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BBVA-ARIES: A Forecasting and Simulation Model for EMU

FERNANDO C. BALLABRIGA[1]* AND SONSOLES CASTILLO[2]
[1] *ESADE, Barcelona, Spain*
[2] *Research Department, BBVA*

ABSTRACT
This paper describes the BBVA-ARIES, a Bayesian vector autoregression (BVAR) for the European Economic and Monetary Union (EMU). In addition to providing EMU-wide growth and inflation forecasts, the model provides an assessment of the interactions between key EMU macroeconomic variables and external ones, such as world GDP or commodity prices. A comparison of the forecasts generated by the model and those of private analysts and public institutions reveals a very positive balance in favour of the model. For their part, the simulations allow us to assess the potential macroeconomic effects of macroeconomic developments in the EMU. Copyright © 2003 John Wiley & Sons, Ltd.

KEY WORDS EMU; Forecasting; Bayesian VAR

INTRODUCTION

The inauguration of Economic and Monetary Union (EMU) on 1 January 1999 marked a decisive step forward in the process of European integration. As of then, the euro became the single currency for all the countries that entered monetary union; a currency that in the year 2002 has ultimately replaced these countries' national fiat money. A further major change brought by the EMU is that decisions on interest rates and exchange rates are now the responsibility of a single monetary authority, the European Central Bank (ECB). Experience at a national level shows the importance of having available short- and medium-term forecasts for certain economic variables such as inflation and growth which form the basis for the monetary authority's decision making.

In this sense, the advent of the EMU also represents a significant milestone in macroeconomic forecasting, as the focus of economic analysis has shifted from the study of individual countries to the aggregate encompassing the current eleven EMU participants. As a result, both the European Central Bank and private institutions have been forced to develop instruments for predicting the behaviour of key variables such as prices, GDP, exchange rates, monetary aggregates or wages. Inflation forecasting has become a paramount objective to the extent that price stability, defined as a rate of increase of prices below 2%, is the primary goal of the ECB.

* Correspondence to: Fernando C. Ballabriga, European Commission, Office BU1 3/187, B-1049 Brussels, Belgium. E-mail: ballabriga@esade.edu

In response to this new analytical framework, we have developed the BBVA-ARIES model, a Bayesian vector autoregression (BVAR) model designed to analyse the aggregate behaviour of EMU variables. In contrast to traditional models—univariate time series models and structural models—VAR models use only a minimum set of restriction. The Bayesian dimension, which incorporates as prior information assumptions about the probability distribution of the coefficients, allows us to overcome the problem of overparameterization initially raised by VAR models.

The model thus aims to serve a dual purpose. On the one hand, it has the primary goal of forecasting. The BBVA-ARIES model provides projections for the key economic variables of the EMU economic area at 1-, 2- and 3-year time horizons. These variables are basically prices and growth, although others such as the monetary aggregate M3 and wages are also included on account of their relationship with the former. On the other hand, the model has been used to conduct a set of simulations intended to enable us to gain a greater understanding of the interrelationships existing among the economic variables included in the model, and especially to evaluate the potential impact of certain variables on the behaviour of inflation and growth.

The paper is organized as follows. The next section presents a brief description of basic aspects of the methodology applied in the development of the model. The third section describes the construction of the database. The fourth section contains the empirical results obtained with the model. We test the accuracy of the first forecasting exercise by comparing our results with those of a pool of private and public analysts. We also present a simulation exercise which illustrates some of the key interactions in the model.

METHODOLOGY AND ESTIMATION

The BBVA-ARIES model is a Bayesian VAR model constructed to forecast the behaviour of macroeconomic variables in the euro area. As such, it starts from a vector autoregression (VAR) model and complements it with the incorporation of stochastic prior information. This approach, developed by Litterman (1980), is an alternative method to traditional models and in recent years has steadily acquired prestige as a competitive forecasting instrument.[1]

After a brief description of the BVAR methodology, we go on to describe the specification and estimation process of the model, which was based on three types of decision: the choice of a vector of variables, the determination of lag structure and the specification of prior information.

The BVAR model

Economic variables are primarily characterized by their high degree of correlation, and this feature, among others, has led to the development of multivariate time series models in which all the model's variables are endogenous. Vector autoregressions (VARs) are a good example. A VAR model explains the behaviour of a vector of variables using the information provided by its own past. Specifically, a VAR may be written as follows:

$$Y_t = B_t(L)Y_t + D_t Z_t + \varepsilon_t \quad \forall t \tag{1}$$

[1] The application of Bayesian methodology in forecasting economic variables for the aggregates of the EU (Bikker, 1998) and industrial countries (Artis and Zhang, 1990) have yielded good results in comparison with the forecasts produced by structural models.

where Y is a vector of n components (equations), each of which depends on its own past, on the past of the other components and on a vector Z of deterministic components and dimension d. The t index is a time index. $B(L)$ is a matrix polynomial of order m in the lag operator L, with the $n \times n$ matrices containing the coefficients on the n variables and their corresponding lags. D is an $n \times d$ matrix of coefficients on the deterministic component, which includes variables such as a constant term, seasonal dummies or a time trend. ε is an n-dimensional vector of random disturbances. This model, proposed by Sims (1972, 1980), has been widely developed and discussed in the literature over the past two decades.

