000), who did not provide fully conclusive results. It is reserved for future work.

The first step is to determine the number of factors in the following equation:[16]

[15] The fourth and fifth factors account for 3.5% of total variance. Regarding interpretation of the factors, the third represents production prices. Share prices and long term interest rates are located on the fourth factor (as well as on the sixth factor). The fifth factor is highly correlated with import and export prices as well as real/nominal exchange rates. Unprocessed food prices appear on the seventh factor, while energy prices are scattered on axis number 3, 5, 7, 8 and 10. Also note that according to the Bai&Ng's (2000) criterion, only 5 factors are needed to summarize the panel. In addition industrial production and car registration data are not well represented on any of these axis. This lead us to create a specific block for these two sets of variables (aci), with, as we will see below, quite good forecasting performance, when added to other indicators.

[16] According to Stock and Watson (1999) PCA has to be implemented with stationary series. We therefore focus on the transformed price series $X_t = (1 - L)\log(P_t)$ and, accordingly, we assume that prices are

$$\pi^{12}_{t+h} - h.\pi^1_t = \phi + \sum_{i=1}^{P} \alpha_i(L) F_{it} + \gamma(L)\Delta\pi^1_t + \varepsilon_{t+h} \qquad (5)$$

Bai and Ng's (2000) criterion was implemented but was, in the end, not used to select the optimal model, since the authors indicate that it is not optimal for forecasting. This criterion leads us to retain many factors.[17] Following standard practice, we used the standard Schwarz criterion although its performance for out-of-sample forecast is low.[18]

In the end we decided to keep only one factor to represent each country, since the second factor does not improve the forecast.

Tables 6 and 7 summarize the best models for euro area total and core inflation.[19]

	$F^{base}[1]$	$F^{Be}[1]$	$F^{Fr}[1]$	$F^{emu}[1]$	RW	AR
RMSE	0.664	0.676	0.612	0.649	0.672	0.712
Rel.MSE	0.87	0.90	0.74	0.83	0.89	1
Std.dev	0.05	0.04	0.14	0.05	0.20	–
p-value	0.00	0.00	0.03	0.00	0.29	–
Conc.	0.710	0.71	0.73	0.72	0.71	0.69

Table 6: Forecasting performance of factors models to predict total HICP at 12 month horizon

1) Regarding total inflation, the results from DFA do not improve upon the previous results obtained with indicators. In addition, we observe that the p-values have slightly deteriorated in comparison to the models using indicators only.

The factor from the complete panel does not perform well. The same goes for the factor derived from the unemployment block (not reported in the table): a euro area Phillips curve therefore appears to be a fragile instrument. As already mentioned, one explanation may be the existence of lags in the business cycle between euro area countries when considering monthly data. Nevertheless, we report below encouraging results for the employment factor when included jointly with an indicator.

I(1) (which is confirmed by Unit Root tests). However, as indicated in 2.1, in the forecasting regressions, we introduce the first difference of the monthly inflation rate, with the dependent variable defined as the difference between the annual inflation rate and 12 times the monthly rate. Therefore, the regression is rather associated with a I(2) representation of prices. This choice is imposed by the persistence of the annual inflation series (as also confirmed by Unit Root tests). According to Clements and Hendry (1998) over-differencing could improve forecasts, if there is a structural break in the sample. All in all, different specifications do not change the results dramatically.

[17] The Bai and Ng (2000) criterion seems to be difficult to use for stationary but highly persistent series. It performs better on financial series (yields) for which inter-temporal correlation is low.

[18] We tried to fix *a priori* the number of factors and lags, yielding somewhat better results. Such a result provides further evidence of the possible discrepancy between in-sample and out-of sample results.

[19] The number of factors used in a given block is indicated within brackets. For example, [1] indicates that only the first factor is used.

	$F^{base}[1]$	$F^{sur}[1]$	$F^{Be}[1]$	$F^{Fr}[1]$	$F^{emu}[1]$	RW	AR
RMSE	0.432	0.419	0.359	0.416	0.397	0.571	0.509
Rel.MSE	0.72	0.68	0.50	0.67	0.61	1.26	–
Std.dev	0.20	0.20	0.17	0.27	0.14	–	–
p-value	0.08	0.05	0.00	0.11	0.00	–	–
Conc.	0.650	0.63	0.67	0.60	0.60	0.67	0.68

Table 7: Forecasting performance of factor models to predict core HICP at 12 months horizon

The factor exhibiting the lowest p-value (at 0.00, with "Rel MSE" of 0.83 and standard deviation of 0.05) is derived from the block made of euro area indicators (Emu), i.e. $F^{emu}[1]$, which represents a wider information set.

2) Similarly, for core inflation, the results are not as good as those provided by aggregate indicators except for the "Belgian" factor $F^{BE}[1]$ ("Rel. MSE" of 0.5, with p-value of 0.00), which is a direct competitor to the model with two indicators presented in section 3.3, with "Rel. MSE" of 0.49 and p-value of 0.00. As indicated before (see section 3.1), there is no obvious reason of the stylised fact that Belgium seems to exhibit good forecasting properties for the euro area, in particular during the 1996-1998 period (see section 6.1). In addition, the Emu factor is significant with a p-value of 0.00.

As indicated previously, the performance of the factor model is lower when using a second factor from the same block (or from the complete panel), or when adding a factor from another block. Such a conclusion is similar to the one found by Stock and Watson (1999). The results are not reported here to save space. In the following section we therefore try a new strategy, namely models including one indicator and one factor.

4.2 Combining one economic indicator with one factor

We decide now to combine the results of the preceding sections with indicators and factors. In order to limit the number of combinations, we limit ourselves to one indicator and one of the first two factors from the different blocks. For the complete panel, recall that the second factor is always selected since it is homogeneous to price variables, unlike the first factor which is more correlated to survey and employment series. Note that this result is in line with the conclusions of Angelini et al. (2001) who claim that using nominal factors is preferable for HICP forecasts, irrespective of the horizon. For the other blocks, the first two axis have almost the same contribution to total variance and it turns out that it is the second factor which exhibits the best forecasting performance.

The best results are reported in tables 8 and 9.

For total inflation, the models with combined factor and indicator display quite similar performance to the ones of the double indicator models. Note that, among them, the model with the lowest RMSE, namely $CB_{12}^{prc}[2]$, includes total unemployment and the second factor of the price block. The other model includes the second factor from the

	$CB_5^{emp}[2]$	$CB_{12}^{prc}[2]$	RW	AR
RMSE	0.600	0.556	0.672	0.712
Rel.MSE	0.71	0.61	0.89	1
Std.dev	0.05	0.09	0.20	-
p-value	0.00	0.00	0.29	-
Conc.	0.71	0.830	0.710	0.690

Table 8: Forecasting performance for total inflation: one indicator with one factor

	$CB_5^{aci}[2]$	$CB_1^{dbase}[2]$	$CB_{10}^{emp}[2]$	RW	AR
RMSE	0.384	0.345	0.387	0.571	0.509
Rel.MSE	0.57	0.46	0.58	1.26	1
Std.dev	0.12	0.11	0.13	-	-
p-value	0.00	0.00	0.00	-	-
Conc.	0.73	0.77	0.73	0.67	0.68

Table 9: Forecasting performance for core inflation: one indicator and one factor

employment block as well as the euro area aggregate response to the "household financial survey over the last twelve months (LI_5). Both models provide evidence in favor of the Phillips curve (with the usual criterion of "Rel MSE"). The similarity between the two approaches (double indicator and combined model) is also supported by the concordance index.

For core inflation, the performance remains poorer than that of the double indicator model, even if the $CB_5^{aci}[2]$ model exhibits reasonable performance. It includes the LI_5 indicator and the *second* factor from *aci* block (made of industrial production and car registration indices) which is representative of the manufacturing sector. The order book position in the industrial sector (LI_{10}) together with the second factor in the employment block exhibit similar results. The only model with better performance than the double leading indicator is the $CB_1^{dbase}[2]$ model, where the factor component is based on the complete panel in first difference in the line of Cristadoro et al. (2001). Such an option (i.e. running DFA on variables in first difference instead of levels, as chosen in the current paper) is reserved for future work.

To conclude, factor models combined with indicators provide statistically better results than the AR model; moreover, these results for total inflation are similar to the ones obtained with the double indicator models, while they are in general slightly inferior for core inflation. However, Charts in Appendix 3 indicate that all models failed to recognize the upturn in inflation in 1999-2000 in a timely manner, even if the lag is not very substantial.

In the following section, we construct a synthetic core indicator which provides, in contrast to the models presented so far, good forecasting performance especially for the more recent period, when one refers to the corresponding charts. The performance of the indicator, which includes information on energy prices, is satisfactory for core inflation which incorporated the 1999-2000 oil price shock with a lag.

5 Constructing a "synthetic" euro area core inflation indicator

The synthetic core inflation indicator represents a smoothed version of total inflation. We explain its construction before presenting its forecasting performance. Such an indicator expresses the underlying trends in inflation that may have an impact on future expected inflation. This might therefore be, in the line of Clarida et al. (1998), the target that monetary authorities might decide to choose, referring to expected rather than observed inflation.

5.1 Construction

In order to derive the synthetic core inflation indicator we use the complete panel of data. We run a PCA on the whole period. For the out-of-sample projections we run recursive PCAs on the 1996-2001 period. The euro area "synthetic core" series is then reconstructed by projecting the national total inflation on the factor space. From the national HICPs, we only keep the common component by minimizing the number of factors, on the basis of a standard PCA where each variable is modelled as the sum of a common component (shared by all series) and an idiosyncratic component (see also Cristadoro et al, 2001 for a similar approach using spectral analysis). An intermediate step is however necessary: by adding up the monthly price changes over the last 12 months we obtain annual price changes.

Formally, we define $X_{i,t}$ as the monthly change in HICP in country i and $F_{j,t}$ the factors extracted from the complete panel at each date t. Let $\omega_{i,t}$ be the weight of country i at date t in total euro area inflation; m is the number of factors selected to model the common component.[20]:

$$X_{i,t}^{(c)} = \sum_{j=1}^{m} \Lambda_{i,j,t} F_{j,t} \tag{6}$$

$$\widetilde{\pi}_{i,t}^{12} = \sum_{s=t-11}^{t} X_{i,s}^{(c)}, \tag{7}$$

Subtracting the mean and dividing by the standard deviation, one gets:

[20] $\mu_{i,t} = \frac{1}{t-t_0} \sum_{t'=t_0}^{t} \pi_{i,t'}$
$\sigma_{i,t} = \frac{1}{t-t_0} \sum_{t'=t_0}^{t} \left(\pi_{i,t'} - \mu_{i,t}\right)^2$, with t_0 denoting the first date of the sample.
μ_t^{emu} and σ_t^{emu} was built as $\mu_{i,t}$ and $\sigma_{i,t}$.

$$\pi_{i,t}^{cr} = \frac{(\widetilde{\pi}_{i,t}^{12} - \overline{\widetilde{\pi}_{i,t}^{12}})}{\sigma_{i,t}} \tag{8}$$

Finally, one can compute "synthetic core" inflation ($\pi_{sc,t}^{12}$) as:

$$\pi_{sc,t}^{12} = \sigma_t^{emu} \sum_{i \in \theta} \omega_{i,t} \pi_{i,t}^{cr} + \mu_t^{emu} \tag{9}$$

On the basis of the spectral decomposition of the correlation matrix used in the PCA, we already noted that 10 factor axis associated with the 10 highest eigenvalues explain 50.5 % of total variance. The first axis contributes to 20 % of total variance, the second one to 9 %, the third to 5 %.[21] We select factors F_2 and F_3, that are homogeneous to the least volatile price variables. As already mentioned, this is in line with Angelini et al (2001), who show that the factors extracted from a database made of nominal variables exhibit higher forecasting performance than those from a database which also contains real variables, when HICP is forecast. The other factors are constructed from variables that are too volatile to enter into the "synthetic core indicator", since we are looking for a rather smooth series. The first factor is excluded since it is mainly constructed from survey data which is not very useful in forecasting, as already mentioned in the previous sections.

The forecasting performance of the indicator is as follows in tables 10 to 12 for total and core inflation, for the full period, as well as for two sub-periods.

	Total inflation			Core inflation		
	π_{sc}^{12}	RW	AR	π_{sc}^{12}	RW	AR
RMSE	0.523	0.672	0.712	0.394	0.571	0.509
Rel.MSE	0.54	0.89	1.00	0.60	1.26	1.00
Std.dev	0.17	0.20	-	0.25	-	-
p-value	0.00	0.29	-	0.05	-	-
Conc.	0.79	0.71	0.69	0.68	0.67	0.68

Table 10: Forecasting performance of "synthetic core" indicator, total and core inflation, whole period

The overall forecasting performance is not better than the previous models. Nevertheless, anticipating more systematic results on model stability, it appears from the last two tables that the model is quite good at forecasting inflation over the 1999-2002 period, since the synthetic core indicator is able to anticipate the inflation upturn in a more timely fashion. One should however acknowledge that the indicator is not able to outperform the AR

[21] For details, see note in section 4 on DFA.

