
NOTES D'ÉTUDES

ET DE RECHERCHE

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INDICATORS: THE CASE OF FRANCE**

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Forecasting Inflation using Economic Indicators: the Case of France*

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Abstract

In order to provide short-run forecasts of headline and core HICP inflation for France, we assess the forecasting performance of a large set of economic indicators, individually and jointly, as well as using dynamic factor models. We run out-of-sample forecasts implementing the Stock and Watson (1999) methodology. We find that, according to usual statistical criteria, the combination of several indicators -in particular those derived from surveys- provides better results than factor models, even after pre-selection of the variables included in the panel. However, factors included in VAR models exhibit more stable forecasting performance over time. Results for the HICP excluding unprocessed food and energy are very encouraging. Moreover, we show that the aggregation of forecasts on subcomponents exhibits the best performance for projecting total inflation and that it is robust to data snooping.

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

JEL: C33, C53, E37

Résumé

De façon à fournir des prévisions d'inflation à court terme pour la France en termes d'IPCH total ou sous-jacent, nous étudions les performances d'un grand nombre d'indicateurs conjoncturels, soit individuellement, soit en combinaison, soit enfin en utilisant des modèles factoriels dynamiques. Nous produisons des prévisions hors échantillon, en appliquant la méthodologie de Stock and Watson (1999). Il apparaît que selon les critères statistiques usuels, la combinaison de plusieurs indicateurs -et notamment les variables tirées des enquêtes- fournissent de meilleurs résultats que les modèles factoriels dynamiques, même après pré-sélection des variables incluses dans le panel. Cependant, l'inclusion des facteurs dans un VAR offre des performances plus stables dans le temps. Les résultats sur l'IPCH hors énergie et alimentaire non transformé sont très encourageants. De plus, nous montrons que l'agrégation de prévisions sur des sous-composantes offre les meilleures performances pour prévoir l'inflation totale et qu'elle est robuste au risque de "surexploitation des données" (data snooping).

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

JEL: C33, C53, E37.

Non technical summary

The paper investigates the information content of real and financial macro-economic variables for the short and medium run forecast of inflation in France. It extends the methodology introduced by Stock and Watson (1998 and 1999) for the US where these authors studied the forecasting performance of a large number of variables et suggested to rely on dynamic factor analysis (i.e. a recursive version of Principal Component Analysis or PCA) in order to summarize the information available in a large panel of data. The paper investigates the behaviour of several “leading indicators” in order to forecast the annual (year on year) change in inflation one year (12 months) ahead, but we also provide variant at six and eighteen months. On the sample period (1988-2001), recursive forecast are provided, starting in 1996:1.

In comparison with the previous literature, we put some emphasis on the provision of standard errors for the Root Mean Square Error (RMSE), in order to assess whether the different models improve significantly upon the autoregressive (AR) model, which only includes current inflation. Several charts are also provided in order to judge how the models fared over such a period, which was hit by the 1999-2000 oil shock.

We build a database comprising more than 200 macro-economic variables. The price series are the Harmonised Index of Consumer Prices, as well as the “core” indicator (excluding energy and unprocessed food). Both are corrected for change in VAT rates. The conclusion of this exercise is that several variables have significant forecasting power.

- For “core” inflation, the unemployment rate and the future production trend in the Banque de France business survey have good forecasting properties but the best model includes the unemployment rate, the household confidence indicator and the oil prices.

- For total inflation, we offer different models, either recombining total inflation from its sub-components (using, in particular, the projection of “core inflation”), or using factors from dynamic factor models. In that case, we use blocks of homogeneous variables in our database, either from business surveys or from employment indicators. However, whereas survey indicators are available with a very short lag, employment data are not very timely, so that they are less useful for real-time forecasts.

- The performance of the models for total inflation is unstable over time, with significantly better results from 1999 onwards, while the AR models usually performs better before. Indeed, the AR model is quite good at tracking stable or trend-stationary inflation (in particular the convergence of inflation rates in Europe to German level before EMU).

- We also compare the forecasts derived from these models to the forecasts produced by bivariate Vector Auto-regressive models (inflation in a given month only depends on inflation and an indicator, both measured in the previous month). In that case, one produces stepwise inflation projections for $t+1$, $t+2$,..., $t+h$, and not directly at $t+h$. Our results highlight the good performance of such a model for underlying inflation with the first dynamic factor from the complete database. It is not the case for total inflation. This difference of results may be explained by the more progressive pick-up in core inflation than in total inflation following the oil shock.

Résumé non technique

Le papier étudie le contenu en information d'indicateurs macro-économiques réels et financiers pour la prévision d'inflation à court/moyen terme en France. Le papier s'inspire des travaux

réalisés par Stock et Watson (1999) sur les Etats-Unis, dans lequel les auteurs étudiaient les performances prédictives d'un grand nombre de variables et proposaient de recourir aux modèles factoriels dynamiques (c'est-à-dire une version récursive de l'analyse en composante principale, ACP) pour résumer l'information disponible sur un panel de données. Le papier passe en revue différents "indicateurs avancés" pour prévoir le glissement annuel des prix à l'horizon de h mois, avec h généralement fixé à 12, c'est-à-dire pour des prévisions à un an (nous présentons aussi des variantes avec $h=6$ ou 18 mois). Sur la période considérée (1988-2001), des prévisions glissantes sont fournies en étendant progressivement la taille de l'échantillon à partir de 1996:1.

Par rapport à la littérature antérieure, le papier met l'accent sur le calcul de l'écart-type associé à l'erreur quadratique moyenne sur la prévision (RMSE), de façon à juger si l'introduction des indicateurs améliore significativement la prévision par rapport à un modèle auto-regressif (AR) simple n'incluant que l'inflation courante et quelques retards. Plusieurs graphiques sont aussi fournis pour juger de la performance des différents modèles sur une période marquée par le choc pétrolier de 1999-2000.

Nous construisons une base de données comprenant plus de 200 indicateurs macro-économiques. Les séries de prix sont celles de l'IPCH total et "sous-jacent", c'est-à-dire hors énergie et alimentation non transformée, corrigées des effets des changements de TVA.

Il ressort de cet exercice que plusieurs indicateurs présentent de bonnes propriétés prédictives.

- Pour l'inflation sous-jacente, le taux de chômage et la tendance future de la production tirée de l'enquête mensuelle de conjoncture de la Banque de France ont de bonnes propriétés prédictives, mais le meilleur modèle inclut le taux de chômage, l'indice de confiance des ménages et les prix du pétrole.

- Pour l'inflation totale, nous proposons différents modèles, soit en recombinaison l'inflation totale à partir de ses sous-composantes (c'est-à-dire en utilisant notamment la prévision d'inflation "sous-jacente"), soit à partir de facteurs issus de l'analyse factorielle dynamique. Dans ce cas, nous utilisons des sous-ensembles homogènes de données, soit issues des enquêtes de conjoncture, soit des variables d'emploi. Toutefois, alors que les données d'enquêtes sont disponibles sans délai, les variables d'emploi ne sont publiées qu'avec retard, ce qui réduit leur intérêt pour la prévision en temps réel.

- Les modèles utilisés pour l'inflation totale voient néanmoins leur performance varier fortement dans le temps, puisqu'ils sont nettement meilleurs que le modèle AR à partir de 1999, alors que l'AR présente de bonnes performances avant cette date. En effet, le modèle AR semble assez performant pour prévoir une inflation stable ou suivant une tendance (en l'occurrence, la convergence des taux d'inflation au niveau européen avant la mise en place de l'UEM).

- Nous comparons aussi les prévisions issues de ces modèles à celles de modèles VAR (vectoriels autoregressifs) bivariés (c'est-à-dire où l'inflation à un mois donné ne dépend que de l'inflation et d'un indicateur, tous les deux pris au mois précédent). Dans ce cas, les prévisions sont effectuées "pas à pas", c'est-à-dire en $t+1$, $t+2$, $t+h$, et non pas directement en $t+h$. Nos résultats mettent en évidence d'assez bonnes performances pour un modèle bivarié où l'inflation "sous-jacente" est associée au premier facteur dynamique issu de l'analyse factorielle sur l'ensemble de notre base de données. Ce n'est pas le cas pour l'inflation totale. Cette différence de résultats s'explique par la remontée plus progressive de l'inflation sous-jacente par rapport à l'inflation totale en 1999-2000, ce qui est bien mesuré par le modèle VAR.

1 Introduction

With European Monetary Union, forecasting inflation has become an essential ingredient of monetary policy. Although monetary policy is defined at the euro area level, and responds to euro area inflation developments, forecasting inflation at the national level remains important for many reasons. First of all, as indicated by Marcellino, Stock and Watson (2003), forecasting inflation at the country level and aggregating the forecasts increases the accuracy of euro area forecasts as compared to directly forecasting at the euro area level. Second, as labour markets and wage bargaining are still, to a large extent, decentralised it remains useful to have a clear picture of future inflationary tensions at the national level. It is an important element of national central banks' communication.