From a theoretical point of view, the VAR approach has the positive virtue of being very general, though it creates certain difficulties from an empirical standpoint. The main drawback of a model which places a minimum set of exogeneity restrictions is overparameterization. That is, as there is generally a limited number of observations, the choice of a large number of variables unduly reduces the degrees of freedom of the model. In a VAR model, the number of parameters to be estimated increases exponentially with the number of endogenous variables.

The normal strategy to overcome the degrees of freedom problem has been to use the information provided by economic theory (structural models) in order to include other information in the model over and above the sample information itself. Several authors (Litterman, 1980; Doan, Litterman and Sims, 1984) have put forward an alternative solution to the overparameterization problem based on the Bayesian approach. Thus, instead of 'arbitrarily' eliminating some regressors, which would be equivalent to reducing their coefficients to zero, each of the model's coefficients are assigned a probability distribution. This distribution makes it possible to control the likelihood of a given coefficient taking a particular value. This is the 'prior information' of the model, which embeds the basic principle of Bayesian VARs (BVARs): namely, to avoid the inclusion/exclusion dichotomy of each regressor by allowing a reasonable range of uncertainty about the parameter values.[2]

The inclusion of prior information requires the specification of a distribution for the coefficients, which may be represented as:

$$b_{ij}^{s} \approx f_{ij}^{s}(\tau) \tag{2}$$

where i refers to the number of the equation in the system, j *to* the number of the explanatory variable (stochastic and deterministic) and s to the lag number. That is, the coefficient on each of the regressors of the n equations is assigned a distribution function characterized by a vector of parameters τ. The prior information is usually specified on the basis of a set of generic assumptions corresponding to that which has become known as the Minnesota prior, as developed by Litterman (1980). This prior embeds two fundamental premises: first, that the random walk is a good proxy for the behaviour of economic variables through time; second, that the more recent past of a variable yields more information about its behaviour than its more distant past. On this basis, normal distributions independent of each other are assigned to the coefficients on lags, such that their mean is equal to one for the coefficient on the first own lag and equal to zero for the other lags; and their variance is lower for other lags than for own lags and decreases as lag distance increases.

Thus the design of a BVAR model involves as a distinctive element the specification of a vector of (hyper)parameters τ synthesizing all the prior information included in the model. This vector is

[2] For a more comprehensive and formal analysis of BVAR methodology see Ballabriga (1997).

obtained by optimizing a target function which depends on these hyperparameters and which is a measure of the model's goodness of fit.

Specification and estimation

The model is developed in three stages: first, selection of the variables that characterize the aggregate EMU economy; second, choice of the lag structure; finally, specification of the prior information and estimation of the coefficients of the model through an optimization process based on forecasting performance.

Selection of variables

The BBV-ARIES model has been designed as an instrument of empirical analysis for the EMU. The model is intended to provide forecasts with confidence bands for the area's key economic variables, while also making it possible to simulate the effects of different economic policy measures, both monetary and fiscal, on the system.

The choice of variables for the model is directly determined by this goal. A total of 11 variables thought to be representative of key sectors of the EMU economy were selected, leading to the estimation of an 11-equation model. A diagram of the variables in the system, grouped into four blocks, is presented in Figure 1, from which it can be seen that initially all the variables or blocks are interrelated.

The international economic environment is reflected in a block that includes the behaviour of commodity prices, the GDP of the 'rest of the world' and short-term interest rates in the United States. The behaviour of commodity prices, measured by the Commodity Research Bureau (CRB) index,[3] has been a major source of external shocks for industrial countries since the 1970s. The pronounced swings observed in the price of crude oil during the late 1990s represent one of the most recent episodes. The GDP of the 'rest of the world' (non-euro OECD countries, Brazil and Argentina) accounts for 45% of world GDP and captures the real external shocks for the EMU originating in industrial countries. The US interest rate seeks to capture external financial shocks.

For the domestic European sector, we include three blocks:

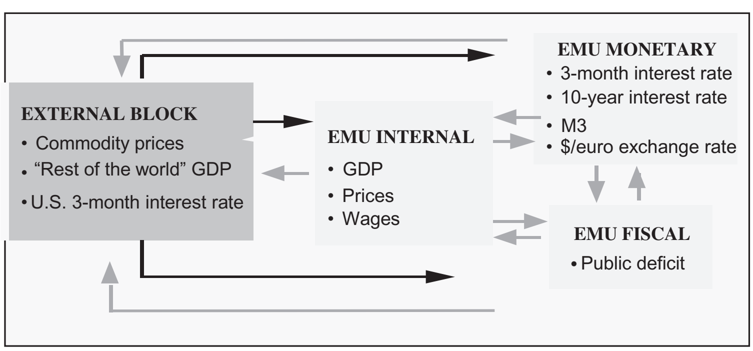


Figure 1. Groups of variables in the system

[3] The Commodity Research Bureau index is a weighted average of 17 commodities, each having an equal weight. It can be organized into four main groups: energy, grain and seeds, industrial raw materials, precious metals and soft commodities (coffee, cocoa, orange juice, etc.).

