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In 2004 all publications will carry a motif taken from the €100 banknote.

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CONTENTS

Abstract

In this paper we investigate whether the forecast of the HICP components (indirect approach) improves upon the forecast of overall HICP (direct approach) and whether the aggregation of country forecasts improves upon the forecast of the euro-area as a whole, considering the four largest euro area countries.

The direct approach provides clearly better results than the indirect approach for 12 and 18 steps ahead for the overall HICP, while for shorter horizons the results are mixed. For the euro area HICP excluding unprocessed food and energy (HICPX), the indirect forecast outperforms the direct whereas the differences are only marginal for the countries. The aggregation of country forecasts does not seem to improve upon the forecast of the euro area HICP and HICPX. This result has however to be taken with caution as differences appear to be rather small and due to the limited country coverage.

Keywords: Forecasting short-term inflation, HICP sub-components/aggregation, Bayesian VARs, Model Selection

JEL Classification: C11, C32, C53, E31, E37

Non-technical summary

Inflation forecasting for the euro area continues to receive a lot of attention both amongst academics and applied researchers. Moreover, forecasting inflation is of great importance for policy makers and for the implementation of monetary policy. Some important aspects of inflation forecasting have however not been extensively explored in the literature. In this paper we investigate whether the forecast of the main HICP sub-components improves upon the forecast of overall HICP, and whether the aggregation of country forecasts improves upon the forecast of the euro-area as a whole. The four largest euro area countries are considered.

Our paper contributes to the existing literature in two ways: first it explores both issues described above simultaneously, using homogenous techniques and procedures. Second, the paper makes use of an extensive analysis for selecting the most appropriate model for each HICP component. The models are selected, first, on the basis of their forecast accuracy and, second, on the basis of their economic meaningfulness in terms of coefficients. Each selected model is then used in the aggregation process instead of using the same forecasting model across all components.

An interesting finding of this paper is that for both the euro area and the four largest euro area countries, the direct forecast of HICP clearly yield better results than the component-based forecast for a forecast horizon beyond one year, while for shorter horizons the results are more mixed. In the case of HICP excluding unprocessed food and energy, the component-based forecast generally outperforms the direct forecast for the euro area, while the differences are only marginal for the countries. Overall, while these results underline the difficulties in modelling the volatile food and energy components of the HICP, they generally tend to support the usefulness of a component based approach for the HICP excluding these volatile items. Furthermore, it is shown that the aggregation of country forecasts does not generally improve upon the forecast of the euro area HICP and HICP excluding unprocessed food and energy. This result however has to be taken with great caution given that it depends on the specific models selected and that forecast differences of alternative models appear to generally be quite small. Moreover, it is worth to stress that the analysis covers the four biggest euro area countries accounting for close to 80% of the euro area aggregate and should be extended to the remaining euro area countries in order to check the robustness of the results obtained.

1 Introduction

In this paper we focus on short-term inflation forecasting for the euro area and the four biggest euro area countries (Germany, France, Italy and Spain) using a set of alternative forecasting models. For each examined country and HICP component, we apply an homogenous procedure to select the best performing model amongst a broad set of alternatives. The main selection criterion is the Root Mean Squared Error (RMSE) in the out-of-sample period from January 1998 to June 2002. After having selected a forecasting model, we are interested in providing an answer to the following questions:

1. Does the forecast of the main HICP sub-components (indirect approach) improve upon the forecast of overall HICP (direct approach) in terms of forecast accuracy?
2. Does the aggregation of country forecast improve upon the forecast of the euro-area aggregate HICP inflation (aggregated versus non-aggregated approach)?

The first issue regarding the comparison of a direct versus an indirect approach to forecast HICP in the short-run has been explored in the literature by Hubrich (2003) for the euro area, by Fritzer et al. (2002) for Austria and by Reijer and Vlaar (2003) for the euro area and the Netherlands. Results depend on the type of model used and on the forecasting horizon considered but do not seem to suggest that aggregating forecasts by components necessarily improves forecasting accuracy.

The second point regarding aggregation of country forecasts versus a euro area forecast has been recently explored by Marcellino et al. (2003) on a broader set of macroeconomic variables concluding that forecasts constructed by aggregating country specific models are generally more accurate than forecast made using the aggregated data. Similar evidence regarding short-term real GDP forecasting was also found by Orlandi (2003), even if inference analysis on the difference between the RMSE of the two approaches was not conclusive.

Our paper contributes to the existing literature in two ways: first it explores both issues described above simultaneously using homogenous techniques and procedures. Second, the paper makes use of an extensive analysis for selecting the most appropriate model for each HICP component. Each selected model is then used in the aggregation process instead of using the same forecasting model across all components. For this purpose, both univariate and multivariate models have been used. Univariate models have been included not only to have a simple 'benchmark' against which the multivariate models are tested but also to test whether they are able to provide better forecasts than multivariate models (see, for example, Marcellino et al. (2003), Gardner (1985), Hubrich (2003) and Meyler et al. (1998)). Within the class of multivariate models, the following are considered: vector autoregressive models (VAR), Bayesian VAR models (BVAR) and single equation models. BVAR models are tested given the stream of literature reporting on their usefulness for forecasting inflation in the euro area and in the euro area countries (see Artis and Zhang (1990), Ballabriga and Castillo (2000), Bikker (1998) and Canova (2002)). Moreover, BVAR models may help to tackle the problem of over-parameterisation, which is particularly relevant in small samples (see Doan et al. (1984)). The use of error correction models is not included, as the relatively short sample would make the finding of a co-integrating long-run relationship difficult. Dynamic factor models (see for example Angelini et al.(2001)) are also not considered in this study as they involve very high set-up costs.

The model selection is based on the RMSE of recursive dynamic out-of-sample forecasts, as widely used in the literature (see for example Stock and Watson (1999)). This criterion ensures that the models are selected in an objective way and are rather homogenous across countries and the euro area and also across components, which contributes to the transparency and comparability of the exercise. However, after having identified the model with the minimum RMSE, some standard additional checks were considered. In particular, the variables included, the signs of the estimated coefficients and the short-term sensitivity to changes in the exogenous variables (for the multivariate models) were evaluated. This procedure could lead to the selection of a model with slightly higher RMSE, but with reasonable characteristics (see next section for a detailed description of the procedure). Given the broad scope of the exercise in terms of countries examined and HICP sub-components and the emphasis on exploring different approaches regarding components and countries, respectively, a relative simple selection procedure had to be followed to choose among alternative models.

The remainder of the paper is structured as follows: Section 2 describes the modelling strategy and the data used. Sections 3 and 4 present the results for the euro area and the four largest euro area countries, respectively, focusing on the model selected for each component. In section 5 we first evaluate the direct and indirect approach to forecast HICP, then the forecasts for the euro are compared with the aggregate of the forecasts for the four largest euro area countries. Section 6 concludes.

2 Modelling strategy

Univariate (random walk, ARIMA, exponential smoothing) and multivariate (VAR, Bayesian VAR, single equations) models are estimated for the five main components of the HICP, the overall HICP and the HICP excluding energy and unprocessed food (HICPX) for the euro area and the four largest euro area countries. The data used in the analysis are described in section 2.1, section 2.2 explains the strategy for the selection of the models while section 2.3 outlines the models and their specification. The models are presented in a generalised form, while they differ for the individual HICP components across countries regarding the variables and the number of lags included.

2.1 Data

The sample covers monthly data from 1990:1 to 2002:6 for the euro area as a whole, France and Italy. Data for Germany and Spain are available from 1991:1 and 1992:1 onwards, respectively (for a detailed description of the data, see Appendix A1). The data used are not seasonally adjusted given that official seasonally adjusted HICP data are available only at the euro area level and not for the euro area countries. Moreover, seasonal adjustment of HICP data is rather complicated owing to several structural breaks that are largely related to the harmonisation of the HICP data at the country level. Furthermore, the officially available seasonally adjusted HICP data for the euro area is not completely free of seasonality, which means that its use would not have helped to better extract the signal from the time series. Last but not least, the use of seasonally adjusted price levels would generally imply inflation rates, which differ from those officially published by Eurostat and we had a strong preference for the use of official inflation figures. To take account of the seasonality of the data, either the 12^{th} lag of the endogenous variable or seasonal dummies are included in the models. To tackle the problem of a changing season in non-energy industrial goods prices due to the introduction of sales prices in the HICP for Italy and Spain from 2001 onwards, synthetic series for this HICP component (see Appendix A2) are used.

In addition to data for overall HICP, HICPX and the five HICP components (unprocessed food, energy, processed food, non-energy industrial goods and services) the data set comprises the following variables: oil and non-oil commodity prices (in euro terms), the nominal effective exchange rate of the euro, short-term interest rates, compensation per employee[2] and real GDP growth[3]. These are variables that are commonly thought to influence inflation developments in the short-run. Some other additional variables, which are expected to improve the inflation forecast, such as information on taxes (value-added tax, VAT, and energy taxation), import prices and producer prices for consumer goods are also included in the data set.

Standard stationarity analysis suggests that price levels are generally non-stationary whilst first differences of the log-levels (inflation rates) are stationary. Notwithstanding the relatively short-sample period used to perform such analysis, results are confirmed using both the Augmented Dickey-Fuller and Phillips-Perron tests with different lagged terms (see Appendix A3 for results for the price level and the log differences).

2.2 Forecast evaluation

All models are selected on the basis of their forecast accuracy. The main criterion for the selection of the models is the RMSE of recursive dynamic out-of-sample forecasts. The last four and a half years of the sample are used to evaluate the forecast performance, i.e. the first out-of-sample exercise starts in 1998:1 on the basis of the sample 1990:1 (1991:1 for Germany, 1992:1 for Spain) to 1997:12. The sample is then extended sequentially by one month up until June 2002. Each time, the models are re-estimated and a set of forecasts computed for up to 18 months ahead.

The forecast error is evaluated for the year-on-year rate of change in the respective HICP component. The annual inflation rate is chosen given the relevance of this indicator from a monetary policy viewpoint.

The formula for the RMSE is given by:

$$RMSE(steps) = 100 \times \left[\frac{1}{T} \sum_{T} \left(\hat{\pi}_{t+steps}\Big|_{t} - \pi_{t+steps} \right)^2 \right]^{1/2}$$

2 In the medium term, unit labour costs (ULC) might be more adequate to explain prices than compensation per employee. However, as the focus is on short-term forecasts, the latter variable is used. Moreover, the forecast performance of models with ULC instead of compensation per employee changed only marginally, while most of the coefficients on ULC were statistically not different from zero.

3 GDP and compensation per employee are interpolated to a monthly frequency using a linear interpolation. Chow-Lin interpolation procedure using monthly indicators, such as industrial production, has been tested and provided similar results.

with T the number of periods, *steps* the numbers of steps (months) ahead to forecast, and π year-on-year growth of the HICP component. A hat (^) denotes the forecasted variable according to the selected model.

The RMSE is calculated for a broad range of forecast horizons, namely 1, 3, 6, 12 and 18 months ahead. However, looking at all these horizons might cause problems when selecting the best model, as it is likely that one model performs well only at a specific horizon. Given that there is no preference for a specific horizon but the emphasis of the paper is on short-term forecasting, a simple average of the RMSEs over the five horizons is used as the main selection criterion.

Another important issue is the information set on which the forecasts are based. This is certainly not a problem in a univariate environment. However, as also multivariate models are employed, the question arises how to treat other variables (non-HICP) in the system. The RMSEs should be preferably based on unconditional forecasts for all the variables in the system. However, the following problems are inherent to this approach: first, the range of models also comprises single equations, so that one would need ad-hoc forecasts of the exogenous variables. Second, the forecast performance would no longer be comparable with the set of univariate models estimated. Therefore, in this study the forecasting performance of the multivariate models is assessed on forecasts, which are *conditional* on observed historical data of all other variables than HICP. As a general robustness test, we have also checked the unconditional forecast performance of the VAR and the BVAR of the selected models for overall HICP.

A benchmark model is usually very helpful in obtaining an idea about the relative forecasting performance of the different models. In the analysis, a so-called *naïve* forecast is used as a benchmark, which sets all the forecasts ahead equal to the latest observed annual inflation rate available. The benchmark model is based on the assumption that the year-on-year rate of change in prices is stationary.

After having identified the model with the minimum RMSE, some simple additional checks were implemented in terms of the variables included, the signs of the estimated coefficients and the short-term sensitivity to changes in the exogenous variables. For example, the coefficients of the exogenous variables should have economically plausible signs and simple simulation exercises such as a change in oil prices should deliver reasonable results. This procedure may lead to a selection of a second best model in terms of the RMSE but it is crucial to ensure the selection of forecasting models with plausible economic interpretation, especially in the context of the rather short sample on which the evaluation of the forecast accuracy is based.

2.3 Forecasting models and specification

A large number of different models, of univariate and multivariate nature, are estimated in order to evaluate their forecasting performance. Univariate models are also included for several reasons. First, they provide another 'benchmark' against which the multivariate models are tested. Second, the literature reports examples in which univariate models are able to perform satisfactorily compared to multivariate models (see, for example, Marcellino et al. (2003), Gardner (1985), Hubrich (2003) and Meyler et al. (1998)).

The models are estimated for the five components of the HICP and also for the overall HICP and the HICPX, for the euro area as a whole and for the four largest euro area countries (Germany, France, Italy and Spain).

2.3.1 Univariate models

Within the univariate framework, three models are used: random walk, ARIMA and exponential smoothing. The *random walk* is specified with a constant and with seasonal dummies. For the *ARIMA*, different combinations of AR and MA terms are tested allowing for up to 5 lags and the lag structure, which produces the smallest RMSE is selected. Moreover, a seasonal lag is included for both the autoregressive and the moving average components in order to capture the seasonality in the data.

The *exponential smoothing method* is the third univariate model used. This method focuses upon the trend and the seasonal behaviour of the data. As these two aspects may dominate the developments in price series at the very short term, they may perform well in forecasting especially in the case of volatile components. Given that the exponential smoothing technique is computationally very simple, exponential smoothing models are specified for both first differences and log-levels. When specified in log-levels the model includes a linear trend and multiplicative seasons, while the model for first differences is estimated without trend and with additive seasons. This approach is chosen because it is consistent with the seasonal adjustment method of HICP data (see ECB (2000)).

2.3.2 Multivariate models

The following multivariate models are considered: vector autoregressive regression models (VAR), Bayesian VAR models (BVAR) and single equation models. All models include a constant and take account of the seasonality in the data, either via the inclusion of the 12th lag of the dependent variable or seasonal dummies.

Error correction models are not included, as the relatively short sample would make the finding of a co-integrating long-run relationship difficult. Dynamic factor models (see for example Angelini et al. (2001)) are not considered here as they go beyond the scope of this study.

As regards *VARs*, the strategy is to start with a standard model. This model always consists of seven variables, i.e. the respective HICP variable and six exogenous variables: oil prices, non-energy commodity prices, nominal effective exchange rate, short-term interest rates, compensation per employee and real GDP. The selection of the optimal lag is based on the RMSE criterion, allowing for up to five lags. In a second step, the model is refined to improve upon the RMSE and ensure economically reasonable results. This implies running the standard VAR with either seasonal dummies or the 12th lag depending on which one has the lowest RMSE, skipping insignificant variables or those which are wrongly signed and testing for inclusion of some additional variables such as VAT rates or producer prices. Hence, a general to specific procedure is employed to narrow down the number of variables included in the VAR to avoid over-parameterisation. Here again, the selection of the lag length is based on the RMSE.

The use of *BVAR* models may help to tackle the problem of over-parameterisation which is particularly relevant in small samples (see Doan et al. (1984)) and have been successfully employed to forecast inflation in the euro area and in the euro area countries (see for example Bikker (1998, 1999), Ballabriga and Castillo (2000) and Canova (2002)). For an interesting literature overview on BVAR see Ciccarelli and Rebucci (2003). The BVAR models used in the analysis are rather simple relying on a standard prior specification. More specifically, for all BVAR the random walk (Minnesota) prior originally proposed by Litterman (1986) is assumed, which is based on the idea that each series is best described as a random walk around an unknown deterministic component. Optimal values for the three hyperparameters, i.e. overall restriction (tightness), restriction on cross-lags (weight) and restrictions on higher lags (lag decay), are obtained from a grid search sequential procedure. First, the parameter for the tightness, which delivers the smallest RMSE is identified. Second, given this tightness, the procedure is repeated to find the best value for the weight parameter (with regard to the smallest RMSE) and, third, the parameter for the best lag decay is selected. After having identified the hyperparameters, the optimal lag length is determined by minimising the RMSE. To allow for comparability with the VAR, the BVAR models include the same variables as the VAR, i.e. the standard BVAR includes the HICP series plus the six variables as described above. The refined BVAR models use those variables, which are found via the general-to-specific approach for the VAR as described before. The choice of the Minnesota prior as well as the sequential grid search procedure could be supplemented and enriched with more sophisticated techniques (for example diffuse or conjugate prior) at the expense of significantly higher computing costs.

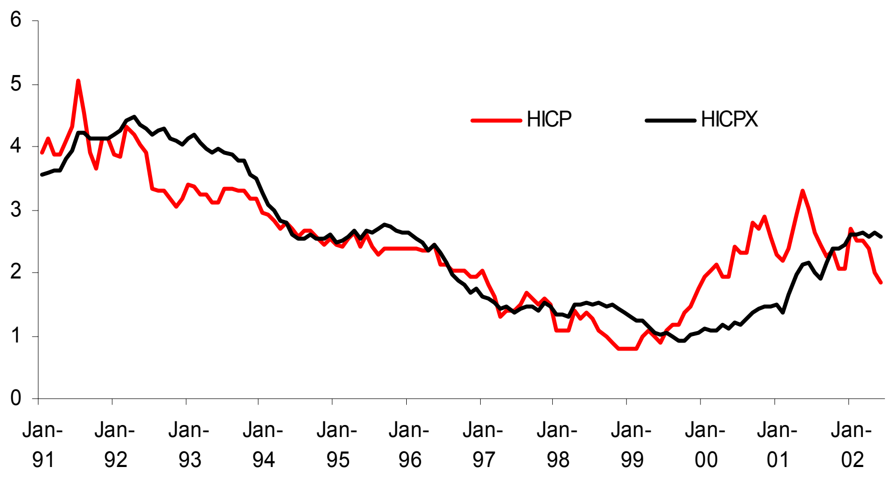
Finally, *single equations* are included in the analysis, as they allow for more flexibility in terms of lag length and the inclusion of additional variables than the VAR and BVAR. However, single equations are not generally estimated for all components and all countries but only in those cases where the analysis of the VAR hinted that single equations could improve the forecasting performance.

It should be noted that the same sample period for the selection within a model class, and between models of different classes, i.e. the forecast evaluation, is used. This implies that the RMSE is not based on a fully-fledged out of sample period, as the same period is used twice in a case where one model selection procedure depends on the outcome of the other. However, the sample is too short to split it further to have a second out-of-sample evaluation period. Another solution would be to choose models within a model class based on in-sample information criteria (as for example the Akaike or the Schwarz criteria) and between model classes based on the RMSE, which is however difficult to apply to BVAR models.

3 Results for the euro area

Chart 1 shows the behaviour of overall HICP and HICPX inflation in the euro area over the sample period. Most of the period until the beginning of 1999 is characterised by a decline of inflation rates from levels around 4% in 1991 to 1-1.5% at the beginning of 1999. From then onwards, inflation rates strongly increased, with a steaper increase for overall HICP than for HICPX, due to the effect of increasing oil prices and the unprocessed food price shocks. HICPX also increased, though somewhat later and to a lesser extend, mainly as a result of the indirect effect of higher oil prices. The chart suggests that oil prices should be one of the main explanatory variables of our models, in order to explain the period from the start of Stage III of EMU onwards.

Chart 1 HICP and HICPX inflation during the sample period



In presenting the results, we deal first with the two volatile components, HICP unprocessed food and energy and then with the results for the remaining components, HICP processed food, non-energy industrial goods and services as well as for overall HICP and HICPX. The main results of the selected model for each component are presented in Table 1 below, while more detailed documentation can be found in Appendix A4. Appendix A5 contains a table of the RMSE per step ahead forecast for each component and all models. Unconditional RMSEs for the overall HICP are presented in Appendix A6 showing that the forecast performance obtained are similar to those of the conditional forecast discussed below.[4]

3.1 Unprocessed food prices

The model chosen for unprocessed food prices is a single equation model, including the lags 1, 10 and 12 of the dependent variable and seasonal dummies. Column 2 of Table 1 shows the selected model for unprocessed food prices, along with the relative RMSE and the RMSE of the benchmark model, i.e. the naïve model (last two rows in Table 1). The relative RMSE is the value of the average RMSE of the selected model relative to the RMSE of the benchmark model. A value smaller than one indicates that the selected model performs better than the benchmark in the out-of-sample exercise.

[4] We focused on overall HICP in order to have comparable results across the euro area and the countries. For other HICP components we have sometimes selected single equation models, which do no allow the production of unconditional forecasts

The results indicate that the selected model for unprocessed food prices performs notably better than the benchmark. However, a comparison with the other models (see Appendix A5) shows that the gain with respect to the random walk with drift and a BVAR with 2 lags including real GDP is limited. Adding a lagged dependent variable therefore seems to add valuable information for forecasting, while the additional information from the GDP variable is less clear-cut. The seasonal dummies indicate that unprocessed food prices are significantly higher in January and April, while they are significantly lower from June to August.

It should be noted that the RMSE of all models for unprocessed food prices is high relative to most other HICP components (except energy), with an average forecast error of 2.3 p.p. This is because most strong movements of unprocessed food prices are due to bad weather conditions or animal diseases (for example BSE and the foot-and-mouth disease). As no variables can satisfactorily track and correctly forecast these factors, it is not surprising to find a relatively ‘simplistic’ model for this component.

3.2 Energy prices

For energy, a dynamic single equation with five lags for the dependent variable, contemporaneous and lagged oil prices, contemporaneous energy taxes and seasonal dummies performed best (see column 3 of Table 1). According to the estimation, an increase in euro denominated oil prices by 1% leads to an increase in energy price inflation of 0.13 p.p. (percentage point) after 2 months and 0.16 p.p. after 6 months. A rise in energy taxes by 1% would lead to a rise by 0.28 p.p. after 6 months.

