# A PROCEDURE FOR SHORT-TERM GDP FORECASTING

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## Introduction

Characterising the conjunctural situation of the economy and projecting its future performance are particularly important tasks for a central bank. In general, short- and medium-term macroeconomic projections take an analytical approach based on the use of the most recent conjunctural information and on a structural knowledge of the economy within the framework of the National Accounts. This article describes a tool for forecasting short-term GDP growth, which takes its place alongside others used internally by the Banco de España.[1]

There is a wide range of quantitative techniques for forecasting macroeconomic variables of interest, among which GDP is of particular importance, each with its distinct advantages and limitations. One way of classifying the various techniques available for forecasting this variable in the short term consists of distinguishing the direct approaches (those which use short-term indicators to yield a result in the form of a GDP projection) from the indirect approaches (those in which projections of the various demand and supply-side components of GDP are generated for subsequent aggregation).[2]

This article summarises the main features of BEST *(Banco de España Short-Term forecasting model),* a GDP direct forecasting procedure. Specifically, a wide range of indicators is used to estimate a similarly high number of multivariate vector auto-regressive models which include GDP and a series of indicators chosen according to statistical criteria. The results of these models are averaged to give a GDP projection. The predictive power of the model is assessed for the period from 2008 Q1 to 2014 Q2, a span dominated by the double-dip recession of the Spanish economy which posed significant challenges for the obtainment of macroeconomic projections.

Following this brief introduction, the structure of the article is as follows. The second section enumerates the indicators forming part of the database used. Next, the modelling strategy used is described. The fourth section analyses the predictive quality of the proposed procedure by comparing the projections obtained from the BEST model with those yielded by a simple statistical model. The last section of the article presents the main conclusions.

## Database

The database prepared for this study contains 133 economic indicators of widely varying natures, including real variables of activity and demand (quantitative and qualitative), prices and the financial situation relating to the Spanish economy along with variables for other economies of interest. The sample period begins in 1995 Q1 and ends in 2014 Q2. The criterion used to build the database was to include all economic indicators having a priori importance in the analysis of GDP behaviour. To be included in the database, an indicator had to meet three criteria: first, availability of a long time series allowing its inclusion in an econometric model; second, publication prior to the release of the quarterly National Accounts; and third, a monthly periodicity allowing new information to be included during the course of the quarter, although this posed some modelling difficulties, as discussed in the next section.

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**1** See, for example, Camacho and Pérez Quirós (2011).

**2** The organisations which customarily make projections use different approximations and, in many cases, the same organisation has a more or less broad range of short-term forecasting models.

The selection of indicators posed some difficulties which had to be resolved. Often the published time series, unlike GDP time series, were unadjusted for calendar and seasonal effects, so it was necessary to make these adjustments, the TRAMO-SEATS methodology being used for this purpose. Also, some indicators refer to nominal variables, which have to be deflated in order for them to provide meaningful information on the behaviour of output in real terms. Finally, for some series the time range available was too short. This problem was resolved by using statistical retropolation techniques.[3]

The database indicators are divided into seven groups based on their economic content, so as to facilitate the prediction of GDP using its components. Table 1 shows these groups along with a selection of the most representative indicators in each group and their correlations with the quarter-on-quarter change in GDP for the total sample in the most recent period, which begins in 2008 Q1 and is more closely linked to the latest economic crisis. The correlations with output are particularly strong for survey (sentiment) indicators and activity indicators and, on the contrary, are weak for public sector variables or monetary and financial variables. Indicators generally tended to show stronger correlations with GDP in the period 2008-2014. For some indicators, the correlation with the GDP of the following quarter is stronger than the contemporaneous correlation. This leading-indicator status is all the more useful for forecasting purposes. Chart 1 portrays a selection of the time series studied. It shows that the relationship of indicators with GDP varies over time, which is a reason for including a wide range of indicators in forecasting models.

## Modelling strategy

When choosing the most appropriate econometric technique, analysts have to take decisions of different types. First, a wide range of econometric techniques are available for use in forecasting exercises. In the BEST, it has been decided to use VAR methodology. This type of multivariate models means that each variable depends both on its own past and on the past of the other variables considered. These models have been used in forecasting since the pioneering work of Doan, Litterman and Sims (1984). Some more recent work [Camba-Méndez *et al.* (2001) and Rünstler *et al.* (2008)] has added conjunctural indicators in bivariate VAR models.