(1) An internal block that groups together real GDP in EMU as an activity indicator, inflation measured in terms of the Harmonized Index of Consumer Prices (HICP) and wages as an indicator for the European labour market.
(2) A monetary and financial block that comprises both short- and long-term EMU interest rates (3-month and 10-year rates, respectively) and the European broad monetary aggregate M3. This block also includes the euro/dollar exchange rate as a variable of potential interest to the monetary authority.[4]
(3) Finally, a fiscal block that includes the public sector deficit as a percentage of GDP.

The main goal of the model is to quantify the effect of the first three blocks on the internal block, which contains prices and the level of activity.

Choice of lag length and prior information

The first specification step is to choose a maximum number of lags. For our choice, we have made use of the structure of the model's residuals. The number of lags is the smallest number necessary to preserve the white noise structure for the error terms of the VAR. On the basis of this criterion, the number of lags is set to 4.

As noted above, and in line with other work (Ballabriga *et al*., 1998), the calibration process of the model consists of optimizing an objective function which depends on the hyperparameter vector that characterizes the prior distribution of the coefficients and which provides a measure of the model's goodness of fit. The goodness of fit criterion used was the minimization of forecasting error measured in terms of the mean square error (MSE). Specifically, we have:

$$\begin{aligned} R_j &= \sum_{t=1}^{s} MSE_{jt} && j = 1, \ldots, n \\ s &= i * fq && i = 1, 2, 3 \\ fq &= 4 && \textit{data frequency} \end{aligned}$$

where the sub-indices j and t represent variable and time, respectively, and n is the number of equations in the system.

Then the following function is minimized:

$$MSE_i = \sum_{j=1}^{n} R_j / \sigma_{\varepsilon j} \quad i = 1, 2, 3$$

Thus, for example, for $i = 1$, we compute the mean square error at one, two, three and four quarters, weighting it in turn by the standard deviation and choosing the set of hyperparameters that minimizes this error. We have looked at several forecasting horizons: at 1-, 2- and even 3-year. We have also considered the possibility of minimizing the mean square forecasting error for only GDP and inflation. In the end, we opted for a time horizon of eight to twelve quarters taking into account forecasting accuracy for the whole set of eleven variables. That is, we have taken those

[4] This decision was taken in the expectation that the exchange rate would be an important variable in ECB policy making. Nonetheless, the passive attitude adopted over the past year during the continued depreciation of the euro against the dollar seems to contradict this idea.

Table I. Goodness of fit of the model

	Statistics	
	MSE	Likelihood
UVAR model	5442.580	185.629
'Minnesota prior' BVAR model	130.371	8096.504
BBVA-ARIES model	73.741	10022.111

hyperparameters that minimize the forecasting error of the whole system at a 2- to 3-year time horizon.

The hyperparameter vector contains eight elements controlling, respectively, the following dimensions: parameters tau1 and tau2 represent the prior mean of the first lag of the variables in the system, tau1 for a first group of variables (all except interest rates, the exchange rate and the fiscal deficit) and tau2 for a second group of variables; the hyperparameter tau3 represents the overall uncertainty of the system, such that the closer it is to zero, the greater the importance of the prior information relative to the sample; tau4 measures the relative uncertainty of lags other than own lags; tau5 represents the influence of the lags of EMU variables on the external block; tau6 indicates the influence of the lags of external block variables on EMU variables (that is, the values assigned to these two hyperparameters, tau5 and tau6, control the exogeneity of the external block and/or the internal block); tau7 enables us to examine the random walk hypothesis for a number of variables—in this case, interest rates and the exchange rate; finally, tau8 controls the weight of lags higher than the first. Appendix B presents the hyperparameter values obtained after the optimization process.

Some of the findings that emerge from this process are as follows. First, forecasting performance is greatly improved by reducing the overall prior variance, or, in other words, when a large relative weight is attached to prior information. Second, the model's fit also improves considerably when the external block is taken to be almost exogenous, that is, as being virtually unaffected by the behaviour of EMU variables. Finally, there is also a marked improvement in the model's forecasting capacity when we model the behaviour of interest rates (internal and external) and the exchange rate as following a near random walk.

The Bayesian approach delivers improvements on the goodness of fit of the model. This can be illustrated by comparing the likelihood and the mean square forecasting error of the estimated model with those of an unrestricted VAR estimation (UVAR) — equivalent to reducing the relative weight of prior information to zero—and with those of a BVAR based on the Minnesota prior. Table I presents these statistics for the three models.

