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Reconsidering the role of monetary indicators for euro area inflation from a Bayesian perspective using group inclusion probabilities

Michael Scharnagl

Christian Schumacher

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Deutsche Bundesbank, Wilhelm-Epstein-Strasse 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-1
Telex within Germany 41227, telex from abroad 414431

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax +49 69 9566-3077

Internet http://www.bundesbank.de

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Abstract

This paper addresses the relative importance of monetary indicators for forecasting inflation in the euro area in a Bayesian framework. Bayesian Model Averaging (BMA) based on predictive likelihoods provides a framework that allows for the estimation of inclusion probabilities of a particular variable, that is the probability of that variable being in the forecast model. A novel aspect of the paper is the discussion of group-wise inclusion probabilities, which helps to address the empirical question whether the group of monetary variables is relevant for forecasting euro area inflation. In our application, we consider about thirty monetary and non-monetary indicators for inflation. Using this data, BMA provides inclusion probabilities and weights for Bayesian forecast combination. The empirical results for euro area data show that monetary aggregates and non-monetary indicators together play an important role for forecasting inflation, whereas the isolated information content of both groups is limited. Forecast combination can only partly outperform single-indicator benchmark models.

Keywords: inflation forecasting, monetary indicators, Bayesian Model Averaging, inclusion probability

JEL-Classification: E31, E37, C52, C11

Non-technical summary

Forecasting inflation in the euro area is a matter of particular interest, as the European Central Bank has to maintain price stability and its monetary policy strategy assigns a certain role to macroeconomic forecasts. This paper addresses the relative importance of monetary indicators for forecasting inflation in the euro area. The analysis is carried out in a Bayesian framework that explicitly considers model uncertainty with potentially many explanatory variables. Compared with earlier work, we do not restrict the forecast model to include a particular set of indicators. We rather apply a Bayesian Model Averaging (BMA) exercise that selects the relevant indicators endogenously according to their marginal contribution to forecast inflation. The models are estimated and combined without tight restrictions on the number and composition of variables included in the forecasting models. The analysis considers many different models where monetary and non-monetary indicators are separated, and of course models, where both monetary and non-monetary indicators are included.

To assess the empirical relevance of the indicators for inflation, in particular the relevance of monetary indicators, we estimate individual inclusion probabilities. This is the posterior probability of a particular variable being in the forecast model. A novel aspect of the paper is the introduction of group inclusion probabilities, which helps to address the empirical question whether the group of monetary variables is relevant for forecasting euro area inflation. If single indicators don't have a constant information content for inflation over time, which is a well-known fact from the empirical literature, the group-specific probabilities provide less detailed, but more stable information on the relevance of indicators for inflation.

In our empirical application, a dataset of about thirty monetary and non-monetary indicator variables is used as a potential set of indicators for future euro area inflation. Model evaluation is carried out using out-of-sample forecasts over the evaluation sample $1999Q1$ until $2005Q4$ for forecast horizons up to twelve quarters.

The empirical results for euro area data show that apart from a trend measure of M3, the individual inclusion probabilities of monetary indicators are rather low and not constant over time. On the other hand, empirical group inclusion probabilities are high for joint forecast models. These models are characterized by the inclusion of at least one representative of the monetary indicator and one of the group of non-monetary indicators. Hence, the empirical results for euro area data show that monetary aggregates and non-monetary indicators together play an important role for forecasting inflation, and neither monetary indicators nor non-monetary indicators should be neglected when forecasting inflation.

The results show that the Bayesian forecast combination can outperform single-indicator forecast models and simple benchmark models only in the second half of the evaluation sample. Also the single-indicator forecast models often used in the literature can only partly outperform simple benchmark models. These results are similar to findings from the 'Great Moderation' literature and indicate that in an era of price stability, it can be difficult for sophisticated models to perform well in forecast comparisons.

Nicht-technische Zusammenfassung

Die Prognose der Inflationsrate im Euroraum ist - nicht zuletzt vor dem Hintergrund, dass die Europäische Zentralbank zur Sicherung der Preisstabilität verpflichtet ist und dafür auf Vorhersagen zurückgreift - von großem Interesse. Die vorliegende Arbeit analysiert die relative Bedeutung von monetären Indikatoren für die Prognose der Inflationsrate im Euroraum. Die Analyse wird in einem Bayesianischen Modellrahmen durchgeführt, der explizit Modellunsicherheit und potenziell eine große Zahl von erklärenden Variablen zulässt. Verglichen mit bestehenden Arbeiten aus der Literatur nehmen wir keine Beschränkung des Prognosemodells in Hinblick auf die zu berücksichtigenden Variablen vor. Stattdessen wird die Auswahl der relevanten Prognoseindikatoren endogen vorgenommen, und zwar jeweils anhand des empirischen Beitrags eines Indikators zur Prognosegüte für die Inflationsrate. Die Modelle werden ohne harte Restriktionen bezüglich der Zahl der zu berücksichtigenden Indikatoren oder der Kombination der Indikatoren geschätzt. Die Analyse berücksichtigt daher viele verschiedene Modelle, also sowohl separate Modelle, die nur durch monetäre und nicht-monetäre Indikatoren bestimmt werden, als auch Modelle, die gleichzeitig monetäre und nicht-monetäre Indikatoren enthalten.

Um die empirische Relevanz der Inflationsindikatoren einzuschätzen, insbesondere die Relevanz monetärer Variablen, werden Inklusionswahrscheinlichkeiten verwendet. Dies sind die im Bayesianischen Ansatz ermittelten a posteriori Wahrscheinlichkeiten, dass eine Variable zum Prognosemodell gehört. Ein neuer Aspekt dieses Papiers ist die Einführung von gruppenweisen Inklusionswahrscheinlichkeiten, welche dazu beitragen, die Bedeutung der Gruppe der monetären Variablen für die Inflationsprognose herauszuarbeiten. Wenn einzelne Indikatoren keinen zeitstabilen Informationsgehalt für die Inflations haben - was ein stilisiertes Faktum in der empirischen Literatur ist -, können die gruppenweise berechneten Inklusionswahrscheinlichkeiten zwar weniger detailierte, aber dafür stabilere Informationen über die Relevanz von Indikatoren geben.

In der empirischen Anwendung wird ein Datensatz von etwa dreissig monetären und nicht-monetären potenziellen Variablen für die Prognose der Inflationsrate im Euroraum verwendet. Die Evaluierung der Modelle wird mit Prognosen ausserhalb des Schätzzeitraums vorgenommen. Die Evaluierungsperiode liegt zwischen $1999Q1$ und $2005Q4$. Der Prognosehorizont beträgt jeweils bis zu zwölf Quartale.

Die empirischen Ergebnisse für den Euroraum zeigen, dass mit Ausnahme des Trends für M3 die indivduellen Inklusionswahrscheinlichkeiten für einzelne monetäre Indikatoren eher gering und nicht zeitstabil sind. Gruppenweise Inklusionswahrscheinlichkeiten für Modelle, in denen sowohl monetäre als auch nicht-monetäre Indikatoren auftreten, sind jedoch hoch. Dies bedeutet, dass jeweils Repräsentanten aus der Gruppe der monetären und nicht-monetären Indikatoren Eingang in das Prognosemodell finden. Den Ergebnissen zufolge spielen für den Euroraum sowohl monetäre als auch nicht-monetäre Indikatoren eine große Rolle für die Inflationsprognose; weder die eine noch die andere Gruppe von Indikatoren sollte vernachlässigt werden.

Die Prognoseergebnisse zeigen, dass die aus der Bayesianischen Schätzung abgeleitete Prognosekombination nur in der zweiten Hälte des Evaluierungszeitraums besser prognostiziert als Modelle mit Einzelindikatoren und naive Vergleichsmodelle. Auch die in der Literatur häufig verwendeten Einzelindikatoren können die naiven Vergleichsmodelle nur vereinzelt schlagen. Insgesamt scheinen die Ergebnisse vergleichbar mit denen aus der Literatur zur „Great Moderation" zu sein. Auch dort zeigt sich, dass in Zeiten hoher Preisstabilität anspruchsvolle Modelle bei Prognosevergleichen nicht notwendigerweise gut abschneiden.