	Jan.1996-Dec.1998			Jan.1999-March.2002		
	π_{sc}^{12}	RW	AR	π_{sc}^{12}	RW	AR
RMSE	0.436	0.517	0.280	0.593	0.789	0.950
Rel.MSE	>1	>1	1.00	0.390	0.690	1.00
Std.Dev.	-	-	-	0.07	0.05	-
p-value	-	-	-	0.00	0.00	-
Conc.	0.780	0.970	0.970	0.790	0.440	0.460

Table 11: Forecasting performance of "synthetic core" indicator on total inflation, two sub-periods

	Jan.1996-Dec.1998			Jan.1999-March.2002		
	π_{sc}^{12}	RW	AR	π_{sc}^{12}	RW	AR
RMSE	0.419	0.544	0.381	0.372	0.594	0.603
Rel.MSE	>1	>1	-	0.38	0.97	-
Std.Dev.	-	-	-	0.11	0.12	-
p-value	-	-	-	0.00	0.40	-
Conc.	0.64	0.81	0.81	0.77	0.54	0.56

Table 12: Forecasting performance of "synthetic core" indicator on core inflation, two sub-periods

model for the 1996-1998 period, which was characterized by a strong decrease in inflation during the convergence period before EMU.

6 Sensitivity analysis

To assess the robustness of our results, we now study how sensitive the results are to sample period.[22] After running the same models on subperiods, we compare the results to in-sample forecasts.

[22] Additional sensitivity analysis was performed but not reported here: (i) the use of VAR models to produce dynamic monthly forecasts, which turned out to be useful in the case of France (see Bruneau et al, 2002) but not at the euro area level ; (ii) the aggregation of sector forecasts (i.e recombining total inflation using forecasts on core inflation and the volatile components) indicating the same difficulty to project the volatile components (energy and unprocessed food) (iii) the introduction of different forecast horizons yielding interesting results at the 18-month horizon.

6.1 Stability over time

In order to assess the stability of the results over time, we split the sample into two subperiods: [January 1996- December 1998] and [January 1999-March 2002]. As already reported in Table 1, we observe that for the AR model, the first sub-period RMSE is 3 times smaller for total inflation and twice smaller for core inflation. This provides evidence of the inability of the AR model to anticipate the early 1999 up-turn. For core inflation, many of the models that we selected exhibit more stable performance -as measured by their RMSE for the two sub-periods- than the AR model. This is in particular the case of the $DLI_{2,15}$ model which includes the oil prices which naturally becomes better in the second sub-period, although such a feature is expected not to be permanent. As a consequence, the performance of the $DLI_{3,10}$ model appears to be less contingent on the time period. Concerning total inflation, the RMSE of the $DLI_{3,8}$ is twice bigger in the second than in the first period, as compared to three times higher for the AR model. See tables 13 to 15

As shown in the charts in Annex 3, one should acknowledge that most models are unable to accurately forecast the upturn in total inflation. But, for core inflation, the upturn occurs later with the "second-round" effects of the energy shock through wage-price adjustments. Accordingly, the synthetic inflation index, which partially includes the surge of energy prices, performs better than all models in recognizing the inflation upturn (see figure 14). Note also that for total inflation, apart from the "synthetic core" (see figure 13), the factor model $F^{Emu}[1]$ as well as the $DLI_{3,8}$ model are the most capable to outperform the AR models and to anticipate a bit earlier than other models the upturn of inflation observed over the last period. See figures 10 and 11.

	Sample : Jan 1996-Dec 1998					
	$DLI_{3,10}$	$DLI_{2,15}$	$F^{Be}[1]$	$CB_5^{aci}[2]$	$CB_{10}^{emp}[2]$	AR
RMSE	0.290	0.365	0.247	0.323	0.290	0.381
Rel.MSE	0.58	0.92	0.42	0.72	0.58	1.00
Std.Dev.	0.32	0.17	0.10	0.11	0.07	-
p-value	0.09	0.32	0.00	0.00	0.00	-
Conc.	0.81	0.81	0.81	0.81	0.81	0.810

Table 13: Forecasting performance of the combined models factor/indicator for core inflation, 1996-1998

6.2 In-sample results

Another way of assessing the stability over time is to consider the difference between in-sample and out-of-sample performance.

When considering in-sample forecasts over the whole period, results are considerably improved in terms of standard errors of Rel MSE, whatever the model considered in this

	Sample : Jan. 1999-March 2002					
	$DLI_{3,10}$	$DLI_{2,15}$	$F^{Be}[1]$	$CB_5^{aci}[2]$	$CB_{10}^{emp}[2]$	AR
RMSE	0.409	0.357	0.439	0.435	0.455	0.603
Rel.MSE	0.46	0.35	0.53	0.52	0.57	1.00
Std.Dev.	0.11	0.15	0.24	0.14	0.17	-
p-value	0.00	0.00	0.02	0.00	0.01	-
Conc.	0.72	0.62	0.54	0.67	0.67	0.56

Table 14: Forecasting performance of the combined model factor/indicator for core inflation, 1999-2002

	jan.1996-dec.1998				jan.1999-march.2002			
	LI_2	$DLI_{3,8}$	$F^{emu}[1]$	AR	LI_2	$DLI_{3,8}$	F^{emu}	AR
RMSE	0.189	0.347	0.217	0.280	0.817	0.678	0.876	0.950
Rel.MSE	0.46	1.54	0.60	1.00	0.74	0.51	0.85	1.00
Std.Dev.	0.04	-	0.07	-	0.07	0.10	0.05	-
p-value	0.00	-	0.00	-	0.00	0.00	0.00	-
Conc.	0.97	0.97	0.97	0.97	0.56	0.77	0.49	0.46

Table 15: Forecasting performance of factor or indicator models for total inflation, two sub-periods

paper,[23] even if the upturn of inflation in the last period is never fully recognized in time. To recognize the upturn, on the basis of in-sample analysis, note that it is obviously better to include oil prices in the model, while this was not sufficient in the case of the out-of-sample analysis. This provides evidence of instability of the coefficients over time.

If one limits the investigation to the 1996-2002 period (table 16), period over which out-of-sample performance was assessed, one observes that the AR has similar performance for in- and out-of-sample in the projection of core or total inflation. It is still unable to recognize the 1999-2000 upturn in time, exactly like all models presented in the previous sections. Regarding the other models, one can observe that their performances are generally similar to the ones obtained out-of-sample. For example, for $DLI_{2,8}$ the relative MSE is 0.63 in-sample compared to 0.64 out-sample. This proximity between both performances is confirmed by the quite good stability of the estimates of the coefficients over time.

All in all, the lessons of this exercise is, that the last surge of energy prices remains difficult to capture, even in-sample. In addition the performance obtained out-of sample is broadly confirmed by in-sample analysis.

[23] The results are available from the authors upon request.

	Total inflation				Core inflation			
	$F^{emu}[1]$	$DLI_{2,8}$	RW	AR	$F^{Be}[1]$	$DLI_{3,13}$	RW	AR
RMSE	0.581	0.503	0.671	0.634	0.335	0.310	0.571	0.479
Rel.MSE	0.840	0.630	1.120	-	0.490	0.420	1.420	-
Conc.	0.810	0.760	0.770	0.770	0.730	0.730	0.670	0.670

Table 16: In-sample results (1996:1-2002:3)

7 Real-time forecasts, an example.

We now consider the implementation of these various models to produce real time forecasts, where the actual information set of the forecasters is taken care of. Survey indicators are usually available in a very timely fashion. They do not create any problem since that they are generally available before the release of the HICP data, which are plublished with a two-week to a one-month lag. However, data for the labour market (unemployment and wages) are usually published two months after the HICP. This may create some problems for the factors we have estimated with the variables.

In order to derive our factors, we implement the unbalanced panel algorithm which extends the shorter series in the database by filling the gaps by factor methods (see Annex C for details). Such an algorithm can be used for both the complete panel or for blocks, with better results for blocks of variables that are sufficiently diverse.

We provide here two examples that indicate that factor models are not too much affected by real-time forecasts. In Table 17 for total inflation, the RMSE of the balanced panel (first column) and the unbalanced panel (second column) are almost identical. This is also the case, for core inflation on the complete panel in first difference: the RMSE only increases from 0.345 to 0.359.

	Total inflation			Core inflation		
	$F^{emu}_{BP}[1]$	$F^{emu}_{UBP}[1]$	AR	$F^{dbase}_{BP}[2]$	$F^{dbase}_{UBP}[2]$	AR
RMSE	0.649	0.652	0.712	0.345	0.359	0.509
Rel.MSE	0.83	0.84	1.00	0.46	0.50	1.00
Std.dev	0.05	0.05	-	0.11	0.13	-
p-value	0.00	0.00	-	0.00	0.00	-
Conc.	0.72	0.72	0.69	0.77	0.77	0.68

Table 17: Forecasting performance in real time of both factor models, total and core inflation, whole period.

8 Data snooping

In the previous sections, we have reported the relative predictive performance of different models compared to the AR benchmark model. However, the set of models we have examined is quite large. Indeed, among these models, one can search for the best models over (i) Single Economic Indicator models, (ii) Double Leading Indicator models,(iii) models with one single factor from DFA, or (iv) models combining one factor with one economic indicator. All in all, this amounts to a total of around 660 different models. Moreover a great number of these models are nested models. Against this background, any conclusion regarding the predictive superiority of a given model over the benchmark could be more driven by chance than by the inherent merit of the model. Accordingly, the p-values we give in the previous sections could be too optimistic. This issue is the so-called data snooping problem outlined by White (2000), who proposes a procedure for testing the null hypothesis that the best model encountered in a specification search has no predictive superiority over a given benchmark model. However, according to Hansen (2001), the procedure should be questioned. The problem would come from the fact that the asymptotic distribution of the test statistic under the null hypothesis is not the right one.

By noting as k, the index of one of the K alternative models, the null hypothesis is specified as:

$$H_0 : \{\forall k, 1 \leq k \leq K, \, \mu_k \leq 0\}$$

where μ_k denotes the difference between the theoretical MSE of the benchmark and the one of the alternative model k.

The test statistics used by White is simply the maximum $Max_{\forall k, 1\leq k \leq K}(\overline{X_{n,k}})$ where $\overline{X_{n,k}}$ denotes the estimate of μ_k. Hansen (2001) proves that the asymptotic distribution of this statistics only depends on the models for which $\mu_k = 0$. The distribution used by White does not take into account of this property. The dimension of the asymptotic covariance matrix in White's procedure is therefore too high (K against m, if m denotes the number of models satisfying $\mu_k = 0$). As a consequence, the test statistics is not precise enough providing too high p-values and making the test too conservative. We have implemented the procedure with the correction proposed by Hansen (2001) and we confirm the bias induced by the White's (2000) procedure.

Hansen proposes to estimate consistently the p-values by filtering the paths used in the bootstrap procedure as following:

$$X^*_{k,b} = X_k(\theta_b(t)) - g(\overline{X}_{n,k})$$

$$\begin{aligned} g(x) &= 0, \text{ if } x \leq -A_{n,k} \\ &= x \text{ otherwise} \end{aligned}$$

where $A_{n,k}=\frac{1}{4}n^{-1/4}\sqrt{\widehat{var}(n^{1/12}\overline{X}_{n,k})}$, $\widehat{var}(n^{1/12}\overline{X}_{n,k}) = B^{-1}\sum_{b=1}^{B}(n^{1/2}\overline{X}^{*}_{n,k,b} - n^{1/2}\overline{X}_{n,k})^2$, and $\overline{X}^{*}_{n,k,b} = n^{-1}\sum_{t=1}^{n} X_k(\theta_b(t))$. One generates B resamples ($b = 1, ..., B$) of the X_k statistics. Each resample is made of draws from the X_k distribution. The θ_b vector provides the index of the random draws from the initial distribution for each b resample. $X(\theta_b)$ is the new vector of the X_k statistics.

The main results are the following.

1) As indicated in figure 17, for total inflation, the test procedure provides low p-values (a few percentage points), even if the set of alternative models is the largest one.

This can be interpreted as follows. In the case of core inflation, there are many models which have a very similar relative predictive performance close to the average, with a limited dispersion across models. Accordingly, the asymptotic distribution of the statistics, obtained by bootstrap, is based on the paths of very similar models, so that the value observed for the statistics in the sample is likely not to be in the tails of the distribution. This happens when one cannot choose one model among the others as a better candidate to outperform the benchmark, which is meanwhile outperformed by several models, according to the value of the relative MSE or purely graphical information.

On the other hand, for total inflation, one can find one alternative model which behaves significantly better than the other ones and which exhibit reasonable properties to predict inflation, as compared to the AR model; this is the model based on the "synthetic index" from DFA (See section 5).

2) In contrast, concerning core inflation, we find p-values which are significantly higher than the ones reported in the previous sections (figure 18). This occurs when the set of alternative models include the 660 previously mentioned models. The p-value is around 0.13. However, if we limit the set of alternative models to the set of models with one factor or based on a single economic indicator (60 models), the p-value is much lower (0.012)

It is worth emphasizing that the Hansen's procedure is not able to filter efficiently the bad models which have a relatively high volatility. To give an example, the class of "problematic" models includes one model with the price of Brent oil, which appears to be very volatile over the second sub-period (mean and standard error respectively equal to -0.168 and 0.353). In that case one can find a p-value very close to one (see figure 19). The correction factor $A_{n,k}$ has thus a high absolute value so that the model is centered around 0 in the re-sample procedure and it contributes to the asymptotic distribution of the test statistic ($\mu_k = 0$). In the bootstrap procedure, the model may generate paths with a (relatively) high positive values of the test statistic above the value observed in sample. As a consequence, the estimated p-value mechanically increases. This kind of drawback indicates that the test should be modified so as to take into account not only the observed value of the mean $(\overline{X_{n,k}})$ but also maybe the ratio of the observed volatility (over time) to this mean.

