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Short-term inflation projections: A Bayesian vector autoregressive approach

Domenico Giannone[a,b,c], Michele Lenza[a,d,b,*], Daphne Momferatou[d], Luca Onorante[d,e]

[a] Université Libre de Bruxelles, Belgium
[b] ECARES, Belgium
[c] CEPR, London, United Kingdom
[d] European Central Bank, Germany
[e] Cenral Bank of Ireland, Ireland

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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 Prices (HICP) and their determinants. The model generates accurate conditional and unconditional forecasts in real-time. We find a significant pass-through effect of oil-price shocks on core inflation and a strong Phillips curve during the Great Recession.

1. 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 determine whether such forces have 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 are among the regular tasks performed within the context of the broader framework of the quarterly Eurosystem/ECB projections. In between such projections, the assessment of inflation developments is updated with the latest information available. Several different approaches are used at different times and frequencies.[1]

Within the ECB, several tools have been developed for the short-term forecasting of inflation, as measured by the Harmonized Index of Consumer Prices (HICP). The main feature of such tools is that they enable the timely use of detailed disaggregated information on inflation that is not always easy to incorporate in the stylized structural macroeconomic models which are typically used, in the Eurosystem, as 'work horse' models when building medium-term projections (see Fagan & Morgan, 2005).

Models devoted to the forecasting of inflation in the short-term should meet two main requirements. Firstly, they should take into account the maximum amount of information available 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, as well as 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 the HICP by component (i.e. the HICP in the unprocessed food, processed food, non-energy industrial goods, energy and services sectors). The tools are generally

* Correspondence to: European Central Bank, Kaiserstrasse 29, 60311, Frankfurt am Main, Germany. Tel.: +49 69 13445671.
E-mail address: michele.lenza@ecb.europa.eu (M. Lenza).

[1] For more details on the projection process, see ECB (2001).

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used for preparing conditional forecasts, i.e., projections of inflation that are based on historical data and are conditional 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 paths are partially known in advance, due to the implementation lags of fiscal policy).

In order to meet these requirements, short-term forecasting tools should have the ability to capture all possible interactions among determinants and between determinants and the HICP, including possible spill-overs between HICP components. However, this flexibility may come at the cost of a proliferation of the parameters needed to capture all of these mechanisms. This issue is commonly known as the "curse of dimensionality".

In this context, the curse of dimensionality problem has traditionally been addressed by modelling each HICP component separately, and by selecting the inflation determinants and their lags using heuristic procedures that combine expert judgment with a statistical assessment of the predictive accuracy (see Benalal, Diaz del Hoyo, Landau, Roma, & Skudelny, 2004, for a detailed description). The models constructed using this approach have a number of drawbacks. First, they have limited abilities to capture the pass-through of shocks along different components of prices ("indirect effects"). Second, they cannot account for "second round effects", since the determinants of inflation, such as wages, are treated as pre-determined. Third, they can only be used for forecasting when a full set of assumptions, i.e., the entire path for all of the determinants of inflation, is provided. Finally, assessing the uncertainty surrounding the model predictions is difficult, since the same data set is used both to select the model and to estimate the parameters in the selected model (see Danilov & Magnus, 2004).

In this paper, we propose an alternative modelling strategy that preserves all possible complex interactions across variables, hence allowing for possible direct, indirect and second round effects. In order to deal with the curse of dimensionality, we resort to Bayesian shrinkage, which provides reliable estimates under general assumptions (see De Mol, Giannone, & Reichlin, 2008). Specifically, we construct a large Bayesian autoregressive (BVAR) model in the spirit of Banbura, Giannone, & Reichlin, 2010. This modelling strategy is confronted with the issue of setting the relative weights of prior and sample information. We follow Giannone, Lenza, & Primiceri, 2012 and treat the coefficients that govern the tightness of the prior distribution as unknown parameters.

The proposed framework has several potential uses in the context of policy analysis. First, it could be used to compute conditional and unconditional forecasts. Second, it could be used for scenario analysis, in the form of forecasts of inflation conditional on alternative paths for both HICP components and its determinants. Finally, it can provide a theoretically-grounded assessment of the uncertainty surrounding predictions.

The paper is organized as follows. In Section 2, we begin by briefly describing the data we use in our BVARs. Since the choice of the variables is based on the individual equations approach described above, we also discuss such approaches briefly in the data section. In Section 3, we describe the model and assess the accuracy of the conditional and unconditional real-time predictions of the model. Finally, we illustrate the complexity of the interactions captured by our model by means of two exercises. First, we study the propagation of an oil price shock through the model, allowing for effects beyond the immediate direct impact on energy price inflation. Second, we study the strength of the Phillips curve during the Great Recession. Finally, the last section concludes.