Contents

Reconsidering the role of monetary indicators for euro area inflation from a Bayesian perspective using group inclusion probabilities†

1 Introduction

In order to serve its objective of maintaining price stability in the euro area, the ECB follows a two-pillar framework for the assessment of the risks to price stability. Under the first pillar, the so-called 'economic analysis', a wide range of non-monetary economic and financial variables is monitored and assessed. The 'monetary analysis', on the other hand, reflects the prominent role money plays in the ECB's monetary policy strategy. It consists of a comprehensive assessment of liquidity and credit conditions containing an analysis of M3 growth in relation to its reference value as well as the investigation of developments within the components of M3 growth, see ECB (2004), p. 65. A cross-checking of the information from both pillars allows for an overall judgement on the risks to price stability according the ECB's definition.

The important role assigned to money in the monetary policy strategy was motivated by the conviction that the development of the price level in the medium to longer term is a monetary phenomenon, see ECB (1999). Related to this argument, a number of empirical studies indeed found that developments of M3 and related monetary indicators had predictive content for future inflation in the euro area, see Nicoletti Altimari (2001), Trecroci and Vega (2002), and Gerlach and Svensson (2003). Other studies tried to identify longer-term or trend movements of M3 as inflation predictors, see Neumann and Greiber (2004). Another strand of the literature, such as Assenmacher-Wesche and Gerlach (2006), relates to both components of the ECB's monetary policy strategy and specifies two-pillar inflation forecast models, where indicators reflecting both the economic and monetary analysis are included. A thorough discussion of the forecasting properties of monetary aggregates and their role relative to the economic analysis is provided in Fischer et al. (2006). They also find some information content of M3 that goes beyond

†Correspondence: Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main, Michael Scharnagl: Phone: ++49/+69-9566-2305, E-mail: michael.scharnagl@bundesbank.de, Christian Schumacher: Phone: ++49/+69-9566-2939, E-mail: christian.schumacher@bundesbank.de. This paper represents the authors' personal opinions and does not necessarily reflect the views of the Deutsche Bundesbank. We are grateful to Heinz Herrmann, Sune Karlsson, Karl-Heinz Tödter, Jens Ulbrich and seminar participants at the Bundesbank for helpful comments. We also thank Boris Hofmann for kindly making available his euro area dataset to us.

the economic analysis, although richer combinations of indicators can partly offset this information content.

Although the above cited papers find some evidence in favor of money as a predictive indicator for inflation, the ECB's monetary policy strategy and in particular the monetary analysis have often been subject to criticism. In addition to theoretical arguments, it is questioned whether money is a reliable indicator for inflation because of shifts in velocity, see for example Estrella and Mishkin (1997) and De Grauwe and Polan (2005). In a recent investigation, Hofmann (2006) finds empirical evidence for a decline of forecasting accuracy for M3 over time.

Against the background of this discussion, we reassess the information content of monetary indicators for euro area inflation in an out-of-sample forecast exercise. We compare the forecasting performance of both monetary and non-monetary indicators from a large data set of about 30 indicator variables to investigate the relative importance of the two groups of indicators. The analysis covers short and longer-term forecast horizons up to twelve quarters. To consider possible declines in forecasting accuracy as found in other comparable studies, we also split the forecast evaluation sample and compare results from both subsamples.

The distinguishing feature of this paper to the papers cited above is that an endogenous model selection procedure is used for the specification of the inflation forecast model. In particular, we follow Jacobson and Karlsson (2004) and Eklund and Karlsson (2006) and apply Bayesian Markov Chain Monte Carlo (MCMC) methods for Bayesian model averaging (BMA). These methods help to identify the relevant leading indicator variables for future inflation without tight restrictions on the number and composition of variables included in the forecasting models. We allow for linear multiple forecast regression models with up to ten indicators as inflation determinants, containing many different models where monetary and non-monetary indicators are separated, and of course models, where both monetary and non-monetary indicators are included. Previous work on euro area inflation as cited above usually applies only one or two indicators to forecast inflation. Since there might be more complicated relationships between indicators and inflation, a relaxation of the maximum number of models might be worthwhile.

The key novel aspect of the paper is the usage of inclusion probabilities: The MCMC methods applied here allow for calculating inclusion probabilities for each variable, it is the probability that a variable is contained in the inflation model. We will discuss this statistic for the monetary aggregates in our dataset. As a methodological complement to existing work, this paper extends the concept of inclusion probabilities to groups of variables: In our case, we can assess the relative importance of the two groups of monetary versus non-monetary indicators. Hence, the exercise allows for a group-wise analysis of the relative importance of monetary and other economic indicators for inflation in the euro area and may therefore help to address issues regarding the relative importance of the monetary and economic analysis as part of the ECB's monetary policy strategy. As the estimation will be carried out recursively, the relative importance of variables and groups of variables can change over time, for related empirical evidence for the euro area, see Banerjee et al. (2005). De Mol et al. (2006), p. 23, find that the composition of indicators for US inflation changes and that chosen single indicators are sometimes difficult to interpret. A solution to this might be an aggregation to groups of variables in order to smooth changes over time. Behind this stands the idea that the importance of different representatives of groups of variables might change over time, but the relevance of the whole group remains relatively constant. In our framework, the ECB's monetary policy strategy provides a natural background to distinguish the two groups of monetary and non-monetary indicators. Below, we will discuss the empirical group-specific inclusion probabilities for the monetary indicators in order to assess the relative importance of this indicator group. The group inclusion probabilities employed here complement the statistics proposed by Ley and Steel (2006) or Doppelhofer and Weeks (2005), who investigate the probability of joint inclusion of pairs of variables in an empirical growth model context. Below, we will discuss the relationship between the different approaches.

In addition to inclusion probabilities, we discuss the forecast accuracy of the monetary indicators. As the MCMC approach chosen here also allows for Bayesian forecast averaging of the different models, we will also explore the empirical forecast ability of monetary and non-monetary indicators in this framework. Forecast averaging or pooling is also carried out in Wright (2003) for US inflation, Kapetanios et al. (2005) for UK inflation and by Hofmann (2006) for Euro area inflation. However, in those cases the set of potential models is restricted a priori, for example to bivariate or trivariate specifications as in Hofmann (2006). Wright (2003) explicitly applies BMA, whereas Kapetanios et al. (2005) apply BMA and information theoretic weighting schemes. Hofmann (2006) uses equal weighting for forecast pooling. Our work is again in line with Jacobson and Karlsson (2004) and Eklund and Karlsson (2006), where the Bayesian forecast combination is carried out in a more general way.

The paper proceeds as follows: Section 2 reviews the Bayesian model framework for forecasting, and introduces the group-specific inclusion probabilities. Section 3 describes the data used, the out-of-sample forecast design, as well as the forecast results and empirical inclusion probabilities. Section 4 concludes.