Table 1 also shows that the single equation performs significantly better than the benchmark, with an average forecast error of 2 p.p. as compared to 7 p.p. for the benchmark. However, it has to be borne in mind that this forecast is conditional on observed oil prices (in euro) and energy taxes. Nonetheless, Appendix A5 shows that the single equation significantly outperforms all other models. In particular, all univariate models yield RMSEs which are more than twice as large as the multivariate models, as the second set of equations all include oil prices and energy taxes. However, additional lags of the explanatory variables do not seem to improve the forecast, so that the single equation with lags only for the dependent variable is selected.

Table 1 Model results and impulse responses (euro area)

	Unprocessed food		Energy		Processed food		Non-energy industrial goods		Services		Overall HICP		HICPX	
Model selected	Single equat		Single equat.		Single equat.		Single equat.		BVAR		VAR		BVAR	
Variables included	LDV(1,10,12), SD		LDV(1 to 5) OIL(0,1) ENETAX, SD		LDV(1 to 4) COMFD(2) VAT WAGES(0 to2) SD		LDV(1,6,12) WAGES(2) PPI_CONS(1) VAT SD		WAGES PPI_CONS HICPFDUNPR (all lags 1 to 5 and 12)		WAGES, PPI_CONS, OIL, SD (all lags 1 to 5)		WAGES, PPI_CONS (all lags 1 to 5 and 12)	
Cumulated response to a 1% increase in each variable 2 and 6 months ahead:														
	2 m.	6 m.	2 m.	6 m.	2 m.	6 m.	2 m.	6 m.	2 m.	6 m.	2 m.	6 m.	2 m.	6 m.
OIL			0.13	0.16							0.01	0.01		
ENETAX			0.22	0.28										
COMFD						0.01								
VAT					0.05	0.08	0.06	0.06						
WAGES					0.09	0.29		0.07	0.09	0.24	0.16	0.25	0.09	0.16
PPI_CONS							0.15	0.14	0.11	0.09	0.18	0.32	0.10	0.18
HICPFDUNPR									0.04	0.07				
Benchmark RMSE	2.81		7.01		0.74		0.36		0.41		0.60		0.41	
Relative RMSE	**0.82**		**0.29**		**0.76**		**0.81**		**0.58**		**0.58**		**0.79**	

LDV: lagged dependent variable; SD: seasonal dummies; OIL: euro denominated oil prices; ENETAX: energy taxes; COMFD: food commodity prices (in euro terms); VAT: value-added tax rate; WAGES: compensation per employee; PPI_CONS: producer prices for consumer goods; HICPFDUNPR: HICP unprocessed food.
Numbers between brackets are the lags included in the models.
The cumulated responses are calculated by subtracting the forecasted year-on-year growth rate when introducing a 1% increase in the variable from the year-on-year rate of change in the baseline forecast. 2 m. means the second month, including the shocked month, while 6 m. is the 6^{th} month including the shocked month.
The relative RMSE is the RMSE of the model relative to the RMSE of the benchmark model.

3.3 Processed food prices

The lowest RMSE for processed food prices is obtained with a dynamic single equation, including 4 lags of the dependent variable, food commodity prices (in euro) with two lags, the contemporaneous VAT rate, and lags 0 to 2 of wages, together with seasonal dummies (see column 4 of Table 1). While food commodity prices have a very small impact, an increase in the VAT rate from a euro area average of around 18% to 19%, i.e. a one p.p. change, would result in a cumulated rise in processed food price inflation by 0.08 p.p. after 6 months. Concerning wages, the cumulated response to a 1% shock amounts to 0.09 p.p. after 2 months and to 0.29 p.p. after 6 months.

The average RMSE of this model is significantly lower than that of the benchmark, assuming however that the out of sample development of the exogenous variables (food commodity prices, VAT and wages) is known. Although the multivariate models perform in general better than the univariate models, the single equation has by far the lowest RMSE (Appendix A4). The selection of a dynamic single equation model is mainly due to the fact that it is more flexible in terms of the lag structure of the right hand side variables. For example, the VAT rate has only a contemporaneous effect, so that a VAR model would add too many lags.

3.4 Non-energy industrial goods prices

The modelling of non-energy industrial goods prices is particularly complicated through the introduction of sales prices in the HICP in Italy and Spain in 2001. The back data are corrected as described in Appendix A2. The euro area HICP for non-energy industrial goods is then obtained through chain weighting over all euro area countries, and HICP total and HICPX are the chain weighted sum of the euro area HICP components.[5]

As there are generally two major sales per year, the 6th lag is also included in the regressions to test for the best model. The selected model is a dynamic single equation model, including the 1st, 6th and 12th lag of the dependent variable, lagged producer prices of consumer goods, the 2nd lag of wages and the contemporaneous VAT rate, together with monthly dummies to pick up further seasonality (see column 5 of Table 1). The average RMSE of this model is significantly lower than that of the benchmark, while it is slightly higher than that of the full

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[5] Although the Eurostat index is computed through aggregating the overall HICP and HICPX over the countries, the method used here differs only marginally.

BVAR model (Appendix A4). However, the latter did not lead to intuitive impulse responses and was therefore not selected for this component.

The results indicate that a 1% increase in the VAT rate results in a cumulated 0.06 p.p. increase in the annual rate of change in non-energy industrial goods prices after 2 months. The cumulated response to a 1% increase in wages amounts to 0.07 p.p. and that of a 1% increase in consumer producer prices amounts to 0.14 p.p. after 6 months.

3.5 Services prices

For services prices, a BVAR with wages, producer prices of consumer goods and unprocessed food prices as endogenous variables, including the 1st to the 5th and the 12th lag yields the lowest average RMSE (see column 6 of Table 1). The inclusion of unprocessed food prices in this model can be justified by their impact on restaurant prices, which comprise a large share of services prices. The hyperparameters are chosen so as to minimise the RMSE, resulting in a tightness of 0.1, other weights of 0.9 and the decay parameter of 0.1. The regression results indicate that a 1% increase in wages leads to an increase by 0.09 p.p. increase in service price inflation after 2 months, while the cumulated response after 6 months amounts to 0.24 p.p. The effect of a 1% increase in producer prices after 6 months is 0.09 p.p. An increase in unprocessed food prices by 1% results in a cumulated 0.07 p.p. increase in services HICP after 6 months. For the calculation of the RMSE, the forecast is conditioned upon observed wages and producer prices of consumer goods, and forecasted unprocessed food prices resulting from the model described in section 3.1.

The one-step ahead forecast from the selected model performs slightly worse than the naïve benchmark (see Appendix A5), but from then onwards the RMSE of the model is equal to (step 3) or lower than the RMSE of the benchmark. Surprisingly, the 12-month ahead out of sample forecast performs better than the 6-month ahead forecast. Overall, the average forecast error of the selected model is significantly below those of the other models.

3.6 Overall HICP

The selected model for overall HICP is a VAR with lags 1 to 5 and 12, including wages, consumer producer prices, euro denominated oil prices and seasonal dummies (see column 7 of Table 1), resulting in an average out-of-sample forecast error of 0.35 p.p. The results are very similar to those obtained with a BVAR, and both models perform significantly better than the other tested models (see Appendix A5). The cumulated responses indicate that a 1%

increase in oil prices yields a 0.01 p.p. increase in overall HICP inflation after 2 months, with no further significant increase afterwards. This is similar to the effect obtained when multiplying the effect of oil prices on HICP energy (see column 3 of Table 1) with the weight of energy in overall HICP (8.2% in 2003). The effect a 1% increase in wages amounts to 0.16 p.p. after 2 months and to 0.25 p.p. after 6 months. Finally, a 1% increase in producer prices of consumer goods leads to a 0.18 p.p. rise after 2 months, and a 0.32 p.p. rise after 6 months. The effect of wages and of consumer goods producer prices is somewhat higher than what we find when taking the weighted sum of the effect on the individual components.

3.7 HICP excluding unprocessed food and energy

For the HICPX, a BVAR model with lags 1 to 5 and 12, including wages and producer prices of consumer goods produces the lowest average RMSE. The optimal tightness, weights and decay parameters are 0.1, 0.9 and 0.2, respectively. The variables and lags included are therefore the same as for overall HICP, except for oil prices. Similarly to overall HICP, multivariate models perform in general better than univariate models.

The estimation results indicate that a 1% increase in wages leads to a 0.09 p.p. increase in HICPX inflation after 2 months, and 0.16 p.p. after 6 months, while the cumulated responses to a 1% increase in producer prices of consumer goods amounts to 0.10 p.p. after 2 months and 0.18 p.p. after 6 months. This is rather similar to the weighted sum of the effect of these variables on the individual components.

Summarising the results per HICP component for the euro area, one can say that for all components except for services, a single equation approach performs best in terms of the average RMSE. This seems to be related to the fact that single equations are more flexible in terms of the lag structure of the exogenous variables. For the VAT rate, for example, the effect on HICP should be contemporaneous, so that lags for this variable appeared to be statistically insignificant in the regressions. For overall HICP and HICPX a VAR and a BVAR yield lower RMSEs.

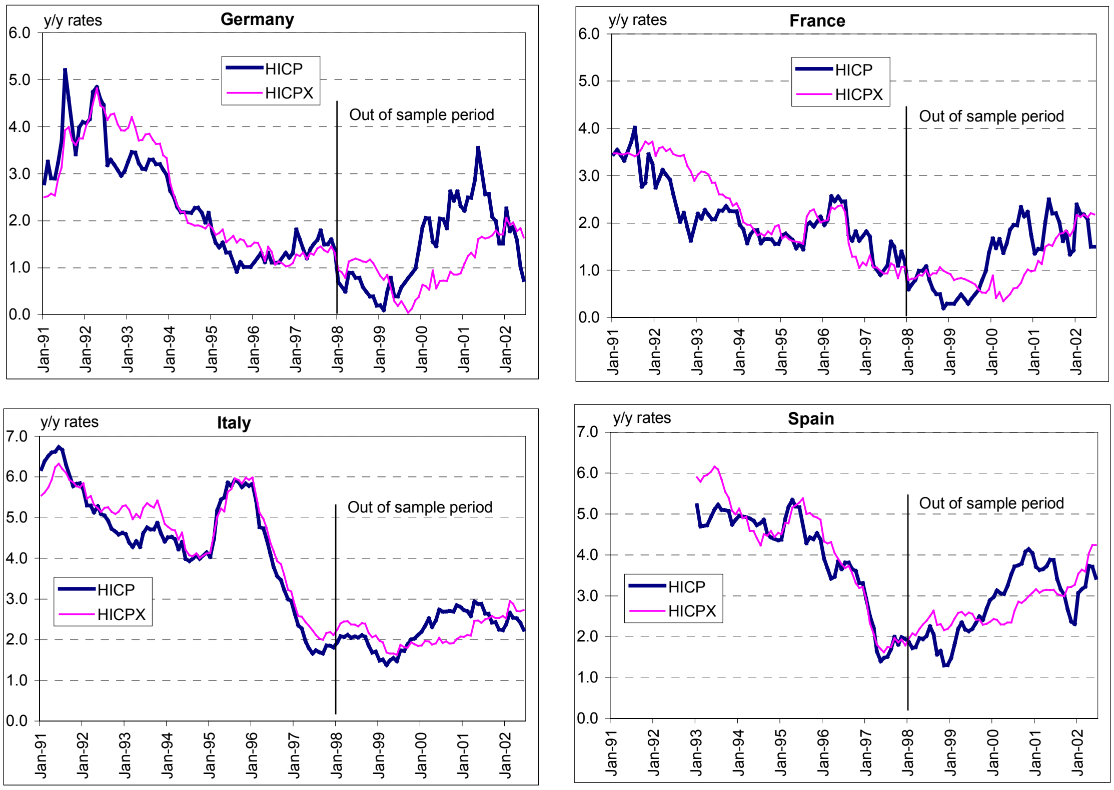
The second conclusion from the selected models is that the variables impacting the short-term inflation forecast are oil and food commodity prices (both in euro terms), wages, producer prices and taxes. At first glance, it might be surprising not to find import prices and exchange rates among the explanatory variables. However, the effect of import prices is to a non-negligible extent captured through producer prices. The reason that short-term interest rates were retained in no model might be explained by the fact that the model choice is based on the short term forecast performance, while interest rates might be significant only in the medium to longer term. Some other variables like changes in administrative prices play an important role in the very short term, but due to a lack of data for the estimation period they are not included in the models.

4 Results for the four largest euro area countries

The modelling strategy applied to the four largest euro area countries (Germany, France, Italy and Spain) is the same as for the euro area as a whole, as described in section 2.3. This section briefly summarises the models selected for each HICP component. The best model obtained is reported in terms of relative RMSE. The results are presented for each component across countries, as the strategy and problems faced were quite similar in all countries. In particular, for every component a summary table shows the model selected, the set of variables included, the values of the cumulated responses to a shock (see below), the average RMSE of the benchmark and the relative RMSE of the selected model. Appendix A4 provides detailed information on the model results, while Appendix A7 gives the RMSE for all models.

Before showing the results by component in detail across the countries, it may be relevant to briefly describe the behaviour of the annual growth rates of the overall HICP and HICPX in these economies, especially during the out-of-sample period (January 1998 to June 2002). As can be seen in Chart 2 below, overall HICP inflation declined in all these economies notably up to the end of 1998 and increased thereafter, reflecting among other factors, higher oil prices. However, in the case of Italy, inflation remained relatively subdued during the most recent period in comparison with the inflation rates seen in the mid-1990s. This apparent change in the behaviour of the series, close to the out-of-sample period, may help to explain some modelling difficulties faced in the case of Italy, as explained in more detail below.

Chart 2 The behaviour of HICP and HICPX inflation during the sample period



4.1 Unprocessed food prices

With respect to unprocessed food prices, a BVAR model is selected for Germany, Italy and Spain, whilst a simple exponential smoothing specification is considered as the most appropriate in the case of France (see Table 2 below). As can be seen in more detail in Appendix A7, in general, multivariate methods do not seem to significantly improve the results in terms of relative RMSE, compared to those obtained with univariate models, and even in some cases the random walk with drift seems to perform relatively well. For all countries examined, seasonality plays a crucial role in modelling unprocessed food prices. In the case of Germany and Italy, real GDP is included as an explanatory variable whilst in the case of Spain a more general model with the full set of exogenous variables (as described in Section 2.1) is used.

Table 2 HICP unprocessed food

	Germany	France	Italy	Spain
Model selected	BVAR	Exp. Smoothing Trend&Seasonal	BVAR	BVAR
Variables included	lag (1) Sd, GDP	-	lag (1-5) Sd, GDP	lag (1-2) All, Sd
Benchmark RMSE (average)	3.90	3.32	1.73	2.38
Relative RMSE (vs. benchmark)	0.76	0.83	0.87	0.82

LDV: lagged dependent variable; SD: seasonal dummies; Numbers between brackets are the lags included in the models.
The relative RMSE is the RMSE of the model relative to the RMSE of the benchmark model.

In all countries, the model selected performs better than the benchmark in terms of RMSE for most of the forecast horizons considered (1, 3, 6, 12 or 18 steps ahead). However, the forecast errors 12 and 18 steps ahead are generally quite large (see Appendix A7). In the table above, no cumulated responses to shocks for real GDP are reported, as their values are generally very small, meaning that the driving forces are seasonality and unexplained factors, such as weather conditions.

4.2 Energy prices

For HICP energy, the smallest relative RMSE for all countries is always found in the single equation specification, as can be seen in Table 3 below. In contrast to the unprocessed food component, the single equation notably improves the benchmark results. However, as shown in Appendix A7 the forecast errors 12 and 18 steps ahead are also generally quite large.

The variables included in the equations are the contemporaneous and lagged oil prices in euro, country specific taxes on gasoline and lags of HICP energy. In more detail, the number of lags included for the HICP energy varied across countries, with Italy and France having up to 5 lags and Spain only one. Regarding seasonality, seasonal dummies are included in the cases of Italy and Germany[6].

[6] The inclusion or exclusion of seasonal dummies had a minor impact on the results in terms of relative RMSE.

Table 3 HICP Energy

	Germany	France	Italy	Spain
Model selected	Single equat.	Single equat.	Single equat.	Single equat.
Variables included	ldv(1,4) enetax, oil (0,1)	ldv(1-5,12) enetax, oil (0,1)	ldv(1-5), sd enetax, oil(0,1)	ldv(1,12) enetax, oil(0,1)
Cumulated response - 6m				
oil	0.15	0.10	0.14	0.12
taxes	0.25	0.28	0.70	0.37
Benchmark RMSE (average)	7.59	7.25	6.36	8.12
Relative RMSE (vs. benchmark)	0.39	0.36	0.36	0.29

LDV: lagged dependent variable; SD: seasonal dummies; OIL: euro denominated oil prices; ENETAX: energy taxes; Numbers between brackets are the lags included in the models.
The cumulated responses are calculated by subtracting the forecasted year-on-year growth rate 6 months ahead when introducing a 1% increase in the variable from the year-on-year rate of change in the baseline forecast.
The relative RMSE is the RMSE of the model relative to the RMSE of the benchmark model.

The table reports the cumulated responses, 6 months ahead, of HICP energy inflation to a shock in each of the variables, as explained in section 3. According to these results, a 1% increase in oil prices (in euro terms) implies an increase of the year-on-year rate of change of the HICP energy 6 months ahead of between 0.10 p.p. in France and 0.15 p.p. in Germany. The specification and the cumulated responses are on average similar to the models for the euro area aggregate, except for the relatively high elasticity on energy taxes for Italy.

4.3 Processed food prices

When modelling HICP processed food, relatively similar models are selected across countries (see Table 4). For Germany and Spain, BVAR models, including wages as an explanatory variable, give the best results in terms of relative RMSE. The Spanish model includes seasonal terms. For France, a VAR model with wages had the lowest relative RMSE. In any case, it should be pointed out that these multivariate models only slightly improve the results compared to univariate specifications. In the case of Italy, no model is capable of beating the benchmark, therefore the benchmark model is used. Looking at the RMSEs at different steps ahead (see Appendix A6), forecast errors reach close to 1 p.p. after three months in the case of Spain while, in contrast, they remain relatively low (maximum of 0.8 p.p.) in France for all the forecast horizons considered (up to 18 months ahead). This mainly seems to reflect the different behaviour of the series, as shown in the different size of the average benchmark RMSE in both countries in Table 4.

The impacts obtained after 6 months when imposing a shock of 1% in wages vary notably across countries, with a relatively larger sensitivity of processed food prices to wage developments in the case of France. As opposed to the euro area model, the VAT does not reduce the RMSE and is therefore not included in the models.

Table 4 HICP processed food

	Germany	France	Italy	Spain
Model selected	BVAR	VAR	-	BVAR
Variables included	lag (1-5, 12), wages	lag (1-2, 12), wages	-	lag (1-4), wages, sd
Cumulated response - 6m Wages	0.00	0.40	-	0.15
Benchmark RMSE (average)	1.17	0.57	0.64	1.58
Relative RMSE (vs. benchmark)	0.79	0.91	-	0.75

LDV: lagged dependent variable; SD: seasonal dummies; WAGES: compensation per employee; Numbers between brackets are the lags included in the models.
The cumulated responses are calculated by subtracting the forecasted year-on-year growth rate 6 months ahead when introducing a 1% increase in the variable from the year-on-year rate of change in the baseline forecast.
The relative RMSE is the RMSE of the model relative to the RMSE of the benchmark model.

4.4 Non-energy industrial goods prices

Regarding non-energy industrial goods prices, multivariate methods deliver better results, in terms of relative RMSE, than univariate specifications. In particular, a VAR model is selected for Germany, whilst a BVAR model seems to perform better for France, Italy and Spain (see Table 5 below)[7]. Compensation per employee turns out to be a key explanatory variable in all countries. Moreover, the size of the estimated reaction of HICP non-energy industrial goods inflation to changes in wages is around 0.1 p.p. and relatively similar across countries and when compared with the euro area as a whole, except in Italy where it is negligible. However, there were also some modelling difficulties for Italy regarding this component. In Germany,

[7] Due to the introduction of sales in the HICP series as of January 2001, back-data for Italy and Spain have been corrected (see Appendix A2).

real GDP is also included in the set of explanatory variables while in Italy the nominal effective exchange rate (neer) was included.

Table 5 HICP non-energy industrial goods

	Germany	France	Italy	Spain
Model selected	VAR	BVAR	BVAR	BVAR
Variables included	lag (1-4,12) Wages, GDP	lag (1-5,12) Wages	lag (1-5,12) Wages, Neer	lag (1-5,12) Wages
Cumulated response - 6m				
Wages	0.08	0.10	0.00	0.09
GDP	0.00	-	-	-
Neer	-	-	-0.03	-
Benchmark RMSE (average)	0.35	0.47	0.42	0.37
Relative RMSE (vs. benchmark)	0.80	0.90	1.00	0.88

LDV: lagged dependent variable; SD: seasonal dummies; WAGES: compensation per employee; NEER: nominal effective exchange rate. Numbers between brackets are the lags included in the models.
The cumulated responses are calculated by subtracting the forecasted year-on-year growth rate 6 months ahead when introducing a 1% increase in the variable from the year-on-year rate of change in the baseline forecast.
The relative RMSE is the RMSE of the model relative to the RMSE of the benchmark model.

In all countries except Italy, the model selected performs better than the benchmark, in terms of RMSE, for most of the forecast horizons considered (see Appendix A6). However, for short-term horizons, 1 to 6 months ahead the model selected does not outperform the benchmark or delivered practically the same results. In the case of Italy, the performance worsens at longer horizons and in particular for the 18 steps ahead. Modelling non-energy industrial goods in the case of Italy is particularly challenging and the selected model is not fully satisfactory. First, the seasonality in the data associated with sales prices is difficult to model, even after the correction of back-data. Second, the observed steep fall in inflation in the period 1996-1998 – before the start of Stage III of EMU – is a one-off effect that affects the results in-sample and poses some difficulties in forecasting within the out-of-sample period when the inflation rate turned out to be more stable.