In this study, the VAR models used include GDP and a set of indicators, the number of which is based on statistical criteria. In practice, the indicators are published before GDP is, so it is useful to incorporate this more recent information into the estimate of the rate of change of GDP for the current quarter *(nowcast)* or for the quarter just ended *(backcast).* To take this information into account, use is made in this work of the conditional forecasting techniques developed by Waggoner and Zha (1999). Intuitively, the starting point taken is a GDP forecast which does not include the information from the indicators in the current quarter (unconditional forecast); it is then adjusted optimally as and when that conjunctural information is received during the course of the quarter.[4]

The different periodicity of the indicators (monthly) and of GDP (quarterly) poses a difficulty in the modelling. In BEST it was decided to include monthly forecasts of the indicators to

3 These techniques are based on the construction of time series of the indicator from the profiles of similar indicators.

4 Without loss of generality, we can take a VAR model with two variables: GDP and an indicator. The unconditional forecast depends on the lags of the two variables, since the expected value of the disturbance term is zero. However, knowing the indicator provides an estimate of the forecasting error made for it and, therefore, the expected value conditional on this new information of the error for GDP is different from zero.

QUARTER-ON-QUARTER CORRELATION OF GDP WITH REPRESENTATIVE INDICATORS OF THE DATABASE TABLE 1

| Indicator (a) | 1995 Q1 - 2014 Q2 | | 2008 Q1 - 2014 Q2 | |
|---|---|---|---|---|
| | Contemporaneous | Leading by one quarter | Contemporaneous | Leading by one quarter |
| **1 Real indicators of demand** | **0.39** | **0.38** | **0.32** | **0.37** |
| Synthetic indicator of consumption | 0.64 | 0.64 | 0.56 | 0.41 |
| Synthetic indicator of equipment | 0.60 | 0.67 | 0.59 | 0.74 |
| Commercial vehicle registrations | 0.44 | 0.54 | 0.38 | 0.59 |
| EC services confidence. Synthetic indicator | 0.83 | 0.79 | 0.61 | 0.29 |
| Intermediate goods imports | 0.40 | 0.50 | 0.67 | 0.72 |
| Intermediate goods exports | 0.23 | 0.32 | 0.49 | 0.57 |
| **2 Real indicators of activity** | **0.60** | **0.56** | **0.53** | **0.47** |
| Total sales (Tax Authorities) - Industry | 0.66 | 0.71 | 0.60 | 0.83 |
| Electricity consumption | 0.84 | 0.72 | 0.67 | 0.29 |
| Total IPI (Industrial production index) | 0.68 | 0.74 | 0.70 | 0.87 |
| Total sales (Tax Authorities) - Sales of real estate activities | 0.24 | 0.15 | 0.04 | -0.21 |
| Indicator of services sector activity | 0.75 | 0.76 | 0.73 | 0.75 |
| Total average Social Security registrations | 0.93 | 0.91 | 0.94 | 0.80 |
| Total sales (Tax Authorities) - Agriculture | 0.11 | 0.00 | 0.32 | 0.21 |
| Ministry of Economy total activity synthetic industry indicator | 0.79 | 0.85 | 0.73 | 0.85 |
| **3 Public sector indicators** | **0.33** | **0.41** | **0.35** | **0.47** |
| Public administration, education and health (b) | 0.53 | 0.48 | 0.27 | 0.05 |
| Net indirect taxes | 0.20 | 0.10 | 0.23 | 0.04 |
| **4 Opinion indicators** | **0.52** | **0.51** | **0.53** | **0.55** |
| Composite PMI. New orders | 0.48 | 0.49 | 0.65 | 0.65 |
| EC retail trade confidence indicator | 0.84 | 0.87 | 0.59 | 0.64 |
| EC industrial confidence. Activity | 0.80 | 0.85 | 0.51 | 0.67 |
| Manufacturing PMI. Employment expectations | 0.88 | 0.82 | 0.92 | 0.79 |
| EC industrial confidence. Employment expectations | 0.71 | 0.69 | 0.06 | 0.08 |
| Services PMI. Activity | 0.89 | 0.88 | 0.82 | 0.88 |
| **5 International indicators** | **0.46** | **0.52** | **0.35** | **0.42** |
| EUROSTOXX broad index | 0.28 | 0.43 | 0.31 | 0.60 |
| Competitiveness of Spain vis-à-vis EU-17 countries (with consumer prices) | 0.31 | 0.27 | 0.36 | 0.31 |
| Euro area economic sentiment | 0.26 | 0.37 | 0.52 | 0.82 |
| Germany IPI | 0.48 | 0.42 | 0.80 | 0.71 |
| **6 Price indicators** | **0.49** | **0.48** | **0.49** | **0.51** |
| CPI | 0.42 | 0.34 | 0.49 | 0.25 |
| Imported oil price | 0.32 | 0.23 | 0.78 | 0.51 |
| **7 Monetary and financial indicators** | **0.62** | **0.63** | **0.65** | **0.66** |
| 3-month EURIBOR | 0.42 | 0.30 | -0.20 | -0.42 |
| Lending to firms and households | 0.70 | 0.66 | -0.31 | -0.50 |
| Means of payment | 0.38 | 0.53 | -0.22 | 0.21 |
| Madrid Stock Market General Index | 0.25 | 0.41 | 0.17 | 0.46 |