All in all, we confirm the main results we pointed out in the previous sections. It seems to us that the superiority of the models we retained can not be suspected to provide better results than the AR model just by chance. Of course the statistical tools are central in the paper, but they provide only guidelines to conduct forecast exercices. The economic interpretation has also to provide arguments to choose one model rather another, especially when the statistical results are not contrasted enough.

	Total inflation	Core inflation
Best Model	π_{SC}^{12}	$CB_1^{dbase}[2]$
Max Stat	0.232	0.140
p-value	0.00	0.12

Table 18: p-values of the test for SPA for Total and Core inflation forecast.

9 Conclusion

From our extensive assessment of indicator and factor models in order to forecast euro area inflation, we finally come up with a certain number of models that improve upon the simple AR model. We now review the results, before drawing a few general conclusions regarding future research.

1.1) For core inflation, and considering the 12-month horizon, factor models (in particular the "Belgian" model) exhibit forecasting performance which are quite close to that of the double leading indicator models including indicators of "order books" in manufacturing industry, as well as in the construction sector. For total inflation, it is rather the models associating one factor with one indicator that fare similarly to the double leading indicators, in the sense of exhibiting "Rel MSEs" vis-à-vis the AR model that are significantly below 1. This is also confirmed by concordance indexes.

1.2) However, total inflation remains difficult to forecast because the 1999-2001 upturn of inflation is never regognized timely, except perhaps for the "EMU" factor model, $F^{Emu}[1]$, and the $\mathrm{DLI}_{3,8}$ model which perform reasonably well from that point of view.

It is worth pointing additional results out.

1.3) Firstly, contrary to the performance of the double indicator models, single factor models or models combining one leading indicator with one factor appear to be stable over time when core inflation is forecast.

1.4) Secondly, for total inflation the predictive performance of the EMU factor model is also stable over time.

1.5) Thirdly, we construct a "synthetic core model", that appears to improve upon the AR on the period 1999-2002 for core as well as total inflation, especially in anticipating the upturn in inflation. From that point of view, the factor models appear to be useful to predict total inflation. From an economic point of view, the synthetic index gives an interesting synthesis of information, obtained from a linear combination of a great number of variables which receive varying weights over time. For the period under study, the energy prices appear to have played an important role in contributing to inflation. The global factor used to build the synthetic index includes leading information about inflation from the Industry Survey. One can exclude the possibility, however, that, under other circumstances, other variables might be at work through the index.

From a more methodological point of view, our investigation also leads us to make a few more general remarks regarding future research.

2.1) The sample period matters.

In the literature, the factor models that appear to yield the most convincing results to forecast inflation rely on individual country samples and long sample periods. The sensitivity of the results to particular shocks (BSE crisis and 1999-2000 oil shock) makes it necessary to multiply the statistics to assess the performance of the models. It is worth noting that none of the studies available so far, except Cristadoro et al. (2001), include the upturn of inflation observed from 1999.

2.2) The next challenge is to improve upon the most volatile components.

Given the reasonably good results on core HICP, one cannot avoid the question of whether it is possible or not to significantly improve forecasts of the energetic and unprocessed food sectors (Jondeau et al., 1999).

2.3) Dynamics may also matter.

In addition, one has to stress the need to rely on really dynamic models which has not been made so far in the literature. In the paper we use unbalanced panels to implement real-time forecasts. When data are not available, the problem is to obtain reliable estimates for the missing observations. However, in the literature, the results on the advantages of using unbalanced panels appear to be mixed or even inconclusive: Angelini et al. (2001) find that predictive performance is unstable; Artis et al. (2001) build their best model on unbalanced panels. Stock and Watson, 1998, suggest the method but do not implement it for forecasting inflation in their 1999 paper. Forni et Lippi (1997) and the latter papers using the spectral analysis methodology (Forni et al., 2001, Cristadoro et al., 2001) do introduce dynamics in their modelling in the sense mentioned previously; they replace missing values through the projections on the future common components spanning the factor model. We have found models which seem to be unsensitive to using unbalanced panels, but more investigation of the practical improvement is warranted. In addition a more structural approach of the dynamics of the models would be warranted.

2.4) Data snooping

Finally, we have investigated the effects of the so-called Data-Snooping problems by implementing the test procedure proposed by Hansen (2001) in the lines of White's (2000) Reality Check. We confirm the bias of White's procedure, as outlined in Hansen (2001). However we have also observed that the test is sensitive to the problematic cases where the relative performance of bad models (in the sense of Diebold and Mariano,1995) is associated with high volatility. The identification of bad models should take into account jointly the mean and the volatility of the measure of the relative performance. This requires to look for an extention of the Hansen's procedure.

References

[1] Altissimo, F. A. Bassanetti, R. Cristadoro, L. Reichlin and G. Veronese (2001) "The construction of coincident and leading indicators of the euro area business cycle", Banca d'Italia, *Temi di discussione*, December.

[2] Angelini, E, J. Henry and R. Mestre (2001) "Diffusion-index based inflation forecasts for the euro area" *European Central Bank Working Paper* 61, April.

[3] Angeloni, I and L. Dedola (1999), "From the ERM to the euro: new evidence on economic and policy convergence among EU countries" European Central Bank, *Working Paper*, n° 4.

[4] Artis, M. J., A. Banerjee and M. Marcellino (2002) "Factor forecasts for the UK", *CEPR Discussion Paper*, n° 3119, January.

[5] Atkeson, A. and L. E. Ohanian (2001) "Are Phillips Curve Useful for Forecasting Inflation?" *Federal Reserve Bank of Minneapolis Quarterly Review*, vol. 25, n°1, Winter, pp 2-11.

[6] Bai, J. and S. Ng (2000) "Determining the number of factors in approximate factor models", *manuscript*, Boston College, Dept of Economics, December.

[7] Bernanke, B. and J. Boivin (2001) "Monetary policy in a data rich environment", *NBER Working Paper*, n° 8379, July.

[8] Bruneau, C., O. De Bandt, A. Flageollet and E. Michaux (2002) "Forecasting inflation using economic indicators: the case of France", *manuscript*, Banque de France.

[9] Cecchetti, S.G., Chu, R. S. and Steindel, C. (2000), "The unreliability of inflation indicators", Federal Reserve Bank of New York, *Current Issues in Economics and Finance*, April.

[10] Clarida, R., J. Gali and M. Gertler (1998a), "Monetary Rules in Practice: Some International Evidence ", *European Economic Review* , 42(6), 1033-1067

[11] Clarida, R., J. Gali and M. Gertler (1998b),"Monetary Rules in Practice and Macroeconomic Stability: Evidence and Some Theory," *CEPR Discussion Paper* 1908.

[12] Cristadoro, R., M. Forni, L. Reichlin and G. Veronese (2001) "A core inflation index for the euro area", Banca d'Italia, *Temi di discussione*, n° 435, December.

[13] DEMETRA (2000), Seasonal Adjustment interface for Tramo/Seats, User manual, version 1.4, Eurostat, the Statistical Office of the European Communities.

[14] Doz, C. (1998), *Econométrie des modèles à facteurs dynamiques et exemples d'application en macroéconomie*, Ph.D dissertation, Department of Economic, University of Paris IX-Dauphine, France.

[15] Fagan, G., J. Henry and R. Mestre (2001) "An Area-wide Model (AWM) for the euro area", European Central Bank, Working Paper, January.

[16] Forni, M., M. Hallin, M. Lippi and L. Reichlin (2001) "Do financial variables help forecasting inflation and real activity in the euro area?" in "*Financing European Economies: issues and policy options*" Conference of the Fondation Banque de France, November.

[17] Forni, M., M. Hallin, M. Lippi and L. Reichlin (2001) "The generalized factor model: identification and estimation", *The review of Economic and Statistics*, vol. 82 (4), 540-554.

[18] Hansen P.R.,. (2001) "An Unbiased and Powerful Test for Superior Predictive Ability", Brown University, Working Paper, November.

[19] Hendry and Clements, (1998), *Forecasting Economic Time Series*, Cambridge University Press.

[20] Jondeau, E., H. Le Bihan and F. Sédillot (1999)"Modélisation et prévision des indices de prix sectoriels", Banque de France, *Notes d'Etudes et de Recherche*, n° 68.

[21] Marcellino, M., J.H. Stock and M.W. Watson (2000) "Macroeconomic forecasting in the euro area: country specific versus area wide information", manuscript (revised: June 2001).

[22] Sargent, T.J. and D. Quah, (1993), "A Dynamic Index Model for a Large Cross Sections",.ch 7 in J.H. Stock and M.W. Watson (eds.), *Business Cycles, Indicators, and Forecasting*, Universty of Chicago Press for the NBER, 1993, 285-306.

[23] Stock, J.H. and M.W. Watson (1999) "Forecasting inflation", *Journal of Monetary Economics*, 44, 293-305.

[24] Stock, J.H. and M.W. Watson (1998) "Diffusion indexes", *NBER Working paper*, n° 6702 (revised version: "Macroeconomic forecasting using diffusion indexes", June 2001)

[25] Stock, J.H. and M.W. Watson (1991) "A Probability Model of the Coincident Economic Indicator" in K. Lahiri and G. Moore (eds) *Leading economic indicators: new approaches and forecasting records*, Cambridge University Press, 63-89.

[26] Vanhaelen, J. J., L. Dresse and J. De Muldur (2000) "The Belgian industrial confidence indicator: leading indicator of economic activity in the euro area?" National Bank of Belgium, *Working Paper*, n° 12

[27] White H. (2000), "A Reality Check for data snooping", *Econometrica*, vol.68 (5), 1097-1126.

A Mnemonics of the variables used in the tables

We provide below some explanations on the models presented in the main text. More details on the data are also available in Annex B.

A.1 Leading indicators

- LI_1: Construction confidence indicator (EU)
- LI_2: Construction survey, activity compared to last month (EU)
- LI_3: Construction survey, order book position (EU)
- LI_4: Consumer confidence indicator (EU)
- LI_5: Consumer survey, financial situation last 12 month (EU)
- LI_6: Economic confidence indicator (EU)
- LI_7: Retail survey, orders placed with suppliers (EU)
- LI_8: Retail survey, future business situation (EU)
- LI_9: Retail survey, current business situation (EU)
- LI_{10}: Industry survey, order book position (EU)
- LI_{11}: Industry survey, production expectation for month ahead (EU)
- LI_{12}: Unemployment Total (EU)
- LI_{13}: Industrial production index Total (EU)
- LI_{14}: Industrial production index Manuf (EU)
- LI_{15}: brent oil price

A.2 Double leading indicators

$DLI_{i,j}$: LI_i & LI_j, with $i = \{1, .., 15\}$ and $j = \{1, ..., 15\}$.
For example:

- $DLI_{2,8}$: Construction survey, activity compared to last month (LI_2) & Retail survey, future business situation (LI_8)
- $DLI_{3,10}$: Construction survey, order book position (LI_3) & Industry survey, order book position (LI_{10})

A.3 Factor

- F^{base}: All disaggregated series
- F^{prc}: Disaggregated HICP and producer prices series
- F^{emp}: Disaggregated employment series, national series of unemployment employment and available wages
- F^{aci}: Disaggregated car registration and IPI series
- F^{int}: Disaggregated interest rate series (3 months, 12 months and over 7 years)
- F^{sur}: Disaggregated survey series
- F^{prvl}: Disaggregated prices of energy, unprocessed food...
- F^{Be}: All available series for Belgium
- F^{Fr}: All available series for France
- F^{emu}: All available leading indicators for EMU

A.4 Combined model: indicator and factor

$CB_i^j = LI_i$ & F^j, with $i = \{1, ..., 15\}$, et $j = \{base, prc, ...\}$

For example:

- $CB_1^{prc} : LI_1 + F^{prc}$, Construction confidence indicator (EU) & first or second factor from PCA of prices block.
- $CB_5^{aci} : LI_5 + F^{aci}$, Consumer survey, financial situation last 12 month (EU) & first or second factor from PCA "aci" block (IPI and car registration).

B Data used

Our database is mainly composed of disaggregated series at the national level. Data sources include Eurostat, as well as OECD and the Bank for International Settlements database. The table 19 displays the types of the variables, the transformations which is applied to the variables, as well as the number of desaggreted series includes in the complete panel.

	Number of series*	Data transformation
Surveys	82	none
Consumer prices	48	$(1-L)\log$
Producer prices	27	$(1-L)\log$
Export/import prices	11	$(1-L)\log$
Industrial production	12	$(1-L)\log$
Employment Unemployment stats	35	$(1-L)$
Interest rates	18	$(1-L)\log$
Monetary aggregates	8	$(1-L)\log$
Effective Exchange rates	11	$(1-L)\log$
Share prices	11	$(1-L)\log$
Wages	5	$(1-L)\log$
Other indicators	12	$(1-L)\log$

*the number of series excludes the euro zone aggregated series, only disaggregated series.

