Spain-STING: Spain Short Term INdicator of Growth*

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Abstract

We develop a dynamic factor model to compute short term forecasts of the Spanish GDP growth in real time. With this model, we compute a business cycle index which operates as an indicator of the business cycle conditions in Spain. To examine its real time forecasting accuracy, we use real-time data vintages from 2008.02 through 2009.01. We conclude that the model exhibits good forecasting performance anticipating the recent and sudden downturn.

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1. Introduction

Due to the economic disturbances affecting the world economy in the 2008-2009 recession, there has been an explosive interest in the early assessment of the short term evolution of economic activity. The academic literature and the press are full of references to the GDP growth rate releases, its revisions and its forecasts, paying special attention to the progressive deterioration of the GDP growth rates when more news about economic developments become available. However, even though there is a lot of interest in early assessment of current and future values of GDP growth, the vast majority of the forecasts released by relevant institutions do not always make explicit the methodology followed to compute their forecasts. Therefore, it is difficult to replicate and intuitively understand these forecasts and up to what point these forecast reflect subjective or objective measures of economic activity.

In fact, the forecasts of many of the institutional forecasters explicitly or implicitly rely on the judgment of experts, which might be helpful in terms of increasing the precision of their forecasts, but implies two serious drawbacks. The first drawback is that personal judgments based on personal experience make the forecasting process a black box which is only clear to the mind of the forecaster. The second drawback is that forecasts which rely on personal judgments make the forecasting process a subjective exercise instead of an objective quantitative and measurable analysis. This way, forecasters may read the news, and be affected by a general climate that may or may not be accurate to describe the current economic situation. But at the same time, forecasters may even affect the news and therefore, may contribute to create expectations which, if not objectively quantifiable, may only be a partial description of the economic situation.

To avoid these problems, in this paper we propose a judgment-free algorithm which automatically computes the forecasts when new information becomes available. Doing so, our algorithm has the same advantages as the judgmental forecast, referring to the ability to adapt to new information, but it avoids the serious inconveniences mentioned before. The forecasting method is easy to interpret, easy to replicate, and easy to update.

Regarding the automatic forecasting methods, the most familiar are the standard time series processes popularized by Box and Jenkins and their posterior refinements, including multivariate time series process and error correction models. To predict the GDP, these models usually rely on quarterly series which have a tendency to be published with a delay that ranges from about 45 to 60 days. Therefore, as of today, January 25th 2009, when forecasting the next quarter of GDP growth (second quarter of 2009) the majority of standard time series models would use data corresponding to the third quarter of 2008. These forecasts, apart from not capturing the abrupt economic changes occurred in the fourth quarter of 2008 and the first month of 2009, will be subject to strong revisions in the reference series. With this outdated information, since the traditional autoregressive models usually exhibit strong mean reverting, their forecasts are seriously biased towards the mean, which may lead to misleading forecasts in an environment of economic turbulences.

To diminish this problem, we propose a dynamic factor model which makes use of economic indicators related to GDP growth, but are published much more promptly. One potential alternative specification could be based on transfer functions which include the set of indicators as explanatory variables. However, estimating these models becomes problematic when the number of indicators increases. For this reason, dynamic factor models become the most appropriate framework to compute the forecasts. These specifications are based on the assumption that the joint dynamics of GDP growth and the indicators can be separated into two components. For each indicator, the first component refers to the common dynamics whereas the second component refers to its idiosyncratic dynamics.

In the recent empirical literature, two alternative dynamic factor models are being used. On the one hand, we have the factor models based on large sets of economic indicators which are estimated by using approximate factor models as in Angelini et al. (2008) for Euro-area data and Camacho and Sancho (2003) for Spanish data. On the other hand we have the small scale factor models which rely on previous reasonable pre-screenings of the series. These specifications, which have recently been applied by Camacho and Perez Quiros (2010) and by Frale, Marcellino, Mazzi and Proietti (2008) to Euro-area data, are estimated by using strict factor models.

The debate about using large versus small scale factor models, is far from being settled.

Boivin and Ng (2006) point out that the asymptotic advantages of large-scale factor models require a set of assumptions clearly violated in empirical applications. This fact may lead to the fact that more data not to be necessarily better. In addition, Alvarez, Camacho and Perez Quiros (2010) examine the empirical pros and cons of forecasting with large versus small factor models. The main conclusion of this line of research is that in empirical applications small scale factor models can be better than large scale factor models when the serial correlations of the idiosyncratic components and the factors are large, when the correlation within different economic categories of indicators is high, when some categories are oversampled and when addition noisy indicators to those which are representative of each category. Finally, Bai and Ng (2008) have demonstrated the importance of having parsimonious specifications in order to improve the forecasting ability of factor models.

In line with the previous discussion, we propose a small scale factor model to compute short term forecasts of the Spanish GDP growth rate in real time, in line. The model is constructed to deal with the typical problems affecting real-time economic releases. Firstly, the model deals with ragged edges in order to take into account that the available information is released in a non-synchronous way. Secondly, the model accounts for data with mixed frequencies so it can handle with monthly indicators and quarterly GDP. Thirdly, the model is a simple algorithm that can be automatically updated. This allows the model to deal with potential economic instabilities, because, if the predictive power of any variable diminishes during the course of some periods, the variable will reduce its weight and its loading factor. Finally, the model is dynamically complete, in reference to the fact that it accounts for the dynamics of all the indicators used in the analysis.

The empirical reliability of the model has been evaluated using both in-sample data from 1990.01 until 2009.01 and real-time data from February 2008. This exercise describes the main outputs obtained by the model in each of the automated forecasts. The outputs show that the factor works reasonably well as an indicator of the recent economic evolution in Spain. As expected, the loading factors are positive and statistically significant which reinforces the standard view that the indicators are procyclical. In addition, as in Banbura and Runstler (2007) or Camacho and Perez Quiros (2010), the empirical results show that a suitable treatment of publication lags may lead some indicators to provide important sources of information in predicting the GDP beyond the information provided in the in-sample estimates of the loading factors.

The paper is organized as follows. Section 2 outlines the proposed methodology. Section 3 evaluates the empirical reliability of the model. Section 4 contains the conclusions.

2. Description of the model

In this section, we develop the model to compute short term forecasts of the Spanish GDP growth in real time which are based on a set of indicators that may include mixing frequencies and missing data.

2.1. Selection of indicators

The series used in the estimation of the model are listed in Table 1. The selection of these variables is based on the model suggested by Stock and Watson (1991). Their idea follows the logic of national accounting of computing GDP from three different points of view, the supply side, the demand side, and the income side. Therefore, to obtain accurate estimates of activity with a monthly frequency they use the Industrial Production Index (supply side), Total Sales (demand side), Real Personal Income (income side). In addition, they use Employment to capture the idea that productivity does not change dramatically from one period to the other. Since we do not have a reliable income variable for the Spanish economy, we have started our selection of indicators by using Industrial Production Index (excluding construction) from the *Instituto Nacional de Estadistica*, the Spanish Statistical Institute, Total Sales of Large Firms from *Agencia Tributaria* (Spanish Internal Revenue Service) and Social Security Contributors from Spanish Ministry of Labor.