2 Bayesian forecast combination and inclusion probabilities

2.1 Bayesian forecast combination using predictive measures

In our empirical application, we will employ a model for inflation that can be cast in vector form according to

$$\mathbf{y} = \mathbf{Z}\boldsymbol{\gamma} + \boldsymbol{\varepsilon}, \tag{1}$$

where $\mathbf{y}$ denotes the $(T \times 1)$ vector of available observations of the dependent variable, which is inflation in our application below, with effective sample size T. The $(T \times (k+1))$ matrix $\mathbf{Z} = (\boldsymbol{\iota}, \mathbf{X}^{\text{sel}})$ contains the explanatory variables including a constant, where the k explanatory variables $\mathbf{X}^{\text{sel}}$ are a particular selection from a $(T \times N)$ full set of indicators $\mathbf{X}$, that can potentially enter (1), so $\mathbf{X}^{\text{sel}} \subset \mathbf{X}$. The $((k+1) \times 1)$ vector $\boldsymbol{\gamma}$ contains the coefficients, and $\boldsymbol{\varepsilon}$ contains the residuals. To consider model uncertainty in the Bayesian framework employed below, we will investigate many different models in terms of different compositions of the indicators included in (1). We assess a model space $\mathfrak{M} = \{\mathcal{M}_1, \ldots, \mathcal{M}_M\}$, where a particular model denoted as $\mathcal{M}_j$ is characterized by the particular selection of elements (columns) chosen in $\mathbf{X}^{\text{sel}}$. To evaluate the relative importance of a model, we concentrate on posterior model probabilities, see Eklund and Karlsson (2006) for example. According to Bayes formula, each model $\mathcal{M}_j$ can be fully characterized by the prior distribution of the parameters $p(\boldsymbol{\gamma}_j|\mathcal{M}_j)$ and the likelihood $L(\mathbf{y}|\boldsymbol{\gamma}_j, \mathcal{M}_j)$ resulting in the posterior probability of model $\mathcal{M}_j$ given by

$$p\left(\mathcal{M}_j|\mathbf{y}\right) = \frac{m\left(\mathbf{y}|\mathcal{M}_j\right) p\left(\mathcal{M}_j\right)}{\sum_{r=1}^{M} m\left(\mathbf{y}|\mathcal{M}_r\right) p\left(\mathcal{M}_r\right)}, \tag{2}$$

where $p\left(\mathcal{M}_j\right)$ is the prior probability of model $\mathcal{M}_j$, and $m\left(\mathbf{y}|\mathcal{M}_j\right)$ is the marginal likelihood of model $\mathcal{M}_j$ defined as

$$m\left(\mathbf{y}|\mathcal{M}_j\right) = \int L\left(\mathbf{y}|\boldsymbol{\gamma}_j, \mathcal{M}_j\right) p\left(\boldsymbol{\gamma}_j|\mathcal{M}_j\right) d\boldsymbol{\gamma}_j, \tag{3}$$

see Jacobson and Karlsson (2004). For forecasting purposes, Eklund and Karlsson (2006) propose using the predictive likelihood as an alternative to the marginal likelihood for generating the weighting scheme. The posterior predictive density of $\tilde{\mathbf{y}}$ conditional on $\mathbf{y}^*$ and $\mathcal{M}_j$ is defined as

$$p\left(\tilde{\mathbf{y}}\,|\mathbf{y}^*, \mathcal{M}_j\right) = \int L\left(\tilde{\mathbf{y}}|\boldsymbol{\gamma}_j, \mathbf{y}^*, \mathcal{M}_j\right) p\left(\boldsymbol{\gamma}_j|\mathbf{y}^*, \mathcal{M}_j\right) d\boldsymbol{\gamma}_j, \tag{4}$$

based on a sample split of $\mathbf{y}$ into the training sample m and evaluation sample l, so $T = m + l$ holds. The expression $L\left(\tilde{\mathbf{y}}|\boldsymbol{\gamma}_j, \mathbf{y}^*, \mathcal{M}_j\right)$ represents the likelihood of future observations $\tilde{\mathbf{y}} = (y_{m+1}, ..., y_T)'$ conditional on an estimated model for $\mathbf{y}^* = (y_1, ..., y_m)$, and $p\left(\boldsymbol{\gamma}_j|\mathbf{y}^*, \mathcal{M}_j\right)$ is the posterior distribution of the coefficients. Details on the computation of (4) are provided in the technical appendix. Given $p\left(\tilde{\mathbf{y}}\,|\mathbf{y}^*, \mathcal{M}_j\right)$, we can determine predictive weights as an alternative to the posterior probability (2) according to

$$w\left(\mathcal{M}_j|\tilde{\mathbf{y}}, \mathbf{y}^*\right) = \frac{p\left(\tilde{\mathbf{y}}|\mathbf{y}^*, \mathcal{M}_j\right) p\left(\mathcal{M}_j\right)}{\sum_{r=1}^{M} p\left(\tilde{\mathbf{y}}|\,\mathbf{y}^*, \mathcal{M}_r\right) p\left(\mathcal{M}_r\right)}. \tag{5}$$

Compared with the marginal likelihood, Eklund and Karlsson (2006) find from simulation results that the predictive likelihood is preferable, if not all relevant variables are included in the dataset or if there is a structural break in the data generating process. Whereas marginal likelihood measures the in-sample fit of the proposed model, predictive likelihood can be considered as the sum of three components: in-sample fit for the training sample, a penalty term for model size and out-of sample forecast precision. Hence, the predictive likelihood is more closely related to forecast applications.

Evaluating (4) for many models can be computationally burdensome in empirical applications, as there are at most N explanatory variables implying 2^N different models. To reduce the computational effort, we follow the literature and apply MCMC techniques that search over the regions of high posterior probability of the model space $\mathfrak{M}$. In particular, we use the Metropolis-Hastings algorithm for model search. Details are provided in the appendix.

The predictive weights (5) serve mainly two purposes: The first purpose is to provide weights for combining the forecasts of all individual models as suggested in Geweke and Whiteman (2006), equation (10), for example. In our case, the different model forecasts are weighted by the posterior model weight $w(\mathcal{M}_j\,|\widetilde{\mathbf{y}}, \mathbf{y}^*)$, see Eklund and Karlsson (2006), p. 4. Hence, models with high posterior predictive weight will contribute more to the weighted forecast. In our empirical application below, we will compute the Bayesian forecast combination for euro area data in order to investigate the forecast performance relative to individual forecast approaches. A second use of the posterior model probabilities is the calculation of inclusion probabilities. These statistics help to determine the relative importance of individual indicators or groups of indicators. As the inclusion probabilities are particularly relevant in our context of the discussion about the relative importance of monetary indicators for euro area inflation, this issue will be discussed in more detail in the next subsection.

2.2 Variable and group inclusion probabilities

To investigate the relative importance of an individual indicator variable x_i for model (1), we employ inclusion probabilities, which are quite standard statistics in BMA frameworks, see for example Fernandez et al. (2001a, b), Koop (2003), chapter 11, or Jacobson and Karlsson (2004). Assume that we have N indicator variables x_i for $i = 1, \ldots, N$, and these variables are collected in the set of variables $\mathcal{X}$, corresponding to the sample data $\mathbf{X}$ in (1). The individual variable inclusion probability for variable x_i is given by

$$p(x_i\,|\widetilde{\mathbf{y}}, \mathbf{y}^*) = \sum_{j=1}^{M} \mathbb{I}\{x_i \in \mathcal{X}\,|x_i \in \mathcal{M}_j\} w(\mathcal{M}_j\,|\widetilde{\mathbf{y}}, \mathbf{y}^*), \tag{6}$$

using the predictive weights $w(\mathcal{M}_j\,|\widetilde{\mathbf{y}}, \mathbf{y}^*)$ defined above and the variable-specific indicator function $\mathbb{I}\{x_i \in \mathcal{X}\,|x_i \in \mathcal{M}_j\}$, where $\mathbb{I}\{\cdot\}$ denotes the indicator function that equals one if the set defined by the condition inside curly brackets is non-empty, or zero otherwise. The statistic (6) is equal to the sum of the posterior weights of all models that contain variable x_i. It can thus be regarded as the posterior probability of a variable x_i being in the forecast model.

In a time series context, it can be necessary to complement the individual inclusion probabilities by a broader statistic. From Banerjee et al. (2005) and Banerjee and Massimilano (2006) it is known that the information content of single forecast indicators for inflation is subject to changes over time. Some indicators can in one period be important for forecasting and be an important part of a model, but be irrelevant in later periods due to structural change. In the context of monetary indicators, similar results have been found in Hofmann (2006). Also De Mol et al. (2006) report Bayesian model selection results for US inflation, where the composition of indicators changes. The authors indicate that representatives of clusters or groups of variables might change over time, see De Mol et al. (2006), p. 18. This implies that although single indicators might be unstable over time, it could be possible to identify groups of variables that have a stable contribution to forecasting.

