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INTEGRATED MODEL OF SHORT-TERM FORECASTING OF THE SPANISH ECONOMY (MIPRED MODEL)*

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This paper presents a methodology for predicting in real-time Gross Domestic Product (GDP) and its demand components (private consumption, public consumption, investment in equipment, investment in construction, exports and imports) simultaneously. The model, on the one hand, consists of a set of dynamic factor models for both GDP and its demand components, which will provide individual forecasts for each. On the other hand, a balancing procedure is incorporated to ensure the transversal consistency of these forecasts, thus providing a consistent set of estimates based on the statistically most useful indicators about current economic activity and demand developments. The methodology is applied to the Spanish economy, presenting real-time quarterly forecasts of GDP and its demand components.

Key words: dynamic factor models, short term economic analysis, spanish economy, Kalman filter, forecasting, nowcasting, national accounts, balancing.

JEL classification: C22, C53, C82, E27.

Real time forecasts of GDP are very much discussed in the recent literature. Advances in information technology have made available to the researchers a great amount of information with unprecedented update frequency. Therefore, most central banks or international institutions which are in charge of monitoring and analysing business cycle developments, have estimated mod-

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els in order to update at high frequency the assessment of business cycle conditions. Recent examples include Angelini *et al*. (2008) or Camacho and Pérez-Quirós (2010) for the Euro area, Aruoba *et al*. (2009), Giannone *et al*. (2008) or Higgings (2014) for the US, Liu *et al*. (2010) for Latin America, Barhoumi *et al*. (2008) for France, Nunes (2005) for Portugal, etc.

For the case of Spain, three models have already been published. Camacho and Pérez-Quirós (2008) constructed a small scale factor model for the Bank of Spain (Spain-Sting). Cuevas and Quilis (2011) proposed a large scale model for the Ministry of Economy (FASE) and Camacho and Domenech (2011) constructed another small scale model for BBVA (MICA), where they pay special attention to several financial variables available to BBVA. More recently, Cuevas *et al*. (2015) extended the coverage of those models to forecast simultaneously the GDP and its demand-side breakdown (consumption, investment, exports and imports).

This paper relies heavily on the former model, providing an innovative and updated approach to monitor the key macroeconomic variables that determine the stance of the fiscal policy. The key variables that the government has to forecast when preparing macroeconomic and fiscal projections are GDP and its components. The government projects the main macro variables with a time horizon of one to four years ahead, depending on the exercise that has to undertake. Obviously, all the projections are based on short term forecasts. If the current and following quarters are accurately forecasted, the one-year ahead forecast will be reliable and the forecasts for further years ahead will be more precise.

It is well established in the literature that dynamic factor models that exploit the information content in the join dynamics of the macro variable and related timely indicators are the best tools for short term forecasting, as shown in the recent surveys of Banbura *et al*. (2013) or Camacho *et al*. (2013). Therefore, the AIReF, in line with what has been done by other institutions, relies on its own model for analysing the implications of current conditions of the economy for budgetary stability and financial sustainability.

Obviously, our proposed model cannot ignore previous attempts made to model the Spanish economy data. There is some overlap with previous models, although there are some definitely distinct characteristics, which make our model different with respect to the previous specifications.

The main distinctive feature of our approach is that we forecast on a real time basis not only GDP, but also its complete breakdown from the expenditure side. We have specific models to forecast private consumption, public consumption, investment in capital goods, investment in construction, exports and imports. We integrate all of them in one consistent set of forecasts for all the demand components of GDP by using the balancing technique developed in van der Ploeg (1982, 1985). The name of the model, MIPred makes reference to that integration, (Modelo Integrado de Predicción in Spanish, Integrated Prediction Model in English).

To our knowledge, this is the first integrated methodology to forecast in real time all the variables that define the core of the macroeconomic scenario (GDP and its demand-side components), not only for the case of Spain but for any other country. All the automatized methods developed in the literature forecast only GDP or, additionally, the variables included as indicators in the model.

A second distinctive feature is that, for most of the variables forecasted in the model, and, especially for GDP, we only use information freely available to the general public. We do not rely on any confidential series or any other series whose information is restricted to those who pay a fee. Therefore, the results of the model are fully replicable by any researcher and the forecasts are completely transparent and easy to interpret. This replicability, although not critical from a technical view, is relevant for public institutions that want to promote transparency.

Finally, a third distinctive feature is that the selection of indicators has been made using the proposed methodology of Camacho and Pérez-Quirós (2010). We start from a very parsimonious specification, in line with Stock and Watson (1991), and we only extend the model if the variance of GDP explained by the common factor increases. The variables included in the model are selected following the order of putting in first the one contributing most to increase the variance of the factor. We stop the process of extending the model when any additional variable biases the factor toward sectors whose indicators are correlated among themselves, following idiosyncratic components, but which do not have any additional explanatory power over GDP movements. Details of the bias-induced problem can be found in Álvarez *et al*. (2016).

The paper is structured as follows. Section 1 reviews the indicators that have been selected for each macro aggregate and the preliminary processing they have gone through. The econometric methodology is explained in section 2, where we discuss the detailed structure of the dynamic factor model, how we have dealt with missing observations and the balancing procedure used to ensure the transversal consistency of GDP forecasts with the independent forecasts of its demand components. Section 3 presents the output of the model and section 4 concludes.

1. Data

1.1. Selection of indicators

The selection process was carried out under the premise that the indicators should be available timely and should provide a meaningful economic signal of the demand components of the national economy. The estimation sample covers from 1990.Q1 until the last observation available.

