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Real-time forecasting US GDP from small-scale factor models

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Real-time forecasting US GDP from small-scale factor models*

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Abstract

This paper proposes two refinements to the single-index dynamic factor model developed by Aruoba and Diebold (AD, 2010) to monitor US economic activity in real time. First, we adapt the model to include survey data and financial indicators. Second, we examine the predictive performance of the model when the goal is to forecast GDP growth. We find that our model is unequivocally the preferred alternative to compute backcasts. In nowcasting and forecasting, our model is able to forecast growth as well as AD and much better than several baseline alternatives. In addition, we find that our model could be used to predict more accurately the US business cycles.

Keywords: real-time forecasting, US GDP, business cycles.

JEL: E32, C22, E27.

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1. Introduction

The Great Recession of 2008/9 came as a big shock to policy makers and the business world. The rapid downturn in the economy triggered drastic reactions by policy makers who implemented monetary and fiscal policies to combat the adverse economic situation. In addition, the pervasive effects on retirement plans, stock portfolios and part-time work drastically changed private agents' economic decisions. Since being late entailed dramatic economic consequences, the economic agents seemed to learn the lesson when the recovery started. They acknowledged the need for new tools to monitor economic developments in real time.

In the context of the US economy, Auroba and Diebold (AD, 2010) is an excellent contribution to the warming debate. In line with the seminal proposal of Stock and Watson (1991), they use a small-scale single-index dynamic factor model to produce an accurate economic indicator of US business conditions in real time. As in the Stock-Watson proposal, the model benefits from the information provided by four monthly coincident economic indicators, industrial production, payroll employment, real personal income less transfers, and trade sales. Using the method proposed by Mariano and Murasawa (2003), Aruoba and Diebold (2010) adjust the factor model to handle the different start and finish dates of the indicators, as they are typical in real-time forecasting due to differing release timeliness. In addition, their extension is useful to deal with indicators of monthly and quarterly frequencies, which allows them to include real GDP as an additional fifth coincident indicator to the constituent Stock-Watson set of indicators.

Although Aruoba and Diebold (2010) find that the movements in the real activity indicator strongly cohere with the NBER chronology, plunging during recessions and recovering its average level during expansions, some questions remain unanswered from their study. First, is it worth enlarging the set of factors used in the forecasting equation with soft and financial indicators? Since financial indicators could lead the real activity, to examine this question the baseline model is extended to include leading along with coincident indicators, following the lines suggested by Camacho and Domenech (2012).

Second, can the dynamic factor model be used to produce accurate forecasts of real GDP growth? To develop this analysis, the predictive model is estimated in such a way as to take into account that the goal is to compute short-term forecasts of US GDP growth. The exercise is developed thorough a pseudo real-time analysis where the data vintages are constructed by taking into account the lag of synchronicity in data publication that characterizes real-time data flow. In addition, according to the standard literature on forecasting, the forecasts are computed in a recursive way. Therefore, the model is re-estimated and the forecasts for different horizons are computed with every new vintage as it would have been done by a real-time forecaster.

Our main results can be summarized as follows. First, we find a high performance of the coincident indicator as a business cycle indicator since it is in striking accord with the professional consensus of the history of US business cycle. Second, we ascertain that the percentage of the variance of GDP growth that is explained by the model is slightly above 75%, indicating the high potential ability of the indicators used in the model to explain US growth. Third, our pseudo real-time analysis shows that dynamic factor models clearly outperform univariate forecasts, especially when forecasting the next unavailable figure of GDP growth. This encourages real-time forecasters to back-check the bulk of monthly real and survey data which are published in the respective quarter before the next GDP release. In this context, our extension of Aruoba and Diebold (2010) produces the most accurate forecasts.

The structure of this paper is as follows. Section 2 outlines the model, shows how to mix frequencies, states the time series dynamic properties, and describes the state space representation. Section 3 contains data description and the main empirical results. Section 4 concludes and proposes several future lines of research.

2. The model

2.1. Mixing frequencies

Let us assume that the level of quarterly GDP, Y_t^*, can be decomposed as the sum of three unobservable monthly values Y_t, Y_{t-1}, Y_{t-2}. For instance, the GDP for the third quarter of a given year is the sum of the GDP corresponding to the three months of the third quarter

(1) $$Y^*_{III} = Y_{09} + Y_{08} + Y_{07}$$

or equivalently

(2) $$Y^*_{III} = 3\left(\frac{Y_{09} + Y_{08} + Y_{07}}{3}\right)$$

Among others, Mariano and Murasawa (2003) have shown that if the sample mean of equation (2) can be well approximated by the geometric mean

(3) $$Y^*_{III} = 3(Y_{09} + Y_{08} + Y_{07})^{1/3}$$

then the quarterly growth rates can be decomposed as weighted averages of monthly growth rates. Taking logs of expression (3) leads to

