

# Short-Term Inflation Projections: a Bayesian Vector Autoregressive approach

Domenico Giannone (Université Libre Bruxelles)

Michele Lenza (European Central Bank)

Daphne Momferatou (European Central Bank)

Luca Onorante (European Central Bank)

This version 10 March 2010<sup>1</sup>

## Abstract

In this paper, we construct a large Bayesian Vector Autoregressive model (BVAR) for the Euro Area that captures the complex dynamic inter-relationships between the main components of the Harmonized Index of Consumer Price (HICP) and their determinants. The model is estimated using Bayesian shrinkage. We evaluate the model in real time and find that it produces accurate forecasts. We use the model to study the pass-through of an oil shock and to study the evolution of inflation during the global financial crisis.

## I. Introduction

Short-term inflation projections provide an important input into the monetary policy decision making process. Assessing the short term evolution of inflation entails identifying the prospective driving forces of inflation and interpreting their nature. In particular, it is important to assess whether such forces may display only temporary effects on inflation or are likely to be more persistent and thus relevant with respect to the medium term objective of price stability.

Forming and regularly updating short-term projections for euro area inflation is one of the regular tasks performed either within the context of the broader framework of the quarterly Eurosystem/ECB projections or in between in order to make sure that the assessment of inflation developments and outlook ahead are up to date with the latest information available. Several approaches are used at different times and frequencies.<sup>2</sup>

The main feature of short-term inflation tools is that they enable the timely use of disaggregated and detailed information on inflation that is not always easy to incorporate in

---

<sup>1</sup> The views expressed in this paper are those of the authors and do not necessarily reflect those of the ECB or the Eurosystem.

<sup>2</sup> For more details on the projection process see “A Guide to Eurosystem Macroeconomic Projection Exercises”, ECB, June 2001.

the large and more stylized structural macroeconomic models (e.g. indirect taxes/administered prices). Such large-scale macroeconomic models are typically used as 'work horse' models when building medium-term projections, in the sense that they can incorporate information, judgement and projections coming from other tools.<sup>3</sup>

Within the ECB, several tools have been developed for the short-term forecasting of inflation measured by the Harmonized Index of Consumer Prices (HICP). Such tools have been designed with two aims in mind. Firstly, they should allow taking into account the maximum amount of available information on inflation at any given point in time. This can include, inter alia, information about recent and expected developments in the main drivers of inflation, potentially drawing on other projections for these variables or market expectations, and announced government policy measures (for instance on indirect taxes). Second, they should offer a good interpretation of short-term inflation fluctuations, particularly within a model structure based on HICP by component (i.e. HICP in the unprocessed food, processed food, non-energy industrial goods, energy and services sectors). The tools are generally used in order to prepare conditional forecasts, i.e. projections of inflation that are based on historical data and are conditioned on an assumed future path of a set of inflation determinants ("assumptions"). Such an approach allows for an inflation outlook that is set within and thus affected by a clearly-described, albeit imperfectly known in advance, macroeconomic environment (including for example, fiscal variables whose path is partly known in advance due to the implementation lags of fiscal policy).

In trying to achieve the aims outlined above, we would like to allow for the capturing of all possible interactions among determinants and between determinants and the HICP, including possible spill-overs between HICP components. In such an effort, we are faced with the proliferation of parameters needed to capture all these mechanisms and thus with the curse of dimensionality. In essence, there is a need to reduce the parameters to estimate, given a relatively short estimation sample.

In this context, one route to address the problem consists in modelling each HICP component separately and assuming no interaction between components. For each component, the determinants and their lags entering each equation are selected by first using judgment on possible informative variables and then following a general-to-specific approach. In this framework, inflation determinants are assumed to be exogenous.

Such an approach has indeed been used in the individual equation model used within the ECB as a main short-term forecasting tool (see Benalal et al., 2004 for a detailed description

---

<sup>3</sup> See "Econometric models of the Euro area central banks" (2005), G. Fagan and J. Morgan eds.

of the approach). It has the advantage of providing a simple way to interpret inflation fluctuations, of allowing for forecasting inflation conditional on specific future paths of its determinants listed above and for focusing on the heterogeneity of HICP subcomponents. However, it limits the ability of the model to capture the pass-through mechanism of certain prices to others and to overall inflation. For example, independence across components limits the ability of such a model to capture the so called “indirect effects”, while the exogeneity of assumptions on wages and unit labour costs limits the ability of capturing “second round effects”. In addition, the exogeneity condition implies that the model can only be used for forecasting when a full set of assumptions is provided.

In this paper, we offer an alternative proposal, in a Bayesian estimation framework. We use a large unrestricted Vector Autoregressive model that preserves all possible complex interactions across variables (for example the possible direct, indirect and second round effects). Following Banbura, Giannone and Reichlin (2010), in order to deal with the curse of dimensionality we resort to Bayesian shrinkage, which has been recently shown to provide reliable estimates under general assumptions (De Mol, Giannone and Reichlin, 2008).

Our large Bayesian Vector Autoregressive Model (BVAR) allows for incomplete conditioning. It thus has the desirable property of avoiding the need for a full set of assumptions or back-of-the-envelope calculations to fill in the missing variables or values to condition upon. Such a model can have several uses in the context of policy analysis. First, it can be used for scenario analysis, in the form of forecasts of inflation conditional to alternative paths of assumptions. In addition, as explained above, the model can also be run on the basis of incomplete conditioning or no conditioning at all. Sometimes the scope of a scenario analysis might be to assess the impact of one or a subset of conditioning variables only. In some cases, the desired conditioning may actually be on variables other than the assumptions that are standard in the Eurosystem practice, even on inflation itself. For example, it may be of interest to condition on a particular inflation path and reverse engineer the path of underlying inflation determinants consistent with assumed inflation developments.

Second, it can provide a risk assessment surrounding the projections/forecasts since the product of the model is a distribution of projections. The median baseline scenario is thus complemented and offered a better perspective once embedded within a risk assessment, in the form of measures of forecast uncertainty.

Finally, it can accommodate the inclusion of judgement. While allowing for a much wider range of interactions should minimise the need for the inclusion of judgement, it is

important that this is still allowed for. In addition, it is desirable that the model imposes that judgement in a consistent and realistic manner. Often a part or a variable in a forecasting model is corrected on the basis of informed judgement, but the interaction of the variable with the rest of the model is neglected, and possibly important economic mechanisms are excluded from the analysis. For example, in a model of inflation components (such as the ones described in this paper) the inclusion of judgement on the forecast of the energy component should not only have direct, but also indirect and possibly second round effects on the other HICP components.

In the rest of the paper we first shortly describe the individual equations approach and the data used in it as well as the BVARs. We subsequently proceed to describe the conditional and unconditional BVARs and study the accuracies of forecasts from these models in an out-of-sample forecasting evaluation. Next, we illustrate how the pass-through of an oil price shock propagates through the model, allowing for effects beyond the immediate direct impact on energy price inflation. We also present an exercise showing the impact of different conditional activity paths on inflation, so as to illustrate the extent to which our model captures a Phillips curve relationship and allows us to capture turning points in inflation given the observed path for GDP from August 2007 to October 2009. Finally, we use our model in the current juncture (i.e. from the third quarter of 2008 to the third quarter of 2009) to assess the uncertainty around the median BVAR projection and the possibility of deflation. The last section concludes.

