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FORECASTING INFLATION IN THE EURO AREA: COUNTRIES MATTER!

by Angela Capolongo* and Claudia Pacella**

Abstract

We construct a Bayesian vector autoregressive model with three layers of information: the key drivers of inflation, cross-country dynamic interactions, and country-specific variables. The model provides good forecasting accuracy with respect to the popular benchmarks used in the literature. We perform a step-by-step analysis to shed light on which layer of information is more crucial for accurately forecasting euro area inflation. Our empirical analysis reveals the importance of including the key drivers of inflation and taking into account the multi-country dimension of the euro area. The results show that the complete model performs better overall in forecasting inflation excluding energy and unprocessed food, while a model based only on aggregate euro area variables works better for headline inflation.

JEL Classification: C32, C53, E31, E37.
Keywords: inflation, forecasting, euro area, Bayesian estimation.

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1 Introduction[1]

The primary objective of the European Central Bank is to maintain price stability in the euro area as a whole. This general goal has been further specified in terms of keeping the year-on-year increase in the euro area Harmonised Index of Consumer Prices (HICP) below, but close to 2% over the medium term.

Given this objective, a timely assessment of the economic drivers and the most likely outlook for inflation are a fundamental input for monetary policy. However, as reviewed by Faust and Wright (2013), while a large number of models have been proposed to forecast inflation, interpreting the inflation dynamics and providing an informed view on the inflation outlook has always been a challenging exercise.

For the US, Atkeson and Ohanian (2001) show that it is difficult to outperform very simple models as the random walk, while Stock and Watson (2007) find that the inflation process is well represented by a univariate unobserved component time-varying trend-cycle model. Similarly, for the euro area, Fischer et al. (2009) highlight the good inflation forecasting performance of the random walk model, and Diron and Mojon (2005) provide evidence that the central bank's objective targets yield more accurate forecasts than most inflation forecast models.

The aim of this paper is to contribute to the literature on forecasting inflation in the euro area at the short- and medium-term horizon. We consider forecasts for both the headline HICP and the HICP excluding energy and unprocessed food, which is often referred to as a measure of core inflation, meant to capture the most persistent component of consumer prices. Specifically, we address the question of which information is crucial to forecast aggregate inflation in the euro area. While this question is quite traditional in the literature on inflation forecasting, the unique nature of the euro area, as a monetary union among highly interconnected but heterogeneous countries (see Figure 1), adds another possible layer of complexity to it. Moreover, it also raises the issue whether taking into account country information may improve the accuracy of euro area inflation forecasts.

In our approach we consider three (overlapping) levels of information for the forecast exercise: *inflation key drivers*, *cross-country dynamic interactions* and *country-specific variables*. This is done through two steps.

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First, we employ a large Bayesian Vector Autoregressive model (BVAR) for the biggest four euro area countries (Germany, Spain, France, and Italy) to produce individual country inflation forecasts, which are then aggregated to obtain a forecast for the euro area inflation. Concerning the variables chosen as inflation determinants, the model is broadly inspired to the "triangle model" introduced by Gordon (1982)[2] with a cross-country twist.
The modelling strategy is drawn from Altavilla et al. (2014), who, differently from our aim, use it to evaluate the effects of standard and nonstandard monetary policy shocks on the biggest four euro area countries. As shown by Bańbura et al. (2010), a BVAR takes advantage of Bayesian shrinkage to tackle the high-dimensionality problem and allows to capture the dynamic inter-relationships between HICP components and their determinants in a fully unrestricted framework, as opposed to alternative models used in the literature, such as factor models (e.g. Forni et al. (2003)), panel VARs (e.g. Dées and Güntner (2017)), and global VARs (e.g. Pesaran et al. (2009)). We first validate our model, by comparing it with the random walk, which is often used in the literature as a benchmark and it corresponds to the prior in our model specification. We also compare the forecasting accuracy of our model to the one obtained with the Unobserved Component Stochastic Volatility (henceforth UC-SV) of Stock and Watson (2007). It is a simple but tough-to-beat benchmark, especially in US. We find that our model with the three layers of information, i.e. the multi-country model with aggregate and country-specific variables (our *baseline model*), produces accurate pseudo out-of-sample inflation forecasts, comparable with the alternative benchmarks considered. This performance seems remarkable given that our sample covers not only the financial crisis, but also the period of the unexpected low inflation both in the US and the euro area (see Coibion and Gorodnichenko (2015), Bobeica and Jarocinski (2017)), in which our model remains able to generate accurate pseudo out-of sample forecast.

Second, we perform a step-by-step analysis of the model to shed light on the elements that are crucial for a more accurate forecast of euro area inflation. On the one hand, including as many variables as possible seems a good hedging strategy against omitting relevant information. On the other hand, this strategy risks to increase the complexity of the model without gains in terms of forecasting accuracy. Specifically, we carry out three additional exercises. First, we assess if the *inflation key drivers* play a determinant role in forecasting inflation, as the economic theory based on the

[2] It consists in an extension of the Phillips curve, realized using inflation data together with its three determinants: inflation persistence, demand-pull inflation and cost-push inflation

