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SELECTING PREDICTORS BY USING BAYESIAN MODEL AVERAGING IN BRIDGE MODELS

by Lorenzo Bencivelli*, Massimiliano Marcellino† e Gianluca Moretti‡

Abstract

This paper proposes the use of Bayesian model averaging (BMA) as a tool to select the predictors' set for bridge models. BMA is a computationally feasible method that allows us to explore the model space even in the presence of a large set of candidate predictors. We test the performance of BMA in now-casting by means of a recursive experiment for the euro area and the three largest countries. This method allows flexibility in selecting the information set month by month. We find that BMA based bridge models produce smaller forecast error than fixed composition bridges. In an application to the euro area they perform at least as well as medium-scale factor models.

JEL Classification: C22, C52, C53.
Keywords: business cycle analysis, forecasting, Bayesian model averaging, bridge models.

Contents

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1 Introduction

The conduct of monetary policy relies heavily on the correct assessment of the current "state of the economy" . However, analysts face problems related to the delayed release of quantitative data, especially GDP. Indeed, quarterly GDP is released between 50 and 60 days after the end of the reference quarter (even longer in some countries); this complicates the conduct of economic policy and raises the need for models that allow the timely forecast of the current evolution of economic activity.

Among the methods used to produce reliable and timely now-cast for economic activity, bridge models have become very popular because they combine statistical simplicity with a precise and accurate variable selection process. Bridge models relate information published at monthly frequency to quarterly national account data. To the best of our knowledge, the prime theoretical contribution in this field is from Klein and Sojo (1989). These models have since been extensively used by practitioners and researchers in policy institutions, e.g. Baffigi et al. (2004), Diron (2006), Golinelli and Parigi (2007).

Bridge models are usually based on a single equation or small scale systems of equations, whose specification relies on a thorough knowledge of the characteristics of the series involved both as target and as predictors. By contrast, large scale factor models, widely developed in recent years, tend to weight the predictors endogenously, so that a particularly fine screening and selection of the variables employed is not strictly needed.

In this paper we investigate the performance of bridge models in a context where variable selection is based on Bayesian model averaging (BMA). The method employed is computationally feasible and selects for each period the best set of predictors according to the posterior probability distribution of the model space explored.[1] This allows us to test and efficiently select a much larger number of variables than that frequently used to compute bridge models. More specifically, this methodology endogenously allows us to select a set of variables that, at a certain moment of time, are the most likely explanatory variables for developments in real activity. In a "pseudo" real-time exercise we show that models constructed using BMA outperform standard bridge models based on a fixed selection of variables (mostly, industrial production and manufacturing PMI) for the three largest European countries (Germany, France and Italy) and for the euro area as a whole. In

[1] Based on the methodology used and illustrated in the paper, the computation of a forecast requires just a few minutes.

particular, for the euro area, BMA bridge models produce smaller forecast errors than a small-scale dynamic factor model and an indirect bridge model obtained by aggregating country specific models.

The paper is organized as follows: in section 2 we briefly describe the methodology. In section 3 we present the design of the real time exercise and the information sets employed for each country, with a discussion on the variable selection according to BMA. In section 4 we present the outcome of the empirical application. Section 5 concludes.

2 Methodology

The idea of combining different models' forecasts was proposed for the first time by Bates and Granger (1969), who show how the combination of unbiased forecasts may yield a forecast error smaller than those of each model combined. The issue has been extensively explored in the past twenty years. For example, Palm and Zellner (1992) outline the Bayesian procedure to combine forecasts, providing evidence that it represents the optimal solution when there is little information on the performance of individual models. Nearly ten years later, Fernandez et al. (2001a) stress that BMA provides a "practical and theoretically sound method for inference" returning an estimate of posterior probability of inclusion for each predictor. As we will see, the posterior probability will prove particularly useful in determining the relative importance of each predictor over time. More recently, Hoogerheide et al. (2010) show in a pseudo real-time exercise that averaging across model does yield considerable improvements in forecasting accuracy. One of the applications reported in the paper refers to US GDP growth, and the models employed are quarterly time series models. Here is the main difference between this work and the one just cited. Indeed, we reconcile bridging monthly to quarterly information with BMA techniques in order to obtain monthly monitoring of economic activity based on the optimal subset of a large information set.

The BMA technique is extensively explained in Hoeting et al. (1999) and Koop (2003). Herein we briefly describe the methodology as applied to our problem.

Given n possible predictors, the set of all possible models to explore in order to pick the best one has 2^n elements. Hence, when n is large estimating all possible models is computationally very demanding. To reduce the size of the model space, one could define a specific search path. This argument drives the solution proposed by Hoover and Perez (1999) and implemented in PcGets by Hendry and Krolzig (see also Hendry and Krolzig, 1999). Basically, the selection process starts from the largest possible model[2] that is shrunk by deleting one variable at each step according to their t-stat, and submitting each resulting model to a battery of tests until the remaining model fails to pass one or more tests of significance. A hierarchical method like this does not explore the entire model space. It yields the model that maximizes the probability of selection conditional on the selection path adopted, which does not necessarily coincide with the unconditional probability.[3] In particular, as Granger and Timmermann emphasize (1999), in the presence of outliers, of parameters' instability, of non-linearities or when the search starts far from the *true* model, this approach does not necessarily yield the correct model.

Unlike selection methods such as GETS, BMA explicitly takes into account model uncertainty by averaging across all possible models, which are weighted according to their posterior probability. In formal terms, the posterior density of a quantity of interest $\hat{y}$ (in our case the forecast of GDP growth) can be written as:

$$p(\hat{y}|Y) = \sum_{i=1}^{n} p(\hat{y}|Y, M_i)p(M_i|Y) \qquad (1)$$

where Y is the available information set. In practice, the number of terms in (1) can be very large and, consequently, the posterior can be hard to evaluate. Madigan et al. (1995) suggest that the posterior can be approximated *via* a Monte Carlo Markov Chain model composition (MC^3) algorithm, based on Metropolis Hastings (M-H henceforth) sampling. MC^3 draws in the parameter space approximating the posterior distribution without exploring the entire model space. In fact, the algorithm generates a Markov chain in which the new draw is retained if its posterior probability is sufficiently higher than that of the previous one, and rejected otherwise. In practice, according to M-H, only the fraction with higher probability of the support of the posterior density function is explored, thus accelerating the speed of the simulation.