## **2. A short description of the euro area individual equations approach**

In this section we describe the tools used at the ECB as support for the Short Term Inflation Projections. The approach is based on single equation modelling and has been described by Benalal et al., (2004).<sup>4</sup>

Under the individual equations framework, each HICP component is modelled separately and the components are then aggregated based on HICP weights to derive the projection for overall HICP, implicitly assuming no interaction between components. With this in mind, six equations have been developed, one for each of the main HICP components (unprocessed food, processed food, energy, non-energy industrial goods and services) and one for the consumer goods Producer Price Index (PPI); the latter is then used as an input

---

<sup>4</sup> Individual equations tools have been developed for the euro area as a whole and for the five largest euro area countries (Germany, France, Italy, Spain and the Netherlands). In this paper we focus on short-term forecasts and projections for the euro area.

for the equations for the main HICP components. All equations are specified in terms of the seasonally adjusted monthly rates of increase of the variables. A parsimonious representation is achieved by including only a few variables (four at the maximum) which are drawn from three broad groups (see also Table I below for more details). First, the external environment assumptions, including the paths of oil and non-oil commodity prices, including food, and the exchange rate (both euro/dollar and effective). Further conditioning variables come from available information on fiscal issues, such as VAT. At the point where no more information is available, tax rates are kept flat at the last month for which information is available. Finally, wages, unit labour costs and GDP are assumed to evolve according to the latest macroeconomic projections available. Equations are specified in terms of the monthly growth rates of the various variables.

**Table I: Euro area individual equations**

Variables used in equation for (numbers denote lag(s) used):	Unprocessed food	Processed food	Non-energy industrial goods	Energy	Services	Consumer goods PPI
Oil (\$)				0 to 1		
Non-oil commodities (Euro)						6
Food commodities (Euro)		9				
Exchange rate (\$)				0 to 1		
Exchange rate (Effective)			1			4
VAT			X			
Energy Tax				X		
Tobacco Tax		X				
Unit labour costs (3mma)		5				
Compensation per Employee (3mma)					3, 9	
GDP			X			1
Constant	X	X	X	X	X	X
Lagged dependent variable	1 to 12	1 to 2	5 to 6		1 to 5	1 to 4
Seasonal Dummies	Jan			Jan, Nov		
Consumer goods PPI			5		5, 7	

**Note:** The table reports the structure of the individual equations for the five sub-components of HICP and PPI consumer goods. In the first column, the regressors that appear in the equations are reported, while the remaining columns refer each to one of the five HICP sub-components and PPI consumer goods equations. The numbers in the columns refer to the lags with which the regressors in column 1 enter in the different equations. An x signals that a specific regressor enters contemporaneously in an equation. 3mma stands for 3 months moving average. *Source: Update of Benalal et al., (2004).*

### 3. Data

Our dataset is very close to the one described in the previous section for the individual equation approach, it is of monthly frequency, and includes 14 variables. Namely, the 5 components of HICP, PPI consumer goods, unit labour costs, GDP, compensation per

employee, oil price in US dollars, food commodity prices, commodity prices excluding food, EUR/USD exchange rate and nominal effective exchange rate.<sup>5</sup>

In order to mimic the information available to forecasters in real time, we gathered, to the extent possible, 39 vintages of the real-time data available for the corresponding quarterly Eurosystem/ECB staff projection exercises from March 2000 to September 2009. We reconstruct the availability of official data, as well as the assumptions on future paths that were available in real time for almost all the variables which are used to condition the inflation forecast in the individual equation and the conditional BVAR.<sup>6</sup> For the quarterly variables (unit labour costs, GDP and compensation per employee), we make use of the historical data, as well as the, publicly available, projected path of annual GDP growth rates.<sup>7</sup> For what concerns unit labour costs and compensation per employee, no particular future projected path is assumed. Oil and non-oil commodity prices are based on Bloomberg data on spot and futures prices. As the back-data were not complete for all of the 39 vintages, we reconstructed the oil and non-oil commodities real-time database on the basis of spot and futures' prices available at earlier points in time. Finally, exchange rates are unrevised and the assumed future path in the forecasting exercises in their case is actually flat at the latest observed value at each different data cut-off point of the different quarterly projections (implied random walk assumption). Notice that taxes also enter the original individual equations. Accordingly, we make use of them in the study of the forecasting performance of the individual equations. However, in our BVARs, we have chosen to exclude them since they were not found to improve on forecast accuracy.

## 4. The model

### 4.1 Specification and estimation

We aim to appropriately capture the dynamic interrelationships among the set of variables described in the previous section. This requires the specification of a very general model, able to capture both rich relationships across variables and rich dynamics.

Define as  $X_{i,t}$  ( $i=1 \dots N$ ) the N-dimensional set of HICP components and their determinants. A relatively unrestricted description of the statistical properties of the data is provided by the following VAR model

---

<sup>5</sup> Quarterly variables are interpolated to get monthly figures.

<sup>6</sup> Only for the HICP and the PPI we have no real-time history, but they are little revised.

<sup>7</sup> Notice that Eurosystem projections are published in form of ranges. In order to obtain point estimates, we follow the practice in Fischer, Lenza, Pill and Reichlin, (2009) and take the mid-point of the ranges.

$$X_{i,t} = C + A_1 X_{i,t-1} + \dots + A_p X_{i,t-p} + e_{i,t}$$

where  $A_0 \dots A_p$  are N-dimensional square matrices of the parameters while  $e_{i,t}$  is the N-dimensional vector of the disturbances.

Excluding taxes, the HICP components and their determinants amount to 14 variables (i.e.  $N=14$ ). We do not pre-transform variables to achieve stationarity and specify the VAR in log-levels. In order to capture the dynamic properties of our monthly dataset, we allow for 13 lags in the VAR model (i.e.  $p=13$ ). Since our sample starts only in January 1991, the task of estimating this VAR model with classical methods is not trivial. This issue is commonly known as the “curse of dimensionality”: estimating a model of such size is either unfeasible or, if feasible, would lead to unreliable results due to overfitting.

In order to solve this problem, for the estimation of the model we rely on a Bayesian approach with a Minnesota prior as recently proposed in De Mol, Giannone and Reichlin (2008) and Banbura, Giannone and Reichlin (2010). More precisely, we impose the Litterman (1986) prior model, the random walk model with drift, a very naive representation of the data that excludes rich dynamics and cross-correlation among variables since each variable  $i$  at time  $t$  depends only on a constant, its own first lag with a coefficient equal to one and a stochastic disturbance  $a_{i,t}$

$$X_{i,t} = C + X_{i,t-1} + a_{i,t}$$

We assume a normal prior distribution for the parameters of the model that is centred around the values assumed by the parameters in the prior model (i.e. one for the first lag of each variable in its own equation and zero for all other parameters). In addition we also further force the sum of the VAR coefficients towards the identity by imposing a sum-of-coefficients prior.<sup>8</sup> When imposed exactly, the latter restriction is the one implied by a VAR in first differences. Here we are using it as a prior and hence it can be seen as a form of “inexact differencing”. Standard Bayesian techniques are employed to update the prior model with sample information (represented by the normal likelihood of the model)<sup>9</sup>. The output of such procedure is the entire posterior distribution of the parameters. Such approach is convenient in that it allows a complete description of the statistical properties of the estimated parameter space and, hence, provides an appropriate framework to

---

<sup>8</sup> I.e. we impose  $A_1 - \dots - A_p = I$ .

<sup>9</sup> More precisely we use a Normal inverted Wishart prior. See Banbura, Giannone and Reichlin, 2010 for details.

describe the uncertainty around functions of the parameters like forecasts or impulse response functions or, even, model based scenarios.