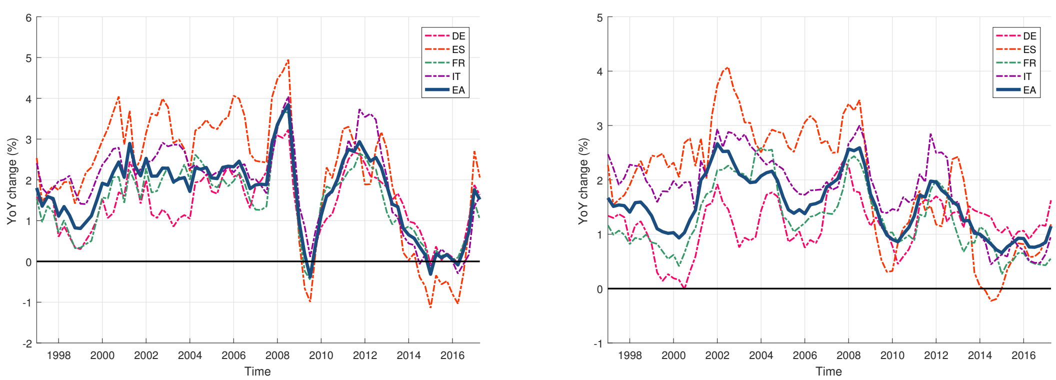
Phillips curve would suggest. Therefore, we compare our baseline model to a BVAR including only the inflation rates in the four largest euro area countries, i.e. a pure multi-country autoregressive model of inflation. Second, in order to evaluate the importance of *cross-country dynamic interactions*, we compare the accuracy of the euro area inflation forecasts obtained in our baseline model with the one produced by aggregating the forecasts, one for each country, produced by country-specific models. Finally, our goal is to assess if *country-specific variables* matter for the euro area inflation forecasting accuracy. Hence, we build a model including only the euro area aggregates and we compare it with our baseline model.

The results show that, generally, our baseline multi-country BVAR compares favourably to all the other benchmarks VAR models obtained by excluding the information layers, as discussed above. These results suggest that our modeling strategy, which consists in including the inflation key drivers and explicitly accounting for the multi-country dimension of the euro area, is supported by the data. The results in favor of the baseline model are stronger for what concerns HICP excluding energy and unprocessed food, while, for headline HICP, the aggregate euro area BVAR remains quite competitive. An interpretation of the latter finding is that HICP excluding energy and foodhas a stronger domestic component, for which it is beneficial to consider country-specific information. Instead, headline inflation dynamics are more strongly affected by global factors, like those driving commodity prices, which rather homogeneously affect the different euro area countries.

Turning to our contribution to the literature, we refer here to the studies strictly relevant for our analysis.
A first strand of literature concerns the euro area inflation forecasting. As reviewed by Bańbura and Mirza (2013), few studies focus on the out-of-sample inflation forecasting performance in the euro area, among these an exhaustive comparison of model performance is provided by Canova (2007). Our paper shows the importance of accounting for key inflation determinants to produce accurate euro area inflation forecasts, in line with the findings of Giannone et al. (2014).
Another strand of the literature has focused on the comparison between the inflation forecasting performance of aggregate and disaggregate models. Several forecasting exercises of euro area inflation have been performed by aggregating the forecasts of sub-components: sectors of economic activity (e.g. Hubrich (2005), Hendry and Hubrich (2011), Giannone et al. (2014)), countries (e.g. Marcellino et al. (2003), Cristadoro et al. (2013)) or both (Benalal et al. (2004)). While the theoretical literature, as proved in Kohn (1982), agrees on the improvement obtained by using the

disaggregate forecasts, with respect to a direct aggregate approach, the empirical evidence is still mixed. Our contribution to this literature is to build a large-scale model, free from restrictions, which accounts for multi-country dimensions, to forecast inflation in the euro area. In our case, the aggregate approach remains quite competitive for headline inflation, while for what concerns the inflation excluding energy and unprocessed food, that is more driven by domestic factors, our disaggregate approach is more accurate. The underlying idea is in line with Monteforte and Siviero (2010), who highlight the economic relevance of accounting for heterogeneity among the countries in the euro area. This suggests that policy making is more effective when supported by disaggregate (multi-country) rather than aggregate (area-wide) econometric models. A data-rich model, as the one we propose, presents indeed many advantages with respect to the country-models: it can be easily used for scenario analysis and for the assessment of a shock propagation, although these policy-relevant applications are not the focus of this paper.

The paper is structured as follows. Section 2 describes the data, the model specification and the estimation. Section 3 presents the results. Section 4 concludes.



(a) HICP

(b) HICP excluding energy and unprocessed food

Figure 1: Country-specific inflation rates. Note: Figure (a) shows the year-on-year percentage change of HICP index. Figure (b) shows the year-on-year percentage change of HICP index excluding energy and unprocessed food. The countries are Germany (DE), Spain (ES), France (FR), Italy (IT), and the euro area (EA).

2 Model

2.1 Data

The choice of the time series used to forecast inflation is entirely based on the economic theory. As anticipated in Section 1, we follow the idea of Gordon (1982)'s "triangle model" to identify the main inflation key drivers. The first driver is the built-in inflation, i.e. the inertial component that can be identified for example by lagged inflation, inflation expectations, cost of labor and prices of producers. The second driver is the demand-pull inflation factor, which is a measure of economic activity, as the Gross Domestic Product (GDP). The third driver is the cost-push shock, that can be measured by a global driver of inflation as the oil price, which affects inflation also through the exchange rate.

Therefore, our dataset is composed by 26 quarterly variables, which are classified in two groups: country-specific and euro area wide variables. The first group includes HICP overall index (HICP), HICP excluding unprocessed food and energy (HICPex), Unit Labour Cost (ULC), Producer Price Index (PPI), Gross Domestic Product (GDP) and the European Commission Consumer Survey on inflation for each of the four countries considered. The second group includes oil price and the Effective Exchange Rate (EER), which are common to the whole area. Moreover, in order to perform the comparison with an alternative model built to directly obtain euro area forecasts, we also consider the corresponding euro area aggregates of the variables listed above in the country-specific group [3].

