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11 A BVAR Forecasting Model for the Spanish Economy

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INTRODUCTION

Prediction is often a high-risk exercise. It certainly is in the social sciences, for 3 reasons at least: (1) the relationship between the determinants of the phenomena to be predicted tend to be complex and, as a result, only partially known; (2) these determinants tend to be numerous; and (3) perhaps most importantly, the changes in most of these factors are driven largely by random components.

Naturally, economics is not impervious to these factors. However, any economic decision-making process requires weighing, to a greater or lesser extent, the trend of given future variables, so that even with all the attendant risks, economic predictions are perceived as necessary and are thus called for. In particular, forecasts concerning the main macroeconomic variables are of vital interest to any policy-maker responsible for macroeconomic stabilization as they can indicate how the economy will behave if economic policies remain unchanged and can thus serve as a warning that alternative policies should be implemented.

Whether explicitly or implicitly, economic forecasts are always based on a model. Predictions based on econometric models often have a more transparent, explicit basis than predictions made by experts, owing to the element of subjectivity usually present in the latter.

It is important that the assumptions on which projections are based be made explicit from a statistical standpoint, to facilitate the probabilistic characterization of future economic developments, something that is often not properly appreciated. As mentioned above, economic forecasts are inherently difficult, and this difficulty is visibly reflected in the high degree of uncertainty usually surrounding predictions. The logical approach in this situation is to attempt a meaningful characterization of this uncertainty. However, although it can be paradoxical, it is more common to encounter discussions about the decimal differences of various mean projections than about the probability that an economic variable will follow a given future path. Econometric models that incorporate a statistical specification of all their variables in fact make possible an assessment of the uncertainty of projections. This is a basic advantage over alternative procedures, and, in particular, over projections based on subjective perceptions.

For the Spanish economy, most macroeconomic forecasts made with a higher frequency than a year are based either on univariate time series models or on expert predictions,[1] producing a void in terms of forecasts based on econometric models that capture the interrelationships between economic variables and provide both objective measurements of the uncertainty surrounding forecasts as well as reliable quantifications of the probability of occurrence of given events. This void can be filled by building multivariate econometric models.

Following the change in monetary policy strategy brought about by the approval of the Law of Autonomy of the Banco de España and the consequent definition of future inflation[2] objectives, the analysis and prediction of prices have become even more important from the standpoint of the central bank. Consequently, the need for meaningful inflation forecasts has increased sharply, and so has the motivation for developing tools to make them. Because the work is as difficult as it is essential, the range of instruments developed to accomplish it must necessarily be wide. This being so, the multivariate econometric model discussed in this chapter supplements the existing methods of predicting inflation.

This chapter presents a small macroeconometric model for the Spanish economy. The model provides forecasts of the most relevant economic variables and can serve as an aid in making economic policy decisions. Following this introduction, we describe the basic aspects – both theoretical and practical – of the Bayesian Vector Autoregression (BVAR) methodology, which is the methodology chosen for the construction of the model. We describes the variables included in the forecasting model and the reasons for their selection. We then deal with the practical application of the methodology and highlight how it differs from customary uses of the BVAR methodology,[3] and present evidence of the forecasting performance of the model, with special emphasis on predicting inflation and using uncertainty intervals for forecast growth rates. A few final comments, complete the chapter.

BRIEF DESCRIPTION OF THE BVAR METHODOLOGY

VAR Models as a General Frame of Reference

According to Todd (1984), it is useful to think of the construction of an econometric model as a process which, in accordance with certain criteria, combines the historical information contained in the sample data with the prior statistical and economic information provided by the econometrician. The various modeling techniques can then be compared in terms of the type of prior information used and the weight assigned to it.

Of course, every modeling technique requires a minimum of prior information if it is to be usable, i.e. at least the information needed to select a group of relevant variables for purposes of the analysis and to establish an algebraic relationship among them. In fact, the selection of a vector Y of n components under the assumption that each of these components depends linearly on its own past values, the past values of the remaining components, and a vector Z with d deterministic variables (for example, an intercept or seasonal dummy variables), yields a model that in recent years has become a part of the empirical economist's tool kit:

$$Y(t) = B_1Y(t-1) + B_2Y(t-2) + \ldots + B_mY(t-m) + DZ(t) + \epsilon(t) \quad (11.1)$$

where t is a temporal index, B_i represents matrices of order $n \times n$, D is $n \times d$, and ϵ is a vector of random disturbances of order n. Since (11.1) relates a vector of variables to its own past values, it is given the name Vector Autoregression (VAR). Moreover, because it includes only a minimum set of prior restrictions, it is often called the Unrestricted Vector Autoregression (UVAR) model.

As a theoretical framework, the UVAR model is quite general. Granger and Newbold (1986) assert that if the number of lags is not restricted and the matrices of coefficients are time-dependent, any random process can be expressed as a UVAR model. This general aspect of the model makes it an attractive point of departure for econometric modeling and a frame of reference indicative of the type of restrictions actually incorporated into alternative models, since representations of type (11.1) encompass any econometric simultaneous equations or time-series model.

Philosophy of the BVAR Methodology

While a source of theoretical appeal, the generality of the UVAR representation, because it is based on a generous parameterization of the model, also contains the seed of its chief practical deficiency. In fact, the number of coefficients to be estimated in a model such as (11.1) is $n(nm + d)$, which number increases quadratically with the size of the vector Y and multiplicatively with the number of lags included in each of its components. Thus, for example, a model with five endogenous variables, four lags per variable, and an intercept in each equation, would require the estimation of a total of 105 coefficients.

This is a serious problem in the adverse context in which empirical economic research is conducted, characterized as it is by the existence of sample information that tends to be both scarce and highly contaminated by random variability. What this actually means is that the econometrician cannot estimate UVAR models consisting of more than a relatively small number of variables without running the risk of overfitting, i.e. without running the risk that his estimates will be excessively influenced by accidental sample variability (*noise*), in contrast to systematic relationships (*signal*). The phenomenon of overfitting is very likely to occur when 3 elements converge in empirical analysis: a large number of parameters to be estimated, relatively scarce sample information, and a method of estimation designed to explain (fit) the sample data as fully as possible (e.g. least squares methods). These 3 elements definitely converge in UVAR models when the objectives of the analysis require the inclusion of a fairly large number of variables, as is usually the case, for example, when the variables that shape an economy's macroeconomic environment are to be modeled. Consequently, UVAR models are generally not recommended for forecasting.

The BVAR methodology was originally developed by Litterman (1980) and Doan, Litterman and Sims (1984) to propose a solution to the problem of overfitting UVAR models other than that which relies strictly on economic theory as a source of exclusion restrictions, as is the case of structural simultaneous equation models. In other words, an attempt was made to find a way of avoiding the influence in the estimates of accidental sample variability without having to choose whether to include or exclude lags from the different variables. In most cases, this dilemma prevents a realistic expression of the prior information normally available to the analyst, since there is generally no absolute certainty that the value of a coefficient is zero nor complete ignorance as to the value of the coefficients included in the model.

Stating the problem thus, the adoption of a Bayesian approach seems to be the natural solution. In other words, an information source expressed as a probability distribution for the coefficients of the model can be used, which – without putting all the weight on a single value and without being absolutely non-informative – represents a reasonable range of uncertainty and may therefore be modified by sample information if the two information sources differ substantially. If prior information is not excessively slack (minimally informative), only the systematic sample variability (*signal*) will be able to modify it, but not the accidental variability (*noise*), thereby reducing the risk of overfitting.

This concept is put into practice by combining (11.1) with a prior probability distribution for its coefficients. This combination results in what is known as a Bayesian vector autoregression (BVAR).

Specification of a BVAR Model

Undoubtedly, the distinguishing and most important feature of the process of specifying a BVAR model is the selection of the prior information. In principle, this information can come from many sources and take very different forms. The information described in this section originated in the empirical analysis of macroeconomic data and became known as the 'Minnesota prior' because of the professional relationship of its proponents with the Federal Reserve Bank of Minneapolis. The prior information used in more recent applications of the methodology tends to be more elaborate but has the same objective and retains many of the basic characteristics of the Minnesota prior information.

As indicated on p. 371, it is used to reduce the risk of overfitting, and this is the first aspect that should be stressed: the information is purely instrumental, and, as such, is not expected to be necessarily correct in average terms, but rather to contain a realistic range of possible data-generating mechanisms, the most appropriate of which can be selected to explain the variability of sample data.

The second notable aspect of the prior information used in the specification of a BVAR model is its empirical/statistical origin and the resultant lack of economic content. Specifically, the information incorporates 3 empirical regularities derived from the statistical analysis of time series:

1 The hypothesis that the best prediction of the future value of a series is its current value (the so-called random walk representation) is a good approximation of the behavior of many economic series
2 Lagged values that are closer together in time usually have more informative content concerning the current value of a given variable than lagged values that are farther apart in time
3 A variable's own lagged values usually have more informative content *vis-à-vis* its current value than the lagged values of other variables.