We follow this conjecture of De Mol et al. (2006) and investigate the role of groups of variables based on an identification of representatives of particular groups of indicators. For this purpose, we define inclusion probabilities for groups of indicators, which are by far less standard statistics in economics compared with variable-specific probabilities. Assume that we can separate the set of indicator variables $\mathcal{X}$ into the proper subsets $\mathcal{X}_1$ and $\mathcal{X}_2$, so $\mathcal{X}_1 \cup \mathcal{X}_2 = \mathcal{X}$ and $\mathcal{X}_1 \cap \mathcal{X}_2 = \varnothing$ hold. To assess the relevance of the first group $\mathcal{X}_1$, we compute the group inclusion probability

$$p_{\exists}(\mathcal{X}_1\,|\widetilde{\mathbf{y}},\mathbf{y}^*) = \sum_{j=1}^{M} \mathbb{I}\{x_i \in \mathcal{X}_1, x_k \in \mathcal{X}_2\,|\exists x_i \in \mathcal{M}_j \cap \forall x_k \notin \mathcal{M}_j\} w(\mathcal{M}_j\,|\widetilde{\mathbf{y}},\mathbf{y}^*). \quad (7)$$

Here, $\exists x_i \in \mathcal{M}_j$ simply means that there should be at least one variable out of $\mathcal{X}_1$ that is also element of model $\mathcal{M}_j$. Hence, we search for representatives of the group. Probability $p_{\exists}(\mathcal{X}_1\,|\widetilde{\mathbf{y}},\mathbf{y}^*)$ sums the weights of those models that contain at least one variable of the group $\mathcal{X}_1$, but no element from $\mathcal{X}_2$ following the condition $\forall x_k \notin \mathcal{M}_j$. Accordingly, we can compute the exclusive group inclusion probability $p_{\exists}(\mathcal{X}_2\,|\widetilde{\mathbf{y}},\mathbf{y}^*)$ for the second subset of indicator variables by using the indicator function $\mathbb{I}\{x_i \in \mathcal{X}_1, x_k \in \mathcal{X}_2\,|\exists x_i \notin \mathcal{M}_j \cap \forall x_k \in \mathcal{M}_j\}$. To assess the relevance of a particular group of variables, it can also be interesting to investigate how often a joint occurrence appears in the model. In our context, such a joint perspective is motivated by two-pillar inflation models proposed by Assenmacher-Wesche and Gerlach (2006), for example, where both monetary and non-monetary indicators are essential for forecasting. In order to check the joint occurrence of variables from groups $\mathcal{X}_1$ and $\mathcal{X}_2$, we use

$$p_{\exists}(\mathcal{X}_1 \cap \mathcal{X}_2\,|\widetilde{\mathbf{y}},\mathbf{y}^*) = \sum_{j=1}^{M} \mathbb{I}\{x_i \in \mathcal{X}_1, x_k \in \mathcal{X}_2\,|\exists x_i \in \mathcal{M}_j \cap \exists x_k \in \mathcal{M}_j\} w(\mathcal{M}_j\,|\widetilde{\mathbf{y}},\mathbf{y}^*). \quad (8)$$

In the context of research on growth determinants, Doppelhofer and Weeks (2005) as well as Ley and Steel (2006) discuss pair-wise inclusion probabilities similar to probability (8). The main difference of our joint probability to the ones used in Ley and Steel (2006), p. 6, is the identification of a representative. They define jointness of groups on the basis of the posterior assigned to those models having *all* regressors from the set of indicators. Hence, they would compute (8) using the indicator function $\mathbb{I}\{x_i \in \mathcal{X}_1, x_k \in \mathcal{X}_2 \,|\forall x_i \in \mathcal{M}_j \cap \forall x_k \in \mathcal{M}_j\}$ by replacing $\exists$ by $\forall$. Let's denote this probability proposed by Ley and Steel (2006) as $p_\forall(\mathcal{X}_1 \cap \mathcal{X}_2 \,|\widetilde{\mathbf{y}}, \mathbf{y}^*)$. Hence, in general, $p_\exists(\mathcal{X}_1 \cap \mathcal{X}_2 \,|\widetilde{\mathbf{y}}, \mathbf{y}^*) \geq p_\forall(\mathcal{X}_1 \cap \mathcal{X}_2 \,|\widetilde{\mathbf{y}}, \mathbf{y}^*)$ holds, and the representative perspective is less restrictive for measuring the role of joint importance. The choice of representative inclusion probabilities is motivated by the time series context of our paper. Again, from Banerjee and Massimilano (2006) it is known that single indicators have changing information content for future inflation over time. Some indicators within a group can in one period be included in a model, but be excluded in a later period. Hence, a full group inclusion probability as proposed in Ley and Steel (2006) is close to zero in such a case, and using the representative concept could provide additional insights. Furthermore, as the grouping in the present context of the paper into the groups of monetary and non-monetary indicators aggregates over many different measures of activity, in particular over the group of non-monetary indicators, we can't expect that all indicators of a group are important at the same time. Of course, the representative inclusion probability is just another measure of the relative importance of groups of variables. However, it fits to the quite general question as the one under consideration here, and can be useful in a time-series context in the presence of structural instabilities.

3 Inflation forecasts for the euro area: The role of money reconsidered

In the empirical section below, we apply the methods introduced above to forecast euro area inflation. As part of the BMA exercise, we compute the individual and group inclusion probabilities as defined before and evaluate the out-of-sample forecasting accuracy of the models over time.

3.1 Forecast equation, data and recursive simulation design

According to the general model (1), the models for forecasting inflation h periods ahead are based on

$$\pi^h_{t+h} = \alpha + \mathbf{X}^{\text{sel}}_t \boldsymbol{\beta} + \varepsilon_{t+h}, \tag{9}$$

where π^h_{t+h} is defined as $\pi^h_{t+h} = (400/h)\ln(HICP_{t+h}/HICP_t)$, the h-period ahead rate of change in the HICP. α is a constant, and the k-dimensional vector of indicators $\mathbf{X}^{\text{sel}}_t$ in

(9) contains selected contemporaneous indicators from the N-dimensional full indicator vector $\mathbf{X}_t$, so $\mathbf{X}_t^{\text{sel}} \subset \mathbf{X}_t$. In our empirical example below $\mathbf{X}_t$ contains the monetary and non-monetary indicators $\mathbf{X}_t^{\text{mon}}$ and $\mathbf{X}_t^{\text{non-mon}}$ for the euro area as well as lagged inflation $\pi_t = 400 \ln(HICP_t/HICP_{t-1})$, so $\mathbf{X}_t = [\mathbf{X}_t^{\text{mon}\prime}, \mathbf{X}_t^{\text{non-mon}\prime}, \pi_t]'$. Regarding the timing of the variable for forecasting purposes, note that inflation is $t+h$-dated, whereas the indicators are t-dated. Hence, we follow Stock and Watson (1999) and Jacobson and Karlsson (2004) and specify the forecast model (9) as a direct multi-step model, for details see Marcellino et al. (2006). Note that $\mathbf{X}_t$ does not contain lags of the indicators. The methods employed here allow to consider lags in principle, see Eklund and Karlsson (2006), p. 18. However, due to the additional computational burden an inclusion would necessitate, we will not consider lags in our application. Using single indicator models in a frequentist approach following Stock and Watson (1999) showed that the additional information content of additional lags is rather limited, so neglecting lags in the BMA exercise should not affect the results too much.

As an alternative to the forecast combination from BMA, we also report forecast results using single indicator models as employed in Stock and Watson (1999) and Hofmann (2006). These models are similar to equations (9) and (1), but include only one indicator at a time. Moreover, lags of the indicators as well as inflation are allowed for. Lag length selection is carried out using the BIC. The forecast equations are estimated by OLS. As some of these models have performed well in Hofmann (2006), they might also be strong competitors to the BMA forecasts discussed here.