Considering the abovementioned variables, we are able to detect the main factors affecting inflation in the euro area, as for example outlined by European Central Bank (2017). On the domestic side, the business cycle represents one of the main drivers of inflation. Movements of GDP, feeding into the labour market, tend to put pressure on wages. The latter can, in turn, push unit labor cost and, hence, affect the cost pressures for firms, which modify the producer prices and thereby inflation. This mechanism could be further amplified or moderated through the inflation expectations, which represent one of the key driving force of inflation. On the global side, several factors may affect the inflation development. We picked oil price because, in the recent period, as also explained by Draghi (2015) and shown by Ciccarelli and Osbat (2017), it represents the main driver of global disinflationary shocks that has contributed to lead inflation in the euro area being persistently below target

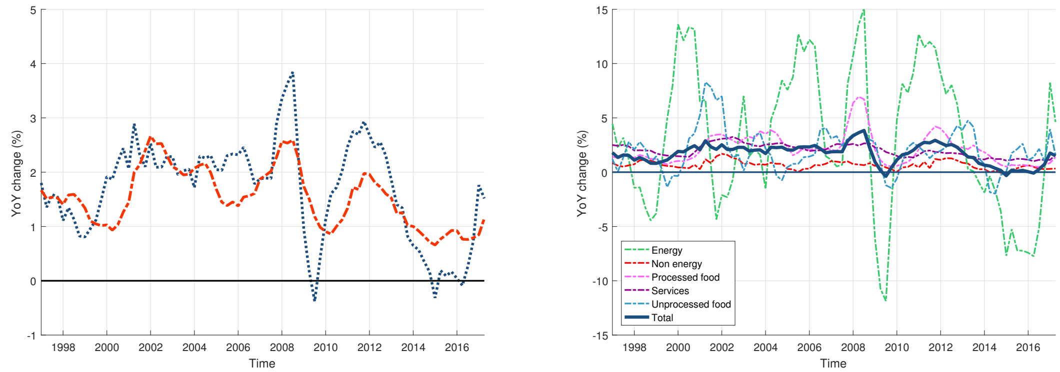
[3] See Appendix A and B for further details.

since 2011. The oil price exerts not only direct effects on inflation, via the energy sub-component, but also second-round effects on wage and price-setting, boosted by inflation expectations, which could affect medium-term price developments. The exchange rate lies in between global and domestic factors as juncture between the two, as the main pass-through channel.

The choice of the inflation data, key variables of the analysis, deserves further explanations. First, the decision of using HICP rather than other inflation measures, as for example the GDP deflator or the Consumer Price Index[4], is mainly driven by cross-country comparability reason. The HICP, differently from the alternative measures, is computed according to a harmonized approach, allowing for full comparability across euro area countries. Second, the choice of including in our model both the overall index (HICP) and the HICP excluding the most volatile components (HICPex), i.e. unprocessed food and energy, is motivated by two main reasons. On the one hand, considering both measures, we are able to perform and compare the forecasting accuracy of our model for both indices. The presence of the volatile components could indeed negatively affect the forecasting accuracy of HICP. On the other hand, the inclusion of both indicators allows us to account for direct, indirect and second-round effects on Euro Area inflation. As shown by European Central Bank (2016), over short horizon the HICP overall has a better predictive power than the HICPex. However, the latter is more informative for medium-term inflationary trends, because it excludes the more volatile components (see Figure 2). Therefore, in our model we prefer considering both together to preserve their relationship and informational content, which is of particular interest since 2014, when HICP has dipped below the HICPex.

The countries considered are the four largest economies of the whole area: Germany, Spain, France, and Italy. They account for about 80% of whole Euro Area GDP growth. The normalized weights considered to aggregate the country-specific HICP forecasts did not change significantly in the period considered. In the forecasting exercise we use every period the latest available weights. The model is estimated over the sample period 1996Q1 - 2017Q2.

[4] This two measures differ from each other for the composition of the underlying basket. CPI includes only goods bought by consumers, both domestic and imported. The GDP deflator is a measures of prices of all domestic goods and services. They both rely on national definition and hence, they are not easy to aggregate across countries.



(a) HICP and HICPex

(b) HICP by sector components

Figure 2: Euro area inflation rates. Note: Figure (a) shows the year-on-year percentage change of HICP index for the euro area (blue line) and HICP index excluding energy and unprocessed food for the euro area (orange line). Figure (b) shows the year-on-year percentage change of the different components of HICP index.

2.2 Estimation and Forecasting Methodology

In this section, we first describe the model estimation and then the forecasting methodology of our baseline model.

The model for performing short- and medium-term inflation projections is represented by the following vector autoregression (VAR) specification:

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

$$e_t \sim N(0, \Sigma)$$

where $X_{i,t}$ $(i = 1, \ldots, N)$ is the N-dimensional matrix of data, $A_0, \ldots, A_p$ are the $N \times N$ matrices of the parameters, $e_{i,t}$ is a vector of size N of the disturbances. The dataset used in the analysis is composed by $N = 26$ variables. The VAR is specified in log-levels and the variables are not pre-transformed to achieve stationarity. Since our analysis aims at detecting the dynamic properties of our quarterly dataset, we allow for five lags in the VAR model ($p = 5$). Hence, the total amount of parameters to estimate is 3757[5]. Since the sample available for the analysis has a short length (86

[5] It is given by the sum of $(26 \times 26) \times 5$ autoregressive coefficients, 26 parameters and $26 \times 27/2$ parameters of the covariances of the residuals.

quarters), there is a clear over-parametrization. This issue is addressed by applying a Bayesian shrinkage.

