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SHORT TERM INFLATION FORECASTING: THE M.E.T.A. APPROACH

by Giacomo Sbrana§, Andrea Silvestrini§§ and Fabrizio Venditti§§

Abstract

Forecasting inflation is an important and challenging task. In this paper we assume that the core inflation components evolve as a multivariate local level process. This model, which is theoretically attractive for modelling inflation dynamics, has been used only to a limited extent to date owing to computational complications with the conventional multivariate maximum likelihood estimator, especially when the system is large. We propose the use of a method called "Moments Estimation Through Aggregation" (M.E.T.A.), which reduces computational costs significantly and delivers prompt and accurate parameter estimates, as we show in a Monte Carlo exercise. In an application to euro-area inflation we find that our forecasts compare well with those generated by alternative univariate constant and time-varying parameter models as well as with those of professional forecasters and vector autoregressions.

JEL Classification: C32, C53, E31, E37.
Keywords: inflation, forecasting, aggregation, state space models.

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1 Introduction[1]

The interest for inflation forecasts has traditionally been motivated by the existence of nominal contracts whose real value is determined, among other factors, by the changes in the purchasing power of money. Forecasting inflation is therefore crucial for nominal obligations, among others those of governments. The issue has gained further importance since the adoption by a large number of central banks of explicit or implicit inflation targets that have a forward looking flavour, like the below but close to 2 percent medium-term target stated by the European Central Bank (ECB), or the long-run 2 percent target adopted by the Fed in 2012.

When building models to predict inflation two issues arise. First, by targeting inflation aggressively, central banks have weakened the correlation between consumer prices and inflation determinants, making the job of forecasting inflation difficult. In practice it is hard to find models that outperform naive inflation forecasts, see Marcellino et al. (2003), D'Agostino et al. (2006) and Bańbura and Mirza (2013). A second issue regards the fact that models that work well at very short horizons tend to perform poorly at longer horizons. Similarly, models that track reasonably well *changes* in the inflation rate over the medium term have difficulties in getting the starting point right so that they can end up missing the level of inflation quite markedly.

The tension between short and medium-term forecasting models is at the heart of the comprehensive review by Faust and Wright (2013). These authors stress that to obtain accurate inflation forecasts at different horizons two crucial ingredients are needed: first, the starting point must be predicted accurately; second, longer horizon forecasts must be somewhat anchored to the inflation target adopted by monetary policy. In practice, they find that it is hard to outperform a strategy in which the starting point is elicited from professional forecasters and the subsequent inflation path is obtained as a smooth transition to the inflation target.

These findings have far reaching implications for research on inflation forecasting since they take some emphasis out of long-term and trend inflation forecasting, which is the focus of a large and growing literature (Cogley, 2002; Chan et al., 2013; Garnier et al., 2013 and Clark and Doh, 2014, among others), and place it on shorter horizons, on which the literature is

[1]While assuming the scientific responsibility for any error in the paper, the authors would like to thank David de Antonio Liedo, Davide Delle Monache, Giuseppe Grande, Joris Wauters, Jonathan Wright and participants at Ghent University "Macro research group meeting" for useful comments and suggestions. The views expressed are those of the authors and do not necessarily reflect those of the Bank of Italy.

relatively scant. Motivated by this observation, our paper contributes to the debate on inflation forecasting focusing on the short end of the inflation forecast curve. In particular, we propose a modelling framework that provides accurate one step ahead inflation predictions, and that can therefore be seen as a useful starting platform for longer horizon forecasts.

Central to our forecasting framework is a *multivariate local level* model, MLL henceforth, which extracts the permanent components from a panel of elementary inflation series composing the core index (overall index net of food and energy). The model represents the multivariate extension of the approach originally proposed by Muth (1960) and subsequently employed also in forecasting U.S. inflation (see for example Nelson and Schwert, 1977, and Barsky, 1987). In its *univariate* version, the local level model has attracted the attention of the recent literature mainly owing to its ease of computation. Stock and Watson (2007), for example, use it for forecasting inflation in the U.S. during the Great Moderation period, allowing for changes over time of the signal to noise ratio. On the other hand, the *multivariate* version of the local level has attracted less attention due to the computational issues arising with maximum likelihood estimation even for systems of low dimensions.[2] We show that a new estimation method for the MLL model, recently proposed by Poloni and Sbrana (2015), allows to circumvent these computational problems and makes it possible to evaluate the forecasting performance of relatively large systems. The method, defined as *"Moments Estimation Through Aggregation"* (M.E.T.A. henceforth), consists of breaking down the complex problem of estimating a (potentially large) multivariate system into a more manageable problem of estimating the parameters of many univariate equations. The latter are used to estimate the moments of the system and eventually to derive the parameters of the multivariate model through a closed-form relation between the moments and the model parameters.

Our contribution is twofold. First, in an extensive Monte Carlo exercise, we show that the M.E.T.A. is considerably faster and more accurate (especially for large dimensional systems) than the traditional multivariate maximum likelihood estimator, and it is the only viable method beyond a certain model size.[3] This result opens up the use of the MLL model to a whole new set of applications, making MLL estimation feasible even for large dimensional systems. Our second contribution is to employ this model in an empirical application to euro-area infla-

[2]Notable exceptions are Proietti (2007) in the context of U.S. monthly core inflation rates and Stella and Stock (2012).

[3]We refer to Kascha (2012) for an overview and a comparison of estimation algorithms proposed in the literature for the general class of VARMA models.

tion forecasting at short horizons. We find that the predictions derived from the MLL model are more precise than those obtained with univariate and vector autoregressive (VAR) models, as well as the time varying local level model. They also compare well with those of professional forecasters. A feature that stands out is that the M.E.T.A. approach allows assessing the relative benefits of different aggregation levels of elementary price indices to forecast aggregate (headline) inflation: indeed, by using the M.E.T.A., we find that a preliminary aggregation of price indices improves forecast accuracy, a result that could not have been obtained solely on the basis of the traditional multivariate maximum likelihood estimator.

The rest of the paper is structured as follows. Section 2 describes the model, points out the problematic aspects of estimation and presents in details the M.E.T.A. methodology. Section 3 shows through a Monte Carlo exercise the computational and accuracy gains attained by the M.E.T.A. approach. Section 4 discusses the empirical application. Section 5 concludes.

2 The multivariate local level model

Our paper uses a multivariate local level model to construct core inflation forecasts. The MLL posits that all the series in the system are driven by series-specific random walks, Harvey (1989). Its state-space representation, which is also known as structural form, is the following:

$$\begin{aligned} y_t &= \mu_t + \epsilon_t \\ \mu_t &= \mu_{t-1} + \eta_t \end{aligned} \tag{1}$$

The vector y_t, of dimension d, collects the percentage change on the previous period of the elementary items that constitute the core index and $t = 1, 2, \dots, T$ is the number of observations. Thus, in (1), the multivariate time series y_t is decomposed into a stochastic trend μ_t evolving as a multivariate random walk and a vector white noise (η_t).

It is also assumed that the noises are $i.i.d.$ with zero mean and the following covariances:

$$cov \begin{pmatrix} \epsilon_t \\ \eta_t \end{pmatrix} = \begin{pmatrix} \Sigma_\epsilon & 0 \\ 0 & \Sigma_\eta \end{pmatrix} \tag{2}$$

where Σ_ϵ, Σ_η are $(d \times d)$ matrices. In the unobserved components literature, Σ_ϵ and Σ_η are called structural parameters.

It is assumed that Σ_ϵ, Σ_η are both positive definite. The positive definiteness assumption can be relaxed by allowing Σ_η to have eigenvalues equal to zeros. This is the case when cointegration arises such that the model is driven by a lower number of random walks. In principle, our method can be extended to this case: however, this will be the object of a separate paper.

In the empirical application we will experiment with two different levels of aggregation of the core inflation index, so that d in (1) will take values between 3 and around 40.

2.1 The mapping between the structural and the reduced form parameters

Taking first differences in (1), we obtain the stationary representation of the multivariate local level model (see Harvey, 1989):

$$z_t = y_t - y_{t-1} = \eta_t + \epsilon_t - \epsilon_{t-1} = \xi_t + \Theta\xi_{t-1} \tag{3}$$

where ξ_t is an uncorrelated vector process with $E(\xi_t \xi_t^T) = \Omega$. In fact, the autocovariances of z_t are:

$$\begin{aligned} \Gamma_0 &= E(z_t z_t^T) = \Sigma_\eta + 2\Sigma_\epsilon = \Omega + \Theta\Omega\Theta^T \\ \Gamma_1 &= E(z_t z_{t-1}^T) = -\Sigma_\epsilon = \Theta\Omega \\ \Gamma_n &= E(z_t z_{t-n}^T) = 0 \quad \forall n \geq 2 \end{aligned} \tag{4}$$

Therefore, the stationary vector process z_t is a moving average process of order one and y_t can be represented as an integrated vector moving average process of order one, i.e., a vector IMA(1,1).[4] Based on (4), the structural parameters Σ_ϵ and Σ_η can be easily recovered using the autocovariances of the stationary representation z_t, i.e., Γ_0 and Γ_1:

$$\begin{aligned} \Sigma_\epsilon &= -\Gamma_1 \\ \Sigma_\eta &= \Gamma_0 + 2\Gamma_1 \end{aligned}$$

[4]See e.g. Brockwell and Davis (2002) Proposition 2.1.1, p. 50.