The estimation is in log-levels,[5] with the exception of interest rates (short- and long-term for EMU and short-term for the United States) and the fiscal deficit (expressed as a percentage of GDP) which were entered in per cent. Data are quarterly and the calibration sample period spans from the first quarter of 1970 to the fourth quarter of 1997. As noted above, the number of lags entered into the model was four. Forecasts are for a three-year time horizon. Finally, a number of point dummies

[5] Sims *et al*. (1990) argue that the practice of converting the model's variables to stationary variables, either by differentiating them or by specifying cointegration relationships among the variables, is unnecessary in the case of BVARs. Using a Monte Carlo experiment, Alvarez and Ballabriga (1994) suggest that non-stationarity does not raise problems in the case of BVAR methodology.

were introduced (in 1990 and 1991) to correct for the effect of German reunification on most of the statistics for the economic variables under consideration.

DATA AND AGGREGATION METHOD

The establishment of EMU has made it necessary to compile aggregate statistics for the euro area. Back in 1998, when the design of this model for EMU was proposed, official statistics at an aggregate level were still unavailable. As a result, we had to compile our own database for EMU on the basis of national statistics. The basic sources for the latter were Eurostat and the OECD, and aggregation was carried our considering all eleven countries and envisaging a specific solution for each variable. That is, we chose to eschew the use of an aggregation method based on GDP weights for all the variables, meaning that the share of each country in the aggregate depends on the variable considered. Thus, for instance, the Consumer Price Index is weighted with private consumption, the fiscal deficit with GDP, wages with employment, etc. From the moment official statistics became available, a comparison of the two data-sets reveals that they do not differ to any noticeable extent.[6] This section briefly outlines the aggregation method used to obtain aggregate data from the national data.

As soon as it became clear that EMU would initially comprise eleven countries (Belgium, Germany, Spain, France, the Netherlands, Italy, Ireland, Luxembourg, Portugal, Austria and Finland), we drew up a database covering a sufficiently representative set of variables, including: GDP, the consumer price index, wages, the fiscal deficit, short- and long-term interest rates and the broad monetary aggregate.

The aggregation of national variables in order to obtain an area aggregate has been undertaken using a variety of methods, though in the literature there is as yet no consensus as to the most appropriate. In our case, we have opted to apply the following criteria. For real variables, such as GDP, we take the view that the priority in the transformation of national currency series to a single currency (euros) is to retain the original dynamics of each country's GDP. The only way to do so is to apply an exchange rate from some base year to the national series, since if we were to apply an exchange rate to each period, we would be contaminating the original series with exchange rate variability. In this way, the real variables do not incorporate the effects of relative exchange rates. For nominal variables, such as the monetary aggregate M3, the conversion of the national series to a single currency is done using the exchange rate in each period.[7] Finally, for series expressed as indices or rates, each national index is assigned a weight that varies from year to year and which depends on the variable in question. Thus, for the harmonized index of consumer prices (HICP), we use each country's share in aggregate private consumption, for wages we use salaried employment and for interest rates and the fiscal deficit we use the share in aggregate GDP. The advantage of this method of aggregation is that the aggregate so obtained is the one generally employed by international organizations such as the OECD and the European Commission itself.

[6] The European Statistics Office EUROSTAT and the ECB only began to publish EMU statistics towards the middle and end of 1998, respectively. In addition, the data initially available were not of the frequency and time span needed for forecasting and econometric analysis. The updating of the database after 1997 makes use of official statistics.

[7] If, for instance, today we want to calculate GDP at current prices for a set of countries, it is reasonable to apply the current exchange rate to the GDP of each country and add them up once they are in a common currency. For this reason, an exchange rate is applied for each time period.

Table II. Country shares of EMV aggregates (%) (average 1970–1997)

Country	GDP	HICP	Employment
Germany	29.9	29.1	30.8
France	23.1	22.0	22.1
Italy	20.8	21.3	18.2
Spain	9.3	10.9	10.4
Netherlands	5.6	5.5	5.4
Belgium	3.8	4.1	3.7
Austria	3.1	2.5	3.2
Finland	2.4	1.6	2.3
Portugal	1.2	2.1	2.9
Ireland	0.8	0.9	1.0
EMU	100.0	100	100

Source: BBVA and OECD

Table II reports each country's average share in the aggregate for each of the variables constructed after applying the above aggregation criteria.

THE BBVA-ARIES MODEL

This section presents forecasting and simulation exercises undertaken with the double aim of evaluating the quality of the model's forecasts and assessing the potential macroeconomic effects of developments that unfolded in the final quarters of the 1990s.