4.5 Services prices

Modelling service prices proves to be rather difficult in all four countries. Two common features of the selected models should be highlighted: first, compensation per employee is selected in all countries and, second, all equations involve a high degree of dynamics in terms of lags of both the dependent and the independent variables. This is also the case in the model for the euro area.

Table 6 HICP services

	Germany	France	Italy	Spain
Model selected	Single equat.	BVAR	BVAR	Single equat.
Variables included	ldv(12,5), GDP(1) wages(1, 2, 7) hicpfdunpr(2)	lag (1-3, 12), hicpfdunpr wages	lag (1-4, 12), hicpfdunpr wages	ldv(12) wages(5, 8, 15)
Cumulated response - 6m				
Unprocessed food	0.09	0.02	0.13	-
Wages	0.00	0.35	0.00	0.08
Benchmark RMSE (average)	0.42	0.58	0.35	0.54
Relative RMSE (vs. benchmark)	0.74	0.96	0.82	0.79

LDV: lagged dependent variable; SD: seasonal dummies; WAGES: compensation per employee; HICPFDUNPR unprocessed food prices; Numbers between brackets are the lags included in the models. The cumulated responses are calculated by subtracting the forecasted year-on-year growth rate 6 months ahead when introducing a 1% increase in the variable from the year-on-year rate of change in the baseline forecast.

The relative RMSE is the RMSE of the model relative to the RMSE of the benchmark model.

For France and Italy, quite similar models give the best results, namely BVAR systems including wages and unprocessed food (see Table 6). As unprocessed food prices enter the model, when calculating the RMSE, this variable is forecasted, using the methods previously described. For Germany, a single equation is selected including the 5th and 12th lag of the dependent variable in combination with lags of wages. Real GDP and unprocessed food prices are included. In the case of Spain a single equation is also selected, including the 12th lag of the dependent variable in combination with lags of wages[8].

Although wages are significant for explaining service prices in all countries, the magnitude of the impacts of wages on HICP services is noticeably different across countries, also reflecting the differences across countries of the lag structure of wages. Finally, a 1% change in unprocessed food prices has an impact of 0.02-0.13 p.p. on services price inflation in the short-term, which is in line with the results for the euro area as a whole.

[8] Unprocessed food prices were statistically significant but did not significantly improve the results in terms of RMSE.

Finally, it should be stressed that although the average RMSE is lower than the benchmark for all countries, HICP services remains a problematic component to be modelled. This is especially true in the case of France, where the improvement compared to the benchmark is only marginal. Moreover, as can be seen in Appendix A6, forecast errors are above 0.5 p.p. in France from the 6 step ahead to reach around 1 p.p. 18 months ahead, while in the cases of Germany, Italy and Spain, RMSEs remain below 0.5 p.p. for all the forecast horizons. A reason for the difficulties in finding satisfactory forecasting models might be that services, especially at the country level, are strongly affected by developments in administered prices. However, long series on these prices are not available. Note that this finding is also true for the 1 month ahead forecast for the euro area aggregate forecast.

4.6 Overall HICP

As to overall HICP, a VAR model is selected for Germany and BVAR models for France, Italy and Spain (see Table 7). In all cases, relatively good results, in terms of relative RMSE, are obtained. As can be seen in Appendix A6, relatively good forecast performances are obtained in the cases of Italy and Spain, where forecast errors remain below 0.5 p.p. for all forecast horizons. In contrast, RMSEs seem to be large for 12 and 18 steps ahead in Germany, around 0.8 p.p., in spite of a clear improvement of the selected model in relation to the benchmark and other models.

A common factor is that compensation per employee is a crucial explanatory variable for all countries. In the case of France, no additional variable, apart from lags of the HICP, are found to improve the outcome. In Germany, oil prices in combination with seasonal terms are also included, while real GDP growth and the nominal effective exchange rate contributes in explaining overall HICP in Italy. For Spain, a broader set of variables is used, yielding a relatively low average RMSE.

Table 7 Overall HICP

	Germany	France	Italy	Spain
Model selected	VAR	BVAR	BVAR	BVAR
Variables included	lag (1-3), wages, oil sd	lag (1-4, 12), wages	lag (1-5, 12), GDP, wages, neer	lag (1-5, 12), GDP, wages, oil, comx, neer, r_st
Cumulated response - 6m				
Wages	0.18	0.20	0.00	0.06
GDP	-	-	0.05	0.05
Oil prices	0.00	-	-	0.00
Commodity prices	-	-	-	0.00
Neer	-	-	-0.02	-0.03
Short term interest rate	-	-	-	0.00
Benchmark RMSE (average)	0.81	0.64	0.41	0.71
Relative RMSE (vs. benchmark)	0.70	0.81	0.81	0.51

LDV: lagged dependent variable; SD: seasonal dummies; OIL: euro denominated oil prices; ENETAX: energy taxes; R_ST: nominal short-tern interest rates.; WAGES: compensation per employee; COMX: non-oil commodity prices; NEER: nominal effective exchange rate. Numbers between brackets are the lags included in the models.
The cumulated responses are calculated by subtracting the forecasted year-on-year growth rate 6 months ahead when introducing a 1% increase in the variable from the year-on-year rate of change in the baseline forecast.
The relative RMSE is the RMSE of the model relative to the RMSE of the benchmark model.

Overall, the most important explanatory variable is compensation per employee and the size of the estimated reaction of HICP inflation to changes in wages is relatively strong in the cases of Germany and France, around 0.2 p.p., relatively small in Spain and negligible in the case of Italy.

4.7 HICP excluding unprocessed food and energy

Finally, the models selected for HICP excluding unprocessed food and energy are relatively similar to those considered for the non-energy industrial goods component. In more detail, multivariate methods deliver better results, in terms of relative RMSE, compared to univariate methods. In particular, a VAR is selected for Germany, whilst a BVAR is selected for France, Italy and Spain (see Table 8 below). Compensation per employee is included as an explanatory variable in all countries, and France shows, as in some of the main HICP components, a relatively larger impact of changes in wages. For Germany, real GDP is also included in the set of explanatory variables. The variables included in the different models are similar to those selected for the euro area, with however somewhat different cumulated responses.

It is worth noting that in all countries the models selected are not able to notably outperform the benchmark, and even in the case of Italy the model selected performs slightly worse than the benchmark in terms of RMSE.

Table 8 HICPX

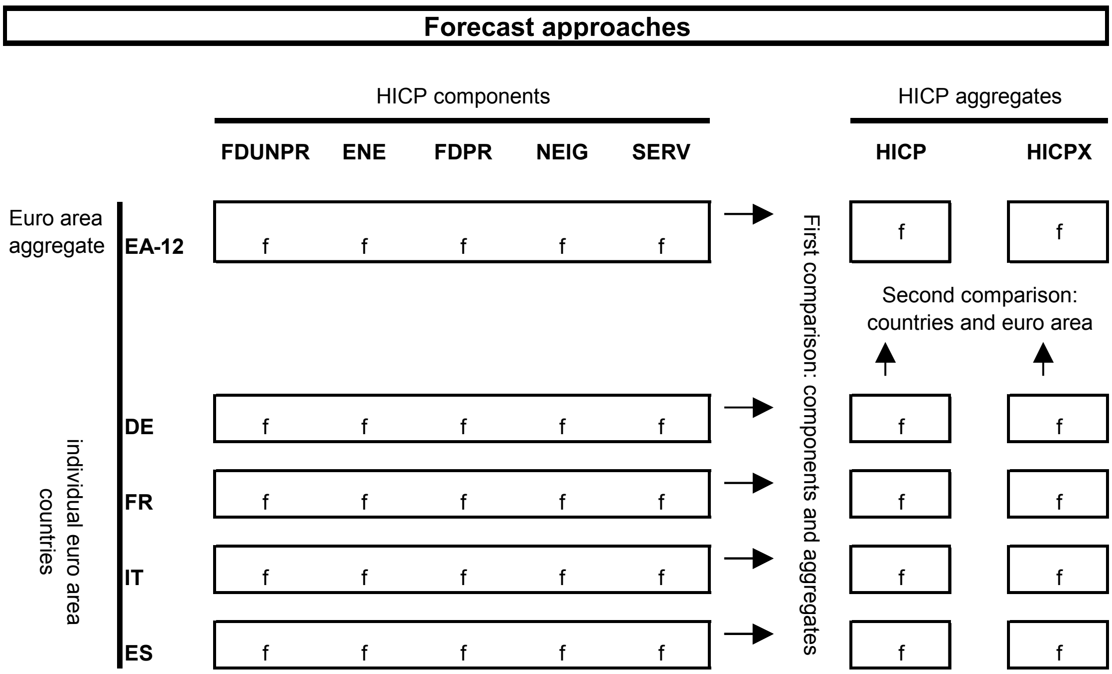
	Germany	France	Italy	Spain
Model selected	VAR	BVAR	BVAR	BVAR
Variables included	lag (1-3,12) Wages, GDP	lag (1-5,12) Wages	lag (1,12) Wages,GDP, Neer	lag (1-5,12) Wages
Cumulated response - 6m				
Wages	0.02	0.19	0.00	0.04
GDP	0.00	-	0.00	-
Neer	-	-	-0.00	-
Benchmark RMSE (average)	0.48	0.43	0.31	0.39
Relative RMSE (vs. benchmark)	0.94	0.96	1.04	0.86

LDV: lagged dependent variable; SD: seasonal dummies; WAGES: compensation per employee; NEER: nominal effective exchange rate. Numbers between brackets are the lags included in the models.
The cumulated responses are calculated by subtracting the forecasted year-on-year growth rate 6 months ahead when introducing a 1% increase in the variable from the year-on-year rate of change in the baseline forecast.
The relative RMSE is the RMSE of the model relative to the RMSE of the benchmark model.

Summing up the country models, multivariate specifications are selected in most of the cases except single equations for the energy component. In particular, BVAR models seem to perform relatively well. Among the different explanatory variables, wages appear to play a crucial role in most of the components and countries. Comparing to the benchmark, the models selected do not perform particularly well for the HICPX in all countries and for the non-energy industrial goods component in the case of Italy. In contrast, the models selected for overall HICP perform relatively well.

5 Direct versus indirect approach and aggregated versus non-aggregated approach

As already mentioned in the introduction, we are interested in two types of comparisons. First (as indicated in the top row of the diagram below), we compare the direct forecast of the overall HICP and the HICPX with the forecast of these aggregates through the components-based forecasts (direct versus indirect approach). This exercise is done for the euro area (in section 5.1) and for the individual countries (section 5.2). Second, we are interested in comparing the forecast of HICP and HICPX for the euro area as a whole with the forecast when aggregating country forecasts, i.e. a non-aggregated versus aggregated approach (as indicated by the rows 2 to 5 of the diagram). This exercise is presented in section 5.3.



f represents the forecast obtained for the respective country/aggregate and component. FDUNPR: unprocessed food, ENE: energy, FDPR: processed food, NEIG: non-energy industrial goods, SERV: services.

5.1 Direct versus indirect approach for the euro area

In this section, the direct forecast of euro area overall HICP and the HICPX (direct approach, sections 3.6 and 3.7) is compared with the aggregate of the forecasts obtained above for the individual HICP components (indirect approach, sections 3.1 to 3.5) and a benchmark (unchanged year-on-year rate). This analysis should show whether forecasting the main components of the HICP could lead to gains in terms of lower RMSE compared to a direct approach. Moreover, it is interesting to check whether these potential gains occur at specific forecasting horizons and whether the results are common across countries.

As can be seen in Table 9, concerning overall HICP, the indirect approach performs slightly better than the direct approach only for the 1 and 3 months ahead forecast. For longer horizons, the RMSE is higher for the indirect approach, with the gap between the two widening notably with the length of the forecast horizon. This indicates that direct forecasting of the overall HICP outperforms aggregating the forecast for the various components (indirect approach). In contrast, as to HICPX, the aggregate of the components based forecast performs substantially better than the forecast of the direct approach for all forecast horizons. In a similar exercise, Hubrich (2003) also finds that the aggregate of a components based forecast has a smaller RMSE than the forecast of the aggregate for the HICPX, while the results are much less clear-cut for overall HICP. This is likely to be explained by the fact that it is much more difficult to forecast the two volatile components HICP unprocessed food and energy. Overall, however, the exercise seems to support the benefits of a component based approach for forecasting developments in the non-volatile components of the euro area HICP, while this does not hold for overall HICP.

Table 9 Euro area: RMSEs direct versus indirect approach

	HICP			HICPX		
	Benchmark	Direct approach	Indirect approach	Benchmark	Direct approach	Indirect approach
Step 1	0.21	0.17	**0.12**	**0.08**	0.16	**0.09**
Step 3	0.38	0.26	**0.22**	0.18	0.29	**0.14**
Step 6	0.50	**0.33**	0.37	0.33	0.28	**0.24**
Step 12	0.85	**0.50**	0.71	0.61	0.42	**0.40**
Step 18	1.07	**0.48**	0.83	0.84	0.47	**0.47**
Average	0.60	**0.35**	0.45	0.41	0.32	**0.27**
Relative		**0.58**	0.75		0.79	**0.66**

The relative RMSE is the RMSE of the model relative to the RMSE of the benchmark model.

5.2 Direct versus indirect approach for the countries

In this section the forecast performance of the direct approach to forecast overall HICP and HICPX (as described in Sections 4.6 and 4.7 respectively) is compared to an indirect approach, where overall HICP and HICPX forecasts are obtained by aggregating the results from the forecasts for the various components, using the models selected for each component (as described in Sections 4.1 to 4.5). Table 10 below reports the RMSE of the benchmark, of the direct approach (i.e. the model selected to the forecast aggregates HICP and HICPX) and the RMSE of the indirect approach (components based forecast) for Germany, France, Italy and Spain.

Table 10 Germany, France, Italy and Spain: RMSEs direct versus indirect approach

	HICP			HICPX		
	Benchmark	Direct approach	Indirect approach	Benchmark	Direct approach	Indirect approach
Germany						
Step 1	0.33	**0.26**	0.28	0.17	**0.16**	0.20
Step 3	0.55	**0.43**	0.45	**0.27**	0.28	0.31
Step 6	0.70	**0.55**	0.71	0.42	**0.42**	0.43
Step 12	1.14	**0.83**	1.23	0.69	**0.64**	0.64
Step 18	1.33	**0.76**	1.50	0.88	0.78	**0.77**
Average	0.81	**0.57**	0.83	0.48	**0.46**	0.47
Relative		**0.70**	1.03		**0.94**	0.97
France						
Step 1	0.28	**0.24**	0.25	0.14	**0.14**	0.18
Step 3	0.49	**0.41**	0.45	0.22	**0.22**	0.27
Step 6	0.56	**0.52**	0.58	0.34	**0.34**	0.37
Step 12	0.86	**0.75**	0.97	0.63	**0.62**	0.69
Step 18	0.98	**0.64**	1.07	0.85	**0.77**	0.96
Average	0.64	**0.51**	0.66	0.43	**0.42**	0.49
Relative		**0.81**	1.04		**0.96**	1.14
Italy						
Step 1	0.14	0.14	**0.13**	0.12	**0.12**	0.13
Step 3	0.24	0.22	**0.19**	0.19	**0.19**	0.20
Step 6	0.37	**0.31**	**0.36**	**0.28**	0.29	0.30
Step 12	0.59	**0.50**	0.60	0.45	0.47	**0.44**
Step 18	0.70	**0.48**	0.75	**0.53**	0.54	0.55
Average	0.41	**0.33**	0.41	**0.31**	0.32	0.32
Relative		**0.81**	1.00		**1.04**	1.04
Spain						
Step 1	0.23	**0.20**	0.20	0.13	**0.13**	0.18
Step 3	0.48	**0.34**	0.37	0.27	**0.24**	0.30
Step 6	0.69	**0.42**	0.46	0.41	**0.36**	0.35
Step 12	0.96	**0.48**	0.68	0.51	**0.44**	0.45
Step 18	1.19	**0.39**	0.78	0.65	0.51	**0.49**
Average	0.71	**0.37**	0.50	0.39	**0.34**	0.35
Relative		**0.51**	0.70		**0.86**	0.90

For the four largest euro area countries the direct approach to forecast HICP and HICPX generally delivers better results than the indirect approach based on the forecast of the main HICP sub-components. It is worth noting that in Spain, contrary to the other countries examined, in the case of overall HICP the average RMSE of the indirect approach is still well below the benchmark. However, the differences in performance between the direct and the indirect approaches for 1 to 6 steps ahead for the HICP, and up to 12 steps ahead for the HICPX, are only marginal. The intuition behind this result is that forecasting the volatile components, such as unprocessed and processed food, is extremely difficult especially at longer horizons. This is a similar result to that obtained for the euro area models. This seems to be confirmed by the finding that in all these countries the bulk of the increase in the RMSE of the indirect approach, compared to the direct one, occurs 12 and 18 steps ahead.

5.3 Aggregated versus non-aggregated approach

In the following section, we aggregate the direct forecasts for HICP and HICPX produced with the country models and we compare them with the euro area forecast (aggregated versus non-aggregated approach). Given that country forecasts are available only for the biggest four euro area countries, we need to create a synthetic euro-area in order to allow for comparability. To achieve this, the euro area models are estimated with data for a "synthetic" euro area, consisting of the weighted average of the big four countries, which cover about 80% of the euro area. For this exercise, we use for the synthetic euro area the same models (i.e. model class, lag order, variables) obtained from the minimisation of the RMSE for the euro area (see section 3).

Results are presented in Table 11 below. Regarding total HICP, the performance in terms of RMSE of the aggregated country forecast and the forecast for the synthetic euro area is relatively similar. However, the synthetic euro area forecast performs slightly better than the aggregated country forecast (especially 1, 12 and 18 steps ahead). For HICPX, the synthetic euro area forecast generally performs slightly better than the aggregated country forecast.

Table 11 Euro area: Aggregated vs. non-aggregated approach (direct)

	HICP			HICPX		
	Benchmark	Non-aggregated	Aggregated	Benchmark	Non-aggregated	Aggregated
Step 1	0.21	**0.15**	0.35	**0.09**	0.10	0.20
Step 3	0.38	**0.28**	0.28	0.17	**0.16**	0.17
Step 6	0.50	0.39	**0.38**	0.30	**0.27**	0.28
Step 12	0.81	**0.46**	0.59	0.54	**0.45**	0.51
Step 18	1.00	**0.41**	0.53	0.74	**0.53**	0.67
Average	0.58	**0.34**	0.43	0.37	**0.30**	0.37
Relative		**0.58**	0.74		**0.81**	0.99

The relative RMSE is the RMSE of the model relative to the RMSE of the benchmark model. Non-aggregated models are estimated with data for a "synthetic" euro area whilst aggregated results are obtained aggregating country forecasts.

As a robustness check, we implement the same type of analysis focusing on the indirect approach over components (see Table 12 below). We therefore compare the synthetic euro area forecast obtained aggregating the five HICP sub-components with the aggregation of the country forecast obtained aggregating for each country the sub-components. For both HICP and HICPX the average RMSE of the synthetic euro area forecast is lower compared to the aggregation of countries, however differences are marginal and even negligible in the case of HICPX.

Table 12 Euro area: Aggregated vs. non-aggregated approach (indirect)

	HICP			HICPX		
	Benchmark	Non-aggregated	Aggregated	Benchmark	Non-aggregated	Aggregated
Step 1	0.21	**0.14**	0.23	**0.09**	0.10	0.15
Step 3	0.38	**0.22**	0.23	0.17	0.15	**0.14**
Step 6	0.50	**0.35**	0.38	0.30	0.27	**0.23**
Step 12	0.81	**0.69**	0.74	0.54	0.47	**0.46**
Step 18	1.00	**0.75**	0.87	0.74	**0.52**	0.62
Average	0.58	**0.43**	0.49	0.37	**0.30**	0.32
Relative		**0.71**	0.84		**0.73**	0.87

The relative RMSE is the RMSE of the model relative to the RMSE of the benchmark model. Non-aggregated models are estimated with data for a "synthetic" euro area whilst aggregated results are obtained aggregating country forecasts.

All in all, it seems that the aggregation of country forecasts does not improve upon the direct forecast of the euro area synthetic HICP and HICPX. This result has however to be taken with great caution given that differences in the RMSE of alternative models appear to be generally quite small. Moreover, the results are based on 4 of the 12 current members of the euro area, and might change when other countries are included.

6 Conclusions

The aim of this paper is to assess several aggregation issues regarding short-term inflation forecasting for the euro area. In particular, we investigate whether the forecast of the main HICP sub-components (indirect approach) improves upon the forecast of overall HICP (direct approach), and whether the aggregation of country forecasts improves upon the forecast of the euro-area aggregate (aggregated versus non-aggregated approach).

Our paper contributes to the existing literature in two ways: first, it simultaneously explores both aggregation issues described above using homogenous techniques and procedures. Second, the paper makes use of an extensive analysis for selecting the most appropriate model for each HICP component. Each selected model is then used in the aggregation process instead of using the same forecasting model across all components. To achieve this purpose, we first run a large number of univariate and multivariate models for the five main components of the HICP and for overall HICP and HICP excluding energy and unprocessed food. This is done for the euro area and for the four largest euro area countries (Germany, France, Italy and Spain). We use a homogeneous selection method, investigating the relative performance of each model in terms of RMSE in the out of sample period 1998:1 to 2002:6.

Estimation results for the euro area suggest that single equations perform best in terms of the average RMSE for all sub-components except for the case of services where a BVAR is selected. However, for overall HICP and HICPX, a VAR and a BVAR yield lower RMSEs. These results seem to be related to the fact that a single equation framework allows more flexibility in terms of the lag structure of the exogenous variables chosen. The most relevant variables in the short-term inflation forecast are oil and food commodity prices (both in euro terms), wages, producer prices and taxes.

Concerning the results for Germany, France, Italy and Spain, BVAR models perform relatively well. As for the euro area, wages appear to play a crucial role in explaining inflation in most of the components. Compared to the benchmark, in all countries examined the selected models do not perform particularly well for the HICPX and for the non-energy industrial goods component in the case of Italy. In contrast, the models selected for overall HICP are quite satisfactory.