Also the reduced form parameters Θ and Ω can be recovered using the autocovariances of z_t. Indeed, as shown in Poloni and Sbrana (2015), there exists a unique mapping between Γ_0 and Γ_1 and the reduced form parameters Θ and Ω. That is:

$$\begin{aligned} \Theta &= \frac{1}{2}\left(\Gamma_0\Gamma_1^{-1} + \left(\Gamma_0\Gamma_1^{-1}\Gamma_0\Gamma_1^{-1} - 4I\right)^{\frac{1}{2}}\right) \\ \Omega &= 2\left(\Gamma_0\Gamma_1^{-1} + \left(\Gamma_0\Gamma_1^{-1}\Gamma_0\Gamma_1^{-1} - 4I\right)^{\frac{1}{2}}\right)^{-1}\Gamma_1 \end{aligned} \tag{5}$$

The proof of (5) is given in Appendix A.

An important aspect of this model is that both Γ_0 and Γ_1 are symmetric matrices as determined by the properties of the noises as in (2). The symmetry of Γ_1 in particular turns out to be a necessary condition for the implementation of the M.E.T.A approach, as it will become clear in the following subsection.[5]

The mapping between Γ_0, Γ_1 and Θ is particularly important in our context, since Θ in (3) is crucial in order to forecast the y_t vector. Indeed, once an estimate of Θ is available, then the following recursion can be employed to derive the forecasting error (Muth, 1960; Harvey, 1989):[6]

$$\hat{\xi}_{t+1} = \sum_{j=0}^{\infty} -\hat{\Theta}^j z_{t+1-j} \tag{6}$$

This recursion does not need an infinite number of lags of z_{t+1-j} as long as the eigenvalues of Θ are smaller than one.[7]

The estimator for Θ as in (5) is simple and fast to compute. However, its accuracy relies upon the estimates of the autocovariances of z_t. Unfortunately, the use of the sample autocovariances $\hat{\Gamma}_0 = \frac{1}{N}\sum_{t=1}^{N} z_t z_t^T$, $\hat{\Gamma}_1 = \frac{1}{N}\sum_{t=1}^{N} z_t z_{t-1}^T$ might not be accurate enough, especially in small samples. To overcome this problem, Poloni and Sbrana (2015) develop a simple estimation method defined as *"Moment Estimation Through Aggregation"* (i.e., M.E.T.A.) and establish the asymptotic properties (consistency and asymptotic normality) of the proposed estimator.[8]

[5]For more general (non orthogonal) specifications of (4), where for example $cov(\varepsilon_t \eta_t^T) \neq 0$, the symmetry of Γ_1 does not hold.

[6]A proof that $(I - \Theta L)^{-1} = \sum_{j=0}^{\infty}(\Theta L)^j$ can be found in Abadir & Magnus (2005), p. 249.

[7]Equation (6) will be used in our empirical analysis when forecasting the underlying items of the core industrial goods and services inflation aggregates. A forecast for core industrial goods (or services) inflation is then obtained aggregating predictions for the disaggregate items: $w_{t+1}^T z_{t+1}$, where w_{t+1} is a vector of known core industrial goods/services weights.

[8]Poloni and Sbrana (2015) show that these asymptotic properties hold when ϵ_t and η_t are *i.i.d.*, meaning that noises should not necessarily be Gaussian. This also explains why we do not assume normality in (1).

Since this approach is novel to forecasting economic times series we describe it in detail in the next subsection.

2.2 The estimation problem: the M.E.T.A. solution

In order to provide an intuition for the M.E.T.A. estimation method let us make two observations:

1. A linear transformation of a vector MA(1) process possesses itself an MA(1) representation. Indeed, the moving average (MA) class of models (of generic q order) is closed with respect to linear transformations (see Lütkepohl, 2007, Proposition 11.1, p. 435). As a consequence, if we take two generic elements of the vector z_t, their sum is itself an MA(1).

2. Maximum likelihood is faster and more precise when applied to the estimation of the parameters of univariate, rather than vector processes.

The M.E.T.A. approach exploits these two facts to recover an estimate of Θ and Ω via Γ_0 and Γ_1 in (5). In what follows we illustrate how to build the M.E.T.A. estimator by means of a simple example.

For the sake of simplicity and without loss of generality, let us consider the following bivariate process in (3):

$$\begin{pmatrix} z_{1t} \\ z_{2t} \end{pmatrix} = \begin{pmatrix} \eta_{1t} \\ \eta_{2t} \end{pmatrix} + \begin{pmatrix} \epsilon_{1t} - \epsilon_{1,t-1} \\ \epsilon_{2t} - \epsilon_{2,t-1} \end{pmatrix} = \begin{pmatrix} \xi_{1t} \\ \xi_{2t} \end{pmatrix} + \begin{pmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{pmatrix} \begin{pmatrix} \xi_{1,t-1} \\ \xi_{2,t-1} \end{pmatrix} \tag{7}$$

This model can be reparametrized equation-by-equation as:

$$z_{1t} = \upsilon_{1t} + \psi_1 \upsilon_{1,t-1}$$
$$z_{2t} = \upsilon_{2t} + \psi_2 \upsilon_{2,t-1}.$$

Each element of the vector z_t (i.e., z_{1t} and z_{2t}) is a linear transformation of the bivariate system in (7): for instance, $z_{1t} = \begin{pmatrix} 1 & 0 \end{pmatrix} \begin{pmatrix} z_{1t} \\ z_{2t} \end{pmatrix}$. Therefore, each z_{it} has a univariate MA representation with parameter ψ_i and innovation variance $E(\upsilon_{it}^2) = \sigma_i^2$ $(i = 1, 2)$ (see, e.g., Lütkepohl, 1987, p. 102).

Furthermore, consider the process derived after contemporaneous aggregation of the two individual components:

$$z_{(1+2),t} = z_{1t} + z_{2t} = a_{(1+2),t} + \delta_{(1+2)} a_{(1+2),t-1}.$$

The aggregate process $z_{(1+2),t}$ also has an MA representation with parameter $\delta_{(1+2)}$ and innovation variance $E(a^2_{(1+2),t}) = \sigma^2_{(1+2)}$.

Next, we show that the autocovariances Γ_0 and Γ_1 of the system in (7) can be recovered by knowing those of the individual components z_{1t} and z_{2t} as well as those of the pairwise aggregate process $z_{(1+2),t}$. First, notice that the diagonal elements of Γ_0 and Γ_1 are pinned down by the autocovariances of the individual processes.

Turning to the off-diagonal elements, note that $E(z^2_{(1+2),t}) = E(z^2_{1t}) + E(z^2_{2t}) + 2E(z_{1t}z_{2t})$. This means that the off-diagonal elements of Γ_0 can be computed as $E(z_{1t}z_{2t}) = \frac{1}{2}(E(z^2_{(1+2),t}) - E(z^2_{1t}) - E(z^2_{2t}))$. Similarly, we have that: $E(z_{(1+2),t}z_{(1+2),t-1}) = E(z_{1t}z_{1,t-1}) + E(z_{2t}z_{2,t-1}) + 2E(z_{1t}z_{2,t-1})$, since $E(z_{1t}z_{2,t-1}) = E(z_{2t}z_{1,t-1})$ given that $\Gamma_1 = \Gamma_1^T$. This implies that the off-diagonal elements of Γ_1 can be computed as $E(z_{1t}z_{2,t-1}) = E(z_{2t}z_{1,t-1}) = \frac{1}{2}(E(z_{(1+2),t}z_{(1+2),t-1}) - E(z_{1t}z_{1,t-1}) - E(z_{2t}z_{2,t-1}))$.