[2]In the latest version of the program, the largest possible model is itself the result of a pre-screening process that erases from the information set the irrelevant variables using a loose significance level.

[3]In the website of PcGets (`http://www.pcgive.com/pcgets/`), Hendry and Krolzig refute this critique stating that "a unique outcome results, with the property that it is congruent and undominated, resolving any 'path dependence' critique: since PcGets ensures a unique outcome, the path does not matter".

Let n be the number of possible predictors and $R = 2^n$ the number of all possible models and T the number of observations. The s-th model may be written as:

$$y = \alpha_s \mathbb{1}_T + X_s \beta_s + \epsilon, \tag{2}$$

where $\mathbb{1}$ represents a $T \times 1$ vector of ones and X_s is the exogenous variable set for model s ($T \times K_s$). The ϵ vector is $N(0, h^{-1} I_T)$. The columns of X_s are a subset of the columns of X: let ρ be a $n \times 1$ random vector whose entries are 0 and 1 (we will see in a while how the elements of ρ are chosen), the i-th column of X is selected if the i-th entry of $\rho = 1$.

For the prior of the model, we follow the strategy proposed in Fernandez et al. (2001a), therefore, we set for the error precision the noninformative prior:

$$p(h) \propto \frac{1}{h}.$$

Even for the intercept of the model we impose a noninformative prior:

$$p(\alpha) \propto 1.$$

In order to let the prior for the intercept have the same interpretation for all the models, all the variables are demeaned, without consequences on the slope coefficients. For these we set the normal prior:

$$\beta_s | h \sim N(\bar{\beta}_s, \frac{1}{h} \bar{V}_s)$$

where we set $\bar{\beta}_s = 0$ and $V_s = [g_s X_s' X_s]^{-1}$ with g_s a scalar in the interval $[0, 1]$. This is the so called Zellner (1986) prior as proposed in Koop (2003) setting g_s according to:

$$g_s = \begin{cases} \frac{1}{K^2} & \text{if } T \leq K^2 \\ \frac{1}{T} & \text{otherwise.} \end{cases}$$

The marginal likelihood y conditional on model s can be computed in the following way:

$$p(y|M_s) \propto \left(\frac{g_s}{1+g_s} \right)^{\frac{k_s}{2}} \left[\frac{1}{g_s+1} y' P_{X_s} y + \frac{g_s}{1+g_s} (y - \bar{y} \mathbb{1}_T)'(y - \bar{y} \mathbb{1}_T) \right]^{-\frac{T-1}{2}} \tag{3}$$

where

$$P_{X_s} = I - X_s (X_s' X_s)^{-1} X_s',$$

k_s is the number of parameters of model s and $\bar{y}$ represents the sample mean of y.

The posterior probability of the model follows

$$p(M_s|y) \propto p(y|M_s)p(M_s), \tag{4}$$

where we set the unconditional probability $p(M_s)$ equal for each model so we can ignore this term (we could eventually use this probability if we decided to attribute a priori a higher weight to some models in the parameter space than others).

The model M^{s+1} is picked in the set comprehending all the models that either add a variable to the model M^s or remove a variable from M^s. In practice, let ρ_s^p be the p-th entry of the vector ρ_s (p is drawn randomly at each iteration of the posterior distribution simulation):

$$\rho_{s+1}^p = \begin{cases} 1 & \text{if } \rho_s^p = 0 \\ 0 & \text{otherwise.} \end{cases}$$

In this case, the acceptance probability takes the form:

$$p(M^s, M^{s+1}) = min\left[\frac{p(y|M^{s+1})p(M^{s+1})}{p(y|M^s)p(M^s)}, 1\right], \tag{5}$$

under the hypothesis of equal weights for all the models, the priors in both the numerator and the denominator, cancel out.

As Koop (2003) emphasizes posterior results based upon the sequence of models from the MC^3 in equation (5) may be obtained by simple averaging across draws. Given

$$\hat{y}_{t+h}^s = E\left[y_{t+h}|y_t, M^s, \beta^s\right]$$

the prediction h steps ahead implied by model s. The average of the forecast density is computed as

$$\hat{y}_{t+h} = \frac{1}{S}\sum_{s=1}^{S} E\left[y_{t+h}|y_t, M^s, \beta^s\right], \tag{6}$$

where $s = 1 \ldots S$, and after the burn in period iterations are discarded. Hence, at each iteration of the MC^3, a two periods ahead forecast implied by the current model is computed. By doing so, we end up with the posterior forecast density of the model that returns us the point forecast, as indicated in equation (6) and the confidence bands indicating the uncertainty surrounding that forecast. To evaluate the posterior density, we compute 10^6 Metropolis steps plus a burn-in period of 10^5 iterations.

3 Data and design of the empirical application

Using Bayesian model averaging to forecast GDP growth was already proposed by Fernandez et al. (2001a) and Min and Zellner (1993) who evaluate the forecasting performance of Bayesian model averaging in a cross-country environment. They find evidence that Bayesian averaging outperform non-Bayesian averaging methods and, more generally, non-compounded forecasts. More recently, Hoogerheide et al. (2010) assess the predictive accuracy of BMA techniques in a forecasting exercise on US GDP growth over a time span of roughly 20 years. In their paper, the authors do not report results on series usage throughout the simulation and, more importantly, they do not bridge monthly information to quarterly series, as they run the exercise with quarterly data only. The scope of this paper is to assess the advantages of a BMA framework in forecasting the GDP of the euro zone and its three largest countries in a pseudo "real-time" context, accounting for the staggered release of the data. For this reason, we design a real-time exercise where predictions from a BMA bridge model are compared with those from standard univariate and multivariate bridge models and from a medium-scale dynamic factor model.

3.1 Design of the now-casting exercise

The pseudo real-time exercise accounts for the staggered release of the data in the following way[4]: we freeze the lag structure of the data as available at the end of the second month of the quarter and then replicate it for each month of the sample.[5] To account for the missing observations at the end of the sample, we balance the dataset using univariate AR models. In table (1) we report the latest available information at the end of each month per series class and the lag in the number of days with respect to the end of the reference period. Since national accounting data are published around at the middle of the second month of the quarter following the reference one, the forecasting cycle lasts until the end of the quarter following the reference one. To replicate the quasi real-time framework more accurately, in the first month of the quarter we produce a back-cast of the previous quarter and a

[4]As emphasized by Diron (2006) for euro area real GDP, the pseudo-real time exercise produces reliable assessments of the forecasting models under analysis.