In the paper, we present methods to forecast inflation in France on the basis of a set of economic indicators that are available monthly. We follow the methodology advocated by Stock and Watson (1999) to select the variables that are necessary to monitor future price developments. For that purpose we estimate forecasting equations recursively and produce out-of sample forecasts in order to compare the different models. We use individual equations, where single indicators are used to forecast inflation and introduced individually, as well as dynamic factor models, where information is extracted from a large panel of indicators that are pooled together.

While implementing these techniques for France, the paper attempts to offer answers to several questions that arise in the literature. First, we examine the gain from using dynamic factor models in line with Stock and Watson (1998, 1999), and Lippi *et al.* (1999), which have been identified as having good forecasting performance.¹ In particular, Cristadoro *et al.* (2005) construct an index of core inflation which is presented as having superior forecasting properties. In the paper, we construct factor models and study their inflation forecasting performance as compared to individual indicators. We introduce two types of improvements: we combine indicators, instead of studying single indicator forecasting equations, and, before computing the factors, we pre-select the set of underlying indicators to be included in the panel.

Second, since the final objective is to forecast the overall Harmonised Index of Consumption Prices (HICP) which is the indicator monitored by the ECB, we put emphasis on forecasting this variable. While fairly good results are obtained for the index excluding unprocessed food and energy, we make particular efforts to provide the best model of overall inflation. We therefore show that it is even better to use a model on the sub-components of the overall index, *i.e.* the HICP excluding energy and unprocessed food, the unprocessed food index and the energy index, and to recompose the overall index, rather than forecast it directly. Such a conclusion for France attenuates the results obtained by Hubrich (2005) for the euro area and over a smaller period, indicating that it is better to directly forecast overall inflation. As regards national inflation, the conclusions are more similar to ours. Duarte and Rua (2005) show for Portugal that the disaggregated

¹The growing literature on factor models includes, among others, at the quarterly frequency: Angelini *et al.* (2001) ; at the monthly frequency: Marcellino *et al.* (2003) on euro area data, Artis *et al.* (2003) on the UK.

approach performs better than the direct approach at horizons of less than 5 months, while Fritzer, Moser and Scharler (2002) for Austria indicate that for all ARIMA models and for VAR models at horizons of 10 to 12 months, disaggregated forecasts exhibit lower RMSE than direct forecasts. Den Reijer and Vlaar (2003) also provide evidence of the superiority of disaggregated forecasts for the Netherlands. In the case of France, we stress that the superiority of the disaggregated forecast is based on the use of business survey indicators to project the HICP excluding unprocessed food and energy.

Third, while most papers in the literature focus on multistep forecasts, 12 months ahead, we test the sensitivity of these models and run VAR models in order to produce dynamic forecasts.²

Fourth, since the major challenge is to detect the upturn in inflation in 2000 after the recovery of oil prices, we consider whether intercept correction, as advocated by Clements and Hendry (1999), improves upon these inflation forecasts. Such a method was used with success for some New EU Member States by Banerjee, Marcellino and Marsten (2004). In our case, a reduction in RMSE was only found for one model.

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 the inflation rate itself are related to the current change in inflation. These models can be interpreted as a reduced form of a more complete model, where inflation is affected by short run supply and demand shocks and the central bank's behaviour obeys a reaction function, so that the coefficient associated with the indicator integrates the systematic response of monetary policy. Such an analysis assumes that the inflation process is not subject to major breaks.³ The analysis of Bilke (2005) -although on the national CPI and not on the HICP that we use here in order to be consistent with the ECB monetary policy objective- indicates that the inflation process in France is stable, with the last break taking place in 1983 -when a significant disinflationary process took place - i.e. before the period under review here (1988-2003).

This model will be used as a benchmark to compare the predictive performance of different single-equation models, obtained by substituting various economic indicators for the unemployment rate.

Against the background of monetary policy decisions taken on a monthly basis,⁴ we use monthly data which offer a more detailed approach to inflation forecasting than quarterly data.⁵ The drawback is that a smaller number of indicators is available at that frequency.

The paper is set out as follows: Section 2 describes the methodology used and the forecasting equations. Section 3 presents the database. Section 4 and 5 discuss the empirical results and their robustness, including tests for data snooping. Section 6 concludes.

²Hendry (1995) investigates the general conditions under which the long-run h-step ahead regression does better than an iterated forecast on an AR model. Marcellino *et al.* (2004) provide evidence for price variables in the US on the good forecasting properties of dynamic forecasts from high order autoregressions.

³See Atkeson and Ohanian (2001).

⁴The ECB Council which meets twice a month, but usually addresses monetary policy matters only once a month.

⁵For results at a quarterly frequency and on the euro area, see Angelini *et al* [2001], *op. cit.*

2 Forecasting methods

2.1 Forecasting equations

In order to forecast inflation in France, we use various specifications of the Phillips curve. We follow the approach proposed by Stock and Watson (1999) by introducing various indicators of the business cycle x_t .

The model used is:

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

where $\pi_t^{12} = \log(P_t/P_{t-12})$ 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 $t+h$. $\pi_t = \log(P_t/P_{t-1})$ is the one-month inflation rate. By multiplying by 12, we obtain a consistent definition of the change in the inflation rate on the left-hand side. In our case, P_t is either the Harmonised Index of Consumer prices (hereafter labelled “total” HICP), or the HICP excluding unprocessed food and energy (hereafter labelled “core”⁶). The 12-month inflation rate is forecast h -months ahead using current and past inflation and various lags of x_t .

Our baseline results are based on $h = 12$, so that equation (1) is actually:

$$\pi_{t+12}^{12} - 12.\pi_t = \phi + \beta(L)x_t + \gamma(L)\Delta\pi_t + e_{t+h} \quad (2)$$

Such a specification is based on the assumption that π_t^{12} is non stationary. Indeed, stationarity tests indicate that total HICP inflation and core inflation rates are I(1). We run alternative specifications yielding similar results.⁷

2.2 Comparing forecast performance

Different choices are possible for x_t . In the literature, following Stock and Watson (1999), individual indicators of the business cycle are introduced one by one. Alternatively information is extracted from large panels of indicators, using dynamic factor models.

The different indicators are compared using out-of-sample simulation exercises. We recursively estimate our equations and produce rolling forecasts. For example, let us focus

⁶Several definitions of core inflation are available in the literature. They differ as to which volatile components are excluded. Some of them are based on the exclusion of such components by looking at the distribution of price changes at each period (truncated means). For the rest of the paper, “core” inflation always refer to the HICP indicator after exclusion of the same volatile components, namely energy and unprocessed food.

⁷Among the alternative specifications, we ran:

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

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.

on the forecast of the 12-month inflation rate, 12 months ahead, *i.e.* between 1995:1 and 1996:1. In this case, the forecasting equation is estimated, information criteria are computed and lag lengths are selected using annual inflation data from 1987:1 to 1995:1.⁸ Next, moving forward one month, the model is reestimated using data from 1987:1 to 1995:2 and forecasts are made for 12-month inflation until 1996:2. 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 (RMSE), defined as $\sqrt{\frac{1}{N-12} \sum_{t=1}^{N-12} (\hat{\pi}_{t+12}^{12} - \pi_{t+12}^{12})^2}$, with N being the number of time periods considered until the end of the sample, for forecasts of the 12-month inflation, 12 months ahead. 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 beat the AR model, which is defined as equation (1) without the distributed lags on the indicator.⁹

We present the RMSE of the benchmark model, as well as the Mean-Squared Error (MSE) for the different models relative to that of the benchmark model ("Rel. MSE"). The performance of the alternative models is compared to the benchmark using the Diebold and Mariano (1995) test¹⁰.

Contrary to the approaches in 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 comparable RMSE so that a combination of the two (or more) indicators $x_{i,t}$ might be better. For p indicators, we run:

$$\pi_{t+12}^{12} - 12.\pi_t = \phi + \sum_{i=1}^p \beta_i(L)x_{i,t} + \gamma(L)\Delta\pi_t + e_{t+h} \quad (3)$$

3 Description of the data

For our analysis we use two types of data. First, data on total and core HICP. Both are available from Eurostat.¹¹ Nevertheless, due to the significance of VAT changes we made a correction of the series, following Pluyaud (2002). The method is described more fully in Annex C. An alternative method would have been to introduce at least one dummy variable to correct for the most significant shift, namely the one that occurred in 1995, but this is far from being the most rigorous approach.

⁸Actually, for producing forecasts from 1995:1 to 1996:1, the econometric relationship is estimated on inflation data until 1995:1, but the x_t variable is used until 1994:1 since it is introduced with a 12-month lag. Data on x_t in 1995:1 is only used to get a forecast of inflation in 1996:1, assuming the estimated relationship is still valid for this extended period.

⁹Another possible candidate for the benchmark is the random walk model: $E_t(\pi_{t+h}^{12}) = \pi_t^{12}$. As indicated in table 1 below, our sample both models have equivalent forecasting properties for total inflation. Note that for the random walk model, the RMSE is just $\sqrt{\frac{1}{N-12}(\pi_{t+h}^{12} - \pi_t^{12})^2}$.