The quarterly dataset used here is taken from Hofmann (2006) and consists of a wide range of macroeconomic indicators for the euro area over the time span $1985Q1$ until $2005Q4$. To the group of monetary indicators belong loans, the aggregates M1, M2, and M3. Below, the growth rates (first differences of logarithms) of these series will be denoted as dlloans, dlm1, dlm2, and dlm3, respectively. Furthermore, a trend of M3 computed using a one-sided Hodrick-Prescott filter is included (denoted as dlm3t). We further consider three M3 indicators derived from a long-run money demand model: the change in p-star (dpstar), the real money gap (mgap) and the monetary overhang (mov). These indicators are derived from a recursively estimated long-run M3 demand function using the current consensus specification proposed by Calza et al. (2001). The non-monetary indicators include interest rates, labour market indicators, an output gap measure, interest rates and spreads. A detailed list and description of the variables can be found in the appendix. Overall, we have 8 monetary and 20 non-monetary indicators.

Below, these groups will be used respectively to identify the monetary and non-monetary indicators $\mathbf{X}_t^{\text{mon}}$ and $\mathbf{X}_t^{\text{non-mon}}$ for the computation of the inclusion probabilities. To investigate the question regarding the role of money alone, a look at inclusion probabilities (7) over time might be useful. If the group of monetary indicators $\mathbf{X}^{\text{mon}}$ is irrelevant for forecasting inflation, the probability should be small over forecast horizons and over recursions. To assess the relevance of both groups of variables together, the inclusion probability based on (8) is most useful, as it considers models with indicators from both groups of variables to be included. Hence, conditional on the set of indicators and forecast framework chosen, it provides a combined two-pillar inclusion probability with variables from both indicator groups, following the discussion by Gerlach (2004) and Assenmacher-Wesche and Gerlach (2006).

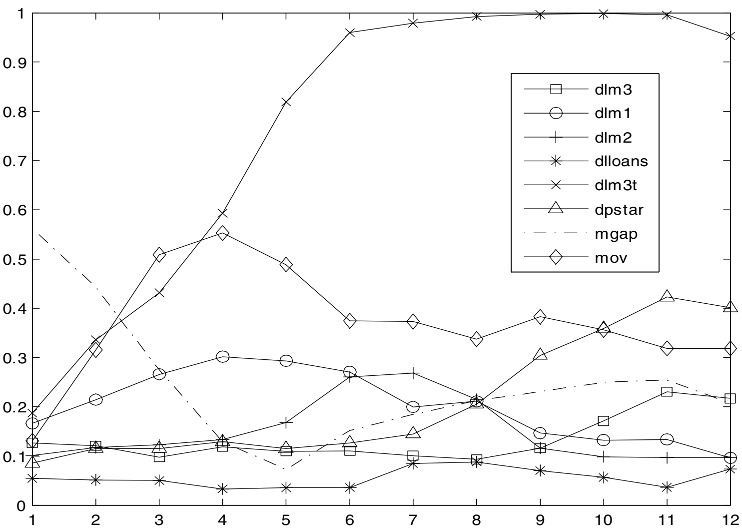
The estimation and forecast comparison is carried out in a recursive way, where the estimation sample is increased every recursion by adding an observation at the end of the sample. At each recursion, the BMA exercise provides inclusion probabilities and forecast combinations. Note that the model composition can change over recursions in the BMA exercise, as the Markov chain is recomputed when new observations become available. This is also an aspect not allowed for in previous studies. The evaluation sample starts in $1999Q1$ and ends $2005Q4$. For estimation and forecast evaluation, we consider forecast horizons up to $h = 12$ quarters.

3.2 Empirical inclusion probabilities of individual variables and groups of variables

The importance of the monetary indicators in our empirical example is now discussed at the individual level. In figure 1, we report the variable-specific inclusion probabilities according to (6). To get a first impression about the importance, we report an average of the individual inclusion probabilities over the recursions from $1999Q1$ until $2005Q4$, which is in line with Eklund and Karlsson (2006), p. 21. Trend M3 has a large inclusion probability close to one at horizons $h > 6$. Other indicators have a much smaller inclusion probability, for example the money overhang has inclusion probability of around 0.4 over all horizons. However, this finding is not robust over the recursions, as a split of the forecast sample in two periods of same length shows, see figure 2. The first half of the sample covers the period from $1999Q1$ until $2002Q2$, whereas the second covers the period from $2002Q3$ to $2005Q4$. As in the full sample, trend M3 has a large inclusion probability, in particular, at larger horizons. For the other indicators, the inclusion probabilities differ considerably between the two subsamples. This indicates that apart from trend M3 and for shorter horizons up to 5 quarters, there does not seem to be an outstanding monetary indicator in terms of inclusion probabilities. Nonetheless, this doesn't necessarily imply that money plays no role at all at short horizons. It could be the case that one representative indicator out of the group of monetary indicators might still be included in the forecasting models. However, this representative could change over time. Hence, this finding is in line with the evidence by Banerjee et al. (2005) and De Mol et al. (2006) who find time-varying contributions of individual indicators for forecasting. To investigate whether representatives of groups of variables can be found in our dataset, we now turn to the group-specific inclusion probabilities as introduced above.

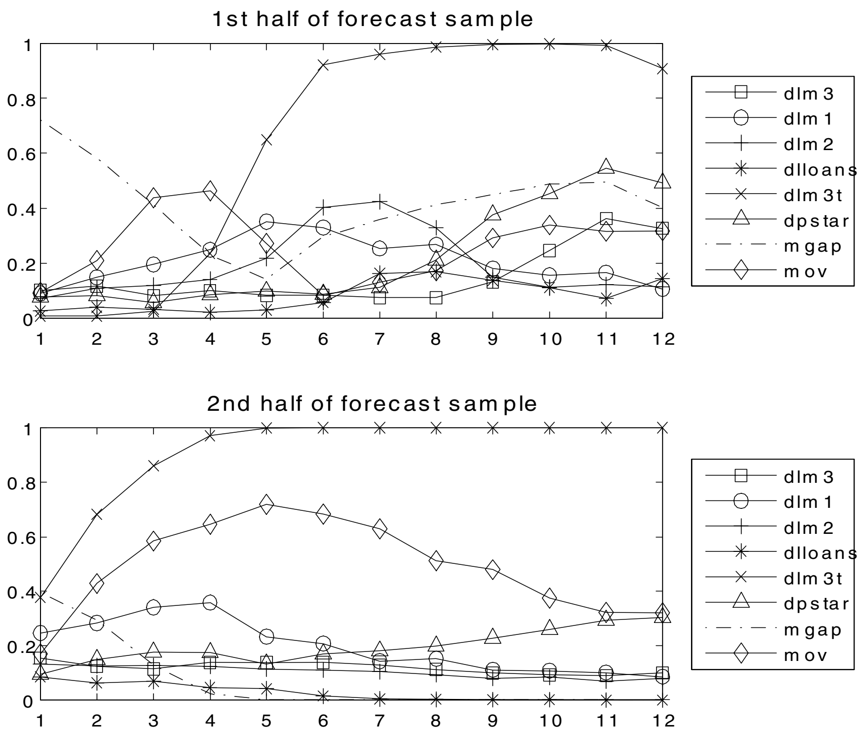
Below, we report the group-wise inclusion probabilities (7) and (8) for the groups of

Figure 1: Individual inclusion probabilities over forecast horizons



Note: The figure shows individual inclusion probabilities for the different monetary indicators according to (6). The inclusion probabilities are averaged over the whole evaluation period. Data abbreviations are explained in section 3.1.

Figure 2: Individual inclusion probabilities over forecast horizons, two-sample split



Note: The figure shows individual inclusion probabilities for the different monetary indicators according to (6). The inclusion probabilities are averaged over the two subsamples of the evaluation period. Data abbreviations are explained in section 3.1.