2. The euro area individual equations approach and the database

Concerning the dataset, our model draws heavily on past experience of the models developed at the ECB as support for the short-term inflation projections (see Benalal et al., 2004).[2]

The following components of the HICP enter the model separately: unprocessed food, processed food, energy, non-energy industrial goods and services. The components are then aggregated based on HICP weights in order to derive the projection for the overall HICP.[3] Additional variables include the producer price index (PPI) for consumer goods, unit labour costs, GDP, compensation per employee, oil price in US dollars, food commodity prices, commodity prices excluding food, the EUR/USD exchange rate and the nominal effective exchange rate.[4]

In order to mimic the information available to forecasters in real-time, we gathered, as far as possible, the real-time data available for the corresponding quarterly Eurosystem/ECB staff projection exercises from June 2002 to June 2012. Four of these exercises are conducted each year, and hence, we have been able to collect 41 data vintages. Generally, these vintages reflect the data availability experienced in the third week of the second month of each quarter; i.e., the so-called *cut-off date* of our database is placed in the third week of the second month of each quarter. In each vintage, data samples start in January 1992. We reconstruct the availability of the official data, as well as the assumptions on future paths that were available in real-time, for almost all of the variables which are used to condition the inflation forecasts in the individual equations and the conditional BVAR. For the quarterly variables (unit labour costs, GDP and compensation per employee),

2 Tools for individual equations have been developed both 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.

3 For more information on the aggregation procedure, see the data appendix at the end of the paper.

4 Taxes on energy, tobacco and value added also enter the model of Benalal et al. (2004). We have chosen to exclude these variables from the BVAR model since they have been found to have little impact on the forecast accuracy, most probably because such variables often change slowly, making it hard to pin-down their contribution to the dynamics of other variables.

we make use of both the historical data and the (publicly available) projected path of annual GDP growth rates,[5] while no particular future projected path is assumed in relation to unit labour costs and compensation per employee. Oil and non-oil commodity prices are based on Bloomberg data on spot and futures prices. The exchange rates are unrevised, and in their case, the assumed future path in the forecasting exercises is flat at the latest observed value (i.e., the exchange rate is assumed to follow a random walk in levels without drift). For HICP components and PPI consumer goods, we use ex-post revised historical data; however, there is little revision of the HICP data, so this aspect should not have any serious effect on our results (see Giannone, Henry, Lalik, & Modugno, 2012, on this point). In order to reconstruct the end-of-sample availability of HICP data as well, we have analysed the calendar of releases of HICP, and found that, at the cutoff dates of our database (i.e., the third week of the second month in each quarter), we normally have the HICP data for the first month of the current quarter, while we only have PPI consumer goods for the last month of the previous quarter. Importantly, our HICP sample finishes in June 2012, which is the final date at which we can evaluate the forecasting performance of our models. Further details on the database, namely on the interpolation of quarterly variables, seasonal adjustments and the aggregation of consumer prices' sub-components, are available in the data appendix at the end of the paper.

3. The model

3.1. Specification and estimation

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

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

$$X_{i,t} = A_0 + A_1 X_{i,t-1} + \cdots + A_p X_{i,t-p} + e_{i,t},$$

where $A_0, \ldots, A_p$ are square matrices of size N of the parameters, while $e_{i,t}$ is a vector of size N of the disturbances. Excluding taxes, the HICP components and their determinants amount to fourteen variables (i.e., $N = 14$). We do not pre-transform the 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 thirteen lags in the VAR model (i.e., $p = 13$). Since our sample starts only in January 1992, the task of estimating this VAR model with classical methods is not trivial. This issue is commonly known as the "curse of dimensionality", and estimating models of such a size is either infeasible or, if feasible, unreliable, with poor results due to overfitting.

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

We address this issue by shrinking the model's coefficients toward those of the naïve and parsimonious random walk with drift model, $X_{i,t} = \delta_i + X_{i,t-1} + u_{i,t}$. Banbura et al. (2010) and De Mol et al. (2008) have shown that this approach reduces the estimation uncertainty without introducing a substantial bias. This desirable property is due to the tendency for macro time series to co-move over the business cycle, which creates scope for the data to point "massively" in the same direction against a naïve prior model that does not allow for any dynamic interaction. The resulting model offers a parsimonious but reliable estimate of the complex dynamic interactions among the macro, monetary and financial variables included in the data set.

In more detail, we use a normal-inverted Wishart prior centred on a random walk model. For Σ, the covariance matrix of the residuals, we use an inverted Wishart with the scale parameter given by a diagonal matrix Ψ and $d = n + 2$ degrees of freedom. This is the minimum number of degrees of freedom that guarantees the existence of the prior mean of Σ, which is equal to $\Psi/(d - n - 1) = \Psi$.

For the autoregressive coefficients $(A_1, \ldots, A_p)$, we use the Minnesota prior, the sum of coefficients priors, and the "dummy-initial-observation" prior, originally proposed by Doan, Litterman, and Sims (1984), Litterman (1986) and Sims (1993), respectively. In relation to the Minnesota prior, conditional on the covariance matrix of the residuals, the prior distribution of the autoregressive coefficients is normal, with the following means and variances:

$$E(A_1) = I_n \qquad \text{while } E(A_2) = \cdots = E(A_p) = 0_{n,n}$$
$$\mathrm{Cov}\{(A_s)_{ij}, (A_r)_{hm}\} = \lambda^2 \Sigma_{ih}/(s^2 \Psi_{ii}),$$
$$\text{if } m = j \text{ and } r = s, \text{ zero otherwise.}$$

Note that the variance of this prior distribution decays with the lag, and that the coefficients associated with the same variables and lags in different equations are allowed to be correlated. The factor $1/s^2$ is the rate at which the prior variance decreases with an increasing lag length, and Σ_{ih}/Ψ_{ii} accounts for the different scale and variability of the data. Finally, the key hyperparameter is λ, which controls the scale of all of the prior variances and covariances, and effectively determines the overall tightness of this prior. For $\lambda = 0$, the posterior equals the prior and the data do not influence the estimates. For $\lambda \to \infty$, on the other hand, the posterior expectations coincide with the ordinary least squares (OLS) estimates.