(4) $$\ln Y^*_{III} = \ln 3 + \frac{1}{3}(\ln Y_{09} + \ln Y_{08} + \ln Y_{07})$$

which allows us to compute the quarterly growth rate for the third quarter as

(5) $$\ln Y^*_{III} - \ln Y^*_{II} = \frac{1}{3}(\ln Y_{09} + \ln Y_{08} + \ln Y_{07}) - \frac{1}{3}(\ln Y_{06} + \ln Y_{05} + \ln Y_{04}) = \\ = \frac{1}{3}[(\ln Y_{09} - \ln Y_{06}) + (\ln Y_{08} - \ln Y_{05}) + (\ln Y_{07} - \ln Y_{04})]$$

and by redefining these terms as $y^*_{III} = \ln Y^*_{III} - \ln Y^*_{II}$, and $y_j = \ln Y_j - \ln Y_{j-1}$, one can define

(6) $$y^*_{III} = \frac{1}{3} y_{09} + \frac{2}{3} y_{08} + y_{07} + \frac{2}{3} y_{06} + \frac{1}{3} y_{05}$$

This expression can directly be generalized as

(7) $$y^*_t = \frac{1}{3} y_t + \frac{2}{3} y_{t-1} + y_{t-2} + \frac{2}{3} y_{t-3} + \frac{1}{3} y_{t-4}$$

This aggregation rule represents the quarterly growth rate as the weighted sum of five monthly growth rates.

2.2. Dynamic properties

The model follows the lines proposed by Camacho and Perez Quiros (2010) and Aruoba and Diebold (2010), which are extensions of the dynamic factor model suggested by Stock and Watson (1991). Let us assume that the indicators included in the model admit a dynamic factor representation. In this case, the variables can be written as the sum of two stochastic components: a common component, x_t, which represents the overall business cycle conditions, and an idiosyncratic component, which refers to the particular dynamics of the series. The underlying business cycle conditions are assumed to evolve with *AR(p1)* dynamics

(8) $$x_t = \rho_1 x_{t-1} + \ldots + \rho_{p1} x_{t-p1} = e_t$$

where $e_t \sim iN(0, \sigma_e^2)$.

Apart from constructing an index of the business cycle conditions, we are interested in computing accurate short-term forecasts of GDP growth rates. To compute these forecasts, we start by assuming that the evolution of the 3-month growth rates depends linearly on x_t and on their idiosyncratic dynamics, u_t^y, which evolve as an *AR(p2)*

(9) $$y_t = \beta_y x_t + u_t^y,$$

(10) $$u_t^y = d_1^y u_{t-1}^y + \ldots + d_{p2} u_{t-p2}^y + \varepsilon_t^y$$

where $\varepsilon_t^y \sim iN(0, \sigma_y^2)$. In addition, the idiosyncratic dynamics of the k monthly indicators can be expressed in terms of autoregressive processes of $p3$ orders:

(11) $$z_t^i = \beta_i x_t + u_t^i$$

(12) $$u_t^i = d_1^i u_{t-q}^i + ... + d_{p3} u_{t-p3}^i + \varepsilon_t^i$$

where $\varepsilon_t^i \sim iN(0, \sigma_i^2)$. Finally, we assume that all the shocks e_t, ε_t^y, and ε_t^i, are mutually uncorrelated in cross-section and time-series dimensions.

2.3. State space representation

Let us first assume that all the variables included in the model were observed at monthly frequencies for all periods. Since GDP is used in quarterly growth rates, y_t^*, according to expressions (7)-(9) it enters into the model as

(13) $$y_t^* = \beta_y \left(\frac{1}{3} x_t + \frac{2}{3} x_{t-1} + x_{t-2} + \frac{2}{3} x_{t-3} + \frac{1}{3} x_{t-4}\right) + \left(\frac{1}{3} u_t^y + \frac{2}{3} u_{t-1}^y + u_{t-2}^y + \frac{2}{3} u_{t-3}^y + \frac{1}{3} u_{t-4}^y\right)$$

The unit roots of hard indicators are accounted for by using the time series in their monthly growth rates. Soft indicators, such as the consumer confidence and the purchasing managers' index, are used in levels. Calling Z_t^* the monthly growth rates of hard or the level of soft variables, the dynamics of these variables are captured by

(14) $$Z_{it}^* = \beta_i x_{t-j} + u_t^i$$

with $i = 1, 2, ..., k1$.

Finally, following the suggestions of Wheelock and Wohar (2009), financial indicators are treated as leading indicators of the current business conditions[1]. Accordingly, following the lines suggested by Camacho and Domenech (2012), we establish the relationship between the level (in the case of term spread) of the financial indicator, Z_{ft}^*, and the h-period future values of the common factor, as follows:

(15) $$Z_{ft}^* = \beta_f x_{t+h} + u_t^f$$

As it is shown in the Appendix, this model can be easily stated in state space representation and estimated by using the Kalman filter. However, we assumed that the time series do not contain missing data which becomes clearly an unrealistic assumption since our data exhibits ragged ends and mixing frequency problems. Fortunately, Mariano and Murasawa (2003) show that the Kalman filter can be used to estimate the model's parameters and infer unobserved components and missing observations. These authors propose replacing the missing observations with random draws ∂_t, whose distribution cannot depend on the parameter space that characterizes the Kalman filter[2]. Hence, while this procedure leaves the matrices used in the Kalman filter conformable, the rows containing missing observations will be skipped from the updating in the recursions and the missing data are replaced by estimates. In this way, forecasting is very simple since forecasts can be viewed as missing data located at the end of the model's indicators.