¹⁰A possible drawback of such an approach is that the alternative model nests the benchmark model, which is a restricted model. Therefore, in section 5.4, we run Clark and Mc Cracken (2002) long-horizon evaluation exercise using bootstrapping, which confirms the initial results.

¹¹Eurostat data are only available since January 1990. Back data of Laspeyres-chained indexes were produced on the basis of the French CPI for the period before 1990.

In addition, we collected a large set of indicators (a total of 177 variables) for the French economy, drawing heavily on Eurostat, OECD, INSEE (the French National Statistical Institute) and the Banque de France databases. They include:

- unemployment rates for different categories (total, workers aged 25 years and over, male workers aged 25 years and over);
- capacity utilisation rate, car registration data;
- household consumption of manufactured goods in various sub-sectors;
- survey data: industry, households and retail sector;
- import unit value indices;
- price of raw materials, Brent oil prices;
- interest rates.

All series that were not previously seasonally adjusted were transformed, using the TRAMO-SEATS method available in DEMETRA (2000). This applies to import prices, money aggregates and HICP series.

One difficulty was establishing what kind of transformation should be applied to obtain stationary variables. In the case of France, as in many other euro area countries, the unemployment rate is non-stationary, in contrast to the US. As a consequence the unemployment gap, measured by the difference between the observed unemployment rate and its unconditional mean is not stationary. The equation above cannot therefore be estimated unless we substitute u_t by a stationary variable x_t , e.g. the unemployment rate in first difference.

Various transformations are possible for each candidate variable. Data can be introduced either in logarithms, when stationary, or in difference of logarithms.

Headline and core HICP 12-month inflation are $I(1)$, but we verify that the transformed inflation, *i.e.* the left-hand-side of equ. (2) and (3) variables are stationary, although in many instances we face borderline cases.

4 Empirical results

We concentrate on forecasts 12 months ahead, using our total and core HICP, corrected for changes in VAT. We search for variables x_t having leading indicator properties for inflation. The specification used is equation (2) presented above. We consider here the complete panel with 177 indicators.

The AR model is often used as the benchmark model and we follow this convention. It is defined as equation (2) without any x_t variable. The random walk (RW) model could have been an alternative benchmark, but from table 1, it appears, on the basis of the Diebold and Mariano (1995) statistic (hereafter DM statistic), that they are equivalent.

		Random Walk	
	RMSE	Rel. MSE ₍₁₎	DM Stat.
Total inflation	0.75	0.77	0.93
Core inflation	0.46	0.64	3.03**
		AR model	
Total inflation	0.86	-	-
Core inflation	0.58	-	-

(1) as compared to the AR model

(*) 10% level; (**) 5% level

Table 1: Forecasting performance of benchmark models.

The RMSE of total inflation is 0.86 for the AR model and 0.75 for the RW model, with the DM statistic being 0.93, indicating that we cannot reject the null hypothesis that the two models have equivalent forecasting properties. Since our focus is on total inflation we disregard the fact that the RW model has better forecasting properties than the AR model for the HICP excluding energy and unprocessed food.¹² The concentration on total HICP is also justified by the higher volatility of such a variable.

Indeed, we first note that for the AR model, the RMSE associated with core HICP is lower than for total HICP (0.58% against 0.86%). This result highlights the impact of the shocks affecting the energy and unprocessed food components of HICP. Hence total HICP turns out to be more difficult to forecast than core HICP and constitutes the real challenge to forecasters.

We present the results from different approaches: multiple indicator models, an aggregate model and factor models. Additional results are also presented in Section 5 to assess the robustness of our findings to the sample period, the horizon and the set of models we consider.

4.1 Multiple indicator models

After investigations, it appears that only a few indicators have significant forecasting power for total inflation, which is consistent with Cecchetti *et al.* (2000), confirming the poor performance of single indicators used to forecast total inflation. We propose therefore to use a combination of indicators. Given the central role of the Phillips curve to explain inflation, we use the total unemployment rate in all equations and search through the other indicators to uncover those which exhibit additional forecasting power according to equation (3).

a) Core inflation forecasting. A comparison of the performance of the various

¹²Since we have a one-sided test $H_0: \text{MSE}_{\text{mod}} = \text{MSE}_{AR}$ vs $H_a: \text{MSE}_{\text{mod}} < \text{MSE}_{AR}$, the values of Student statistics are $t = 1.28$ (10%), $t = 1.64$ (5%), or $t = 2.33$ (1%). It may be objected, however, that the relevant distribution is not Student, given the number of models considered. For the computation of p-values that are robust to potential data-snooping, see Hansen (2001) and Section 5.5.

models tends to indicate that there are models for which the combination of indicators (unemployment rate + one additional variable) improves upon the AR model ("Rel. MSE" significantly below 1). However, only a small number of indicators do better than the unemployment rate alone: a model with oil price or the "expected production trend in the consumption goods industry" from the Banque de France business survey improves upon both the AR and the employment only models, in terms of a (significantly high) DM statistics. In addition, its "Rel MSE" is quite low, together with low standard deviation. We should also mention "order books in the agri-food industry", as well as "inventories of raw materials in the agri-food industry".

These results suggest that it might be possible to improve forecasts further by adding a third variable. Indeed, forecasting core inflation, with the unemployment rate, the "expected production trend in the consumer goods industry" and the price of raw materials in the agri-food industry" yields a DM statistics of 2.56 and a "Rel. MSE" of 0.41 (hereafter *core_mul* model).¹³

b) Total inflation forecasting. Concerning total inflation, we try to get rid of the idiosyncratic noise component by adding oil prices to the unemployment rate. Unlike for core inflation, the best model uses only a combination of two indicators: the unemployment rate and the 3-month oil price "future" index, with a "Rel. MSE" of 0.81 and a standard error of 0.12 (*tot_mul* model, Figure 3 in Annex D). It improves upon the unemployment only model, but not significantly upon the AR model.

It appears therefore that multiple indicators help improve the forecasts. However, the large standard errors indicate that the forecasts remain quite volatile, because the model for total inflation seems to fail to adequately project the unprocessed food and energy components, which may be affected by specific shocks. In order to correct for that, we suggest a new modelling framework which aggregates the three components.

4.2 Aggregate model

In the line of the discussion raised by Hubrich (2005), Duarte and Rua (2005), den Reijer and Vlaar (2005), we will now consider the aggregation of the forecasts on the different components. The model is therefore:

$$\hat{\pi}_{t+12}^{12} = \sum_{j=1}^3 \omega_j (\hat{\pi}_{t+12}^{12})_j \quad (4)$$

Such a framework isolates each of the three sub-components (core, unprocessed food and energy) which are forecast independently before being aggregated to provide a projection of total inflation. The latter is computed using the historical weights ω_j of the sub-components.¹⁴ As before, we look for the combination of sub-components which offers

¹³When compared to the random walk, the 3 indicator model (*core_mul*) also outperforms the latter model in terms of "Rel MSE". This is confirmed when using the DM test which is significant from 2000 onwards, as well as running the data snooping test (see Section 5.5).

¹⁴Actually, we should write ω_{jt} since the weights are slowly moving as they are revised annually, but we keep the weights constant at the last value for the forecast period.

the lowest “Rel. MSE”. Core inflation is measured as equation (3):

$$\pi_{core,t+h}^{12} - 12 \cdot \pi_{core,t} = \phi_{core} + \sum_i \beta_{i,core}(L)x_{i,t} + \gamma_{core}(L)\Delta\pi_{core,t} + e_{core,t+h} \quad (5)$$

However, if we obtain reasonably good models for the “core” sub-component (see models above), inflation for the energy sub-component, and for the unprocessed food sub-component appear to be items difficult to forecast.¹⁵ For unprocessed food, we use the following model:

$$\pi_{uf,t+12}^{12} = \alpha_{1,uf} + \alpha_{2,uf}\pi_{uf,t}^{12} + \alpha_{3,uf}\text{Log}(RM_t/RM_{t-12}) + \alpha_{4,uf}\text{Log}(W_t/W_{t-12}) + e_{uf,t+12} \quad (6)$$

RM is the price of imported agri-food raw materials, and W are hourly wages in the private sector.¹⁶

Regarding the energy subcomponent, we use the following equation:

$$\pi_{e,t+12}^{12} = \alpha_{1,e} + \alpha_{2,e}\pi_{e,t}^{12} + \alpha_{3,e}\text{Log}(B_t/B_{t-12}) + e_{e,t+12} \quad (7)$$

where B is the price of Brent oil in dollars per barrel, converted into euro, using the current exchange rate.

Table 2 below summarises the results for the different subcomponents and provides the results on the final aggregate model (*tot_agg* model hereafter), based on the weighted sum of the forecast on the subcomponents. As indicated in the table, only the model for unprocessed food significantly improves upon the AR model for such a component on the basis of the DM statistic. In addition, its relative MSE is significantly below one. However, the *tot_agg* model is better than the AR model for total inflation at the 10% level. In addition, it exhibits better forecasting properties than the indicator model for total inflation (*tot_mul* model).

The relatively good performance of the *tot_agg* model aggregating inflation sub-components is confirmed by the visual inspection of the forecast path in Figure 3b of Annex D. As indicated below, this is mainly explained by its good performance on the final part of the sample. This points to the need for further research in order to find better models for forecasting unprocessed food and energy inflation.