In relation to the sum of coefficients priors, the additional restriction we impose on the autoregressive coefficients is the same as performing "inexact differencing"; i.e., it is a simple modification of the Minnesota prior involving linear combinations of the VAR coefficients. More precisely, rewrite the VAR equation in error correction form:

$$\Delta X_t = A_0 - (I_n - A_1 - \ldots A_p) X_{t-1} + B_1 \Delta X_{i,t-1} + \cdots + B_{p-1} \Delta X_{i,t-p+1} + e_t.$$

A VAR in first differences implies the restriction $(I_n - A_1 - \ldots A_p) = 0$. We follow Doan et al. (1984) and set a prior that shrinks $\Pi = (I_n - A_1 - \ldots A_p)$ towards zero. This can be understood as "inexact differencing", and is usually implemented in the literature by adding dummy observations. The tightness of this additional prior is controlled by the hyperparameter μ. As μ goes to infinity, the prior becomes diffuse, while as μ goes to 0, we approach the case of exact differencing, which implies the presence of a unit root in each equation.

The fact that, in the limit, the sum-of-coefficients prior is not consistent with cointegration, motivates the use of an additional prior that was introduced by Sims (1993), known as the "dummy-initial-observation" prior. This prior states that a no-change forecast for all variables is a good forecast at the beginning of the sample. The hyperparameter γ controls the tightness of the prior implied by this artificial observation. As γ goes to infinity, the prior becomes uninformative, while as γ goes to 0, all of the variables of the VAR are forced to be at their unconditional means, otherwise the system is characterized by the presence of an unspecified number of unit roots without drift. As such, the dummy-initial-observation prior is consistent with cointegration.

Summing up, the setting of these priors depends on the set of hyperparameters λ, μ, γ and Ψ, which reflect the informativeness of the prior distribution for the model's coefficients. These parameters have usually been set on the basis of subjective considerations or rules of thumb. We instead follow the theoretically grounded approach proposed by Giannone et al. (2012). This involves treating the coefficients which govern the tightness of the prior as additional parameters, in the spirit of hierarchical modelling. As hyperpriors, we use proper but almost flat distributions.[6]

The VAR model can be used to compute both unconditional forecasts and forecasts which are conditional on particular assumptions on the future paths of specific variables in the system (see Doan et al., 1984, and Waggoner & 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, & Lenza, 2013, which is able to handle large dynamic systems by using Kalman filtering techniques and the algorithm of Carter & Kohn, 1994. Essentially, the conditional forecasts are the expected value of the variables of interest, given not only all of the available data but also the future paths of the conditioning variables.

3.2. Forecasting evaluation

In this sub-section, we report the outcomes of the real-time forecasting evaluation of our model. We evaluate our models in terms of the forecasting accuracy for the overall index of harmonized consumer prices (HICP), as well as for a sub-aggregate that excludes energy prices and unprocessed food prices, which we define briefly as core inflation (HICPex). The latter, accounting for about 80% of the entire HICP basket of goods, is often considered as a measure of medium-term inflation pressures, since it excludes the most volatile components of consumer prices.

Defining the natural logarithm of consumer prices (HICP or HICPex) as p_t, the target variables in our forecasting exercises are the h-period annualized changes in prices

$$\pi_{t+h} = \frac{12}{h}\left(p_{t+h} - p_t\right),$$

and we evaluate the forecast accuracy of our model for horizons (h) ranging from three to twelve months ahead for the data vintages available at the time of the forecasting exercises conducted between 2002 Q2 and 2012 Q1 (40 quarterly forecasting exercises). Notice that, at the data cut-off points of the four quarterly projections conducted each year, the last available HICP data are generally those referring to the first month of the quarter (i.e., January in the Q1 exercise, April in Q2, July in Q3 and October in Q4). This implies that, when we evaluate, say, six-month-ahead forecasts, we compare them with the observed HICP in July (Q1 exercise) and October (Q2 exercise) of the same year, and January (Q3 exercise) and April (Q4 exercise) of the subsequent year. Our forecast accuracy statistic in Table 1 below is the mean squared forecasting error (MSFE):

$$\mathrm{MSFE}_h^m = \frac{1}{K_h} \sum_{v=2002\,\mathrm{Q2}}^{2012\,\mathrm{Q2}-h/3} \left(\pi_{v,v+h}^m - \pi_{v+h}\right)^2,$$

where K_h is the number of exercises between 2002 Q2 and 2012 Q1 over which the MSFE for horizon h is computed,[7] m is the model used to compute the inflation forecast $\pi_{v,v+h}^m$ for the date $v+h$ using vintage v data, and π_{v+h} is the observed h-period annualized change in prices.