Table 19: Transformation of the series

C The dynamic factor structure DFA in the lines of Stock and Watson (1998)

C.1 The main assumptions

Let y_t denote a scalar series, and X_t be a N-dimensional multiple time series which will be used to forecast y_t. The factor structure is as follows:

$$X_t = \Lambda_t F_t + u_t \tag{10}$$

where the dimensions are respectively : $N \times 1$, $N \times r$, $r \times 1$ and $N \times 1$. The common part of X_t is ΛF_t and u_t denotes its idiosyncratic part. Note that, in the previous model, the dynamics are introduced in three ways:

1. The factors are assumed to evolve according to a time series (multivariate) process which is not observable.
2. The idiosyncratic error terms are serially correlated.
3. The factors can enter with lags (or even with leads).

In the static factor model , the factor loadings are constant ($\Lambda_t = \Lambda_0$), the idiosyncratic terms are serially uncorrelated , F_t and u_{jt} are mutually uncorrelated and are *i.i.d.*. The model becomes approximatively static if the idiosyncratic disturbances are weakly correlated across series (for different j) ; for exemple, see Chamberlain and Rothshild (1983). The factor structure is used to estimate $E(y_t/X_t)$ where y_t denotes the series of interest:

$$y_{t+1} = \beta_t' F_t + \varepsilon_{t+1} \tag{11}$$

The disturbance ε is supposed to be such that:

$$E(\varepsilon_{t+1}/\underline{X_t}; \underline{y_t}; \underline{\beta_t}) = 0 \tag{12}$$

where $\underline{Z_t}$ denotes the set of the variables $Z_{t-i}, i \geq 0$, for any process Z.

C.2 Constant loadings

By the suitable redefinition of the factors and the idiosyncratic disturbances, the dynamic factor model can be rewritten such that Λ_t is constant. If the factor model states:

$$\begin{aligned} X_{it} &= \sum_{j=0}^{p} \sum_{h=1}^{r} \alpha_{ij,h} f_{h,t-j} + u_{it} \text{ for } i = 1, ...N \\ u_{it} &= \sum_{j=1}^{q} \phi_j u_{it-j} + \eta_{it} \end{aligned}$$

one can describe the $Nq \times 1$ dimensional vector $Z_t = (X_t', X_{t-1}', ..., X_{t-q+1}')'$ according to the factor structure :

$$Z_t = \Lambda F_t + v_t$$

where the factor component $F_t = (f_t', f_{t-1}', ..., f_{t-p}', ..., f_{t-q}', f_{t-q+1}', ..., f_{t-q-p+1}')'$ has the dimension $(p+1)qr \times 1$, because the model has r factors : $f_t = (f_{1t}, ..., f_{rt})'$. The factor loading Λ is $Nq \times (p+q)r$ and the idiosyncratic term is the $Nq \times 1$ dimensional vector:

$$v_t = (u_t', u_{t-1}', ..., u_{t-q+1}')'$$

where $A_j = (\alpha_{1j}', ..., \alpha_{Nj}')'$is a Nxr dimensional matrix with $\alpha_{ij} = (\alpha_{ij,1}, ..., \alpha_{ij,r})$[24]. Accordingly, Λ is a $Nq \times (p+1)qr$-dimensional matrix. So one is led to extract dynamic factors using contemporaneous as well as lagged values of X_t. Note that, if one is ready to accept that the residual terms are serially correlated in the factor structure, one can write the factor model with constant parameters, as follows :

$$Z_t = \Lambda F_t + u_t$$

where $Z_t = X_t$, $u_t = v_t$ are $N-$dimensional vectors, while the factor $F_t = (f_t', f_{t-1}', ..., f_{t-p}')'$and the factor loading $\Lambda = (A_0, ..., A_p)$ have the dimensions $r \times (p+1)$ and $N \times (p+1)r$ respectively. So the factors can be extracted by using contemporaneous values of X only.

C.3 Estimation of the parameters of the factor model

We successively examine the cases of balanced and unbalanced panels.

C.3.1 Case of balanced panels

The strong parametric assumptions are the following : (i) $\Lambda_t = \Lambda_0$ and, (ii) the disturbances u_t are i.i.d. independent across series, normally distributed so that the covariance matrix Σ of the vector of residuals $u = (u_1, ..., u_T)$ is diagonal. (Its seems to be possible to allow a weak correlation structure between the u_{jt} for any date t (Chamberlain and Rothshild (83)).

[24] More precisely, Λ is expressed as follows:

$$\Lambda = \begin{bmatrix} A_0 & A_1 & ... & A_p & 0 & ... & 0 \\ 0 & A_0 & ... & ... & A_p & ... & 0 \\ . & & & & & & \\ . & & & & & & \\ . & & & & & & \\ 0 & ... & ... & A_0 & A_1 & ... & A_p \end{bmatrix}$$

$F = (F_1', ..., F_T')'$ is treated as a $T \times r$ dimensional non random vector of parameters to be estimated. The estimator of (Λ_0, F) solves the non-linear least squares problem with the objective function [25]:

$$V_{NT}(\Lambda_0, F) = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} I_{it}(X_{it} - \lambda_{i0} F_t)^2 \tag{13}$$

where $I_{it} = 1$ if the variable is observed at time t and equal to 0, otherwise.

For given Λ_0, F_t^* must satisfy the first order condition (which gives the usual OLS estimator of F_t, in the regression of X_t on $\Lambda_0 = (\lambda_{10}', ..., \lambda_{n0}')'$ with $\lambda_{i0} = (\lambda_{i0}^{(1)}, ..., \lambda_{i0}^{(r)})$:[26]

$$F_t^* = \left(\sum_{i=1}^{N} I_{it} \lambda_{i0}' \lambda_{i0} \right)^{-1} \left(\sum_{i=1}^{N} I_{it} \lambda_{i0}' X_{it} \right) \tag{14}$$

and, conversely, for given F_t, Λ_0^* must satisfy the first order condition (which gives the usual OLS estimator of Λ_0 in the regression of X_t on F) :

$$\lambda_{i0}^{*\prime} = \left(\sum_{t=1}^{T} I_{it} F_t F_t' \right)^{-1} \left(\sum_{t=1}^{T} I_{it} F_t X_{it} \right) \tag{15}$$

Thus, the optimal values, $F_t^*$and Λ_0^* jointly solve the two previous equations.

In what follows, one supposes that all observations are available. Accordingly, the optimal value for F is obtained by reporting (15) in (13), and by solving an eigenvalue problem;

$$Min_F V_{NT}(F, \Lambda_0^*) = Min_F \left\{ \left(\frac{1}{NT} \sum_{i=1}^{N} \underline{X}_i' \underline{X}_i \right) - \frac{1}{NT} \left(\sum_{i=1}^{N} \underline{X}_i' P_F \underline{X}_i \right) \right\} \tag{16}$$

where $\underline{X}_i = (X_{i1}, ..., X_{iT})$ and $P_F = F(FF')^{-1}F'$ denotes the orthogonal projector on the subspace generated by the columns of $F = (F^{(1)}, ..., F^{(r)})$, with $F^{(h)} = (F_{1h}, ..., F_{Th})'$ under the normalization condition:$\frac{1}{N}\Lambda'\Lambda = I_{dr}$

[25] Note that these estimators are not Maximum Likelihood estimators, even under the normality assumption.(contrary to what is claimed in the NBER working paper by Stock and Watson (1998). Indeed, the log-likelihood is:

$$-\frac{NT}{2} - \frac{T}{2} \sum_{i=1}^{N} \log(\sigma_i^2) - \frac{1}{2} \sum_{i=1}^{N} \frac{1}{\sigma_i^2} \sum_{t=1}^{T} (X_{it} - \lambda_{i0} F_t)^2$$

[26] cf. $\forall t, F_t^* = (\Lambda_0'\Lambda_0)^{-1}\Lambda_0' X_t$, according to Zellner's theorem.

These r eigenvectors are the first r principal components of X_t. The previous analysis is a standard principal component analysis (with the only difference being that dynamic features are taken into account). Up to now, the number of factors r is supposed to be given. Recently, Bai and Ng (2000) have proposed to use relevant information criteria to determine the number of factors in the S&P framework.

C.3.2 Case of the unbalanced panels

A different approach must be used when the sample is unbalanced. One minimizes the previous objective function using the EM algorithm.

One notes $X_{it}^{*(q)}$ the latent value of X_{it} at step (q) of the algorithm; it is defined as $X_{it}^{*} = X_{it}$ if it is observed and $X_{it}^{*(q)} = \lambda_{i0}^{*(q-1)\prime} F_t^{*(q-1)}$otherwise, where $\lambda_{i0}^{*(q-1)}$ and $F_t^{*(q-1)}$solve the minimization problem:

$$Min \left\{_{\Lambda_0;F}\right\} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} I_{it}(X_{it}^{*(q-1)} - \lambda_{i0} F_t)^2$$

The same kind of eigenvalues problems as in the balanced case has to be solved. At step (q), the factors $F^{*(q)}$ are computed as the r eigenvectors of

$$\frac{1}{N} \sum_{i=1}^{N} \underline{X}_i^{*(q)} \underline{X}_i^{*(q)\prime}$$

corresponding to the r largest eigenvalues.

The unbalanced panel estimators are obtained by iterating the previous process until convergence. Note that this procedure can be applied for situations with mixed sampling frequencies.

D Charts

D.1 Recursive estimation of the factors

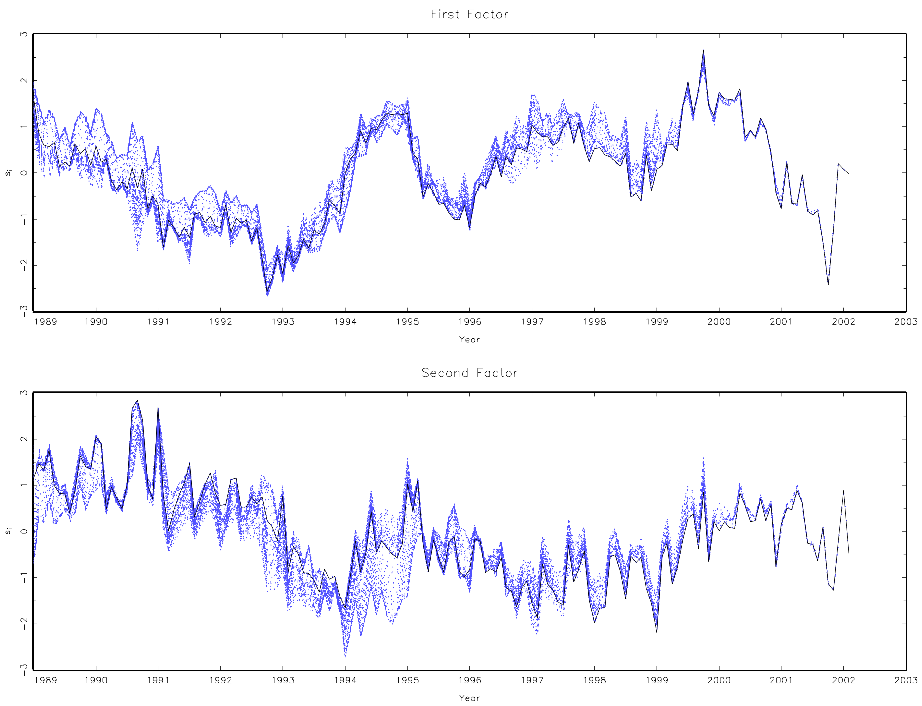

Figure 1 : Recursive estimation of the first two factors extracted from complete **balanced** panel with differenced-survey series.

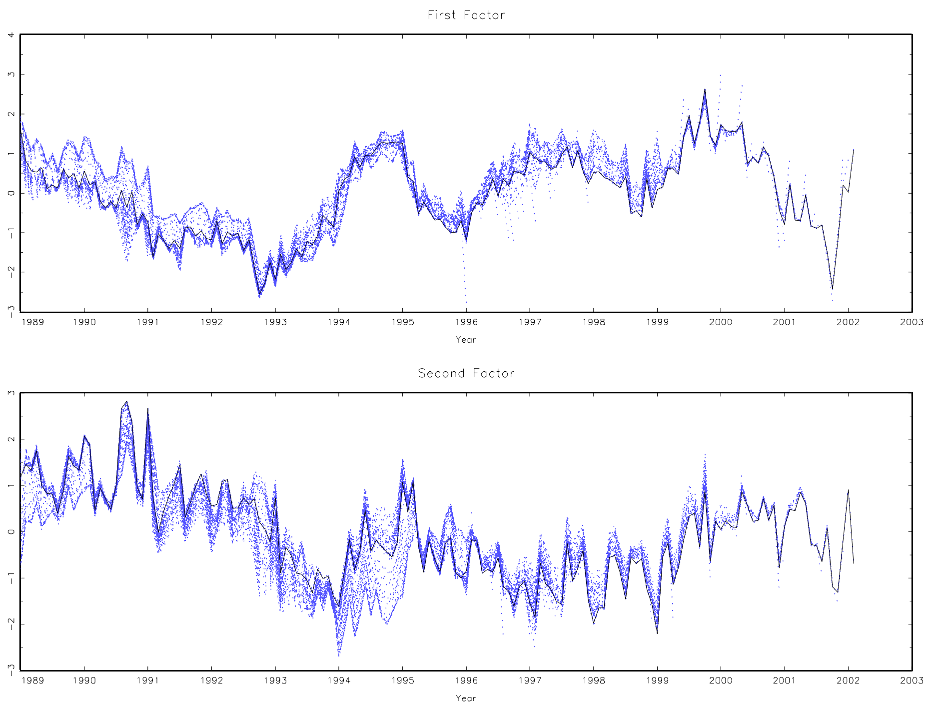

Figure 2 : Recursive estimation of the first two factors extracted from complete **unbalanced** panel with differenced-survey series.