However, as pointed out in Camacho and Perez Quiros (2010) the delay in the publication of some of these series (see Table 1), and the fact that some of them are subject to serious revisions, makes it difficult to follow the real time economic evolution using only these three indicators. Following their paper, we extend the Stock-

Watson initial set of indicators in two dimensions. In the first extension, we include soft indicator series which have the characteristic of being early indicators of activity as well as the fact that they are available with almost no publication delays. From the supply side, the earliest indicators available are the Industrial Confidence Indicator, released by the European Comission at the end of the current month and the Services Purchasing Managers Index, (PMI Services) released by the Institute for Supply Management two days after the end of the month. From the demand side, we chose the Retail Sales Confidence Index also released by the European Commision at the end of the current month which it is also the earliest available indicator of demand for the Spanish economy. With this set of variables, we estimate an exact factor model, following the lines of Stock and Watson (1991) taking into account the possibility of ragged ends as in Mariano and Murasawa (2003)[1]. Remarkably, with this specification we get to explain 79% of the variance of GDP growth with the evolution of the common factor.

In the second extension of the Stock-Watson set of indicators, we follow the procedure described in Camacho and Perez Quiros (2010) which is based on including more variables into the model whenever they increase the variance of GDP explained by the common factor. Contrary to standard techniques, more explanatory variables do not always increase the variance of GDP explained by the model. Particularly, when the additional variables are correlated with the idiosyncratic part of some of the other variables, the estimation of the factor is biased toward this subgroup, making the variance of GDP explained by the factor decrease.

With this criterion in mind, the only variables that we have found to increase the variance of GDP explained by the factor are, on the supply side, an indicator of the services sector, Overnight Stays, i.e. number of nights spent by foreigners in Spanish hotels released by the Spanish Statistical Institute and an indicator of the construction sector, Consumption of Cement, released by OFICEMEN, Cement Producers Association. On the demand side, we add indicators of trade, Imports and Exports, released from customs data by the Ministry of Economy. The variance of GDP explained by the factor with this enlarged model increases to 80%.

[1] Details of the specifications will be explained later

Notably, this final set of indicators was very robust to other potential enlargements. We tried to enlarge the model with more series of the *Agencia Tributaria* such as Wages Paid by Large Firms, Exports of Large Firms and Imports of Large Firms. In addition, we tried to add disaggregated versions of the variables already included in the model such as Industrial Production. Finally, we tried to add financial indicators such as Stock Market Returns and Interest Rates. However, in all of these cases, we failed to improve the variance of GDP explained by the factor

One final remark regarding the indicators is that the monthly growth rates of most of the Spanish hard indicators are extremely noisy. To avoid this problem, we have included these series in the model in annual growth rates.[2] Additionally, we have included the soft indicators in levels, because according to the European Commission, these indicators are designed to capture annual growth rates of the series of interest. The unit root problems associated with the annual growth rates and the levels of the soft indicators are solved by specifying the model with a monthly factor, but taking into account that the indicators are in function of a current and up to eleven lags of this factor.[3]

The following two subsections are the description of the econometric methodology. Since this is similar to the one used in the Euro-Sting model of Camacho and Perez Quiros (2010), readers familiar to the model can skip these sections.

2.2. Mixing quarterly and monthly observations

The model is based on the idea of obtaining early estimates of quarterly GDP growth by exploiting the information in monthly indicators which are promptly available. Linking monthly data with quarterly observations needs to express quarterly growth rate observations as an evolution of monthly figures.

For this purpose, let us assume that the quarterly GDP can be decomposed as the sum of three unobservable monthly values of GDP. Mariano and Murasawa (2003) show that if

[2] We use seasonally and calendar adjusted data although the model is robust to estimation with raw data.

[3] See Camacho and Perez Quiros (2010) for further details in data transformation.

the sample mean of these three data can be well approximated by the geometric mean, the quarterly growth rates of a flow variable such as GDP can be expressed as the average of monthly latent observations:

$$y_t = \frac{2}{3}x_t + \frac{1}{3}x_{t-1} + x_{t-2} + \frac{1}{3}x_{t-3} + \frac{2}{3}x_{t-4}.$$

It is worth saying that approximating sample means with geometric means is appropriate since the evolution of macroeconomic series is smooth enough to allow for this approximation. In related literature, Proietti and Moauro (2006) avoid this approximation at the cost of moving to a complicated non-linear model. Aruoba, Diebold and Scotti (2009) also avoid the approximation but assuming that the series evolve as deterministic trends without unit roots.[4]

2.3. Bridging with factors

The practical application of the procedure described in the previous section exhibits two econometric problems that separate our specification from the standard factor models. The first problem is that the procedure is specified in monthly frequencies. This implies the need to handle with missing data such as the quarterly growth rates for the first two months of each quarter. The second problem is that the model has to deal with unbalanced datasets since some series start late, and some series (those with longer publication delays) end too soon.

The dynamic factor model is an appropriate framework to deal with these drawbacks. This model can also characterize the co-movements in those macroeconomic variables that admit factor decomposition. In particular, the extension of the single-index dynamic factor model used in this paper is based on the premise that the dynamic of each series can be decomposed into two components. The first component, called common component and denoted by f_t, captures the collinear dynamics affecting all the variables and can be interpreted as a coincident indicator of the GDP growth rate. The second

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[4] In the recent extensions of their model, these authors abandon their filter and use growth rates. See: http://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index

component, called idiosyncratic component and denoted for each indicator j by u_{jt}, captures the effect of those dynamics which only affect that particular variable.

Let x_t be the monthly GDP growth rate and let z_t be the k-dimensional vector of economic indicators in annual growth rates (for hard indicators) or in levels (for soft indicators). According to the idea that soft indicators are related with annual growth rates of the series of interest, the levels of soft indicators are assumed to depend on a 12 month moving average of the common factor[5], Obviously, by construction, the annual growth rate of the hard indicators also presents this 12 month dependence. Taking into account the relation between quarterly and monthly growth rates stated in the previous subsection, the joint dynamics of these series can be written as:

$$\begin{pmatrix} y_t \\ z_t \end{pmatrix} = \begin{pmatrix} \beta_y/3 & 2\beta_y/3 & \beta_y & 2\beta_y/3 & \beta_y/3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \beta_1 & \beta_1 & \beta_1 & \beta_1 & \beta_1 & \beta_1 & \beta_1 & \beta_1 & \beta_1 & \beta_1 & \beta_1 & \beta_1 \\ \ldots\ldots & & & & & & & & & & & \cdots \\ \ldots. & & & & & & & & & & & \ldots. \\ \beta_n & \beta_n & \beta_n & \beta_n & \beta_n & \beta_n & \beta_n & \beta_n & \beta_n & \beta_n & \beta_n & \beta_n \end{pmatrix} \begin{pmatrix} f_t \\ f_{t-1} \\ \ldots. \\ f_{t-10} \\ f_{t-11} \end{pmatrix}_t + \begin{pmatrix} u_{yt} \\ u_{zt} \end{pmatrix} \tag{1}$$

where $u_{zt} = (u_{1t}, u_{2t}, ..., u_{kt})$. The (n+1) parameters β are known as the factor loadings and capture the correlation between the unobserved common factor and the variables. To complete the statistical representation of the model, we have to take into account the dynamics of the shocks:

$$\begin{pmatrix} u_{yt} \\ u_{zt} \end{pmatrix} = \begin{pmatrix} 1/3u_{xt} + 2/3u_{xt-1} + u_{xt-2} + 2/3u_{xt-3} + 1/3u_{xt-4} \\ \sum_{i=0}^{11} u_{l,t-i} \end{pmatrix} \tag{2}$$

Where $u_{l,t}$ are the shocks to the monthly growth rates of the hard indicators and to the first differences of the soft indicators[6].