Summing up, one can recover Γ_0 and Γ_1 as follows:

$$\begin{aligned}
\Gamma_0 &= \begin{bmatrix} E(z^2_{1t}) & \frac{E(z^2_{(1+2),t})-E(z^2_{1t})-E(z^2_{2t})}{2} \\ \frac{E(z^2_{(1+2),t})-E(z^2_{1t})-E(z^2_{2t})}{2} & E(z^2_{2t}) \end{bmatrix} \\
&= \begin{bmatrix} (1+\psi_1^2)\sigma_1^2 & \frac{(1+\delta^2_{(1+2)})\sigma^2_{(1+2)}-(1+\psi_1^2)\sigma_1^2-(1+\psi_2^2)\sigma_2^2}{2} \\ \frac{(1+\delta^2_{(1+2)})\sigma^2_{(1+2)}-(1+\psi_1^2)\sigma_1^2-(1+\psi_2^2)\sigma_2^2}{2} & (1+\psi_2^2)\sigma_2^2 \end{bmatrix}
\end{aligned}$$

$$\begin{aligned}
\Gamma_1 &= \begin{bmatrix} E(z_{1t}z_{1,t-1}) & \frac{E(z_{(1+2),t}z_{(1+2),t-1})-E(z_{1t}z_{1,t-1})-E(z_{2t}z_{2,t-1})}{2} \\ \frac{E(z_{(1+2),t}z_{(1+2),t-1})-E(z_{1t}z_{1,t-1})-E(z_{2t}z_{2,t-1})}{2} & E(z_{2t}z_{2,t-1}) \end{bmatrix} \\
&= \begin{bmatrix} \psi_1\sigma_1^2 & \frac{1}{2}[\delta_{(1+2)}\sigma^2_{(1+2)} - \psi_1\sigma_1^2 - \psi_2\sigma_2^2] \\ \frac{1}{2}[\delta_{(1+2)}\sigma^2_{(1+2)} - \psi_1\sigma_1^2 - \psi_2\sigma_2^2] & \psi_2\sigma_2^2 \end{bmatrix}.
\end{aligned}$$

In the general multivariate case, in accordance with the notation used earlier, let us define a pairwise aggregate process as $z_{(i+j),t} := z_{it} + z_{jt}$ $(i, j = 1, 2, \ldots, d)$, built aggregating pairs of individual components. Let $\gamma_k^{(i+j)}$ be its autocovariances, with $k = 0, 1$. Then, the (i, j)-th entry of Γ_k is given by:

$$(\Gamma_k)_{i,j} = \begin{cases} \gamma_k^{(i)} & i = j, \\ \frac{1}{2}\left(\gamma_k^{(i+j)} - \gamma_k^{(i)} - \gamma_k^{(j)}\right) & i \neq j. \end{cases} \tag{8}$$

In particular, the d diagonal entries are just the autocovariances of the individual components $\gamma_k^{(i)}$ while the off-diagonal entries are uniquely determined given the autocovariances of the $\frac{d(d-1)}{2}$ pairwise aggregate processes. That is, for each individual component we have:

$$z_{it} = v_{it} + \psi_i v_{i,t-1}, \quad E[v_{it}^2] = \sigma_i^2,$$

and for the pairwise aggregate we have:

$$z_{(i+j),t} = z_{it} + z_{jt} = a_{(i+j),t} + \delta_{(i+j)} a_{(i+j),t-1},$$

with moving average parameter $\delta_{(i+j)}$ and innovation variance $E(a_{(i+j),t}^2) = \sigma_{(i+j)}^2$.

As seen in the bivariate case, it is possible to establish a mapping between the MA(1) parameters of the individual components ψ_i and σ_i^2 and the autocovariances $\gamma_0^{(i)}$ and $\gamma_1^{(i)}$. This of course holds also for the pairwise aggregate processes, so that one can use the parameters $\delta_{(i+j)}$ and $\sigma_{(i+j)}^2$ to recover $\gamma_0^{(i+j)}$ and $\gamma_1^{(i+j)}$.

More specifically, for the individual components we have:

$$\begin{aligned} \gamma_0^{(i)} &= (1 + \psi_i^2)\sigma_i^2, \\ \gamma_1^{(i)} &= \psi_i \sigma_i^2. \end{aligned} \tag{9}$$

while for the pairwise aggregate:

$$\begin{aligned} \gamma_0^{(i+j)} &= (1 + \delta_{(i+j)}^2)\sigma_{(i+j)}^2, \\ \gamma_1^{(i+j)} &= \delta_{(i+j)}\sigma_{(i+j)}^2. \end{aligned} \tag{10}$$

This suggests an estimation procedure that can be summarised in four steps. Given T observations of the multivariate process as in (3):

1. For each individual component, say z_i, and for each pairwise aggregate process, defined as $z_{(i+j),t} := z_{it} + z_{jt}$, estimate an MA(1) model obtaining respectively $(\hat{\psi}_i, \hat{\sigma}_i^2)$ and $(\hat{\delta}_{(i+j)}, \hat{\sigma}^2_{(i+j)})$.

2. Construct $\hat{\gamma}_k^{(i)}$ and $\hat{\gamma}_k^{(i+j)}$ for $k = 0, 1$ using formulas (9) and (10).

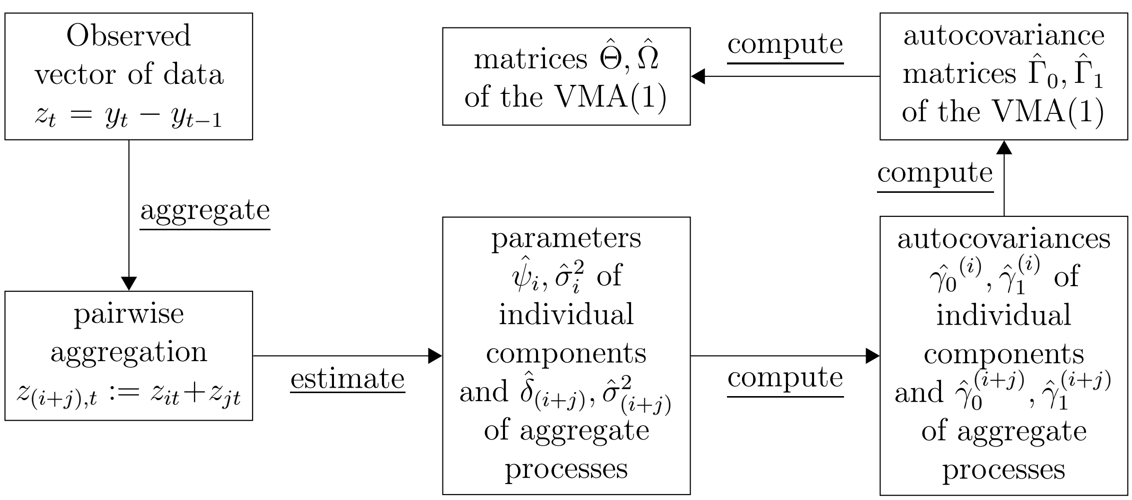
3. Recover estimates of the autocovariance matrices Γ_0 and Γ_1 using (8).

4. Recover estimates of Θ (and of Ω) using the closed-form relation in (5).

The estimated Θ is then used to produce forecasts based on (6).

In order to better visualise the four steps that make up the estimation procedure, a graphical representation of the M.E.T.A. approach is represented in Figure 1. As highlighted by Poloni and Sbrana (2015), a multivariate maximum likelihood estimator of the local level model in (1) and (2) would follow directly the "missing arrow" on the diagram in Figure 1 between the observed vector z_t and the reduced form parameters $\hat{\Theta}$ and $\hat{\Omega}$.

Figure 1: The M.E.T.A. estimation approach



The main advantage of the procedure described in steps 1–4 is that it exploits the univariate maximum likelihood estimation for MA(1) processes, yielding remarkably accurate values for the autocovariances and the parameters and low computational cost.[9] Most importantly, this estimation method is much faster than a multivariate maximum likelihood estimator and has

[9]In fact, as highlighted by Poloni and Sbrana (2015), it reduces the problem from one d-dimensional maximum likelihood estimation to $\frac{d(d+1)}{2}$ univariate maximum likelihood problems.

clear computational advantages. Indeed, a likelihood routine estimating directly the MLL model as in (1) is affected by numerical convergence issues and bad complexity, growing with the dimensionality of the model (see, e.g., Kascha, 2012).

In the next section we will provide convincing evidence on this point through a Monte Carlo exercise.

3 M.E.T.A. vs. multivariate Maximum Likelihood: comparing speed and accuracy

This section shows the results from a Monte Carlo experiment in order to compare the performance of the M.E.T.A. approach vis-à-vis the standard multivariate maximum likelihood estimator (MLE). We generate the multivariate local level model as in (1) using three different dimensions. Model 1 refers to a model with $d = 4$; Model 2 refers to $d = 8$; Model 3 refers to $d = 12$. We did consider dimensions higher than 12 but, given the difficulties for the MLE to converge, we decided not to pursue on this direction. On the contrary the M.E.T.A. always converges, regardless of the dimension, since the likelihood of the univariate processes easily achieves the maximum.

It can be noted that, given the results as in (5), the matrix of parameters Θ is only function of the covariances of the noises (2). In addition, as shown in Appendix A, the eigenvalues of Θ are always between 0 and -1. More specifically, one can observe that the higher the norm of Σ_ϵ compared with the norm of Σ_η (i.e. the more noisy are the observed data), the closer to -1 are the eigenvalues of Θ. On the contrary, the smaller the norm of Σ_ϵ with respect to Σ_η, the closer to 0 are the eigenvalues of Θ. Given that for the euro-area inflation the Θ matrix tends to have roots between -0.5 and -1, this led us to consider the covariances of the noises (2) as reported in Appendix B. Note that also Stock and Watson (2007), Table 3, p. 13, find an MA coefficient between -0.5 and -1 for US inflation in the 1984:I–2004:IV sub-sample.

More specifically, these are the eigenvalues of Θ spanned by the covariances of the noises (2) considered for our three models:

Model 1: $\{-0.865942, -0.80089, -0.748561, -0.723538\}$

Model 2: $\{-0.905346, -0.869581, -0.782246, -0.737551,$

$- 0.70656, -0.68095, -0.6586, -0.631203\}$

Model 3: $\{-0.884203, -0.86085, -0.853193, -0.832998,$
$- 0.806906, -0.767359, -0.752035, -0.73833,$
$- 0.729815, -0.709633, -0.704937, -0.670387\}$.

