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Departamento de Estadística
Universidad Carlos III de Madrid
Calle Madrid, 126
28903 Getafe (Spain)
Fax (34) 91 624-98-49

CONSIDERATIONS ON ECONOMIC FORECASTING: METHOD DEVELOPED IN THE BULLETIN OF EU and US INFLATION AND MACROECONOMIC ANALYSIS

Antoni Espasa and Rebeca Albacete*

Abstract

This article presents economic forecasting as an activity acquiring full significance when it is involved in a decision-making process. The activity requires a sequence of functions consisting of gathering and organising data, the construction of econometric models and ongoing forecast evaluations to maintain a continuous process involving correction, perfecting and enlarging the data set and the econometric models used, systematically improving forecasting accuracy. With this approach, economic forecasting is an activity based on econometric models and statistical methods, applied economic research with all its general problems. One of these is related to economic data. The widespread belief that if economic information is published, it is valid for

Keywords: time disaggregation, functional disaggregation, geographic disaggregation, leading indicators, congruent econometric models, VEqCM, ARIMA, combined forecasts, cointegration.

*Espasa, Departamento de Estadística, Universidad Carlos III de Madrid, C/ Madrid 126, 28903 Getafe (Madrid), e-mail: espasa@est-econ.uc3m.es; Albacete, Departamento de Estadística, Universidad Carlos III de Madrid, e-mail:albacete@est-econ.uc3m.es. This work is based on the macroeconomic forecasting experience of the team led by Professor Espasa, obtained over the ten years that the Instituto Flores de Lemus, of the Universidad Carlos III in Madrid has been publishing the monthly Bulletin of EU and US Inflation and Macroeconomic Analysis. During this period, a large number of people have generously and innovatively been involved in the Bulletin. Some of them have directly contributed to the methods currently employed. They are: Rebeca Albacete, Nicolás Carrasco, César Castro, José Ramón Cancelo, Antonio Garre, Arsinoe Lamadriz, Fernando Lorenzo, José Manuel Martínez, Iván Mayo, Román Minguez, Israel Muñoz, Lorena Saiz, Ángel Sánchez, Eva Senra and Juan de Dios Tena. The director is deeply grateful to them all. The work done in the period was possible thanks to the Forecasting and Macroeconomic Analysis Chair financed by the Universidad Carlos III Foundation, currently held by the leading author. This article is part of project BEC2002-03720 financed by the Ministry of Science and Technology's Directorate General for Research.

any analysis is leading to too much value being given to macroeconomic information based on qualitative indicators built from very simple surveys, which can be obtained rapidly and at a low cost, and too little being given to the need to obtain reliable quantitative data on the variables of interest for economic theory, in order to perform an econometric analysis. The old debate on measuring without theory could become important again today.

For the results of economic forecasting to be used in a decision-making process, they have to fit the actual figures finally observed and provide information on the factors used to estimate them. Since final economic variables are uncertain, users do not require occasional forecasts which may be deceiving, but forecasts providing the probability that future data will be within certain value ranges. The fan chart made popular by the Bank of England in its inflation forecasts is a good way of presenting the forecasts that decision-makers need.

Forecasting accuracy depends on the nature of the economic phenomenon concerned – and this does not depend on the analyst -, the data set employed and the quantitative model used. The basic data set is the past and present of the phenomenon of interest and it is called univariate. It can be used to build models such as ARIMA, for instance, which not only generate forecasts but also formalise the trend, seasonal and cyclic characteristics of the phenomenon under study.

The data set can be enlarged in different, non-exclusive directions. They can be classified as follows: (a) frequency enlargement, using more frequent data; (b) enlargement by functional and geographic disaggregation of an aggregate variable; (c) enlargement with other series with which an empirical dependency ratio is detected; and (d) enlargement with other time series with which a theoretical relationship is postulated. The first is of special interest in short and medium-term forecasting. The second is of general interest if, as occurs in most cases, economic theory guides how it is implemented and also if, largely due to this theoretical basis, the resulting components have different trends, but with restrictions among them (cointegration relations). The third is an enlargement which often consists of adding leading indicators as exogenous variables. The combination of these three enlargements results in data sets with the largest possible observational frequency, based on disaggregation which significantly increases the trend and seasonal and cyclic information on the phenomenon in question. With this data set, it is possible to construct vector models with equilibrium correction mechanisms with a diagonal block structure and with exogenous variables, which are very useful for forecasting macroeconomic variables such as gross domestic product, inflation, industrial production, etc. The Bulletin of Inflation and Macroeconomic Analysis published by the Instituto Flores de Lemus of the Universidad

Carlos III, Madrid has developed a forecasting method based on this type of models, which is summarised in section 6.

Finally, enlargement of the data set allows us to include variables with a causal relationship, according to economic theory, with the phenomenon of interest. It can be used to construct congruent models, which means that they include all the relevant information available, they are specified in terms of parameters of interest according to economic theory and they are formulated in terms of parameters or meta-parameters which remain constant over time. Unlike previous alternatives, there models also provide an explanation of the factors on which the forecasts are based. Congruent models cannot frequently be constructed on the highest frequency level, which is usually a month, but on more aggregated levels, such as quarters. However, disaggregated vector models with leading indicators can normally be constructed on a monthly basis. Consequently, these monthly models generally result in more accurate forecasts that quarterly congruent models, but they do not provide an explanation of the forecast. To achieve both goals, accuracy and explanation, we discuss a procedure based on the aforementioned Bulletin in which we relate the two forecasts, transferring the causal explanation from the congruent model to the monthly disaggregated model. This is in line with the thick modelling approach proposed by Granger and Jeon (2004).