A first accuracy test of the BBVA-ARIES model

The first forecasting exercise conducted with the BBVA-ARIES model was carried out with data up to 1997 and a 3-year time horizon. Nonetheless, this exercise incorporated additional information. Specifically, the forecast was made incorporating information available about developments in a number of variables in the first half of 1998 and the likely path of some of them in the second half of the year. Thus, we imposed an upward path for commodity prices, a recovery that was in fact later borne out, and a downwards trend for interest rates both in Europe and in the United States.[8]

Thus, with the inclusion of this information in the model by imposing restrictions on the value of the above-mentioned variables, the forecast generated suggested that GDP growth in EMU would accelerate modestly in 1998 to 2.6%, followed by a slowdown to just over 2% in the next two years. The model therefore anticipated the turnaround that would in fact take place in the EMU economic cycle only two years into the expansion that got under way in 1996. The cyclical peak was reached in the second quarter of 1998, just as the model had anticipated (Figure 2).

[8] The hypothesis of recovery in commodity prices was supported by the prospect of production cuts by the oil-producing countries, especially with Russia in the grip of a deepening crisis at the time. Monetary policy loosening was likely given the strong prospect of interest rates converging downwards in Europe and the high degree of monetary restriction in the US economy.

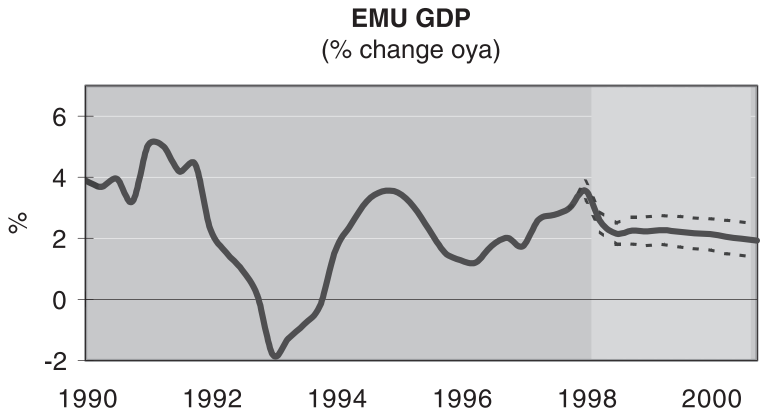


Figure 2. BBVA-ARIES GDP forecast

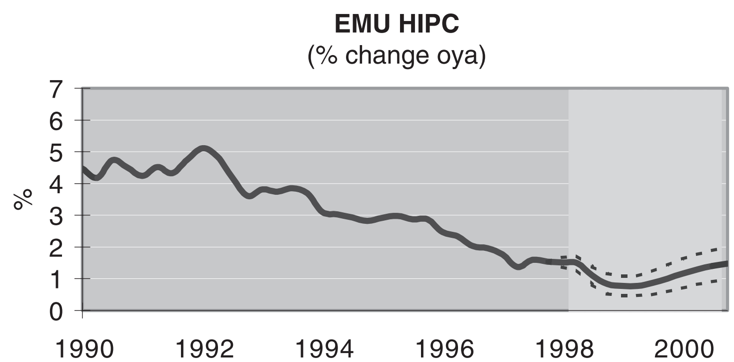


Figure 3. BBVA-ARIES inflation forecast

The growth slowdown in EMU was clearly determined by the behaviour of world output growth, which in 1998 was negatively affected by episodes such as the Asian and Russian crises, and which with a certain time lag eventually affected the European economies.

As far as price developments were concerned, the forecast signalled that the gradual reduction of inflation observed since the early 1990s would continue in 1998 and 1999. In 1999, in fact, the model predicted that inflation would stand at under 1%, by EMU standards a historically low rate of inflation (Figure 3).

In this case, the reduction in inflation was also favourably influenced by external factors. In 1998, commodity prices, as measured by the CRB index, were on average 12% lower than in 1997, mainly as a result of the slump in the price of oil. As shown in the next section, this variable is crucial to explaining price developments.

The model's forecasting capacity can be tested from two perspectives: in absolute terms, by comparing it with the actual growth rates of prices and GDP, and in relative terms, by comparing it with

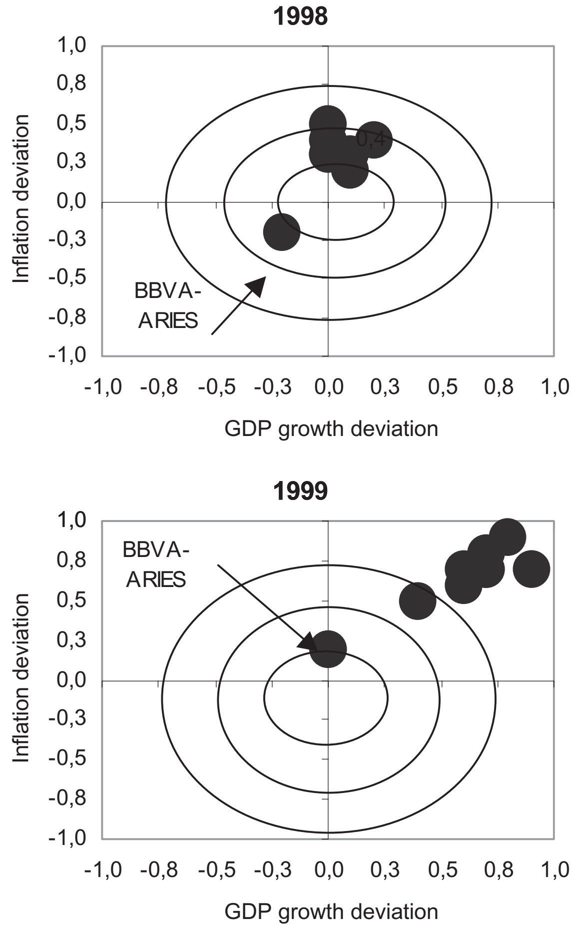


Figure 4. Forecasts of inflation and growth in 1998 and 1999. BBVA-ARIES model versus other institutions