After selecting the most appropriate model for each component for the euro area as a whole and for the four countries, we first investigate whether the direct approach to forecast HICP improves upon the indirect approach in terms of forecast accuracy. Secondly, we study whether the aggregation of country forecasts improves upon the forecast of the euro-area HICP inflation (aggregated versus non-aggregated approach).

Concerning the first question, an interesting finding is that for both the euro area and the four largest euro area countries, the direct approach provides clearly better results than the component-based forecast (indirect approach) for 12 and 18 steps ahead for the overall HICP, while for shorter horizons the results are more mixed. For the euro area HICPX, the indirect forecast outperforms the direct approach for 3 to 18 steps ahead, while the differences are only marginal for the countries. Overall, while these results underline the difficulties in modelling the volatile food and energy components of the HICP, they generally tend to support the usefulness of a component based approach for the HICP excluding these volatile items. As to the second question, it seems that in general the aggregation of country forecasts does not improve upon the forecast of the euro area synthetic HICP and HICPX. This result however has to be taken with caution given that differences in the RMSE of alternative models appear to generally be quite small. Moreover, it is worth to stress that the models are estimated with data for a "synthetic" euro area, consisting of the weighted average of the four largest euro area countries examined in this paper, which cover about 80% of the euro area. In order to check the robustness of the results obtained, a natural follow-up of this work would be to extend the scope of the analysis to the remaining euro area countries.

References

Angelini, E., J. Henry and R. Mestre (2001), 'Diffusion index-based inflation forecasts for the euro area', ECB Working Paper No. 61.

Artis, M.J. and Zhang (1990), W., 'BVAR forecasts for the G-7', International Journal of Forecasting, 6, 349-362.

Ballabriga, F.C. and S. Castillo (2000), 'BBVA-ARIES: A Forecasting and Simulation Model for the EMU Economy', mimeo, ESADE and BBVA Research Department.

Bikker, J.A. (1999), 'Macro-Economic Forecasting for the Majour Four EU Countries: A Two-Step Baysean VAR Approach', Cahiers Economiques de Bruxelles 162:203-231.

Bikker, J.A. (1998), 'Inflation Forecasting for Aggregates of the EU-7 and EU14 with Bayesian VAR Models', Journal of Forecasting, 17:147-165.

Canova, F. (2002), 'G7 inflation forecasts', ECB Working Paper No. 151.

Ciccarelli, M. and Rebucci (2003), A., 'Bayesian VARs: A Survey of the Recent Literature with an Application to the European Monetary System', IMF Working Paper, May.

Doan, T., R. Littermann and C. Simo (1984), 'Forecasting and conditional Projection Using Realistic Prior Distributions', Econometric Review, 3(1): 1-100.

Fisher, J.D.M., C.T. Liu and R. Zhou (2002), 'When can we forecast inflation?', Economic Perspectives 10:32-44.

Fritzer, F., Moser, G. and Scharler Johann (2002), 'Forecasting Austria HICP and its components using VAR and ARIMA Models', Osterreiche NationalBank Working paper 73, 2002.

ECB (2000), 'Seasonal Adjustment of Monetary Aggregates and the HICP for the Euro Area', August.

Gardner, E.S. (1985), 'Exponential Smoothing: The State of the Art', Journal of Forecasting, 4:1-28.

Hubrich, K. (2003), 'Forecasting Euro Area Inflation: Does Aggregating Forecasts by HICP Component Improve Forecast Accuracy?', ECB Working Paper No. 247.

Littermann, R. (1986), 'Forecasting with Bayesian Vector Autoregression: Five Years of Experience', Journal of Buisness and Economic Statistics, Vol 4, pp 25-38.

Kadiyala, K.R. and S. Karlsson (1996), ’Numerical Methods for Estimation and Inference in Bayesian VAR-Models‘, Journal of Applied Econometrics 12:99-132.

Kenny, G., A. Meyler and T. Quinn (1998), ’Bayesian VAR Models for Forecasting Irish Inflation Central Bank of Ireland‘, Technical Paper 4/RT/98.

Marcellino, M., Stock, J.H. and Watson M.W. (2003), ‘Macroeconomic Forecasting in the Euro Area: Country specific versus area-wide information’, European Economic Review.

Meyler, A., G. Kenny, and T. Quinn (1998), ’Forecasting Irish Inflation Using ARIMA Models‘, Technical Paper 3/RT/98.

Orlandi, F (2003). ‘Forecasting Euro Area Real GDP growth in the short-run: Area wide versus country level Information’, mimeo ECB.

Reijer, A.H.J. and Vlaar, P.J.G. (2003). “Forecasting Inflation: An art as well as a science!”, Dutch Central Bank, mimeo.

Sekine, T. (2001), ’Modelling and Forecasting Inflation in Japan‘, IMF Working Paper WP/01/82.

Stock, J.H. and M. W. Watson (1999), ‘Forecasting Inflation’, National Bureau of Economic Research Working Paper, 7023, March.

Appendix A1. Data sources and transformations

The following variables have been considered. Within brackets the different codes used in the programs.

HICP

- Overall HICP (hicp)
- HIPC excluding unprocessed food and energy (hicpx)
- Five main HICP components: unprocessed food (hicpfdunpr)
energy (hicpene)
processed food (hicpfdpr)
non-energy industrial goods (hicpneig)
services (hicpserv).
- Source: Eurostat. Original series (NSA).
- All the indices start in January 1990, except in Spain when they start in January 1992.
- In Spain and Italy, as explained in Appendix A2, the non-energy industrial goods component has been re-computed, and also the HICP and HICPX.

Other monthly price data

- Producer consumer goods prices (ppi_cons) in the euro area, Germany, Spain and Italy (long series not available for France).
- Eurostat database. Original series (Neither seasonally nor working day adjusted series).

External cost factors

- Oil prices in USD per barrel converted into domestic currencies using nominal exchange rates (oil).
- Non-oil commodity prices (comx) in euro/domestic currency. HWWA index.
- Food commodity prices (comfd) in euro/domestic currency. HWWA index.
- Nominal Effective Exchange Rate (neer) in domestic currency (until 1999)/euro (thereafter)

Activity variables

- Real GDP (yerin). Original series. Non-seasonally adjusted Eurostat. In quarterly terms. Converted into monthly series through linear interpolation. Chow-Lin interpolation procedures using monthly indicators, as industrial production, have been tested and provided similar results. Real GDP in Germany starts in 1991.

Labour costs

- Compensation per employee in the total economy (wenin). Eurostat. Quarterly frequency. Converted into monthly series using linear interpolation.

Fiscal factors

- VAT (vat). Standard value added tax rate. European Commission, VAT rates applied in the Member States of the European Community, DOC/2908/2002. The VAT rate for the euro area is a weighted average using country weights in the overall HICP.

- Energy taxation (enetax) i.e. excise tax on unleaded gasoline in national currency per litre. Report on Energy Prices and Taxes, 1st quarter 2002, International Energy Agency. The energy tax for the euro area is a weighted average using country weights in the energy component of the HICP.

Interest rates

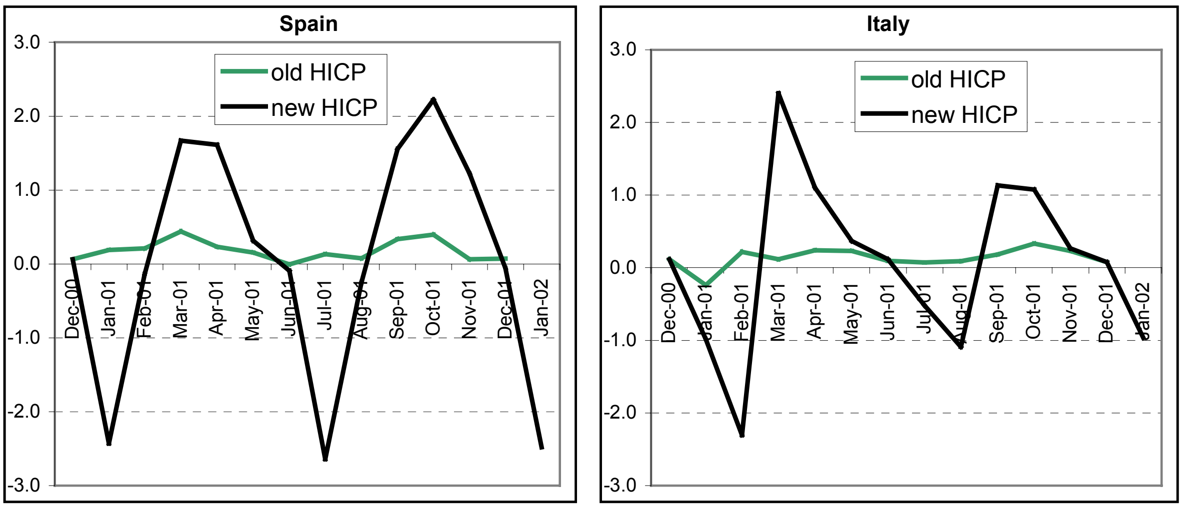
- Short-term (3 months) nominal interest rates (r_st). Up to 1999 national short-term interest rate, from 1999 onwards for euro area as a whole.

Appendix A2. Treatment of the statistical changes in the HICP in Spain and Italy

The release in January 2002 of HICP figures for Spain and Italy marked the implementation by their respective national statistical institutes, in agreement with Eurostat, of relevant statistical changes. The most important one has been the inclusion in the HICP of price reductions due to seasonal sales. This change caused a break in the series, which altered inflation rates published by Eurostat for 2001 and made the short-term HICP inflation modelling more difficult.

In Spain and Italy, the introduction of price reductions in the indices introduced from January 2001 onwards created a break in the series distorting markedly the annual growth rates computed for 2001. The new indices changed dramatically the monthly profiles and therefore the previous seasonal patterns, especially during the sales periods. The change of the monthly patterns is mainly concentrated in the non-energy industrial goods component, which includes items such as clothing, footwear, textiles, household accessories and electric household appliances. As it can be seen in the Chart 3 , comparing the monthly rates in 2001 between the old and the new indices for this HICP component, the introduction of sales prices created a marked seasonality in the monthly rates, with strong declines in January-February and July-August and, consequently, sharp rebounds in the next months.

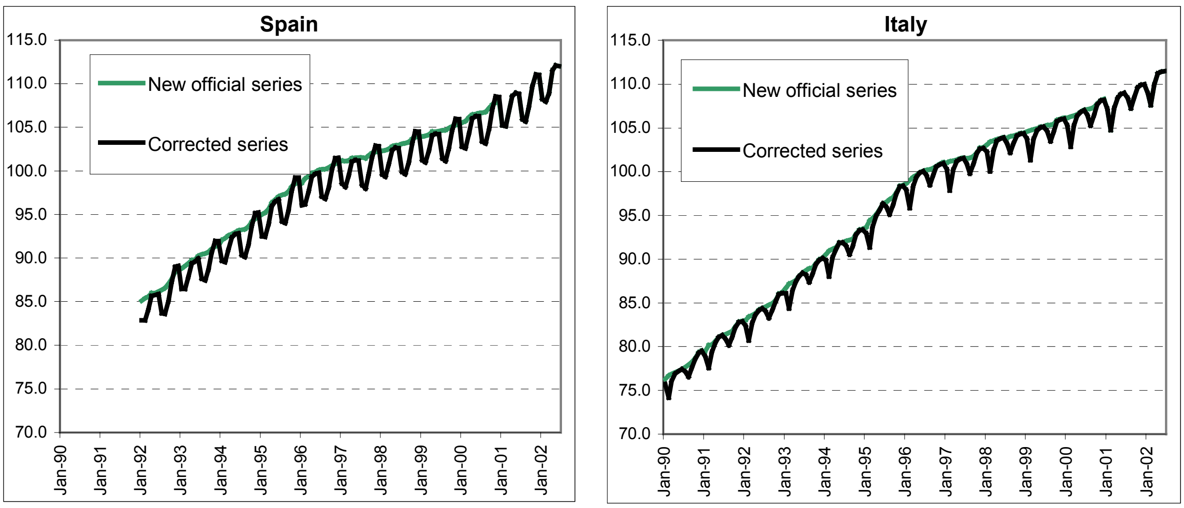
Chart 3 Monthly growth rates in the non-energy industrial goods component



There were mainly two different options to deal with these breaks. One option was to model the new official series (with the break in the indices) but to incorporate some dummy variables so as to estimate and take into account the impact of these changes. Another option was to re-compute backward the series in order to correct these breaks. Both options had problems and inconveniences. However, the first one had the serious inconvenience that the break was so recent that the estimated coefficient could change unexpectedly with the inclusion of new data. Moreover in running out of sample estimates over the year 2001, a key element in the modelling strategy selected, this option faced technical problems difficult to solve. This was the case given that the out-of-sample exercise starts in 1998:1 and includes the structural break introduced by the inclusion of sales in the computation of the index. It was therefore preferred to re-compute backward the series.

Though in the Spanish case other series were also affected, it was decided to re-calculate only the non-energy industrial goods component and then to obtain the two main indices (HICP and HICPX) by aggregating with the other components. The euro area series of HICP non-energy industrial goods prices, HICP excluding unprocessed food and total HICP were also recomputed on the basis of these corrected national series. To re-compute the non-energy industrial goods component, the year-on-year growth rates excluding the sales price adjustment until and including 2001 were applied backwards to the numbers including the price adjustment for 2001. Basically, with this procedure, the year-on-year growth rates in the corrected series are by construction the same as in the previous original series up to December 2001 (therefore correcting the break in 2001), while thereafter they are the same as the year-on-year rates newly reported. Following this procedure, however, meant introducing mechanically a new seasonal monthly pattern in previous years only on the basis of the information for 2001. Chart 4 shows a comparison between the new official series and the corrected one (use in the models) for this component.

Chart 4 The corrected HICP non-energy industrial goods component



After having selected the best forecasting models in terms of RMSE for the corrected non-energy industrial goods components we made further analysis to check that the procedure used was appropriate. In particular, we estimated the same models as selected for the corrected series using the official non-corrected series (i.e. the data with a structural break) and inserting a country specific dummy variable taking into account the effect of seasonal sales as of 2001. This country specific dummy variable was computed as the difference between the "new" and the "old" HICP non-energy industrial goods series as published by Eurostat for the year 2001. The country specific dummy variables turned out to be highly significant, as expected, for both Italy and Spain. More importantly, the coefficients of the estimated models were broadly similar to those estimated for the corrected series[9]. This analysis is important to highlight that the solution chosen in the paper, namely the correction of the back data for the non-energy industrial goods component in Italy and Spain, appears to be preferable. This is the case given that the solution of correcting the back data yielded results similar to those that would have been obtained in-sample using the non-corrected data and including a dummy with the important advantage of being tractable in the out-of-sample evaluation exercise (given the removal of the structural break).

[9] Results obtained are not reported in the paper and are available upon request.

Appendix A3. Stationary analysis

1. Price levels

	de_hicp	de_hicpx	de_hicpfdunpr	de_hicpfdpr	de_hicpene	de_hicpneig	de_hicpserv
adf_1	-2.26 ***	-1.8 ***	-5.5	-1.6 ***	-1.9***	-1.68 ***	-1.8 ***
adf_2	-2.3***	-2.1 ***	-4.9	-1.8 ***	-1.8 ***	-2.1 ***	- 1.5**
adf_3	-2.3***	-1.8 ***	-5.2	-1.9 ***	-2.1***	-2.4 ***	-1.5***
pp_1	-2.1***	-1.8 ***	-3.7	-2 ***	- 1.9***	-2.5***	- 1.6***
pp_2	-2.1***	-1.8 ***	-4.0	-2 ***	- 1.9***	-2.5***	- 1.5***
pp_3	-2.1***	-1.8 ***	-4.0	-2 ***	- 1.9***	-2.5***	- 1.5***

	es_hicp	es_hicpx	es_hicpfdunpr	es_hicpfdpr	es_hicpene	es_hicpneig	es_hicpserv
adf_1	- 3.0***	-3.46*	-2.7***	-1.7***	-2.5***	-8.0	-3.0***
adf_2	- 2.2***	-2.6***	-1.8***	-1.8***	-2.3***	-4.8	-3.48*
adf_3	-2.0***	-2.6***	-2***	-1.9***	-2.5***	-2.68***	-3.34**
pp_1	-2.7***	-3***	-2.6***	-1.6***	-2.2***	-5.3	-3.6*
pp_2	-2.7***	-3***	-2.4***	-1.6***	-2.2***	-5.3	-3.6*
pp_3	-2.5***	-2.8***	-2.4***	-1.7***	-2.3***	-4.7	-3.6*

	fr_hicp	fr_hicpx	fr_hicpfdunpr	fr_hicpfdpr	fr_hicpene	fr_hicpneig	fr_hicpserv
adf_1	-2.9***	-2.8***	-2.0***	-2.2***	-3.0***	-3.15**	-2.7***
adf_2	-2.9***	-2.8***	-1.8***	-2***	-2.8***	-2.9***	-2.9***
adf_3	-2.9***	-3***	-1.1***	-1.7***	-2.9***	-2.9***	-2.9***
pp_1	-2.8***	-2.9***	-1.9***	-2.1***	-2.6***	-3.18**	-3***
pp_2	-2.9***	-2.9***	-1.9***	-2.2***	-2.7***	-3.1***	-3***
pp_3	-2.9***	-3***	-1.7***	-2.1***	-2.7***	-3.0***	-3***

	it_hicp	it_hicpx	it_hicpfdunpr	it_hicpfdpr	it_hicpene	it_hicpneig	it_hicpserv
adf_1	-2.2***	-1.9***	-2.7***	-0.7***	-2.6***	-3.36**	-1.9***
adf_2	-1.8***	-1.4***	-2.8***	-0.9***	-3***	-2.3***	-2.3***
adf_3	-1.9***	-1.3***	-2.8***	-1***	-3***	-1.7***	-2***
pp_1	-1.8***	-1.6***	-2.3***	-1.3***	-2.2***	-3***	-2.4***
pp_2	-1.8***	-1.5***	-2.4***	-1.3***	-2.4***	-2.8***	-2.4***
pp_3	-1.8***	-1.5***	-2.4***	-1.3***	-2.4***	-2.5***	-2.3***

	i2_hicp	i2_hicpx	i2_hicpfdunpr	i2_hicpfdpr	i2_hicpene	i2_hicpneig	i2_hicpserv
adf_1	-2.7***	-2.3***	-2.7***	-1.6***	-2.5***	-3.16**	-1.8***
adf_2	-2.8***	-2.3***	-2.6***	-1.7***	-2.3***	-2.2***	-2***
adf_3	-2.8***	-2.4***	-2.4***	-1.8***	-2.6***	-2.3***	-2.2***
pp_1	-2.6***	-2.1***	-2***	-2.2***	-2.2***	-2.7***	-1.9***
pp_2	-2.6***	-2.2***	-2.2***	-2.1***	-2.2***	-2.6***	-1.9***
pp_3	-2.7***	-2.2***	-2.3***	-2.1***	-2.3***	-2.4***	-1.9***

No star means that the variable is stationary at 1% level. * Stationary at 5% ** Sationary at 10%
***** Non stationary**

adf_1(2,3) Augmented Dicky Fuller including a constant, a ternd and 1 (2,3) differenced terms
pp_1 (2,3) Philips-Perron test including a constant, a trend and 1 (2,3) differenced terms

2 Log Differences

	de_hicp	de_hicpx	de_hicpfdunpr	de_hicpfdpr	de_hicpene	de_hicpneig	de_hicpserv
adf_1	-8.2	-8.6	-7.7	-6.7	-8.8	-6.5	-10.0
adf_2	-7.4	-7.5	-6.6	-5.2	-6.4	-4.3	-10.2
adf_3	-6.5	-6.1	-6.8	-4.2	-6.3	-4.3	-8.3
pp_1	-9.6	-9.2	-7.7	-10.9	-12.1	-8.1	-9.8
pp_2	-9.5	-9.1	-7.6	-10.9	-12.1	-8.0	-9.6
pp_3	-9.5	-9.0	-7.5	-11.0	-12.1	-8.1	-9.5

	es_hicp	es_hicpx	es_hicpfdunpr	es_hicpfdpr	es_hicpene	es_hicpneig	es_hicpserv
adf_1	-10.8	-10.7	-10.8	-5.8	-7.1	-11.9	-7.1
adf_2	-11.8	-15.2	-6.5	-5.0	-5.6	-17.3	-7.0
adf_3	-9.3	-10.6	-4.7	-4.6	-5.4	-15.9	-5.9
pp_1	-8.0	-8.1	-10.0	-7.1	-8.1	-8.2	-7.7
pp_2	-7.8	-7.9	-9.9	-7.1	-8.0	-8.0	-7.7
pp_3	-7.4	-7.5	-9.9	-7.2	-8.0	-7.6	-7.6

	fr_hicp	fr_hicpx	fr_hicpfdunpr	fr_hicpfdpr	fr_hicpene	fr_hicpneig	fr_hicpserv
adf_1	-9.7	-8.0	-8.9	-9.1	-8.0	-11.7	-6.4
adf_2	-7.8	-6.7	-9.2	-8.3	-6.5	-10.0	-5.2
adf_3	-7.3	-6.0	-6.8	-7.5	-6.9	-12.3	-4.5
pp_1	-10.3	-10.7	-11.0	-10.9	-9.3	-13.4	-8.1
pp_2	-10.2	-10.7	-11.0	-10.9	-9.2	-13.6	-8.1
pp_3	-10.1	-10.7	-10.9	-10.9	-9.2	-14.1	-8.1

	it_hicp	it_hicpx	it_hicpfdunpr	it_hicpfdpr	it_hicpene	it_hicpneig	it_hicpserv
adf_1	-9.6	-10.0	-6.6	-5.6	-6.7	-11.7	-6.3
adf_2	-9.9	-10.6	-4.8	-4.6	-5.9	-11.9	-3.36 *
adf_3	-9.4	-10.2	-4.8	-3.8	-5.6	-15.6	-2.87**
pp_1	-11.1	-11.5	-7.1	-9.4	-10.2	-12.5	-9.8
pp_2	-11.1	-11.5	-7.0	-9.5	-10.3	-12.6	-9.8
pp_3	-11.1	-11.6	-7.0	-9.6	-10.3	-13.2	-10.0

	i2_hicp	i2_hicpx	i2_hicpfdunpr	i2_hicpfdpr	i2_hicpene	i2_hicpneig	i2_hicpserv
adf_1	-8.5	-7.7	-7.6	-5.8	-8.3	-13.4	-8.8
adf_2	-6.5	-5.6	-6.8	-4.6	-6.3	-11.7	-8.0
adf_3	-5.8	-5.0	-5.8	-4.0	-6.1	-19.7	-6.3
pp_1	-8.7	-8.4	-9.0	-9.2	-10.2	-9.5	-8.5
pp_2	-8.6	-8.3	-9.0	-9.3	-10.1	-9.2	-8.4
pp_3	-8.5	-8.3	-8.9	-9.4	-10.1	-8.9	-8.2