1.- ECONOMIC FORECASTING AS APPLIED RESEARCH: characteristics, social impact and problems.

Forecasting in decision-making processes.

Economic forecasting is not an end in itself, but it is of special interest and significance when involved in the decision-making processes of individual economic agents, businesses of public bodies. Delrieu (2003) provides an excellent description of the issue on a business level. This author emphasises that planning and especially budgeting -which is where a macroeconomic scenario for the integration of sales, price and production factor cost forecasts providing a credible and consistent cash flow estimation is generated- provides the link where forecasting and management functions are integrated. This article is largely focused on macroeconomic forecasting which, being an important part of forecasting within a company, is also decisive input for monetary, budgetary and economic policy-making in general.

The quantitative process required to generate reliable forecasts.

Economic forecasting is a costly process, since it involves: (1) collecting a relevant set of data on which to base the forecast, (2) organising said information in consistent conceptual context, (3) constructing econometric models, (4) generating forecasts and (5) monitoring the results to maintain a process in which the data set and the econometric models employed are continuously corrected, improved and enlarged. These five functions reveal that the design, construction and implantation of an economic forecasting scheme, based on econometric models and with appropriate statistical tests to detect future imperfections, is a function of applied research. Only with this concept is it possible to establish a sequence in which it is possible to forecast increasing numbers of economic variables, with more accuracy, referring to all the necessary horizons and with the desired level of disaggregation.

The negative social impact arising when economic forecasts are not based on applied research.

If the above functions are not performed when forecasting, reliability will be limited. Consequently, if economic forecasting in a society or country is not based on the above, its results will be far from satisfactory and not appreciated by economic agents. However, the latter may go unnoticed for a long time on a social level. The question is that economic forecasting is necessary because the vast majority of the decisions made in the economic field are based on forecasts even when they are subjective, merely well meant guesses or conjecture. This is often the type of forecasting performed in business, and it may be difficult to eradicate if it means executives losing their power.

On a macroeconomic level, the need for forecasting had led many institutions, many of them private, to publish forecasts on leading economic variables and they, or part of them, are used to edit consensus forecasts based on the mean or the median. These consensus forecasts are usually given considerable coverage in the media and the decision-makers in firms and institutions prefer to depend on consensus and not on specific forecasts, either their own or published by others, even though they are more reliable, because if a consensus forecast is wrong they will not be made responsible for what is in fact a widespread error.

Risks associated to consensus forecasts. Steps to be taken.

The problem lies in the fact that the quality of many of the forecasts included in a consensus forecast, particularly on a national scale, is poor, and in most cases not based on econometric models. Indeed, the different participants often change their forecasts depending on how they differed from the last published consensus value. Considering the social impact of consensus forecasts, it would appear to be necessary to introduce some type of standard concerning how a consensus forecast should be generated and the requirements for the specific forecasts included. As when survey results are published, it is mandatory to publish a data sheet with its principal characteristics, for a macroeconomic forecast to be published it should be mandatory to include a data sheet describing the data on which the forecast is based, whether econometric models have been used or not and, if they have, the type of model employed, a log of past errors, etc.

Implications of the fact that economic data is not generated by the investigator himself.

We herein describe economic forecasting as applied research and, in this respect, it faces the same problems as all research of this type. One of them lies in the fact that, in general, economic investigators do not generate their own data, but obtain them from external sources, so in-depth knowledge of the data is not normally required or particularly valued in academic literature. However, good applied research requires the investigator to be familiar with the data concerned, how it has been generated, its basic properties, the possible errors or sources of error involved, etc. In general, reaching this level requires a great deal of time when compared with the time required for the research. The situation is even worse when the data contains errors, the samples are not homogeneous or the characteristics of the data lead to changes in the approach to the research. This means that successful applied research requires much more time than theoretical research in aspects which are not the investigator's leading motivation. Moreover, applied research on individual national economies, with the exception of just a few countries, is often difficult to publish in international journals. The limited importance given socially to economic forecasting, then, is combined with a lack of incentives, preventing sufficient investigators from working in the field.

In a context of problems with data, an investigator may choose to study them in depth and suggest what has to be done to solve them before undertaking applied research. Since it is often believed that any published data is valid for analysis and the solutions to data problems are usually expensive, they are not implanted and the application which the investigator refused to perform is carried out with the data available by profit-making service companies which are not in a position say no to a client's commission.

Speed and quality when editing economic statistics. Implications for applied research.

There is currently a social trend which values national statistics offices more for the promptness with which data is published than for their quality. With a view to rapid publication, qualitative statistics are increasingly predominant over quantitative statistics, and they are also much cheaper to produce, although they are much less informative and more volatile. Indeed, compared with the complexity of building econometric models with a nation's quarterly accounting data, which is published about two months after the month of reference, there are increasing numbers of analyses of several hundred different partial variables (indicators) aimed at estimating the current status of economic growth and forecasting said status for the future. In economics, quantitative analysis does not provide the quantity of high-quality results required to fully comprehend the economic situation and we can therefore not afford to disregard a certain quantitative approach. In this respect, the immense econometric analysis being generated on economic indicators is more than welcome. However, it may be dangerous if we start to undervalue the need to obtain reliable quantitative data on the variables of interest according to economic theory, in order to perform an econometric analysis in a theoretical context allowing the results to be interpreted and used for economic policy purposes. The old measuring without theory debate may return today.

We can conclude that good applied research in general, and economic forecasting in particular, requires, among other things, more sensitivity to the data, both on a social and institutional scale and by investigators themselves. The latter are also associated to the problem of how to generate sufficient incentives for investigators to spend a great deal of time truly understanding the data construction process, and the implications they introduce to the properties of such data.