[5]For the sake of simplicity, we decided to consider the second month of the quarter as it is the one in which national accounting data are released. In general, we believe that this represents the typical structure of the edge of the data in each month, where industrial production and other real data are updated two or three months behind the current month and survey based data and financial data are up to date.

Time / Variables	Jul-11	Aug-11	Sep-11	Oct-11	Nov-11	Lag (days)
GDP available for	**2011Q1**	**2011Q2**	**2011Q2**	**2011Q2**	**2011Q3**	**45-50**
GDP forecast	2011Q2 2011Q3	2011Q3	2011Q3	2011Q3 2011Q4	2011Q4	
Industrial production	May-11	Jun-11	Jul-11	Aug-11	Sep-11	45-50
External trade	Apr-11	May-11	Jun-11	Jul-11	Aug-11	55-60
Money aggregates	Jun-11	Jul-11	Aug-11	Sep-11	Oct-11	25-30
Retail sales	May-11	Jun-11	Jul-11	Aug-11	Sep-11	45-50
Surveys	Jul-11	Aug-11	Sep-11	Oct-11	Nov-11	0
Leading indicator	May-11	Jun-11	Jul-11	Aug-11	Sep-11	45-50
Interest rates	Jul-11	Aug-11	Sep-11	Oct-11	Nov-11	0

Notes: The release dates reported in the table refer to the latest available period at the end of each month (columns) for each class of variables (rows). Release dates are roughly homogenous among European countries with some exceptions occour: e.g. Italian retail sales series lag by 20-25 days behind those of the other countries.

Table 1: The calendar of the series classes.

now-cast of the current one.[6] In the second and third months of the quarter we only compute current quarter now-casts.

Finally, we collapse monthly data at quarterly frequency using the last data of the quarter for soft indicators and the mean value for the hard indicators. This is in line with the standard practices followed in bridge modeling.

The BMA is run for each month of the sample 1995Q1-2010Q1, computing 1,000,000 iterations at each step, plus a burn in period of 100,000 iteration to get rid of the initial condition biases.

3.2 The dataset

In our exercise, the learning sample starts in January 1995 and the testing sample starts in January 2004 when we start with the forecast for 2003Q4 and 2004Q1. To avoid a variable selection bias, we select the variables for each country in the most homogeneous way possible. In particular, for each country we consider business and consumer surveys, industrial data, monetary aggregates, retail sales where available and external trade data. In each dataset we also include the OECD Composite Leading Indicator (CLI). This variable has the advantage of being available for each economy

[6] The current quarter now-cast in the first month takes as unknown the GDP growth in the previous quarter and uses the back-casted value.

under consideration and homogeneously computed among them, although it is released with some delay and is often revised. Among surveys, PMI data deserve particular attention. For each economy, we included in the dataset the country-specific manufacturing PMI to gain a timely insight into industrial activity. We also included euro-area PMI manufacturing and composite, to keep track of the euro-area industrial and business cycle dynamics as a whole, particularly relevant for European economies.

To account for the importance of the external environment in the euro area economy, we also included in the dataset the crude brent price, US dollar to euro and UK pound to euro exchange rates. Although these variables might be very relevant over the whole sample, their contribution to explaining fluctuations in euro-area economic activity have become more important in recent years. Finally, we also consider changes in the interest rates on government bonds, in particular the slope of the yield curves and changes in equity indexes. As widely shown in the literature,[7] financial variables are also supposed to have predictive power for economic activity, especially the yield curve slope, as pointed out by Fornari and Lemke (2010). In total, the information set of each country is composed by 20 to 30 variables. With the exception of the survey data, all the variables are transformed into quarterly growth rates. The number of lags for the exogenous variables was set as the one that maximizes the absolute value of the correlation with the target between lag 0 and lag 5. The order of the autoregressive part is set by minimizing the root mean square forecasting error.

Table (2) reports the list of variables that are most correlated with quarterly GDP growth. Not surprisingly, industrial production has the highest correlation and its inclusion in the dataset is somewhat straightforward. Exports and imports also have a high correlation. This is not surprising given the high degree of openness of the largest European economies. As expected, monetary aggregates are somewhat less correlated and they are related to activity with a substantial lag.

The reader is referred to the appendix for a complete list of the variables used.

3.3 BMA variables selection

One appealing feature of BMA is the flexibility with which the method selects the different predictors in different periods and composes the best information set to be used for the forecast. To have an idea of how the

[7] See for example, Estrella and Mishkin (1996), Fornari and Lemke (2010).

	EMU		Germany		France		Italy	
	corr	**lag**	**corr**	**lag**	**corr**	**lag**	**corr**	**lag**
OECD CLI	-0.40	3	0.67	0	0.42	0	0.55	0
Consumer Confidence	0.67	1	0.55	1	0.51	1	0.34	1
Business Climate Index	0.82	1	0.62	1	0.77	1	0.81	1
Industrial Production	0.79	0	0.68	1	0.77	0	0.82	0
Retail Sales	0.48	0	0.40	0	0.23	0	0.16	2
Extra EMU Export	0.61	0	0.61	0	0.52	0	0.53	0
Extra EMU Import	0.57	0	-0.39	5	0.62	0	0.57	0
M3 Money Supply	0.51	4	0.30	3	0.40	2	-0.16	4
PMI Composite	0.85	0	0.68	0	0.84	0	0.81	0
PMI Manuf. EMU	0.85	0	0.69	0	0.79	0	0.78	0
PMI Manuf. country			0.71	0	0.79	0	0.76	0

Notes: The table reports the values for the main variables which are included in any country-specific information set.

Table 2: The variable set.