the forecasts produced by other public and private institutions. In order to obtain a correct comparison, these institutions' forecasts must only be compiled up to the second quarter of 1998, and not thereafter, as this was the information used by the model.

Figure 4 portrays the deviation of the forecasts produced by both the BBVA-ARIES model and other institutions relative to actual inflation and growth data. The figure allows us to evaluate the accuracy of these forecasts for the years 1998 and 1999.

In this first test it would seem that the BBVA-ARIES model compares very favourably with other alternatives. A first study of the results allows at least two conclusions to be drawn. The first is that, over the shortest time horizon (four quarters), the model has generated forecasts comparable on average with those of other institutions. The most remarkable point to note is that the model's forecasts are almost at the opposite extreme to those of other analysts. Thus, whereas public institutions and analysts anticipated higher growth in prices and GDP, the model charted a less optimistic path for growth and a more favourable one for inflation.

Second, the model seems to display a relatively better forecasting performance at time horizons of four quarters and over. Starting out from the information available in the fourth quarter of 1997, the deviation of inflation in 1999 was very small (barely two tenths of a point), while that of GDP was virtually zero. This result is coherent with the calibration of the model, which emphasizes forecasting performance at time horizons over one year.

Simulation exercise: the effects of a fall in commodity prices

Both the year leading up to the establishment of EMU and its first year in existence saw a number of developments which clearly must have affected growth, and, in particular, inflation developments in the area. One such development was a slump in the price of oil of over 30% in the course of 1998, and a resulting 12% fall in the CRB index. It may be expected that this is likely to have had a favourable effect on both GDP and inflation in Europe.

We now present the results of a simulation aimed at evaluating the likely impact that may have derived from this fall in commodity prices. In the baseline scenario, we impose for 1998 the actual behaviour of the monetary (M3 and interest rates) and fiscal variables (public deficit) along with a stable growth path for commodity prices similar to the one seen in the years leading up to the crisis: that is, an annual rate of growth close to 3%. In the alternative scenario, we impose the sharp downturn observed in commodity prices during 1998 (11.8%). Figure 5 shows the impact on inflation and GDP in EMU. The positive (negative) values indicate that the corresponding variable has risen (fallen) as a consequence of the favourable evolution of commodity prices.

As regards the impact on prices, the simulation confirms that the decline in commodity prices may have had a substantial disinflationary effect. As can be seen in the first panel of Figure 5, the fall in commodity prices after the middle of 1997 would have translated into a declining rate of inflation, the pace of decline quickening until a peak is reached after nine quarters and inflation is two percentage points lower than in the baseline scenario. Thereafter, the strength of the impact tends to weaken. This exercise reveals, first, that commodity prices effects on inflation are empirically relevant. Indeed, the response of inflation is seen to be of considerable magnitude, though it must be remembered that this is not a one-off shock, but rather one that builds up over an 18-month period. The second point to note is that, instead of disappearing in 1998, the disinflationary effect carried over into 1999, and gradually faded with the passage of time.

The second and third panels of Figure 5 depict the effect on output in EMU and the rest of the world, respectively. The results suggest, first, that the downturn in commodity prices had a positive impact on EMU as a whole, helping to bring up to a 0.5-point increase in GDP relative to a scenario with a less marked commodity price weakness. The second finding is that the impact on GDP in EMU and in the rest of the world looks different, in terms of both magnitude and timing. The impact on EMU shows up more slowly, with a time lag of between three and four quarters, whereas in the rest of the world it takes effect from the first quarter onwards. Also the impact on EMU is stronger than on the rest of the industrial countries. The high point in Europe is reached after twelve quarters and exceeds that of the 'rest of the world', which comes between seven and eight quarters after the shock. This dynamics is consistent with the calibration of the model, in which the GDP of the 'rest of the world' has a greater effect on the GDP of EMU than vice versa. The impact of com-