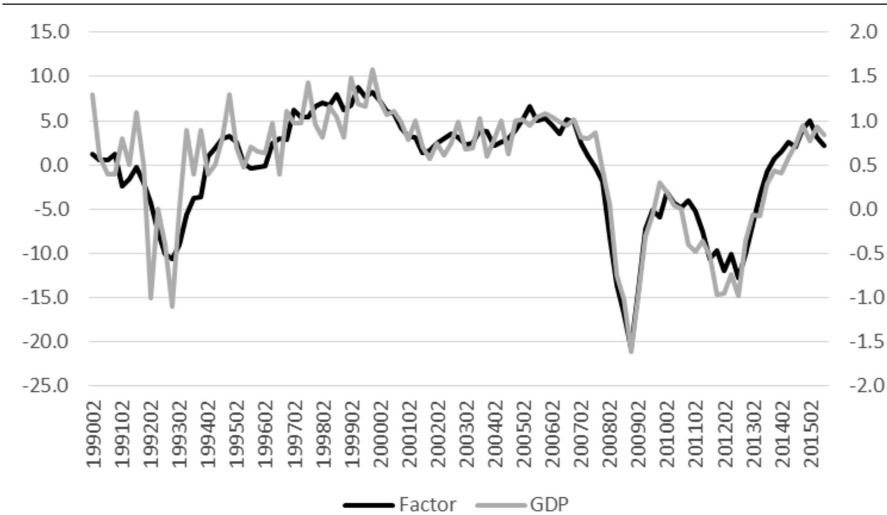
The criteria for the choice of these variables is to consider all the main indicators used in the compilation of the Quarterly National Accounts, see Álvarez (1989), Martínez and Melis (1989), INE (1993) and Álvarez (2005). To fulfill this goal, we have prepared a set of monthly and quarterly indicators, both real and financial, which facilitates a fairly comprehensive basis for analyzing and monitoring GDP and its demand components[1]. In this way, this set offers a high-frequency approximation to the behavior of these main macroeconomic aggregates.

(1) The starting point for the selection of indicators is the list of Cuevas and Quilis (2011). For the GDP components we use the corresponding variables. For example, if for the aggregate GDP we use Industrial Production, for aggregate consumption we use Industrial Production of consumption goods. This implies that indicators used in the modelization of the components are usually not included in the GDP except when the component indicator is not available (for example, for imports we use Industrial Production because there is not an indicator that capture Industrial Production with foreign parts needed.

The selection of the final set of indicators has followed a stepwise procedure, as suggested in Camacho and Pérez-Quirós (2010). The starting point is a minimal set of indicators for each aggregate that represents unequivocally its behavior. For instance, in the GDP model, the "core" group is formed by key economic variables: index of industrial production (supply side indicator of GDP), total deflated sales of large firms (demand side of GDP), large firms compensation of employees deflated (income side of GDP) and employment measured by the labor force survey. This initial selection follows Stock and Watson (1991) and try to mimic the three dimensions of GDP (demand, supply and income) and its direct projection on the labor market (employment). In addition, given the knowledge we have about the determinants of the last recession, we include an indicator of financial conditions (total credit to private resident non-financial sectors) and, as a leading soft indicator the PMI of services, which is freely available. Just with these indicators, we obtain a factor (also named tracker) that it is strongly correlated with GDP growth (the factor is calculated in monthly frequency but can be transformed into quarterly). In particular, the correlation is as high as 0.81 for the 1990.Q1-2015.Q1 sample and 0.83 when the sample starts in 1995.

The selection procedure adds at each step the indicator which is most correlated with the dynamic factor model in order to estimate a new aggregate tracker. If the correlation of the new aggregate tracker increases, the indicator is added to the model. Otherwise, the indicator is dropped from the list. The step is repeated until the full list of possible indicators is exhausted. The final selection produces a correlation of 0.91 for the full sample and 0.96 for the sample starting in 1995. The selected variables are displayed in the first panel of Table 1.

Figure 1: GDP GROWTH RATE AND COINCIDENT FACTOR



Source: INE and Author's calculation.

Table 1: LIST OF INDICATORS

	Starting date	Unit	Source	Release delay
GROSS DOMESTIC PRODUCT (GDP)				
Social security system: registered workers	2001m1	Thousand people	Ministry of Labour	t+1
Employed Labor Force Survey	1990 q1	Thousand people	National Statistical Institute	t+30
Index of Industrial Production	1990 m1	Volume index	National Statistical Institute	t+35
Apparent consumption of cement	1990 m1	Thousand tons	Cement Producers Association	t+22
Electric power consumption	1990 m1	Million Kw/h	Spanish Electricity Network	t+1
Imports of goods deflated by the unit value index	1990 m1	Deflated value index	Tax State Agency/GDMA	t+50
PMI services index for Spain	1999m8	Index between 0 and 100	Markit economics	t+1
Credit to companies and households deflated by consumer price index	1995 m1	Deflated value index	Bank of Spain	t+35
Large companies sales. Deflated total sales	1995 m1	Deflated value index	Tax State Agency	t+35
Large companies sales. Deflated compensation of employees	1995 m1	Deflated value index	Tax State Agency	t+35
HOUSEHOLDS CONSUMPTION				
Index of Industrial Production: consumption goods	1990 m1	Volume index	National Statistical Institute	t+35
Real wage income indicator	1990 m1	Deflated value index	General Directorate Macro. Analysis	t+35
Retail trade index, deflated	1995 m1	Deflated value index	National Statistical Institute	t+27
Consumer confidence index	1990 m1	Index between -100 and 100	European Commission	t-1
Imports of consumption goods deflated by the unit value index	1990 m1	Deflated value index	Tax State Agency/GDMA	t+50
Credit to households for consumption deflated by consumer price index	2003 m1	Deflated value index	Bank of Spain	t+35
Large companies sales. Consumption sales deflated	1995 m1	Deflated value index	Tax State Agency	t+35
Large companies sales. Number of recipients	1995 m1	Deflated value index	Tax State Agency	t+35
GOVERNMENT CONSUMPTION				
Social security system: registered workers in public administration	1995 m1	Thousand people	Ministry of Labour	t+1
State nominal final consumption deflated	1995 m1	Deflated value index	General Audit Office	t+35
Withholding employment income of workers in the public administration deflated	1996 m1	Deflated value index	Tax State Agency	t+35
FIXED CAPITAL INVESTMENT: EQUIPMENT				
Index of Industrial Production: equipment	1990 m1	Volume index	National Statistical Institute	t+35
Cargo and bus registrations	1990 m1	Units	General Directorate of Traffic	t+1
Industrial Confidence Indicator: equipment	1993 m1	Percentage balances	Ministry of Industry, Energy and Tourism	t-1
Imports of capital goods at constant prices	1990 m1	Deflated value index	Tax State Agency/GDMA	t+50
Credit to resident companies deflated	1995 m1	Deflated value index	Bank of Spain	t+35
IBEX-35 Share price index	1990 m1	Index, Jan. 1994=100	Madrid Stock Exchange	t+1
Utilization of productive capacity	1990 q1	Percentage of utilization	Ministry of Industry, Energy and Tourism	t+27
FIXED CAPITAL INVESTMENT: CONSTRUCION				
Social security system: registered workers in construction	2001 m1	Thousand people	Ministry of Labour	t+1
New building visas: total area to build	1991 m11	Buildable floorage (m2)	Ministry of Public Works	t+35
Number of housing transaction: new housing	2007 m1	Units	Ministry of Public Works	t+35
Apparent consumption of cement	1990 m1	Thousand tons	Cement Producers Association	t+22
Confidence index in construction sector	1993 m1	Percentage balances	Ministry of Industry, Energy and Tourism	t-1
Credit to households for housing acquisition and rehabilitation	2003 m1	Deflated value index	Bank of Spain	t+35
Large companies sales. Construction sales deflated	1995 m1	Deflated value index	Tax State Agency	t+35
EXPORTS OF GOODS AND SERVICES				
Total entry of tourist	1995 m1	Thousand people	Ministry of Industry, Energy and Tourism	t+23
Foreign orders. Total industry	1993 m1	Percentage balances	Ministry of Industry, Energy and Tourism	t+23
Total exports of goods at constant prices	1990 m1	Deflated value index	Tax State Agency/GDMA	t+35
Tourism revenues	1990 m1	Deflated value index	Bank of Spain	t+23
World trade in goods	1991 m1	Volume index	Central Planning Bureau (Netherlands)	t+30
PMI index. Industry	1998 m2	Index between 0 and 100	Markit economics	t-1
Large companies sales. Exports sales deflated	1995 m1	Deflated value index	Tax State Agency	t+35
IMPORTS OF GOODS AND SERVICES				
Index of Industrial Production	1990 m1	Volume index	National Statistical Institute	t+35
Total imports of goods at constant prices	1990 m1	Deflated value index	Tax State Agency/GDMA	t+35
Balance of payments. Tourism payments	1996 m1	Deflated value	Bank of Spain	t+60
World trade in goods	1991 m1	Volume index	Central Planning Bureau (Netherlands)	t+20
PMI index. Industry	1998 m2	Index between 0 and 100	Markit economics	t-1
Large companies sales. Imports sales deflated	1995 m1	Deflated value index	Tax State Agency	t+35