2.- FORECASTING AND ECONOMETRIC MODELS.

The stochastic nature of economic data determines that forecasting should be based on econometric models.

In the previous section, we have stated that economic forecasting is fully useful when involved in a decision-making process. In this case, forecasts should provide values which are later seen to be accurate and information on the factors on which such values are based. In other words, economic forecasts should be reliable and with sufficient explanatory structure.

Future economic variables are uncertain and should be considered stochastic. Consequently, point forecasts are of limited interest and may sometimes be a fraud. What is important for decision-makers is the probabilities of future values falling within certain ranges. Ideally, what a forecast user wants is, given a set of different value intervals, an estimate of the probabilities of future values falling within said intervals. In statistical terms, what is important is to determine the density function of each forecast. This type of forecasting has to be performed with quantitative models including tested statistical formulations; in other words, econometric models.

Indeed, within the framework of an econometric model and based on a given sample, it is possible to test relationships between data that are stable over time and then to use these relationships to forecast the future, assessing the likelihood of different value ranges occurring. Econometric forecasting thus has two important aspects. One of them consists of forecasts being based on firm and tested data regularity to provide the reliability and objectiveness which is not possible with subjective forecasting procedures involving incomplete, heterogeneous data sets with different frequencies, etc. These sets are usually too large to be analysed with econometric models at the current stage of development, but there is no guarantee that subjective processing of all that information will provide correct information on which to systematically base future forecasts. Also, since these systems are not objective, they cannot be passed on to others, and it is therefore difficult to establish a learning process based on forecasting errors aimed at improving the procedure. However, testing econometric forecasts against new observations helps to identify incorrect aspects of the model and suggest corrections or enlargements, all of which can be tested against future observations. Econometric forecasting, then, is subject to a continuous assessment and improvement process.

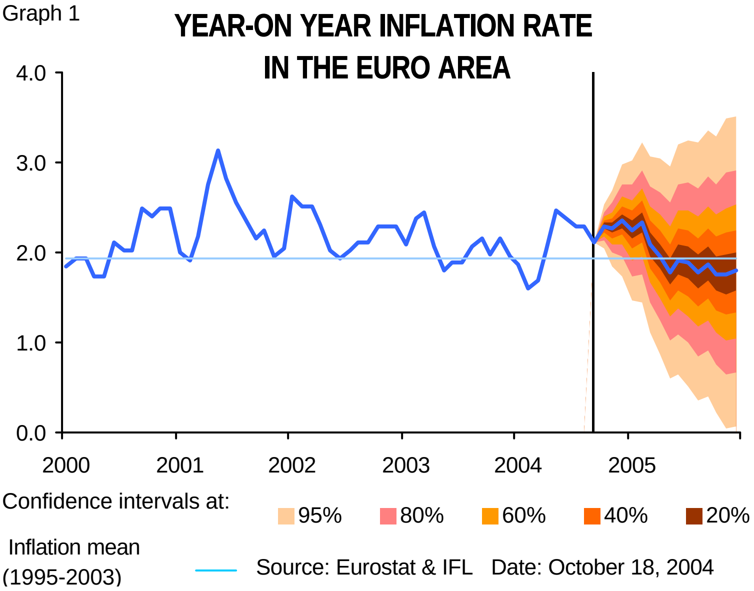
The other aspect of econometric forecasting is the fact that a forecast is not a value in time – which has practically zero probability of occurring- but a set of probabilities referring to a set of value ranges which specify the probability of the future observation falling within one of the defined ranges.

Measuring uncertainty in a forecast's range of values. The confusion arising from a single point forecast.

The importance of estimating probabilities for different value ranges was shown some years ago by the Bank of England in the context of the inflation forecasts that the Bank needed to determine its monetary policy. This led to the use of what is called a fan chart, which is now very popular. This graph provides forecast for a sequence of moments in time, the months remaining in the current year and all the following year, for instance. For each month, it provides a set of value ranges with the probabilities that inflation in the month in question will be within them. These probabilities are represented by different colours and, since the uncertainty of the forecast, and therefore the width of the ranges, increases with the distance between the forecast month and the last month with an observed value, the graph takes on the fan shape from which it has taken its name. Fan charts are constructed from a relatively long log of forecasting errors. On this type of chart and its practical use, see Wallis (2003) and references quoted therein.

The Bulletin of EU and US Inflation and Macroeconomic Analysis published by the Instituto Flores de Lemus, Universidad Carlos III, publishes these charts for different inflation variables. Graph 1, taken from the Bulletin, shows an estimate of the graph corresponding to inflation in the euro zone with information up to April, 2004. Among other things, the chart shows that the probability of deflation in the 2004-2005 period is practically null, but that the probability of inflation in 2004 exceeding the reference value of 2% is high. If we have a sufficient register of past forecasts, this type of graph is very useful for leading macroeconomic variables such as gross domestic product, industrial production, employment, unemployment, current account balance deficit, etc.

Graph 1



The way in which this type of chart opens to the future depends on the nature of the phenomenon concerned, even if the best possible forecasting model is available. In industrial production, the chart is more open than in inflation and less than in exports. This is why single-point forecasts can be very deceiving. Indeed, the user of a single-point forecast, albeit unconsciously, always subjectively assigns a relatively high probability of occurrence to a relatively narrow range of values around the single-point forecast value. If, after experiencing this use in said single-point forecast of a certain variable, he receives single-point forecasts on another variable, but with much more future uncertainty, but he is unaware of this, and he applies the same range with the same probabilities, he will obtain an incorrect idea of the future values of the new variable.