D.2 Forecast Charts

D.2.1 Core Inflation

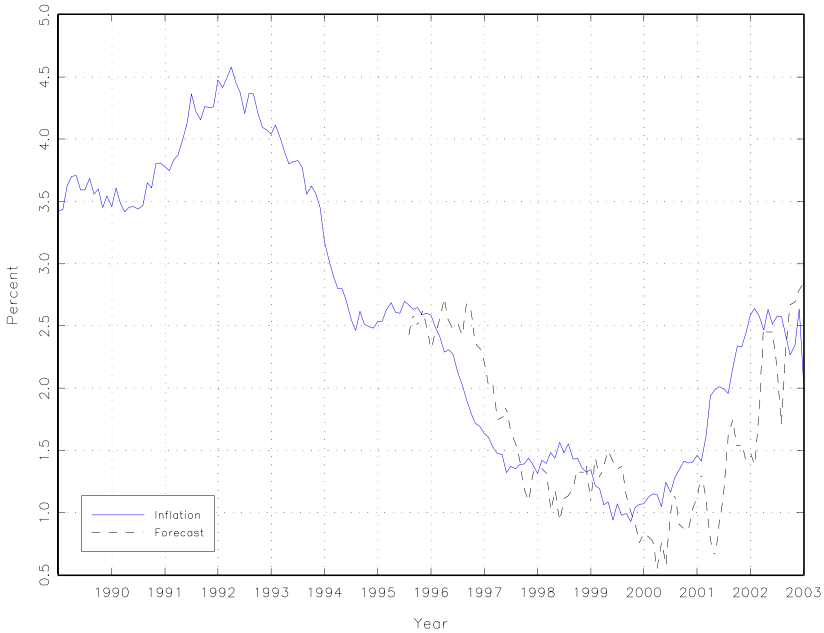

Figure 3 : Out-of-sample forecast of Core inflation with AR model.

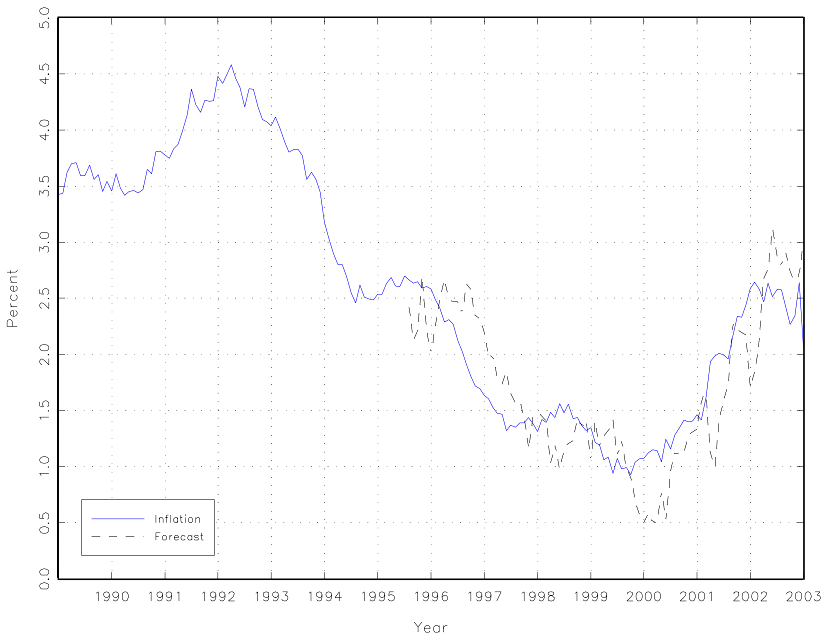

Figure 4 : Out-of-sample forecast of Total inflation with one indicator model (LI_{15}).

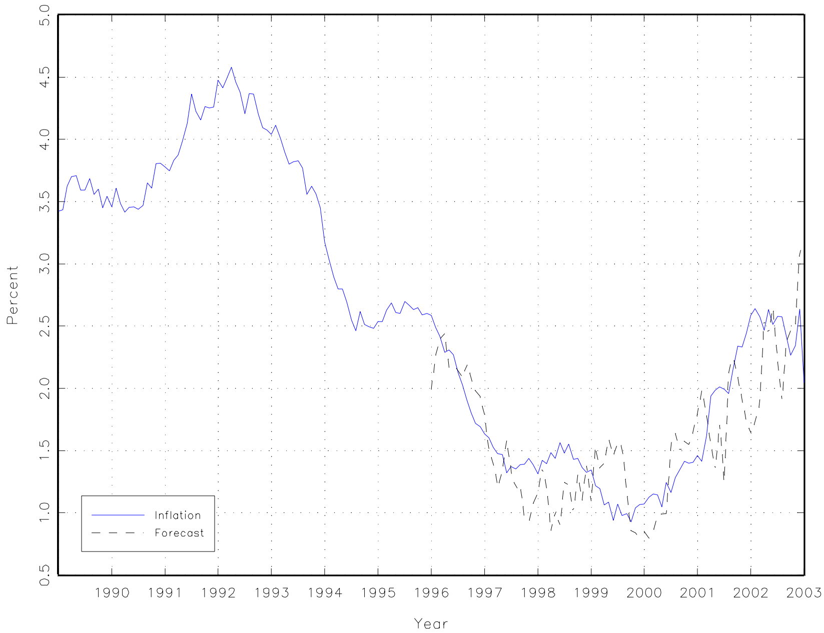

Figure 5 : Out-of-sample forecast of Total inflation with two indicators model ($DLI_{3,10}$).

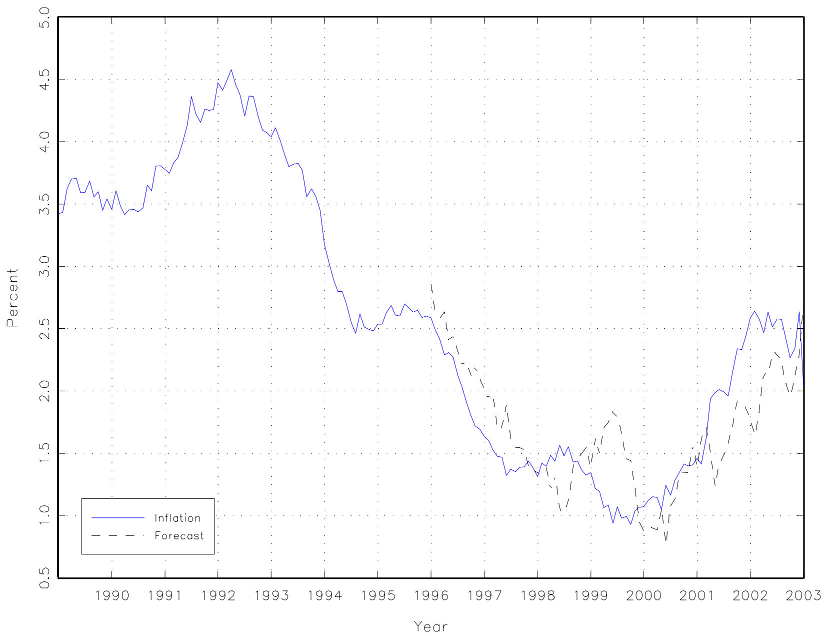

Figure 6 : Out-of-sample forecast of Core inflation with "belgian" factor model (F^{Be}).

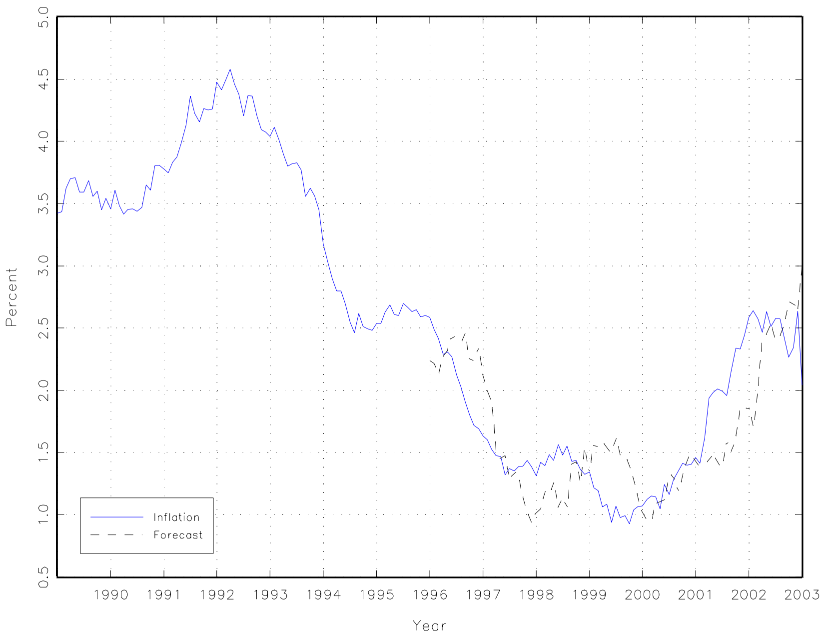

Figure 7 : Out-of-sample forecast of Core inflation with combined model (CB_5^{aci}).

D.2.2 Total inflation

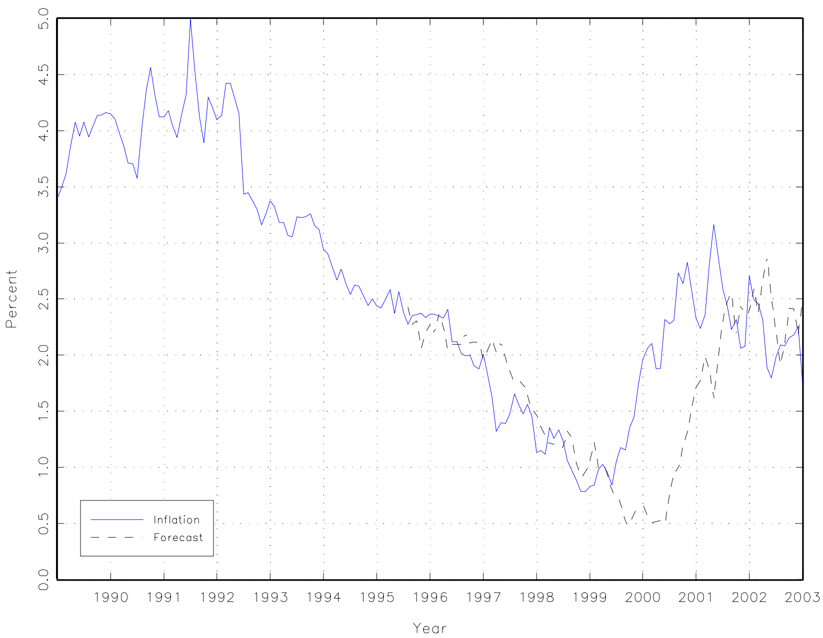

Figure 8 : Out-of-sample forecast of Total inflation with AR model.

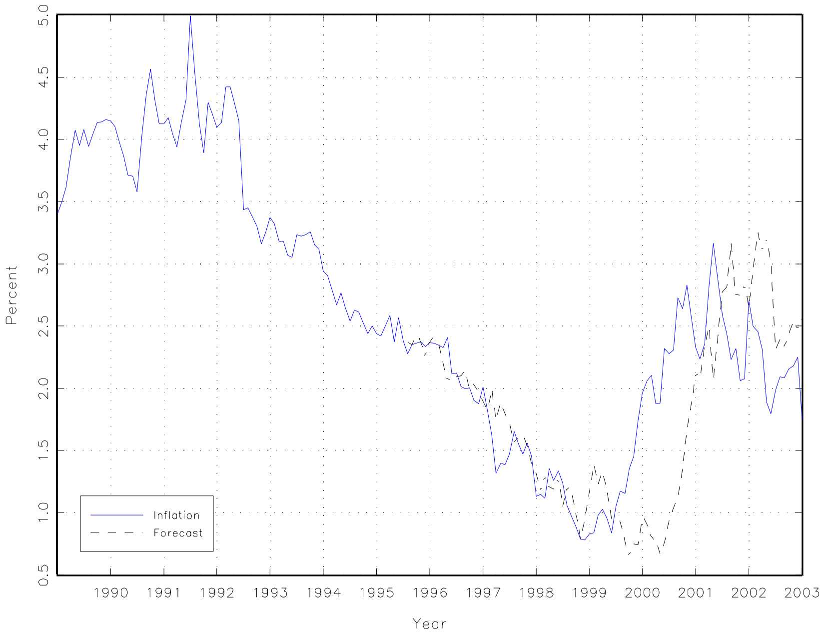

Figure 9 : Out-of-sample forecast of Total inflation with one indicator model (contruction survey, LI_2).