The most direct method of formalizing these regularities is to define independent normal distributions in accordance with statements 1–3 for each of the coefficients of (11.1). Attempting an individualized specification of each of the distributions, however, brings us back to the problem of overfitting, which is precisely what we wish to avoid. The best way, then, of rendering the concept operational is to establish functional dependency between all of the distributions and a small set of parameters (known as 'hyperparameters' in the methodological jargon) which can be used to control their basic dimensions in line with regularities 1–3.

Figure 11.1 shows, in terms of probability density functions, the type of prior distribution being described for the coefficients of a representative

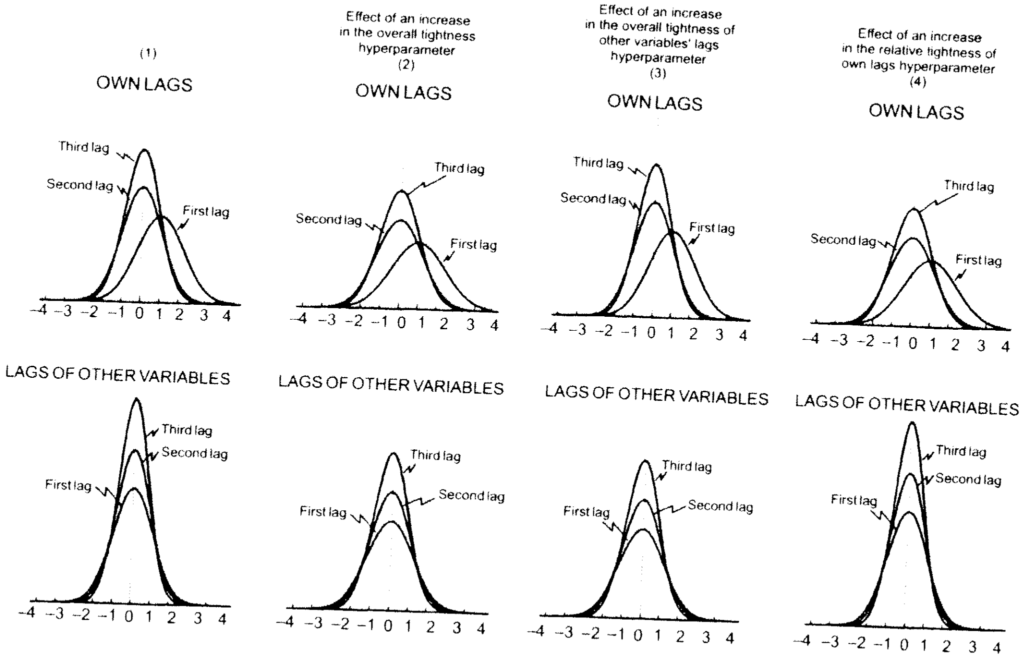

Figure 11.1 Prior distribution of the coefficients

equation of the system (11.1), where, for the sake of simplicity, it will be assumed that there are 3 lags. Column (1) shows how empirical regularities 1–3 are taken into account:

- 1 is represented by specifying the distribution of the coefficient of the first own lag with unit mean and the rest of the distributions with zero mean
- 2 is represented by reducing the variance of the distribution of the coefficients as the lag distance increases; thus, the more distant the lag, the more certain it is that its coefficient is zero
- the incorporation of 3 can be verified by comparing the upper part of the first column with the lower part and noting that the coefficients of the own lag have greater variance than the coefficients of other variables, showing that there is greater certainty as to the zero value of the latter.

These representations provide an idea of the nature of the small set of control parameters (or hyperparameters). Thus, one parameter will control the value of the distribution mean of the coefficient of the first own lag, another will control the variance of the own lag distributions, and a third will control the variance of the distributions of the lags of other variables. To avoid specifying parameters that control the variance for each lag, consideration is usually given to a functional form that inversely relates variance to the number of the lag, thereby introducing a fourth parameter to control the speed of variance reduction as lags increase.

Another frequently specified parameter controls the degree of overall uncertainty (*overall tightness*) of all the coefficients. It is also a determinant of the weight that sample information receives when the model is estimated.

Returning to Figure 11.1, column (2) shows the effect of an increase in this last parameter, which, as can be seen, causes a general rise in the variance of all the distributions. This implies reducing the weight of prior information relative to the weight of sample information. Column (3) shows the effect of an increase in the parameter that controls the uncertainty of the lags of other variables, which causes the variance of the distributions of the coefficients of these lags to increase without affecting own lags. This suggests greater interrelationship among variables. The opposite happens when the parameter that controls the variance of own lags (column (4)) is increased.

Perhaps the complete lack of economic content in the prior information of BVAR analysis may seem surprising. Recalling its instrumental nature can help in understanding it. In other words, while it is true that having an instrumental nature and incorporating economic content is not incompatible, it is no less so that the instrumental nature is purer if it is not mixed with possibly controversial economic assumptions. It is in this connection that it seems more appropriate to opt for economic neutrality *a priori*, so that a single specification can be accepted by economists with very different views of the true structure of the economy.

The specification of a BVAR model is completed when prior information is combined with sample information, which is done using Bayes' rule to obtain the posterior distribution of the coefficients of the model. The mean and the variance of this posterior distribution provide, respectively, the point estimators and the variances of the various coefficients of 11.1.

Advantages and Disadvantages of the BVAR Methodology

The main concepts described so far in this section can be properly summarized by saying that the attraction of the BVAR methodology is the flexibility and objectivity it brings to the process of specifying an econometric model. This is perhaps the main asset of the methodology.

The flexibility referred to means the flexibility to incorporate various types and forms of information into the specification process, to make possible a realistic and systematic expression of the uncertainty surrounding the working interrelationships in the economy under analysis. Intuition suggests that a flexible and systematic method of imposing restrictions can lead to greater accuracy in extracting the empirical regularities underlying sample variability. This being so, the estimators obtained will have to be more accurate (although they may be biased) than those derived using least squares methods. The result is that the final model will theoretically be of a better quality in terms of forecasting, and this will have been achieved through an objective process, i.e. a process based on the use of explicit statistical mechanisms that are perfectly reproducible and capable of probabilistically characterizing the future course of the modeled variables.

Regarding the reference in the preceding paragraph to the term 'forecasting', it should be briefly explained that it is being used in a broad sense, i.e. it refers both to what in the methodological jargon is known as unconditional forecasting and to conditional forecasting. The latter is conditional upon the set of sample data and a given restriction on the future course of the variables in the model. Unconditional forecasting, on the other hand, is conditional only upon the set of sample data and is, undoubtedly, the one most widely used in applications of the methodology, including the application described in this article.

The reason for this clarification is, in any case, twofold: (1) to emphasize the multivariate function of the BVAR methodology and its crucial importance in extracting stable interrelationships, and (2) to highlight the fact that one of the aims of the methodology is to overcome being a 'black box' by attempting to extract stable interrelationships that may be capable of a certain economic interpretation and thus may be useful, for example, in projecting the impact of given economic policy actions. Its purpose, therefore, is to be a substitute for or a complement to structural multivariate methods.

The question immediately arises, then, of how a plausible economic interpretation is to be obtained from a model that has been described thus far as lacking in economic content. The answer is that extracting an economic interpretation from the analysis requires that the BVAR model be supplemented with an additional set of economic restrictions. This is the identification stage of the model, which, in the BVAR methodology in particular and in the VAR methodology in general, follows the specification stage and is characterized by the use of the smallest and least controversial set of restrictions possible.[4]

Because the process of identifying the model is the final stage, a clear distinction can be made between the restrictions used in specifying the probabilistic mechanism of the model from those intended to give it economic content. On the other hand, the fact that the identification is based on a minimum number of restrictions renders the mechanism of economic interrelationships much less clear than it would be in an empirical model derived from a set of explicit theoretical assumptions. This lack of interpretative transparency is probably the most obvious disadvantage of the VAR methodology (UVAR or BVAR), but it is accepted because of the possibility of conforming the model more closely to the stable regularities of sample data.

Forecasting Performance of BVAR Models Compared to Other Procedures

Flexibility, objectivity, and the consequent possibility of a more accurate model constitute the logical framework highlighted in the preceding section as the main advantage of the BVAR methodology. That is certainly the theoretical logic, and one way of verifying whether this logic has a practical application is to examine the predictive record of BVAR models compared to other models.

Most of the literature on the comparative evaluation of unconditional forecasts of BVAR models in macroeconomic contexts take the 1980s as a reference period.[5] Their main conclusions are the following:

1 BVAR models are, on the whole, competitive with large-scale structural models and with univariate time series models, such as ARIMA models for example
2 BVAR models tend to be superior to large-scale structural models and univariate models in medium-and long-term predictive horizons
3 Their informative content usually differs from that of structural models; consequently, their predictions may be substantially different
4 BVAR models are clearly superior to UVAR models.