No star means that the variable is stationary at 1% level. * Stationary at 5% ** Sationary at 10%

adf_1(2,3) Augmented Dicky Fuller including a constant and 1 (2,3) differenced terms
pp_1 (2,3) Philips-Perron test including a constant and 1 (2,3) differenced terms

Appendix A4. Selected models

Euro area

Unprocessed food
Linear Regression - Estimation by Least Squares
Dependent Variable DI2_HICPFDUNPR
Monthly Data From 1990:01 To 2002:06
Usable Observations 137

Centered R**2	0.5901
R Bar **2	0.5431
Standard Error of Estimate	0.0051
Sum of Squared Residuals	0.0031
Regression F(14,122)	12.5471
Significance Level of F	0.0000
Durbin-Watson Statistic	1.9741

Variable	Coeff	T-Stat
DI2_HICPFDUNPR{1}	0.2254	2.6328
DI2_HICPFDUNPR{10}	0.2325	2.5544
DI2_HICPFDUNPR{12}	-0.1670	-1.8478
Constant	0.0028	1.7939
SD1	0.0112	4.8349
SD2	-0.0065	-2.7302
SD3	-0.0017	-0.8052
SD4	0.0053	2.3958
SD5	0.0038	1.6851
SD6	-0.0041	-1.7401
SD7	-0.0079	-3.4712
SD8	-0.0128	-5.2293
SD9	-0.0014	-0.5604
SD10	-0.0026	-1.2077
SD11	-0.0026	-1.1064

Energy
Linear Regression - Estimation by Least Squares
Dependent Variable DI2_HICPENE
Monthly Data From 1990:01 To 2002:06
Usable Observations 144

Centered R**2	0.6966
R Bar **2	0.6501
Standard Error of Estimate	0.0068
Sum of Squared Residuals	0.0058
Regression F(19,124)	14.9846
Significance Level of F	0.0000
Durbin-Watson Statistic	2.0034

Variable	Coeff	T-Stat
DI2_HICPENE{1}	-0.1200	-1.6552
DI2_HICPENE{2}	-0.0593	-1.0641
DI2_HICPENE{3}	0.0558	1.0173
DI2_HICPENE{4}	0.1060	1.8598
DI2_HICPENE{5}	0.1350	2.4445
DI2_OIL	0.0738	9.3230
DI2_OIL{1}	0.0687	6.6175
DI2_ENETAX	0.2483	5.6015
Constant	0.0009	0.4276
SD1	0.0024	0.7955
SD2	0.0021	0.6985
SD3	-0.0015	-0.5068
SD4	0.0005	0.1640
SD5	-0.0027	-0.9262
SD6	-0.0015	-0.5084
SD7	-0.0016	-0.5533
SD8	0.0015	0.5172
SD9	0.0020	0.6746
SD10	-0.0010	-0.3446
SD11	-0.0005	-0.1770

Processed food
Linear Regression - Estimation by Least Squares
Dependent Variable DI2_HICPFDPR
Monthly Data From 1990:01 To 2002:06
Usable Observations 145

Centered R**2	0.6032
R Bar **2	0.5392
Standard Error of Estimate	0.0010
Sum of Squared Residuals	0.0001
Regression F(20,124)	9.4251
Significance Level of F	0.0000
Durbin-Watson Statistic	2.0876

Variable	Coeff	T-Stat
DI2_HICPFDPR{1}	0.2654	3.0900
DI2_HICPFDPR{2}	0.0165	0.1872
DI2_HICPFDPR{3}	0.2690	3.0971
DI2_HICPFDPR{4}	0.0078	0.0959
DI2_COMFD{2}	0.0055	2.4612
DI2_VAT	0.0453	1.8990
DI2_WENIN	0.1827	1.9830
DI2_WENIN{1}	-0.2024	-1.4632
DI2_WENIN{2}	0.1710	1.8485
Constant	0.0002	0.5899
SD1	0.0030	6.6856
SD2	-0.0001	-0.2060
SD3	0.0007	1.3825
SD4	-0.0011	-2.1812
SD5	0.0001	0.1128
SD6	-0.0006	-1.3116
SD7	-0.0003	-0.7604
SD8	0.0000	0.0881
SD9	0.0003	0.5981
SD10	0.0002	0.5470
SD11	0.0004	0.9319

Non-energy industrial goods
Linear Regression - Estimation by Least Squares
Dependent Variable DI2_HICPNEIG
Monthly Data From 1990:01 To 2002:06
Usable Observations 137

Centered R**2	0.9724
R Bar **2	0.9685
Standard Error of Estimate	0.0009
Sum of Squared Residuals	0.0001
Regression F(17,119)	246.6179
Significance Level of F	0.0000
Durbin-Watson Statistic	1.8233

Variable	Coeff	T-Stat
DI2_HICPNEIG{1}	-0.0488	-0.9411
DI2_HICPNEIG{6}	0.4536	5.7059
DI2_HICPNEIG{12}	0.3302	4.0824
DI2_PPI_CONS{1}	0.1301	2.4808
DI2_WENIN{2}	0.0682	1.6679
DI2_VAT	0.0579	2.7509
Constant	0.0000	-0.0225
SD1	-0.0022	-4.1267
SD2	-0.0018	-2.7307
SD3	0.0032	4.7944
SD4	0.0005	0.8778
SD5	-0.0005	-1.3045
SD6	-0.0006	-1.6815
SD7	-0.0024	-4.6645
SD8	-0.0003	-0.4463
SD9	-0.0001	-0.1222
SD10	0.0017	3.5015
SD11	0.0009	2.2193

Services
BVAR hyperparameter

Tightness	0.1
Weights	0.9
Decay	0.1

VAR/System - Estimation by Mixed Estimation
Dependent Variable DI2_HICPSERV
Monthly Data From 1990:01 To 2002:06
Usable Observations 137

Centered R**2	0.771133
R Bar **2	0.771133
Standard Error of Estimate	0.0014
Sum of Squared Residuals	0.0003
Durbin-Watson Statistic	2.3464

Variable	Coeff	T-Stat
DI2_HICPSERV{1}	0.0424	0.8937
DI2_HICPSERV{2}	-0.0752	-1.5883
DI2_HICPSERV{3}	-0.1109	-2.4243
DI2_HICPSERV{4}	-0.0688	-1.5289
DI2_HICPSERV{5}	0.0783	1.7661

HICP
VAR/System - Estimation by Least Squares
Dependent Variable DI2_HICP
Monthly Data From 1990:01 To 2002:06
Usable Observations 146

Centered R**2	0.5721
R Bar **2	0.4914
Standard Error of Estimate	0.0014
Sum of Squared Residuals	0.0002
Durbin-Watson Statistic	2.0347

Variable	Coeff	T-Stat
DI2_HICP{1}	-0.0382	-0.3852
DI2_HICP{2}	-0.1089	-1.1045
DI2_HICP{3}	-0.0082	-0.0878
DI2_WENIN{1}	0.1677	1.2730
DI2_WENIN{2}	-0.1400	-0.7292
DI2_WENIN{3}	0.2700	2.0576
DI2_OIL{1}	0.0081	4.8093
DI2_OIL{2}	-0.0018	-0.9815
DI2_OIL{3}	0.0015	0.8305
DI2_PPI_CONS{1}	0.1772	1.9373

Services

BVAR hyperparameter	
Tightness	0.1
Weights	0.9
Decay	0.1

VAR/System - Estimation by Mixed Estimation
Dependent Variable DI2_HICPSERV
Monthly Data From 1990:01 To 2002:06
Usable Observations 137

Centered R**2	0.771133
R Bar **2	0.771133
Standard Error of Estimate	0.0014
Sum of Squared Residuals	0.0003
Durbin-Watson Statistic	2.3464

Variable	Coeff	T-Stat
DI2_HICPSERV{1}	0.0424	0.8937
DI2_HICPSERV{2}	-0.0752	-1.5883
DI2_HICPSERV{3}	-0.1109	-2.4243
DI2_HICPSERV{4}	-0.0688	-1.5289
DI2_HICPSERV{5}	0.0783	1.7661
DI2_HICPSERV{12}	0.5120	11.9006
DI2_WENIN{1}	0.1063	1.1503
DI2_WENIN{2}	0.0291	0.2526
DI2_WENIN{3}	0.1890	1.7484
DI2_WENIN{4}	-0.0263	-0.2400
DI2_WENIN{5}	-0.0165	-0.1901
DI2_WENIN{12}	0.0867	1.2967
DI2_PPI_CONS{1}	0.0865	1.4903
DI2_PPI_CONS{2}	-0.0344	-0.6140
DI2_PPI_CONS{3}	0.0339	0.6216
DI2_PPI_CONS{4}	-0.0132	-0.2481
DI2_PPI_CONS{5}	0.0263	0.5020
DI2_PPI_CONS{12}	0.0561	1.1424
DI2_HICPFDUNPR{1}	0.0375	2.6398
DI2_HICPFDUNPR{2}	0.0305	2.1961
DI2_HICPFDUNPR{3}	0.0081	0.5908
DI2_HICPFDUNPR{4}	0.0031	0.2343
DI2_HICPFDUNPR{5}	0.0010	0.0761
DI2_HICPFDUNPR{12}	-0.0045	-0.3599
Constant	0.0002	0.6411

F-Tests, Dependent Variable DI2_HICPSERV

Variable	F-Statistic	Signif
DI2_HICPSERV	36.9612	0.0000
DI2_WENIN	3.2922	0.0047
DI2_PPI_CONS	0.7582	0.6040
DI2_HICPFDUNPR	2.3098	0.0373

HICPX

BVAR hyperparameter	
Tightness	0.1
Weights	0.9
Decay	0.2

VAR/System - Estimation by Mixed Estimation
Dependent Variable DI2_HICPX
Monthly Data From 1990:01 To 2002:06
Usable Observations 137

Centered R**2	0.6494
R Bar **2	0.6494
Standard Error of Estimate	0.0010
Sum of Squared Residuals	0.0001
Durbin-Watson Statistic	1.9502

Variable	Coeff	T-Stat
DI2_HICPX{1}	0.0088	0.1696
DI2_HICPX{2}	-0.0511	-1.0351
DI2_HICPX{3}	-0.0037	-0.0756
DI2_HICPX{4}	-0.0568	-1.2044
DI2_HICPX{5}	0.0119	0.2548
DI2_HICPX{12}	0.3975	9.3424
DI2_WENIN{1}	0.1056	1.7269
DI2_WENIN{2}	0.0186	0.2513
DI2_WENIN{3}	0.0238	0.3516
DI2_WENIN{4}	-0.0192	-0.2872
DI2_WENIN{5}	0.0400	0.7458
DI2_WENIN{12}	0.0783	1.8526
DI2_PPI_CONS{1}	0.0101	0.2761
DI2_PPI_CONS{2}	0.1162	3.3035
DI2_PPI_CONS{3}	0.0240	0.7024
DI2_PPI_CONS{4}	-0.0186	-0.5648
DI2_PPI_CONS{5}	0.0142	0.4416
DI2_PPI_CONS{12}	0.0390	1.3862
Constant	0.0003	1.8939

F-Tests, Dependent Variable DI2_HICPX

Variable	F-Statistic	Signif
DI2_HICPX	15.3965	0.0000
DI2_WENIN	2.4011	0.0309
DI2_PPI_CONS	2.4381	0.0286

HICP

VAR/System - Estimation by Least Squares
Dependent Variable DI2_HICP
Monthly Data From 1990:01 To 2002:06
Usable Observations 146

Centered R**2	0.5721
R Bar **2	0.4914
Standard Error of Estimate	0.0014
Sum of Squared Residuals	0.0002
Durbin-Watson Statistic	2.0347

Variable	Coeff	T-Stat
DI2_HICP{1}	-0.0382	-0.3852
DI2_HICP{2}	-0.1089	-1.1045
DI2_HICP{3}	-0.0082	-0.0878
DI2_WENIN{1}	0.1677	1.2730
DI2_WENIN{2}	-0.1400	-0.7292
DI2_WENIN{3}	0.2700	2.0576
DI2_OIL{1}	0.0081	4.8093
DI2_OIL{2}	-0.0018	-0.9815
DI2_OIL{3}	0.0015	0.8305
DI2_PPI_CONS{1}	0.1772	1.9373
DI2_PPI_CONS{2}	0.1078	1.1770
DI2_PPI_CONS{3}	0.0617	0.6661
Constant	0.0006	1.1546
SD1	0.0007	1.2270
SD2	0.0003	0.5018
SD3	0.0029	4.1876
SD4	0.0015	2.2371
SD5	0.0007	1.0945
SD6	-0.0004	-0.6779
SD7	-0.0011	-1.8549
SD8	-0.0013	-2.2163
SD9	0.0007	1.0625
SD10	0.0003	0.4160
SD11	0.0004	0.6156

F-Tests, Dependent Variable DI2_HICP

Variable	F-Statistic	Signif
DI2_HICP	0.4889	0.6906
DI2_WENIN	4.5692	0.0045
DI2_OIL	8.0168	0.0001
DI2_PPI_CONS	2.9492	0.0355

Notation

HICPFDUNPR	HICP Unprocessed food component
HICPENE	HICP Energy component
HICPFDPR	HICP Processed food component
HICPNEIG	HICP Non-energy ind. goods component
HICPSERV	HICP Services component
HICPX	HICP excl. unproc food & energy
HICP	Overall HICP
WENIN	compensation per employee
YERIN	Real GDP
PPI_CONS	producer prices for consumer goods
OIL	Euro denominated oil prices
NEER	Nominal effective excgange rate
COMFD	food commodity prices (in euro terms)
COMX	Non-oil commodity prices (in euro terms)
ENETAX	Energy taxes
VAT	Value added tax rate
R_ST	Short-term interest rates
SD	Seasonal Dummy

Germany

Unprocessed food

BVAR hyperparameter

Tightness	0.1
Weights	0.1
Decay	0.9

VAR/System - Estimation by Mixed Estimation
Dependent Variable dde_hicpfdunpr
Monthly Data From 1991:01 To 2002:06
Usable Observations 136

Centered R**2	0.7017
R Bar **2	0.6752
Standard Error of Estimate	0.0079
Sum of Squared Residuals	0.0078
Durbin-Watson Statistic	1.8266

Variable	Coeff	T-Stat
dde_hicpfdunpr{1}	0.0809	1.1796
dde_yerin{1}	0.0011	0.0389
Constant	0.0067	2.7888
SD1	0.0174	5.1252
SD2	-0.0005	-0.1342
SD3	-0.0087	-2.5901
SD4	0.0040	1.2113
SD5	0.0001	0.0355
SD6	-0.0067	-2.0209
SD7	-0.0171	-5.0521
SD8	-0.0286	-8.2146
SD9	-0.0153	-4.0452
SD10	-0.0106	-3.0419
SD11	-0.0044	-1.3014

F-Tests, Dependent Variable dde_hicpfdunpr

Variable	F-Statistic	Signif
dde_hicpfdunpr	1.3913	0.2404
dde_yerin	0.0015	0.9690

Processed food

BVAR hyperparameter

Tightness	0.5
Weights	0.1
Decay	0.9

VAR/System - Estimation by Mixed Estimation
Dependent Variable dde_hicpfdpr
Monthly Data From 1991:01 To 2002:06
Usable Observations 125

Centered R**2	0.0851
R Bar **2	0.0851
Standard Error of Estimate	0.0021
Sum of Squared Residuals	0.0005
Durbin-Watson Statistic	2.0206

Variable	Coeff	T-Stat
dde_hicpfdpr{1}	0.1112	1.2623
dde_hicpfdpr{2}	0.0906	1.0721
dde_hicpfdpr{3}	0.0570	0.7470
dde_hicpfdpr{4}	0.0883	1.2300
dde_hicpfdpr{5}	0.0260	0.3819
dde_hicpfdpr{12}	-0.0049	-0.1069
dde_wenin{1}	0.0059	1.0050
dde_wenin{2}	-0.0020	-0.3770
dde_wenin{3}	0.0031	0.7408
dde_wenin{4}	0.0013	0.3560
dde_wenin{5}	0.0024	0.7923
dde_wenin{12}	-0.0006	-0.3748
Constant	0.0006	2.5389

F-Tests, Dependent Variable dde_hicpfdpr

Variable	F-Statistic	Signif
dde_hicpfdpr	1.2602	0.2806
dde_wenin	0.3898	0.8845

Energy

Linear Regression - Estimation by Least Squares
Dependent Variable DDE_HICPENE
Monthly Data From 1990:01 To 2002:06
Usable Observations 145

Centered R**2	0.6765
R Bar **2	0.6672
Standard Error of Estimate	0.0092
Sum of Squared Residuals	0.0119
Durbin-Watson Statistic	2.1679

Variable	Coeff	T-Stat
DDE_HICPENE{1}	-0.2417	-4.0143
DDE_HICPENE{4}	0.1169	2.3657
DDE_OIL	0.0857	9.0051
DDE_OIL{1}	0.0865	7.4288
DDE_ENETAX	0.2561	10.3769

Non-energy industrial goods

VAR/System - Estimation by Least Squares
Dependent Variable dde_hicpneig
Monthly Data From 1990:01 To 2002:06
Usable Observations 125

Centered R**2	0.3937
R Bar **2	0.3103
Standard Error of Estimate	0.0011
Sum of Squared Residuals	0.0001
Durbin-Watson Statistic	2.1381

Variable	Coeff	T-Stat
dde_hicpneig{1}	0.2902	2.9877
dde_hicpneig{2}	-0.0365	-0.3534
dde_hicpneig{3}	0.1814	1.8211
dde_hicpneig{4}	0.0517	0.5755
dde_hicpneig{12}	0.1351	1.5657
dde_yerin{1}	0.0077	0.2371
dde_yerin{2}	0.0191	0.6232
dde_yerin{3}	-0.0396	-0.9993
dde_yerin{4}	-0.0335	-1.0008
dde_yerin{12}	0.0794	2.8517
dde_wenin{1}	0.0091	1.1191
dde_wenin{2}	-0.0074	-0.9974
dde_wenin{3}	0.0297	2.4350
dde_wenin{4}	0.0164	1.4948
dde_wenin{12}	-0.0040	-0.5881
Constant	0.0001	0.6180

F-Tests, Dependent Variable dde_hicpneig

Variable	F-Statistic	Signif
dde_hicpneig	5.8186	0.0001
dde_yerin	2.2096	0.0584
dde_wenin	3.3746	0.0071

Services
Linear Regression - Estimation by Least Squares
Dependent Variable dde_hicpserv
Monthly Data From 1990:01 To 2002:06
Usable Observations 130

Centered R**2	0.7723
R Bar **2	0.7612
Standard Error of Estimate	0.0026
Sum of Squared Residuals	0.0008
Durbin-Watson Statistic	2.3162

Variable	Coeff	T-Stat
dde_hicpserv{12}	0.5160	8.0455
dde_hicpserv{5}	0.1583	2.8293
dde_wenin{1}	-0.0544	-3.5146
dde_yerin{1}	0.1381	3.1693
dde_wenin{2}	0.0496	4.7907
dde_hicpfdunpr{2	0.0611	2.8055
dde_wenin{7}	0.0345	3.2993

HICPX
VAR/System - Estimation by Least Squares
Dependent Variable dde_hicpx
Monthly Data From 1990:01 To 2002:06
Usable Observations 125

Centered R**2	0.6775
R Bar **2	0.6430
Standard Error of Estimate	0.0015
Sum of Squared Residuals	0.0002
Durbin-Watson Statistic	2.0672

Variable	Coeff	T-Stat
dde_hicpx{1}	0.0174	0.2480
dde_hicpx{2}	-0.1258	-1.7526
dde_hicpx{3}	0.0157	0.2250
dde_hicpx{12}	0.7076	11.6499
dde_yerin{1}	0.0384	1.0709
dde_yerin{2}	-0.0451	-1.1194
dde_yerin{3}	-0.0307	-0.7038
dde_yerin{12}	0.1157	2.9625
dde_wenin{1}	-0.0143	-1.5595
dde_wenin{2}	0.0192	1.8765
dde_wenin{3}	0.0201	1.4533
dde_wenin{12}	-0.0130	-1.4446
Constant	0.0003	1.3093

F-Tests, Dependent Variable dde_hicpx

Variable	F-Statistic	Signif
dde_hicpx	41.2069	0.0000
dde_yerin	3.2253	0.0151
dde_wenin	3.8155	0.0060

HICP
VAR/System - Estimation by Least Squares
Dependent Variable dde_hicp
Monthly Data From 1990:01 To 2002:06
Usable Observations 134

Centered R**2	0.5580
R Bar **2	0.4798
Standard Error of Estimate	0.0021
Sum of Squared Residuals	0.0005
Durbin-Watson Statistic	2.0555

Variable	Coeff	T-Stat
dde_hicp{1}	-0.0705	-0.7194
dde_hicp{2}	0.1971	2.0724
dde_hicp{3}	0.0864	0.9215
dde_wenin{1}	0.0284	0.4509
dde_wenin{2}	0.0645	1.0804
dde_wenin{3}	0.0147	0.3504
dde_oil{1}	0.0094	3.3419
dde_oil{2}	-0.0065	-2.2159
dde_oil{3}	-0.0019	-0.6568
Constant	-0.0015	-0.6023
SD1	0.0012	0.7213
SD2	0.0041	0.6687
SD3	0.0063	0.9075
SD4	0.0068	1.3624
SD5	0.0068	1.7933
SD6	0.0033	1.5154
SD7	0.0040	1.9202
SD8	-0.0010	-0.4452
SD9	-0.0024	-1.0023
SD10	-0.0015	-0.6530
SD11	0.0009	0.3943