Source: Author's compilation.

Although later on we will explain at length the econometric approach used to estimate the factor, Figure 1 represents the factor in quarterly growth rates and the evolution of GDP for the whole sample. As can be seen in the figure, the model that we select, which does not include GDP growth itself, shows an extremely close relation with GDP growth. All the turning points are perfectly captured, and it is noticeable that, even with this small set of variables, there is not much room for improvement in the fitting of GDP growth.

Regarding the GDP demand components, we repeat the same procedure to select the indicators finally chosen to obtain accurate estimation of each GDP component. Table 1 displays the list of the indicators selected for each variable of interest and its publication lag.

1.2. Preliminary processing

The main objective of the model is to provide a synthetic measure of the rate of growth of each macroeconomic variable. This goal requires identifying a reliable signal of growth to be fitted by the factor model. In order to emphasize the short-term information contained in the indicators, we have chosen as signals, for "hard" indicators, the regular first difference of the log time series, and for "soft" indicators, the levels of the series, as in Camacho and Pérez Quiros (2010). We consider these indicators in levels for two reasons. On the one side, according to the statistical offices, soft indicators are designed to achieve as high correlation as possible with the year-on-year growth of the coincident series, see European Commission (2006). On the other side, it is in levels how these indicators are interpreted in the industry, as can be seen when they are reported in the press.

For this filtering not to be distorted by the presence of seasonal and calendar factors, they have been removed by means of seasonal adjustment and time series techniques (Maravall and Gómez, 1996; Caporello and Maravall, 2004). We could have estimated the model directly with non-seasonally adjusted data, but following Camacho *et al*. (2015), we understand that the noise induced by estimating the model with raw data distorts the results and produce worse forecasts than those produced by using seasonally adjusted data. Obviously, out of consistency, all the variables have to be corrected by the same type of factors (seasonal and calendar factors).

2. Econometric approach

The econometric approach used in this paper integrates three main elements. In the first place, a set of dynamic factor models that represent in a compact and parsimonious way the joint dynamics of each macro aggregate and the corresponding short-term indicators. The second element is the treatment of missing observations that can arise as a result of differences in the timing of data publication or as a result of the combination of time series sampled at different frequencies (e.g. monthly and quarterly). Finally, the third element of the methodology is a balancing procedure that ensures in an objective and sensible way the consistency of the GDP forecasts with the forecasts of its components.

2.1. Design of trackers using dynamic factor analysis

For each macro aggregate listed in the previous section (Y_t) a tracker ($f_{j,t}$) is estimated by means of a dynamic one-factor model which captures in a parsimonious way the dynamic interactions of a set of monthly economic indicators ($Z_{i,j,t}$). Given that we are combining quarterly and monthly information for N series, it is important to clarify the notation from the beginning. The subindex "t" refers to quarterly time, i.e., 1990.Q1, 1990,Q2, etc… the subindex "j" refers to monthly time in a given quarter, and it takes the values 1, 2, 3 referring to the first, second or third month of quarter “t”. Finally, the subindex “i” refers to the corresponding ith series when we have more than one series. Therefore, (Y_t) is a quarterly series, ($f_{j,t}$) is a monthly series and ($Z_{i,j,t}$) is the ith monthly series.

The common factor of the system ($f_{j,t}$) is estimated by means of the Kalman filter, after formulating the factor model in state space form. The entire procedure has been adapted to operate with unbalanced data panels, following the procedure of Mariano and Murasawa (2003).

Dynamic factor analysis is based on the assumption that a small number of latent variables generate the observed time series trough a stochastically perturbed linear structure. Thus, the pattern of observed co-movements is decomposed into two parts: commonality (variation due to a small number of common factors) and idiosyncratic effects (specific elements of each series, uncorrelated along the cross-section dimension).

In this paper we assume that the observed, stationary growth signals of k_1 monthly indicators are generated by a factor model:

$$z_{i,j,t} = \lambda_i f_{j,t} + u_{i,j,t} \qquad [1]$$

Being:

- $t = 1 \ldots T$, quarterly time index.
- *$j = 1 \ldots 3$ month within quarter index.*
- $i = 1 \ldots k_1$
- $z_{i,j,t}$ = i-th indicator growth signal at time j,t.
- λ_i: i-th indicator loading on common factor.
- $f_{j,t}$: common factor at time j,t.
- $u_{i,j,t}$: specific or idiosyncratic component of i-th indicator at time j,t.