This set of conclusions, although pertaining to a specific sample period, shows that BVAR models are comparably accurate predictive instruments with certain additional advantages that other econometric models lack. This is especially reassuring since, as mentioned in the preceding section, VAR models – and BVAR models in particular – tend to be the only ones designed to associate objective probabilities with future economic events and a good predictive record is a good guarantee that such probabilities are reliable.

In summary, this section has described BVAR models as an alternative to simultaneous-equation models for making practical use of the general theoretical frame of reference provided by unrestricted VAR (UVAR) models, whose generous parameterization leads to overfitting when attempting to model more than a relatively small number of variables. BVAR models result from combining UVAR models with an *a priori* distribution for their coefficients. This distribution is empirical in origin and strictly instrumental in nature, as it does not attempt to give the model economic content, but rather to make its specification more flexible and more objective, which aspects ensure good predictive properties and are perhaps the main advantage of the BVAR methodology. These considerations suggest that the BVAR methodology may be useful in constructing a forecasting model. The following sections present the details and results of a specific application of this methodology to the Spanish economy.

SELECTION OF THE PRINCIPAL VARIABLES OF THE SPANISH ECONOMY

In most cases, the first decision to be made in building general econometric models is the selection of variables. In fact, the constraint imposed by data availability restricts the size of the model, so that despite the fact that the set of potentially relevant economic variables is large, a selection must be made. In Spain, this problem is complicated by the short time span of official statistics. The quarterly National Accounts time series start in 1970, whereas most monetary series begin in 1974. Models including both types of variables should therefore be used only for the analysis of sample periods beginning in 1974.

In short, the problem is one of obtaining as general a picture of the Spanish economy as possible, as the number of variables used in such a characterization cannot be very large, given the available sample period. With these premises, the first question should not be which are the most relevant variables in the Spanish economy, but in which sectors can this economy be structured? Once this sectorization has been accomplished, the next step is to determine which minimum set of variables characterizes each sector. The aim of this approach is to ensure that the set of variables chosen is both restricted and capable of characterizing the economy as a whole. The last step in this process consists of selecting the available statistical series that best approximate the selected variables. In keeping with this approach, the method of economic sectorization used in this study is based on the distinction between the external, monetary-financial, public and private (non-monetary) sectors, thus providing a complete, structured description of the Spanish economy. The variables and series selected for each sector are explained below. Table 11.1 shows the variables grouped by sector, the series used, and their sources.

External Sector

This sector represents the behavior of economic agents operating in the international environment, which is becoming increasingly important for the Spanish economy. In fact, the opening up of the Spanish economy to external markets (markedly so in the last decade) has led to a sharp increase in the relationships between the international and the domestic variables.

It therefore seems relevant to include in this model some variable(s) explicitly reflecting the external environment in which the Spanish economy has evolved. Given that one of the primary links between economies is the trade balance, it seems appropriate to base the selection on its determinants. Buisán and Gordo (1993) identify two determinants of Spanish exports and imports: competitiveness and world trade, respectively. In the

Table 11.1 Selection of variables

Sector	*Variable (abbreviation)*	*Series*	*Source*
EXTERNAL	WORLD ACTIVITY (*GDP**)	GDP at constant prices of the OECD countries, base 1990. Seasonally adjusted series	OECD
	EXCHANGE RATE (*E*)	Nominal effective exchange rate *vis-à-vis* industrial countries. Index 1990 = 100, average of monthly data.	Banco de España
PUBLIC	PUBLIC DEFICIT (*D*)	Net government financing (revenue less expenditure), cumulative total of monthly data Series converted with non-centred moving averages of four terms, expressed as a percentage of nominal GDP	Banco de España
MONETARY	INTEREST RATE (*I*)	1-month interest rate in the interbank market, average of monthly data	Banco de España
	MONEY STOCK (*M*)	Liquid assets held by the public, average of monthly data, million pesetas.	Banco de España
PRIVATE	PRICES (*CPI*)	Consumer Price Index, index 1992 = 100, average of monthly data.	Instituto Nacional de Estadistística; Matea and Regil (1993)
	WAGES (*W*)	Compensation per wage earner in national accounting terms, thousand pesetas.	Banco de España
	LEVEL OF ACTIVITY (*GDP*)	GDP at constant prices, base 1986, billion pesetas	Instituto Nacional de Estadística
	EMPLOYMENT (*L*)	Employed population according to the Labor Force Survey, thousand individuals	Instituto Nacional de Estadística; García Perea and Gómez (1994)

model, the exchange rate and the level of world activity will be used to approximate these concepts.

Generally speaking, the selection of the exchange rate has a dual purpose: (1) as a variable that conditions monetary policy, and (2) as the transmitter of external effects on the economy's purchasing power. Thus, the exchange rate will be indicative of the competitiveness of the national economy. To incorporate the exchange rate as a determinant of monetary policy, a good approximation of this variable for recent years would be the peseta/D-Mark exchange rate series. However, if a perspective based on competitiveness is adopted, as is the case in this study, a more appropriate series is the nominal effective exchange rate (E) *vis-à-vis* industrial countries.

The key issue in selecting the series that approximates world activity is its geographical coverage. The existing empirical results for the Spanish economy (see Buisán and Gordo, 1994) suggest that the OECD environment is the most appropriate; consequently, the series selected was real gross domestic product at market prices for the OECD countries (GDP^*).

Monetary Sector

This sector represents the action of the monetary authority and the financial institutions. Two variables are considered: the interest rate and the money stock.

The interest rate is not only the preferred instrument for implementing monetary policy; it is also a determinant of the consumption, savings, and investment decisions of economic agents. Although numerous interest rates may be employed – both real and nominal, short- and long-term – a single interest rate is used for simplicity. It therefore seems appropriate that the selection of this interest rate be determined by the dual role of representing the effectiveness of monetary policy and its influence on the spending decisions of economic agents. The available evidence suggests that interbank market interest rates can adequately fulfil this dual role. Accordingly, the series selected is the '1-month interbank market interest rate' (I).

Consideration of the money stock variable is prompted by the fact that despite the loss of stability and predictability of the demand for money equations estimated in recent years, the money stock has been the intermediate objective of monetary policy until 1994 and is currently used as a preferred indicator in monetary programming. Consequently, the series selected to approximate the money stock is 'liquid assets held by the public' (M).

Public Sector

The purpose of this sector is to capture public sector economic activity. The complexity and diversity of public sector activity can be summed up by focusing on the budgetary aspect, which can in turn be characterized by the public deficit. Despite the limitations involved in reducing this sector to a single variable, this decision has the advantage of helping to keep the size of the model within manageable limits.

The series selected was Net Government Financing (*D*), for the following reasons: (1) because it accurately represents the net financial position of the government, as it records payments, collections, and financial operations on a daily basis, regardless of how the government keeps track of its operations; (2) because it is a deficit concept in a broad sense, which not only includes current expenditure and revenue, but also reflects the government's financial position; and (3) because it represents a compromise between fiscal shocks through the components of aggregate demand and through their effects on monetary variables.

Since much of the variability of this series is administrative in origin, it should not have economic effects.[6] The series was therefore smoothed using moving averages. In addition, the series is used in terms of nominal GDP, which is how it is usually presented.

Private Sector (Non-monetary)

The purpose of this sector is to represent the decisions of domestic agents with regard to production, investment, labor, and consumption. Price, wage, employment, and output levels were selected as variables characterizing the actions of domestic agents.

The inclusion of the price variable is justified for at least two reasons: (1) it is an important reference variable in the decision-making of economic agents, and (2) it directly reflects the national economy's inflationary situation, control of which is one of the monetary authority's highest priorities. The series chosen to represent prices was the consumer price index (*CPI*), as it is the series to which private economic agents usually refer.

The wage variable indicates the labor market situation and, no less importantly, the existence of nominal pressures on the economy that affect inflation. The series chosen to approximate this variable was compensation per wage earner (*W*). This variable is preferable to those derived from the official Wage Survey as it includes all wage costs relevant to production decisions.

Lastly, employment and output were the variables selected to reflect the level of real activity in the economy. The specific series chosen were the employed population (*L*) and gross domestic product (*GDP*).