See Appendix A (equation (15)) for the derivation of the eigenvalues as function of the covariances of the noises. It should be noted that the considered eigenvalues mimic those estimated using the Euro-area inflation sub-indexes. For example, the prices of core industrial goods, being more noisy, tend to have roots closer to -1, while those of services tend to have roots closer to -0.5.[10]

For each model, we generate time series of three different sample sizes $T = 200$, 400 and 800, and estimate them using both approaches. Each experiment is repeated 500 times and the simulations are carried out using MATHEMATICA 8 by Wolfram and its TIMESERIES 1.4.1 package.[11]

As error measure, we use the relative error in the Frobenius norm (root mean squared error of the matrix entries) for the estimates of Θ. That is:

$$RMSE = \frac{\left\|\hat{\Theta} - \Theta\right\|_F}{\|\Theta\|_F}, \tag{11}$$

where $\|\Theta\|_F := \left(\sum_{i=1}^{m}\sum_{j=1}^{n}\Theta_{ij}^2\right)^{1/2}$. The results are reported in Table 1. The first column, comparing M.E.T.A. and MLE, contains the mean relative (normalized) RMSE multiplied by 1000. The second column reports the average time (in seconds) taken by each estimation procedure.

Overall, the results are clearly in favor of the M.E.T.A. estimator that seems to outperform the rival estimator all the times in terms of accuracy. Moreover, the last column of Table 1 reveals the computational difficulties of the MLE for medium-high dimensional systems. This is evident from the results relative to Model 2 and 3, where the M.E.T.A. tends to be faster than the MLE (with the exception of Model 2, with 800 observations). More specifically, when the dimension increases and the sample size is not large enough, the MLE faces convergence

[10]Two plots of the eigenvalues for core industrial goods and services are available from the authors upon request.

[11]See the webpage `http://media.wolfram.com/documents/TimeSeriesDocumentation.pdf`

issues and this impacts on its performance (see the gaps between the RMSE). This is not the case for Model 1, where the MLE seems to be faster than the M.E.T.A., although less accurate.

Summing up, these results show that the M.E.T.A. estimator is faster and more accurate than standard multivariate maximum likelihood algorithms, especially for large dimensional systems. We can fairly claim that the M.E.T.A. is probably the only feasible method to estimate a system with more than 20 equations, leading to very significant time saving.

These nice features are clearly due to the fact that we have replaced the traditional multivariate maximum likelihood estimation with a procedure that requires estimating univariate processes only. Indeed, this makes the estimation fast and accurate, surmounting the computational difficulties met when maximising a multivariate likelihood. Finally, the univariate approach also allows estimating even medium-large systems. The benefits will become clearer in the empirical application, where we will be able to assess the relative gains of different disaggregation levels of the core price sub-indexes for inflation forecasting, an appraisal that would not be feasible using the multivariate maximum likelihood estimator.

4 Empirical application

Our empirical investigation consists of a pseudo real time out-of-sample forecasting exercise of euro-area inflation. We estimate all the models using data from January 1996 and run the forecast exercise with an out-of-sample ranging from January 2005 to April 2014 (112 observations). Our target variable is the year on year change of the headline euro-area Harmonized Index of Consumer Prices (HICP):[12]

$$(HICP_{t+h}/HICP_{t+h-12} - 1) \times 100 \tag{12}$$

that is the transformation in terms of which the ECB target is defined. Our focus is on one step ahead forecasts (i.e., $h = 1$ in equation (12)).

We are particularly interested in contrasting the accuracy of our model forecasts with that

[12]Forecasts of the headline index are obtained by aggregating core inflation predictions, obtained either with the integrated VMA(1) model estimated applying the M.E.T.A. approach or with alternative time series models, with forecasts for the volatile components (energy and food prices). The models used to forecast volatile components are quite standard, and follow closely those in ECB (2010) for energy prices, and in Ferrucci et al. (2012) and in Porqueddu and Venditti (2013) for food prices. Since they do not constitute the novelty of the paper we refer the interested reader to the Appendix C for the details on how they are specified.

of the professional forecasters, which provide a hard to beat benchmark, as documented by Faust and Wright (2013). To make this comparison meaningful we need to replicate as closely as possible the information set available to them when their forecasts are elicited. We clarify this issue in Appendix D.

Besides the comparison with the Bloomberg forecasts, we further test the value of our approach against other model based forecasts. Unless otherwise specified, all models are estimated on seasonally adjusted monthly price changes.[13] Seasonality and deterministic effects are modelled separately.[14] Forecasts are then computed for the annual HICP inflation rate, as in (12).

The full battery of models that we consider is summarised here below:

1. "VMA(1) - large" uses the integrated VMA(1) model estimated with the M.E.T.A. approach for core inflation but exploiting a lower aggregation of the core index (around 25 elementary consumer price series for goods and 40 for services, see Tables A1 and A2 in the Appendix).

2. "VMA(1) - small" uses the integrated VMA(1) model estimated with the M.E.T.A. approach for core inflation using a relatively high aggregation level (5 sub-indexes for goods and 3 for services, see Tables A3 and A4 in the Appendix). The choice of this level of aggregation is led by the results obtained by Sbrana & Silvestrini (2013). Indeed, using the multivariate local level model, the authors derive conditions on the parameters under which the variance of the contemporaneously aggregated process achieves its minimum (p. 188). These conditions are met here using 5 sub-indexes for goods and 3 for services.[15]

3. "VAR(1)", "VAR(2)" and "VAR(3)" employ the same type of information as "VMA(1) - large" but use Vector Autoregressions rather than a multivariate local level to jointly

[13] Seasonal adjustment is carried out regressing the monthly price changes on a constant and eleven time dummies. Some intervention variables are also included in the regressions in order to remove the influence of outliers. The models "VMA(1) - large", "VMA(1) - small", VAR(1), VAR(2) and VAR(3) are fitted to seasonally adjusted monthly price changes, in first differences. With the "Sum-ARIMA" approach instead, univariate ARIMA(p,1,q) models are fitted to seasonally adjusted monthly price changes. Also the "T.V.P. IMA(1,1)" model is estimated on seasonally adjusted monthly price changes.

[14] Forecasts for the seasonal and deterministic components are added to forecasts of the seasonally adjusted month-on-month inflation series.

[15] In order to preserve the out-of-sample nature of the forecasting exercise, the parameters of the multivariate local level model are estimated once with information ranging from January 1996 up to December 2004. On the basis of these estimates, the preferred aggregation levels for core goods and services are chosen and then kept fixed over the whole out-of-sample period.

model the behaviour of the goods and services inflation series, in first differences.

4. "Sum-ARIMA" fits univariate ARIMA(p,1,q) models to the individual items of the core index. The same level of disaggregation as in "VMA(1) - large" is used. The Schwartz Information Criterion, BIC, is applied in order to select p and q, noting that the maximum AR and MA order is set equal to three.

5. "IMA(1,1)" employs the univariate integrated moving average process with constant parameters to model the two goods and services inflation series.

6. "T.V.P. IMA(1,1)" uses the univariate integrated moving average process with time varying parameters popularised by Stock and Watson (2007) to model the two goods and service inflation series.[16]

7. Finally, we compute a direct Random Walk forecast of the headline index that, given the high persistence of the year on year rate, constitutes a fairly challenging benchmark. This is obtained as:

$$E_t(HICP_{t+h}/HICP_{t+h-12} - 1) \times 100 = (HICP_t/HICP_{t-12} - 1) \times 100$$

Table 2 shows the Root Mean Squared Forecast Errors (RMSFE) of the models described above together with those obtained on the basis of the mean estimate of the Bloomberg poll. The left column displays results for the whole out-of-sample (2005:01-2014:04), while the central and right columns show results for two equally split sub-samples (2005:01-2009:9 and 2009:10-2014:04).

Six findings emerge:

1. Forecasts produced using the integrated VMA(1) models are more accurate than those of the professional forecasters, especially when a higher level of aggregation (VMA(1) - small) is used. In this case the improvement in terms of forecast accuracy over the Bloomberg forecast is of around 15 percent. In turn, the performance of the Bloomberg forecast is comparable to that obtained through standard VARs.

[16] We follow the UC-SV specification as in Stock and Watson (2007) and fix the variances of the stochastic volatilities shocks to $\gamma = 0.2^2$. The model is estimated by Markov Chain Monte Carlo (MCMC). Estimation results are based on 5000 draws and a burn-in period of 100 draws. The results are very robust to changes of these parameters.

2. Higher levels of aggregation yield a better performance, as the forecasts of the VMA(1) - small are more accurate than those of the VMA(1) - large. These empirical results seem to confirm theoretical results obtained by Sbrana and Silvestrini (2013, p. 188). Therefore, when forecasting contemporaneously aggregated local level processes, the aggregation level should be chosen in order to meet conditions that minimize the MSFE.

3. The VMA(1) - large provides forecasts that are more accurate than those of the other multivariate competitors as well as Bloomberg and random walk. As noted above, this comparison would have not been feasible without the implementation of the M.E.T.A. approach given the huge number of parameters. Therefore it emerges that the use of VMA(1) model improves the forecasts accuracy with respect to the VARs. This represents a novel empirical result deserving further investigation in future applied research.