Following Doan et al. (1984), we use a Minnesota prior for the autoregressive coefficients $(A_1, \ldots, A_p)$. Hence, we shrink the model's coefficients towards a naïve random walk model with drift, i.e. $X_{i,t} = \delta_i + X_{i,t-1} + u_{i,t}$. Moreover, we use a normal-inverted Wishart prior for the covariance matrix of the residuals, Σ. The scale parameter is a diagonal matrix Ψ and it has $n+2$ degrees of freedom, that is $\Sigma \sim IW(\Psi, n+2)$, which implies $E(\Sigma) = \Psi$. Therefore, the prior distribution of the autoregressive coefficients, conditional on the covariance matrix of the residuals, is normal with the following mean and covariance:

$$E[(A_s)_{ij}] = \begin{cases} I_n & \text{if } s = 1 \text{ and } i = j \\ 0 & \text{otherwise} \end{cases}$$

$$cov[(A_s)_{ij})(A_r)_{hm})] = \begin{cases} \lambda^2 \frac{\Sigma_{ij}}{(s^2\,\Psi_{ii})} & \text{if } m = j \text{ and } r = s \\ 0 & \text{otherwise} \end{cases}$$

where $\frac{\Sigma_{ij}}{\Psi_{ii}}$ accounts for the different scale and variability of the data, $1/s^2$ is the rate at which the prior variance decreases with an increasing lag length and λ controls for the scale of the prior covariance. The latter hyperparameter determines the overall tightness of the prior. For $\lambda \to \infty$, the prior is defined as "diffuse", since we attribute a small weights to our beliefs, hence, the posterior expectations coincide with the ordinary least square estimations. For $\lambda \to 0$, vice versa, the prior is "dogmatic" centred at the random walk, since the posterior is equal to the prior, hence, the estimates are not influenced by the data. In the literature, this hyperparameter, λ, has been traditionally set on the basis of ad-hoc procedures. The first method, proposed by Litterman (1980), consists in choosing the λ that maximizes the out-of-sample forecasting performance of the model, calibrated as $\lambda = 0.2$. Bańbura et al. (2010) show that, in order to get the desired in-sample fit, the tightness λ of the prior needs to increase with the size of the model. To reduce the subjective choices in the setting of the prior informativeness, Giannone et al. (2015) introduce a hierarchical approach. The main idea is to interpret the model as a hierarchical model and treat the hyperparameters as additional unknown parameters, i.e. random variables on which we can conduct inference. Here we follow this approach on λ, whose posterior distribution is given by:

$$p(\lambda|y) \approx p(y|\lambda)p(\lambda)$$

where y represents the data, hence, $p(y|\lambda)$ is the marginal likelihood and $p(\lambda)$ is the prior on the hyperparameter, also defined as hyperprior. For the latter we choose a proper but almost flat distribution, hence the shape of the posterior of λ can be approximated with the marginal likelihood.

We employ a recursive scheme to perform out-of-sample forecast of the HICP for the period 2006Q1-2017Q2, using an increasing data window using all the available data from 1996Q1. The highest forecast horizon, H, consists of 8 periods (two years). The target variable in our forecasting exercise is expressed in terms of h-period annualized average growth change in prices:

$$\hat{y}_{c,t+h|t} = \tfrac{400}{h} \log \left(\tfrac{\hat{x}_{c,t+h|t}}{x_{c,t}} \right)$$

where $x_{c,t}$ is the HICP (level) for the c-th country ($c = 1, \ldots, 4$).

The modelling strategy used to produce euro area inflation forecasts follows a bottom-up approach in a single model framework. This forecasting procedure consists of two steps. In the first step, we produce country inflation forecasts for h quarters ahead for Germany, Spain, France, and Italy. In the second step, we aggregate the country-specific forecasts to obtain forecasts for euro area inflation using country weights to inflation at time t:

$$\hat{y}_{t+h|t} = \sum_{c=1}^{4} w_{c,t} \ \hat{y}_{c,t+h|t}$$

3 Forecasting Evaluation

In this section we present the results of the forecasting exercise. The forecasting accuracy of our model is measured both in terms of point forecasts and density forecasts.

First, to evaluate the point forecast we use the mean squared forecasting error (MSFE), which is the average of the squared the difference between the median of the predictive density forecast and the realized observation.

$$\text{MSFE}_h = \tfrac{1}{T-T_0+1} \sum_{t=T_0-h}^{T-h} (\hat{y}_{t+h|t} - y_{t+h})^2$$

where $\hat{y}_{t+h|t}$ is the median of the density forecast for horizon h ($h = 1, \ldots, 8$), T_0 is the first forecast period, and T is the last forecast period.

We compare the MSFE of our model to the one of a benchmark naïve model, as introduced by Theil (1966). The resulting metrics, so-called relative MSFE (RMSFE) or Theil's U-statistics, can be computed as follows:

$$\mathrm{RMSFE}_h = \frac{\mathrm{MSFE}_h}{\mathrm{MSFE}_h^{RW}}$$

where MSFE_h^{RW} is the MSFE of a random walk in levels with drift. If this ratio is bigger than one, the naïve model performs better than the model in terms of forecasting accuracy, and vice versa. In order to assess if the difference between two RMSFEs is statistically significant, we use the test of Diebold and Mariano (1995), which is a t test with HAC standard errors. The outcomes of the test should be considered as suggestive because we compare the forecast performance of nested models. Moreover, our forecasts are produced using a recursive scheme, while the reliability of the test has been proved only for forecasts obtained via a rolling scheme (Giacomini and White (2006)).