F-Tests, Dependent Variable dde_hicp

Variable	F-Statistic	Signif
dde_hicp	1.8184	0.1478
dde_wenin	3.3007	0.0230
dde_oil	5.0613	0.0025

Notation

HICPFDUNPR	HICP Unprocessed food component
HICPENE	HICP Energy component
HICPFDPR	HICP Processed food component
HICPNEIG	HICP Non-energy ind. goods component
HICPSERV	HICP Services component
HICPX	HICP excl. unproc food & energy
HICP	Overall HICP
WENIN	compensation per employee
YERIN	Real GDP
PPI_CONS	producer prices for consumer goods
OIL	Euro denominated oil prices
NEER	Nominal effective excgange rate
COMFD	food commodity prices (in euro terms)
COMX	Non-oil commodity prices (in euro terms)
ENETAX	Energy taxes
VAT	Value added tax rate
R_ST	Short-term interest rates
SD	Seasonal Dummy

France

Unprocessed food

Exponential Smoothing
Model with Trend = None
Seasonal = Additive
Estimated Coefficients
alpha = 0.02
delta = -0.11
(See Rats v.5 Reference Manual)

Processed food

VAR/System - Estimation by Least Squares
Dependent Variable dfr_hicpfdpr
Monthly Data From 1990:01 To 2002:06
Usable Observations 137

Centered R**2	0.2945
R Bar **2	0.2620
Standard Error of Estimate	0.0026
Sum of Squared Residuals	0.0009
Durbin-Watson Statistic	1.9495

Variable	Coeff	T-Stat
dfr_hicpfdpr{1}	0.0386	0.4568
dfr_hicpfdpr{2}	-0.0520	-0.6500
dfr_hicpfdpr{12}	0.2795	3.1903
dfr_wenin{1}	0.2128	2.1892
dfr_wenin{2}	0.1473	1.5632
dfr_wenin{12}	-0.2274	-2.6169
Constant	0.0014	3.0260

F-Tests, Dependent Variable dfr_hicpfdpr

Variable	F-Statistic	Signif
dfr_hicpfdpr	3.5536	0.0163
dfr_wenin	6.4339	0.0004

Energy

Linear Regression - Estimation by Least Squares
Dependent Variable DFR_HICPENE
Monthly Data From 1990:01 To 2002:06
Usable Observations 137

Centered R**2	0.5481
R Bar **2	0.5161
Standard Error of Estimate	0.0070
Sum of Squared Residuals	0.0062
Durbin-Watson Statistic	2.0292

Variable	Coeff	T-Stat
DFR_HICPENE{1}	0.0104	0.1405
DFR_HICPENE{2}	0.0368	0.5791
DFR_HICPENE{3}	0.0764	1.2251
DFR_HICPENE{4}	-0.1029	-1.6629
DFR_HICPENE{5}	0.1594	2.7672
DFR_HICPENE{12}	0.0358	0.6479
DFR_OIL	0.0508	6.1578
DFR_OIL{1}	0.0662	7.0314
DFR_ENETAX	0.2244	4.4846
Constant	0.0001	0.1504

Non-energy industrial goods

BVAR hyperparameter

Tightness	0.9
Weights	0.1
Decay	0.1

VAR/System - Estimation by Mixed Estimation
Dependent Variable dfr_hicpneig
Monthly Data From 1990:01 To 2002:06
Usable Observations 137

Centered R**2	0.8224
R Bar **2	0.8224
Standard Error of Estimate	0.0022
Sum of Squared Residuals	0.0007
Durbin-Watson Statistic	2.2671

Variable	Coeff	T-Stat
dfr_hicpneig{1}	-0.2090	-3.4794
dfr_hicpneig{2}	-0.1353	-2.2540
dfr_hicpneig{3}	-0.0477	-0.8595
dfr_hicpneig{4}	-0.1231	-2.2369
dfr_hicpneig{5}	-0.1725	-3.2308
dfr_hicpneig{12}	0.7001	12.0620
dfr_wenin{1}	-0.1366	-1.4065
dfr_wenin{2}	-0.0667	-0.6711
dfr_wenin{3}	0.0394	0.4161
dfr_wenin{4}	0.1715	1.8011
dfr_wenin{5}	0.0818	0.8919
dfr_wenin{12}	0.0995	1.1954
Constant	0.0002	0.5724

F-Tests, Dependent Variable dfr_hicpneig

Variable	F-Statistic	Signif
dfr_hicpneig	60.2139	0.0000
dfr_wenin	2.4412	0.0284

Services

BVAR hyperparameter

Tightness	0.3
Weights	0.9
Decay	0.2

VAR/System - Estimation by Mixed Estimation
Dependent Variable dfr_hicpserv
Monthly Data From 1990:01 To 2002:06
Usable Observations 137

Centered R**2	0.6370
R Bar **2	0.6370
Standard Error of Estimate	0.0013
Sum of Squared Residuals	0.0002
Durbin-Watson Statistic	2.1256

Variable	Coeff	T-Stat
dfr_hicpserv{1}	0.0813	1.2997
dfr_hicpserv{2}	-0.0073	-0.1182
dfr_hicpserv{3}	0.1539	2.4118
dfr_hicpserv{12}	0.5667	9.5498
dfr_wenin{1}	-0.0251	-0.5039
dfr_wenin{2}	0.1701	3.0194
dfr_wenin{3}	-0.0342	-0.6092
dfr_wenin{12}	-0.0238	-0.4425
dfr_hicpfdunpr{1}	0.0017	0.1623
dfr_hicpfdunpr{2}	0.0242	2.3844
dfr_hicpfdunpr{3}	0.0151	1.4492
dfr_hicpfdunpr{12}	0.0222	2.3364
Constant	0.0000	0.1882

F-Tests, Dependent Variable dfr_hicpserv

Variable	F-Statistic	Signif
dfr_hicpserv	37.4833	0.0000
dfr_wenin	3.2247	0.0145
dfr_hicpfdunpr	3.6719	0.0071

HICPX

BVAR hyperparameter

Tightness	0.9
Weights	0.1
Decay	0.2

VAR/System - Estimation by Mixed Estimation
Dependent Variable dfr_hicpx
Monthly Data From 1990:01 To 2002:06
Usable Observations 137

Centered R**2	0.6006
R Bar **2	0.6006
Standard Error of Estimate	0.0013
Sum of Squared Residuals	0.0002
Durbin-Watson Statistic	2.0068

Variable	Coeff	T-Stat
dfr_hicpx{1}	-0.0426	-0.6154
dfr_hicpx{2}	0.0226	0.3387
dfr_hicpx{3}	0.1059	1.5915
dfr_hicpx{4}	0.0146	0.2249
dfr_hicpx{5}	-0.0540	-0.8579
dfr_hicpx{12}	0.5425	7.7482
dfr_wenin{1}	-0.0896	-1.7294
dfr_wenin{2}	0.0335	0.6501
dfr_wenin{3}	0.0453	0.9169
dfr_wenin{4}	0.1116	2.1774
dfr_wenin{5}	0.0137	0.2821
dfr_wenin{12}	0.0089	0.2247
Constant	0.0003	1.1612

F-Tests, Dependent Variable dfr_hicpx

Variable	F-Statistic	Signif
dfr_hicpx	14.2000	0.0000
dfr_wenin	2.9612	0.0095

HICP

BVAR hyperparameter

Tightness	0.1
Weights	0.9
Decay	0.1

VAR/System - Estimation by Mixed Estimation
Dependent Variable dfr_hicp
Monthly Data From 1990:01 To 2002:06
Usable Observations 137

Centered R**2	0.2757
R Bar **2	0.2757
Standard Error of Estimate	0.0019
Sum of Squared Residuals	0.0005
Durbin-Watson Statistic	2.0859

Variable	Coeff	T-Stat
dfr_hicp{1}	0.0303	0.4977
dfr_hicp{2}	-0.0626	-1.0648
dfr_hicp{3}	0.0628	1.0848
dfr_hicp{4}	-0.0588	-1.0343
dfr_hicp{12}	0.0839	1.5274
dfr_wenin{1}	-0.0473	-0.6430
dfr_wenin{2}	-0.0815	-1.3447
dfr_wenin{3}	0.0375	0.5300
dfr_wenin{4}	0.2013	2.8275
dfr_wenin{12}	0.0073	0.1154
Constant	0.0011	3.0846

F-Tests, Dependent Variable dfr_hicp

Variable	F-Statistic	Signif
dfr_hicp	1.1484	0.3380
dfr_wenin	4.9296	0.0004

Notation

HICPFDUNPR	HICP Unprocessed food component
HICPENE	HICP Energy component
HICPFDPR	HICP Processed food component
HICPNEIG	HICP Non-energy ind. goods component
HICPSERV	HICP Services component
HICPX	HICP excl. unproc food & energy
HICP	Overall HICP
WENIN	compensation per employee
YERIN	Real GDP
PPI_CONS	producer prices for consumer goods
OIL	Euro denominated oil prices
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COMFD	food commodity prices (in euro terms)
COMX	Non-oil commodity prices (in euro terms)
ENETAX	Energy taxes
VAT	Value added tax rate
R_ST	Short-term interest rates
SD	Seasonal Dummy

Italy

Unprocessed food

BVAR hyperparameter

Tightness	0.9
Weights	0.1
Decay	0.1

VAR/System - Estimation by Mixed Estimation
Dependent Variable dit_it_hicpfdunp
Monthly Data From 1990:01 To 2002:06
Usable Observations 144

Centered R**2	0.6093
R Bar **2	0.5767
Standard Error of Estimate	0.0030
Sum of Squared Residuals	0.0012
Durbin-Watson Statistic	1.9028

Variable	Coeff	T-Stat
dit_it_hicpfdunp{1}	0.4578	5.1149
dit_it_hicpfdunp{2}	0.0004	0.0046
dit_it_hicpfdunp{3}	0.2767	2.8345
dit_it_hicpfdunp{4}	-0.1216	-1.2177
dit_it_hicpfdunp{5}	-0.0407	-0.4521
dit_yerin{1}	0.0322	0.3102
dit_yerin{2}	0.0319	0.2915
dit_yerin{3}	0.0993	0.9918
dit_yerin{4}	0.0841	0.8487
dit_yerin{5}	0.0397	0.4475
Constant	0.0017	1.0602
SD1	0.0007	0.3831
SD2	-0.0046	-1.5090
SD3	-0.0029	-0.7675
SD4	0.0024	0.7428
SD5	0.0022	0.7169
SD6	0.0017	0.8284
SD7	-0.0080	-3.3974
SD8	-0.0044	-1.7114
SD9	-0.0006	-0.2427
SD10	0.0015	0.6622
SD11	-0.0009	-0.4230

F-Tests, Dependent Variable dit_it_hicpfdunp

Variable	F-Statistic	Signif
dit_it_hicpfdunp	11.9687	0.0000
dit_yerin	0.9306	0.4634

Processed food

Energy

Linear Regression - Estimation by Least Squares
Dependent Variable DIT_HICPENE
Monthly Data From 1990:01 To 2002:06
Usable Observations 144

Centered R**2	0.4737
R Bar **2	0.3931
Standard Error of Estimate	0.0085
Sum of Squared Residuals	0.0089
Durbin-Watson Statistic	2.1986

Variable	Coeff	T-Stat
DIT_HICPENE{1}	0.0925	1.2294
DIT_HICPENE{2}	0.1413	1.9901
DIT_HICPENE{3}	-0.0384	-0.5354
DIT_HICPENE{4}	-0.0121	-0.1689
DIT_HICPENE{5}	0.1925	2.7260
DIT_OIL	0.0391	4.1607
DIT_OIL{1}	0.0541	5.2781
DIT_ENETAX	0.3557	6.1282
SD1	0.0029	0.8233
SD2	0.0014	0.3986
SD3	0.0006	0.1640
SD4	-0.0028	-0.7516
SD5	-0.0047	-1.3088
SD6	0.0001	0.0348
SD7	-0.0030	-0.8198
SD8	-0.0023	-0.6130
SD9	0.0023	0.6259
SD10	0.0020	0.5496
SD11	0.0021	0.5795
Constant	0.0008	0.3158

Non-energy industrial goods

BVAR hyperparameter

Tightness	0.1
Weights	0.9
Decay	0.1

VAR/System - Estimation by Mixed Estimation
Dependent Variable dit_hicpneig
Monthly Data From 1990:01 To 2002:06
Usable Observations 137

Centered R**2	0.9737
R Bar **2	0.9737
Standard Error of Estimate	0.0019
Sum of Squared Residuals	0.0005
Durbin-Watson Statistic	2.0540

Variable	Coeff	T-Stat
dit_hicpneig{1}	-0.1574	-4.3940
dit_hicpneig{2}	-0.1006	-2.7284
dit_hicpneig{3}	0.1572	3.9919
dit_hicpneig{4}	0.0147	0.4286
dit_hicpneig{5}	-0.0190	-0.6150
dit_hicpneig{12}	0.6610	18.5237
dit_neer{1}	-0.0066	-0.8463
dit_neer{2}	-0.0066	-0.8603
dit_neer{3}	-0.0173	-2.3116
dit_neer{4}	-0.0039	-0.5213
dit_neer{5}	-0.0115	-1.5973
dit_neer{12}	-0.0073	-1.0748
dit_wenin{1}	0.0191	2.2319
dit_wenin{2}	-0.0438	-4.3926
dit_wenin{3}	-0.0062	-0.5689
dit_wenin{4}	-0.0032	-0.2896
dit_wenin{5}	0.0353	3.9489
dit_wenin{12}	0.0228	3.3966
Constant	0.0008	2.3023

F-Tests, Dependent Variable dit_hicpneig

Variable	F-Statistic	Signif
dit_hicpneig	295.7501	0.0000
dit_neer	2.0893	0.0584
dit_wenin	9.6001	0.0000

Services

BVAR hyperparameter		
Tightness	0.9	
Weights	0.1	
Decay	0.1	
VAR/System - Estimation by Mixed Estimation		
Dependent Variable dit_hicpserv		
Monthly Data From 1990:01 To 2002:06		
Usable Observations 137		
Centered R**2		0.6141
R Bar **2		0.6141
Standard Error of Estimate		0.0014
Sum of Squared Residuals		0.0003
Durbin-Watson Statistic		1.9839

Variable	Coeff	T-Stat
dit_hicpserv{1}	0.0211	0.2851
dit_hicpserv{2}	0.0145	0.2393
dit_hicpserv{3}	0.3267	4.8424
dit_hicpserv{4}	0.0595	0.8507
dit_hicpserv{12}	0.3879	6.0185
dit_wenin{1}	0.0003	0.0520
dit_wenin{2}	-0.0035	-1.3295
dit_wenin{3}	0.0136	2.8258
dit_wenin{4}	-0.0008	-0.1578
dit_wenin{12}	0.0058	1.2814
dit_hicpfdunpr{1}	0.0514	2.2163
dit_hicpfdunpr{2}	0.0468	2.0022
dit_hicpfdunpr{3}	-0.0249	-1.0570
dit_hicpfdunpr{4}	0.0132	0.5767
dit_hicpfdunpr{12}	0.0176	0.8407
Constant	0.0002	0.6905

F-Tests, Dependent Variable dit_hicpserv

Variable	F-Statistic	Signif
dit_hicpserv	27.7898	0.0000
dit_wenin	2.7595	0.0209
dit_hicpfdunpr	2.9511	0.0146

HICPX

BVAR hyperparameter		
Tightness	0.1	
Weights	0.6	
Decay	0.1	
VAR/System - Estimation by Mixed Estimation		
Dependent Variable dit_hicpx		
Monthly Data From 1990:01 To 2002:06		
Usable Observations 137		
Centered R**2		0.9001
R Bar **2		0.9001
Standard Error of Estimate		0.0016
Sum of Squared Residuals		0.0004
Durbin-Watson Statistic		1.7374

Variable	Coeff	T-Stat
dit_hicpx{1}	-0.0134	-0.3735
dit_hicpx{12}	0.8257	30.0817
dit_yerin{1}	0.0037	0.1623
dit_yerin{12}	0.0023	0.1254
dit_wenin{1}	-0.0057	-1.2497
dit_wenin{12}	0.0054	1.2374
dit_neer{1}	-0.0030	-0.5930
dit_neer{12}	-0.0016	-0.3792
Constant	0.0004	1.8218

F-Tests, Dependent Variable dit_hicpx

Variable	F-Statistic	Signif
dit_hicpx	467.5665	0.0000
dit_yerin	0.0223	0.9779
dit_wenin	1.3994	0.2503
dit_neer	0.2450	0.7831

HICP

BVAR hyperparameter		
Tightness	0.1	
Weights	0.9	
Decay	0.1	
VAR/System - Estimation by Mixed Estimation		
Dependent Variable dit_hicp		
Monthly Data From 1990:01 To 2002:06		
Usable Observations 137		
Centered R**2		0.8959
R Bar **2		0.8959
Standard Error of Estimate		0.0015
Sum of Squared Residuals		0.0003
Durbin-Watson Statistic		1.9888

Variable	Coeff	T-Stat
dit_hicp{1}	-0.0608	-1.3405
dit_hicp{2}	-0.0014	-0.0317
dit_hicp{3}	0.3109	6.7485
dit_hicp{4}	-0.0546	-1.2203
dit_hicp{5}	-0.0186	-0.4283
dit_hicp{12}	0.4072	9.4687
dit_yerin{1}	0.0503	1.5566
dit_yerin{2}	-0.0337	-1.0551
dit_yerin{3}	0.0352	1.1744
dit_yerin{4}	0.0016	0.0557
dit_yerin{5}	-0.0029	-0.1036
dit_yerin{12}	-0.0203	-0.7667
dit_wenin{1}	-0.0035	-0.4574
dit_wenin{2}	-0.0264	-3.5710
dit_wenin{3}	0.0101	1.2206
dit_wenin{4}	-0.0006	-0.0709
dit_wenin{5}	0.0279	3.5975
dit_wenin{12}	0.0202	3.1946
dit_neer{1}	-0.0052	-0.8356
dit_neer{2}	-0.0041	-0.6753
dit_neer{3}	-0.0107	-1.8117
dit_neer{4}	-0.0015	-0.2606
dit_neer{5}	-0.0020	-0.3463
dit_neer{12}	-0.0038	-0.7019
Constant	0.0008	2.7494

F-Tests, Dependent Variable dit_hicp

Variable	F-Statistic	Signif
dit_hicp	47.7991	0.0000
dit_yerin	0.8190	0.5570
dit_wenin	8.1965	0.0000
dit_neer	1.0019	0.4268

Notation

HICPFDUNPR	HICP Unprocessed food component
HICPENE	HICP Energy component
HICPFDPR	HICP Processed food component
HICPNEIG	HICP Non-energy ind. goods component
HICPSERV	HICP Services component
HICPX	HICP excl. unproc food & energy
HICP	Overall HICP
WENIN	compensation per employee
YERIN	Real GDP
PPI_CONS	producer prices for consumer goods
OIL	Euro denominated oil prices
NEER	Nominal effective excgange rate
COMFD	food commodity prices (in euro terms)
COMX	Non-oil commodity prices (in euro terms)
ENETAX	Energy taxes
VAT	Value added tax rate
R_ST	Short-term interest rates
SD	Seasonal Dummy

Spain

Unprocessed food

BVAR hyperparameter

Tightness	0.1
Weights	0.2
Decay	0.9

VAR/System - Estimation by Mixed Estimation
Dependent Variable des_hicpfdunpr
Monthly Data From 1991:01 To 2002:06
Usable Observations 120

Centered R**2	0.5413
R Bar **2	0.4946
Standard Error of Estimate	0.0062
Sum of Squared Residuals	0.0041
Durbin-Watson Statistic	1.7994

Variable	Coeff	T-Stat
des_hicpfdunpr{1}	0.0258	0.3719
des_hicpfdunpr{2}	-0.0155	-0.3165
des_wenin{1}	0.0015	0.1002
des_wenin{2}	-0.0005	-0.0630
des_yerin{1}	0.0076	0.3170
des_yerin{2}	0.0003	0.0246
des_oil{1}	0.0005	0.2750
des_oil{2}	0.0001	0.0847
des_neer{1}	0.0007	0.0563
des_neer{2}	-0.0009	-0.1292
des_comx{1}	0.0008	0.1669
des_comx{2}	0.0001	0.0462
des_r_st{1}	0.0008	0.2258
des_r_st{2}	0.0003	0.1728
Constant	0.0093	5.9712
SD1	0.0232	0.7608
SD2	-0.0201	-7.6925
SD3	-0.0073	-2.5245
SD4	-0.0054	-2.0634
SD5	-0.0092	-3.7284
SD6	-0.0135	-5.4519
SD7	-0.0038	-1.4653
SD8	0.0002	0.0762
SD9	0.0003	0.1325
SD10	-0.0125	-4.9885
SD11	-0.0076	-2.9227

F-Tests, Dependent Variable des_hicpfdunpr

Variable	F-Statistic	Signif
des_hicpfdunpr	0.1102	0.8957
des_wenin	0.0070	0.9930
des_yerin	0.0506	0.9507
des_oil	0.0415	0.9594
des_neer	0.0098	0.9902
des_comx	0.0151	0.9850
des_r_st	0.0411	0.9598

Energy

Linear Regression - Estimation by Least Squares
Dependent Variable DES_HICPENE
Monthly Data From 1990:01 To 2002:06
Usable Observations 113

Centered R**2	0.7064
R Bar **2	0.6955
Standard Error of Estimate	0.0069
Sum of Squared Residuals	0.0051
Durbin-Watson Statistic	1.6600

Variable	Coeff	T-Stat
DES_HICPENE{1}	0.1167	1.6856
DES_HICPENE{12}	0.1112	1.9019
DES_OIL	0.0954	11.1853
DES_OIL{1}	0.0539	4.8398
DES_ENETAX	0.3605	6.6424