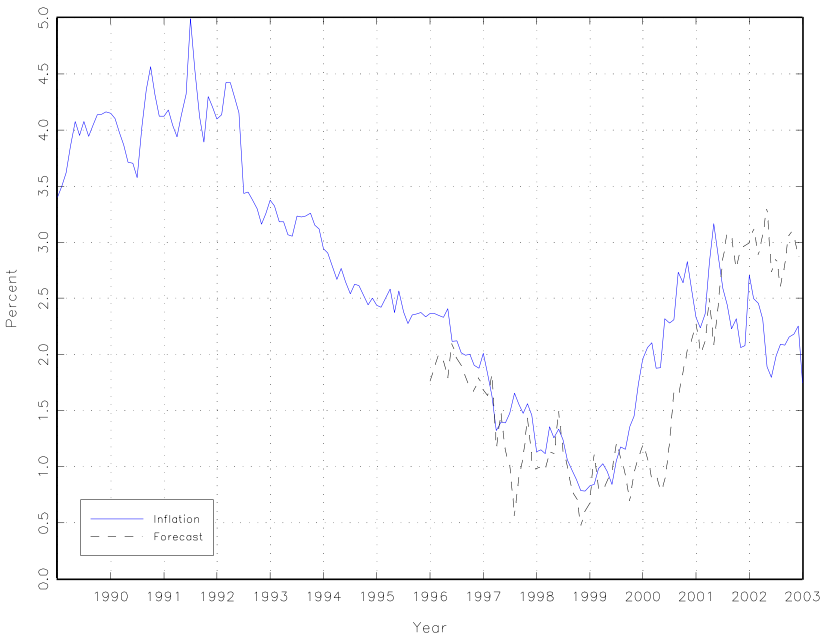

Figure 10 : Out-of-sample forecast of Total inflation with two indicators model ($DL_{3,8}$).

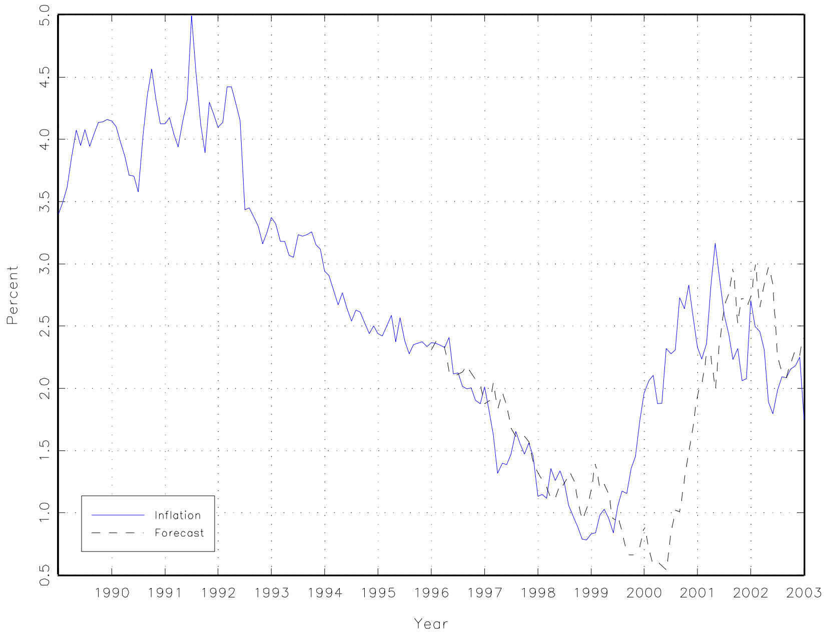

Figure 11 : Out-of-sample forecast of Total inflation with "E.M.U." factor model (F^{emu}).

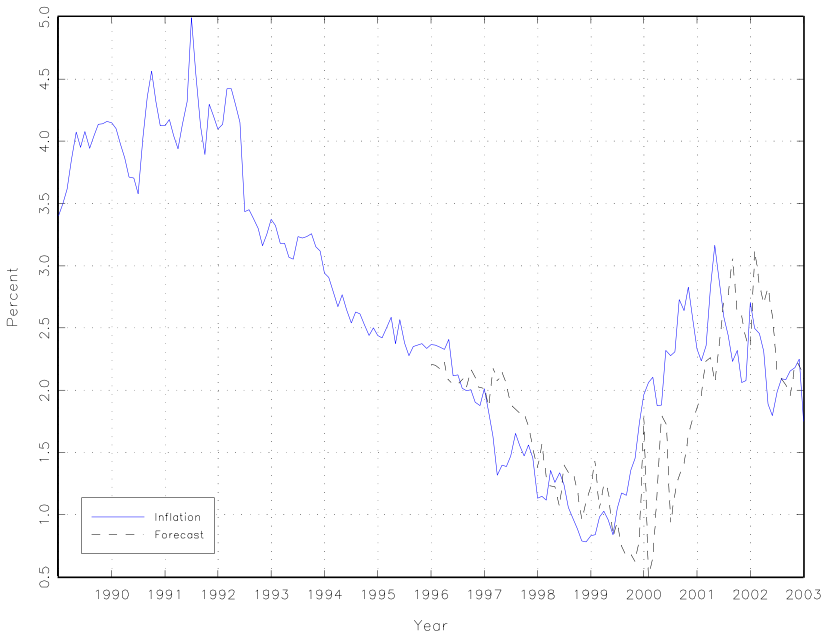

Figure 12 : Out-of-sample forecast of Total inflation with combined model model (CB_{12}^{prc}).

D.2.3 Synthetic core

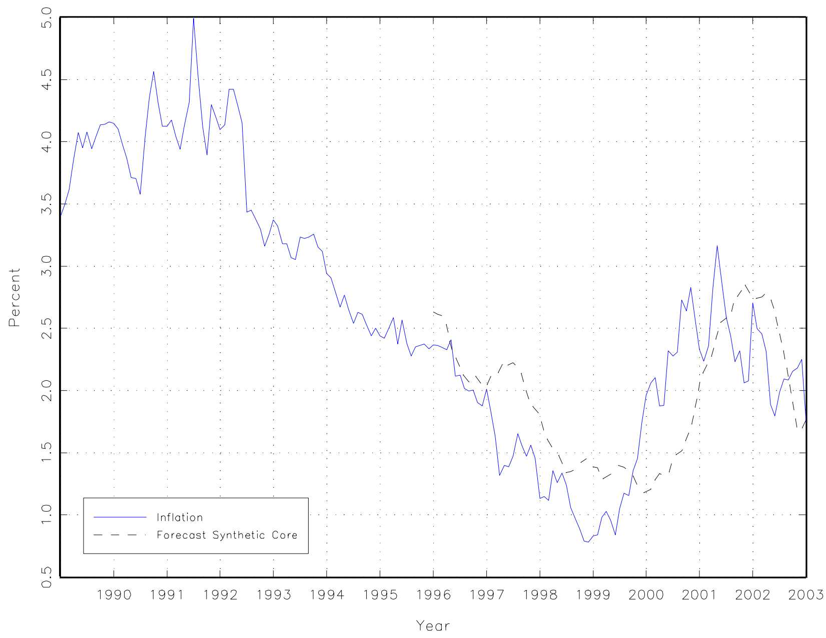

Figure 13 : Out-of-sample forecast of Total inflation with *synthetic core* model.

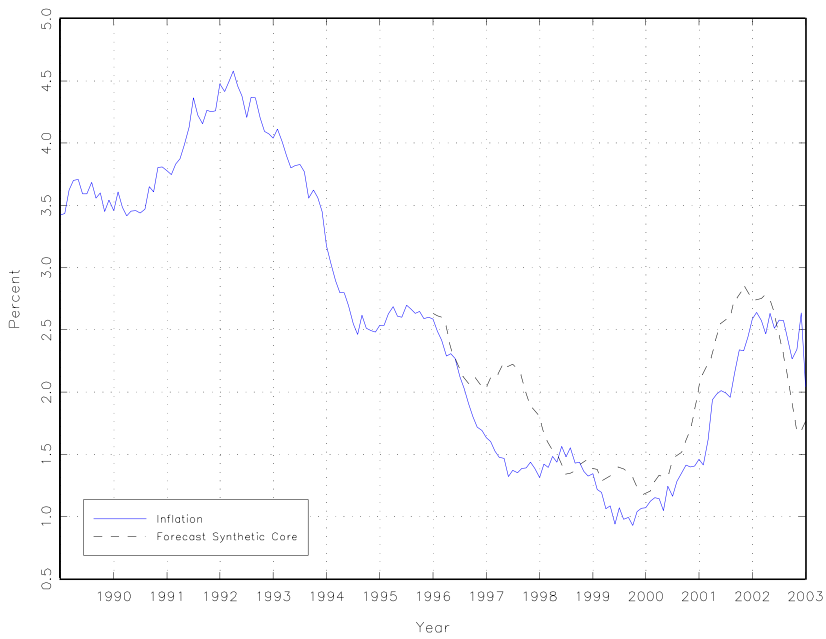

Figure 14 : Out-of-sample forecast of Core inflation with *synthetic core* model.

D.2.4 Real-time forecast

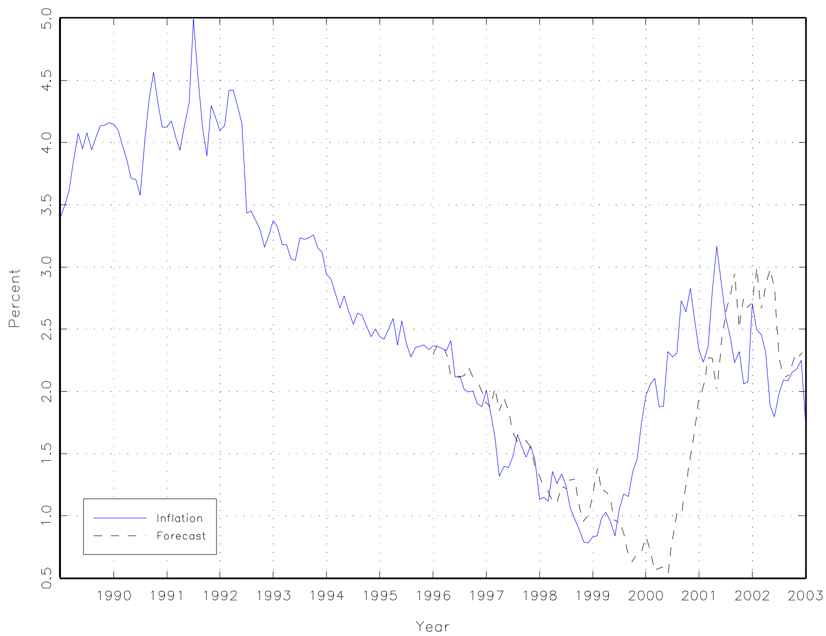

Figure 15 : Out-of-sample forecast of Total inflation with "E.M.U." factor extracted from unbalanced panel..

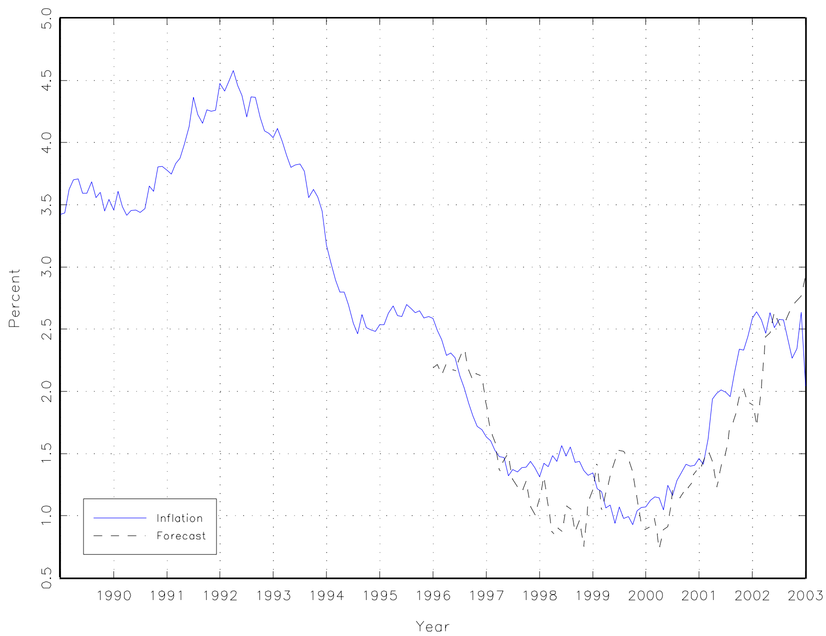

Figure 16 : Out-of-sample forecast of Core inflation with second factor extracted from unbalanced complete panel and construction survey (LI_1)..

D.3 Hansen's test for data snooping

To illustrate how the Hansen (2001) test works, we provide three figures. Each one of them features the performance measure and the p-value for the best performance observed in different configurations.

In the North-West sub-figure, the grey line represents the difference between the MSEs of the alternative models and the benchmark ("good" models have a positive value), whereas the dark line represents the correction factor $-A_{n,k}$ for each alternative model. The different models are ranked on the x-axis. In the South-West sub-figure, the solid line represents the p-values of the test for SPA (superior predictive ability) corresponding to the best performance obtained when one extends progressively the number of models considered (from 1 to 660). The horizontal line is the 5%-threshold. In the South-East sub-figure, the dashed line represents the performance observed over the whole set of alternative models and the solid line represents the maximum values obtained by bootstrapping. In the North-East sub-figure, the solid line identifies on the y-axis the model number each time it crosses the best observed performance in the South-East sub-figure.