Second, to assess the density forecast we use the average log predictive score, LS_h that is the arithmetic mean of the log scores, $\mathrm{LS}_{t,h}$, computed in each period as:

$$\begin{aligned} LS_h &= \frac{1}{T-T_0+1}\sum_{t=T_0-h}^{T-h} LS_{t+h|t} \\ &= \frac{1}{T-T_0+1}\sum_{t=T_0-h}^{T-h} ln\left(f\left(y_{t+h}|I_t\right)\right) \end{aligned}$$

where $f\left(y_{t+h}|I_t\right)$ is the predictive density for y_{t+h} constructed using information up to time t and evaluated at the realized y_{t+h}. It follows that the same MSFE can correspond to very different log score depending on the uncertainty around the median, i.e. the second moment of the distribution. A more accurate forecast is characterized by a greater average log score. In our case, we use a Gaussian kernel approximation of the predictive density for all models. The log scores of two models can be compared using the test introduced by Amisano and Giacomini (2007). It is a t test, whose null hypothesis states the absence of difference between the weighted logarithmic scores of two models. In our framework, we use an unweighted version of the test with HAC standard error.

To evaluate the forecasting accuracy of our baseline model we follow three main steps. First, in the subsection 3.1, we assess the performance of the baseline BVAR model with respect to the traditional benchmarks used in the literature, i.e. the random walk and the UC-SV model. Second, in the subsection 3.2, we perform a step-by-step analysis of the model, by relaxing each assumption at a time, to shed light on the elements necessary to improve the euro area inflation forecasts. Finally, in subsection 3.3, we assess the robustness over time of the predictive accuracy of our model with respect to alternative models.

3.1 Model Validation

We first evaluate the overall performance of the baseline model by making a comparison, in terms of forecasting accuracy, with the random walk model with drift. This naïve model forecasts the future inflation as the average historically observed inflation without any further variable for predicting the future path of inflation. We chose the random walk as benchmark for two main reasons. First, as shown in the literature, it often exhibits good forecasting accuracy for inflation. Second, it is the prior for our model specification, hence, as argued by Bańbura et al. (2010), if the model outperforms the random walk, this implies that it is able to extract valuable information from the sample.

We then compare the forecasting accuracy of a simple benchmark model often used in the literature, the UC-SV model of Stock and Watson (2007). The UC-SV is an univariate unobserved component model with stochastic volatility and consists in decomposing inflation into a stochastic trend and a cycle, whose shocks have time-varying variances. The model is defined as follows:

$$\begin{aligned}
\pi_t &= \tau_t + e^{\frac{1}{2}h_t}\varepsilon_t^{\pi} \\
\tau_t &= \tau_{t-1} + e^{\frac{1}{2}g_t}\varepsilon_t^{\tau} \\
h_t &= h_{t-1} + \omega_h \varepsilon^h \\
g_t &= g_{t-1} + \omega_g \varepsilon^g
\end{aligned}$$

where $\varepsilon_t^{\pi}, \varepsilon_t^{\tau}, \varepsilon^h, \varepsilon^g \sim N(0,1)$, and ω_h, ω_g are parameters to be estimated. The point forecast for inflation at horizon $t+h$ is obtained as the estimate of the current trend:

$$\hat{\pi}_{t+h|t} = \hat{\tau}_t.$$

The results, summarized in Table 1, show that the baseline model (henceforth *BVAR-Base*) outperforms the random walk and produces forecasts comparable to the UC-SV, both for the HICP and HICPex. In particular, by looking at the Theil's U-statistics, i.e. the relative mean squared error, we can reach two main conclusions.

First, the forecasts produced by the BVAR-Base are uniformly more accurate than the random walk model forecasts up to two-year ahead horizon. Second, the UC-SV model produces worse inflation forecasts than the BVAR-Base for horizon longer than one year, for both the inflation measures considered. These results are confirmed by the Diebold and Mariano (1995) test (Table 2).

Table 1: RMSFE of benchmark models

	HICPex		HICP	
horizon	BVAR-Base	UC-SV	BVAR-Base	UC-SV
one quarter	0.76	0.54	0.92	0.78
two quarters	0.75	0.47	0.88	0.91
one year	0.74	0.88	0.89	1.02
two years	0.97	1.50	0.92	1.39

Relative MSFE with respect to benchmark models. Note: RW is the random walk model; BVAR-Base is our large multi-country model, UC-SV is the unobserved component stochastic volatility model of Stock and Watson (2007). A value smaller than 1 indicates that the model outperforms the RW. The forecasts are computed over the period 2006Q1-2017Q2.

Table 2: Diebold and Mariano (1995) test with respect to benchmark models

horizon		HICPex	HICP
		BVAR-Base	BVAR-Base
one quarter	RW	3.05	1.11
	UC-SV	-1.46	-0.94
two quarters	RW	2.68	1.51
	UC-SV	-1.97	0.15
one year	RW	2.45	1.30
	UC-SV	0.88	0.98
two years	RW	0.19	0.66
	UC-SV	3.56	2.78

Note: RW is the random walk model; BVAR-Base is our large multi-country model;UC-SV is the unobserved component stochastic volatility model of Stock and Watson (2007). A negative value of the t statistic indicates that the model on the table's row is more accurate than the model on the table's column. The forecasts are computed over the period 2006Q1-2017Q2.

3.2 A step-by-step analysis

In this section, we perform a step-by-step analysis of our baseline large multi-country model, which includes three levels of information: *inflation key drivers*, *cross-country dynamic interactions* and *country-specific variables*. The goal is to validate our model, by analysing if every group of variables included does help improving the projections of the euro area inflation. We proceed in three steps: (i) we remove from the baseline model one piece of information; (ii) we perform the Euro Area inflation forecasts by means of the new model obtained in the first step; (iii) we make a comparison between the forecast performance of this model and our baseline model to assess if any improvement is reached. Therefore, we introduce three alternative models to our baseline multi-country large BVAR, BVAR-Base.