The Bayesian estimation method in this paper can be interpreted as imposing inexact restrictions to the model parameters through a mixed estimation approach: our estimates of the parameters (the mean of the posterior distribution of the parameters, for concreteness)<sup>10</sup> can be seen as a sort of weighted average of the parameters in the prior distribution and in the sample (basically, the latter are the OLS estimates). The variance of the prior distribution of the parameters affects the weights in the combination, i.e. how tight the prior model is assumed to be or, alternatively, how close we are to imposing exactly the prior restrictions to the data. A very small variance of the prior distribution of the parameters (tight prior) amounts to assuming that the restrictions imposed by the random walk model are exactly satisfied, while a high variance (loose prior) assigns only a limited weight to the prior restrictions in the estimate of the parameters. The tightness of the Random Walk prior, i.e. the “degree of shrinkage”, and of the sum-of-coefficients prior (see footnote 8) is to be chosen a-priori. The next sub-section deals with the issue of how we select the tightness of the priors.

The VAR model can be used to compute unconditional forecasts but also forecasts conditional on particular assumptions on the future path of specific variables in the system (see Doan, Litterman and Sims, 1984 and Waggoner and Zha, 1999). In our case, in order to compute the entire posterior distribution of the conditional forecasts we use the algorithm developed by Banbura, Giannone and Lenza (2009) which is able to handle large dynamic systems by using Kalman filtering techniques and the algorithm of Carter and Kohn (1994). Essentially, the conditional forecasts are estimated to be the expected value of the variables of interest given not only all the available data but also the future paths of the conditioning variables.

#### *4.2 Model selection: the tightness of the prior*

The tightness of the priors is selected by maximizing the out-of-sample predictive accuracy of the model in a training sample. The training sample is given by the first 16 vintages of data, i.e. the data that were available in real time in the 16 exercises conducted between 2000Q1 (i.e., the first quarter of 2000) and 2003Q4. This training sample is chosen in order to maximise comparability with the sample used to set up the individual equations. The

---

<sup>10</sup> Notice that in the Bayesian framework it is inappropriate to refer to a final estimate of the parameters since the outcome of the Bayesian algorithm is rather the distribution of the parameters. Here, loosely, the final estimate of the parameters is referring to the mean of the posterior distribution.



measure of forecast accuracy we wish to maximize is the mean squared forecast error of the annual growth rate of aggregate HICP at the horizon of one year ahead.

More formally, define as  $\tilde{p}_{v,t+12}(\tau, \mu)$  the forecast of the log-level of the HICP<sup>11</sup> prepared by using data on HICP available until month  $t$  (for example, month  $t$  would be April for the Q2 or, alternatively, June exercises since the data of HICP for April are the last available at the cut-off date on mid-May) for an horizon of 12 months ahead in the context of the forecasting exercise (data vintage)  $v$ . The forecast of annual HICP inflation is given by

$$\tilde{\pi}_{v,t+12}(\tau, \mu) = \tilde{p}_{v,t+12}(\tau, \mu) - \tilde{p}_{v,t}$$

Notice that the forecast is a function of the tightness of the priors. Defining as  $\pi_{v,t+12}$  the annual inflation rate actually observed, we set the tightness of the random walk and the sum-of-coefficients prior ( $\tau$  and  $\mu$ , respectively) as

$$[\tau, \mu] = \arg \min \frac{1}{16} \sum_{v=2000Q1}^{2003Q4} (\tilde{\pi}_{v,t+12}(\tau, \mu) - \pi_{v,t+12})^2$$

### 4.3 Forecasting evaluation

In this sub-section, we report the outcomes of a real time forecasting evaluation of our model. We evaluate our forecasts produced for the data vintages available between 2004 Q1 and 2008 Q2 (18 quarterly forecasting exercises).

The target variable in our forecasting exercises is the year-on-year HICP inflation rate

$$\pi_{t+h} = p_{t+h} - p_{t+h-12}$$

and we evaluate the forecast accuracy of our model for horizons ( $h$ ) ranging from one month ahead (nowcast) to 18 months ahead. The evaluation sample ranges from April 2004 until October 2009. Notice that the 18 months horizon of the last data vintage we consider in this evaluation (2008 Q2, for which the last available HICP data is April 2008) is exactly October 2009. Indeed, we limit our evaluation to the 2008 Q2 data vintage because we only consider the data vintages for which we have the whole evaluation horizon available. Our statistic of forecast accuracy in Table 2 below is given by the Mean Squared Forecasting Error (MSFE):

$$MSFE(h) = \frac{1}{K} \sum_{v=2004Q1}^{2008Q2} (\tilde{\pi}_{v,t+h} - \pi_{t+h})^2$$

---

<sup>11</sup> The forecast of aggregate HICP is obtained by aggregating the forecasts from the sub-components obtained in our VAR. We aggregate HICP components by using the weights that were assigned in real time to the different components

where  $K$  is the number of exercises over which the MSFE for horizon  $h$  is computed. The Mean Squared Forecasting Error is the sum of two components: the bias (mean of forecast errors) and the variance of the forecast errors. The bias component reflects how good a forecast is to track the average level of the target variable while the variance of the forecast errors provides information on the ability of the forecast to track fluctuations in the target variables. Table 2 below reports the forecast bias in order to allow the decomposition of MSFE in its two components.

Table 2 reports results from four different forecasting models. Rows 1 and 2 report respectively the BVAR results for the conditional and the unconditional exercises. The third row reports the results for the (conditional) exercises run with the individual equations described in section 2. Notice that, differently from the BVAR models, the individual equations assume that all the variables listed as regressors in table 1 are exogenous and, hence, they cannot produce forecasts without relying on a set of conditional assumptions for all such variables. In section 3, we describe our real time database highlighting that it includes also the publicly available projected paths of almost all the regressors of the individual equations. In order to obtain projected paths for unit labor costs and wages, in the individual equations we use as projected paths their BVAR forecasts. Finally, row 4 report results from a Naïve benchmark model: the random walk in levels with drift, which forecasts future inflation as the average historically observed inflation (Prior Model).

**Table 2: Outcomes of forecasting evaluation**

Horizon	3	6	9	12	15	18
<b>Mean Squared Forecasting Errors</b>						
<i>BVAR Conditional</i>	0.09	0.23	0.58	0.90	1.27	1.43
<i>BVAR Unconditional</i>	0.11	0.24	0.62	1.03	1.59	1.86
<i>Individual equations</i>	0.12	0.30	0.60	0.93	1.38	1.66
<i>Random Walk (Prior model)</i>	0.13	0.28	0.56	0.81	1.27	1.55
<b>Bias</b>						
<i>BVAR Conditional</i>	-0.10	-0.20	-0.23	-0.25	-0.18	-0.09
<i>BVAR Unconditional</i>	-0.13	-0.22	-0.22	-0.22	-0.10	0.02
<i>Individual equations</i>	-0.15	-0.30	-0.35	-0.40	-0.30	-0.19
<i>Random Walk (Prior model)</i>	-0.17	-0.29	-0.31	-0.32	-0.17	-0.05

**Note:** The upper panel of the table reports the mean squared forecast errors for the four models defined in column 1 for the forecast horizons from 3 to 18 months ahead. The lower panel, instead report results in terms of bias.

As can be seen in Table 2 above, the real-time conditional BVAR forecasts perform satisfactorily when compared to the individual equations at all horizons. Conditioning information seems to be important in order to achieve this result, as unconditional BVAR

forecasts do not perform as well as conditional forecasts. The conditional BVAR forecasts are also more accurate than the random walk forecasts up to six months ahead; at longer horizons random walk forecasts are harder to outperform, although the accuracy of BVAR forecasts improves again in relative terms with respect to random walk forecasts at horizons longer than one year. The difficulty to outperform random walk forecasts of inflation in the recent sample across a wide range of models and institutional forecasters both in the US and the euro area is not surprising (see, for example, D'Agostino, Giannone and Surico, 2006 for the US and Fischer, Lenza, Pill and Reichlin, 2009 for the euro area). In bias terms, the superiority of the BVARs, and particularly the conditional BVAR, is very clear. It is worth noting that all other models are characterised by sizeable negative biases with the individual equations almost consistently suffering from the highest negative bias. Finally, in order to show the features of the BVAR forecasts, in figure I we report the different quantiles from the distribution of the six-months ahead projection for HICP annual inflation produced by the model in real time: i.e. estimating the models using the official data and the conditioning assumptions (see description in section 3) that were available in real time at each round of the Eurosystem/ECB staff macroeconomic projections. To evaluate the reliability we also report the inflation that has been observed afterward for each period (solid black line).