4. The VMA(1) - small model slightly improves both on the IMA(1,1) with constant parameters as well as on the T.V.P. IMA(1,1). The univariate IMA(1,1) and T.V.P. IMA(1,1) models have a comparable performance, indicating that stochastic volatility is not a relevant feature of our dataset. Notice that these three MA models are closely related. Specifically, the model generated after contemporaneous aggregation of the integrated VMA(1) is itself an integrated MA(1): as already explained, the vector moving average of order one is in fact closed with respect to linear transformations. In turn, the univariate IMA(1,1) with constant parameters is a restricted version of the T.V.P. IMA(1,1). In this particular application we find that a prediction built aggregating forecasts of the whole integrated VMA(1) process is more accurate in mean squared error sense that a prediction built forecasting directly the aggregate series with an IMA(1,1) model, both with constant and time varying parameters.[17] This outcome further stresses the importance of having an estimation method that allows to easily estimate multivariate systems.

5. All the models and the professional forecasts improve quite substantially upon the Random Walk.

6. The ranking across models is stable across sub-samples, although the improvement over the Random Walk is larger in the 2005-2009 period than in the following five years.

[17] This result has been formally proven by Lütkepohl (1987) under the assumptions of a known data generation process and no estimation uncertainty.

To gauge whether the differences in forecast accuracy highlighted in Table 2 are statistically significant we run equal forecast accuracy and forecast encompassing tests. The hypothesis of equal forecast accuracy is analysed through the standard Diebold-Mariano (1995) test, in which the null hypothesis is that the difference in either the squared or the absolute prediction errors of two competing models are not significantly different from each other. The null hypothesis of forecast encompassing tests, instead, is that, given two competing forecasts for the same target variable, there is no significant gain in (linearly) combining the predictions of the two models. In this case we use the test by Harvey et al. (1998). We take as benchmark our preferred model, i.e., the VMA(1) - small, and run both forecast accuracy and encompassing tests against this benchmark. The results are reported in Table 3.

The fact that the sum-ARIMA models produce forecasts that are similar to those of the integrated VMA(1) model is reflected in p-values of the Diebold-Mariano test close to 1. Also in the case of the Bloomberg forecasts the observed difference in forecast accuracy in favour of the integrated VMA(1) model does not turn out to be statistically significant. The null hypothesis of equal forecast accuracy can be rejected at conventional confidence levels in all the remaining pairwise comparisons. Turning to forecast encompassing tests, the VMA(1) - small model encompasses most competitors but it is itself encompassed by the VMA(1) - large and by the Bloomberg forecasts. This latter result suggests that a further improvement in forecast accuracy can be obtained by combining the multivariate local level model predictions with those of professional forecasters.

We explore the gains of pooling forecasts from the VMA(1) - small and the Bloomberg survey by letting the relative weights of these two models vary over time as a function of their relative forecast accuracy in the recent past. More specifically, for each of the two models to be combined we compute in each period in the forecast sample the mean squared errors over the previous L periods, and use the inverse of these MSFE (normalized by their sum) as model weights. This means that at time T we weigh each model j using the time varying weight:

$$w_{j,T} = \frac{\left((1/L)\sum_{t=T-L-1}^{T-1} FE_{j,t}^2\right)^{-1}}{w_{1,T} + w_{2,T}} \tag{13}$$

where $FE_{j,t}$ is the (out-of-sample) one step ahead prediction error of model j at time t. In the exercise we set $L = 24$, that is we use the inverse MSE over the previous two years as weights.[18] In Table 4 we report a comparison of the RMSFE of the individual models relative to those of the forecast combination, together with the results of equal forecast accuracy and forecast encompassing tests in which the reference model is the combined VMA(1) - small/Bloomberg forecast.

The relative RMSFEs displayed in the first column of Table 4 show that the combined forecast provides indeed more accurate predictions than the individual models, with a gain ranging from 8% (with respect to the VMA(1) - small) to 24% (with respect to the forecasts from the Bloomberg survey). Looking at the results of the Diebold-Mariano tests, this combined forecast significantly outperforms single model forecasts, including the IMA(1,1) and the T.V.P. IMA(1,1) model. Also, it significantly encompasses single model forecasts while, with the exception of the random walk, it is not encompassed by them.

4.1 Robustness checks and comparison with the literature

To assess the robustness of the proposed approach we conduct two further exercises. The former is an extension to the three largest euro-area countries (Germany, France and Italy). Such a check is needed to dispel the doubt that there is something specific about the euro-area data that favours our approach. The latter consists of considering two steps ahead forecasts. Notice that this is not the ideal setting for our model that, being a vector MA(1), has only one lag memory. This implies that, for multi-period predictions, its forecast reverts to the unconditional mean. To shorten the discussion, in both analyses we consider fewer models, the VMA(1) - small model, the VAR(1), the Random Walk and the sum-ARIMA. The results obtained for the individuals countries are shown in Table 5.[19]

Three key results emerge. First, on the whole out-of-sample the RMSE of the integrated VMA(1) model is lower than for the remaining models for Germany and Italy; furthermore, the improvement on the Random Walk and on the VAR(1) model is statistically significant at the 10% confidence level according to the Diebold-Mariano test. For France only the sum-ARIMA model gives more accurate predictions. Second, the performance is quite stable over the two

[18] Results obtained with a larger L as well as with constant weights are similar.

[19] In the forecast exercise for the countries we assume the same information flow as for the euro area and therefore combine one step ahead forecasts for the core components with nowcasts of energy prices based on fuel price data on the current month.

half samples. Taken together, the results are quite reassuring on the validity of the integrated VMA(1) estimated with the M.E.T.A. approach for one month ahead predictions of inflation.

The results of the two steps ahead forecast exercise are reported in Table 6. In this case the performance of the VMA(1) - small model and that of the VAR(1) and sum-ARIMA models are very similar, with a slight prevalence of the competitors. Overall, it appears that the differences in favour of the integrated VMA(1) model observed when considering one step ahead forecasts vanish at longer horizons. As highlighted above this is not surprising given the lag memory of the MA(1) model.

Finally, we discuss how our model forecasts compare with those produced by alternative methods recently appeared in the literature, namely the MIDAS model in Moretti and Monterforte (2013) and the factor model by Modugno (2011). The former analyses the information content of financial variables for forecasting inflation, while the latter uses a mixed-frequency dynamic factor model to forecast inflation in a large dataset environment. Both have an application to forecasting euro-area inflation.

For the sake of brevity we do not discuss here the relative merits of ours and their approach, as our main concern is gauging whether the performance of our method is comparable to that of other state-of-the-art methodologies. We do this in the only feasible (albeit rather coarse) way, that is by collecting forecasts over the ample periods considered by these studies and comparing results. Between June 2002 and September 2007, the VMA(1) - small model yields a RMSFE of 0.096, as opposed to the 0.148 attained by aggregating the daily one step ahead forecasts obtained with the best MIDAS specification in Monteforte and Moretti (2013, Table 1). Between January 2002 and December 2009 the VMA(1) - small model achieves an RMSFE of 0.10, against the 0.156 obtained by the factor model in Modugno (2011, Table 1).[20] Needless to say, we do no take these results as conclusive evidence in favour of our approach, yet we read them as indicative of the fact that our methodology constitutes a serious benchmark for short term inflation forecasting.

[20]The latter figure is obtained by multiplying the ratio to the Random Walk RMSFE (0.56) presented in Table 1 in Modugno (2011), by the Random Walk RMSFE over the same period, 0.277.

5 Conclusions

In this paper we propose to forecast euro-area inflation assuming that the underlying components of the core inflation index evolve as a multivariate local level model. We circumvent the estimation problems faced by the multivariate maximum likelihood estimator through the *"Moments Estimation Through Aggregation"* (M.E.T.A.) approach recently proposed by Poloni and Sbrana (2015).

We illustrate the advantages of this estimation method through a Monte Carlo experiment and an application to forecasting euro-area inflation at short horizons. In the Monte Carlo simulations we show that the M.E.T.A. outperforms the standard multivariate maximum likelihood estimator both in speed and in accuracy. In the empirical application the multivariate local level model estimated with the M.E.T.A. approach is found to provide predictions more accurate than those obtained by other multivariate models and that compare well with those polled by Bloomberg. Important gains in forecast accuracy can be obtained by combining our model forecasts with those provided by professional forecasters using time varying combination weights. A robustness check conducted on the three largest euro-area countries confirms the validity of the approach for a wider range of applications.

In terms of future research, further work may refer to the recent literature on forecasting inflation using univariate models with time varying parameters, along the lines of the IMA(1,1) process with stochastic volatility proposed by Stock and Watson (2007). A challenging extension would be to consider a multivariate generalization of this model, developing an estimation procedure that allows us to overcome the computational difficulties that are known to emerge even in the univariate framework.