In the end, even if the combination of indicators helps improve the forecast of total inflation, there is an obvious limit to such an exercise given the large number of possible models one would have to explore in order to minimise the RMSE. If we wish to incorporate all relevant information, an alternative method should be considered, namely dynamic factor models.

¹⁵The models we propose are I(0) models of inflation, which does not contradict the previous assumption of I(1) headline inflation, since core inflation is a I(1) process.

¹⁶Such a model could be improved upon by introducing a dummy variable to take into account the effect of the foot and mouth disease in 1999-2000.

Components	Rel. MSE ₍₁₎	DM Stat.
Core (<i>core_mul</i>)	0.41	2.56**
Energy	0.96	0.19
Unprocessed food	0.45	2.32**
Total (<i>tot_agg</i>)	0.47	1.35*

(1) as compared to the AR model

(*) 10% level; (**) 5% level

NB: *tot_agg* model based on aggregation of forecasts on subcomponents

Table 2: Forecasting performance of the aggregated model

4.3 Dynamic factor models

Dynamic factor models are alternative models that summarise the information from a large set of indicators and therefore compete against models with one or multiple indicators. In this case, it is assumed that the large panel of time series that we possess at date t has the following structure:

$$X_t = \Lambda F_t + e_t \quad (8)$$

where F_t , of dimension $(T \times k)$ with k smaller than the number of variables, are (a relatively small number of) unobserved factors that summarize the systematic information in the data set (See Stock and Watson, 1999 for details). In a second step F_t , derived from (8), is directly introduced as an indicator in equation (2).

Several approaches are used: dynamic factor models on (i) the complete set of variables, or (ii) a set of economically homogeneous variables (of smaller dimension). For this analysis, we used the information gathered in the previous sub-section on single or multiple indicators. In the version used here, although we refer to the dynamic factor model in the sense of Stock and Watson (1998 and 1999), we only extract factors from contemporaneous variables.

a) Complete panel. We run dynamic factor analysis (DFA) on the full panel of data. Table 3 summarises the forecasting performance of the first factor in equation (2). The corresponding forecast in Figure 4 (Annex D).

For core HICP, DFA improves upon the AR model, with MSE significantly below that of the AR model on the basis of the DM test for the first factor. Indeed, Figure 4 indicates that the model is able to capture the pickup in inflation in a more timely way for the first factor. Like the results on individual indicators, this improvement achieved through the use of factors is larger for core than for total HICP. However, our DFA models are worse than the models that combine multiple indicators (*core_mul* and *tot_mul*).

b) Pre-selected indicators. Some individual indicators exhibit better forecasting performance than others. It could be useful to take these findings into account by running DFA on this selected set of indicators. We therefore choose to keep in the panel the indicators which individually exhibit a “Rel. MSE” significantly below 1 at the 5 or 10%

Core inflation	
Rel. MSE ₍₁₎	0.53
DM Stat.	2.29**
Total inflation	
Rel. MSE ₍₁₎	0.97
DM Stat.	0.92

(1) as compared to the AR model
(**) 5% level

Table 3: Forecasting performance of the first dynamic factor

level for core HICP (we use this sample for both total and core inflation, given the small number of indicators which indeed turn out to have a significant forecasting power. Worse results are found for total HICP and we report only the results for core HICP in Table 4.

Core inflation	
Rel. MSE ₍₁₎	0.51
DM Stat.	2.28**

(1) as compared to the AR model
(**) 5% level

Table 4: Dynamic Factor after pre-selection of indicators (10% level)

The conclusion of this exercise is therefore that no obvious gain is obtained from pre-selecting indicators on the basis of a purely statistical selection device.

c) Blocks of indicators. Another route to improve upon standard DFA on the complete panel is to run DFA on blocks made of economically homogeneous sets of variables. We define these different blocks here and run DFA on each of them, using the first factor.¹⁷ For this purpose we construct (non disjoint) blocks of variables, with a sufficient number of variables. They are defined as followed:

- All survey data: Survey block;
- All data on employment (and unemployment): Employment block;
- The Banque de France and INSEE surveys on manufacturing industry: Industry block;
- Price data (wholesale prices, price data from surveys): Price block;

To simplify, in Table 5, we only report results on the first factor. This is the one that usually contributes the most to the forecast.

¹⁷When implementing Factorial Analysis, it is advisable to run it on an homogeneous set of variables, so that the first axes explain a substantial share of total variance.

Core inflation			
Groups	Surveys	Employment	Prices
Rel. MSE ₍₁₎	0.53	0.51	0.81
DM Stat.	2.29**	2.17**	1.56*
Total inflation			
Rel. MSE ₍₁₎	0.97	0.95	1.09
DM Stat.	0.92	0.94	-0.36

(1) as compared to the AR model

(*) 10% level; (**) 5% level

Table 5: Forecasting performance of first factor from blocks of variables

For core inflation, the employment and survey blocks exhibit the best forecasting performance. The price block also has some forecasting properties (see Figure 5 in Annex D for employment model). For total inflation, there is no significant gain.

5 Additional results

In order to confirm the validity of our approach, we now provide additional results to check the robustness of our results to the sample period and to assess its ability to detect changes in the direction of inflation. We investigate whether the results are sensitive to the forecasting horizon by introducing VAR models. We also test the gain from introducing past errors (intercept correction). We finally consider two possible biases that in the end do not appear to be prevalent in our empirical analysis: the effect of model nesting on forecast comparison and potential data snooping.

5.1 Stability of results and changes in the direction of inflation

In order to test the ability of our model to forecast inflation, we consider different time periods. We also consider whether the model is able to predict changes in the direction of inflation, *i.e.* whether it accurately predicts an acceleration/deceleration in inflation. This is particularly relevant in our case, since the sample includes a significant oil shock in 1999-2000. For this purpose, we compute a “concordance indicator” on a few of our preferred models following Artis *et al.* (2003). Such an indicator measures the correlation between expected and realized acceleration/deceleration.¹⁸ Besides the naive model (AR),

¹⁸Let us define $z_{t+12} = \pi_{t+12}^{12} - \pi_t^{12}$ and $\hat{z}_{t+12} = \hat{\pi}_{t+12}^{12} - \pi_t^{12}$, as well as $i_{t+12} = I(z_{t+12} > 0)$ and $\hat{i}_{t+12} = I(\hat{z}_{t+12} > 0)$. For N out-of-sample forecasts, the concordance indicator is defined as:

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

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

we investigate the following models:¹⁹

Core inflation:

- model with unemployment, expected production trend in the consumption goods industry, and the price of raw materials (*core_mul*);
- model using the first factor from a DFA on the complete sample (*core_fac_compl*);
- model with the factor based on the Employment blocks (*core_fac_empl*).

Total inflation:

- model with unemployment and oil prices and price of raw materials (*tot_mul*);
- model combining core inflation, energy and unprocessed food (*tot_agg*);
- model using the first dynamic factor from a DFA on the complete panel (*tot_fac_compl*).

All these models anticipate any acceleration or deceleration of prices at least as well as the naive model (Table 6). The superiority of the *tot_agg* model for total inflation is also confirmed. In addition, the models using factors from DFA (*tot_fac_compl* for total inflation and *core_fac_compl* for core inflation) yield rather worse results than those combining indicators. Their dominance over the AR model is less obvious.

Core inflation				
Models	AR	<i>core_mul</i>	<i>core_fac_compl</i>	<i>core_fac_empl</i>
Conc. index ₍₁₎	0.68	0.74	0.72	0.74
Rel. conc. ₍₂₎	1	1.11	1.08	1.11
Total inflation				
Models	AR	<i>tot_mul</i>	<i>tot_agg</i>	<i>tot_fac_compl</i>
Conc. index ₍₁₎	0.64	0.64	0.78	0.69
Rel. conc. ₍₂₎	1	1	1.23	1.08

(1) see footnote 19

(2) concordance of model/concordance of AR model

(2) a ratio above one indicates a better model than the benchmark

Table 6: Directional forecasting accuracy

We also run the same exercise on different sub-periods. The sample is divided between 2 sub-periods: January 1996-December 1998 and January 1999-December 2003. The choice between these two periods is dictated by the introduction of the single currency in January 1999. In addition, the second sub-period is characterized by an oil shock (after the low point reached by oil prices in January 1999). This offers a good opportunity to detect changes in price trends.

¹⁹An AR component is introduced in all models.

a) Core inflation. Table 7 indicates that the models are stable from one period to another, in that there is no significant change in their relative forecasting performance. It should however be mentioned that the RMSE on the AR model is much higher for the second period (Figure 2 in Annex D), so that it is easier for the other models to “beat” the AR model. The same conclusion can be drawn from the concordance indicator: the concordance of the AR model is highest during the first period, while it is lowest during the second period. Also note that the model combining indicators (*core_mul*) exhibits the best performance.