Non-energy industrial goods

BVAR hyperparameter

Tightness	0.1
Weights	0.9
Decay	0.1

VAR/System - Estimation by Mixed Estimation
Dependent Variable des_hicpneig
Monthly Data From 1991:01 To 2002:06
Usable Observations 113

Centered R**2	0.9835
R Bar **2	0.9835
Standard Error of Estimate	0.0020
Sum of Squared Residuals	0.0004
Durbin-Watson Statistic	1.7547

Variable	Coeff	T-Stat
des_hicpneig{1}	-0.0797	-2.4961
des_hicpneig{2}	-0.1285	-4.4143
des_hicpneig{3}	-0.1061	-3.4144
des_hicpneig{4}	-0.1364	-4.0325
des_hicpneig{5}	-0.1175	-3.6203
des_hicpneig{12}	0.7655	24.8682
des_wenin{1}	-0.0171	-0.5545
des_wenin{2}	0.0105	0.3492
des_wenin{3}	-0.0253	-0.8697
des_wenin{4}	0.1049	3.5036
des_wenin{5}	0.0274	1.0324
des_wenin{12}	0.0284	1.1707
Constant	0.0012	3.6769

F-Tests, Dependent Variable des_hicpneig

Variable	F-Statistic	Signif
des_hicpneig	288.3884	0.0000
des_wenin	3.6482	0.0024

Processed food

BVAR hyperparameter

Tightness	0.2
Weights	0.9
Decay	0.2

VAR/System - Estimation by Mixed Estimation
Dependent Variable des_hicpfdpr
Monthly Data From 1990:01 To 2002:06
Usable Observations 121

Centered R**2	0.4663
R Bar **2	0.4125
Standard Error of Estimate	0.0036
Sum of Squared Residuals	0.0014
Durbin-Watson Statistic	1.8586

Variable	Coeff	T-Stat
des_hicpfdpr{1}	0.3232	3.8194
des_hicpfdpr{2}	0.0636	0.7375
des_hicpfdpr{3}	0.0483	0.5531
des_hicpfdpr{4}	0.0096	0.1165
des_wenin{1}	0.0805	0.8953
des_wenin{2}	-0.0274	-0.2917
des_wenin{3}	-0.0595	-0.6529
des_wenin{4}	0.1833	2.1901
Constant	0.0003	0.1256
SD1	0.0083	3.3430
SD2	-0.0005	-0.1409
SD3	-0.0014	-0.3145
SD4	-0.0034	-0.8731
SD5	0.0000	-0.0078
SD6	0.0006	0.2472
SD7	0.0023	0.7687
SD8	0.0021	0.8652
SD9	0.0019	0.7363
SD10	-0.0003	-0.1332
SD11	-0.0009	-0.3502

F-Tests, Dependent Variable des_hicpfdpr

Variable	F-Statistic	Signif
des_hicpfdpr	5.4339	0.0005
des_wenin	1.2447	0.2964

Services

Linear Regression - Estimation by Least Squares
Dependent Variable des_hicpserv
Monthly Data From 1990:01 To 2002:06
Usable Observations 113

Centered R**2	0.6467
R Bar **2	0.6336
Standard Error of Estimate	0.0019
Sum of Squared Residuals	0.0004
Durbin-Watson Statistic	1.9706

Variable	Coeff	T-Stat
des_hicpserv{12}	0.3624	4.7055
des_wenin{5}	0.0682	3.6631
des_wenin{8}	0.1430	6.3018
des_wenin{15}	0.0403	2.9495
Constant	0.0013	4.3142

HICPX

BVAR hyperparameter	
Tightness	0.1
Weights	0.9
Decay	0.1

VAR/System - Estimation by Mixed Estimation
Dependent Variable des_hicpx
Monthly Data From 1990:01 To 2002:06
Usable Observations 113

Centered R**2	0.9255
R Bar **2	0.9255
Standard Error of Estimate	0.0016
Sum of Squared Residuals	0.0003
Durbin-Watson Statistic	1.7728

Variable	Coeff	T-Stat
des_hicpx{1}	0.0290	0.6205
des_hicpx{2}	-0.0437	-1.0866
des_hicpx{3}	-0.0388	-0.9185
des_hicpx{4}	-0.0654	-1.4819
des_hicpx{5}	-0.0226	-0.5492
des_hicpx{12}	0.6230	14.9944
des_wenin{1}	-0.0301	-1.3334
des_wenin{2}	-0.0162	-0.7361
des_wenin{3}	-0.0306	-1.4482
des_wenin{4}	0.0753	3.4117
des_wenin{5}	0.0125	0.6105
des_wenin{12}	0.0279	1.5157
Constant	0.0012	3.2520

F-Tests, Dependent Variable des_hicpx

Variable	F-Statistic	Signif
des_hicpx	45.9649	0.0000
des_wenin	4.4186	0.0005

Notation

HICPFDUNPR	HICP Unprocessed food component
HICPENE	HICP Energy component
HICPFDPR	HICP Processed food component
HICPNEIG	HICP Non-energy ind. goods component
HICPSERV	HICP Services component
HICPX	HICP excl. unproc food & energy
HICP	Overall HICP
WENIN	compensation per employee
YERIN	Real GDP
PPI_CONS	producer prices for consumer goods
OIL	Euro denominated oil prices
NEER	Nominal effective excgange rate
COMFD	food commodity prices (in euro terms)
COMX	Non-oil commodity prices (in euro terms)
ENETAX	Energy taxes
VAT	Value added tax rate
R_ST	Short-term interest rates
SD	Seasonal Dummy

HICP

BVAR hyperparameter	
Tightness	0.1
Weights	0.9
Decay	0.1

VAR/System - Estimation by Mixed Estimation
Dependent Variable des_hicp
Monthly Data From 1991:01 To 2002:06
Usable Observations 113

Centered R**2	0.8723
R Bar **2	0.8723
Standard Error of Estimate	0.0017
Sum of Squared Residuals	0.0003
Durbin-Watson Statistic	1.8605

Variable	Coeff	T-Stat
des_hicp{1}	0.0537	0.9849
des_hicp{2}	-0.0733	-1.5644
des_hicp{3}	0.0638	1.2942
des_hicp{4}	-0.0824	-1.7044
des_hicp{5}	-0.0211	-0.4519
des_hicp{12}	0.2909	6.1780
des_wenin{1}	0.0079	0.2973
des_wenin{2}	-0.0372	-1.4110
des_wenin{3}	-0.0082	-0.3064
des_wenin{4}	0.0911	3.4096
des_wenin{5}	0.0045	0.1807
des_wenin{12}	0.0648	2.9554
des_yerin{1}	0.0001	0.0025
des_yerin{2}	-0.0664	-1.6688
des_yerin{3}	-0.0371	-1.0233
des_yerin{4}	0.1076	2.7961
des_yerin{5}	-0.0021	-0.0575
des_yerin{12}	0.0150	0.4322
des_oil{1}	0.0035	2.1952
des_oil{2}	0.0001	0.0934
des_oil{3}	-0.0009	-0.6270
des_oil{4}	-0.0006	-0.4250
des_oil{5}	-0.0007	-0.5089
des_oil{12}	-0.0001	-0.0561
des_neer{1}	-0.0089	-0.6655
des_neer{2}	-0.0125	-0.9723
des_neer{3}	-0.0064	-0.5149
des_neer{4}	0.0081	0.6843
des_neer{5}	-0.0053	-0.4584
des_neer{12}	-0.0081	-0.7511
des_comx{1}	0.0034	0.8000
des_comx{2}	-0.0025	-0.6164
des_comx{3}	0.0038	0.9502
des_comx{4}	0.0023	0.5790
des_comx{5}	-0.0007	-0.1758
des_comx{12}	-0.0020	-0.5651
des_r_st{1}	0.0065	2.3179
des_r_st{2}	0.0022	0.8170
des_r_st{3}	0.0011	0.4196
des_r_st{4}	-0.0024	-0.9476
des_r_st{5}	-0.0002	-0.0795
des_r_st{12}	0.0019	0.7887
Constant	0.0017	3.8786

F-Tests, Dependent Variable des_hicp

Variable	F-Statistic	Signif
des_hicp	8.2172	0.0000
des_wenin	3.8858	0.0015
des_yerin	2.2022	0.0479
des_oil	0.9356	0.4726
des_neer	0.4935	0.8121
des_comx	0.4178	0.8659
des_r_st	1.3256	0.2516

Appendix A5. RMSEs for all euro area models

Euro area

	Std.Dev.	Bench-mark	Random walk with drift	SARIMA	Expon. smoothing (levels)	Expon. smoothing (dlogs)	VAR	Refined VAR	BVAR	Refined BVAR	Single equation
hicpfdunpr	2.46										
Model				(0,1)			1 lag	1 lag	5 lags	2 lags	1)
Step 1		0.84	0.64	0.67	0.68	0.64	0.81	0.63	0.77	**0.62**	**0.63**
Step 3		1.82	1.35	1.52	1.73	1.38	1.88	1.37	1.74	**1.35**	**1.33**
Step 6		2.47	2.04	2.29	2.64	**2.04**	2.87	2.11	2.54	**2.04**	**2.00**
Step 12		4.04	3.56	3.92	4.00	3.96	4.96	3.75	3.66	3.57	**3.54**
Step 18		4.87	3.88	4.59	4.27	4.54	5.96	4.12	4.09	**3.90**	3.95
Av. RMSE		2.81	2.30	2.60	2.67	2.51	3.30	2.40	2.56	2.30	**2.29**
Rel. RMSE			**0.82**	**0.93**	**0.95**	**0.90**	1.17	**0.85**	**0.91**	**0.82**	**0.82**
hicpene	4.52										
Model				(2,3)			3 lags	4 lags	3 lags	4 lags	2)
Step 1		1.90	1.47	1.45	1.68	1.51	1.18	1.17	1.18	1.17	**0.93**
Step 3		3.60	2.73	2.68	3.20	3.01	1.73	1.90	1.75	1.91	**1.31**
Step 6		5.87	4.49	4.23	5.00	5.10	2.36	2.57	2.34	2.59	**1.94**
Step 12		10.45	7.45	7.31	8.12	9.52	3.97	4.15	3.96	4.20	**3.04**
Step 18		13.22	7.80	7.89	8.93	12.15	4.30	4.32	4.44	4.37	**3.06**
Av. RMSE		7.01	4.79	4.71	5.39	6.26	2.71	2.82	2.73	2.85	**2.06**
Rel. RMSE			**0.68**	**0.67**	**0.77**	**0.89**	**0.39**	**0.40**	**0.39**	**0.41**	**0.29**
hicpfdpr	1.03										
Model				5,1			1 lag	4 lags	4 lags	4 lags	3)
Step 1		0.16	0.16	0.14	0.20	0.14	0.16	**0.13**	0.15	**0.13**	0.14
Step 3		0.35	0.36	0.26	0.51	0.28	0.31	0.25	0.29	**0.24**	**0.24**
Step 6		0.63	0.68	0.50	0.98	0.50	0.54	0.48	0.52	0.46	**0.45**
Step 12		1.11	1.32	1.03	1.20	1.08	1.00	0.94	0.94	0.96	**0.92**
Step 18		1.46	1.32	1.24	1.37	1.42	1.20	1.06	**1.02**	1.16	1.06
Av. RMSE		0.74	0.77	0.63	0.85	0.68	0.64	0.57	0.58	0.59	**0.56**
Rel. RMSE			1.03	**0.85**	1.15	**0.92**	**0.86**	**0.77**	**0.78**	**0.79**	**0.76**
hicpneig	0.95										
Model				(5,0)			5 lags	5 lags	5 lags	5 lags	4)
Step 1		**0.09**	0.24	0.11	0.17	0.17	0.14	0.24	0.16	0.24	0.12
Step 3		**0.19**	0.40	0.21	0.47	0.26	0.25	0.35	0.23	0.35	0.20
Step 6		0.30	0.50	0.34	0.55	0.25	0.27	0.31	**0.23**	0.31	0.24
Step 12		0.51	0.99	0.68	0.53	0.43	0.37	0.48	**0.33**	0.48	0.39
Step 18		0.68	1.00	0.98	0.59	0.57	0.51	0.50	**0.36**	0.50	0.48
Av. RMSE		0.36	0.63	0.46	0.46	0.33	0.31	0.37	**0.26**	0.37	**0.29**
Rel. RMSE			1.76	1.30	1.30	**0.94**	**0.87**	1.05	**0.74**	1.05	**0.81**
hicpserv	1.40										
Model				(0,5)			4 lags	3 lags	5 lags	5 lags	
Step 1		**0.14**	0.19	0.15	0.27	**0.14**	0.16	**0.14**	0.16	0.16	
Step 3		0.21	0.43	0.23	0.61	**0.19**	0.27	0.22	0.22	0.20	
Step 6		0.33	0.82	0.41	1.09	0.32	0.40	0.33	0.33	**0.27**	
Step 12		0.58	1.65	0.77	0.88	0.55	0.64	0.45	0.44	**0.32**	
Step 18		0.80	1.63	1.10	1.02	0.75	0.85	0.58	0.48	**0.41**	
Av. RMSE		0.41	0.94	0.53	0.77	0.39	0.46	0.34	0.32	**0.27**	
Rel. RMSE			2.29	1.29	1.88	**0.95**	1.12	**0.84**	**0.79**	**0.66**	
hicp	0.95	0.41	0.94								
Model				(1,1)			4 lags	3 lags	4 lags	3 lags	
Step 1		0.21	0.20	0.20	0.26	0.18	0.20	**0.17**	0.19	**0.17**	
Step 3		0.38	0.36	0.39	0.80	0.32	0.39	**0.26**	0.36	**0.26**	
Step 6		0.50	0.57	0.51	1.10	0.47	0.50	**0.33**	0.49	0.33	
Step 12		0.85	0.97	0.73	0.85	0.80	0.80	**0.51**	0.70	0.51	
Step 18		1.07	0.76	0.68	0.86	0.99	0.80	**0.48**	0.63	0.49	
Av. RMSE		0.60	0.57	0.50	0.77	0.55	0.54	**0.35**	0.47	**0.35**	
Rel. RMSE			0.95	**0.83**	1.28	**0.91**	**0.89**	**0.58**	**0.79**	**0.58**	
hicpx	1.09										
Model				(2,5)			4 lags	5 lags	5 lags	5 lags	
Step 1		0.09	0.21	0.16	0.20	0.17	**0.16**	**0.16**	0.17	**0.16**	
Step 3		**0.18**	0.41	0.31	0.61	0.30	0.31	0.30	0.30	**0.29**	
Step 6		0.33	0.62	0.33	0.87	0.31	0.34	0.32	0.30	**0.28**	
Step 12		0.61	1.23	0.71	0.85	0.60	0.56	0.51	0.49	**0.42**	
Step 18		0.84	1.22	1.02	0.96	0.83	0.69	0.59	0.54	**0.47**	
Av. RMSE		0.41	0.74	0.51	0.70	0.44	0.41	0.37	0.36	**0.32**	
Rel. RMSE			1.81	1.24	1.71	1.08	1.01	**0.92**	**0.88**	**0.79**	

1) hicpfdunpr{1,10,12}, seaonsal dummies
2) hicpene{1 to 5}, oilpr{0 to 1}, enetax, seasonal dummies
3) hicpfdpr{1-4}, comfd{2}, vat, wenin{0 to 2}, seasonal dummies
4) neig{1,6,12}, ppi_cons{1}, wenin{2}, VAT, seasonal dummies

Appendix A6. Unconditional RMSEs for overall HICP

	Model	Benchmark	Conditional	Unconditional
Euro Area	VAR			
Step 1	(1 - 3)	0.21	0.17	0.17
Step 3	sd	0.38	0.26	0.31
Step 6	ppi_cons	0.50	0.33	0.45
Step 12	wages	0.85	0.51	0.63
Step 18	oil	1.07	0.48	0.61
Av. RMSE		0.60	0.35	0.43
Germany	VAR			
Step 1	(1 - 3)	0.33	0.26	0.26
Step 3		0.55	0.43	0.46
Step 6	sd	0.70	0.55	0.59
Step 12	wages	1.14	0.83	0.89
Step 18	oil	1.33	0.76	0.80
Av. RMSE		0.81	0.57	0.60
France	BVAR			*
Step 1	(1 - 4, 12)	0.28	0.24	0.22
Step 3		0.49	0.41	0.36
Step 6	wages	0.56	0.52	0.46
Step 12		0.86	0.75	0.66
Step 18		0.98	0.64	0.54
Av. RMSE		0.64	0.51	0.45
Italy	BVAR			*
Step 1	(1 - 5, 12)	0.14	0.14	0.12
Step 3		0.24	0.22	0.19
Step 6	wages	0.37	0.31	0.27
Step 12	gdp	0.59	0.50	0.44
Step 18	neer	0.70	0.48	0.43
Av. RMSE		0.41	0.33	0.29
Spain	BVAR			*
Step 1	(1 - 5, 12)	0.22	0.20	0.15
Step 3		0.54	0.34	0.30
Step 6	wages, GDP,	0.93	0.42	0.45
Step 12	oil, neer,	1.27	0.48	0.62
Step 18	comx, r_st	1.47	0.39	0.63
Av. RMSE		0.89	0.37	0.43

* Re-optimised hyperparameters.

Appendix A7. RMSEs for all country models

Germany

	Bench-mark	Random walk with drift	SARIMA	Expon. smoothing (levels)	Expon. smoothing (dlogs)	VAR	Refined VAR	BVAR	Refined BVAR	Single equation
hicpfdunpr			1,2			2 lags	2 lags	5 lags	1 lag	lags (1-2)
Model						sd	yerin, sd	sd	yerin, sd	yerin (0 to 2), sd
Step 1	1.26	1.01	**1.01**	1.03	1.01	1.09	1.04	1.09	1.01	1.06
Step 3	2.71	**1.87**	2.05	1.94	2.05	2.02	1.92	1.91	1.89	1.93
Step 6	3.60	2.64	2.88	2.75	2.94	2.86	2.74	**2.63**	2.66	2.70
Step 12	5.60	4.46	5.04	4.64	5.22	4.81	4.58	**4.38**	4.49	4.41
Step 18	6.33	4.75	5.57	5.09	5.46	5.04	4.83	**4.69**	4.81	4.71
Av. RMSE	3.90	2.94	3.31	3.09	3.34	3.16	3.02	**2.94**	2.97	2.96
Rel. RMSE		0.75	0.85	0.79	0.86	0.81	0.77	**0.75**	0.76	0.76
hicpfdpr			4,0			3 lags	5 lags	5 lags	5 lags	
Model							wenin		wenin, 12th lag	
Step 1	0.33	0.27	0.27	0.29	0.36	**0.26**	0.27	**0.26**	0.27	
Step 3	0.63	0.53	0.52	0.62	0.86	0.51	0.52	**0.50**	0.51	
Step 6	0.99	0.87	**0.77**	0.98	1.19	0.82	0.79	0.80	0.78	
Step 12	1.71	1.58	1.48	1.49	2.25	1.50	1.46	1.48	**1.46**	
Step 18	2.19	1.67	1.69	1.66	2.45	1.64	1.64	1.64	**1.63**	
Av. RMSE	1.17	0.98	0.95	1.01	1.42	0.94	0.94	0.93	**0.93**	
Rel. RMSE		0.84	0.81	0.86	1.21	0.81	0.80	0.80	**0.79**	
hicpneig			4,0			2 lags	2 lags	4 lags	5 lags	
Model							wenin, yerin, 12th		wenin, yerin, 12th	
Step 1	0.11	0.12	0.09	0.12	0.11	0.11	0.10	0.09	**0.09**	
Step 3	0.21	0.29	0.20	0.31	0.28	0.26	0.22	0.20	**0.20**	
Step 6	0.32	0.50	0.30	0.38	0.52	0.34	**0.28**	0.28	0.30	
Step 12	0.51	0.92	0.42	0.45	0.65	0.53	**0.40**	0.41	0.46	
Step 18	0.60	0.98	0.46	0.51	0.71	0.47	0.40	**0.40**	0.53	
Av. RMSE	0.35	0.56	0.29	0.36	0.45	0.34	0.28	**0.28**	0.32	
Rel. RMSE		1.61	0.84	1.02	1.30	0.97	0.80	**0.79**	0.90	
hicpene			3,4			1 lag	3 lags	1 lag	3 lags	lag (1), lag (4)
Model						sd	oil, sd	sd	oil, sd	oil, oil (1), enetax
Step 1	2.52	1.94	2.21	2.44	2.02	1.57	1.60	1.63	1.58	**1.15**
Step 3	4.18	3.31	3.37	4.01	3.80	2.29	2.21	2.37	2.38	**1.65**
Step 6	6.49	5.31	4.76	6.14	6.23	3.42	3.26	3.69	3.55	**2.71**
Step 12	11.09	8.67	7.38	9.94	10.41	5.75	5.04	6.76	5.82	**4.60**
Step 18	13.67	9.26	8.21	10.86	12.82	6.53	5.45	7.77	6.50	**4.78**
Av. RMSE	7.59	5.70	5.19	6.68	7.05	3.91	3.51	4.44	3.97	**2.98**
Rel. RMSE		0.75	0.68	0.88	0.93	0.52	0.46	0.59	0.52	**0.39**
hicpserv			0,5			1 lag	2 lags	5 lags	3 lags	ldv{12,5},wen{1,2,7}
Model							wenin, yerin, 12th		wenin, yerin	yer{1},hicpfdunpr{2}
Step 1	0.31	0.29	0.28	0.39	0.29	0.33	0.30	0.31	0.29	**0.27**
Step 3	0.39	0.53	0.37	0.72	0.40	0.53	0.39	0.47	0.38	**0.35**
Step 6	0.52	0.97	0.55	1.03	0.64	0.67	0.51	0.54	0.48	**0.47**
Step 12	0.75	1.85	0.82	1.96	0.87	1.11	0.75	0.77	0.73	**0.50**
Step 18	0.89	1.77	0.99	1.98	0.90	1.39	0.81	0.80	0.79	**0.52**
Av. RMSE	0.57	1.08	0.60	1.22	0.62	0.81	0.55	0.58	0.54	**0.42**
Rel. RMSE		1.90	1.06	2.14	1.09	1.41	0.97	1.01	0.94	**0.74**
hicp (total)			0,1			2 lags	3 lags	5 lags	4 lags	
Model						sd	wen, oil, sd	sd	wen, oil, sd	
Step 1	0.33	0.27	0.28	0.31	0.28	0.26	0.26	0.27	0.27	
Step 3	0.55	0.45	0.53	0.78	0.48	0.45	0.43	0.45	0.43	
Step 6	0.70	0.63	0.66	1.05	0.70	0.62	0.55	0.60	0.57	
Step 12	1.14	1.04	0.90	0.98	1.14	1.03	0.83	0.97	0.91	
Step 18	1.33	0.84	0.83	1.05	1.24	0.83	0.76	0.83	0.80	
Av. RMSE	0.81	0.64	0.64	0.83	0.77	0.64	**0.57**	0.62	0.59	
Rel. RMSE		0.79	0.79	1.02	0.94	0.79	**0.70**	0.77	0.73	
hicpx			1,3			1 lag	3 lags	5 lags	5 lags	
Model					`		wenin, yerin, 12th		wenin, yerin, 12th	
Step 1	0.17	0.17	0.16	0.21	0.16	0.18	0.16	0.16	**0.15**	
Step 3	0.27	0.37	0.26	0.46	0.26	0.33	0.28	0.27	**0.26**	
Step 6	0.42	0.66	0.40	0.63	0.43	0.48	0.42	0.39	**0.37**	
Step 12	0.69	1.30	0.67	0.72	0.70	0.83	**0.64**	0.69	0.65	
Step 18	0.88	1.30	0.96	0.84	0.85	1.10	0.78	0.79	**0.73**	
Av. RMSE	0.48	0.76	0.49	0.57	0.48	0.58	0.46	0.46	**0.43**	
Rel. RMSE		1.57	1.01	1.18	0.99	1.21	0.94	0.95	**0.89**	