3.- DATA SETS AND ECONOMETRIC MODELS.

Forecasting accuracy depends on the economic phenomenon considered – about which the analyst can do nothing –, the data set employed and the quantitative model employed. It is easy to provide empirical evidence showing that forecasting accuracy often increases more with relevant information than with a sophisticated econometric model in which part of it is ignored.

Univariate data sets. ARIMA models. Innovations.

The minimal acceptable data set only includes the past and present value of the variable concerned; it is called a univariate set. With such information it is possible to construct univariate models in which the present value of the variable of interest is explained by how it is related to its past values. Economic variables show trends -such as systematic growth over large periods of time– and seasonal fluctuations –cyclical changes which tend to be repeated every year- , which persist over time, even when there are no new shocks or innovations affecting the system. And they have other properties, such as business cycle or short-term fluctuations which, in the absence of innovations, tend to disappear. The dependency of an economic phenomenon on its past values – dynamic relationship – is of a different kind when related to a persistent relationship, with trends and seasonality, than when related to cyclic and short-term fluctuations. The persistence relation is shown in a dynamic relationship which, because of its mathematical properties, is called a unit-root relationship. For example, the value of an economic variable at time t, X_t is given by

$$X_t = X_{t-1} + m + W_t, \qquad \textbf{(1)}$$

where ì is a constant representing the mean growth of the variable and W_t is the component of fluctuations of X_t around its persistency path, which in the example is X_{t-1}+ì. In this example, the economic phenomenon shows trend persistence due to the unit coefficient (root) with which X_{t-1} is included in the value of X_t. From (1) we can obtain data related to W_t, taking the first differences -(X_t-X_{t-1})- from the original data and eliminating the mean ì. As W_t is no longer persistent, it is said to have a stationary compartment. Component W_t depends on its past in a non-persistent manner, for example as

$$W_t = 0.6W_{t-1} + a_t,$$

where a_t is a random shock added at time t. Considering that

$$W_t = \left(X_t - X_{t-1}\right) - \mu, \qquad \textbf{(2)}$$

and replacing W_t in (1) with its value in (2), we obtain the following model for X_t:

$$X_t = \underbrace{X_{t-1} + \mu}_{a} + \underbrace{0.6\left[\left(X_{t-1} - X_{t-2}\right) - \mu\right]}_{b} + \underbrace{a_t}_{c}. \qquad \textbf{(3)}$$

In (3), component (a) includes the persistence path given on the level of X_t and (b) and (c) show the stationary deviations, W_t, on said path. These deviations have a known part at time (t-1), factor (b) in equation (3) and a random part, unknown at (t-1) and unpredictable, factor (c).

Models like (3) are known as ARIMA models, and they were proposed by Box and Jenkins (1970) for forecasting purposes. A more standard textbook way of presenting this model would be:

$$\left(X_t - X_{t-1}\right) = c + 0.6\left(X_{t-1} - X_{t-2}\right) + a_t, \qquad \textbf{(4)}$$

where c = μ - 0.6μ. Interpreting the properties of X_t from (4) can be difficult for non-experts. However, from (3) one can clearly see that X_t evolves to include its previous level, X_{t-1}, adding a fixed component μ (mean growth) and a temporary fluctuation, which is 60% of the discrepancy in growth at (t-1) – (X_{t-1}-X_{t-2}) – in relation to the mean (μ). Finally, X_t assimilates a random shock, a_t, which occurs at time t.

In the previous example, if we have observed the phenomenon up to time (t-1) and wish to forecast X_t, the forecast, $\hat{X}_t$, would be

$$\hat{X}_t = X_{t-1} + m + 0.6\left[\left(X_{t-1} - X_{t-2}\right) - m\right] \quad .$$

When X_t is observed, we can calculate the forecasting error,

$$X_t - \hat{X}_t = a_t ,$$

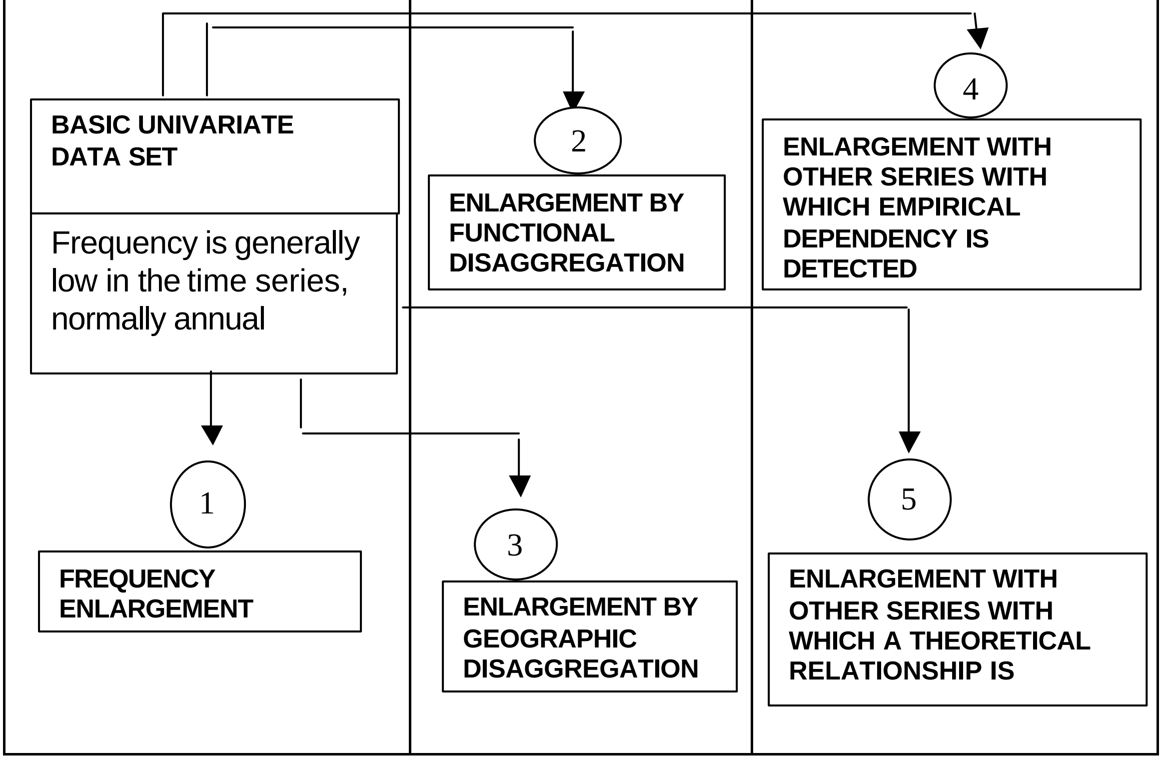
which is no other than the shock occurring at t.