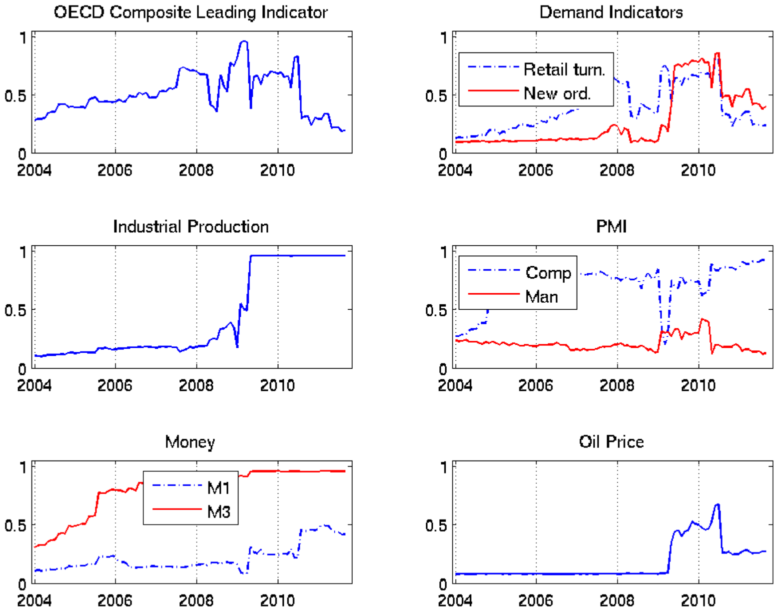
predictive content of the regressors has evolved over time we first take a look at the posterior inclusion probability of some of the variables used in our pseudo real-time experiment. For the sake of simplicity we only show in figures (1) to (4) the inclusion probability of some predictors of euro-zone GDP growth.[8]

Some features are worth noting. First of all, the OECD Composite Leading Indicator displays a significant inclusion probability over the entire sample, falling below 30% from the end of 2010 onward. Retail trade turnover, new industrial orders and industrial production all show a significant inclusion probability in the last part of the sample. The low probability of inclusion on industrial prodution might be mainly due to the high probalability of the composite PMI: the two variables are highly correlated but the latter is available around 45 days before the former. However, it is interesting to note that since the onset of the crisis the probability of inclusion of industrial production sharply has risen sharply to one. This can be explained, in our view, with reference to the fact that during the crisis the performance of the PMI in capturing the amplitude of GDP movements worsened markedly. Finally, money supply, especially M3, and oil price seem to convey relevant information for the forecast, in particular in the second part of the sample. The more frequent inclusion of monetary variables in the most recent years may be related to the financial nature of the last crisis.

The model for Germany (results in Figure 2) attributes low weight to

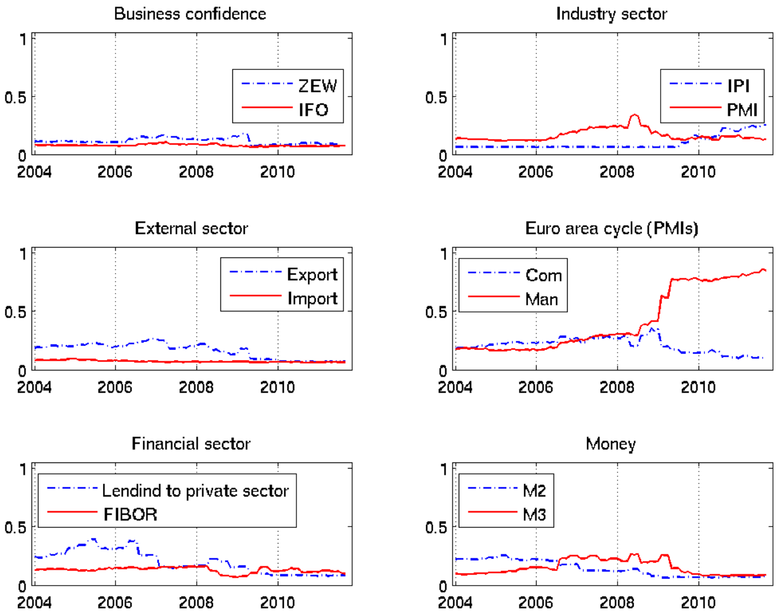
[8]The inclusion probabilities series not reported are available upon request.

Figure 1: Euro area, probability of inclusion



Notes: From the upper left panel to the lower right: OECD Composite Leading Indicator (CLI); retail trade turnover (dashed dotted line) and new industrial orders (continuous line); industrial production; composite (dashed dotted line) and manufacturing (continuous line) PMI; M1 and M3 money supply and oil price, BRENT quality.

Figure 2: Germany, probability of inclusion



Notes: From the upper left panel to the lower right: Business confidence measured by the indexes produced by ZEW (dashed dotted line) and IFO (continuous line); industrial production (dashed dotted line) and manufacturing PMI (continuous line) for Germany to account for industrial activity; export (dashed dotted line) and import (continuous line); composite (dashed dotted line) and manufacturing (continuous line) euro area PMIs to account for the European activity cycle; loans to private sector and 3 months interbank rate and the money supply.

all the variables listed (and even lower to those not listed). Manufacturing PMI indicators, especially those referring to the euro area are supposed to convey very relevant information for our purposes. By contrast, industrial production does not seem to be as informative as euro area PMIs included to account for the European real activity cycle. The lack of appeal of the German model is probably due to the volatility of the target process that will be discussed later on. It is to be emphasized that as the sample size increases, this model is likely to become more precise.

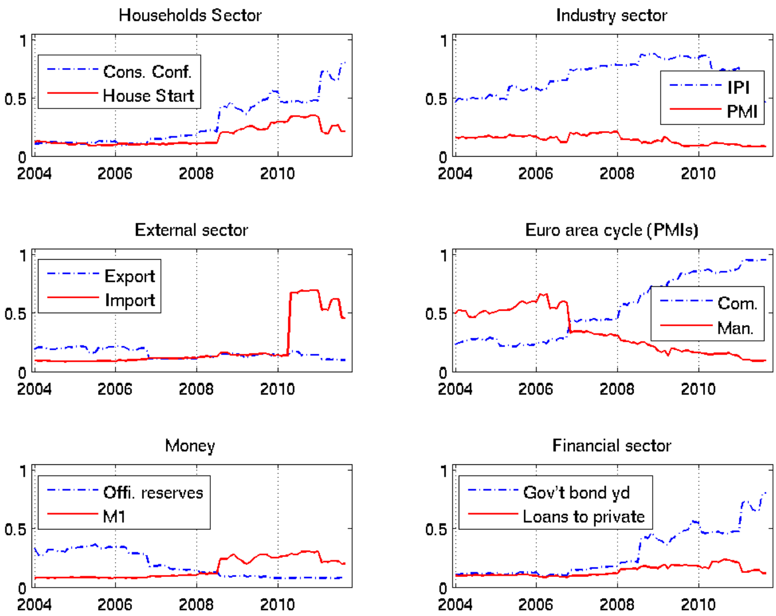
The inclusion probabilities for the French predictors (results in Figure 3) suggest that the household sector conveys more relevant information than in other countries. The industry dynamic is well captured by the industrial production indicator instead of the French manufacturing PMI. This result is rather striking considering the leading character of PMI with respect to industrial production. Confirming the importance of internal demand in the French economy, imports display a significant probability of inclusion by comparison with exports, while the European activity cycle shows a rising influence on French GDP forecasts. Finally, in the set of indicators belonging to the monetary and financial sectors the 3 months government guaranteed bond yields is particularly relevant.