[5] This deals with the potential unit root problems of the levels of soft indicators.

[6] Given that the objective of the models is not to forecast all the indicators but the GDP growth, we directly model u_{zt} as $u_{zt} = u_{lt}$

In addition, we assume the following dynamic specification for the variables.

$$\phi_x(L)u_{xt} = \varepsilon_{xt}, \tag{3}$$

$$\phi_f(L)f_t = \varepsilon_{ft} \tag{4}$$

$$\phi_l(L)u_{lt} = \varepsilon_{lt} \quad l = 1....n \tag{5}$$

where $\phi_x(L)$, $\phi_f(L)$, and $\phi_l(L)$ are lag polynomials of order *p*, *q* and *r*, respectively. In addition, we consider that all the errors in these equations are independent and identically normal distributed with zero mean and diagonal covariance matrix.

Dealing with balanced panels, i.e, when all the variables are observed in each period, the model can be easily stated in state space representation which can be estimated by maximum likelihood procedures (see Hamilton 1999, and references therein) using the Kalman Filter. When datasets are unbalanced, the Kalman filter is also the natural statistical method to deal with missing observations. Following Mariano and Murasawa (2003), we replace the missing observations by random draws (means, medians or zeroes are also valid alternatives). The substitutions allow the matrices in the state-space representation to be conformable but they have no impact on the model estimation since the missing observations add just a constant in the likelihood function to be estimated by the process.

The model can be written in state space form. Let us collect the quarterly growth rates of GDP, the annual growth rates of the hard indicators, and the levels of the soft indicators in the vector Y. The observation equation is

$$Y_t = Hs_t + w_t, \tag{5}$$

where $w_t \sim iN(0, R)$. Calling s_t the state vector, the transition equation is

$$s_t = Fs_{t-1} + v_t, \tag{6}$$

where $v_t \sim iN(0, Q)$.

The details about the specific form of the matrices H, R, F, and Q, and of the state vector, s_t, are described in the Appendix.

One interesting result obtained from dynamic factor models are the weights or cumulative impacts of each indicator to the forecast GDP growth and can be obtained from the Kalman filter. Skipping details, which are stated in Camacho and Perez Quiros (2010), the state vector s_t can be expressed as the weighted sum of available observations in the past.[7] Assuming a large enough t such that the Kalman filter has approached its steady state it holds that h-period ahead forecasts of GDP growth are approximately

$$y_{t+h} = \sum_{j=0}^{\infty} W_j' Y_{t-j} . \tag{7}$$

In this expression, W_j is the vector of weights and leads the forecaster to compute the cumulative weight of series i in forecasting GDP growth as $\sum_{j=0}^{\infty} W_j(i)$, where $W_j(i)$ is the i-th element of W_j.

3. Empirical analysis

In this section, the model is used to compute in-sample maximum likelihood estimates which are intuitively interpreted. In addition, the model is applied to the real-time vintages of data sets from 2008.02 through 2009.01 to examine its accuracy in accounting for the recent and sudden downturn.

3.1. In-sample results

The in-sample dataset available on January 25, 2009 includes data from 1990.01 to

[7] See Stock and Watson (1991) for further details.

2008.12, and it is depicted in Figure 1.[8] The key series to be forecasted is quarterly growth rate which starts in 1992.1 and ends in 2008.3 and is plotted in the first graph. The three soft indicators, which are based on survey data, are plotted in levels in graphs 2 to 4. The last seven graphs show the evolution of hard indicators which are plotted in annual growth rates. As can bee seen in the graphs, some of the ten indicators used in the model are shorter time series since they started to be published in the mid nineties. In addition, it is also clear than, despite the particularities exhibited in their respective dynamics, all of them seem to share a common pattern with two significant slowdowns at the beginning and at the end of the sample.

The particular publication pattern of these series can be examined in Table 2 which shows the last figures of the time series. Since GDP is published quarterly, the two first months of each quarter are treated as missing data. Typically, surveys have very short publishing lags and are frequently published within the current month while hard data are released with a relatively longer delay of about two months. The last available release of GDP was in September 2008 and from this date until June 2009 we add nine months of missing data. The Kalman filter employed in the model will fill in these missing observations by computing dynamic forecasts.[9] Accordingly, the nine-month forecasting horizon will be moved forward when GDP for the last quarter will be published.

The model used in this paper is based on the notion that co-movements among the macroeconomic variables have a common element, the common factor, which moves according to the Spanish business cycle dynamics. In this context, Figure 2 shows the estimated factor (bottom line) and the annual growth rates of the Synthetic Index of Economic Activity (*Indicador Sintético de Actividad Económica*, top line) which is elaborated by the Spanish Ministry of Economy since 1995 to account for the recent economic evolution in Spain. From this figure, it is clear that the business cycle fluctuations of these two time series are in close agreement which validates the view

[8] To understand notation, for example 2008.1 or 08.1 refer to first quarter of year 2008 while 2008.01 or 08.01 refer to first month of year 2008.

[9] Therefore, the model computes forecasts for the last quarter of 2008 and the first two quarters of 2009.

that our factor agrees with the dynamics of the Spanish economic activity.

As can be seen in the figure, the indicator starts the nineties on its average value (dotted line) and suffers from the first temporary drop in 1992 and 1993. After the summer of 1993, the indicator increased substantially and reaches above-average values until mid nineties, when a much milder slowdown characterized the winter of 1995/96. During the next decade and until 2008, the indicator is uninterruptedly either on, or above, the average and its flatted trend marks the period of high growth which characterizes the Spanish economy in those years. In the middle of 2007, way before the GDP shows negative growth, there is a marked breakpoint in the evolution of the factor. The figures of the indicator turn negative and the pattern followed by the indicator becomes a clear negative trend. It's worth pointing out that, in terms of abruptness and deepness, the trend observed in all the economic indicators except exports are in line with the trend marked by the factor. Using the information up to January 2009, signals of recoveries are not visible by the model predictions at least until the end of 2009.