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Tables

Table 1: Mean relative (normalized) RMSE of the estimates of Θ

	Sample size	M.E.T.A. $\hat{\Theta}$	MLE $\hat{\Theta}$	M.E.T.A. Time	MLE Time
Model 1	200	108.65	136.33	1.12	0.65
	400	69.43	86.74	2.32	0.94
	800	43.89	58.25	2.44	0.96
Model 2	200	183.52	279.33	2.52	4.33
	400	120.51	154.32	5.01	6.44
	800	79.69	98.85	8.76	6.76
Model 3	200	208.18	588.34	8.16	21.93
	400	139.85	202.34	16.86	32.17
	800	88.48	118.67	33.71	35.29

Note to Table 1. The first column, comparing M.E.T.A. and MLE, reports the average relative root mean squared error of the estimated Θ multiplied by 1000. The second column, comparing M.E.T.A. and MLE, reports the average number of seconds required for a single run of the estimation procedure.

Table 2: Forecast accuracy (RMSFE)

	2005-2014	*2005-2009*	*2009-2014*
VMA(1) - small	0.128	0.114	0.141
VMA(1) - large	0.137	0.123	0.149
VAR(1)	0.141	0.129	0.153
VAR(2)	0.150	0.145	0.155
VAR(3)	0.143	0.134	0.152
Bloomberg	0.147	0.134	0.160
Random Walk	0.271	0.304	0.233
sum-ARIMA	0.130	0.115	0.143
IMA(1,1)	0.134	0.117	0.149
T.V.P. IMA(1,1)	0.134	0.118	0.147

Note to Table 2. The RMSFE in the 2005-2014 column are based on 112 recursive forecasts between January 2005 and April 2014. Those in the 2005-2009 column are based on 56 recursive forecasts between January 2005 and August 2009. Those in the 2009-2014 column are based on 56 recursive forecasts between September 2009 and April 2014.

Table 3: Equal forecast accuracy and forecast encompassing tests (benchmark model is VMA(1) - small)

	Forecast accuracy tests				Forecast encompassing tests			
	Mean Squared errors		Absolute errors		VMA(1) - small encompasses		VMA(1) - small is encompassed	
	Stat	p-val	Stat	p-val	Stat	p-val	Stat	p-val
VMA(1) - large	-3.143	0.002	-1.502	0.133	4.033	0.000	2.161	0.031
VAR(1)	-2.212	0.027	-2.124	0.034	4.322	0.000	0.558	0.577
VAR(2)	-2.723	0.007	-2.947	0.003	4.306	0.000	0.071	0.943
VAR(3)	-1.778	0.076	-1.706	0.088	3.811	0.000	0.965	0.334
Bloomberg	-1.385	0.166	-0.530	0.596	4.827	0.000	3.258	0.001
RW	-4.320	0.000	-5.241	0.000	5.130	0.000	0.652	0.514
sum-ARIMA	-0.373	0.709	0.919	0.358	1.607	0.108	0.914	0.361
IMA(1,1)	-2.627	0.009	-1.283	0.199	3.402	0.001	1.842	0.066
T.V.P. IMA(1,1)	-2.724	0.007	-1.259	0.208	3.580	0.000	1.853	0.064

Note to Table 3. The table shows the results of the tests of equal forecast accuracy and forecast encompassing between the model VMA(1) - small and the models indicated in the rows. The forecast accuracy test is the Diebold-Mariano test based on, respectively, squared and absolute errors. The forecast encompassing test is the Harvey-Leybourne-Newbold test.

Table 4: Equal forecast accuracy and forecast encompassing tests (benchmark model is forecast combination)

		Forecast accuracy tests				Forecast encompassing tests			
	Relative RMSFE	Mean Squared errors		Absolute errors		Combined encompasses		Combined is encompassed	
		Stat	p-val	Stat	p-val	Stat	p-val	Stat	p-val
VMA(1) - small	1.08	-1.404	0.160	-2.458	0.014	3.346	0.001	0.750	0.453
VMA(1) - large	1.14	-2.042	0.041	-2.482	0.013	4.037	0.000	0.422	0.673
VAR(1)	1.19	-2.646	0.008	-3.254	0.001	5.208	0.000	1.176	0.240
VAR(2)	1.28	-2.992	0.003	-3.994	0.000	4.984	0.000	0.847	0.397
VAR(3)	1.22	-2.252	0.024	-2.954	0.003	4.517	0.000	1.569	0.117
Bloomberg	1.24	-3.001	0.003	-2.684	0.007	4.662	0.000	0.518	0.605
Random Walk	2.28	-4.625	0.000	-6.580	0.000	4.959	0.000	2.087	0.037
sum-ARIMA	1.10	-1.382	0.167	-1.499	0.134	3.503	0.001	1.169	0.242
IMA(1,1)	1.13	-1.951	0.051	-2.598	0.009	3.893	0.000	0.366	0.714
T.V.P. IMA(1,1)	1.12	-2.002	0.045	-2.676	0.008	3.952	0.000	0.308	0.758

Note to Table 4. The table shows the results of the tests of equal forecast accuracy and forecast encompassing between the combination of the VMA(1) - small and the Bloomberg forecasts and models indicated in the rows. The forecast accuracy test is the Diebold-Mariano test based on, respectively, squared and absolute errors. The forecast encompassing test is the Harvey-Leybourne-Newbold test.

Table 5: Forecast accuracy - country results

		VMA(1) - small	VAR(1)	Random Walk	sum-ARIMA
	2005-2013	0.217	$\underline{0.360}$	$\underline{0.338}$	0.243
Germany	2005-2009	0.232	$\underline{0.339}$	$\underline{0.349}$	0.217
	2009-2013	0.204	$\underline{0.376}$	$\underline{0.329}$	$\underline{0.262}$
	2005-2013	0.187	0.200	$\underline{0.300}$	$\underline{0.171}$
France	2005-2009	0.150	0.157	$\underline{0.355}$	0.146
	2009-2013	0.212	0.230	0.248	$\underline{0.189}$
	2005-2013	0.260	$\underline{0.327}$	$\underline{0.312}$	0.271
Italy	2005-2009	0.173	$\underline{0.312}$	$\underline{0.258}$	$\underline{0.202}$
	2009-2013	0.312	0.339	0.349	0.315

Note to Table 5. The table shows the one step ahead RMSE of the models indicated in the columns. For the models VAR(1), Random Walk and Sum ARMA we have underlined the RMSEs for which the Diebold-Mariano test rejects the null hypothesis of equal forecast accuracy between the forecasts produced with these models and those of the benchmark model VMA(1) - small.

Table 6: Forecast accuracy (RMSFE) – two steps ahead forecasts

	2005-2014
VMA(1) - small	0.241
VAR(1)	0.236
Random Walk	0.425
sum-ARIMA	0.237

Note to Table 6. The RMSFE in the 2005-2014 column are based on 110 recursive two steps ahead forecasts between 2005:01 and 2014:04.

Appendix

A The mapping between the autocovariances and the reduced form VMA parameters

In order to show the mapping between the autocovariances of z_t and the reduced form parameters Θ and Σ, let us consider the autocovariances of the process in first differences, which is a vector MA(1) – VMA(1) – model:

$$E(z_t z_t^T) = \Gamma_0 = \Omega + \Theta\Omega\Theta^T = \Sigma_\eta + 2\Sigma_\epsilon$$
$$E(z_t z_{t-1}^T) = \Gamma_1 = \Theta\Omega = -\Sigma_\epsilon$$

Note that $\Gamma_1 = \Gamma_1^T = \Theta\Omega = \Omega\Theta^T$. Hence, Γ_0 can also be expressed as follows:

$$\Gamma_0 = \Omega + \Gamma_1\Omega^{-1}\Gamma_1$$

Post-multiplying the previous expression for Γ_0 by Ω^{-1}, we have:

$$\Gamma_0\Omega^{-1} = I + \Gamma_1\Omega^{-1}\Gamma_1\Omega^{-1} = I + \Theta\Theta = \Gamma_0\Gamma_1^{-1}\Theta$$

Therefore we have the following quadratic matrix equation:

$$\Theta\Theta - \Gamma_0\Gamma_1^{-1}\Theta + I = 0$$

It can be seen that the previous expression is satisfied whenever:

$$\Gamma_0\Gamma_1^{-1} = \Theta + \Theta^{-1} \tag{14}$$

Therefore Θ shares the same eigenvectors of the matrix ratio $\Gamma_0\Gamma_1^{-1}$ which can always be diagonalized. Indeed, as shown in Theorem 7.6.3 of Horn and Johnson (1985) p. 465, we can express $\Gamma_0\Gamma_1^{-1} = -\Sigma_\eta\Sigma_\epsilon^{-1} - 2I = PEP^{-1}$ (where P are the eigenvectors and E is the diagonal matrix of the eigenvalues). Given that Σ_η and Σ_ϵ^{-1} are positive definite matrices by definition we have that the eigenvalues of $-\Sigma_\eta\Sigma_\epsilon^{-1}$ are strictly negative. Therefore, all the eigenvalues in

E are strictly negative and smaller than -2. It follows that:

$$PEP^{-1} = \Theta + \Theta^{-1} \quad \Rightarrow \quad \Theta + \Theta^{-1} = P(G + G^{-1})P^{-1}$$

Moreover, the equality (14) is satisfied whenever $G + G^{-1} = E$, that is, post-multiplying both sides by G, whenever $G^2 - EG + I = 0$. Given that G and E are diagonal matrices, and bearing in mind that E has all diagonal values smaller than -2, then the eigenvalues of Θ are $G = \frac{1}{2}\left(-E \pm (E^2 - 4I)^{\frac{1}{2}}\right)$. However the only solution that guarantees the invertibility of the VMA(1) as in (3) is $G = \frac{1}{2}\left(-E + (E^2 - 4I)^{\frac{1}{2}}\right)$. This is the solution with the roots of G constrained between 0 and -1. A closed-form estimator for the matrix Θ is then the following:

$$\Theta = \frac{1}{2}\left(\Gamma_0\Gamma_1^{-1} + \left(\Gamma_0\Gamma_1^{-1}\Gamma_0\Gamma_1^{-1} - 4I\right)^{\frac{1}{2}}\right) = P\left(\frac{1}{2}\left(-E + (E^2 - 4I)^{\frac{1}{2}}\right)\right)P^{-1} \tag{15}$$

Note that $\Gamma_0\Gamma_1^{-1}$ is not symmetric in general and this feature holds also for Θ. Once Θ is known, Ω can be easily derived simply considering that $\Omega = \Theta^{-1}\Gamma_1$. This completes the proof.