The mean squared forecasting error (MSFE) depends on two components: the bias (mean of forecast errors) and variance of the forecast errors. The bias component reflects how good a forecast is at tracking 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 1 below reports the forecast bias as well, in order to allow the decomposition of MSFE into its two components.

The results reported in Table 1 refer to the point forecasts (obtained as the medians of the forecast distributions of the models) of three models: the random walk model in levels with drift (i.e., the prior model, which forecasts future inflation as the average historically observed inflation), and the unconditional and conditional BVARs. In the top panel of Table 1, the first row reports the MSFEs of the random walk model, while the second and third rows, respectively, report the outcomes for the unconditional and conditional BVAR forecasts. The lower panel of the table,

[6] As hyperpriors for λ, μ and γ, we choose Gamma densities with modes equal to 0.2, 1 and 1 and standard deviations equal to 0.4, 1 and 1, respectively. Our prior on ψ, i.e., the prior mean of the main diagonal of Σ, is an Inverse-Gamma with scale and shape equal to $(0.02)^2$. For a thorough discussion of the motivations for this prior set-up and its practical implementation, see Giannone et al. (2012).

[7] Specifically, we have $K_h = 40, 39, 38$ and 37 for $h = 3, 6, 9$ and 12 months, respectively, given that, as has been stressed, our HICP sample stops in June 2012. Obviously, we must exclude the 2012 Q2 data vintage from the evaluation because our HICP data cover the period until June 2012, and the three-month-ahead forecast at the time of the 2012 Q2 exercise, the shortest horizon we consider, refers to the HICP in July 2012.

Table 1
Outcomes of the forecasting evaluation.

Models	3 m ahead		6 m ahead		9 m ahead		12 m ahead	
	HICPex	*HICP*	*HICPex*	*HICP*	*HICPex*	*HICP*	*HICPex*	*HICP*
	Mean squared forecast errors							
Random walk	0.56	2.96	0.40	1.78	0.37	1.24	0.36	0.94
Unconditional BVAR	0.56	4.63	0.29	2.56	0.34	2.14	0.40	1.92
Conditional BVAR	0.49	2.23	0.32	1.77	0.33	1.53	0.34	1.34
	Bias							
Random walk	0.39	0.04	0.40	0.09	0.40	0.10	0.42	0.12
Unconditional BVAR	−0.35	−0.97	−0.09	−0.54	0.01	−0.37	0.05	−0.29
Conditional BVAR	0.26	−0.10	0.27	−0.06	0.28	−0.05	0.31	−0.03

Note: The upper panel of the table reports the mean squared forecast errors for the three models defined in column 1 for forecasting horizons of 3–12 months ahead. The lower panel reports corresponding results in terms of bias levels. The point forecasts we evaluate are the medians of the predictive distributions of the conditional and unconditional BVAR and random walk models.

on the other hand, reports the bias in the random walk, unconditional and conditional BVAR forecasts.[8]

First, the much larger size of the MSFEs for HICP compared to those for HICPex reveals that the HICP forecast errors are dominated largely by those incurred when forecasting the energy and unprocessed food components, consistently across horizons and models.

For HICP excluding energy and unprocessed food prices, the BVAR forecasts, both unconditional and conditional, are consistently more accurate than the random walk forecasts. Although the unconditional BVAR forecasts perform quite well, they are outperformed by conditional forecasts at both the shortest and longest horizons we analyse. At very short horizons, the assumptions on future paths of the variables, on which the forecasts are conditioned, complement the information included in the lags of the BVAR variables. On the other hand, for long horizons, where the assumptions reveal hardly any relevant information, the observed improvement in forecasting accuracy is also related to the smoothing effect of the future assumptions on the BVAR forecasts.

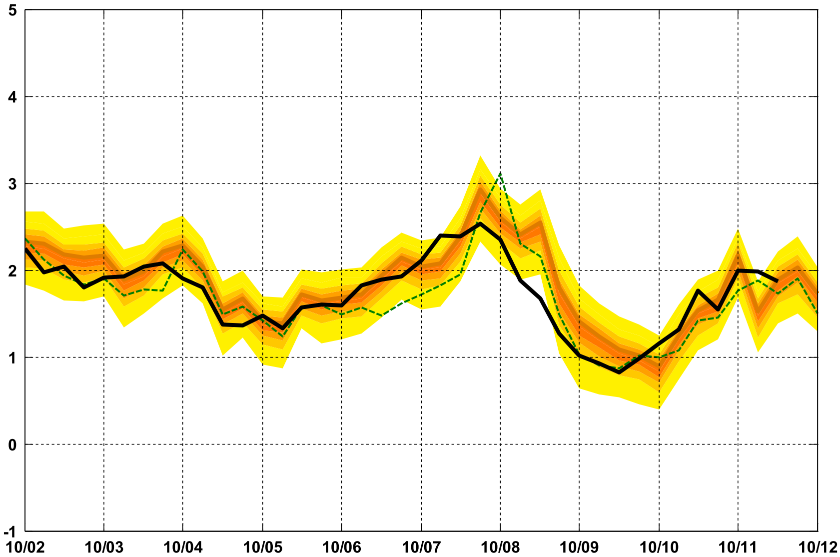
Turning to the overall HICP, we find that the unconditional BVAR forecasts never improve on the random walk. However, thanks to the assumptions on future paths, it is possible to provide fairly good forecasts compared to the random walk, at least at short horizons. The difficulties in outperforming random 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 are not surprising; see for example D'Agostino, Giannone, and Surico (2006) for the US and Fischer et al. (2009) for the euro area. In this respect, we complement existing analyses by pinning down the source of the forecasting errors more precisely, as being mostly in the energy and unprocessed food components.