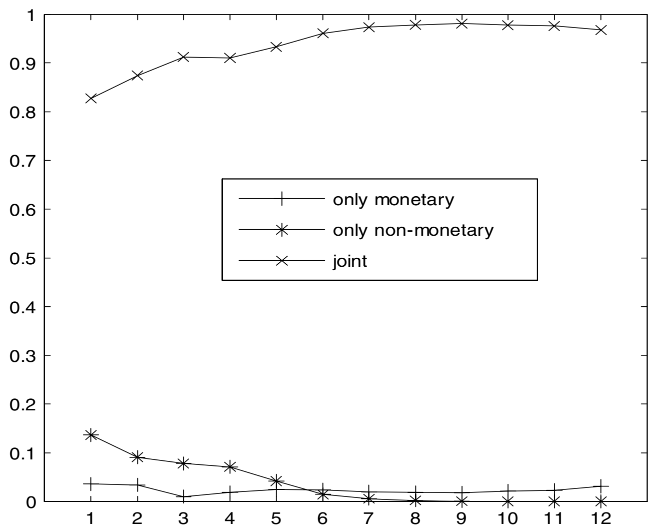
monetary and non-monetary indicators in the euro area. At first, we report only an average of the group inclusion probabilities over the full evaluation sample, followed by a discussion of the subsample results. According to the full sample results in figure 3, the groups of monetary and non-monetary indicators alone have a low inclusion probability. The highest probability over all forecast horizons is obtained by combinations of variables from both groups. Over horizons, there seems to be a slight increase of the joint probability, whereas non-monetary indicators only are slightly more relevant at short horizons. The results are relatively stable over the recursions, as a sample split into two subperiods shows, see figure 4. As can be seen from the results, monetary indicators are in almost all of the cases part of the forecast models for inflation at longer horizons and in most of the models for shorter horizons. Although the individual inclusion probabilities in figure 2 showed that single monetary indicators are present in the forecast models in only 50% of the cases for short horizons, there is in more than 80% of the cases at least one representative indicator in the forecast model, see figure 4. Hence, according to these results, the overall finding is that money is non-negligible for the BMA, but with changing representatives. Furthermore, joint models with monetary and non-monetary indicators are the most important ones, so the isolated information content is limited.

As a check for robustness of the results, we computed the whole exercise also without the trend of M3. Trend M3 had high individual inclusion probabilities, see figure 2, and we wanted to check whether this indicator also dominates the group-wise probabilities. After removing trend M3, it turned out that the group inclusion probabilities for the combined monetary and non-monetary indicators were still the highest, but decreased to a small extend compared with the results with M3 trend included. Hence, even without trend M3 there are in most of the cases representatives from the group of monetary indicators in the forecasting model, and the key results remain the same.

3.3 Forecast results

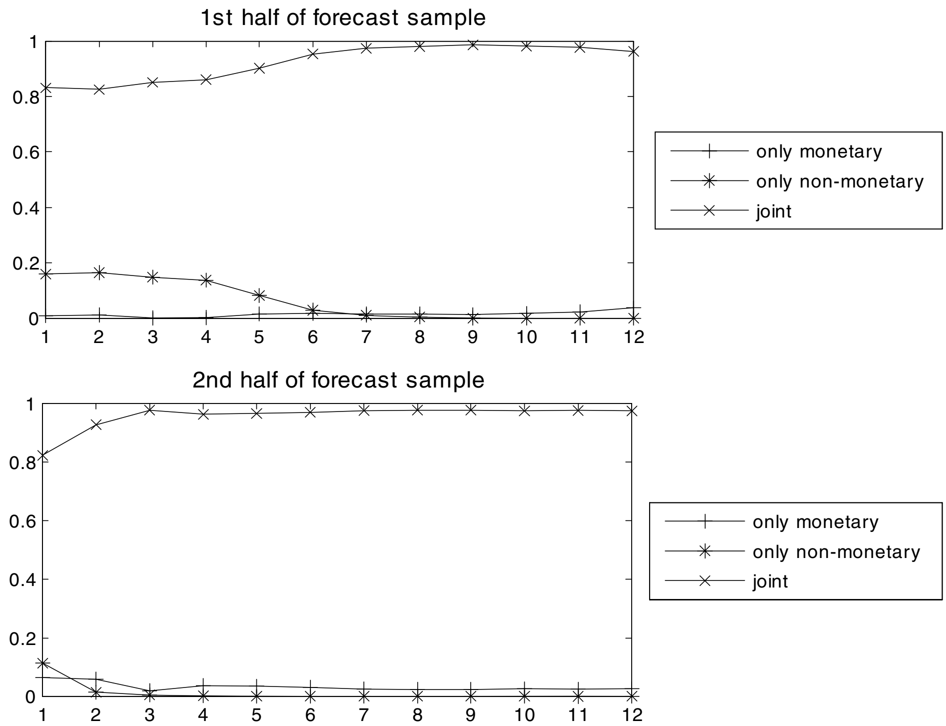
Below, we report results on the forecast performance of the BMA. From the models accepted in the Markov chain, we present forecast results of combination of all the models accepted, where the predictive weights (5) determine the relative contribution of the individual models. Additionally, we report forecasts of the best model in terms of posterior predictive density as well as the combination of the ten best models, see Eklund and Karlsson (2006), in order to investigate whether model selection performs better than pooling over all models. In addition to the BMA results, we also report forecasting results using single-indicator models as employed in Hofmann (2006). As the forecasting performance of M3 in Hofmann (2006) is good compared with other monetary indicators, and M3 trend also plays an important role in terms of posterior inclusion probability, we report single-indicator forecasting results for M3 and M3 trend only. We have also compared forecasts using all other indicators in our dataset, in particular using those from the group of non-monetary indicators. However, these models generally didn't provide

Figure 3: Group-wise inclusion probabilities over forecast horizons



Note: The figure shows group-specific inclusion probabilities for the groups of monetary and non-monetary indicators: the exclusive group probabilities according to (7) and the joint probability according to (8). The inclusion probabilities are averaged over the whole evaluation period.

Figure 4: Group-wise inclusion probabilities over forecast horizons, two-sample split



Note: The figure shows group-specific inclusion probabilities for the groups of monetary and non-monetary indicators: the exclusive group probabilities according to (7) and the joint probability according to (8). The inclusion probabilities are averaged over the two subsamples of the evaluation period.

better results than the examples we will present below, and, hence, we skipped those. An extensive discussion of the forecast results using these models can be found in Hofmann (2006). As a final benchmark, we report the forecasts using the in-sample mean of inflation. In previous studies, such as D'Agostino et al. (2006), it turned out that this simple forecast method yields quite accurate forecasts in periods of macroeconomic stability. To investigate whether the forecasting accuracy has declined in the past couple of years, we again split the evaluation period in two parts. Hence, the results complement Hofmann (2006), where mean-squared forecast errors (MSE) are computed as averages over the full time period between 1999 and 2006. In table 1, the out-of-sample MSEs relative to a AR benchmark model together with a ranking of the forecast models can be found. The AR model is specified recursively in the same way as the single-indicator model using BIC. Panel A of table 1 shows that M3 performs better than BMA over all the horizons in the first half of the sample, where both M3 and trend M3 rank first and second in all of the cases. However, over the second half of the sample, see panel B of table 1, BMA outperforms M3 and trend M3 alone for most of the forecast horizons. It is important to note that monetary aggregates are part of the relevant model set of the BMA, and thus play a role for forecasting, see again figure 2. Relative to the AR model, only BMA provides better forecasts, as the relative MSEs are smaller than one in most of the cases, the exceptions are shorter horizons $h = 2, \ldots, 5$. Hence, in line with findings by Hofmann (2006), outperforming the AR model over all horizons is difficult, although BMA is clearly better for long horizons, see again panel B of table 1. The naive forecast based on the in-sample mean is a strong competitor to the other models in the second half of the sample for horizons up to $h = 4$, whereas it is typically outperformed over the first part of the sample, see panel A. Among the BMA forecasts, there is no clear winner in terms of forecasting accuracy. Depending on the horizon, sometimes the forecast using best model, the ten best models as well as the full set of models yields the best results.