SOURCES: Eurostat, Instituto Nacional de Estadística, Ministerio de Economía y Competitividad, Ministerio de Trabajo y Seguridad Social, Intervención General de la Administración del Estado, Markit and Banco de España.

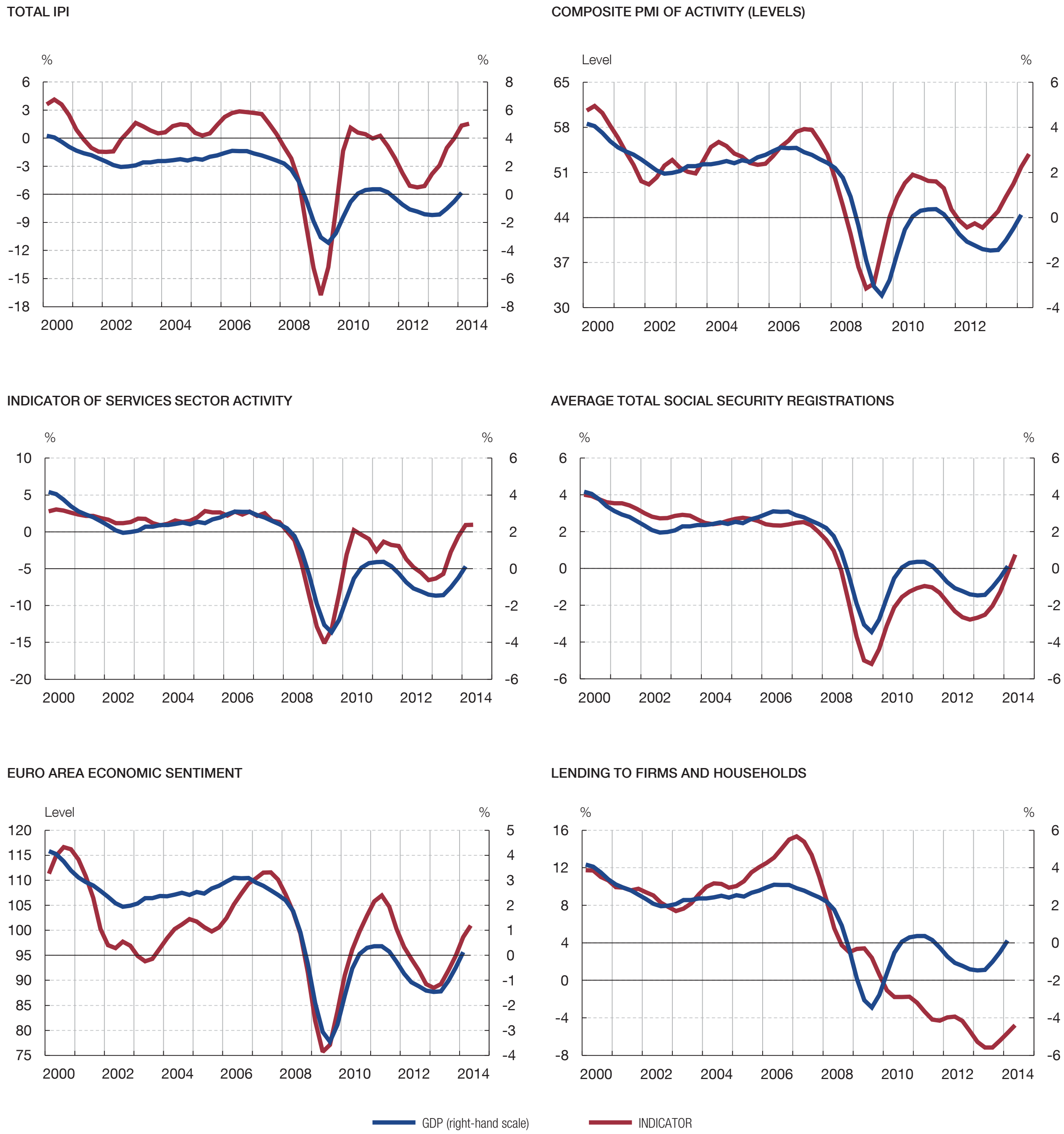
a The correlations by area are calculated as the average of all the available indicators assigned for each area in the database.
Breakdown of indicators by area: demand 27; activity 38; public sector 3; opinions 28; international 8; prices 7; financial and monetary 22.