To examine the correlation of these indicators and the factor, Table 3 shows the maximum likelihood estimates of the factor loadings (standard errors within parentheses). Apart from the GDP, the economic indicators with larger loading factors are those corresponding to, Services Purchasing Managers Index, (PMI Services), Industrial Production Index (IPI), Total Sales of Large Firms, and Social Security Contributors. The indicator with lower correlation with the latent common factor is Exports (and to less extent, Overnight Stays) which it is only marginally significant.[10] However, the estimates are always positive and statistically significant, indicating that these series are procyclical, i.e., positively correlated with the common factor. One final remark is the positive correlation between Imports and the factor. Contrary to the standard view in national accounting, Imports are interpreted within the models as an indicator of final demand, and therefore it does have procyclical behavior.

[10] Despite the values of its loading factors, Exports remains in the model for two reasons. It is followed by experts who track the Spanish economic developments and it increases the percentage of GDP's variance which is explained by the factor. If the deterioration persists, it might be a candidate to be excluded from the model.

Forecasts of the GDP can be examined in Figure 3 and panel A of Table 4. Figure 3 plots the monthly estimates of GDP quarterly growth rates along with their actual values. According to the methodology employed in this paper, the Kalman filter anchors monthly estimates to actual data whenever GDP is observed. Hence, for those months where GDP is known, actual and estimates coincide. Table 4 shows how the model anticipates the next three future values of GDP growth. Following the nine-month forecasting period, the model computes GDP growth rates for quarters 2008.4, 2009.1 and 2009.2., which are usually known as backcasting (fourth quarter of 2008), nowcasting (current quarter, first quarter of 2009) and forecasting (second quarter of 2009) exercises . These forecasts predict that the Spanish economic conditions are likely to deteriorate for the immediate future and will continue the negative path initiated in 2008, with the GDP growing at a historically low quarterly growth rate of about -0.9 in 2009.1. Also worth mentioning is that the previsions suggest a mild signal of a starting recovery in 2009.2 for since we expect milder losses. However, one should wait until updated data will be added to the model to consider whether this relatively mild signal will finally become the floor of the recession.

In addition to GDP forecasts, the model computes accurate forecasts for the whole set of indicators since their specifications are dynamically complete inside the model. The accuracy of these forecasts is crucial in the forecasting exercise to address the question of how surprises in these indicators affect the expected changes in GDP predictions. Table 4 (Panel B) shows the forecasts for the next unavailable month of each indicator.

Figure 4 shows an example of how this forecasting procedure works. On the day before the last release of IPI data, the figure shows the expected GDP growth rates for 2009.01 which are associated to different potential releases of IPI annual growth rate. According to the current negative economic situation, the model will forecast negative GDP growth rates for any reasonable realization of IPI annual growth rates. In fact, IPI would have to grow almost 30 annual percentage points to convert the IPI signal into positive forecasts of GDP growth rates. The actual IPI figure was -16.73 and this value implied a GDP growth forecast of -0.91.

One of the interesting output predictions of the dynamic factor model estimates, are the weights or cumulative impact of each indicator to forecast GDP growth. The weights (standardized to sum 1) of the indicators in forecasting GDP growth are shown in Table 5[11]. According to the characteristic of the model, rows labeled as 2008.06 and 2008.09 reveal that, when GDP is published, the cumulative forecast weights of all the indicators on GDP forecasts are zero.[12] The series only have weights different from zero during the periods in which they are available and the corresponding GDP is not. As can be seen in the table, these weights change according to the information available in each period of time. For example, in the row labeled 2008.12, the indicators contributing in a higher scale to form GDP forecasts are Social Security Contributors (weight of 0.60), and to less extent the Services Purchasing Managers Index (weight of 0.24). When all the indicators are available (row 2008.10), Sales is the one with the largest cumulative weight (0.45) in forecasting GDP, decreasing substantially the weight of the Social Security Contributors (0.21). When there is none of the inf

3.2. Real-time assessment of the recent downturn

Although examining the forecasting accuracy of new proposals by using out-of-sample exercises is an extended exercise, Stark and Croushore (2002) show that this might not be enough to address the performance of a model. They argue that the measures of a forecast error can be deceptively lower when using latest-available data rather than pure real-time data. According to this reasoning, in this section we examine the real time accuracy of the model against other standard alternatives.

For this purpose, we have constructed different datasets that give the forecasters an overview of the data available at any given day of the last year. Our first dataset is dated on the 20th of February of 2008 and we added new datasets to this overview every time that new releases came available until the 25th of January 2009. Therefore, we created a composition of 70 different datasets.

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[11] These cumulative weights are difficult to calculate with missing observations. In the way we have calculated can be interpreted as the weights of each variable if the forecast of GDP assuming that the only available information for the whole period were the series available in period t. For a detailed explanation of these weights see Camacho and Perez Quiros (2010)

[12] The published data is a *sufficient* statistic for the actual figure of GDP and its cumulative forecast weight is one.

With these datasets we computed real time forecasts for the four quarters of 2008 which are plotted in Figure 5.[13] This figure helps us to address a question that has been the source of many debates in the Spanish economy: When did the authorities realize that the downturn had started? It is worth recalling that forecasting this turning point was a rather difficult task. The financial turmoil had increased the forecast uncertainty to forgotten levels. In addition, at the beginning of the recession period, the financial variables and the soft indicators were giving signals of recessions that were not associated with clear signals from real activity. Finally, it turned out to be the first negative quarterly growth in fifteen years of sustainable growth. Despite the difficulties associated to the turning point identification, this figure shows that signals of a business cycle turning point started to become clear around the summer of 2008[14].

To examine the evolution of the daily forecasts and their uncertainty in each forecasting period more profoundly, Figure 6 shows the daily evolution of the Spain-STING forecasts for 2008.3 during the nine month forecasting period initiated at the beginning of 2008 together with their one standard error bands. For comparison purposes, forecasts from a standard autoregressive model of order 2 (top line) and the actual GDP growth values (bottom line) are added to the figure. This figure displays several noticeable features which illustrate the advantages of real-time forecasting with the Spain-STING model against traditional forecasts. Both forecasts display decreasing patterns as the impact of the global downturn increasingly affected the Spanish economy. However, the Spain-STING forecasts are much more reliable. This model anticipated negative growth rates for 2008.3 since June while the AR forecasts never fell below 0.47. The final release of this figure (dotted line) was -0.2.

Figure 6 can also help us to illustrate an additional advantage of the Spain-STING

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[13] To make Figure 5 readable, confidence bands have been omitted. Uncertainty can be examined in Figure 6.

[14] The time of this first negative forecast is compatible with the time of decline in activity that we found in figure 2. As we can see in Figure 5, we have had systematic positive surprises in GDP growth during 2008, i.e. positive evolution of the idiosyncratic shocks, that systematically increased the forecast of GDP growth to levels above the forecast of the common component of activity.

model which has to do with the frequency of the reactions. The Spain-STING model changes its predictions whenever any of the indicators used to construct the model is updated whereas the AR model reacts only twice, when GDP for quarters 2008.1 and 2008.2 become available. In particular, at the beginning of the forecasting period in February, the Spain-STING forecast of GDP about 0.55 percentage points. From this date, the forecasts initiate a decreasing pattern until September when the forecasts stabilized at around its final value of -0.2.