The result that pooling - in our paper using Bayesian methods - is not always the best choice in terms of forecasting accuracy has also been found by Banerjee et al. (2005), p. 809. Furthermore, it is a more general finding that forecasting in an era of 'Great Moderation', as discussed in D'Agostino et al. (2006) for example, has become a more and more difficult task. Following this line of argumentation, it is difficult for many sophisticated models to outperform simple benchmarks. Euro area evidence on this is provided in Fischer et al. (2006), where simple random-walk benchmarks can also partly outperform richer models of inflation. Overall, as the predictability of inflation using both monetary and non-monetary indicators has recently diminished in countries, where inflation has been stabilized at low levels, forecasting using sophisticated methods has become a difficult task.

Table 1: Forecast results

A. First half of sample

horizon	1	2	3	4	5	6	7	8	9	10	11	12
	Relative MSE to the AR model											
bma best	1.385	1.847	1.786	1.651	2.894	1.631	2.790	2.802	2.273	2.034	2.075	1.747
bma top10	1.379	1.579	1.550	1.675	2.396	1.574	2.786	2.735	2.344	2.175	2.051	1.792
bma all	1.385	1.554	1.292	1.427	1.898	1.410	2.563	2.638	2.388	2.162	1.988	1.885
dlm3t	0.864	0.765	0.615	0.577	0.601	0.547	0.659	1.111	1.178	1.063	0.701	0.421
dlm3	1.019	1.057	1.037	0.999	0.633	0.686	0.649	0.630	0.513	0.449	0.314	0.192
mean	1.348	2.612	3.274	2.686	3.682	3.366	2.948	2.383	1.935	1.581	1.139	0.947
	Ranking (smallest relative MSE ranks first)											
bma best	6	5	5	4	5	5	5	6	4	4	6	4
bma top10	4	4	4	5	4	4	4	5	5	6	5	5
bma all	5	3	3	3	3	3	3	4	6	5	4	6
dlm3t	1	1	1	1	1	1	2	2	2	2	2	2
dlm3	2	2	2	2	2	2	1	1	1	1	1	1
mean	3	6	6	6	6	6	6	3	3	3	3	3

B. Second half of sample

horizon	1	2	3	4	5	6	7	8	9	10	11	12
	Relative MSE to the AR model											
bma best	1.207	1.257	1.720	4.014	2.533	1.106	0.799	0.304	0.197	0.805	0.993	0.578
bma top10	0.924	1.223	1.529	2.908	1.908	1.138	0.809	0.545	0.384	0.598	0.588	0.329
bma all	0.780	1.055	1.361	2.146	1.274	0.759	0.623	0.545	0.438	0.416	0.258	0.192
dlm3t	1.078	1.080	1.354	2.490	2.121	2.131	2.369	2.256	2.549	2.315	1.646	1.825
dlm3	1.071	1.088	1.267	2.240	1.677	1.789	2.086	1.813	2.185	2.319	1.590	1.549
mean	0.728	0.790	1.042	1.730	1.400	1.167	1.202	1.019	1.130	1.155	1.046	1.284
	Ranking (smallest relative MSE ranks first)											
bma best	6	6	6	6	6	2	2	1	1	3	3	3
bma top10	3	5	5	5	4	3	3	3	2	2	2	2
bma all	2	2	4	2	1	1	1	2	3	1	1	1
dlm3t	5	3	3	4	5	6	6	6	6	5	6	6
dlm3	4	4	2	3	3	5	5	5	5	6	5	5
mean	1	1	1	1	2	4	4	4	4	4	4	4

Note: 'bma best', 'bma top10', and 'bma all' denotes the BMA forecasts using the best model, the ten best models or all accepted models from the Markov chain, respectively. 'dlm3t' is the single-indicator forecast using the log change trend of M3, whereas 'dlm3' is based on M3 only. 'mean' denotes the forecast by using the recursive mean of inflation over the respective estimation sample.

4 Conclusions

This paper applies Bayesian techniques to investigate the relevance of different determinants of euro area inflation, in particular monetary and non-monetary indicators. The current analysis expands on previous results from the literature, where in many cases more restrictive models in terms of included indicators have been used for forecasting. Here, the Bayesian estimation considers model uncertainty in a particular framework, leading to an endogenous selection and combination of relevant indicators for inflation.

The empirical results show that money is an integral part of the forecasting model, as representatives of the monetary indicators are part of most of the models used in the BMA exercise according to individual and group-wise inclusion probabilities. Models that include exclusively monetary variables play, however, only a minor role. The same holds for models that exclusively contain non-monetary indicators. The key finding of the paper is that the majority of models includes both monetary and non-monetary indicators. Hence, the present work supports to some extent the specifications proposed by Assenmacher-Wesche and Gerlach (2006), for example, where also both monetary and non-monetary indicators are the main driving forces of inflation.

Regarding the predictive accuracy of the BMA, the results are rather mixed. In the first part of the sample under consideration, BMA performs worse than single-indicator models with money, whereas BMA can outperform in the second part of the evaluation sample, particularly for longer forecast horizons. However, single-indicator models sometimes perform also worse than simple benchmark models, indicating more far-reaching difficulties in forecasting euro area inflation. These difficulties may be due to the more general problem of forecasting in an era of stability, as discussed by Atkeson and Ohanian (2001), Banerjee and Marcellino (2006) and D'Agostino et al. (2006) for the Great Moderation in the US.

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A Data appendix

The quarterly dataset for the euro area is taken from Hofmann (2006) and covers the time span 1985$Q1$ until 2005$Q4$. To the group of monetary indicators, loans, the aggregates M1, M2, and M3. Below, the growth rates (first differences of logarithms) of these series will be denoted as dlloans, dlm1, dlm2, and dlm3, respectively. Furthermore, a trend of

M3 computed using a one-sided Hodrick-Prescott filter is included (denoted as dlm3t). The smoothing parameter was set to 1600. We further consider three M3 indicators derived from a long-run money demand model: the change in p-star (dpstar), the real money gap (mgap) and the monetary overhang (mov). These indicators are derived from a recursively estimated long-run M3 demand function. Hofmann (2006) follows Calza et al (2001) and specifies money demand by $(m_t - p_t) = a_0 + a_1 y_t + a_2 oc_t + u_t$, where m_t is the logarithm of M3, p_t is the log of the GDP deflator, y_t is log real GDP and oc_t is the opportunity cost of holding M3, measured as the spread of the three months money market rate over M3's own rate of return, see again Hofmann (2006), p. 8. After estimating the long-run money demand function using OLS, the long-run trend price level p-star is equal to $p_t^* = m_t - \widehat{a}_0 - \widehat{a}_1 y_t^* - \widehat{a}_2 oc_t^*$, where an asterisk denotes the long-run trend level of a variable which was calculated using a one-sided HP filter with smoothing parameter equal to 1600. The change in p-star is then given by the first difference of that expression, yielding p-star growth (dpstar). The real money gap (mgap) is given by $(m_t - p_t) - (m_t - p_t^*)$, and the monetary overhang (mov) is simply the long-run residual given by $\widehat{u}_t = (m_t - p_t) - \widehat{a}_0 - \widehat{a}_1 y_t - \widehat{a}_2 oc_t$. Overall, we have 8 monetary aggregates including 3 money-demand-based series.

The non-monetary indicators include: Quarterly real GDP growth (dgdpr), the level and first difference of the output gap (ygap and dygap), defined as $y_t - y_t^*$ as in the money demand functions above, the level and first difference of the unemployment rate (unr and dunr), the quarterly growth rate of total employment (dlemp), the level and first difference of the short-term interest rate (irs and dirs), level and first difference of the long-term interest rate (irl and dirl), the yield spread (long-term rate less short-term rate), the quarterly rate of change in the share price index (dlsp), the log level and quarterly growth rate of real unit labour costs (lrulc and dlrulc), quarterly growth rate of nominal unit labour costs (dlulc), quarterly nominal wage inflation (dlwage), quarterly import price inflation (dlimpp), the quarterly rate of change in the nominal effective exchange rate (dlexr), the quarterly rate of change in the euro based commodity price index (dcom) and the quarterly rate of change the euro based world oil price index (doil). Overall, we consider 20 non-monetary indicators.