$\square$

B Details on the Monte Carlo experiment

We generate the multivariate local level model as in (1) using three different dimensions. Model 1 refers to a model with $d = 4$; Model 2 refers to $d = 8$; Model 3 refers to $d = 12$. The covariances of the noises have been randomly generated as follows:

Model 1

$$\Sigma_\eta = \begin{pmatrix} 8.54 & 1.1 & 0.779 & 1.47 \\ 1.1 & 5.15 & 1.13 & 1.64 \\ 0.779 & 1.13 & 7.34 & 0.848 \\ 1.47 & 1.64 & 0.848 & 2.76 \end{pmatrix}$$

Model 1

$$\Sigma_\epsilon = \begin{pmatrix} 96.2 & 15.1 & 16.7 & 15.7 \\ 15.1 & 108. & 8.84 & 12.7 \\ 16.7 & 8.84 & 75.6 & 11.6 \\ 15.7 & 12.7 & 11.6 & 96.9 \end{pmatrix}$$

Model 2

$$\Sigma_\eta = \begin{pmatrix} 8.23 & 1.22 & 0.63 & 0.695 & 1.34 & 1.17 & 1.35 & 0.687 \\ 1.22 & 1.89 & 0.865 & 1.22 & 0.633 & 0.475 & 1.02 & 0.794 \\ 0.63 & 0.865 & 10.9 & 0.649 & 1.13 & 0.999 & 1.5 & 1.38 \\ 0.695 & 1.22 & 0.649 & 8.12 & 1.26 & 1.34 & 0.852 & 1.24 \\ 1.34 & 0.633 & 1.13 & 1.26 & 10.2 & 1.83 & 1.84 & 1.39 \\ 1.17 & 0.475 & 0.999 & 1.34 & 1.83 & 7.25 & 1.73 & 1.69 \\ 1.35 & 1.02 & 1.5 & 0.852 & 1.84 & 1.73 & 2.2 & 0.445 \\ 0.687 & 0.794 & 1.38 & 1.24 & 1.39 & 1.69 & 0.445 & 7.12 \end{pmatrix}$$

Model 2

$$\Sigma_\epsilon = \begin{pmatrix} 85.0 & 6.94 & 11.7 & 16.2 & 10.6 & 7.95 & 12.8 & 10.0 \\ 6.94 & 103. & 13.4 & 12.1 & 16.3 & 13.7 & 19.1 & 12.9 \\ 11.7 & 13.4 & 56.4 & 11.4 & 7.63 & 14.7 & 14.8 & 13.4 \\ 16.2 & 12.1 & 11.4 & 59.7 & 12.9 & 11.4 & 9.33 & 14.3 \\ 10.6 & 16.3 & 7.63 & 12.9 & 62.1 & 12.7 & 12.7 & 16.2 \\ 7.95 & 13.7 & 14.7 & 11.4 & 12.7 & 112. & 13.2 & 7.31 \\ 12.8 & 19.1 & 14.8 & 9.33 & 12.7 & 13.2 & 88.3 & 18.7 \\ 10.0 & 12.9 & 13.4 & 14.3 & 16.2 & 7.31 & 18.7 & 62.7 \end{pmatrix}$$

Model 3

$$\Sigma_\eta = \begin{pmatrix} 10.7 & 0.87 & 0.79 & 1.21 & 1.13 & 1.32 & 0.73 & 1.09 & 1.23 & 1.77 & 1.55 & 1.14 \\ 0.87 & 8.91 & 1.4 & 1.09 & 1.72 & 1.14 & 1.63 & 0.83 & 0.77 & 1.55 & 0.94 & 0.91 \\ 0.79 & 1.40 & 2.52 & 0.58 & 0.67 & 1.02 & 0.57 & 1.7 & 1.03 & 1.88 & 0.91 & 1.19 \\ 1.21 & 1.09 & 0.58 & 8.35 & 1.12 & 1.03 & 1.15 & 1.65 & 1.29 & 0.77 & 0.82 & 1.18 \\ 1.13 & 1.72 & 0.67 & 1.12 & 2.95 & 1.31 & 0.65 & 0.93 & 0.98 & 1.25 & 1.03 & 1.19 \\ 1.32 & 1.14 & 1.02 & 1.03 & 1.31 & 4.44 & 0.72 & 1.52 & 1.29 & 1.25 & 1.28 & 1.21 \\ 0.73 & 1.63 & 0.57 & 1.15 & 0.65 & 0.72 & 7.85 & 0.63 & 0.55 & 0.75 & 1.08 & 1.22 \\ 1.09 & 0.83 & 1.70 & 1.65 & 0.93 & 1.52 & 0.63 & 8.09 & 1.74 & 0.47 & 1.88 & 1.28 \\ 1.23 & 0.77 & 1.03 & 1.29 & 0.98 & 1.29 & 0.55 & 1.74 & 7.63 & 0.61 & 0.83 & 1.65 \\ 1.77 & 1.55 & 1.88 & 0.77 & 1.25 & 1.25 & 0.75 & 0.47 & 0.61 & 7.39 & 1.11 & 1.04 \\ 1.55 & 0.94 & 0.91 & 0.82 & 1.03 & 1.28 & 1.08 & 1.88 & 0.83 & 1.11 & 3.29 & 1.63 \\ 1.14 & 0.91 & 1.19 & 1.18 & 1.19 & 1.21 & 1.22 & 1.28 & 1.65 & 1.04 & 1.63 & 3.27 \end{pmatrix}$$

Model 3

$$
\Sigma_\epsilon = \begin{pmatrix}
106. & 16.9 & 15. & 12.9 & 7.12 & 12.8 & 13.2 & 11.9 & 12.4 & 11.5 & 15.6 & 18.4 \\
16.9 & 80.6 & 17.4 & 16.6 & 16.9 & 13.8 & 11.8 & 8.18 & 13.2 & 13.6 & 14.8 & 12.3 \\
15. & 17.4 & 84.2 & 13.2 & 7.11 & 8.35 & 14.9 & 10.3 & 15.9 & 18.5 & 10. & 13.9 \\
12.9 & 16.6 & 13.2 & 58.7 & 12.5 & 14.2 & 11.8 & 16.8 & 14.2 & 10.1 & 16.5 & 16.6 \\
7.12 & 16.9 & 7.11 & 12.5 & 84.1 & 12.1 & 13.6 & 15.3 & 13.6 & 15.4 & 10.6 & 15.3 \\
12.8 & 13.8 & 8.35 & 14.2 & 12.1 & 110. & 15.8 & 10.8 & 12.9 & 13.8 & 14. & 15.7 \\
13.2 & 11.8 & 14.9 & 11.8 & 13.6 & 15.8 & 109. & 17.3 & 15. & 12.6 & 10.1 & 12.7 \\
11.9 & 8.18 & 10.3 & 16.8 & 15.3 & 10.8 & 17.3 & 88.3 & 10.2 & 8.93 & 13.9 & 11.3 \\
12.4 & 13.2 & 15.9 & 14.2 & 13.6 & 12.9 & 15. & 10.2 & 86.5 & 12.6 & 13.8 & 13.4 \\
11.5 & 13.6 & 18.5 & 10.1 & 15.4 & 13.8 & 12.6 & 8.93 & 12.6 & 70.7 & 10.9 & 16.4 \\
15.6 & 14.8 & 10. & 16.5 & 10.6 & 14. & 10.1 & 13.9 & 13.8 & 10.9 & 74.3 & 11.2 \\
18.4 & 12.3 & 13.9 & 16.6 & 15.3 & 15.7 & 12.7 & 11.3 & 13.4 & 16.4 & 11.2 & 109.
\end{pmatrix}
$$

C Models for Energy and Food prices

As explained in the main text, we obtain headline inflation forecasts through a bottom up procedure, in which we aggregate core inflation forecasts with forecasts for the more volatile components. The models for volatile components described below (energy and food prices) are quite standard from a methodological point of view, but are somewhat tailored to euro-area inflation in terms of the information on commodity prices that they exploit. Besides food and energy we also strip from the core components clothing and footwear prices, whose behaviour has proved particularly erratic in the past few years owing to seasonal sales and a number of methodological breaks. For this component we therefore rely on a random walk forecast based on the year-on-year growth rate.