1: To facilitate the analysis, following Giannone, Reichlin and Small (2008) financial data enter into the model as monthly averages since the bulk of information compiled from the indicators is monthly.
2: We assume that $\partial_t \sim N(0, \sigma_\partial^2)$ for convenience but replacements by constants would also be valid.

3. Empirical results

3.1. Preliminary analysis of data

The data set managed in this paper, which was collected on January 29, 2012, spans the period from January 1960 to December 2011. Regarding the potential set of indicators that could be used in the analysis, we only choose those that verify four properties. First, they must exhibit high statistical correlation with the GDP growth rate, which is the target series to be predicted. Second, for a given quarter they should refer to data of this quarter, which must be published before the GDP figure becomes available in the respective quarter. Third, they must be relevant in the model from both theoretical and empirical points of view. Finally, they must be available in at least one third of the sample.

We started the analysis with the set of coincident economic indicators used in Aruoba and Diebold (2010), real quarterly GDP, monthly industrial production, payroll employment, real personal income less transfers, and trade sales, which exhibit a strong link with the GDP cycle. This set is enlarged with early published hard (economic activity) indicators, which are typically available with a delay of one or two months, and soft (based on opinion surveys) indicators, which do not exhibit publication delays. Among the set of hard indicators, we include new industrial orders, housing starts and the SP500. Among the set of soft indicators, from those which are available we include the Conference Board consumer confidence index and the ISM manufacturing PMI. Finally, the set of indicators is enlarged by including the term spread, which is available on a timely basis. In this paper, the term spread is measured as the difference between the yields on long-term and short-term maturities (10-year Treasury bond yield at constant maturity minus Federal Funds effective rate).

The indicators used in the empirical analysis and their respective release lag-time are listed in Table 1. All the variables are seasonally adjusted. GDP enters in the model as its quarterly growth rate; hard indicators enter in monthly growth rates; and soft and financial indicators enter with no transformation. Before estimating the model, the variables are standardized to have a zero mean and a variance equal to one. Therefore, the final forecasts are computed by multiplying the initial forecasts of the model by the sample standard deviation, and then adding the sample mean.

Table 1
Final variables included in the model

	Series	Sample	Source	Publication delay	Data transform
1	Real Gross Domestic Product (GDP, SAAR, Bil. Chn.2005$)	60.1 11.4	BEA	3	QGR
2	Industrial Production Index (IPI) (SA, 2007=100)	60.01 11.12	Fed. Reserve	2	MGR
3	All Employees: Total Nonfarm Payrolls (Empl, SA, Thous)	60.01 11.12	BLS	1.5	MGR
4	Real Personal Income Less Transfer Payments (Income, SAAR, Bil.Chn.2005$)	60.01 11.11	BEA	2	MGR
5	Retail Sales & Food Services (Sales, SA, Mil.$)	67.01 11.12	Census	2	MGR
6	Mfrs' New Orders: Nondefense Capital Goods ex Aircraft (MNO, SA, Mil.$)	92.03 11.12	Census	0	MGR
7	Conference Board: Consumer Confidence (CC, SA, 1985=100)	67.02 11.12	Conference Board	0	L
8	ISM Manufacturing: PMI Composite Index (PMI, SA, 50+=Increasing)	60.01 11.12	ISM	0	L
9	House Housing Starts (House, SAAR, Thous.Units)	60.01 11.12	Census	2	MGR
10	Standard & Poor's 500 Stock Price Index (SP500, 1941-43=10)	60.01 11.12	NYT	0	MGR
11	Slope Yield Curve 10Y-Fed (Slope)	62.01 11.12	Treasury & FRB	0	L

Notes: SA means seasonally adjusted. MGR, QGR and L mean monthly growth rates, quarterly growth rates and levels, respectively.
Source: BBVA Research

3.2. In-sample analysis

Selecting the indicators that must be included in a dynamic factor model from the universe of potentially available time series is still an open question in empirical studies. For instance, Boivin and Ng (2006), have found that selecting a smaller subset of the potential set of available indicators, and using the factors that summarize the information in that smaller subset of data in the forecasting equation, substantially improves forecast performance.

In this paper, the selection of the US indicators to be used in the dynamic factor model, follows the recommendations suggested by Camacho and Perez Quiros (2010)[3]. Following Stock and Watson (1991), we start with a model that only includes monthly coincident measures of real economic activity such as industrial production, employment, income and sales. The estimated factor loadings, which measure the correlation between the economic indicators and the common factor, appear in the row labeled as M1 in Table 2. All of them are positive, indicating that these economic indicators are procyclical. In all cases, the factor loadings are statistically significant.