A FORECASTING MODEL FOR THE SPANISH ECONOMY

Description of the Structure of the Model[7]

As mentioned above, the specification of prior information is not limited to the use of the Minnesota prior, although it can be viewed as a point of departure for more specific prior information, which will depend on the data used and the problem under study. Thus, in an effort to accommodate the existing characteristics, the prior information used in the model specified for the Spanish economy has the following characteristics:[8]

1 Unlike the Minnesota prior, in which the prior mean of the coefficient of the first own lag takes the value of one for all variables, two groups of variables with different means,[9] τ_0 and τ_1, are distinguished in the model. Deterministic variables have a zero prior mean.
2 As usual, it is assumed that the matrix of prior variances and covariances is diagonal; therefore, the coefficients of the model are independent.
3 All of the prior variances of the system depend on a global hyperparameter τ_2, which determines the relative weight of prior information. Thus, a zero value means that sample information is not taken into account, while an infinite value means that prior information is ignored.
4 The prior variance of own lags depends on hyperparameter τ_4, while the variance of the lags of the remaining variables depends on hyperparameters τ_3 and τ_4. The effect of these hyperparameters is the following: hyperparameter τ_3 controls the significance of the lags of the other variables. A small value means that there is little interaction between variables, while a large value means that the interactions are stronger. Hyperparameter τ_4 indicates to what extent lags closer together in time will have more informative content than lags more distant in time. Thus, if the value of this parameter is large, the distant coefficients are, *a priori*, less important, while their importance will be greater if the value is small.
5 The prior variance of the intercept term depends on hyperparameter τ_5. A large τ_5 value means that there is scarcely any prior information about the possible value of the constant, and a zero value means that the intercept is not included in the model.
6 Since the model includes variables that exhibit seasonal behavior (i.e. the consumer price index, liquid assets held by the public, and employment), seasonal dummies are included in the equations. Their prior variance depends on hyperparameter τ_6. A large τ_6 value indicates a high degree of uncertainty about the possible value of the coefficients associated with these seasonal variables, while a zero value means that they are not included.
7 In this study, it is assumed that coefficients vary over time. Specifically, each coefficient follows a random walk, the variance of which is given by hyperparameter τ_7. Obviously, if τ_7 is zero, the model does not vary over time.
8 The prior information under consideration implicitly assumes that all of the variables are endogenous. However, in small economies such as

that of Spain, is it more appropriate to consider world activity as exogenous, i.e. that it is not affected by domestic variables. To attain this objective, additional hyperparameters are introduced. The first of these, τ_8, captures the relative uncertainty of domestic variables in the equation for world activity. Exogeneity is obtained if τ_8 is zero. Hyperparameter τ_9, on the other hand, can be used to control the relative uncertainty of world activity in the rest of the system.

9 Although the VAR methodology tends to ignore the prior existence of exogenous variables, it is assumed in this model that the interest rate follows an AR(1) process exogenous to the rest of the system variables.[10]

10 The GDP and employment equations contain two broken trends as deterministic variables, with a break point at 1985:I. It should be noted that the use of deterministic trends in other cases (especially at the end of the sample period) usually creates serious problems when it comes to forecasting, as the resulting predictions are fairly inflexible in terms of taking into account new information. However, this is not necessarily true of models (such as the one under consideration) which time-varying coefficients as this variation allows for adapting the forecasts in light of the new information.

Estimation of Reduced Forms

Most of the series referred to in this analysis can be characterized as non-stationary processes. To take account of this fact, one possibility would be to estimate the model in differences. However, this method of proceeding would involve disregarding information on the presumable long-term relationships among these series. The unrestricted estimation of VAR models in levels gives consistent estimators that are asymptotically equivalent to those obtained using maximum likelihood.[11] On the other hand, the consistency of the estimators is unaffected by the introduction of prior information.[12] Consequently, the model was estimated without differencing the series.

In the model, the logarithmic transformation of all the series is considered, except for the interest rate and the public deficit, which are used in levels. The sample period used begins in 1974: I and ends in of 1993: II. The number of lags is 4.[13]

Efficiency gains occur in BVAR models if the system is jointly estimated instead of equation by equation, as is usually the case in the literature.[14] However, in this model, there were two reasons for preferring an equation by equation estimation procedure: (1) the high computational costs involved in a model of this size,[15] and (2) the preliminary results of joint estimation did not reveal any major differences relative to equation by equation estimation.

Reduced form estimation[16] requires specifying an objective function in terms of the set of parameters τ. Although it is common practice to maximize[17] the likelihood of the system, an alternative criterion, given that this is a forecasting model, is minimization of the mean square forecasting error.[18] The forecasting horizon selected was 1 year.[19]

The vector of hyperparameters (τ) that optimizes the criterion adopted[20] and coincides with the optimal vectors of the 2- and 3-year mean square errors is shown in Table 11.2.

The Forecasting Performance of the Model

Once the quarterly macroeconometric model has been specified and estimated, it must be evaluated in terms of its forecasting performance. An

Table 11.2 Hyperparameters associated with the reduced form

Hyperparameters	*Estimated values*
τ_0	0.921
τ_1	0.632
τ_2	0.58×10^{-2}
τ_3	0.0476
τ_4	1.688
τ_5	9×10^{6}
τ_6	81×10^{9}
τ_7	0.103×10^{-5}
τ_8	0.00
τ_9	1.00

Notes:
1. τ_0 Prior mean of the first lag of the dependent variable for the first group of variables $\{GDP^*, M, W, CPI, GDP, L\}$.
2. τ_1 Prior mean of the first lag of the dependent variable for the second group of variables $\{E, I, D\}$.
3. τ_2 Overall tightness.
4. τ_3 Relative tightness of other variables' lags.
5. τ_4 Relative tightness of own lags.
6. τ_5 Relative tightness of the constant term.
7. τ_6 Relative tightness of seasonal dummies.
8. τ_7 Variation of the coefficients over time.
9. τ_8 Relative tightness of the domestic variables in the world activity equation.
10. τ_9 Relative tightness of world activity in the rest of the system.
11. The set of seasonal variables consists of $\{M, CPI, L\}$. The set of non-seasonal variables consists of $\{GDP^*, E, I, D, W, GDP\}$.

Source: Authors' calculations.

initial evaluation can be based on the criterion used to estimate the model, i.e. the use of the 1-year mean square error as an optimizing criterion makes it a certainty that, within sample, this model is the one with the minimum forecasting error within this horizon.

Moreover, there are at least 3 other aspects of interest:[21] (1) how the model performs with horizons other than one year; (2) how well the model forecasts inflation, as the above-mentioned statistic is global. If it is especially important to obtain accurate forecasts for inflation, which is the case for the monetary authority, this global statistic is not necessarily relevant and it becomes necessary to perform a more detailed analysis of inflation forecasts; and, (3) the significance of the interrelationships between the different variables in the model. The estimate of the hyperparameter that controls the uncertainty associated with other variables (see Table 11.2) is low which, together with the low value of the estimate for the hyperparameter associated with overall uncertainty, suggests that there is little interaction in the model, and, therefore, that this model is not very different from a model consisting of nine equations, in which each variable depends exclusively on its past values, which is what would happen if the hyperparameter that controls the uncertainty of other variables were zero.

To answer these questions, two alternative models[22] were considered. The results of these models will be compared with those obtained with the BVAR model. The first model considered was obtained by setting to zero the relative weight of the prior information, i.e. an unrestricted VAR (UVAR) model. In the second model, the prior information used in the BVAR model is restricted in order to block any interaction among variables, so that a set of equations is obtained in which each variable is determined exclusively by its own lags (referred to as a BAR model in the following, as it contains Bayesian prior information and an AR specification). Both models provide interesting benchmarks as, on the one hand, they allow for an assessment of the advantages of using a Bayesian approximation as opposed to an unrestricted estimate (when the BVAR model is compared with the UVAR model), and, on the other, they facilitate weighing the benefits of adopting a multivariate as opposed to a univariate model (when the BVAR model is compared with the BAR model).

As shown in Table 11.3, an initial approach to comparing these models can be based on their goodness of fit, approximated by the mean square forecasting error (MSFE). This table reveals the superiority of the BVAR model over the other models in all of the statistics used, showing that the BVAR model generally possesses better predictive qualities than the BAR and UVAR models, not only for one year, but for more extended periods as well.

Table 11.3 Overall fit of the models

	Models		
	BVAR	*BAR*	*UVAR*
Probability	4248.00	4006.00	685.00
1-year MSFE[1]	62.55	75.62	119.51
2-year MSFE	227.65	278.37	550.24
3-year MSFE	516.65	628.83	1599.66

Notes:
1. MSFE: mean square forecast error.
2. The larger the probability value, the better the fit of the model.
3. The larger the MSFE value, the worse the predictive performance of the model.

Source: Authors' calculations.

Although these statistics are global in nature and consequently make no distinction between variables, the main reason for using this model – as explained throughout this chapter – is to obtain accurate predictions of inflation, as well as those associated with the other private sector variables. Each variable must therefore be analyzed separately. One way of performing this analysis is to observe the mean absolute forecasting error of the different variables and models.

The results (see Table 11.4) leave no room for doubt. The BVAR model, analyzing each variable individually and for different forecasting horizons, represents, with few exceptions, a marked improvement over the other models. The improvements are especially remarkable in the case of the price variable, where the significant differences in the more distant horizons stand out. As for the other private sector variables, the BVAR model again proves superior in respect of wages, GDP, and employment, although at less distance from the BAR model for the last two variables.