In terms of the bias, the superiority of the BVARs, and particularly the conditional BVAR, is very clear for the HICP excluding energy and unprocessed food. For HICP, again, assumptions relating to future paths help to mitigate the bias. In fact, in absolute terms, the conditional BVAR forecasts generally exhibit the lowest biases among all forecasts, while the unconditional BVAR forecasts are the most biased.

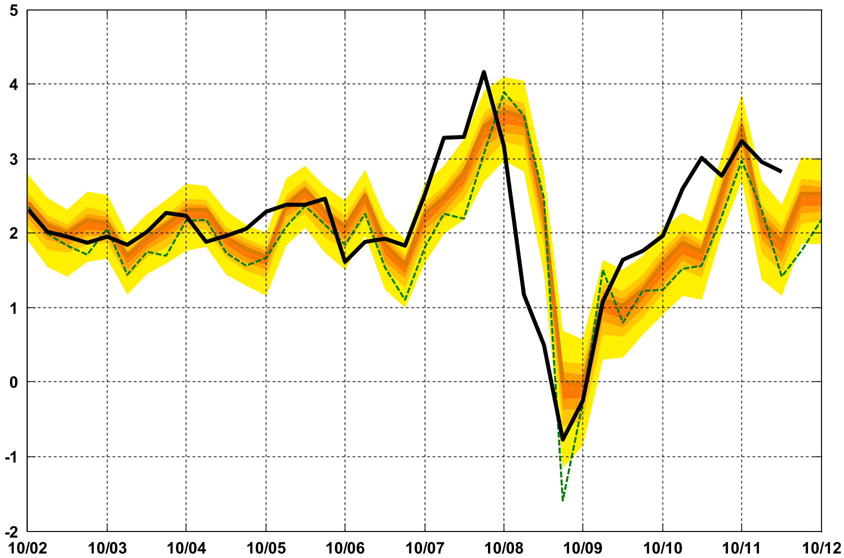
In Fig. 1, we report the real-time conditional BVAR distributions of the six-month-ahead forecasts for HICPex (panel a) and HICP (panel b) annual inflation (trimming 5% of the distributions). In order to evaluate the reliability of the predictive densities and the contributions of the assumptions on future paths, we also report the observed HICP and HICPex annual inflation (solid black line), and the median of the respective unconditional BVAR forecasts (dashed green line). When evaluating the predictive distributions, it should be clear from the outset that the forecast uncertainty we compute cannot take into account the uncertainty around the conditioning assumptions, which are treated as if they were the true data, rather than uncertain forecasts of future paths. Of course, this fact may distort our estimate of the forecast uncertainty. Notice also that, instead, we take into account the uncertainty intrinsic in the prior selection procedure, given that our predictive densities are also obtained by drawing the values of the hyperparameters governing the tightness of the priors from their posterior distributions.

Panel a of Fig. 1 shows how remarkably well the predictive density of the conditional BVAR forecasts tracks observed HICPex inflation. Only in the first quarters of 2009, at the trough of the economic recession following the financial turmoil of 2007/2008, is the observed HICPex inflation slightly below the lowest quantile in the figure, i.e. the 2.5% quantile. Focusing on the median of the unconditional forecasts, we can also see how the conditioning assumptions helped to track the HICPex inflation in the

[8] Note that we could also compare the BVAR models with the individual equation approach. We do not carry out this comparison for a number of reasons. First, individual equations assume the exogeneity of the inflation determinants, and hence, they can produce forecasts for all components only if the entire set of assumptions relating to the future paths on which to condition the forecasts were available, which is not the case in our real-time database. Second, the individual equations approach has been revised several times over the years (see ECB, 2010, for a description of some new features in this approach), and it is hard to reconstruct the different model vintages, as well as defining the samples and general features to allow a fair forecasting comparison. In the working paper version of this paper, available as CEPR DP 7746, we carry out a comparison of the BVAR forecasts with those from a particular version of the individual equations approach, in which we replace the missing conditioning assumptions on future paths with the corresponding BVAR forecasts and limit ourselves to only 18 forecasting exercises, carried out on the period 2004–2009. In that context, we show that conditional BVAR forecasts are consistently more accurate than those from individual equations.



(a) HICP excluding energy and unprocessed food.



(b) HICP.