Table 2

Loading factors

Model	GDP	IP	Empl	Inc	Sales	MNO	CC	PMI	House	SP500	Slope	% var
M1	---	0.57 (0.03)	0.58 (0.03)	0.33 (0.03)	0.20 (0.02)	---	---	---	---	---	---	---
M2	0.25 (0.01)	0.59 (0.03)	0.56 (0.03)	0.35 (0.03)	0.21 (0.02)	---	---	---	---	---	---	76.64%
M3	0.26 (0.01)	0.61 (0.03)	0.55 (0.03)	0.35 (0.03)	0.22 (0.02)	0.29 (0.03)	---	---	---	---	---	76.44%
M4	0.25 (0.01)	0.60 (0.03)	0.55 (0.03)	0.35 (0.03)	0.22 (0.02)	0.28 (0.03)	0.05 (0.01)	---	---	---	---	76.36%
M5	0.24 (0.01)	0.59 (0.03)	0.54 (0.03)	0.34 (0.03)	0.21 (0.02)	0.28 (0.03)	0.06 (0.01)	0.04 (0.01)	---	---	---	77.76%
M6	0.24 (0.01)	0.58 (0.03)	0.54 (0.03)	0.37 (0.03)	0.22 (0.02)	0.27 (0.03)	0.06 (0.02)	0.04 (0.02)	0.10 (0.02)	0.12 (0.03)	---	78.06%
M7	0.25 (0.01)	0.58 (0.03)	0.54 (0.03)	0.36 (0.04)	0.22 (0.02)	0.27 (0.03)	0.06 (0.02)	0.04 (0.02)	0.10 (0.02)	0.12 (0.03)	0.01 (0.01)	78.19%

Notes. The loading factors (standard errors are in brackets) measure the correlation between the common factor and each of the indicators appearing in columns. See Table 1 for a description of these indicators.
Source: BBVA Research

Aruoba and Diebold (2010) use the modified Stock-Watson model proposed by Mariano and Murasawa (2003) to add GDP to the initial set of four economic indicators[4]. The estimated loading factors of this model are displayed in the row labeled as M2 in Table 2. Notably, the loading factors of the monthly indicators are quite similar to those displayed in row M1, which correspond to the model that does not use GDP. The loading factor of real GDP is also positive and statistically significant. The percentage of the variance of GDP that is explained by the model stands slightly above 75%, indicating the high potential ability of the indicators used in the model to explain GDP.

The delay in the publication of some of these five indicators makes it interesting to check if the forecasting performance of economic activity can be improved upon in real time by including additional early available indicators. For this purpose, manufacturing new orders and some soft indicators such as consumer confidence and manufacturing PMI were included in the model. In addition, due to their role in the recent downturn, housing starts and the SP500 were also included. According to the rows labeled as M3, to M6 in Table 2, the loading factors of these indicators are positive and statistically significant and the percentage of GDP explained by the model increases to 78.06 in M6.

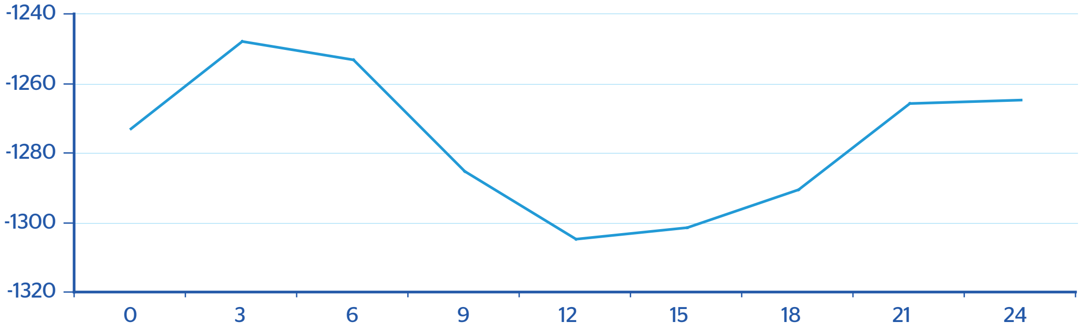
The final enlargement of the model is conducted by including the term spread. In this context it is worth quoting the recent survey by Wheelock and Wohar (2009), who present mixing evidence on the role of the term spread in forecasting GDP. Notably, they find that, if any, the correlation between GDP growth and the slope of the yield curve appear when the spread is assumed to lead from one to six quarters. According to these results, financial indicators are assumed to lead the business

3: All the dynamic factor models use *p1= p2=p3=2*.

4: Note that this implies handling indicators of mixing frequencies and indicators that may start at different periods and that may exhibit different publication lags.

cycle dynamics in h months, with h=1,...,24. To select the optimal number of leads, we compute the log likelihood associated with these lead times. According to Figure 1, the maximum of the likelihood function is achieved when the term spread leads the common factor by three months. The estimated loading factor of the model that includes the term spread leading the factor by three months, which is displayed in the row labeled as M7 in Table 2, shows it is not statistically significant. Therefore, the term spread is not included in the model[5].