b APEDUSAN: public administration, education and health.

SHORT-TERM BEHAVIOUR OF VARIOUS ECONOMIC INDICATORS IN RELATION TO GDP

CHART 1

RATE OF CHANGE OF THREE-QUARTER MOVING AVERAGES IN RELATION TO THAT OF THE PREVIOUS THREE QUARTERS. REAL SEASONALLY-ADJUSTED INDICATORS, UNLESS OTHERWISE INDICATED




SOURCES: Eurostat, INE, Ministerio de Economía y Competitividad, Ministerio de Trabajo y Seguridad Social, Markit and Banco de España.

complete the current quarter.[5] This is common practice among statistical institutes responsible for the estimation of GDP and among other central banks [Bell *et al.* (2014)]. Alternatively, mixed-frequency models could be used.

Once the modelling strategy has been adopted, the next decision concerns the selection of the most suitable indicators. In practice, the inclusion of additional variables in a model does

5 Transfer function or univariate models are used for this purpose.

not always guarantee better predictive behaviour. On one hand, the inclusion of more indicators permits, a priori, a better approximation of reality. However, on the other, it also means an increase in the number of parameters estimated, which may reduce the accuracy of the estimations and, consequently, that of the forecasts themselves. In fact, there is no consensus in the literature about the optimum number of variables which should be considered, models with a very high number of indicators coexist with others that contain few variables. In this project an intermediate approach was chosen: small-sized models are used to avoid estimating a very high number of parameters, but numerous models are estimated so that information from a broad set of indicators can be gathered. In order to choose the variables included in each model, *forward selection* is used, namely, at each stage an additional indicator is included [see Bai and Ng (2008)]. Specifically, the starting point is 133 bivariate models (one per each available indicator) which include GDP together with one of the database indicators and additional database variables are added to them up to the point where introducing a new variable does not contribute relevant additional information to the model. Thus, each of these 133 models may show a different number of lags.

The approach includes estimating 133 models and obtaining their corresponding point forecasts. To condense the information of these models their results can be combined by using a weighting criterion. The literature on combining forecasts is very extensive and, in general, tends to show that the combination of models with different sets of information provides more accurate forecasts than a single model, since the omission of variables is less likely in the model derived from combining other models and, furthermore, such models are usually more robust to structural changes.

In simple terms, there are two general approaches to combining forecasts in order to use information optimally. The first approach consists of eliminating models with a less satisfactory predictive power and the second comprises weighting each model using certain measurements of its predictive power. In the exercises presented below, the average of the most accurate 5% of models is considered as well as the average weighted by the inverse of the mean square error.[6] The simple average is also used.

## Results

A straightforward exercise was performed to evaluate the BEST procedure which comprised the calculation of the forecasting error of the quarter-on-quarter rate of change of GDP for each quarter in the period from 2008 Q1 to 2014 Q2. This error is defined as the difference between the INE's first estimate and the projection obtained from the information of the various indicators available on each of these dates which is known in the literature as a *pseudo real time exercise*[7]. As is customary in this type of exercises, the model's goodness of fit is compared with that of a benchmark simple statistical model, specifically, with that of a first-order auto-regressive process.[8] Additionally, in order to assess the accuracy of the forecasts, the results for the above-mentioned sub-periods are shown.

Table 2 shows the mean square error (MSE) relative to that of the simple auto-regressive model for the three forecasting combination procedures described. Values higher than unity of this ratio imply that the univariate model is more accurate than BEST, whereas values lower than unity mean that BEST has a greater predictive power.