The negative trend followed by the Spain-STING forecasts is marked by several sudden slowdowns. The first substantial decrease in GDP previsions occurred in June 27th when the Industrial Confidence Indicator, the Retail Sales Confidence Indicator, and Total Sales of Large Firms became available. Their respective figures were -17.1, -24.7 and -6.12. They represented unprecedented low values which led the GDP forecasts to moderations from around 0.21 to 0.11 percent.

The sharpest decrease in GDP forecasts occurred at the beginning of July, when the series of Social Security Contributors in June released negative annual rates for the first time since its publication and at the same time the Services Purchasing Managers Index reached its all time lowest value. According to the remarkable bad news reflected by these indicators, the expected GDP experienced a sharp reversal to -0.06 percent. Notably, from this day until the end of the forecasting period, the actual growth for that quarter remained within the confidence bands. However, reflecting the subsequent news, expected GDP was sharply revised and reduced from the earlier -0.13 to -0.26 percent in September.

Finally, using the information up to January 2009, the model suggests that a recession is already under way and that there are no clear signals of recovery in the next few months.

4. Conclusion

In this paper, we provide a simple mathematical framework within which we are tracking the short term evolution of GDP growth rate in Spain from 1990.01 to 2009.01.

We think that this constitutes a noticeable contribution to the literature on forecasting the Spanish GDP growth since it deals with all the data problems that characterize the real time forecasting. The method is based on small scale dynamic factor models which allow the user to evaluate the impact of several monthly relevant indicators in quarterly growth forecasts.

One output of the dynamic factor model proposed in the paper is the factor itself. We provide evidence that the factor can be considered as a trustworthy indicator of the Spanish economic developments in the last two decades. In addition, the model has proved its effectiveness in real time forecasting by using pure real-time databases which contain the information sets that were available at the time of the forecasts. We also concluded that the model was able to anticipate the sudden and sharp recent downturn. For these reasons, we consider that the model can be useful to construct accurate forecasts of the ongoing Spanish economic developments.

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Appendix

This appendix describes the state space representation of the dynamic factor model stated in Section 2. Let $0_{m,l}$ and $1_{m,l}$ be matrices of $m\times l$ zeroes and ones, and I_m the m-dimensional identity matrix. Let us assume that p=2, q=2 r=2, and that all the variables are observed at monthly frequency. Finally, since all indicators are treated in the same way, let us assume that we use just one indicator, and then k=1. The observation equation, $Y_t = Hs_t + w_t$ with $w_t \sim iN(0,R)$, can be expressed as

$$Y_t = (y_t, z_t)',$$

$$w_t = 0_{2,1},$$

$$R = 0_{2,2},$$

$$s_t = (f_t,\ldots,f_{t-11},u_{xt},\ldots,u_{xt-5},u_{1t},u_{1t-1})'.$$

The matrix H is

$$H = \begin{pmatrix} H_{11} & 0_{1,7} & H_{12} & 0_{1,2} \\ H_{21} & H_{21} & 0_{1,6} & H_{22} \end{pmatrix},$$

where, $H_{12} = \begin{pmatrix} \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} \end{pmatrix}$, $H_{11} = \beta_1 H_{12}$, $H_{21} = \beta_2 1_{1,6}$ and $H_{22} = \begin{pmatrix} 1 & 0 \end{pmatrix}$.

In this example, the transition equation, $s_t = Fs_{t-1} + v_t$ with $v_t \sim iN(0,Q)$, can be stated as follows. Let Q is a diagonal matrix in which the entries inside the main diagonal are determined by the vector

$$(\mathrm{var}(f_t), 0_{1,11}, \mathrm{var}(u_{xt}), 0_{1,5}, \mathrm{var}(u_{1t}), 0)'$$

The matrix F is

$$F = \begin{pmatrix} F_1 & 0_{12,6} & 0_{12,2} \\ 0_{6,12} & F_2 & 0_{6,2} \\ 0_{2,12} & 0_{2,6} & F_3 \end{pmatrix},$$

Where

$$F_1 = \begin{pmatrix} \phi_{f1} & \cdots & \phi_{f6} & \cdots & 0 & 0 \\ 0 & 1 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & 0 \end{pmatrix}, \; F_2 = \begin{pmatrix} \phi_{y1} & \cdots & \phi_{y5} & \phi_{y6} \\ 0 & \cdots & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 1 & 0 \end{pmatrix}, \text{ and } F_3 = \begin{pmatrix} \phi_{z1} & \phi_{z2} \\ 1 & 0 \end{pmatrix}.$$

Table 1. Data description

Indicators Selected for the Spain-STING Model:

Variable	Acronyms	Source	Periodicity/ Indicator	Sample	Reporting Lags
GDP growth	GDP	SSI	Quarterly/Hard	1992.1-2008.4	+45 days
Industrial Production Index (excl.. energy)	IPI	SSI	Monthly/Hard	1993.01-2008.11	+35days
Total Sales of Large Firms	Sales	AT	Monthly/Hard	1996.01-2008.11	+32 days
Social Security Contributors	SSC	ML	Monthly/Hard	1996.01-2008.12	0
Retail Sales Confident Indicator	RS	EC	Monthly/Soft	1990.01-2008.12	0
Services Purchasing Managers Index	PMI Serv.	ISM	Monthly/Soft	1999.08-2008.12	+2 days
Industrial Confident Indicator	ICI	EC	Monthly/Soft	1990.01-2008.12	0
Imports	Imports	ME	Monthly/Hard	1992.01-2008.10	+50days
Exports	Exports	ME	Monthly/Hard	1992.01-2008.10	+50days
Overnight Stays (Nights Spent by foreigners in hotels)	Stays	SSI	Monthly/Hard	1991.01-2008.11	+23 days
Cement Consumption	Cement	CPA	Monthly/Hard	1992.01-2008.10	Not a fix date

Notes. SSI refers to Spanish Statistical Institute, AT refers to Agencia Tributaria (Spanish IRS), ML refers to Ministry of Labor, EC refers to European Commission, ISM referst to Institute for Supply Management, ME refers to Ministry of Economy, and CPA refers to Cement Producers Association.

Table 2. Data set available on the day of the forecast

	GDP	ICI	RS	PMI	IPI	Sales	Exports	Imports	Stays	Cement	SSC
2008.06	0.15	-17.10	-24.70	36.70	-10.26	-9.67	-4.75	-4.22	-2.15	-32.73	-0.07
2008.07	na	-16.40	-25.60	37.10	-5.31	-6.25	6.65	-2.81	0.88	-26.50	-0.52
2008.08	na	-17.50	-35.40	39.00	-8.43	-6.58	2.75	-2.10	-1.33	-24.32	-0.85
2008.09	-0.24	-22.10	-32.90	36.10	-10.27	-8.50	8.50	-4.39	-1.84	-30.06	-1.48
2008.10	na	-27.20	-29.80	32.20	-13.79	-11.32	0.33	-12.34	-4.54	-33.65	-2.41
2008.11	na	-32.60	-26.20	28.20	-16.73	-13.21	na	na	-10.71	na	-3.43
2008.12	na	-37.60	-33.90	32.10	na	na	na	na	na	na	-4.32
2009.01	na	na	na	na	na	na	na	na	na	na	na
2009.02	na	na	na	na	na	na	na	na	na	na	na
2009.03	na	na	na	na	na	na	na	na	na	na	na
2009.04	na	na	na	na	na	na	na	na	na	na	na
2009.05	na	na	na	na	na	na	na	na	na	na	na
2009.06	na	na	na	na	na	na	na	na	na	na	na

Notes. See Table 1 for acronyms. Figures labelled as "na" refer to either missing data or data that are not available on the day of the forecast.