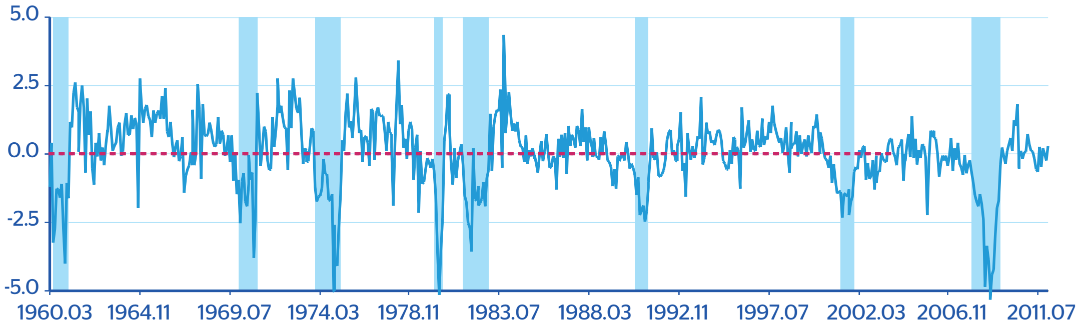
Figure 1
Log likelihood and lead time of the term spread



Notes. The term spread at time t has been related to the common factor at time $t+h$. In this figure, h appears in the horizontal axis and the log likelihoods reached by the dynamic factor model appear in the vertical axis.
Source: BBVA Research

Our model is based on the notion that co-movements among the macroeconomic variables have a common element, the common factor that moves in accordance with the US business cycle dynamics. To check whether the business cycle information that can be extracted from the common factor agrees with the US business cycle, the coincident indicator along with shaded areas that refer to the NBER recessionary periods are plotted in Figure 2. The figure shows the high performance of the coincident indicator as a business cycle indicator since it is in striking accord with the professional consensus as to the history of US business cycle. During periods that the NBER classifies as expansions, the values of the coincident indicator are usually positive. At around the beginning of the NBER-dated recessions the common factor drastically falls and remains low until around the times the NBER dates the end of the recessions.

Figure 2
Common factor



Notes: Shaded areas correspond to recessions as documented by the NBER.
Source: BBVA Research

To analyze in depth the accuracy of the common factor to compute business cycle inferences, let us assume that there is a regime switch in the index itself[6]. For this purpose, we assume that the switching mechanism of the common factor at time t, xt, is controlled by an unobservable state variable, st, that is allowed to follow a first-order Markov chain. Following Hamilton (1989), a simple switching model may be specified as:

(16) $$x_t = c_{s_t} + \sum_{j=1}^{p} \alpha_j x_{t-j} + \varepsilon_t \ ,$$

5: This result does not imply that financial indicators are not leading economic indicators. This implies that the leading information provided by financial variables is already contained in the rest of the economic indicators included in the model.
6: Camacho, Perez Quiros and Poncela (2012) show that although the fully Markov-switching dynamic factor model is generally preferred to the shortcut of computing inferences from the common factor obtained from a linear factor model, its marginal gains rapidly diminish as the quality of the indicators used in the analysis increases. This is precisely our case.

where ε_t~$iidN(0, \sigma)$ [7]. The nonlinear behavior of the time series is governed by c_{s_t}, which is allowed to change within each of the two distinct regimes $s_t=0$ and $s_t=1$. The Markov-switching assumption implies that the transition probabilities are independent of the information set at $t-1$, X_{t-1}, and of the business cycle states prior to $t-1$. Accordingly, the probabilities of staying in each state are

(17) $$p(s_t=i/s_{t-1}=j, s_{t-2}=h, \dots, X_{t-1}) = p(s_t=i/s_{t-1}=j)=p_{ij}.$$

Taking the maximum likelihood estimates of parameters, reported in Table 3, in the regime represented by $s_t=0$, tthe intercept is positive and statistically significant while in the regime represented by $s_t=1$, it is negative and statistically significant. Hence, we can associate the first regime with expansions and the second regime with recessions. According to related literature, expansions are more persistent than downturns (estimated p_{00} and p_{11} of about 0.98 and 0.91, respectively). These estimates are in line with the well-known fact that expansions are longer than contractions, on average.