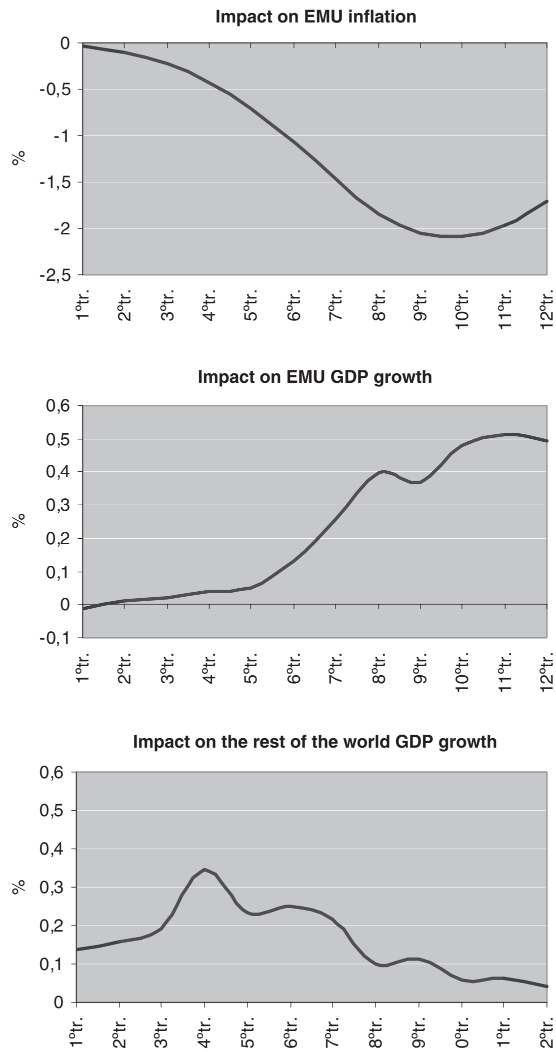


Figure 5. Impact of the fall in commodity prices

modity prices on GDP in EMU comes therefore through two basic channels: one direct, and the other indirect through the expansion of GDP in the other industrial countries (mainly the United States and the United Kingdom).

In sum, the simulation carried out indicates that the decline in commodity prices over a period of more than 18 months is likely to have had a beneficial effect on the EMU economy in two ways. On the one hand, it would have served to help reduce inflation by feeding through into consumer prices, and, on the other, it would have supported an acceleration in growth.

CONCLUSIONS

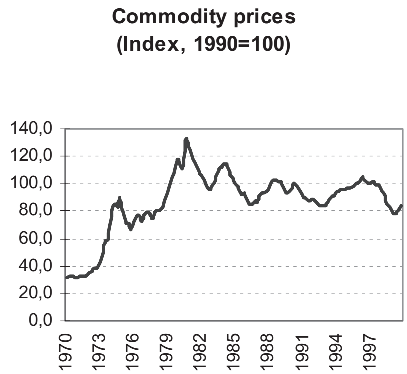
The forecasting of EMU-wide inflation and growth is of paramount importance to the ECB. Its monetary policy decisions will be marked not only by the most recent price developments but also fundamentally by medium-term inflation expectations. The formation of expectations is related to forecasts of price increases, and, to that effect, a variety of methods are used to predict their future behaviour.

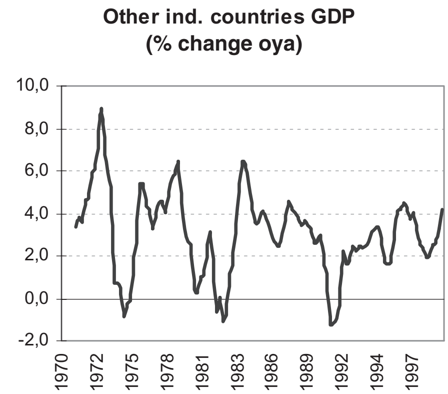
This article presents the BBVA-Aries model, a multivariate macroeconometric model for EMU, which has as one of its primary objectives the forecasting of EMU-wide inflation and growth. It is a quarterly model with eleven variables based on the BVAR methodology. A first test of the model's goodness of fit, comparing the deviation of its forecast with respect to the actual value with-that of other analysts, yields clearly favourable results in the forecasting of both growth and inflation.

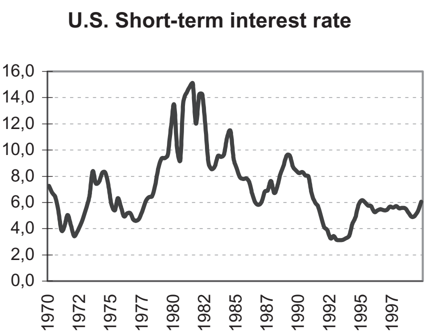
A second priority objective of the model is to attempt to characterize the interrelationships among EMU macroeconomic variables. In this regard, inflation may be said to be primarily affected by commodity prices, and less strongly so by the broad monetary aggregate and wages. Moreover, EMU growth is directly linked to world GDP (excluding EMU).