First, we compare our model to a BVAR including only the inflation rates of the four largest countries, henceforth *BVAR-H*. Our goal is to understand whether the information provided by *inflation key drivers* is valuable to predict euro area inflation. The results show that the BVAR-Base has higher predictive power than the BVAR-H, for both HICPex and HICP . When considering the point forecast, in Table 3, the MSFE shows that the model excluding all key determinants, BVAR-H, generates better forecasts than the random walk model only at a very short horizon. As shown in Table 4 this result is very robust: the t statistic is negative at every horizon for both the measures of inflation, thus pointing to higher forecasting accuracy of the BVAR-Base than the BVAR-H. If we consider the entire predictive density this result is confirmed. Table 5 shows that the average difference of log scores is always positive, meaning that the BVAR-Base performs better than the BVAR-H.

Second, we analyze the euro area inflation forecast obtained by our BVAR-Base with respect to those produced by aggregating the four forecasts, one for each country, generated by country-specific BVARs, henceforth *BVAR-C*[6]. Our aim is to assess whether *cross-country dynamic interactions* matter for the euro area inflation forecasting accuracy. The comparison with this alternative methodology allows to understand if taking into account all existing dynamic relationships among variables of different countries really matters for forecasting euro area inflation. We find that the forecasting accuracy, for HICP and HICPex, differs among short- and medium-term forecasts. This result is valid for both point (Table 3) and density forecast (Table 5). In particular, for the first year of the forecasting horizon, the forecasts for euro area inflation obtained through country-specific models, BVAR-C, outperform those

[6] The country forecasts are aggregated using normalized country weights to inflation.

of the large multi-country model, BVAR-Base. In the second year, the forecasting exercise shows an opposite evidence. This could lead to conclude that in the very short horizon the informational content of cross-country dynamic interactions is actually disregarded. However, it becomes an important element for the medium-term horizon inflation forecasts.

Third, we compare our disaggregate BVAR-Base, which is built using an indirect two-step approach, to an aggregated model with only euro area variables, which uses a direct approach, henceforth *BVAR-EA*. The final purpose is to understand if a model exploiting *cross-country heterogeneity*, as the BVAR-Base, is able to produce accurate forecasts for the euro area as a whole. By looking at Tables 3 and 5, we can detect different findings for HICP and HICPex. For HICP, the model including euro area aggregates, BVAR-EA, shows superior forecasting accuracy at all horizons, although the improvement is small in magnitude. For HICPex, the multi-country model, BVAR-Base, performs better in terms of forecasting accuracy for the medium-term, that is for one year onward. The different results between the two indices might potentially be explained by the diverse trend of HICP and HICPex in the out-of-sample period considered (see Figure 1). While the HICP differentials, defined as the difference between country inflation rates and euro area inflation rate, have been decreasing since the beginning of the financial crisis, the HICPex differentials have remained quite large. Therefore, in the last case there is a great amount of country information to exploit. Albeit the short sample size available and the big number of country-level variables, our multi-country model produce results comparable to a smaller model including euro area aggregates.

Table 3: RMSFE of alternative models

	HICPex			
horizon	BVAR-Base	BVAR-H	BVAR-C	BVAR-EA
one quarter	0.76	0.84	0.51	0.50
two quarters	0.75	0.83	0.50	0.56
one year	0.74	0.89	0.69	0.83
two years	0.97	1.21	1.26	1.12
	HICP			
horizon	BVAR-Base	BVAR-H	BVAR-C	BVAR-EA
one quarter	0.92	0.98	0.73	0.66
two quarters	0.88	1.01	0.78	0.72
one year	0.89	1.04	0.86	0.81
two years	0.92	1.12	0.91	0.57

Relative MSFE with respect to the random walk model of the pseudo out-of-sample forecasts computed by using different models. Note: BVAR-Base is our large multi-country model; BVAR-H is the model including only inflation variables; BVAR-C refers to the forecast obtained from country-specific BVAR models; BVAR-EA is the model considering the euro area as a whole. A value smaller than 1 indicates that the model outperforms the RW. The forecasts are computed over the period 2006Q1-2017Q2.

Table 4: Diebold and Mariano (1995) test with respect to alternative models

	HICPex		
horizon	BVAR-H	BVAR-C	BVAR-EA
one quarter	-1.53	2.06	1.63
two quarters	-1.57	1.82	0.97
one year	-2.54	0.37	-0.33
two years	-2.38	-1.41	-0.39
	HICP		
horizon	BVAR-H	BVAR-C	BVAR-EA
one quarter	-1.45	1.94	2.09
two quarters	-2.64	1.13	1.19
one year	-2.77	0.25	0.49
two years	-2.41	0.12	2.45

Note: BVAR-Base is our large multi-country model; BVAR-H is the model including only inflation variables; BVAR-C refers to the forecast obtained from country-specific BVAR models; BVAR-EA is the model considering the euro area as a whole. A negative value of the t statistic indicates that the BVAR-Base is more accurate than the model on the table's column. The forecasts are computed over the period 2006Q1-2017Q2.

Table 5: Average difference between log scores of alternative models

	HICPex			HICP		
horizon	BVAR-H	BVAR-C	BVAR-EA	BVAR-H	BVAR-C	BVAR-EA
one quarter	0.04 *(0.03)*	-0.18 *(0.11)*	-0.22 *(0.13)*	0.04 *(0.03)*	3.02 *(2.43)*	-0.23 *(0.10)*
two quarters	0.08 *(0.05)*	-0.12 *(0.21)*	-0.17 *(0.27)*	0.46 *(0.37)*	2.86 *(2.26)*	0.37 *(0.53)*
one year	0.26 *(0.15)*	0.26 *(0.39)*	0.14 *(0.53)*	0.61 *(0.40)*	5.58 *(5.04)*	-0.31 *(0.36)*
two years	0.49 *(0.40)*	0.39 *(0.49)*	-0.34 *(0.22)*	0.68 *(0.58)*	1.52 *(1.61)*	-0.79 *(0.59)*