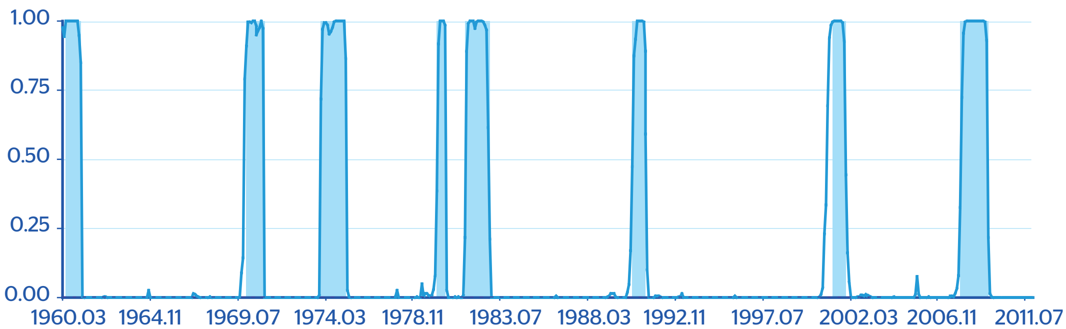
Table 3
Markov-switching estimates

c_0	c_1	σ_2	p_{00}	p_{11}
0.39 (0.04)	-1.99 (0.11)	0.88 (0.05)	0.98 (0.01)	0.91 (0.02)

Notes. The estimated model is $x_t = c_{s_t} + \varepsilon_t$, where x_t is the common factor, s_t is an unobservable state variable that governs the business cycle dynamics, ε_t~$iidN(0, \sigma)$, and $p(s_t = i/ s_{t-1} = j) = p_{ij}$.
Source: BBVA Research

Finally, Figure 3 displays the estimated smoothed probabilities of recessions along with shaded areas that refer to the periods classified as recessions by the NBER. The figure illustrates the great ability of the model to capture the US business cycle and validates the interpretation of state $s_t=1$ as a recession and the probabilities plotted in this chart as probabilities of being in recession.

Figure 3
Filtered probabilities from common factor



Notes: Shaded areas correspond to recessions as documented by the NBER.
Source: BBVA Research

3.3. Simulated real-time analysis

Among many others, Stark and Croushore (2002) suggest that the analysis of in-sample forecasting performance of competitive models is questionable since the results can be deceptively lower when using real-time vintages. This happens because the in-sample analysis misses three aspects of real-time forecasting: (i) the recursive estimation of the model parameters; (ii) the real time data flow, i.e. the fact that data are released at different point in time; and (iii) the real time data revisions.

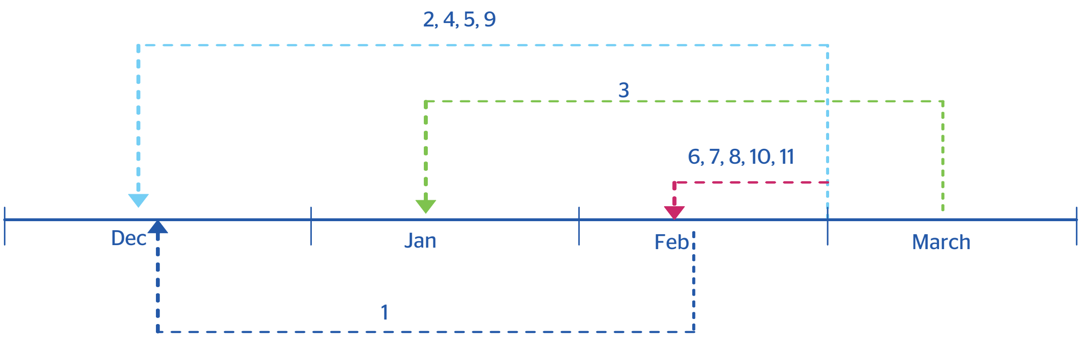
However, although developing real-time data sets is conceptually simple, producing real-time vintages is, as in our case, unfeasible since the historical records of many time series are not available. In the context of dynamic factor models, an interesting alternative to the real-time forecasting analysis is the pseudo real-time forecasting exercise suggested by, among others, Giannone, Reichlin and Small (2008). Their proposal consists of taking into account the recursive estimate of the models and the real time data flow (and hence the publication lags) but, due to data availability constraints, does not consider data revisions.

7: According to Camacho and Perez Quiros (2007), we included no lags in the factor. We checked that the resulting model is dynamically complete in the sense that the errors are white noise.

The proposal is based on trying to mimic as closely as possible the real time analysis that would have been performed by a potential user of dynamic factor models when forecasting, at each period of time, on the basis of different vintages of data sets. The experiment considers that the releases of each vintage contain missing data at the end of the sample reflecting the calendar of data releases. This allows us to reproduce every 15 days the typical end of the sample unbalanced panel faced by the forecaster due to the lack of synchronization of the data releases. Accordingly, the experiment is labeled as "pseudo" because the vintages are not obtained in pure real time but from the latest available data set.

Since the data is released in blocks and the releases follow a relatively stable calendar, each forecast is conditional on the updated set of data releases that follow the stylized schedule depicted in Figure 4. For example, if the data vintage is updated on February 1, the data set is enlarged with new industrial orders, the consumer confidence and purchasing manufacturing indexes, the term spread and the SP500, whose latest figures refer to January. In addition, the data set is also enlarged with industrial production, income, sales and house starts, whose latest figures refer to December. However, when the data vintage is updated on February 15, the data set is enlarged with employment, whose last figure refers to January. Finally, the data vintage is updated with GDP at the start of February, May, August, and November, whose latest figures refer to December, March, June and September, respectively.