The results for the Italian economy (Figure 4) are somewhat similar to those for the French economy, especially for as concerns the industrial sector and the euro-area real activity cycle. Internal demand is weakly captured by the inclusion probability of household confidence, while the external sector seems to play a minor role. Money supply displays a limited significance in predicting GDP.

3.4 Convergence of the Markov chain

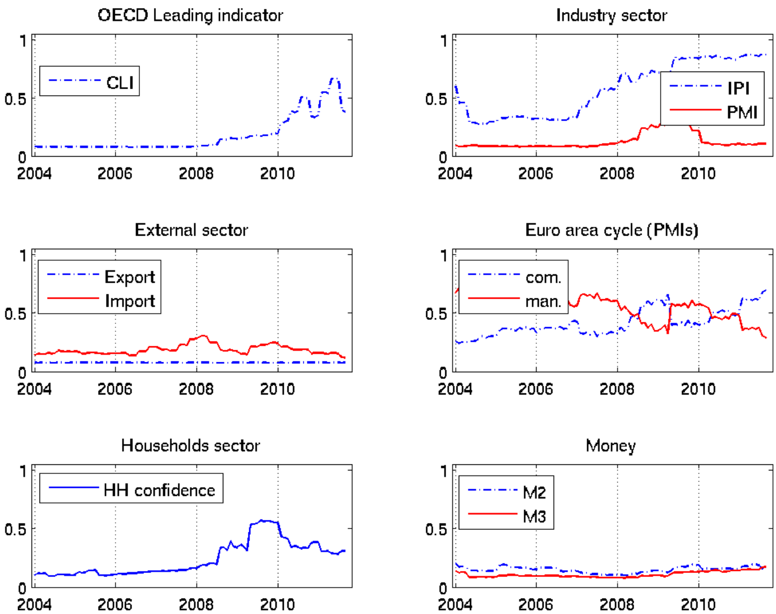
To check for the MC^3 algorithm convergence, Fernandez et al. (2001b) suggest limiting the analysis to the subset of the model space spanned throughout the simulation. This procedure is equivalent to aproximating to zero the probability of all the models that are not visited by the algorithm. In practice, to verify the convergence we need to compare the empirical frequency of each model to its Bayes factor as represented in equation (5). For the economies we considered, the correlation between the Bayes factor and the empirical frequency lies between 85% to 90%, which we consider high enough to guarantee the convergence of the simulated posterior to the true posterior.

Figure 3: France, probability of inclusion



Notes: From the upper left panel to the lower right: Consumers' confidence (dashed dotted line) and start of new civilian buildings (continuous line); industrial production (dashed dotted line) and PMI manufacturing (continuous line); export (dashed dotted line) and import (continuous line); composite (dashed dotted line) and manufacturing (continuous line) PMI for euro area; official reserves (dashed dotted line) and M1 money supply; the 3 months government bond yield (dashed dotted line) and loans to private sector.

Figure 4: Italy, probability of inclusion



Notes: From the upper left panel to the lower right: OECD composite leading indicator; industrial production (dashed dotted line) and manufacturing PMI (continuous line); export (dashed dotted line) and import (continuous line); composite (dashed dotted line) and manufacturing (continuous line) PMI for euro area; household confidence indicator; M2 and M3 money supply.

4 Forecasting results

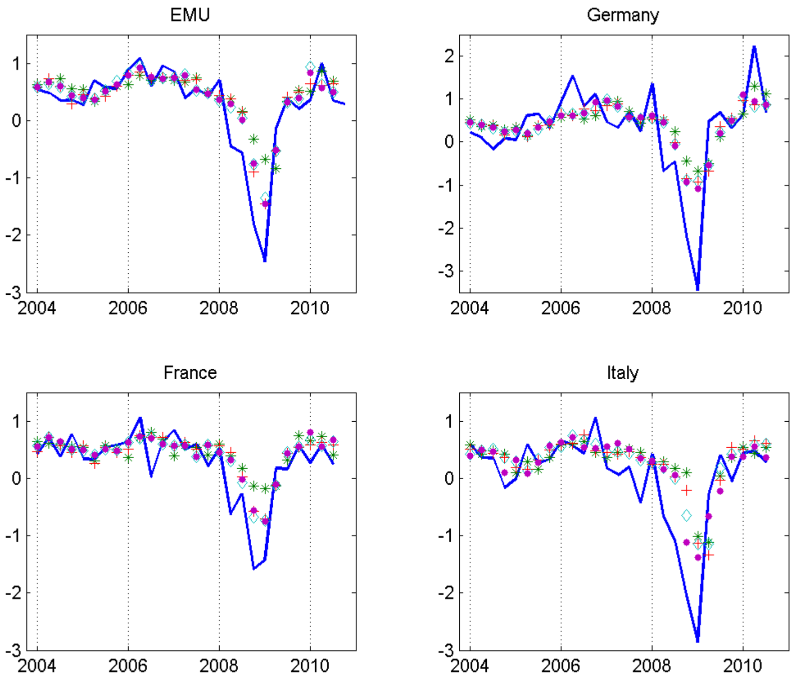
The q-o-q GDP growth now-cast and the back-cast for the four countries from the BMA bridge are graphed in Figure (5), together with the actual q-o-q GDP growth. At first glance, it is possible to see how none of the models were able to evaluate correctly the depth of the crisis. Any now-cast and back-cast for the period 2008Q1-2009Q1 has overrated the growth rate. This is the probable consequence of the alignment of the data matrices with univariate models that used only time series features to fill the missing data at the end of the sample. Indeed, multivariate indicators, such as €-coin, by better exploiting the complexity of information in large datasets, have clearly shown the possibility of a large fall in economic activity in advance with respect to univariate time series models. It is interesting to notice the pattern of the revision from one month to the next. For this purpose we compute the root mean square revision from the first to the second month, from the second to the third and from the third to the back-cast. The results are reported in table (3).