France

	Bench-mark	Random walk with drift	SARIMA	Expon. smoothing (levels)	Expon. smoothing (dlogs)	VAR	Refined VAR	BVAR	Refined BVAR	Single equation
hicpfdunpr										
Model			0,0			2 lags	3 lags	5 lags	5 lags	Idv1= 1,yerin(o to 2),
							yerin	sd	sd,yerin	sd
Step 1	1.29	**0.95**	1.01	1.24	**0.95**	1.06	1.07	0.95	0.95	0.97
Step 3	2.54	1.90	2.06	2.31	**1.83**	2.02	2.05	1.89	1.89	1.92
Step 6	3.00	2.52	2.71	3.07	**2.43**	2.88	2.68	2.53	2.52	2.50
Step 12	4.54	4.28	4.29	5.20	4.07	4.44	**3.98**	4.25	4.25	4.27
Step 18	5.25	4.66	4.86	5.65	4.49	4.57	**4.30**	4.60	4.60	4.61
Av. RMSE	3.32	2.86	2.98	3.49	**2.75**	2.99	2.82	2.84	2.84	2.85
Rel. RMSE		0.86	0.90	1.05	**0.83**	0.90	0.85	0.86	0.85	0.86
hicpfdpr										
Model			1,2			1 lag	2 lags	5 lags	2 lags	
							wenin	sd	sd,werin	
Step 1	0.20	0.18	0.25	0.24	**0.17**	0.23	0.23	0.18	0.18	
Step 3	0.32	0.31	0.42	0.55	0.31	0.37	0.31	**0.29**	**0.29**	
Step 6	**0.46**	0.50	0.61	0.83	0.54	0.55	0.48	0.48	0.49	
Step 12	0.79	0.88	0.92	1.28	1.01	0.84	**0.78**	0.82	0.86	
Step 18	1.10	0.87	1.03	1.26	1.08	0.92	**0.81**	0.84	0.87	
Av. RMSE	0.57	0.55	0.65	0.83	0.62	0.58	0.52	**0.52**	0.54	
Rel. RMSE		0.96	1.13	1.46	1.09	1.02	0.91	**0.91**	0.94	
hicpneig										
Model			2,4			1 lag	5 lags	4 lags	5 lags	
						sd	wenin		wenin	
Step 1	**0.26**	0.41	0.30	0.41	0.32	0.40	0.28	0.33	0.27	
Step 3	**0.30**	0.49	0.34	0.48	0.38	0.48	0.32	0.33	0.30	
Step 6	0.38	0.52	0.43	0.53	0.42	0.48	0.39	**0.35**	0.38	
Step 12	0.62	0.91	0.75	0.60	0.69	0.77	0.55	0.59	**0.54**	
Step 18	0.80	0.88	1.10	0.63	0.84	**0.60**	0.62	0.68	0.62	
Av. RMSE	0.47	0.64	0.58	0.53	0.53	0.55	0.43	0.46	**0.42**	
Rel. RMSE		1.35	1.24	1.12	1.13	1.16	0.91	0.97	**0.90**	
hicpene										
Model			1,0			1 lag	1 lag	3 lags	5 lags	Idv1 to 5, enetax,
						sd	sd,oil,rst,taxes		oil,rst,taxes	oil 0 to 1
Step 1	2.04	1.55	1.58	1.77	1.65	1.36	1.37	1.40	1.35	**1.21**
Step 3	3.98	2.92	2.79	3.06	3.30	2.10	2.12	2.43	2.29	**1.92**
Step 6	6.23	4.52	4.27	4.61	5.69	2.99	2.96	3.31	3.10	**2.53**
Step 12	10.77	7.22	7.20	7.78	11.48	4.60	4.30	4.96	5.09	**3.86**
Step 18	13.23	7.42	7.74	8.46	14.19	4.78	4.29	4.77	4.75	**3.67**
Av. RMSE	7.25	4.73	4.72	5.13	7.26	3.16	3.01	3.37	3.32	**2.64**
Rel. RMSE		0.65	0.65	0.71	1.00	0.44	0.41	0.47	0.46	**0.36**
hicpserv										
Model			0,2			3 lags	3 lags	3 lags	3 lags	
							wenin, hicpfdunp		wenin, hicpfdunp	
Step 1	0.17	0.22	0.16	0.26	**0.15**	0.18	0.17	0.18	0.17	
Step 3	0.29	0.49	0.31	0.64	**0.26**	0.30	0.27	0.30	0.28	
Step 6	0.50	0.89	0.56	1.04	0.46	**0.46**	0.47	0.47	0.49	
Step 12	0.86	1.77	0.85	0.94	0.85	**0.66**	0.79	0.67	0.78	
Step 18	1.10	1.86	0.89	1.04	1.10	**0.75**	1.12	0.76	1.08	
Av. RMSE	0.58	1.05	0.55	0.78	0.56	**0.47**	0.56	0.48	0.56	
Rel. RMSE		1.80	0.95	1.35	0.97	**0.81**	0.97	0.82	0.96	
hicp (total)										
Model			2,5			1 lag	4 lags	4 lags	4 lags	
						sd	wenin		wenin	
Step 1	0.28	0.25	0.26	0.30	0.24	**0.22**	0.25	0.25	0.24	
Step 3	0.49	0.41	0.42	0.67	0.41	**0.36**	0.42	0.42	0.41	
Step 6	0.56	0.58	0.53	0.99	0.57	0.55	**0.52**	0.54	0.52	
Step 12	0.86	0.89	0.77	0.78	0.82	0.97	**0.72**	0.77	0.75	
Step 18	0.98	0.70	0.68	0.76	0.90	0.91	0.64	**0.64**	0.64	
Av. RMSE	0.64	0.56	0.53	0.70	0.59	0.60	**0.51**	0.52	0.51	
Rel. RMSE		0.89	0.84	1.10	0.93	0.95	**0.80**	0.82	0.81	
hicpx										
Model			3,4			4 lags	4 lags	3 lags	5 lags	
						sd	sd,wenin		wenin	
Step 1	**0.14**	0.17	0.17	0.18	0.15	0.18	0.17	0.16	0.14	
Step 3	0.22	0.31	0.29	0.38	**0.21**	0.27	0.26	0.23	0.22	
Step 6	0.34	0.57	0.39	0.66	**0.32**	0.38	0.43	0.36	0.34	
Step 12	0.63	1.12	0.68	0.72	0.63	**0.56**	0.83	0.64	0.62	
Step 18	0.85	1.14	0.85	0.81	0.81	**0.51**	0.94	0.69	0.77	
Av. RMSE	0.43	0.66	0.48	0.55	0.42	**0.38**	0.53	0.42	0.42	
Rel. RMSE		1.53	1.10	1.27	0.98	**0.87**	1.21	0.96	0.96	

Italy

	Bench-mark	Random walk with drift	SARIMA	Expon. smoothing (levels)	Expon. smoothing (dlogs)	VAR	Refined VAR	BVAR	Refined BVAR	Single equation
hicpfdunpr										
Model			5,2			2 lags	5 lags	5 lags	5 lags	Idv 1 to 2,
						sd	Sd,Yerin	Sd	Sd,Yerin	yerin {0 to 2}
Step 1	0.47	0.46	0.46	0.46	0.46	0.46	0.46	0.46	**0.42**	0.44
Step 3	**0.85**	0.97	0.87	1.37	1.02	0.89	0.86	**0.85**	0.85	0.87
Step 6	1.44	1.62	**1.42**	2.47	2.07	1.52	1.56	1.53	1.55	1.59
Step 12	2.55	2.41	2.46	2.62	3.44	**2.03**	2.22	2.19	2.21	2.27
Step 18	3.36	2.61	3.08	2.99	3.99	**2.37**	2.52	2.56	2.53	2.61
Av. RMSE	1.73	1.61	1.66	1.98	2.19	**1.45**	1.52	1.52	1.51	1.55
Rel. RMSE		0.93	0.96	1.14	1.26	**0.84**	0.88	0.87	0.87	0.90
hicpfdpr										
Model			1,2			1 lag	3 lags	4 lags	4 lags	
							comx,wenin		comx,wenin	
Step 1	0.25	0.32	**0.20**	0.42	0.26	0.23	0.23	0.21	0.21	
Step 3	0.47	0.80	**0.42**	1.03	0.61	0.47	0.54	0.46	0.46	
Step 6	**0.66**	1.50	0.73	1.30	1.13	0.87	0.93	0.86	0.86	
Step 12	**0.90**	2.86	1.42	1.40	1.50	1.79	1.75	1.79	1.78	
Step 18	**0.92**	2.83	1.55	1.53	1.41	2.11	2.06	2.00	1.99	
Av. RMSE	**0.64**	1.66	0.86	1.13	0.98	1.09	1.10	1.06	1.06	
Rel. RMSE		2.61	**1.36**	1.78	1.54	1.72	1.73	1.67	1.66	
hicpneig										
Model			0,1			5 lags	5 lags	3 lags	5 lags	
						sd	Sd,wenin,neer		wenin,neer	
Step 1	0.20	0.24	0.20	0.33	0.20	0.22	**0.20**	0.20	0.20	
Step 3	0.33	0.50	0.32	0.86	0.32	0.35	0.31	0.32	**0.31**	
Step 6	0.43	0.91	0.44	1.23	0.40	0.47	0.41	0.42	**0.38**	
Step 12	**0.56**	1.80	0.68	1.69	0.62	0.79	0.73	0.57	0.58	
Step 18	0.57	1.77	0.66	1.88	0.58	0.92	0.89	**0.54**	0.63	
Av. RMSE	0.42	1.04	0.46	1.20	0.42	0.55	0.51	**0.41**	0.42	
Rel. RMSE		2.49	1.10	2.86	1.01	1.31	1.21	**0.98**	1.00	
hicpene										
Model			1,3			3 lags	5 lags	5 lags	2 lags	Idv1 to 5, enetax,
	`						Oil,Yerin,Wenin,Sd		Oil,Yerin,Wenin,Sd,taxes	sd, oil 0 to 1
Step 1	1.35	1.18	1.04	1.23	1.11	1.05	1.07	1.04	1.06	**1.03**
Step 3	2.92	2.34	2.05	2.50	2.40	1.59	1.80	1.72	**1.57**	1.65
Step 6	5.38	4.11	3.72	4.12	4.48	**2.08**	2.56	2.38	2.18	2.21
Step 12	9.85	6.86	6.93	7.07	8.92	3.46	3.54	3.51	**3.11**	3.27
Step 18	12.30	6.89	7.36	7.62	11.68	3.73	**3.12**	3.64	3.20	3.14
Av. RMSE	6.36	4.27	4.22	4.51	5.72	2.38	2.42	2.46	**2.23**	2.26
Rel. RMSE		0.67	0.66	0.71	0.90	0.37	0.38	0.39	**0.35**	0.36
hicpserv										
Model			1,5			1 lag	5 lags	4 lags	4 lags	
							wenin, hicpfdunpr		wenin, hicpfdunpr	
Step 1	0.13	0.21	0.12	0.29	0.12	0.13	0.13	0.12	**0.11**	
Step 3	0.21	0.56	0.23	0.66	0.24	0.25	0.21	0.22	**0.20**	
Step 6	0.31	1.10	0.38	1.04	0.36	0.35	0.27	0.34	**0.25**	
Step 12	0.51	2.21	0.57	0.99	0.57	0.51	0.49	0.52	**0.40**	
Step 18	0.60	2.24	0.69	1.16	0.66	**0.48**	0.64	0.55	0.48	
Av. RMSE	0.35	1.27	0.40	0.83	0.39	0.34	0.35	0.35	**0.29**	
Rel. RMSE		3.62	1.13	2.37	1.11	0.98	0.99	1.00	**0.82**	
hicp (total)										
Model			0,3			4 lags	2 lags	5 lags	5 lags	
							wenin,yerin,neer		wenin,yerin,neer	
Step 1	0.14	0.19	0.14	0.28	**0.13**	0.16	0.14	0.15	0.14	
Step 3	0.24	0.49	0.25	0.79	0.24	0.29	0.24	0.22	**0.22**	
Step 6	0.37	0.95	0.41	1.37	0.40	0.42	0.36	**0.31**	**0.31**	
Step 12	0.59	1.82	0.74	0.98	0.63	0.51	0.60	**0.49**	0.50	
Step 18	0.70	1.69	1.04	1.04	0.73	0.71	0.89	**0.48**	0.48	
Av. RMSE	0.41	1.03	0.51	0.89	0.43	0.42	0.45	**0.33**	0.33	
Rel. RMSE		2.53	1.26	2.19	1.04	1.03	1.09	**0.81**	0.81	
hicpx										
Model			0,2			2 lags	2 lags	1 lag	1 lag	
							wenin,yerin,neer		wenin,yerin,neer	
Step 1	**0.12**	0.20	0.12	0.29	0.13	0.13	0.12	0.12	0.12	
Step 3	**0.19**	0.53	0.22	0.79	0.24	0.21	0.21	0.19	0.19	
Step 6	0.28	1.04	0.35	1.20	0.39	0.33	0.32	**0.28**	0.29	
Step 12	0.45	2.07	0.56	1.25	0.58	0.59	0.56	**0.44**	0.47	
Step 18	0.53	2.07	0.66	1.42	0.60	0.81	0.77	**0.48**	0.54	
Av. RMSE	0.31	1.18	0.38	0.99	0.39	0.41	0.39	**0.30**	0.32	
Rel. RMSE		3.80	1.23	3.19	1.25	1.33	1.27	**0.97**	1.04	

Spain

	Bench-mark	Random walk with drift	SARIMA	Expon. smoothing (levels)	Expon. smoothing (dlogs)	VAR	Refined VAR	BVAR	Refined BVAR	Single equation
hicpfdunpr			3,2			2 lags	2 lags	2 lags	5 lags	lags (0)
Model							wenin, yerin, r_st, 12th	sd	wenin, yerin, r_st, sd	yerin (0 to 2), sd, ct
Step 1	0.71	0.56	0.79	0.79	0.56	0.69	0.62	0.60	**0.56**	0.61
Step 3	1.53	1.24	1.45	1.68	1.25	1.43	1.25	**1.20**	1.22	1.37
Step 6	2.20	1.87	1.94	2.20	1.88	1.98	**1.69**	1.81	1.88	2.01
Step 12	3.43	3.04	2.92	**2.74**	3.27	3.45	2.96	2.93	3.01	3.40
Step 18	4.04	3.32	**2.82**	2.87	3.84	4.10	3.48	3.25	3.28	3.63
Av. RMSE	2.38	2.00	1.98	2.05	2.16	2.33	2.00	**1.96**	1.99	2.20
Rel. RMSE		0.84	0.83	0.86	0.91	0.98	0.84	**0.82**	0.84	0.93
hicpfdpr			0,2			3 lags	4 lags	4 lags	4 lags	
Model						sd	wenin, sd	sd	wenin, sd	
Step 1	0.48	0.40	**0.34**	0.52	0.36	0.43	0.44	0.39	0.34	
Step 3	1.04	0.90	0.85	1.46	0.86	1.05	1.00	0.91	**0.84**	
Step 6	1.58	1.28	1.29	1.71	1.19	1.48	1.44	1.17	**1.09**	
Step 12	2.32	2.08	1.82	1.95	2.25	2.12	2.24	**1.60**	1.79	
Step 18	2.50	2.06	1.92	2.37	2.45	1.87	2.04	**1.59**	1.88	
Av. RMSE	1.58	1.34	1.24	1.60	1.42	1.39	1.43	**1.13**	1.19	
Rel. RMSE		0.85	0.78	1.01	0.90	0.88	0.90	**0.72**	0.75	
hicpneig			1,5			1 lag	5 lags	4 lags	5 lags	
Model						sd	wenin, neer, sd		wenin	
Step 1	0.20	0.19	0.23	0.29	**0.18**	0.21	0.20	0.21	0.20	
Step 3	0.24	0.30	0.29	0.78	**0.22**	0.32	0.25	0.24	0.27	
Step 6	0.31	0.51	0.33	1.09	0.30	0.43	0.34	**0.27**	0.32	
Step 12	0.48	0.97	0.57	1.01	0.47	0.74	0.49	**0.29**	0.38	
Step 18	0.62	0.92	0.66	1.09	0.58	0.72	0.54	**0.34**	0.45	
Av. RMSE	0.37	0.58	0.41	0.85	0.35	0.48	0.36	**0.27**	0.33	
Rel. RMSE		1.56	1.12	2.30	0.95	1.30	0.98	**0.73**	0.88	
hicpene			0,3			2 lags	5 lags	s3 (lags 1-3)	5 lags	lags (1), lag (12)
Model						sd	neer, oil, r_st, sd	sd	neer, oil, r_st, sd	oil, oil (1), enetax
Step 1	2.17	1.71	1.57	1.68	1.67	1.45	1.46	1.43	1.46	**0.94**
Step 3	4.52	3.45	3.50	3.61	3.52	2.24	2.13	2.24	2.15	**1.86**
Step 6	6.92	5.12	5.34	5.39	5.53	2.49	2.24	2.57	2.31	**2.06**
Step 12	11.93	8.11	8.68	8.57	10.93	3.15	**2.90**	3.48	3.01	3.31
Step 18	15.09	8.25	9.79	9.36	13.78	3.16	**2.97**	3.32	3.11	3.64
Av. RMSE	8.12	5.33	5.78	5.72	7.09	2.50	**2.34**	2.61	2.41	2.36
Rel. RMSE		0.66	0.71	0.70	0.87	0.31	**0.29**	0.32	0.30	0.29
hicpserv			0,4			1 lag	4 lags	5 lags	4 lags	ldv{10,12},
Model							wenin, 12th		wenin, 12th	wenin{5,8,15},c
Step 1	0.20	0.26	0.24	0.36	0.25	0.25	0.24	0.27	0.24	**0.19**
Step 3	0.39	0.53	0.46	1.05	0.54	0.51	0.45	0.52	0.49	**0.37**
Step 6	0.64	0.78	0.64	1.74	0.79	0.74	0.65	0.65	0.67	**0.53**
Step 12	0.75	1.31	0.74	0.99	1.04	0.85	0.74	0.58	0.68	**0.51**
Step 18	0.71	1.33	0.92	1.07	0.89	0.98	0.78	0.52	0.71	**0.51**
Av. RMSE	0.54	0.84	0.60	1.04	0.70	0.67	0.57	0.51	0.56	**0.42**
Rel. RMSE		1.57	1.12	1.94	1.31	1.24	1.07	0.95	1.04	**0.79**
hicp (total)			3,4			3 lags	1 lag	5 lags	2 lags	
Model						sd	oil, r_st, sd		oil, r_st, 12th	
Step 1	0.23	0.23	0.21	0.38	0.22	0.21	**0.19**	0.20	0.24	
Step 3	0.48	0.50	0.48	1.27	0.54	0.48	0.43	**0.34**	0.43	
Step 6	0.69	0.71	0.81	1.72	0.93	0.71	0.68	**0.42**	0.46	
Step 12	0.96	0.99	1.37	1.34	1.27	0.71	0.96	0.48	**0.44**	
Step 18	1.19	0.76	1.68	1.49	1.47	0.74	0.90	0.39	**0.36**	
Av. RMSE	0.71	0.64	0.91	1.24	0.89	0.57	0.63	**0.37**	0.39	
Rel. RMSE		0.89	1.28	1.74	1.24	0.80	0.89	**0.51**	0.54	
hicpx			1,4			5 lags	5 lags	4 lags	5 lags	
Model						sd	wenin, sd		wenin	
Step 1	0.13	0.18	0.13	0.30	0.16	0.21	0.15	**0.13**	**0.13**	
Step 3	0.27	0.40	0.32	1.10	0.34	0.46	0.34	**0.24**	0.24	
Step 6	0.41	0.63	0.59	1.60	0.49	0.58	0.51	0.36	**0.36**	
Step 12	0.51	1.13	1.10	1.13	0.70	0.83	0.65	**0.42**	0.44	
Step 18	0.65	1.09	1.52	1.22	0.68	0.80	0.56	**0.47**	0.51	
Av. RMSE	0.39	0.69	0.73	1.07	0.47	0.57	0.44	**0.32**	0.34	
Rel. RMSE		1.75	1.86	2.72	1.20	1.46	1.13	**0.82**	0.86	

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