Figure 4
Stylized real time data realizations



Notes: Number correspond to indicators as Table 1 summarizes.
Source: BBVA Research

The forecast performance analysis was conducted to simulate real-time forecasting. The first data vintage of this experiment refer to August 1, 1989 and, although it was collected from the information of the latest available data set, it preserved the data release calendar that a forecaster would have faced on that day. Using this data vintage, we computed nine-month blocks of forecasts. Among them, some refer to the last quarter's GDP growth before its official release (backcasts), others refer to current quarter GDP growth (nowcasts), while others refer to the next quarter's GDP growth (forecasts). Following the stylized calendar described above, the data vintages were recursively updated on the first day and fifteenth day of each month. All parameters, factors, and so forth were then re-estimated, and nine-month blocks of backcasts, nowcasts and forecasts were then computed. The final pseudo real-time nine-month block of forecasts was made on May 15, 2012, leading to 540 different blocks of forecasts.

Plots of actual and pseudo real-time predictions are shown in Figure 5. The straight lines depict simulated real-time forecasts of US GDP growth while dashed lines refer to the corresponding final quarterly data, which are equally distributed among the respective days of the quarter for the sake of comparison. Overall, the forecasts follow sequential patterns that track the business cycle marked by the evolution of GDP releases. However, the real-time estimates become more accurate in the case of backcasts (top panel) since the predictions are computed immediately before the end of the quarter, which allow them to use the latest available information of the respective quarter. Accordingly, nowcasts (middle panel) and forecasts (bottom panel) track the GDP dynamics with some delays since they use poorer information sets to compute predictions although they are available sooner.

Figure 5

Real time predictions and actual realizations

Notes: Actual realizations of GDP growth (dotted line) and real time predictions, backcasts (top), nowcasts (middle) and forecasts (bottom panel).

Source: BBVA Research

The predictive accuracy of our model is examined in Table 4. The table shows the mean-squared forecast errors (MSE), which are the average of the deviations of the predictions from the final releases of GDP available in the data set. Results for backcasts, nowcasts and forecasts appear in the second, third and fourth columns of the table, respectively. In addition to the factor model described in Section 2 (labeled as "our model"), two benchmark models are included in the forecast evaluation. The former is an autoregressive model of order two (AR) which is estimated in real-time producing iterative forecasts, and the latter is a random walk (RW) model whose forecasts are equal to the average latest available real-time observations. Finally, the pseudo real-time forecasting exercise constitutes a natural framework to evaluate the value added in forecasting GDP from our model with respect to the seminal model proposed by Aruoba and Diebold (2010).

Table 4
Predictive accuracy

	Backcasts		Nowcasts		Forecasts	
Mean Squared Errors						
Our model	0.226		0.360		0.436	
	E: 0.193	R: 0.465	E: 0.243	R: 1.195	E: 0.219	R: 1.958
RW	0.404		0.500		0.504	
	E: 0.210	R: 2.531	E: 0.211	R: 2.554	E: 0.217	R: 2.569
Our model/RW	0.359		0.721		0.866	
AR	0.358		0.431		0.491	
	E: 0.208	R: 1.435	E: 0.208	R: 2.007	E: 0.209	R: 2.413
Our model/AR	0.629		0.838		0.888	
AD	0. 257		0.369		0.445	
	E: 0.218	R: 0.536	E: 0.243	R: 1.264	E: 0.218	R: 2.033
Our model/AD	0.879		0.977		0.980	
Equal predictive accuracy tests						
Our model vs RW	0.003		0.016		0.006	
Our model vs AR	0.018		0.092		0.004	
Our model vs AD	0.016		0.543		0.269	

Notes. The forecasting sample is 1989.3-2011.4, which implies comparisons over 540 forecasts. The top panel shows the Mean Squared Errors (MSE) of our dynamic factor model, a random walk (RW), an autoregressive model of order two (AR), and the dynamic factor model proposed by Aruoba and Diebold (2010), along with the relative MSEs over that of our model. R and E refer to recessions and expansions periods according to NBER. The bottom panel shows the p-values of the Diebold-Mariano (DM) test of equal predictive accuracy.
Source: BBVA Research

Note that the MSE leads to a ranking of the competing models according to their forecasting performance. However, it is advisable to test whether the forecasts made with the dynamic factor model are significantly superior to the other models' forecasts. To analyze whether empirical loss differences between two or more competing models are statistically significant, there are a large number of tests proposed in the literature. The last three rows of the table shows the pairwise test introduced by Diebold and Mariano (DM, 1995) which seems to be the most influential and most widely used test.