C.1 Energy prices

Following ECB (2010), Meyler (2009) and Venditti (2013) we model the prices of diesel, petrol and gasoil with Error Correction models (ECM) where a cointegration relationship between fuels and brent prices drives the long-run equilibrium.[21] Specifically for each of the three types

[21] The models are in first differences of the levels, rather than of the log levels, as motivated by Meyler (2009).

of fuels mentioned above we set up a model of the form:

$$\Delta p_t = \alpha + \beta(p_{t-1} - \gamma brent_{t-1}) + \sum_{i=1}^{p} \Delta p_{t-i} + \sum_{i=1}^{q} \Delta brent_{t-i} + u_t$$

where p_t is the price of either diesel, petrol or gasoil collected from the European Commission and published in the Weekly Oil Bulletin.[22] Weekly Oil Bulletin data are very timely, so that a precise nowcast of this component is available at the end of the month, a few days before the HICP flash estimate is released. This means that the above model is only used for two steps ahead forecasts, while for the one step ahead exercise we aggregate the weekly data from the Weekly Oil Bulletin to the monthly frequency and use them to nowcast fuels prices.

Gas and electricity prices are forecast on the basis of dynamic regressions in which the only predictor is a long moving average of past oil prices. This captures the sluggishness with which these prices respond to changes in energy commodity prices, due to tariffs regulation in a number of euro-area countries.

C.2 Food prices

To forecast food prices inflation we build on the results in National Bank of Belgium (2008), Ferrucci et al. (2012), and Porqueddu and Venditti (2013), which document a strong impact of international commodity food prices on the whole pricing chain, from producer to consumer prices.[23] The pricing chain of food products is captured by bivariate Vector Error Correction Models in which:

- There is a long-run cointegration relationship between consumer prices and producer prices driving the forecasts in the medium term.
- International food commodity prices enter the systems as exogenous variables.

Finally, tobacco prices (which are included in the processed food subcomponent) are forecast with a random walk.

[22] The lag length (p and q) is chosen based on standard Information Criteria.

[23] An issue, first raised by the National Bank of Belgium (2008) in the transmission of food commodity shocks to euro-area inflation, regards the price caps imposed by the Common Agricultural Policy. To take this into account we construct a synthetic index of food commodity prices using the farm gate prices collected by the European Commission, which explicitly account for the role of the Common Agricultural Policy, see Porqueddu and Venditti (2013).

D The information timeline

In what follows, we describe the conditioning information set used for short term inflation forecasting and how this relates to the one available to Bloomberg. We briefly clarify how we treat the timing of the information flow with a practical example. Suppose we are interested in forecasting the inflation rate for September. Professional forecasters, surveyed by Bloomberg each month, produce such a forecast around the fourth week of September, i.e. a few days before an estimate of the September HICP (the so called *flash* estimate) is released by Eurostat. By that time, the available information set is constituted by:

1. the full breakdown of the HICP index for August. Since the HICP is typically released with a two weeks delay, this information has been available since mid September;

2. food and oil commodity prices for August;

3. fuel prices (diesel, petrol and gas) for the whole of September as available from the European Commission Weekly Oil Bulletin.

We therefore forecast September inflation combining one step ahead forecasts for core and food inflation (using information in 1 and 2) with a *nowcast* of fuels prices (using information in 3). This procedure makes our information set broadly comparable to that available to professional forecasters. Some imprecisions cannot be avoided, as the number of weeks of energy price data available to Bloomberg respondents could vary depending on the precise day of the poll. On the other hand, important data for some countries (like Germany) are sometimes available to private analysts ahead of the survey on euro-area inflation, giving them an advantage over models that do not use such information. Overall, while we do not claim that our exercise constitutes an exact horse race, we believe that it provides a sensible level playing field between ex-post model based and real time judgemental forecasts.

Table A1: Harmonised indices of consumer prices (HICP), breakdown by type of product for NEIG

No.	**Industrial goods excluding energy (NEIG)**
	Other goods
1	Materials for the maintenance and repair of the dwelling
2	Water supply
3	Furniture and furnishings
4	Carpets and other floor coverings
5	Household textiles
6	Glassware, tableware and household utensils
7	Tools and equipment for house and garden
8	Non-durable household goods
9	Medical products, appliances and equipment
10	Purchase of vehicles excluding motor cars
11	Motor cars
12	Spares parts and accessories for personal transport equipment
13	Equipment for the reception, recording and reproduction of sound and pictures
14	Photographic and cinematographic equipment and optical instruments
15	Information processing equipment
16	Recording media
17	Major durables for indoor and outdoor recreation including musical instruments
18	Games, toys and hobbies
19	Equipment for sport, camping and open-air recreation
20	Gardens, plants and flowers
21	Pets and related products
22	Newspapers, books and stationery
23	Electrical appliances for personal care
24	Personal effects n.e.c.
	Clothing and footwear
1	Clothing materials
2	Garments
3	Other articles of clothing and clothing accessories
4	Footwear

The breakdown is in accordance with the classification of individual consumption by purpose adapted to the needs of the HICP (COICOP/HICP). The breakdown shown is the one mainly used by the ECB.

Table A2: Harmonised indices of consumer prices (HICP), breakdown by type of product for Services

No.	**Services**
1	Cleaning, repair and hire of clothing
2	Actual rentals for housing
3	Services for the maintenance and repair of the dwelling
4	Refuse collection
5	Sewerage collection
6	Other services relating to the dwelling n.e.c.
7	Repair of furniture, furnishings and floor coverings
8	Repair of household appliances
9	Domestic services and household services
10	Out-patient services
11	Hospital services
12	Maintenance and repair of personal transport equipment
13	Other services in respect of personal transport equipment
14	Passenger transport by railway
15	Passenger transport by road
16	Passenger transport by air
17	Passenger transport by sea and inland waterway
18	Combined passenger transport
19	Other purchased transport services
20	Postal services
21	Telephone and telefax equipment and services
22	Repair of audio-visual, photographic and information processing equipment
23	Maintenance and repair of other major durables for recreation and culture
24	Recreational and sporting services
25	Cultural services
26	Package holidays
27	Education
28	Restaurants, cafés
29	Canteens
30	Accommodation services
31	Hairdressing salons and personal grooming establishments
32	Social protection
33	Insurance connected with the dwelling
34	Insurance connected with health
35	Insurance connected with transport
36	Other insurance
37	Financial services n.e.c.
38	Other services n.e.c.

The breakdown is in accordance with the classification of individual consumption by purpose adapted to the needs of the HICP (COICOP/HICP). The breakdown shown is the one mainly used by the ECB.

Table A3: HICP: Aggregation for NEIG – VMA(1) - small

No.	**Industrial goods excluding energy (NEIG)**
	Other goods
1	
	Materials for the maintenance and repair of the dwelling
	Furniture and furnishings
	Medical products, appliances and equipment
	Purchase of vehicles excluding motor cars
	Spares parts and accessories for personal transport equipment
	Information processing equipment
	Major durables for indoor and outdoor recreation including musical instruments
	Electrical appliances for personal care
	Personal effects n.e.c.
2	
	Water supply
	Motor cars
	Equipment for the reception, recording and reproduction of sound and pictures
	Recording media
	Games, toys and hobbies
3	
	Carpets and other floor coverings
	Glassware, tableware and household utensils
	Non-durable household goods
	Photographic and cinematographic equipment and optical instruments
	Newspapers, books and stationery
4	
	Household textiles
	Gardens, plants and flowers
5	
	Tools and equipment for house and garden
	Equipment for sport, camping and open-air recreation
	Pets and related products

Table A4: HICP: Aggregation for Services – VMA(1) - small

No.	**Services**
1	
	Cleaning, repair and hire of clothing
	Actual rentals for housing
	Services for the maintenance and repair of the dwelling
	Other services relating to the dwelling n.e.c.
	Repair of furniture, furnishings and floor coverings
	Repair of household appliances
	Domestic services and household services
	Refuse collection
	Sewerage collection
	Passenger transport by railway
	Passenger transport by road
	Repair of audio-visual, photographic and information processing equipment
	Maintenance and repair of other major durables for recreation and culture
	Cultural services
	Education
	Hairdressing salons and personal grooming establishments
	Social protection
	Insurance connected with the dwelling
	Insurance connected with health
	Insurance connected with transport
	Other insurance
	Other services n.e.c.
	Out-patient services
	Hospital services
2	
	Maintenance and repair of personal transport equipment
	Other services in respect of personal transport equipment
	Restaurants, cafés
	Canteens
3	
	Passenger transport by air
	Passenger transport by sea and inland waterway
	Combined passenger transport
	Other purchased transport services
	Postal services
	Telephone and telefax equipment and services
	Recreational and sporting services
	Package holidays
	Accommodation services
	Financial services n.e.c.

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