Table 3. Factor loadings

GDP	ICI	RS	PMI	IPI	Sales	Exports	Imports	Stays	Cement	SSC
0.13	0.05	0.03	0.05	0.07	0.06	0.01	0.04	0.02	0.05	0.06
(0.04)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)

Notes. See Table 1 for acronyms. Standard errors are in parentheses. Data set ends in December 2008.

Table 4. Model-based forecasts

Panel A				Panel B	
Series	2008.4	2009.1	2009.2	Series	Next Month
				ICI	-40.32
GDP	-0.92	-0.91	-0.80	RS	-33.79
	(0.19)	(0.22)	(0.25)	PMI	29.47
				IPI	-18.46
				Sales	-14.95
				Exports	3.12
				Imports	-11.77
				Stays	-8.77
				Cement	-36.05
				SSC	-4.78

Notes. See Table 1 for acronyms. Standard errors are in parentheses. Data set ends on December 2008.

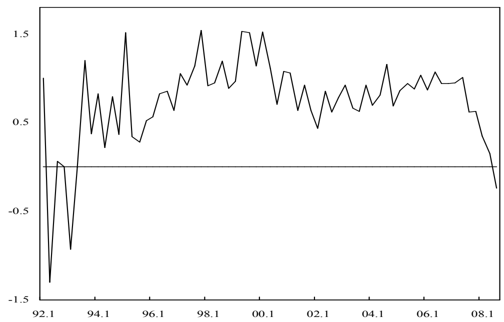
Table 5. Cumulative weights

	GDP	ICI	RS	PMI	IPI	Sales	Exports	Imports	Stays	Cement	SSC
2008.06	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2008.07	0.00	0.04	0.02	0.08	0.05	0.45	0.01	0.05	0.01	0.09	0.21
2008.08	0.00	0.03	0.02	0.08	0.05	0.47	0.01	0.05	0.01	0.08	0.20
2008.09	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2008.10	0.00	0.04	0.02	0.08	0.05	0.45	0.01	0.05	0.01	0.09	0.21
2008.11	0.00	0.04	0.02	0.09	0.05	0.56	0.00	0.00	0.01	0.00	0.23
2008.12	0.00	0.10	0.06	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.60
2009.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2009.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2009.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2009.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2009.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2009.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes. See Table 1 for acronyms. Data set ends on 02/11/08.

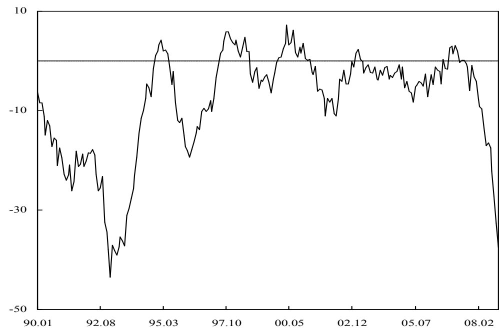
Figure 1. Time series used in the model

GDP growth rate



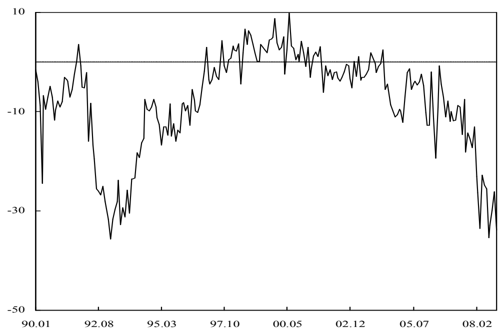
Sample 92.1-08.3

Industrial Confident Indicator



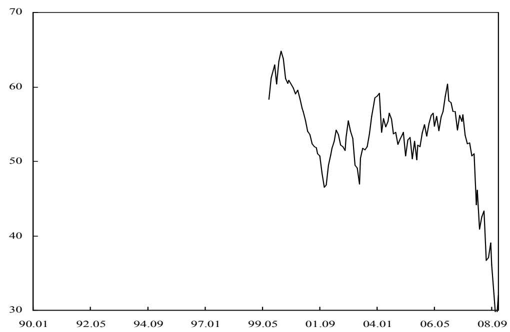
Sample 90.01-08.12

Retail Sales Index



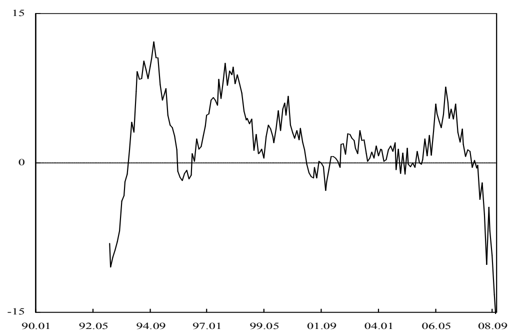
Sample 90.01-08.12

Production Manufacture Index



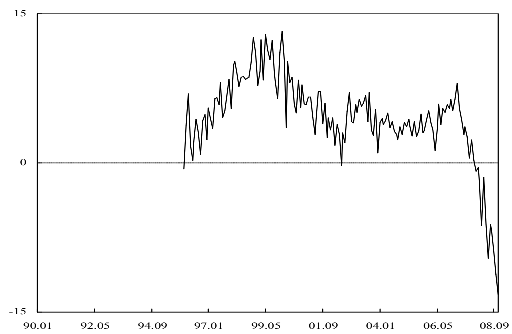
Sample 99.08-08.12

Industrial Production



Sample 93.01-08.11

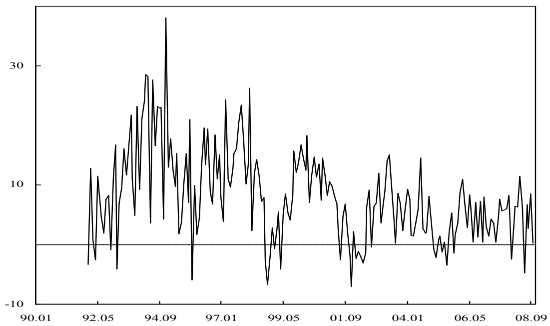
Total Sales of Large Firms



Sample 95.01-08.11

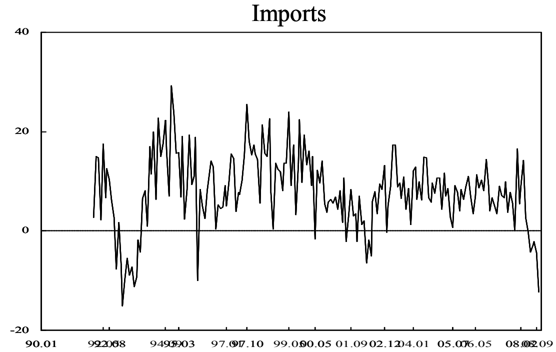
Figure 1. Time series used in the model (continued)