The loadings λ_i measure the sensitivity of the growth signal of each indicator with respect to changes in the factor.

When k quarterly indicators –including the variable to track (Y_t)– are considered, we have to take into account that the quarterly indicators are related to monthly activity through time aggregation:

$$Y_t = \frac{1}{3}x_{3,t} + \frac{2}{3}x_{2,t} + x_{1,t} + \frac{2}{3}x_{3,t-1} + \frac{1}{3}x_{2,t-1} \qquad [2]$$

Where Y_t is the quarterly macroeconomic aggregate (or a quarterly tracker), and $x_{j,t}$ is the unobserved monthly macroeconomic aggregate (or unobserved monthly tracker).

The unobserved monthly macro aggregate has the same structure than [1]:

$$x_{j,t} = \lambda_Y f_{j,t} + u_{Y,j,t} \qquad [3]$$

The subindex Y is just to indicate that we are talking about the decomposition of the Y variable (i.e. GDP, household consumption, etc).

Therefore:

$$Y_t = \frac{1}{3}\lambda_Y f_{3,t} + \frac{2}{3}\lambda_Y f_{2,t} + \lambda_Y f_{1,t} + \frac{2}{3}\lambda_Y f_{3,t-1} + \frac{1}{3}\lambda_Y f_{2,t-1} + \frac{1}{3}u_{Y,3,t} + \frac{2}{3}u_{Y,2,t} + u_{Y,1,t} + \frac{2}{3}u_{Y,3,t-1} + \frac{1}{3}u_{Y,2,t-1} \qquad [4]$$

The case displayed in equation [4] refers to the variable we want to track. If we have some additional quarterly indicators, the structure will be the same (i.e. employment measured by the labor force survey).

Finally, in the special case of the k_2 soft indicators, which are considered in levels, given that they are related to the year on year growth of hard indicators, they need a long structure of the factor that covers 12 months. In addition, according to the literature [Camacho and Doménech (2011)] they usually present a leading behavior. Therefore, they are related to the annual growth rate of the series of interest, but with a few periods leading behavior. After trying for different leading periods, we conclude that three months is the preferred lead time, when the correlation between the indicator and activity is higher. Therefore, our specification for the soft indicator variables is:

$$S_{i,j,t,} = \lambda_i \left(f_{3,t+1} + f_{2,t+1} + \dots + f_{1,t-2} \right) + u_{i,j,t} \quad [5]$$

Being:

- $S_{i,j,t}$ = i-th soft indicator in levels at time j,t.
- $i = k_1+1 \dots k_1+k_2$
- λ_i: i-th indicator loading on common factor.
- $f_{j,t}$: common factor at time j,t.
- $u_{j,t}$: specific or idiosyncratic component of i-th soft indicator at time t.

Equations [1] to [5] do not consider the dynamics in the idiosyncratic part or in the factor structure. Therefore, inference about future activity cannot be made. The model should be expanded in order to adapt it to a time series framework, thereby adding a dynamic specification for the common factor and the idiosyncratic elements, in addition to the dynamics of the series sampled quarterly and the soft indicators.

A second-order autoregression, AR(2), provides a sufficiently general representation for the common factor, in the sense that it is the AR model of minimal order that can generate monotonic or oscillatory paths:

$$\begin{aligned} &(1-\varphi_1 B - \varphi_2 B^2) f_{j,t} = e_{f,j,t} \\ &e_{f,j,t} \sim iid\ N(0,1) \end{aligned} \quad [6]$$

In [6] B is the backward operator and the variance of the innovation has been normalized to one. Depending on the characteristic roots of $\phi_2(B)$ the model may exhibit a wide variety of dynamic behaviors.

We also consider an AR(2) specification for the dynamics of the specific elements, allowing for some degree of persistence:

$$\begin{aligned} &(1-\psi_{i,1} B - \psi_{i,2} B^2) u_{i,j,t} = e_{i,j,t} \\ &e_{i,j,t} \sim iid\ N(0, v_i)\ for\ i = 1 \dots (k_1 + k_2) \end{aligned} \quad [7]$$

$$\begin{aligned} &(1-\psi_{Y,1} B - \psi_{Y,2} B^2) u_{Y,j,t} = e_{Y,j,t} \\ &e_{Y,j,t} \sim iid\ N(0, v_Y) \end{aligned} \quad [8]$$

Finally, we assume that all innovations of the system are orthogonal.

Model [1]-[8] attempts to represent the static as well as the dynamic features of the data. We estimate the common and idiosyncratic factors using the Kalman filter, after a suitable reparameterization of the model in state-space form. The reparameterization requires the introduction of a state vector that encompasses all the required information needed to project future paths of the observed variables from their past realizations. In our case, this vector is:

$$\eta_t = [f_{3,t+1} \cdots f_{1,t-2}, u_{Y,3,t} u_{Y,2,t}, u_{Y,1,t}, u_{Y,3,t-1}, u_{Y,2,t-1}, u_{1,3,t} u_{1,2,t}, \ldots. u_{k1+k2,3,t} u_{k1+k2,2,t}]' \quad [9]$$

The corresponding measurement equation is:

$$Z_t = H\eta_t \quad [10]$$

With $Z_t = (Y_t, Z_{i,t}, S_{it})$ and H is a vector of coefficients that match the dynamics stated in [1], [4] and [5].

This equation allows us to derive the observed indicators from the (unobservable) state vector.

The transition equation completes the system and characterizes its dynamics:

$$\eta_t = G\eta_{t-1} + V_t \quad [11]$$

Where G is the matrix that capture the dynamic behavior in equations [6] to [8].

The innovations vector V_t is:

$$V_t = [\; e_{f,3,t+1} \cdots e_{f,2,t-2} \quad e_{Y,3,t} \cdots e_{Y,2,t-1} \quad e_{1,3,t} \ldots. e_{k1+k2,2,t} \;]' \quad [12]$$

V_t evolves as a Gaussian white noise with diagonal variance-covariance matrix as follows:

$$Q = E\left[V_t V_t'\right] = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & V_Y & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & V_{k1+k2} \end{bmatrix} \quad [13]$$

We assume that the time index t goes from 1 to T. The application of the Kalman filter requires $\Theta = [H, G, Q]$ to be known. This requirement is fulfilled using the maximum likelihood estimates of Θ, derived by means of numerical maximization of the likelihood function. Note that this optimization is feasible thanks to the iterative computations performed by the Kalman filter.