Given the relevance of inflation analysis for the purposes of this book, and despite the global nature of the model, a closer examination of the characteristics of inflation forecasts generated by the BVAR model is necessary. Thus, from the standpoint of analyzing the economic environment, both the profile of the forecasts as well as their change (as new information is included) are key elements in defining the behavior of inflation. Accordingly (see Figures 11.2 and 11.3), forecasts were made for 1993–1995, using 1993: III as the initial forecasting origin and rolling this forecasting origin to the following quarters.[23]

One of the most striking details revealed by comparing the BVAR and UVAR models (see Figure 11.2) is the extreme instability of the UVAR-model, which leads to significant variations in the forecasts, with inflation

Table 11.4 Mean absolute error of forecast, 1990–4

	PRICES			*GDP*			*EMPLOYMENT*			*WAGES*		
	BVAR	*BAR*	*UVAR*	*BVAR*	*BAR*	*UVAR*	*BVAR*	*BAR*	*UVAR*	*BVAR*	*BAR*	*UVAR*
1 quarter	0.26	0.50	1.27	0.18	0.19	0.31	0.57	0.67	0.61	0.45	0.61	0.87
1 year	0.45	1.67	4.46	1.54	1.54	3.82	2.80	2.89	2.38	1.16	2.63	2.47
2 years	0.97	3.87	6.14	4.12	4.21	14.67	7.00	7.14	10.51	1.96	6.85	7.77
3 years	1.09	6.66	20.16	7.76	8.16	27.38	14.80	15.04	18.04	1.66	12.25	26.44
	Money stock			*Exchange rate*			*Interest rate*			*Public Deficit*		
	BVAR	*BAR*	*UVAR*	*BVAR*	*BAR*	*UVAR*	*BVAR*	*BAR*	*UVAR*	*BVAR*	*BAR*	*UVAR*
1 quarter	0.55	0.87	0.96	1.81	2.18	2.82	0.81	0.81	3.20	0.54	0.56	0.72
1 year	1.59	2.65	3.09	5.26	6.63	6.67	2.28	2.28	4.41	1.07	1.12	1.39
2 years	4.13	4.74	8.16	9.60	11.67	16.89	2.79	2.79	11.51	2.15	1.95	4.20
3 years	7.41	7.29	14.61	12.93	15.26	43.00	3.75	3.75	32.97	3.52	2.71	7.22

Notes:
1. Values in per cent of series level.
2. The shaded boxes correspond to the model with least absolute error.

Source: Authors' calculations

forecasts running as high as 12 percent. This instability is caused by the fact that the model overfits and, therefore, extrapolates as a signal non-systematic relationships among variables. In contrast, the BVAR model is distinguished both by the stability of predictions as new information is included and by the closeness of its forecasts to actual values, including those for extended forecasting horizons. The comparison of the BVAR and BAR models (see Figure 11.3) also puts the latter in a negative light. Despite its lack of stability problems, the BAR model predicts inflation rates very different from the actual rates, while at the same time appearing to be overly optimistic.[24]

In conclusion, the results obtained provide answers to the above questions:

1 The forecasting superiority of the BVAR model is not limited to 4 quarters, but encompasses shorter as well as longer horizons, both jointly (see Table 11.3) and for individual variables (see Table 11.4)
2 It is in forecasting the price variable that the superiority of the BVAR model over the other models becomes clear, and the differences are quite important (see Table 11.3 and Figures 11.2 and 11.3).

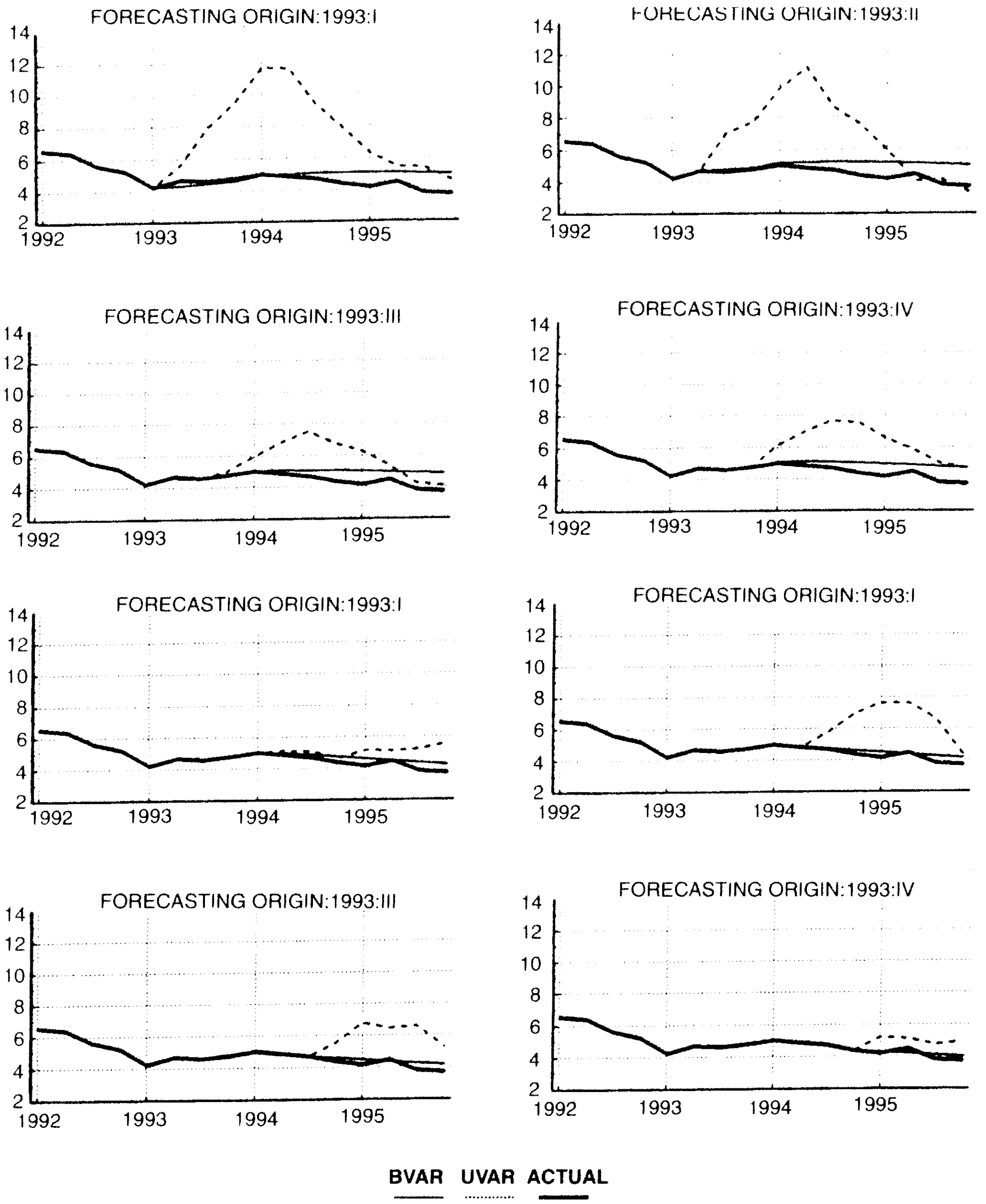

Figure 11.2 Comparison of BVAR and UVAR model forecasts, 1992–5, year-on-year inflation rate[1]

Note: 1 The inflation data for 1995 are adjusted for the effect of changes in indirect taxation.
Sources: Authors' calculations and INE.

3 Although the estimated hyperparameters and the resulting scant interrelationship among variables might suggest that the BVAR model does not differ significantly from a model consisting of a set of nine univariate models, comparing the price forecasting performances of the BVAR and BAR models (see Figure 11.3) clearly shows that the differences between them are important and that the influence of the model's other variables is considerable when the BVAR model is used to forecast inflation.