1996:1 - 1998:12			
Models	<u>core_mul</u>	<u>core_fac_compl</u>	<u>core_fac_empl</u>
Rel. MSE ₍₁₎	0.48	0.49	0.57
DM Stat.	4.07**	3.24**	3.30**
Rel. conc. ₍₂₎	0.94	0.97	0.83
1999:1 - 2003:12			
Rel. MSE ₍₁₎	0.37	0.55	0.47
DM Stat.	1.77**	1.58*	1.67**
Rel. conc. ₍₂₎	1.26	1.29	1.40

(1) as compared to the AR model; (2) concordance of model/concordance of AR model

(*) 10% level; (**) 5% level

Table 7: Core inflation: stability results

b) Total inflation. Conversely, it appears from Table 8 that hardly any model for forecasting total inflation is stable over time. The other result that emerges from the Table is the better concordance of the alternative models, which is mainly due to the second sub-period. The poor performance of *tot_mul* model in terms of stability stems from its small information set. The aggregated *tot_agg* model exhibits only slightly better forecasting performance: while it is better in the second period, its Rel. MSE in the first period is not significantly below 1 at the 10% level only. Table 7 and 8, with good performance of the *core_mul* model on the core subcomponent, point, once again, to the need to develop good forecasting models of the energy and unprocessed food components.

Nevertheless the better performance of the *tot_mul* and *tot_agg* models in the second period indicates that the information encapsulated in the exogenous variables is better than the “naive” AR model to detect a change in the direction of inflation (“Rel. MSE” and “Rel. concordance” below 1).

In addition, it appears that the models with a combination of indicators (*core_mul* for core inflation, *tot_mul* and *tot_agg* for total inflation) have better forecasting performance in the second sub-period as compared to those using factor analysis: these models seem the most capable of capturing the rebound in inflation starting in January 2000.

An additional difficulty comes from the specification used to predict at a 12-month horizon. Under the specification we use, of the type of equation (2), exogenous variables come into play with a 12-month lag with respect to the pick-up in inflation. It is therefore

1996:1 - 1998:12			
Models	<u>core_mul</u>	<u>tot_agg</u>	<u>tot_fac_compl</u>
Rel. MSE ₍₁₎	1.14	1.30	0.93
DM Stat.	-0.42	-0.94	0.23
Rel. conc. ₍₂₎	1	0.91	0.97
1999:1 - 2003:12			
Rel. MSE ₍₁₎	0.76	0.32	0.90
DM Stat.	1.17	1.68*	0.38
Rel. conc. ₍₂₎	1.03	1.53	1.08

(1) as compared to the AR model; (2) concordance of model/concordance of AR model

(*) 10% level; (**) 5% level

Table 8: Total inflation: stability results

important that these variables lead inflation by 12 months. If we wish to relax this assumption, we need to use a dynamic forecast with a VAR model.²⁰

5.2 VAR models

The use of a VAR model makes it possible to consider all variables to be endogenous in order to produce a forecast. By performing iterated one-step ahead forecasts, it allows us to provide an alternative to the direct (multistep) forecast presented above.²¹ This specification is applied to the factors from DFA, not to indicators. The reason for this choice is the relatively good stability of the indicator models, while factor models exhibit somewhat lower performance.

In addition, modelling exogenous indicators in a VAR would be inconsistent, while factors are by definition endogenous.²² The final model is therefore given by equation 9:

$$Y_t = A_0 + A_1 Y_{t-1} + \dots + A_p Y_{t-p} + \varepsilon_t \quad (9)$$

²⁰In the same vein as in the following section on VAR, we also investigated whether the results were sensitive to the forecasting horizon. The horizon considered so far has been 12 months, but it might be useful to also consider shorter horizons: 3, 6 or 9 months.

We find that, for core inflation, the longer the forecasting horizon below 12 months, the higher the number of indicators that have a “Rel. MSE” significantly below 1, *i.e.* which do better than the AR naive model. It should be borne in mind that the absolute performance of the latter model decreases with the horizon (the RMSE on the AR model increases with the horizon), so that it becomes easier to beat it as the horizon increases. However, beyond 12 months the number of indicators exhibiting forecasting properties decreases rapidly. For total inflation, the relative performance of indicators increases with the horizon, since the AR model fares worse as the horizon extends.

²¹See Marcellino, Stock and Watson (2004) for references to the literature as well as evidence in favour of the better forecasting properties of VAR models for the US.

²²One should however keep in mind that the factors are estimated from a first step DFA, so that statistical inference should be affected. This is not taken into account in the analysis and reserved for future work.

where $Y_t = (\Delta\pi_t^{12} \ F_{1t} \ \dots \ F_{kt})'$, F_{it} is factor i and A_j is a matrix of dimension $(k+1) \times (k+1)$. The model is dynamically simulated in terms of a $VAR(1)$,²³ and $\hat{\pi}_{t+12}^{12}$ is reconstructed from cumulating forecasts of $(\Delta\hat{\pi}_{t+i}^{12})$ in order to obtain $\hat{\pi}_{t+12}^{12}$ from π_t^{12} . Also note that since the factors are assumed to be stationary,²⁴ we do not use a VECM.

The lower panel of Table 9 indicates that the dynamic simulation from a VAR on total inflation and the first factor from DFA do not yield satisfactory results: “Rel. RMSE” is always below 1 during the first period 1996:1-1998:12 but the large standard errors imply a low DM statistics.

Sample	Core inflation		
	1996:1 - 1998:12	1999:1 - 2003:12	1996:1 - 2003:12
Rel. MSE ₍₁₎	0.21	0.63	0.47
DM Stat.	4.03**	1.50*	2.85**
Rel. conc. ₍₂₎	1	1.14	1.06
Total inflation			
Rel. MSE ₍₁₎	0.93	0.90	0.91
DM Stat.	0.23	0.38	0.42
Rel. conc. ₍₂₎	0.97	1.09	1.08

(1) as compared to the AR model; (2) concordance of model/concordance of AR model

(*) 10% level; (**) 5% level

Table 9: Dynamic simulation with VAR and dynamic factor on complete panel

Conversely, the results for core inflation indicate a much better model than the benchmark (Rel MSE=0.41 and DM statistic of 2.85), with relatively stable results over the two subperiods. However, its performance is slightly inferior to that of the *core_mul* model. See Figure 6 in Annex D for the simulation of the VAR.

The superior performance of the Core inflation VAR with respect to Total inflation may be explained by the more progressive acceleration of core inflation following the 1999

²³Every VAR (p) model with order $p > 1$, can be rewritten in state-space form as a VAR(1) with state-vector:

$$X_t = (Y_t \ Y_{t-1} \ \dots \ Y_{t-p+1} \ 1)'$$

and companion matrix:

$$B = \begin{bmatrix} A_1 & A_2 & \dots & A_p & A_0 \\ I_d & 0 & \dots & 0 & 0 \\ 0 & I_d & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & \dots & \dots & I_d & 0 \\ 0 & 0 & \dots & \dots & 1 \end{bmatrix}$$

so that

$$X_t = BX_{t-1} + E_t$$

with $E_t = (\varepsilon_t, 0, \dots, 0)'$.

²⁴This is a consequence of running DFA on a sample of variables that are transformed in order to be stationary.

Sample	Surveys		
	1996:1 - 1998:12	1999:1 - 2001:12	1996:1 - 2003:12
Rel. MSE ₍₁₎	0.21	0.60	0.46
DM Stat.	4.05**	1.56*	2.91**
Rel. conc. ₍₂₎	1	1.14	1.05
	Employment		
Rel. MSE ₍₁₎	0.21	0.60	0.47
DM Stat.	4.05**	2.06**	3.53**
Rel. conc. ₍₂₎	0.97	1.09	1.03
	Prices		
Rel. MSE ₍₁₎	0.36	0.94	0.72
DM Stat.	2.33**	0.32	1.48*
Rel. conc. ₍₂₎	1.03	0.89	0.98

(1) as compared to the AR model; (2) concordance of model/concordance of AR model

(*) 10% level; (**) 5% level

Table 10: Dynamic simulation with VAR and factors from blocks of variables on core inflation

recovery in oil prices (Figure 1, in Annex C). Such a result can also be obtained on the different blocks (Table 10) with a particularly good performance of the "survey" block and even more significantly from the "employment" block which does slightly better than the DFA on the complete panel. In the case of the "employment" block, as indicated in Figure 5, the forecast tracks the trend in inflation quite well.

VAR modelling of core inflation could therefore be used as an alternative to the standard forecasting equation since it may provide much better results in terms of greater stability. They remain, however, indistinguishable from a statistical point of view.

5.3 Intercept correction

One conclusion from the various figures is the significant lag between the pick up in prices in 2000 and the recognition of this trend by the forecasting models. As advocated by Clements and Hendry (1999), in case of a shift in the series, past errors may be introduced to force the forecast to return on track. The authors suggest different forms of corrections (constant or variable correction factor), but from a forecasting point of view, without information on the direction of the shift, only the variable intercept is relevant, namely adding to the forecast at horizon $t + 12$, the error e_t observed at time t for a projection made at period $t - 12$. Formally, with $\hat{\pi}_{t+12}^{12}$ the projection given by a given model, the forecast becomes $\hat{\pi}_{t+12}^{12} + e_t$. When implementing such a method, Banerjee et al. (2004) conclude that it should be used with care.