Fig. 1. Six-month-ahead BVAR forecasts. Note: The figures show the distribution (trimming the upper and lower 2.5% quantiles) of the six-month-ahead conditional BVAR forecasts produced in 41 quarterly exercises, carried out between 2002 Q1 and 2012 Q2. The forecasts are produced for the period October 2002–October 2012 (as reflected in the horizontal axis), and relate to the annual change in HICP excluding energy and unprocessed food prices (panel a), and HICP (panel b). The black solid line represents the observed inflation in the available sample (ending in June 2012), while the dashed green line is the median of the distribution of the unconditional BVAR forecasts. The figures on the vertical axes are expressed in percentage points. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2006–2008 period, when HICPex was increasing rapidly and the unconditional forecasts were lagging. Finally, note that the positive bias in the conditional BVAR forecasts is due mostly to the post-Lehman collapse period, in which HICPex dropped faster than was foreseen by the BVAR model.

Turning to HICP inflation (panel b), we notice again that the predictive densities of the conditional BVAR forecasts are quite accurate, though less so than the corresponding ones for HICPex. The decline in inflation that accompanied the global recession was a big surprise for the model. In particular, the observed decline is outside the bands at the beginning, but the model adapted after few months. Also, the increases in HICP, driven by increases in global oil prices in 2007/8 and over the last few years, have been hard to forecast, although the median of the conditional BVAR forecasts is closer to the observed inflation than that of the unconditional forecasts, confirming that the conditioning assumptions help to forecast inflation, and energy prices in particular. The two recent episodes of rising oil prices just mentioned are those which explain the negative biases in BVAR forecasts for HICP inflation.

4. Inspecting the mechanisms

In this section, we aim to show some of the economic mechanisms captured by our BVAR models. In particular, because of their importance in the inflation debate, we estimate the transmission of a global oil price shock to domestic euro area inflation, and assess the strength of the correlation between economic activity and inflation during the Great Recession.

4.1. An illustration of the pass-through of global prices to domestic inflation: an oil price shock

In this section, we show how our model can capture the mechanism through which an initial shock to a variable cannot only have a direct impact, but also propagates further as it passes through to different price variables and HICP components. The example also 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 a permanent, exogenous, one-off increase to the oil price of 10% from the baseline (unconditional) forecast, at time t. The dynamics for the subsequent months are left unrestricted. Since the euro area accounts for a large share of the world's activity, we cannot treat oil prices as exogenous. We therefore use a recursive identification according to which the oil price can react instantaneously to non-energy prices, labour costs and real activity. Energy prices, exchange rates and commodity prices, on the other hand, are assumed to affect oil prices only with a delay of at least one month. The identification procedure is implemented by imposing the condition that, in the month of the oil shock, non-energy prices, labour costs and real activity are kept at the baseline level, i.e., the level of their unconditional forecasts in that month. The dynamics for the subsequent months are left unrestricted.[9] We then assess the effects of this change on the overall HICP and its components over the two subsequent years, so that we can trace the contributions from the different HICP components along the forecast horizon.

Panel a of Fig. 2 illustrates the impulse responses of the log-level of the global oil price to the exogenous shock, while panel b refers to the response of the log-level of HICP, and decomposes its dynamics in to the contributions from the HICP energy and unprocessed food and the other components (with the latter being the sum of the contributions of processed food, non-energy industrial goods and services) at the time of the shock and at some selected horizons (from six to 24 months after the shock).

Concerning the response of the oil price, the size of the shock is defined as raising the oil price by 10% on impact. The level of the oil prices subsequently decreases, reaching a level about 5% higher than in the pre-shock period, two years after the shock.

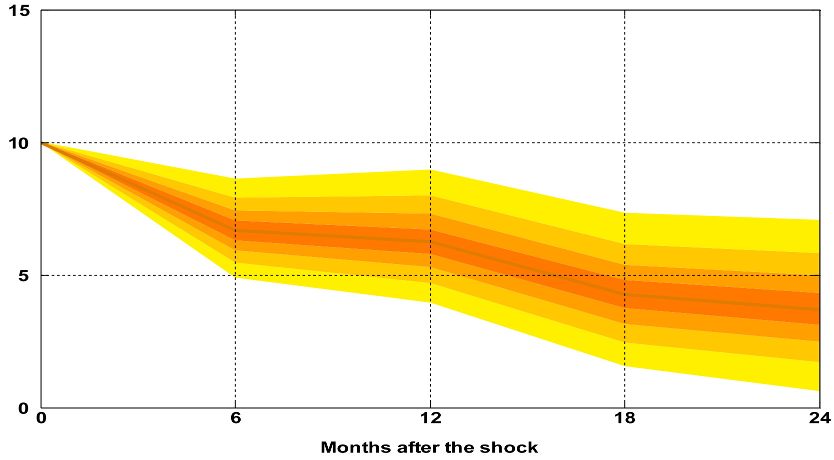
As the lower panel of Fig. 2 shows, the level of HICP immediately increases by about 0.1%. It then continues to increase for six months, before decreasing. This path of the overall HICP can be explained by the behaviours of the different HICP components. Our identification mechanism implies that the initial impact on HICP is due entirely to the energy component. After the initial impact, the contribution of HICP energy to the overall HICP levels off, and subsequently shows a tendency to decrease. The complex pass-through mechanics, allowed for in our BVAR, can be seen in the responsiveness of the non-energy components, whose contribution increases continuously as the oil price shock feeds through, because of both 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 seems to be able to capture the interactions between differing price determinants and components, and, as such, enables us to study the effects of an oil shock on the medium-term outlook for inflation appropriately.