B Technical appendix

B.1 MCMC sampling scheme and model prior

The sampling is based on Metropolis-Hastings algorithm generating a chain of models denoted by $\mathcal{M}^{(s)}$ for $s = 1, ..., S$. $\mathcal{M}^{(s)}$ represents the model drawn at iteration s and is defined by a specific choice of explanatory variables. To sample from the model space, we start from the model $\mathcal{M}^{(s-1)}$ of the previous draw $s-1$ and change one variable of the model. This yields a new model, the so-called candidate model $\mathcal{M}^*$. We draw one variable at random. With a probability of p_m the variable is added to model $\mathcal{M}^*$, if it is not already included in the previous model $\mathcal{M}^{(s-1)}$. Similarly, a variable is deleted, if it is included in model $\mathcal{M}^{(s-1)}$. With a probability of $(1 - p_m)$ the variable is swapped with a randomly chosen variable in the model. In our application, p_m is equal to 0.5. In the next step, the posterior of the candidate model, $p(\tilde{\mathbf{y}}|\mathbf{y}^*, \mathcal{M}^*)\, p(\mathcal{M}^*)$, is compared with the posterior of the actual model, $p\left(\tilde{\mathbf{y}}|\mathbf{y}^*, \mathcal{M}^{(s-1)}\right) p\left(\mathcal{M}^{(s-1)}\right)$. The candidate model is accepted with probability

$$\alpha = \min\left\{1, \frac{p(\tilde{\mathbf{y}}|\mathbf{y}^*, \mathcal{M}^*)\, p(\mathcal{M}^*)}{p\left(\tilde{\mathbf{y}}|\mathbf{y}^*, \mathcal{M}^{(s-1)}\right) p\left(\mathcal{M}^{(s-1)}\right)}\right\}. \tag{10}$$

If it is accepted, then $\mathcal{M}^{(s)} = \mathcal{M}^*$, and $\mathcal{M}^{(s)} = \mathcal{M}^{(s-1)}$ otherwise. According to the decision rule above, the lower the posterior of $\mathcal{M}^{(s)}$ relative to $\mathcal{M}^{(s-1)}$, the lower the probability of getting accepted. Furthermore, the Markov chain concentrates on models with high posteriors, but allows for occasional acceptance of models with low posteriors.

The model prior $p(\mathcal{M})$ is determined as follows: As one dominant result in empirical forecasting is that parsimoniously parameterized models are superior to models including many variables, we assume that models with a small number of variables are more probable than those with many variables:

$$p(\mathcal{M}_j) = \delta^k (1 - \delta)^{k'-k}. \tag{11}$$

The parameter δ is assumed to be equal to 0.2. k' is the maximum number of variables in a model, and set equal to 10, which implies that the models include seven variables on average a priori. Due to the sparsity prior, the predictive likelihood below includes a penalty term for model complexity. Note that we also checked the sensitivity of the results with respect to the choice of prior parameters. In particular, imposing a much sparser model with $\delta = 0.1$ with about two to three variables in the model, leads the main results of the paper unchanged. The same holds for less parsimonious specifications using $\delta = 0.3$.

To initialize the chain, the first model is chosen randomly. The first 20000 replications serve as burn-in replications of the chain and are not taken into account in the forecasting exercise. Finally, $S = 100000$ replications are evaluated. We also tried a different numbers of replications for the Markov chain, which again had no considerable effect on the results.

B.2 Priors on model parameters and predictive density

The Bayesian estimation of the parameters of model $\mathcal{M}_j$ uses a g-prior for the coefficients of the parameters $\boldsymbol{\gamma}$ according to

$$\boldsymbol{\gamma}|\sigma^2 \sim N\left(0, c\sigma^2 \left(\mathbf{Z}^{*\prime}\mathbf{Z}^*\right)^{-1}\right), \tag{12}$$

where $\mathbf{Z}^*$ is the $m \times (k+1)$-dimensional training sample partition of the regressor matrix according to $\mathbf{y}^*$. $\mathbf{Z}$ contains a column of ones and the particular k columns selected from the indicators $\mathbf{X}^*$ according to model $\mathcal{M}_j$. In the application, the constant is set equal to $c = (k')^3$. The prior for the variance is uninformative

$$p\left(\sigma^2\right) \propto \frac{1}{\sigma^2}. \tag{13}$$

The predictive density for $\tilde{\mathbf{y}} = (y_{m+1}, y_{m+2}, ..., y_T)'$ is

$$\tilde{\mathbf{y}}|\tilde{\mathbf{Z}}, \mathbf{Z}^*, \mathbf{y}^*, \boldsymbol{\gamma}^*, \sigma^2 \sim N_l\left(\tilde{\mathbf{Z}}\boldsymbol{\gamma}^*, \sigma^2 \mathbf{I}_l\right), \tag{14}$$

where $\tilde{\mathbf{Z}}$ is a $l \times (k+1)$ matrix of observations of future exogenous variables, see Bauwens et al. (1999). Under the priors on the model parameters above, the predictive density of $\tilde{\mathbf{y}}$ is under these assumptions multivariate student t-distributed

$$\tilde{\mathbf{y}}|\tilde{\mathbf{Z}}, \mathbf{Z}^*, \mathbf{y}^* \sim t_l\left(\tilde{\mathbf{Z}}\boldsymbol{\gamma}_1, S^*, \left(\mathbf{I}_l + \tilde{\mathbf{Z}}\left(\mathbf{M}^*\right)^{-1}\tilde{\mathbf{Z}}\right)^{-1}, m\right), \tag{15}$$

where

$$S^* = \frac{c}{c+1}\left(\mathbf{y}^* - \mathbf{Z}^*\hat{\boldsymbol{\gamma}}^*\right)'\left(\mathbf{y}^* - \mathbf{Z}^*\hat{\boldsymbol{\gamma}}^*\right) + \frac{1}{c+1}\mathbf{y}^{*\prime}\mathbf{y}^*,\ \mathbf{M}^* = \frac{c+1}{c}\mathbf{Z}^{*\prime}\mathbf{Z}^* \text{ and } \boldsymbol{\gamma}_1 = \frac{c}{c+1}\hat{\boldsymbol{\gamma}}^*. \tag{16}$$

Here, $\hat{\boldsymbol{\gamma}}^*$ is the OLS estimate of $\boldsymbol{\gamma}$ using the training sample. The density function of $\tilde{\mathbf{y}}$ given $\tilde{\mathbf{Z}}$, $\mathbf{Z}^*$, and $\mathbf{y}^*$ is

$$\begin{aligned} &p\left(\tilde{\mathbf{y}}|\tilde{\mathbf{Z}}, \mathbf{Z}^*, \mathbf{y}^*\right) \propto \\ &\left(S^*\right)^{\frac{m}{2}} \frac{\left|\mathbf{M}^*\right|^{\frac{1}{2}}}{\left|\mathbf{M}^* + \tilde{\mathbf{Z}}'\tilde{\mathbf{Z}}\right|^{\frac{1}{2}}} \times \left[S^* + \left(\tilde{\mathbf{y}} - \tilde{\mathbf{Z}}\boldsymbol{\gamma}_1\right)'\left(I_l + \tilde{\mathbf{Z}}\left(\mathbf{M}^*\right)^{-1}\tilde{\mathbf{Z}}\right)^{-1}\left(\tilde{\mathbf{y}} - \tilde{\mathbf{Z}}\boldsymbol{\gamma}_1\right)\right]^{-\frac{T}{2}}. \end{aligned} \tag{17}$$

To split the sample into training and the hold-out sample, we chose $m = 0.6T$ and $l = 0.4T$, where T denotes the effective number of observations available. The predictive likelihood is used in the Markov chain for selecting models. The forecasts themselves are based on estimating the models using the full sample, so the distinction between training sample and evaluation sample is used only for the forecast weights determination.

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