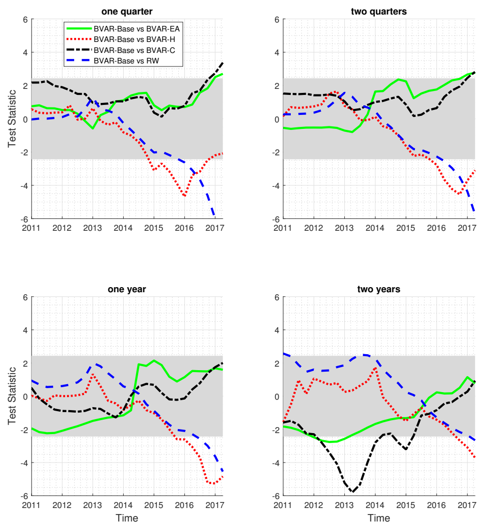
Note: BVAR-Base is our large multi-country model; BVAR-H is the model including only inflation variables; BVAR-C refers to the forecast obtained from country-specific BVAR models; BVAR-EA is the model considering the euro area as a whole. A negative value indicates that the model outperforms the BVAR-Base. HAC standard errors are in parentheses. The forecasts are computed over the period 2006Q1-2017Q2.

3.3 Predictive accuracy over time

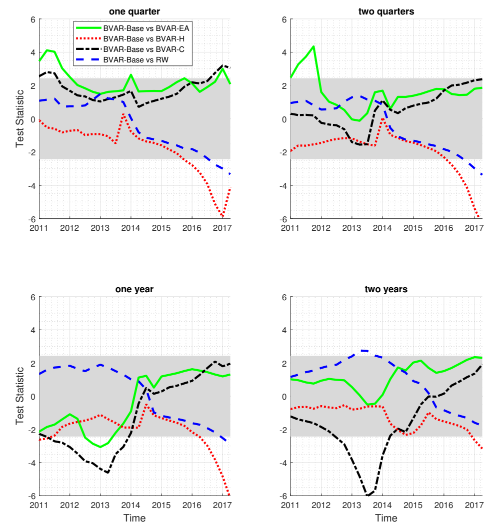
The high instability of the period under analysis, specifically concerning inflation development, requires further investigation. Since the aftermath of the financial crisis the inflation has been showing a puzzling behavior for both scholars and policymakers. Two phenomena about the evolution of the inflation after the Great Recession have been in the spotlight (Constâncio (2015)). First, the "missing disinflation puzzle, concerning the period right after the 2008-2009 financial crisis, when inflation did not drop as much as it was expected given the depth of the recession. Second, the "missing inflation puzzle after 2012, when inflation started dropping far below the 2% price stability objective. Therefore we perform the Giacomini and Rossi (2010)'s fluctuation test to compare the evolution over time of the relative forecasting performance of the BVAR-Base with respect to the Random Walk, the BVAR-H, the BVAR-C and the BVAR-EA.

Figure 3 shows the test statistic for the point and density forecasts for both the measures of HICP at different forecast horizons. In every chart the test statistic is computed over a 5-year window, the dates on the horizontal axis are located at the end-point of the window and the grey shaded area identify the rejection area as bounded by critical values at a 5%-significance level. For point forecasts this test is a rolling version of the Diebold and Mariano (1995): when the test statistic is below zero the BVAR-Base performs better than the alternative model, and when it is below the negative critical value the results are statistically significant. For density forecasts it is a rolling version of the Amisano and Giacomini (2007), thus the figure has to be interpreted in the opposite way: the BVAR-Base performs better than the alternative model if the test statistic is above the critical value.

The results can be summarized as follows. First, the two sets of tests on point and density forecasts are overall consistent over time and across forecast horizons. Second, regarding HICPex the tests confirm that the BVAR-Base performs significantly better than all the alternatives for every forecast horizon. This result is very robust for medium-term forecasts throughout the entire period. Third, for what concerns HICP, the evidence is mixed. By looking at the tests on density forecasts we reject the null hypothesis that the forecasting performance of BVAR-Base and the BVAR-EA is the same over time because the test statistic is below the lower bound. We conclude in favor of the model including the euro area as a whole. When analyzing the point forecasts the BVAR-Base seems to be significantly better than the BVAR-H, the BVAR-C and the RW, while the BVAR-EA appears to be a challenging benchmark especially in the first half of the evaluation period.

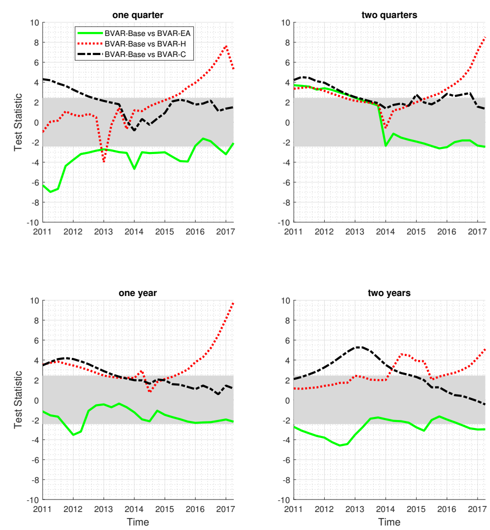


(a) HICPex: Diebold-Mariano test



(b) HICP: Diebold-Mariano test

(c) HICPex: Amisano-Giacomini test



(d) HICP: Amisano-Giacomini test

Figure 3: Giacomini and Rossi (2010)'s fluctuation test. Note: The test is performed over a window of 5 years at a significance level of 5%. The dates on the Time axis are located at the end-point of the window and the grey shaded area identify the rejection area as bounded by critical values.

4 Conclusions

In this paper, we build a large multi-country Bayesian VAR model for the EA. It is able to capture information on *inflation key drivers*, *cross-country dynamic interactions* and *country-specific variables*. We proceed in two steps.