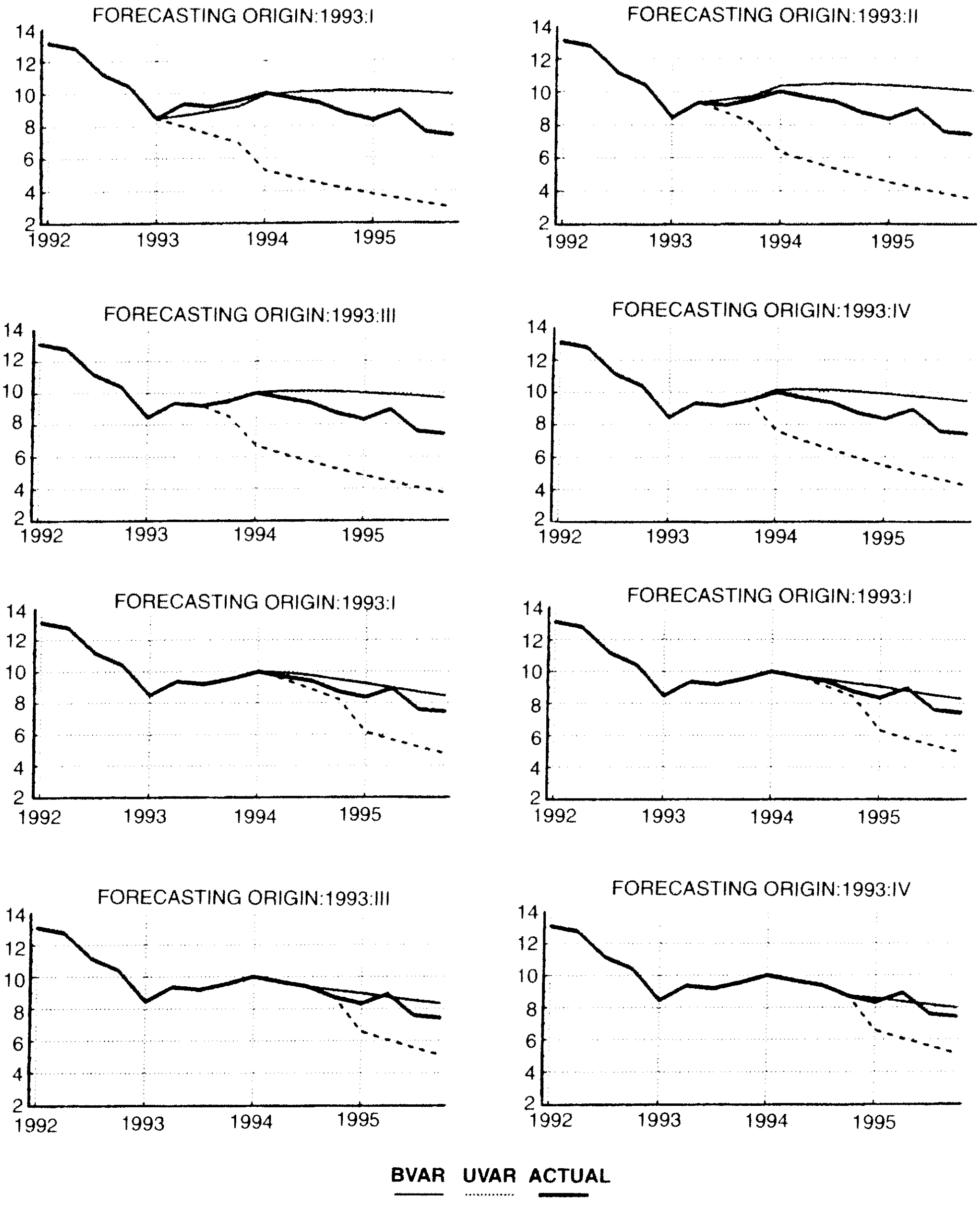

Figure 11.3 Comparison of BVAR and BAR model forecasts, 1992–5, year-on-year inflation rate[1]

Note: 1 The inflation data for 1995 are adjusted for the effect of changes in indirect taxation.
Sources: Authors' calculations and INE.

Forecasting and Uncertainty

Thus far, all references to forecasts, predictive qualities, and forecasting performance have been based on *point* estimates of the future values of the variables of the model. However this should not obscure the fact that when forecasts are based on econometric models, there is considerable interest in obtaining measurements of the uncertainty associated with these forecasts.

Knowledge of the uncertainty associated with forecasts is highly informative, as it allows not only for assessing with what accuracy the prediction was made (the greater the uncertainty, the less relevant the point forecast), but also how different forecasts are from actual values. In short, when attention is focused solely on point predictions, very important information is disregarded that could help the user of these forecasts assess their accuracy and arrive at an informed opinion.

Despite these considerations, economic authorities, international organizations, and private institutions rarely present forecasts accompanied by uncertainty measures, which may be due in part to a theoretical void. In fact, while numerous results are available for establishing confidence intervals in terms of forecasting the level of a series, this is not the case when interest is focused on its growth rate, which is what usually happens in macroeconomic forecasting, where, for example, GDP and CPI data are not usually expressed in terms of level values but in terms of growth rates. In this connection, and to ensure that the information extracted with the BVAR model described in this chapter is as complete as possible, Álvarez, Ballabriga and Jareño (1996b) analytically derive the probability distribution of the aforesaid growth rates when a VAR model has been used.

By way of example, Figure 11.4 illustrates uncertainty bands for inflation.[25] Specifically, the chart defines the values between which – according to the model – the projected inflation rate for 1994 and 1995 should be with a probability of 25 per cent (dark area), 50 per cent (including the medium and dark areas), and 75 per cent (including all 3 areas of the figure). As can be seen, although the point forecast (thick line) showed a gradual decline in inflation from 5 per cent to approximately 4 per cent, the model projected a probable band wider than one percentage point during most of the forecasting horizon.

The usefulness of this tool is not limited to gauging the reliability of forecasts; it can also be used for other purposes such as assessing the probability that a certain variable will be located below a given value, which can be relevant in the present situation.

One of the basic concerns in the current monetary policy strategy of the Banco de España, which is based on the establishment of direct inflation objectives, is assessing the probability that such objectives will be attained.[26] Once the probability density function of the projected inflation rate is known, the problem is estimating the cumulative probability within the target range. Figure 11.5 illustrates the nature of the problem. If an inflation rate below a given value is defined as a monetary policy objective (represented in the figure as 'objective'), the probability that this objective is attained is expressed quantitatively by the value of the area below the probability density function for values less than the target value.

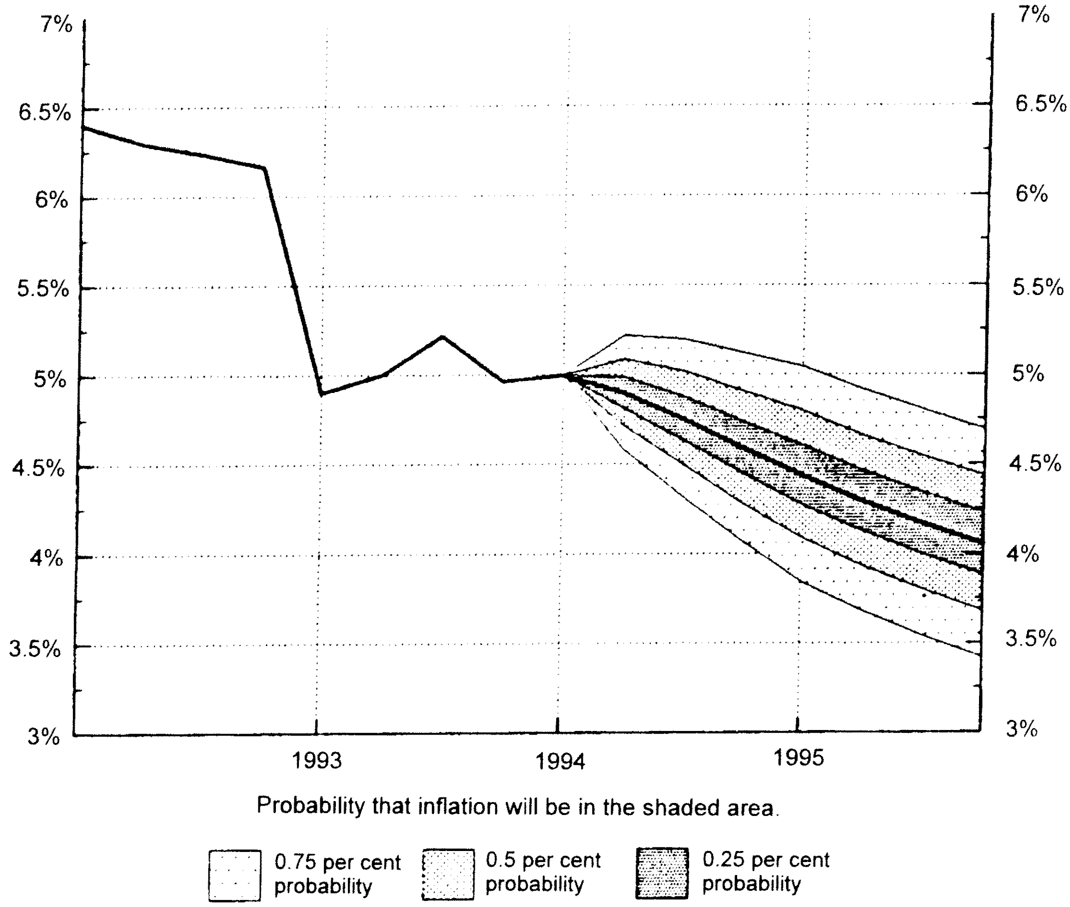

Figure 11.4 Uncertainty of forecast, 1992–5, year-on-year inflation rate

Notes: 1 Projections based on information up to 1994: 1.
2 The inflation data for 1995 are adjusted for the effect of changes in indirect taxation.
3 The shaded areasdelineate the region of uncertainty for the forecast associated with their corresponding probability level.
Sources: Authors' calculations and INE.