INSERT FIGURE I HERE

The figure highlights how the forecasts have been on average pretty accurate and with a slight negative bias (the downward bias has also characterized the judgemental forecasts, see Fisher, Lenza, Pill and Reichlin, 2009). The decline in inflation that has accompanied the global recession has been a big surprise for the model. In particular, the observed decline is at the beginning outside of the bands, but after few months the model adapted. It must be stressed that the forecast uncertainty we compute does not take into account the uncertainty around the conditioning assumptions which are treated as if they were the true data, rather than forecasts. We will investigate later the most recent episode by conditioning on the ex-post observed value for economic activity.

## **5. Capturing the price pass-through mechanism – an illustration using an oil price shock**

In this section we show how our model can capture the mechanism through which an initial shock to a variable can have not only a direct impact, but also propagate further as it passes

through to different price variables and HICP components. The example highlights the ability of the model to assess the effects of persistent shocks beyond the short-term horizons and, hence, to reflect their consequences at horizons that are more relevant for monetary policy.

The exercise is performed in the following way: we implement an exogenous, permanent, one-off increase to the oil price by 10% from the baseline (unconditional) forecast, at time  $t$ . The dynamics for the subsequent months are left unrestricted. The identification of the shock is done under no restriction on the effect of the oil price shock on energy prices and exchange rates (potentially fast variables), but we assume a restricted responsiveness of prices, wages and real variables, so that at time  $t$  are kept at the baseline level (slow variables). The dynamics for the subsequent months are left unrestricted.<sup>12</sup>

We then assess the effects over the two subsequent years on overall HICP and its components, so that we can trace the contributions from the different HICP components along the forecast horizon.

Figure 2 illustrates the impulse response of log-level of overall HICP to the oil shock. Figure 3 decomposes the dynamics of the log-level of overall HICP in the contributions from the HICP energy and non-energy components (the latter is the sum of the contributions of unprocessed and processed food, non-energy industrial goods and services). We report the distribution of the impulse response functions, although below we comment the median response.

INSERT FIGURES 2 AND 3 HERE

The upper panel of figure 2 describes the shock to the oil price and the subsequent endogenous dynamics of the latter as captured by the BVAR. The shock is defined as raising the oil price by 10% on impact. Subsequently, the level of the oil prices only slightly decreases, remaining at levels that are by about 9% permanently higher than in the pre-shock period.

As seen in the lower panel of figure 2, the level of HICP increases immediately when the shock is imposed by somewhat less than 0.1%. It then continues to increase until the end of the forecast horizon, but at a much weaker pace. Turning to figure 3, we can see more clearly how this path of overall HICP is explained by the behaviour of the different HICP components. The first jump in the level of HICP, is entirely due the energy component. After the initial impact, the contribution of the level of HICP energy to overall HICP

---

<sup>12</sup> These identification restrictions make our exercise equivalent to impulse response functions to an oil shock identified using a recursive (Cholesky) scheme.

stabilizes with a slight tendency to decrease. Notice that in the case of the individual equations, where no interaction is allowed for between components and the assumptions are assumed to be exogenous, the only impact on overall HICP would be the direct and basically immediate one through HICP energy. The more complex pass-through mechanics, allowed for in our BVAR, can be seen by the responsiveness of the non-energy components, whose contribution continuously increases as the oil price shock feeds through, because of the higher energy costs implied (indirect effects) and the impact of higher wages due to the initial increase in HICP inflation (second round effects).

In conclusion, the BVAR model seem to be able to capture the interactions between differing price determinants and components and as such enables to appropriately study the consequences of an oil shock on the medium-term outlook for inflation.

## **6. Does the model capture a Phillips curve in the euro area?**

A fundamental block of theoretical and empirical models of inflation is the Phillips curve. The exact formulation of the curve has been revised several times since its introduction in the 1950s, but its central hypothesis remained the one of a short-run positive relationship between economic activity and inflation. In a simple exercise we test how strong is the Phillips curve trade-off in the euro area.

The exercise is organized as follows. Taking the model estimated over the whole sample, we conduct an unconditional forecast on the period August 2007- October 2009. We then produce a second forecast on the same sample conditional only on the observed GDP from August 2007 onwards, thus taking into account the information about the economic cycle in the last two years. Figure 4 plots the BVAR unconditional forecasts (brown dashed line), the distribution of the forecasts conditional on GDP (shades of red) and the inflation outcomes (black solid line) over the January 2004 – October 2009 sample.

INSERT FIGURE 4 HERE

The figure shows that, according to our model, the euro area economy presents a relevant inflation-output relationship as considering information on the economic cycle in the post-August 2007 period determines a major improvement in tracking inflation relative to unconditional forecasts. Even during the recent very pronounced up and downswing, in which inflation reached both the absolute peak and trough in the euro area sample, inflation is relatively well described by the conditional forecasts, and the turning points in inflation are correctly picked up by the model. This results strikes in contrast with the well

documented evidence that the Phillips curve relation has almost disappeared in the last two-three decades. As a consequence inflation has become much harder to predict<sup>13</sup>. Our results indicate that the Phillips curve has come back during the recent recession. This result is in line with Stock and Watson (2008) who suggest some forms of non-linearities that make the Phillips curve stronger when deviations of unemployment from its natural level are large.

Finally, notice that both the peak and the trough of inflation lie in the most extreme quantiles of the forecast distribution, showing how unusual the recent experience of inflation has been in the euro area sample and how the information in GDP is not able to fully account for the inflation fluctuations in the recent conjuncture. This exercise provides evidence that real activity is one of the main drivers of price developments, and shows at the same time that the model is able to capture the inflation-output relationship.

## **7. Recent juncture: Uncertainty around the inflation projections and deflation risks**

In this section we will show an example of HICP inflation projections produced by the conditional BVAR, conditioned on assumptions similar to the ones underlying the last 5 quarterly Eurosystem/ECB projection rounds up to and inclusive of September 2009. As stressed in the introduction, our framework can be used to provide an assessment of the uncertainty around the forecasts; in an illustration of this technical capability of our model we report the distribution of the forecasts around the median projection. Each projection is run based on available data at the start of the month preceding the one when the projection is released. Hence, the 1-month-ahead forecast of HICP is essentially a nowcast. For example, the first projection shown here is based on a set of assumptions similar to the ones underlying the projection exercise conducted in September 2008, with a cut-off date for data in mid-August 2008 and the 1-month-ahead projection being the projection for HICP inflation in August 2008.

INSERT FIGURE 5 HERE

Moving from the earlier to the most recent exercises, the whole of the distribution has shifted downwards, most noticeably in the March 2009 (panel C) exercise. For this exercise

---

<sup>13</sup> For evidence in the US and in the euro area see, respectively, Atkeson and Ohanian (2001) and Fischer, Lenza, Pill and Reichlin (2009).

the downward shift of the distribution brings it almost as a whole below the zero line around mid-2009. Turning to the latest two exercises, the differences are rather small. The distribution becomes narrower, in line with the fact that a larger and larger part of 2009 annual inflation becomes data and thus less is left to be forecasted. In addition, the median and the distribution as a whole shifted slightly upwards. More in details, in the case of the June 2009 (panel D) exercise, the picture hardly changes compared to March 2009, as the impact of the higher than expected commodity prices compensates for the negative revisions on the real side of the economy. In the September 2009 (panel E) exercise the new assumed outlook for both activity as well as commodity prices implies a slight upward shift for the median and the whole distribution, which has now narrowed a lot compared to the previous 4 panels.