	I-II month	**II-III month**	**III month to BC**
EMU	0.25	0.12	0.08
GER	0.19	0.12	0.13
FRA	0.13	0.16	0.10
ITA	0.14	0.17	0.08

Table 3: Root mean square revision.

On average, larger revisions occur between the first and the second month for EMU and Germany, and between the second and the third month for France and Italy. The back-cast produces small revisions as the information set already available at the end of the third month of the quarter allows us to forecast quite accurately the quarterly figure of the monthly indicator. The revision occurring between the second and the third month is attributable to real variables (especially industrial production) that enter the quarter and substantially increase the precision of the information set available for the ongoing period. This is what we read in the France and Italy now-cast revision. For Germany and the euro area, the explanation is that when industrial production and other real variables enter the quarter, the information content is already, at least partially, embedded in the data available up to that moment. For these two countries manufacturing PMI and the other surveys convey accurate information on real activity in the period.

Figure 5: Simulation results



Notes: From the top left panel to the bottom right: EMU, Germany, France and Italy. In each panel, the blue line represents the q-o-q GDP growth; the green asterisk is the first month now-cast, the red plus is the second month now-cast, the turquoise diamond is the third month now-cast and the violet spot is the back-cast.

4.1 Forecast evaluation of benchmark models

We now assess the forecasting accuracy of BMA bridge models relative to some alternative standard tools. First we computed univariate bridge models fed with industrial production and manufacturing PMI.[9] To account for any lagged dependency among variables, we even estimated a three-variate VAR model using the same series as before.[10] Finally, only for euro-zone GDP, we used a medium-scale factor model similar to the one proposed by Camacho and Perez-Quiros. These models were chosen in order to have a homogeneous measure of the predictability of GDP in each of the countries we considered. Furthermore, PMI and industrial production are the most commonly used variables by practitioners. The number of lags to be included in the model are computed each month according to the optimization of the AKAIKE information criterion spanning from 1 to 8 lags for quarterly data.

We start by showing the forecasting performance of the benchmark models in table (4): on the left panel those referring to bridge models and on the right the VARs' statistics. In order to evaluate the impact of the 2008-2009 crisis on the forecasting performance of the models, we present the results for two samples: the first excludes the period 2008Q1:2009Q2 (upper panel in the table), while the second includes the entire time span up to the second quarter of 2011 (lower panel).

Benchmark models display some interesting features. In particular, it is worth noting how the VAR models, which should explicitly account for the cross-correlation of the variables, do not perform better than simple bridges. This is likely due to some overfitting in the VARs. Furthermore, the forecasting precision of VAR models worsens significantly during the recession. One possible explanation for this is the extra sensitiveness of VAR models to breaks in parameter values, which are likely to have occurred in the last two years. This signals that parsimony is a relevant issue for nowcasting and raises the need for a reliable selection method for bridge models.

At a disaggregated level, the EA models produce the lowest RMSFE, while the German model produces the highest. The lower predictability of German GDP q-o-q growth turns out to be a consequence of the particularly high volatility in Germany (especially at high frequencies), see table (5), attributable to large fluctuations not originating in the manufacturing sector

[9]For the sake of completeness, we also used composite PMI, retrieving no improvements in the model forecast accuracy relative to the model with only its manufacturing counterpart.

[10]We set the VAR in the frequency common to all variables included. The reduction of the monthly variables to quarterly frequency is done via quarterly average.

	Bridge				VAR			
	B.C.	**I**	**II**	**III**	**B.C.**	**I**	**II**	**III**
	Sample: 2004Q1-2007Q4 & 2009Q3-2011Q2							
EMU	0.28	0.26	0.25	0.27	0.24	0.79	0.24	0.24
GER	0.41	0.50	0.48	0.44	0.50	1.03	0.50	0.50
FRA	0.33	0.31	0.32	0.31	0.31	0.56	0.31	0.31
ITA	0.35	0.39	0.37	0.35	0.41	0.63	0.41	0.41
	Sample: 2004Q1-2011Q2							
EMU	0.36	0.59	0.49	0.42	0.62	0.99	0.62	0.62
GER	0.55	0.98	0.87	0.68	0.87	1.30	0.87	0.87
FRA	0.40	0.50	0.53	0.44	0.55	0.72	0.55	0.55
ITA	0.45	0.68	0.65	0.54	0.72	0.95	0.72	0.72

Notes: The statistics refer to bridge (left panel) and VAR (right panel) models to now-cast and back-cast real GDP, as explained in the text. Models account for staggered release in the information set: the second and sixth columns report previous quarter back-casts produced in the first month of each quarter (**B.C.** on top); the third to fifth and seventh to ninth columns report current quarter now-casts computed, respectively, in the first (**I**), second (**II**) and third (**III**) month of each quarter. The statistics reported in the upper panel refer to the exercise run without the 2008-2009 crisis, while in the lower panel the sample spans from 2004Q1 to 2010Q4.

Table 4: The benchmark models Root Mean Squared Forecasting Errors.

	EMU	Germany	France	Italy
Low frequencies	0.61	0.77	0.50	0.68
High frequencies	0.77	1.24	0.65	0.89
Total	0.66	0.91	0.55	0.74

Notes: The target series are bandpass filtered; low frequencies are those between 0 and $\frac{\pi}{2}$ (for quarterly data lower than yearly) while high frequencies are between $\frac{\pi}{2}$ and 2π. The total refers to non filtered processes.

Table 5: The volatility of the target processes

and therefore not well described by the manufacturing variables included in these naive models.[11]

4.2 A closer look at the euro area

The results for the euro-area deserve particular attention. Forecasts for euro-area GDP can be obtained either indirectly from aggregating country-specific GDP forecasts or directly by a model for aggregate euro-area real GDP. The direct approach does not necessarily yield better forecasts than the indirect one.[12] Hence, we present the outcome of an indirect bridge model obtained by aggregation of the direct country specific models cited above. The weights of the model are obtained by regressing the euro-area GDP quarterly growth on those of the country specific models for France, Germany and Italy.

We also report the forecasting performance of BMA bridge models relative to a small-scale dynamic factor model with mixed frequency data similar to the Euro-STING recently proposed by Camacho and Perez-Quiros (2010). This model uses as input a limited number of euro area variables, seven plus the target in our case, and allows for missing data and mixed frequency.[13] The Root Mean Squared Forecast Error (RMSFE) of both the

[11]The housing sector in Germany has shown wide fluctuations due to particularly uncommon weather conditions in some periods of the sample considered, which have caused large swings in GDP q-o-q growth.