In order to implement such a correction in our case, the first 12 months of projections

are then used for the following forecast, which are again run recursively²⁵. The results are reported in Table 11 below where we report the initial model as well as the equivalent model with intercept correction. Table 11 indicates that intercept correction is not helpful in most cases: RMSE is slightly higher than without intercept correction. The model with aggregation (*tot_agg*) is not challenged by the same model including an intercept correction.²⁶ In one case, however, i.e. for the factor model with prices, intercept correction does reduce RMSE. The overall result of a small gain from intercept correction confirms the absence of significant regime shift in the inflation process over the sample period.

Models	MSE	RMSE	Rel MSE	DM
Total inflation				
-AR	0.76	0.87		
-AR with IC	1.54	1.24		
-tot_agg	0.36	0.60	0.47	1.35
-tot_agg with IC	0.77	0.88	0.50	1.79
-aggregation of components with IC	0.65	0.81	0.42	2.36
Core inflation				
-AR	0.32	0.56		
-AR with IC	0.50	0.71		
-core_fac_prices_var	0.14	0.38	0.81	1.02
-core_fac_prices_var with IC	0.10	0.31	0.44	2.64

NB: indicators computed on 1997:1-2003:12

Table 11: Effect of intercept correction

5.4 Controlling for model nesting

Given our testing strategy, the benchmark model is defined as a restricted version of the alternative model. The models that are compared are therefore nested (see Annex A for details). As indicated by Clark and McCracken (2001 and 2002), under the null hypothesis, the forecast errors are perfectly correlated for the benchmark and the alternative.

²⁵In Table 11 the statistics are not strictly comparable with the previous tables, although they are very close, since the intercept corrected projections start 12 months later. This convention was adopted in order to build the estimated model with a sufficient number of observations.

²⁶For the *tot_agg* model there are actually two possible intercept corrections (IC): one where IC is applied to the aggregate forecast, and another one where individual IC forecasts on the components are then aggregated.

The tests have therefore non standard distributions, in particular because the asymptotic distribution depends on the data generating process.

To assess the possible bias on our results, we use a bootstrap method for inference, as introduced by Clarck and McCracken. We concentrate on the HICP excluding energy and unprocessed food and the *core_mul* model with 3 indicators. When implementing such a method, the data generating process is assumed to be a 4-dimensional VAR model. The model is simulated under the restriction imposed by the null hypothesis that leading indicators have no predictive power for inflation. The bootstrapped time series are used to recursively estimate our long (12-month) horizon forecasting model. Two types of model are considered: *core_mul* vs the *AR* (benchmark) and the model with unemployment (U) vs the AR. Table 12 reports the results from bootstrapping for equal accuracy tests (MSE-T for Diebold and Mariano, 1995) as well as encompassing tests, i.e. whether the alternative model contains additional information with respect to the benchmark (ENC-T for Harvey, Leybourne and Newbold’s (1998) test and ENC-NEW for the variant proposed by Clark & McCracken, 2001 and 2002 for long horizon forecasts). The p-values appear in square brackets. They are all significantly smaller than 0.01, indicating that the null hypothesis of equal MSE or encompassing are strongly rejected at standard levels. The *core_mul* model with 3 indicators and the model with unemployment therefore contain statistically more useful information for forecasting than the AR model. These findings point, at least for core inflation, to the robustness of our results.

Models	MSE-T	ENC-T	ENC-NEW
<i>core_mul</i> vs <i>AR</i>	2.20 [0.00]	2.91 [0.01]	87.22 [0.00]
<i>U</i> vs <i>AR</i>	2.04 [0.01]	3.39 [0.00]	48.90 [0.00]

Notes:

1. The test statistics are compared against bootstrapped critical values.
2. The number of bootstrap draws is 2000.
3. The p-values are between brackets.

Table 12: Tests for equal forecast accuracy and encompassing based on nested models

5.5 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. All in all, just considering the indicator models (single and double), this amounts to a total of around 350 different 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. 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 appears to come from the fact that the asymptotic distribution of the test statistic under the null hypothesis is not the right one.

By denoting 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 that of the alternative model k .

The test statistic used by White is simply the maximum $\max_{\forall k, 1 \leq k \leq K} (\bar{X}_{n,k})$ where $\bar{X}_{n,k}$ 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 this property into account. 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 follows:

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

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

where $A_{n,k} = \frac{1}{4}n^{-1/4} \sqrt{\hat{V}(n^{1/12}\bar{X}_{n,k})}$, $\hat{V}(n^{1/12}\bar{X}_{n,k}) = B^{-1} \sum_{b=1}^B (n^{1/2}\bar{X}_{n,k,b}^* - n^{1/2}\bar{X}_{n,k})^2$,

and $\bar{X}_{n,k,b}^* = n^{-1} \sum_{t=1}^n X_k(\theta_b(t))$. We generate B resamples ($b = 1, \dots, B$) 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.

Regarding total inflation, we run two different experiments reported in Figure 7. First we consider only the set of indicator models for total inflation (top four figures in 7a). Then we assess the effect of introducing the aggregate model on subcomponents (bottom four figures in 7b).

1) In the first case, the South-West subfigure in 7a indicates that the p -value becomes quite large as we increase the number of models that are investigated. Indeed, 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 no one model can be chosen among 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.

2) In contrast, when introducing the aggregate model for total inflation (figure 7b), the p-value remains below the standard threshold. The best alternative model (i.e. the aggregate model) behaves significantly better than the other ones and exhibits reasonable properties for predicting inflation, as compared to the AR model.

All in all, we confirm the main results highlighted in the previous sections. It seems to us that the superiority of the models we used cannot be assumed to provide better results than the AR model just by chance. Of course the statistical tools are central in the paper, but they only provide guidelines for conducting forecast exercises. The economic interpretation also has to provide arguments for choosing one model rather than another, especially when the statistical results are not contrasted enough.

6 Discussions and Conclusions

The systematic investigation of a large set of monthly economic indicators tends to indicate that some of them have forecasting content for total and especially core inflation. When reviewing the different models, the combination of several indicators appears to be an interesting avenue, which we have started to explore. Indeed, for core inflation we exhibit the very good properties of an equation with the unemployment rate, the expected production trend in the consumer goods sector and the price of raw materials. The relevance of business surveys for forecasting is also highlighted. When extending this result to the forecast of total inflation, we provide a model for unprocessed food and another for energy, which remain the most difficult components to forecast. In the end, it appears slightly better to recombine forecasts on total inflation from the forecasts of the sub-component rather than to directly forecast total inflation. We also exhibit good forecasting properties from the Dynamic Factor model, especially when using blocks of homogeneous variables, in particular those derived from survey data and from employment/unemployment data, once again confirming the validity of the Phillips curve approach. To assess the validity of our approach we also provide evidence for the stability of our results, their ability to anticipate changes in the direction of inflation ("concordance" is often much better than for the AR model), the quality of dynamic simulations, as well as dynamic forecasts from VAR models on the factors derived from dynamic factor analysis which provides a significant improvement for core inflation in terms of stability. Testing for data snooping, we also show that the aggregate model significantly improves upon the benchmark and that this result is not derived by chance.

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A Clark and Mc Cracken tests of equal forecast accuracy

To perform the Clark and Mc Cracken tests, we need to produce artificial series under the null of no forecasting power of indicators. The data are therefore generated with a VAR including either inflation and 3 indicators or inflation and the unemployment rate. We illustrate the method here, without loss of generality, on a forecasting model with two indicators $\{x_{1t}, x_{2t}\}$ in order to predict annual inflation π_{t+12}^{12} . In this case, we obtain the following forecasting models:

$$\begin{aligned} (A) & : \pi_{t+12}^{12} - 12.\pi_t = \phi + \gamma(L)\Delta\pi_t + e_{1,t+12} \\ (B) & : \pi_{t+12}^{12} - 12.\pi_t = \phi + \gamma(L)\Delta\pi_t + \beta_1(L)x_{1t} + \beta_2(L)x_{2t} + e_{2,t+12} \end{aligned}$$

Recall that annual inflation $\pi_{t+12}^{12} = \sum_{s=1}^{12} \pi_{t+s}$ where $\pi_t = \log(P_t/P_{t-1})$. The benchmark model (A) is clearly nested in the model (B). Clark and McCracken (2001, 2002) show that the distributions of tests for equal forecast accuracy and encompassing are non-standard. In particular, for h -step ahead forecasts, the distributions of tests depend on the parameters of the data-generating process. Thus, Clark and McCracken suggest a model-based procedure for bootstrapping the distribution of the test statistics. Their basic bootstrap algorithm is a simplified version of Kilian's (1999), which is briefly described in the next paragraph.