We can also compare the conditional BVAR projections for overall 2009 inflation with the ones derived by the unconditional BVAR and the mid-point of the quarterly Eurosystem/ECB macroeconomic projections(see Table 3).<sup>14</sup> Notice that the latter projections are not reported in terms of point estimates, but of ranges as also in Table 3. Here, again, we follow Fischer, Lenza, Pill and Reichlin., 2009 and use the mid-point of the range for our comparisons. In the first two exercises, the BVARs were above the mid-point of the quarterly Eurosystem/ECB macroeconomic projections, while in the three last rounds the BVARs are suggesting a weaker inflation outlook. In general (with the exception of the June 2009 exercise) the conditional BVAR lies closer to the quarterly Eurosystem/ECB macroeconomic projections than the unconditional BVAR; this is related to the fact that they are both conditional on similar information. Finally, the conditional BVAR forecast distribution is less volatile than the unconditional, as expressed by the standard deviations in the smaller numbers under the projected HICP inflation rates. This is due to the fact that the assumptions on future paths of the variables on which the conditional projection rest are supposed to be known with certainty while the unconditional forecasts distribution also incorporates the uncertainty about the future of inflation determinants.

---

<sup>14</sup> The Eurosystem staff as a whole conducts two projection exercises per year, one in June and one in December. In the intervening quarters, ECB staff conducts two additional projection rounds (March and September).

**Table 3: Comparison of HICP inflation projections**

2009-Inflation	Sep-08	Dec-08	Mar-09	Jun-09	Sep-09
<b>Conditional BVAR</b>	2.5 0.54	1.7 0.52	0.1 0.42	0.2 0.22	0.3 0.13
<b>Unconditional BVAR</b>	3.3 0.83	1.9 0.66	-0.6 0.61	0.3 0.36	0.3 0.15
<b>Quarterly Eurosystem/ECB staff macroeconomic projections*</b>	2.3 – 2.9 [2.6]	1.1 – 1.7 [1.4]	0.1 – 0.7 [0.4]	0.1 – 0.5 [0.3]	0.2 – 0.6 [0.4]

**Note:** The table reports the projected 2009 annual inflation rates, conditioned on assumptions similar to the ones underlying the corresponding Eurosystem/ECB projection rounds as produced by the BVARs and compares it to the actual Eurosystem/ECB projections. The standard deviation of the BVARs is also reported in smaller fonts.

\* **Source:** ECB Monthly Bulletins of the respective months. The table reports the published projection ranges, as well as the mid-point of the published ranges in brackets below.

## 8. Conclusions

The approach to short-term inflation forecasting presented in this paper has been shown to perform in a satisfactory way when compared to existing alternatives. This suggests that the better ability of the BVARs to capture more complex mechanisms in the pricing chain may be relevant for gaining accuracy in euro area inflation forecasts. This feature has been illustrated in more detail with an example of an oil price shock and how its pass-through to different price variables and HICP components is captured by our model. In this, we show that immediate direct effects on energy are propagated as they pass-through to producer prices, wages and further HICP components (indirect and second-round effects). In addition, we find that the BVAR manages to limit the bias in the forecasts quite significantly. Particularly compared with the individual equations approach, the improvement is striking as the latter suffers from negative bias consistently in all horizons.

We have used our model for two sets of exercises.

First, we investigated the extent to which our models points towards the presence of a Phillips curve relationship in the euro area. We find that there is indeed a relevant inflation-output relationship in the euro area as considering information on the economic cycle in the post-August 2007 period determines a major improvement in tracking inflation relative to unconditional forecasts.

We have then used our model to produce a baseline forecast for overall inflation surrounded by uncertainty bands based on the different quantiles of the forecast



distribution produced. Making use of the density forecasts produced for the last five quarterly projection rounds, up to September 2009, we have shown how our model can support a baseline projection with an assessment of uncertainty and, hence, offer insights on issues such as the recent discussion on deflation risks.

Our analysis has also made clear that the structure of the model is such that it can be used in both a conditional and an unconditional version. Having the option of running a forecast with or without a full set of conditioning variables implies a flexibility that is particularly important in an environment of staggered data releases which implies that, in most cases, only a subset of the most recent releases of the variables in the model is available at the time of the projections. In essence our model is able to work with unbalanced datasets, thus allowing for taking into account of each additional data release and use of the latest information to optimally improve the forecast.

Furthermore, our model is easily re-estimated, so that all available information at any given point, even as part of an unbalanced part dataset, contributes to the refinement of the parameters.

Finally, our model also allows for the inclusion of expert judgement. We are currently looking into incorporating tax-related information via judgement, but it can also be used to complement the model forecast with any information outside the information set of the model variables. Most importantly, any judgement entered in one variable is by construction allowed to impact all other possibly relevant ones, thus ensuring the internal consistency of the judgemental projection.

## REFERENCES

- Atkeson A. and L. Ohanian (2001): “Are Phillips Curve useful for forecasting Inflation”, *Reserve Bank of Minneapolis, Quarterly Review*, 25(1), Pages 2–11.
- Banbura M., D. Giannone and M. Lenza (2009): “A large Bayesian VAR for the euro area”, mimeo ECB.
- Banbura M., D. Giannone and L. Reichlin (2010): “Large Bayesian VARs”, *Journal of Applied Econometrics*, Vol. 25(1), pages 71-92,.
- Benalal N., J.L. Diaz del Hoyo, B. Landau, M. Roma and F. Skudelny (2004): “To aggregate or not to aggregate?” Euro Area Inflation Forecasting, ECB Working Paper series No. 374.
- Carter C. K. and P. Kohn (1994): “On Gibbs sampling for state space models” *Biometrika*, Vol. 81, Pages 115-131.
- D’Agostino, A., D. Giannone and P. Surico (2006): “(Un)predictability and macroeconomic stability”; ECB Working Paper N. 605.
- De Mol C., D. Giannone and L. Reichlin (2008): “Forecasting using a large number of predictors: is Bayesian regression a valid alternative to principal components?”, *Journal of Econometrics*, Vol. 146, No. 2, Pages 318-328.
- Doan T., R. Litterman and C. Sims (1984): “Forecasting and conditional projection using realistic prior distributions”, *Econometric Reviews*, Vol. 3, Pages 1-100.
- ECB (2001), “A Guide to Eurosystem Macroeconomic Projection Exercises”.
- G. Fagan and J. Morgan eds. (2005), “Econometric models of the Euro area central banks”, Edward Elgar Publishing.
- Fischer, B., M. Lenza, H. Pill and L. Reichlin (2009): “Money and monetary policy in the euro area 1999-2006”, *Journal of International Money and Finance*, pp. 1138-1164.

Kadiyala, K. R. and S. Karlsson (1997): "Numerical methods for estimation and inference in Bayesian VAR-Models", *Journal of Applied Econometrics*, Vol. 12, Pages. 99-132.

Litterman R. (1986): "Forecasting with Bayesian Vector Autoregressions – five years of experience", *Journal of business and economic statistics*, Vol. 4, Pages 25-38.