[12]Recently Hendry et al. (2011) have shown that using disaggregated forecast may be less accurate than forecasting directly the aggregate through lagged aggregate information or using disaggreagate information in direct model.

[13]The model is fed with industrial production, new orders index, retail sales, extra EMU exports, consumers' confidence index, economic sentiment indicator for euro area and IFO business confidence indicator for Germany. All variables used in the factor models were also employed in the BMA bridge models.

indirect bridge and the factor model relative to our BMA bridge models are reported in table (6).

	No Crisis				**Whole Sample**			
	B.C.	**I**	**II**	**III**	**B.C.**	**I**	**II**	**III**
Ind. Bridge	0.29	0.27	0.26	0.28	0.44	0.65	0.62	0.49
DFM	0.38	0.51	0.59	0.44	0.44	0.98	0.78	0.6

Notes: The statistics refer to the indirect bridge model (Ind. Bridge) obtained by aggregating the country bridge models, whose statistics are in table (4), and to the small-scale dynamic factor model(DFM). Models account for staggered release in the information set: the second and sixth columns report previous quarter back-casts produced in the first month of each quarter (**B.C.** on top); the third to fifth and seventh to ninth columns report current quarter now-casts computed, respectively, in the first (**I**), second (**II**) and third (**III**) month of each quarter. The statistics reported in the left panel refer to the exercise run without the 2008-2009 crisis, while in the right panel the sample spans from 2004Q1 to 2010Q4.

Table 6: Some more benchmark models

A few features in table (6) are worth noting. First, similarly to the case of the bridge models in table (4), the crisis has worsened the forecasting performance of the models. Second, the composition of three country specific models performs as well as the direct model, indicating that there are no reasons to fear for an error propagation from country specific models to the euro area one: forecast errors largely offset each other. Furthermore, the indirect bridge precision drops significantly during the recent crisis, as, supposedly, the relation between predictors and target has changed considerably - albeit to a different extent across countries. The small-scale dynamic factor model produces less precise forecasts and its performance worsens slightly during the recession.

4.3 The forecasting precision of BMA bridge

We now turn to the forecasting precision of our BMA models. Table (7) reports the RMSFE of the BMA bridge model relative to that of all benchmark models we have considered whose forecasting statistics are reported in table (4) and table (6). BMA produces improvements in forecasting error statistics with respect to PMI-IPI bridges, concentrated in the sample that excludes the crisis and for EMU, France and Italy. The results are less clear cut for the sample including the crisis period. BMA bridges for Germany do

Relative forecasting performance of BMA								
	B.C.	**I**	**II**	**III**	**B.C.**	**I**	**II**	**III**
	No crisis				**Whole sample**			
	PMI-IPI bridge							
EMU	0.76	0.80	0.89	0.74	1.21	0.86	1.03	1.06
GER	1.66	2.28	1.00	1.05	1.64	1.29	0.96	1.13
FRA	0.78	0.85	0.83	0.84	0.79	1.03	0.91	0.88
ITA	0.87	0.83	0.84	0.81	0.88	1.02	0.99	0.87
	Indirect PMI-IPI bridge euro area							
	0.73	0.76	0.84	0.73	0.99	0.79	0.82	0.90
	DFM							
	0.56	0.41	0.37	0.46	0.99	0.52	0.64	0.74

Notes: The left section of the table reports the root mean square prediction error of the BMA relative to the PMI-industrial production bridge models (top panel), to the indirect bridge models (middle panel) and the Dynamic Factor Model for EMU (lower panel) in the sample without crisis (2004Q1:2007Q4-2009Q3:2011Q2). In the right section the entire sample (2004Q1:2011Q2) is spanned. In the bottom panel indirect BMA model errors are compared to those of the indirect bridge model.

Table 7: Prediction error improvements statistics

systematically worse than the PMI-IPI bridge. Including the crisis period, the BMA relative performance worsens, with forecasting precision not unlike from that of the PMI-IPI bridges.

Similar conclusions hold for the comparison with the indirect bridge model and dynamic factor model: the improvements of BMA are generalized to the entire sample. With almost full information, BMA bridges perform as well as both benchmarks in the entire sample.

5 Conclusions

This paper proposes Bayesian model averaging to address the indicator selection problem in mixed frequency contest. It applies BMA bridge models for back-casting GDP growth in the euro area and three major European countries using a large set of monthly indicators.

Technically, the proposal is to use MC^3 sampler techniques to span the model space in order to evaluate its posterior distribution.

The results of the pseudo real-time forecasting exercise show that BMA bridge models may yield some improvements over benchmark bridge models based on industrial production and the Purchasing Managers' Index. This advantage becomes critical considering that single equation forecasting models must be respecified periodically.

Although some of the models explored during the MC^3 may be more accurate than the forecast density in signaling the correct outcome, the advantage of the BMA searching technique may be worth more than a slight improvement (or no improvement) of the forecasting performance.

In general, in periods of low macroeconomic volatility, the BMA bridge for the euro area outperforms a small-scale factor model similar to Euro-STING. Furthermore, BMA bridge models provide a useful tool for interpretation since the inclusion probabilities indicate in each period the most significant variables for forecasting purposes.

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A The composition of the dataset

	Series	Lags	Treatment	Quarter
1	Composite Leading Indicator (OECD)	0	$\Delta\%$	stock
2	EUROSTOXX stock price index	0	$\Delta\%$	nanmean
3	3 months EURIBOR	0	*none*	nanmean
4	UK£ to € exchange rate	0	Δ	nanmean
5	US$ to € exchange rate	3	Δ	nanmean
6	Oil price (Brent quality)	1	$\Delta\%$	nanmean
7	Indsutrial production, total (EA17)	0	$\Delta\%$	nanmean
8	Money supply: M1	3	$\Delta\%$	nanmean
9	Money supply: M3	0	$\Delta\%$	nanmean
10	Consumers' confidence indicator (EC)	0	*none*	nanmean
11	Business climate indicator(EC)	0	*none*	stock
12	Retail confidence indicator	0	*none*	stock
13	Extra EMU exports	0	$\Delta\%$	nanmean
14	Extra EMU imports	0	$\Delta\%$	nanmean
15	3 years Government bond index (DE)	1	*none*	nanmean
16	5 years Government bond index (DE)	1	*none*	nanmean
17	10 years Government bond index (DE)	1	Δ	nanmean
18	Business confidence indicator (BG)	0	*none*	stock
19	Industrial new orders	0	$\Delta\%$	nanmean
20	Retail sales turnover (deflated)	0	$\Delta\%$	nanmean
21	Unemployment	0	*none*	nanmean
23	PMI composite (EMU)	0	*none*	stock
24	PMI manufacturing (EMU)	0	*none*	stock
25	M1-M3 Spread	0	$\Delta\%$	nanmean