Exports



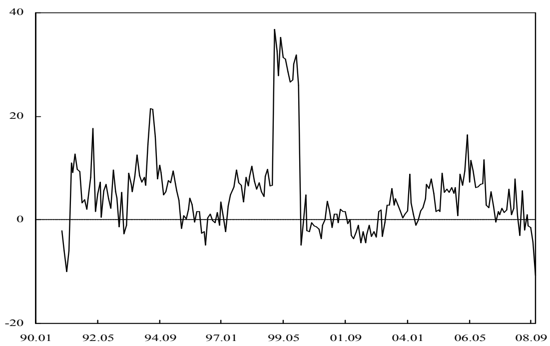
Sample 92.01-08.10

Imports



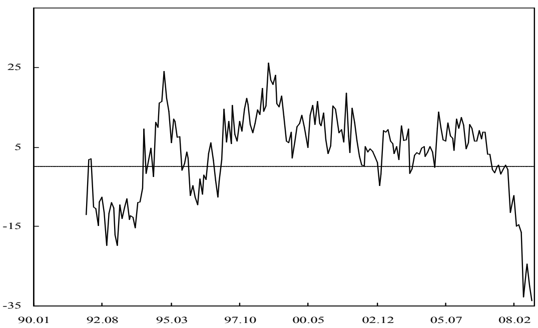
Sample 92.01-08.10

Overnight Stays



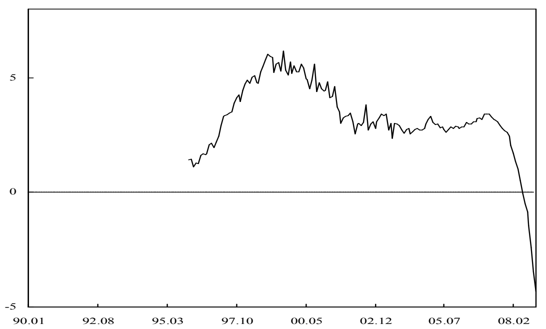
Sample 91.01-08.11

Apparent Consumption of Cement



Sample 92.01-08.10

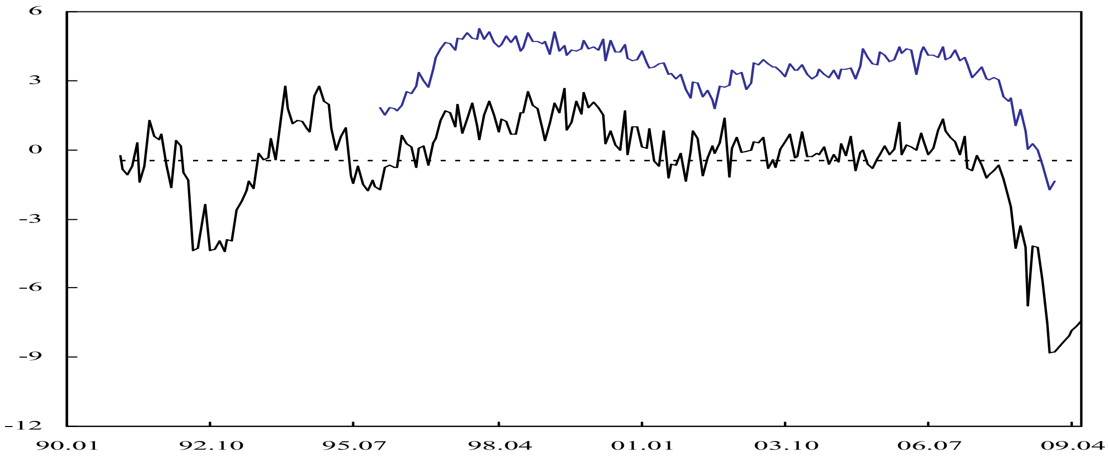
Social Security Contributions



Sample 96.01-08.12

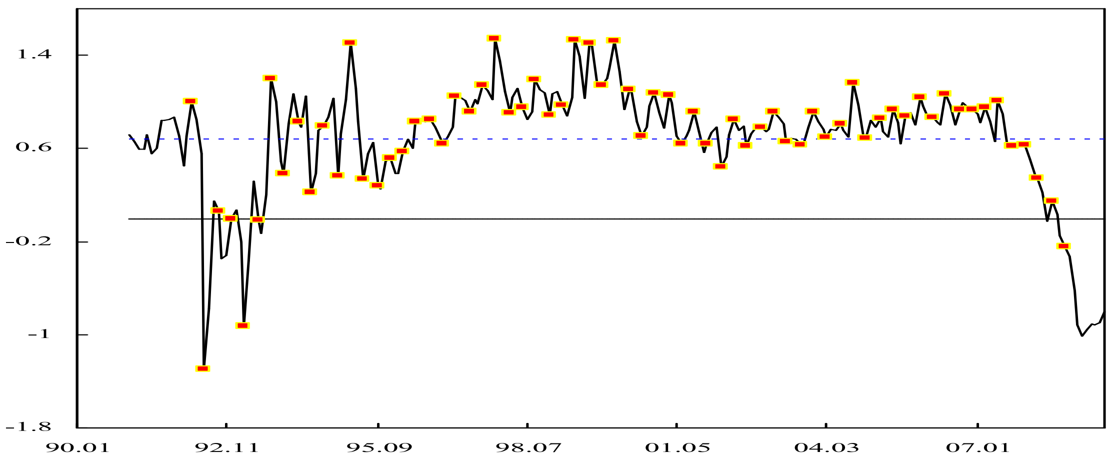
Notes. GDP is in quarterly growth rates. Soft indicators are in levels. Hard indicators are in annual growth rates.

Figure 2. Common factor and *Indicador Sintético de Actividad*



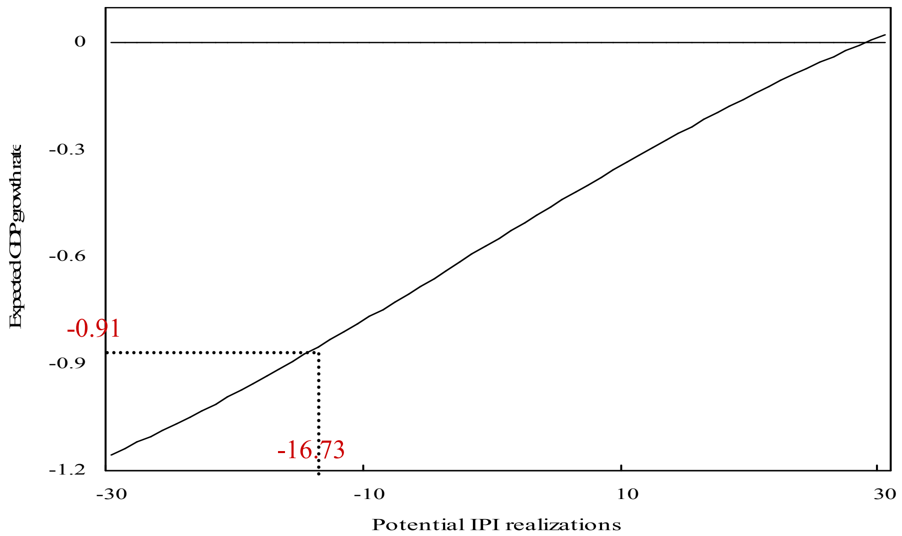
Notes. The factor (bottom line) is estimated from 91.01 to 09.06 with information in December 2008. Top line refers to the annual growth rates of *Indice Sintético de Actividad*. Dotted line refers to the averaged value.