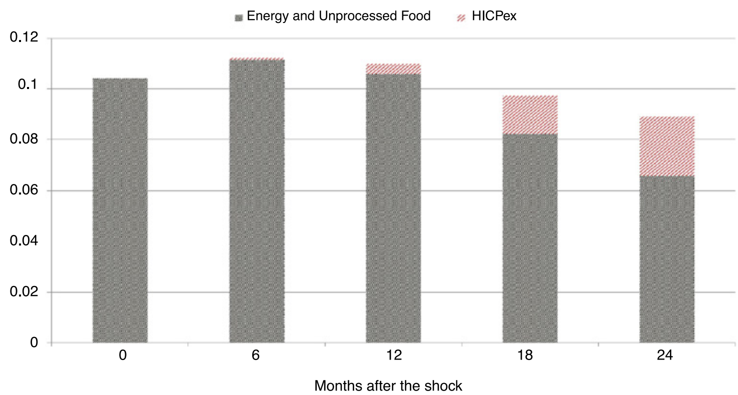
4.2. Does the model capture a Phillips curve in the euro area?

A fundamental building 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 has remained that of a short-run positive relationship between economic activity and inflation. In a simple exercise, we test the strength of the Phillips curve trade-off in the euro area. The exercise is organized as follows. Taking the model estimated over the whole sample, we produce unconditional forecasts for the period August 2007–June 2012. We then produce a second set of forecasts on the same sample, conditional exclusively on the observed GDP from August 2007 onwards, thus taking into account the information about the economic cycle over the last five years. Note that when we refer to "forecasts" in this subsection, we use the terms in a different sense to that used in the rest of the paper. Here, in fact, we are drawing the model parameters and hyperparameters from their posterior distributions estimated on the *whole sample*, and hence, we are not producing fully "out-of-sample"

[9] These identification restrictions make our exercise equivalent to the impulse response functions to an oil shock identified using a recursive (Cholesky) scheme. In practice, we assume the following ordering of the variables in the BVAR: the prices of non-energy industrial goods, services and food, GDP, wages and unit labor costs are ordered above the oil price, while the two exchange rates, food commodity prices, non-energy commodity prices and energy prices are ordered below the oil price. Our identification differs from studies such as that of Clark and Terry (2010), in which oil prices are ordered first, so that the oil prices are assumed to be exogenous with respect to all other current-period shocks. However, ordering oil prices after economic activity variables yielded qualitatively similar results in their analysis. We have tested the robustness of our results to that perturbation of the identification scheme, and the results are largely unchanged. We have also tested several other orderings, and have found that, in general, the qualitative result of significant indirect effects of an oil price shock remains, although the results are somewhat attenuated if we assume oil prices to be exogenous to all other current-period shocks.



(a) Response of the oil price.



(b) Response of HICP.

Fig. 2. Impulse response functions of the levels of oil prices and HICP to a 10% shock in oil prices. Note: The upper panel of the figure shows the distribution (trimming the upper and lower 2.5% quantiles) of the impulse response function (IRF) of the log-level of the oil price to a shock amounting to a 10% exogenous increase in the oil price in month 0. The lower panel reports the median of the distribution of the HICP log-level IRF, together with its decomposition into the contributions from energy and unprocessed food prices (grey solid bars) and that from the HICP excluding energy and unprocessed food prices aggregate (red dotted bar). In both panels, figures on the vertical axis are expressed in percentage points, while the horizontal axis reports how many months have passed since the realisation of the shock. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

forecasts, such as those we evaluated in Section 3. Fig. 3 plots the BVAR unconditional forecasts (green dashed line), the distribution of the forecasts conditional on GDP (shades of red, and again we symmetrically trim 5% of the distribution), and the inflation outcomes (black solid line) over the January 2005–June 2012 sample.

The figure shows that, according to our model, the euro area economy presents a relevant inflation–output relationship, since a consideration of the information available on the economic cycle in the post-August 2007 period finds a major improvement in tracking inflation relative to the unconditional forecasts. Even during the very pronounced up- and down-swings experienced in the 2007–2009 episode of rapidly rising and falling oil prices, during which inflation reached both its absolute peak and trough in the euro area sample, inflation is described relatively well by the conditional forecasts, and the turning points in inflation are tracked by the model correctly. This result is in striking contrast to the well-documented evidence that the Phillips curve relationship has almost disappeared over the last two to three decades, and that, as a consequence, inflation has become much harder to predict (see Atkeson & Ohanian, 2001, and Stock & Watson, 2008, for the US, and Fischer et al., 2009 for the euro area). Instead, our results indicate that the Phillips curve has revived during the recent recession. Stock and Watson (2008, 2010) for the US economy, and Smets (2010) for the euro area found similar evidence, suggesting some forms of non-linearities that make the Phillips curve stronger when the deviations of unemployment from its natural level are large.