2.2. Dealing with missing observations

The fact that we have to combine monthly and quarterly frequencies imply that we have necessarily to deal with missing observations, because quarterly data are available only every three months. In addition, our monthly variables are not released simultaneously, and most of them are not available for the whole sample. Therefore, we have to confront daily with an unbalanced dataset, where we have missing observations both at the end and at the beginning of the sample.

In order to deal with this problem we follow Mariano and Murasawa (2003). The idea of this method is to substitute the missing observations with extractions from a random normal distribution. We then estimate a Kalman filter with time varying coefficients where the row that corresponds to the missing observations is multiplied by 0 and we add a noise.

The model is then estimated with this specification. After we estimate the model, the forecast and the filling in of the missing observations is done by substituting the missing value by the number obtained in the Kalman filter with the full matrix *H* not multiplied by 0 in any of its rows.

2.3. Balancing method

The application of dynamic factor models provides us with independent forecasts of the macro aggregates of MIPred (GDP, Households consumption, etc.). As we have seen, these forecasts combine the available information of the relevant short-term indicators with the dynamics of the macroeconomic variable in an efficient way, but do not take into account the transversal (static) constraints that link the macroeconomic variables. These constraints derive from the compilation process of the National Accounts and, in particular, from the decomposition of GDP from the expenditure side.

In order to incorporate these constraints in the forecasting process, we have relied on a balancing procedure that ensures their internal consistency. In particular, we use the one proposed by van der Ploeg (1982, 1985) for the compilation of the National Accounts[2].

The van der Ploeg method starts with an initial (unbalanced) set of forecasts for each macro aggregate ($Y_{m,t}$) where $m = 1..., M$, and a measure of their uncertainty embedded in the variance-covariance matrix Σ_t. The final (balanced) forecasts (W_t) must satisfy h linear constraints of the form[3]:

$$AW = a \qquad [14]$$

Where $A:hxM$ and $a:hx1$ represent, respectively, the general structure and the final numerical values of such restrictions written in matrix form. For example, *A* may require that certain components of *W* are equal to each other and that the sum of a subset of variables is equal to the sum of another subset. Many other constraints can be envisaged.

The van der Ploeg procedure determines *W* as the solution of the following constrained quadratic optimization program:

$$\underset{W}{MIN} \quad (W-Y)'\Sigma^{-1}(W-Y) \qquad s.t. \quad AW = a \qquad [15]$$

The objective function weights the squared deviations of each unbalanced forecast with respect to its balanced version, using as weights their precisions (the inverse of their corresponding standard error). Note that in the formulation of the objective function [15] the full covariance of the precisions can be considered (Σ). Solving the quadratic optimization program [15] yields to the following solution:

(2) See Abad *et al*. (2006) for a large-scale application to the Spanish Quarterly National Accounts.

(3) In the following, we will drop the time index due to the static nature of the van der Ploeg method.

$$W = Y - \Sigma A'[A\Sigma A']^{-1}(AW - a) \qquad [16]$$

The interpretation of this equation is straightforward: the balanced vector (*W*) is the result of adjusting the preliminary forecasts (*Y*) on the basis of the observed discrepancy (*AW-a*). These discrepancies are weighted according to their precision, i.e. inversely to the uncertainty associated with the initial forecasts. The van der Ploeg method has some interesting features:

- The (absolute) magnitude of revision increases with the variance of the initial estimate ($\sigma_{m,m}$), where $m = 1 \dots M$. That is, the greater the uncertainty surrounding the initial forecast, the greater is the corresponding change.
- Assuming that a given preliminary estimate is known with absolute certainty ($\sigma_{m,m} = 0$), then no adjustment is made: $w_m = y_m$. In this way, we can easily perform what-if scenarios or to impose a hierarchy in the forecasting process.
- If the uncertainty that can be attached to the estimation of two variables is positively related (i.e., the higher the uncertainty when estimating consumption, the higher the uncertainty when estimating investment, $\sigma_{m,n} > 0$), their revisions will also adjust them in the same direction, both upward or both downward. If, on the other hand, this covariance is negative, adjustments will be made in opposite directions: one upward and one downward.

Note that, given the form of the solution, knowledge of the covariance matrix of the preliminary estimates (Σ) is a crucial element. Usually Σ is not known, so it must be estimated, usually in two stages: (a) estimation of variances and (b) estimation of the covariances. The estimation of the variances is linked to the standard errors of the forecasts provided by the set of dynamic factor models for each macro aggregate, while covariances can be derived from the historical correlations of the series that must be balanced. In that case, covariances are derived according to:

$$\sigma_{\mathrm{m,n}} = \rho_{\mathrm{m,n}} \sqrt{\sigma_{\mathrm{m,m}} \sigma_{\mathrm{n,n}}} \qquad [17]$$

The balancing procedure proposed by van der Ploeg avoids some limitations of competing mehods, like the biproportional RAS method [Bacharach (1965)]. In particular, it can manage very general linear constraints, taking into account at the same time different degrees of uncertainty of the forecasts, a quite interesting feature from the point of view of the forecasting practice. In this way, as can be seen in equation [16], the balanced solution avoids the pro-rata adjustment that discredits the RAS method.

The implementation of the van der Ploeg procedure in MIPred considers as inputs the quarter-on-quarter (qoq) rates of GDP and the qoq growth contributions of the remaining macroeconomic variables. The constraint represents the GDP decomposition from the expenditure side:

$$A = \begin{bmatrix} 1 & -1 & \cdots & -1 & 1 \end{bmatrix} \qquad a = 0 \qquad [18]$$

The final (balanced) forecasts impose a hierarchy among them, conferring priority to the initial GDP forecast, setting $\sigma_{GDP} = 0$. This hierarchy reflects the compiling practice of the Spanish QNA, which gives temporal precedence to the estimation of the GDP figure[4] over the estimation of its breakdown. This precedence is not merely a timing issue. When the GDP breakdown is published, the subsequent revisions of the initial GDP estimate are very small. This fact indicates that the information provided by the breakdown has a limited impact on the aggregate GDP estimate, suggesting a top-bottom modelling approach.