Figure 3. GDP second growth rate: actual and estimates



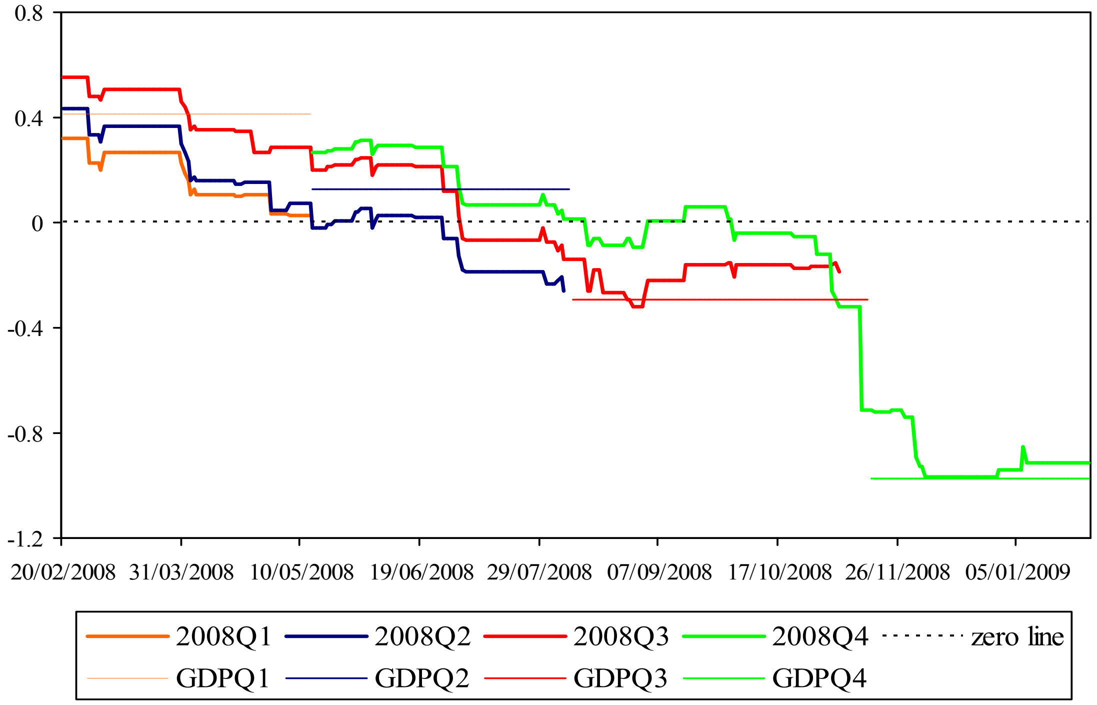
Notes. GDP growth rates are estimated from 91.01 to 09.06 with information on December 2008. Dots over this line refer to actual data (third month of each quarter; last one in 2008.3). Dotted line refers to the averaged value.

Figure 4. GDP forecast in 2009.1 and IPI potential releases



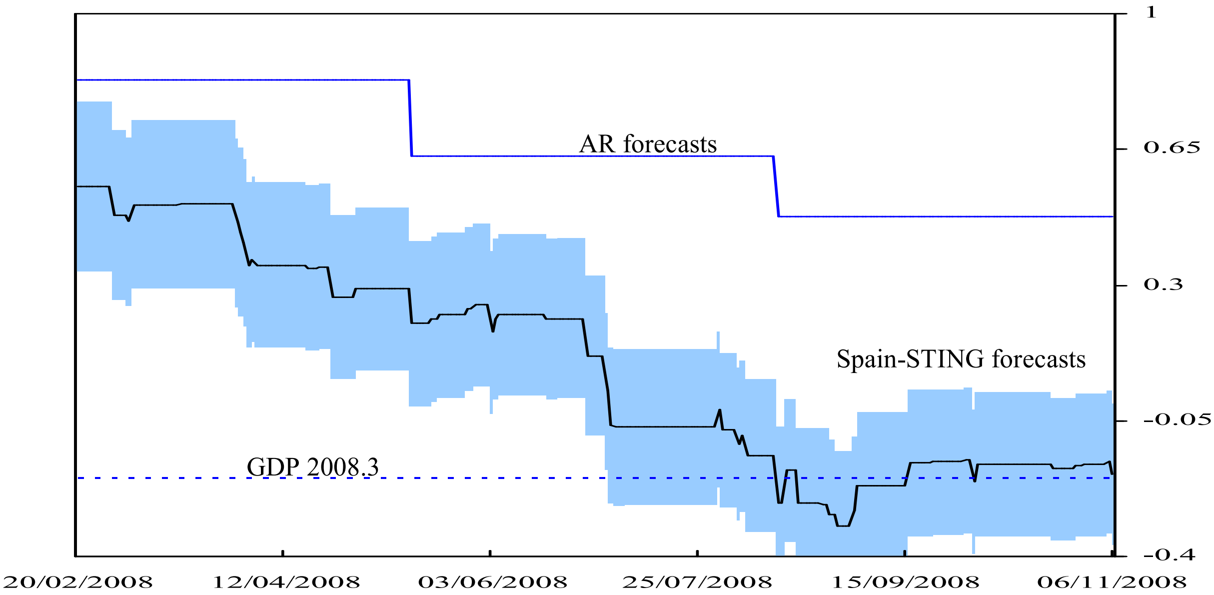
Notes. Potential releases of IPI in annual growth rates and their associated expected GDP growth rate for 2009.1. Actual IPI was -16.73 which refer to an expected growth rate of -0.91.

Figure 5. Real time growth rates forecasts for 2008Q1, 2008Q2, 2008Q3 and 2008Q4
20/02/2008 – 25/01/2009



Notes. The figure plots the real time forecast of growth rates of GDP and its realization. For example, the green thick line shows the forecast for the fourth quarter of GDP from the first day in which the model produces the forecasts (20/02/2008). The thin green horizontal line is the realization.

Figure 6. Real time forecast of growth rate for 2008.3



Notes. Spain-STING forecasts are calculated each day of the nine-month forecasting periods described in the text. Shaded area refers to one standard error bands. Top and bottom lines refer to AR (2) forecasts and actual GDP, respectively.