First, we validate the model, by measuring its predictive power in comparison to benchmarks traditionally used in the literature. Covering not only the financial crisis, but also the period of the unexpected low inflation in the euro area, we find the model to produce accurate pseudo out-of-sample inflation forecasts for both short- and medium-term horizon. Therefore, we can conclude that our baseline model contains valuable information to forecast inflation in the euro area and, as such, it can be applied for empirical studies.

Second, we perform a step-by-step analysis of the model to shed light on which features are more crucial for forecasting euro area inflation. By comparing our baseline BVAR with three different alternatives, we are able to analyse the importance of the informational content of our model to forecast euro area inflation. This is of fundamental importance in our forecasting exercise, because if on the one side, including as much information as possible is indeed desirable for forecasting purpose, on the other side, the risk of overfitting could be increasing the instability, hereby deteriorating the model forecasting accuracy. Our results show that the large multi-country BVAR model presents a good performance in comparison to the alternatives; in some cases, as for the HICP excluding energy and unprocessed food in the medium-term horizon, the model is able to produce an improvement in terms of forecasting accuracy with respect to all the alternatives considered in the analysis.

Therefore, we can conclude that including information concerning *inflation key drivers* and *country-level variables* in a multi-country model may help improving the forecasting accuracy of inflation in the euro area, compensating the instability due to the data-richness and the period of high uncertainty.

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A Data

Table 6 reports the definition and data transformations of the $N(=26)$ variables included in the analysis. We estimate the model in (log-)levels. For the monthly time series, i.e. HICP, HICPex, PPI, EC Consumer Survey of inflation expectations, oil price and exchange rate, we compute the 3-month average to obtain quarterly values. We adjust all variables for seasonality effect using X-12 ARIMA procedure. The data series are mainly retrieved from Eurostat, except on the oil price, taken from U.S. Energy Information Administration (EIA) database. The sample period considered starts in 1996Q1, which is the first available data for euro area HICP, and end in 2017Q2.

Table 6: Variable definitions and transformations

Country	Variable	Frequency	Transformation
France (FR)	HICP	M	4*Log-levels
	HICP excluding energy and unprocessed food	M	4*Log-levels
	Producer Price Index	M	4*Log-levels
	Real GDP	Q	4*Log-levels
	Unit Labor Cost	Q	4*Log-levels
	EC consumer survey of inflation expectations	M	Raw
Germany (DE)	HICP	M	4*Log-levels
	HICP excluding energy and unprocessed food	M	4*Log-levels
	Producer Price Index	M	4*Log-levels
	Real GDP	Q	4*Log-levels
	Unit Labor Cost	Q	4*Log-levels
	EC consumer survey of inflation expectations	M	Raw
Italy (IT)	HICP	M	4*Log-levels
	HICP excluding energy and unprocessed food	M	4*Log-levels
	Producer Price Index	M	4*Log-levels
	Real GDP	Q	4*Log-levels
	Unit Labor Cost	Q	4*Log-levels
	EC consumer survey of inflation expectations	M	Raw
Spain (ES)	HICP	M	4*Log-levels
	HICP excluding energy and unprocessed food	M	4*Log-levels
	Producer Price Index	M	4*Log-levels
	Real GDP	Q	4*Log-levels
	Unit Labor Cost	Q	4*Log-levels
	EC consumer survey of inflation expectations	M	Raw
Euro Area (EA)	Oil price (Dollars per barrel)	M	4*Log-levels
	Exchange rate	M	Raw
	HICP	M	4*Log-levels
	HICP excluding energy and unprocessed food	M	4*Log-levels
	Producer Price Index	M	4*Log-levels
	Real GDP	Q	4*Log-levels
	Unit Labor Cost	M	4*Log-levels
	EC consumer survey of inflation expectations	M	Raw

Table 7, for each component of the HICP overall index, displays the percentage weights on the overall HICP year-on-year percentage change as of 2017 and the standard deviation in the period 1996Q1-2017Q2. The HICP index is a measure of the prices of consumer goods and services acquired by households. As shown in the Table 7, energy and unprocessed food represent the residual part of this indicator, hence, HICPex accounts for about 80% of the entire HICP basket of goods.

Table 7: HICP by components

Component	weight (%)	standard deviation
Services	41.5	0.5
Energy	11.0	6.3
Non Energy	28.5	0.4
Processed food	12.0	1.4
Unprocessed food	7.0	2.2

B European Commission consumer survey of inflation expectations

In Section 2 and 3, we use the European Commission's consumer survey as measure of inflation expectations. It provides freely available country-specific measures of inflation expectations for a long time-span (starting from 1985) at monthly frequency. This survey is indeed conducted at the national level, and the results for the euro area are compiled by aggregating country data. The consumers are asked to indicate whether they expect inflation to rise, fall or remain unchanged. Therefore, the questions are qualitative and provide information on the directional change in prices over the past and next 12 months. The results are summarised using the so-called "balance statistic", which shows the difference between the percentage of consumers thinking that consumer prices will increase and the percentage of consumers stating that prices will decrease or remain unchanged.

Specifically, answers are weighted attributing weight $\frac{1}{2}$ to the extreme answers (1) and (5), weight 1 to the moderate responses (2) and (4) and zero weight to the middle response (3) and the "don't know" response (6). The balance statistic is thus computed as:

$$P(1) + \tfrac{1}{2}P(2) - \tfrac{1}{2}P(4) - P(5)$$

where $P(i)$is the frequency of response (i) with $i = 1, 2, \ldots, 6$. The balance statistic ranges between ± 100.

Since May 2003, the European Commission has been collecting, via this consumer survey, direct quantitative information on consumers' inflation perceptions and expectations in the euro area. However, these data do not fit the time span of our model.

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