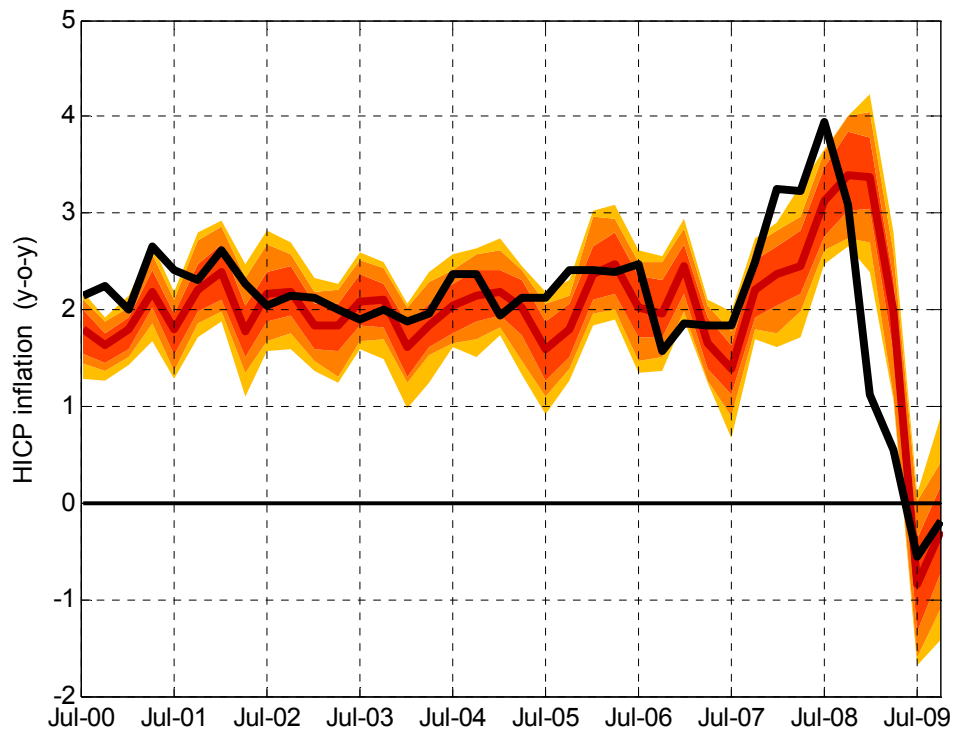
Robertson, J. C. and E. W. Tallman (1999): "Vector Autoregressions: forecasting and reality", *Economic Review (Q1)*, 4-18.

Stock, J. H. and Watson, M. W. (2008): "Phillips Curve Inflation Forecasts", NBER Working Paper N. 14322.

Waggoner D. F. and T. Zha (1999): "Conditional Forecasts In Dynamic Multivariate Models," *The Review of Economics and Statistics*, Vol. 81, Pages 639-651.

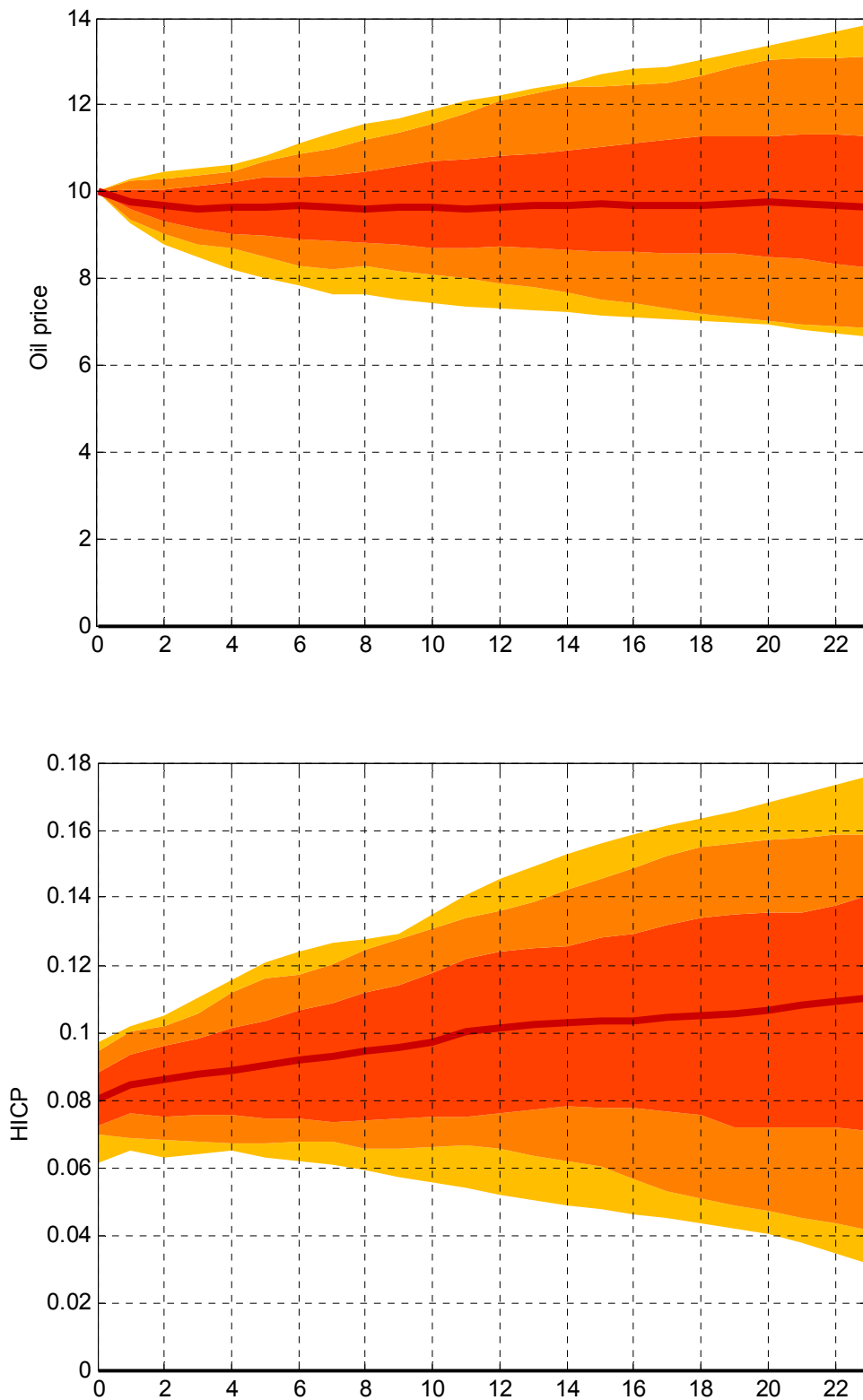
## FIGURES IN TEXT

Figure I: Six months ahead BVAR forecasts



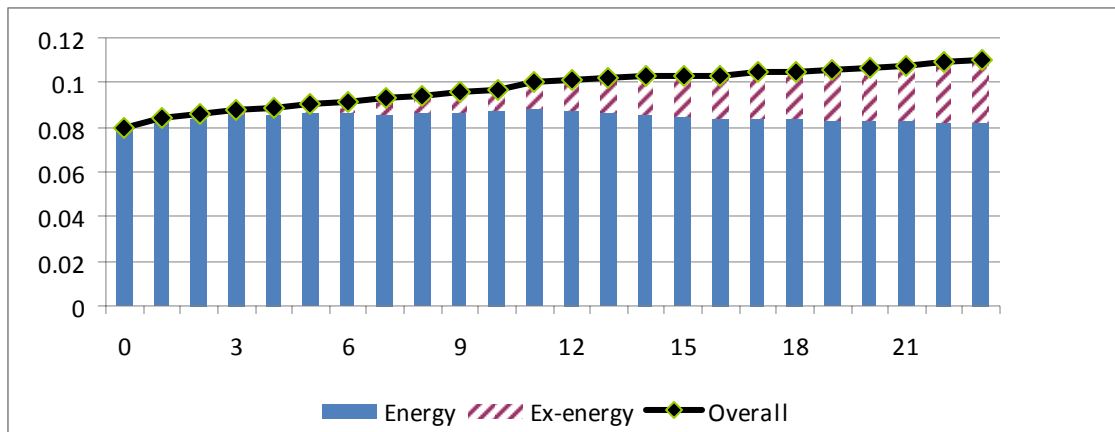
**Note:** The figure shows the distribution of the six months ahead forecasts of HICP inflation in the sample July 2000 to October 2009. More precisely, the median and different quantiles of from 68% (darker) to 95% (lighter). The black solid line represents observed inflation in the sample. Figures on the vertical axes are expressed in percentage points.