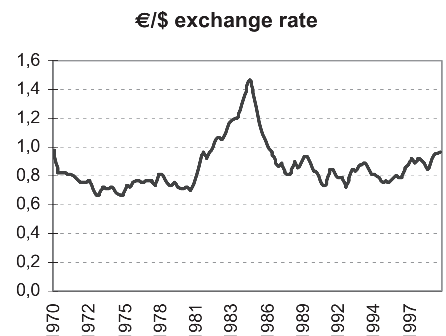
The simulation exercise presented shows that the sharp and prolonged decline in commodity prices observed from the middle of 1997 onwards, which lasted until 1999, seems to account for low inflation in EMU in 1999 (0.8% at an annual rate). It may also be interpreted as a factor contributing to faster growth in the area.

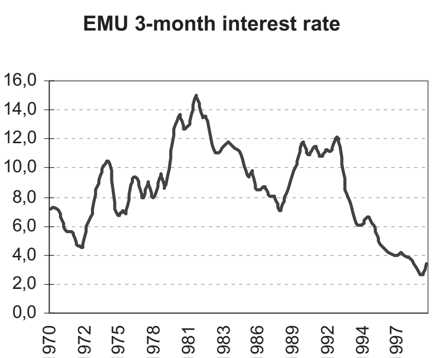
APPENDIX A VARIABLES OF THE MODEL

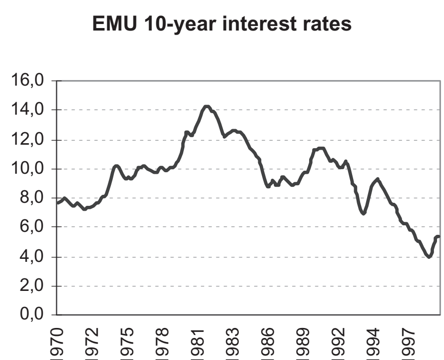




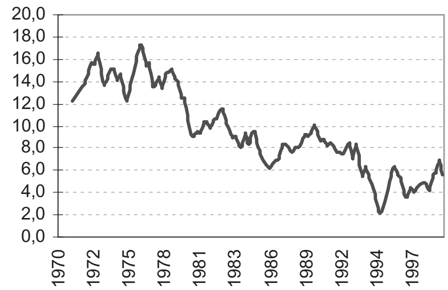




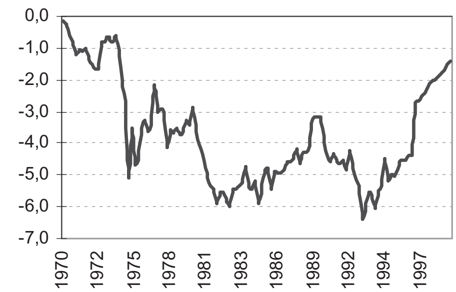




M3
(% change oya)

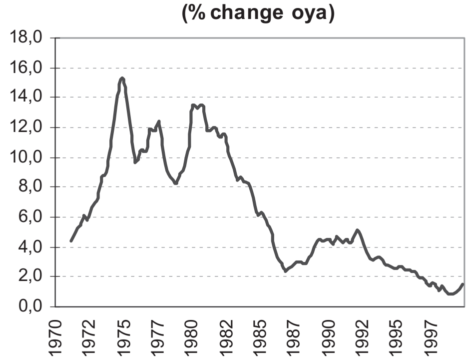


Fiscal deficit
(% GDP)

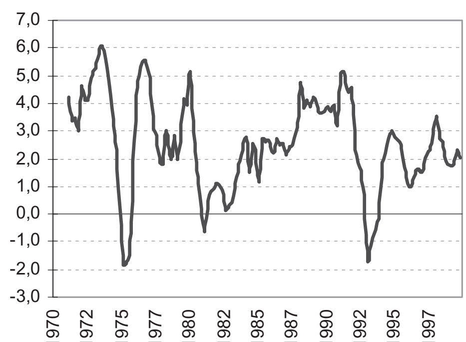


Hourly earnings, manufacturing
(% change oya)

Harmonized Index of Consumer Prices
(HICP)
(% change oya)



EMU GDP
(% change oya)



APPENDIX B HYPERPARAMETER VECTOR

tor	
tau1	0.92710
tau2	0.84210
tau3	0.00109
tau4	0.21620
tau5	0.32930
tau6	32.52490
tau7	3.21E-17
tau8	46.3848

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Authors' biographies:

Fernando C. Ballabriga received his PhD in Economics from the University of Minnesota in 1988 and is a Full Professor of Economics at ESADE, Barcelona, Spain. He held research positions in the Ministry of Finance, Spain, 1988–1990, in the Research Department of the Bank of Spain, 1990–1999, and in the Research Department of the BBVA, 1998–2000.

Sonsoles Castillo is a graduate in Economics at the University of Alcalá de Henares. He has held research positions in the Department of Economic Analysis, University of Alcalá, 1992–93, and in the Foundation for Applied Economic Studies (FEDEA), 1993–7. Currently he works in the Research Department of the BBVA, with a special focus on industrialized economies and macroeconomic forecasting.

Authors' addresses:

Ferando C. Ballabriga, European Commission, BU1 3/187, B-1049 Brussels, Belgium.
Sonsoles Castillo, Research Department, BBVA.