Figure 11.6 shows the variation in 1995 of the probability of attaining the intermediate inflation objective defined by the Banco de España[27] for the first few months of 1996. As shown in the figure, with information from the first quarter of the year, the probability was about 45 per cent. With information from the second quarter, probability decreased slightly to 40 per cent, at which point the outlook began to improve, with the result that probability climbed to 65 per cent with third quarter information and to 95 per cent with year-end information.

CONCLUDING REMARKS

This chapter has described a multivariate macroeconometric forecasting model that has recently been prepared for the Spanish economy. The model,

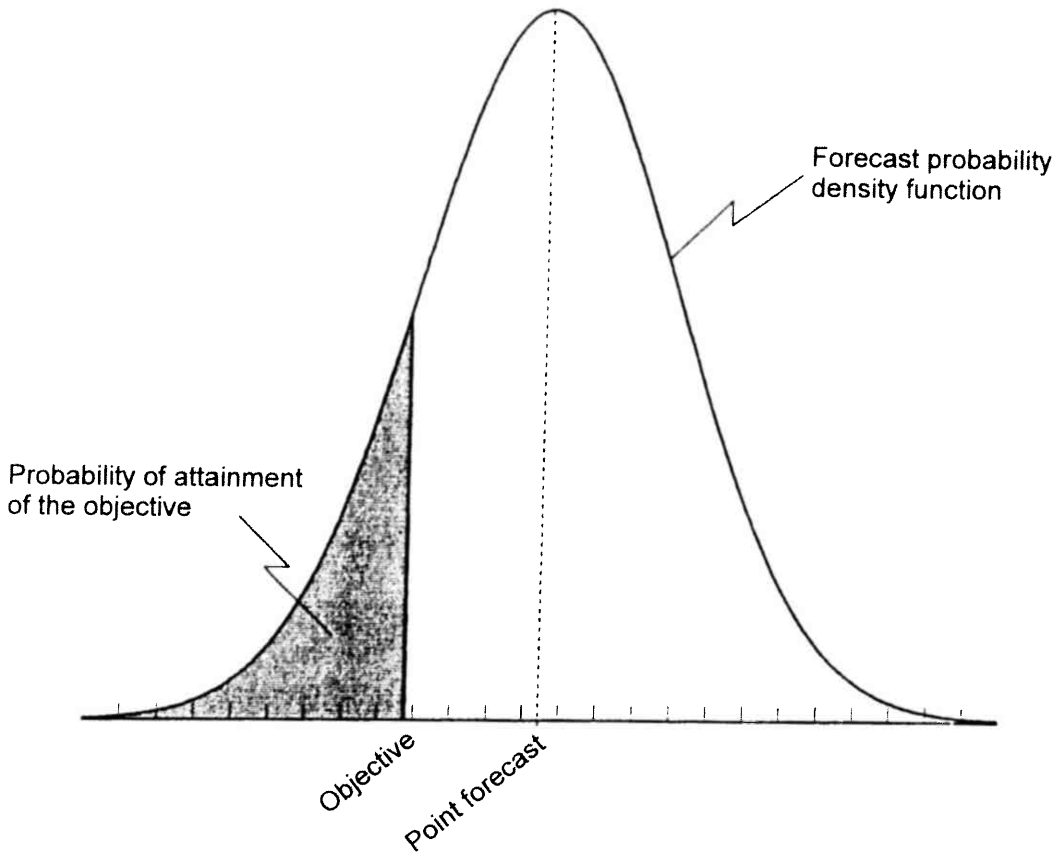

Figure 11.5 Probability distribution and attainment of objectives
Sources: Authors' calculations.

which is quarterly and includes a small number of variables, was built to advance the empirical characterization of the Spanish macroeconomy using Bayesian techniques and elements typical of time series analysis.

While any advance in the empirical characterization of the Spanish economy is important in and of itself, the framework established by the recent Law on the Autonomy of the Banco de España sparked interest in the use of instruments that can aid in monetary policy-making. Specifically, the monetary policy strategy based on inflation objectives clearly highlights the importance of progressing in the identification of the determinants of inflation in Spain, as well as projecting its future trend.

As explained in the chapter, forecasting is a risky business. Therefore, measures of the uncertainty associated with projections become essential, as they make possible a complete description of the model's predictive implications and provide a more comprehensive means of responding to questions of interest to economic policy-makers.

The exercises presented concerning the model suggest that the interaction among different variables aids in forecasting the future behavior of inflation with greater accuracy than if the past of prices alone were consid-

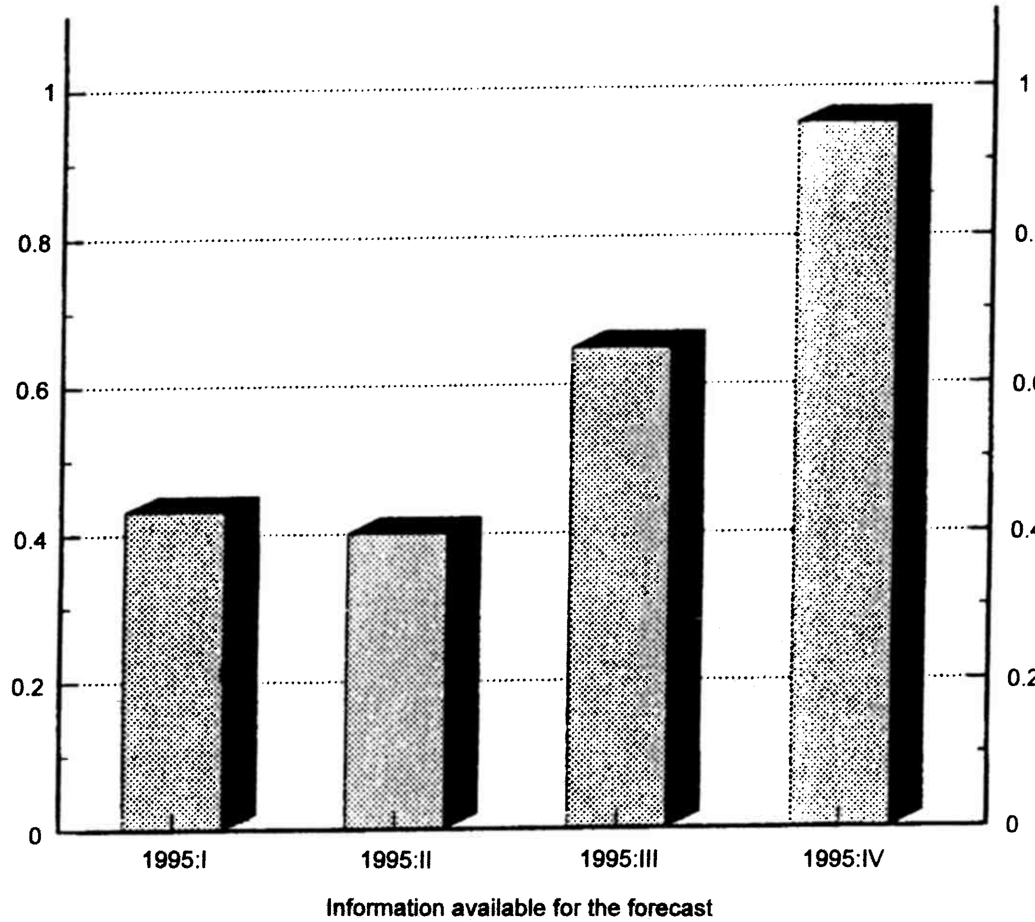

Figure 11.6 Probability of attainment of the intermediate inflation objective[1]
Note: 1 Objective defined as inflation below 4 per cent in 1994:1.

ered. Also of note is the stability of forecasts when new information is received, especially when these projections are compared with others obtained using methods that impose no restrictions on the data. These results confirm that the BVAR model presented in this chapter, in addition to being able to provide a general characterization of Spain's present and future economic situation, can serve as a useful supplementary tool for analyzing and forecasting inflation in Spain.

Appendix: The Prior Distribution Used in the BVAR Model

The purpose of this Appendix is to present the functional forms used in the BVAR model to relate the prior distribution of the model's coefficients to the set of hyperparameters.

It is assumed that the model's coefficients follow a Gaussian multivariate prior distribution. Defining the column vector that captures all of the model's coefficients as β yields:

$$\beta \sim N_{nm+d}(\mu, \Sigma) \tag{11A.1}$$

where n is the number of variables in the system, m is the number of lags in the VAR, and d the number of deterministic variables.