This example also illustrates the double role to be played by forecasting in economic analysis. On the one hand, before t, the forecast estimated the future value of the phenomenon concerned at time t, which will be used for planning or investing purposes and so on. When X_t is observed, economic agents will not have to react – and indeed they do not do so – to its global value, but only to the normally small amount, a_t, in which the value has surprised them. Imagine that in (1) μ is zero and X_t is the unemployment rate. If the forecast was 10.4% and the observed value at t is $\hat{X}_t$ = 10%, the agents will react to a fall of 0.4%, so a high unemployment observation could push the financial markets up.

Table 1

DATA SETS

UNIVARIATE	MULTIVARIATE	
	INTERNAL	EXTERNAL
They only include the time series for the phenomenon of interest, X_t.	They include time series of n components in which X_t can be broken down.	They include the time series of interest, X_t, and another K series, Z_{1t}, ..., Z_{kt}, with which it is related.



Frequency disaggregation.

The basic univariate data set can be enlarged in different directions, as shown in table 1. One of them consists of increasing the frequency with which the phenomenon of interest is observed. In this case, we continue to observe a single phenomenon and the resulting data set is still univariate. In fact, what usually happens is that there is a certain habit of analysing information on monthly averages when there is basic data on a weekly or daily basis. Examples of this are the monetary aggregates published by a central bank or sales information in firms. Another example is the national accounts of a country in which, besides the annual figures which are usually calculated as accurately as possible, many statistical offices also publish quarterly data based on less information than the annual numbers.

In these cases, the frequency of the sample used by the analyst depends on the nature of the problem being approached. In short-term forecasting and when analysing the economic situation, quarterly national account data is to be preferred over annual information, because recent data and the short-term dynamic relationship between the present and the past are the most important factors when improving short-term forecasting.

Imagine, for example, that there is a monthly econometric model to forecast the monthly monetary mass in a central bank. However, weekly information is available on the components of the monetary mass. It is easy to discover that a simple weekly ARIMA model, including information on some of the weeks in the current month, provides forecasts which are closer to the monetary mass in the month in question than the monthly econometric model that ignores recent weekly information. This result, according to which in forecasts referring to a concrete unit of time, a month for instance, disaggregation of the information within the time unit of reference, into weeks for example, increases the accuracy of the forecast, is widespread for short-term forecasting covering the current and immediately following time unit. In broader horizons, for the potentially greater accuracy obtained from more disaggregated information is applicable to the actual application, the model with more time disaggregation must be well constructed. Since it is more difficult to construct an appropriate model on a weekly than on a monthly basis, as seen when forecasting a company's sales, or on a monthly than on a quarterly basis, as when forecasting foreign trade, in medium-term forecasting, the more disaggregated model may provide less accurate forecasts.

Medium and long-term forecasts.

However, if we are interested in long-term forecasting or testing economic theories on the determination of the phenomenon in question, it is important to have time series covering many years, and the homogeneous time series of national accounts normally cover no more than 20 or 25 years. But even if the number of years in a quarterly series is large enough for the long-term problem under study, their use is not necessarily advisable. Indeed, quarterly series contain marked cyclic and short-term fluctuations which, if they are not well explained, generate imperfections in the model which could alter the estimates of the factors on which theories are to be tested or the long-term forecast is to be based. Short and medium-term fluctuations are much less important in annual series, so if they are long enough, they can constitute a relevant data set for the study of long-term problems. This suggestion finds formal theoretical support in the work of Marcellino (1999), which shows that the aggregation of economic data in time does not distort its long-term properties such as trend, cointegration with other variables, and so on, although it does distort its seasonal, cyclic and short-term properties.

A good example of the convenience of series covering many years for long-term forecasting and testing economic theories can be found in Hendry (2001), who used a 125-year series on English inflation to show that no specific economic theory is capable of explaining inflation over such a long period and that the explanation is obtained with the eclectic attitude including all the theories put forwards on how to determine inflation. In other words, he shows that, to explain inflation, it is necessary to include the disequilibria of all the national, monetary, financial, goods and services, employment markets, etc., and indicators of the disequilibria on the international markets.

4.- FORECASTING AND DISAGGREGATION.

In forecasting, enlarging the data set is only of interest if the information included is relevant. The data set should therefore be constructed based on economic theory, as shown earlier with reference to inflation.