6 To obtain these weightings, the information available at any given time is used so that the pseudo real-time nature of the exercise is maintained.

7 The exercise is *pseudo real time* because the revisions to the series over time are not taken into account. In any event, the revisions of most of the indicators are not very significant.

8 To ensure the consistency of the exercise, the forecasts are made by re-estimating the model each quarter with the information available at any given time.

MEAN SQUARE ERROR RELATIVE TO AR(1) TABLE 2

| Model | 2008 Q1 - 2014 Q2 | 2008 Q1 - 2010 Q4 | 2011 Q1 - 2014 Q2 |
|---|---|---|---|
| Simple average | 0.27 | 0.22 | 0.55 |
| Average weighted by mean square error | 0.29 | 0.26 | 0.54 |
| Average of best 5% of models | 0.22 | 0.19 | 0.47 |

SOURCE: Banco de España.

The main conclusion of this exercise is that BEST, regardless of the forecasting combination strategy applied, is considerably more accurate than the simple model. For the sample as a whole, the error is between one-fifth and one-third of the auto-regressive model. This result is maintained for the various time periods considered. Noteworthy among the various combination procedures used, is the average of the best 5% of models, since it displays a lower mean square error than the simple average of all the models or the average of the models weighted by the inverse of the mean square error. Specifically, with this metric, the error is practically one-fifth of that associated with the simple model.

The upper panels of Chart 2 shows the various forecasts made for each quarter of the most recent sub-period together with the GDP growth estimates. Except for 2012 Q4, where the decline of GDP was underestimated,[9] the errors are generally small both in periods when GDP has slowed and quickened.

The three procedures described for combining the results summarise the projections of the set of models estimated each quarter, however, the analysis of the distribution of these forecasts is interesting in itself insofar as it makes it possible to discern whether the various models present similar or divergent results. For example, the lower panels of Chart 2 show the distribution of the forecasts for 2014 Q1 and Q2. In the case of Q1, the distribution of the forecasts indicated growth of approximately 0.1 pp higher than that observed[10]. For 2014 Q2 most of the models projected GDP growth of 0.6%, coinciding with the figure estimated by the INE.

## Conclusions

This article describes a tool for forecasting short-term GDP growth, which takes its place alongside others used regularly at the Banco de España. Unlike other alternatives, this procedure incorporates a large number of conjunctural indicators which are processed efficiently and it represents a novel approach in forecasting techniques developed in Spain. For this purpose, 133 vector auto-regressive models are considered and conditioned forecasting techniques are employed which use a large volume of recent conjunctural information. These models are small-sized so as to avoid estimating models with a high number of parameters.

The assessment of the proposed procedure shows promising results, although the sample period considered is still relatively short. Also, as a result of the forthcoming publication of the quarterly series of GDP in accordance with the European System of Integrated Economic Accounts (ESA 2010), it will be necessary to reassess the properties of this GDP projection procedure. This short-term forecasting procedure can be used to forecast other macroeconomic variables of interest. Specifically, a natural extension would be to create models for the various GDP components from the standpoint of demand and of supply.

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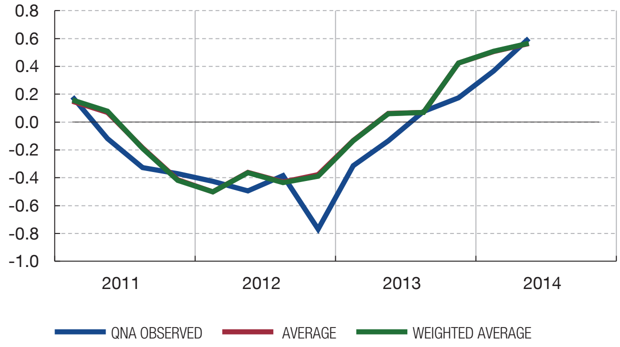
9 Note that this quarter represented a very pronounced negative surprise for most analysts since the conjunctural indicators showed less adverse changes than those in GDP.