**Figure 2: Impulse response functions of the levels of oil price and HICP to 10% shock in oil prices**



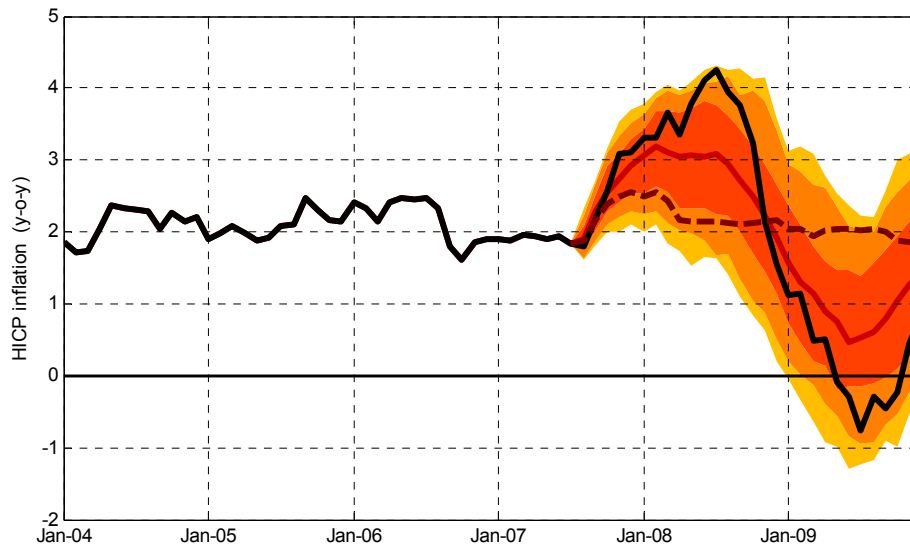
**Note:** The figure shows the distribution of the impulse response function (IRF) of the oil price (upper panel) and the log-level of HICP (lower panel) to a shock amounting to a 10% increase of the oil price and happening in month 1. The figures report the distributions of the IRF; more precisely, the median and different quantiles of from 68% (darker) to 95% (lighter). On the vertical axis, figures are expressed on percentage points.

**Figure 3: Contribution of energy and non-energy components to the response of the log-level of HICP**



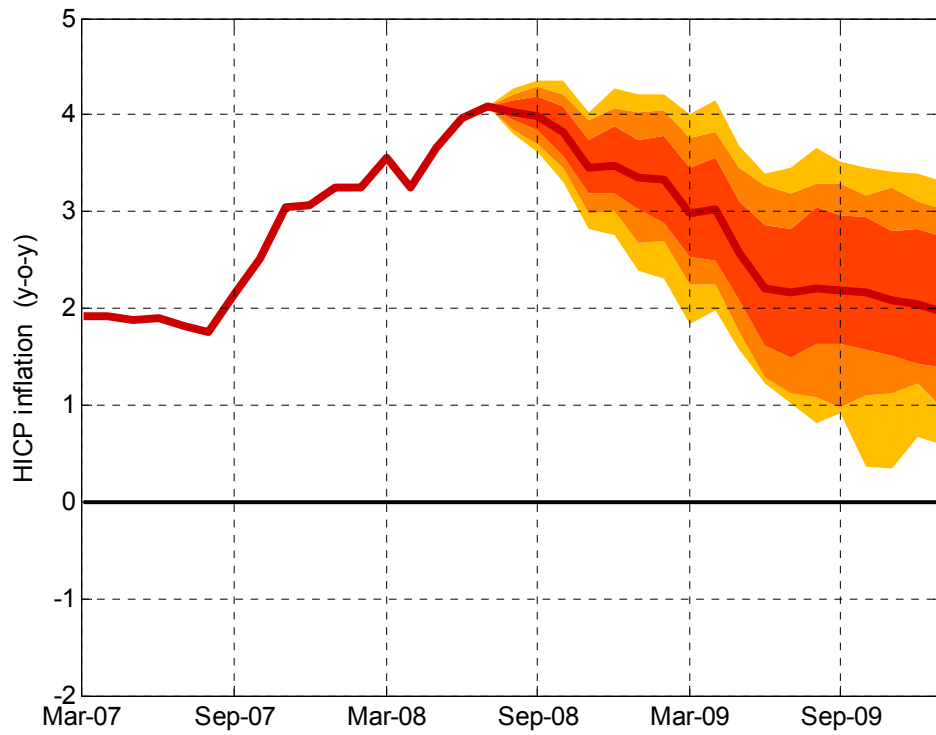
**Note:** The figure shows the contribution of the energy (blue bars) and non-energy (red dashed bars) components to the response of the HICP log-level (black line).

**Figure 4: Euro area Phillips curve**

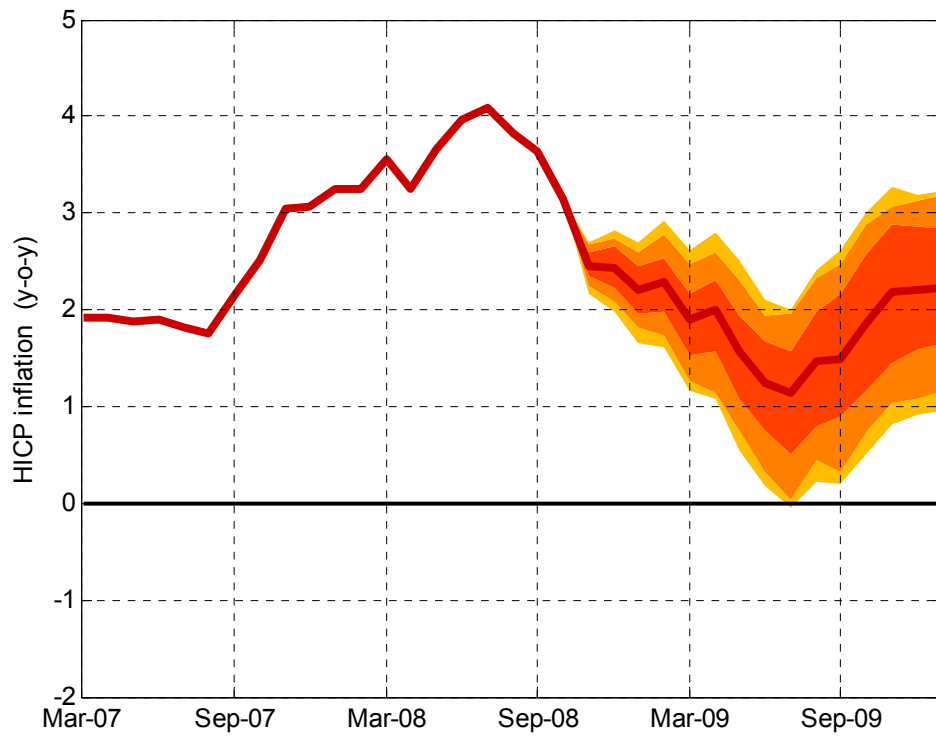


**Note:** The figure shows the distribution of the forecasts of HICP inflation in the sample August 2007 to October 2009. More precisely, the median and different quantiles of from 68% (darker) to 95% (lighter). The brown dashed line represents the unconditional BVAR HICP inflation forecasts. The black solid line represents observed inflation in the sample January 2004 – October 2009. Figures on the vertical axes are expressed in percentage points.