The immediate conclusion obtained when comparing the forecasts from multivariate models with those from univariate models is that the former clearly outperforms the latter. Although the gains diminish with the forecast horizon (the relative MSE range from 0.40 to 0.88), according to the p-values of the DM test, the differences in forecasting performance are always statistically significant. To analyze the stability of the forecasting performance over time, Table 4 also incorporates within-recessions and within-expansion MSEs, which are computed from the cycles already identified by NBER. The corresponding figures show that the forecasting improvements become especially important during the NBER recessions. These results encourage real-time forecasters to check back at the bulk of monthly real and survey data which are published in the respective quarter before the next GDP release, especially in the midst of a recession.

Notably, our extension of the Aruoba and Diebold (2010) dynamic factor model exhibits forecast improvements over the seminal proposal. Again, the gains in using the dynamic factor model in forecasting GDP growth depend on the forecast horizon. In the backcasting exercise, the differences between the MSE results of these two factor models are noticeable (relative MSE of 0.879) and statistically significant (p-value of 0.016). In nowcasting and forecasting, our model still exhibits lower MSEs although the gains diminish considerably (relative MSE of about 0.98) and the differences are not statistically significant.

4. Conclusions

We set out an extension of the dynamic factor model proposed by Aruoba and Dieblod (2010) which was originally designed to produce high frequency measurement of macroeconomic activity in a systematic, replicable, and statistically optimal manner from GDP, industrial production, sales and employment data. Our extension allows us to examine the informational content of additional real activity data, survey indexes and financial indicators to produce short-term forecasts of US GDP growth.

We find a high performance of the coincident indicator as a business cycle indicator since it is in striking accord with the professional consensus as to the history of US business cycle. By means of a simulated real-time empirical evaluation, which was designed to replicate the data availability scheme faced in a true real-time application, we show that our model produces more accurate forecasts than several benchmarks univariate models. Notably, our extension exhibits forecast improvements over the seminal Aruoba-Diebold proposal, especially when the target is the next figure of GDP growth. Therefore, we consider that our model is a valid tool to be used for short-term analysis.

Appendix

Without loss of generalization, we assume that our model contains only GDP, one non-financial monthly indicator and one financial monthly indicator, which are collected in the vector $Y_t = (y_t^*, Z_{it}^*, Z_{ft}^*)'$. For simplicity's sake, we also assume that $p1 = p2 = p3 = 1$, and that the lead for the financial indicator is $h = 1$. In this case, the observation equation, $Y_t = Z\alpha_t$, is

$$
\text{(A1)} \quad \begin{pmatrix} y_t^* \\ Z_{it}^* \\ Z_{ft}^* \end{pmatrix} = \begin{pmatrix} 0 & \frac{\beta_y}{3} & \frac{2\beta_y}{3} & \beta_y & & \frac{2\beta_y}{3} & \frac{\beta_y}{3} & \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} & 0 & 0 \\ 0 & \beta_i & 0 & & \dots & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ \beta_f & \beta_f & & & & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_{t+1} \\ x_t \\ \vdots \\ x_{t-4} \\ u_t^y \\ \vdots \\ u^y_{t-4} \\ u_t^i \\ u_t^f \end{pmatrix}
$$

It is worth noting that the model assumes contemporaneous correlation between non-financial indicators and the state of the economy, whereas for financial variables, the correlation is imposed between current values of the indicators and future values of the common factor.

The transition equation, $\alpha_t = T\alpha_{t-1} + \eta_t$, is

$$
\text{(A2)} \quad \begin{pmatrix} x_{t+1} \\ x_t \\ \vdots \\ x_{t-4} \\ u_t^y \\ \vdots \\ u^y_{t-4} \\ u_t^i \\ u_t^f \end{pmatrix} = \begin{pmatrix} \rho_1 & \dots & 0 & 0 & 0 & \dots & & & 0 \\ 1 & & & 0 & & \dots & & & 0 \\ \vdots & \ddots & & \vdots & & \dots & & & \vdots \\ 0 & \dots & 1 & 0 & & \dots & & & 0 \\ 0 & \dots & & 0 & d_1^y & 0 & 0 & & 0 \\ \vdots & \dots & & \dots & & \ddots & & & \vdots \\ 0 & \dots & & & & 1 & 0 & & 0 \\ 0 & \dots & & & & 0 & 0 & d_1^i & 0 \\ 0 & \dots & & & & 0 & 0 & 0 & d_1^f \end{pmatrix} \begin{pmatrix} x_t \\ x_{t-1} \\ \vdots \\ x_{t-5} \\ u^y_{t-1} \\ \vdots \\ u^y_{t-5} \\ u^i_{t-1} \\ u^f_{t-1} \end{pmatrix} \begin{pmatrix} e_{t+1} \\ e_t \\ \vdots \\ e_{t-5} \\ \varepsilon^y_{t-1} \\ \vdots \\ \varepsilon^y_{t-5} \\ \varepsilon^i_t \\ \varepsilon^f_t \end{pmatrix}
$$

where $\eta_t \sim iN(0,Q)$ and $Q = diag(\sigma_e^2, 0, \dots, 0, \sigma_y^2, 0 \dots 0, \sigma_i^2, \sigma_f^2)$.

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