Indeed, in order to build a bootstrapped vector of data $\{\pi_t^*, x_{1t}^*, x_{2t}^*\}$, we need to estimate a restricted Vector Autoregression (VAR). The VAR imposes that indicators x_{1t}, x_{2t} -which only belong to (B)- have no predictive power for $\Delta\pi$. Thus, in our case we have:

$$\begin{aligned} \Delta\pi_t & = k_1 + \sum_{i=1}^m \alpha_{0i} \Delta\pi_{t-i} + u_{1,t} \\ x_{1t} & = k_2 + \sum_{i=1}^m \alpha_{1i} \Delta\pi_{t-i} + \sum_{i=1}^m \delta_{11i} x_{1t-i} + \sum_{i=1}^m \delta_{12i} x_{2t-i} + u_{2,t} \\ x_{2t} & = k_3 + \sum_{i=1}^m \alpha_{2i} \Delta\pi_{t-i} + \sum_{i=1}^m \delta_{12i} x_{1t-i} + \sum_{i=1}^m \delta_{22i} x_{2t-i} + u_{3,t} \end{aligned}$$

Once we have estimated the restricted VAR (see Hamilton, 1994 p.311), we store the residuals for sampling. Bootstrapped time series on $\Delta\pi_t$, x_{1t} and x_{2t} are generated by drawing with replacement from the residuals $\{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3\}$ and using the autoregressive structure of the models to iteratively construct data. We select the initial observations by picking one date at random. Following Kilian (1999), the number of replications is 2000. At the end of this step, we obtain the resampled vector (for all dates) $\{\boldsymbol{\pi}^*, \mathbf{x}_1^*, \mathbf{x}_2^*\}$.

In each bootstrap replication and for the two models (A) and (B), we recursively estimate both equations from the artificial dataset and produce out-of-sample forecasts of $\pi_{t+12}^{*12} - \pi_t^*$. Then, we compute the three statistics, namely the MSE-T, ENC-T and ENC-NEW. The test for equal forecast accuracy, MSE-T, is actually the Dieblod and Mariano test (1995) described in the text, whereas ENC-T and ENC-NEW are tests for encompassing:

$$ENC - T = (N - 12)^{1/2} \frac{\bar{c}}{\sqrt{\widehat{S}_{cc}}}$$

$$ENC - NEW = (N - 12) \frac{\bar{c}}{MSE_{(B)}}$$

with $\widehat{c}_{t+12} = \widehat{e}_{1,t+12} (\widehat{e}_{1,t+12} - \widehat{e}_{2,t+12})$. \bar{c} is the average of \widehat{c}_{t+12} over the $N - 12$ out-of-sample forecasts. \widehat{S}_{cc} is the autocorrelation consistent variance of \widehat{c}_{t+12} . $MSE_{(B)}$ is the mean-squared-error of the model (B). Finally, each critical value is computed from the bootstrapped distribution.

B Hansen's test for data snooping

To illustrate how the Hansen (2001) test works, we provide two sets of 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 the number of models considered is progressively extended (from 1 to 350). 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 7a, for example, illustrates, for total inflation, the case where the p -value in the South-West sub-figure increases sharply after the two indicator models are included in the set of alternative models (models are sorted so that one indicator models are introduced first and two indicator models enter next). On the basis of the full set of models, the null hypothesis of equivalent forecasting ability cannot be rejected (the p -value is close to one).

In figure 7b, the South-West sub-figure indicates that, when extending the number of models to include the aggregation of forecasts, the p -value returns below the 5 % threshold. In the bootstrap analysis, the best performing model is never outperformed.

C Correction for the impact of VAT rate changes on the various price indexes

In order to model inflation on the basis of the Harmonised Index of Consumer Prices, it appears important to isolate the few exogenous shocks that affect the VAT rate. For that purpose, we propose a method to isolate the “mechanical” impact of changes in the VAT rate on total HICP, core HICP, and their sub-components: unprocessed food, energy, manufactured goods and services.

Among the various methods available, a VAT index can be computed using a geometric mean of the various VAT rates at each date, weighted by the share in the National Consumer Price Index of the different items on which VAT is levied. Such a method requires detailed information on the VAT rate at a very fine level of disaggregation, information which is not usually publicly available.

A second method would measure the real impact of VAT changes using data on value added from quarterly national accounts. The correction would only be available at a quarterly frequency and plagued with substantial uncertainties due to exemptions as well as lags in the effective payment of VAT by companies.

Against this background, we decided to use a method inspired by Pluyaud (2002) which measures the “effective” impact of VAT rate changes on the main HICP sub-components. While the “mechanical” impact of rate changes can be computed directly (although with varying degrees of accuracy, as indicated above), the “effective” impact is more difficult to assess, as it depends on how much companies change their final price. This depends in particular on the level of competition in the product market. In addition, the time profile of the impact is uncertain. While acknowledging these difficulties, the method consists in correcting each component for the observed shock. Working at the disaggregated level (third disaggregation level), we first measure the “effective” impact on a sub-component by the difference between the observed monthly change in the sub-component and the monthly change that would have been expected in the absence of VAT rate change. The latter is identified as the average over the last 5 years of the monthly change in the (non seasonally adjusted) price index of the sub-component. Once this effect is measured, a correction factor is applied to the relevant aggregate index using the weight of the sub-component in the aggregate index²⁷. In order to take into account changes that occur in the middle of the month, this method is implemented for the current and the following month. The main VAT rate changes are reported in Table 12.

Note that for processed food, VAT rate changes in 1995 and 2000 were too small to have a sufficiently significant impact. We therefore decided not to correct the series. The corrected series for total and core inflation are plotted in Figure 1. The corrections on the annual rate appear to be the most pronounced from August 1995 to July 1996 and

²⁷No HICP weights are available for the period before 1990. The time series of the weights of the different sub-component in the first level of disaggregation of the HICP (i.e. manufactured products, services, processed food, unprocessed food, energy) was constructed using the weights in the National CPI. For more details, see Baudry (1998).

Date	Rate change	Sectors concerned
September 1987	33.33% → 28%	Automobile
January 1988	33.33% → 28%	Household appliances, audio-visual equipment, recording media, jewelery
September 1989	28% → 25%	Household appliances, audio-visual equipment, recording media, jewelery
September 1990	25% → 22%	Household appliances, audio-visual equipment, recording media, jewelery
April 1992	22% → 18.6%	Household appliances, audio-visual equipment, recording media, jewelery
August 1995	18.6% → 20.6%	Overall sectors (normal rate increase)
January 2000		Abolition of a tax on rentals lower than around 5500 euros
April 2000	20.6% → 19.6%	All sectors (normal rate decrease)
January 2001		suppression of a tax on rentals higher than around 5500 euros

Source: INSEE

Table 12: VAT rate changes taken into account in corrected series

from April 2000 to March 2001, following the VAT rate changes in August 1995 and April 2000.