**Figure 5, Panel A: September 2008**

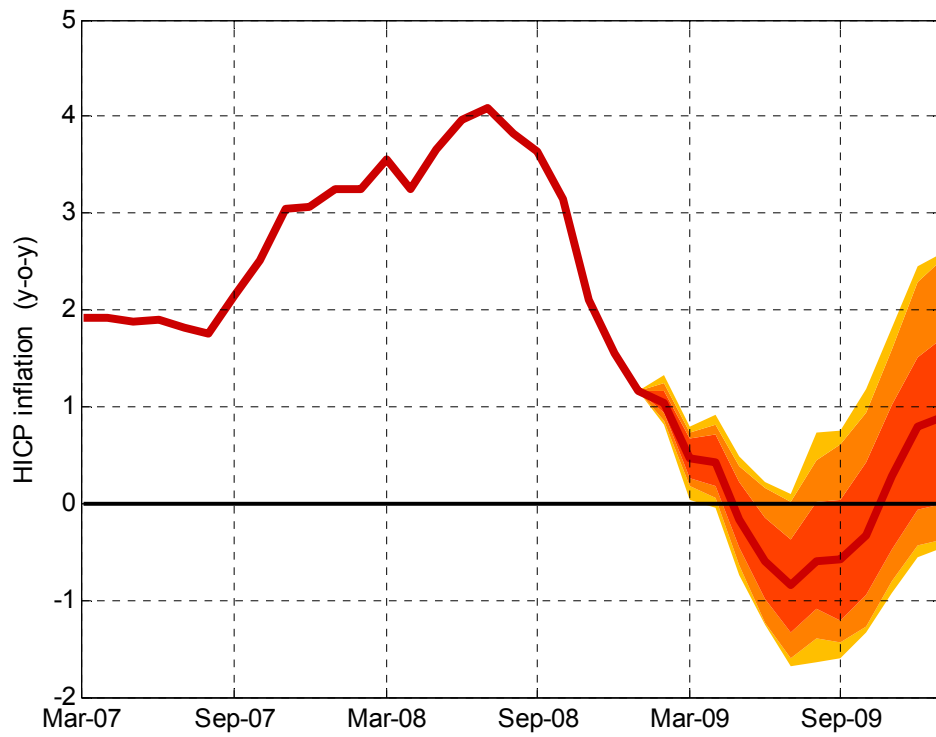


**Figure 5, Panel B: December 2008**

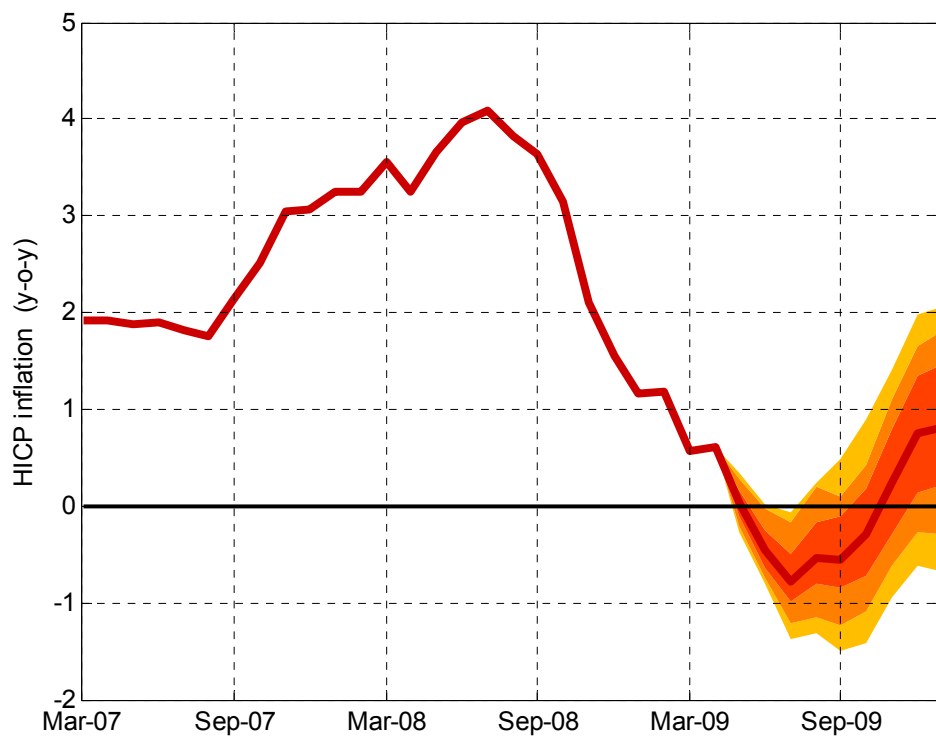




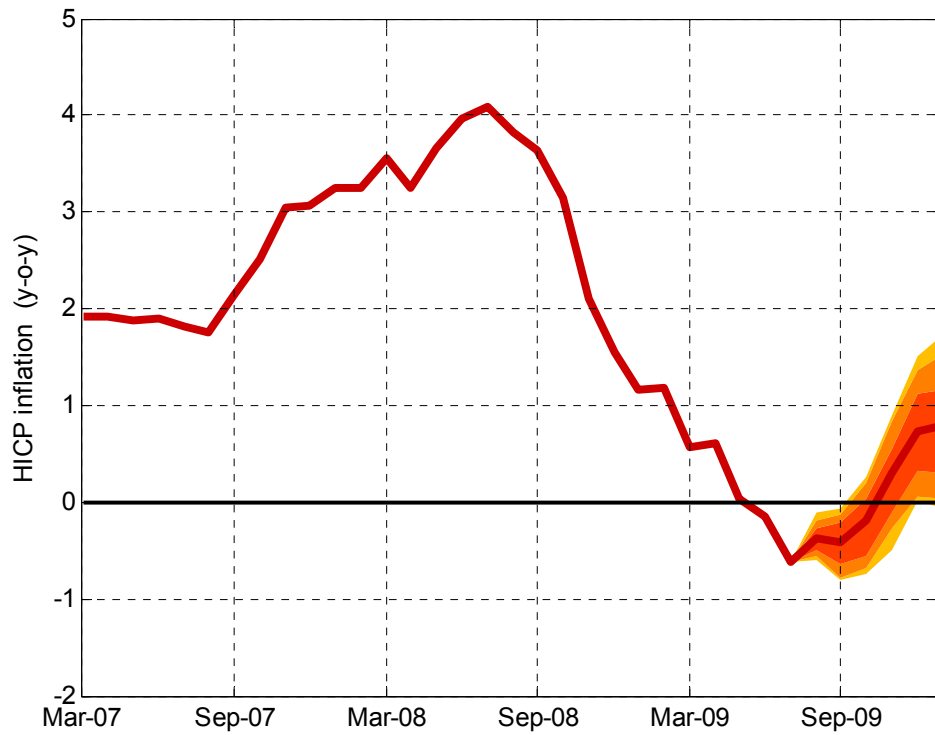
**Figure 5, Panel C: March 2009**



**Figure 5, Panel D: June 2009**



**Figure 5, Panel E: September 2009**



**Note:** The panels A to E show the distribution of the forecasts from one to 18 months ahead of HICP inflation as would have been described by the BVAR conditional on the information available in real-time in the forecasting exercises conducted in September 2008 (Panel A), December 2008 (Panel B), March 2009 (Panel C), June 2009 (Panel D) and September 2009 (Panel E). More precisely, in each panel we report, the median and different quantiles from 68% (darker) to 95% (lighter).