It is important to enlarge the data set with a view to relating the variable of interest with the variables on which it is based, since this allows us to construct econometric models capable of generating accurate forecasts and at the same time provide an explanation. We will be returning to this later, but this section will contemplate enlargement with reference to the variable of interest itself, whenever it is an aggregate variable.

In an aggregate variable, such as the total sales of different company products, industrial production, national exports, the level of employment, a consumer price index, etc., one way of increasing the information is to apply a certain functional disaggregation to construct an econometric model on the time series of the components. Functional disaggregation can be by groups of markets, production sectors, population sectors, types of demand, and so on. A consumer price index, for instance, can be disaggregated into sub-indices of prices corresponding to food, energy, other goods and services markets. Industrial production can be disaggregated into industrial sectors producing food, energy, other intermediate goods, other non-durable consumer goods, durable consumer goods and capital goods. Employment can be disaggregated by population groups according to age, sex and education. This type of disaggregation is relevant when the components show trends, seasonal or cyclic behaviour or different short-term fluctuations. In particular, disaggregation is important when the components show trends generated by more than one common factor.

On occasions, the same variable can be disaggregated in alternative ways based on different criteria. For example, gross domestic product can be divided in at least two alternative ways. One refers to the type of demand: private consumption, public consumption, gross fixed capital formation, variations in inventories, imports and exports. The other refers to the production sector: primary, industrial, construction, market services, non-market services and net production taxes. Since each alternative disaggregation may contain different and valuable information on different factors determining the trend of the gross domestic product, in order to forecast this value these disaggregations should not be taken as exclusive, in the sense that an econometric analysis is performed on one but not on the other, but complementary. In other words, the two analyses are performed and it is at a final stage when we assess whether a combination of the two GDP forecasts is better or not than the individual forecasts themselves. A debate has recently arisen in the econometric field on two approaches to the construction of models. One, narrow modelling – an outstanding representative of this approach is Prof. Hendry, see Hendry (1995)-, consisting of eliminating alternatives by statistical testing, and performing the structural analysis or forecast on the final mode. The other, thick modelling –recently defended by Granger, see Granger and Jeon (2004)-, consists of maintaining more than one alternative in the model construction process, since the tests used are only valid for long samples, which are unusual, and several statistic tests have often been designed for the same purpose. In these cases, the results are often different according to the statistic applied, or involve rejecting a hypothesis using a 10% significance level in the test, but on a 5% level. In these circumstances, it is advisable to construct econometric models for each of the hypotheses contemplated and decide in the final stage. The combination of forecasts derives from econometric models on alternative disaggregations of gross domestic product is consistent with the thick modelling approach. Minguez and Espasa (2004) show the advantages of using such a combination to forecast the gross domestic product of the euro area. This article shows that the combination of GDP forecasts from econometric models on disaggregations derived from demand and production, both in univariate models, single-equation models with leading indicators or vector models with an equilibrium correction mechanism, always improves the quality of the separate alternative forecasts.

Another possible disaggregation of an aggregate variable is by geographic areas: the regions in a country, or the states in a federal state or economic and monetary union.

Espasa et al. (2001), analysing inflation in the euro area, provides empirical evidence that the two disaggregations are important. Espasa and Albacete (2004) show that the combination of inflation forecasts in the euro area from functional and by-country disaggregations improves individual forecasts.

When we have a functional disaggregation criterion that can be applied in each geographic unit of a State or supra-State unit, it is worth analysing whether disaggregation combining the two criteria is feasible and, if so, whether it improves forecasting quality. Espasa and Albacete (2004) show that this is so when inflation in the euro area is analysed, although the resulting model is somewhat complex.

To implant a forecasting procedure based on functional or geographic or both criteria, either for a macroeconomic variable or for a variable in a large corporation, we must first estimate the benefits expected from said procedure. The starting point is as follows. Based on the hypothesis that:

(a) Disaggregation provides relevant information on the principal characteristics of the aggregate;

(b) It concludes with components for which time series of good quality data are available, and

(c) The analyst is capable of constructing an appropriate model with the different components,

forecasting based on a disaggregated model cannot be worse than that obtained with a model based on the aggregate.

Point (b) is not always the case, and this is the first thing to verify before analysing anything else. If the quality of the data is reasonable, the next step consists of studying whether the disaggregated series contain relevant information on the aggregate. To do this, we can analyse different aspects of the aggregate and its components, such as trend, seasonality, economic cycles, short-term fluctuations, etc. Of all these, trend is usually the most important characteristic. When a variable is disaggregated into n components, the idea is to see how many different unit root trends there are in the vector of the time series of the n components. If there is only one, in general, disaggregation would not be important from this perspective. This is not the result in most cases, and we usually observe that there are a number r, less than n, of different trend factors which are common to the n components. In this case, disaggregation can potentially generate better forecasts that an aggregate model. The final step consists of constructing an appropriate model for the vector of n components. One essential aspect of this modelling is discussed below.

If, in an aggregate with n components, r common trend factors have been estimated, this implies that their evolution includes (n-r) long-term or cointegration relationships. The econometric model has to include these long-term restrictions in the time series of the n components. This generally requires modelling the vector of n components. Since cointegration relations include the disequilibrium in each observation in relation to the long-term pattern, the resulting model is called a vector equilibrium correction model or VEqCM (see Clements and Henry, 1999).