Figure n°17 for example illustrates, for total inflation, the case where the p-value in the South-West sub-figure decreases sharply after model n°60 is included in the set of alternative models. One also observes that this is the only model above the best observed performance line, according to the resampled paths. On the basis of the full set of models, the null hypothesis of equivalent forecasting ability is rejected (the p-value is close to zero).

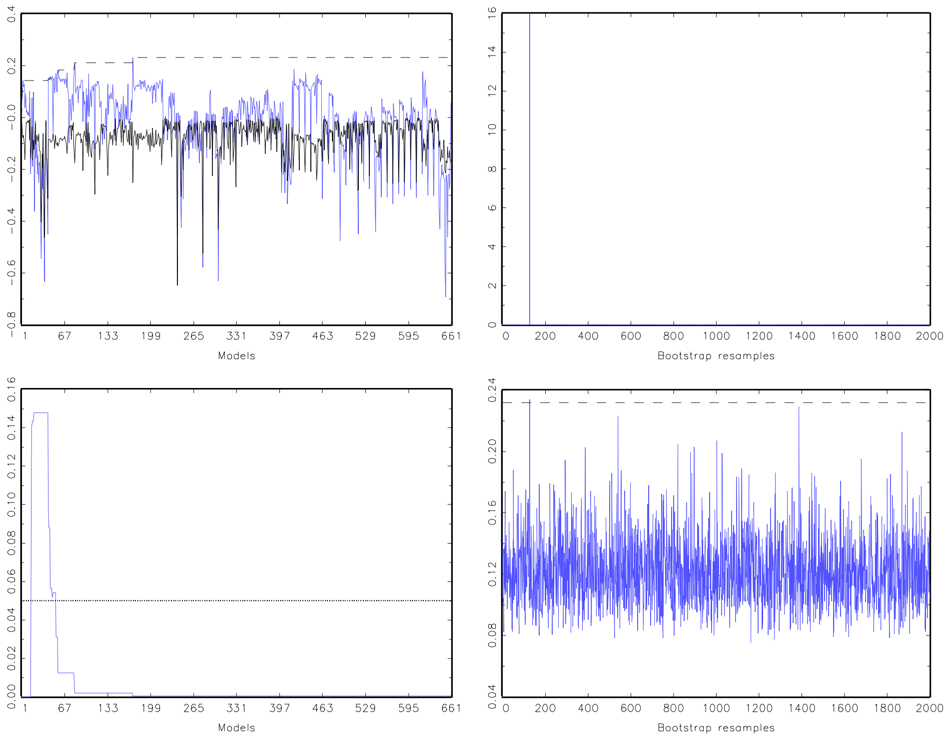

Figure 17 : MSE and p-values for the best model, Total inflation forecast, whole period.

In figure 18, for core inflation, the South-West sub-figure indicates that, when extending the number of models, the p-value fails to remain below the 5 % threshold. In the bootstrap analysis, the best performing model is often outperformed.

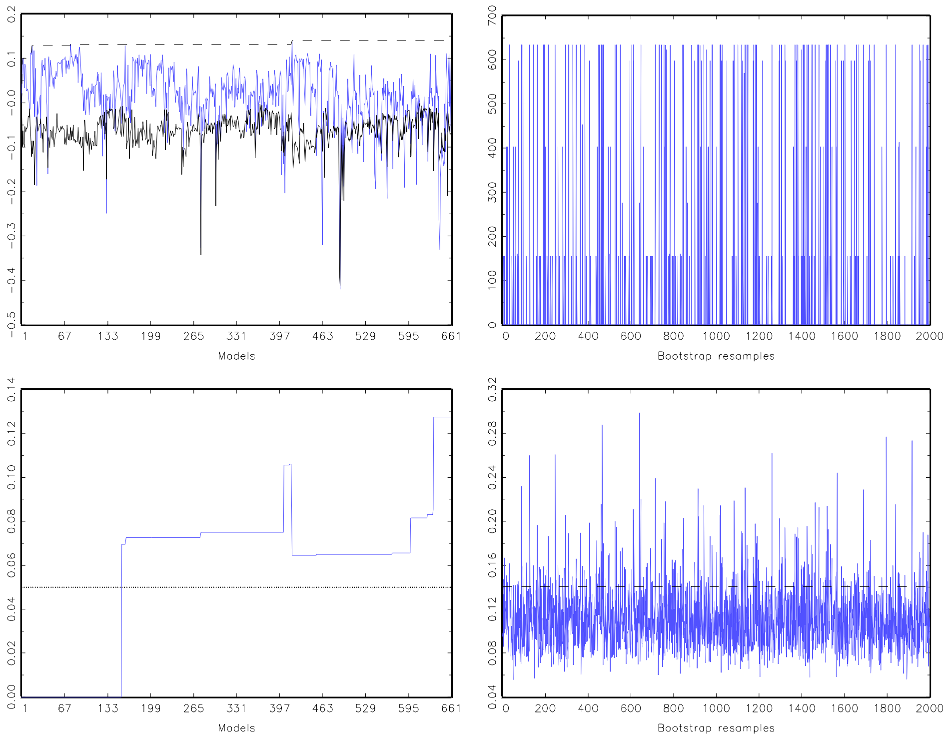

Figure 18 : MSE and p-values for the best model, Core inflation forecast, whole period.

In figure 19, for total inflation on the 1999-2002 sub-period, we assess the sensitivity of the Hansen test to the high variance of a few models. Here, the models ranked around n°20 in the North-West and North-East sub-figures distort the test, yielding p-values around 1. When excluding these models, the p-value would be below the 5% threshold.

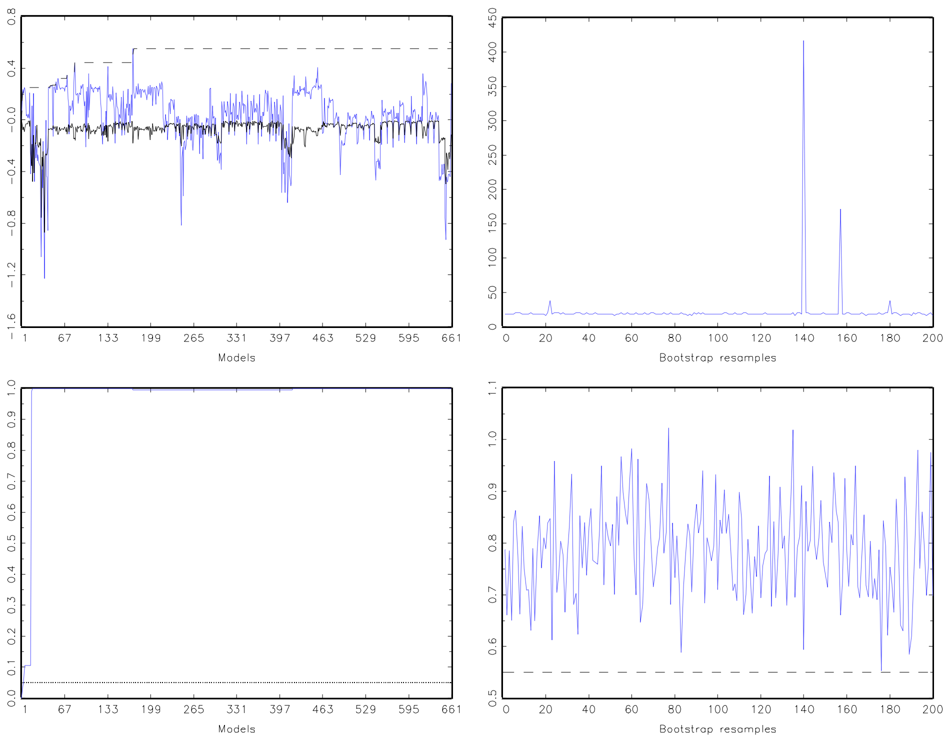

Figure 19 : MSE and p-values for the best model, Total inflation forecast, 1999-2002.

D.4 Rolling estimate of coefficients for two models given as examples.

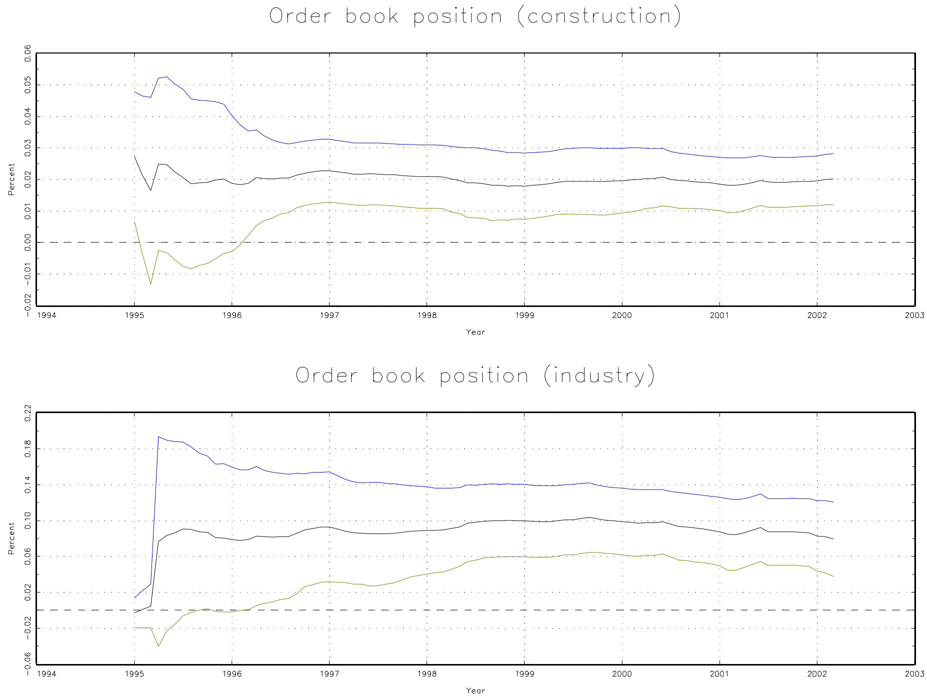

Figure 20 : Varying coefficients for $DLI_{3,10}$.

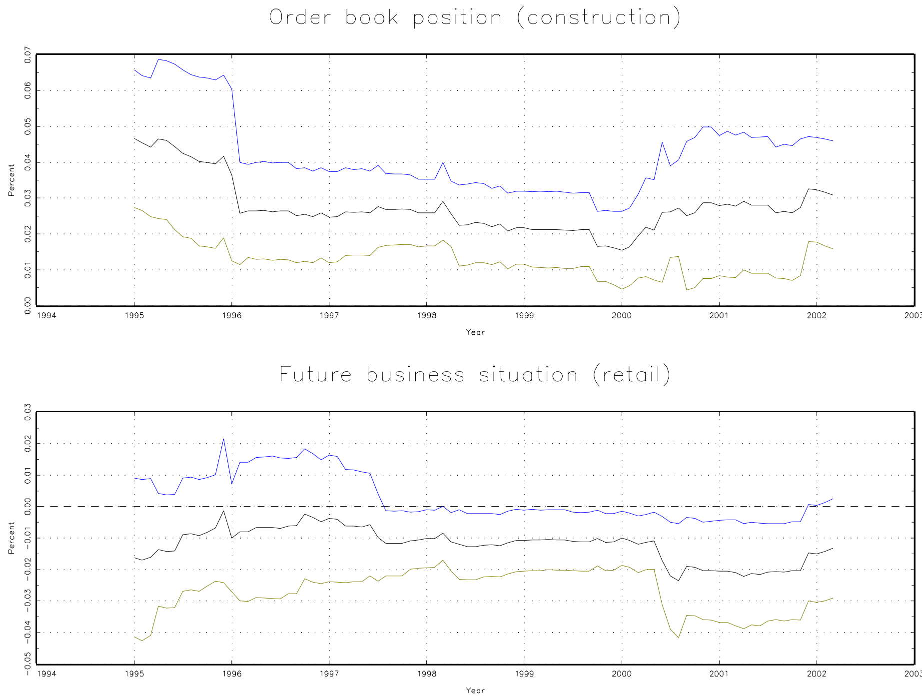

Figure 21 : Varying coefficients for $DLI_{3,8}$.

Notes d'Études et de Recherche

1. C. Huang and H. Pagès, “Optimal Consumption and Portfolio Policies with an Infinite Horizon: Existence and Convergence,” May 1990.

2. C. Bordes, « Variabilité de la vitesse et volatilité de la croissance monétaire : le cas français », février 1989.

3. C. Bordes, M. Driscoll and A. Sauviat, “Interpreting the Money-Output Correlation: Money-Real or Real-Real?,” May 1989.

4. C. Bordes, D. Goyeau et A. Sauviat, « Taux d'intérêt, marge et rentabilité bancaires : le cas des pays de l'OCDE », mai 1989.

5. B. Bensaid, S. Federbusch et R. Gary-Bobo, « Sur quelques propriétés stratégiques de l’intéressement des salariés dans l'industrie », juin 1989.

6. O. De Bandt, « L'identification des chocs monétaires et financiers en France : une étude empirique », juin 1990.

7. M. Boutillier et S. Dérangère, « Le taux de crédit accordé aux entreprises françaises : coûts opératoires des banques et prime de risque de défaut », juin 1990.

8. M. Boutillier and B. Cabrillac, “Foreign Exchange Markets: Efficiency and Hierarchy,” October 1990.

9. O. De Bandt et P. Jacquinot, « Les choix de financement des entreprises en France : une modélisation économétrique », octobre 1990 (English version also available on request).