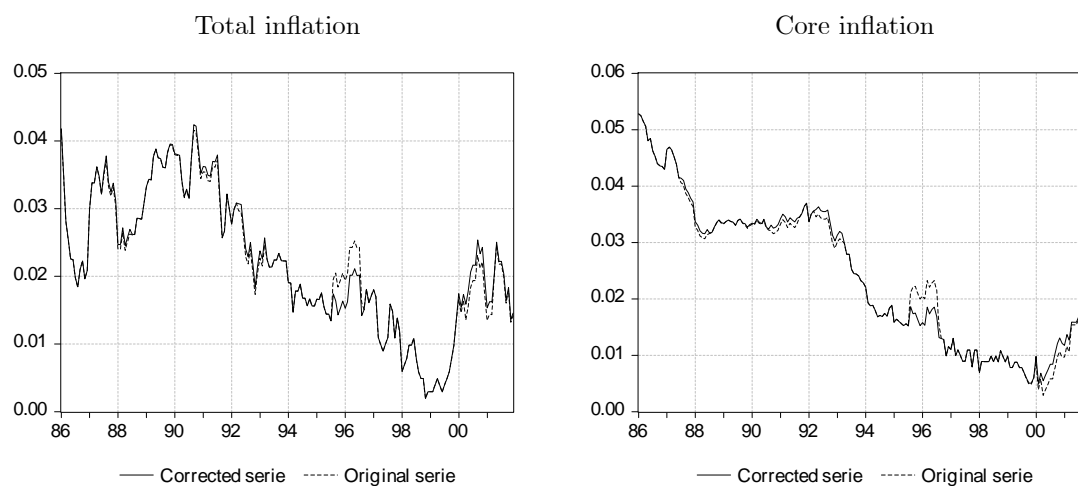


Fig. 1: Original and corrected HICP

D Out-of-sample forecast results

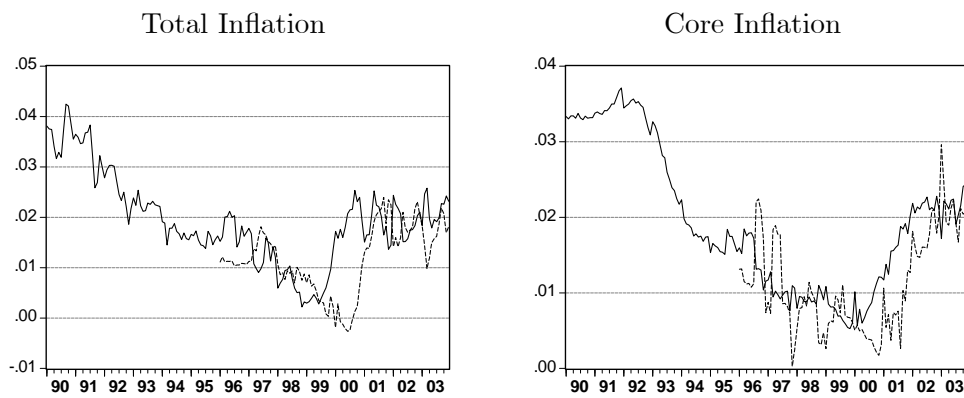


Fig 2: Out-of-sample forecast with "naive" AR model

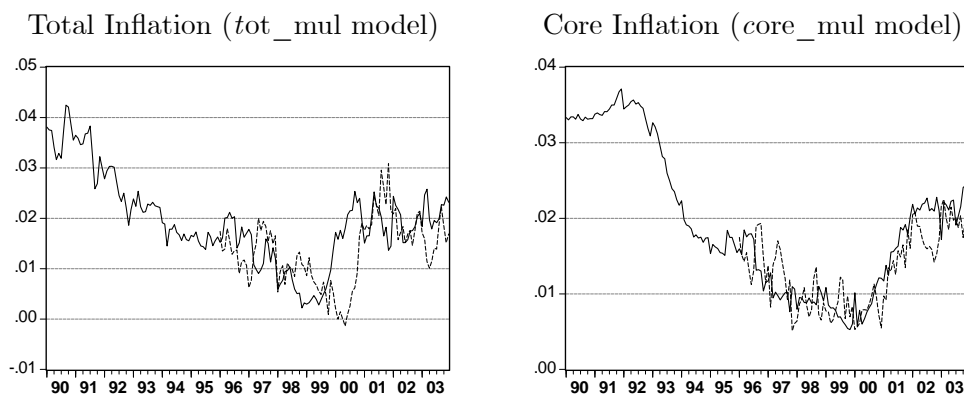


Fig 3a: Forecast with multiple indicators

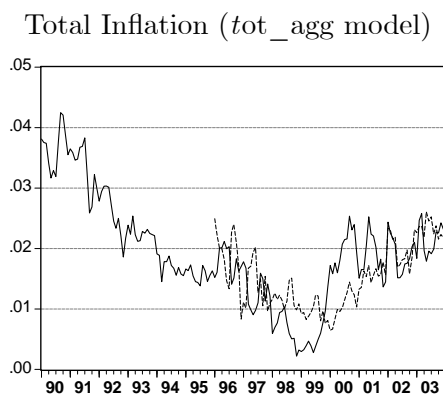


Fig 3b: Forecast aggregation for total inflation

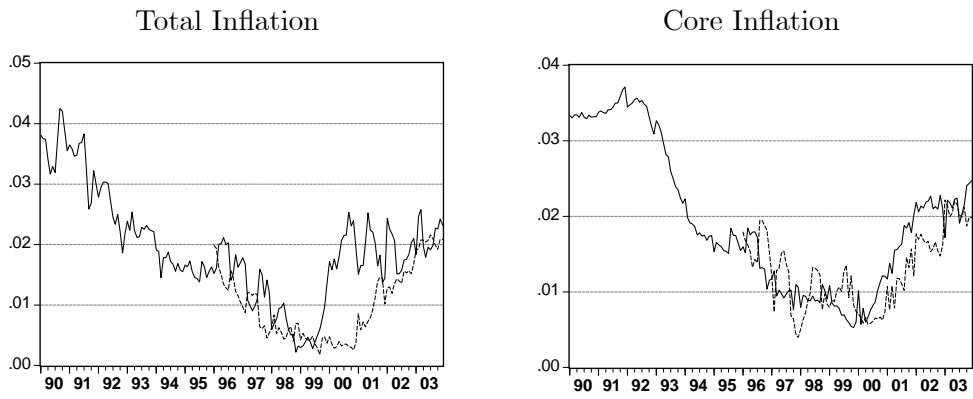


Fig 4: Forecast with the first factor from dynamic factor model on the complete panel

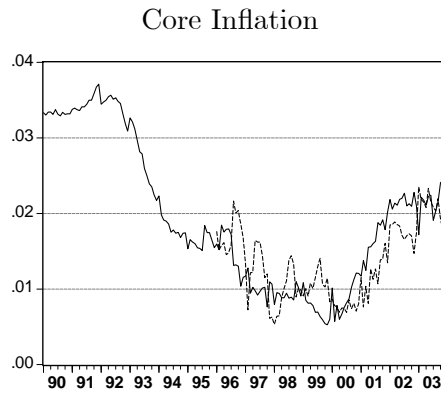


Fig 5: Forecast with the first factor from dynamic factor analysis on the Employment block

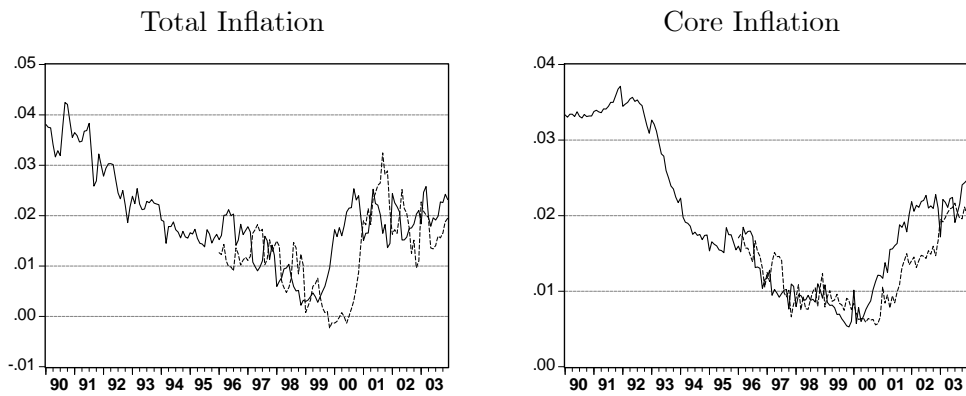
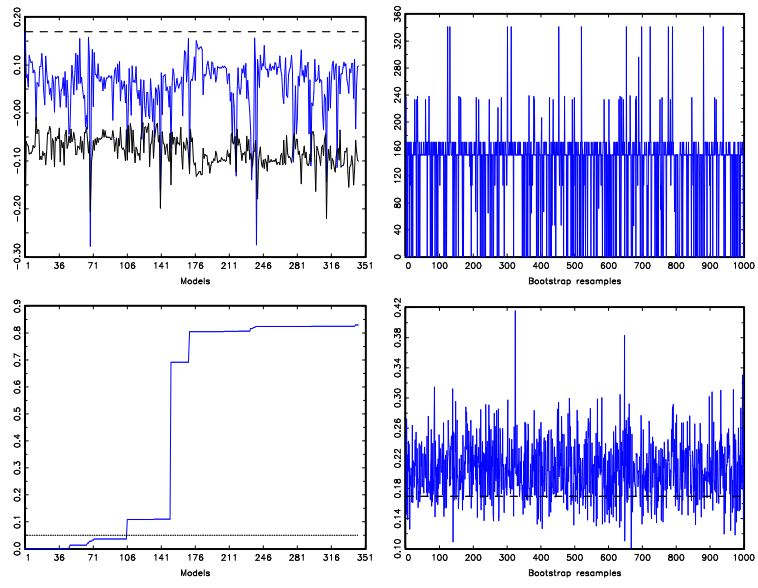
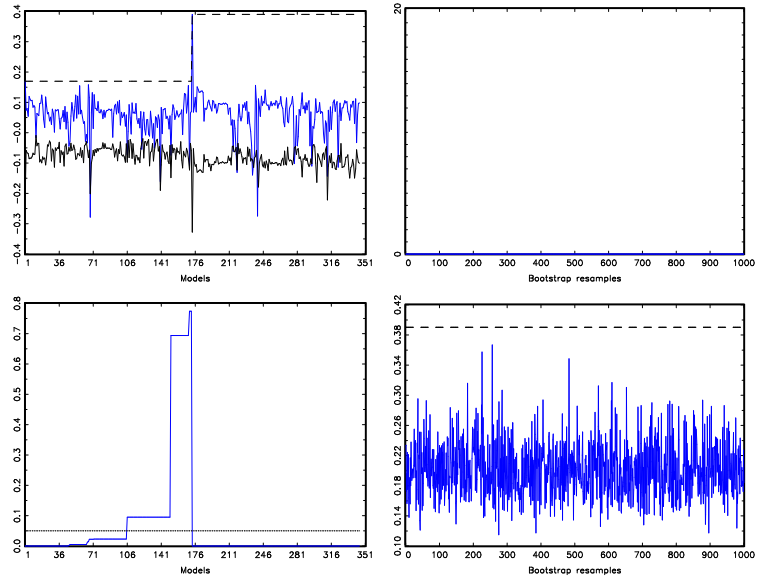


Fig 6: Dynamic simulation (VAR model on the first factor)



a-Without aggregate model



b-With aggregate model

Fig 7: Hansen's test for total inflation

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