If the number of components is high, more than 10 for instance, the VEqCM model may be difficult to formulate and its result not very reliable in view of the sample size of most macroeconomic time series. This problem normally arises when disaggregation combines functional and geographic criteria, in which case a simplification of the VEqCM is decisive. Espasa and Albacete (2004) introduce restrictions consisting of dividing the vector of n components into blocks, so that there can be long-term restrictions between the time series of each block, but not between different blocks. This article shows that restricted VEqCM models –called diagonal block VEqCM- produce better forecasts of inflation in the euro area than non-restricted VEqCM models.

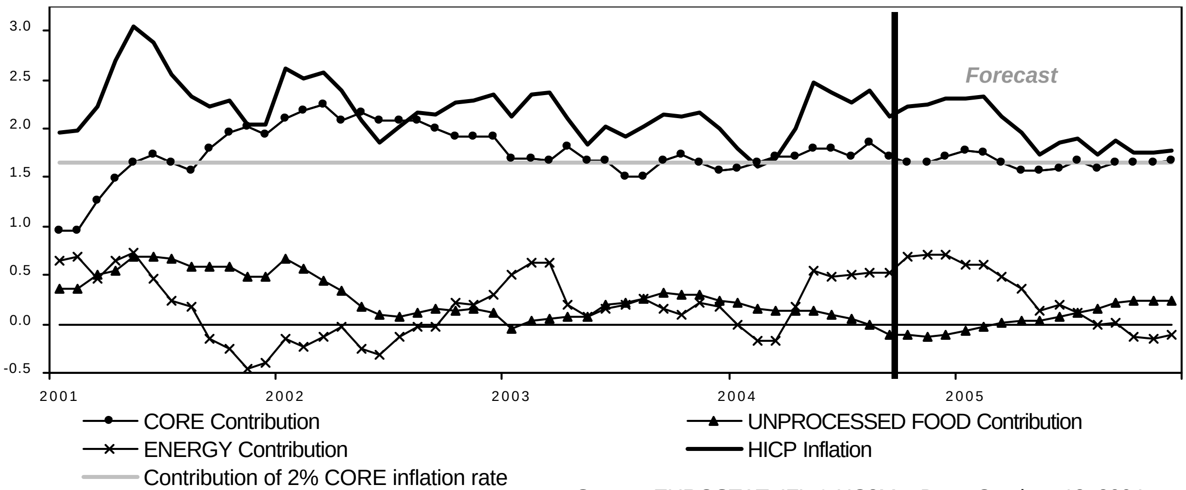
Functional and geographic disaggregation can give rise to more accurate forecasts than an aggregate model and this is shown in our previous references to GDP and inflation in the euro area.

The Bulletin of EU and US Inflation and Macroeconomic Analysis, which is published monthly and now in its tenth year, provides forecasts for macroeconomic variables in the euro zone and Spain and inflation in the United States, and shows that disaggregation improves forecasting considerably. Other authors find no advantages in disaggregated forecasting, but neither do they all contemplate the introduction of the cointegration relation of the components in the econometric model.

In disaggregated models, the hypothesis of the linear model may not be acceptable for some components. In this case, it is important to consider non-linear procedures, as do Minguez and Espasa (2004) when they study the European GDP or the Bulletin of EU and US Inflation and Macroeconomic Analysis when it forecasts domestic energy prices based on international prices.

Disaggregated models are based on a multivariate data set which is internal in the sense that it does not include information on other phenomena related to the phenomenon of interest, but is limited to information on its components from a functional and geographic perspective. Econometric models, therefore, cannot provide an explanation of the factors on which their forecasts are based. However, when the forecast of the aggregate is produced from forecasts of its components, it is easy to see which components are most influential and therefore obtain certain ideas of the principal factors behind the forecast. Therefore, disaggregated forecasting, regardless of its degree of accuracy, is or more interest for an analysis of the phenomenon in question than mere aggregate forecasting. Graph 2 shows how the forecasts of core inflation and inflation in non-processed food and energy prices influence the forecasts of total inflation in the euro area. The graph shows that the forecast of a reduction of inflation in 2005 compared with 2004 is not based on core inflation, but on the inflation of the other two components, primarily energy, which is partly determined by the heavy fluctuations in international crude oil prices.

Figure 2: **Year-on-Year rate of intlation in the euro-area and contribution of main components**



Source: EUROSTAT, IFL & UC3M Date: October 18, 2004

5.- FORECASTING WITH LEADING INDICATOR MODELS OR CONGRUENT ECONOMETRIC MODELS.

In many other cases, the enlargement of the data set involves including data on other external variables.

The relationship between the phenomenon of interest and the new variables may be merely empirical, like the relationship between the industrial production index and an industrial confidence indicator, the export level and a foreign order portfolio indicator, a consumer price index and a production price index, etc. These additional variables are usually called indicators, often leading indicators, of the phenomenon of interest. If they really are indicators, causality in Granger's sense will go from them to the phenomenon of interest, and not vice versa. In these cases, these indicators are usually considered to be exogenous variables and included as such in the aforementioned ARIMA or VEqCM models.

In other cases, new variables are added based on economic theory approached, with which, in Prof. Hendry's words, congruent models can be built. Briefly, a congruent econometric model can be defined as one which includes all the available information that is relevant for analysing the phenomenon in question, is specified in terms of the parameters of interest according to economic theory and therefore includes the causality relationships between variables according to such theory, and is formulated in terms of parameters which are constant over time. The principal property of these models is that they are causal models according to a certain economic theory. These models, when applicable, include the long-term restrictions – cointegration relations – between the phenomenon of interest and other economic variables.