3. Output of the model

In order to show the forecasting performance of the model, two exercises have been carried out:

- A full real time estimation exercise for the GDP model in the last four quarters (2014:Q4 – 2015:Q3), and their corresponding disaggregation by demand side components.
- A pseudo-real time estimation exercise since 2007Q1 for the GDP model and their demand components.

3.1. Full real time estimation

The graphs in figure 2 show the evolution of the real-time forecast of GDP in these quarters on a daily basis, including a one standard deviation confidence interval for the forecast value. The time interval during which real time forecasts for each variable are shown in the graphs is defined by the period between two consecutive releases of the corresponding flash estimates published by the National Institute of Statistics (these flash estimates are represented by the dotted line):

Those graphs show how the model reacts to the arrival of the information provided by the indicators. Obviously, this process reduces somewhat the amplitude of the confidence interval, as the cross-sectional estimates are replaced by the observed data. Intuitively, when only "soft" indicators are available, the uncertainty associated with the estimate is greater. Later, when "hard" information arrives (social security contributors, industrial production index, large companies sales, etc.), the estimate becomes less uncertain.

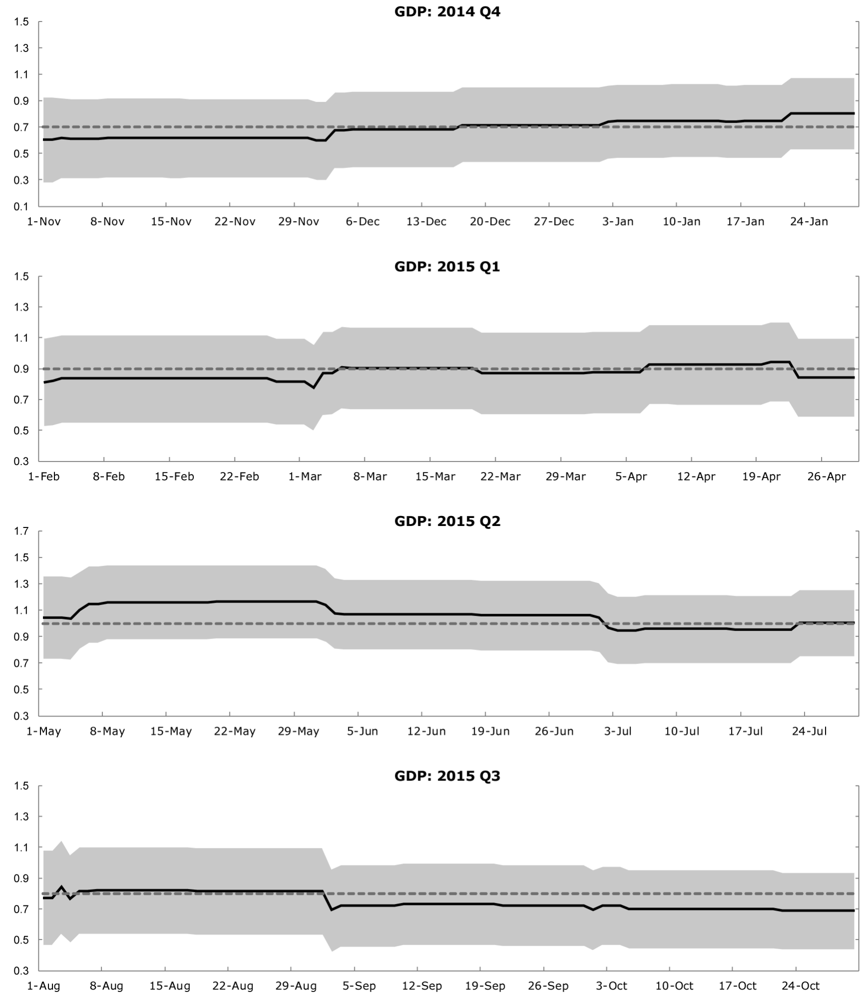
Additionally, the four graphs show that these forecasts were close to the GDP flash release disseminated by the National Statistical Institute and the subsequent final figure (second estimate). It can be seen clearly that, in all cases, the flash data published has fallen within the confidence intervals associated with the estimation, and very close to the central estimation.

On the other hand, and summarizing figures for simplicity, Table 2 shows the final forecast for the different macroeconomic variables in those quarters and their corresponding confidence intervals, comparing them with the final data released in the second estimate of the Quarterly National Accounts.

It can be seen that the forecasts of the components, in most cases, fall within the confidence intervals and the ratio error / standard deviation falls within 1 in absolute value (in order to have a measure that weighs the prediction error in relation with the volatility of the series).

(4) The GDP flash estimate is released about four weeks after the end of the quarter. The second estimate, incorporating the complete GDP breakdown, is released just four weeks after the flash.

Figure 2: GDP GROWTH RATE REAL-TIME FORECASTS



Source: Author's calculation.

It has to be noticed that some sub-aggregates, as in the cases of the series of investment or external trade, have a higher intrinsic volatility that involves wider confidence intervals, making them more difficult to predict.

3.2. Pseudo real time estimation

In order to have a broader idea of the predictive performance of the model, it has been carried out a pseudo real time exercise since 2007Q1 (more than 100 quarters). In this experiment, we have tried to replicate the real-time application of the