5. Conclusions

We have constructed a medium-scale Bayesian VAR model that is able to capture the complex dynamic inter-relationships between the main components of the Harmonized Index of Consumer Prices (HICP) and their determinants. We show that the model can be used

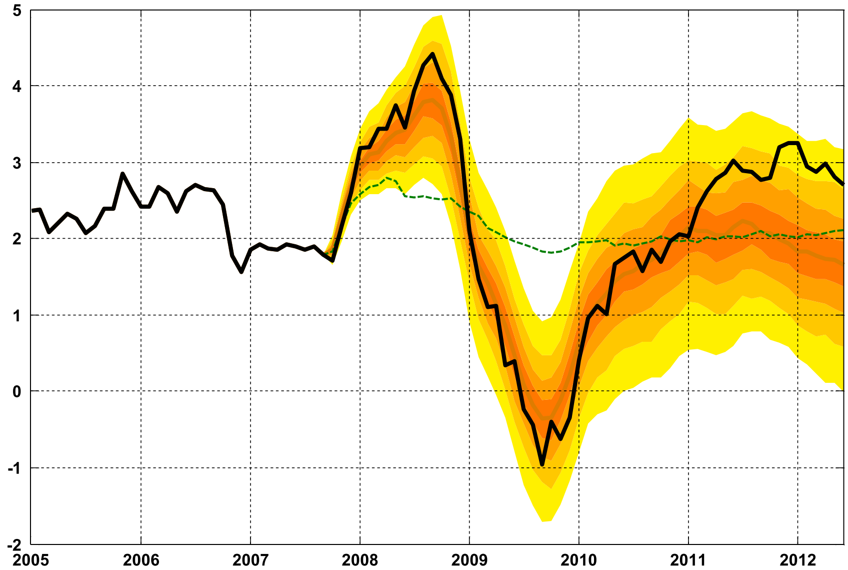


Fig. 3. Euro area Phillips curve. Note: The figure shows the distribution of the annual forecasts of HICP inflation forecasts (sampled monthly), conditional on the observed real GDP, in the sample August 2007–June 2012. The green dashed line represents the unconditional BVAR HICP inflation forecasts. The black solid line represents observed inflation in the sample January 2005–June 2012. The figures on the vertical axes are expressed in percentage points. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

fruitfully for forecasting, both in real-time and for scenario analysis.

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Appendix. Data appendix

Table 2 reports the definitions of the variables in the BVAR model, the frequencies at which they are available, and the data transformations implemented in order to include them in the models.

Aggregation of HICP. The HICP components (source: Eurostat) are aggregated by simply summing their weighted levels. The weights change year by year and are provided by the Eurostat (http://epp.eurostat.ec.europa.eu/portal/page/portal/hicp/data/database). In our real-time forecasting evaluation, we took into account the changes in HICP weights across forecasting exercises. For both of the exercises in Section 4, instead, we considered only the 2012 weights, for the sake of simplicity. The 2012 weights for each of the five HICP sub-components are reported in Table 2, in parentheses.

Interpolation of quarterly series. GDP, compensation per employee and unit labor costs are interpolated to obtain monthly values. The interpolation follows the procedures implemented in the context of the individual equations framework, and is conducted using the procedure of Litterman (1983). In practice, the interpolation is carried out by using the Kalman smoother to derive the monthly values of the series, under the assumptions that (i) the monthly levels of the variables follow a random walk process, and (ii) the quarterly level of the variable is the average of the three consecutive monthly levels in the quarter.

Table 2
Variables in the database.

Variable	Frequency	Transformation
Unprocessed food prices (7%)	Monthly	Log-levels
Processed food prices (12%)	Monthly	Log-levels
Non-energy industrial good prices (28.5%)	Monthly	Log-levels
Energy prices (11%)	Monthly	Log-levels
Services prices (41.5%)	Monthly	Log-levels
Oil price (euros)	Monthly	Log-levels
Non-energy commodity prices (euros)	Monthly	Log-levels
Food commodity prices (euros)	Monthly	Log-levels
Producer Price Index (PPI) consumer goods	Monthly	Log-levels
Real GDP	Quarterly	Log-levels
Compensation per employee	Quarterly	Log-levels
Unit labour costs	Quarterly	Log-levels
Nominal effective exchange rate	Monthly	Log-levels
US Dollar/Euro exchange rate	Monthly	Log-levels

Seasonal adjustment. HICP energy, commodity prices (oil, food and excluding oil) and the exchange rates are not seasonally adjusted, the remaining variables are seasonally adjusted.

Data sources. The HICP data are taken from Eurostat, and the commodity prices (both spot and future prices) from Reuters. Real GDP, compensation per employee, unit labour costs, PPI consumer goods and the exchange rates can also be taken from the ECB Statistical Data Warehouse.

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Domenico Giannone is professor of Economics at the Université Libre de Bruxelles.

Michele Lenza is Principal Economist at the European Central Bank.

Daphne Momferatou is Economist at the European Central Bank.

Luca Onorante is Head of Joint Macro Modelling Project at the Central Bank of Ireland.