One example of an external multivariate data set enlarged according to theory appears, for example, when forecasting inflation. To forecast quarterly inflation, we can consider including information on variables such as unitary labour costs, gross domestic product, potential gross domestic product, quantity of money, interest rate differentials, an import price index, international raw material price indicators, an effective exchange rate index, etc. In these cases, if:

(a) the quality of the additional information is good,
(b) the investigator is capable of constructing a congruent model, and
(c) the variables explaining inflation can be reliably forecast,

it is to be expected that, with no structural changes, the congruent econometric model will generate more accurate forecasts than a simple ARIMA model, the construction of which is based exclusively on past inflation values. Obviously, the construction of the econometric model is much more complex and costly than the ARIMA model.

Congruent econometric models can also be applied when the phenomenon of interest is studied through its components in a disaggregated model. The resulting model will be a VEqCM including n equations for the components of the aggregate plus m additional equations for the non-exogenous economic variables included. In general, the complexity of the resulting model will demand the use of diagonal block restrictions. This type of model could be an ideal structure for forecasting, because if it is well constructed it will provide accurate forecasts, and it also provides an explanation of the factors behind them.

As we mentioned earlier, economic agents demand reliable forecasts which also include an explanation of the factors on which they are based. The latter is important when the forecast is to be used in a decision-making context and can only be obtained with congruent econometric models. This is the reason for the interest of econometric models in forecasting.

When a congruent econometric model is constructed, the investigator often finds that the variable of interest is observed in a more frequent time unit than some of its explanatory variables. For example, in forecasts relating to the tourist sector, it is found that the number of foreign tourists, which may well be the variable of interest, is observed on a monthly basis, but that relevant explanatory variables such as the income of tourists is only available on a quarterly basis. Something similar occurs in businesses, with regards to sales for instance. In general, there is monthly information relating to variables like prices, foreign trade, industrial production, unemployment and monetary and financial variables but if explanatory variables are required, such as gross domestic product, productivity, unitary labour costs, etc., on both a national and international scale, the information available is usually published quarterly. In these cases, there are two basic alternatives: (a) the construction of monthly models, either aggregate or disaggregated and either including indicators or not, or (b) the construction of congruent quarterly econometric models including fundamental relations with economic variables.

As we mentioned earlier, in short-term forecasting the model with the highest level of frequency disaggregation for the variable of interest is advisable. For medium-term forecasting, the preferred option would be a time disaggregation both including relevant economic variables and, therefore, allowing for the construction of congruent econometric models.

In these cases, it continues to be true that the interest of the user of forecasts is for them to be as accurate as possible and explain the factors behind them. A monthly model complies with the first requirement, but not with the second. This problem is contemplated in the Bulletin of EU and US Inflation and Macroeconomic Analysis when forecasting inflation. The solution adopted consisted of a monthly forecasting path for the current and following year and an economic explanation of the forecasts on a quarterly level. The latter is obtained from a regression like this:

$$y_t = a + bx_t + r_t, \qquad \textbf{(6)}$$

where Y_t is an inflation forecasting path from the monthly model disaggregated by market but aggregated on a quarterly level and X_t is the forecasting path of a quarterly aggregate model. In regression (6), if the hypothesis that a=0 and b=1 is not rejected, the regression can be used to explain forecasts Y_t in terms of the factors explaining forecasts X_t and r_t. Here, r_t is interpreted as the effect on total inflation of the inflation differentials on all the markets.

The above procedure can also be applied to forecasting other types of variable, and it has the advantage that it makes use of the forecasting accuracy obtained with a monthly model including an important functional disaggregation for the problem in question, and the economic explanation provided by a quarterly congruent econometric model.

The consequences of this are evident. Economic forecasting cannot ignore relevant information, but for such information to increase forecasting accuracy on different horizons, it has to be part of an appropriate econometric model. The difficulty of constructing an econometric model increases with the amount of information to be processed, and its cost may be excessive in relation to the additional benefits expected from more forecasting accuracy and an explanation of the factors on which forecasting is based. In practice, analysts must be capable of coordinating the use of relevant information with appropriate econometric models, increasing the data set and the complexity of the models according to the expected benefits.

Combination of forecasts

We have seen how it is possible to obtain forecasts from different types of ARIMA model, single-equation models, vector models either contemplating functional and geographic disaggregations or not and either including indicators or not, and congruent econometric models. In this situation, the different forecasts stem from different data sets and models with different structures in the long-term formulation of variables. In these cases, Clements y Hendry (1999) point out that the combination of forecasts proposed some time ago by Prof. Granger could be of use. On the other hand, Guerrero and Peña (2002) obtain a theoretical result showing that the combination of forecasts for an aggregate variable from an aggregate model with those obtained with a disaggregated model improves the result of the individual procedures. It is therefore highly advisable for the analyst to examine whether a combination of forecasts increases forecasting accuracy.

6.- PROPOSED METHOD

The result of the above is a proposed method for economic forecasting which has been developed over the ten years that we have been publishing the Bulletin of EU and US Inflation and Macroeconomic Analysis at the Instituto Flores de Lemus, Universidad Carlos III, Madrid.

The basic points of the method are as follows:

(a) Use a functionally, and occasionally also geographically, disaggregated data set, adding the long-term restrictions between the components to the corresponding econometric model.

(b) Use the greatest possible frequency disaggregation in short-term forecasting.

(c) Include specific and general indicators in the explanation of the different components of the aggregate phenomenon.

(d) Use non-linear formulations when necessary.

(e) Combine forecasts from different models if this improves the accuracy of the forecasting paths, normally constructed for the current and following years.

(f) If, as if often the case, congruent econometric models cannot be built using the highest level of frequency disaggregation, since they require more aggregation, relate previous forecasts to those of a congruent model and thus provide an economic explanation of the former.

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