Table 2: GDP AND DEMAND AGGREGATES GROWTH RATE REAL-TIME FORECASTS

Q-O-Q Rates. Volume SAC data	Lower limit	Central forecast	Upper limit	Observed data	Error	Error / Std. Dev.
			2014 Q4			
Private Consumption	0.3	0.8	1.2	0.9	0.2	0.4
Public Consumption	-1.6	-0.3	1.0	-1.0	-0.7	-0.5
Investment in equipment	0.3	1.7	3.1	1.4	-0.4	-0.3
Investment in construction	-0.5	0.7	1.9	1.4	0.8	0.6
Exports	-0.9	0.7	2.3	0.0	-0.8	-0.5
Imports	-1.8	0.2	2.1	-0.6	-0.8	-0.4
			2015 Q1			
Private Consumption	0.3	0.7	1.2	0.7	0.0	0.0
Public Consumption	0.0	1.3	2.6	1.6	0.3	0.2
Investment in equipment	2.9	4.2	5.6	1.4	-2.8	-2.1
Investment in construction	0.4	1.6	2.8	1.5	-0.1	-0.1
Exports	-0.5	1.1	2.7	1.0	-0.1	-0.1
Imports	0.6	2.3	4.0	0.8	-1.5	-0.9
			2015 Q2			
Private Consumption	0.7	1.0	1.3	1.0	0.0	0.0
Public Consumption	-0.7	0.5	1.7	0.4	-0.1	-0.1
Investment in equipment	2.9	4.3	5.7	3.2	-1.1	-0.8
Investment in construction	1.0	2.1	3.1	1.4	-0.7	-0.6
Exports	2.0	3.3	4.6	1.6	-1.7	-1.3
Imports	2.8	4.3	5.8	2.3	-2.0	-1.3
			2015 Q3			
Private Consumption	0.2	0.8	1.4	1.0	0.2	0.3
Public Consumption	-1.2	0.4	2.1	0.9	0.5	0.3
Investment in equipment	1.7	3.2	4.8	2.3	-0.9	-0.6
Investment in construction	0.1	0.9	1.8	0.6	-0.3	-0.3
Exports	0.0	1.4	2.7	2.8	1.4	1.0
Imports	0.3	1.7	3.2	4.0	2.2	1.5

Source: INE and Author's compilation.

models as closely as possible. We do not have at hand a complete real-time datasets that comprises both macro aggregates and indicators. However we have taken into account the publication lags in the individual monthly or quarterly series and we have considered a sequence of three forecasts within each quarter. That is, with the information available at the beginning of the quarter estimation period (after the flash estimate of the previous quarter was published), at the middle and at the end. These forecasts have been computed from 1 to 3 quarters in the prediction horizon, which is the usual context where these models are used.

In addition, to obtain a predictive reference of alternative models, we have computed an ARIMA model for GDP and each demand component. The selection and estimation of the best univariate model has been carried out with the TRAMO-SEATS program (see Gómez and Maravall (1996) and Caporello and Maravall, 2004) for a detailed description) in its automatic mode.

Table 3: MAE OF GDP FORECAST AND THEIR DEMAND COMPONENTS

MIPred model:

		GDP	Private Cons.	Public Cons.	Inv. Equip.	Inv. Const	Exports	Imports
1 quarter	end	0.20	0.40	0.41	1.44	0.95	1.00	1.16
	middle	0.20	0.41	0.43	1.49	1.02	1.03	1.27
	beginning	0.21	0.42	0.45	1.72	1.07	1.20	1.33
2 quarter	end	0.26	0.43	0.44	1.84	0.95	1.39	1.71
	middle	0.27	0.43	0.46	1.91	0.94	1.51	1.99
	bbeginning	0.28	0.46	0.48	2.07	1.06	1.65	2.20
3 quarter	end	0.31	0.52	0.52	2.07	1.01	1.68	2.35
	middle	0.33	0.57	0.51	2.21	1.01	1.73	2.38
	beginning	0.38	0.61	0.54	2.33	1.07	1.73	2.38

ARIMA model:

	GDP	Private Cons.	Public Cons.	Inv. Equip.	Inv. Const	Exports	Imports
1 quarter	0.34	0.69	0.53	2.15	1.38	1.97	2.49
2 quarter	0.53	0.83	0.71	2.62	1.69	1.98	2.88
3 quarter	0.65	0.97	0.86	2.70	1.97	1.85	2.77

Source: Author’s calculation.

The mean absolute error (MAE) for both models for quarter on quarter growth rate of GDP and each aggregate is summarize in Table 3. Of these results, it is possible to emphasize the following characteristics. On the one hand, as expected, MAE increases with the forecast horizon, and decreases when new information is available within each quarter. On the other hand, it is evident that for any forecast horizon the error produced by the best univariate models are systematically greater than those of the integrated factor model.

In addition, we can ask the question of whether a model that generates GDP from predictions of its demand components would be a better predictor of GDP than the specific model proposed for GDP itself.

For this purpose, a GDP has been compiled from the predictions of its demand components (so called *derived GDP*), that is, from the predictions of the components that are not required to comply with the prediction constraint of the GDP model.

The results are shown in Table 4. It can be seen how the model that directly predicts the GDP generates more precise forecasts than the model that derives it by direct aggregation.

Table 4: MAE OF GDP FORECAST: DIRECT MODEL VS AGGREGATED DEMAND COMPONENTS

		GDP	Derived GDP
1 quarter	end	0.20	0.27
	middle	0.20	0.27
	beginning	0.21	0.32
2 quarter	end	0.26	0.32
	middle	0.27	0.33
	beginning	0.28	0.33
3 quarter	end	0.31	0.34
	middle	0.33	0.35
	beginning	0.38	0.39

Source: Author's calculation.

Finally, we have made a preliminary analysis of the revisions of the GDP growth during the period 2005-2016, digging into published documents and files. The results are in the Appendix A and show a clear evidence that the estimation of the detailed GDP breakdown does not modify the initial flash estimate of the GDP. This evidence is consistent with a top-bottom approach in the compilation of GDP and rationalizes the top-bottom methodology used in this paper.

4. Conclusions

A wide range of public and private institutions (Bank of Spain, AIReF, BBVA, etc.) are interested in monitoring and forecast the main macro variables of the Spanish economy. The key variables that the government has to forecast when preparing macroeconomic and fiscal projections are GDP and its components.

The main distinctive feature of the methodology we use is that we forecast, on a real time basis, not only GDP but also its complete breakdown from the expenditure side. We have specific models to forecast private consumption, public consumption, investment in equipment, investment in construction, exports and imports. We integrate all of them in a consistent set of forecasts for all the variables that compose GDP.

The model provides a judgement-free measure of current economic conditions, thus offering a timely and easy to interpret output which summarizes these conditions through the GDP growth profile, including its demand-side decomposition.