Thus, to characterize this distribution completely, it is necessary to specify the vector of means (μ) and the matrix of variances and covariances (Σ). Now, as it is assumed that the matrix of variances and covariances is diagonal, the coefficients of the model are independent. In other words, the following is obtained for each coefficient:

$$\beta_{ij}(s) \sim N(\mu_{ij}(s), \sigma_{ij}^2(s)) \quad \begin{array}{l} i = 1, \ldots, n \\ j = 1, \ldots, n, \ldots, n+d \\ s = 1, \ldots, m \end{array} \tag{11A.2}$$

where i is the number of the equation, j is the number of the explanatory variable (both for the stochastic variables n of the system and for the deterministic variables d) and s is the lag number. Therefore, to characterize the distribution of each coefficient completely, it is only necessary to specify its prior mean and variance.

PRIOR MEAN OF THE STOCHASTIC VARIABLES[28]

$$\mu_{ij}(s) = \begin{cases} \tau_0 & i = j, i \in C_1 \\ & s = 1 \\ 0 & \text{otherwise} \end{cases} \tag{11A.3}$$

where C_1 refers to the set of world activity, money stock, compensation per wage earner, price, output, and employment variables. C_2 refers to the set of exchange rate, interest rate, and public deficit variables.

$$\mu_{ij}(s) = \begin{cases} \tau_1 & i = j, i \in C_2 \\ & s = 1 \\ 0 & \text{otherwise;} \end{cases} \tag{11A.4}$$

PRIOR MEAN OF THE DETERMINISTIC VARIABLES

$$\mu_{ij}(s) = 0 \quad \begin{array}{l} i = 1, \ldots, n \\ j = n+1, \ldots, n+d \\ s = 0 \end{array} \tag{11A.5}$$

$s = 0$, as it is assumed that the deterministic variables only have a contemporaneous effect.

PRIOR VARIANCE OF OWN LAGS[29]

$$\sigma_{ij}^2(s) = \frac{\tau_2}{s^{\tau_4}} \sigma_i^2 \quad i = j \quad \begin{array}{l} i = 1, \ldots, n \\ s = 1, \ldots, m \end{array} \tag{11A.6}$$

PRIOR VARIANCE OF THE LAGS OF THE OTHER VARIABLES

$$\sigma_{ij}^2(s) = \frac{\tau_2 \tau_3}{s^{\tau_4}} \frac{\sigma_i^2}{\sigma_j^2} \quad i \neq j \quad \begin{array}{l} i = 1, \ldots, n \\ j = 1, \ldots, n \\ s = 1, \ldots, m \end{array} \tag{11A.7}$$

PRIOR VARIANCE OF THE CONSTANT TERM

$$\sigma_{ij}^2(s) = \tau_2 \tau_5 \sigma_i^2 \quad \begin{array}{l} i = 1, \ldots, n \\ j = n+1 \\ s = 0 \end{array} \tag{11A.8}$$

PRIOR VARIANCE OF THE BROKEN TREND

$$\sigma_{ij}^2(s) = \tau_2\tau_5\sigma_i^2 \quad \begin{array}{l} i = 8, 9 \\ j = n+2 \\ s = 0 \end{array} \tag{11A.9}$$

where the eighth equation represents GDP and the ninth employment.

PRIOR VARIANCE OF THE SEASONAL DUMMIES

$$\sigma_{ij}(s)^2 = \tau_2\tau_6\sigma_i^2 . I_i \quad \begin{array}{l} i = 1, \ldots, n \\ j = n+3, n+4, n+5 \\ s = 0 \end{array} \tag{11A.10}$$

where I_i is 1 when the i variable is seasonal (as is true of the money stock, price, and employment variables) and 0 otherwise.

PRIOR VARIANCE OF THE LAGS OF THE REST OF THE SYSTEM IN THE WORLD ACTIVITY EQUATION

$$\sigma_{ij}^2(s) = \frac{\tau_2\tau_3\tau_8}{s^{\tau_4}} \frac{\sigma_i^2}{\sigma_j^2} \quad \begin{array}{l} i = 1 \\ j = 2, \ldots, n \\ s = 1, \ldots, m \end{array} \tag{11A.11}$$

PRIOR VARIANCE OF WORLD ACTIVITY IN THE REST OF THE SYSTEM

$$\sigma_{ij}^2(s) = \frac{\tau_2\tau_3\tau_9}{s^{\tau_4}} \frac{\sigma_i^2}{\sigma_j^2} \quad \begin{array}{l} i = 2, \ldots, n \\ j = 1 \\ s = 1, \ldots, m \end{array} \tag{11A.12}$$

where the world activity equation is the first in the system.

PRIOR VARIANCE OF THE LAGS OF THE REST OF THE SYSTEM IN THE INTEREST RATE EQUATION

$$\sigma_{ij}^2(s) = \begin{cases} \tau_2 \sigma_i^2 I & i = j = 4 \\ & s = 1 \\ & 0 \end{cases} \qquad (11A.13)$$

where the interest rate equation is the fourth in the system.

Notes

1 There are quarterly, single equation models for some variables, however.
2 See Banco de España (1995).
3 The very nature of this section requires a technical discussion. Readers uninterested in these technical details can skip this section without jeopardizing their understanding of the rest of the chapter.
4 Bernanke (1986), Blanchard and Watson (1986), Sims (1986b), and Blanchard and Quah (1989) are seminal references in the literature on identification in the VAR analytical framework. Several applications to the Spanish economy can be found in Álvarez, Jareño and Sebastián (1993), Ballabriga and Sebastián (1993), and Álvarez and Sebastián (1995).
5 Notable references are Litterman (1986), McNees (1986), Runkle (1987), and Artis and Zhang (1990). Canova (1995) provides a fairly exhaustive review of the literature on the predictive capacity of the VAR methods.
6 For example, the fact that a surplus attributable to the tax schedule is generated in one quarter does not mean that economic agents perceive it as an improvement in the government's accounts.
7 Readers not interested in the technical aspects can skip pp. 380–3 without risking not understanding the rest of the chapter.
8 Note that the specification used is broader than the one used in Álvarez, Ballabriga and Jareño (1995). The updated specification can be found in Álvarez, Ballabriga and Jareño (1996a).
9 The functional relationship between the prior means and variances and the set of hyperparameters used is discussed in the Appendix.
10 The reason for this modeling is purely statistical, as it allows for improving both fit and predictive capacity. Taking this approach, tests performed with the exchange rate variable and the fiscal variable yielded no improvements, so that they were not finally modeled as AR(1) processes.
11 See Sims, Stock and Watson (1990) and Park and Phillips (1989).
12 See Sims (1991) and Álvarez and Ballabriga (1994).
13 Unrestricted models with five lags revealed a marked predictive decline.
14 See, for example, Sims (1989).
15 In this case, the ratio in terms of computing time for single equation versus multi equation estimation is 1:14,000.
16 Ballabriga (1991) describes the details of the estimation process.
17 For maximization purposes, once the objective function has been established, the Kalman filter and the nonstandard maximization routine described in Sims (1986a) are used.

18 The model is re-estimated with information up to t and is used to predict $t+s, s=1,\ldots,k$. The range of t is the available sample.

19 The statistic averages the mean square errors of the different variables for the various predictive horizons. To prevent the criterion from excessively penalizing equations with high variability, the mean square error of each equation is divided by the residual variance of the *AR(m)* model.

20 The likelihood of the system as an estimation criterion was also used. However, the results in terms of forecasting are somewhat inferior to those presented here.

21 The focus of this section is the model's capacity to forecast inflation, given the considerable relevance of this variable, as noted throughout this chapter. Consequently, other possible uses of the model, such as analysis of the overall consistency of its projections or the performance of simulation exercises, are not addressed.

22 Four lags are considered in both models.

23 The model was re-estimated with each new observation. However, the prior information did not vary.

24 The purpose of this exercise is obviously not to compare the BVAR model with a set of individual univariate specifications. Specifically, its interest lies in assessing the contribution to forecasting of the relationships between the model's several variables.

25 These forecasts are the result of a retrospective exercise taking into account information available up to 1994:I.

26 Another no less important concern would be the establishment of a reference path for inflation that leads to attainment of the stated objective. An analytical method based on the forecasts of ARIMA models, which can be used to estimate these paths, is found in Álvarez, Delrieu and Jareño (1997).

27 Although this intermediate objective is defined in terms of keeping the inflation rate, based on monthly data, between 3.5 per cent and 4 per cent, the definition used for this exercise considers the objective attained when the inflation rate is below 4 per cent, based on quarterly data.

28 It must be remembered that both prior means and prior variances are defined for the coefficients associated with the different variables of the model, and not for the variables themselves.

29 The σ_i^2 and σ_j^2 parameters measure the variability of the i and j variables, computed on the basis of the residual variance of *AR(m)* univariate models, where m is the number of lags in the VAR.

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