10. B. Bensaid and R. Gary-Bobo, “On Renegotiation of Profit-Sharing Contracts in Industry,” July 1989 (English version of NER n° 5).

11. P. G. Garella and Y. Richelle, “Cartel Formation and the Selection of Firms,” December 1990.

12. H. Pagès and H. He, “Consumption and Portfolio Decisions with Labor Income and Borrowing Constraints,” August 1990.

13. P. Sicsic, « Le franc Poincaré a-t-il été délibérément sous-évalué ? », octobre 1991.

14. B. Bensaid and R. Gary-Bobo, “On the Commitment Value of Contracts under Renegotiation Constraints,” January 1990 revised November 1990.

15. B. Bensaid, J.-P. Lesne, H. Pagès and J. Scheinkman, “Derivative Asset Pricing with Transaction Costs,” May 1991 revised November 1991.

16. C. Monticelli and M.-O. Strauss-Kahn, “European Integration and the Demand for Broad Money,” December 1991.

17. J. Henry and M. Phelipot, “The High and Low-Risk Asset Demand of French Households: A Multivariate Analysis,” November 1991 revised June 1992.

18. B. Bensaid and P. Garella, “Financing Takeovers under Asymetric Information,” September 1992.

19. A. de Palma and M. Uctum, "Financial Intermediation under Financial Integration and Deregulation," September 1992.

20. A. de Palma, L. Leruth and P. Régibeau, "Partial Compatibility with Network Externalities and Double Purchase," August 1992.

21. A. Frachot, D. Janci and V. Lacoste, "Factor Analysis of the Term Structure: a Probabilistic Approach," November 1992.

22. P. Sicsic et B. Villeneuve, « L'afflux d'or en France de 1928 à 1934 », janvier 1993.

23. M. Jeanblanc-Picqué and R. Avesani, "Impulse Control Method and Exchange Rate," September 1993.

24. A. Frachot and J.-P. Lesne, "Expectations Hypothesis and Stochastic Volatilities," July 1993 revised September 1993.

25. B. Bensaid and A. de Palma, "Spatial Multiproduct Oligopoly," February 1993 revised October 1994.

26. A. de Palma and R. Gary-Bobo, "Credit Contraction in a Model of the Banking Industry," October 1994.

27. P. Jacquinot et F. Mihoubi, « Dynamique et hétérogénéité de l'emploi en déséquilibre », septembre 1995.

28. G. Salmat, « Le retournement conjoncturel de 1992 et 1993 en France : une modélisation VAR », octobre 1994.

29. J. Henry and J. Weidmann, "Asymmetry in the EMS Revisited: Evidence from the Causality Analysis of Daily Eurorates," February 1994 revised October 1994.

30. O. De Bandt, "Competition Among Financial Intermediaries and the Risk of Contagious Failures," September 1994 revised January 1995.

31. B. Bensaid et A. de Palma, « Politique monétaire et concurrence bancaire », janvier 1994 révisé en septembre 1995.

32. F. Rosenwald, « Coût du crédit et montant des prêts : une interprétation en terme de canal large du crédit », septembre 1995.

33. G. Cette et S. Mahfouz, « Le partage primaire du revenu : constat descriptif sur longue période », décembre 1995.

34. H. Pagès, "Is there a Premium for Currencies Correlated with Volatility? Some Evidence from Risk Reversals," January 1996.

35. E. Jondeau and R. Ricart, "The Expectations Theory: Tests on French, German and American Euro-rates," June 1996.

36. B. Bensaid et O. De Bandt, « Les stratégies "stop-loss" : théorie et application au Contrat Notionnel du Matif », juin 1996.

37. C. Martin et F. Rosenwald, « Le marché des certificats de dépôts. Écarts de taux à l'émission : l'influence de la relation émetteurs-souscripteurs initiaux », avril 1996.

38. Banque de France - CEPREMAP - Direction de la Prévision - Erasme - INSEE - OFCE, « Structures et propriétés de cinq modèles macroéconomiques français », juin 1996.

39. F. Rosenwald, « L'influence des montants émis sur le taux des certificats de dépôts », octobre 1996.

40. L. Baumel, « Les crédits mis en place par les banques AFB de 1978 à 1992 : une évaluation des montants et des durées initiales », novembre 1996.

41. G. Cette et E. Kremp, « Le passage à une assiette valeur ajoutée pour les cotisations sociales : Une caractérisation des entreprises non financières “gagnantes” et “perdantes” », novembre 1996.

42. S. Avouyi-Dovi, E. Jondeau et C. Lai Tong, « Effets “volume”, volatilité et transmissions internationales sur les marchés boursiers dans le G5 », avril 1997.

43. E. Jondeau et R. Ricart, « Le contenu en information de la pente des taux : Application au cas des titres publics français », juin 1997.

44. B. Bensaid et M. Boutillier, « Le contrat notionnel : efficience et efficacité », juillet 1997.

45. E. Jondeau et R. Ricart, « La théorie des anticipations de la structure par terme : test à partir des titres publics français », septembre 1997.

46. E. Jondeau, « Représentation VAR et test de la théorie des anticipations de la structure par terme », septembre 1997.

47. E. Jondeau et M. Rockinger, « Estimation et interprétation des densités neutres au risque : Une comparaison de méthodes », octobre 1997.

48. L. Baumel et P. Sevestre, « La relation entre le taux de crédits et le coût des ressources bancaires. Modélisation et estimation sur données individuelles de banques », octobre 1997.

49. P. Sevestre, “On the Use of Banks Balance Sheet Data in Loan Market Studies : A Note,” October 1997.

50. P.-C. Hautcoeur and P. Sicsic, “Threat of a Capital Levy, Expected Devaluation and Interest Rates in France during the Interwar Period,” January 1998.

51. P. Jacquinot, « L’inflation sous-jacente à partir d’une approche structurelle des VAR : une application à la France, à l’Allemagne et au Royaume-Uni », janvier 1998.

52. C. Bruneau et O. De Bandt, « La modélisation VAR structurel : application à la politique monétaire en France », janvier 1998.

53. C. Bruneau and E. Jondeau, “Long-Run Causality, with an Application to International Links between Long-Term Interest Rates,” June 1998.

54. S. Coutant, E. Jondeau and M. Rockinger, “Reading Interest Rate and Bond Futures Options’ Smiles: How PIBOR and Notional Operators Appreciated the 1997 French Snap Election,” June 1998.

55. E. Jondeau et F. Sédillot, « La prévision des taux longs français et allemands à partir d’un modèle à anticipations rationnelles », juin 1998.

56. E. Jondeau and M. Rockinger, “Estimating Gram-Charlier Expansions with Positivity Constraints,” January 1999.

57. S. Avouyi-Dovi and E. Jondeau, “Interest Rate Transmission and Volatility Transmission along the Yield Curve,” January 1999.

58. S. Avouyi-Dovi et E. Jondeau, « La modélisation de la volitilité des bourses asiatiques », janvier 1999.

59. E. Jondeau, « La mesure du ratio rendement-risque à partir du marché des euro-devises », janvier 1999.

60. C. Bruneau and O. De Bandt, “Fiscal Policy in the Transition to Monetary Union: A Structural VAR Model,” January 1999.

61. E. Jondeau and R. Ricart, “The Information Content of the French and German Government Bond Yield Curves: Why Such Differences?,” February 1999.

62. J.-B. Chatelain et P. Sevestre, « Coûts et bénéfices du passage d’une faible inflation à la stabilité des prix », février 1999.

63. D. Irac et P. Jacquinot, « L’investissement en France depuis le début des années 1980 », avril 1999.

64. F. Mihoubi, « Le partage de la valeur ajoutée en France et en Allemagne », mars 1999.

65. S. Avouyi-Dovi and E. Jondeau, “Modelling the French Swap Spread,” April 1999.

66. E. Jondeau and M. Rockinger, “The Tail Behavior of Stock Returns: Emerging Versus Mature Markets,” June 1999.

67. F. Sédillot, « La pente des taux contient-elle de l’information sur l’activité économique future ? », juin 1999.

68. E. Jondeau, H. Le Bihan et F. Sédillot, « Modélisation et prévision des indices de prix sectoriels », septembre 1999.

69. H. Le Bihan and F. Sédillot, “Implementing and Interpreting Indicators of Core Inflation: The French Case,” September 1999.

70. R. Lacroix, “Testing for Zeros in the Spectrum of an Univariate Stationary Process: Part I,” December 1999.

71. R. Lacroix, “Testing for Zeros in the Spectrum of an Univariate Stationary Process: Part II,” December 1999.

72. R. Lacroix, “Testing the Null Hypothesis of Stationarity in Fractionally Integrated Models,” December 1999.

73. F. Chesnay and E. Jondeau, “Does correlation between stock returns really increase during turbulent period?,” April 2000.

74. O. Burkart and V. Coudert, “Leading Indicators of Currency Crises in Emerging Economies,” May 2000.

75. D. Irac, “Estimation of a Time Varying NAIRU for France,” July 2000.

76. E. Jondeau and H. Le Bihan, "Evaluating Monetary Policy Rules in Estimated Forward-Looking Models: A Comparison of US and German Monetary Policies," October 2000.

77. E. Jondeau and M. Rockinger, "Conditional Volatility, Skewness, ans Kurtosis: Existence and Persistence," November 2000.

78. P. Jacquinot et F. Mihoubi, « Modèle à Anticipations Rationnelles de la COnjoncture Simulée : MARCOS », novembre 2000.

79. M. Rockinger and E. Jondeau, "Entropy Densities: With an Application to Autoregressive Conditional Skewness and Kurtosis," January 2001.

80. B. Amable and J.-B. Chatelain, "Can Financial Infrastructures Foster Economic Development? ," January 2001.

81. J.-B. Chatelain and J.-C. Teurlai, "Pitfalls in Investment Euler Equations," January 2001.

82. M. Rockinger and E. Jondeau, "Conditional Dependency of Financial Series: An Application of Copulas," February 2001.

83. C. Florens, E. Jondeau and H. Le Bihan, "Assessing GMM Estimates of the Federal Reserve Reaction Function," March 2001.

84. J.-B. Chatelain, "Mark-up and Capital Structure of the Firm facing Uncertainty," June 2001.

85. B Amable, J.-B. Chatelain and O. De Bandt, "Optimal capacity in the Banking Sector and Economic Growth," June 2001.

86. E. Jondeau and H. Le Bihan, "Testing for a Forward-Looking Phillips Curve. Additional Evidence from European and US Data," December 2001.

87. G. Cette, J. Mairesse et Y. Kocoglu, « Croissance économique et diffusion des TIC : le cas de la France sur longue période (1980-2000) », décembre 2001.

88. D. Irac and F. Sédillot, "Short Run Assessment of French Economic activity Using OPTIM," January 2002.

89. M. Baghli, C. Bouthevillain, O. de Bandt, H. Fraisse, H. Le Bihan et Ph. Rousseaux, « PIB potentiel et écart de PIB : quelques évaluations pour la France », juillet 2002.

90. E. Jondeau and M. Rockinger, "Asset Allocation in Transition Economies," October 2002.

91. H. Pagès and J.A.C Santos, "Optimal Supervisory Policies and Depositor-Preferences Laws," October 2002.

92. C. Loupias, F. Savignac and P. Sevestre, "Is There a Bank Lending Channel in France ? Evidence from Bank Panel Data," November 2002.

93. M. Ehrmann, L. Gambacorta, J. Martínez-Pagés, P. Sevestre and A. Worms, "Financial systems and The Role in Monetary Policy transmission in the Euro Area," November 2002.

94. S. Avouyi-Dovi, D. Guégan et S. Ladoucette, « Une mesure de la persistance dans les indices boursiers », décembre 2002.

95. S. Avouyi-Dovi, D. Guégan et S. Ladoucette, "What is the Best Approach to Measure the Interdependence between Different Markets? ," December 2002.

96. J.-B. Chatelain and A. Tiomo, "Investment, the Cost of Capital and Monetray Policy in the Nineties in France: A Panel Data Investigation," December 2002.

97. J.-B. Chatelain, A. Generale, I. Hernando, U. von Kalckreuth and P. Vermeulen, "Firm Investment and Monetary Policy Transmission in the Euro Area," December 2002.

98. J.-S. Mésonnier, « Banque centrale, taux de l'escompte et politique monétaire chez Henry Thornton (1760-1815) », décembre 2002.

99. M. Baghli, G. Cette et A. Sylvain, « Les déterminants du taux de marge en France et quelques autres grands pays industrialisés : Analyse empirique sur la période 1970-2000 », janvier 2003.

100. G. Cette and C. Pfister, "The Challenges of the "New Economy" for Monetary Policy," January 2003.

101. C. Bruneau, O. De Bandt, A. Flageollet and E. Michaux, "Forecasting Inflation using Economic Indicators: the Case of France," May 2003.

102. C. Bruneau, O. De Bandt and A. Flageollet, " Forecasting Inflation in the Euro Area," May 2003.

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

For any comment or enquiries on the Notes d'Études et de Recherche, contact the library of the Centre de recherche at the following address :

BANQUE DE FRANCE
41-1391 - Centre de recherche
75049 Paris Cedex 01
tél : (0)1 42 92 49 55
fax : (0)1 42 92 62 92
email : thierry.demoulin@banque-france.fr