Appendix a: a preliminary analysis of gdp revisions

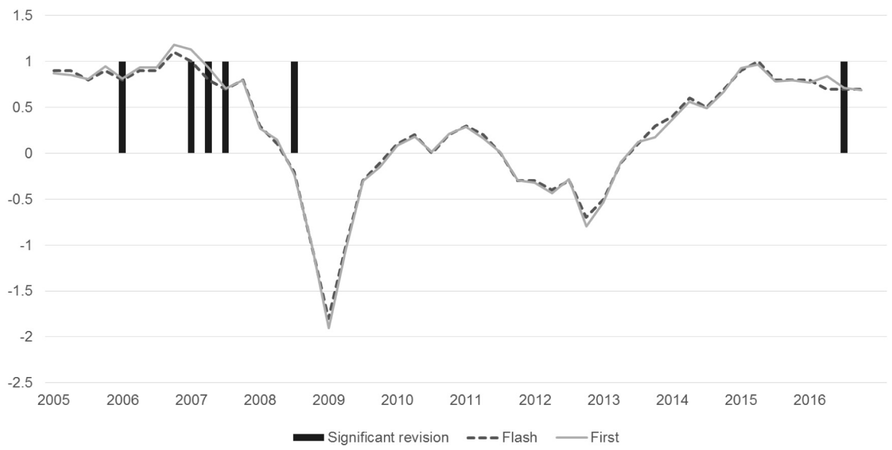
The combination of the GDP forecasts with those of its components uses a benchmarking procedure that guarantees their transversal consistency. Among the available benchmarking procedures we have chosen one that imposes balancing across the components, keeping constant the initial GDP forecast. In other words, the forecasts of the components may be revised but the GDP forecast will not be revised.

This hierarchical structure mimics the compilation procedure of the Spanish QNA, in which the early (or "flash") GDP estimate is slightly revised when its full breakdown is published around one month later.

The flash estimate of the GDP only consists of an estimate of its rate of growth rounded to one decimal place. Flash estimates do not revise previous estimates of the GDP growth.

The first estimate revises the flash estimate introducing a full-length decimal representation and its complete breakdown: demand-side, supply-side, income decomposition and employment. This breakdown includes raw and seasonally adjusted data and, when applicable, valuation at current prices and valuation using volume measure (by means of chain-linking). If the relative sizes of both releases are compared, the flash estimate shows one new number, whereas the first estimate generates a minimum of 180 numbers (in absence of revisions). Moreover, this figure can easily jump to 700 providing revisions are introduced. This large amount of new information barely changes the flash estimate. In fact it can be seen when we consider the significant revision: a number that is outside of the range compatible with a figure rounded to one decimal place. All the significant revisions are made upwards and only occur around 12% of the times. The next figure shows clearly this fact:

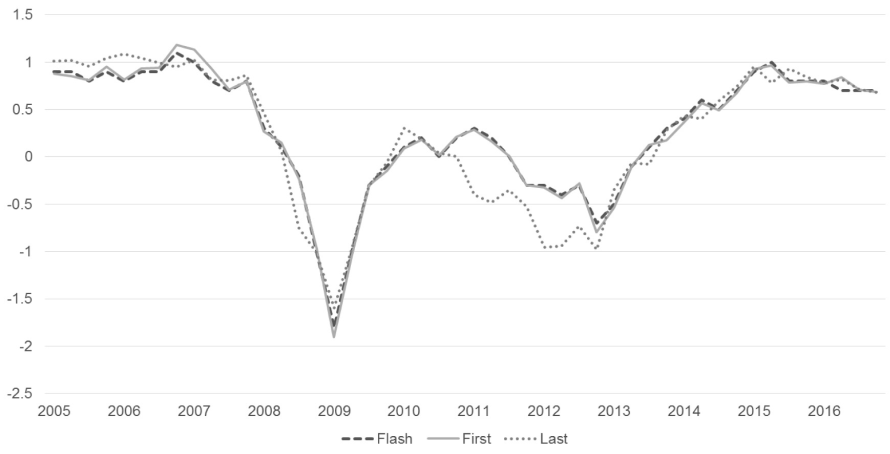
Figure A1: GDP QOQ growth. Flash estimate vs first estimate



Source: INE and Author's calculation.

Apart from the significant revisions, concentrated in the period 2006-2008, the comparison between the first estimate and the last available estimate (from the March 2017 release) allows us to confirm the minimal role attributable to the additional information provided by the GDP components to refine its flash estimate. The next figure compares the three releases:

Figure A2: GDP QOQ growth. Flash estimate vs first estimate vs last estimate (march 2017)



Source: INE and Author's calculation.

What drives the more noticeable revision between the first and the last estimate? A complete exploration of the sources of revision is beyond the scope of this paper. Nevertheless we could infer that the methodological and quantitative changes are these drivers due to the base changes and the benchmarking process that ensures the temporal consistency between the annual data and the quarterly data. The benchmarking process is made once per year, usually in August, and lines up the quarterly data to the independently revised annual data. The statistical features of the revisions are summarized in the next table.

Table A1: Revisions of the GDP QOQ growth

	First vs Flash	Last vs First	Last vs Flash
Mean	0.00	-0.06	-0.06
First quartile	-0.03	-0.19	-0.19
Third quartile	0.02	0.10	0.11
Interquartile rank	0.05	0.29	0.30
Min	-0.13	-0.69	-0.70
Max	0.14	0.31	0.29
Total rank	0.26	1.00	0.99

Source: Author's calculation.

The dominant role of revisions that take place after the moment in which the GDP components are first estimated is clear, suggesting a negligible role in their estimate. Apart from the more sizable revisions introduced after the first release with respect to the initial revisions, their biased nature (in a downward direction) and their asymmetrical shape are evident.

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RESUMEN

Este trabajo presenta una metodología para la predicción del Producto Interior Bruto (PIB) en tiempo real y sus componentes de demanda (consumo privado, consumo público, inversión en equipo, inversión en construcción, exportaciones e importaciones) de manera simultánea. El modelo, por un lado, comprende un conjunto de modelos factoriales dinámicos, tanto para el PIB como para sus componentes de la demanda, que van a proporcionar predicciones individuales para cada uno de ellos. Por otro lado, se incorpora un procedimiento de equilibrado para asegurar la consistencia transversal de estas previsiones, proporcionando así un conjunto coherente de estimaciones basadas en los indicadores estadísticamente más útiles acerca de la actividad económica actual y la evolución de la demanda. La metodología se aplica a la economía española, presentándose previsiones trimestrales del PIB en tiempo real, así como de sus componentes de demanda.

Palabras clave: modelos de factores dinámicos, análisis económico a corto plazo, economía española, filtro de Kalman, previsión, predicción inmediata, cuentas nacionales, equilibrio.

Clasificación JEL: C22, C53, C82, E27.