10 To simplify, the distribution of forecasts was rounded to the first decimal place in the chart.

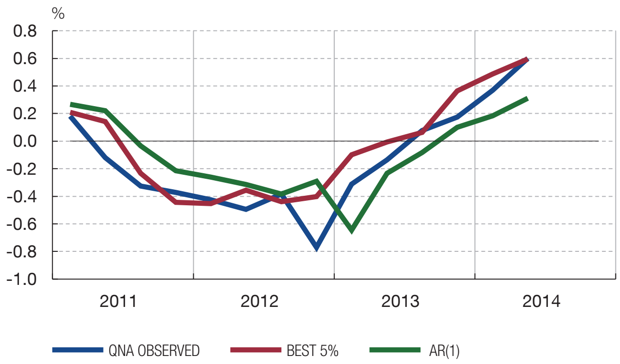
FORECASTS AND QUARTER-ON-QUARTER FORECASTING ERRORS OF GDP IN PSEUDO REAL TIME

CHART 2

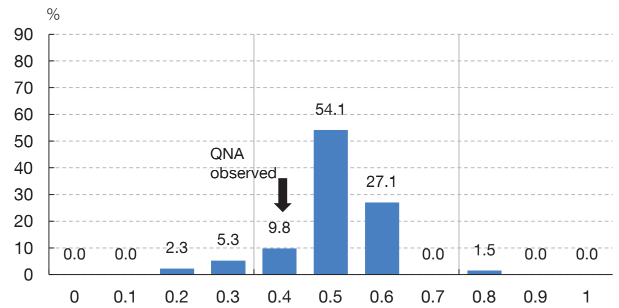
COMPARISON OF VARIOUS FORECASTING MODELS



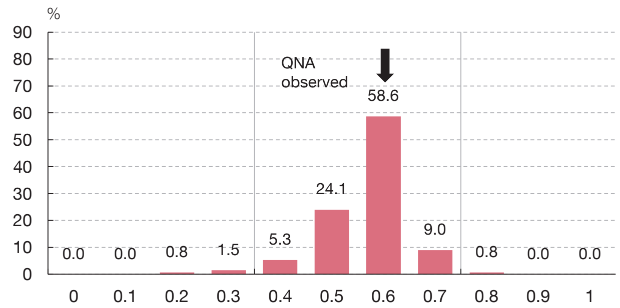

COMPARISON OF VARIOUS FORECASTING MODELS




DISTRIBUTION OF FORECASTS FOR 2014 Q1




DISTRIBUTION OF FORECASTS FOR 2014 Q2




SOURCES: INE and Banco de España.

## REFERENCES


BAI, J., and S. NG (2008). "Forecasting economic time series using targeted predictors", *Journal of Econometrics,* Vol. 146, No. 2, October, pp. 304-317.

BELL, V., L. W. CO, S. STONE and G. WALLIS (2014). "Nowcasting UK GDP Growth", *Quarterly Bulletin,* Q1, Bank of England.

BULLIGAN, G., M. MARCELLINO and F. VENDITTI (2012). *Forecasting economic activity with higher frequency targeted predictors,* Banca d'Italia Working Paper, No. 847.

CAMACHO, M., and G. PÉREZ QUIRÓS (2011). *SPAIN-STING: Spain Short-Term INdicator of Growth,* The Manchester School, Vol. 79, No. S1, pp. 594-616.

CAMBA-MÉNDEZ, G., G. KAPETANIOS, R. J. SMITH and M. R. WEALE (2001). "An automatic leading indicator of economic activity: forecasting GDP growth for European countries", *Econometrics Journal 4,* pp. 56-90.

DOAN, T., R. B. LITTERMAN and C. A. SIMS (1984). "Forecasting and Conditional Projection Using Realistic Prior Distributions", *Econometric Reviews,* Vol. 3, Issue 1.

KITCHEN, J., and R. M. MONACO (2003). "Real-time forecasting in practice: the US treasury staff's real-time GDP forecast system", *Business Economics,* 38 (4), pp. 10-19.

GOMEZ, V., and A. MARAVALL (1996). *Programs TRAMO and SEATS, Working Papers,* No. 9628, Banco de España.

RÜNSTLER, G., K. BARHOUMI, S. BENK, R. CRISTADORO, A. DEN REIJER, A. JAKAITIENE, P. JELONEK, A. RUA, K. RUTH and C. VAN NIEUWENHUYZE (2009). "Short-Term Forecasting of GDP Using Large Datasets: A Pseudo Real-Time Forecast Evaluation Exercise", *Journal of Forecasting,* 28, pp. 595-611.

WAGGONER, D. F. and T. ZHA (1999). "Conditional Forecasts In Dynamic Multivariate Models", *The Review of Economics and Statistics,* MIT Press, Vol. 81 (4), November, pp. 639-651.