Table 8: The composition of the dataset of the model for the euro area

	Series	Lag	Treatment	Quarter
1	ZEW indicator of economic sentiment	0	*none*	stock
2	ZEW present economic situation	2	*none*	stock
3	IFO business expectations	0	*none*	stock
4	Gfk consumer confidence indicator	1	*none*	stock
5	Unemployment	0	*none*	stock
6	IFO business climate index	1	*none*	stock
7	Vacancies (pan bd from m0790)	1	$\Delta^{12}\%$	stock
8	Employed persons	3	*none*	stock
9	Industrial production including construction	1	$\Delta^{12}\%$	nanmean
10	Industrial production: manufacturing	2	$\Delta\%$	nanmean
11	Manufacturing orders	2	$\Delta\%$	nanmean
12	DAX share price index	2	$\Delta\%$	nanmean
13	Retail sales turnover (deflated)	1	$\Delta\%$	nanmean
14	Exports	4	$\Delta\%$	nanmean
15	Imports	3	$\Delta\%$	nanmean
16	Exports FOB	4	$\Delta\%$	nanmean
17	Imports CIF	3	$\Delta\%$	nanmean
18	Money supply - M2	4	$\Delta\%$	nanmean
19	Money supply - M3	1	$\Delta\%$	nanmean
20	Industrial production in construction (civil)	0	$\Delta^{12}\%$	nanmean
21	Industrial production in construction (structural)	0	$\Delta^{12}\%$	nanmean
22	Wage&salary, hrly.basis	3	Δ^{12}	nanmean
23	Lending to enterprises & individuals	0	$\Delta\%$	nanmean
24	Long term government bond yield - 9-10 years	0	Δ	nanmean
25	FIBOR - 3 month (mth.avg.)	0	Δ	nanmean
26	PMI composite reconstructed (EMU)	0	*none*	stock
27	PMI manufacturing reconstr (EMU)	0	*none*	stock
28	PMI manufacturing reconstr (DE)	0	*none*	stock
29	Germany long-short term spread	5	*none*	nanmean
30	Germany medium-short term spread	4	*none*	nanmean
31	Germany long-medium term spread	5	*none*	nanmean

Table 9: The composition of the dataset of the model for Germany

	Series	Lag	Treatment	Quarter
1	Composite leading indicator (OECD)	1	*none*	stock
2	Government guaranteed bond yield	3	$\Delta\%$	nanmean
3	Household confidence indicator	1	*none*	stock
4	Survey: manufacturing output level	1	*none*	stock
5	Housing started	0	$\Delta^{12}\%$	nanmean
6	Industry bankruptcies	1	Δ	nanmean
7	New car registrations	4	$\Delta\%$	nanmean
8	Industrial production excluding construction	0	$\Delta\%$	nanmean
9	Industrial production - manufacturing	0	$\Delta\%$	nanmean
10	Effective exchange rate	2	$\Delta\%$	nanmean
11	Share price index SBF-250	0	$\Delta\%$	nanmean
12	Household consumption manufactured prd	4	$\Delta\%$	nanmean
13	Exports fob	5	$\Delta\%$	nanmean
14	Imports fob	5	$\Delta\%$	nanmean
15	Official reserves	3	$\Delta^{12}\%$	nanmean
16	Money supply - M1	0	$\Delta^{12}\%$	nanmean
17	Money supply - M2	2	$\Delta\%$	nanmean
18	Money supply - M3	2	$\Delta\%$	nanmean
19	Loans to resident private sector	4	$\Delta^{12}\%$	sum
20	French Francs to US $ (mth.avg.)	2	Δ	nanmean
21	Pibor - 3 month	5	Δ^{12}	nanmean
22	France long-short term spread	0	*none*	nanmean
23	France medium-short term spread	4	*none*	nanmean
24	France long-medium term spread	4	*none*	nanmean
25	PMI manufacturing (FRA)	0	*none*	stock
26	PMI composite (EMU)	0	*none*	stock
27	PMI manufacturing (EMU)	0	*none*	stock

Table 10: The composition of the dataset of the model for France

	Series	Lag	Treatment	Quarter
1	Composite leading indicator (OECD)	0	*none*	stock
2	Household confidence index	1	*none*	stock
3	Business confidence indicator	1	*none*	stock
4	New passenger car registrations	4	$\Delta^{12}\%$	nanmean
5	Industrial production	0	$\Delta\%$	nanmean
6	Industrial production - manufacturing	0	$\Delta\%$	nanmean
7	Milan COMIT general share price index	4	$\Delta\%$	nanmean
8	Contractual hourly wage	2	$\Delta\%$	nanmean
9	New orders	0	$\Delta\%$	nanmean
10	Exports of goods fob	5	$\Delta\%$	nanmean
11	Imports of goods cif	0	$\Delta\%$	nanmean
12	Money supply M1	3	$\Delta^{12}\%$	nanmean
13	Money supply M2	4	$\Delta\%$	nanmean
14	Money supply M3	4	$\Delta\%$	nanmean
15	Discount rate	5	*none*	nanmean
16	Interbank deposit rate	5	*none*	nanmean
17	Government bond gross yield	1	Δ	nanmean
18	Import unit value index	0	$\Delta\%$	nanmean
19	Export unit value index	4	$\Delta\%$	nanmean
20	Retail sales deflated turnover	0	$\Delta\%$	nanmean
21	PMI composite (EMU)	0	*none*	stock
22	PMI manufacturing (EMU)	0	*none*	stock
23	PMI manufacturing (ITA)	0	*none*	stock
24	Italy long-short term spread	5	*none*	stock
25	Italy medium-short term spread	5	*none*	stock
26	Italy long-medium term spread	2	*none*	stock

Table 11: The composition of the dataset of the model for Italy

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